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THE PREDICTION OF RESERVOIR SEDIMENTATION ACROSS ENGLAND AND WALES

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The sands of time were eroded by the river of constant change.

Genesis

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Abstract

The principal aim of this thesis is to produce a comprehensive assessment of the spatial variation of reservoir sedimentation for the population of surface water storage reservoirs, exhibiting a degree of catchment-coupling, across England and Wales. This is the first time that such a study has been undertaken. To achieve this, a valid model had to be developed to predict reservoir sedimentation for those sites where no direct measurements were available. Using readily available secondary data describing catchment and reservoir basin factors identified to influence reservoir sedimentation, two lumped-empirical models were developed. The first model used the traditional modelling technique of multiple regression; the second used fuzzy set multi-criteria evaluation (MCE), a technique not previously applied to reservoir sedimentation modelling. Both techniques were applied to a population data set (established herein). The models were validated using primary data from bathymetric surveys.

Through multiple regression, models predicting reservoir annual percentage capacity loss (APL) could not be verified and validated due to violations of the assumptions of the technique. A major reason for these failures was the inability of the approach to account for uncertainty and error associated with the quantification of the dependent and independent variables, and the specification of the respective relationships.

Through fuzzy set MCE, a model predicting the degree of reservoir sedimentation for the population data set was verified and validated to a reasonably good level; as was an associated defuzzification model converting the predicted fuzzy number to a predicted APL rate. The fuzzy set MCE modelling technique was identified as the most suitable for accomplishing the principal aim because, unlike multiple regression, it was able to account for uncertainty and error associated with the quantification and specification of the catchment and reservoir basin factors that influence reservoir sedimentation.

Upon operationalization, the fuzzy set MCE model and associated defuzzification model identified the upland areas of Cumbria, Wales, the southern Pennines and the southwest as

experiencing the largest levels of reservoir sedimentation. This is primarilly attributed to these areas having high mean annual rainfall and large areas of highly erosive soil types. The outputs of the fuzzy set MCE model and associated defuzzification model allow attention to be focused by reservoir undertakers on areas where sustainability of water supply may be most sensitive to loss of reservoir capacity from sedimentation.

1. Introduction – Principal Aim & Objectives

The principal aim of this research is the comprehensive assessment of the spatial variation of reservoir sedimentation for the population of surface water storage reservoirs exhibiting a degree of catchment-coupling across mainland England and Wales. The term catchment-coupled refers to reservoirs that collect and store water directly from their catchment areas. Reservoirs which exhibit a degree of catchment-coupling are not directly connected to their catchment areas, principally due to the presence of management structures (e.g. bywash channels, additional pumped storage inputs etc.).

There are two major types of catchment-coupled surface storage reservoirs; those based on pre-existing lakes (expanded lakes), and those created as fresh impoundments on the floors of river valleys (flooded valleys). Expanded lakes inherit the hydrological conditions of the original lake, modified only by the raising of the water level submerging previously higher areas. This acts to increase the sediment trap efficiency of the water body, increasing rates of basin infilling (Section 2.11.2.1). However, more dramatic hydraulic changes are induced through the construction of flooded valley reservoirs (McManus, 1985).

In natural, unmodified river reaches, when viewed over a relatively short segment of time (e.g. 100 years), a graded condition, or dynamic equilibrium exists (Schumm and Lichty, 1965; Thornes and Brunsden, 1977). Such a condition can be defined as exhibiting balanced fluctuations about a mean value, or average system behaviour that itself has a trending, non-repetitive mean value (Thorn, 1988). In fluvial systems under dynamic equilibrium, an approximate balance exists with respect to sediment inflow and outflow, and stability in elevation, gradient and channel form is implied (Wolman, 1967). However, dam construction for the formation of flooded valley reservoirs punctuates the dynamic equilibrium, creating an impounded river reach with lower flow velocities and efficient sediment trapping. The impounded reach will accumulate sediment and lose reservoir storage capacity until new conditions of dynamic equilibrium are established. This normally occurs after the reservoir becomes filled with sediment and can no longer provide water storage (Morris and Fan, 1997). Therefore, both expanded lake and flooded valley reservoirs have the potential to experience sedimentation.

The ensuing process of sedimentation clearly has the potential to undermine the security of water supply from surface storage reservoirs (Figure 1.1). However, across England and Wales the process reservoir sedimentation as a threat to water resources has received little attention from researchers. Two factors explain this:

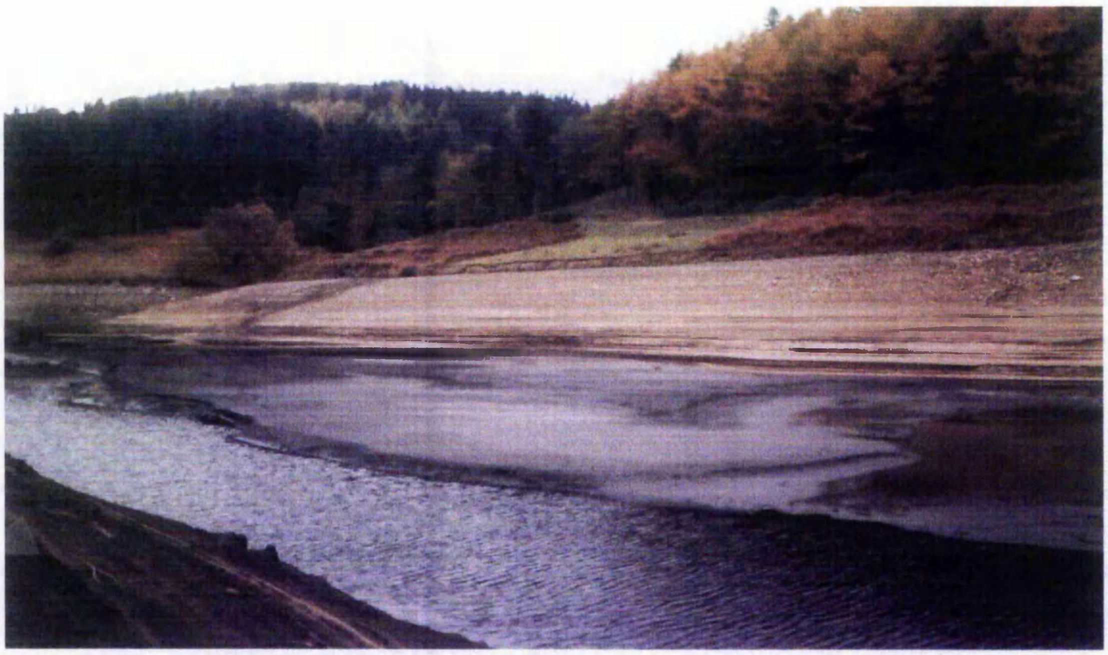
1. The process of sedimentation is a relatively slow process and due to the typical nature of its accumulation underwater, it is removed from popular, political and engineering consciousness (Morris and Fan, 1998).

2. The mean sediment yield transported by British rivers is low in global terms. Walling (1987) identified a mean suspended sediment yield of around 50 t km^{-2} $year^{-1}$ for Great Britain whereas Walling and Webb (1996) stated that the global maximum reported mean annual specific suspended sediment yields typically exceed 10000 t km^{-2} $year^{-1}$. Therefore, since the greatest proportion of sediment that accumulates in British reservoirs is typically produced externally to the accumulation basin and delivered through the respective catchment sediment yield (Labadz *et al.,* 1999, 2002), sedimentation at face value does not appear to be a major problem in the context of water resource management across England and Wales.

However, Labadz *et al.* (2002) identified problems of reservoir sedimentation with regards to water supply across England and Wales as upstream sites were favoured because they generate sufficient head to supply to distant towns. These areas are typically conducive to higher erosion rates and sediment yields due to steeper relief, reduced sediment storage opportunities and greater rainfall. In addition, highly erodible soils, poor vegetation cover and intense agricultural activity may exacerbate this. A database compiled by Labadz and Butcher for the Halcrow report (2001) collated all the limited available information to date on rates of reservoir sedimentation across Great Britain. The report showed the mean value of annual percentage capacity loss (APL) from 121 reservoirs was 0.13% of original capacity per year, with the maximum being 1.01%. For the many reservoirs across England and Wales built in the 1800s to supplement the growth of manufacturing and large urban populations, such an annual percentage loss will by now have a serious effect on storage capacity.

As a result of this concern, a comprehensive assessment of reservoir sedimentation across England and Wales is required to help maintain the security of water resources. This thesis attempts to deliver this through the achievement of the principal aim and supporting objectives (classified below) based around the modelling of reservoir annual percentage capacity loss rates across England and Wales for water resource planning. It is not an objective of this research to develop a detailed process-based model of sedimentation within individual reservoir basins.

Figure 1.1 Sedimentation at Howden Reservoir - stage nine metres below top water level (Lees, 2003 pers. comm.)



1.1 Principal Aim

- The production of a comprehensive assessment of the spatial variation of reservoir sedimentation for the population of surface water storage reservoirs exhibiting a degree of catchment-coupling across mainland England and Wales.

The term reservoir in this investigation is used to define all impounded water bodies that are present in the BRE dams data set (Tedd *et al.*, 1992) and fall under the Reservoir Act, 1975. It is from the BRE dams data set that the population of reservoirs for this research was extracted (Section 4.2). It was initially intended to include Scottish reservoirs in the population, but the prohibitive cost of secondary data necessitated their exclusion from the current research.

The population of surface water storage reservoirs exhibiting a degree of catchment-coupling across mainland England and Wales was defined as those reservoirs present in the Flood Estimation Handbook software (FEH) (1999) that appear directly connected to the fluvial network (Section 4.2.1). (Indeed, the information extracted from the FEH (1999) for the parameterization of the models developed herein can only be obtained for those reservoirs that are directly connected to the fluvial network.) This implies that the reservoir is catchment-coupled as opposed to being completely pump storage for example. However, whilst reservoirs may appear directly connected to the fluvial network in the FEH (1999), they may not necessarily be completely catchment-coupled. The term catchment-coupled in this study describes a reservoir basin that is connected completely and exclusively to the corresponding catchment and its associated processes of sediment production and delivery. Some reservoirs, however, whilst being directly connected to the corresponding catchment are not completely linked due to residuum lodge entrapment upstream for example; whereas some are not connected exclusively due to catchwater inputs from other watersheds for example (see Section 2.11.2.2). However, such information is not present in the FEH (1999) (or obtainable from any other readily available secondary data source), therefore reservoirs identified as being directly connected to the fluvial network in FEH (1999) can only ever be assured of exhibiting a **degree** of catchment-coupling.

1.2 Objectives

1. The collation of secondary data from standard, widely-available sources for the defined reservoir population. These standard, widely-available data sources incorporate the BRE dams data set, the Flood Estimation Handbook (1999), the national soils map of England and Wales and the land cover map of Great Britain that together depict catchment and reservoir basin factors that influence reservoir sedimentation.

2. The collection of primary data concerning reservoir annual percentage capacity loss rates to supplement the parameterization data set collated from the literature, ensuring it is representative of the defined reservoir population, and form a validation data set.

3. The production of two parameterized, verified, validated and operationalized empirical models predicting reservoir sedimentation for the defined reservoir population from catchment and reservoir basin factors using two different modelling techniques: multiple regression analysis and fuzzy set multi-criteria evaluation. The former represents a more traditional empirical modelling approach; the latter has not been applied in such studies before.

4. The evaluation and comparison of the multiple regression and fuzzy set multi-criteria approaches and the subsequent selection of the most robust and reliable model in the prediction of sedimentation for the defined reservoir population.

1.3 Contribution to knowledge

The through completion of the aforementioned principal aim and supporting objectives the contribution to knowledge of this investigation will be primarily twofold. Firstly, the premier comprehensive assessment of reservoir sedimentation across England and Wales will be made providing increased understanding of the nature and spatial variation of the process across the two countries. This is due to the fact that standard, widely-available secondary data sources incorporating England and Wales (the BRE dams data set, the Flood Estimation Handbook (1999), the national soils map of England and Wales and the land cover map of Great Britain) have not been applied before to investigate broad-scale reservoir sedimentation. In addition, the data set compiled by Labadz and Butcher for the Halcrow report (2001) collating all the published measured rates of reservoir sedimentation across England and Wales has not been accessed and applied before to provide the most comprehensive parameterization data set possible for model development. Each of these secondary data sources are utilized herein.

Secondly, the study assesses the application of fuzzy set theory in predicting reservoir sedimentation in comparison to the traditional multiple regression approach, identifying the most suitable modelling technique for such broad-scale investigations. Such an application of fuzzy set theory has not been undertaken before; indeed, the technique is relatively new to all aspects of water resources management as a whole (Mujumdar, 2002). This represents an important contribution to knowledge as previous applications of multiple regression analysis concerning reservoir sedimentation in the UK have proved relatively unsuccessful (e.g. Duck and McManus, 1990; Butcher *et al.*, 1992a; White, 1993; Labadz *et al.*, 1995) prompting the requirement for alternative methods.

2. Review of reservoir sedimentation

2.1 Introduction

This chapter identifies why reservoir sedimentation should be of concern to water resource and associated catchment managers, and describes the nature of the reservoir sedimentation process and the factors that influence sedimentation rates. This leads to the formulation of a conceptual model of sedimentation in surface water storage reservoirs exhibiting a degree of direct catchment-coupling.

2.2 Sedimentation rates for UK reservoirs

The data set compiled by Labadz and Butcher for the Halcrow report (2001) collated all of the evidence available at the time on reservoir sedimentation rates across the UK. From the BRE dams data set (Tedd *et al.*, 1992) that contains over 2500 reservoirs that fall under the Reservoirs Act, 1975, information regarding sedimentation (reservoir annual percentage capacity loss - APL) was only available for 121 reservoirs (Table 2.1). From Table 2.1 it can be seen that the reservoir sedimentation data available are sparse. Regional reservoir sedimentation assessments of varying comprehensiveness are essentially only available across the UK for the Pennine reservoirs surveyed by White, Labadz and Butcher (1996 etc.), northwest England surveyed by Foster and Lees (1999 etc.) as part of the NERC LOIS project, and the Midland Valley of Scotland reservoirs surveyed by Duck and McManus (1987, 1994 etc.). The remaining information is mostly for single reservoirs which have been the subject of an individual research project, or where sedimentation was of particular concern to the undertaker. In the context of this study, this does not provide a comprehensive assessment of reservoir sedimentation across England and Wales.

The mean APL value across the 121 reservoirs is 0.13% of original capacity per year, with the maximum being 1.01%. The regional mean APL values for the Pennine, east midlands and Midland Valley of Scotland reservoirs are 0.115%, 0.091% and 0.174% respectively. The mean date of reservoir construction from the Halcrow (2001) data set is 1897 (with a standard deviation of 55.76 years). Therefore an average APL of 0.13% extrapolated over 107 years (from 1897 to 2004) renders an average total percentage of reservoir capacity loss (TPL) of 13.91%. Mahmood (1987) states that the global average for the useful life of a reservoir, often defined as the time taken for 90% of the live reservoir storage to be depleted (Labadz *et al.*, 2002), is less than 25 years. Clearly, with an average TPL of 13.91%, the average useful life of British reservoirs is considerably longer. However, whilst these average values of sedimentation in British reservoirs appear low in global terms, they may be of increasing significance as water resources become more pressurized associated with climate change and increased demand (Section 2.3). In addition, the results do identify high APL values in certain reservoirs, thus having a serious effect on respective storage capacities. Indeed, for Abbeystead and Blakeley reservoirs, the two cases with the largest APL rates across England and Wales, the loss of total reservoir capacity over a century is essentially 100% and 76% respectively. Abbeystead reservoir was originally constructed to provide compensation water in conjunction with a water abstraction scheme supplying Lancaster. It was latterly maintained as a flood attenuation structure but almost complete sedimentation has rendered it obsolete for both functions (Rowan *et al.*, 1995).

Table 2.1 Reservoirs extracted from the Halcrow (2001) data set with a measure of annual percentage capacity loss (APL) (nb. includes Scotland)

Dam name	Undertaker	Annual % capacity loss
Abbeystead	North West Water	0.686
Alton Water	Anglian Water	0.016
Angram	Yorkshire Water	0.028
Ardleigh	Tendring Hundreds Water Co	0.238
Baitings	Yorkshire Water	0.205
Barden Lower	Yorkshire Water	0.035
Barden Upper	Yorkshire Water	0.075
Beaverdyke	Yorkshire Water	0.073
Bilberry	Yorkshire Water	0.602
Blackmoorfoot	Yorkshire Water	0.066
Blackmoss Lower	North West Water	0.090
Blackmoss Upper	North West Water	0.160
Blagdon	Bristol Waterworks Company	0.040
Blakeley	Yorkshire Water	0.751
Boltby	Yorkshire Water	0.041
Booth Wood	Yorkshire Water	0.001
Boshaw Whams	Yorkshire Water	0.109

Broadstones	Yorkshire Water	0.015
Broomhead	Yorkshire Water	0.088
Butterley	Yorkshire Water	0.402
Cameron (East)	Fife Regional Council	0.073
Carron Valley	Central Regional Council	0.817
Castle Howard Great Lake	Castle Howard Estate	0.220
Chelker	Yorkshire Water	0.042
Chew Valley Lake (Chew Stoke)	Bristol Waterworks Company	0.089
Chorley	Environment Agency	0.217
Covenham	Anglian Water	0.000
Dale Dyke	Yorkshire Water	0.064
Damflask	Yorkshire Water	0.032
Dean Head Lower	Yorkshire Water	0.030
Dean Head Upper	Yorkshire Water	0.093
Deanhead	Yorkshire Water	0.024
Deerhill	Yorkshire Water	0.028
Diddington (Grafham Water)	Anglian Water	0.148
Doe Park	Yorkshire Water	0.124
Drumain	Fife Regional Council	0.012
Earlsburn No.1	Central Regional Council	0.089
Eldwick	Yorkshire Water	0.124
Elslack	Yorkshire Water	0.067
Embsay	Yorkshire Water	0.117
Empingham (Rutland Water)	Anglian Water	0.153
Fewston	Yorkshire Water	0.009
Foxcote	Anglian Water	0.063
Glenfarg (East)	Fife Regional Council	0.044
Gorple Lower	Yorkshire Water	0.066
Gorple Upper	Yorkshire Water	0.055
Gorpley	Yorkshire Water	0.095
Gouthwaite	Yorkshire Water	0.204
Graincliffe	Yorkshire Water	0.109
Green Withens	Yorkshire Water	0.017
Harden	Yorkshire Water	0.094
Harperleas	Fife Regional Council	0.014
Hewenden	Yorkshire Water	0.150
Holl	Fife Regional Council	0.053
Hollowell	Anglian Water	0.110
Holmestyes	Yorkshire Water	0.005
Hopes	Lothian Regional Council	0.082
Howden	Severn-Trent Water	0.000
Ingbirchworth	Yorkshire Water	0.086
John OGaunts	Yorkshire Water	0.028
Kelly	Strathclyde Regional Council	0.135
Kinder	North West Water	0.180
Langsett	Yorkshire Water	0.169

Leeshaw	Yorkshire Water	0.130
Lindley Wood	Yorkshire Water	0.036
Lintrathen	Tayside Regional Council	0.027
Loch Benachally	Tayside Regional Council	0.339
Loch Lee	Tayside Regional Council	1.009
Lower Laithe	Yorkshire Water	0.096
Mixenden	Yorkshire Water	0.003
North Esk	M R Jones	0.086
North Third	Central Regional Council	0.186
Ogden	Yorkshire Water	0.026
Ogden Lower	North West Water	0.085
Ogden Upper	North West Water	0.210
Pickup Bank	North West Water	0.180
Pinmacher	Strathclyde Regional Council	0.037
Pitsford	Anglian Water	0.156
Ponden	Yorkshire Water	0.067
Ramsden	Yorkshire Water	0.163
Ravensthorpe	Anglian Water	0.079
Redmires Lower	Yorkshire Water	0.009
Redmires Middle	Yorkshire Water	0.065
Redmires Upper	Yorkshire Water	0.085
Reva	Yorkshire Water	0.145
Riding Wood	Yorkshire Water	0.167
Ringstone	Yorkshire Water	0.000
Rivelin Lower	Yorkshire Water	0.159
Rivelin Upper	Yorkshire Water	0.075
Roundhill	Yorkshire Water	0.039
Royd Moor	Yorkshire Water	0.051
Ryburn	Yorkshire Water	0.008
Scammonden	Yorkshire Water	0.288
Scar House	Yorkshire Water	0.120
Scout Dike	Yorkshire Water	0.090
Silsden	Yorkshire Water	0.471
Snailsden	Yorkshire Water	0.175
Strines	Yorkshire Water	0.150
Strinesdale Lower	North West Water	0.070
Strinesdale Upper	North West Water	0.070
Stubden	Yorkshire Water	0.082
Sunnydale	Yorkshire Water	0.102
Ten Acres	Yorkshire Water	0.019
Thoresby Lake (Upper)	Thoresby Estates	0.330
Thornton Moor	Yorkshire Water	0.102
Torside	North West Water	0.100
Tunnel End	British Waterways Board	0.487
Underbank	Yorkshire Water	0.035
Walshaw Dean Lower	Yorkshire Water	0.115

Walshaw Dean Middle	Yorkshire Water	0.052
Walshaw Dean Upper	Yorkshire Water	0.093
Walverden	North West Water	0.225
Water Sheddles	Yorkshire Water	0.037
Wessenden Head	Yorkshire Water	0.038
Wessenden Old	Yorkshire Water	0.229
Whinny Gill	Yorkshire Water	0.172
Widdop	Yorkshire Water	0.044
Windleden Lower	Yorkshire Water	0.074
Windleden Upper	Yorkshire Water	0.066
Wyresdale Lake	JA & J Whewell	0.228
Yateholme	Yorkshire Water	0.002

2.3 Threat to water resources

The UK water industry is currently in a dynamic and challenging period of water resource management and planning (McIntyre *et al.*, 2003). For the water companies of England and Wales, this was first prompted by a run of extremely dry years from 1990 to 1996 that forced many water companies to implement demand restrictions and call on emergency resources (Marsh, 1996). This highlighted the inadequacies of water resources in numerous resource zones. In terms of surface storage reservoirs, the major systems in the Pennines and Lake District supplying large areas of northern and midland Britain declined to below 20% of capacity in 1995, posing a real threat to resources (Marsh, 1996). During this drought, supply was maintained for large areas of Yorkshire only by standpipes and a huge tankering operation (Fleming, 2003). Similar stresses on water supply were exerted in 2003 with England and Wales experiencing one of the driest 12 months in 74 years (Fleming, 2003). Table 2.2 identifies the state of surface storage reservoir totals for the principal water companies across England and Wales in late autumn 2003.

Table 2.2. State of reservoir capacities for the principal water companies of England and Wales, autumn 2003 after Fleming (2003).

Water Company	State of reservoirs autumn 2003
Bristol Water	Reservoirs 46% full, 38% lower than autumn 2002.
Welsh Water	Southeast Wales reservoirs 33% full.
Anglian Water	70% full, just below average.
South West Water	Reservoirs 49% full, usually 70% for late autumn.
Severn Trent	Concern over capacity of Elan Valley (43%), Derwent Valley (38%) And Tittesworth (50%) reservoirs.
Thames Water	Farmoor reservoir 40% full. Pumping 140 ML/day from north London aquifer for the first time since 1997.
Southern Water	Darwell reservoir 30 % full, usually 65% for late autumn. Bewl Water and Powdermill reservoirs - 55% and 46% full respectively, both usually 80% for late autumn.
United Utilities	Reservoirs 50% full, usually 70% for late autumn.
Yorkshire Water	Reservoirs 50% full, usually 70% for late autumn.

Clearly climatic stresses that threaten water supply can be exerted on surface storage reservoirs across England and Wales. Such stresses are deemed likely to increase with the UK climate becoming warmer. The Environment Agency's annual review of water resources (2002) states that from present climate change scenarios, by the 2080s:

- Annual average temperature across the UK may rise between 2°C and 3.5°C, with greater warming in the south and east.
- Winters will become wetter and summers drier everywhere, but by the 2020s, changes will be within the range of natural variations experienced now.
- Hot dry summers will happen much more frequently than they do now.

Increasing demand, which is deemed likely to continue (Scott and Molyneux, 2001), compounds the effect of increasing climate stresses on water resources. The Environment Agency's water resource strategy report (2001) states that across much of England and Wales, water is already a scarce resource and improvements to capacity and supply over the next 25 years are necessary. For example, in some catchments, particularly in southeast England, there is no additional water available to meet future demand (Environment Agency, 2001).

The report recommends the enhancement of public water supply by up to 1100 Ml/d above present levels after environmental improvements have been taken into account. These environmental improvements include proposed enhancement of existing resource systems and the development of some new large schemes. Examples of proposed existing system enhancement include the transfer of water from more secure supply areas due to hydro-meteorological factors and/or reduced demands, to areas where additional supplies are required (e.g. the proposed transfer of water from the Thames basin to Southern and/or Anglian regions), and increasing the capacity of existing reservoirs. New reservoir schemes are currently being considered in the lowlands of the Thames region, East Anglia and southeast England (Environment Agency, 2001; Scott and Molyneux, 2001).

Clearly the effect of sedimentation reducing the storage capacity and useful life of a reservoir can further compound the stresses on water resources induced by climate and increased demands. For one water company in the north of England, the costs of lost water yield due to reservoir sedimentation were estimated at £74 million (White *et al*, 1996a).

2.4 Threat to reservoir operation

Sedimentation in the impounded basin can affect the operation of the reservoir through numerous ways.

The process of reservoir sedimentation can threaten dam stability if excessive build up occurs on the upstream side. This is because sediment deposits have a greater mass than water (Cedergren, 1975). All dams holding 25,000m^3 must be inspected annually under the terms of the Reservoir Act, 1975; close to 2,500 dams fall under the Act (listed in the BRE dams data set). There are typically three to four major leakage incidents each year requiring remedial action on dams that fall under the Reservoirs Act, 1975 (Mylius, 2003). Dam failure is of increasing engineering and political concern. Originally, most dams were situated many miles away from urban development but relentless urbanization since the peak of dam construction has pushed development into the path of water which would be released by dam failures (Mylius, 2003). It is this concern that prompted the investigation of water and sediment release by dam failures in the Halcrow report (2001). In addition, dam scour and drawoff works can become blocked with sediment threatening the safety of dam operation (Mylius, 2003). This can result in periodic reservoir drawdown to excavate sediment or abandonment of bottom outlet facilities.

If the dam has been constructed for hydroelectric power generation, an increased sediment load coarser than 0.1mm causes significant abrasion of the turbine runners, undermining plant efficiency (Morris and Fan, 1998).

2.5 Increased flood risk on influent streams

Upstream of a reservoir the local base level of the influent streams is raised to that determined by the height of the dam spillway. This in itself can threaten adjacent land, although is compounded by induced sediment aggradation.

The comparatively slow velocity of flow in the reservoir basin inhibits the forward motion of influent streams causing the backing up of flow. The level to which backing up occurs is principally dependent upon the water level in the reservoir, as this defines the local energy base, and the stream discharge (McManus, 1985). The reduced velocity and turbulence of influent streams causes a decrease in stream competency and initiates aggradation and consequent delta formation first in the influent stream channels. The rate of delta progression into reservoirs is dependent on the stream discharge, the reservoir basin geometry and catchment characteristics (McManus, 1985). Aggradation induces a positive feedback response through raising the channel floor bed and decreasing the local channel gradient. This can be manifested many kilometres upstream and can increase the extent of flooding across adjacent land. Consequent overbank flow can cause "warping" through fresh deposition of coarser sediment on the flood plain. In addition, this risk can cause waterlogging and soil salinization, affecting communities and agricultural activity on the floodplains (Morris and Fan, 1998). If the deltas become colonized by vegetation, the positive feedback response can be intensified through the increase in hydraulic roughness inducing further aggradation, thus spreading the detrimental effects over a wider area (Dingman, 1994).

Arnot *et al* (1969, page 254) observed these processes caused by the damming of the Shire River in Malawi, "…the flow is stated to have stopped when the lake was low owing to the presence of sand and silt bars in the tributary streams…their growth assisted by the growth of reeds, creeping grass and papyrus." Such processes can impair navigation through the catchment network especially in the vicinity of locks, approach channels, boat ramps and marinas (Morris and Fan, 1998).

2.6 Threat to ecology

Aggradation of sediment within the reservoir and influent streams can also severely affect ecology. Sedimentation leads to aquatic habitat degradation through the progressive transition of open water to wetlands, and eventually raised elevated areas (Brookes *et al*, 1996). This reduces physical habitat diversity, a key characteristic of productive water bodies, through the destruction of appropriate ranges of water depths and velocities required for spawning habitats (Brookes *et al*, 1996). Continued aggradation also reduces the velocity and turbulence of flow lowering the dissolved oxygen content and reducing the delivery of nutrients and pollution dispersal (Brookes *et al*, 1996). Furthermore, fresh-water pollution from point sources (e.g. discrete pipes or canals) and/or nonpoint sources (e.g. groundwater and diffuse flows from the land surface) can increase through contaminant adsorption from free cation exchange surfaces on the deposited sediment (Dingman, 1994).

The reduction of dissolved oxygen content in reservoirs due to the reduction of the velocity and turbulence of flow can be intensified by biological activity when coupled with extreme water detention times. Priha (1969) states that the danger inherent in too long a detention is that biological activity uses up all the oxygen after which the water begins to deteriorate. However, Priha (1969) also states that too short a detention time does not allow biological activity to purify the water. The loss of dissolved oxygen, however, is immediately remedied by cascading water at the reservoir outlets (Morris and Fan, 1998).

2.7 Threat to water quality

If the reservoir is used for water supply, sedimentation can affect the water quality, especially if organic rich sediments are present and become dessicated during dry summers whereupon they release colour on rewetting (Butcher *et al*, 1992b). In addition, as mentioned in the previous section, an increase in the fine sediment fraction of the sediment yield may lead to increases in the number of exchange sites available for the transport of sediment-associated contaminants thus affecting water quality (Foster and Lees, 1999a).

Through the analysis of the sediment geochemistry of Silsden reservoir, Foster and Lees (1999a) identified anoxic conditions associated with increased levels of organic matter. This was partly induced by the phosphorous (P) content of the inflowing suspended sediment into the reservoir basin associated with use as an agricultural fertilizer. The small iron:manganese (Fe:Mn) ratio of the sediment helped identify the anoxic conditions in the reservoir. The Fe:Mn ratio is frequently used to identify redox changes. Mn is generally more mobile under anoxic conditions and thus yields a smaller ratio under such conditions (Foster and Walling, 1994). The small Fe:Mn ratio value in the Silsden basin sediment was partly attributed to the P content of the reservoir sediment increasing levels of organic matter production to such an extent as to induce anoxia. Indeed, a significant negative relationship was found between P and the Fe:Mn ratio, with the latter being inversely correlated with organic matter content (determined by loss on ignition). This is to be expected as greater P levels incorporated into reservoir sediment induces greater organic matter production which subsequently leads to a depletion of the water's oxygen supply and the onset of anoxia (as reflected by a low Fe:Mn ratio) (Foster and Walling, 1994).

2.8 Direct use of research

In addition to providing increased scientific knowledge of reservoir sedimentation, the nature of the research is of direct use in many related hydrological applications:

2.8.1 Water resource management

Water companies in England and Wales are responsible for water resource plans submitted to the Environment Agency setting out how water resources will be managed over the proceeding 25 years in light of climate change and changes in demand scenarios. The Environment Agency keeps these plans under annual review (Environment Agency, 2002). The prediction of reservoir sedimentation will provide information directly useful to these water resource plans, allowing both the water companies and Environment Agency to assess the impact of basin infilling on the capacity of reservoirs as part of a water resources security risk assessment. In addition the model could be applied to identify reservoirs of more secure supply and capacity in terms of reduced sedimentation rates, and assess the potential rate of infilling in new hydrological developments. Through the nature of the model predicting reservoir sedimentation from catchment and reservoir basin factors, insights into the effect of catchment management strategies on reservoir operation could also be obtained.

2.8.2 Environmental Act, 1995 enforcement

The prediction of reservoir sedimentation is also of use to the Environment Agency. The Environment Act, 1995 gives the Agency a duty to promote the conservation and enhancement of flora and fauna of inland and coastal waters and associated land (Environment Agency, 2001). Reservoir sedimentation can degrade habitats and adversely affect adjacent land (Section 2.6). The identification of reservoir catchments experiencing nationally high levels of sedimentation could form part of an initial assessment regarding risk to associated habitats, directing further ecological research.

2.8.3 Engineering perspectives

As discussed in Section 2.4, the issue of dam failure is of increasing political and engineering concern. As a result, Mylius (2003) calls for a risk-based approach to identify potential dam failures considering the reservoir volume, catchment factors such as topography, land use and the dam dimensions. Comprehensive information on lake and reservoir sedimentation provided through this investigation could provide important supplementary information for such an approach.

In assessing potential dam failure (e.g. Halcrow, 2001), especially with regards to sedimentation, further concern is expressed regarding large ornamental lakes that fall under the Reservoir Act, 1975 (Mylius, 2003). Dams and reservoir basins constructed for water supply, hydroelectric power generation and other industrial uses typically have information available concerning original capacities, bathymetry etc. However, no such information is often available for large ornamental lakes; therefore the establishment of the quantity of deposited sediment or rate of deposition based upon the original basin capacity is very difficult. The application of the model produced through this research will provide a very useful evaluation tool in such circumstances.

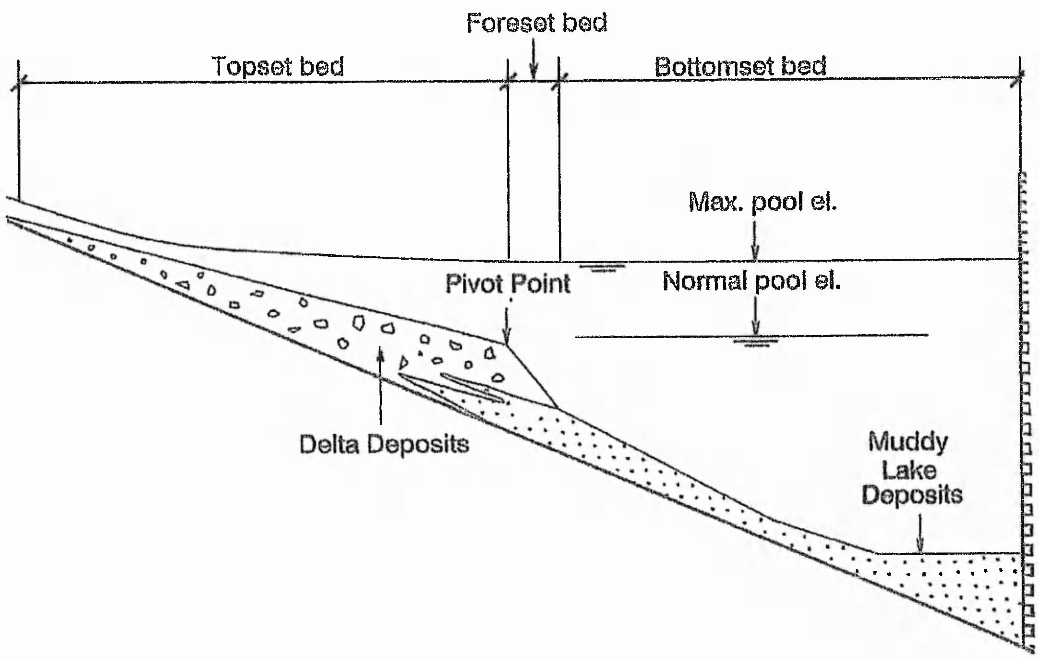
In addition, the model predictions will allow the potential degree of reservoir sedimentation to be incorporated into the design of new reservoirs; i.e. the designs of new schemes in the Thames basin, East Anglia and the southeast (Environment Agency, 2001). Verstraeten *et al.* (2002) state that an accurate estimate of reservoir sedimentation rates should be made during the planning of new reservoirs.

2.9 Sediment deposition in reservoirs

The mechanics of sediment deposition in reservoirs is extensively covered in the technical literature (e.g. McManus, 1985; Mahmood, 1987; Julien, 1995) and is only briefly described here.

As the inflow (transporting sediment) enters the reservoir basin, its velocity is quickly reduced as a result of backwater from the dam and an increase in the channel cross-sectional area. In addition the dampening of water turbulence occurs. These effects decrease the stream competency to maintain sediment motion and therefore induce deposition (Heinemann, 1984). The pattern of sediment deposition is dependent upon many factors including the size and texture of sediment particles, the physical characteristics of the reservoir basin, the water level of the reservoir and reservoir operation (Boreland and Miller, 1960). Typically the coarser particles greater than 0.06mm in diameter are deposited first in the reservoir headwaters, whilst progressively finer particles are carried further into the reservoir basin. The resultant lobate deposit of sediment builds out into the reservoir around the mouth of the influent channel forming a delta. The delta deposits are comprised of topset beds and foreset beds, both becoming finer in sediment grain size downstream (Figure 2.1). The downstream limit of the topset beds corresponds to the downstream limit of bed material transport in the reservoir. The foreset beds represent the face of the delta that slopes down into the reservoir and typically lie at a steeper gradient than the topset beds. Fine sediment particles are transported further into the reservoir and are eventually deposited on the floor of the basin forming bottomset beds.

Figure 2.1 Generalized depositional zones in a reservoir (after Morris and Fan, 1998)



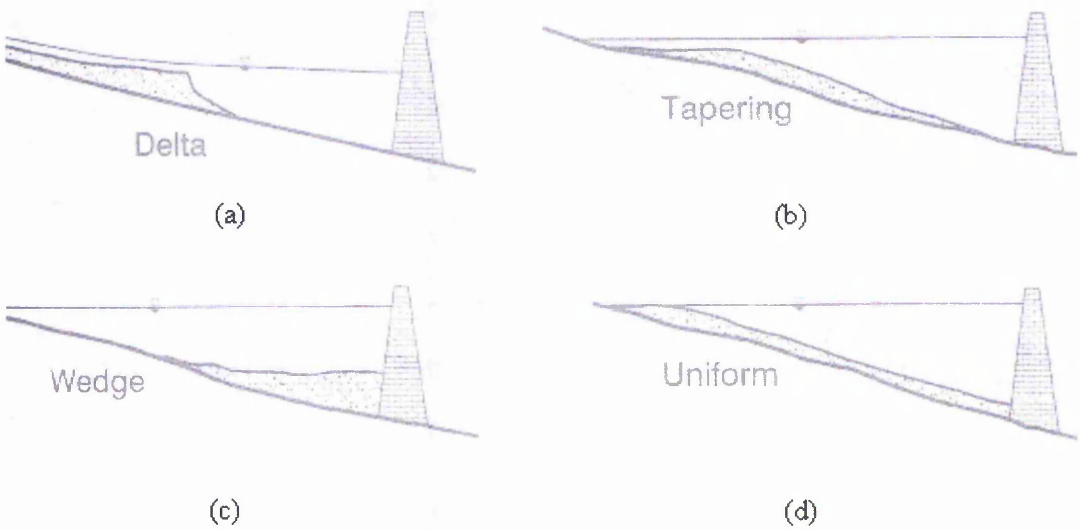
In addition to delta deposits, Morris and Fan (1998) identify three other generalized patterns of sediment deposits, depending on inflowing sediment characteristics and reservoir operation (Figure 2.2):

1. Wedge-shaped deposits (Figure 2.2b) become thicker downstream towards the dam typically caused by the transport of large quantities of fine sediment in density currents. Such deposits commonly occur in large reservoirs operated at low water levels where the velocity of the influent streams increases upon entry into the reservoir basin resulting in increased scour. The eroded material can then be transported further into the basin, towards the dam before deposition (McManus, 1985).

2. Tapering deposits (Figure 2.2c) become thinner downstream towards the dam reflecting increased deposition upstream on entry into the reservoir. This is a common pattern in long reservoirs normally held at a high pool level (Morris and Fan, 1998).

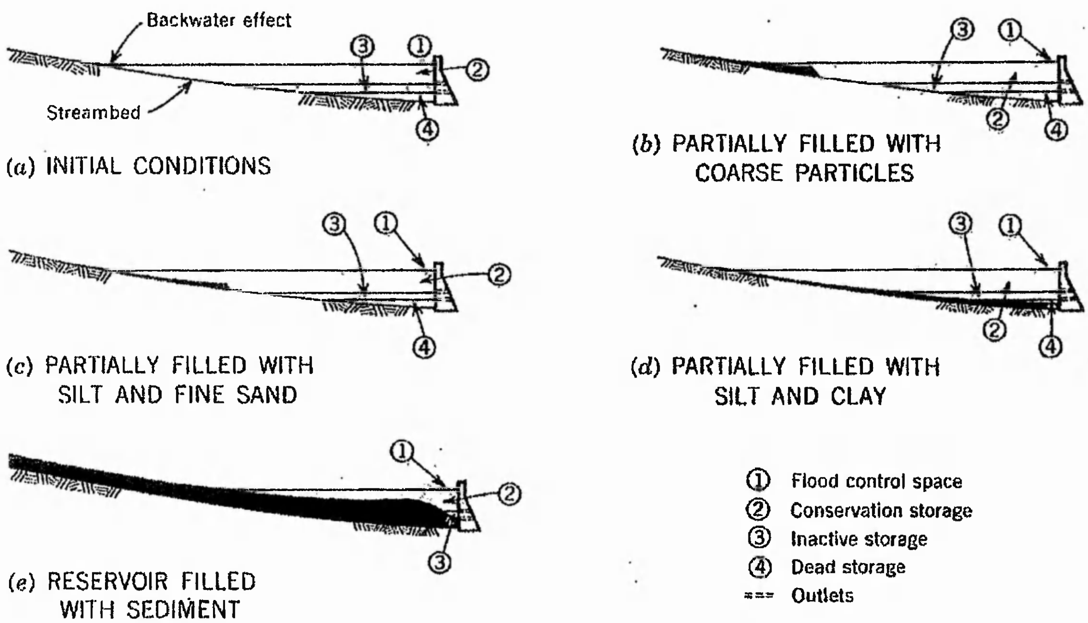
3. Uniform deposits (Figure 2.2d) consist of the same approximate thickness of sediment deposited in the reservoir and are comparatively rare. Typically uniform deposits occur in narrow reservoirs with frequent water level fluctuation and a small sediment yield (Morris and Fan, 1998).

Figure 2.2 Longitudinal patterns of sediment deposition in reservoirs (after Morris and Fan, 1998)



Upon initial deposition sediment may be resuspended and moved from shallow to the deepest parts of the basin by water currents. This process, which results in greater net accumulation in the deepest parts of the basin, is termed sediment focusing (Davis and Ford, 1982). However, it is a common misconception that reservoir sedimentation acts to deplete all of the dead storage (the storage below the lowest drawoff level) first before encroaching on the live storage (Labadz *et al.*, 2002). Borland and Miller (1960) identify that the deposition of coarse particles and silt and fine sand can deplete the live storage from the onset of the sedimentation process (Figure 2.3). Numerical modelling techniques have been used to predict/explain the distribution of sediment within reservoir basins (e.g. Thomas and Prasuhu, 1977; Chang, 1988) based on equations of motion and continuity for water and sediments over a mobile bed (Bruk, 1985).

Figure 2.3 Reservoirs under various sedimentation conditions (Borland and Miller, 1960)



2.10 Sediment production

Deposited sediment within reservoir basins may be produced within the basin itself (autochthonous sediment production), or produced externally and transported into the basin (allochthonous sediment production).

2.10.1 Autochthonous sediment production

Inorganic autochthonous sediment may be generated within the reservoir basin by wave-induced mass movement (e.g. landslips), beach scour or bank erosion. From a study of the Southern Indian Lake Reservoir in northern Manitoba, Canada, Newbury and McCullough (1984) identified significant contributions of basin sediment derived from shoreline erosion. This was attributed to the erosion of permafrost fine grained materials (typically peat) which proceeded in a repeated annual sequence of melting, slumping and removal. However, such reservoir basin conditions do not typify those across England and Wales.

Lloyd *et al.* (1998) identified significant contributions of basin sediment derived from shoreline erosion induced by livestock grazing and trampling in small farm hillcrest and hillslope dams in southeast Australia. With regards to the larger British reservoirs being modelled in this study, such direct livestock access to waterlines is not usually available, thus reducing this form of potential autochthonous sediment production. In addition to this, in the study by Lloyd *et al.* (1998) the small farm dams typically had no catchment areas. However, where catchment areas did exist (typically for hillslope dams), the study identified predominant sediment sources other than shoreline erosion. In such reservoirs shoreline erosion typically accounted for 40% of the respective sediment, thus implying more significant allochthonous sediment sources. The reservoirs across England and Wales being modelled in this study all exhibit a degree of catchment-coupling and thus by definition have catchment areas. As a result, in general, more significant allochthonous sediment contributions may be likely (Section 2.10.2).

The processes of flocculation and aggregation can also contribute to reservoir basin infilling. Flocculation involves the mixing of water causing colloidal particle collision. Typically colloidal particles are negatively charged and thus remain stable in suspension through their mutual repulsion. However, flocculation ensues when the colliding colloidal particles are subjected to net attractive forces from a coagulant (typically salts) resulting in destabilization and the subsequent formation of "clumps", termed flocs (Curran *et al.*, 2004; Fox *et al.*, 2004). Fine particles in a floc sink more quickly than they would as single grains, effectively increasing removal rates from the transporting flow (Fox *et al.*, 2004). Aggregation proceeds with the continued collision of flocs with smaller suspended particles as they are transported and settle through the water column (Curran *et al.*, 2004).

Organic material synthesized by autotrophs (primary production) such as algae within the reservoir itself can contribute to basin infilling (Duck and McManus, 1987; van der Post *et al*, 1997). New reservoirs are particularly vulnerable to inputs from primary production as newly subsumed material is decomposed, as are reservoirs where nutrient input from fertilizers is high, typically in more lowland areas favourable for cultivation (Duck and McManus, 1990). Although much organic matter is decomposed in the water column, a proportion can become incorporated into the reservoir bed sediments.

In addition, the presence of diatoms that deposit frustules among introduced sediment particles can contribute to reservoir basin infilling. McManus and Duck (1985) identified that diatom frustules provide a significant contribution to the sediment budget in the Glenfarg and Glenquey reservoirs of the Midland Valley, Scotland. From scanning electron microscopy of surface and core sediments from the respective reservoirs, visual estimates of the diatom content varied from 10% to 40%, with an average of 20% (McManus and Duck, 1985). Therefore, with regards to organic autochthonous material, Duck and McManus (1990) state that such material produced by phytoplanktonic micro-organisms and microbiological decay processes can be significant, particularly in eutrophic lakes and reservoirs. However, Battarbee *et al.* (1985) identified that such an autochthonous sediment component is negligible in acid waters, thus being of little significance in the uplands of Yorkshire (Labadz *et al.*, 2002) where many surface water storage reservoirs exhibiting a degree of catchment-coupling are located in England.

However, whilst autochthonous sediment production potentially contributes to reservoir basin infilling in certain cases, Labadz *et al.* (1999, 2002) state that typically the majority of sediment that accumulates in British reservoirs is allochthonous. The aforementioned results of Newbury and McCullough (1984), Lloyd *et al.* (1998), and Battarbee *et al.* (1985) concerning the respective production of inorganic and organic autochthonous sediment under conditions that do not typify those of the British reservoirs being modelled in this study indirectly support this assertion. Duck and McManus (1987) directly support this assertion made with regards to **inorganic sediment**. They stated that the assumption that all sediment deposited in the nine surveyed reservoirs across the Midland Valley of Scotland is derived from catchment erosion is true for the inorganic fractions. Regarding the organic fraction of reservoir basin sediment, Duck and McManus (1987) stated that only some was allochthonous. However, for each surveyed reservoir, the inorganic sediment yield calculated from sediment cores comprised the majority of the respective total sediment yield (Table 2.3). Therefore, the fact that the inorganic sediment fraction is sourced from catchment erosion and comprises the majority of the respective catchment sediment yields supports the assertion by Labadz *et al.* (1999, 2002). Foster and Lees (1999b) obtained similar results to Duck and McManus (1987) for nine reservoir catchments across northeast England. Sediment yields derived from respective reservoir basin sediment cores were principally composed of inorganic material. Changes in the sediment yields for the nine lake catchments over time were related to changes in respective catchment land use, again implying the significance/dominance of allochthonous sediment.

Table 2.3 Sediment yields in reservoir catchment areas surveyed by Duck and McManus (1987) (n.r. = not reported).

Catchment	**Total sediment yield (t km $^{-2}$ yr $^{-1}$)**	**Inorganic sediment yield (t km $^{-2}$ yr $^{-1}$)**
Lambieletham	2.1	1.8
Harperleas	13.8	11.5
Drumain	3.9	3.3
Cullaloe	30.8	26.2
Glenfarg	52.0	39.0
Glenquey	15.1	10.0
Kelly	41.0	n.r.
N Esk	26.0	n.r.
Hopes	25.0	n.r.

With regards to **organic sediment** Foster and Lees (1999a) state that in general lake autochthonous organic matter content is inversely related to sedimentation rate and sediment yield. This is induced particularly by light extinction in turbid, suspended sediment-laden water and the reduction of available forms of necessary nutrients through adsorption with inorganic sediment particles limiting primary production (Morris and Fan, 1998). Therefore, in the studies of reservoir sedimentation across the UK identifying high rates of capacity loss detrimental to reservoir operation (e.g. Rowan *et al.*, 1995; White *et al.*, 1996a), the influence of autochthonous organic matter is likely to be low. Indeed, those studies that have attributed high UK reservoir sedimentation rates to organic sediment have sourced the respective sediment from the erosion of blanket peat within the associated catchments, thus representing an allochthonous sediment input (e.g. Rowan *et al.*, 1995; White, 1996a; Foster and Lees, 1999a; Labadz *et al.*, 1999).

From the preceding discussion it can be seen that whilst autochthonous sediment production contributes significantly to reservoir basin infilling in certain cases, it is likely that the majority of sediment that accumulates in British reservoirs is allochthonous, thus supporting the assertion made by Labadz *et al.* (1999, 2002). Indeed Lloyd *et al.* (1998) state that it is generally assumed that sediment stored in dam impoundments has been derived exclusively from catchment erosion (i.e. allochthonous sources) as opposed to autochthonous sources (e.g. Cisternas *et al.*, 2001). This supports the modelling methodology employed herein: the prediction of reservoir sedimentation from catchment and reservoir basin factors (objective three), which principally involves the consideration of factors that influence allochthonous sediment production/delivery (Sections 2.11). In addition to the general consensus of scientific theory supporting the modelling methodology, from a practical perspective concerning the prediction of reservoir sedimentation for the large population of surface water storage reservoirs across England and Wales exhibiting a degree of catchment-coupling, secondary data are only readily available describing/depicting the influence of such allochthonous sources.

2.10.2 Allochthonous sediment production

There are two primary sources of allochthonous sediment production: the catchment hillslopes and the catchment stream channel network (Knighton, 1996). Sediment is produced from both sources through weathering, erosion and mass movement and is subsequently transported by the fluvial system to the reservoir basin as catchment sediment yield (as documented by Foster and Walling (1994)). Sediment yield is defined as the portion of gross erosion within a catchment area that is not deposited before being transported from the catchment area by a stream (Walling, 1988). The time it takes for sediment to move through the catchment system and be represented in the sediment yield can be large. For a small mountainous catchment in Oregon, Dietrich and Dunne (1978) identified that whilst one half of the soil discharged to channels was carried away as suspended load, the remainder was stored temporarily in tributaries, debris fans, and the floodplain. The residence times of sediment in these storage elements increased downvalley from decades to approximately 10,000 years.

Regarding hillslope soil erosion across Great Britain, Morgan (1996) states that due to the the absence of intense rainfall and the presence of hedgerows and trees in the landscape across Britain, it is invariably assumed that soil erosion is unimportant and rarely occurs. However, there is evidence showing that soil erosion in Great Britain is not insignificant and can represent a source of sediment yield (Boardman, 1990a).

In a study of the extent of soil erosion across upland England and Wales, McHugh *et al.* (2002) estimated extensive degraded land at almost 25,000ha. In addition, over 80% of the eroded field sites investigated failed to retain a proportion of eroded material and less than 1% of eroded material remained within 50m of erosion features (McHugh *et al.*, 2002). As a result, soil erosion in such catchments represents a potential contribution to sediment yield and consequently reservoir sedimentation.

Material from polluted precipitation and dry atmospheric deposition provide additional allochthonous inputs, frequently overlooked by studies (Foster *et al.,* 1985). Barrett *et al.* (1987) state that for the southern Pennines, total inputs of wet and dry deposition during the period 1981-1985 were in the region of 10 t $km^{-2} yr^{-1}$. However, this atmospheric input represented a relatively small proportion of the estimated stream solute loads. It is probable that high solute loads from polluted precipitation and dry atmospheric deposition were largely a result of anthropogenic inputs which peaked across Great Britain during the industrial revolution, and thus do not represent such a significant source in modern times. As a result, the contribution of atmospheric wet and dry deposition to reservoir sedimentation across Great Britain is likely to be small in comparison to that sourced from the catchment hillslopes and stream channel network and delivered through influent streams. In addition, with regards to dry atmospheric deposition (aeolian dust), Lloyd *et al.* (1998) stated that in a region of southeast Australia, such allochthonous inputs into small farm reservoirs were negligible given the "high" mean annual rainfall of the area (976mm yr^{-1}) and the almost complete, year round pasture coverage of the catchment. This can be considered the case for the population of directly catchment-coupled surface storage reservoirs modelled herein. From the population data set for this research (described in Chapter 4), the mean annual rainfall (1961-1990) is higher at 1066.15mm yr^{-1}, and the average percentage catchment cover of inland bare ground and tilled land (which experiences no coverage for part of the year) is only 0.79% and 15.32% respectively (Appendix 1, Table 1), thus inducing comparatively greater limiting conditions for dry atmospheric dust deposition. These observations support the assertion made by Labadz *et al.* (1999, 2002) that in most cases, the greatest proportion of allochthonous sediment is a product of catchment erosion delivered to the reservoir via the fluvial system.

2.10.3 Allochthonous sediment delivery to reservoirs through the fluvial system

For sediment produced from the catchment hillslopes to be transported to the stream channel network, and potentially represented in the sediment yield, requires strong hillslope-channel coupling. Michaelides and Wainwright (2002, page 1441) define hillslope-channel coupling as:

"...the degree of connectivity between the hillslope and channel in terms of the runoff and sediment delivery rates from the hillslope to the channel, and in terms of the fluvial activity imposed by the channel on the hillslope base...It is the effectiveness, direction and speed with which localized changes are transmitted away from the source (hillslope) and propagated throughout the hillslope system to the channel and ultimately the catchment outlet."

With strong hillslope-channel coupling, the hillslope-derived sediment is relatively unimpeded in crossing the boundary between the hillslope and fluvial regimes provided by the channel banks and channel head. Subsequent transport of hillslope-derived material, and that sourced from the stream channel itself, depends upon whether the fluvial system is supply-limited or capacity-limited. Supply-limited conditions occur when the stream capacity is greater that that required to entrain and transport the available sediment. Capacity-limited conditions occur when more material is available than can be entrained and transported (Julien, 1995). Across Great Britain, supply-limited conditions typically prevail (Foster and Lees, 1999b; Labadz *et al.*, 2002). Much material supplied to streams from catchment hillslopes has a grain size that will enable it to be transported by suspension at almost any given discharge (Richards, 1985). As a result of this, the transport of this fraction is largely controlled by the supply of the material. By contrast, coarse material greater than 0.06mm in diameter is capacity-limited where flows capable of its entrainment and transport only occur intermittently during higher runoff events (Richards, 1985). Therefore much of the coarser material goes into storage on hillslopes, floodplains or within the river channel itself.

2.11 Factors influencing allochthonous sediment production

In principle, two sets of factors affect the magnitude of sediment production and delivery from both hillslope and catchment stream channel sources: catchment factors and reservoir basin factors (Labadz *et al.*, 2002). The factors influencing sedimentation in each set are not mutually exclusive. Those catchment factors that influence erosion have the potential to influence the process from both sources of sediment within the catchment; the hillslopes and stream channel network. The catchment factors influence erosion principally through the production of overland flow. This can induce hillslope erosion through rilling and gullying etc., and stream channel erosion though increased discharges and flow velocities increasing shear stresses on channel beds and banks.

The identification and measurement of catchment and reservoir basin factors that influence catchment sediment production and delivery will be used to predict the sedimentation rate for the population of online surface water storage reservoirs across mainland England and Wales (objective three).

2.11.1 Catchment Characteristics

2.11.1.1 Catchment rainfall

Catchment meteorology influences soil erosion directly through rainfall and wind, and indirectly through influencing soil character (e.g. moisture content) and farming practice (e.g. drilling dates) (Boardman *et al.*, 1990b), all of which can influence the magnitude of soil erosion. Typically the most important erosion agent across England and Wales in terms of reservoir sedimentation is water; therefore catchment rainfall is a crucial factor to quantify in sedimentation rate prediction.

Rainfall provides one of the most widespread and important processes of particle detachment caused by raindrop impact (Farres, 1987). The strength of the force of raindrop impact is related to the terminal velocity of the raindrop and it's mass. In addition to providing a force for particle detachment, rainfall provides an erosion agent for particle entrainment and transportation through the production of both Hortonian (infiltration-excess) and saturated overland flow, which can lead to rill and gully erosion (Summerfield, 1996).

Across England and Wales both forms of overland flow production can be induced. On bare soil, Morgan (1996) documented that short-lived intense storms frequently of convectional origin can produce Hortonian overland flow. He also identified that storms of long duration and low intensity can produce saturated overland flow. Both forms of overland flow generation induced rill erosion (although those rills produced through

Hortonian overland flow were of a greater magnitude) and thus represented a potential source of sediment yield.

Boardman *et al.* (1990c) and Wilby *et al.* (1997) identified significant positive correlations between rainfall, and soil erosion and lake sedimentation across Great Britain respectively. Boardman *et al.* (1990c) demonstrated a strong positive correlation between median soil loss (m^3 ha^{-1}) through erosion and a rainfall index on the South Downs. Using this relationship and the Erosion Productivity Impact Calculator model (EPIC), Boardman *et al.* (1990c) predicted that an increase in rainfall of up to 15% in winter would increase erosion up to 27% by 2050 (assuming no land use change) and stated that if channel networks exist this could theoretically increase sediment yield.

Using radionuclide concentrations to date sediment cores from four British lakes, Wilby *et al.* (1997) identified the frequency of winter cyclonic weather patterns as the most significant variable correlating with historic sediment yields. This was attributed to winter cyclonic activity capturing a greater number of extreme events, shorter storm interval times, rainfall of greater intensity and higher antecedent soil moisture conditions.

From Boardman *et al.* (1990c) and Morgan (1996) it is clear that rainfall has the potential to induce reservoir sedimentation sourced from the catchment hillslopes, subject to the degree of hillslope-channel coupling and transport capacity of the channel flow. However, rainfall may also induce reservoir sedimentation sourced from the catchment stream network itself. Rainfall increases stream discharge through entry into channels by direct input, overland flow, and bank seepage. The corresponding increase in flow velocity and shear stress can cross critical thresholds inducing channel bed and bank erosion (Hjulstrom, 1935; Shields, 1996). This is supported by Chorley and Morgan (1962) who, through a study concerning morphometric landscape features, associated higher drainage densities (indicative of stream channel erosion) with higher rainfall intensities and greater mean basin slopes. This highlights the importance of rainfall and topography (due to high relief) in inducing sediment production from stream channels and demonstrates how the initiating factors are not necessarily mutually exclusive.

2.11.1.2 Topography

Erosion increases with slope steepness and slope length as a result of increases in the velocity and volume of overland flow (Morgan, 1996). Furthermore, the action of rainsplash acts to move increasing proportions of sediment downslope as the gradient increases (Briggs and Smithson, 1994). These processes can act to increase the sediment yield.

In a study of five experimental stations in the USA, Zingg (1940) expressed the relationship between erosion and slope as:

$$E \propto \tan^{1.4}\theta \, L^{0.6} \qquad \text{Eq. 2.1}$$

Where E is the soil loss per unit area, α denotes proportionality, θ is the slope angle and L is the slope length. Morgan (1996) documented evidence to suggest that this equation has general validity.

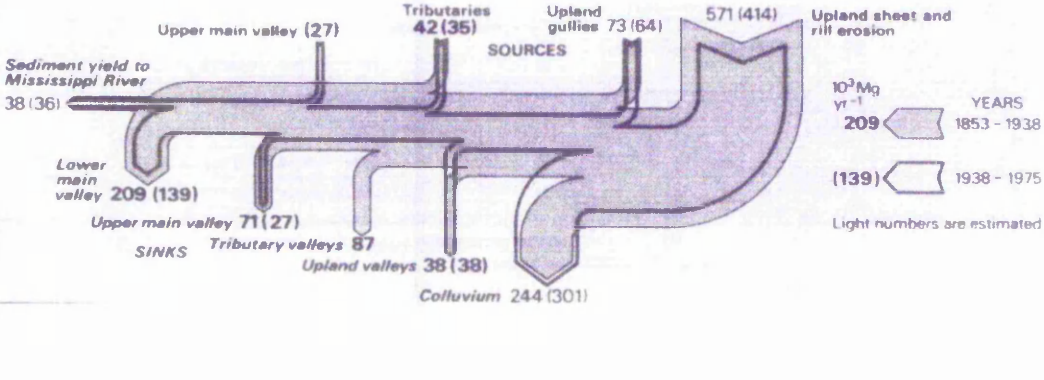
In a study concerning the Jialing and Jinsha catchment areas in China (two tributaries of the Upper Yangtze river), Zhang and Wen (2004) associated greater sediment yields in the latter basin due to the presence of steep topography inducing deeply dissected landforms through gully erosion and mass movement. Sediment yields were lower in the Jialing catchment due to the presence of more gentle rolling landforms, inducing sediment yield through sheet and rill erosion.

However, in studies across England and Wales, Evans (1990) found that undulating terrain is most vulnerable to water erosion whereas long planar slopes are least at risk. In addition he stated, "...convexities and valley floors are trigger points for erosion; the steepness of a slope is not of overriding importance for determining where and how much erosion occurs, but the presence of a complexity is," (Evans, 1990, page 126). Furthermore, across the uplands of England and Wales, McHugh *et al.*, (2002) identified a significant negative relationship between erosion and slope above seven degrees. This trend was attributed to the development and subsequent degradation of blanket peat on low-angled slopes, the soil class identified to have the greatest erodibility across the uplands of England and Wales, and highlights the fact that Equation 2.1 only has general validity.

Topography also influences catchment storage of sediment. Not all of the sediment eroded within a catchment area is represented in the sediment yield and transported into the reservoir basin. Typically only a small fraction will comprise the sediment yield as deposition and temporary or permanent storage may occur where gradients decline downslope, at the base of slopes, in swales, on the floodplain, or in the stream channel network itself (Walling, 1983) (Figure 2.4). Walling and Webb (1996) state that there is increased opportunity for deposition and storage of eroded material from hillslopes associated with reduced slope gradients. Trimble (1983) states that, in terms of catchment sediment budgets, storage is typically the greatest component and sediment yield is the smallest. The storage opportunities within catchment areas create a "bottleneck" that limits the amount of sediment that can be flushed from the catchment area in a given time period (Trimble, 1983) (see Figure 2.4).

As a result of catchment storage, the volume of sediment deposited in reservoir basins may not be directly sourced from catchment hillslope or stream channel erosion. The sediment may be derived from remobilisation of alluvium accumulated in valley systems or colluvium accumulated at the base of hillslopes prior to reservoir construction (Clayton, 1968; Trimble, 1976; Walling, 1983). Alluvial and colluvial deposits accumulate in catchments where sediment transport is capacity limited (Section 2.10.3).

Figure 2.4 The magnitude of sediment production from different sources in the disturbed Cook Creek catchment, USA. Based on data presented by Trimble (1983), diagram after Gregory (1985).



Topography can influence the magnitude of hillslope-channel coupling (as discussed in Section 2.11.1.1). From observations in a steep upland catchment in southern Alberta, Canada, Campbell (1992, page 461) states, "...that because of the steep nature of the topography, and the generally extremely restricted possibilities for sediment storage, almost all of the eroded hillslope material is delivered into the streams."

However, finding a numeric parameter representing the influence of slope steepness on sediment yield is difficult. Verstraeten and Poesen (2001) identified that mean catchment slope is not highly correlated to sediment yield; of more importance is the spatial distribution of slopes within the catchment. Where steeper slopes are located in the most remote regions of a catchment, near the drainage divide, eroded soil particles need to travel longer distances to the catchment outlet and are therefore more prone to deposition. In contrast, where steeper slopes are distributed throughout the catchment, the mean travel distance of eroded soil particles will be lower, reducing the potential for deposition. However, Verstraeten and Poesen (2001) state that it is very difficult to express the spatial distribution of slopes in one single catchment parameter, which illustrates the drawback of any lumped modelling technique that attempts to relate sediment yield/reservoir sedimentation to simple catchment properties (Section 3.2.1).

2.11.1.3 Altitude

Typically, greater catchment erosion occurs at higher altitudes. Increased altitude may represent a change in non-mutually exclusive factors such as climate, vegetation or soil that influence erosion processes.

Changes associated with higher altitudes include lower temperatures, more frequent ground frosts and higher rainfall which act to degrade vegetation cover and density and increase overland flow production (McHugh *et al.*, 2002). The corresponding exposed soil may also be more mobile at higher altitudes because of the higher wind speed and greater precipitation (McHugh *et al.*, 2002). In addition, McHugh *et al.* (2002) state that as altitude affects soil development, a greater area and depth of peat soil (one of the most highly erosive soil classes across England and Wales – Evans, 1990) and consequently increased erosion is expected with height above sea level. In addition, higher altitudes increase physical weathering in terms of freeze-thaw, providing greater quantities of particles available for entrainment and transport (Summerfield, 1996).

2.11.1.4 Lithology/soil type

Soil type determines the erodibility of soil. Erodibility defines the resistance of the soil to erosion. Morgan (1996) recognizes the importance of soil type in determining the erodibility of soil, identifying that although the resistance of soil to erosion depends in part on topographic position, slope steepness, and the amount of disturbance, the properties of the soil are the most important determinants. Erodibility varies with soil texture, aggregate stability, shear strength, infiltration capacity and organic and chemical content (Morgan, 1996).

2.11.1.4.1 Soil texture

The term soil texture is used to express the percentage of the three main fractions (sand, silt and clay) present in a soil mass (Jumikis, 1965). Coarse grained sand particles (ranging from 0.2mm to 2mm – Briggs and Smithson, 1994) and clay particles (<0.002mm – Briggs and Smithson, 1994) are most resistant to erosion. This is due to the greater frictional resistance to movement of sand and the high degree of cohesion associated with clays (Terzaghi *et al.*, 1996). Evans (1990, page 126), in his study of soil erosion in England and Wales, uses clay content as an indicator of erodibility stating "…as clay content increases water erosion decreases and eroded volumes are less." Evans (1990) states that the least resistant particles are fine sands (0.06mm to 0.2mm – Briggs and Smithson, 1994) and silts (0.002mm to 0.06 mm – Briggs and Smithson, 1994).

2.11.1.4.2 Aggregate stability

Clay content combines with organic matter to form aggregates. The stability of these contributes in determining the resistance of soil to erosion. Soils with a high content of base minerals are more stable as they make up soil cations contributing to the chemical bonding of aggregates. In a study of soil erosion in southern England, Boardman (1983) identified that soil with low clay and organic matter contents are susceptible to slaking (where the wetting of dry clays causes swelling and the subsequent collapse of aggregates). Farres

(1987) identifies the importance of aggregate stability in determining the resistance of soil to rainsplash erosion.

2.11.1.4.3 Shear strength

Shear strength is defined as the maximum resistance of a material to applied stress (Jumikis, 1965). The two major sources of resistance in soil are cohension and friction; when the shearing stress (e.g. that exerted by gravity, moving fluids and mechanical loads) exceeds the shear strength of a material failure occurs (Terzaghi *et al.*, 1996).

2.11.1.4.4 Infiltration capacity

The infiltration capacity is the maximum sustained rate at which soil can absorb water (Dingman, 1994). It is influenced by pore size, pore stability and the form of the soil profile (Morgan, 1996). Overland flow can be produced leading to potential erosion when rainfall intensity exceeds the infiltration rate (Hortonian overland flow) or when all the soil pores are saturated inhibiting infiltration. Studies by Boardman (1983) and Heathwaite *et al* (1990) have identified both mechanisms of overland flow generation across Great Britain. These observations contradict the commonly held precept that in the UK rainfall intensities are too low for the infiltration capacity of most soils to be exceeded initiating Hortonian overland flow (Kirkby, 1978).

2.11.1.4.5 Organic & chemical content

The organic and chemical constituents of the soil influence soil erodibility through their effects upon aggregate stability (Morgan, 1996). Evans (1980) identified soils with an organic matter content of less than 3.5% organic content to be erodible due to reduced aggregate strength. Morgan (1996) states that most soils contain less than 15% organic content, and many of the sands and sandy loams have less than 2%. This illustrates the potential for soil erosion. Morgan (1996) further identifies the origin of organic material to be important in lowering the erosivity of soil, identifying that organic material from grass leys and farmyard manure contributes to the stability of the soil aggregates; whilst peat and undecomposed haulm merely protect the soil and do little to increase aggregate strength. Indeed, where blanket peat increases sediment yields across the British Isles, the sediment is often produced by mass movement as opposed to soil erosion (Dykes and Warburton, 2004).

The most important chemical control over erodability is the proportion of easily dispersible clays in the soil (Morgan, 1996). In temperate environments such as Great Britain, the replacement of base minerals with sodium increases water uptake and the likelihood of swelling and aggregate collapse (Morgan, 1996). Again this can cause slaking and the subsequent formation of a surface crust which reduces the infiltration rate and produces overland flow (Boardman, 1983).

2.11.1.4.6 Erosion risk of soil associations

Evans (1990) evaluated the actual erosion risk of each of the 296 soil associations of the National Soil Map of England and Wales. This classification was based on land use, landform and soil properties, and took into account the extent and rates of erosion in the uplands and lowlands from various studies. He defined accelerated erosion risk as erosion caused by human actions, such as exposing soil to grow arable crops, burning or draining moorland for raising sheep or grouse, overgrazing by livestock, and recreation. Those catchment soil associations represented at least once in the population of reservoirs available for this research with a high, or very high risk of accelerated erosion are presented in Table 4.2 (Section 4.2.2.3).

2.11.1.5 Geology

Fox (1949) states that exposed porous rock outcrops can act to reduce catchment erosion and sediment yield due to the direct percolation of rainfall into the ground. However, the exposure of impervious rock outcrops can increase overland flow and stream channel discharges, increasing catchment sediment yield and potential reservoir sedimentation. The magnitudes of these geological effects on sediment production are dependent upon the extent of the area of rock outcrop and rainfall coverage.

However, where rock outcrops are minimal, lithology appears the more significant control on sediment production. Duck and McManus (1987, page 376) concluded that the variation between sediment yields in nine Scottish catchments could not be attributed to bedrock controls; "...drift deposits serve as the principal supplier of detritus and the nature of the underlying bedrock is largely immaterial to the rates of sediment yield."

Sekhar and Rao (2002) investigated sediment yield in India and postulated that reduced sediment yields would be apparent in the regions composed of older, harder igneous and metamorphic rocks, in comparison to those regions of younger, softer sedimentary rocks. However, high sediment yields and soil erosion problems were identified in all regions due to problem lithologies, thus supporting the conclusion of Duck and McManus (1987).

2.11.1.6 Land use

Catchment land use is a major factor in determining rates of erosion and sediment yield (Boardman, 1990a). From studies in humid tropical forests in Malaysia and Northern Australia, Clayton (1968) suggests that human activity can increase sediment yield a hundredfold. Edwards and Whittington (2001) investigated lake sediments deposited during the Holocene across Great Britain and Ireland. They concluded that landscape impacts upon sedimentation are readily evident in many areas and most have signs of anthropogenic disturbance especially within the Neolithic period: "At many sites there is a near instant sedimentary response to landscape activity. At others, increased sedimentation often follows...with periods of woodland clearance and agricultural activity," (Edwards and Whittington, 2001, page 168).

The influence of land use in increasing soil erosion and sediment yield is principally manifested through the effect of vegetation cover, structure and density (Mitchell, 1990; Viles, 1990). Dunne (1979) and Francis and Thornes (1990) both identify increased soil erosion associated with decreasing vegetation cover density. Across Great Britain, Boardman (1990a) states that only vegetation cover in excess of about 30% inhibits erosion.

Across Great Britain, the removal of natural vegetation and replacement with the land use practices of afforestation, cultivation, grazing and urbanization has significantly increased catchment erosion and sediment yield principally through increased overland flow production and transmission of storm rainfall (Boardman, 1990b; Evans, 1993; Hall, 1981; Heathwaite *et al.*, 1990).

2.11.1.6.1 Afforestation

Afforestation began in the early 1900s when the Forestry Commission was founded to produce export substitution softwoods and intensified in the post-war years when incentives were given to plant conifers. Evans (1993) states that since World War 2, 6% of Britain has been planted with conifers.

Studies of lakes and reservoirs across Great Britain by Stretton (1984, 1998), Duck and McManus (1987), Stott (1987) and Foster and Lees (1999b) have all identified increased sedimentation associated with afforestation. This is caused typically by ground preparation involving major programmes of drainage and fertilization. The land is cleared of vegetation and deep furrows ploughed at 90° to the slope contours in many cases (Stretton, 1984; 1998) inducing extensive rill and gully formation from incident rainfall. This effect has been shown to have five to ten-fold increases in stream wash load and bed load (Newson, 1986).

Foster and Lees (1999b) identified high sediment yields (over 40 t km^{-2} yr^{-1}) produced as a result of afforestation for up to a decade after planting. Yields subsequently declined to pre-planting levels (*c.* 12 t km^{-2} yr^{-1}). However, in mature afforested upland catchments in the southern Pennines, afforestation has lead to a continued increase in sediment yield. Stott (1987) identified severe stream incision and gully development in the catchment of the Trentabank reservoir beginning 15-20 years after the completion of the afforestation programme. Analysis of sediment cores from Trentabank reservoir revealed an increase in subsoil (as opposed to topsoil) from 30% to 70% between 1929 and 1981, after canopy development over most of the catchment area. This was related to root damage to the underlying tile drains and the development of a thick needle layer – both inducing overland flow. A positive feedback response was then generated with bank collapse of the steep sided slopes and vegetation removal. Stott (1987) stated that these observations have important implications for resource management in upland Britain because the extensive plantations of the 1960s and early 1970s are at the stage of development when gullying commenced in the catchments of Trentabank reservoir; the stage which previous studies suggest minimal impacts of forestry on sediment production and transport due to vegetation maturity (e.g. Foster and Lees, 1999b).

However, in natural forested areas erosion and overland flow production is extremely limited. Cheng *et al.* (2002) evaluated the hydrologic influences of natural forests in the headwaters of catchments across Taiwan and observed that despite the rainfall intensity typically exceeding 100 mm hr^{-1}, overland flow is rarely generated on the forest soils. This limits soil erosion and mass movement, which the environment is otherwise very prone to. The effect of canopy interception and high annual evapotranspiration rates totaling 800-1200 mm yr^{-1} reduce overland production and streamflows. In addition, forest stands enhance slope stability with their root systems (Greenwood and Norris, 1999). The value of forests limiting soil loss, through erosion and mass movement, and sediment yield has long been recognized in these Asian environments as indicated by the Chinese proverbs, "green mountains yield clean and steady water" and "whoever controls the mountains governs the streams," (Cheng *et al.* (2002).

2.11.1.6.2 Cultivation

Agricultural land use is one of the major controls on the source and magnitude of sediment transfer to the stream channel network (Heathwaite *et al*, 1990); consequently, the plough and spade have been termed the most significant geomorphological agents today (Clayton, 1968). The conversion of grassland to arable increases soil erosion through reducing organic matter levels in the soil, which is critical in soil particle cohesion and in the maintenance of soil structural stability (Morgan, 1996). The addition of sodium-containing fertilizers can also result in structural deterioration of the soil on wetting increasing the erodibility (Morgan, 1996). As discussed previously in Section 2.11.1.4.5, reduced organic matter content also reduces the infiltration capacity of the soil, as does compaction by machinery in cultivation practices (Higgitt, 1993). Therefore, highly erosive overland flow can be induced under arable conditions. Evans (1990, page 126) states that "...erosion is likely to occur when land is down to arable especially where a wide range of crops is grown as then some fields are bare of crop and at risk of erosion by water or wind at most times of the year."

Boardman (1990b) and McIntyre (1993) identify how row crops such as sugar beet and potatoes, often ploughed at 90° to the slope contours, dramatically increase the potential for rill and gully erosion and the transmission of overland flow. However, of greater significance across England and Wales, because of the large areas involved, has been the sharp rise in erosion associated with the increase in the growing of winter cereals. Evans (1993) observed that land drilled in autumn for winter cereals is sensitive to water erosion as most soils can be saturated for much of the winter period, thus maximizing the chances of overland flow. The drilling of land under saturated conditions can produce compacted vehicle wheel tracks which can act as sites for overland flow generation and subsequent rill and gully erosion (Foster *et al*, 1990a). Furthermore, the ability to cultivate slope of up to 25° with cereal crops intensifies this problem (Boardman, 1990b). Evans (1993) stated that during some years across England and Wales, as much as 25% of the arable land most sensitive to rilling has experienced such erosion.

Duck and McManus (1990) identified that reservoir catchments dominated by arable farming in the Midland Valley of Scotland show higher sediment yields (31-52 t km^{-2} yr^{-1}) than those of open moorland (4-41 t km^{-2} yr^{-1}). Foster and Lees (1999b) identified similar results in catchments of northeast England, identifying that those dominated by forestry and grazing produced the lowest sediment yields, whilst arable catchments had sediment yields higher by a factor of around three. Reid *et al.* (1990) make similar observations, but also identify significant soil erosion losses caused by flooding in arterial waterways constructed to "improve" field drainage.

2.11.1.6.3 Grazing

The grazing of animals acts to reduce the infiltration capacity of the soil and increase the bulk density. This coupled with the removal of the protective vegetation cover facilitates overland flow production and subsequent erosion and weathering, and in the case of the study by Christiansson (1979), can result in significant increases in reservoir sedimentation rates.

Across England and Wales studies by Heathwaite *et al.* (1990), Foster and Walling (1994) and van der Post *et al.* (1997) identify the significance of erosion from pasture areas in contributing to catchment sediment yield. Winder *et al.* (1985) attribute sedimentation associated with the Empingham dam (of Rutland Water) to overgrazing by sheep.

The effect of managing pasture areas may also induce erosion. Through the burning of moorland to improve grazing conditions for livestock vegetation cover is reduced and the soil hydrological characteristics are altered typically through the production of a non-wettable layer. Together, these effects act to decrease the infiltration capacity of the soil and induce overland flow production (Brown, 1990; Evans, 1993). In addition, the installation of drainage to drain wet moorland for pasture can also increase sediment yield through channel erosion and increased efficiency of sediment delivery from the land surface to the stream channel network (Evans, 1993; Russell *et al.*, 2001; Foster *et al.*, 2002).

2.11.1.6.4 Urbanization

Urban development acts to cover the catchment area by roofs, roads and paved areas. As a result of this impervious cover infiltration of incident rainfall into the upper soil horizons is reduced, which may ultimately result in decreased local surface erosion rates (Nelson and Booth, 2001). However, a greater proportion of rainfall is directed into the surface water drainage system, increasing the total volume of runoff (Hall, 1981). The low vegetation density in urban areas in comparison to rural sites limits evapotranspiration and may also contribute to the increased volume of runoff (Goudie, 1981).

The surface water drainage network in urban areas is invariably modified by the realignment of natural watercourses or their complete replacement by sewerage. The designs of both systems provide increased flow velocities over the natural channels that they replaced providing a flashier hydrograph where the peak and falling limb are reached much more quickly (Hall, 1981). The delivery of a larger volume of runoff within a shorter time interval causes the peak discharge to increase and acts to increase the discharge for a particular storm recurrence interval (Goudie, 1981; Hall, 1981; Nelson and Booth, 2001). Upon flow transmission into the natural watercourses downstream, these throttling effects can induce bed and bank erosion, increasing the sediment yield.

However, Goudie (1981) states that the effect of urbanization on increased runoff is greater for small floods and diminishes as the size of the flood and its respective recurrence interval increase. This is attributed to non-urbanized catchments becoming saturated during severe, prolonged storms so that they begin to behave hydrologically as if they were impervious catchments.

Nelson and Booth (2001) investigated sediment sources in a mixed land use catchment in Washington, USA identifying increased sediment yield associated with urbanization principally through the effect of increased stream discharges. The estimated current rate of catchment sediment production is 44 t km^{-2} yr^{-1}, compared to a pre-urban development sediment production of 24 t km^{-2} yr^{-1}. Erskine *et al.* (2003) produced similar results for catchments in western Sydney, Australia.

2.11.1.6.5 Comparative losses under land use types

Using land use as a predictor of sediment production requires information of comparative soil losses under each type of cover. Collins (1981) incorporates a land use/catchment vegetation factor into multiple regression models after those summarized by Kirkby (1969) for the southeast USA:

% Pastureland x 0.03 mm yr^{-1}

% Scrub-oak/woodland x 0.10 mm yr^{-1}

% Cultivated land x 20 mm yr^{-1}.

These factors agree with the observations made by Christiansson (1979), McIntyre (1993), Verstraeten and Poesen (2001), and Erskine *et al.* (2003) that out of these three land use types, cultivated land (arable) typically produces the greatest quantities of sediment, and pasture the least.

Heathwaite *et al.* (1990) conducted hillslope plot experiments in the Merrifield catchment of Slapton, UK and produced similar results. From Table 2.4 it can been seen that cultivated cereals have a high sediment delivery rate in comparison to lightly grazed pasture. However, pasture becomes a much greater source of sediment when the stocking density is increased, inducing overgrazing, and where grazing occurs in close proximity to the catchment fluvial network where poaching can occur.

Table 2.4 Rainfall simulation of the effect of land use on surface runoff from hillslope plots. Rainfall intensity = 12.5 mm hr $^{-1}$ (after Heathwaite *et al.*, 1990).

Land use	**Runoff (mm)**	**% runoff as rainfall**	**Sediment delivery rate (mg mm $^{-1}$)**
Temporary grass	2.3	5	65
Cereal	3.7	7	84
Bare ground	10.6	21	480
Lightly grazed pasture	11.6	23	32
Heavily grazed pasture	26.5	53	840

2.11.1.6.6 Summary of land use influence

Each of the preceding land use types can increase the sensitivity of the landscape through the lowering of geomorphological thresholds that have to be crossed for erosion to occur, promoting erosion to take place more frequently. However, for sediment deposited in reservoir basins to be directly sourced from land use areas requires strong hillslope-channel coupling (Section 2.10.3). Studies by McIntyre (1993) and Ferro *et al.* (1998) identify the need for erosive areas to be in close proximity to the fluvial channel network for the eroded material to contribute to sediment yield. In addition to such local effects, Verstraeten and Poesen (2001), Price and Lovett (2002a, 2002b) and Prosser and Karssies (2001) identify that small anthropogenic landscape elements such as banks, hedges, furrows, parcel borders, tillage direction, filter strips and riparian buffer zones can have a major influence on sediment delivery, and thus sediment yield.

2.11.1.7 Catchment area

It is commonly well understood that suspended sediment yields, and consequently reservoir sedimentation rates, are influenced by catchment area (Walling and Webb, 1996). However, conjecture arises in the literature as to whether this relationship is broadly positive or negative. Dedkov and Moszherin (1992) identify that both positive and negative relationships can exist between catchment area and specific sediment yield (t $km^{-2} yr^{-1}$) depending upon the principal sediment source; whether the catchment hillslopes or fluvial channel network.

2.11.1.7.1 Positive relationships

From investigations over a range of morphoclimatic zones, Dedkov and Moszherin (1992) suggest that positive relationships between sediment yield and catchment area are found in catchments where stream channel erosion is most dominant. Across Great Britain positive relationships may occur in undisturbed, densely vegetated catchments and upland areas characterized by resistant rocks reducing soil erosion and the associated hillslope input (Imeson, 1974; Dearing, 1992; Hutchinson, 1995; Walling and Webb, 1996). Under these conditions erosion rates will increase downstream in response to greater entrainment and transport of sediment resulting in a positive relationship between sediment yield and catchment area (Dedkov and Moszherin, 1992). Ashmore (1992) agrees with this, adding that such relationships can also be attributed to the secondary remobilization of sediments stored in larger catchments and/or lowland systems by channel erosion. Dedkov and Moszherin state that the positive relationship can be amplified where lowland areas have been intensively developed, increasing stream channel erosion.

However, these explanations do not account for the observed positive relationship between catchment area and annual area-specific reservoir volume loss ($m^3 km^{-2} yr^{-1}$) identified by Butcher *et al.* (1993) in the southern Pennines. Here blanket peat dominates the upland catchments and is highly susceptible to erosion (Labadz *et al.,* 1991). As a result, hillslope erosion provides the major proportion of sediment yield. This positive relationship was attributed to the reservoir catchments surveyed being small, not having the flatter gradients and developed floodplains perceived to induce negative relationships (see Section

2.11.1.7.2), and because the catchments all occupy similar environments, it is to be expected that increasing catchment size will provide increasing values of sediment infill through greater inflows (Butcher *et al.,* 1993). This supports the conclusions of Duck and McManus (1987) regarding the observed positive relationship between sediment yield/reservoir sedimentation and catchment area across the Midland Valley of Scotland.

2.11.1.7.2 Negative relationships

Dedkov and Moszherin (1992) suggest that negative relationships between sediment yield and catchment area are found in situations where land cover is disturbed by human activity (e.g. agriculture), or with a poor vegetation cover, where hillslope erosion becomes the most dominant sediment source. Under these conditions most erosion will be concentrated in the headwater areas, contributing to sediment yield due to two factors: the reduced proportion of mobilized sediment from the hillslopes being deposited through the catchment system, and the associated higher degree of hillslope-channel coupling in comparison to downstream areas. This results in an inverse relationship between sediment yield and catchment area (Langbein and Schumm, 1958; Dendy and Bolton, 1976; Walling, 1983; Higgitt, 1993). This effect is paralleled by a decrease in sediment yield in downstream areas due to reduced relief and catchment coverage by rainfall events, reducing overland flow production (Walling and Webb, 1996).

However, it appears that these explanations for inverse relationships between sediment yield and catchment area overlook the continued action of stream channel erosion downstream, which may act to eliminate such negative relationships. However, Figure 2.4 (Section 2.11.1.2) identifies that if a catchment is disturbed by human activity and/or has a poor vegetation cover, the upland contribution to the sediment yield from hillslope sheet and rill erosion can be of such a great magnitude in comparison to fluvial channel erosion in the tributaries, that the effects of continued channel erosion downstream are subsumed. In addition, Russell *et al.* (2001) discuss several studies across the UK that identify stream channel erosion decreasing in importance as a sediment source as catchment area increases. Furthermore, Walling (1983) and Higgitt (1993) state that as catchment areas increase, there is increased opportunity for sediment deposition associated with flatter gradients and developed floodplains. Thus, a greater proportion of sediment deposited over downstream floodplains by moderate, frequent floods most effective at transporting sediment in fluvial geomorphology (Wolman and Miller, 1960) may act to uphold such negative relationships. However, Wolman and Miller (1960) state that overbank flows contribute only a small part of the floodplain sediment; most deposition of stream channel sediment occurs in point bars associated with lateral movement of stream channels forming the downstream floodplains.

Verstraeten and Poesen (2001), however, identify that positive or negative relationships between sediment yield and catchment area can exist depending on the units used to define sediment yield. Expressing sediment yield as tonnes per year (t yr^{-1}) yielded a positive relationship with catchment area. This was attributed to the continued supply of sediment in a downstream direction. However, when expressing sediment yield as t ha^{-1} yr^{-1}, a negative relationship with catchment area became apparent. Verstraeten and Poesen (2001) state that this is because when dividing the sediment yield over the catchment area, as the area increases, so does the fraction of less steep slopes and developed floodplains where deposition occurs. Therefore, less sediment is produced on these gentler slopes, so the relative proportion of sediment sources will decrease with increasing catchment area.

Butcher *et al.* (1992a) make a similar observation. A positive relationship was found between catchment area and both absolute reservoir capacity losses, and annual capacity loss rates. However, annual area-specific capacity loss and sedimentation rates showed much poorer relationships.

2.11.1.7.3 Discussion

The influence of catchment area on reservoir sedimentation is likely to be associated with a positive relationship as demonstrated by Butcher *et al.* (1993) and Duck and McManus (1987). This is because catchment-coupled reservoirs are typically built towards the headwaters of stream channel networks to generate sufficient head to supply to distant towns and where urban development tends to be less, thus smaller dams can be built in comparison to those required for downstream areas. As a result of the reservoir population occupying similar upstream/headwater environments, it is to be expected that as catchment area increases, so does sediment yield and reservoir sedimentation. The observations by

Butcher *et al.* (1993) and Dedkov and Moszherin (1992) identify that this positive relationship can be induced by erosion from hillslope and/or stream channel sources. The relative magnitude of sediment loss from either source is likely to be catchment specific. Because observations of catchment area and reservoir sedimentation are only being made over upstream/headwater environments, the perceived positive relationship between catchment area and sediment yield cannot be extrapolated for the entire longitudinal profile of the respective catchments.

2.11.1.8 Hypsometry

Verstraeten and Poesen (2001) identify the importance of the hypsometric integral in explaining sediment dynamics and thus sediment yield/reservoir sedimentation. The hypsometric integral is dimensionless parameter ranging between zero and one that relates horizontal cross sectional area of a drainage basin to the relative elevation above the basin mouth. Strahler (1952) used the hypsometric integral as a measure of the erosional state or geomorphic age of the catchment. Catchments with low values, where the average slope decreases and the fraction of wide valley bottoms with developed floodplains increases, represent old eroded landscapes. For such catchments, this results in lower values of sediment yield. High hypsometric integrals represent catchments that are recently incised and are in the early phases of the erosional cycle, characterized by high erosion rates and sediment yield (Verstraeten and Poesen, 2001).

Verstraeten and Poesen (2001) state that catchments with a high hypsometric integral have high sediment losses in upstream areas due to the dominance of erosional processes, but since fluvial transport processes are less dominant, i.e. the system is typically capacity limited, only a minor portion is delivered to the outlet as sediment yield. Conversely, catchments with a low hypsometric integral only produce relatively small amounts of sediment, but the dominance of fluvial processes ensures that the major part of the sediment is delivered to the outlet (Verstraeten and Poesen, 2001); thus such systems are typically supply limited.

In the context of reservoirs typically situated in the upstream/headwater areas of catchment systems, catchments with high hypsometric integrals produce much sediment in the upstream/headwater areas. Therefore, if strong hillslope-channel coupling exists in these areas, potentially large quantities of sediment will be delivered to the reservoir basins over time.

Through the hypsometric integral it can be seen that the stage a catchment area is within the geomorphic cycle, progressing from early youth through to maturity (Strahler, 1952; Schumm and Lichty, 1965; Thorn 1988), can influence sediment yield and therefore reservoir sedimentation.

2.11.2 Reservoir basin factors

In addition to the catchment characteristics of the reservoir, sedimentation is also a function of the morphological characteristics and operation of the reservoir itself (Labadz *et al*, 2002).

2.11.2.1 Trap efficiency

Some of the incoming sediment yield into the reservoir will be trapped. How much sediment will be trapped in the reservoir can be estimated based on the concept of trap efficiency. Trap efficiency is defined as the ratio of the deposited sediment to the total sediment inflow into the reservoir (Frenette and Julien, 1996). Heinemann (1981) considers trap efficiency as the most important descriptor of a reservoir.

Trap efficiency does not exhibit stationarity; it typically declines from a maximum at the time of reservoir construction to the present day as sedimentation ensues (Butcher *et al.,* 1993). Factors influencing reservoir trap efficiency are (1) the relation of capacity to inflow, (2) the inflowing sediment content, and (3), the discharge location and capabilities (Heinemann, 1984).

2.11.2.1.1 Capacity to inflow relationship

The capacity-inflow relationship corresponds to the retention time and the size and geometry of a reservoir (Frenette and Julien, 1996). The greater the retention time, the lower the average transit velocity and associated turbulence and the greater the rate of deposition.

Deposition is highly influenced by the morphology of the reservoir basin. Narrow, shallow reservoirs will experience maximum sedimentation rates well into the basin, whereas wide, deep reservoirs will experience maximum sedimentation close to the stream inlets (Heinemann, 1984). In addition, in very small reservoirs the sediment inflow will be in close proximity to the dam; thus there will be little opportunity for even the larger suspended particles to be deposited far from the dam. The situation will be very different in large reservoirs (Heinemann, 1984).

Other factors affecting the long-term capacity are the patterns of deposition through time, consolidation effects, density currents, sediment management (e.g. flushing and dredging), dam operation and the age of the reservoir as capacity decreases with time (Frenette and Julien, 1996).

2.11.2.1.2 Inflowing sediment content

Storm intensity and the discharge of the influent streams control the size and quantity of sediment particles eroded in the catchment and transported to the reservoir basin (Heinemann, 1984). Additionally, chemicals present in the soil or water may cause flocculation and aggregation affecting the particle or aggregate size, density and fall velocity (Heinemann, 1984). This affects the deposition and distribution of sediment in a reservoir basin.

2.11.2.1.3 Discharge location and capabilities

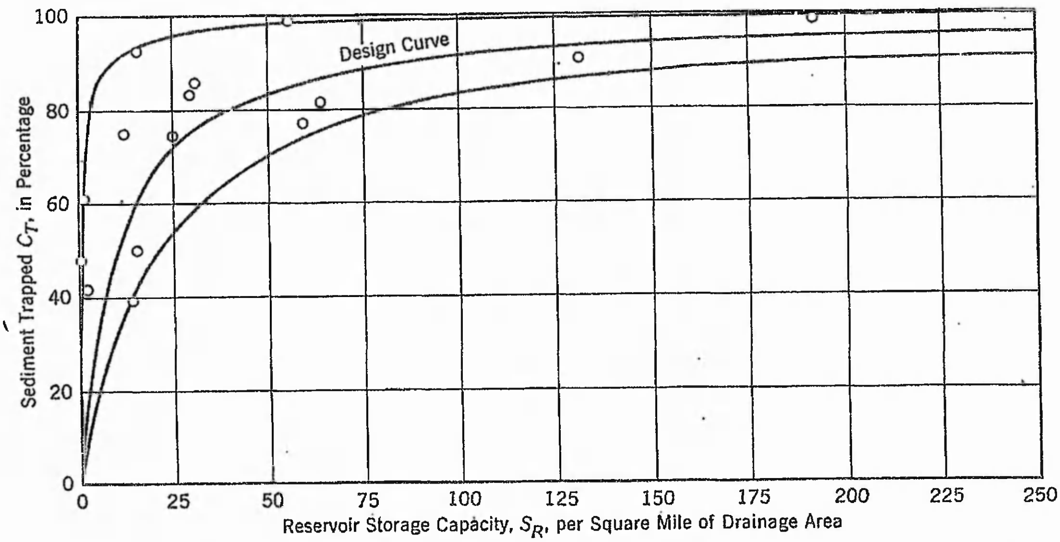
The dam spillway characteristics of elevation, capacity, design and roughness will control the sediment carrying capacity of the spillway outflow (Heinemann, 1984). This with sediment fall velocity, depth of fall, amount to be discharged, temperature and current velocity will determine the detention time and the sediment yield of the outflow, i.e. the quantity of sediment held in the reservoir basin and the quantity released (Heinemann, 1984). The sediment passing through reservoirs is usually clays and highly dispersed particles (Morris and Fan, 1997).

The lowering of the reservoir elevation level through the operation of the dam can also decrease the retention time and consequently the trap efficiency. In terms of reducing potential sedimentation, this can be very effective if done during periods of higher magnitude flows with high sediment concentrations. However, such operations are limited by storage and environmental requirements.

2.11.2.1.4 Trap efficiency estimation

There are many empirical methods of trap efficiency estimation (see Heinemann, 1984). Two of the most renowned methods are Brown's (1944) and Brune's (1953). Brown (1944) developed a curve relating trap efficiency to the ratio of original reservoir capacity and catchment area based on 15 reservoirs (Figure 2.5). He attributed greater percentage trap efficiencies to smaller and more variable catchment overland flow, coarse or highly coagulated sediments and reservoirs with greater storage capacities.

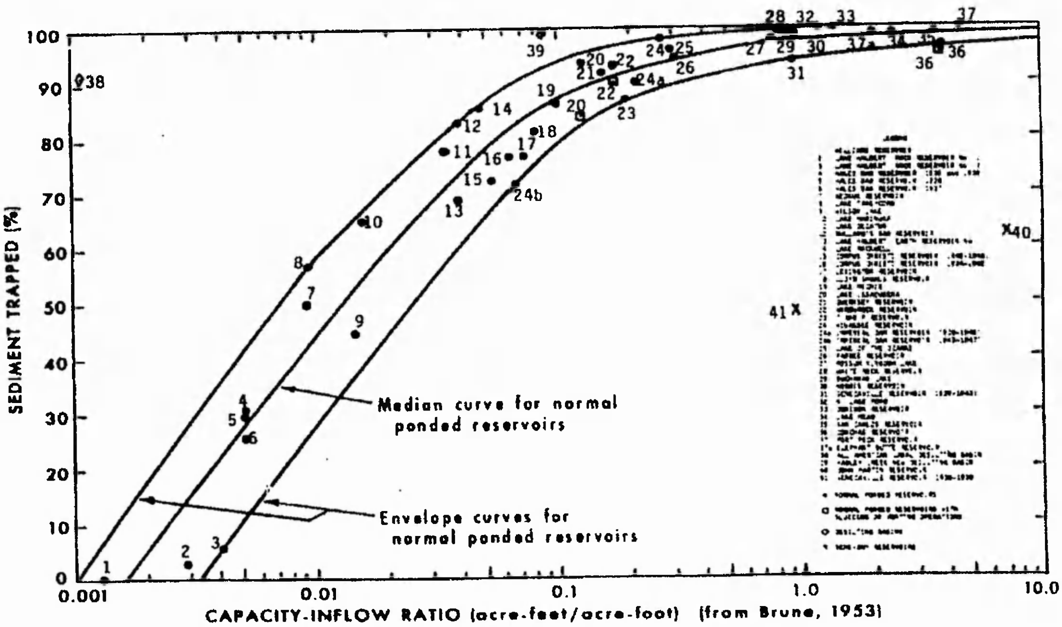
Figure 2.5 Brown's (1944) curve for reservoir trap efficiency estimation



RELATION OF RESERVOIR TRAP EFFICIENCY, C_T, TO RESERVOIR STORAGE CAPACITY, S_R

Brune (1953) developed a curve relating trap efficiency to the ratio of original reservoir capacity and reservoir inflow (Figure 2.6). Brune (1953) concluded that that the capacity to inflow method is more representative of trap efficiency than the capacity to catchment area. Brune's curves have been used more widely than other methods, especially for the estimation of trap efficiencies in smaller reservoirs (Heinemann, 1984). However, Butcher *et al* (1993) identified that Brown's method does provide an accurate prediction for British upland reservoirs, and is more suitable than Brune's method where no inflow data are available.

Figure 2.6 Brune's (1953) curve for reservoir trap efficiency estimation



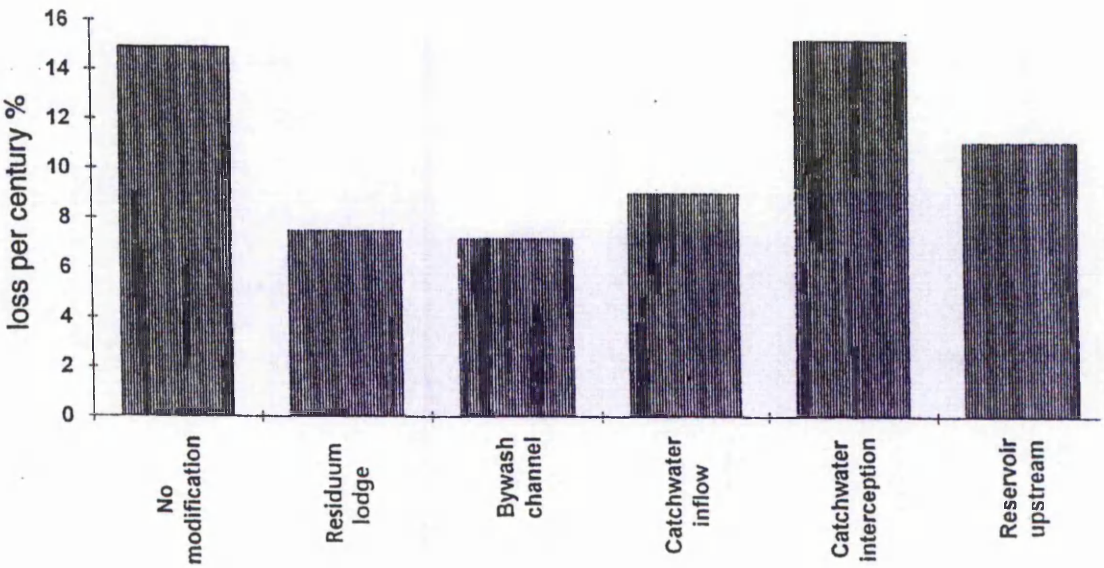
2.11.2.2 Sediment control structures & management

Studies by Labadz *et al.* (1995) and White *et al.* (1996a) highlight the impact of sediment control structures, built typically by Victorian engineers, on sedimentation rates in the southern Pennines. Sediment control structures consist of three primary modifications: residuum lodges, bywash channels, and catchwaters that serve both to increase the natural catchment area and allow trapping or bypassing of flows with a high sediment yield (White *et al.*, 1996a). Residuum lodges are impoundments built upstream from reservoirs that trap sediment by reducing the velocity of the channel flow. Bywash channels divert flows with high sediment yields around the reservoir perimeter by means of weirs and automatic gates. Catchwaters act to enlarge the effective catchment area of a reservoir by directing flow from nearby stream channels. As a result, they increase potential sediment inflows.

Figure 2.7 identifies the mean percentage loss of capacity per century for southern Pennine reservoirs with each type of sediment control structure calculated by White *et al.* (1996a) (although the inter-group difference is not statistically significant). For the sample of reservoirs, residuum lodges and bywash channels were associated with mean decreases of $53m^3\ km^{-2}\ yr^{-1}$ and $25m^3\ km^{-2}\ yr^{-1}$ respectively in terms of area-specific sedimentation. A slight decrease in sedimentation was also observed where reservoirs were located upstream trapping sediment from an otherwise direct catchment. The influence of reservoirs acting as effective sediment traps, reducing the gross sediment yield of rivers, is supported by Higgitt and Lu (2001), and Zhang and Wen (2004) regarding sediment yield attenuation in the Upper Yangtze basin, China.

However, regarding sediment control structures, Butcher *et al.* (1993) and White *et al.* (1996a) state that their influence is extremely difficult to quantify and their selective operation makes the sediment delivery process complex both spatially and temporally.

Figure 2.7 Loss of reservoir capacity under sediment control structures (after White *et al.*, 1996a)

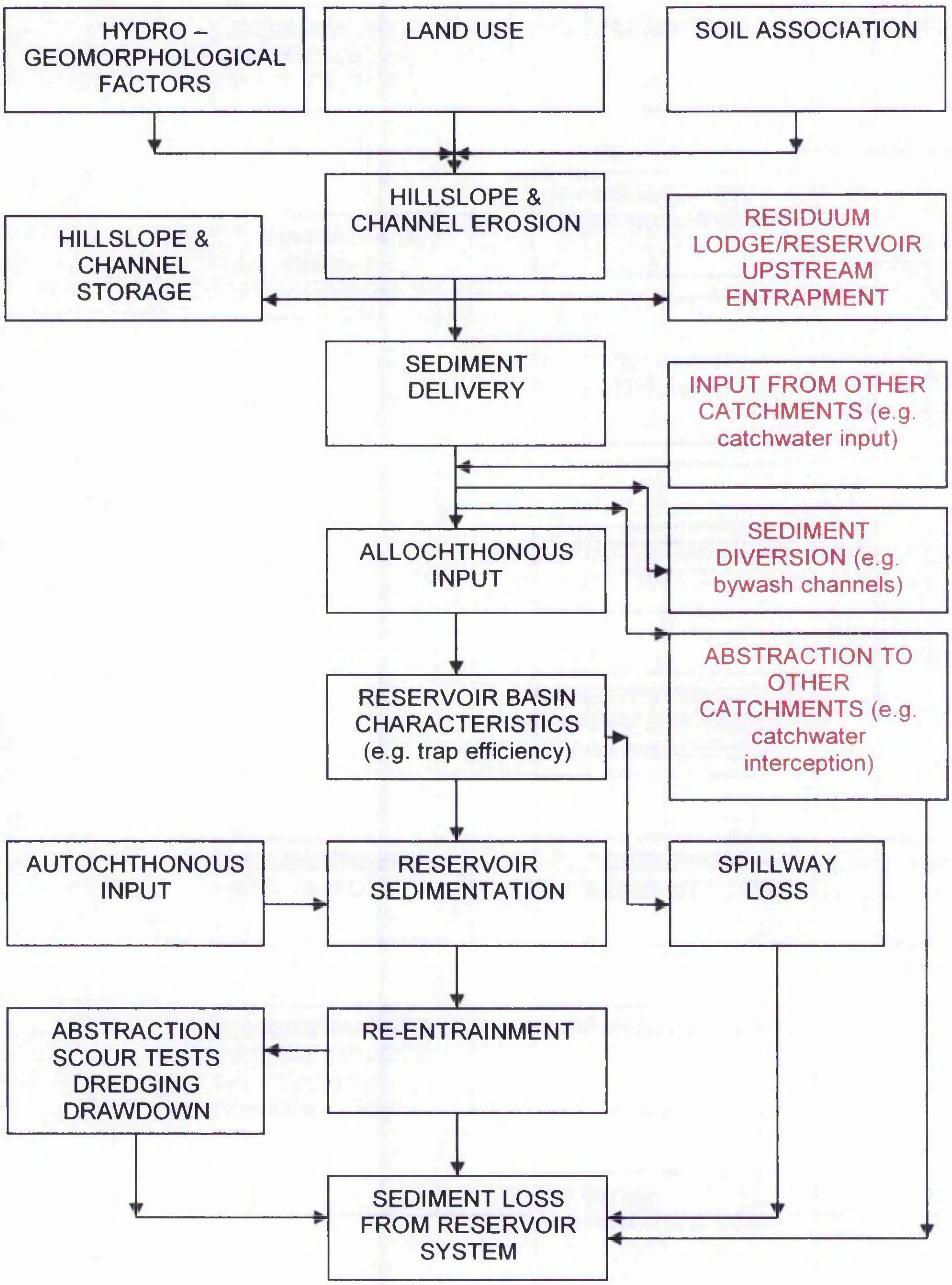


Differing management practices to combat sedimentation can also influence rates of basin infilling as mentioned in Section 2.11.2.1.1. Three principal practices exist: sediment flushing, sediment sluicing, and sediment dredging (Mahmood, 1987). Sediment flushing is the method of hydraulically eroding existing sediment accumulation behind a dam via reservoir drawdown through a low level outlet. This effect can also be produced through reservoir scour value tests where the lowest outlet pipe in the reservoir, the scour pipe, is opened to test the ability of the water company to rapidly lower the level of the reservoir in the event of structural failure of the dam. Sediment sluicing is an operational design where the bulk of sediment load entering a reservoir is "tapped" and released along with the flow before settling can occur. Sediment dredging involves the mechanical excavation of reservoir sediment.

2.12 Conceptual model of reservoir sedimentation

Through Section 2.11 the sources, processes, fluxes and stores influencing sedimentation in surface water storage reservoirs exhibiting a degree of catchment-coupling were identified. This knowledge of the system can be represented in a conceptual model illustrating the theoretical understanding of the system (Figure 2.8). The empirical models predicting reservoir sedimentation produced through this investigation (objective 3) represent an abstraction from the conceptual model. Through the quantification of catchment characteristics (i.e. hydro-geomorphological, land use and soil association) and reservoir basin factors (e.g. trap efficiency), which together provide direct and surrogate data regarding the sources, processes, fluxes and stores identified in Figure 2.8, reservoir sedimentation will be predicted. The empirical models produced will therefore inherently assume that the deposited reservoir basin sediment represents an allochthonous input. Through the discussion of sediment production in Section 2.10, this does not represent an unrealistic assumption as the majority of sediment that accumulates in British reservoirs is allochthonous. However, the models will not be able to account for catchment specific management influences which cannot be readily identified from secondary data sources. The modelling approach selected for this investigation and the data aquired to provide the predictor variables are discussed in Chapters 3 and 4 respectively.

Figure 2.8 Conceptual model for sedimentation in surface water storage reservoirs exhibiting a degree of catchment coupling. The red text denotes catchment specific management influences.



3. Modelling of sedimentation rates

3.1 Introduction

This chapter discusses the broad modelling approaches used in previous studies of reservoir sedimentation/sediment yield and identifies the approach employed in this research to investigate the principal aim: the production of a comprehensive assessment of the spatial variation of reservoir sedimentation for the population of surface water storage reservoirs exhibiting a degree of catchment-coupling across mainland England and Wales.

The focus of the modelling approach within this research was capacity loss of reservoir basins due to sedimentation from the consideration of factors that influence sediment production/delivery; as opposed to the modelling of the spatial distribution of sedimentation within a reservoir basin. This represents a fundamental classification of models applied to the issue of reservoir sedimentation. In terms of modelling the latter, numerical sediment transport models simulate flows into reservoir basins and are based on equations of motion and continuity for water and sediments over a mobile bed (Bruk, 1985). Such models typically use the finite difference method which solves distributed equations over a region of space or time through grids of cells, and the respective calculation of quantities/fluxes between centralized nodes in each cell (Hardisty *et al.*, 1996; Morris and Fan, 1998; Mulligan, 1998, pers.comm). Examples of such numerical models include HEC-6 (Thomas and Prasuhn, 1977) and FLUVIAL (Chang, 1988). However, such models (as typified by HEC-6 and FLUVIAL) are strongly data-dependent and require adequate data for calibration and verification (Morris and Fan, 1998). Bruk (1985) identifies the following primary data collection required to parameterize such numerical models:

- Reservoir topography survey,
- Continuous water level observations and measurements – at several points along the rivers feeding the reservoir, the reservoir itself and downstream from it,
- Continuous water discharge measurements – related to the water level observations,

- Sediment investigations – suspended load discharge, estimation of bed load, the determination of grain size distribution of suspended sediment load, density of bed materials and sediment deposits, and measurement of bed forms (e.g. dunes etc.) is important.

In the context of UK reservoirs, much of these required data are not readily available as secondary data and would therefore have to be collected as primary data if modelling the distribution of sediment accumulation within reservoir basins was the approach adopted in this research. Due to this requirement for extensive primary data collection, such a modelling approach was impractical in terms predicting reservoir sedimentation over a large number of sites in order to investigate the principal aim of the research. As a result, attention was focused on modelling approaches conducive to the prediction of gross reservoir capacity loss from standard, widely-available secondary data sources. This is discussed in the proceding sections of this chapter.

3.2 Modelling approaches

A further classification can be made concerning the modelling of reservoir sedimentation/sediment yield in general: lumped and distributed. Lumped models involve a single value being applied to each parameter representing the whole catchment (Kirkby *et al.*, 1987; Refsgaard, 1997). As a result, lumped models do not take into account spatial variability within the catchment. Distributed models, by contrast, break up the catchment, typically into grid cells, where values for each parameter are represented in each grid cell. This acts to account for spatial variability within the catchment and allows the routing/calculation of fluxes through the catchment (Kirkby *et al.*, 1987; Refsgaard, 1997). Examples of both approaches are discussed below in relation to the principal aim of this investigation.

3.2.1 Lumped models

Many studies that have developed reservoir sedimentation/sediment yield models over large spatial scales have used a lumped empirical approach, attempting to obtain meaningful relationships between sediment records stored in impounded water bodies or sediment yield measurements, and catchment characteristics perceived to initiate sediment production. Studies by Anderson (1957), Jansen and Painter (1974), Collins (1981), Bazzoffi *et al.* (1996), Verstraeten and Poesen (2001), DeBonis *et al.* (2002) and Sekhar and Rao (2002) all used multiple regression analysis successfully to predict and reservoir sedimentation or sediment yield from catchment and reservoir morphology factors identified to influence sediment production over regional/nationwide areas. As a result of this, multiple regression analysis may be potentially successful in the large-scale application of this research.

However, in such large-scale studies there are limited alternative modelling approaches. This is because modelling the linkage of on-site soil erosion rates within a catchment to the sediment yield at the outlet/reservoir basin requires detailed input data (Van Rompaey *et al.*, 2001). Whilst this is often obtainable for small-scale investigations practically and logistically, it is not for large-scale investigations.

Price *et al.* (2000b) developed a lumped parameter time model of suspended sediment load transmission through the Wyresdale Park Reservoir in Lancashire. The model relates rainfall to suspended sediment load at the reservoir outlet on an event-based temporal scale. The Price *et al.* (2000b) model comprises two components: a rainfall to suspended sediment load model, and a suspended sediment load at the reservoir inflow to reservoir outflow model. Using a daily measured rainfall series, the model uses transfer functions to reconstruct daily sediment deposition rates. However, this approach is not suitable for the investigation herein as it involves the prediction of sediment movement **through** the reservoir basin which is not within the remit of this study. In addition, such an approach cannot be applied as it requires high temporal resolution data which is not readily available for many reservoirs across England and Wales.

Ferro *et al.* (1998) developed a sophisticated lumped model to predict the mean annual sediment yield of nine investigated Italian catchments by dividing each one into several homogenous morphological units. This lumped approach takes into account some of the spatial variation due to topography and therefore sediment delivery, thus rendering the model more distributed in nature. For each morphological unit, soil erosion is calculated using the Universal Soil Loss Equation (USLE) and the mean travel time of eroded sediment using an empirical model. The output of the model is the sediment delivery ratio for each morphological unit and the total catchment sediment delivery ratio.

However, the approach of Ferro *et al.*, (1998) is not suitable for this investigation as the predicted sediment delivery ratio from each morphological unit can only be validated through extensive fieldwork, determining the soil loss from each unit. Again, within the timeframe of this study, this is not achievable for a large-scale investigation, practically and logistically. Ferro *et al.* (1998) validated the predicted sediment delivery ratios of the respective catchment morphological units using caesium-137 analysis. This involved the comparison of the predicted sediment yield of each morphological unit with the corresponding sampled caesium-137 loss. Such validation is essential if the advantages of this modelling approach are to be utilized fully.

3.2.2 Distributed models

Van Rompaey *et al.*, (2001) developed a spatially distributed model predicting mean annual sediment yield for 24 instrumented catchments in central Belgium. The model consists of three components:

1) The mean annual erosion rate is calculated for each grid cell using an adapted version of the empirical Revised Universal Soil Loss Equation (RUSLE),

2) An assessment of the mean annual transport capacity is made for each cell,

3) A sediment routing algorithm redistributes the produced sediment over the catchment accounting for the topology of the catchment and spatial pattern of the transport capacity.

When compared to measured mean annual sediment yields comprising the validation data set, the predictions from the distributed model were significantly more accurate than those made using a lumped multiple regression model (Van Rompaey *et al.*, 2001). In addition it was possible to identify the critical areas delivering most of the sediment to the river system; this would not have been possible using a lumped approach. Van Rompaey *et al.* (2001) state that multiple regression analysis performed poorly in comparison to the distributed model because of the different dominant catchment land use types inducing diverse sediment yield observations.

Kim and Steenhuis (2001) developed the GRIEROM (grid-based soil-water erosion and deposition model) distributed model with the principal aim to predict temporal variations and spatial distributions of sediment transport for storm events in a New York State catchment, USA. This model used **process-based submodels** to simulate surface and subsurface flow, and soil-water erosion and deposition. The use of process-based submodels is in contrast to Ferro *et al.* (1998) and Van Rompaey *et al.* (2001) who employ the **empirical models** of USLE and RUSLE respectively to predict soil erosion.

GRIEROM generates overland flow depth, discharge, sediment concentration, and flux at each grid outlet for a given time interval using the input data of eight georegistered 10m x 10m gridded maps. The gridded maps represent the catchment elevation, stream and surface drainage channels, land use, soil, porosity, field capacity, and initial soil moisture condition respectively. Reasonable comparisons were made between the observed and predicted sediment concentration at the catchment outlet for four monitored storm events. The success of this model was limited as it was not validated for the distributed observations of sediment concentration throughout the catchment.

It is not possible to consider a distributed modelling approach for the research herein as these models are highly parameterized and require extensive field calibration (Price *et al.*, 2000b), and therefore can only applied to individual catchments or small regions (e.g. Kothyari *et al.*, 1994; Van Rompaey *et al.*, 2001). In addition, the required input data needs to be available at very high spatial resolutions as such models are scale dependent (Van Rompaey *et al.*, 2001). For example, Van Rompaey *et al.* (2001) identified that predicted sediment yield decreased in relation to observed values with decreased data spatial resolution (increased/coarser grid sizes of data); therefore the model transport capacity coefficients had to be recalibrated when running at a coarser grid size. Digital data (e.g. land use and soil type) available at such high spatial resolutions are highly expensive and therefore not obtainable for this large-scale investigation.

3.2.3 Empirical and process-based models

The comparison between the empirical factor approach of Ferro *et al.* (1998) and Van Rompaey *et al.* (2001) and the process modelling approach of Kim and Steenhuis (2001) to predict soil erosion identifies an important sub-division in modelling approaches between the two methodologies.

Empirical models are based upon observation rather than theory and involve the definition of a mathematical/statistical relationship (e.g. through regression analysis) between the dependent variable being modelled and factors perceived to influence the dependent variable. An example of an empirical model is the Universal Soil Loss Equation which predicts soil loss from a rainfall erosivity factor, a soil erodibility factor, a slope gradient factor, a crop management factor and an erosion control practice factor (Wischmeier and Smith, 1978). Empirical models tend to be good predictors but offer comparatively poor explanations of processes (Mulligan, 1998, pers.comm.). Price *et al.* (2000a, page 65) state that such models "...are ideally applied to systems where the overall input-output behaviour is of primary importance and the internal mechanisms, while important, are uncertain."

Process-based models encompass the modelling of the actual processes involved (and not the definition of an arbitrary relationship between an output) and factors perceived to influence the output. Therefore the model parameters have a direct physical interpretation with regards to the process being modelled. For example, the GRIEROM model (Kim and Steenhuis, 2001) incorporates equations concerning stream power, sediment entrainment and sediment flux, and thus models the actual process of soil erosion through the catchment system. The WEPP (Water Erosion Prediction Project) model (Flanagan and Nearing,

1995) is a process-based (distributed) model that is able to predict spatial and temporal distributions of net soil loss and deposition for a wide range of temporal and spatial scales (i.e. at the catchment area scale and the hillslope scale). The model takes into account climate, soils, topography, management and supporting conservation practices. Infiltration is estimated through the modified Green-Ampt equation, and runoff is routed over the land surface on the basis of kinematic equations. A steady state continuity equation is used to calculate the erosion rate as the sum of rill and interrill erosion amounts (Flanagan and Nearing, 1995).

In contrast to empirical models, process-based models offer superior explanations of processes but commonly have weaker predictive power (Mulligan, 1998 pers.comm.). The prime purpose of the model(s) employed in the research herein, in relation to the principal aim, is in prediction as opposed to explanation. This is because of the requirement to focus water company/reservoir undertaker attention on potential problem reservoirs without extensive primary data collection.

In relation to process-based models, Ferro *et al.* (2001) state that whilst they may be theoretically preferable to empirical factor approaches, they typically contain numerous parameters that are difficult to measure, and the uncertainties in the equations simulating the erosion and deposition processes at the catchment scale renders the outputs questionable. Ferro *et al.* (2001) add that at present, sediment yield estimates from process-based models are comparable with those obtained by an empirical factor approach like RUSLE (Revised Universal Soil Loss Equation). This view is also shared by Morgan (1995) who identifies that the present state of model development relating to sediment transport, erosion and deposition models is such that a simple empirical model is often more successful in prediction than a complex process-based one.

3.2.4 Modelling approach selection

From the preceding discussion of modelling approaches used in the prediction of reservoir sedimentation/sediment yield, a lumped empirical modelling approach was chosen to fulfil the principal aim of this research, the production of a comprehensive assessment of the spatial variation of reservoir sedimentation for the population of surface water storage reservoirs exhibiting a degree of catchment-coupling across mainland England and Wales. Gordon (1978) states that is the purpose of a particular study that determines the nature of the model. The successful results of Anderson (1957), Jansen and Painter (1974), Collins (1981), Bazzoffi *et al.* (1996), Verstraeten and Poesen (2001), DeBonis *et al.* (2002) and Sekhar and Rao (2002) each demonstrate the utility of the lumped-empirical approach.

The lumped approach in particular was most suitable for application practically and logistically in terms of the large number of sites in the population data set for which variables influencing reservoir sedimentation had to be ascertained, the availability of the secondary data, the associated time and cost implications of the huge secondary data collation, and the desire to make best value use of existing data. Ultimately, the lumped approach allowed the potential achievement of the principal research aim within the timeframe of the study.

The empirical methodology was most suitable due to the nature of the data readily available and collated for this research (Table 4.5) describing catchment characteristics and reservoir basin factors identified to influence reservoir sedimentation/sediment yield in Section 2.11. These data provide direct and surrogate information regarding the sources, processes, fluxes and stores identified in the conceptual model (Figure 2.8) for sedimentation in surface water storage reservoirs exhibiting a degree of direct catchment-coupling, as opposed to that directly required for process-based equations of particle detachment, entrainment, transport and deposition (e.g. HEC-6, FLUVIAL, GRIEROM and WEPP). In the context of this research, the data required for such process-based modelling are not readily available from secondary sources, being obtainable only from primary data collection. In addition, the application of such process-based models places a large demand on validation data. As these models focus on explanation, it is necessary to know whether the prediction has been arrived at in the correct way. Therefore, it is essential that the validation of process-based models is extended to cover all of their constituent variables (Morgan, 1995).

For this study, the application of process-based models in general was again not suitable practically and logistically due to the large number of sites, and the associated time and cost implications of such a huge primary data collection to meet the requirement of detailed catchment-scale data. Therefore, as with the adoption of the lumped modelling approach, the use of the empirical methodology allowed the potential achievement of the principal aim within the timeframe of the study.

The use of "off the shelf", already developed empirical models such as the Universal Soils Loss Equation/Revised Universal Soil Loss Equation and the Morgan, Morgan and Finney method (Morgan *et al.*, 1984) could not be considered in this research to predict catchment hillslope erosion (a component of allochthonous reservoir sediment) due to their specific data requirements. Such data are again not readily available from secondary sources, thus requiring a large primary data collection programme which was not possible practically within the timeframe of the investigation. In addition, such models are typically parameterized for field-scale soil erosion prediction and therefore cannot be directly used to predict catchment sediment yield as they do not account for deposition. Amore *et al.* (2004) incorporated the Universal Soil Loss Equation into three distributed models of sediment yield prediction for three respective Sicilian catchments. In each case the sediment delivery ratio was estimated. However, this approach required detailed intra-catchment primary data for the distributed models (Section 3.2.2) and provided a poorer estimate of sediment yield than predictions made using the WEPP model. Hrissanthou (2002) also identifies that "off the shelf" soil erosion models are typically developed from small experimental fields and are therefore not particularly adaptable/transportable in accounting for different local conditions.

Using the lumped-empirical modelling approach, two different modelling techniques were employed in this investigation to produce a model predicting reservoir sedimentation: multiple regression and fuzzy set multi-criteria evaluation (objective three). The former represents an approach often applied in such investigations; the latter represents a relatively new approach applied in hydro-geomorphological research (Mujumdar, 2002). These two techniques are discussed and applied in the proceeding chapters. The application of either of these two validated lumped-empirical models can act as a first assessment of the nature of reservoir sedimentation across England and Wales. Upon identification of a reservoir sedimentation problem, further research can be directed employing other modelling techniques such as the HEC-6 model, the WEPP model, or the distributed models developed by Van Rompaey *et al.* (2001) and Kim and Steenhuis (2001) that will give a greater insight into the erosion and sediment delivery processes occurring within the respective catchment.

4. Data sources and primary data collection results

4.1 Introduction

This chapter undertakes objectives one and two:

1. The collation of secondary data from standard, widely-available sources for the defined reservoir population.

2. The collection of primary data concerning reservoir annual percentage capacity loss rates to supplement the parameterization data set collated from the literature, ensuring it is representative of the defined reservoir population, and form a validation data set.

The chapter describes:

- The formulation of the data set representing the population of surface water storage reservoirs across mainland England and Wales exhibiting a degree of catchment-coupling (termed hereafter the population data set),
- The secondary data collated to represent the catchment and reservoir basin factors identified to influence reservoir sedimentation in Chapter 4 for the population data set,
- The secondary data collated concerning reservoir sedimentation rates, forming a sub-set of the population data set (termed hereafter the parameterization data set) for model formulation,
- The primary data collected to comprise a model validation data set (termed hereafter the validation data set),
- The quality of the secondary and primary data.

4.2 Establishment of the population data set

This section discusses the acquisition and use of secondary data sets for the formulation of the population data set, and for characterization of the individual reservoirs and catchments within the population data set. Objective two of this study was that, where possible, secondary data should be obtained from standard, widely-available sources. The use of secondary data was essential in investigating the principal research aim as it was clearly not possible to collect primary data to characterize the spatial variation of catchment and reservoir basin factors that influence reservoir sedimentation rates across England and Wales. The data characterizing the individual reservoirs and catchments of the population data set represents that which describes direct and surrogate information concerning the sources, processes, fluxes and stores identified to induce sedimentation in surface water storage reservoirs exhibiting a degree of catchment-coupling. This is depicted in the conceptual model of the process (Figure 2.8).

4.2.1 Establishment of initial reservoir population – BRE dams data base & FEH (1999)

The initial step in identifying the population of surface water storage reservoirs exhibiting a degree of catchment-coupling was the acquisition of the Building Research Establishment's (BRE) data set of over 2500 British dams, which includes all reservoirs that fall under the Reservoirs Act, 1975 (Tedd *et al.*, 1992). This data set formed the basis of the reservoir population for this study. For each of these reservoirs the Flood Estimation Handbook software (FEH) (1999) was then used to obtain catchment information.

The FEH (1999) software provides catchment information for any identified position on the registered stream channel networks across mainland Great Britain. The process of data extraction from the FEH (1999) for reservoirs across Great Britain reduced the population in a major way. Catchment information could only be extracted for those reservoirs resolvable in the FEH (1999) coupled to a respective catchment area (i.e. those reservoirs that collect and store water directly from a respective catchment area as opposed to pump storage reservoirs for example) through the identification of an outflow channel from the dam, providing compensation water to the downstream fluvial network. This is due to the nature of the FEH (1999) software, providing catchment information for any identified position on the registered stream channel networks across mainland Great Britain. This, in theory, enabled surface storage reservoirs fed exclusively by catchwaters or pumped storage inputs (i.e. not being catchment-coupled) to be omitted from the population. This omission is important as sedimentation in such reservoirs cannot be predicted using catchment characteristics derived from the FEH (1999) as the catchments from where their influent water originates cannot be ascertained.

The issue of attempting to identify a population of directly catchment-coupled reservoirs across Great Britain is also important with regards to the soundness of the general modelling approach; the prediction of reservoir sedimentation using catchment characteristics identified to influence the process as stated in the research objectives (Section 1.2). Uncertainty is introduced regarding sediment delivery when a reservoir is only intermittently catchment-coupled through selective management operation, and therefore is not continually under the influence of factors conducive to sediment production within the catchment area. This will contribute to the error produced concerning sedimentation prediction from the aforementioned approach. As a result of this, an effort was made to remove, from the population, those dams readily identifiable in the BRE dams database as washlands; an embanked floodplain area into which a river is diverted in times of flood to alleviate further flooding downstream. Management structures such as catchwater interceptions and bywash channels have a similar effect of inducing intermittent catchment-coupling through their selective activation (Labadz *et al.*, 1995). However, these are much more difficult to readily identify for each reservoir as they are not listed in the BRE dams data set and not discernable in the FEH (1999). As a result, those reservoirs identified as catchment-coupled in the FEH (1999) with these structures present in their catchments will potentially have larger levels of error associated with their sedimentation predictions.

In addition, uncertainty is introduced regarding reservoir basin sediment delivery associated with inputs external to coupled catchments through catchwater inputs/conduits and additional pump storage. Again, these influences are difficult to readily identify for each reservoir, not being listed in the BRE dams data set and not discernable in the FEH (1999), and therefore also increase potential levels of error associated with respective sedimentation predictions. Thus, through the population data set construction, effort is focused upon potential error recognition and elimination associated with the modelling approach where practically possible.

The initial criteria for entry into the reservoir population data set of mainland Great Britain (the presence of an apparently directly catchment-coupled surface storage reservoir resolvable in the FEH (1999) with a channel outflow, not denoted in the BRE dams data set as a washland), produced a population of 1941 reservoirs from the initial listing of 2500 in the BRE dams data set.

4.2.2 Secondary data for catchment characterization

4.2.2.1 FEH (1999) catchment characteristics

The catchment characteristics extracted from the FEH (1999) for each reservoir in the aforementioned population are presented in Table 4.1. These were obtained from the FEH software through locating the pixel of outflow from the reservoir dam, with the program determining the upstream catchment boundary and associated characteristics in the process. The information was subsequently exported into an Excel spreadsheet (Table A1.1, Appendix 1).

Table 4.1 FEH (1999) catchment characteristics

Catchment Characteristics
Catchment Area(km^2)
Flood attenuation due to lakes & reservoirs index
Proportion of time soils wet index
Mean altitude (m)
Base flow index
Catchment size & drainage path configuration index
Index of catchment steepness (m/km)
Longest drainage path (km)
Median annual max 1-hr rainfall (mm)
Median annual max 1-day rainfall (mm)
Median annual max 2-day rainfall (mm)
1961-1990 average annual rainfall (mm)
1941-1970 average annual rainfall (mm)
Standard percentage runoff
Concentration of urban & suburban cover index
Fractional urban extent for 1990 index
Index of location of urban & suburban land cover

From the catchment characteristics, the median annual flood was calculated for each reservoir catchment (QMED). If the index of fractional urban extent for 1990 index (URBEXT) was less than 0.025, the reservoir catchment was deemed rural and Equation 4.1 was applied. If the index of fractional urban extent (1990) was greater than 0.025, the reservoir catchment was deemed urban and Equation 4.4 was applied (after Robson and Reed, 1999).

$$QMED_{rural} = 1.172\ AREA^{AE}\ (SAAR/1000)^{1.560}\ FARL^{2.642}\ (SPRHOST/100)^{1.211}\ 0.0198^{RESHOST} \quad \text{(Eq. 4.1)}$$

where:

AE denotes the area exponent given by: $AE = 1 - 0.015 \ln(AREA/0.5)$ (Eq. 4.2)

RESHOST denotes a residual soils term from HOST data (Section 4.4.1.3) given by:

$RESHOST = BFIHOST + 1.30\ (SPRHOST/100) - 0.987$ (Eq. 4.3)

$$QMED = UAF\ QMED_{rural} \quad \text{(Eq. 4.4)}$$

where:

$$UAF = (1+URBEXT)^{0.83}\ PRUAF \quad \text{(Eq. 4.5)}$$

where:

$$PRUAF = 1+0.615\ URBEXT\ ((70/SPRHOST)-1) \quad \text{(Eq. 4.6)}$$

Through the nature of information extraction from FEH (1999) for each reservoir catchment (the selection of the pixel representing the outflow from the reservoir dam to define the associated reservoir catchment area), the computed flood attenuation index due to reservoirs and lakes (FARL) does not effectively disclose information regarding flood attenuation (and thus potential storage through the stream network) **upstream** of the reservoir. This is because the reservoir basin itself is considered in the FARL calculation. As a result of this, the mean flood attenuation index (MEANFARL) was calculated from the associated FARL values of each stream flowing into a particular reservoir. This provides a greater insight into the degree of stream network storage in a respective reservoir catchment.

4.2.2.2 Digital catchment areas

Digital catchment areas for the population of 1941 reservoirs were obtained from the Centre of Ecology and Hydrology (CEH) in the form of an ARCVIEW line file. The digital catchment areas were originally derived from the Institute of Hydrology Digital Terrain Model (IHDTM) which contains elevations held digitally over a 50m x 50m grid. For use in the Idrisi 32 (version 2) GIS (Clark Labs, 2001), the ARCVIEW line file had to be converted to a shape file before being exported; of the 1941 catchment areas, 1912 were resolvable in the shape file. (This difference was due to 29 reservoirs having catchment areas of insufficient size to be represented as identifiable areas due to the spatial resolution of the file in ARCVIEW.) Idrisi 32 is a raster based GIS; therefore the shape file was subsequently converted into a raster file of the same scale and co-ordinates as both of the available digital soils and land cover maps, with a spatial resolution of 1km x 1km.

However, at this point of the population data set construction, the scope of the research had to be downscaled from mainland Great Britain, to mainland England and Wales. This was due to financial considerations concerning the purchasing of the digital soils and land cover information; only that for England and Wales was practicable. This reduced the initial population of 1941 to 1039. As a result, the reservoir number in the population data set of 1039 reservoirs (derived from the position in the data set when ordered alphabetically by reservoir name) had to be matched with the respective rasterized catchment number in Idrisi 32.

After conversion of the shape file to raster format, only 901 reservoirs from the revised population of 1039 could be matched to a respective catchment area in Idrisi 32. This is due to an inherent disadvantage with the raster method. Raster data consists of cell units comprising a region of interest with each cell assigned a value of the category being displayed (e.g. a particular reservoir catchment or soil/land cover type). A cell in this instance is assigned to a category that represents most of the cell, the predominant category rule (Eastman, 2001). The area represented by each cell (in this instance 1km x 1km) determines the spatial resolution of the cell. This provides a comparatively coarse spatial resolution in terms of representing the catchment boundaries as they were initially represented by vector data (the ARCVIEW shape file), which encoded the areas through the connection of their vertices (nodes) by arcs. As a result, the vector format is able to define precisely the catchment boundaries. When in raster format at a spatial resolution of 1km x 1km, the catchment boundaries and associated area cannot be discerned in each instance. This is due to the predominant category rule where some of the smaller catchment areas become subsumed by others, especially where many reservoir catchments lie in close proximity to others (e.g. the Pennines).

The conversion of the ARCVIEW shape file of catchment areas into raster format for use in Idrisi 32 reduced the population data set to 901 reservoirs across mainland England and Wales. This was the number of catchment areas resolvable in raster format.

The matching of the reservoir number and respective catchment area number was achieved manually by displaying the rasterized catchment area image, overlaying it with a vector point image of reservoir dam locations and linking the two. The Idrisi 32 ALLOCATE module which assigns a vector point to the nearest designated feature could not be used as, for example, if a small reservoir catchment was not resolved in the raster image, the respective "floating" vector point location of the dam would still be assigned to the closest catchment area, thus inducing error. Upon achieving the matching of the reservoir number and respective catchment area number, the respective soils and land cover information were extracted for each of the 901 reservoir catchments using a "cookie cutting" procedure in Idrisi 32 and added to that derived from the FEH (1999) in the population data set.

4.2.2.3 The National Soils Map of England & Wales (NATMAP 1000)

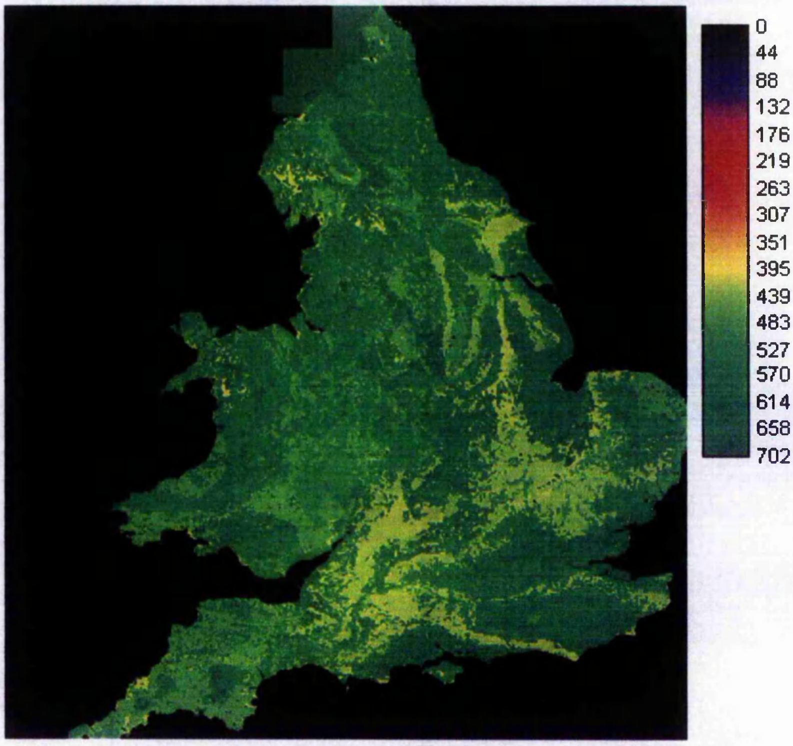
The NATMAP1000 was obtained from the National Soil Resources Institute and used in this investigation to extract the area of the dominant soil type in each 1km x 1km catchment cell across the respective reservoir catchments. This data source is derived from the National Soil Map, the product of sixty years of soil survey work across England and Wales.

The raw data comprising the national soils map of England and Wales consist of four principal columns in spreadsheet form (Table 4.2). The first two columns define the *x* and *y* coordinates of each 1km x 1km cell in geographical space. The third column represents the percentage cover of a particular soil type that is disclosed in column 4. As a result, there are as many cell *x* and *y* iterations as there are percentage covers of soil types present in each respective cell. To transfer this information into Idrisi 32 requires the construction of an ASCII file in which there can only be one *x*, *y* and *z* representation for each cell. As a result of this, the raw data spreadsheet was broken down depicting only one iteration for each cell; the soil association with the largest percentage cover. This was achieved through a simple "if, then, else" statement in Excel. From this revised raw data spreadsheet, a map of the dominant soil type in each cell (in terms of largest percentage cover) was produced (Figure 4.1). The ASCII file constructed to produce Figure 4.1 in Idrisi 32 consisted of the coordinates of each cell comprising the respective *x* and *y* values, and the soil association number comprising the *z* value. The soil association numbers had to be revised as in the raw data they contain letters; ASCII files for importation into Idrisi 32 must be wholly numeric.

Table 4.2 Excerpt of the raw data comprising the NATMAP 1000

Easting (*X*)	Northing (*Y*)	Unit % cover (*Z*)	Map unit
135000	25000	76.29	0611b
135000	25000	23.57	0871a
135000	25000	0.1	0612b
135000	25000	0.04	lake

Figure 4.1 The dominant soil association, in terms of percentage cover, across England and Wales. The legend refers to the revised soil association number.



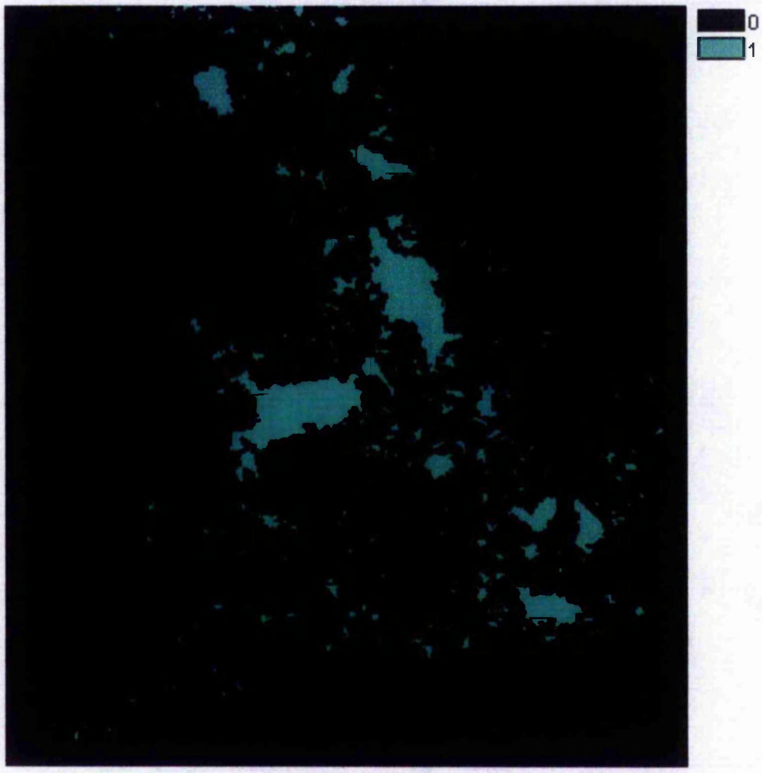
From the 296 soil associations represented in the national soils map, Evans (1990) identifies 15 at a high risk of accelerated erosion and 4 at a very high risk of accelerated erosion (Table 4.3). As a result, the ASCII file used to produce Figure 4.1 was sorted in Excel with regards to the respective soil association numbers. From the sorted spreadsheet separate ASCII files were extracted for each of the 19 soil types and each imported into Idrisi 32. Respective soil association images were formed depicting the distribution of each soil association across England and Wales. Those cells that did contain one of the 19 soil associations as the largest percentage cover assumed a cellular value of that soil association; those that did not had a cellular value of 0. Rasterized catchment boundaries were subsequently superimposed onto each soil association image "cookie cutting" out the respective cells representing each soil association.

Table 4.3 Those catchment soil associations represented at least once in the population of reservoirs available for this research with a high, and very high risk of accelerated erosion after Evans (1990) and NATMAP 1000 (1999).

High Risk Soil Associations	**Description**
Revidge	Shallow peat over sandstone
Bangor	Shallow peat over hard rock
Bromsgrove	Deep loam
South Petherton	Silty over sandstone
Wick 2	Deep loam
Frilford	Deep sandy
Bromyard	Loam over sandstone
Fyfield 2	Loam over sandstone
Everingham	Seasonally wet, deep sandy
Adventurers 1	Peat
Winter Hill	Blanket peat, thick acid raw peat soil perennially wet
Very High Risk Soil Associations	**Description**
Bearsted 1	Loam over sandstone
Bridgeworth	Sandy over red sandstone
Cuckney 1	Sandy over red sandstone
Newport 1	Deep sandy

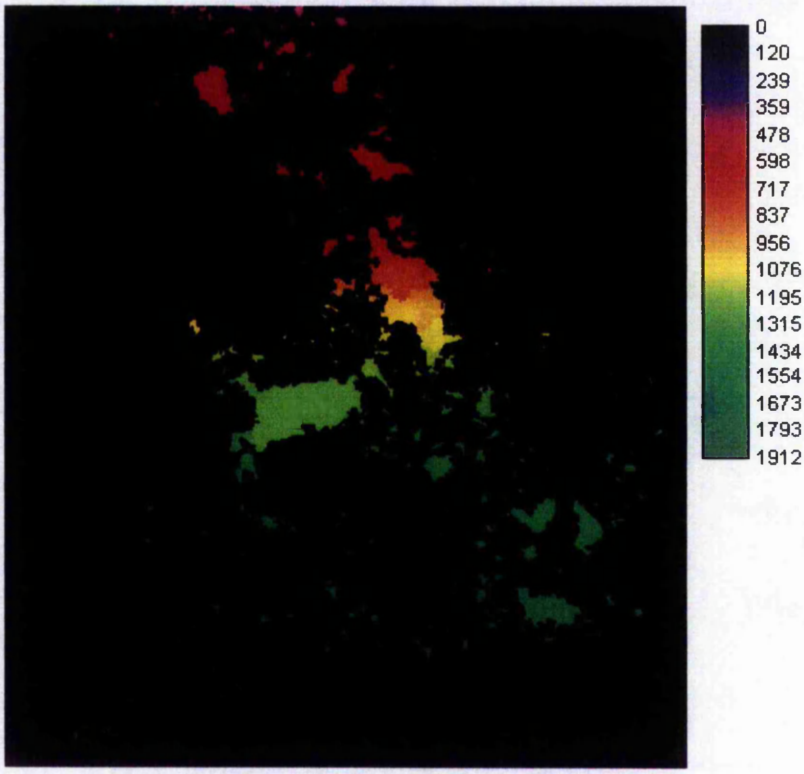
The "cookie cutting" procedure works through the production of a Boolean overlay in Idrisi 32. A Boolean image of the rasterized catchment areas was created (Figure 4.2). In the Boolean image, each of the 901 numbered catchment areas in the image are represented by a respective cell value of 1; the areas of England and Wales not part of the 901 catchment areas are represented by a cell value of 0. Each of the 19 images representing the distribution of the respective soil associations across England and Wales was overlain and multiplied by the Boolean catchment area image. This procedure acted to screen out the areas of each soil association not falling within one of the 901 catchment areas.

Figure 4.2 Boolean image of area covered by reservoir catchment areas across England and Wales



The area of the 19 soil associations in each of the 901 reservoir catchments was calculated using the Idrisi 32 EXTRACT module. Through the EXTRACT module, the total number of 1km x 1km "cookie cut" pixels was determined for each catchment area using both the Boolean catchment area image (Figure 4.2) and the rasterized catchment area image (Figure 4.3), thus determining the area of each of the 19 soil associations in each catchment area. This information was subsequently entered into the data set describing catchment and reservoir basin characteristics for the population of reservoirs. Those soil associations represented at least once in the population of reservoirs are presented in Table 4.3.

Figure 4.3 Rasterized reservoir catchment area across England and Wales. The legend refers to the catchment area number assigned in the original ARCVIEW data set from CEH.



4.2.2.4 Land cover map of Great Britain (LCMGB)

The LCMGB was obtained from the Centre for Ecology and Hydrology. It was used in this study to extract the average percentage cover of the 26 land cover types presented in Table 4.4 for each reservoir catchment in the population data set. The raw data comprising the LCMGB consists of a separate ARCINFO binary format file for each of the 26 cover types. Each file was imported into Idrisi 32 to produce a respective raster image identifying the percentage cover of the respective cover type in each 1km x 1km cell. Using the "cookie cutting" procedure described in Section 4.2.2.3, the mean percentage cover of each land cover type, in each catchment area was calculated using the Idrisi 32 EXTRACT module and entered into the population data set of 901 reservoirs.

There was no occurrence of the sea/estuary, beach and coastal bare, and saltmarsh cover classes within the catchment areas of the reservoir population. In addition, the unclassified class was omitted, as the influence of this classification upon the degree of reservoir sedimentation is unknown. As a result of this, the remaining 22 cover classes were represented in the population data set.

Table 4.4 Land cover classes represented in the land cover map of Great Britain (LCMGB)

Land Cover Class	Description
Beach & Coastal Bare	Intertidal mud, silt, sand, shingle and rocks.
Bracken	Dominated by *Pteridium aquilinum*. Upland or lowland, mixed with grass etc.
Coniferous Woodland	Coniferous species and holly, Rhododendron etc. In leaf all year round.
Deciduous Woodland	Woodland bare in winter
Dense Shrub Moor	Includes heather, ling and bilberry moorlands. Some moor-burning
Dense Shrub Heath	Mostly evergreen, heather, gorse etc. Typically on sandy soils.
Felled Forest	Large quantities of brush-wood etc. As they revegetate first colonized by ruderal weeds, then rough grassland.
Grass Heath	Inland grasslands typically on sandy soils. Large quantities of dead plant litter in winter.
Inland Bare Ground	Natural surfaces (e.g. rock, sand, gravel) and those bared by human activity surfaced with natural materials.
Inland Water	Water covered areas all year round; fresh waters and estuarine.
Lowland Bog	*Myrica gale* and *Eriophorum* spp. Highly characteristic.
Meadow/Verge/Semi-natural	Includes managed grasslands to lesser extent than mown/grazed class. Swards used for hay/low intensity grazing
Moorland Grass	Upland swards of mostly deciduous grasslands. Lightly grazed by sheep. Sparse cover of upland dwarf shrubs.
Mown/Grazed Turf	Managed as agriculturally productive swards or mown as amenity grasslands. Cut and maintained throughout growing period.
Open Shrub Heath	Complements grass heath class. Because grazing of lowland heaths no longer practiced, incidence is rare.
Open Shrub Moor	Commonplace on marginal hill grazing land where grazing prevents dominance of dwarf shrubs. Extensive in *Calluna*.
Rough/Marsh Grass	Lowland herbaceous vegetation of fens, marshes, upper saltmarshes and rough or derelict ground. Swards not cropped/grazed.
Ruderal Weed	Generally bare ground (e.g. abandoned arable, setaside or derelict industrial works) colonized by

	annuals/short lived plants.
Saltmarsh	Intertidal sand, silt or mud-based habitats.
Scrub/Orchard	Deciduous areas, often substantial herbaceous vegetation.
Sea/Estuary	Included all open sea, coastal waters and estuaries.
Suburban/Rural Development	Includes villages, small retail sites, railway stations etc.
Tilled Land	Includes all land under annual tillage, especially for weeds, horticulture etc.
Unclassified	Within the 25m classification data about 2% of Great Britain is unclassified e.g. due to cloud obstruction of Landsat TM imagery.
Upland Bog	Many species of grass and dwarf shrub heaths and moors. Characterized by water-logging and surface water.
Continuous Urban	Includes cities, large towns, major industrial and commercial sites and permanent associated bare ground (e.g. car parks).

Therefore. through the land cover data, the percentage cover of each cover type in each cell can be resolved and subsequently averaged for each catchment area. However, due to the nature of the ASCII file required to represent the soils data in Idrisi 32, each cell could only be labeled with the numbered soil association that accounted for the principal coverage in that particular cell. As a result of this, only the **area** of each principal soil type could be calculated for each catchment, as opposed to the **average percentage cover** of each land cover type for each catchment (percentage cover being the original units for both data sources).

4.2.2.5 BRE dams data set - trap efficiency

From Section 2.11.2, it was shown that morphological factors describing the reservoir basin have important influences on trap efficiency, and thus sedimentation. The BRE dams data set contains information concerning dam height and length, reservoir surface area, and basin capacity; however, much of this is information is incomplete. The omission of reservoirs with incomplete information regarding these potential sedimentation predictor variables would dramatically reduce the population for this study, thereby impacting upon the principal aim; the production of a comprehensive assessment of the spatial variation of reservoir sedimentation for the population of surface water storage reservoirs exhibiting a degree of catchment-coupling across mainland England and Wales. Thus, a trade-off existed between the requirement for factors representing reservoir basin morphology and the ultimate achievement of the principal aim. A compromise was therefore made. Information regarding reservoir basin capacity is most comprehensively represented in the BRE dams data set, therefore this was the only such variable represented in the population data set; the variables of dam height and length, and reservoir surface area were omitted. Using the equation of Brown (1944), trap efficiency was calculated using the basin capacity information from the BRE dams data set and the respective catchment area information obtained from the FEH (1999) (Section 2.11.2.1.4). Heinemann (1981) considers trap efficiency as the most important descriptor of a reservoir. However, the effect of omitting reservoirs from the population data set of 901 on the basis of not having a BRE basin capacity for trap efficiency calculation reduced the population to 797 reservoirs. This was the number that comprised the final population data set (Table A1.1, Appendix 1).

However, it should be noted that the BRE dams data set does not distinguish between an original capacity figure and, where available, a revised capacity figure. Therefore, calculated trap efficiencies may not be directly comparable to each other.

4.2.3 Summary of population data set

The catchment and reservoir basin data collated in the population data set of 797 reservoirs from the FEH (1999), the BRE dams data set, the national soil map of England and Wales, and the land cover map of Great Britain (Table A1.1, Appendix 1), acts to quantify the factors identified in Chapter 2 that influence reservoir sedimentation. The 57 variables summarized in Table 4.5 represent the most comprehensive data set available for this investigation in terms of that obtainable within the time frame of the investigation and within the research budget.

Table 4.5 Catchment and reservoir basin factors collated for each reservoir in the population data set

Variable	Abbreviation	Units
Catchment area	CAREA	km^2
Median annual maximum flood	QMED	$m^3 s^{-1}$
Flood attenuation due to reservoirs & lakes	FARL	Index
Mean flood attenuation due to reservoirs & lakes index	MEANFARL	Index
Proportion of time soils wet index	PROPWET	Index
Mean catchment altitude	ALTBAR	(m above sea level)
Base flow index	BFIHOST	Index
Catchment size & drainage path configuration index	DPLBAR	km
Catchment steepness index	DPSBAR	$m\ km^{-1}$
Longest drainage path	LDP	km
Median annual maximum 1-day rainfall	RMED1D	mm
Median annual maximum 2-day rainfall	RMED2D	mm
Median annual maximum 1-hour rainfall	RMED1H	mm
1960-1990 standard-period average annual rainfall	SAAR	mm
1941-1970 standard-period average annual rainfall	SAAR4170	mm
Standard percentage runoff	SPRHOST	%
Concentration of urban and suburban cover index	URBCONC	Index
Fractional urban extent index (1990)	URBEXT	Index
Location of urban and suburban land cover index	URBLOC	Index
Trap efficiency	TE	%
Revidge soil association	S401	km^2
Bangor soil association	S405	km^2
Bearsted 1 soil association	S454	km^2
Bromsgrove soil association	S454	km^2
South Petherton soil association	S469	km^2
Wick 2 soil association	S475	km^2
Bridgenorth soil association	S486	km^2
Cuckney 1 soil association	S487	km^2
Newport 1 soil association	S489	km^2
Frilford soil association	S495	km^2
Bromyard soil association	S506	km^2
Fyfield 2 soil association	S507	km^2
Everingham soil association	S660	km^2
Winter Hill soil association	S686	km^2
Adventurers 1 soil association	S692	km^2
Bracken	BRACKEN	%

Coniferous woodland	CONIF	%
Deciduous woodland	DECID	%
Dense shrub moor	DSHRUB	%
Dense shrub heath	DSHRUBH	%
Felled forest	FELLED	%
Grass heath	GRASS	%
Inland bare ground	IBARE	%
Inland water	IWATER	%
Lowland bog	LOWBOG	%
Meadow/Verge/Semi-natural	MEADOW	%
Moorland grass	MOORLAND	%
Mown/grazed turf	MOWN	%
Open shrub heath	OPENSHRUBH	%
Open shrub moor	OPENSHRUB	%
Rough/marsh grass	ROUGH	%
Ruderal weed	RUDERAL	%
Scrub/orchard	SCRUB	%
Suburban/rural development	SUBURB	%
Tilled land	TILLED	%
Upland bog	UPBOG	%
Continuous urban	URBAN	%

4.3 Establishment of parameterization and validation data sets

4.3.1 Parameterization data set – secondary data

From a data set compiled by Labadz and Butcher for the Halcrow report (2001) collating all published measured rates of reservoir annual percentage capacity loss, 59 reservoirs with such a measurement were present in the population data set of 797. Therefore at the time of initial parameterization data set construction, 59 reservoirs represented the most comprehensive data set achievable. These 59 reservoirs formed the basis of the parameterization data set from secondary data for subsequent model construction. This was subsequently supplemented by the collection of primary data regarding annual percentage capacity loss for an additional reservoir (Ystradfellte) selected to improve the representativeness of the parameterization data set (see Section 4.3.2) (Table A1.2, Appendix 1).

To ascertain whether the secondary parameterization data set of 59 reservoirs represented any natural groupings of reservoirs of similar characteristics within the population, cluster analysis was performed on the population data set (Table A6.1, Appendix 6). The results were analyzed in relation to how well the parameterization data set spanned the ranges of each cluster. It was important to ensure that any natural groups within the population were represented in the parameterization data set to produce the most robust multiple regression model with the greatest coefficient of explanation possible, and to allow its subsequent extrapolation over the population of reservoirs.

4.3.1.1 Cluster analysis – a description

Cluster analysis seeks to identify relatively homogenous groups of cases based on selected characteristics (variables) which minimize within-group variation and maximize between group variation (Doornkamp and King, 1971). Therefore, in this application the technique identifies those reservoir catchments which show a better correlation between certain sediment-inducing parameters (or groups of sediment-inducing parameters) and APL than others. DeBonis *et al.* (2002) state that this allows one to determine (and apply) different families of regression models on the result of the clustering.

The first stage in cluster analysis is the establishment of a distance or similarity matrix, where the rows and columns are the units of analysis and the cell entries are a measure of distance for any pair of cases. The standard distance measure is Euclidean distance which is defined as the square root of the sum of the squared differences between two cases (e.g. two reservoirs and the values of their respective catchment and reservoir basin characteristics) (Daly *et al.,* 1997).

The second stage is the selection of a linkage method. The linkage method determines how the distance between two clusters is defined. Initially, each observation constitutes a cluster, where the distance between each cluster is the inter-observation distance. However, for each subsequent amalgamation stage, a linkage rule is necessary for calculating inter-cluster distances when there are multiple observations in a cluster (MINITAB, 2000). The average linkage method was used which defines the distance between two clusters as the mean distance between an observation in one cluster and an observation in the other cluster. MINITAB (2000) states that the average linkage method is effective when clusters are not clearly separated. This is because the method uses a more central measure of cluster location. Single (nearest neighbour) linkage for example defines the distance between two clusters as the minimum distance between an observation in one cluster and an observation in the other cluster. MINITAB (2000) recommends that when the average linkage method is used, it is best to use a squared distance measure. As a result of this, the squared Euclidean distance measure was used, increasing the distances between clusters.

Cluster analysis uses an algorithm that starts with each variable in a separate cluster and amalgamates clusters until only one is left (Daly *et al.*, 1997). Each amalgamation stage of observations into one cluster is graphically depicted in a dendogram. A decision has to be made where to "cut the dendogram" to determine the final grouping of clusters that will identify groups whose observations share common characteristics. This is best made analyzing the similarity levels at each amalgamation step. The similarity level is the percent of the minimum distance at that step relative to the maximum inter-observation distance in the data. The amalgamation step where the values change abruptly typically identifies a good point for cutting the dendogram to determine the final groupings of clusters (MINITAB, 2000).

4.3.1.2 Cluster analysis – results

The results of the cluster analysis are presented in Table A6.1, Appendix 6. The dendogram was cut forming 3 principal clusters within the population. Cluster 1 comprises 288 reservoirs that are typically more lowland in nature, as defined by their larger catchment areas and associated dimensions, and have lower rainfall totals. Cluster 3 comprises 35 reservoirs that have more upland, high altitude catchments associated with smaller areas and high rainfall totals. Cluster 2 comprises 473 reservoirs of an intermediate nature between clusters 1 and 3 in terms of their dimensions and rainfall totals.

To ensure that the parameterization data set (Table A1.2, Appendix 1) was representative of the population it was important to incorporate reservoirs that spanned the range of each cluster, in terms of distances from the centroid; i.e. that fell close to the minimum and maximum distance from the centroid, encompassing the mean and standard deviation of the distances. The distances for each reservoir in each cluster of the parameterization data set are presented below in tabular and graphical form (Tables 4.6 to 4.10 and Figures 4.4 and

4.5). There was no representation of reservoirs from cluster 3 in the parameterization data set due to the fact that no information regarding sedimentation rates in these reservoirs was available from secondary data. The lines in Figures 4.4 and 4.5 assume that the data series are continuous; this is not so, however, this style of graph best illustrates and compares the centroid distances in the parameterization data sets with those for the entire cluster.

Table 4.6 Cluster 1 centroid distances of reservoirs represented in the parameterization data set

Cluster 1 Reservoir	Distance from centroid
Eccup	89
Hewenden	534
Langsett	264
Leeming	123
Leeshaw	678
Leighton	69
Scout Dike	363

Table 4.7 Descriptive statistics for cluster 1 of the population data set

Minimum centroid distance: 39
Maximum centroid distance: 1070
Mean centroid distance: 253.2
Standard deviation range of mean centroid distance: +439.5, -66.9

Figure 4.4 Centroid distances of reservoirs represented in the parameterization data set of cluster 1compared to descriptive statistics for the population of cluster 1

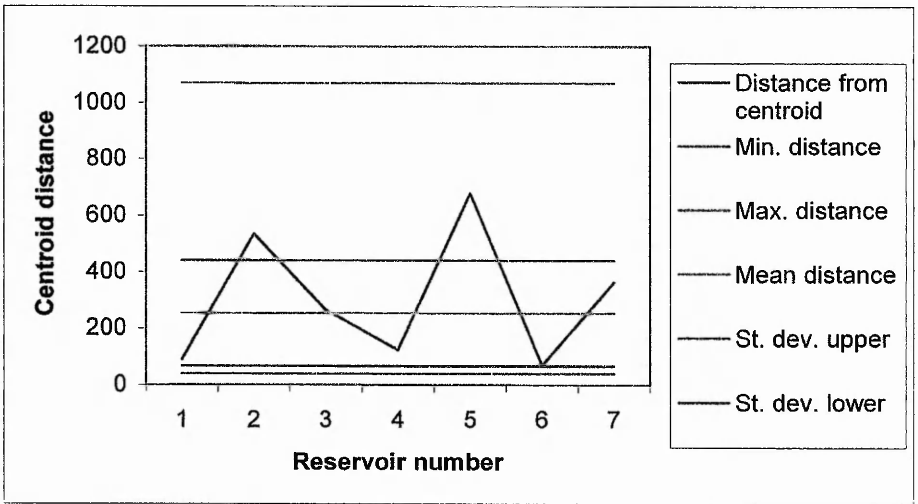


Table 4.8 Cluster 2 centroid distances of reservoirs represented in the parameterization data set

Cluster 2 Reservoir	Distance from centroid
Abbeystead	749
Angram	752
Barden Lower	217
Barden Upper	297
Blackmoorfoot	100
Blakeley	534
Broadstones	116
Broomhead	149
Chelker	274
Dale Dyke	152
Damflask	99
Dean Head Lower	263
Dean Head Upper	267
Deanhead	427
Deerhill	351
Eldwick	303
Embsay	113
Fewston	84
Gorple Lower	410
Gorple Upper	415
Gorpley	538
Green Withens	401
Harden	522
Holmestyes	400
Lindley Wood	370
Ponden	336
Ramsden	711
Redmires Lower	163
Redmires Middle	155
Redmires Upper	161
Riding Wood	719
Rivelin Lower	135
Rivelin Upper	132
Roundhill	99
Royd Moor	173
Ryburn	314
Scammonden	337
Scar House	660
Silsden	284
Snailsden	638
Strines	192
Stubden	195
Tunnel End	480

Underbank	166
Walshaw Dean Lower	396
Walshaw Dean Middle	399
Walshaw Dean Upper	404
Wessenden Head	568
Wessenden Old	562
Widdop	402
Windleden Upper	521

Table 4.9 Descriptive statistics for cluster 2 of the population data set

Minimum centroid distance: 62
Maximum centroid distance: 1333
Mean centroid distance: 482.7
Standard deviation range of mean centroid distance: +740.4, -226.4

Figure 4.5 Centroid distances of reservoirs represented in the parameterization data set of cluster 2 compared to descriptive statistics for the population of cluster 2

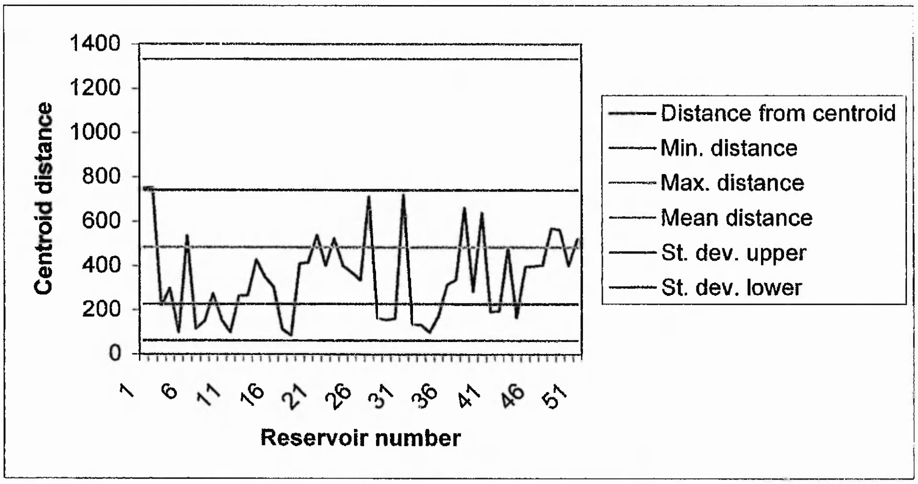


Table 4.10 Descriptive statistics for cluster 3 of the population data set

Minimum centroid distance: 91
Maximum centroid distance: 1080
Mean centroid distance: 362.14
Standard deviation range of mean centroid distance: +560.84, -163.44

The perfect parameterization data set would include individuals from each of the three clusters being represented to the same ratio with respective observations representing the centroid, the maximum and minimum centroid distance, and the standard deviation about the centroid for each cluster. This would allow extrapolations from the multiple regression model predicting reservoir annual percentage capacity loss (APL) to be made from the parameterization data set across the entire population of 797 reservoirs, thus producing a robust model. However, this is not the case. In reality, given the secondary data available, clusters 1 and 2 have a ratio of parameterization data set representation of 1/41 and 1/9 reservoirs respectively, whereas cluster 3 is not represented at all (due to the fact that no information regarding sedimentation rates in these reservoirs was available from secondary data). In addition, the reservoirs represented span the standard deviation of the centroids for clusters 1 and 2 relatively well (Figures 4.4 and 4.5), but not the maximum centroid distances (the outermost limit of each cluster). This will limit the ability of the final multiple regression equation in making a comprehensive assessment of APL across the population of reservoirs as predictions cannot be extrapolated beyond the observed range defined in the parameterization data set.

The perfect solution to the shortcomings of the initial parameterization data set of 59 observations of reservoir annual volume capacity loss (APL) would have been to collect primary data for additional reservoirs using a stratified random sampling scheme, ensuring that each cluster was represented to the same degree (ratio) and that the respective mean centroid value, maximum and minimum centroid distances and standard deviation range about the centroid were represented. This would have favoured the production of a robust multiple regression model allowing extrapolation from the parameterization data set across the population. However, primary data collection concerning APL was also required for a validation data set; therefore this was not practically possible within the time frame of this investigation.

4.3.2 Primary data collection – parameterization and validation data sets

The scheduled fieldwork season for this research of primary data collection had to be reduced due to the outbreak of foot and mouth disease across Great Britain in 2001; the measures employed to combat the outbreak included severely restricted access to many parts of the countryside, including reservoir sites. As a result of this, nine reservoirs was the maximum number that could be surveyed. Of these nine, it was planned to survey three reservoirs from each cluster to obtain an APL value originally intended to comprise the validation data set. However, a value of APL for Howden reservoir in cluster 2 was obtained from Hutchinson (1995). This value was not included in the data set compiled by Labadz and Butcher for the Halcrow report (2001) which formed the basis of the parameterization dataset; therefore it was included in the validation data set. This reduced the number of reservoirs to be surveyed to eight. A stratified random sampling technique was devised to select the reservoirs to survey. This was done in an effort to try and ensure the representation of each cluster in the validation data sets, and to satisfy the requirement of the employed statistical techniques that samples should be randomly selected. It was deemed important to represent the clusters (i.e. the spread of cases about the respective cluster centroids) in the validation data sets to provide an insight into the robustness of the respective models, i.e. whether consistently good results were produced across the range of observations in each cluster. As a result of these requirements, the reservoirs in each cluster were numbered in alphabetical order and the upper and lower standard deviation limits (the cluster mean plus the standard deviation and the cluster mean minus the standard deviation respectively) about each cluster mean (centroid) were calculated. The reservoirs falling into the corresponding sections (above the upper standard deviation limit, below the lower standard deviation limit, and between the limits) were identified. Using a random number table, a corresponding numbered reservoir was identified from each cluster section to survey (except for that which contained the pre-selected Howden reservoir). Where a particular selected reservoir could not be surveyed due to practical factors (e.g. the granting of permission - as in the case of Hedgecourt Lake) or logistical factors (e.g. ease of access to the waterline with the surveying equipment - as in the case of Bleawater reservoir), the selection process was repeated.

4.3.2.1 Primary data collection – methods

Through the primary data collection, the annual percentage reservoir capacity loss for each reservoir was calculated by subtracting the present-day capacity from an original capacity, and dividing the subsequent capacity loss by the age of the reservoir. The original capacity and age of each reservoir was obtained from the BRE dam data set.

The revised capacity for each surveyed reservoir was computed using an OHMEX Sonarlite echo sounder to produce a bathymetric plot. The echo sounder has a transducer frequency of 200 kHz which offers a high degree of accuracy in determining the water/reservoir bottom interface if properly calibrated (to within +/- 0.025 m) (OHMEX, 2000). Echo sounders with a lower transducer frequency (around 60 kHz) can have difficulty in determining the water/reservoir bottom interface where the bottom is soft and muddy, and can indicate the interface to be 10-15cm deeper than the true value (Jobson, 1985). Echo sounders operating in higher frequencies (around 200 kHz) produce a stronger backscatter, detecting a sharper change in the propagation of the wave due to the change in the intrinsic properties between the water and reservoir bottom, thus improving accuracy (Dunbar *et al.*, 1988). For each survey, the echo sounder was checked for calibration through the comparion of the sensor depth measurements with direct measurements.

The geolocation of the echo sounder at the time a depth measurement was taken was determined using a Leica 500 differential GPS (Figures 4.6 and 4.7). This GPS model has an accuracy of +/- 1 cm (Leica Geosystems, 2004). Accurate geolocation defining the absolute *x*, *y*, *z* coordinates of the reservoir bottom is important; Butcher *et al.* (1993) identified geolocation as the principal source of error in the computation of reservoir volumes without using a GPS.

Figure 4.6 Bathymetric survey – geolocation of echo sounder depth measurements using differential GPS

Figure 4.7 Bathymetric survey - differential GPS

The data from the echo sounder and GPS were post-processed to generate a bathymetric plot for each surveyed reservoir using the LISCAD software package. From the bathymetric plot, LISCAD was used to calculate the volume of each surveyed reservoir basin. For the preparation of the plot, where logistically and practically possible, the network of reservoir traverses were spaced significantly less than the shore-to-shore traverse length to minimize interpolation problems during post-processing, as contouring algorithms perform better as data density increases (Morris and Fan, 1997).

4.3.2.2 Primary data collection results

Table 4.11 presents the result of the primary data collection. The respective basin plots are presented in Appendix 7. As cluster 3 was not represented in the parameterization data set (due to the fact that no information regarding sedimentation rates in these reservoirs was available from secondary data), it was decided that Ystradfellte reservoir be removed from the validation data set and entered into the parameterization data set, thus increasing the number of observations in the parameterization data set to 60. Ystradfellte was selected over the other two reservoirs surveyed from cluster 3 (Wet Sleddale and Beacons) as the revised capacity concerning Wet Sleddale was found to have increased since dam commission. This could have been due to errors in the original capacity surveys, or undisclosed dam modifications for example (Section 4.4.4). In relation to Beacons reservoir, the revised capacity identified no real capacity loss since the data of dam commission 106 years ago (Table 4.11). Given the nature of the catchment (e.g. its altitude, median annual rainfall values etc. – Table A1.1, Appendix 1) and its physical similarity and proximity to the Ystradfellte catchment, this result was deemed unlikely. This again could have been due to errors in the original capacity surveys, or undisclosed dam modifications for example (Section 4.4.4). As a result of this, Wet Sleddale and Beacons reservoirs were omitted from the final validation data set, reducing the constituent number to 6 reservoirs (including Howden reservoir from secondary data).

Table 4.11 Reservoirs surveyed comprising the primary data collection

Cluster	Reservoir	Date of Commission	Original Capacity (ML) (from BRE dams database)	Revised Capacity (ML)	Annual Percentage Capacity Loss (APL)
1	Appleton	1848	235	203.43	0.087
1	The Great Lake	1862	770	753.59	0.015
1	Weirwood	1954	5623	5580.32	0.015
2	Bough Beech	1969	10440	10391.03	0.014
2	Eyebrook	1940	8096.59	7894.97	0.052
3	Beacons	1897	1579	1577.22	0.001
3	Wet Sleddale	1967	2282	2688.54	N/A
3	Ystradfellte	1914	3200	2947.08	0.089

4.3.3 Fuzzy sets multi-criteria evaluation population data set

The preceding sections documented the construction of the population data set (encompassing 797 reservoirs) and parameterization data set (encompassing 60 reservoirs) which were applied to the multiple regression modelling approach (Tables A1.1 and A1.2, Appendix 1). However, both data sets had to be modified for the fuzzy set multi-criteria evaluation (MCE) modelling approach.

To conduct fuzzy sets MCE modelling in Idrisi 32 requires a raster image to be constructed for each variable to be considered in the analysis. Therefore, from the population data set, a raster point image documenting the location of each reservoir had to be constructed determining the respective value for each of the associated 57 catchment and reservoir basin factors that influence reservoir sedimentation (Table 4.5). However, whilst the population of 797 reservoirs can each be represented in vector format, upon conversion to a raster format of a spatial resolution of 1km x 1km, those reservoir dam locations falling within 1km of each other cannot each be resolved. This is especially the case for those reservoirs forming a cascade (e.g. Blackmoss Upper and Lower). As a result of this, the population associated with the fuzzy sets MCE modelling approach was reduced to 771 reservoirs (Table A1.3, Appendix 1) and the original parameterization data set of 60 reservoirs (used in this modelling methodology as a verification data set – see Section 6.5.1) was reduced to 54 reservoirs (Table A1.28, Appendix 1).

4.4 Data Quality

This section highlights potential sources of error and uncertainty associated with the original form of each of the 57 catchment and reservoir basin variables (see Table 4.5), and calculated reservoir annual percentage capacity loss (APL). As these variables will be used to parameterize models of reservoir sedimentation prediction, any error and uncertainty will act to reduce the accuracy of the model outputs.

4.4.1 FEH (1999) catchment descriptors

4.4.1.1 Landform descriptors

The Institute of Hydrology Digital Terrain Model (IHDTM) contains elevations held digitally over a 50m x 50m grid and uses digitized river information taken from 1:50000 OS maps to position river valleys. The IHDTM includes a 50m x 50m grid of drainage path directions from which a catchment area can be derived, based on the steepest route to neighbouring grid nodes (Bayliss, 1999). The digital catchment areas used to "cookie cut" soil and land use information from the respective national maps (Section 4.2.2.2) were obtained from the IHDTM, and its incorporation in the FEH (1999) CD-ROM is used to directly extract the catchment land form descriptors of catchment area, longest drainage path, mean drainage path length, mean altitude and mean drainage path slope. There is error and uncertainty associated with the IHDTM in terms of the digitization of information from OS 1:50000 maps, the data quality of the OS 1:50000 maps and that used to construct the grid elevations, and the spatial resolution of the data inducing cartographic generalization. This acts to reduce the accuracy of the aforementioned FEH variables.

Bayliss (1999) validated the computation of catchment area from the FEH (1999) CD-ROM (derived from the IHDTM) through the comparison of 1000 catchment areas obtained manually from undisclosed maps. From the results, the IHDTM-derived catchment area was within 2% of the manually-derived area for more than 70% of catchments, while 87% of catchments were less than 5% different. Bayliss (1999) concluded that this shows the IHDTM can be used to produce catchment boundaries quickly and accurately for the majority of catchments. A few catchments (5%) differed in area by 10% or more. This was attributed to some catchments having boundaries which, through drainage diversion, do not follow the topography defined in the IHDTM. In other cases, the generation of drainage paths through the IHDTM has been flawed by difficulties encountered through using digitized rivers to fix the location of valleys. For example, Bayliss (1999) observed that problems may arise when rivers appear (from the supplied river and contour information) to flow uphill, or where two digitized rivers are located within 50m of each other, the capture of one river by the other can occur. This identifies the effect of factual errors and cartographic generalization (Robinson *et al.*, 1995) in inducing error and uncertainty into the FEH (1999) CD-ROM. This error and uncertainty will act to reduce the accuracy of the reservoir APL predictions.

4.4.1.2 Flood attenuation due to reservoirs & lakes index (FARL)

The flood attenuation index due to reservoirs and lakes directly connected to the catchment stream channel network is calculated from Equation 4.6:

$$\text{FARL} = \prod_{i \in \text{reservoirs and lakes}} \alpha_i \qquad \text{(Eq. 4.6)}$$

where the effect for individual reservoirs and lakes is indexed by:

$$\alpha = (1 - \sqrt{r})^{w} \qquad \text{(Eq. 4.7)}$$

where r is the relative size of the reservoir or lake to its subcatchment, i.e.

r = surface area / subcatchment area

and w is a weight which reflects the importance of the reservoir or lake in terms of the flood behaviour at the catchment scale defined by:

w = subcatchment area / catchment area

(after Bayliss, 1999)

The surface areas of the reservoirs and lakes represented in the FEH CD-ROM are in raster format, obtained from shoreline vector data from OS 1:50000 maps. This induces error into the FARL calculation associated with the cartographic generalization of the reservoir and lake shorelines (analogous to the rasterization of the catchment boundaries discussed in Section 4.2.2.2), and inherent inaccuracies in the OS 1:50000 maps. In addition, factual error is introduced as the shoreline data relates to the 1980s; therefore reservoirs built subsequently will not be represented.

The FARL index remains very much an approximation of the attenuation effect of reservoirs and lakes as whilst it depends on the storage characteristics of the water body, typically well represented by the included surface area variable (Bayliss, 1999), it is also highly dependant upon the discharge characteristics of the outlet, which are not represented (Bayliss, 1999). In addition, the FARL index fails to account for the flood attenuation effect from isolated reservoirs and lakes, i.e. those not directly connected to the catchment stream channel network.

4.4.1.3 Climate and soils

The average annual rainfall (1941-70 and 1961-90) and median annual maximum rainfall (hourly, daily and bi-daily) is calculated in the FEH (1999) CD-ROM for each catchment from a respective Met Office 1km x 1km gridded data set. The interpolation between the rainfall measures in each data set calculates a respective value for each cell in a defined catchment, enabling average annual rainfall and median annual maximum rainfall measures. Clearly, there is error and uncertainty associated with such interpolation.

The standard percentage runoff and base flow index for a defined catchment area is calculated using the 29-class Hydrology of Soil Types (HOST) classification (Boorman *et al.*, 1995). The HOST classification delineates UK soils according to their hydrological properties from standard Soil Survey information and is available as a 1km x 1km grid which records, for each grid square, the percentage of the 1km x 1km area given to each HOST class present (Bayliss, 1999). Boorman *et al.* (1995) give standard percentage runoff and base flow index values for each HOST class. Therefore, the areal fraction of each HOST class present in a defined catchment area is obtained and multiplied by its respective standard percentage runoff and base flow index. These products are subsequently summed producing total catchment standard percentage runoff and base flow index. Error and uncertainty is introduced associated with the assignment of HOST classes to each 1km x 1km grid square. Specifically, this is due to measurement error associated with the original field survey, and the upscaling of the data to classify a 1km x 1km grid square. In addition, error and uncertainty is introduced through the classification of the UK soil types into 29 HOST classes with respective standard percentage runoff and base flow index values. The fact that such classification modifies feature attributes in an attempt to express the salient character of a distribution (Robinson *et al.*, 1995), acts to reduce the accuracy of quantities/fluxes predicted using these variables.

Generalized soil moisture deficit data produced by the Meteorological Office Rainfall and Evaporation Calculation System (MORECS) for the UK is used to calculate the proportion of time catchment soils are wet in the FEH (1999) CD-ROM. Month-end soil moisture deficit values are derived from meteorological variables measured at over 120 synoptic sites around the country. Daily average soil moisture deficit values are interpolated from these sites to obtain values for 40km x 40km grid squares. Soil moisture deficits derived from daily rainfall, minus actual evaporation, are added to the previous day's soil moisture deficit to produce a month-end value for that square. The data used in the FEH (1999) CD-ROM was calculated for grassland with soil of medium water availability. As a result of this generalization, the sparse synoptic site network, and the coarse spatial resolution of the MORECS grid squares, the soil moisture deficit can only be considered a generalized indication of average soil moisture conditions (Bayliss, 1999).

Through the formulation of the proportion of time catchment soils are wet index (PROPWET), the fraction of the catchment that relates to each MORECS square is calculated and used as a weight to derive catchment soil moisture deficit values. Month-end soil moisture deficit values can then be calculated from 1961-1990 for each defined catchment and converted to daily values by linear interpolation between month end values. A soil moisture deficit threshold of 6mm, above which the catchment is defined as dry, was determined and each day of the daily record from 1961-1990 was defined as either wet or dry. From this the proportion of time a defined catchment can be classified as wet over the

1961-1990 period was calculated. In terms of reservoir sedimentation, typically the greater the period of time a catchment can be defined as wet (i.e. below the 6mm threshold), the greater the potential of flood flows and sediment delivery to a reservoir basin. However, the generalization associated through the computation of the index may reduce the accuracy of a model output if included as a predictor variable.

4.4.1.4 Urban and suburban cover

The indexes of the fractional extent of urban cover (URBEXT), the location of urban and suburban land cover (URBLOC) and the concentration of urban and suburban land cover (URBCONC) were calculated from the urban and suburban classes of the Land Cover Map of Great Britain (LCMGB) (discussed in Section 4.2.2.4), produced by the Institute of Terrestrial Ecology (now the Centre of Ecology and Hydrology – CEH). The LCMGB was produced using supervised maximum likelihood classifications of Landsat Thematic Mapper data and is based on a 25m grid (Fuller, 1995). However, there appears to be frequent misclassification of tilled land especially, as urban or suburban (Bayliss, 1999). As a result of this, the validity of each grid square (at a resolution of 50m) classified as urban or suburban in the LCMGB was assessed through the overlay of digital OS 1:250000 data (Bayliss, 1999). Due to the scale of the OS data, the settlement polygons are often generalized and sometimes displaced to improve clarity; as a consequence the polygons were extended with a 250m buffer to overcome these spatial inaccuracies (Bayliss, 1999). Therefore, if a LCMGB cell designated urban or suburban fell on a settlement polygon or respective buffer zone it was accepted; if not, it was rejected. This procedure was validated against 34 plots providing ground truth information. Bayliss (1999) concludes that overall, this correction of LCMGB urban and suburban classes advanced the data set. However, error in classification is still induced with the 250m buffer zone being too large in some instances resulting in apparently spurious LCMGB being accepted, and in a few instances the buffer appearing too small resulting in authentic data being rejected (Bayliss, 1999). The latter is especially the case where settlements correctly classified by the LCMGB have expanded (beyond the 250m buffer zone) since the OS data was compiled. This identifies how factual error, and error induced by generalization and classification can degrade the accuracy of the URBEXT, URBLOC and URBCONC FEH variables from the outset.

The IHDTM-derived catchment boundaries are used to compute URBEXT for a defined catchment in the FEH (1999) CD-ROM. This variable is composite index of the urban and suburban fractions derived from the refined LCMGB data. As a result of urban areas potentially exerting a greater influence on flood generation through a greater density of impermeable surfaces etc. (Section 2.11.1.6.4), through the computation of the URBEXT index the suburban fraction is multiplied by 0.5. Bayliss (1999) states that this is because urban development might, on average, be expected to occupy one half of each pixel in the suburban land cover class. Therefore, this generalization and the error associated with the IHDTM (Section 4.4.1.1) compound the degradation of accuracy associated with URBEXT.

The IHDTM is also used to calculate URBLOC and URBCONC in the FEH (1999) CD-ROM. The former is an index depicting the location of urban and suburban areas, i.e. whether they are near the defined catchment outlet or in the headwaters. The IHDTM calculates the mean distance along the defined drainage paths from the urban and suburban grid nodes to the catchment outlet. The latter is an index depicting the concentration of urban and suburban land cover. The IHDTM calculates the ratio of the number of urban and suburban grid nodes that flow to a point under examination in the FEH CD-ROM along the defined drainage paths to the number of nodes in total flowing to that point. Therefore, as with the derivation of the URBEXT variable, the generalization and error associated with the IHDTM (Section 4.4.1.1) compounds the degradation of accuracy associated with URBLOC and URBCONC regarding the representation of urban and suburban land use classes in the FEH (1999) CD-ROM.

4.4.1.5 Median annual maximum flood

Equations 4.1 – 4.6 (Section 4.2.2.1) are used to calculate the median annual maximum flood (QMED) for each reservoir in the population data set. Through these equations, QMED is related to the respective catchment area, catchment wetness (SAAR), soils (SPRHOST and RESHOST), and the attenuation effects of upstream reservoirs and lakes (FARL). However, Robson and Reed (1999) state that the direct use of this equation typically gives poor estimates of QMED in comparison to even very short (e.g. two-year) flood records; the respective confidence intervals concerning the prediction are very wide.

This is because the equation incorporates the aforementioned error from the associated catchment descriptors, and through itself represents a simplification of reality. The catchment descriptor equation, however, represents the most readily obtainable/practical measure of QMED for the population data set. As a result of the equation providing only an approximation of QMED, it is more conducive for use in fuzzy set multi-criteria evaluation modelling as opposed to multiple regression as the former quantifies the value of QMED in relation to an arbitary degree of influence upon reservoir sedimentation; thus the actual measure of QMED in cumecs is not considered.

4.4.2 The National Soils Map of England & Wales (NATMAP1000)

As previously discussed in Section 4.2.2.3, the NATMAP1000 used in this investigation to extract the area of the dominant soil type in each 1km x 1km catchment cell across the respective reservoir catchments is derived from the National Soil Map, which is the product of sixty years of soil survey work across England and Wales. An average of two to three observations per square kilometre (outside areas of earlier, more detailed survey) details the distribution of 300 soil associations across the two countries. Error and uncertainty is induced regarding how well these observations represent the respective square kilometre cells and how interpolation is made between them. Typically, soil surveying is based on the concept of the soil-landscape relationship where soil scientists first build a model of the soil-landscape relationship through analyzing the landscape and through extensive fieldwork (Xing Zhu, 2002). Subsequently, the spatial distribution of soil landscape units are delineated to form soil polygons wherein soil samples are taken. However, as previously mentioned, error and uncertainty is induced regarding the “representativeness” of the soil polygons (with small soil bodies typically being omitted) and the unrealistic assumption that soils within the polygons are homogenous bodies and that changes only occur at the boundaries of the polygons (Xing Zhu, 2002). In addition, Xing Zhu (2002) states that most soil mappers base their soil unit delineation solely upon the visual interpretation of stereophotos. This can be problematical as subtle and gradual changes in environmental conditions are often difficult to discern via stereoscoping and it is easy to misplace the boundaries of soil polygons in the manual delineation process.

4.4.3 The Land Cover Map of Great Britain (LCMGB)

The LCMGB used to extract the average percentage cover of the land cover types presented in Table 4.5 for each reservoir catchment in the population data set was produced using supervised classification of Landsat Thematic Mapper data which has a spatial resolution of 30m. Fuller (1995) states that the largest source of error in the LCMGB stems from the classification of the land cover classes. There are three essential steps involved in a typical supervised classification procedure. The first is the training stage where the analyst identifies training areas representative of the land cover types and develops a numerical description of the spectral attributes of each respective land cover type. The second stage is the classification stage where each pixel in the image data is categorized into the land cover class it most resembles. For the production of the LCMGB a maximum likelihood classifier was used which assumes a normal distribution of the cloud of points forming the training data (Lillesand and Kiefer, 1994). The statistical probability of a given pixel value being a member of a particular land cover class is then calculated. The probability of a given pixel occurring in each land use class is calculated and is subsequently assigned to the most likely class, or labeled unknown if the probability values are all below a threshold set by the analyst (Lillesand and Kiefer, 1994). The third stage is the output stage whereupon the entire data set has been classified and the results are presented. Mather (1996) states that the accuracy of a supervised classification depends upon the representativeness of the estimates of the number and statistical nature of the spectral classes present in the image data, and the degree of departure from the assumptions upon which the classification technique is based. As previously mentioned, the maximum likelihood classifier employed in the production of the LCMGB holds only if the assumption that the frequency distribution of each land cover class membership can be approximated by a normal distribution. However, Mather (1996) states that in practice, this assumption holds reasonably well and that the maximum likelihood procedure is not too sensitive to small departures from the assumption provided that the actual frequency distribution of each class is unimodal.

Whilst error and uncertainty can be associated with the maximum likelihood classifier, the resulting classification is deemed more accurate than that produced by other classifiers (i.e.

the minimum distance to means classifier and parallelepiped classifier) as the training sample data is used to provide estimates of the shapes of the distribution of membership of each land cover class as well as the location of the centre point of each class (Mather, 1996).

The use of a combination of summer and winter data improved classification accuracies especially in distinguishing arable fields bare in winter and vegetated in summer, and permanently bare surfaces such as urban (Fuller, 1995). In total, 88% of Britain was classified from combined summer-winter images, and 12% from single-date, mostly summer data (Fuller, 1995). Fuller (1995) states that 0.4% of Britain was obscured by clouds on summer and winter images.

To assess the accuracy of the supervised classification comparisons were made with independent ground truth data. The overall correspondence between field and LCMGB samples was 67% (Fuller, 1995). Fuller (1995) states that the biggest component of map error is probably the misclassification of mixed boundary pixels. From the independent ground truth data set, some 40% of all pixels adjoined or crossed a vector boundary and were thus made up of mixed cover types and additional boundary features: correspondence was raised to 71% when boundary pixels were excluded (Fuller, 1995).

In addition there are minor discrepancies associated with the geometry of the Landsat Thematic Mapper data (Fuller, 1995). The sources of geometric distortions range from variations in the altitude, attitude, and velocity of the sensor platform, to factors such as the earth's curvature, atmospheric refraction, nonlinearities in the sweep of a sensor's instantaneous field of view, panoramic distortion and relief displacement (Lillesand and Kiefer, 1994). However, Landsat images are relatively free from the latter two factors (Barrett and Curtis, 1995). Geometric correction must therefore be undertaken to compensate for distortions induced by these factors so that the corrected image has the geometric integrity of a map. Some distortions are systematic and can be corrected relatively easily, such as correcting for the skewed-parallelogram effect of the Earth rotation beneath the satellite during imaging, whereby each scan is offset by an appropriate amount (Barrett and Curtis, 1995). However, corrections for unsystematic distortions are accomplished through reference to ground control points. The ground control points are located image coordinates on the distorted image and in terms of their geometrically correct ground (map) coordinates. These values are then submitted to a least squares regression analysis to determine coefficients for two transformation equations that interrelate the satellite image and ground sets coordinates. The satellite image can then be resampled onto the geometrically correct image matrix. However, too few ground control points categorizing the scope of the satellite image can undermine the accuracy of the resampling process, as can the failure of the data in complying with the strict assumptions of regression to ensure a robust result (Section 5.2).

Other differences between field and LCMGB samples were attributed to changes in cover between surveys, sometimes two years apart, as the target data for imagery was 1990 plus or minus two years. Fuller (1995, page 2) states, "...if we allow for likely time-based changes, overall correspondence is measured at 76% including boundary pixels, or 82% excluding boundary pixels." However, these observations represent average errors, therefore local discrepancies may be observed which suggest higher or lower accuracy levels. In summary, Fuller (1995) identifies 80-85% as a realistic assessment of the LCMGB accuracy.

4.4.4 Calculated reservoir annual percentage capacity loss (APL) rates

Reservoir annual percentage capacity loss (APL) was calculated for the validation and majority of the parameterization data sets using a GPS/total station and echo-sounder survey to derive current capacities for subsequent subtraction from original capacity data presented in the BRE dams data set.

Associated with the GPS/total station and echo-sounder survey, potential measurement error is introduced through the measurement of the reservoir depth and the location of the echo-sounder at the time the depth is measured. The majority of the APL measurements in the parameterization data set were calculated by Labadz and Butcher using an echo-sounder operating at 146 KHz and total station for associated geo-location.

Bruk (1985) states that in reservoirs with soft muddy bottoms echo-sounders operating around 60 KHz may give misleading information indicating that the interface is 10-15 cm deeper than the true value. However, echo-sounders operating around the 120 KHz frequency can solve this problem and disclose information about the underlying strata although interpretation of the depth trace can be subjective (Bruk, 1985). This potential measurement error is reduced with regards to the validation data. The echo-sounder used to derive these primary data operates at 200 KHz which provides a distinct image of water bottoms (Dunbar *et al.*, 1998). In addition, the use of GPS in the primary data collection to geo-locate the echo-sounder at the time of depth measurement is comparatively more accurate than the use of a total station, providing measurements to within 1 cm accuracy (Leica Geosystems, 2004), free from potential human error. The advantage of GPS as a faster, more efficient method of geo-location also enabled more thorough, comprehensive surveys to be undertaken, potentially increasing the accuracy of subsequent reservoir basin construction through between measurement interpolation in the LISCAD surveying programme. For the primary data collection, the echo sounder was calibrated through the comparison of depth measurements against those made directly in an attempt to limit/reduce associated measurement error. Therefore, the primary data forming the validation data set concerning revised reservoir capacities may be associated with reduced measurement error in comparison to that collected by Butcher *et al.* (1992a, 1992b and 1993) and Labadz *et al.* (1991, 1995 and 1999) which forms the majority of the parameterization data set. However, as a result of this, the overlying degree of measurement error induced by both respective surveying methods is not constant across all of the revised reservoir capacities from the parameterization and validation data sets collectively.

Error is also introduced into the calculation of APL through the original capacity estimate. White *et al.* (1996b) identify three essential difficulties in relation to original capacity data:

- The age of a reservoir and its associated structures may be beyond that of the majority of its users, managers, and regulatory authority, and hence records may have been misplaced or overlooked.

- The variability in accuracy of the original capacity estimates and the practices adopted to achieve a stated level of capacity.

- Historic management practices may alter capacity over time, often without record.

From revised capacity information of nine reservoirs in Yorkshire, White *et al.* (1996b) identified increases in capacity accompanied by an increase in depth. This was attributed to the accepted original capacity being that above the bottom drawoff valve rather than the total volume of water stored. Therefore, these reservoirs may have experienced a loss of capacity, but not sufficient to encroach upon the live storage (White *et al.*, 1996b). However, over-estimation of capacities were also related to inaccurate mapping at the time of reservoir construction where the original basin map does not represent a true depiction of the ground surface at the time but an interpretation of the ground surface as defined by the limitations of the equipment used (White *et al.*, 1996b).

Foster and Lees (1999b) identify the same problem through calculating the average long-term sediment yield rate of Silsden reservoir (reconstructed using a paleolimnological approach based on sediment core analysis) at almost an order of magnitude lower than that given for the same site by Butcher *et al.* (1993) on the basis of a reservoir re-survey. As a result, Foster and Lees (1999b) conclude that reservoir re-survey data should be treated with considerable caution in providing estimates of sediment yields/sedimentation rates where calculations rely on estimates of the original reservoir capacity at the time of construction and where surveys of sediment thickness have not been undertaken. However, in terms of the research herein, primary data collection for a validation data set using such a method was not practical within the timeframe of the investigation.

Such error is present in the BRE dams data set reservoir capacities and is therefore manifested in the calculations of APL. In addition, the reservoir capacities in the BRE dams data set may not represent the original capacities. Where a revised capacity has been calculated, this may have been reported by the reservoir undertakers instead. This is apparent through many of the revised capacities of Yorkshire reservoirs calculated by

Butcher *et al.* (1992a, 1992b and 1993) and Labadz *et al.* (1991, 1995 and 1999) being entered in the BRE data set as "reservoir capacities." Therefore, the ambiguity of the BRE dams data set information may act to induce error in the calculation of APL in the parameterization and validation data sets.

4.4.5 Trap efficiency

The potential error in the "original capacities" from the BRE dams data set reduces the accuracy of reservoir trap efficiency calculated through Brown's equation (1944) (Section 2.11.2.1.4). This equation in itself is a model approximating the relationship between trap capacity:catchment area and trap efficiency and is thus associated with error.

4.4.6 Summary

This chapter has examined some of the sources of potential error associated with the measure of reservoir sedimentation (APL) and each associated predictor variable. The error of each respective variable selected will be manifested in the parameterization of the multiple regression models predicting APL. This will act to degrade the accuracy of the precise, quantified multiple regression outputs. However, fuzzy set multi-criteria evaluation (MCE) accounts for such inherent error through specifying the arbitrary degree of influence the value a particular variable has on the degree of reservoir sedimentation (scaled between 0 and 1). This is different to regression which defines the precise rate of change induced by a variable value on a quantified output. Therefore fuzzy set MCE considers and expresses the degrees of influence particular variables have on the degree of sedimentation over and above the associated error, conceptualized through expert scientific opinion/intuition.

5. Modelling – Multiple Regression Analysis

5.1 Introduction

This chapter describes the multiple regression technique, discusses previous applications in the prediction of reservoir sedimentation/sediment yield, and documents the construction of two final models. One model concerns the prediction of reservoir annual percentage capacity loss (APL) for the population; the other concerns APL prediction for a cluster from the population. The latter assesses the clustering approach used by Jansen and Painter (1974) and DeBonis *et al.* (2002) to improve the coefficient of determination of multiple regression models (Section 5.3.1). All of the respective statistical analysis and results are included in Appendices 3 and 4; only the key results pertinent to the discussion of the regression equations are included in this chapter.

The production of a multiple regression model predicting APL for the population data set contributes in achieving objective three of this research; the production of two parameterized, verified, validated and operationalized empirical models using multiple regression analysis and fuzzy set multi-criteria evaluation respectively.

5.2 Multiple regression analysis – a description

The multiple regression equation takes the form of:

$$Y = a + b_1 X_1 + b_2 X_2 + \ldots b_i X_i \pm e$$

where,

a = intercept value on the y axis

b_1 to b_2 = partial regression coefficients

e = error term

(Shaw and Wheeler, 1994)

The slope coefficients (b) are known as partial regression coefficients since they measure values that are obtained by controlling for each of the independent variables (Shaw and Wheeler, 1994). Each coefficient represents the amount of change in the dependent variable that can be associated with a variation in one of the respective independent variables and are estimates of the unknown population coefficients. The method of least squares is used to estimate the values of the coefficients. Thus, the coefficients selected result in the smallest sum of squared differences between the observed and predicted values of the dependent variable as predicted by the multiple regression model.

The differences between the observed and expected values of Y are error terms. Error is common in geographical applications where partial relationships and not precise mathematical ones are typically investigated (Shaw and Wheeler, 1994).

Stepwise multiple regression was performed throughout this study. This computes an equation through the re-examination of independent variables each time a new one is entered into the equation to identify any that have become superfluous, or to permit the use of previously rejected variables (Shaw and Wheeler, 1994).

To operationalize a multiple regression model, the following assumptions of the technique must be met (Barber, 1988; Norusis, 1994; Ebdon, 1995):

- The relationship between the dependent variable and independent variable(s) is linear.

- Correlation between the independent variables does not exist (multicollinearity).

- The values of the residuals are independent of each other, i.e. they are randomly arranged along the regression line.

- The variance of the dependent variable is constant for all values of the independent variable and normally distributed.

- The values of the residuals have a normal distribution.

5.3 Previous applications of multiple regression

As identified in Section 3.2.1, many studies that have developed lumped empirical reservoir sedimentation/sediment yield models; attempting to obtain meaningful relationships between sediment records stored in impounded water bodies or sediment yield measurements and factors perceived to initiate sediment production, have successfully used multiple regression analysis (Anderson, 1957; Jansen and Painter, 1974; Collins, 1981; Bazzoffi *et al.*, 1996; Verstraeten and Poesen, 2001; DeBonis *et al.*, 2002; Sekhar and Rao, 2002). DeBonis *et al.* (2002) identify that multiple regression is ideally suited to applied geomorphological investigations, in terms of catchment land planning and management, as it is reliable and simple to employ.

Table 5.1 identifies those independent variables employed in the examples of multiple regression analysis cited above. From these previous applications, there are six principal groups of independent variables identified to influence reservoir sedimentation: hydro-meteorological, land use, soil type, catchment network characteristics, catchment morphology and reservoir basin morphology. In order to be as robust as possible, it is important that the prospective multiple regression model has the potential to be parameterized with variables from each of these groups. This represents a criticism of the DeBonis *et al.* (2002) model in particular, where no information regarding land use and hydro-meteorological variables is entered into the multiple regression analysis.

Table 5.1 Independent variables used in previous multiple regression analysis applications.

Author	Year	Dependent Variable	Independent Variables
Anderson	1952	Sediment yield	Rainfall intensity
			Rainfall amount
			Streamflow
			Land use
			Catchment area
			Geology

			Physiography
Jansen and Painter	1974	Sediment yield	Annual average rainfall
			Mean annual temperature
			Rock softness to erosion parameter
			Altitude
			Relief:length ratio
			Catchment area
			Denudation rate
			Vegetation protection factor
Collins	1981	Annual sediment load	Catchment area
			Annual average mean daily discharge
			Land use/catchment vegetation factor
			Area of respective soil erodibility index
			Soil erodibility index unit yield
			Capacity:catchment area ratio
Rooseboom and Lotriet	1992	Sediment yield	Depth ratio
			Mean annual rainfall
White	1993	Reservoir sedimentation	Catchment area
			Erodible surface
			Mean slope
Bazzoffi *et al.*	1996	Reservoir sedimentation	Mean annual rainfall
			Drainage density
			Reservoir surface area
			Dam Height
			Dam length
Halcrow	2001	Reservoir sedimentation	Catchment area
			Capacity:catchment area ratio
			Mean annual rainfall
			Sedimentation susceptibility category
			Catchment area
			Hypsometric integral
			Drainage length
Van Rompaey *et al.*	2001	Sediment yield	Drainage length
			Horizontal distance
			Hypsometric integral
Verstraeten and Poesen	2001	Sediment yield	Weighted average of direct bifurcation ratio
			Catchment area
			Catchment area
DeBonis *et al.*	2002	Sediment yield	Annual precipitation
			Annual runoff
Sekhar and Rao	2002	Sediment yield	Average catchment slope
			Drainage density
			Vegetative cover factor

5.3.1 Limitations of previously published multiple regression analyses

Authors such as Butcher *et al.* (1992a), Rooseboom and Lotriet (1992), White (1993), Labadz *et al.* (1995), and the Halcrow report (2001) were relatively unsuccessful in providing large, significant coefficients of explanation in multiple regression analyses regarding the prediction of reservoir sedimentation/sediment yield from catchment and reservoir basin morphology factors over large spatial scales. This has been attributed to:

1) Inadequate sample size, failing to provide sufficient observations of the natural grouping of catchments with similar attributes that occur in the data (White, 1993; Verstraeten and Poesen, 2001). These natural groupings occur where particular catchments show a higher correlation between some attributes (or groups of attributes) and sedimentation rate. If such natural groupings are not represented in the parameterization data set of the multiple regression model, the resulting equation often cannot be transferred to predict for them. Singh *et al.* (1988) state that this is the main disadvantage of the multiple regression technique.

2) A limited number of variables entered describing catchment and reservoir basin factors (e.g. Rooseboom and Lotriet, 1992), in particular soil and land use (e.g. Jansen and Painter, 1974) and hydro-meteorological variables (e.g. DeBonis *et al.*, 2002).

3) Catchment and channel storage. As a result of catchment and channel storage, greater correlation may exist between catchment variables and gross catchment erosion as opposed to sediment yield (Duck and McManus, 1990). This is because only a fraction of the sediment eroded within a catchment area will usually be represented in the sediment yield (Walling, 1983).

4) A coarse spatial resolution of variables, failing to characterize the spatial diversity of sediment production factors that produce considerable local variations in sediment delivery (Rooseboom and Lotriet, 1992; Verstraeten *et al.*, 2002),

5) The failure to account for the influence of management practices and their selective operation on reservoir capacity loss (Butcher *et al.*, 1993) and the influence of small

anthropogenic landscape elements (e.g. banks, hedges, tillage directions etc.) (Verstraeten and Poesen, 2001; Price and Lovett, 2002a and 2002b; Prosser and Karssies, 2001).

6) The failure to account for autochthonous sediment production that can comprise a significant proportion of reservoir bottom sediments (Duck and McManus, 1987).

In relation to point 1, Jansen and Painter (1974) and DeBonis *et al.* (2002) cluster catchments together with similar attributes and produce a multiple regression model for each respective group. Jansen and Painter (1974) grouped their investigated catchments together on the basis of four climate types. The four models accounted for 93.5%, 86%, 62.8% and 64.5% of the variance in mean annual suspended sediment yield respectively.

DeBonis *et al.* (2002) used cluster analysis to determine two natural groupings in their data set. The two respective multiple regression models produced average errors of 9.5% and 12% respectively. In comparison, the model produced encompassing all of the investigated catchments had an average error of 14%. The use of cluster analysis sharpened the estimate/prediction of sediment yield obtained using the multiple regression analysis method. This is because the catchments within each cluster are very similar in their erosion and sediment-delivery potential; therefore, the unexplained variation in the respective regression equations is less.

Verstraeten and Poesen (2001) support the use of such clustering approaches; they state that when undertaking a large spatial scale investigation of sediment yield, producing one single predictive model is unrealistic; several predictive models should be established for groups of similar catchments.

The multiple regression modelling approach offers potential for large-scale reservoir sedimentation prediction providing the reasons identified for previous failure are taken into account. The application of multiple regression upon cluster analysis results may also act to improve the reliability of the method. As a result of this two forms of multiple regression model were produced: the first predicting APL for the complete population of reservoirs, the second assessing the clustering approach.

5.4 Minimization of identified limitations in multiple regression

This section details the effort made to minimize each of the reasons for previous failure of multiple regression analysis (Section 5.3.1) for the application of the technique in this research.

5.4.1 Limitation 1 – inadequate sample size

Through the construction of the parameterization data set, every effort was made to ensure it represented the population data set in terms of characterizing the three natural clusters of reservoirs that share similar characteristics within the population (Section 4.3.1.2). This is important in developing a robust regression model that can be extrapolated across an entire population. However, due to practical constraints imposed by the time frame of this investigation, only cluster 2 was comparatively well represented (Section 4.3.1.2). As a result of this, the clustering approach (detailed in Section 5.3.1) as employed by Jansen and Painter (1974) and DeBonis *et al.* (2002), was only applied to reservoirs in cluster 2 in an effort to improve predictions for this cluster in comparison to those provided by the model parameterized for the complete population data set. As previously discussed in Section 5.3.1, the clustering approach can yield improved regression model coefficients of determination in comparison to a universal model predicting for an entire population, as the unexplained variation within each cluster is less due to the intra-cluster observations having similar characteristics defined by the independent variables.

Therefore, in summary, the most comprehensive parameterization data set obtainable was collated to produce a multiple regression equation with the intention of predicting reservoir annual volume capacity loss (APL) across the population of reservoirs in accordance with the principal aim of the research (Table 1.2, Appendix 1). The clustering approach was applied to cluster 2, the most represented cluster within the parameterization data set (Table A1.23, Appendix 1), to produce a second multiple regression equation assessing the **potential** of the approach in achieving the principal aim of the research.

5.4.2 Limitation 2 - limited number of factors

The most comprehensive data set obtainable from readily available data sources of hydro-meteorological, land use, soil type, catchment network characteristics, catchment morphology and reservoir basin morphology factors perceived to influence reservoir sedimentation/sediment yield was collated (Chapter 4). In light of the specific criticisms of Jansen and Painter (1974) and DeBonis *et al.* (2002) for not including variables describing soil and land use types, and hydro-meteorological variables respectively (Section 5.3.1), the dataset contains areas of the 15 soil classes at high and very risk of erosion across England and Wales (after Evans, 1990), average percentage covers of 22 land cover types, the proportion of time the catchment soils are classified as wet, the standard percentage runoff of precipitation, median annual flood, a base flow index, median annual maximum hourly, daily and bi-daily rainfall, and mean annual rainfall from 1941-1970 and 1961-1990 for each reservoir catchment (Table 4.5, Chapter 4).

5.4.3 Limitation 3 – catchment & channel storage

The inclusion of variables depicting catchment and channel storage is inherently difficult and can only be attempted through the incorporation of surrogates describing the catchment morphology. Such surrogates in this investigation include catchment area, mean drainage path slope, mean drainage path length, longest drainage path and a flood attenuation index due to reservoirs and lakes.

5.4.4 Limitation 4 – coarse spatial resolution of data

The spatial resolution of the soil and land cover type data was the optimum available within the budget for this research. The spatial resolution of both data sets is 1km x 1km.

However, all such maps are beset by cartographic generalization. Robinson *et al.* (1995) identify five terms associated with cartographic generalization which affect the production of maps, albeit to varying degrees depending upon the nature of the material represented: classification, simplification, exaggeration, symbolization, and induction. Classification acts to express the salient character of a distribution and is the ordering, scaling, and grouping of features by their attribute values (e.g. the allocation of similar qualitative attributes such as land use or vegetation into categories such as cropland and forest). Simplification determines the important characteristics of feature attributes and eliminates unwanted detail. Exaggeration deliberately enlarges or alters a feature to capture its real-world essence (e.g. the exaggeration of the distinctive shapes of countries at smaller spatial scales). Symbolization is the process of graphically coding information and placing it into a map. Induction occurs when inferences are made among map features (e.g. the delineation of soil type areas from surveyed sites). The issue of map scale and data quality and quantity greatly affect the generalization process. Typically at large scales most of the generalization is classification, whereas at smaller scales exaggeration becomes most important (Robinson *et al.*, 1995). However, Robinson *et al.* (1995) identify map scale as an important factor in influencing the degree of generalization; the smaller the map scale, the more generalization will usually be required. Therefore, the error and uncertainty that was propagated into the modelling process of this research as a result of the cartographic generalization of the 1km x 1km soil and land use digital data sets could have been reduced had the procurement of the larger scale respective data sets been possible within the research budget.

5.4.5 Limitations 5 & 6 – management practices and autochthonous sediment production

The effect of management practices, small anthropogenic landscape elements and autochthonous sediment production remain extremely difficult to quantify and consider in such large-scale multiple regression analyses (Butcher *et al.*, 1993), and thus may still prevent significant relationships from being obtained. Indeed, the effect of some management practices on sediment delivery and retention in reservoir basins remains inherently qualitative in the context of this investigation (e.g. reservoir drawdown) and it was not possible to include quantitative representation of these practices within the model.

5.5 Multiple regression application

The validity of an output from multiple regression analysis is dependent upon a number of assumptions being met (Section 5.2). Table 5.2 lists the respective diagnostics applied in this investigation to check for violations of the multiple regression assumptions. These are included in Appendix 3; only the key results pertinent to the discussion of the regression equations are presented in this chapter.

Table 5.2 Multiple regression diagnostics

Assumption	Diagnostic
Linearity	Pearson's correlation
	Scattergraphs - independent variables versus dependent variable
	Analysis of variance
	t statistic
	Leverage
	Cook's distance
Non-multicollinearity	Tolerance statistic
Residual independence	Durbin-Watson test
Residual constant variance	Scattergraphs - residuals versus predicted values
Residual normality	Kolmogorov-Smirnov test
	Frequency histogram of residuals
	Boxplot of residuals

5.5.1 Tests for linearity

To comply with assumption 1, the existence of linear relationships between the dependent and independent variables, Pearson's correlation analysis was performed throughout this study. Those relationships deemed linear through the production of a significant correlation coefficient, and from the analysis of the respective scattergraphs (Harper, 1971), were entered into the stepwise multiple regression analysis.

Pearson's correlation analysis is a parametric technique as thus assumes the respective dependent and independent variables are normally distributed. This is potentially a restricting assumption concerning geographical data (Ebdon, 1995). However, the non-parametric alternative, Spearman's rank, could not be applied concerning any application of multiple regression in this study as it does not allow the comparison between untransformed data correlations, and respective transformed data correlations to be made. This is due to Spearman's rank measuring the relationship between two sets of ordinal values, thus the correlation coefficient, irrespective of the data transformation, will remain the same. This is problematical in assessing whether data transformations improve the degree of linearity between the dependent and independent variable and should be entered into the regression analysis at the expense of the respective untransformed correlation. The use of Pearson's as a precursor to multiple regression analysis is also fundamentally sound as regression assumes data normality (which has to be subsequently tested). Supporting the application of Pearson's correlation in this instance, Norusis (1994) states that the test is robust and can handle reasonable violations of the assumptions.

Following the computation of a regression model, further evidence for linearity between the independent variable(s) and dependent variable can be obtained through the multiple regression diagnostics of analysis of variance ascertaining the F ratio of the regression mean square to the residual mean square, testing the equivalent null hypotheses that there is no linear relationship in the population between the dependent variable and the independent variables, that all of the population partial regression coefficients are zero, and that the population R^2 is 0 (Norusis, 1994); and the t statistic examining the null hypothesis that the population regression coefficients for **each** independent variable are zero (Harper, 1971).

The leverage statistic identifies observations with unusual combinations of values of the independent variables. The statistic measures how far the values for a case are from the means of all of the independent variables. Cases with high leverage values may have a large impact on the estimates of the regression coefficients and thus exert an undue influence on the determination of a linear relationship. Norusis (1994) states that a rule of thumb is to look at observations with leverage values greater than $2p/N$ (0.1 in this case), where p is the number of independent variables in the model and N is the number of observations.

The Cook's distance statistic is also useful in identifying observations with a heavy influence on the regression coefficients. This statistic measures the change in all of the regression coefficients when a case is eliminated from the analysis (Norusis, 1994). The Cook's distance for a case depends on both the residuals and leverage values. Norusis (1994) states that Cook's distances greater than 1 usually deserve scrutiny as they affect the integrity of the regression model.

5.5.2 Test for multicollinearity

The term multicollinearity refers to the situation where high correlation exists between the independent variables. This can be a problem in multiple regression with independent variables explaining much the same variability in the dependent variable causing the precision of estimation to fall (Shaw and Wheeler, 1994). In addition, it is not known which of the independent variables is the most important due to the common variability explained (Hinton, 1995). As a result of these effects, multicollinearity must be eliminated or kept to minimal proportions if present (Norusis, 1994).

To identify multicollinearity, the tolerance statistic can be calculated measuring the strength of the linear relationships among the independent variables (Norusis, 1994). For each independent variable, the tolerance is the proportion of variability that is not explained by its linear relationships with the other independent variables in the model (Norusis, 1994). The values of the tolerance statistic range from 0 to 1. A value close to 1 indicates that an independent variable has little of its variability explained by the other independent variables. A value close to 0, typically below 0.1, indicates that a variable is almost a linear combination of the other independent variables; such data are multicollinear (Norusis, 1994).

5.5.3 Test for residual independence

Residuals are termed independent if there is no systematic variation in their pattern, i.e. there is no correlation between the absolute values of successive residuals (Ebdon, 1995). If such correlation occurs, the residuals are termed autocorrelated.

The Durbin-Watson test was applied to identify the relative extent of autocorrelation; values less than 2 indicate positive autocorrelation; values greater than 2 indicate negative autocorrelation; values approaching 2 indicate negligible autocorrelation.

5.5.4 Test for residual constant variance

Norusis (1994) states that a scattergraph of the residuals versus the predicted values should be drawn to assess whether the regression assumption of constant variance for all values of the independent variable(s) is met (i.e. the shapes of all of the frequency distributions associated with each value of the independent variable(s) are identical – Ebdon, 1995). If the variance is constant, no pattern is present in the data points and the residuals appear to be randomly scattered around a horizontal line through zero (Norusis, 1994).

When assessing model compliance with the regression assumptions of residual constant variance and residual normality, Norusis (1994) recommends the use of studentized deleted residuals as any departures from the aforementioned assumptions can be easily identified. The studentized residual is obtained by dividing each observed residual by an estimate of the standard deviation of the residual at that point; thus standardizing the residuals so that they have a mean of 0 and a standard deviation of 1. Dividing each observed residual by an estimate of its respective standard deviation means that it accounts for the difference in variability across the regression model parameterization data set; cases with independent variable values close to the respective sample means have smaller variability concerning predicted values than cases with values far removed from the sample means. The studentized deleted residual is the studentized residual for a case when the case is removed from the computation of the regression statistics (Norusis, 1994). Therefore, through the calculation the studentized deleted residual, a greater insight is gained into the nature of the residual independent of the influence the respective observed value has on the model prediction. Studentized deleted residuals are used to assess regression model compliance with the assumptions of residual constant variance and residual normality throughout this study.

5.5.5 Test for residual normality

Norusis (1994) states that if the preceding regression assumptions are met (Section 5.2), the distribution of the residuals should be approximately normal. To ascertain normality the Kolmogorov-Smirnov test was performed on the residuals. The respective null hypothesis for the Kolmogorov-Smirov test is that the residuals are normally distributed. In addition, a frequency histogram and a boxplot of the residuals were produced. The former gives credence to the Kolmogorov-Smirnov result and the latter identifies the actual outliers and extreme values that act to undermine the assumption of residual normality. However, Shaw and Wheeler (1994) state that most multivariate statistical methods are fairly reliable under conditions of departure from normality. As a result of this, Norusis (1994) recommends the investigation and correction of the other assumptions of regression before the issue of normality is addressed.

5.6 Population multiple regression application – untransformed data

From the preceding sections establishing the modelling approach suitable for this investigation and the associated precursors required to achieve the most successful result possible, this section details the progression to the formulation of a multiple regression analysis model predicting reservoir annual percentage capacity loss (APL) for the whole population.

5.6.1 Test for linearity – Pearson's correlation

Pearson's correlation coefficients were calculated between each of the 57 independent variables and APL in the parameterization data set. Those significant below the 0.05 level are presented in Table 5.3. The correlation coefficients predominantly suggest only a reasonable degree of linearity between the independent variables and APL. This affirms the use of multiple regression analysis as no one variable is highly correlated with APL (Verstraeten *et al.*, 2003). This suggests that the process of reservoir sedimentation, in terms of APL, is of a complex nature and must involve the consideration of these interacting variables, which together may improve the regression coefficient of determination.

When testing the significance of a number of correlations, the potential problem of multiple significance levels has to be considered. For example, testing individual correlations to a standard significance value of 0.05 means that for every 100 correlations performed, at least 5 may occur by chance. In the context of this particular application with the consideration of 8 correlation coefficients significant at the 0.05 level (Table 5.3), at least 0.4 may occur by chance. This value represents the most extreme minimum number of correlations that may occur by chance as the majority of the correlation coefficients are significant at levels stronger than 0.01.

Table 5.3 Pearson's correlation coefficients significant below the 0.05 between the respective independent variables and reservoir annual percentage capacity loss (APL) – see Table 4.5 for definition of abbreviations.

Independent Variable	r	p	n
QMED	0.416	0.001	60
RMED1H	0.278	0.031	60
RMED1D	0.280	0.030	60
SAAR	0.259	0.046	60
TE	-0.560	0.000	60
S686	0.639	0.000	60
DSHRUB	0.501	0.000	60
UPBOG	0.476	0.000	60

5.6.2 Result and diagnostics

Multiple regression analysis identified Equation 5.1, incorporating the independent variables of the Winter Hill soil association (termed hereafter as S686), trap efficiency (termed hereafter as TE), and median annual maximum 1-hour rainfall (termed hereafter as RMED1H), as having the greatest coefficient of determination (R^2) at 0.57. Therefore, this model accounts for a reasonable 57% of the variance in the dependent variable.

$$APL = 0.409 + (0.011 \times S686) - (0.009 \times TE) + (0.05 \times RMED1H) \qquad \text{(Eq. 5.1)}$$

The essential multiple regression diagnostics assessing the compliance of the result with the assumptions of the technique are presented in Table 5.4.

Table 5.4 Multiple regression diagnostics results; √ denotes compliance with the respective assumption, X denotes non-compliance. For the Leverage and Cook's distance results, the number of cases inducing the non-compliance with the assumption of linearity are presented.

Assumption	Diagnostic	Result
Linearity	Analysis of variance	√
	t statistic	√
	Leverage	X - 5 cases
	Cook's distance	X - 1 case
Non-multicollinearity	Tolerance statistic	√
Residual independence	Durbin-Watson test	√
Residual constant variance	Scattergraphs - residuals versus predicted values	X
Residual normality	Kolmogorov-Smirnov test	√

5.6.3 Summary of Equation 5.1

Equation 5.1 accounts for a reasonable 57% of the variance observed in APL. However, from Table 5.4, it does not meet all of the assumptions required for a valid, robust regression model.

The identification of a small number of highly influential observations through the leverage and Cook's distance statistics undermines the regression assumption of linearity between the dependent and independent variables. Norusis (1994) states that the assumptions of regression are not mutually exclusive and the failure to meet one may have repercussions on meeting others; in particular, violations of the linearity assumption may lead to the undermining of the assumptions of residual constant variance and normality through the production of outliers/extreme values. As a result of this, three standard transformations were applied to each of the 57 independent variables in an attempt to improve the degree of linearity; logs to the base 10, squares, and square roots (Norusis, 1994; Ebdon, 1995). The dependent variable, APL, was subsequently correlated with each respective transformed independent variable.

5.7 Population multiple regression analysis – transformed independent variables

This section documents the incorporation of transformed independent variables (logs to the base 10, squares, and square roots) into a multiple regression analysis predicting APL in an attempt to improve model compliance with the regression assumptions of linearity, residual constant variance, and residual distribution normality.

5.7.1 Test for linearity – Pearson's correlation

The Pearson's correlation results between each respective transformation of the independent variables, significant below the 0.05 level, are presented in Table 5.5. Those variables with a logarithmic transformation to the base 10 are suffixed with LOG10, those with a square transformation are suffixed with SQ, and those with a square root transformation are suffixed with SQRT. This is the labeling convention that has been followed throughout this investigation.

Table 5.5 Pearson's correlation coefficients significant below 0.05 between APL and the respective transformed independent variables

Independent Variable	r	p	n
QMEDLOG10	0.279	0.031	60
RMED1HLOG10	0.276	0.033	60
RMED1DLOG10	0.272	0.035	60
TELOG10	-0.577	0.000	60
S686LOG10	0.358	0.005	60
FELLEDLOG10	0.318	0.013	60
MEADOWLOG10	-0.289	0.025	60
UPBOGLOG10	0.383	0.003	60
QMEDSQ	0.494	0.000	60
RMED1HSQ	0.281	0.030	60
RMED1DSQ	0.280	0.030	60
SAARSQ	0.258	0.046	60
TESQ	-0.542	0.000	60
S686SQ	0.641	0.000	60
DSHRUBSQ	0.535	0.000	60
UPBOGSQ	0.331	0.010	60
QMEDSQRT	0.350	0.006	60

RMED1HSQRT	0.277	0.032	60
RMED1DSQRT	0.277	0.032	60
TESQRT	-0.568	0.000	60
S686SQRT	0.550	0.000	60
DSHRUBSQRT	0.384	0.002	60
UPBOGSQRT	0.494	0.000	60

From the analysis of the significant Pearson's correlation coefficients (Table 5.5) between APL and each of the untransformed and transformed independent variables, there is not one particular relationship that has an outstandingly high correlation coefficient. This again supports the application of multiple regression analysis (Verstraeten *et al.*, 2003).

Where a particular variable had a significant correlation coefficient with APL for more than one transformation, that with the greatest correlation coefficient upon being rounded to one decimal place was entered into the multiple regression analysis. This was done to favour where possible the selection of the untransformed variant of the independent variable into the multiple regression as untransformed variables do not pose such interpretational difficulties (Shaw and Wheeler, 1994). In addition to this, Ebdon (1995) states that the selection of untransformed variables aids the researcher in not overlooking the shortcomings of the data set and the measurement errors involved in data collection. The independent variables entered into the second iteration of multiple regression analysis were: QMEDSQ, RMED1H, RMED1D, SAAR, TE, S686, DSHRUB, FELLEDLOG10, MEADOWLOG10, and UPBOG (see Table 4.5 for the definitions of these abbreviations).

Concerning the potential problem of multiple significance levels (identified in Section 5.6.1), in the context of this particular application, 31 correlation coefficients significant at the 0.05 level were obtained between APL and each of the independent variable variants (Table 5.5). Therefore, at least 1.55 correlations may occur by chance when testing to a significance level of 0.05. However, this value represents the most extreme minimum number of correlations that may occur by chance as the majority of the correlation coefficients are significant at levels stronger than 0.01.

5.7.2 Result and diagnostics

Through the incorporation of transformed independent variables into multiple regression analysis, the same result is produced as that associated with the untransformed independent variables in the preceding application (Equation 5.1). As a result of this, the same shortcomings of Equation 5.1 remain; the reliance of linear relationships between APL and each independent variable on a small number of observations, the lack of residual constant variance, and the residuals not being normally distributed.

Norusis (1994) states that if such transformations of the independent variables fail to increase the validity of the regression result then transformations can be made of the dependent variable. This can be particularly effective if the variance of the dependent variable is not constant (Norusis, 1994), as is the case for Equation 5.1. As a result of this, the same three standard transformations were applied to APL; logs to the base 10, squares, and square roots. Such transformations of variables to predict sediment yield were undertaken by Jansen and Painter (1974), and Collins (1981).

5.8 Population multiple regression analyses - transformed independent & dependent variables

This section documents the incorporation of transformed independent and dependent variables (logs to the base 10, squares, and square roots) into a multiple regression analysis predicting reservoir sedimentation in an attempt to improve model compliance with the regression assumptions of linearity, residual constant variance, and residual distribution normality.

5.8.1 Test for linearity – Pearson's correlation

Pearson's correlation coefficients were calculated between each APL (dependent variable) transformation and each independent variable variant. As in Section 5.6.1, the correlation coefficients significant at the 0.05 level were rounded to one decimal place and those with the greatest r value were entered into the multiple regression analysis for each respective APL transformation. Table 5.6 identifies each independent variable variant selected and entered into the multiple regression analysis for each APL transformation.

Concerning the potential problem of multiple significance levels (identified in Section 5.6.1); the number of correlations significant at the 0.05 level between APLLOG10, APLSQ and APLSQRT, and the respective independent variable variants are 8, 35 and 15 respectively (Tables A1.5, A1.6 and A1.7, Appendix 1). Therefore, the minimum number of correlations significant at the 0.05 level that may have occurred by chance for the aforementioned APL transformations are 0.4, 1.75 and 0.75 respectively. However, these respective values represent the most extreme minimum number of correlations that may occur by chance as the majority of the correlation coefficients associated with each APL transformation are significant at levels stronger than 0.01.

Table 5.6 Pearson's correlation coefficients significant below 0.05 between APL variant and independent variables entered into each respective multiple regression analysis

Dependent Variable	Independent Variable	r	p	n
APLLOG10	TE	-0.307	0.017	60
	S686	0.290	0.025	60
	CONSQ	-0.469	0.000	60
APLSQ	CAREA	0.280	0.030	60
	QMEDSQ	0.559	0.000	60
	RMED1H	0.258	0.046	60
	RMED1D	0.273	0.034	60
	SAAR	0.255	0.050	60
	TE	-0.586	0.000	60
	S686	0.717	0.000	60
	DSHRUBSQ	0.655	0.000	60
	FELLEDLOG10	0.411	0.001	60
	MEADOWLOG10	-0.372	0.003	60
	MOWNLOG10	-0.287	0.026	60
	UPBOG	0.579	0.000	60
APLSQRT	QMEDSQ	0.372	0.003	60
	TE	-0.495	0.000	60
	S686	0.518	0.000	60
	DSHRUB	0.362	0.005	60
	UPBOGSQRT	0.370	0.004	60

5.8.2 Results and diagnostics

The models produced by multiple regression analysis for each APL variant are shown below. Equation 5.2 accounts for 40% of the variation observed in APLLOG10, Equation 5.3 accounts for 73% of the variation observed in APLSQ, and Equation 5.4 accounts for 36% of the variation observed in APLSQRT.

$$APLLOG10 = 1.088 - 0.001 \times CONSQ + 0.028 \times S686 - 0.024 \times TE \qquad (Eq.\ 5.2)$$

$$APLSQ = 0.21013 + 0.0083 \times S686 + 0.0002 \times DSHSQ + 0.0029 \times RMED1H - 0.0035 \times TE \qquad (Eq.\ 5.3)$$

$$APLSQRT = 1.144 + 0.011 \times S686 - 0.0092 \times TE \qquad (Eq.\ 5.4)$$

The essential multiple regression diagnostics assessing the compliance of the result with the assumptions of the technique are presented in Table 5.7.

Table 5.7 Comparison of multiple regression diagnostics results; √ denotes compliance with the respective assumption, X denotes non-compliance. For the Leverage and Cook's distance results, the number of cases inducing the non-compliance with the assumption of linearity are presented.

Assumption	**Diagnostic**	**Eq 5.2 Result**	**Eq 5.3 Result**	**Eq 5.4 Result**
Linearity	Analysis of variance	√	√	√
	t statistic	√	√	√
	Leverage	X - 7 cases	X - 9 cases	X - 6 cases
	Cook's distance	X - 1 case	X - 2 cases	√
Non-multicollinearity	Tolerance statistic	√	√	√
Residual independence	Durbin-Watson test	√	√	√
Residual constant variance	Scattergraphs - residuals versus predicted values	X	X	X
Residual normality	Kolmogorov-Smirnov test	√	X	√
Total number of refutations		3	4	2

5.8.3 Summary of Equations 5.2, 5.3, & 5.4

As a result of Equation 5.1 (incorporating untransformed variables) failing to satisfy conclusively the regression assumptions of linearity and constant variance in particular, despite having a respectable R^2 of 0.57, multiple regression analyses were performed on transformations of APL (APLLOG10, APLSQ, APLSQRT). However, from Table 5.7 each transformation still failed to satisfy the regression assumptions of linearity and residual constant variance unequivocally.

From the analysis of the multiple regression equations incorporating transformed dependent and independent variables, Equation 5.4 associated with the prediction of APLSQRT, on balance, produces the most robust model predicting reservoir sedimentation in terms of compliance with the assumptions of regression. However, it must be stressed again that the assumptions in this instance are not satisfied unequivocally.

The selection of Equation 5.4 as the most robust model incorporating transformed variables demonstrates that the determination of a good/bad regression model predicting reservoir sedimentation cannot be made on the basis of the coefficient of explanation (R^2) alone. This is because in each instance (indeed, throughout this entire investigation), each model refutes the assumptions of multiple regression. Clearly, if the assumptions of multiple regression were satisfied in each case, the evaluation of such regression models and the selection of the optimum one to operationalize could be made on the basis of the coefficient of explanation alone; that which produces the highest respective value would provide the best result. A measure of how good the selected model actually is could then be made from the actual R^2 value; 0% demonstrates no explanation, 50% moderate explanation and 100 % perfect explanation. However, from the analysis of the multiple regression diagnostics associated with Equations 5.2, 5.3 and 5.4, it can be seen that in terms of the application of the technique in this investigation, an assessment of how good a particular model is can only be made through weighing up the number of multiple regression assumptions it refutes. The subsequent comparison of this number with other potential models allows the optimum one to be selected. In relation to the selection of Equation 5.4 over Equations 5.2 and 5.3, this has the lowest R^2 value (36% in comparison to 40% and 73% respectively) but has the least number of assumption violations; therefore this equation depicts the actual relationship between the independent variables and dependent variable most accurately.

5.8.4 Model selection

Through the preceding section an attempt was made to formulate a multiple regression model predicting reservoir sedimentation incorporating transformed variables to provide a more robust, reliable model over Equation 5.1 (incorporating untransformed variables) in terms of compliance with the assumptions of regression (Section 5.2). Equation 5.4, predicting APLSQRT, was identified as optimum model incorporating variable transformations. Through this section a comparison between Equations 5.1 and 5.4 will be made. From this, the most robust model will be operationalized across the population data set.

Table 5.8 compares the total number of multiple regression assumption refutations associated with Equation 5.1 and Equation 5.4. Whilst Equation 5.1 yields a single Cook's distance value that has a heavy influence on the respective regression coefficients, this is offset by the model yielding fewer problematical leverage values and a larger, significant *F*-ratio; the latter identifying that Equation 5.1 accounts for a greater proportion of the variance in the parameterization data set. In addition, this model has a larger coefficient of determination at a reasonable 57% in comparison to the low coefficient of explanation of 36% associated with Equation 5.4. As a result of this, on balance, Equation 5.4 (predicting APLSQRT) does not yield a more robust, reliable model in terms of greater compliance with the assumptions of regression. Therefore, Equation 5.1 (incorporating untransformed variables), is selected as the most robust, reliable multiple regression model obtainable from the parameterization data set to predict reservoir sedimentation (APL) across England and Wales. However, the lack of unequivocal compliance of Equation 5.1 with the assumptions of regression is reflected in the production of only a reasonable coefficient of determination.

Table 5.8 Comparison of multiple regression diagnostics results; √ denotes compliance with the respective assumption, X denotes non-compliance. For the Leverage and Cook's distance results, the number of cases inducing the non-compliance with the assumption of linearity are presented.

Assumption	**Diagnostic**	**Eq 5.1 Result**	**Eq 5.4 Result**
Linearity	Analysis of variance	√	√
	t statistic	√	√
	Leverage	X - 5 cases	X - 6 cases
	Cook's distance	X - 1 case	√
Non-multicollinearity	Tolerance statistic	√	√
Residual independence	Durbin-Watson test	√	√
Residual constant variance	Scattergraphs - residuals versus predicted values	X	X
Residual normality	Kolmogorov-Smirnov test	√	√
Total number of refutations		3	2

5.8.5 Discussion of Equation 5.1

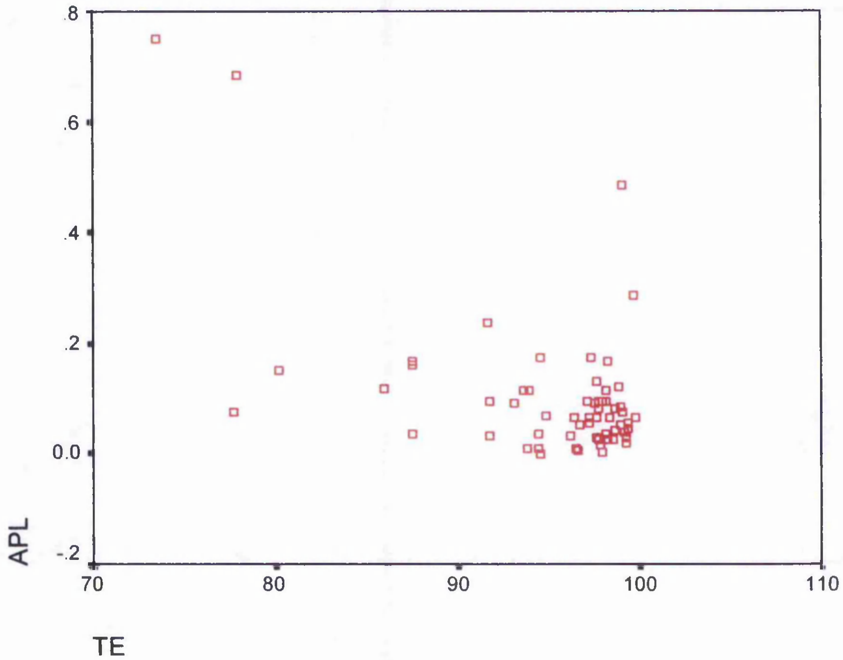
In this section the model selected as the optimum to predict reservoir sedimentation for the population of reservoirs (Equation 5.1) is discussed in relation to the regression assumptions it refutes.

5.8.5.1 Nature of the linear relationships

From the partial regression coefficients of Equation 5.1, S686 and RMED1H are both positively related to APL. These relationships are explained through larger areas (in this case of S686) providing more sites of erosion and therefore greater quantities of sediment yield, and more intense rainfall providing greater quantities of an erosion agent. The selection of RMED1H through the stepwise procedure, as opposed to another measure of rainfall (e.g. RMED2D) suggests that intense storms inducing Hortonian overland flow and consequent soil erosion are important across the parameterization set.

The negative relationship shown by the partial regression coefficient between APL and TE may appear surprising at face value. The literature suggests that TE is positively related to APL (Brown, 1944; Brune, 1954; Heinemann, 1984); thus as TE increases, a greater quantity of the catchment sediment yield is trapped in the reservoir basin. However, this negative relationship between APL and TE can be explained through the nature of the reservoir capacity data extracted from the BRE dams data set (Tedd *et al.*, 1992) that is used to calculate TE across the population data set using the Brown equation (1944). The reservoir capacities listed in the BRE dams data set depict either the original basin capacity or a revised capacity, where a basin survey has been conducted subsequent to dam commission. Unfortunately the BRE dams data set does not identify which the listed capacity relates to and in many cases this cannot be ascertained as the revised capacities have not all necessarily been published in the literature. However, for the majority of the reservoirs in the parameterization data set used to formulate Equation 5.1, the respective basin capacity value in the BRE dams data set represents a revised capacity calculated through published studies (e.g. Stretton, 1984; Butcher *et al.*, 1992a). As a result of this, a broadly negative relationship between APL and TE may be expected as larger APL rates typically induce progressively smaller trap efficiencies from the time of dam commission (Heinemann, 1984). However, the inference from this relationship for reservoirs (in the parameterization data set) may be misleading as particular cases may have comparatively smaller APL rates as a direct result of them having small trap efficiencies at the time of dam commission. In addition, such a relationship is clouded by the fact that trap efficiency typically decreases over time as sedimentation ensues. Therefore, the differing periods of time that have elapsed between dam commission and the revised capacity surveys of the reservoirs renders the calculated trap efficiencies, in relation to an observed APL rate, not directly comparable. From examination of the leverage and Cook's distance statistics associated with the parameterization data set it can be seen that Abbeystead and Blakeley reservoirs are having a large influence on this negative relationship between APL and TE. This is supported through Figure 5.1.

Figure 5.1 Annual percentage loss (APL) versus trap efficiency (TE) - parameterisation data set



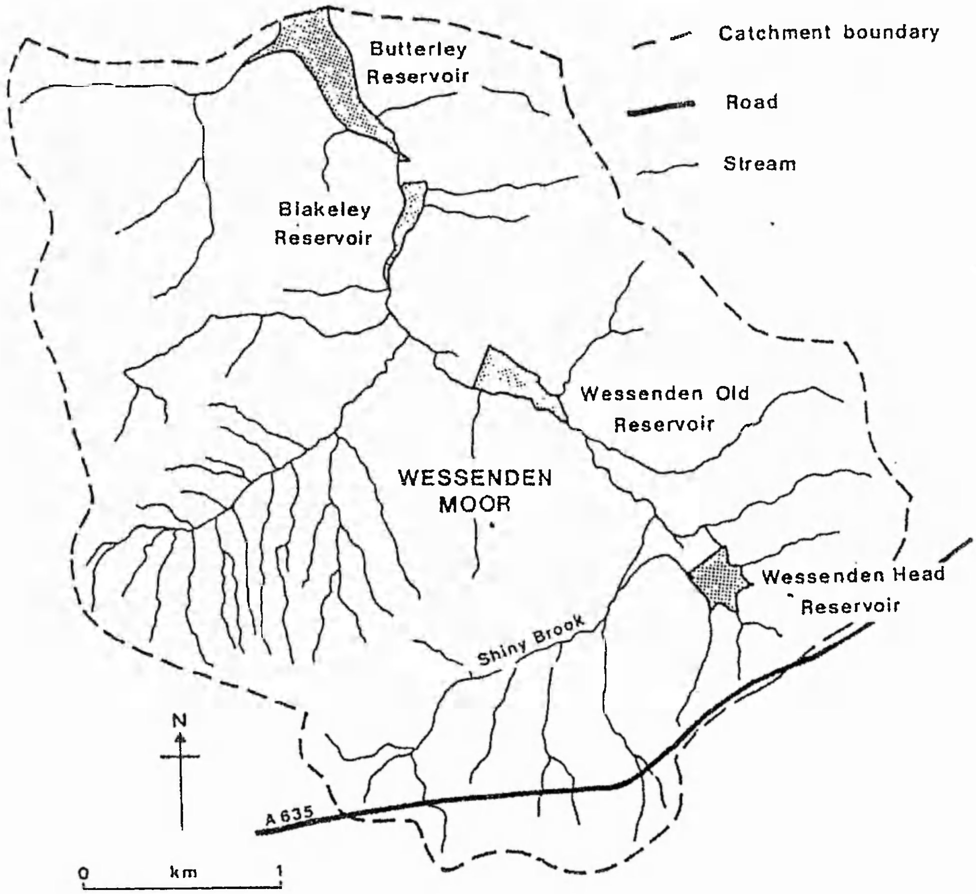
This demonstrates how the ambiguity of the BRE dams data set can induce error and uncertainty into the multiple regression analyses. Even if the published **original reservoir capacities** (listed in the Halcrow data set (2001)) were substituted with the respective revised capacities in the BRE dams data set in an effort to standardize the capacities across the population data set so that they represented the reservoir trap efficiencies at the time of dam commission (thereby potentially inducing a positive relationship between APL and TE), error and uncertainty would still be propagated into the extrapolation of the multiple regression model(s) across the population data set. This would be due to the incorporation of revised capacities from the BRE dams data set which have not been published; as previously mentioned, there is no direct way of determining these capacities.

The undue influence Abbeystead and Blakeley reservoirs have on the partial regression coefficients of Equation 5.1 (S686, TE, and RMED1H), identified through the leverage and Cook's distance statistics associated with the parameterization data set, can also be attributed to unique catchment factors not represented in the model. Abbeystead reservoir has experienced high erosion rates and sediment yields periodically over its lifetime

(Rowan *et al.*, 1995). Shortly after dam completion, the construction of catchwater conduits in the headwaters destabilized the erosion-sensitive headwater streams resulting in extreme stream channel erosion and increased sediment delivery through the diversion of sediment sourced from outside of the direct catchment area. High hillslope erosion and consequent sediment yield was also associated with extensive drain laying operations, improving field drainage for cultivation and pastureland. Subsequently, yields have declined since sluice valves were opened in 1981 to encourage sediment flushing (Rowan *et al.*, 1995). The model does not take into account these management and land use effects/changes.

Blakeley reservoir has a high APL because its catchment is predominantly covered by deep blanket peat. This soil type is highly erodible (Evans, 1990; Labadz *et al,* 1991), and due to the high drainage density of the direct catchment area (excluding the catchments of Wessenden Old and Wessenden Head reservoirs upstream), much eroded material is able to enter the fluvial channel network and be efficiently transported to the reservoir basin (Figure 5.2). The high drainage density of the deep blanket peat catchment is not represented in the model (Equation 5.1). Such an omission may be problematical for this catchment as White (1993) identifies significant positive correlations between catchment characteristics, including drainage density, and percentage loss of capacity per century, for reservoirs such as Blakeley in the southern Pennines. The effect of the high drainage density in the Blakeley catchment and consequent sediment delivery to the reservoir basin appears to override the attenuation effects of Wessenden Old and Wessenden Head reservoirs upstream (however, these reservoirs do not have such high drainage densities - Figure 5.2). In addition, the Blakeley catchment has a catchwater interception upstream which may be associated with reduced reservoir sedimentation rates (White *et al.*, 1996a). However, the selective operation of these control structures does not reduce the APL of Blakeley (0.75%) to a value comparable to the mean of the population (0.11%) (Table A1.1, Appendix 1).

Figure 5.2 Blakeley reservoir catchment area (after Labadz *et al.*, 1999)



In general, the weak nature of the linear relationships between APL and the independent variables identified through the correlation analysis can also be partly attributed to the spatial variation in the parameterization data set. For example, some reservoir catchments may show stronger links with certain sediment inducing variables (such reservoir catchments may be spatially autocorrelated), whilst others may not conform to these relationships, being related to different variables. These "non-conforming catchments" act to degrade the respective correlation coefficients. The clustering approach (Section 5.3.1) seeks to reduce this intra-variable variation through the computation of multiple regression analysis models on catchment areas of alikeness, defined through cluster analysis.

5.8.5.2 Residual variance

Constant variance of residuals is not shown in Figure A3.1, Appendix 3; instead variance appears to increase with the predicted value, tending to become increasingly negative. This may be explained by the effect of catchment area on sediment yield/reservoir sedimentation.

Catchment area, as partly reflected in Equation 5.1 through S686 (incidentally the variable with the highest partial correlation coefficient), is perceived to have an important influence on the magnitude of sediment yield/reservoir sedimentation (Walling and Webb, 1996). From Section 2.11.1.7, increasing reservoir sedimentation across Great Britain has typically been associated with increasing catchment area for basin volumetric (as opposed to area-specific) sedimentation rates (e.g. Duck and McManus, 1987; Butcher *et al.*, 1993). Such positive relationships have been related to undisturbed, densely vegetated catchments and upland areas characterized by resistant rocks, reducing soil erosion and the associated hillslope input (Dedkov and Moszherin, 1992). Under these conditions it is **stream channel erosion** that is inducing the positive relationship between sediment yield and catchment area (Imeson, 1974, Walling and Webb, 1996). Stream channel erosion rates will increase downstream in response to greater discharges and associated entrainment and transport of sediment.

However, across the southern Pennines where highly erosive blanket peat dominates the catchments, **hillslope erosion** is typically the dominant source of sediment yield (Labadz *et al.*, 1991) and allochthonous material deposited in reservoir basins. This is particularly the case for Blakeley reservoir which has one of the highest observed annual percentage capacity loss (APL) rates in the parameterization data set (Labadz *et al.*, 1999). From reservoir sedimentation studies in the southern Pennines, Butcher *et al.* (1993) attribute a positive relationship between reservoir sedimentation and catchment area to the catchments surveyed all occupying very similar environments, thus it is to be expected that increasing catchment size will provide increasing values of sediment infill. However, in the context of the population of reservoirs represented by the parameterization data set occupying many different environments, if the dominant source of sediment in reservoirs experiencing exceptionally high sedimentation rates (which have a large influence on the nature of the relationship between observed APL and S686 in Equation 5.1) is from the hillslopes; greater variation in APL observations (increasingly negative residuals) will be observed with increasing catchment areas (reflected in Equation 5.1 by S686). This is due to the development of flatter gradients and floodplains associated with increasing catchment area in certain instances (Walling, 1983; Higgitt, 1993), which decreases hillslope-channel coupling and the potential contribution of hillslope derived material in the sediment yield (Section 2.11.1.7). This supports the observation by Verstraeten and Poesen (2001) that as catchment area increases, so does variability in erosion and sediment delivery processes. Therefore, the part-depiction of catchment area by the S686 variable contributes to the production of non-constant residual variance associated with increasing APL predictions from Equation 5.1, thus undermining the respective regression assumption.

5.9 Equation 5.1 evaluation

5.9.1 Verification

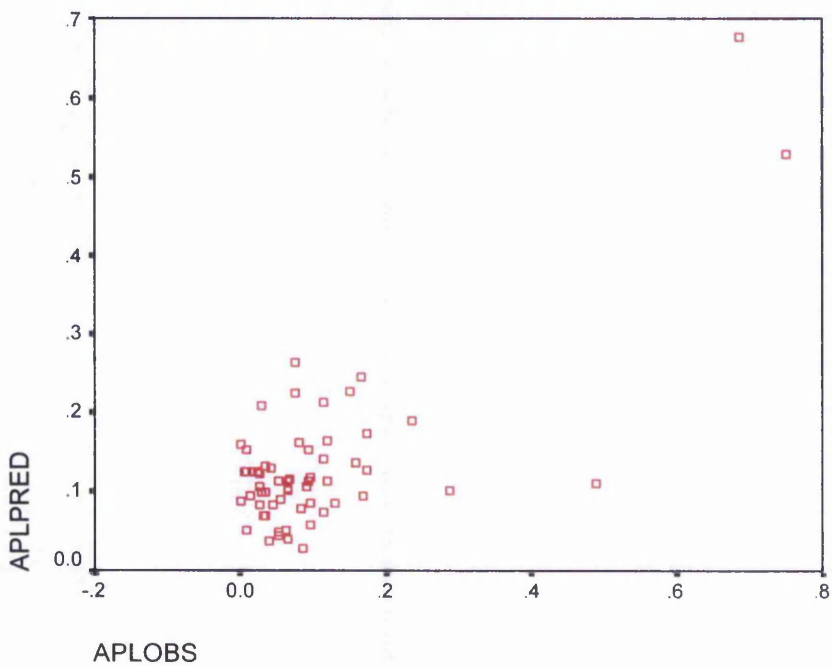
Verification is applied to ensure that the model behaves the way an experimenter intends (Shannon, 1975); i.e. it ascertains whether the model replicates the same relative pattern as the parameterization data set. Verification can be objectively ascertained through correlation analysis testing whether predicted APL moves in the same direction relative to observed APL, and testing whether the difference in means of two related variables (observed APL and predicted APL) is zero. The respective parametric tests of Pearson's correlation and the paired T-test were applied as verification procedures throughout this investigation as both tests are robust and can handle reasonable violations of the assumption of data series normality (Norusis, 1996). Such reasonable violations of the assumption of data series normality were exhibited in each instance concerning both the verification and validation data (Appendix A3.4).

The Pearson's correlation analysis result at face value implies a good relationship between observed and predicted APL, producing a strongly significant correlation coefficient of 0.75 (Table 5.9). However, from Figure 5.3 the strength of the correlation appears heavily influenced by Abbeystead and Blakeley reservoirs, with the main data point cluster showing only a general progression in a positive direction. This suggests that the model may not be predicting APL accurately.

Table 5.9 Verification result – Pearson's correlation and Paired T-test

Verification	**Equation 5.1**
Correlation coefficient	0.753
Significance level	0.01
Number	60
Paired T-test statistic	-2.412
Significance level	0.019
Degrees of freedom	59

Figure 5.3 Predicted APL versus observed APL



From Figure 5.4 it can be seen that whilst the model broadly follows the same relative pattern as that observed, it is not predicting an APL quantity close to that observed (as inferred through the analysis of the respective correlation result); it has a tendency to over-predict. This inference is further supported through the analysis of the associated residuals (the difference between the observed and predicted value of the dependent variable –

Ebdon, 1995). The mean residual value associated with the prediction of APL across the parameterization data set is –0.029 (Table 5.10), thus identifying predominant over-predictions. This observation is supported by the paired T-test result which identifies that the difference in means between the observed and predicted APL values across the parameterisation data set is significantly different from zero (Table 5.9). If the model was predicting APL values close to those observed, or with a random normal distribution about a mean difference of zero, one would expect there to be no significant difference between the mean predicted and observed APL across the parameterization data set. However, Figure 5.4 illustrates that where observed APL values are of only a moderately high value, on average, the associated residuals are comparatively less. This inference is complimented through Figure 5.5.

Figure 5.4 The relative pattern of observed APL & predicted APL for each reservoir

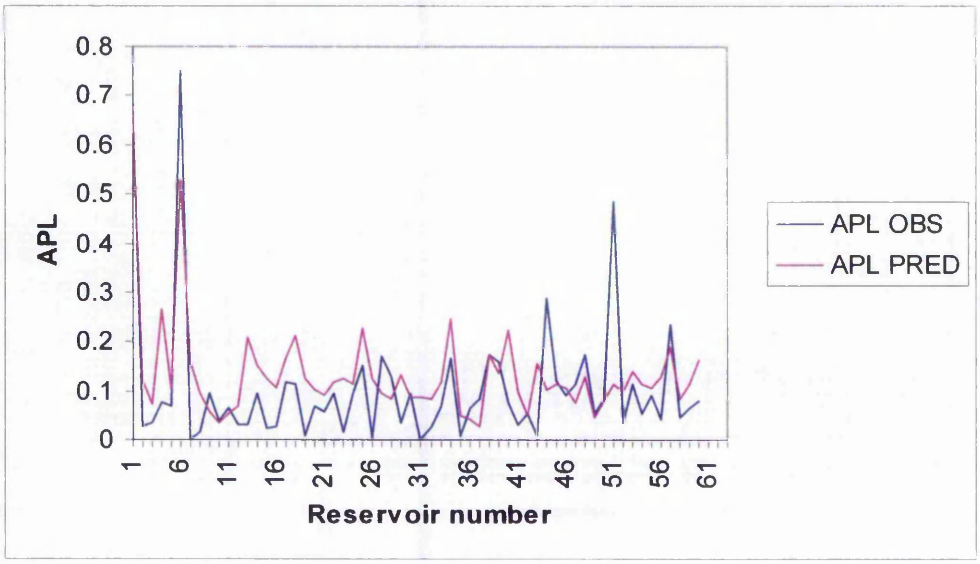


Figure 5.5 Parameterization data set residuals (observed APL – predicted APL)

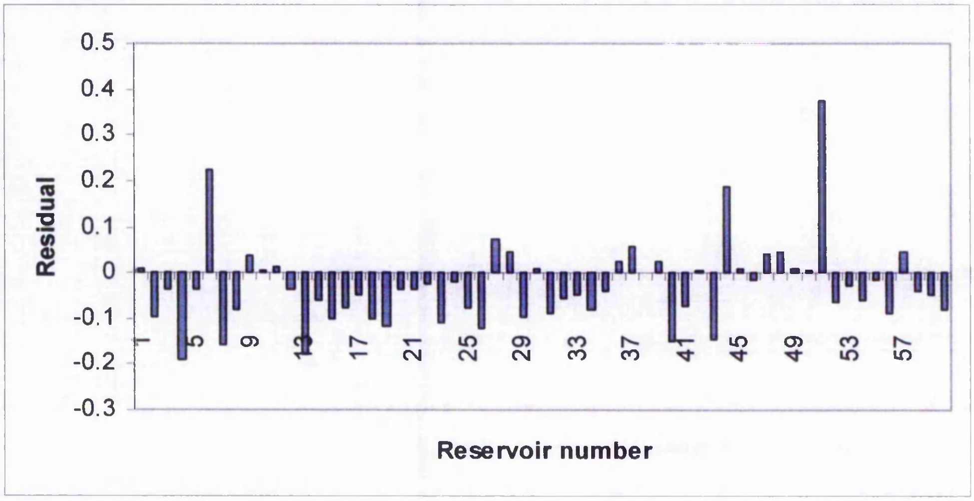


Table 5.10 Key to Figures 5.3 & 5.4 & corresponding observed APL, predicted APL & residual values

Reservoir Number	Reservoir Name	OBSAPL	PREDAPL	Residual
1	Abbeystead	0.686	0.676	0.010
2	Angram	0.027	0.122	-0.096
3	Barden Lower	0.035	0.070	-0.036
4	Barden Upper	0.075	0.264	-0.189
5	Blackmoorfoot	0.066	0.103	-0.036
6	Blakeley	0.751	0.528	0.223
7	Booth Wood	0.001	0.160	-0.159
8	Broadstones	0.015	0.095	-0.080
9	Broomhead	0.096	0.058	0.039
10	Chelker	0.040	0.036	0.004
11	Dale Dyke	0.064	0.052	0.012
12	Damflask	0.032	0.070	-0.038
13	Dean Head Lower	0.030	0.208	-0.177
14	Dean Head Upper	0.093	0.153	-0.060
15	Deanhead	0.024	0.124	-0.100
16	Deerhill	0.028	0.106	-0.078
17	Eldwick	0.118	0.166	-0.047
18	Embsay	0.114	0.213	-0.100
19	Fewston	0.009	0.124	-0.115
20	Gorple Lower	0.066	0.104	-0.037
21	Gorple Upper	0.055	0.090	-0.034
22	Gorpley	0.095	0.119	-0.024
23	Green Withens	0.017	0.126	-0.109
24	Harden	0.094	0.115	-0.020
25	Hewenden	0.150	0.227	-0.077
26	Holmestyes	0.005	0.125	-0.120

27	Langsett	0.169	0.095	0.074
28	Leeshaw	0.130	0.085	0.045
29	Lindley Wood	0.036	0.131	-0.095
30	Lower Laithe	0.096	0.086	0.010
31	Morehall	0.000	0.088	-0.088
32	Ogden	0.026	0.085	-0.058
33	Ponden	0.069	0.116	-0.047
34	Ramsden	0.167	0.246	-0.080
35	Redmires Lower	0.009	0.050	-0.041
36	Redmires Middle	0.065	0.040	0.025
37	Redmires Upper	0.085	0.028	0.057
38	Riding Wood	0.173	0.173	0.000
39	Rivelin Lower	0.159	0.136	0.023
40	Rivelin Upper	0.075	0.225	-0.150
41	Roundhill	0.030	0.100	-0.071
42	Royd Moor	0.052	0.048	0.004
43	Ryburn	0.008	0.154	-0.146
44	Scammonden	0.288	0.102	0.186
45	Scar House	0.120	0.114	0.007
46	Scout Dike	0.091	0.107	-0.015
47	Silsden	0.114	0.074	0.040
48	Snailsden	0.175	0.128	0.047
49	Strines	0.054	0.044	0.009
50	Stubden	0.082	0.080	0.003
51	Tunnel End	0.487	0.112	0.375
52	Underbank	0.035	0.099	-0.064
53	Walshaw Dean Lower	0.115	0.142	-0.027
54	Walshaw Dean Middle	0.052	0.114	-0.062
55	Walshaw Dean Upper	0.091	0.107	-0.015
56	Wessenden Head	0.042	0.131	-0.089
57	Wessenden Old	0.236	0.189	0.047
58	Widdop	0.044	0.084	-0.040
59	Windleden Upper	0.066	0.114	-0.048
60	Ystradfellte	0.080	0.161	-0.081
	Mean	0.105	0.134	-0.029

The larger residuals identified in Figure 5.5 and Table 5.10 are induced by: (1) being observations having an undue influence on the computation of the partial regression coefficients of Equation 5.1, thus exerting an influence on the regression model in multi-dimensional space, yet being situated a distance away from it (as disclosed through the respective leverage and Cook's distance statistics – Table 5.4); and (2) having factors influencing the respective sedimentation rates not accounted for by the model. These two reasons for residual production are not necessarily mutually exclusive. The reservoirs with the largest positive residuals are Blakeley, Scammonden and Tunnel End (0.223, 0.186 and 0.375 respectively) and represent an under-prediction by Equation 5.1. These positive residuals are induced by factors not included in the model that act to increase APL. Blakeley reservoir has a catchment predominantly covered by highly erodible blanket peat with a corresponding high drainage density permitting efficient transport of sediment to the reservoir basin (Section 5.8.5). Scammonden as a positive outlier may be partly explained by it having a catchwater input not considered in Equation 5.1 (as reported in White *et al.* (1996a)). Catchwaters act to enlarge the effective catchment area of a reservoir by directing flow from nearby stream channels. This can increase potential sediment inflows and thus APL. This influence appears to override the potential attenuation effects of a reservoir and intermittent catchwater interception upstream on sediment delivery into the Scammonden basin (Labadz *et al.*, 1995).

Tunnel End may appear as a positive extreme value due to the dam spillway being lowered in 1973. It is estimated that 40000 m^3 of the original reservoir capacity were lost as a result of this modification. The failure to accurately account for this modification could induce error into the revised capacity calculated in 1988 with the capacity loss being attributed to sedimentation (Halcrow, 2001).

The reservoirs with the largest negative residuals are Barden Upper, Dean Head Lower, Rivelin Upper and Ryburn (-0.189, -0.177, -0.150 and -0.146 respectively). These negative residuals, representing model over-predictions, are each associated with catchment management structures that act to reduce sedimentation rates. These are not included in the model. Barden Upper is has a residuum lodge and bywash channel, Dean Head Lower has a catchwater/conduit interception upstream, Rivelin Upper has a catchwater/conduit interception and bywash channel, and Ryburn has a catchwater/conduit interception (White *et al.*, 1996a). In addition Dean Head Lower, Rivelin Upper and Ryburn each have a reservoir situated upstream. This attenuation effect on sediment delivery should be accounted for by the flood attenuation index due to reservoirs and lakes (FARL), which is listed in the population data set, but was not incorporated into Equation 5.1 via the stepwise variable selection procedure.

5.9.2 Validation

Shannon (1975) defines validation as testing the agreement between the behaviour of the model and that of the real system. This can vary from a simple ratiometric comparison through to correlation analysis determining the goodness of fit between real world observations not included in the parameterization data set and the model predictions (Hardisty *et al.*, 1996). To avoid circularity in the validation process, it is important that the model is assessed through its ability to extrapolate from the parameterization data set. Through the process of validation the user's confidence is brought to an acceptable level that any inference derived from the model is correct (Shannon, 1975). Throughout this investigation the respective parametric tests of Pearson's correlation and the paired T-test were applied as validation procedures as both tests are robust and can handle reasonable violations of the assumption of data series normality (Norusis, 1996). Again, reasonable violations of the assumption of data series normality were exhibited in each instance concerning the validation data (Appendix A3.4).

The validation data set for Equation 5.1 comprises five reservoirs not included in the parameterization data set: Appleton, Bough Beech, Eyebrook, Howden, and Weirwood (Table 5.11). The original validation data set comprised six reservoirs; the aforementioned five reservoirs plus The Great Lake (Section 4.3.2.2). However, The Great Lake has values of the independent variables represented as partial regression coefficients in Equation 5.1 beyond the limits defined in the associated parameterization data set. As a result of this, Equation 5.1 cannot be extrapolated to produce an APL prediction for The Great Lake. This represents a limitation of the regression technique (as identified in Section 4.3.1.2).

Table 5.11 Validation data set – respective observed APL, predicted APL and residual values

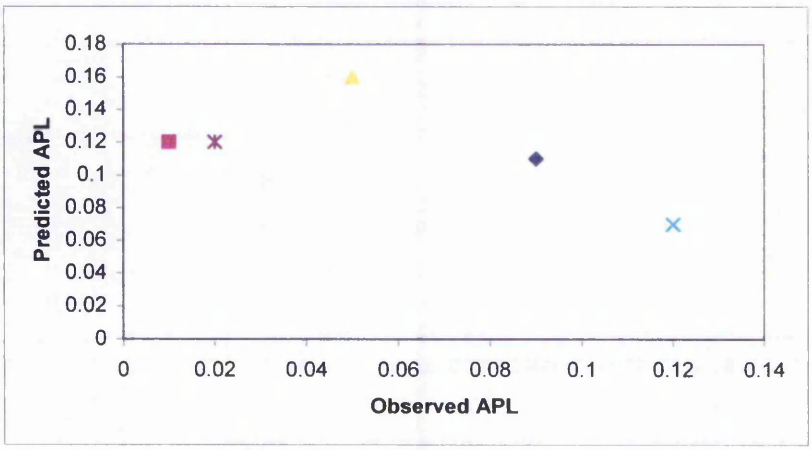
Reservoir	OBSAPL	PREDAPL	Residual
Appleton	0.087	0.108	-0.018
Bough Beech	0.014	0.124	-0.110
Eyebrook	0.052	0.160	-0.108
Howden	0.119	0.070	0.049
Weirwood	0.015	0.123	-0.103
Mean	0.058	0.116	-0.058

The Pearson's correlation result and associated scattergraph imply a poor relationship between the observed and predicted APL of the reservoirs in the validation data set (Table 5.12 and Figure 5.6). This result supports the inference from Figure 5.4 that the model is not replicating the same relative pattern as that observed in the real world APL values.

Table 5.12 Validation results – Pearson's correlation and Paired T-test

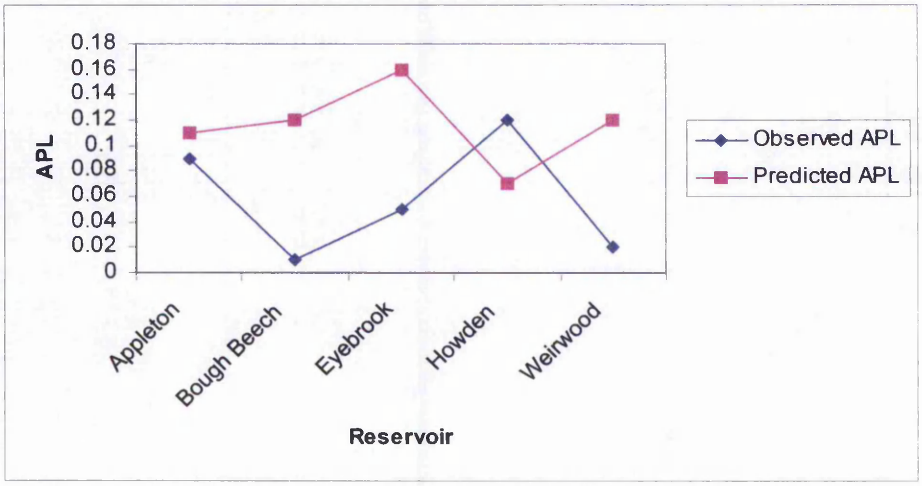
Validation	Equation 5.1
Correlation coefficient	-0.673
Significance level	0.213
Number	5
Paired T-test statistic	-1.822
Significance level	0.143
Degrees of freedom	4

Figure 5.6 Predicted versus observed APL – validation data set



Key: Appleton – royal blue diamond, Bough Beech – pink square, Eyebrook – yellow triangle, Howden –blue cross, Weirwood – purple asterisk.

Figure 5.7 The relative pattern of observed APL & predicted APL – validation data set

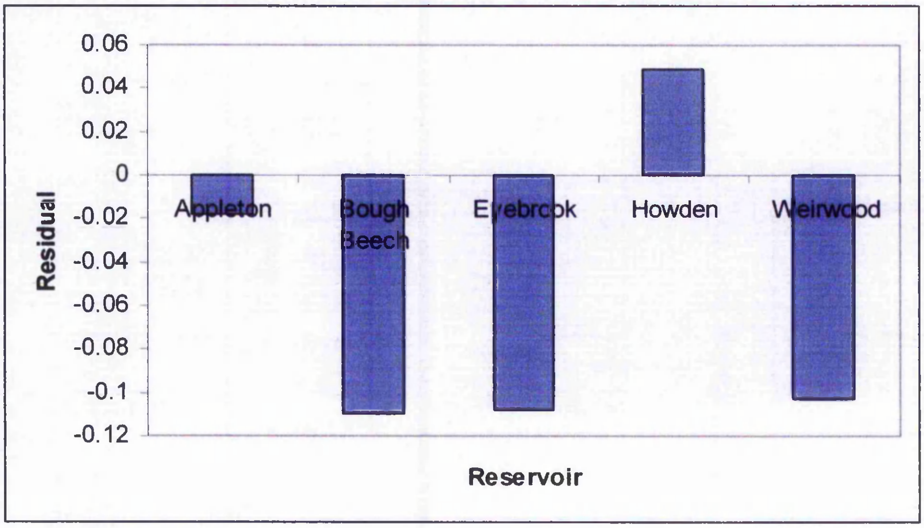


The paired T-test result (Table 5.12), however, identifies that the difference between the mean observed and predicted APL rates is not significantly different from zero, implying that the model is predicting reasonable APL values. However, this broad, overlying result must be treated with caution as Figure 5.7 identifies reasonably good predictions for Appleton and Howden reservoirs through the production of small residuals (i.e. comparatively smaller absolute differences between the respective observed and predicted APL values), but not for Bough Beech, Eyebrook, and Weirwood reservoirs.

From Figure 5.8 and Table 5.11 it can be seen that the residuals (defined as observed minus the predicted value of the dependent variable – Ebdon, 1995) are negative for Appleton, Bough Beech, Eyebrook and Weirwood reservoirs; indicating predominant over-prediction by the model (Equation 5.1). However, the residual associated with Howden is positive, indicating respective under-prediction. The inference from Figures 5.7 and 5.8 support the observation from Section 5.9.1 concerning model verification; Equation 5.1 under-predicts where the observed APL is exceptionally high (i.e. Howden reservoir) and produces generally smaller residuals, associated with over-predictions, where moderately high APL values are observed. The mean residual value associated with the prediction of APL across the validation data set is –0.058 (Table 5.11), identifying the tendency of Equation 5.1 to over-predict. The high positive residual associated with Howden may be explained by the fact that the observed APL for this reservoir was obtained from secondary data

(Hutchinson, 1995). Hutchinson (1995) calculated the respective sedimentation rate from core analysis across the reservoir basin, not from a bathymetric survey using an echo-sounder to determine depth readings (the approach used to collect such primary data herein, see Section 4.3.2.1). This may have induced an over-estimate of observed APL. The high positive residual associated with Howden may also be explained by an additional input from a catchwater/conduit, diverting flow (and potential sediment load) into the reservoir basin from outside of the directly coupled catchment area. Such a management structure is also present at Appleton reservoir, albeit operated only very occasionally (United Utilities, 2003, pers.comm.) and thus may account for the comparatively small over-prediction by Equation 5.1 (Figure 5.7).

Figure 5.8 Validation data set residuals (observed APL - predicted APL)



In conclusion, Equation 5.1 as a model predicting APL for the population of reservoirs cannot be verified and validated. Whilst the model, to a degree, replicates the same relative pattern as the parameterization data set, it does not predict an accurate APL for the parameterization data set. The model has a tendency to over-predict for the majority of observed APL rates across the parameterization data set. However, the model under-predicts for those reservoirs experiencing exceptionally high observed APL rates. As a result, when Equation 5.1 is extrapolated to predict for reservoirs not present in the parameterization data set, poor quality results are produced in terms of the model not replicating the same relative pattern as the observed (validation) data, and failing to provide consistently good APL predictions in terms of small residuals of a consistent sign. The poor results of the verification and validation procedures are induced by the low degree of robustness of Equation 5.1. This is associated with a small number of observations having an undue influence on the computation of the respective partial regression coefficients (as identified by the associated leverage and Cook's distance statistics).

The tendency for Equation 5.1 to under-predict APL for reservoirs with exceptionally high observed APL values seriously undermines the ability of the model to identify potentially problematical sedimentation rates, thus devaluing its potential application. Consistent over-predictions by the model would be much more acceptable as the results would represent a "bleak outlook scenario".

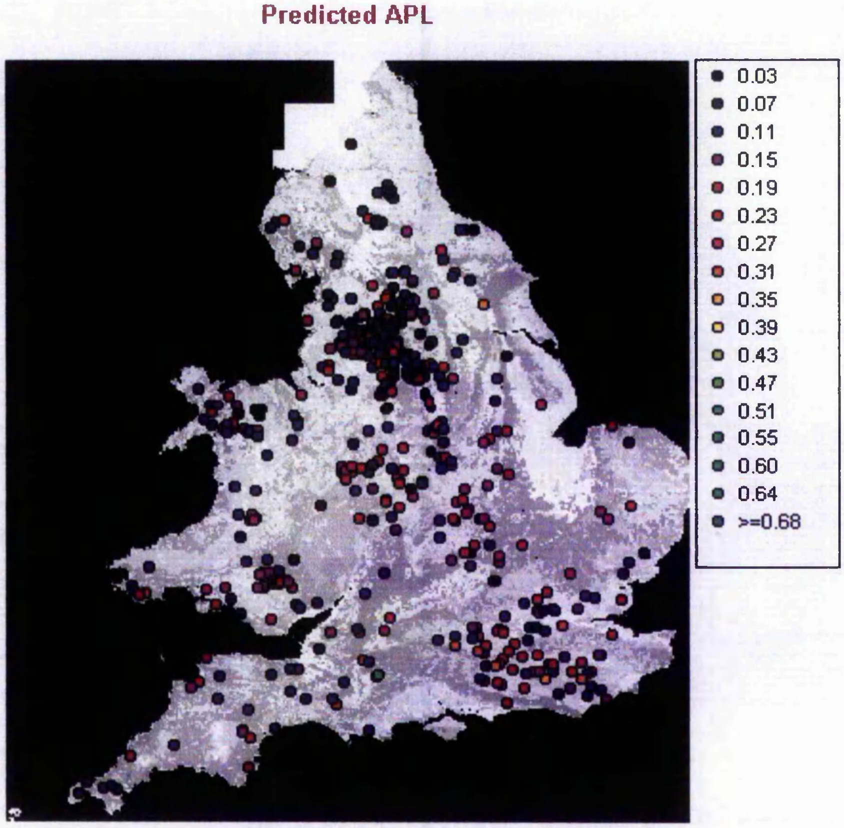
5.9.3 Confidence intervals

For each reservoir represented in the parameterization data set associated with Equation 5.1, SPSS produces a confidence interval relating to the prediction of the APL conditional mean for *all* reservoirs with the same independent variable values as each of those in the parameterization data set. From the results presented in Table A1.2, Appendix 1, only 3 reservoirs from the 60 in the parameterization data set have an observed APL value that fall within the 95% confidence interval of the prediction. Therefore, for only 5% of the parameterization data set is there 95% confidence in the prediction afforded by Equation 5.1 being obtained had the entire reservoir population been available for analysis. This result assists in explaining why the model cannot be validated; it is not representing the population with a high degree of confidence. As a result of this there is little user-confidence that inferences drawn from Equation 5.1 are correct.

5.10 Equation 5.1 Operationalization

Figure 5.9 displays the operationalization of Equation 5.1 for the population. However, the model is confounded by the limits set in the parameterization data set. Therefore regarding the population, extrapolation beyond the limits of the independent variables in the parameterization data set cannot be undertaken (Norusis, 1994). This is a limitation of the regression technique as the model can only be applied to 530 reservoirs from the 797 in the original population. This undermines the achievement of the principal aim of this investigation, the production of a comprehensive assessment of the spatial variation of reservoir sedimentation for the population of surface water storage reservoirs exhibiting a degree of catchment-coupling across England and Wales.

Figure 5.9 Equation 5.1 operationalization – APL prediction



From Figure 5.9 the region of most severe reservoir sedimentation appears to be southeast England, especially the west Weald area. This is surprising. Inferring from the factors identified to induce sediment production and delivery (Section 2.11), smaller upland reservoir catchments typified by higher annual rainfall totals and highly coupled hillslopes should experience greater sedimentation (compare Figures 5.10 and 5.11 with 5.12).

Indeed, Walling (1983) and Higgitt (1993) state that, typically, lowland areas such as the Wealden vales should experience comparatively lower sediment yield (and thus reservoir sedimentation) due to the presence of reduced gradients and wider floodplains which decrease the degree of hillslope-channel coupling and increase potential catchment sediment storage. However, variables reflecting this reasoning were not incorporated into Equation 5.1 through the stepwise independent variable selection process. This may be viewed as a limitation of the stepwise multiple regression technique. The independent/predictor variables extracted from the parameterization data set (S686, TE, RMED1H) represent those that exclusively account for the variance in APL across the aforementioned data set. This is because variable multicollinearity cannot be accommodated in multiple regression. Therefore, the need to satisfy this requirement may have yielded an equation that does not reflect expert scientific opinion and intuition in terms of the broad causes for the spatial variation in reservoir sedimentation.

Figure 5.10 The "upland" catchment of Ystradfellte Reservoir, Brecon Beacons

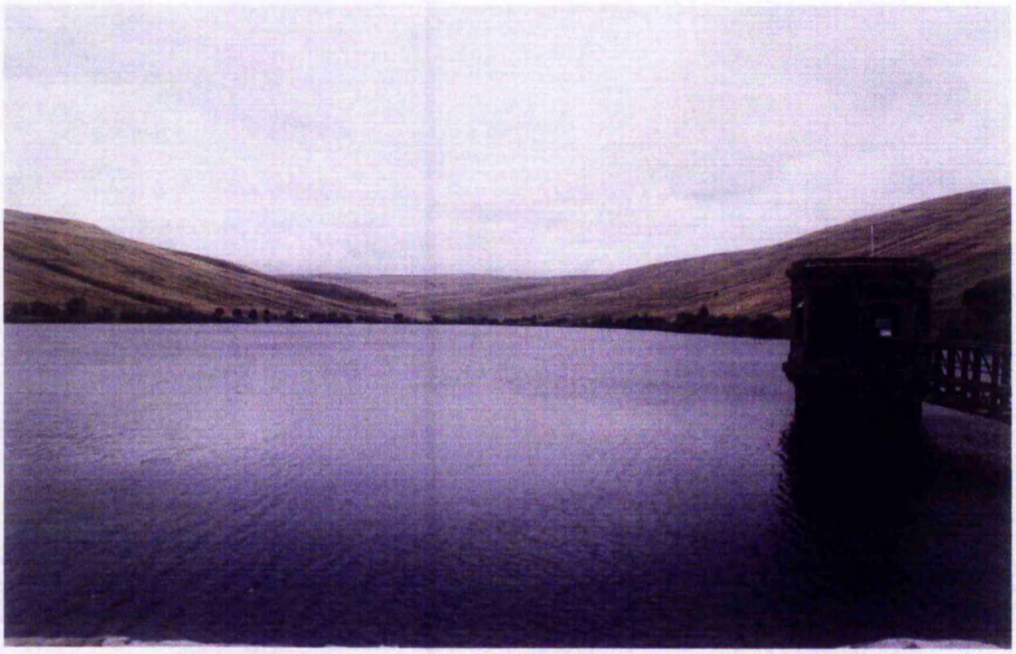


Figure 5.11 The "upland" catchment of Howden Reservoir, The Derbyshire Peak District

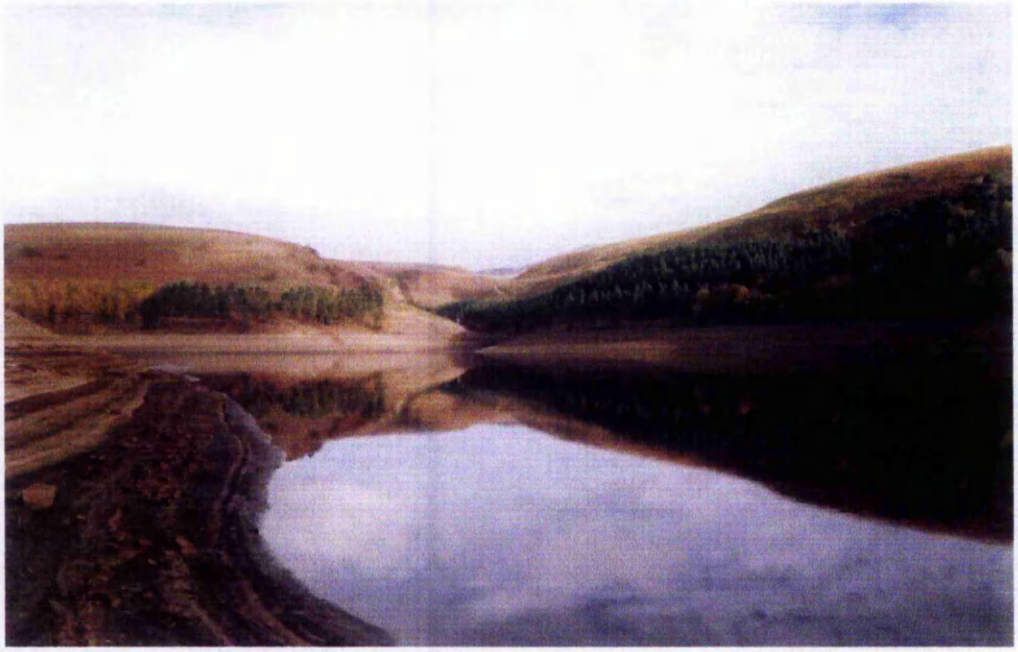


Figure 5.12 The "lowland" Wealden catchment of Weirwood Reservoir, Sussex

In terms of the independent variables of Equation 5.1, reservoir sedimentation is most severe in the Wealden area of southeast England due to comparatively large areas of the Winter Hill soil type, smaller trap efficiencies and reasonably high median annual maximum 1-hour rainfall totals (Figures 5.13, 5.14 and 5.15 respectively). With regards to the Winter Hill soil association this may appear surprising considering the geographic location, although maybe induced by the fact that the soil variable reflects the area of the dominant soil association as opposed to actual percentage cover (Section 4.2.2.3) and that catchment areas are typically larger in lowland, southeast England. However, as identified in Section 5.8.5.1, there are potential problems undermining the integrity of the negative relationship between APL and TE (the respective partial regression coefficient accounts second largest contribution to the overall coefficient of determination given by Equation 5.1). This negative relationship is induced by a few observations which each have revised capacities represented in the BRE dams data set that are used to calculate the respective trap efficiencies (in particular Abbeystead and Blakeley reservoirs). As a result of these cases having high APL rates, the respective TE values are much smaller than would have been depicted had an original capacity been considered – this induces the negative relationship between APL and TE. As a result of reservoir sedimentation not having been perceived to be a problem in southeast England due to the absence of steep relief, high rainfall totals etc. (factors intuitively related to high sediment yields), there have not been any published studies of reservoir sedimentation in this region, as represented by an absence in the Halcrow data set (2001). Thus, there is a strong possibility that the capacities of the southeastern reservoirs in the BRE data set relate to original capacities. As a result of this, the inference from the negative partial regression coefficient concerning TE that these southeastern reservoirs have low TE due to their high APL rates may be misleading: because their low TE values are calculated from original capacity data, they may in fact be experiencing low APL rates partly as a result of having low trap efficiencies at the time of dam commission. Indeed, the association of lower trap efficiencies (such as those across the Weald) with lower sedimentation rates (Brown, 1944) complies with the broad theory that sediment yield decreases as catchment area increases (Walling, 1983; Higgitt, 1993). This is because such lowland-type reservoirs typically have larger catchment areas, and thus greater areas for storage and reduced hillslope-channel coupling, and smaller trap efficiencies in terms of reservoir capacity:catchment area ratios (Brown, 1944).

Figure 5.13 Area of Winter Hill soil class (km $^{-2}$) for the population of reservoirs

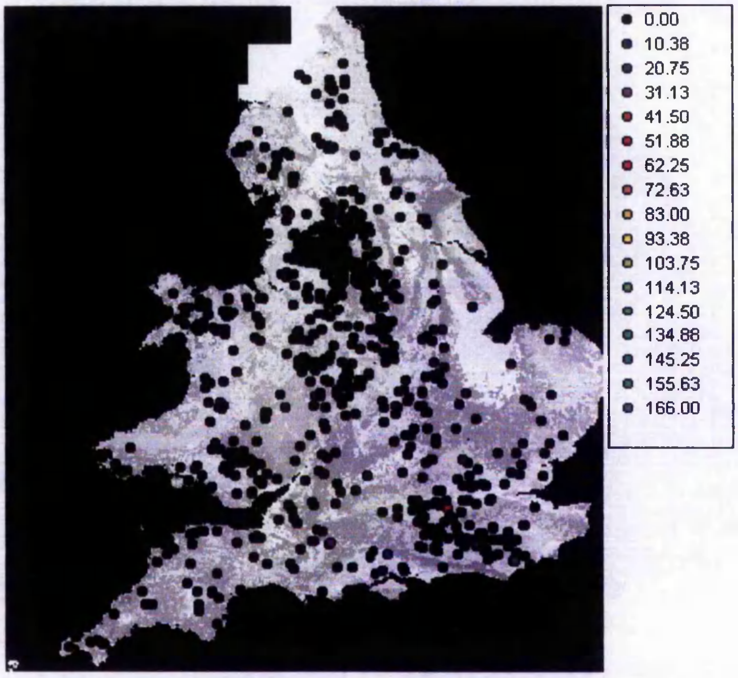


Figure 5.14 Trap efficiency (%) for the population of reservoirs

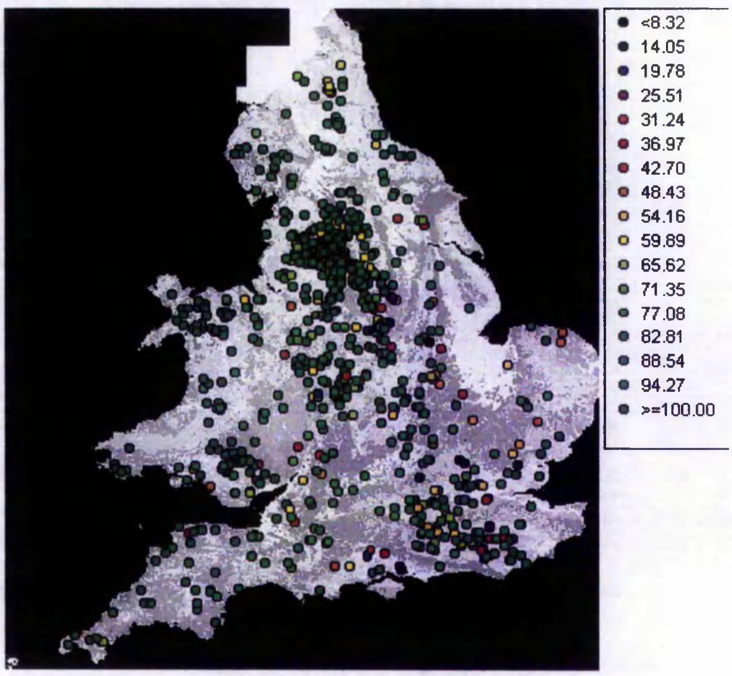
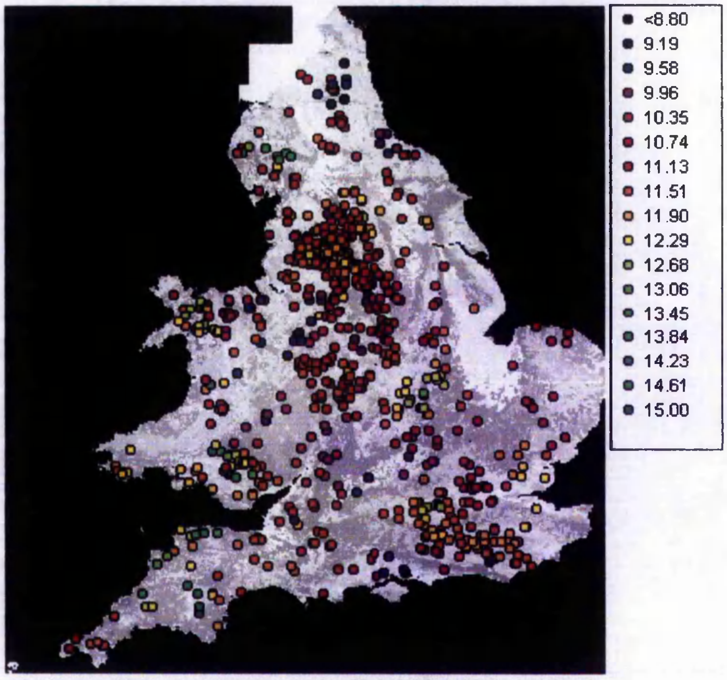


Figure 5.15 Mean annual hourly rainfall (mm hr^{-1}) for the population of reservoirs



5.11 Cluster 2 multiple regression – untransformed data

5.11.1 Introduction

This section details the progression to the formulation of a multiple regression model predicting APL for the population of cluster 2 (Table A1.24, Appendix 1). The evaluation of this model assesses the potential of the clustering approach in achieving the principal aim of the research. This technique proved successful for Jansen and Painter (1974) and DeBonis *et al*, (2002) in improving multiple regression model coefficients of determination. As with the formulation of the population multiple regression model in the preceding sections, all of the respective statistical analysis and results are included in Appendix 4; only the key results relevant to the discussion of the regression equations are included herein.

5.11.2 Test for Linearity – Pearson's correlation

Pearson's correlation coefficients were calculated between APL and each of the 57 independent variables. Those significant below the 0.05 level are presented in Table 5.13. The correlation coefficients suggest only a reasonable degree of linearity between the independent variables and APL for cluster 2. This was also the case regarding the respective analysis associated with the complete parameterization data base (concerning the development of Equation 5.1).

The fact that the individual correlation coefficients each have p-values of stronger significance than the 0.05 significance level is important due to the aforementioned problem of multiple significance levels (Section 5.6.1). From the consideration of 11 correlations significant at the 0.05 level between APL and each respective independent variable, at least 0.55 may occur by chance. However, this value represents the largest minimum number of correlations that may occur by chance as the majority of the correlation coefficients are significant at levels stronger than 0.01.

Table 5.13 Pearson's correlation coefficients significant below 0.05 between APL and the respective independent variables

Independent Variable	r	p	n
QMED	0.442	0.001	51
RMED1H	0.315	0.024	51
RMED1D	0.380	0.006	51
RMED2D	0.331	0.018	51
SAAR	0.383	0.006	51
SAAR4170	0.354	0.011	51
TE	-0.591	0.000	51
S686	0.653	0.000	51
CONIF	0.323	0.021	51
DSHRUB	0.518	0.000	51
UPBOG	0.476	0.000	51

5.11.3 Result and diagnostics

The model produced by multiple regression analysis for the prediction of APL across the cluster 2 population is presented below (Equation 5.5). This model has an R^2 of 0.616.

APL = 0.578 + 0.011 x S686 – 0.009 x TE + 0.007 x RMED1D (Eq. 5.5)

The essential multiple regression diagnostics assessing the compliance of the result with the assumptions of the technique are presented in Table 5.14.

Table 5.14 Multiple regression diagnostics results; √ denotes compliance with the respective assumption, X denotes non-compliance. For the Leverage and Cook's distance results, the number of cases inducing the non-compliance with the assumption of linearity are presented.

Assumption	**Diagnostic**	**Result**
Linearity	Analysis of variance	√
	t statistic	√
	Leverage	X - 7 cases
	Cook's distance	X - 1 case
Non-multicollinearity	Tolerance statistic	√
Residual independence	Durbin-Watson test	√
Residual constant variance	Scattergraphs - residuals versus predicted values	X
Residual normality	Kolmogorov-Smirnov test	X

5.11.4 Summary of Equation 5.5

Equation 5.5 accounts for a reasonable 62% of the variance observed in APL. However, from Table 5.14 it does not meet all of the assumptions required for a robust, reliable regression model. As associated with Equation 5.1 (Section 5.6.2), the lack of robust linear relationships (identified through the leverage and Cook's distance values) appear to be inducing violations of the assumptions of residual constant variance and normality (Norusis, 1994). As a result of this, three standard transformations were again applied to each of the 57 independent variables in an attempt to improve the robustness and reliability of the multiple regression model in the prediction of reservoir sedimentation for the cluster 2 population: logs to the base 10, squares, and square roots.

5.12 Cluster 2 multiple regression analysis – transformed independent variables

This section documents the incorporation of transformed independent variables (logs to the base 10, squares, and square roots) into a multiple regression analysis predicting APL for the cluster 2 population in an attempt to improve model compliance with the regression assumptions of linearity, residual constant variance, and residual distribution normality.

5.12.1 Test for linearity - Pearson's correlation

The Pearson's correlation results between each respective transformation of the independent variables significant below the 0.05 level, are presented in Table 5.15.

Table 5.15 Pearson's correlation coefficients significant below 0.05 between APL and the respective transformed independent variables

Transformation	Independent Variable	r	p	n
Log 10 transform	QMEDLOG10	0.316	0.024	51
	RMED1HLOG10	0.310	0.027	51
	RMED1DLOG10	0.367	0.008	51
	RMED2DLOG10	0.319	0.022	51
	SAARLOG10	0.359	0.010	51
	SAAR4170LOG10	0.332	0.017	51
	TELOG10	-0.609	0.000	51
	S686LOG10	0.408	0.003	51
	FELLEDLOG10	0.343	0.014	51
	MEADOWLOG10	-0.280	0.046	51
	UPBOGLOG10	0.408	0.003	51
Square transform	QMEDSQ	0.502	0.000	51
	RMED1HSQ	0.320	0.022	51
	RMED1DSQ	0.389	0.005	51
	RMED2DSQ	0.339	0.015	51
	SAARSQ	0.406	0.003	51
	SAAR4170SQ	0.373	0.007	51
	TESQ	-0.573	0.000	51
	S686SQ	0.649	0.000	51
	CONIFSQ	0.457	0.001	51
	DSHRUBSQ	0.540	0.000	51
	UPBOGSQ	0.331	0.018	51
Square root transform	QMEDSQRT	0.386	0.005	51

	RMED1HSQRT	0.312	0.026	51
	RMED1DSQRT	0.374	0.007	51
	RMED2DSQRT	0.326	0.020	51
	SAARSQRT	0.371	0.007	51
	SAAR4170SQRT	0.344	0.014	51
	TESQRT	-0.600	0.000	51
	S686SQRT	0.580	0.000	51
	DSHRUBSQRT	0.408	0.003	51
	UPBOGSQRT	0.499	0.000	51

From the analysis of the significant Pearson correlation coefficients (Table 5.15) linear relationships are still only suggested to a reasonable degree.

From the four groups of potential independent variables (untransformed, log10, squared, square root), those with the greatest correlation coefficient rounded to one place of decimal were entered into the multiple regression analysis (as discussed in Section 5.7). The independent variables entered into the multiple regression analysis were: QMEDSQ, RMED1H, RMED1D, REMED2D, SAAR, SAAR4170, TE, S686, CONSQ, DSHRUB, and UPBOG.

In relation to the potential problem of multiple significance levels, 43 correlation coefficients significant at the 0.05 level were obtained between APL and each of the independent variable variants (Tables A1.9, A1.10 and A1.11, Appendix 1). Therefore, at least 2.15 correlations may occur by chance when testing to a significance level of 0.05. However, this value represents the largest minimum number of correlations that may occur by chance as the majority of the correlation coefficients are significant at levels stronger than 0.01.

5.12.2 Result and diagnostics

Through the stepwise multiple regression procedure incorporating potential transformed independent variables, the same result is produced as that for the previous application concerning the untransformed data (Equation 5.5). As a result of this the same shortcomings remain; the reliance of linear relationships between APL and each independent variable on a small number of observations, the lack of residual constant variance, and the residuals not being normally distributed.

In an attempt to improve the validity and robustness of the multiple regression model predicting APL for cluster 2, the same three standard transformations were applied to the dependent variable (APL); logs to the base 10, squares, and square roots.

5.13 Cluster 2 multiple regression analyses - transformed dependent & independent variables

This section details the incorporation of transformed independent and dependent variables (logs to the base 10, squares, and square roots) into a multiple regression analysis predicting APL across the cluster 2 population in an attempt to improve model compliance with the assumptions of linearity, residual constant variance, and residual distribution normality.

5.13.1 Tests for linearity – Pearson's correlation

Pearson's correlation coefficients were calculated between each dependent variable transformation and each independent variable variant (untransformed, logarithmically transformed to the base 10, square transformed and square root transformed). Again, the correlation coefficients significant at the 0.05 level for each independent variable variant were rounded to one place of decimal and those with the greatest value were entered into the multiple regression analysis for each respective APL variant (Table 5.16).

Regarding the potential problem of multiple significance levels, the number of correlations significant at the 0.05 level between APLLOG10, APLSQ and APLSQRT, and the associated independent variable variants are 19, 48 and 40 respectively (Tables A1.12 – A1.22, Appendix 1). Therefore, the minimum number of correlations significant at the 0.05 level that may have occurred by chance for the aforementioned APL transformations are only 0.95, 2.4 and 2 respectively (the majority of the correlation coefficients associated with each APL transformation are significant at levels stronger than 0.01).

Table 5.16 Pearson's correlation coefficients significant below 0.05 between APL variant and independent variables entered into each respective multiple regression analysis

Transformation	Independent Variable	R	p	n
APLLOG10	SAAR	0.303	0.031	51
	SAAR4170	0.312	0.026	51
	TE	-0.401	0.004	51
	S686	0.407	0.003	51
	DECIDLOG10	0.333	0.017	51
	CONIFSQ	0.280	0.047	51
	RUDERALLOG10	0.301	0.032	51
	ROUGHLOG10	0.289	0.039	51
APLSQ	CAREALOG10	0.281	0.045	51
	QMEDSQ	0.560	0.000	51
	RMED1H	0.285	0.043	51
	RMED1D	0.338	0.015	51
	RMED2D	0.291	0.039	51
	SAAR	0.345	0.013	51
	SAAR4170	0.300	0.032	51
	TELOG10	-0.650	0.000	51
	S686	0.718	0.000	51
	CONIFSQ	0.498	0.000	51
	DSHRUBSQ	0.654	0.000	51
	UPBOG	0.577	0.000	51
	FELLEDLOG10	0.420	0.002	51
	MEADOWLOG10	-0.374	0.007	51
	MOWNLOG10	-0.286	0.042	51
APLSQRT	QMEDSQ	0.398	0.004	51
	RMED1H	0.285	0.043	51
	RMED1D	0.355	0.011	51
	RMED2D	0.311	0.026	51
	SAAR	0.375	0.007	51
	SAAR4170	0.363	0.009	51
	TE	-0.530	0.000	51
	S686	0.561	0.000	51
	CONIFSQ	0.389	0.005	51
	DSHRUB	0.396	0.004	51
	UPBOG	0.330	0.018	51
	DPSBAR	0.277	0.049	51

5.13.2 Results and diagnostics

The models produced by multiple regression analysis for each APL variant are shown below. Equation 5.6 accounts for 48% of the variation observed in APLLOG10, Equation 5.7 accounts for 75% of the variation observed in APLSQ, and Equation 5.8 accounts for 49% of the variation observed in APLSQRT.

APLLOG10 = 1.350 + 0.026 x S686 + 0.14 x DECLOG10 + 0.156 x RUDLOG10 – 0.024 x TE (Eq. 5.6)

APLSQ = 1.524 + 0.008 x S686 + 0.0002 x DSHRUBSQ + 0.004 x RMED1D – 0.86 x TE (Eq. 5.7)

APLSQRT = 0.988 + 0.009 x S686 – 0.011 x TE + 0.0002 x SAAR4170 (Eq. 5.8)

The essential multiple regression diagnostics assessing the compliance of the result with the assumptions of the technique are presented in Table 5.17.

Table 5.17 Comparison of multiple regression diagnostics results; √ denotes compliance with the respective assumption, X denotes non-compliance. For the Leverage and Cook's distance results, the number of cases inducing the non-compliance with the assumption of linearity are presented.

Assumption	**Diagnostic**	**Eq 5.6**	**Eq 5.7**	**Eq 5.8**
		Result	**Result**	**Result**
Linearity	Analysis of variance	√	√	√
	t statistic	√	√	√
	Leverage	X – 8 cases	X - 7 cases	X - 8 cases
	Cook's distance	√	X - 2 cases	√
Non-multicollinearity	Tolerance statistic	√	√	√
Residual independence	Durbin-Watson test	√	√	√
Residual constant variance	Scattergraphs - residuals versus predicted values	√	X	√
Residual normality	Kolmogorov-Smirnov test	X	X	√
Total number of refutations		2	4	1

5.13.3 Summary of Equations 5.6, 5.7 & 5.8

Multiple regression analyses were performed on transformed variants of APL (APLLOG10, APLSQ, APLSQRT) due to Equation 5.5 (incorporating untransformed variables) failing to satisfy conclusively the regression assumptions of residual constant variance and normality, and linearity, despite having a respectable R^2 of 0.616.

From the analysis of Table 5.17 it is clear that Equation 5.8 associated with the prediction of APLSQRT on balance produces the most reliable, robust model in terms of compliance with the assumptions of multiple regression. This is primarily due to it exhibiting comparatively stronger linear relationships between the independent variables and dependent variable. Therefore it is this model that needs to be compared to Equation 5.5 (incorporating untransformed variables) to determine the most robust, reliable variant in the prediction of reservoir sedimentation across the cluster 2 population. However, it must be stressed again that the assumptions associated with Equation 5.8 are not satisfied unequivocally.

5.13.4 Model selection

The choice for the most robust, reliable model predicting reservoir sedimentation for cluster 2 lies between Equation 5.5, incorporating untransformed independent and dependent variables with an R^2 of 61%, and Equation 5.8 incorporating the transformed APLSQRT dependent variable with an R^2 of 49%.

Table 5.18 compares the total number of multiple regression assumption refutations associated with Equation 5.5 and Equation 5.8. Clearly Equation 5.8 provides the most sound, robust model due to it satisfying a greater number of the assumptions of multiple regression. This is due to Equation 5.8 having comparatively stronger linear relationships, less reliant on a number of influential points (as identified through the absence of respective Cook's distance values above 1), inducing compliance with the assumptions of residual constant variance and distribution normality. As a result of this Equation 5.8 is selected as the optimum model to predict reservoir sedimentation (APLSQRT) for cluster 2. However, whilst the compliance of Equation 5.8 with the assumptions of regression remains comparatively sounder, the lack of strong linear relationships between reservoir sedimentation and those variables perceived to influence the process is reflected through the relatively low R^2 of 49%.

Table 5.18 Comparison of multiple regression diagnostics results; √ denotes compliance with the respective assumption, X denotes non-compliance. For the Leverage and Cook's distance results, the number of cases inducing the non-compliance with the assumption of linearity are presented.

Assumption	**Diagnostic**	**Eq 5.5**	**Eq 5.8**
		Result	**Result**
Linearity	Analysis of variance	√	√
	t statistic	√	√
	Leverage	X – 7 cases	X - 8 cases
	Cook's distance	X – 1 case	√
Non-multicollinearity	Tolerance statistic	√	√
Residual independence	Durbin-Watson test	√	√
Residual constant variance	Scattergraphs - residuals versus predicted values	X	√
Residual normality	Kolmogorov-Smirnov test	X	√
Total number of refutations		4	1

5.13.5 Discussion of Equation 5.8

In this section Equation 5.8, predicting reservoir sedimentation for the cluster 2 population, is discussed in relation to the regression assumption it fails to unequivocally comply with (linearity).

5.13.5.1 Nature of linear relationships

From the partial regression coefficients of Equation 5.8, S686 and SAAR4170 are both positively related to APLSQRT. These relationships are again explained through larger areas (in this case of S686) providing more sites of erosion and therefore greater quantities of sediment yield, and higher mean annual rainfall totals providing greater quantities of an erosion agent.

The negative relationship shown by the partial regression coefficient between APLSQRT and TE was also apparent in Equation 5.1, the model selected as the most valid and robust to predict reservoir sedimentation (APL) for the complete population. From the associated discussion in Section 5.8.5.1, this can again be attributed to Abbeystead and Blakeley reservoirs in particular having revised capacities listed in the BRE dams data set (Tedd *et al.*, 1992) as opposed to original capacities. Therefore, the calculation of trap efficiency from these revised capacities produces smaller TE values associated with high APLSQRT observations in comparison to those that would have been calculated from original capacity measurements. This is because the rate of sedimentation (between the time of dam commission and the revised capacity survey) is being accounted for.

The extreme rates of APLSQRT associated with Abbeystead and Blakeley reservoirs have a large influence on **each** of the partial regression coefficients associated with Equation 5.8 as identified through their respective leverage values (Appendix 4). However, as discussed in Section 5.8.5.1, these respective sedimentation rates can also be attributed to unique catchment factors not represented in Equation 5.8.

5.14 Equation 5.8 evaluation

5.14.1 Verification

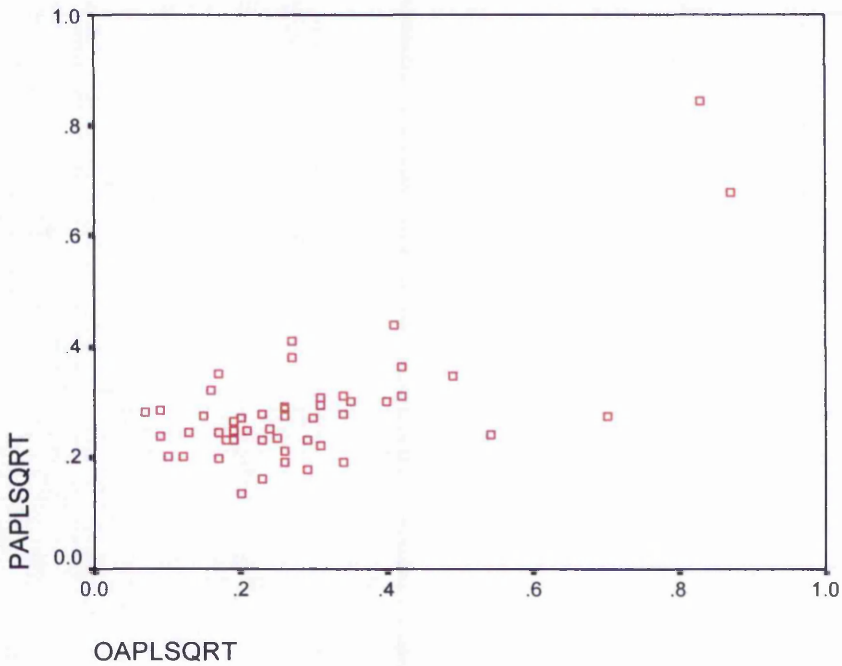
In order to verify objectively Equation 5.8, the Pearson's correlation test and paired T-test were applied to assess the degree to which the model simulates the relative pattern of the observed data, and the accuracy in actual APLSQRT prediction.

The significant Pearson's correlation analysis result (0.699) at face value implies a good relationship between observed and predicted APL (Table 5.19). However, from Figure 5.16 the strength of the correlation does again appear heavily influenced by Abbeystead and Blakeley reservoirs. In contrast, however, to the respective correlation result associated with Equation 5.1 (Figure 5.3), there is a stronger suggestion of a general progression of the main data point cluster in a positive direction. This implies reasonable predictions of reservoir APLSQRT.

Table 5.19 Verification results – Pearson's correlation and Paired T-test

Verification	Equation 5.8
Correlation coefficient	0.699
Significance level	0.000
Number	51
Paired T-test statistic	0.042
Significance level	0.967
Degrees of freedom	50

Figure 5.16 Predicted APLSQRT (PAPLSQRT) versus observed APLSQRT (OAPLSQRT)



From Figure 5.17 it can be seen that the model broadly follows the same relative pattern as that observed, producing an output of predictions that appear balanced through under-predicting where observed APLSQRT values are exceptionally high, and over-predicting where observed APLSQRT observations are very low. This is supported through Figure 5.18 displaying respective positive and negative residuals (observed APLSQRT minus predicted APLSQRT). Indeed, the mean residual value associated with the prediction of APLSQRT across the cluster 2 parameterization data set is 0.0007, identifying neither a predominance of over nor under-predictions (Table 5.20). This observation supports the paired T-test result which identifies that the difference in means between the observed and predicted APL rates is not significantly different from zero (Table 5.20). The model therefore under-predicts for exceptionally high APLSQRT observations and over-predicts for very low APLSQRT observations, thus yielding predictions of reasonable accuracy for the average observed APLSQRT rates typifying the cluster 2 parameterization data set (Figure 5.17).

Figure 5.17 The relative pattern of observed APLSQRT & predicted APLSQRT for each reservoir

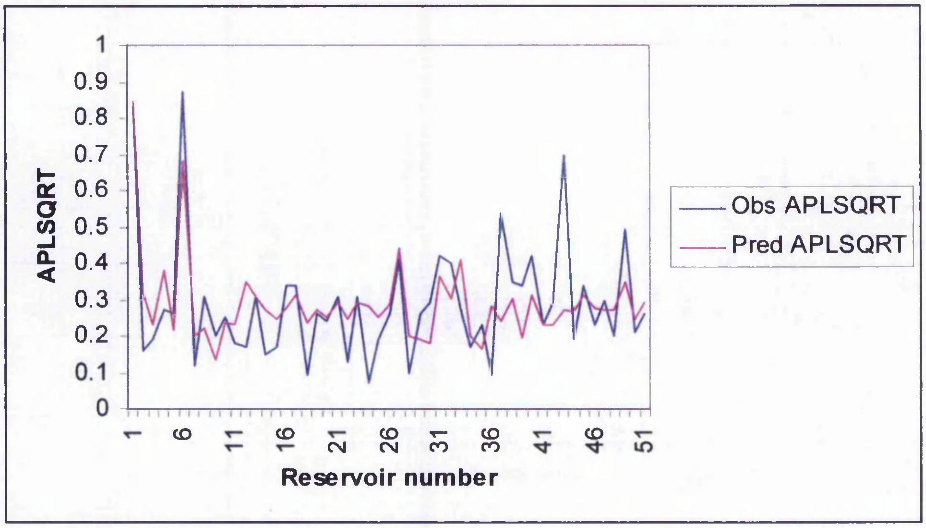


Figure 5.18 Parameterization data set residuals (observed APL – predicted APL)

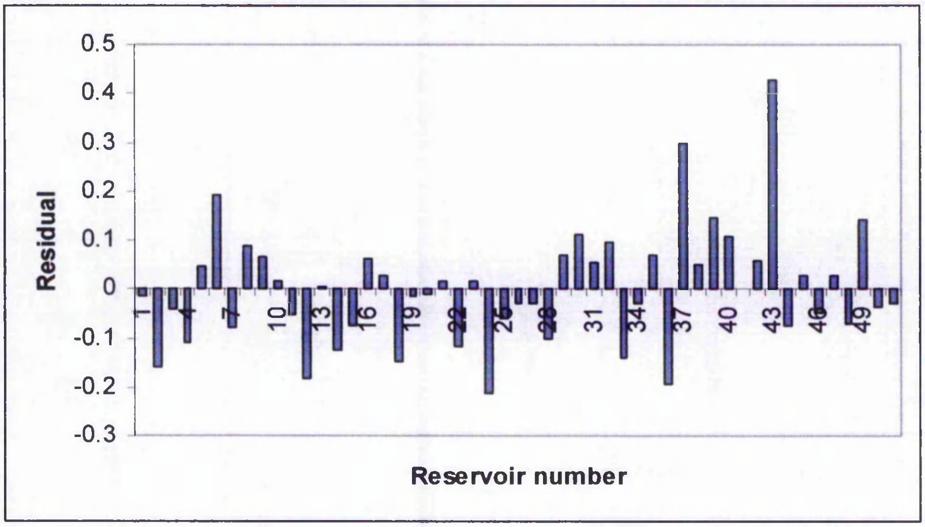


Table 5.20 Key to Figures 5.17 & 5.18 & corresponding observed APL, predicted APL & residual values

Reservoir	Reservoir	Obs APLSQRT	Pred APLSQRT	Residual
1	Abbeystead	0.830	0.845	-0.015
2	Angram	0.160	0.321	-0.161
3	Barden Lower	0.190	0.231	-0.041
4	Barden Upper	0.270	0.380	-0.110
5	Blackmoorfoot	0.260	0.213	0.047
6	Blakeley	0.870	0.680	0.190
7	Broadstones	0.120	0.201	-0.081
8	Broomhead	0.310	0.221	0.089

9	Chelker	0.200	0.135	0.065
10	Dale Dyke	0.250	0.234	0.016
11	Damflask	0.180	0.233	-0.053
12	Dean Head Lower	0.170	0.350	-0.180
13	Dean Head Upper	0.310	0.307	0.003
14	Deanhead	0.150	0.273	-0.123
15	Deerhill	0.170	0.245	-0.075
16	Eldwick	0.340	0.279	0.061
17	Embsay	0.340	0.312	0.028
18	Fewston	0.090	0.238	-0.148
19	Gorple Lower	0.260	0.274	-0.014
20	Gorple Upper	0.240	0.250	-0.010
21	Gorpley	0.310	0.294	0.016
22	Green Withens	0.130	0.246	-0.116
23	Harden	0.310	0.295	0.015
24	Holmestyes	0.070	0.281	-0.211
25	Lindley Wood	0.190	0.249	-0.059
26	Ponden	0.260	0.289	-0.029
27	Ramsden	0.410	0.440	-0.030
28	Redmires Lower	0.100	0.202	-0.102
29	Redmires Middle	0.260	0.191	0.069
30	Redmires Upper	0.290	0.178	0.112
31	Riding Wood	0.420	0.364	0.056
32	Rivelin Lower	0.400	0.303	0.097
33	Rivelin Upper	0.270	0.412	-0.142
34	Roundhill	0.170	0.199	-0.029
35	Royd Moor	0.230	0.162	0.068
36	Ryburn	0.090	0.284	-0.194
37	Scammonden	0.540	0.240	0.300
38	Scar House	0.350	0.301	0.049
39	Silsden	0.340	0.193	0.147
40	Snailsden	0.420	0.313	0.107
41	Strines	0.230	0.230	0.000
42	Stubden	0.290	0.230	0.060
43	Tunnel End	0.700	0.274	0.426
44	Underbank	0.190	0.265	-0.075
45	Walshaw Dean Lower	0.340	0.313	0.027
46	Walshaw Dean Middle	0.230	0.279	-0.049
47	Walshaw Dean Upper	0.300	0.271	0.029
48	Wessenden Head	0.200	0.273	-0.073
49	Wessenden Old	0.490	0.347	0.143
50	Widdop	0.210	0.249	-0.039
51	Windleden Upper	0.260	0.290	-0.030
	Mean	0.288	0.288	0.001

The largest residuals identified in Figure 5.18 and Table 5.20 are again induced by: (1) being observations having an undue influence on the computation of the partial regression coefficients of Equation 5.8; thus exerting an influence on the regression model in multi-dimensional space, yet being situated a distance away from it (see Figure A4.20 and Table A4.26, Appendix 4 concerning the respective Cook's distance and leverage statistics); and (2) having factors influencing the respective sedimentation rates not accounted for by the model. These two reasons for residual production are not necessarily mutually exclusive. The reservoirs with the largest positive residuals are Blakeley, Scammonden and Tunnel End (0.190, 0.300 and 0.426 respectively) and represent an under-prediction by Equation 5.8. These reservoirs also represented the largest positive residuals associated with Equation 5.1 and are induced by the same causal explanations concerning factors acting to increase APL that are not represented in the model (Sections 5.13.5 and 5.8.5). The reservoirs with the largest negative residuals are again predominantly associated with catchment management structures that act to reduce sedimentation rates. Angram, Dean Head Lower, Fewston, Rivelin Upper and Ryburn reservoirs (with respective residuals of -0.161, -0.180, -0.148, -0.142 and -0.194) each have a combination of residuum lodges, bywash channels, additional catchwater/conduit interceptions and reservoirs upstream (White *et al.*, 1996a) that act to reduce observed APL values.

5.14.2 Validation

The validation data set for reservoirs in cluster 2 comprises three reservoirs not included in the parameterization data set: Bough Beech, Eyebrook, and Howden (Table 5.21). Pearson's correlation and the paired T-test were used to compare the model predictions with the observed validation data.

Table 5.21 Validation data set – respective observed APL, predicted APL and residual values

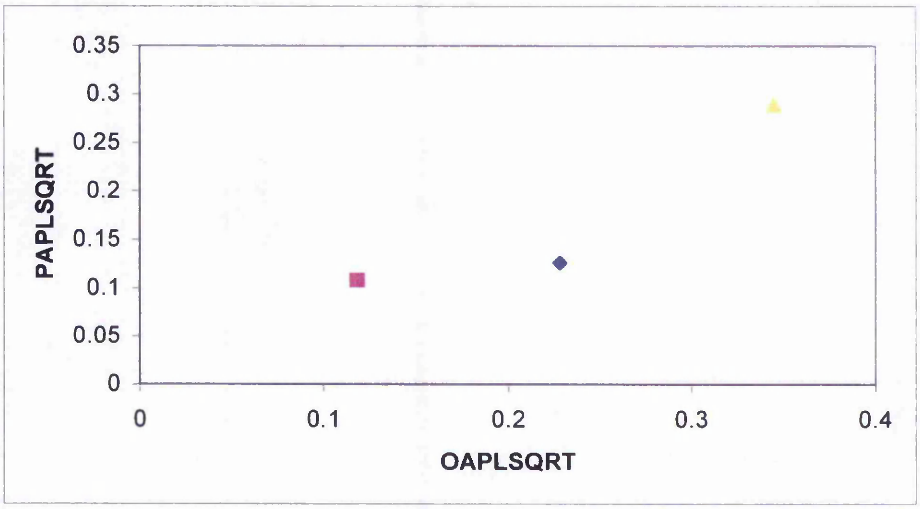
Reservoir	**ObsAPLSQRT**	**PredAPLSQRT**	**Residual**
Bough Beech	0.228	0.126	0.102
Eyebrook	0.118	0.108	0.010
Howden	0.345	0.289	0.056
Mean	0.230	0.174	0.056

The Pearson's correlation result and associated scattergraph imply a reasonable relationship between the observed and predicted APL of the reservoirs in the validation data set (Table 5.22 and Figure 5.19); however, a significant correlation is not produced primarily due to the small sample size. This result supports the inference from Figure 5.20 that the model is replicating, to a degree, the same relative pattern as that observed in the real world APL values.

Table 5.22 Validation result – Pearson's correlation and Paired T-test

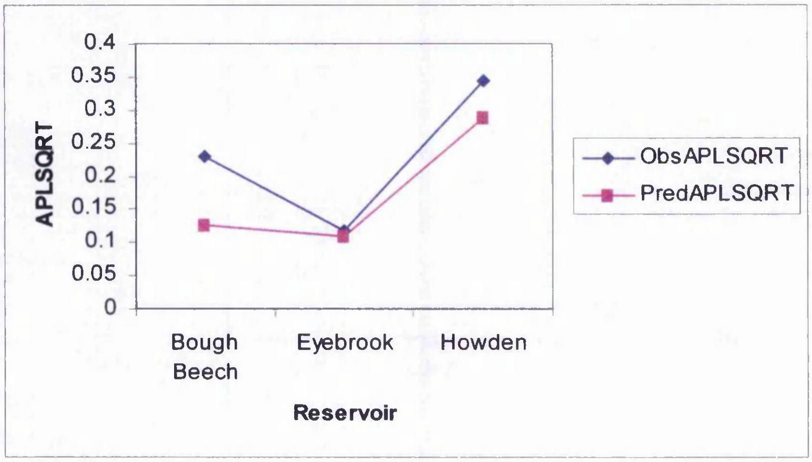
Validation	**Equation 5.8**
Correlation coefficient	0.915
Significance level	0.264
Number	3
Paired T-test statistic	2.119
Significance level	0.168
Degrees of freedom	2

Figure 5.19 Cluster 2 predicted APLSQRT (PAPLSQRT) versus observed APLSQRT (OAPLSQRT) – validation data set



Key: Bough Beech – blue diamond, Eyebrook – pink square, Howden – yellow triangle.

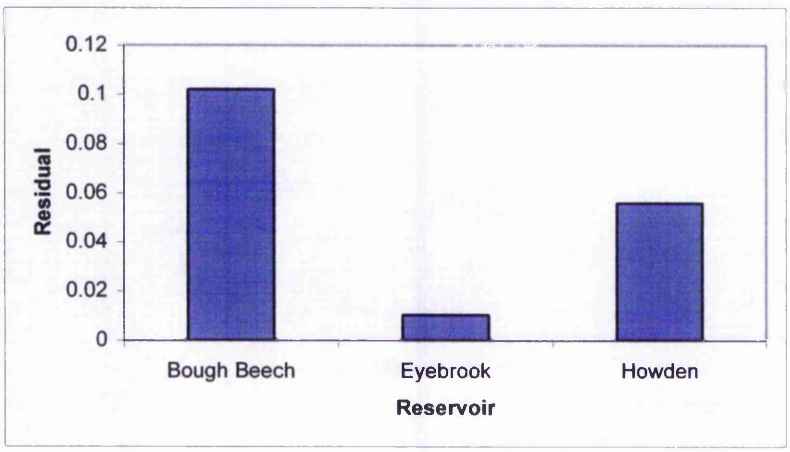
Figure 5.20 The relative pattern of observed APLSQRT & predicted APLSQRT – validation data set



In addition, to the Pearson's correlation result, the paired T-test result (Table 5.22) identifies that the difference in means between the observed and predicted APL rates are not significantly different from zero, implying that the model is predicting results of a reasonably good accuracy.

From Figure 5.21 it can be seen that the residuals are positive for each of the reservoirs in the cluster 2 validation data set indicating consistent under-prediction by Equation 5.8 when extrapolated across the reservoir population of cluster 2. The corresponding mean residual value of 0.056 highlights this consistency in under-prediction.

Figure 5.21 Validation data set residuals (observed APLSQRT minus predicted APLSQRT)



In conclusion, Equation 5.8 as a model predicting APLSQRT for the population of reservoirs in cluster 2 can be verified and validated to a reasonable degree. The model does replicate the same relative pattern as the parameterization data set, as identified through the significant Pearson's correlation coefficient, and does predict APL to a reasonably good accuracy across the reservoirs typifying the cluster 2 parameterization data set, as identified through the paired T-test. As a result, when the model is extrapolated to predict for reservoirs not present in the parameterization data set, results of a reasonable quality are produced in terms of the model prediction and replicating the same relative pattern as the observed (validation) data.

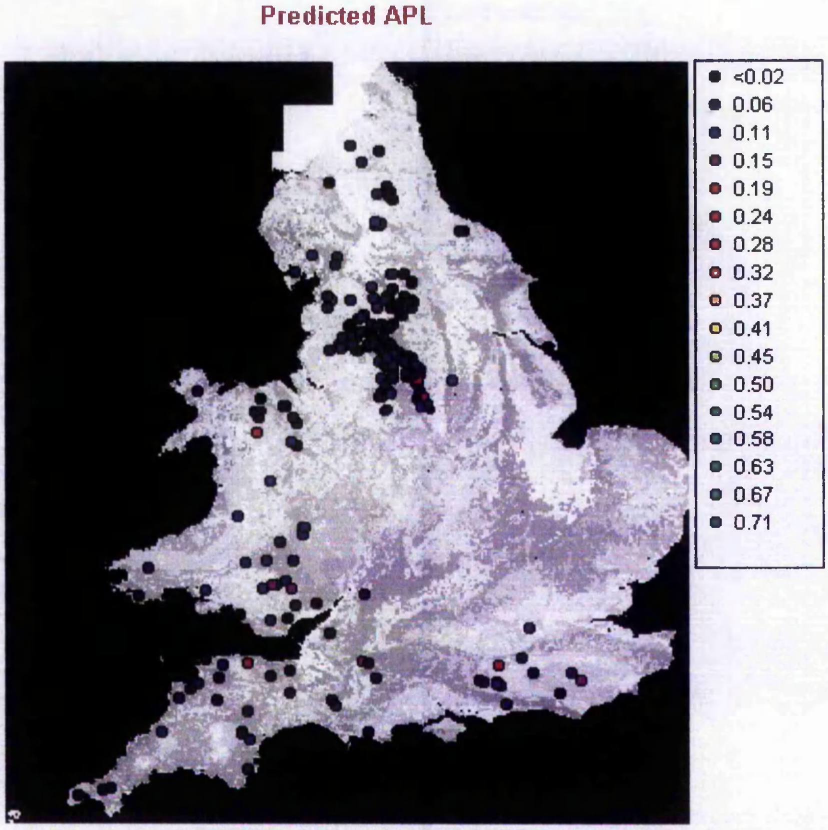
5.14.3 Confidence intervals

From the 95% confidence intervals for each reservoir in the parameterization data set relating to the prediction of the conditional mean APL from Equation 5.8 for *all* reservoirs with the same respective independent variable values; only 2 reservoirs from the 51 in the cluster 2 parameterization data set have an observed APLSQRT value that fall within the respective 95% confidence interval of the prediction (Table A1.24, Appendix 1). Therefore, for only 4% of the cluster 2 parameterization data set is there 95% confidence in the prediction afforded by Equation 5.8 being obtained had the entire reservoir population been available for analysis. This result does not provide high user-confidence that inferences made from Equation 5.8 are correct.

5.15 Equation 5.8 operationalization

Figure 5.22 displays the operationalization of Equation 5.8 for the cluster 2 population with the APLSQRT predictions back-transformed to APL values. This regression model is also confounded by the limits set in the cluster 2 parameterization data set. Therefore, extrapolation beyond the limits of the independent variables in the parameterization data set cannot be undertaken (Norusis, 1994). As a result Equation 5.8 can only be applied to 249 reservoirs from the 473 that comprise the cluster 2 population.

Figure 5.22 Equation 5.8 operationalization – cluster 2 population APL prediction



From Figure 5.22 the most severe regions of reservoir sedimentation appear to be the upland areas of the southern Pennines, north Wales, and Exmoor in particular. In the context of the model this is explained by these areas have comparatively larger areas of the highly erosive Winter Hill soil class (Figure 5.23) and mean annual rainfall totals (Figure 5.25) - conditions that favour sediment production. However, the high APL value in the northwest corner of the Weald in southeast England may be particularly attributed to the problematical negative relationship between APL and trap efficiency defined by the model (Figure 5.24). This negative relationship (and negative respective partial regression coefficient) is again induced by Abbeystead and Blakeley reservoirs having a **revised capacity** in the BRE dams data set (which is used to calculate TE across the population data set). Therefore, from the time of dam commission, it is to be expected that TE decreases with APL. However, such inference is misleading concerning reservoirs with an **original capacity** listed in the BRE dams data set. For these reservoirs, low APL rates may be experienced as a direct result of them having low trap efficiencies. As discussed in Sections 5.8.5.1 and 5.10, it is likely that reservoirs across southeast England have not been resurveyed to obtain a revised capacity (which for certain cases is represented in the BRE dams data set), as sedimentation is not perceived to be a problem in this area. Therefore it is likely that the respective BRE capacities relate to original capacities used to calculate TE. From Section 5.10, reservoirs across southeast England typically have smaller trap efficiencies in terms of reservoir capacity:catchment area ratios (Brown, 1944) as they are more lowland in nature and thus often have larger catchment areas (associated with greater areas for storage and reduced hillslope-channel coupling). As a result, these reservoirs are potentially experiencing smaller APL rates because of their smaller trap efficiencies – inference that is not obtained through Equation 5.8. Therefore, the output from Equation 5.8 concerning reservoirs that have an original capacity used to calculate TE might be misleading.

Figure 5.23 Area of Winter Hill soil class (km^2) for the cluster 2 population of reservoirs

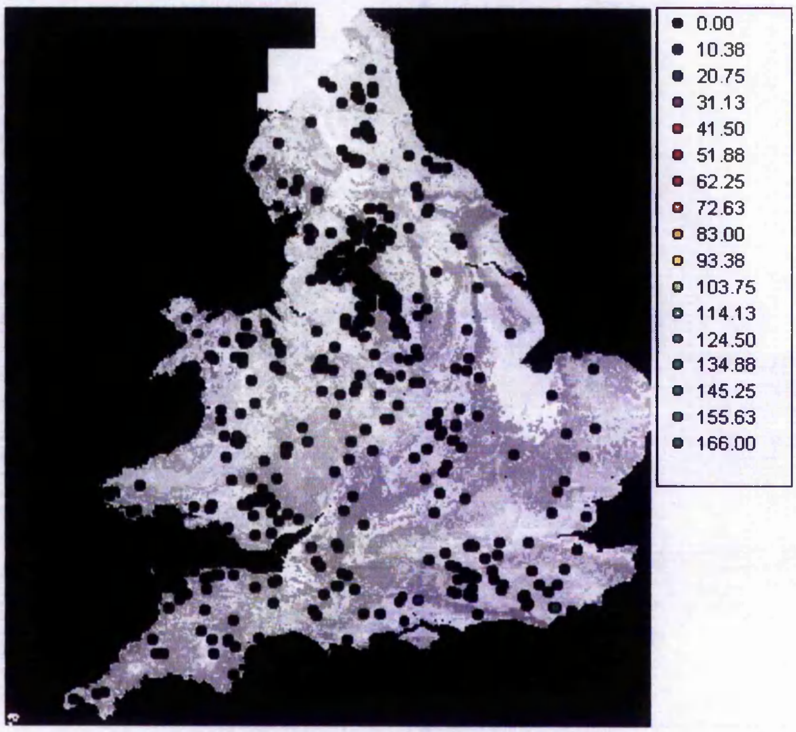


Figure 5.24 Trap efficiency (%) for the cluster 2 population of reservoirs

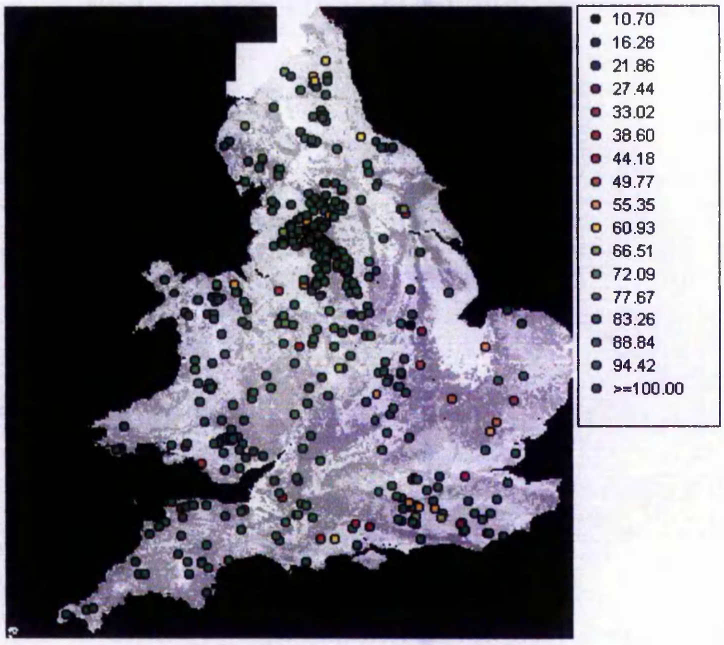
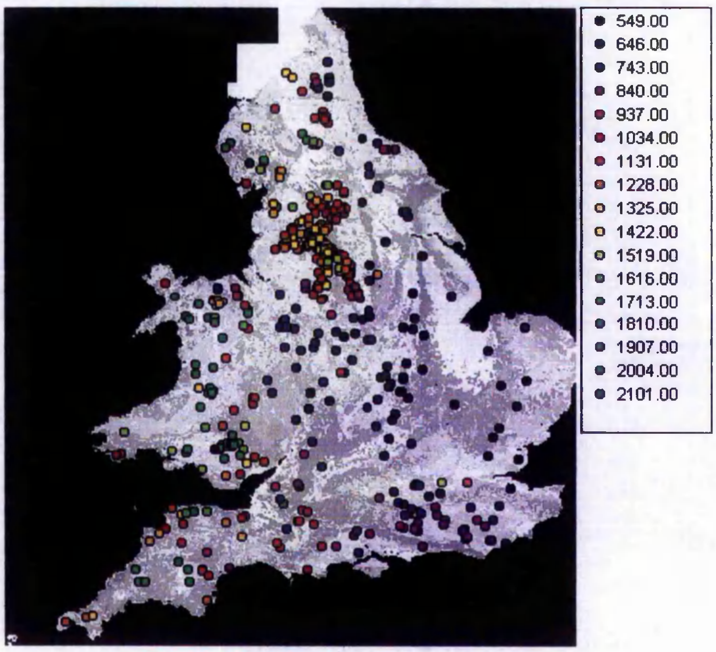


Figure 5.25 Mean annual rainfall (mm yr^{-1}) from 1941-70 for the cluster 2 population of reservoirs



5.16 Comparison of multiple regression analysis approaches

The purpose of performing multiple regression on a cluster from the population data set (cluster 2) was to assess the potential of the clustering approach employed successfully by Jansen and Painter (1974) and DeBonis *et al.* (2002) (wherein a data set of geomorphic parameters was broken down into groups of alikeness and multiple regression analysis performed on each cluster, predicting sediment yield) in achieving the principal aim of the research. For DeBonis *et al.* (2002), this approach produced improved coefficients of explanation for each cluster over the model formulated for the complete data set due to a reduction in residual variation. The residual variation was reduced as stronger correlations existed within the clusters between sediment yield and erosion/sediment transport inducing variables; thus this approach acted to reduce intra-variable variation.

The application of the clustering approach herein, producing a multiple regression model for a subset of the complete population of reservoirs defined using cluster analysis (Equation 5.8), yielded a more robust and valid model in comparison to that parameterized for the prediction of APL for the complete population (Equation 5.1). Despite Equation 5.1 having a greater coefficient of explanation (a reasonable 57%) in comparison to Equation 5.8 (49%), the latter, on balance, produced a more robust result in terms of the regression assumptions being more closely met (Table 5.23). The integrity of Equation 5.8 appears stronger through the greater compliance with the assumptions of linearity, constant variance, and normality.

The comparison of the Cook's distance statistics (Table 5.23) shows that there are no cases having an undue influence on the computation of the regression coefficients associated with Equation 5.8 above the threshold that warrants investigation. Thus, the linear relationships in Equation 5.8, although weaker (as reflected in the coefficient of explanation) are more realistic and representative of the true nature of the data. This acts to improve the degree of residual constant variance associated with Equation 5.8 over Equation 5.1 (Table 5.23).

Table 5.23 Comparison of multiple regression diagnostics results; √ denotes compliance with the respective assumption, X denotes non-compliance. For the Leverage and Cook's distance results, the number of cases inducing the non-compliance with the assumption of linearity are presented.

Assumption	**Diagnostic**	**Eq 5.1**	**Eq 5.8**
		Result	**Result**
Linearity	Analysis of variance	√	√
	t statistic	√	√
	Leverage	X – 5 cases	X - 8 cases
	Cook's distance	X – 1 case	√
Non-multicollinearity	Tolerance statistic	√	√
Residual independence	Durbin-Watson test	√	√
Residual constant variance	Scattergraphs - residuals versus predicted values	X	√
Residual normality	Kolmogorov-Smirnov test	√	√
Total number of refutations		3	1

In terms of verification, the respective predictions of Equation 5.8 replicate the pattern of observed APL in the parameterization data set to a closer degree than those of Equation 5.1. From Figures 5.4 and 5.5, Equation 5.1 has a tendency to over-predict for the majority of reservoirs in the respective parameterization data set, except for those experiencing exceptionally high APL rates. This is reflected by the mean residual value of –0.029. In contrast, from Figures 5.17 and 5.18, Equation 5.8 has the tendency to predict APLSQRT reasonably accurately for the majority of reservoirs in the respective cluster 2 parameterization data set experiencing average/typical rates. This is reflected in the mean residual of 0.001 (Table 5.20). Only for those reservoirs experiencing exceptionally high or low observed APLSQRT rates does the model under-predict and over-predict respectively due to the influence of factors inducing positive and negative residuals, not represented in the model (Section 5.14.1). The comparatively more accurate prediction of the average/typical observed sedimentation rates by Equation 5.8 is supported by the stronger Pearson's correlation coefficient and degree of linearity between observed and predicted APLSQRT for Equation 5.8, and the paired T-test result identifying that the difference in means between the observed and predicted APLSQRT rates is not significantly different from zero (Table 5.24). In terms of the respective paired T-test applied to Equation 5.1, a difference significant from zero was produced between the observed and predicted APL means suggesting comparatively poorer predictions (Table 5.24).

In terms of validation, the predictions of Equation 5.8 also replicate the pattern of observed APLSQRT in the respective validation data set to a closer degree than those of Equation 5.1. From residual analysis (Tables 5.10 and 5.20), Equation 5.8 also produces a slightly smaller absolute mean residual value than Equation 5.1 (0.056 in comparison to –0.058), implying a more accurate prediction. This is reflected through Equation 5.8 producing a stronger, more significant Pearson's correlation coefficient between the respective observed and predicted sedimentation rates (Table 5.24). In addition to this, each of the residuals associated with Equation 5.8, unlike those associated with Equation 5.1, are of the same sign (identifying a consistent under-prediction of APLSQRT), thus inferring a more accurate replication of the relative pattern of the observed APLSQRT rates of the respective validation data set (Figure 5.21). This is supported by the stronger degree of similarity between the mean observed and predicted APLSQRT values demonstrated by the paired T-test result associated with Equation 5.8 (Table 5.24). Therefore, whilst a "bleak outlook scenario" is not suggested through the application of Equation 5.8 due to its consistent under-prediction, the fact that the same relative pattern of observed reservoir sedimentation rates is produced when the model is applied helps compensate for this in terms of the usefulness of the model.

Table 5.24 Summary results of Equations 6.1 & 6.8 verification & validation between respective observed and predicted measures of reservoir annual percentage capacity loss

		Equation 5.1	**Equation 5.8**
Verification	Correlation coefficient	0.753	0.699
	Significance level	0.01	0.000
	Number	60	51
	Paired T-test statistic	-2.412	0.042
	Significance level	0.019	0.967
	Degrees of freedom	59	50
Validation	Correlation coefficient	-0.673	0.915
	Significance level	0.213	0.264
	Number	5	3
	Paired T-test statistic	-1.822	2.119
	Significance level	0.143	0.168
	Degrees of freedom	4	2

The comparative improvement in reservoir sedimentation prediction using the clustering technique may have been more apparent had more observations from clusters 1 and 3 been represented in the complete parameterization data set; 51 reservoirs comprise the cluster 2 parameterization set, in addition to these, a further 9 comprise the complete parameterization data set. Such data could not be collected due to practical and logistical constraints imposed over the duration of this investigation.

However, whilst Equation 5.8 is verified and validated to a greater degree than Equation 5.1, both models are associated with a low degree of confidence concerning the predicted APL conditional means representing the population conditional means. For Equation 5.1 there is 95% confidence in its predictions for only 5% of its respective parameterization data set (Section 5.9.3). For Equation 5.8 there is 95% confidence in its predictions for only 4% of its respective parameterization data set (Section 5.14.3). The apparent differences between the predicted APL conditional means and the respective population conditional means can be attributed to sampling fluctuations, measurement error, and deviations from the assumptions of regression (Ebdon, 1995). Therefore, whilst Equation 5.8 satisfied the assumptions of regression to a larger degree than Equation 5.1 (through having a more representative parameterization data set producing a more robust, reliable model through verification and validation); the lack of improved confidence regarding associated population APL conditional mean prediction suggests that the multiple regression approach is fundamentally not suited to predicting reservoir sedimentation (annual percentage capacity loss) from catchment and reservoir basin factors.

5.17 Evaluation of the multiple regression modelling technique

From the analysis of Equation 5.1, predicting APL for the whole population and Equation 5.8, predicting APLSQRT for cluster 2, it is clear that whilst the most valid, robust models possible have been produced, their integrity and predictive power can only be described as reasonable. This is despite the effort made to account for the reasons attributed to previous failure of multiple regression applications in reservoir sedimentation/sediment yield studies, as discussed in Section 5.4. However, each of these identified reasons for multiple regression failure can still, to a degree, account for the relative failure of the application in this investigation.

5.17.1 Data omission & coarse spatial resolution

Whilst every effort was made to produce the most comprehensive data set across England and Wales regarding factors that influence reservoir sedimentation, information could not be directly obtained/easily calculated from the readily available data regarding important factors such as drainage density and hypsometry. Knighton (1996) highlights the importance of drainage density with regards to sediment yield stating that it has a causative significance in determining the efficiency with which surface runoff is discharged from an area during individual storms. Although this variable can be calculated relatively easily for studies involving fewer cases (e.g. White, 1993), calculation was not deemed practical within the timeframe of this larger scale study. In addition, Duck and McManus (1990) identify the difficulties in measuring drainage density in a reservoir sedimentation study of comparatively smaller scope, in the Midland Valley of Scotland. However, Verstraeten *et al.* (2003) included the hypsometeric intergral in the parameterization data set of a developed multiple regression model predicting reservoir sedimentation in Spain. A statistically stable model, however, was still not produced. As in the case of the multiple regression models developed herein, the good R^2 (0.80) of the Verstraeten *et al.* (2003) model was caused by the undue influence of three observations from a parameterization data set of twenty two observed reservoir sedimentation rates.

Variables also had to be omitted from the data set due to their incompleteness, e.g. dam dimensions and reservoir sediment control structures (e.g. residuum lodges and bywash channels). Initially reservoirs were omitted from the population for not appearing resolvable in the FEH handbook (1999) and their catchments not appearing resolvable in the land cover and soil maps (the latter due to coarse spatial resolution). This was necessary as these data sources contributed a major part of the catchment data in the population data set. However, to remove actual reservoirs from the population for having other incomplete data would have reduced the population dramatically, undermining the principal aim of the production of a comprehensive assessment of reservoir sedimentation rates across England and Wales; thus a careful balance had to be struck (Section 4.2).

In addition, some important variables influencing sedimentation rates could not be readily quantified/easily calculated for the population (parameterization) data set due to their inherent qualitative nature, and/or lack of data from secondary sources; e.g. reservoir sediment control structures, management strategies, allochthonous wet and dry deposition, autochthonous sediment production, and the influence of small anthropogenic landscape elements (e.g. banks, hedges, tillage directions etc.). The unaccountability of the latter group of variables in particular is due to the broad scale nature (and thus coarse spatial resolution) of the study. Such parameter omission potentially introduces uncertainty and structural error into the regression model (Burrough, 1989; Mujumdar, 2002).

Many of the residuals produced through the multiple regression analyses, undermining the inherent assumptions of the technique, have been attributed to reservoir sediment control structures and their influence on sediment delivery to reservoir basins as identified by White *et al*., (1996a) (Section 2.11.2.2). Such reservoirs have a low degree of catchment-coupling and ideally warrant separate consideration for sedimentation prediction. However, theoretically, this cannot be achieved herein as the presence of such structures, as mentioned above, cannot be obtained from secondary data sources other than that compiled by White *et al*., (1996a) for the Pennine reservoirs. Therefore, the exclusion of these reservoirs from the population data set for this study may not necessarily solve the problem of residual production. Different residuals may be produced which cannot be related to such management practices. In addition, from a practical perspective, reservoirs identified by White *et al*., (1996a) as having sediment control structures form the majority of the model parameterization data sets; therefore their exclusion would severely impact upon the representation of the respective populations, threatening the production of robust models.

5.17.2 Inadequate sampling size

As discussed in Section 4.3.2, the parameterization data set fails to account comprehensively for the range and natural groupings of collated variables in the population.

As a result of this, the multiple regression models cannot be over-extrapolated to predict APL for those reservoirs beyond the parameterized range covered by the respective independent variables. Singh *et al.* (1988) and Kim and Steenhuis (2001) state that this is the main disadvantage of the multiple regression technique.

The parameterization data set, being predominantly composed from the Halcrow data set (2001) as a sample of convenience, induced the limited range of prediction for both multiple regression models as it was not "custom-built" for the representation of both respective populations in this study. However, within the timeframe of this study, the parameterization data sets were the most comprehensive obtainable, both practically and logistically.

5.17.3 Parameter error

The multiple regression equations do not take into account inherent error that exists in the respective parameterization data, which acts to undermine the validity of results (Section 4.4). For example, the calculation of APL is dependent upon an original reservoir basin capacity measure. White *et al.* (1996c) identify how extreme inaccuracies can result in original capacity estimates induced by dated surveying techniques. Error is still induced through the surveying methodology employed in this study to calculate a revised reservoir basin capacity. In addition error is present in each of the secondary data sources, the catchment characteristics derived from the FEH handbook, and land cover and soil maps.

As first identified in Section 5.8.5.1, the problematical relationship between APL and TE in Equations 5.1 (predicting APL across the population data set) and 5.8 (predicting APLSQRT across the cluster 2 population data set) may induce misleading results. This is caused by reservoirs with **revised capacities** listed in the BRE dams data set (used to calculate TE) inducing a broadly negative relative relationship between APL and TE, whereas those with **original capacities** listed inducing a positive relationship. This problem was identified through revised reservoir capacities published by Rowan *et al.* (1995), Duck and McManus (1990), and Butcher *et al.* (1992a) for example, being represented in the BRE dams data set as opposed to respective original capacities. Unfortunately, through the

BRE dams data set in the absence of other sources of evidence, there is no way of affirming which each listed capacity relates to (Section 5.8.5.1). An overall negative relationship is specified due to the undue influence of Abbeystead and Blakeley reservoirs which have extremely high APL rates, partly induced by factors not considered in both Equations 5.1 and 5.8 (Section 5.8.5.1).

In addition, error may be introduced in the multiple regression models through the inclusion of an independent variable that is significantly correlated with reservoir annual percentage capacity loss (APL), but may have occurred by chance. This is particularly associated with the potential problem of multiple significance levels. Whilst each individual correlation between the APL and independent variable variants are significant at the 0.05 level, when considered cumulatively the minimum number that may occur by chance increases with the number of significant correlations obtained for a particular APL variant. For example, when considering 100 correlations at a significance level of 0.05, at least 5 may occur by chance. However, the minimum number that may occur by chance for Equations 5.1 and 5.8 are 0.4 and 2 respectively. These values represent the largest minimum number of correlations that may occur by chance for each model as the majority of the correlation coefficients are significant at levels stronger than 0.01. Therefore, the potential of error introduction through the effect of multiple significance levels remains small for both models.

5.17.3.1 Parameter non-stationarity

The variables incorporated into Equations 5.1 and 5.8 do not exhibit stationarity; they change over time. For example, the respective measures of reservoir sedimentation, APL and APLSQRT are average values aggregated over the period of reservoir impoundment and fail to account for the temporal variability of sediment production, delivery and location of sediment sources (Stott *et al.,* 1988). The assumption that the variables do exhibit stationarity is a criticism of this application of multiple regression, rather than the technique itself.

5.17.4 Specification error

Price *et al.*, (2000b) and Thiemann *et al.,* (2001), state that hydrological systems are complex and inherently non-linear, therefore modelling such systems using multiple regression analysis, assuming linear relationships between the dependent and independent variables, appears flawed. This may account for the low degree of user-confidence of both Equations 5.1 and 5.8 in respective population APL conditional mean prediction (Sections 5.9.3 and 5.14.3).

In spite of these contributory reasons for the relative failure of the multiple regression approach in general, Lunneborg (1994) states that when responses in multiple regression are complexly determined (e.g. reservoir sedimentation/sediment yield), any model and its corresponding observational study (where the explanatory variables are observed rather than manipulated as in an experimental study) can only look at part of a complex theoretical structure. Often this means that the postulated explanation maybe relatively weak.

5.17.5 Conclusion

It is clear from the preceding discussion that the error and uncertainty in the parameterization data sets, and the inherent complexity of sediment production and delivery processes prevent robust, reliable multiple regression models being constructed predicting reservoir sedimentation rates. However, fuzzy set multi-criteria evaluation (MCE), the second modelling approach being applied in this investigation, is able to account for such error and uncertainty associated with the quantification and specification of the sediment production and delivery processes. The application of fuzzy set MCE in modelling reservoir sedimentation for the population data set is undertaken in the proceeding chapter, Chapter 6.

6. Modelling - Fuzzy set multi-criteria evaluation (MCE)

6.1 Introduction

This chapter discusses the relatively recent application of fuzzy set multi-criteria evaluation (MCE), in water resources/hydro-geomorphological research (Mujumdar, 2002). It describes the technique and documents the construction of two further models; one concerning the prediction of the **degree** of reservoir sedimentation, the other concerning the defuzzification of this value into an actual APL prediction for the population. Fuzzy set MCE is a particular application of fuzzy set theory. The production of a fuzzy set MCE model predicting APL for the population data set contributes in achieving objective three of this research; the production of two parameterized, verified, validated and operationalized empirical models using multiple regression analysis and fuzzy set multi-criteria evaluation respectively. All of the respective statistical analysis and results are included in Appendix 5; only the key results pertinent to the discussion of the models are included in this chapter.

6.2 Previous fuzzy set MCE applications

Fuzzy set MCE has not been previously applied in reservoir sedimentation prediction. Indeed, Mujumdar (2002) states that the application of fuzzy set theory in water resources management is relatively recent and provides an opportunity for useful research contributions in the future. Applications in soil survey and land evaluation (Burrough, 1989; Burrough *et al.*, 1992), real time reservoir operation (Panigrahi and Mujumdar, 2000; Dubrovin *et al.*, 2002), the prediction of river water quality (Chang *et al.*, 2001), estimating the risk of desertification (Sasikala and Petrou, 2001), and landslide susceptibility (Ercanoglu and Gokceoglu, 2002) have all proved successful in modelling such complex systems.

6.3 Fuzzy set theory – a description

Multiple regression analysis (Chapter 5) produced a relatively poor result in the prediction of the actual sedimentation quantity APL partly due to its inability to cope with uncertainty and vagueness endemic within geographical phenomena. Such uncertainty and vagueness can be associated with:

- Uncertainty in the measurement of variables collated in the data sets from each data source associated with data quality issues, random errors, systematic error etc.
- Subjective uncertainty: expert opinion and intuition associate values of sediment-inducing variables with respective degrees of reservoir sedimentation. Such associations can reflect the non-statistical characteristics in the real world (Cheng *et al.*, 2001).
- Experts often express their knowledge in terms of vague linguistic variables such as "poorly drained", "moderate nutrient availability", "very high risk to erosion", etc. (e.g. Evans, 1990). Even though these terms may be defined with precision, in practice they retain a strong air of qualitative ambiguity (e.g. Halcrow, 2001).
- A variable is often characterized by a measurement that takes continuous values. Forcing this variable into classes according to the value of its measurement (e.g. Rooseboom and Lotriet, 1992), ignores the fact the transition from one class to the other may be gradual and the boundaries between classes fuzzy (Sasikala and Petrou, 2001).

The use of fuzzy set applications can handle such uncertainty and vagueness in a definable way, making it suitable in the application of reservoir sedimentation prediction. Regarding fuzzy sets, Burrough (1989, page 491) states:

"The strength of the fuzzy set approach is that it starts from the premise that nature may be inherently vague or imprecise, and does not try to pretend that the real world, which has been modelled by data entities created by human or machine observation, is more exact, or more perfect than it really is."

Fuzzy sets are sets (or classes) without sharp boundaries; that is, the transition between membership and non-membership of a location in the set is gradual (Zadeh, 1965). A fuzzy set is characterized by a fuzzy membership grade (also called a possibility) that ranges from 0.0-1.0, indicating a continuous increase from non-membership to complete membership. A fuzzy set can be drawn as a membership curve defining how the grade of membership of an individual with an attribute value x is determined (Burrough *et al.,* 1992).

6.4 Application of fuzzy set MCE

6.4.1 Principal components analysis

Fuzzy set MCE was performed in the GIS Idrisi 32 (release 2) (Clark Labs, 2001). Idrisi 32 can only handle a maximum of 32 variables in its FUZZY module, whereas 57 are represented in the data set for this study. In order to reduce the number of variables, principal components analysis was performed on the population data set (Table A1.25, Appendix 1) using the SPSS 10 (1999) statistics package to extract those variables that account for the most variance. The main applications of principal components analysis are: (1) to reduce a large number of variables in a data set to a smaller number of factors or components, and (2) to detect structure in the relationships between variables (Shaw and Wheeler, 1994). Principal components analysis extracts the same number of components from a data set as variables entered; therefore 57 components were extracted. For each of the 57 variables, the component that contained the maximum respective eigenvector was determined (Table 6.1). Where more than one variable had a greatest respective eigenvector in a particular component, only the variable with the largest eigenvector was entered into the fuzzy set analysis. This process reduced the number of variables that had to be entered into the fuzzy set MCE from 57 to 24; these are presented in Tables 6.1 and 6.2.

Table 6.1 The maximum absolute principal component eigenvector loading for each variable. The asterisk denotes the variable that accounts for the most variance in a particular component.

Variable	Principal component	Eigenvector
CAREA	3	0.653
QMED	3	0.472
MEANFARL*	13	0.384
FARL*	18	0.405
PROPWET	1	0.834
ALTBAR	1	0.885
BFIHOST*	9	0.674
DPLBAR*	3	0.696
DPSBAR	1	0.689
LDP	3	0.689
RMED1H	1	0.487
RMED1D	1	0.923
RMED2D	1	0.930
SAAR*	1	0.952
SAAR4170	1	0.949
SPRHOST	1	0.634
URBCONC	1	0.580
URBEXT	7	0.419
URBLOC	1	0.578
TE	3	0.389
S401*	19	0.423
S405*	11	0.639
S454*	20	0.716
S455	2	0.700
S469*	17	0.449
S475	17	0.403
S486*	2	0.716
S487*	14	0.502
S489	2	0.660
S495*	22	0.527
S506	6	0.683
S507*	6	0.693
S660*	21	0.496
S686*	23	0.604
S692	2	0.714
BRACK	11	0.594
CONIF	5	0.487
DECID	5	0.548
DSHRUB	4	0.490
DSHRUBH*	5	0.537
FELLED*	16	0.375
GRASS	10	0.391
IBARE*	25	0.454
IWATER	14	0.502
LOWBOG	5	0.362

MEADOW	4	0.430
MOORLAND	4	0.664
MOWN	4	0.445
OPENS*	4	0.690
OPENSH	5	0.533
ROUGH*	15	0.357
RUDERAL*	10	0.357
SCRUB*	12	0.581
SUBURB	7	0.444
TILLED	4	0.403
UPBOG*	30	0.474
URBAN*	7	0.537

6.4.2 Variable membership curves

Using the range of values for each variable in the population data set, together with expert scientific opinion (as discussed in Chapter 2), a fuzzy membership curve was constructed for each variable. Each variable membership curve specifies the relationship between the values of each variable, and their membership of the fuzzy set depicting the degree to which the respective variable induces reservoir sedimentation. Each variable is assumed to have a mutually exclusive effect on the degree of sedimentation when the membership functions are first constructed. The nature of each membership function is discussed in Sections 6.4.2.1 – 6.4.2.4. For each variable, a linear membership function was used. The inflection points in each membership function were determined by the maximum and minimum values of the respective variable in the population. Thus, the lowest value of a variable in the population has a membership value of 0, and the highest a membership value of 1 (represented as 255 in Idrisi 32, as 0-255 spans the byte level range). The direction of each linear membership function (positive or negative) was determined from the literature and expert scientific opinion.

Burrough (1989) states that the subjectivity involved in assigning fuzzy membership functions and factor weights is the weakest part of fuzzy set theory. However, Panigrahi and Mujumdar (2000) state that, with regards to model operators, the incorporation of expert opinion makes the model more acceptable.

6.4.2.1 Soil Variables

Each of the soil variables, identifying the area of the respective soil class with a very high, or high risk of erosion (after Evans, 1990), has a positive membership curve. The premise is that the larger the area of coverage, the greater the quantity of eroded material and reservoir sedimentation.

6.4.2.2 Land cover variables

The land cover variables identifying the average percentage cover of each represented class in each catchment have a mixture of positive and negative membership curves. Open shrub moor (OPENS) was allocated a positive membership curve as this cover type is very sensitive to erosion induced by grazing (Section 2.11.1.6.3) which prevents the dominance of dwarf shrub species. In addition, under this land cover type fire is used as a management tool for grouse management and to improve conditions for grazing (Evans, 1993; Fuller, 1995). Both of these effects expose the soil surface (typically soils of high erodibility) and induce widespread erosion (Evans, 1993), increasing the potential of reservoir sedimentation (subject to sediment delivery). Therefore the premise is, the larger the average percentage catchment cover of OPENS, the greater the degree of sedimentation.

Dense shrub heath (DSHRUBH) was allocated a negative membership curve as increasing average percentage catchment cover is likely to decrease the degree of runoff, erosion and consequently reservoir sedimentation. This land cover class incorporates high densities of heather, ling, mixed broom, and gorse; being predominantly evergreen, a dense cover is maintained throughout the year (Fuller, 1995). Therefore the premise is, the larger the average percentage catchment cover of DSHRUBH, the smaller the degree of sedimentation.

Urban development (URBAN) was allocated a positive membership curve as increasing average percentage catchment cover of cities, large town centres, major industrial and commercial sites, major areas of concrete and tarmac, and permanent areas of bare ground associated with these developments such as car-parks and tips (Fuller, 1995) increases runoff and produces more flashy hydrographs in the local fluvial system. This is conducive to stream channel erosion and reservoir sedimentation (Section 2.11.1.6.4).

Ruderal weed (RUDERAL), defined as ground colonized by small annual and short-lived perennial plants usually with a considerable remnant of bare ground, especially in winter (Fuller, 1995), was allocated a positive membership curve. Therefore, this land cover type is conducive to erosion.

Scrub/orchard (SCRUB) was allocated a negative membership curve as it is associated with deciduous vegetation, typically with substantial herbaceous vegetation, providing a dense covering (Fuller, 1995). This acts to reduce runoff and erosion.

Rough grassland (ROUGH) includes lowland herbaceous vegetation of rough or derelict ground and was allocated an associated negative membership curve. The characteristic feature of this category is that the swards are not cropped by mowing or grazed by stock forming a high standing crop of vegetation, most of which dies back in winter leaving a dense litter layer (Fuller, 1995). This also acts to reduce runoff and erosion.

Felled forest (FELLED) is associated with bare ground, thereby favouring runoff production and erosion. As a result of this, a positive membership curve was assigned. However, as felled forest areas revegetate (firstly with ruderal weeds and then become rough grassland) runoff production is reduced (Fuller, 1995). This also reduces the potential for felled forest areas contributing to reservoir sedimentation. The inability of the model to account for this temporal change is a major weakness of the methodology.

Inland bare ground (BARE) includes bare natural surfaces such as soil, rock, sand and gravel. However, their origin is not always natural; ground which has been cleared by human activities or by livestock is included (Fuller, 1995). Whilst these bare surfaces are not all erosive they each induce runoff production which has the potential to induce erosion in other parts of the catchment (e.g. stream channels), thus this cover type was assigned a positive membership curve.

Upland bog (UPBOG) was allocated a positive membership curve due to it being an extremely erosive land cover type (Labadz *et al.*, 1991). Whilst upland bogs have many grass and dwarf shrub species, as well as mosses, they are characterized by waterlogging and surface water especially in winter (Fuller, 1995). As a result, much runoff is produced which can induce gullying, piping, bog-bursts and mass movement (e.g. peat slides) (Evans, 1993) forming significant contributions of deposited reservoir sediment (Hutchinson, 1995; Labadz *et al.*, 1999). Erosion of peat bogs is also associated with disturbance of vegetation by pollution or trampling, leading to exposure of bare peat which is very erodible.

6.4.2.3 Hydro-Meteorological Variables

The hydro-meteorological variables of average annual rainfall 1961-1990 (SAAR) and base flow index (BFIHOST) were allocated positive and negative membership curves respectively. The positive membership curve associated with SAAR is explained by the fact that the larger the average annual rainfall, the greater the quantity of water moving the through the catchment system and the greater the quantity of an erosion and sediment transport agent.

BFIHOST has a negative membership curve because a larger value implies a greater degree of rainfall infiltration, thus reducing potentially erosive runoff production. Whilst base flow maintains open stream channel flow, it is the moderate, frequent flows induced by heavy rainfall and runoff (associated with the mean annual flood or with a recurrence interval of every five years) that are most effective in sediment transportation (Wolman and Miller, 1960).

6.4.2.4 Geomorphological variables

The geomorphological variables of the catchment size and drainage path configuration index (DPLBAR), flood attenuation index due to reservoirs and lakes (FARL), and mean flood attenuation index due to reservoirs and lakes (MEANFARL) were each assigned a positive membership curve.

Greater values of DPLBAR induce increased reservoir sedimentation as it implies greater quantities of water moving through the catchment system, increasing potential stream channel erosion and sediment transport. This is the explanation Dedkov and Moszherin

(1992) gave for positive relationships between sediment yield and catchment area in upland areas (Section 2.11.1.7.1).

Values of FARL and MEANFARL approaching 1 indicate reduced flood attenuation upstream of the reservoir. Such attenuation acts to reduce increased sediment transport into reservoir basins associated with larger magnitude events.

6.4.3 Fuzzy set aggregation – weighted linear combination

The prediction of the degree of reservoir sedimentation from the variable membership curves is a form of fuzzy multi-factorial evaluation (MCE). Lu (1998) defines fuzzy MCE as the process where one judges an overall property that is affected by a number of variables of which the influencing degrees are fuzzy. As a result, an aggregation operation is required to combine the variable fuzzy sets to produce the desired single fuzzy set (Sasikala and Petrou, 2001) depicting the ultimate degree of reservoir sedimentation.

Weighted linear combination (WLC) was used in Idrisi 32 as the aggregation operation. Through WLC the products of each standardized variable multiplied by a corresponding weighting factor are summed and divided by the total number of variables, creating a calculated weighted average spanning the Idrisi 32 byte level range from 0-255 for each reservoir. This calculated weighted average is termed the ultimate fuzzy number. Thus, reservoirs with fuzzy numbers approaching 255 represent those with the highest degree of sedimentation, and those approaching 0 represent the lowest.

The use of weighting factors for each of the 24 variable membership curves indicating the relative importance of the respective variable in influencing the degree of sedimentation allows variables to trade off, i.e. the low sediment-inducing potential of one variable can be compensated for by the high sediment-inducing potential of another. The weighting factors were also identified through the principal components analysis (Section 6.4.1); Ercanoglu and Gokceoglu (2002) used this approach to weight factors in an assessment of landslide susceptibility. The eigenvalue (the amount of variance extracted by a given component – Shaw and Wheeler, 1994) of each principal component represented by the 24 variables was divided by the sum of the eigenvalues of the represented principal components. The resultant was applied as a weighting factor to the variable that accounts for most the variance in each principal component. The weighting factors summed to 1, a requirement of WLC (Table 6.2).

Clearly, the model is constructed in a very different way from the previous multiple regression models. As opposed to constructing the model from a parameterization data set and extrapolating it to predict for a population, the fuzzy set MCE approach is directly applied to the population.

Table 6.2 Variables entered into fuzzy set multi-criteria analysis

Variable	Abbreviation	Factor Weight
Average annual rainfall 1961-1990	SAAR	0.179893
Bridgenorth soil association	S486	0.087540
Catchment size & drainage path configuration index	DPLBAR	0.086087
Open shrub moor	OPENS	0.069796
Dense shrub heath	DSHRUBH	0.053212
Fyfield 2 soil association	S507	0.046082
Continuous urban	URBAN	0.042723
Base flow index	BFIHOST	0.035253
Ruderal weed	RUDERAL	0.033742
Bangor soil association	S405	0.031674
Scrub/orchard	SCRUB	0.029548
Mean flood attenuation due to reservoirs & lakes index	MEANFARL	0.027652
Cuckney 1 soil association	S487	0.025891
Rough/marsh grass	ROUGH	0.025412
Felled forest	FELLED	0.025180
South Petherton soil association	S469	0.024296
Flood attenuation due to reservoirs and lakes index	FARL	0.023975
Revidge soil association	S401	0.023783
Bearsted 1 soil association	S454	0.023297
Everingham soil association	S660	0.022999
Frilford soil association	S495	0.022246
Winter Hill soil association	S686	0.021717
Inland bare ground	IBARE	0.020627
Upland bog	UPBOG	0.017375

6.5 Fuzzy set MCE model 1 evaluation

6.5.1 Verification & validation

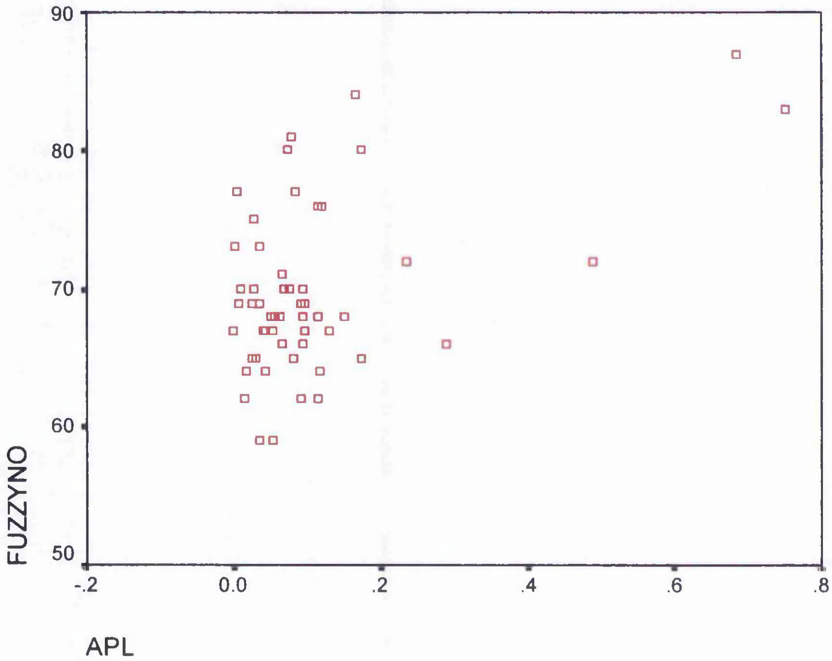
The fuzzy set MCE model 1 was constructed within the Idrisi 32 environment; the output regarding the prediction of a fuzzy number depicting the degree of reservoir sedimentation between 0 and 255 for the population data set is presented in Figure 6.1. As a result of the model being constructed in a different way to the previous regression models, it is verified and validated against the reservoirs with an observed APL that formed the parameterization data set in the previous analysis. However, due to Idrisi 32 being a raster based GIS, only 54 reservoirs are resolvable due to the relatively coarse spatial resolution of the soils and land cover data (others were in the same $1km^2$ pixel as another individual).

Pearson's correlation was applied to assess the degree to which the fuzzy number predicted by the model simulates the relative pattern of the observed APL data. From Table 6.3, a significant positive correlation coefficient of 0.491 is produced between the fuzzy number and observed APL. However, from Figure 6.1 it is apparent that this significant relationship is influenced by a small number of points; there is, however, a general progression of the main data point cluster in a positive direction.

Table 6.3 Verification and validation results – Pearson's correlation and Paired T-test

Verification & validation	Fuzzy MCE Model 1
Correlation coefficient	0.491
Significance level	0.000
Number	54
Paired T-test statistic	-0.001
Significance level	0.999
Degrees of freedom	53

Figure 6.1 Fuzzy Number versus observed APL



The significant correlation coefficient implies that the model is replicating the relative pattern of the observed APL values. This replication is displayed in Figure 6.2, directly comparing the z-scores of both data series. From Figure 6.2 it appears that the model is more extreme in depicting relative differences in the degree of reservoir sedimentation in comparison to the real world observation. The model tends to over-predict when the observed APL rate is high, under-predict when the observed APL rate is low, and produce a fuzzy number very close to the relative magnitude of the respective observed APL values for the reservoirs experiencing average/typical sedimentation rates. This is supported through Figure 6.3 and the mean residual (observed APL z-score minus predicted fuzzy number z-score) of 0.0001 (Table 6.4). This implies that the model is highly sensitive to the degree of influence exerted by the sediment-inducing variables. In addition, the paired T-test result between the two z-score data series identifies no significant difference from zero for the mean of the respective pairwise differences (Table 6.3). This implies good agreement between the two data series and that the model is replicating the real world pattern of observed APL values reasonably well.

Figure 6.2 The relative pattern of the fuzzy number z-score and APL z-score

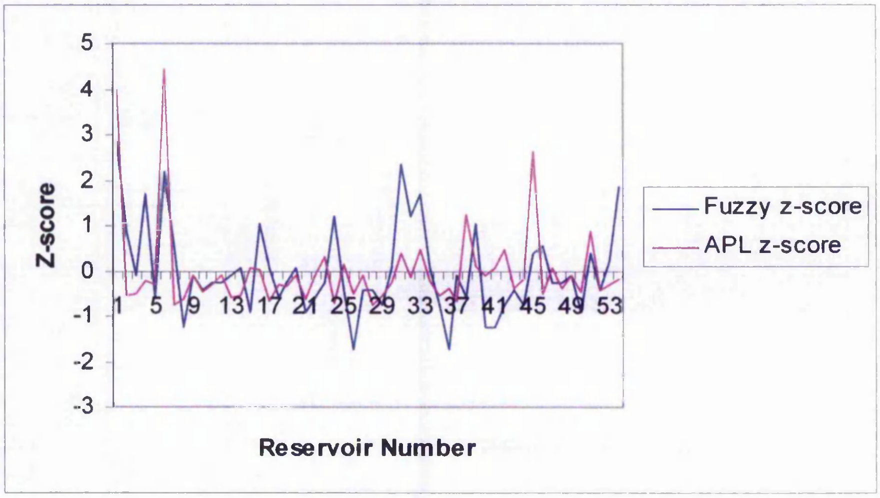


Figure 6.3 Observed APL z-score subtracted from the predicted fuzzy number z-score

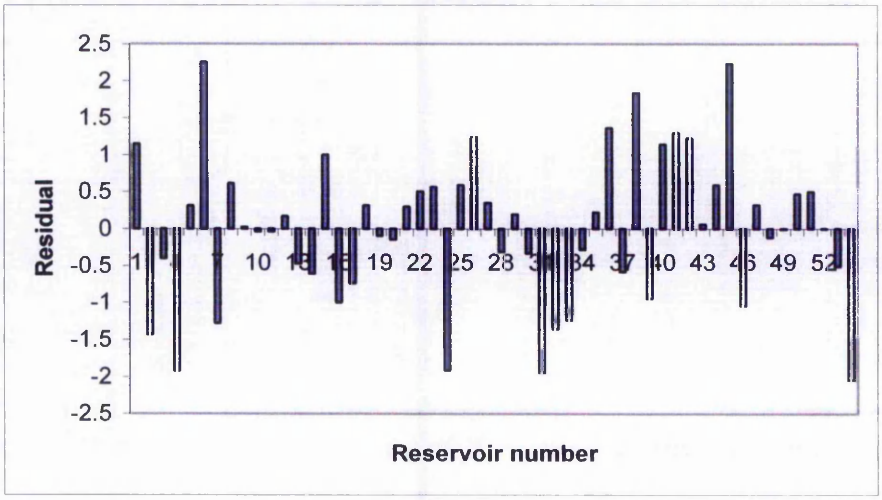


Table 6.4 Key to Figures 6.2 & 6.3 & corresponding observed APL z-score, predicted fuzzy number z-score & residual values

Reservoir Number	Reservoir Name	Fuzzy z-score	APL z-score	Residual
1	Abbeystead	2.836	3.983	-1.147
2	Angram	0.873	-0.562	1.435
3	Barden Lower	-0.109	-0.507	0.398
4	Barden Upper	1.691	-0.230	1.920
5	Blackmoorfoot	-0.600	-0.288	-0.312
6	Blakeley	2.181	4.436	-2.254
7	Booth Wood	0.545	-0.737	1.282
8	Broadstones	-1.254	-0.642	-0.612

9	Broomhead	-0.109	-0.084	-0.025
10	Chelker	-0.436	-0.474	0.037
11	Dale Dyke	-0.273	-0.308	0.035
12	Dean Head Upper	-0.273	-0.104	-0.169
13	Deanhead	-0.109	-0.582	0.473
14	Deerhill	0.054	-0.554	0.608
15	Eldwick	-0.927	0.070	-0.997
16	Embsay	1.036	0.038	0.998
17	Fewston	0.054	-0.685	0.739
18	Gorple Lower	-0.600	-0.288	-0.312
19	Gorple Upper	-0.273	-0.364	0.092
20	Gorpley	0.054	-0.089	0.144
21	Green Withens	-0.927	-0.629	-0.298
22	Harden	-0.600	-0.097	-0.503
23	Hewenden	-0.273	0.290	-0.562
24	Holmestyes	1.200	-0.711	1.910
25	Leeshaw	-0.436	0.150	-0.586
26	Lindley Wood	-1.745	-0.501	-1.245
27	Lower Laithe	-0.436	-0.084	-0.352
28	Morehall	-0.436	-0.745	0.308
29	Ogden	-0.764	-0.566	-0.198
30	Ponden	0.054	-0.274	0.328
31	Ramsden	2.345	0.402	1.943
32	Redmires Upper	1.200	-0.160	1.360
33	Riding Wood	1.691	0.449	1.242
34	Rivelin Upper	0.054	-0.229	0.283
35	Roundhill	-0.764	-0.541	-0.223
36	Royd Moor	-1.745	-0.385	-1.360
37	Ryburn	-0.109	-0.691	0.582
38	Scammonden	-0.600	1.238	-1.838
39	Scar House	1.036	0.085	0.952
40	Scout Dike	-1.254	-0.116	-1.138
41	Silsden	-1.254	0.041	-1.296
42	Snailsden	-0.764	0.457	-1.221
43	Strines	-0.436	-0.377	-0.059
44	Stubden	-0.764	-0.178	-0.586
45	Tunnel End	0.382	2.612	-2.231
46	Underbank	0.545	-0.503	1.049
47	Walshaw Dean Lower	-0.273	0.048	-0.320
48	Walshaw Dean Middle	-0.273	-0.388	0.116
49	Walshaw Dean Upper	-0.109	-0.115	0.006
50	Wessenden Head	-0.927	-0.459	-0.469
51	Wessenden Old	0.382	0.880	-0.498
52	Widdop	-0.436	-0.442	0.005
53	Windleden Upper	0.218	-0.292	0.510
54	Ystradfellte	1.854	-0.194	2.049
	Mean	0.000	0.000	0.000

The larger residuals identified in Figure 6.3 and Table 6.4 are predominantly induced by factors influencing the respective sedimentation rates not accounted for by the model. The reservoirs with the largest positive residuals are Blakeley, Royd Moor, Scammonden and Tunnel End (2.254, 1.360, 1.838 and 2.231 respectively) and represent an under-prediction by the fuzzy set MCE model 1. The production of Blakeley, Scammonden and Tunnel End as positive residuals was discussed in Section 5.5.5 in relation to the multiple regression model (Equation 5.1); the same potential explanations apply here. The production of Royd Moor as a positive residual can be attributed to its catchment being 100% pasture (White *et al.*, 1996a). Studies by Christiansson (1979), Heathwaite *et al.* (1990), Foster and Walling (1994) and van der Post *et al.* (1997) each identify increased sediment yield rates associated with the grazing of pastureland (Section 2.11.1.6.3). This effect is not directly incorporated into the model; it is only inferred through the respective land cover type fuzzy sets.

The reservoirs with the largest negative residuals are Angram, Barden Upper, Blackmoorfoot, Ramsden, Holmestyes and Ystradfellte (-1.435, -1.920, -1.282, -1.943, -1.910 and -2.049 respectively). The over-prediction for the first four reservoirs can be associated with the presence of catchment management structures in the respective catchments, acting to reduce sediment transport into the reservoir basins. These catchment management structures include residuum lodges, catchwater/conduit interceptions, bywash channels and reservoirs upstream (White *et al.*, 1996a). For the latter two reservoirs, the over-prediction of the relative degree of reservoir sedimentation can be attributed to the respective catchments having relatively large areas of land use types that are comparatively less conducive to sediment production, but not included in the fuzzy set MCE analysis. The catchment of Holmestyes reservoir has high average percentage catchment covers of 30% moorland and 6% bracken in comparison to the population data set (Table A1.3, Appendix 1). In addition, it has experienced afforestation that has contributed in reducing sediment yields to limited values after an initial increase in sediment yield associated with open ditching (Burt *et al.*, 1984). Each of these land covers provide good protection against soil erosion (Fuller, 1995), but are not represented in the fuzzy set MCE model 1. Instead, the protective effects of the land covers are offset in the model by the presence of upland bog areas, which are very erosive (Labadz *et al.*, 1991). The catchment of Ystradfellte has high average percentage catchment covers of 32% meadow and 16% deciduous forest in comparison to the population data set (Table A1.3, Appendix 1). Again, both land cover types provide good ground coverage (the former being only lightly grazed in a few circumstances), thus reducing the soil erosion risk (Cheng *et al.*, 2002; Fuller, 1995), but are not represented in the fuzzy set MCE model 1.

In conclusion, from Figures 6.1 and 6.2, and the results of the Pearson's correlation and paired T-test (Table 6.3), it is apparent that the model is behaving in the way scientific opinion/intuition would suggest through the construction of the initial fuzzy membership curves and their respective weightings. In addition, the comparison between the fuzzy number and observed APL z-scores suggests agreement between the behaviour of the model and that of the real world system. Therefore the model is verified and validated to a reasonably good degree.

6.6 Fuzzy set MCE model 1 operationalization

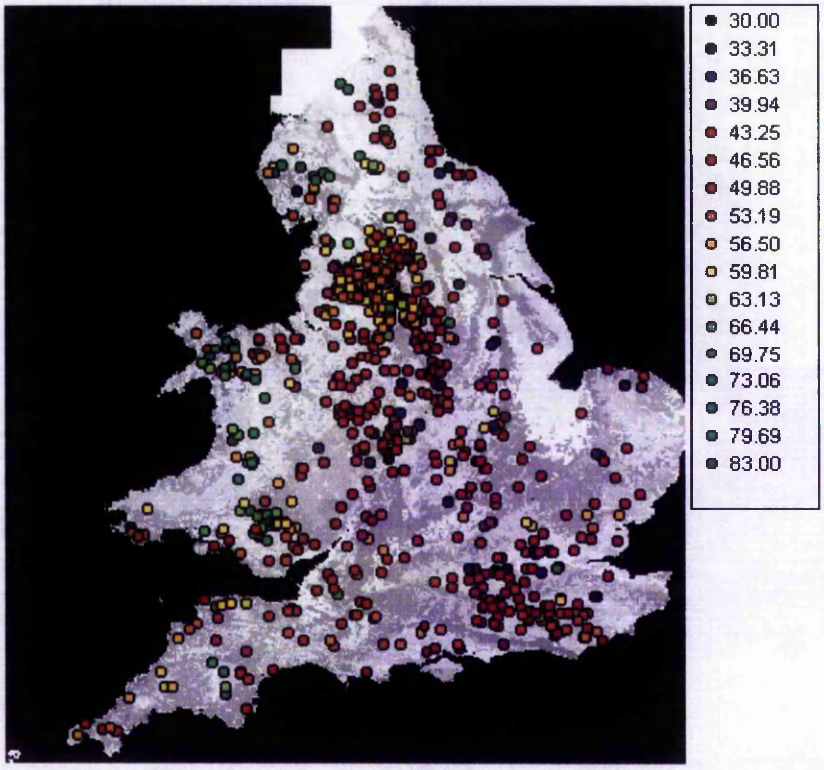
From Figure 6.4 displaying the fuzzy set MCE model 1 output for the population of reservoirs, sedimentation appears most severe in the upland areas of Cumbria, the Brecon Beacons and Cambrian Mountains of Wales, the southern Pennines, and Exmoor and Dartmoor in Devon. From the analysis of the fuzzy numbers calculated for each of the contributory variables (Table A1.3, Appendix 1), this can be principally attributed to increased rainfall (SAAR) and the range of erosive soil types in these areas (e.g. S401, S405 and S454). In addition, the greater average stream lengths (represented through DPLBAR) of these reservoir catchments act to increase sedimentation through conveying greater quantities of potentially erosive streamflow through the catchment system. Indeed, DPLBAR is a surrogate for catchment area which generally has a positive relationship with sediment yield in reservoir catchments across England and Wales (Butcher *et al.,* 1993) (Section 2.11.1.7). These results support the commonly held view regarding the nature of the process across the country (Halcrow, 2001). However, whilst the aforementioned areas of reservoirs experience comparatively high degrees of sedimentation, reservoirs in the Weald and the Vales of Kent and Sussex, are experiencing reasonable degrees of sedimentation (Figure 6.4). This is an interesting insight, as sedimentation has not been perceived to be a problem across southeast England, with no major studies being published.

From Table A1.3 (Appendix 1) this can be broadly attributed to the relatively high degree of open shrub land cover and erosive soil types, particularly shallow silty soils overlying the sandstone Hastings Beds (e.g. S405 and S469), that comprise the catchments.

Whilst there is reasonably good user-confidence in the model across the population (Section 6.5), predictions for the reservoirs in southeast England are theoretically even sounder. Temporal variation in the variables collated is not accounted for in the model. Therefore the older reservoirs in the population (e.g. those built in the Victorian age to supplement the growth of manufacturing and large urban populations especially in northern England) have potentially experienced a greater degree of change in their sediment-inducing variables. This is particularly reflected in trap efficiency and land cover changes. Examples of large-scale land cover changes include the increase in afforestation and felling increased after 1900 when the Forestry Commission was founded to produce export substitution softwoods. Afforestation further increased in the post-Second World War years when incentives were given to plant trees. Such change acts to reduce/increase the degree of reservoir sedimentation over time, yet the model assumes stationarity. Therefore, greater temporal variation in the sedimentation influencing variables induces greater uncertainty in the model prediction. However, many of the reservoirs across southeast England were built around the 1960s to supplement the growth of suburban areas and commuter towns (e.g. Ardingly, Bewl Bridge and Bough Beech). As a result, the potential for temporal variation in sediment-inducing variables over these shorter timespans is reduced, thereby reducing the degree of uncertainty associated with the sedimentation predictions.

The identification of reasonable degrees of reservoir sedimentation across southeast England reiterates the pattern of results produced through Equations 5.1 and 5.8 using multiple regression analysis. However, this could not be previously ascertained due to problematic negative relationships between reservoir sedimentation and trap efficiency – evidence of the comparatively low user-confidence inspired by both models. There is much more confidence in this observation associated with the fuzzy set MCE output as TE is not incorporated into the analysis due to it not having a large eigenvector (Table 6.1).

Figure 6.4 The fuzzy MCE model 1 output. The legend refers to the predicted fuzzy number/degree of reservoir sedimentation.



6.7 Defuzzification

Defuzzification is often employed to convert a fuzzy number into a crisp value of the process and respective units being modelled. This can be achieved through simple linear regression (Kosko, 1994). As a result, simple linear regression analysis was performed on 54 reservoirs from the original parameterization data set with observed APL values and the respective ultimate fuzzy numbers computed through the WLC. Only 54 reservoirs from the original 60 in the parameterization data set were used to parameterize the defuzzification model as these were the only reservoirs resolvable in Idrisi 32. Due to the 1km x 1km spatial resolution of data incorporated into Idrisi 32, those reservoir dam locations within $1km^2$ of each other could not be resolved in raster format due to the coarse resolution. This is discussed in detail in Section 4.3.3.

6.8 Simple linear regression defuzzification – untransformed data

The assumptions of multiple regression analysis identified in Section 5.2 are also applicable to simple linear regression apart from non-multicollinearity, which is not relevant as only one independent variable is incorporated.

6.8.1 Test of linearity – Pearson's correlation

The significant Pearson's correlation coefficient identified in Section 6.5.1 and associated scattergraph (Figure 6.1) affirmed a degree of linearity between observed APL and fuzzy number.

6.8.2 Result and diagnostics

The defuzzification model produced by simple linear regression analysis is shown in Equation 6.1 and accounts for a low 24% of the variation observed in APL.

$$APL = -0.702 + (0.012 \times FUZZYNO) \quad \text{(Eq. 6.1)}$$

The essential regression diagnostics assessing the compliance of the result with the assumptions of the technique are presented in Table 6.5.

Table 6.5 Simple linear regression diagnostics results; √ denotes compliance with the respective assumption, X denotes non-compliance. For the Leverage and Cook's distance results, the number of cases inducing the non-compliance with the assumption of linearity are presented.

Assumption	**Diagnostic**	**Result**
Linearity	Analysis of variance	√
	t statistic	√
	Leverage	X - 8 cases
	Cook's distance	X - 1 case
Residual independence	Durbin-Watson test	√
Residual constant variance	Scattergraphs - residuals versus predicted values	X
Residual normality	Kolmogorov-Smirnov test	X

6.8.3 Summary of Equation 6.1

Equation 6.1 accounts for a relatively poor 24% of the variance observed in APL. In addition, from Table 6.5, the model does not meet all of the assumptions required for a robust, reliable regression model. It appears that the poor degree of linearity between the independent and dependent variable (identified through the leverage and Cook's distance values) is inducing violations of the assumptions of residual constant variance and distribution normality (Norusis, 1994). As a result of this, three standard transformations were applied to each of the 57 independent variables in an attempt to improve the robustness of the simple regression model in the prediction of defuzzified APL: logs to the base 10, squares, and square roots (Ebdon, 1995).

6.9 Simple linear regression defuzzification – independent variable transformations

This section documents the incorporation of transformed independent variables (logs to the base 10 - FUZZYLOG, squares - FUZZYSQ, and square roots - FUZZYSQRT) into a simple regression analysis predicting APL in an attempt to improve the compliance of the defuzzification model with the regression assumptions of linearity, residual constant variance, and residual distribution normality.

6.9.1 Test of linearity – Pearson's correlation

The Pearson's correlation results between the dependent variable (APL) and each of the transformed fuzzy number data series (FUZZYLOG, FUZZYSQ, FUZZYSQRT) are presented in Table 6.6. The respective scattergraphs are presented in Figures 6.5, 6.6 and 6.7.

Clearly none of the fuzzy number transformations yield a significant correlation coefficient greater than that obtained using the untransformed fuzzy number data series of 0.54 (Section 6.8). In addition, the respective comparisons between Figure 6.1 and Figures 6.5, 6.6 and 6.7 suggest no apparent improvement over the reduction in the divergence between the few unduly influential points enforcing the significant correlations and main data clusters. As a result of this, regression was only performed on the transform that yielded the greatest correlation coefficient, that of the square transform (FUZZYSQ).

Table 6.6 Pearson's correlation results between APL and FUZZYLOG, FUZZYSQ & FUZZYSQRT

Fuzzy number variant	r	p	n
FUZZYLOG	0.470	0.000	54
FUZZYSQ	0.510	0.000	54
FUZZYSQRT	0.481	0.000	54

Figure 6.5 Fuzzy number log 10 transform (FUZZYLOG10) versus observed APL

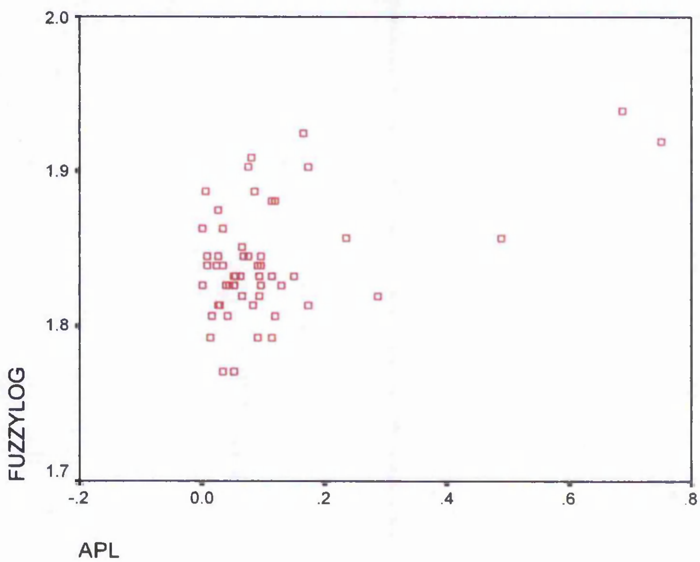


Figure 6.6 Fuzzy number square transform versus observed APL

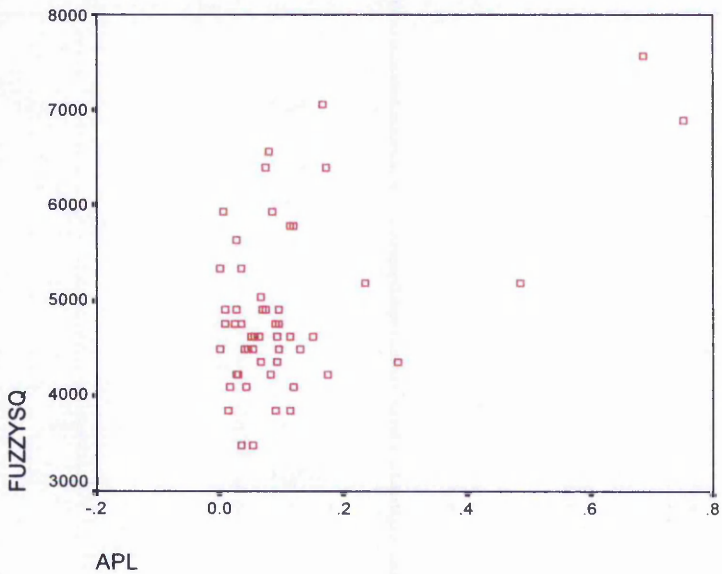
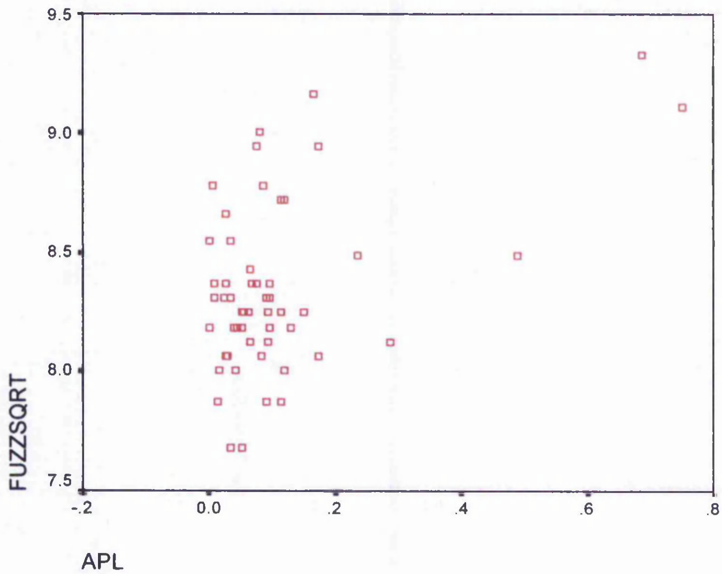


Figure 6.7 Fuzzy number square root transform (FUZZYSQRT) versus observed APL



6.9.2 Result and diagnostics

The potential defuzzification model incorporating the square transformed fuzzy number data series (FUZZYSQ) is shown in Equation 6.2 and accounts for a low 26% of the variation observed in APL.

$$APL = -0.3 + ([8.348 \times 10^{-5}] \times FUZZYSQ) \qquad \text{(Eq. 6.2)}$$

The relevant simple linear regression diagnostics assessing the compliance of the result with the assumptions of the technique are presented in Table 6.7.

Table 6.7 Comparison of simple linear regression diagnostics results; √ denotes compliance with the respective assumption, X denotes non-compliance. For the Leverage and Cook's distance results, the number of cases inducing the non-compliance with the assumption of linearity are presented.

Assumption	**Diagnostic**	**Eq. 6.1 Result**	**Eq. 6.2 Result**
Linearity	Analysis of variance	√	√
	t statistic	√	√
	Leverage	X - 8 cases	X - 8 cases
	Cook's distance	X - 1 case	X - 2 cases
Residual independence	Durbin-Watson test	√	√
Residual constant variance	Scattergraphs - residuals versus predicted values	X	X
Residual normality	Kolmogorov-Smirnov test	X	√
Total number of refutations		3	3

6.9.3 Summary of Equation 6.2

The independent variable (fuzzy number) was transformed in an attempt to improve the degree of linearity between the aforementioned variable and the dependent variable APL. This was undertaken with the purpose of improving the robustness of the ultimate defuzzification regression model.

Equation 6.2 provides a slightly improved coefficient of explanation over the untransformed model, Equation 6.1 (26% in comparison to 24%). However, on balance, concerning the number of assumption violations, there is no real improvement regarding the degree to which the regression assumptions are met (Table 6.7). As a result of this, the same standard transformations were made of the dependent variable APL and correlated with the fuzzy number variants as a precursor to regression analysis, again in an attempt to improve the validity of the ultimate defuzzification model.

6.10 Simple linear regression defuzzification – transformed independent & dependent variables

This section documents the incorporation of transformed independent and dependent variables (logs to the base 10, squares, and square roots) into a multiple regression analysis predicting reservoir sedimentation in an attempt to improve model compliance with the regression assumptions of linearity, residual constant variance, and residual distribution normality.

6.10.1 Tests for linearity – Pearson's correlation

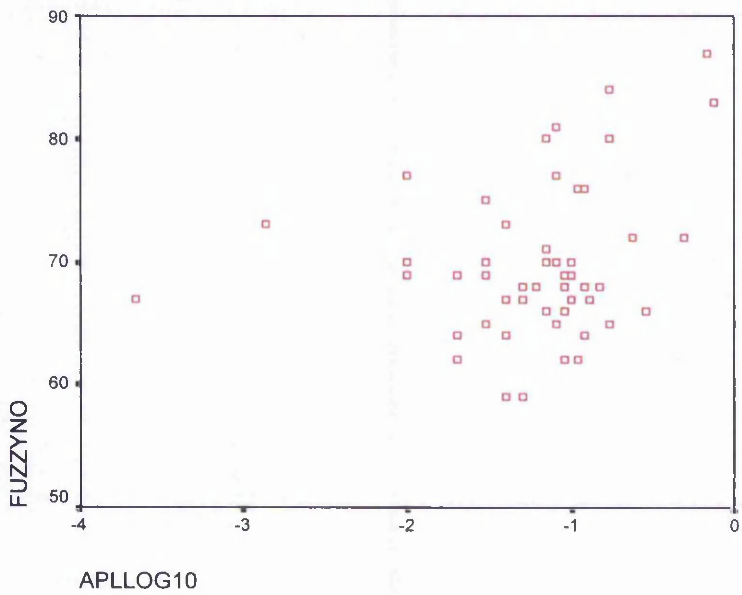
The Pearson's correlation coefficients calculated between each independent and dependent variable variant are presented in Table 6.8.

Table 6.8 Summary of Pearson's correlation coefficients

Dependent Variable	Independent Variable	r	p	n
APLLOG10	FUZZYNO	0.258	0.060	54
	FUZZYLOG	0.245	0.075	54
	FUZZYSQ	0.271	0.048	54
	FUZZYSQRT	0.251	0.067	54
APLSQ	FUZZYNO	0.496	0.000	54
	FUZZYLOG	0.473	0.000	54
	FUZZYSQ	0.517	0.000	54
	FUZZYSQRT	0.484	0.000	54
APLSQRT	FUZZYNO	0.436	0.001	54
	FUZZYLOG	0.418	0.002	54
	FUZZYSQ	0.453	0.001	54
	FUZZYSQRT	0.427	0.001	54
APL	FUZZYNO	0.491	0.000	54

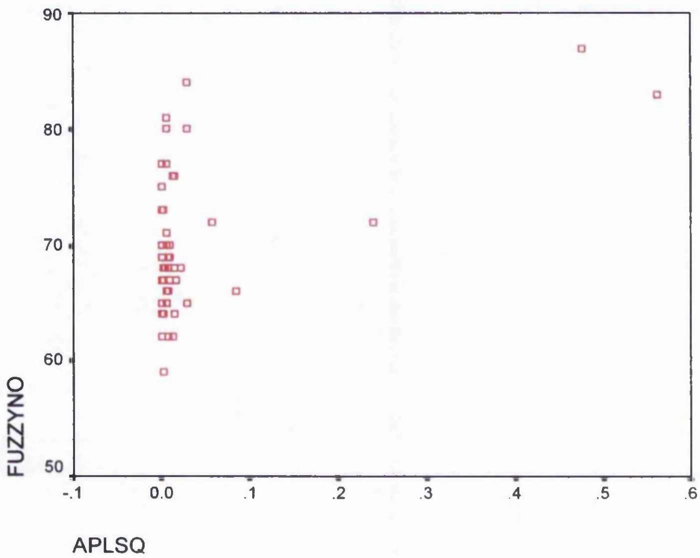
From the analysis of the Pearson's correlation coefficients (Table 6.8) and respective scattergraphs (Appendix 5), it is clear that the log 10 transformation of APL has not improved the degree of linearity between the independent variable variants of FUZZYNO (the untransformed data series), FUZZYLOG, FUZZYSQ and FUZZYSQRT, over that associated with the untransformed independent and dependent variables of FUZZYNO and APL respectively (Section 6.8). Very weak correlation coefficients of low significance are produced with the APLLOG10 dependent variable transformation in comparison to that between APL and FUZZYNO at 0.49 (Table 6.8). In addition, the scattergraphs between APLLOG10 and each independent variable variant (Appendix 5) identify how the calculated correlation coefficients are unduly influenced by a small number of cases, representing no apparent improvement in the robustness of the respective linear relationships over that associated with APL and FUZZYNO. The comparison of Figure 6.8 with Figure 6.1 provides a typical example of this.

Figure 6.8 Untransformed fuzzy number (FUZZYNO) versus APL log 10 transformation (APLLOG10)



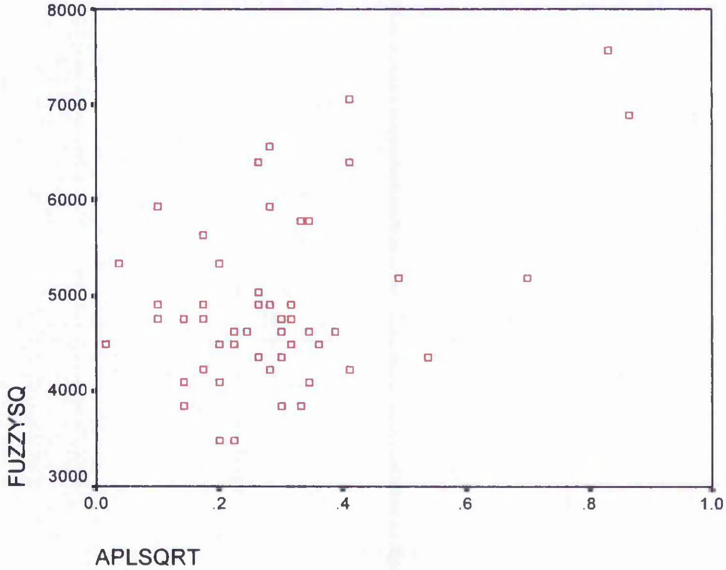
The reasonable, highly significant correlation coefficients between the square dependent variable transform (APLSQ) and the independent variable variants at face value suggest stronger correlations over that associated with the untransformed variables of APL and FUZZYNO (Section 6.8). However from Appendix 5 (with Figure 6.9 as a directly observable example) the respective APLSQ correlations appear more highly dependent on a few points than the original untransformed data. This is shown through the comparison of Figures 6.9 and 6.1.

Figure 6.9 Untransformed fuzzy number (FUZZYNO) versus square APL square transformation (APLSQ)



However, the significant correlations and associated scattergraphs between the square root transformation of APL (APLSQRT) and each of the independent variable variants suggest stronger linear relationships than that obtained through the untransformed data (Table 6.8 and Appendix 5). Whilst the correlation coefficient of 0.49 associated with the untransformed independent and dependent variables (Table 6.3) is greater than the highest incorporating APLSQRT as the dependent variable and FUZZYSQ as the independent variable at 0.45 (Table 6.8); the respective scattergraph graph suggests a stronger degree of linearity with the general progression of cases in a positive direction. This is shown through the comparison of Figures 6.10 and 6.1.

Figure 6.10 Square transformed fuzzy number (FUZZYSQ) versus square root transformed APL (APLSQRT)



From the preceding analysis of the nature of the linear relationships between the dependent variable APL transformations and associated independent variable fuzzy number variants; regression analysis was performed between APLSQRT and FUZZYSQ in an attempt to yield a more robust, valid defuzzification model in comparison to Equation 6.1 (incorporating untransformed independent and dependent variables) and Equation 6.2 (incorporating the transformed independent variable FUZZYSQ).

6.10.2 Result and diagnostics

The defuzzification model incorporating APLSQRT and FUZZYSQ is shown in Equation 6.3 and accounts for a low 21% of the variation observed.

$$\text{APLSQRT} = -0.121 + ([8.352 \times 10^{-5}] \times \text{FUZZYSQ}) \qquad \text{(Eq. 6.3)}$$

The essential simple linear regression diagnostics assessing the compliance of the result with the assumptions of the technique are presented in Table 6.9.

Table 6.9 Comparison of simple linear regression diagnostics results; √ denotes compliance with the respective assumption, X denotes non-compliance. For the Leverage and Cook's distance results, the number of cases inducing the non-compliance with the assumption of linearity are presented.

Assumption	**Diagnostic**	**Eq. 6.1 Result**	**Eq. 6.2 Result**	**Eq. 6.3 Result**
Linearity	Analysis of variance	√	√	√
	t statistic	√	√	√
	Leverage	X - 8 cases	X - 8 cases	X - 8 cases
	Cook's distance	X - 1 case	X - 2 cases	√
Residual independence	Durbin-Watson test	√	√	√
Residual constant variance	Scattergraphs - residuals versus predicted values	X	X	√
Residual normality	Kolmogorov-Smirnov test	X	√	√
Total number of refutations		3	3	1

6.11 Summary of Equation 6.3 & model selection

The dependent variable (APL) was transformed and correlated with each variant of the independent variable in an attempt to improve the degree of linearity between the two variables. This was carried out to produce a defuzzification model that satisfied the assumptions of regression to the greatest degree, thus yielding the most robust, reliable model possible. The APLSQRT dependent variable transformation was selected as it produced the strongest linear relationships for each of the fuzzy number variants over the other dependent variable variants (Section 6.10.1). The corresponding independent variable variant FUZZYSQ was selected as this produced the strongest linear relationship with APLSQRT.

In comparison to Equations 6.1 and 6.2 predicting APL from untransformed and square transformed fuzzy numbers respectively, Equation 6.3 produces a reduced coefficient of explanation at 21% (Equation 6.1 – 24%, Equation 6.2 – 26%). However, for Equation 6.3, the assumptions of regression are met to a greater degree (Table 6.9), induced by a stronger, more robust linear relationship between the independent and dependent variable (as reflected through the Cook's distance statistics) and acts to induce residual constant variance and distribution normality (Norusis, 1996). As a result, Equation 6.3 is selected as the most robust defuzzification model computable from the available data.

6.12 Equation 6.3 evaluation

6.12.1 Verification

To verify Equation 6.3 objectively, the Pearson's correlation test and paired T-test were applied to assess the degree to which the model simulates the relative pattern of the observed APLSQRT data, and the accuracy in actual APLSQRT prediction.

The Pearson's correlation coefficient of 0.453 (significant at the 0.01 level) implies a reasonable linear relationship between observed APLSQRT and DEFUZZAPLSQRT (Table 6.10). In contrast to the respective tests for the multiple regression models (Equations 5.1 and 5.8), this relationship appears less heavily influenced by a small number of observations, thus providing a more robust result (Figure 6.11). This implies that the defuzzification model is predicting reasonable APLSQRT values and producing a relative pattern of sedimentation close to that observed.

Table 6.10 Verification result – Pearson's correlation and Paired T-test

Verification	**Equation 6.3**
Correlation coefficient	0.453
Significance level	0.001
Number	54
Paired T-test statistic	-0.002
Significance level	0.998
Degrees of freedom	53

Figure 6.11 DEFUZZAPLSQRT versus observed APLSQRT

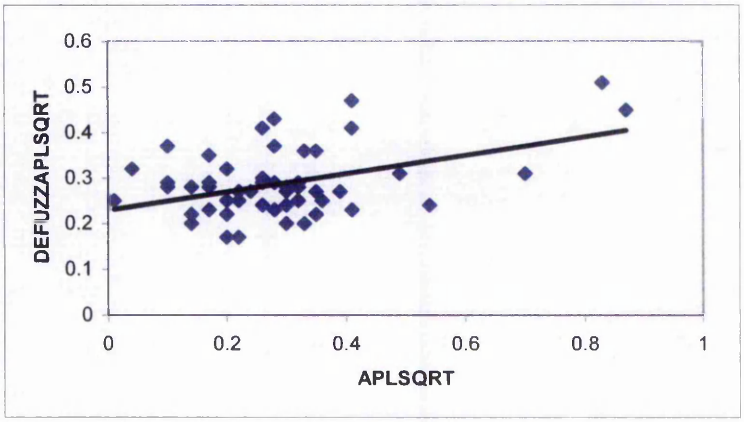


Figure 6.12 supports the assertion from the Pearson's correlation analysis that the defuzzification model (Equation 6.3) is predicting reasonable APLSQRT values and replicating the relative pattern of sedimentation close to that observed. Upon closer inspection of Figure 6.12 it can be seen that the model only tends to under-predict for the few exceptionally high observed APLSQRT values. For all other observed APLSQRT rates there is a tendency for the defuzzification model to provide a reasonably close prediction, or over-predict. This is supported through Figure 6.13 displaying respective positive and negative residuals (observed APLSQRT minus DEFUZZAPLSQRT). In addition, the mean residual value associated with the prediction of APLSQRT is –0.001, identifying an, albeit slight, predominance of over-predictions (Table 6.11).

The paired T-test result identifies that the difference in means between the observed and predicted APL rates is not significantly different from zero (Table 6.10), thus implying reasonably good predictions/fuzzy number defuzzifications of APLSQRT from Equation 6.3.

Figure 6.12 The relative pattern of observed APLSQRT (OBSAPLSQRT) & defuzzified APLSQRT (DEFUZZAPLSQRT) for each reservoir

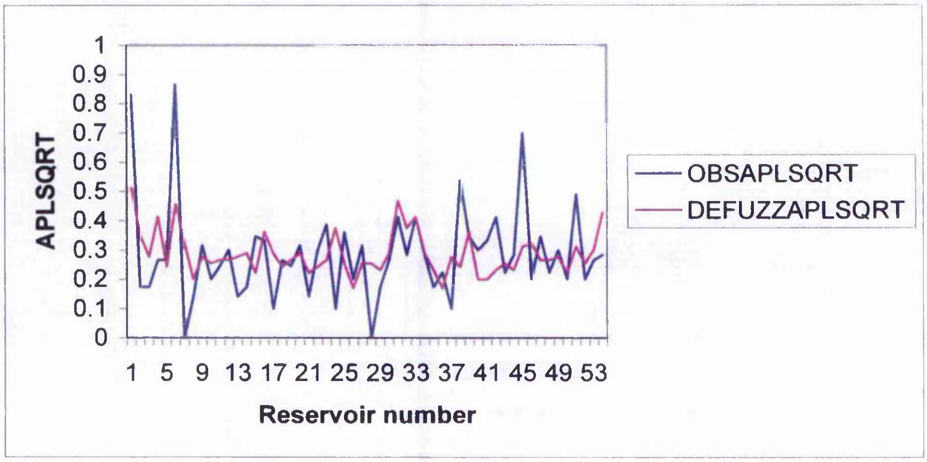


Figure 6.13 Residuals associated with Equation 6.3 (observed APLSQRT minus DEFUZZAPLSQRT)

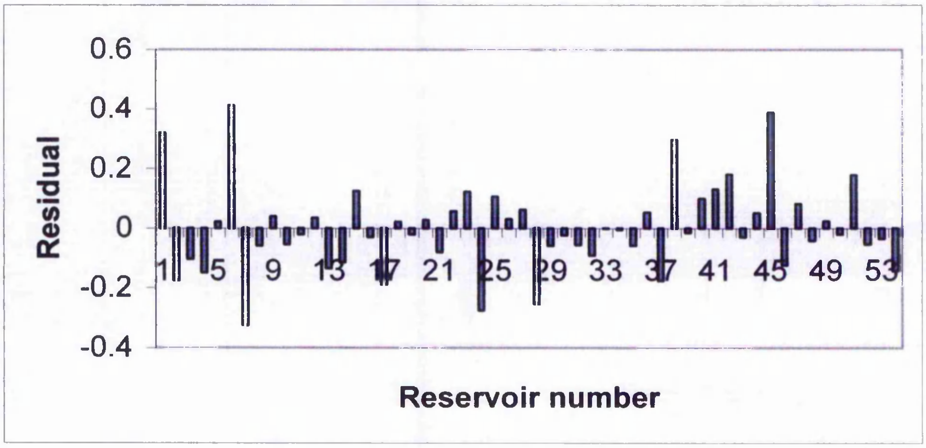


Table 6.11 Key to Figures 6.12 & 6.13 & corresponding observed APLSQRT, predicted DEFUZZAPLSQRT & residual values

Reservoir Number	Reservoir Name	OBSAPLSQRT	DEFUZZAPLSQRT	Residual
1	Abbeystead	0.831	0.511	0.319
2	Angram	0.173	0.349	-0.176
3	Barden Lower	0.173	0.277	-0.103
4	Barden Upper	0.265	0.414	-0.149
5	Blackmoorfoot	0.265	0.243	0.022
6	Blakeley	0.866	0.454	0.412
7	Booth Wood	0.000	0.324	-0.324
8	Broadstones	0.141	0.200	-0.059
9	Broomhead	0.316	0.277	0.040

10	Chelker	0.200	0.254	-0.054
11	Dale Dyke	0.245	0.265	-0.020
12	Dean Head Upper	0.300	0.265	0.035
13	Deanhead	0.141	0.277	-0.135
14	Deerhill	0.173	0.288	-0.115
15	Eldwick	0.346	0.221	0.125
16	Embsay	0.332	0.361	-0.030
17	Fewston	0.100	0.288	-0.188
18	Gorple Lower	0.265	0.243	0.022
19	Gorple Upper	0.245	0.265	-0.020
20	Gorpley	0.316	0.288	0.028
21	Green Withens	0.141	0.221	-0.080
22	Harden	0.300	0.243	0.057
23	Hewenden	0.387	0.265	0.122
24	Holmestyes	0.100	0.374	-0.274
25	Leeshaw	0.361	0.254	0.107
26	Lindley Wood	0.200	0.170	0.030
27	Lower Laithe	0.316	0.254	0.062
28	Morehall	0.000	0.254	-0.254
29	Ogden	0.173	0.232	-0.059
30	Ponden	0.265	0.288	-0.024
31	Ramsden	0.412	0.468	-0.056
32	Redmires Upper	0.283	0.374	-0.091
33	Riding Wood	0.412	0.414	-0.001
34	Rivelin Upper	0.283	0.288	-0.005
35	Roundhill	0.173	0.232	-0.059
36	Royd Moor	0.224	0.170	0.054
37	Ryburn	0.100	0.277	-0.177
38	Scammonden	0.539	0.243	0.296
39	Scar House	0.346	0.361	-0.015
40	Scout Dike	0.300	0.200	0.100
41	Silsden	0.332	0.200	0.132
42	Snailsden	0.412	0.232	0.180
43	Strines	0.224	0.254	-0.030
44	Stubden	0.283	0.232	0.051
45	Tunnel End	0.700	0.312	0.388
46	Underbank	0.200	0.324	-0.124
47	Walshaw Dean Lower	0.346	0.265	0.081
48	Walshaw Dean Middle	0.224	0.265	-0.042
49	Walshaw Dean Upper	0.300	0.277	0.023
50	Wessenden Head	0.200	0.221	-0.021
51	Wessenden Old	0.490	0.312	0.178
52	Widdop	0.200	0.254	-0.054
53	Windleden Upper	0.265	0.300	-0.035
54	Ystradfellte	0.283	0.427	-0.144
	Mean	0.286	0.287	-0.001

The larger absolute residuals identified in Figure 6.13 and Table 6.11 are again partly induced by factors influencing the respective sedimentation rates that are not accounted for by the fuzzy set MCE model 1. As a result of this, the respective observations exert an influence on the computation of the partial regression coefficient associated with the defuzzification model (Equation 6.3), yet are situated a distance away from the regression line (Figure 6.11). The reservoirs with the largest positive residuals are Abbeystead, Blakeley, Scammonden, Tunnel End and Snailsden (0.319, 0.412, 0.296, 0.388 and 0.180 respectively) and represent an under-prediction of defuzzified APLSQRT by Equation 6.3. The production of the first four reservoirs as positive residuals was discussed in Section 5.8.5; the same potential causative explanations apply with regards to Equation 6.3. The production of Snailsden as a positive residual can be attributed to its catchment having an average percentage catchment cover of 95% meadow grass (Table A1.3, Appendix 1), associated with grazing (White *et al.*, 1996a). As discussed in Section 2.11.1.6.3, increased sediment yield rates can be associated with grazing (Heathwaite *et al.*, 1990). This effect is not incorporated into the fuzzy set MCE model 1.

The reservoirs with the largest negative residuals are Holmestyes, Booth Wood, Fewston and Morehall (-0.274, -0.324, -0.188 and -0.253 respectively). The production of Holmestyes as a negative residual was discussed in Section 6.5.1; the same potential causative explanation applies with regards to Equation 6.3. The over-prediction of Booth Wood reservoir may be associated with an inaccurate bathymetric survey that provided the observed APLSQRT rate; it was undertaken in poor weather conditions where fewer transects than ideal were made of the basin (Labadz, 2003, pers.comm.). The over-prediction of a defuzzified APLSQRT value associated with Fewston reservoir may be associated with the presence of catchment management structures in the catchment reducing sediment delivery (White *et al.*, 1996a), which cannot be represented as respective fuzzy sets for potential incorporation into a fuzzy set MCE model. This is primarily due to information concerning their presence across the population data set not being readily available from secondary data sources. For Morehall reservoir, the over-prediction may be associated with the omission of forest land cover variables/fuzzy sets from the fuzzy set MCE model 1, which may act to reduce sediment yield (Cheng *et al.*, 2002). From Table A1.3, Appendix 1, it can be seen that the catchment area of Morehall reservoir is well forested with average percentage catchment covers of 47.667% for coniferous woodland, and 12% for deciduous woodland. Through the variable selection procedure using principal components analysis (Section 6.4.1), neither of these respective fuzzy sets were incorporated into the weighted linear combination aggregation process to yield fuzzy set MCE model 1. The fact that Holmestyes, Booth Wood, Fewston and Morehall reservoirs each have low observed APLSQRT rates (Table A1.3, Appendix 1) influences the computation of the partial regression coefficient of Equation 6.3, acting to balance the effect of the few reservoirs with exceptionally high observed APLSQRT rates, identified in the preceding section. Consequently, the aforementioned reservoirs fall below the defuzzification model regression line, producing negative residuals (Figure 6.11).

6.12.2 Validation

The validation data set of the defuzzification model comprises six reservoirs not included in the parameterization data set used to construct Equation 6.3: Appleton, Bough Beech, Eyebrook, Great Lake, Howden and Weirwood (Table 6.12).

Table 6.12 Validation data set – respective observed APL, predicted APL and residual values

Reservoir Number	Reservoir Name	Observed APLSQRT	DefuzzAPLSQRT	Residual
1	Appleton	0.300	0.210	0.090
2	Bough Beech	0.120	0.270	-0.150
3	Eyebrook	0.230	0.310	-0.080
4	Great Lake	0.120	0.230	-0.110
5	Howden	0.340	0.350	-0.010
6	Weirwood	0.140	0.200	-0.060
	Mean	0.208	0.262	-0.052

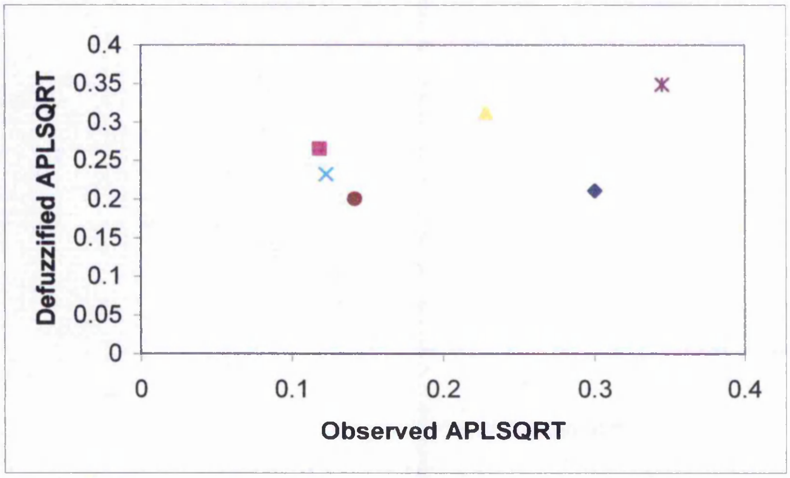
The Pearson's correlation and the paired T-test results comparing the model DEFUZZAPLSQRT predictions with the observed APLSQRT of validation data are presented in Table 6.13.

Table 6.13 Validation result – Pearson's correlation and Paired T-test

Validation	Equation 6.3
Correlation coefficient	0.507
Significance level	0.305
Number	6
Paired T-test statistic	-1.513
Significance level	0.191
Degrees of freedom	5

The Pearson's correlation coefficient (0.507) and associated scattergraph suggest a reasonable degree of linearity between APLSQRT and DEFUZZAPLSQRT for the reservoirs in the validation data set (Table 6.13 and Figure 6.14). The result, however, is not significant at the 0.05 level; induced probably by the small sample size.

Figure 6.14 DEFUZZAPLSQRT versus observed APLSQRT – validation data set



Key: Bough Beech – pink square, The Great Lake – light blue cross, Weirwood – maroon circle, Appleton – yellow triangle, Eyebrook – royal blue diamond, Howden – purple asterisk

However, the inference from Figure 6.15 suggests that the model is broadly replicating the same relative pattern as that observed in the real world data and producing DEFUZZAPLSQRT values of similar magnitudes. This is supported through the production of relatively small residuals (Figure 6.16) with a mean of –0.052 (Table 6.12), and the paired T-test result which identifies that the difference in means between the observed (APLSQRT) and predicted (DEFUZZAPLSQRT) sedimentation rates of the validation data set is not significantly different from zero (Table 6.13).

From Figures 6.15 and 6.16, and Table 6.12, there is a strong tendency for Equation 6.3 to over-predict APLSQRT. This implies that the model assumes a "bleak outlook scenario" which is theoretically preferable; it is better to be risk averse and over-estimate a detrimental process than to under-estimate. The one case of model under-prediction in the validation data set, at Appleton reservoir, can be partly attributed to this reservoir having a catchwater input, bringing in potentially sediment-laden flows from outside of the direct catchment area (United Utilities Ltd., pers.comm.). Howden reservoir also has an additional catchwater input which may explain the production of a very small negative residual from a model that appears to generally over-predict. However, for Howden reservoir, this result may also be induced by the fact that the observed APLSQRT rate was determined from secondary data that employed a different surveying technique to the one adopted herein for respective primary data collection (Section 4.3.2). Together, the Pearson's correlation and paired T-test result, and the interpretation of Figures 6.15 and 6.16, identify that Equation 6.3 is validated to a reasonable degree.

Figure 6.15 The relative pattern of observed APLSQRT & DEFUZZAPLSQRT – validation data set

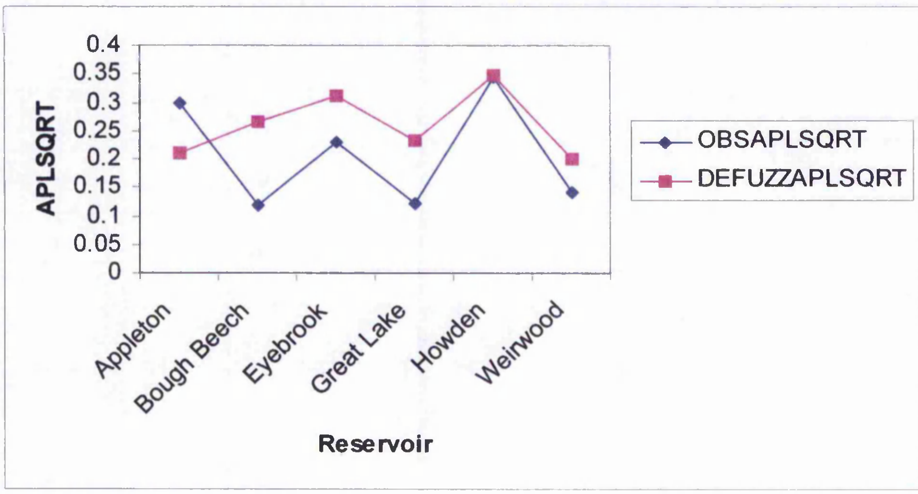
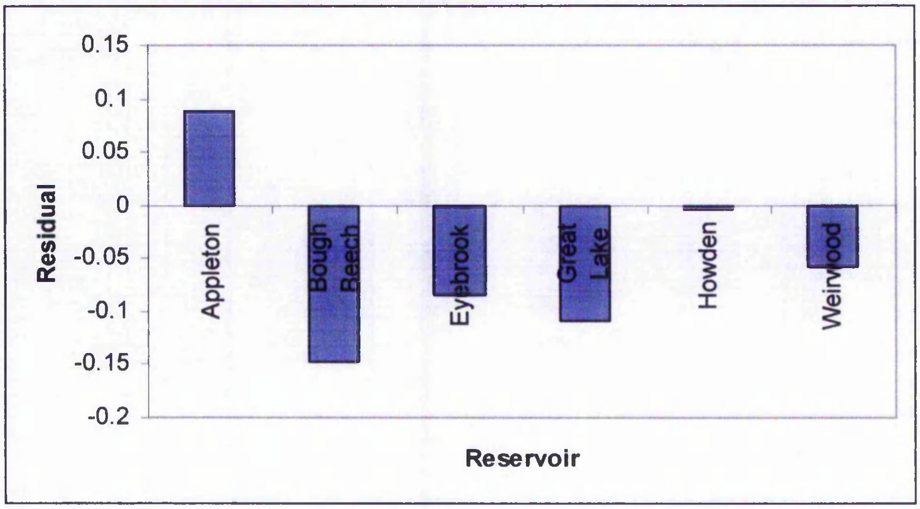


Figure 6.16 Validation data set residuals (observed APLSQRT – predicted APLSQRT)



In conclusion, Equation 6.3 can be verified and validated to a reasonable degree. With regards to the parameterization data set, the model replicates the same relative pattern of the observed data and produces good predictions especially for the average/typical observed APLSQRT rates. With regards to the validation data set, the model replicates the same relative pattern of the observed data and yields relatively small residuals, implying reasonable APLSQRT predictions. Through the verification and validation processes, Equation 6.3 yields a predominance of over-predictions which is theoretically preferable.

6.12.3 Confidence Intervals

From the 95% confidence intervals calculated for each of the 54 reservoirs in the defuzzification model parameterization data set, 20 reservoirs can be shown to have an observed APLSQRT value that falls within the respective 95% confidence interval of the prediction (Table A1.27, Appendix 1). Therefore, for 37% of the respective parameterization data set, there is 95% confidence in the prediction afforded by Equation 6.3 being obtained had the entire reservoir population been available for analysis. This result provides reasonable user-confidence that inferences made from Equation 6.3 are correct.

6.12.4 Summary of Equation 6.3

The defuzzification model (Equation 6.3) converts the fuzzy number from the fuzzy set MCE model 1 into an APLSQRT value. This can be subsequently back-transformed into an actual APL value (Table A1.3, Appendix 1). From the analysis in Section 6.12, Equation 6.3 does replicate the relative pattern of the respective parameterization data set as identified through the significant Pearson's correlation coefficient, and does defuzzify to produce reasonably accurate predictions for the average/typical APLSQRT rates across the parameterization data set, as identified through the paired T-test result. However, Equation 6.3 does have a rather low coefficient of explanation at 21%.

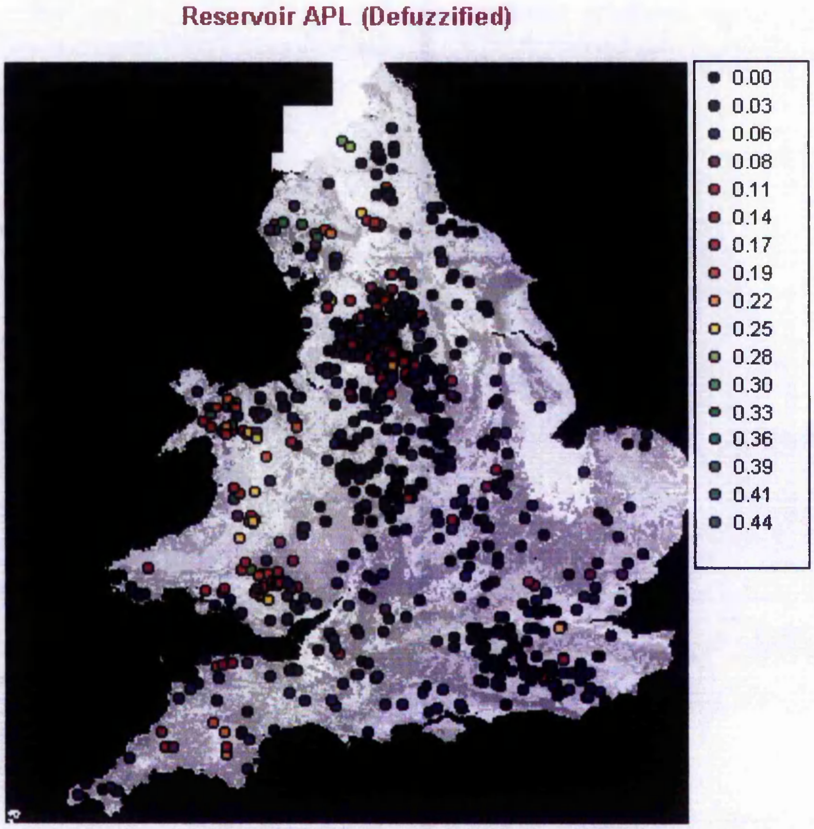
When the model is extrapolated to defuzzify fuzzy numbers for reservoirs in the validation data set, reasonable results are produced with the model broadly replicating the same relative pattern as the observed (validation) data and providing reasonable DEFUZZAPLSQRT values. This is shown through Figure 6.15 and the paired T-test result (Table 6.13) which identifies no significant difference between the observed and defuzzified APLSQRT values. However, despite a reasonable respective correlation coefficient being produced at 0.507, it is not significant at the 0.05 level (Table 6.13). As a result, the defuzzification model (Equation 6.3) inspires reasonable user-confidence but a larger validation data set is perhaps required to ascertain model validation to a higher degree of user-confidence.

Whilst defuzzification is a useful tool in obtaining an actual APL quantity, the production of only a reasonable defuzzification model does not undermine this application of the fuzzy set MCE approach. Burrough (1989) recognises that such fuzzy multi-criteria evaluation approaches producing outputs ranging between 0 and 1 (0 and 255 in Idrisi 32) provide results that are more comprehensible and interpretable in terms of environmental impact for associated catchment area managers (in this instance) to use in policy-making decisions. Burrough (1989) states that such data classification is an essential part of the data reduction process, whereby complex sets of observations and predictions are made understandable. Therefore, defuzzification is not the "be all and end all" of the fuzzy set approach. The application of fuzzy set MCE in predicting the **degree of reservoir sedimentation** has yielded a robust, valid result providing the first comprehensive assessment of reservoir sedimentation across England and Wales.

6.13 Equation 6.3 operationalization

Figure 6.17 displays the APL for the population of reservoirs predicted through fuzzy set WLC, defuzzified through Equation 6.3. The same pattern of reservoir APL is observed across England and Wales as that produced regarding the prediction of the degree of sedimentation (this was discussed in detail in Section 6.6 and will not be repeated here). However, the relative difference between APL rates appears clearer through the transition between reservoirs experiencing low sedimentation and those experiencing high levels being steeper and more abrupt. Reservoir APL values are highest in the upland areas of Cumbria, the Brecon Beacons and Cambrian Mountains in Wales, and to a slightly smaller degree, the Pennines and Dartmoor. The prediction of moderate levels of reservoir sedimentation in southeast England is still apparent. However, due to the lower degree of validation associated with the defuzzification model (Equation 6.3) in comparison to the original fuzzy set MCE model 1 output, user-confidence in terms of the inferences obtained from Figure 6.17 is not as high as that associated with Figure 6.4.

Figure 6.17 The defuzzification model output (Equation 5.3). The legend refers to reservoir annual percentage capacity loss (APL).



6.14 Application of the clustering approach on fuzzy set MCE

6.14.1 Introduction

Analogous to the multiple regression application (Chapter 7), the clustering approach was applied to fuzzy set multi-criteria evaluation (MCE), being performed on cluster 2 from the population data set in an effort to improve the respective degree of reservoir sedimentation predictions over those from the fuzzy set MCE model 1. The evaluation of the respective model (fuzzy set MCE model 2) assessed the potential of the technique in achieving the principal aim of the research.

6.14.2 Application of the clustering approach

Modelling a sub-set of the population defined through cluster analysis improved the validity of model predictions using multiple regression as the respective reservoirs together had stronger correlations with certain variables than others. This acted to reduce the degree of unexplained variation about the respective multiple regression model (Section 5.16). A similar effect was postulated using fuzzy set MCE. Performing principal components analysis on a cluster of reservoirs (that by definition share similar characteristics) will identify those variables accounting for the most variation within a cluster. These variables will therefore be potentially more representative of the factors/processes influencing sedimentation in the cluster of reservoirs than those variables extracted from principal components analysis performed on the complete population (Section 6.4.1). Applying the same methodology as in Section 6.4 (with regards to performing fuzzy set MCE on the population data set) may yield fuzzy number results more strongly correlated with respective annual percentage capacity loss observations.

As with the application of the clustering approach on multiple regression (Chapter 5), fuzzy set MCE was only applied to cluster 2 as this was the most represented cluster with regards to observed annual percentage capacity loss observations (Section 4.3.1.2), enabling model verification and validation. Therefore, the application of the clustering approach on fuzzy set MCE assessed the **potential** of the methodology in achieving the principal aim of the research, as it did for multiple regression.

6.14.3 Principal components analysis

Principal components analysis was performed on cluster 2, derived from the cluster analysis of the original population data set of 797 reservoirs (Section 4.3.1.2). The result is presented in Table A1.26, Appendix 1. Due to the coarse spatial resolution of the associated data in raster form (as discussed in Section 4.3.3), only 460 reservoirs from the original cluster 2 population of 473 were resolvable for application in Idrisi 32. Again, for each of the 57 sedimentation-inducing variables, the principal component that contained the maximum respective eigenvector was ascertained. Where more than one variable had the greatest eigenvector in a particular component, only the variable with the largest eigenvector was entered into the fuzzy set analysis. This process reduced the number of variables that had to be entered into the fuzzy set analysis from 57 to 23; these are presented in Tables 6.14 and 6.15.

Table 6.14 The maximum absolute principal component eigenvector loading for each variable. The asterisk denotes the variable that accounts for the most variance in a particular component; 0 denotes no representation of that variable as the largest eigenvector of a particular principal component.

Variable	Principal component	Eigenvector
CAREA	3	0.732
QMED	1	0.613
MEANFARL*	11	0.420
FARL*	29	0.366
PROPWET	1	0.801
ALTBAR	1	0.837
BFIHOST	1	0.603
DPLBAR*	3	0.800
DPSBAR	1	0.583
LDP	3	0.792
RMED1H	7	0.387
RMED1D	1	0.890
RMED2D	1	0.899
SAAR*	1	0.932
SAAR4170	1	0.929
SPRHOST	1	0.647
URBCONC	0	0.000
URBEXT	3	0.341
URBLOC	0	0.000
TE*	33	0.296
S401*	14	0.568
S405*	9	0.556
S454*	20	0.729
S455	2	0.979
S469*	12	0.501
S475*	25	0.441
S486*	2	0.987
S487	0	0.000
S489	2	0.985
S495*	16	0.391
S506	0	0.000
S507*	21	0.572
S660*	18	0.762
S686	23	0.438
S692	2	0.984
BRACK	9	0.553

CONIF*	8	0.468
DECID	5	0.491
DSHRUB	4	0.516
DSHRUBH*	5	0.663
FELLED*	22	0.414
GRASS*	7	0.400
IBARE	6	0.421
IWATER*	13	0.472
LOWBOG	5	0.570
MEADOW	6	0.529
MOORLAND	4	0.673
MOWN	4	0.444
OPENS*	4	0.692
OPENSH	5	0.661
ROUGH	9	0.387
RUDERAL	11	0.383
SCRUB*	17	0.364
SUBURB	6	0.493
TILLED	5	0.401
UPBOG*	10	0.409
URBAN*	6	0.585

6.14.4 Variable membership curves

Linear fuzzy membership curves were constructed for each of the variables that account for the most variance in a particular component (identified in Table 6.15). This was achieved using the range of respective values in the cluster 2 data set to determine the inflection points in each membership curve, and expert scientific opinion to determine the direction of each linear membership curve.

6.14.4.1 Soil variables

As in Section 6.4.2.1, each of the soil variables identifying the area of the respective soil class with a very high, or high risk of erosion (after Evans, 1990) were allocated a positive membership curve; the premise being that the larger the area of coverage, the greater the quantity of eroded material and reservoir sedimentation.

6.14.4.2 Land cover variables

The positive membership curves of open shrub moor, urban, upland bog, and felled forest land covers and the negative membership curves of dense shrub heath, and scrub/orchard covers are discussed in Section 6.4.2.2 with reference to the application of fuzzy set MCE for the population data set and will not be repeated here. However, in addition to these variables, the application of fuzzy set MCE on the cluster 2 data set incorporates the land cover variables of grass heath, coniferous/evergreen woodland and inland water.

Grass heath (GRASS) includes inland grasslands usually growing on sandy soils (that are typically erosive) and not associated with grazing. In winter, especially in lowland areas, grass heaths have substantial quantities of dead plant litter (Fuller, 1995). These factors act to reduce erosion, thus grass heath was assigned a negative membership curve; as the average percentage catchment cover increases, the degree of overland flow, erosion and reservoir sedimentation decreases.

Coniferous/evergreen woodland (CONIF) was assigned a negative membership curve due to the well-documented effect of natural forest stands reducing potentially erosive overland flow and streamflow production, and increasing soil stability through the binding effect of their root systems (Section 2.11.1.6.1).

Inland water (IWATER) includes all fresh water areas mappable by the Landsat Thematic Mapper (the original data source of the land cover map) at its 30 x 30m spatial resolution (Lillesand and Kiefer, 1994). In the context of reservoirs that are situated predominantly in more upstream areas, such fresh water areas resolvable at this resolution will typically only include upstream reservoirs, lakes and ponds situated within the catchment. Each of these will act as stores, reducing sediment delivery to reservoir basins. As a result of this, inland water was allocated a negative membership curve.

6.14.4.3 Hydro-meteorological variables

The only hydro-meteorological variable represented in this application of fuzzy set multi-criteria evaluation is average annual rainfall (1961-1990) (SAAR). This was allocated a positive membership curve as discussed in Section 6.4.2.3.

6.14.4.4 Geomorphological variables

The geomorphological variables of catchment size and drainage path configuration index (DPLBAR), flood attenuation due to reservoirs and lakes index, and the mean flood attenuation due to reservoirs and lakes index were each assigned positive membership curves as discussed in Section 6.4.2.4. The additional geomorphological variable for the cluster 2 application, trap efficiency (TE), was also allocated a positive membership curve; as this value increases, so does the quantity of sediment retained within the reservoir basin (Section 2.11.2.1). However, as identified in Section 5.8.5.1, in reality a positive or negative relationship between reservoir sedimentation and TE may be induced depending upon whether the reservoir capacities extracted from the BRE dams data set, used to calculate TE across the population data set, relate to original or revised capacities. The broad assumption is that the majority of the values relate to original capacities, thus typically inducing a positive relationship between reservoir sedimentation and TE. This broad assumption is made from the reasoning that reservoir sedimentation is not generally perceived to be a problem across England and Wales (Chapter 2), thus not prompting many revised basin capacity surveys. Whilst this assumption of a positive relationship between reservoir sedimentation and TE is flawed for reservoirs in the population data set with trap efficiencies calculated from revised capacities (Section 5.8.5.1), the fact that TE has the lowest weighting in the weighted linear combination aggregation procedure (Table 6.15) means that it will have a very small, practically negligible influence on the model output.

6.14.5 Weighted linear combination – variable weights

The weights applied to each variable for use in the weighted linear combination aggregation procedure to calculate the ultimate fuzzy number for each reservoir (depicting the degree of reservoir sedimentation) were determined by standardizing the respective component eigenvalues so that they sum to 1 (Table 6.15). This was the same procedure described and undertaken in Section 6.4.3. The fuzzy set multi-criteria evaluation was subsequently performed for the cluster 2 data set.

Table 6.15 Variables entered into fuzzy set multi-criteria evaluation 2

Variable	Abbreviation	Factor Weight
Average annual rainfall 1961-1990	SAAR	0.1788
Bridgenorth soil association	S486	0.0972
Catchment size & drainage path configuration index	DPLBAR	0.0836
Open shrub moor	OPENS	0.0753
Dense shrub heath	DSHRUBH	0.0577
Continuous urban	URBAN	0.0472
Grass heath	GRASS	0.0408
Coniferous forest	CONIF	0.0384
Bangor soil association	S405	0.0353
Upland bog	UPBOG	0.0323
Mean flood attenuation due to reservoirs & lakes index	MEANFARL	0.0311
South Petherton soil association	S469	0.0297
Inland water	IWATER	0.0280
Revidge soil association	S401	0.0277
Frilford soil association	S495	0.0255
Scrub/orchard	SCRUB	0.0254
Everingham soil association	S660	0.0248
Bearsted 1 soil association	S454	0.0241
Fyfield 2 soil association	S507	0.0237
Felled Forest	FELLED	0.0225
Wick 2 soil association	S475	0.0218
Flood attenuation due to reservoirs and lakes index	FARL	0.0168
Trap efficiency	TE	0.0123

6.15 Fuzzy set MCE model 2 evaluation

6.15.1 Verification & validation

The fuzzy set MCE model 2 was again constructed within the Idrisi 32 environment. The model was verified and validated against 48 reservoirs present in cluster 2 with an observed annual percentage capacity loss (APL) from the original parameterization data set, resolvable in the Idrisi 32 raster format.

From Table 6.16 a significant, albeit relatively weak, positive correlation is produced between fuzzy number and observed APL. From Figure 6.18 it is apparent that this relationship is heavily influenced by a small number of observations. This significant correlation coefficient implies that the model is replicating the relative pattern of the observed APL values to a degree. This replication is displayed in Figure 6.19 directly comparing the z-scores of both data series. From Figure 6.19 it appears that the model is more extreme in depicting relative differences in the degree of reservoir sedimentation in comparison to the real world observation, implying it is highly sensitive to the degree of influence the sediment-inducing variables have. This is supported through Figure 6.20 displaying the z-score residuals (observed APL z-score minus predicted fuzzy number z-score) illustrating a balanced production of positive residuals, associated with the under-prediction of the relative extremely high observed APL rates, and negative residuals associated with the over-prediction of the relative low observed APL rates. For all other relative observed APL rates there is a tendency for the fuzzy set MCE model 2 to provide a reasonably close prediction, or over-predict. Such high sensitivity was observed in Section 6.5.1 concerning the prediction of the degree of reservoir sedimentation for the complete population of reservoirs. The paired T-test result between the fuzzy number and observed APL z-score data series identifies no significant difference from zero for the mean of the respective pairwise differences (Table 6.16). This implies good agreement between the two data series, thus the model is replicating the real world pattern of observed APL values reasonably well.

Table 6.16 Verification and validation result – Pearson's correlation and Paired T-test

Verification & validation	**Fuzzy MCE Model 2**
Correlation coefficient	0.312
Significance level	0.031
Number	48
Paired T-test statistic	0.000
Significance level	0.000
Degrees of freedom	47

Figure 6.18 Predicted fuzzy number (FUZZYNO) versus observed APL (OBSAPL)

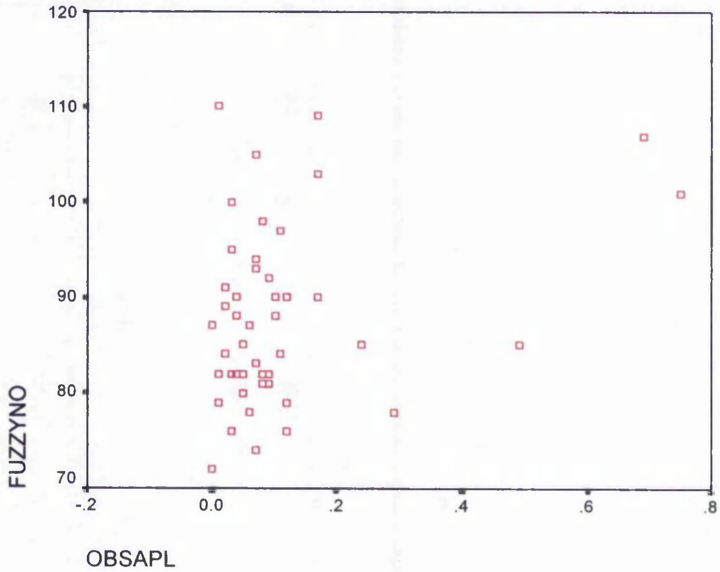


Figure 6.19 Comparison of observed APL z-score & predicted fuzzy number z-score

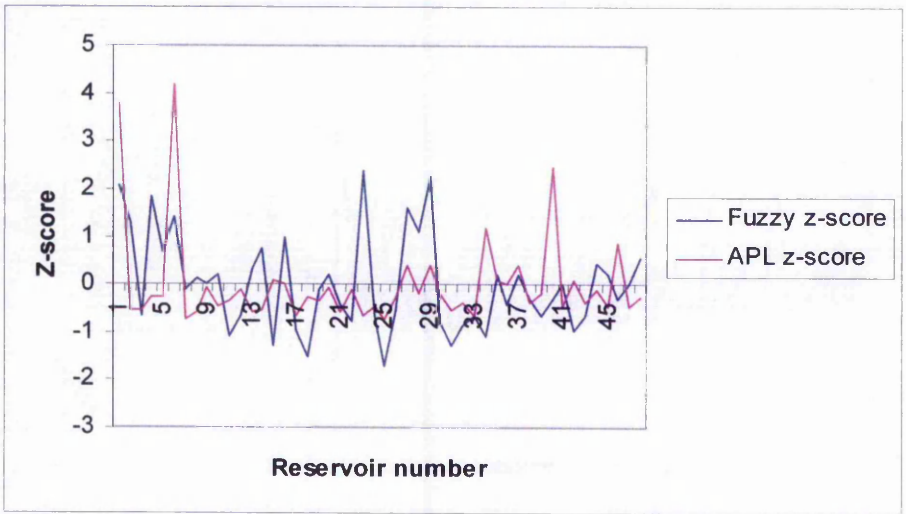


Figure 6.20 Observed APL z-score subtracted from the predicted fuzzy number z-score

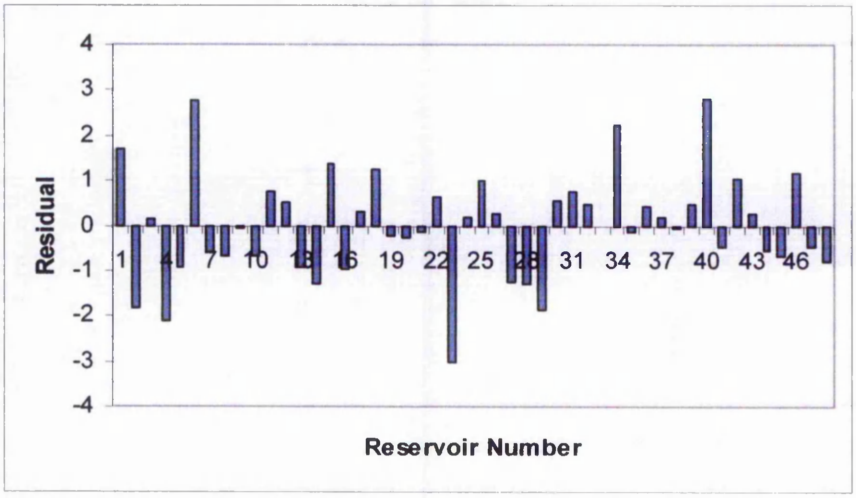


Table 6.17 Key to Figures 6.19 & 6.20 & corresponding observed APL z-score, predicted Fuzzy Number z-score & residual values

Reservoir Number	Reservoir Name	Observed APL z-score	Fuzzy z-score	Residual
1	Abbeystead	3.777	2.055	1.722
2	Angram	-0.523	1.298	-1.821
3	Barden Lower	-0.523	-0.649	0.127
4	Barden Upper	-0.262	1.839	-2.101
5	Blackmoorfoot	-0.262	0.649	-0.911
6	Blakeley	4.168	1.406	2.762
7	Booth Wood	-0.718	-0.108	-0.610
8	Broadstones	-0.588	0.108	-0.696
9	Broomhead	-0.067	0.000	-0.067
10	Chelker	-0.457	0.216	-0.674
11	Dale Dyke	-0.327	-1.082	0.755
12	Dean Head Upper	-0.132	-0.649	0.517
13	Deanhead	-0.588	0.325	-0.912
14	Deerhill	-0.523	0.757	-1.280
15	Eldwick	0.064	-1.298	1.362
16	Embsay	-0.001	0.974	-0.975
17	Fewston	-0.653	-0.974	0.321
18	Gorple Lower	-0.262	-1.515	1.253
19	Gorple Upper	-0.327	-0.108	-0.219
20	Gorpley	-0.067	0.216	-0.283
21	Green Withens	-0.588	-0.433	-0.155
22	Harden	-0.132	-0.757	0.626
23	Holmestyes	-0.653	2.380	-3.033
24	Lindley Wood	-0.457	-0.649	0.192
25	Morehall	-0.718	-1.731	1.013

26	Ponden	-0.262	-0.541	0.279
27	Ramsden	0.390	1.623	-1.233
28	Redmires Upper	-0.197	1.082	-1.279
29	Riding Wood	0.390	2.272	-1.882
30	Rivelin Upper	-0.197	-0.757	0.560
31	Roundhill	-0.523	-1.298	0.776
32	Royd Moor	-0.392	-0.865	0.473
33	Ryburn	-0.653	-0.649	-0.004
34	Scammonden	1.171	-1.082	2.253
35	Scar House	0.064	0.216	-0.153
36	Silsden	-0.001	-0.433	0.431
37	Snailsden	0.390	0.216	0.173
38	Strines	-0.392	-0.325	-0.068
39	Stubden	-0.197	-0.649	0.452
40	Tunnel End	2.474	-0.325	2.799
41	Underbank	-0.457	0.000	-0.457
42	Walshaw Dean Lower	0.064	-0.974	1.037
43	Walshaw Dean Middle	-0.392	-0.649	0.257
44	Walshaw Dean Upper	-0.132	0.433	-0.564
45	Wessenden Head	-0.457	0.216	-0.674
46	Wessenden Old	0.846	-0.325	1.170
47	Widdop	-0.457	0.000	-0.457
48	Windleden Upper	-0.262	0.541	-0.803
	Mean	0.000	0.000	0.000

The large residuals identified in Figure 6.20 and Table 6.17 are predominantly induced by factors influencing the respective sedimentation rates not accounted for by the model. This was also the case for such residuals associated with fuzzy set MCE model 1. The reservoirs with the largest positive residuals, representing under-predictions by fuzzy set MCE model 2, are Abbeystead, Blakeley, Scammonden and Tunnel End (1.722, 2.762, 2.253 and 2.798 respectively). The production of these residuals (as discussed in detail through Section 5.8.5 concerning the multiple regression model Equation 5.1) is caused principally by the influence of factors not represented as fuzzy sets acting to induce exceptionally high observed APL rates (e.g. additional catchwater/conduit inputs from outside of the respective direct catchment areas).

The reservoirs with the largest negative residuals, representing over-predictions by the fuzzy set MCE model 2, are Angram, Barden Upper, Deerhill, Holmestyes, Ramsden, Redmires Upper and Ridingwood (-1.821, -2.101, -1.280, -3.033, -1.233, -1.278 and -1.882

respectively). The over-prediction for Angram, Barden Upper, Deerhill, Ramsden and Redmires Upper can be associated with the presence of catchment management structures in the respective catchments, acting to reduce sediment transport into the reservoir basins. These catchment management structures include residuum lodges, catchwater/conduit interceptions, bywash channels and reservoirs upstream (White *et al.*, 1996a). For Holmestyes and Ridingwood reservoirs, over-predictions can be associated with the respective catchments having relatively large areas of land use types that are comparatively less conducive to sediment production, but not included in the fuzzy set MCE analysis through the principal components analysis selection procedure. Regarding Holmestyes reservoir, this was discussed in Section 6.5. However, for Ridingwood reservoir, the occurrence of comparatively large average percentage catchment covers of 10.667% deciduous woodland and 21.333% meadow (Table A1.28, Appendix 1), which both provide good protection against soil erosion (Fuller, 1995), are not represented in the fuzzy set MCE model 2. Instead, the influence of these land covers on potential sediment production is offset by the comparatively large average percentage catchment cover of open shrub moor (31.333% - Table A1.28, Appendix 1), which is extremely conducive to soil erosion and sediment production (Evans, 1993).

From the preceding results, the fuzzy sets multi-criteria model predicting the degree of reservoir sedimentation for cluster 2 can be verified and validated to only a reasonable degree in terms of the model replicating the relative pattern of observed APL. This is due to the relatively weak correlation between the fuzzy number depicting the degree of reservoir sedimentation and observed APL.

6.16 Comparison of fuzzy set multi-criteria evaluation approaches

Fuzzy set multi-criteria evaluation (MCE) was performed on the cluster 2 data set in an attempt to optimise the modelling technique to provide a more valid, robust model over that produced for the population data set. The rationale behind this was that those reservoirs that comprise the cluster 2 data set (determined through cluster analysis - Section 4.3.1.2) have stronger correlations with certain variables that influence reservoir sedimentation than other reservoirs in the population data set. Therefore, identification of those stronger correlated variables through principal components analysis, and the allocation of a weighting factor derived from the respective component eigenvalue, was deemed to provide a more representative/accurate ultimate fuzzy number than would otherwise be obtained through consideration of the entire population data set. This is because the application of principal components analysis on the population data set extracts principal components accounting for the most variance over three principal clusters of reservoirs (identified through cluster analysis). Each of these three clusters is strongly correlated with different sedimentation-influencing variables. As a result, the extraction of the said principal components for the population data set represents a broad overview/generalization of the variables that actually account for the most variation within the three clusters of the population. Thus, for example, under the fuzzy set MCE model applied to the population data set, the distinct variables that are most strongly correlated with sedimentation in more lowland-type reservoirs (typified across southeast England) are considered along with those most strongly correlated with sedimentation in more upland-type reservoirs (typified across the Lake District and Brecon Beacons), to produce an ultimate fuzzy number depicting the degree of sedimentation for each reservoir in the population. It was postulated that this might produce a model output of inherent lower accuracy in comparison to one produced from modelling a particular cluster within the population.

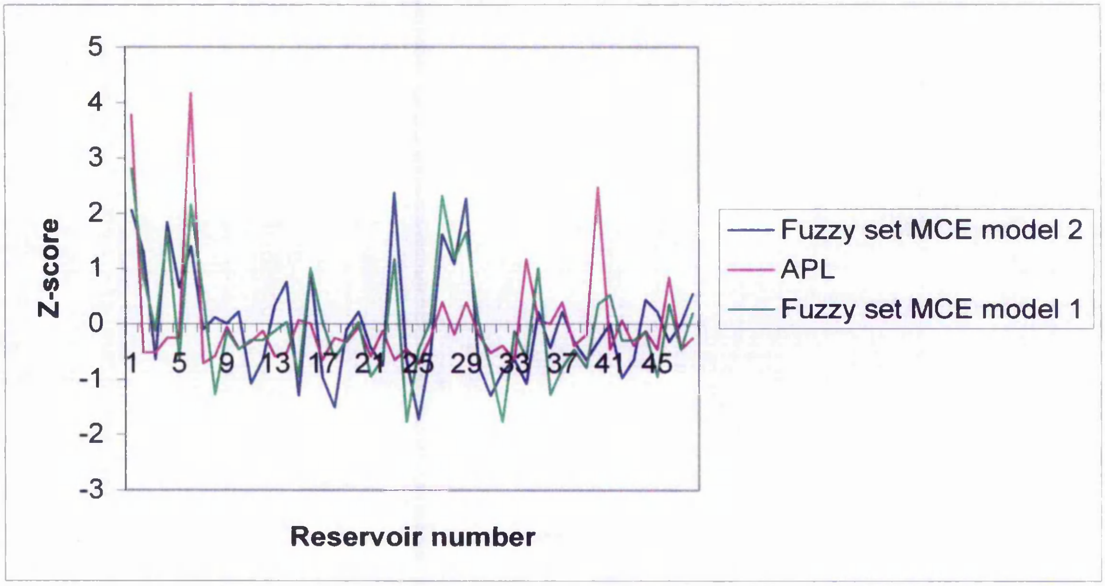
However, from Section 6.15 and Table 6.18 it can be seen that the fuzzy set MCE performed exclusively on the cluster 2 data set (fuzzy set MCE model 2) does not improve the correlation between the model output, the degree of reservoir sedimentation (scaled between 0 and 255), and the observed annual percentage capacity loss (APL). Indeed, the correlation appears heavily influenced by a smaller number of points with the observations not showing such a positive progression (compare Figure 6.1 with Figure 6.18).

Table 6.18 Summary results of fuzzy set MCE model 1 and model 2 verification & validation between observed APL and predicted fuzzy number (degree of reservoir sedimentation)

	Fuzzy set MCE model 1	Fuzzy set MCE model 2
Correlation coefficient	0.491	0.312
Significance level	0.000	0.031
Number	54	48
Paired T-test statistic	-0.001	0.000
Significance level	0.999	1.000
Degrees of freedom	53	47

In contrast, both respective paired T-test results between the associated observed and predicted z-score data series identify no significant difference from zero for the mean of the respective pairwise differences. This implies a broad representation by both models of the relative pattern of sedimentation in the real world data. However, from Figure 6.21 it would appear that the predictions of the degree of reservoir sedimentation from the model associated with the population data set (fuzzy set MCE model 1), on balance, most closely approximate the real world data. Therefore, the fuzzy multi-criteria evaluation model associated with the cluster 2 data set certainly does not provide **improved** predictions, in terms of replicating the relative pattern of real world sedimentation data, over that associated with the population data set as was the intention. As a result of this, the model was not operationalized and a respective defuzzification model was not developed. The fuzzy set multi-criteria model associated with the population data set is therefore the most valid and robust in predicting the degree of reservoir sedimentation for this investigation.

Figure 6.21 Comparison of fuzzy set MCE model 1 output, fuzzy set MCE model 2 output & observed APL rates expressed as z-scores



Therefore, in this instance, the postulated optimization of the fuzzy set modelling methodology has not yielded improved predictions of the degree of reservoir sedimentation as it did for multiple regression analysis in predicting reservoir annual percentage capacity loss. This can be partly attributed to the inclusion of the trap efficiency and coniferous woodland variables in the analysis. As identified in Sections 4.2.2.5 and 5.8.5.1, the relationship between reservoir sedimentation and TE may be positive or negative depending upon whether the reservoir capacities extracted from the BRE dams data set (used to calculate TE across the population data set) relate to original or revised capacities respectively. The broad assumption is that the majority of the values relate to original capacities, thus typically inducing a positive relationship between reservoir sedimentation and TE, therefore a positive fuzzy membership curve was specified. This assumption, however, is flawed for reservoirs in the population data set with trap efficiencies calculated from revised capacities due to progressive sedimentation reducing trap efficiency from the time of dam commission, thus inducing a broadly negative relationship (Section 5.8.5.1). However, as previously mentioned, the fact that TE has the lowest weighting in the weighted linear combination aggregation procedure (Table 6.15) means that the factor has a very small, practically negligible influence on the model output.

Perhaps of greater significance regarding why fuzzy set MCE model 2 has not produced results showing a stronger correlation with observed APL concerns the incorporation of coniferous woodland in the analysis. Whilst the literature supports the influence natural woodland has on reducing erosion and potential sediment delivery (e.g. Cheng *et al.*, 2002), studies by Stretton (1984, 1998), Burt *et al.*, (1984), Duck and McManus (1987), Stott (1987) and Foster and Lees (1999b) have all identified increased sediment yields associated with afforestation initially, which typically decline over time as the vegetation matures (Section 2.11.1.6.1). As a result of this, the broad assumption reflected in the fuzzy membership curve of coniferous woodland is that as the average percentage catchment cover increases, the degree of reservoir sedimentation decreases. This is supported through the positive direction of the (albeit non-significant) Pearson correlation coefficient between average percentage catchment cover of coniferous woodland and observed APL (0.107 - Table A1.4, Appendix 1). However, the influence of afforestation on sediment yield/reservoir sedimentation clearly changes over time and such temporal changes are not represented in the modelling approach. Therefore, the differing amount of time that has elapsed since afforestation for each catchment clouds the derivation of a broad, overarching direction of influence of afforestation on reservoir sedimentation: for some reservoir catchments the influence of afforestation may be increasing sediment yield, whilst for others it may be having the inverse effect.

This again highlights the major problem associated with the general modelling approach employed in this investigation; it does not consider temporal changes in the variables identified to influence reservoir sedimentation. Both the multiple regression and fuzzy set multi-criteria evaluation modelling approaches are lumped spatially and temporally. However, such temporal data are not readily/widely available for every reservoir in the population data set. Therefore, as discussed through Chapter 3, this general approach at present represents the most practical in terms of achieving the principal aim; the production of a comprehensive assessment of the spatial variation of reservoir sedimentation for the population of surface water storage reservoirs exhibiting a degree of catchment-coupling across mainland England and Wales.

The correlation between the output from both fuzzy set MCE models and the observed APL values, whilst both significant, may have been degraded by the omission of variables also important in influencing reservoir sedimentation from the respective population and cluster 2 data sets, thus inducing structural error into the models. As discussed in Section 5.17 in relation to the multiple regression analyses, important variables influencing reservoir sedimentation defining/describing factors such as the hypsometric integral, drainage density, dam dimensions, reservoir sediment control structures, management strategies, allochthonous wet and dry deposition, autochthonous sediment production and the influence of small anthropogenic landscape elements (e.g. banks, hedges, tillage directions etc.) were not included as they were not represented, readily quantifiable, easily calculable or complete in the widely available secondary data sources. However, whilst membership functions could not be derived for each of these variables even if they were quantifiable in the population data set due to the restriction of a maximum 24 variables being entered into the Idrisi 32 FUZZY module; they could all have been included in the principal components analysis to provide a more comprehensive identification of those variables with the largest eigenvectors, influencing the principal components to the largest degree. The restriction, however, of the number of variables that can be entered into the Idrisi 32 FUZZY module represents a limitation of the software as opposed to the modelling technique itself.

7. Discussion of modelling approaches

7.1 Introduction

This chapter represents the fulfilment of objective four: the evaluation and comparison of the multiple regression and fuzzy set multi-criteria approaches, and the subsequent selection of the most robust and reliable model in the prediction of sedimentation for the defined reservoir population.

Multiple regression and fuzzy set MCE represent two different techniques that can be used to construct empirical models predicting reservoir sedimentation from catchment and reservoir basin factors.

7.2 Multiple regression analysis summary

Through multiple regression analysis, two models were produced; the first predicting the reservoir annual percentage capacity loss (APL) for the population; the second predicting APL for a cluster of the population (identified through cluster analysis) that was most represented in the parameterization data set (cluster 2). The first model was produced in an attempt to satisfy the principal aim of the research: the production of a comprehensive assessment of the spatial variation of reservoir sedimentation for the population of surface water storage reservoirs exhibiting a degree of catchment-coupling across mainland England and Wales. The second model was produced to assess the potential of the clustering technique in achieving the principal aim through improving the multiple regression output.

The most robust, valid multiple regression model predicting APL for the population data set was Equation 5.1:

$$APL = 0.409 + (0.011 \times S686) - (0.009 \times TE) + (0.05 \times RMED1H) \qquad \text{(Eq. 5.1)}$$

However, this model could not be verified because the correlation between the observed and predicted APL data series for the parameterization data set was heavily influenced by two cases enforcing the perceived linear relationship. In addition, through the paired T-test analysis, the difference in means between the two respective data series was significantly different from zero. As a result of the poor integrity of the model, Equation 5.1 could not be validated either. A poor, non-significant correlation was determined between the observed APL and predicted APL of the validation data set (r = -0.673, significant at 0.213), and a corresponding paired T-test identified a significant difference between the two data series.

The most robust, valid multiple regression model predicting APL for cluster 2 was Equation 5.8:

$$APLSQRT = 0.988 + (0.009 \times S686) - (0.011 \times TE) + (0.0002 \times SAAR4170) \quad \text{(Eq. 5.8)}$$

In contrast to Equation 5.1, Equation 5.8 was verified to a reasonable degree with the correlation between the observed and predicted data series for the respective parameterization data set being significant and marginally less heavily influenced by a small number of observations (r = 0.702, significant at the 0.01 level). In addition, the paired T-test between the respective data series yielded no pairwise difference significant from zero. As a result of the improved integrity of Equation 5.8 over Equation 5.1, it could be validated to a reasonable degree. A strong correlation coefficient of 0.915 (albeit not significant below the 0.05 level at 0.264) was obtained between the observed and predicted APL of the cluster 2 validation data set, with the paired T-test between the respective data series identifying no pairwise difference significant from zero.

From these results, the production of a model for a particular cluster of alikeness in the population data set (Equation 5.8 for cluster 2) yields a more robust, valid result in comparison to one produced for the entire population (Equation 5.1). The approach of performing multiple regression analysis on groups of reservoirs with similar characteristics (identified through cluster analysis) reduces residual variation, identifying reservoirs with stronger correlations between sedimentation-influencing variables than others. Therefore, within clusters, stronger linear relationships are apparent. This induces greater compliance with the regression assumptions of residual constant variance and normality (Norusis, 1994). However, whilst the regression assumptions are more closely met by Equation 5.8 in comparison to Equation 5.1, the former is still reliant on a small number of highly influential observations inducing the constituent linear relationships, thus undermining the integrity of the model that is associated with a robust multiple regression equation. This is observed through both models having small numbers of predictions in each respective parameterization data set that fall within 95% confidence intervals of population APL conditional mean prediction (Equation 5.1 has three such predictions from a parameterization data set of 60 reservoirs, Equation 5.8 has 2 from a parameterization data set of 51). This is the major problem that besets the application of multiple regression in this study; the satisfaction of the rigorous assumptions of the technique by parameterization data to ensure a robust, valid, reliable result.

As discussed in Section 5.17.3, both Equations 5.1 and 5.8 incorporate a problematic partial regression coefficient specifying a negative relationship between APL and TE. This is caused by reservoirs with **revised capacities** listed in the BRE dams data set (used to calculate TE) inducing a broadly negative relative relationship between APL and TE, whereas those with **original capacities** listed inducing a positive relationship. Unfortunately, through the BRE dams data set alone, there is no way of affirming what each listed capacity relates to (Section 5.8.5.1). Whilst the reservoirs in the parameterization data set each have a revised capacity listed in the BRE dams data set (obtained from studies collated in the Halcrow (2001) data set), it is highly likely that for the majority of the population data set the respective capacities in the BRE dams data set relate to original capacities as reservoir sedimentation is not generally perceived to be a problem across England and Wales (Chapter 2), thus not prompting many revised basin capacity surveys. As a result of this, the inference/predictions from both equations regarding reservoirs with original capacities used to calculate TE may be misleading.

Labadz *et al.* (2002) identify the importance of reservoir basin factors in influencing the rate of basin infilling (Section 2.11.2). Through the compilation of the population data set (Section 4.2) the only variable representing reservoir basin factors is trap efficiency. Heinemann (1981) states that trap efficiency is the most important descriptor of a reservoir.

As a result of this, despite the degree of aforementioned error and uncertainty associated with the calculation of TE, it was deemed important to include the variable in the population data set, leaving it available for multiple regression model incorporation through the stepwise variable selection procedure. In retrospect, the incorporation of trap efficiency in the multiple regression analyses calculated from the reservoir capacities in the BRE dams data set may appear fundamentally wrong. This is due to the potential difference in the direction of the relationship between APL and TE depending upon whether an original or revised capacity is considered. However, the multiple regression approach is unsuitable for this particular application due to the fact that a small number of cases induce significant correlations between the observed APL variants (APL, APLLOG10, APLSQ, APLSQRT) and each of the potential the independent variables available for model incorporation concerning sedimentation prediction across the population data set and the cluster 2 population data set. Therefore, **each** of the potential linear relationships available for incorporation into the respective models through the stepwise variable selection procedure appear unsound and not robust (Figures A2.1-A2.228 and Figures A2.229-A2.456, Appendix 2). In relation to those variables other than TE actually incorporated into Equation 5.1 predicting APL across the population data set (S686 and RMED1H), and Equation 5.8 predicting APLSQRT across the cluster 2 population data set (S686 and SAAR4170), each respective partial regression coefficient is unduly reliant upon a small number of highly influential observations (as identified through the respective leverage statistics in particular). Therefore, regardless of whether the TE variable is omitted from the analyses or not, multiple regression models would still be produced that do not satisfy the fundamental assumption of linearity. This would have repercussions in the satisfaction of the assumptions of residual constant variance and residual distribution normality (Norusis, 1994).

7.3 Fuzzy set multi-criteria evaluation summary

Through fuzzy set multi-criteria evaluation, two fuzzy set models were produced; the first predicting the degree of sedimentation for the population data set; the second predicting the degree of reservoir sedimentation for cluster 2 from the population data set. The former was verified and validated to a reasonably good degree. A reasonably good, significant correlation was obtained between the predicted fuzzy number and observed APL of the parameterization data set (r = 0.491, significant at the 0.01 level – Table 6.3) which demonstrated a general progression towards a linear relationship (Figure 6.1). In addition, no pairwise difference between the respective means, significant from zero, was identified through the corresponding paired T-test (Table 6.3). In comparison to the multiple regression analysis, this result was deemed more robust and reliable as no assumptions associated with the modelling technique were refuted.

The second fuzzy set MCE model was developed to investigate the potential of the clustering approach applied to fuzzy set multi-criteria evaluation in producing a more robust, valid model through the consideration of corresponding variables most strongly influencing reservoir sedimentation in a cluster (cluster 2). However, the clustering technique did not yield an improved output. Whilst the paired T-test between between the respective z-score data series identified no significant difference from zero for the mean of the pairwise differences acorss the cluster 2 parameterization data set, the respective correlation coefficient between the two data series was lower in comparison to that of the population data set at r = 0.312 (Table 6.18). The consideration of coniferous woodland within the respective model (which has been a significant land use change affecting catchments across England and Wales during the lifetime of the reservoir population) and trap efficiency could account for this (Section 6.16).

7.4 Comparison of modelling approaches

The fuzzy set MCE approach produces more robust, valid, reliable models of greater integrity than the multiple regression models (Equations 5.1 and 5.8). This is due to the technique accounting for uncertainty and vagueness regarding the quantification and specification of catchment and reservoir basin factors associated with sediment production and delivery processes. It was this uncertainty and vagueness that undermined the multiple regression results (Section 5.16). In addition, the fuzzy set MCE approach predicting the degree of reservoir sedimentation across England and Wales does not include the trap efficiency variable which can exhibit conflicting relationships with reservoir sedimentation depending upon whether an original or revised reservoir capacity has been used in its calculation.

Fuzzy set multi-criteria evaluation incorporating weighted linear combination (WLC), unlike multiple regression, does not attempt to statistically fit a multidimensional surface to a series of independent variables by defining the precise nature of a perceived linear relationship between a dependent variable. Instead, the value of each respective independent variable observation is fuzzified - scaled between 0 and 1 through a fuzzy set membership curve (scaled between 0 and 255 in Idrisi 32), depicting its degree of influence on the process being modelled. Unlike regression, because the arbitrary degree of influence a respective independent variable value has on a dependent variable (e.g. reservoir sedimentation) is being determined and not a specific related output quantity (e.g. APL), error (measurement and specification) and uncertainty associated with the quantification of both variable values and the specification of a respective relationship is being accounted for.

An important characteristic of the membership curve depicting the degree of influence a variable has (on reservoir sedimentation in this instance) is that it is defined subjectively on the basis of real world observation and expert scientific knowledge and intuition. In addition it can take many forms (e.g. sigmoidal, J-shaped, user-defined) and does not have to specify linear relationships. In regression, the definition of a linear equation through least squares analysis is analogous to the fitting of a fuzzy set membership curve. However, the important difference is that least squares analysis defines the influence a variable has on an output statistically, and does not consider expert scientific knowledge and opinion which can intuitively assess the degree of reservoir sedimentation over and above the issue of error and uncertainty. In addition, through least squares analysis, the depiction of the influence variables have on reservoir sedimentation is constrained through being forced to comply with a linear relationship. This again demonstrates how, in the context of regression, fuzzy set multi-criteria evaluation accounts for specification error regarding the nature of the relationship between independent and dependent variables.

The application of the fuzzy set multi-criteria approach is also more suited to the achievement of the principal aim of the investigation: the production of a comprehensive assessment of the spatial variation of reservoir sedimentation for the population of surface water storage reservoirs exhibiting a degree of catchment-coupling across mainland England and Wales. This is because the technique encompasses the whole population from the outset, eliminating the requirement for a model parameterization data set (as required in multiple regression). This eliminates problems regarding parameterization data set representativeness and potential restrictions regarding extrapolation, as occurred with the application of the multiple regression models (Equations 5.1 and 5.8).

In some model applications predicting reservoir sedimentation, an actual rate as predicted through multiple regression may be more preferable than a predicted arbitrary degree of sedimentation through fuzzy set MCE. Section 6.7 identifies how the fuzzy set MCE model 1 output can be defuzzified into an actual APL quantity. The most robust, reliable defuzzification model obtainable (Equation 6.3) was verified to a reasonable degree; a correlation coefficient of 0.453 (significant at 0.01) (Table 6.10) was obtained between the defuzzified APL and observed APL of the parameterization data set which demonstrated a general progression towards a linear relationship (Figure 6.11). In addition, the paired T-test identified that the difference in means between the respective data series was not significantly different from zero (Table 6.10). With regards to validation, the predicted output from Equation 6.3 produced a good correlation coefficient of 0.507 between the defuzzified APL and observed APL of the validation data set (although only significant at 0.305) (Table 6.13), and through paired T-test analysis, no significant difference from zero for the mean of the pairwise differences between the respective data series was identified (Table 6.13). Whilst this defuzzification model (Equation 6.3) is not verified and validated to the same reasonably good degree as the fuzzy set MCE model 1 output, it is associated with greater user-confidence than the multiple regression models of Equations 5.1 and 5.8: 35% of the observed APLSQRT values fall within 95% confidence intervals of the respective parameterization data set predictions. This is in comparison to 5% and 4% for Equations 5.1 and 5.8 respectively falling within a 95% confidence interval. Indeed, the use of simple linear regression as a defuzzification model is theoretically sounder than in the prediction of reservoir APL from catchment and reservoir basin factors. A linear relationship can be justified between reservoir APL and the degree of sedimentation predicted through the fuzzy set MCE model. Price *et al.*, (2000b) and Thiemann *et al.*, (2001) state that hydrological systems are inherently non-linear, undermining the theoretical application of linear regression in directly modelling reservoir sedimentation.

Whilst the output from the regression defuzzification model is theoretically sounder and more robust than that of Equation 5.1 predicting reservoir APL from catchment and reservoir basin factors, it does not account for the same degree of error and uncertainty as the original fuzzy set MCE model 1 output. As discussed above, through the fuzzy set MCE model measurement error and specification error is accounted for in the prediction of the degree of reservoir sedimentation (fuzzy number). However, when the range of predicted fuzzy numbers are assigned to a new ordinal scale (reservoir APL) through simple linear regression, measurement error concerning the observed APL rates and specification error concerning the low model coefficient of explanation at only 0.21 is introduced. Therefore, the defuzzification model acts to degrade the integrity of the original fuzzy set MCE model 1 output. However, the fact that error and uncertainty have been accounted for in the fuzzy number prediction (the independent variable of the regression defuzzification model) means that the associated APL predictions are comparatively sounder than those associated with Equation 5.1.

Whilst both multiple regression and fuzzy set MCE are techniques that can be used to produce empirical models predicting reservoir sedimentation, fuzzy set MCE has greater explanatory power. In regression, the independent/explanatory variables do not assume deep, metaphysical implications; they merely identify the direction of explanation (Lunneborg, 1994). Through the nature of stepwise multiple regression, the variables selected from the parameterization data set are those which exclusively account for the most variance about a least squares line of best fit (i.e. those which satisfy the strict assumptions of linearity and non-multicollinearity). As a result, the corresponding explanatory variables in the computed model can only look at part of a complex theoretical structure (which is not even fully represented in the parameterization data set). Often this means that the postulated explanation through a multiple regression model maybe relatively weak (Lunneborg, 1994). Therefore, regarding this application of multiple regression, it is not only the nature of the parameterization data that contributes to the formulation of models with relatively weak predictive and explanatory power, but also the nature of the technique itself. In comparison, fuzzy set MCE considers (in theory) all variables in the parameterization data set, which in this application represents the most comprehensive collation of variables obtainable depicting the complex theoretical structure of reservoir sedimentation. Therefore, through the analysis of the fuzzy numbers produced for each variable, one can ascertain which variables are most significant in inducing sedimentation in each reservoir.

However, both modelling approaches are subject to potential structural error in the prediction of reservoir sedimentation through the absence of variables defining/describing catchment hypsometric integrals, drainage density, dam dimensions, reservoir sediment control structures, management strategies, allochthonous wet and dry deposition, autochthonous sediment production, and the influence of small anthropogenic landscape elements (e.g. banks, hedges, tillage directions etc.) etc., all of which exert an influence on reservoir sedimentation. Variables defining/describing these factors are not all readily quantifiable/complete/easily calcuable in the secondary data sources used to collate the independent variables to predict reservoir sedimentation with respect to the large population of reservoirs. As a result, within the timeframe of this research, it was not deemed practical to attempt to determine such variables through primary data collection.

In smaller scale studies, such primary data collection is achieveable practically and logistically. For example, in a small scale study predicting reservoir sedimentation in Spain, Verstraeten *et al.* (2003) undertook primary data collection to assign a score to each reservoir catchment in the model parameterization data set representing the steepness of the slopes near the reservoir and main rivers, and the elevation within five km. This was based on Verstraeten and Poesen's (2001) observations concerning the spatial distribution of slopes within a catchment influencing the magnitude of sediment yield. Where steeper slopes are located in the most remote regions of a catchment, near the drainage divide, eroded soil particles need to travel longer distances to the catchment outlet and are therefore more prone to deposition. In contrast, where steeper slopes are distributed throughout the catchment, the mean travel distance of eroded soil particles will be lower, reducing the potential for deposition. However, concerning the study herein, such primary data collection was not possible practically and logistically within the timescale of the research due to the large scope of the investigation.

The influence, however, of structural error on the predictions from the respective models is somewhat of an illusion as, in the context of the population of reservoirs across England and Wales, these variables defining/describing the aforementioned factors may not be amongst those accounting for the principal variation (which are extracted in both modelling approaches and used as predictor variables).

Through the formulation of the multiple regression and fuzzy set MCE models a small number of residuals (predicted measures of reservoir sedimentation subtracted from observed measures) are produced in each instance, identifying respective under-predictions (positive residuals) and over-predictions (negative residuals). Typically these residuals are produced due to specific catchment area conditions that may well be accounted for through the aforementioned variables which were absent from the population data set, but which are always likely to occur when compiling a model parameterization data set that generalizes a particular process (e.g. reservoir sedimentation) over such a large population. Different reservoirs appeared as residuals for each model due to the different number of reservoirs and/or transformation of variable values being represented in the respective parameterization data sets. However, the consistent representation of Abbeystead, Blakeley, Scammonden and Tunnel End reservoirs as positive residuals for each model was due to their extremely high observed APL rates induced by, as previously mentioned, specific catchment conditions.

7.5 Temporal variation

A fundamental problem associated with the general modelling approach adopted in this investigation (concerning the prediction of reservoir sedimentation from the catchment and reservoir basin factors collated in Chapter 4) is that temporal variation in the independent/predictor variables is not considered. Therefore, through multiple regression model parameterization, "present day" values of catchment and reservoir basin factors are being related to an observed annual sedimentation rate, yet these may not have been responsible for inducing the total quantity of capacity loss. The observed annual sedimentation rate is an "aggregated average sedimentation rate" for the majority of the parameterization data set (determined through the subtraction of a revised reservoir capacity from the original capacity, and the division of corresponding loss by the age of the reservoir), so such temporal changes in reservoir sedimentation rates cannot be discerned. The effect of parameter non-stationarity induces error into the multiple regression models, as discussed in Section 5.16.3.

The assumption of stationarity of catchment and reservoir factor values also induces error into fuzzy set MCE model verification and validation. Here the degree of reservoir sedimentation, as predicted by "present day" fuzzy set membership values of catchment and reservoir basin factors, is compared with an observed aggregated sedimentation rate that may have been influenced by different respective fuzzy set membership values over time. This is also manifested in the defuzzification model (Equation 6.3). The influence of changing coniferous land cover over the lifetime of the reservoir population contributed to the fuzzy set MCE model 2, predicting the degree of reservoir sedimentation over the cluster 2 population of reservoirs, not producing a result of greater validity over fuzzy set MCE model 1, predicting the degree of reservoir sedimentation for the complete population (Section 6.16). Whilst mature forest stands are associated with reduced sediment yield (Cheng *et al.*, 2002), in the context of afforestation sediment yields have been shown to dramatically increase during ground preparation for planting and then typically decline as the vegetation matures (e.g. Stretton, 1984, 1998). As a result of this, the broad assumption reflected in the fuzzy membership curve of coniferous woodland that as the average percentage catchment cover increases, the degree of reservoir sedimentation decreases, may be inaccurate depending upon the period of time that has elapsed since respective catchment planting.

However, Cisternas *et al.* (2001) attempted to correlate lake sedimentation rates with temporal changes in land use (total detectable change rate - % yr^{-1}) identified from aerial photographs taken in 1943, 1955, 1961, 1978, 1981 and 1994. From the six land uses investigated (native forest, heterogeneous bush, deforested areas, exotic forest, urban and grassland), the strongest results were the reasonable positive and negative correlations produced between sediment yield, and exotic forest and grassland respectively. However, even these trends were statistically insignificant. This identifies the difficulty in accounting for land use changes in lake/reservoir sedimentation studies. Such an approach could not have been adopted for the research herein as such detailed catchment information is not readily/practically available for the population of catchment-coupled surface storage reservoirs across England and Wales.

7.6 Conclusion

Despite the issue of temporal variation, fuzzy set MCE model 1 is verified and validated to a reasonably good degree and through the preceding discussion, represents the more suitable, effective technique in investigating the principal aim of this research. A greater degree of user-confidence is associated with this modelling approach because it accommodates uncertainty and vagueness associated with the complex processes of sediment production and delivery to a reservoir basin, and produces a theoretically sounder output. Thorn (1988) states that in evaluating any model, it must be remembered that because they are a simplification of reality, they will always be partial and consequently incorrect to some degree. This reaffirms the effectiveness of the fuzzy set MCE model 1 in predicting the degree of reservoir sedimentation for the population of directly catchment-coupled surface storage reservoirs across mainland England and Wales.

Shannon (1975) states that the purpose of a model is to assist in explaining, understanding, or improving the system under investigation, with one of the most important functions of models being prediction. The fuzzy set MCE model 1 and associated defuzzification model (Equation 6.3) comply with this, and the criteria that define a good model:

- Simple to understand by the user,
- Goal directed, i.e. the objectives of the model must be remembered so that the appropriate model will result,

- Robust, in that it does not give absurd answers,
- Easy for the user to control and manipulate, i.e., it should be easy to communicate with,
- Adaptive, with an easy procedure for model modification or updating (Shannon, 1975).

8. Conclusions

The principal aim of this research was the production of a comprehensive assessment of the spatial variation of reservoir sedimentation for the population of surface water storage reservoirs exhibiting a degree of catchment-coupling across England and Wales. This was achieved through the accomplishment of the four research objectives:

1. The collation of secondary data from standard, widely-available sources for the defined reservoir population. These standard, widely-available data sources incorporate the BRE dams data set, the Flood Estimation Handbook (1999), the national soils map of England and Wales, and the land cover map of Great Britain that together depict catchment and reservoir basin factors that influence reservoir sedimentation.

2. The collection of primary data concerning reservoir annual percentage capacity loss rates to supplement the parameterization data set collated from the literature ensuring it is representative of the defined reservoir population, and form a validation data set.

3. The production of two parameterized, verified, validated and operationalized empirical models predicting reservoir sedimentation for the defined reservoir population from catchment and reservoir basin factors using two different modelling techniques: multiple regression analysis and fuzzy set multi-criteria evaluation. The former represents a more traditional empirical modelling approach; the latter has not been applied in such studies before.

4. The evaluation and comparison of the multiple regression and fuzzy set multi-criteria approaches, and the subsequent selection of the most robust and reliable model in the prediction of sedimentation for the defined reservoir population.

Through objectives 1 and 2, the most comprehensive parameterization data set to date of independent variables influencing reservoir sedimentation across England and Wales was compiled. The 57 independent variables (Table 4.5) were obtained from the FEH (1999) CD-ROM, the BRE dams data set (Tedd *et al.*, 1992), and the land cover and soils maps of England and Wales. In addition to this, the most comprehensive validation data set obtainable within the timeframe of the research was collated.

Through objective three the most robust, reliable and valid multiple regression model obtainable from the parameterization data set (Equation 5.1) was developed to predict reservoir annual percentage capacity loss due to sedimentation (APL) across the population. However, Equation 5.1 could not be verified and validated to any reasonable degree due to violations of the regression assumptions of linearity, residual constant variance and residual distribution normality, thus inspiring little user-confidence in the robustness and reliability of the model output. As a result, when operationalized, the output from Equation 5.1 (Figure 5.9) produced surprising results; predicted APL appeared most severe in the south central/southeast region of England where variables identified to influence catchment sediment production and reservoir sedimentation (e.g. high mean annual rainfalls, large trap efficiencies, steep relief and strong hillslope-channel coupling) are of a lower magnitude in comparison to other areas of England and Wales (e.g. the Pennines, Cumbria and Brecon Beacons). However, through the stepwise multiple regression process formulating Equation 5.1, the incorporation of an apparently problematic negative relationship between trap efficiency (TE) and APL acted to induce this result (Section 5.8.5.1). This was caused by the reservoir capacities listed in the BRE dams data set being an unidentified mixture of original and revised capacities. A broadly negative relationship may be expected when revised capacities are used to calculate TE for every reservoir in the population data set; conversely, a positive relationship is expected when original capacities are used to calculate TE for every reservoir in the population data set. However, neither can be properly ascertained due to the aforementioned mixture of original and revised in the BRE dams data set. There have been no published studies concerning reservoir sedimentation across southeast England; therefore it is highly likely that original capacities have been used to calculate these respective trap efficiencies. As a result of this, they should conform to a positive relationship between APL. However the respective partial regression coefficient specifies a negative relationship due to the undue influence of Abbeystead and Blakeley reservoirs which have extremely high APL rates in relation to their trap efficiencies (being calculated from revised capacities). Therefore, the application of multiple regression analysis (through the operationalization of Equation 5.1) to predict reservoir sedimentation across the population data set, in compliance with the principal aim, proved unsuccessful.

To improve the coefficient of explanation and robustness of multiple regression models through the establishment of stronger linear relationships between dependent and independent variables, Jansen and Painter (1974) and DeBonis *et al.* (2002) employed a clustering technique to predict sediment yields whereupon complete data sets were broken up into separate clusters of alikeness (using cluster analysis), and multiple regression models subsequently parameterized for each cluster. This improved coefficients of determination over models parameterized for the respective complete data due to a reduction in residual variance. The residual variance was reduced as stronger correlations existed within the clusters between sediment yield and erosion/sediment transport inducing variables. As a result of this, the clustering technique was employed, albeit only on cluster 2 from the population data set - the only cluster that was adequately represented in the parameterization data set (Section 4.3.1.2). Consequently, this assessed the **potential** of the clustering technique used with multiple regression analysis in achieving the principal aim. However, the respective model (Equation 5.8), whilst verified and validated to a reasonable degree, still refuted the assumption of linearity in particular, being unduly reliant upon a small number of cases, thus undermining the integrity of the model. In addition, the aforementioned problematic relationship between APL and TE was represented as a partial regression coefficient.

A principal reason for the relative failure of multiple regression in reservoir sedimentation prediction was the inability of the approach to account for inherent error and uncertainty associated with the quantification of the dependent and independent variables of the parameterization data sets, and the specification of the respective relationships.

The fuzzy set multi-criteria evaluation (MCE) modelling approach did yield a model predicting the degree of reservoir sedimentation across the population data set that was verified and validated to a reasonably good level (fuzzy set MCE model 1). The operationalization of the model identified the upland areas of Cumbria, the Brecon Beacons and Cambrian Mountains of Wales, the southern Pennines, and Exmoor and Dartmoor in Devon, as experiencing the largest degree of reservoir sedimentation (Figure 6.4). This is principally attributed to these areas having high mean annual rainfall and large areas of highly erosive soil types. In addition, the model output identified reservoirs in the Weald and the Vales of Kent and Sussex as experiencing reasonable degrees of sedimentation. This is an interesting insight, as sedimentation has not been perceived to be a problem across southeast England, with no major studies being published. This is principally attributed to the relatively high degree of open shrub land cover and erosive soil types, particularly shallow peaty/silty soils overlying the sandstone Hastings Beds that comprise the catchments.

The most robust, reliable defuzzification model (Equation 6.3) associated with fuzzy set MCE model 1 was verified and validated to a reasonable degree. Upon operationalization, Equation 6.3 produced the same relative pattern of reservoir sedimentation across England and Wales as that of fuzzy set MCE model 1. Therefore, this model is a useful tool in providing actual reservoir sedimentation rate (APL) predictions. However, whilst the defuzzification provides a theoretically sounder prediction of APL over Equation 5.1, it does act to degrade the integrity of the original fuzzy set MCE model 1 output through the introduction of measurement error concerning the observed APL rates and specification error concerning the low model coefficient of explanation at only 0.21.

Analogous to the multiple regression modelling approach, fuzzy set multi-criteria evaluation was employed on cluster 2 in an effort to improve the degree of reservoir sedimentation prediction through establishing the principal sedimentation-influencing variables and associated weightings that account for the most variation within a cluster from principal components analysis. It was postulated that these principal variables would be potentially more representative of the factors/processes influencing sedimentation in the cluster of reservoirs than those variables and associated weightings extracted from principal components analysis performed on the complete population; producing fuzzy number results through WLC more strongly correlated with respective annual percentage capacity loss observations. However, a model of greater validity in comparison to fuzzy set MCE model 1 was not produced. This was primarily attributed to the model not accounting for the temporal variation of sediment delivery associated with coniferous afforestation, which has been a significant land use change affecting catchments across England and Wales during the lifetime of the reservoir population. The broad assumption concerning coniferous woodland in the respective fuzzy set membership curve is that as the average percentage catchment cover increases, the degree of reservoir sedimentation decreases. However, in the context of catchment afforestation, sediment yields dramatically increase during ground preparation for planting, which typically decline as the vegetation matures.

Through the investigation of objective four, from the comparison of the modelling approaches, fuzzy set multi-criteria evaluation (MCE) was identified as the most suitable for accomplishing the principal aim. This was because, unlike multiple regression, it is able to account for error (measurement and specification) and uncertainty. In the context of this research, error and uncertainty is associated with the quantification and specification of the standard secondary data representing catchment and reservoir basin factors associated with sediment production/delivery processes. Regarding the application of multiple regression, it was because of this inherent error and uncertainty that the strict assumptions of linearity, residual constant variance and residual distribution normality were not met. In addition to this, the fuzzy set MCE approach is theoretically preferable as there is an incomplete understanding of the processes of sediment production and delivery to reservoir basins reflected through the secondary data collated in the population data set. For example, the quantified influence of sediment control structures (e.g. residuum lodges and bywash channels), reservoir management operations (e.g. reservoir drawdown and sediment flushing) and autochthonous sediment production cannot be readily determined for such a large population of reservoirs. As a result of this, the prediction of an arbitrary degree of sedimentation through fuzzy set MCE, as opposed to a precise, quantified value through multiple regression which is incorrect from the outset due to the inability to fully characterize the system, is theoretically more sound. Consequently, the fuzzy set MCE model 1 produced the most robust, valid, reliable output.

Through this research the most robust, valid and reliable large-scale lumped-empirical model to date has been constructed predicting reservoir sedimentation for the population of directly catchment-coupled surface storage reservoirs across. As a result, this has allowed the first comprehensive assessment of the spatial variation of reservoir sedimentation for the aforementioned population to be made across mainland England and Wales. The fact that a model of reasonably good validity was produced using fuzzy set multi-criteria evaluation demonstrates the utility of the approach for use in such large-scale reservoir sedimentation/sediment yield studies over the application of more traditional modelling techniques such as multiple regression. The model output (Figure 6.4) does identify where reservoir sedimentation may be a potential problem. This is extremely useful for reservoir undertakers, who on the basis of the predictions can direct further investigation into the nature of the process at a more detailed level if required. This could be in the form of a bathymetric survey to establish an accurate revised reservoir capacity, or if interested in the process of sediment production and delivery, in the form of a spatially distributed catchment area model (e.g. Van Rompaey *et al.*, 2001) which can be more easily and effectively applied at such smaller spatial scales.

9. Potential areas for future work

The research herein has provided the first comprehensive assessment of the spatial variation of reservoir sedimentation for the population of surface water storage reservoirs exhibiting a degree of catchment-coupling across England and Wales. This was achieved through the successful application of fuzzy set multi-criteria evaluation producing a lumped-empirical model. As a result of this, potential areas for future work and application of the fuzzy set MCE approach could focus upon:

1. The primary data collection of more observed reservoir sedimentation rates, spanning the range of reservoirs contained within each of the three clusters of reservoirs that share the same sedimentation-influencing factors within the population data set. This would provide more data for model verification and validation, thus producing a more comprehensive, possibly robust result. In addition, this would allow a definitive assessment to be made concerning which approach provides the most robust, valid, reliable results: fuzzy set multi-criteria models produced for the complete population data set, or those produced for the principal clusters within the population data set.

2. The application of the fuzzy set multi-criteria approach to provide the first comprehensive assessments of the spatial variation of reservoir sedimentation for the population of surface water storage reservoirs exhibiting a degree of catchment-coupling across mainland Scotland and Northern Ireland; thus providing a complete assessment across the mainland United Kingdom. This was not possible during the current study because of time and resource constraints.

3. The refinement of the fuzzy set multi-criteria evaluation approach through application at smaller, regional scales through the incorporation of variables defining/describing catchment hypsometric integrals, drainage density, dam dimensions, reservoir sediment control structures, management strategies, allochthonous wet and dry deposition, autochthonous sediment production, and the

influence of small anthropogenic landscape elements (e.g. banks, hedges, tillage directions etc.). It was not practical to investigate/attempt the derivation of variables defining/describing these factors for the larger spatial scale models produced herein, due to the required excess primary data collection. This, however, could be considered over smaller reservoir populations associated with smaller spatial scales.

4. The fuzzy set MCE approach developed herein could help assess the suitability of proposed new reservoirs sites as an integral part of a cost-benefit analysis.

5. The water companies of England and Wales, having identified the degree of reservoir sedimentation occurring over their respective regions through the fuzzy set MCE approach developed herein could target resources for more detailed monitoring/modelling/remediation where necessary. With regards to monitoring, the respective inflowing steams into the reservoir could be instrumented, collecting suspended load samples, or regular bathymetric surveys undertaken to calculate accurate revised capacities and sedimentation rates. In terms of modelling, spatially distributed catchment area models could be developed for particular catchments to obtain more information regarding the process of sediment production and delivery (e.g. Van Rompaey *et al.*, 2001; Kim and Steenhius, 2001). Regarding remediation, sediment flushing, sluicing and/or dredging could be employed (Mahmood, 1987), and/or strategies involving the reduction of sediment yield entering the impoundment. Such strategies involve either the prevention of erosion within the catchment, or the trapping of sediment before it reaches the reservoir basin. Morris and Fan (1998) identify three principal categories of techniques to reduce sediment yield entering reservoir basins:

   - Structural or mechanical measures. These include flow conveyance structures such as bywash channels and washlands (Labadz *et al.*, 1995; Harman *et al.*, 2002); channel/reservoir bank protection and stabilization methods such as revetments (e.g. gabions, riprap, geomats and sheet piling) and riparian tree species (Escarameia, 1998; Simon and Collison, 2002); sediment traps such as residuum lodges and check dams (Labadz *et al.*, 1995; Morris and Fan, 1997); and structural terraces and contour bunds (Morgan, 1995). Typically these measures act to control the movement of surface water to reduce the flow velocity, increase soil/slope stability, increase the surface storage of water, and safely dispose of runoff (Morgan, 1995).

- Vegetative or agronomic measures which rely on the natural, regenerative properties of vegetation, or the management of crop and crop residue to protect the soil (Morris and Fan, 1997). This can include the use of crop contouring, strip cropping, filter strips, conservation tillage, contour-grassed hedges, and riparian buffers (Morgan, 1995; Prosser and Karssies, 2001; Hartwig and Ammon, 2002; Jin *et al.*, 2002; Price and Lovett, 2002a, 2002b, 2002c). These hillslope erosion control measures are particularly used for agricultural land use.

- Operational measures which involve management and scheduling measures employed to minimize erosion potential. These include scheduling harvest and seed drilling activities to avoid periods of excessive soil moisture, and the scheduling of grazing to allow periods of vegetation recovery (Morris and Fan, 1997; Price and Lovett, 2002c).

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Appendix 6. Cluster Analysis Results

764	33	100.00	67877.429	123	162	123	9
765	32	100.00	69858.435	250	445	250	4
766	31	100.00	71885.004	5	33	5	51
767	30	100.00	80075.090	29	426	29	12
768	29	100.00	82117.363	5	34	5	77
769	28	100.00	82428.250	1	17	1	236
770	27	100.00	84448.275	2	111	2	32
771	26	100.00	89107.466	50	88	50	17
772	25	100.00	92746.479	110	172	110	16
773	24	100.00	95199.395	73	228	73	3
774	23	100.00	95917.122	5	241	5	85
775	22	100.00	96235.446	7	16	7	137
776	21	100.00	96473.016	123	425	123	10
777	20	100.00	99012.000	4	50	4	46
778	19	100.00	102021.031	110	164	110	17
779	18	100.00	104029.665	250	380	250	7
780	17	100.00	107212.954	13	49	13	201
781	16	100.00	122961.131	338	437	338	2
782	15	100.00	126952.681	29	123	29	22
783	14	100.00	133676.277	7	311	7	138
784	13	100.00	149669.573	2	110	2	49
785	12	100.00	198372.625	250	338	250	9
786	11	100.00	224401.232	73	250	73	12
787	10	100.00	231925.244	4	187	4	52
788	9	100.00	251690.003	5	7	5	223
789	8	100.00	486390.135	29	73	29	34
790	7	100.00	547187.061	1	4	1	288
791	6	100.00	658025.927	2	5	2	272
792	5	100.00	998013.627	2	13	2	473
793	4	100.00	1.3755E+06	29	422	29	35
794	3	100.00	4.0528E+06	2	29	2	508
795	2	50.00	1.0000E+12	2	453	2	509
796	1	0.10	1.9980E+12	1	2	1	797

Final Partition

Number of clusters: 4

	Number of observations	Within cluster sum of squares	Average distance from centroid	Maximum distance from centroid
Cluster1	288	28418458.752	253.183	1069.916
Cluster2	473	141691305.142	483.374	1332.814
Cluster3	35	5933681.408	362.211	1080.108
Cluster4	1	0.000	0.000	0.000

Cluster Centroids

Variable	Cluster1	Cluster2	Cluster3	Cluster4	Grand centrd
Catchmen	12.0381	11.3240	9.7954	1.1000	11.5021
QMED	2.3319	4.5817	11.0223	0.9490	4.0470
Mean FAR	0.8441	0.8618	0.7541	1.0000	0.8509
Flood At	0.9342	0.9209	0.9270	1.0000	0.9260
Proporti	0.3640	0.4680	0.6371	0.5700	0.4380
Mean cat	123.4271	255.9006	508.1143	294.0000	219.1543
Base flo	0.5271	0.4465	0.3235	0.3290	0.4701
Mean dra	3.1514	2.7664	2.6357	1.1000	2.8977
Mean dra	53.8490	94.7288	270.1314	166.5000	87.7494
Longest	6.1666	5.3839	5.0443	2.2100	5.6478
Median a	11.0993	11.1837	13.0714	11.7000	11.2368
Median a	34.1792	40.2975	70.2571	40.8000	39.4029
Median a	44.2594	53.2228	94.9457	58.0000	51.8221
1961-90	809.0729	1122.3340	2435.6857	1348.0000	1067.0941
1941-70	817.1285	1130.7315	2457.9143	1315.0000	1075.9235
Standard	32.7611	40.6543	52.7514	48.6000	38.3433
Concentr	0.5817	-999999.0000	-999999.0000	-999999.0000	-638644.0696
Fraction	0.0841	0.0006	0.0001	0.0000	0.0308

Index of	0.9990	-999999.0000	-999999.0000	0.0000	-637389.2149
Trap Eff	79.5082	87.8315	96.1415	91.8448	85.1938
401	0.0208	0.0381	0.0000	0.0000	0.0301
405	0.0903	0.1607	0.0000	0.0000	0.1280
454	0.0000	0.0106	0.0000	0.0000	0.0063
455	0.0590	0.2431	0.2000	0.0000	0.1744
469	0.0000	0.0613	0.0000	0.0000	0.0364
475	0.0000	0.0021	0.0000	0.0000	0.0013
486	0.0764	0.2220	0.1429	0.0000	0.1656
487	0.0000	0.0000	0.0286	0.0000	0.0013
489	0.2882	0.1776	0.1714	0.0000	0.2171
495	0.0347	0.0275	0.0000	0.0000	0.0289
506	0.0208	0.0000	0.0000	0.0000	0.0075
507	0.0347	0.0106	0.0000	0.0000	0.0188
660	0.0000	0.0085	0.0000	0.0000	0.0050
686	1.1632	1.0486	0.2571	0.0000	1.0540
692	0.0208	0.0846	0.0000	0.0000	0.0577
Ave%brac	1.9732	1.9760	0.8710	0.0000	1.9240
Ave%coni	2.8922	2.4329	1.3893	0.2500	2.5503
Ave%deci	9.5246	8.7840	8.5617	30.5000	9.0691
Ave%dshr	3.2001	3.7700	2.7923	6.0000	3.5239
Ave%dshr	0.6917	0.5566	0.4676	0.5000	0.6014
Ave%fell	0.1109	0.0833	0.0020	0.0000	0.0896
Ave%gras	4.7168	3.4860	2.8803	2.0000	3.9023
Ave%inla	0.7542	0.8077	0.9503	0.0000	0.7936
Ave%inla	1.8858	1.3941	1.5544	0.5000	1.5777
Ave%lowl	0.0597	0.0516	0.0143	0.0000	0.0528
Ave%mead	17.0563	16.9697	15.2238	2.5000	16.9062
Ave%moor	13.1730	11.5378	10.0129	9.0000	12.0585
Ave%mown	11.4506	11.8880	10.9925	14.5000	11.6939
Ave%open	5.3497	5.1247	2.7344	7.7500	5.1043
Ave%open	0.9521	1.0725	0.6378	6.2500	1.0164
Ave%roug	1.5358	1.2215	0.8359	0.0000	1.3166
Ave%rude	0.2007	0.2975	0.0771	0.0000	0.2525
Ave%scru	0.6274	0.5128	1.1332	0.0000	0.5808
Ave%subu	6.7942	7.4993	11.3471	17.0000	7.4254
Ave%till	12.6384	16.3359	23.9741	2.5000	15.3178
Ave%upla	0.4619	0.4928	0.0748	0.0000	0.4627
Ave%urba	1.8221	1.5928	1.9533	0.7500	1.6904

Distances Between Cluster Centroids

	Cluster1	Cluster2	Cluster3	Cluster4
Cluster1	0.0000	1414213.3422	1414215.2237	999999.8726
Cluster2	1414213.3422	0.0000	1893.0601	999999.0464
Cluster3	1414215.2237	1893.0601	0.0000	1000000.2748
Cluster4	999999.8726	999999.0464	1000000.2748	0.0000

06/05/2004 12:39:56

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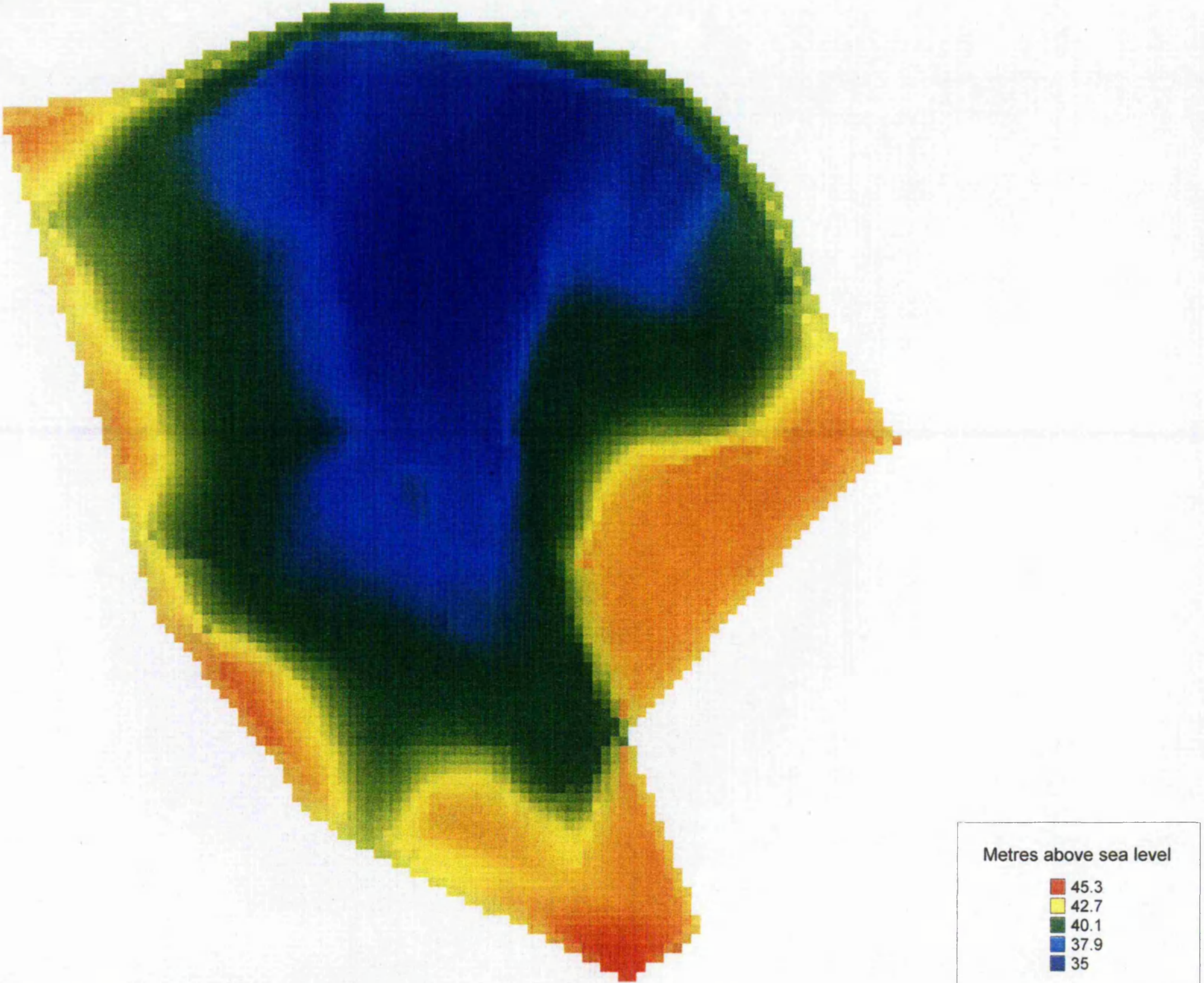
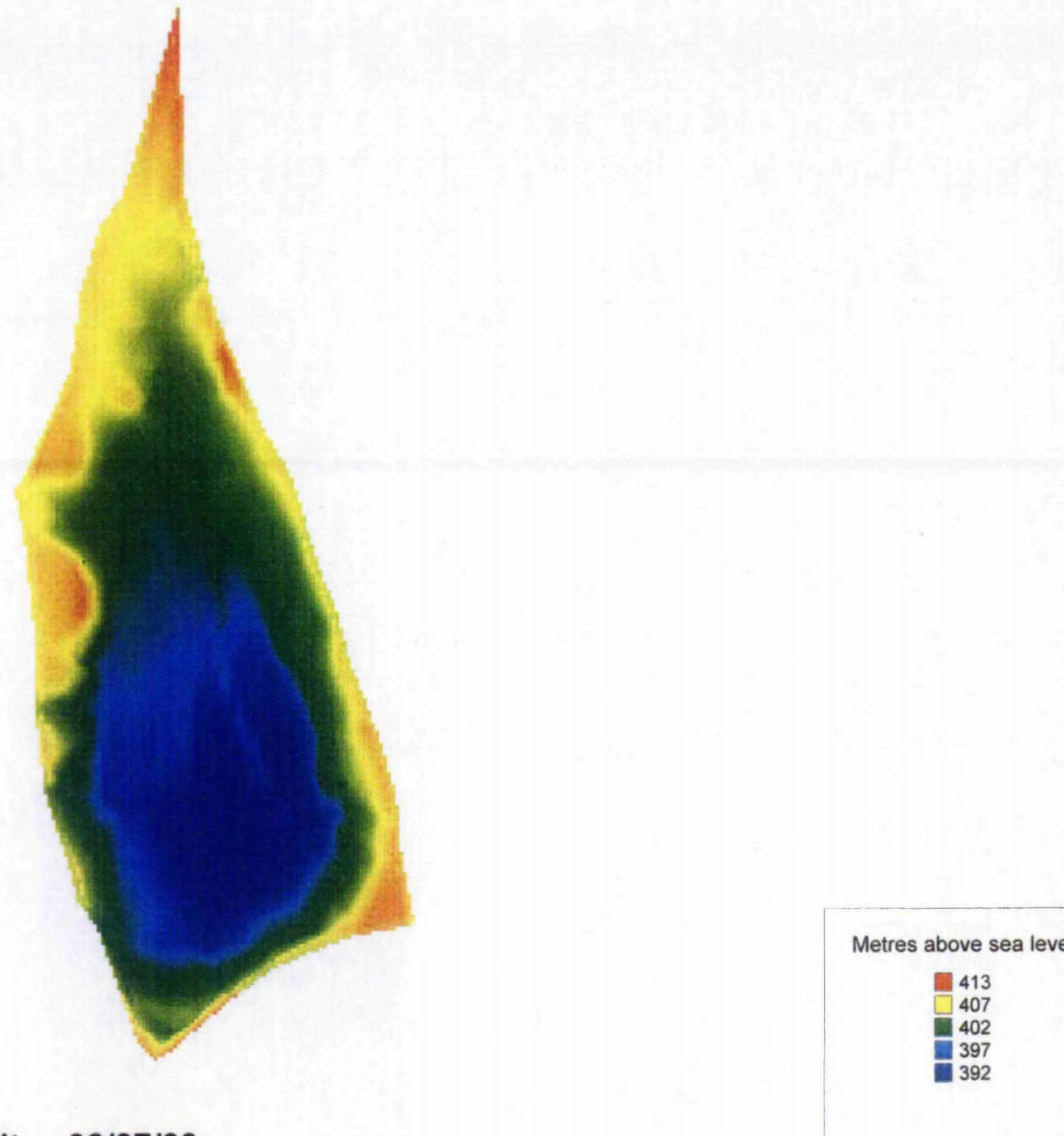
Appendix 7. Bathymetric Plots

APPLETON RESERVOIR



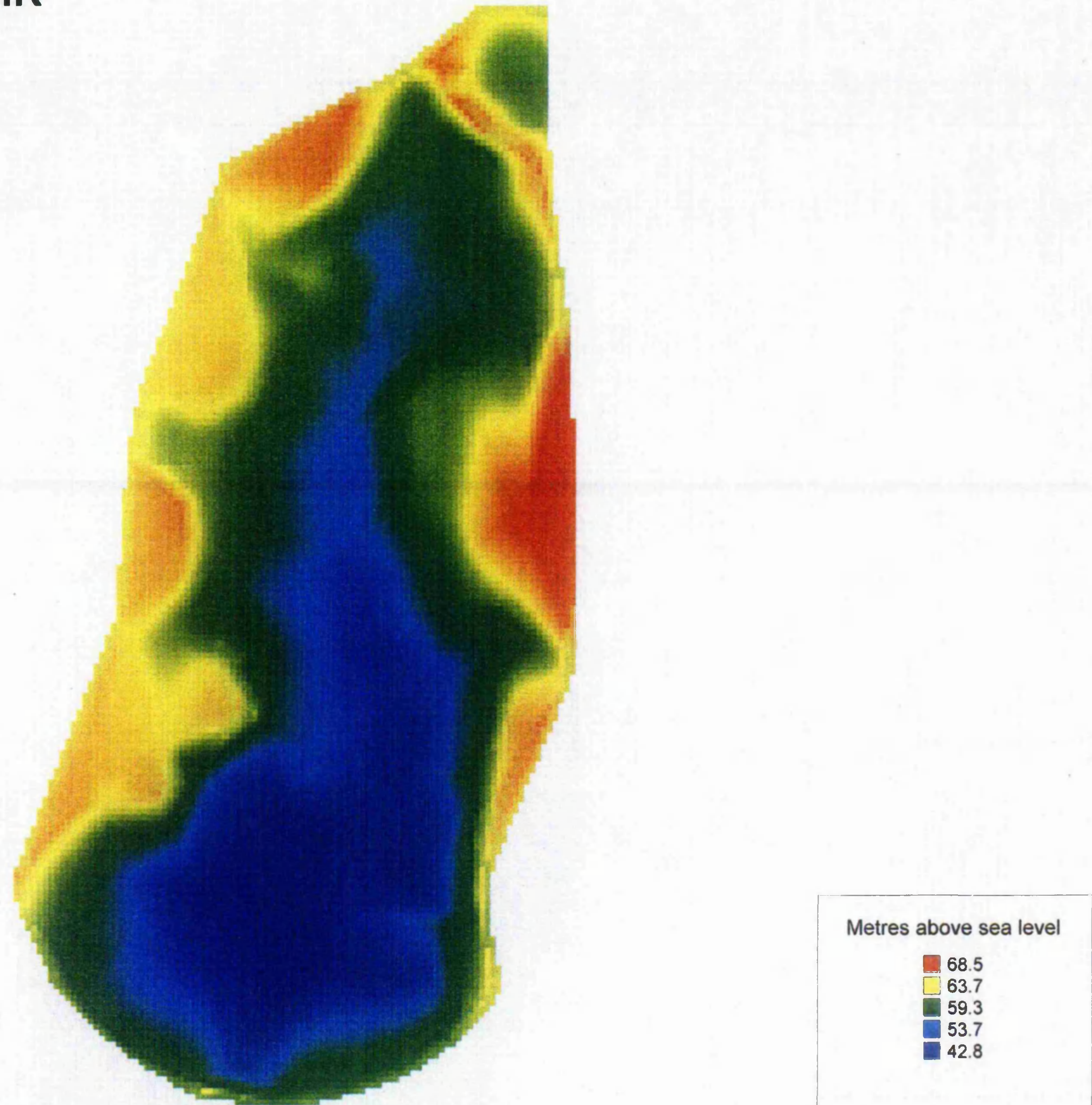
Surveyed by The Nottingham Trent University - 17/0703

BEACONS RESERVOIR



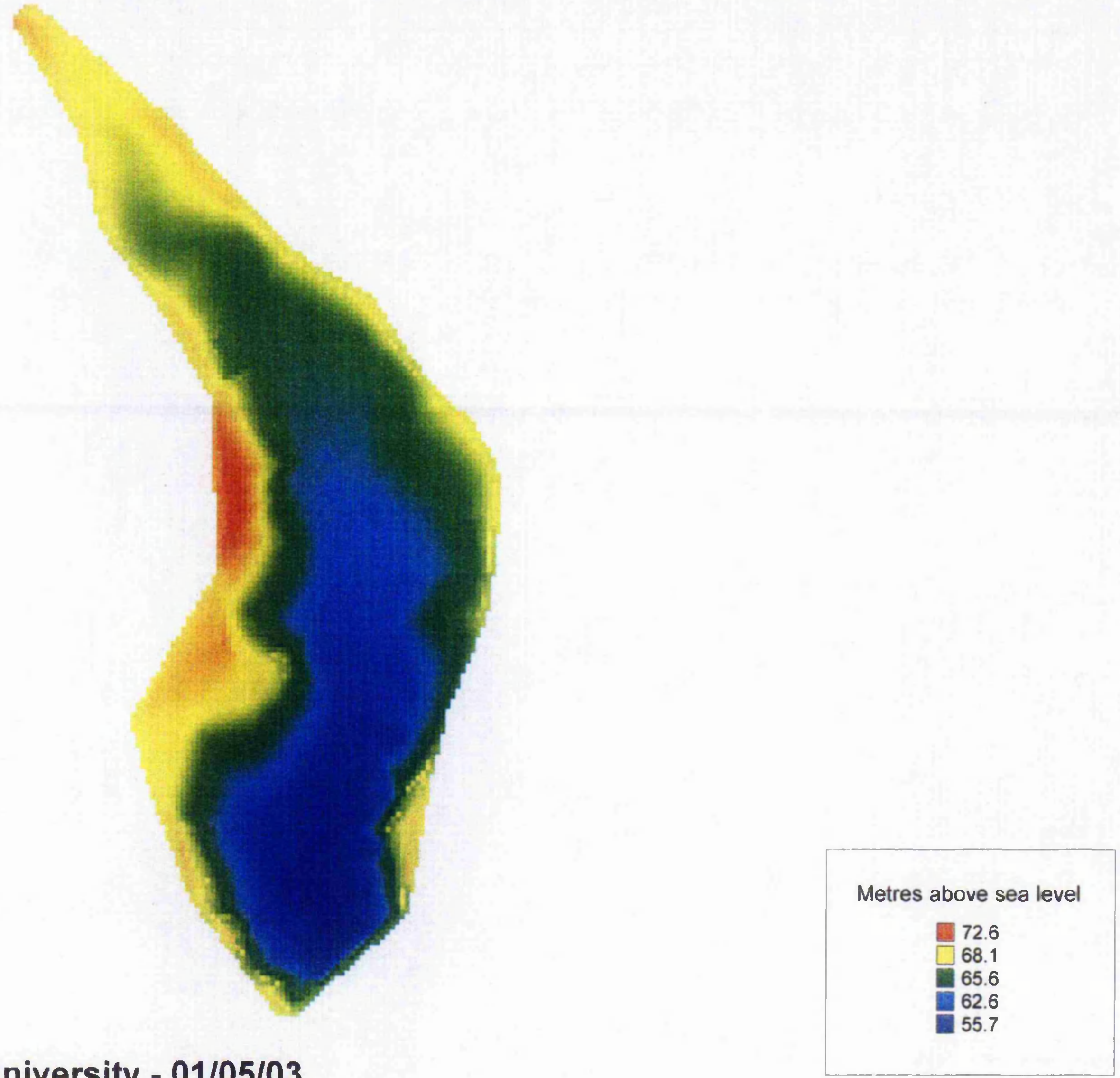
Surveyed by The Nottingham Trent University - 30/07/03

BOUGH BEECH RESERVOIR



Surveyed by The Nottingham Trent University - 08/05/03

EYEBROOK RESERVOIR



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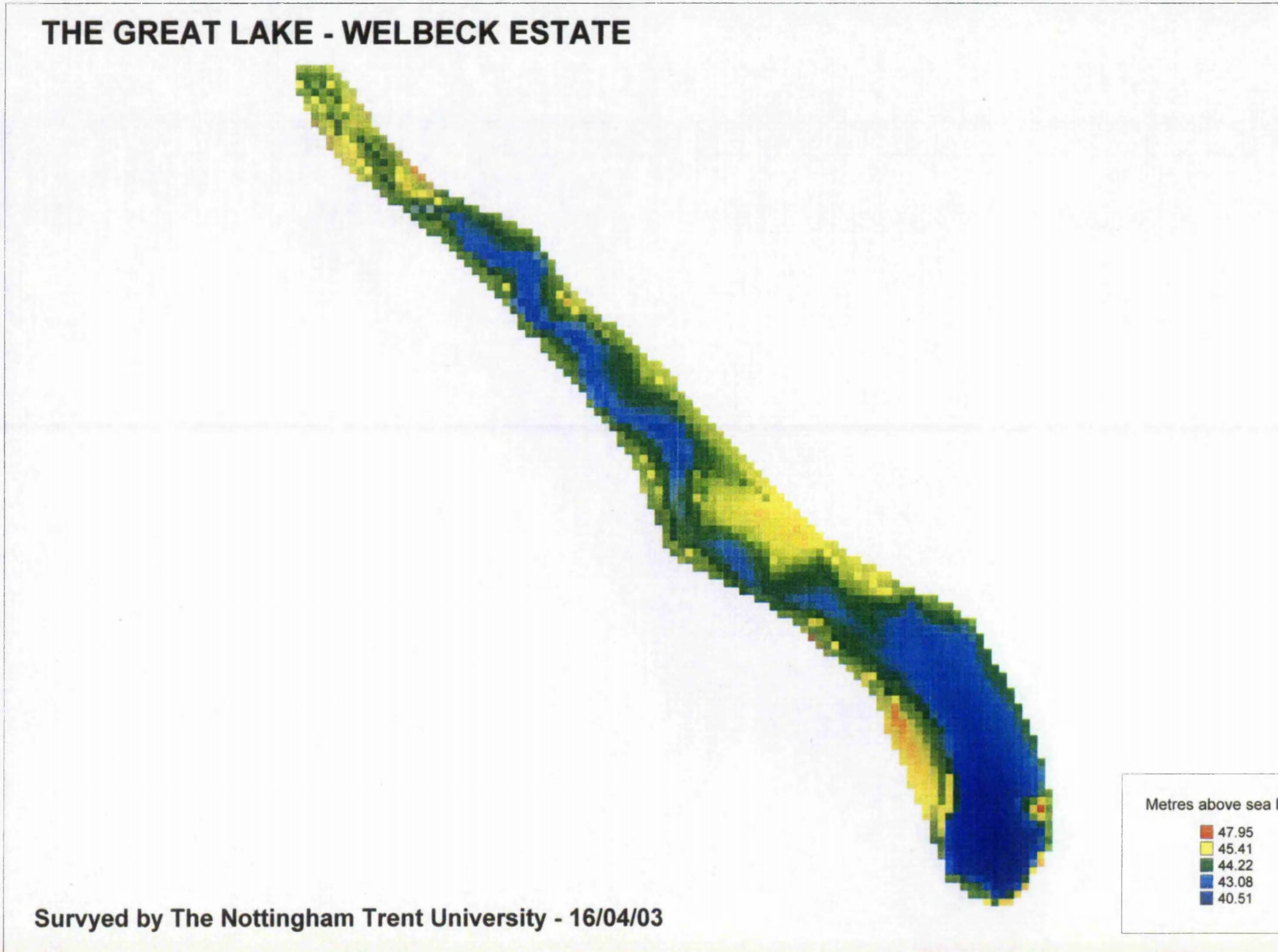
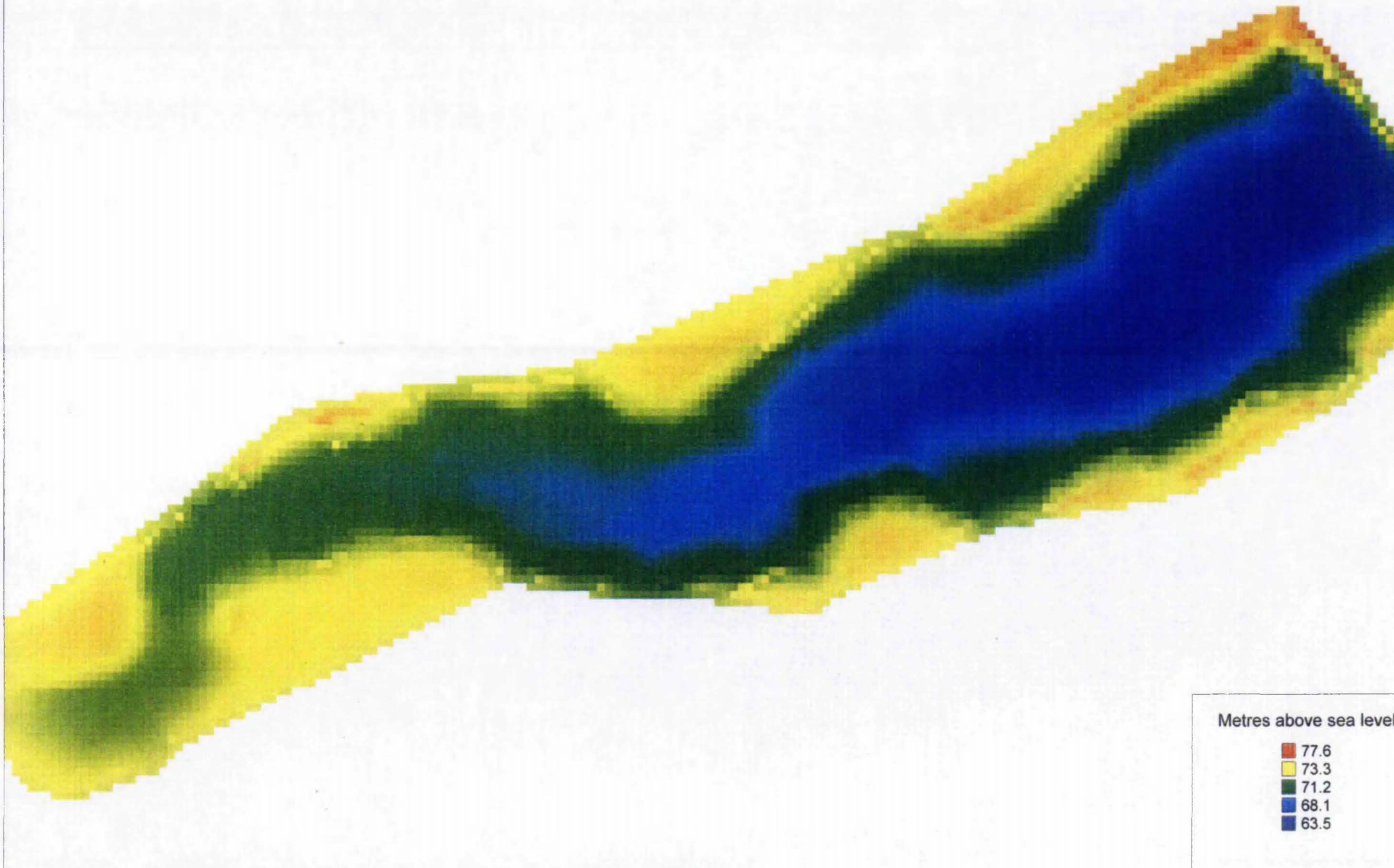

THE GREAT LAKE - WELBECK ESTATE
Metres above sea le
47.95
45.41
44.22
43.08
40.51
Survyed by The Nottingham Trent University - 16/04/03

WEIRWOOD RESERVOIR



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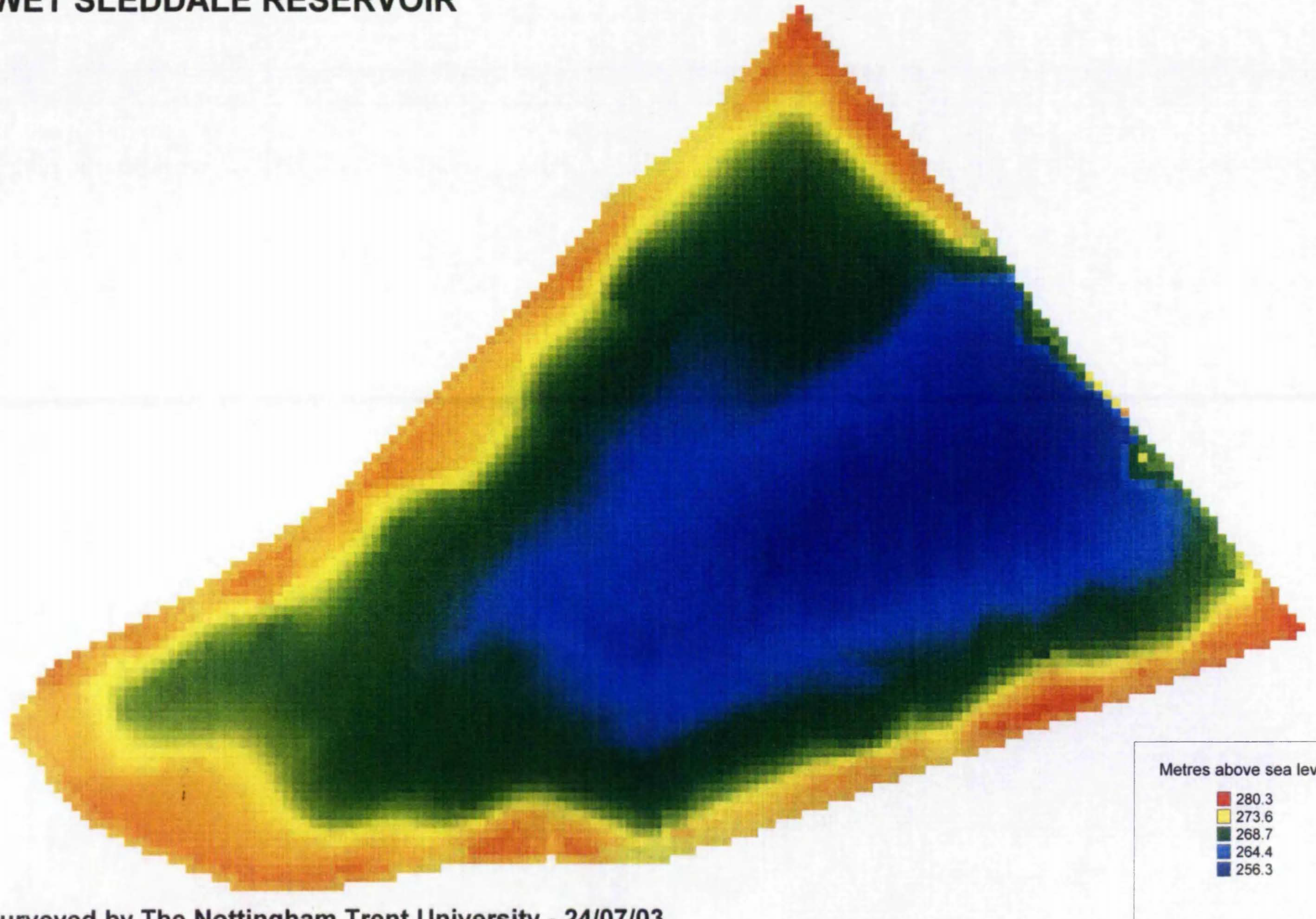
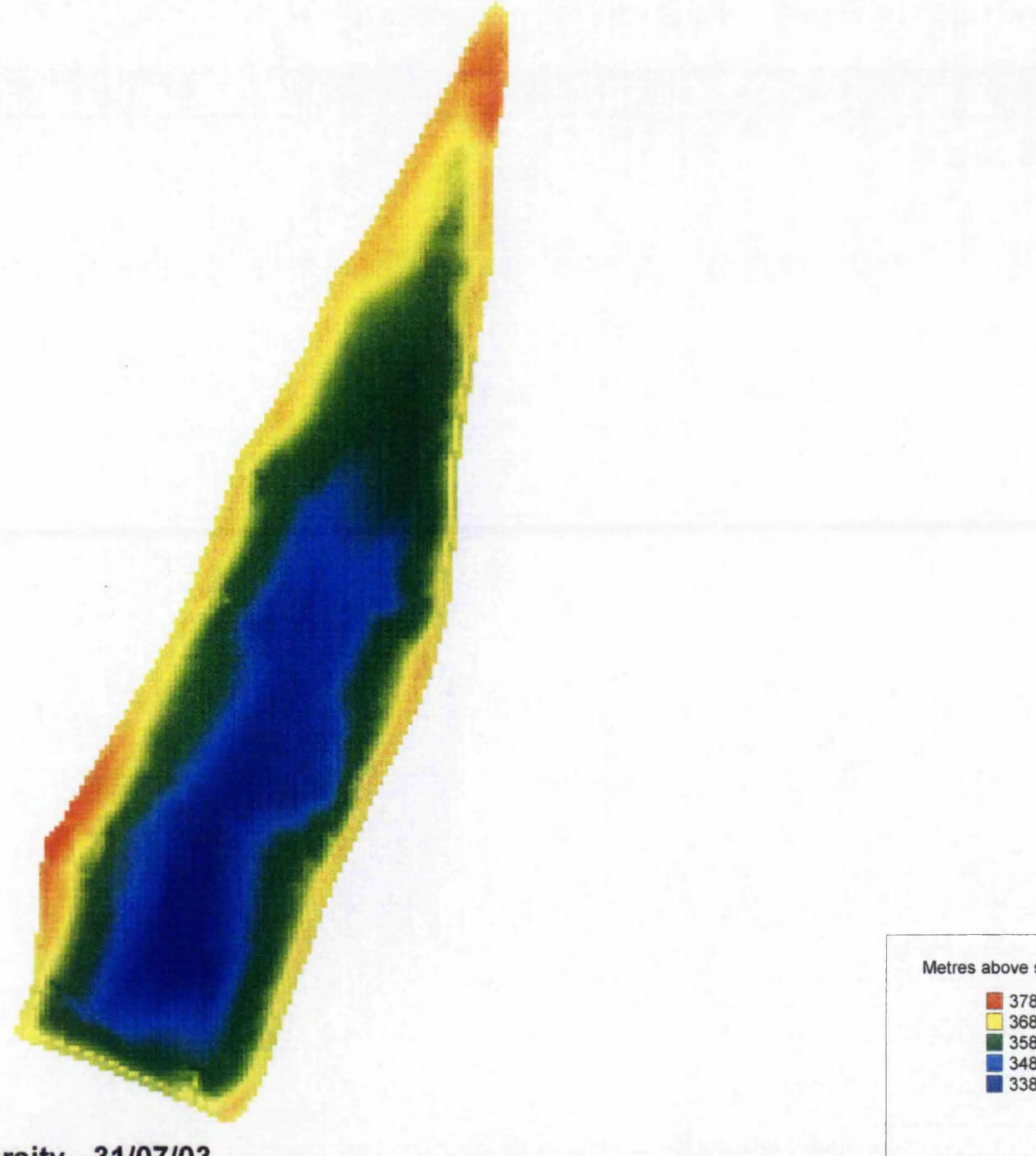
WET SLEDDALE RESERVOIR



Surveyed by The Nottingham Trent University - 24/07/03

YSTRADFELLTE RESERVOIR



Surveyed by The Nottingham Trent University - 31/07/03