

Wavelength-specific Urban Nighttime Light Modulates Expressed Sentiment Across China

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Abstract

As cities brighten under rapidly expanding lighting infrastructure, residents face increasing sentimental risks at night. While artificial light at night (ALAN) is linked to mental health risks, its wavelength-specific effects remain poorly understood. Here we integrate satellite observations of ALAN and sentiment analysis of geotagged social media posts to quantify wavelength-specific associations between urban light exposure and expressed sentiment across China. We find that exposure to blue light (424 – 526 nm) increases negative sentiment by 15.9%, while moderate green light (506 – 612 nm) enhances positive sentiment by 5.0%. Spatial mapping further reveals pronounced disparities both within and between cities, with elevated sentiment risk concentrated in commercial areas and eastern cities of China. Notably, optimizing correlated color temperature reduces sentiment risk by 89.7% compared to intensity reduction alone. These findings provide evidence-based guidance for urban lighting design to promote public mental well-being through spectral optimization, not just brightness control.

1 Main

2 Global urban lighting infrastructure is expanding rapidly¹. Artificial light at night
3 (ALAN) has become a pervasive environmental stressor affecting over 80% of the
4 global urban population². While ALAN provides essential social functions, it
5 disrupts circadian rhythms and impairs sleep quality, leading to adverse health
6 outcomes³. These physiological disruptions are particularly concerning given the
7 escalating global burden of mental health issues. Currently, mental health
8 disorders, including depression, affect approximately 970 million people
9 worldwide⁴. Projections indicate these disorders will become the leading cause of
10 global disease burden by 2030⁵. A particularly concerning aspect is the nocturnal
11 intensification of symptoms: depression and anxiety commonly worsen at night,
12 with suicide attempt risks may increase threefold to fivefold during nighttime
13 hours^{6,7}. While research has extensively examined various nighttime
14 environmental factors – nighttime noise⁸, circadian disruption⁹, and temperature
15 fluctuations¹⁰ – the impact of ALAN, as a pervasive environmental stressor, has
16 been substantially understudied.

17
18 Emerging evidence has linked ALAN exposure to mental health vulnerabilities (e.g.,
19 depression), through controlled laboratory experiments and longitudinal cohort
20 analyses¹¹⁻¹³. However, large-scale investigations of wavelength-specific ALAN
21 effects on individual sentiment in real-world settings remain scarce due to several
22 methodological challenges¹⁴⁻¹⁶. These limitations include the lack of high-
23 resolution data on ALAN exposure, insufficient spectral characteristics of ALAN
24 data, and the challenges of linking individual sentiment states to environmental
25 conditions. As urban lighting infrastructures expand globally, addressing these

limitations is essential for developing evidence-based urban lighting strategies.

Current assessment of ALAN exposure predominantly relies on legacy satellite sensors, such as NPP-VIIRS and DMSP-OLS, which provide only coarse spatial resolutions (e.g., 500m to 1km). While these datasets revealed correlations between satellite-observed light intensity and mental health outcomes, they failed to capture intra-urban light gradients and neglected spectral dimensions, such as wavelength heterogeneity¹⁷⁻¹⁹. Consequently, it is challenging to disentangle the unique influence of different light wavelengths on specific emotional or physiological responses through these datasets. Another major challenge lies in accurately linking individual sentiment states to a diversity of levels of ALAN exposure, considering the large spatial heterogeneity of both population distribution and urban lighting²⁰. On the other hand, traditional approaches relying on cross-sectional surveys or individual tracking data are commonly constrained by limited spatial coverage, sample size, and temporal resolution^{11,12,21}. Thus, how outdoor ALAN, particularly its spectral composition (different wavelengths of ALAN), influenced sentiment expression on a large scale remained unclear, hindering effective design and implementation of targeted interventions.

To address these gaps, our study integrates newly developed high-resolution, multi-spectral ALAN data with geotagged social media sentiment analysis to provide data-driven evidence of the association between outdoor ALAN exposure and expressed sentiment (Fig. 1). Based on the unique color micro-light data from the Sustainable Development Science Satellite 1 (SDGSAT-1)²², we obtained corrected high-resolution (40m) outdoor ALAN measurements in three spectral bands (red, green, and blue) for 200 main cities in China. Coupled with our mega-database of over 4 million geotagged social media posts, we employed advanced

deep learning-based semantic analysis to quantify high-frequency sentiment expression at the individual level. This novel integration enabled a detailed, high-resolution characterization of individual-level outdoor ALAN exposure for millions of urban residents. Through a fixed-effect panel regression model, we addressed three key questions: (a) What are the relationships and wavelength-specific heterogeneity between outdoor ALAN exposure and sentiment expression, with confounding factors effectively controlled? (b) What are the spatial patterns of sentiment risks associated with outdoor ALAN exposure across China? (c) How can urban lighting be optimized to mitigate sentiment risks? Our findings could provide insights into the nuanced relationship between spectral characteristics of outdoor ALAN and human psychological responses, with direct implications for evidence-based urban lighting policies that could enhance population mental wellbeing.

Wavelength-dependent impacts of ALAN exposure on sentiment

Based on 4,203,567 geotagged social media posts collected between 8:00 PM and 12:00 PM across China in 2023, along with ALAN data from the SDGSAT-1 satellite, we applied a high-dimensional fixed effects panel regression model (see Methods). This approach allowed us to isolate the effects of different ALAN intensity bands on sentiment expression by controlling a diversity of potential confounding factors (Equation 1, Methods). Specifically, we analyzed how the average nighttime light radiation intensity, within a 200-meter radius (a 5×5 ALAN pixel window) around each posting location, influenced sentiment responses.

Our findings revealed a non-linear relationship between overall outdoor ALAN intensity and sentiment expression. The likelihood of expressing positive sentiment peaked at an ALAN intensity of approximately 14 nW/cm² sr. At intensities lower or

higher than this point, the probability of negative sentiment expression increased (Fig. 2a). To further explore various wavelength-specific effects of ALAN, we incorporated multi-spectral data from the red (600-894 nm), green (506-612 nm), and blue (424-526 nm) bands into our model (Equation 2, Methods). The results indicated that each spectral band had a statistically significant yet markedly different effect on sentiment (Table S1). Notably, the relationship between outdoor ALAN exposure and sentiment varied significantly across wavelengths of light. For red light, we observed a U-shaped effect. An intermediate intensity of 64.8 nW/cm² sr correlated with heightened negative sentiment, while both dimmer and brighter red light levels corresponded to an increase in positive sentiment (Fig. 2b). Green and blue light exhibited similar patterns. Dim green and blue light exposure intensified negative sentiment. Specifically, dim blue light (1.3 nW/cm² sr) showing the strong effect, with an increase of 15.9% (95% CI: 15.3% to 16.5%). This impact was approximately four times greater than that of green light, and surpassing the effects of other known environmental factors, such as temperature²³ and air pollution²⁰. Conversely, moderate exposure to green and blue light was linked to a notable improvement in sentiment. Green light (14.7 nW/cm² sr) produced the most significant positive sentiment response, with a 5.0% increase (95% CI: 3.7% to 6.4%), roughly double the effect of blue light. These findings underscored that the impact of outdoor ALAN exposure on sentiment was not only determined by intensity, but also critically modulated by wavelength. These outputs effectively explained why previous mechanistic studies led to distinct effects of outdoor ALAN on sentiment expression, due to the lack of consideration of wavelength characteristics.

To ensure the robustness of these findings, we conducted multiple sensitivity analyses (Supplementary Text S1). First, we divided the full sample into multiple

subsets according to time and region to examine whether the main effects remained consistent across groups and conditions. The results demonstrated that the observed effects are robust across different spatial and temporal dimensions. Additionally, we included interaction terms between bands to account for potential correlations between them (Table S2). The results showed that the variation of interaction terms did not significantly alter the estimates, supporting the robustness of independent wavelength effects. Third, we explored the nonlinear relationship between ALAN and sentiment by incorporating logarithmic transformations and quadratic terms of nighttime light intensity. The log-transformed model acquired consistent results, indicating that the observed sentiment effects of ALAN were robust even under more flexible nonlinear specification (Table S3). To investigate potential confounding from socioeconomic factors, we incorporated county-level per capita GDP into our fixed-effects model. The results showed that the direction and magnitude of the ALAN effects, particularly the strong negative association observed for blue and green light, were not substantively altered by the inclusion of this socioeconomic variable (Table S4). In addition, to address potential spatial dependence, we conducted spatial autocorrelation diagnostics and refitted the model using a spatial error model (SEM). The SEM estimates for the effects and significance of ALAN were highly consistent with the original results, indicating that the main conclusions were not biased by spatial autocorrelation (Table S5). All these results provided compelling evidence that the effects of ALAN on sentiment were both intensity- and wavelength-dependent.

Heterogeneous impacts of ALAN exposure on sentiment

The sentiment impact of different wavelengths was found to change significantly with exposure distance. To investigate this heterogeneity, we measured the average light intensity across different spectral bands at distances ranging from

100 to 500 meters from the sample location. Using a fixed-effect model (Equation 3, Methods) and the full sample ($N = 4,203,567$), we estimated the average sentiment effects under varying light intensities at each distance.

As shown in Fig. 3a, the sentiment effects of outdoor ALAN exposure exhibited pronounced non-linear variations with the increase of exposure distance across wavelengths. The positive sentiment effect of red light generally increased with distance, peaking at 500 m, where it was 2.7 times stronger than at 200 m. In contrast, the negative sentiment effect of green light intensified with distance, reaching a maximum of -3.8% (95% CI: -3.9% to -3.7%) at 500 m, which was threefold greater than its effect at 200 m. Interestingly, the sentiment impact of blue light shifted from negative to positive as exposure distance increased. While it initially had a negative effect at 100 meters, it slightly turned positive at 500 meters. These findings highlighted the heterogeneous role of exposure distance in shaping sentiment responses to outdoor ALAN and suggested that the spatial distribution of light sources was a critical factor in understanding these effects.

Given the pronounced seasonal variations in temperature and environmental conditions, we further investigated whether these factors influenced the sentiment impact of ALAN. To do so, we stratified our data by season and nighttime and applied our fixed-effect model (Equation 4, Methods) to examine seasonal and nighttime heterogeneity. The results showed that the impact of red light exposure on sentiment varied with seasons. During winter and spring, red light exposure significantly improved positive sentiment (Fig. 3b, e). However, in summer (Fig. 3c), the same exposure slightly increased negative sentiment. These seasonal variations underscored the role of environmental context in shaping how red light affected sentiment.

For blue light, its effects on negative sentiment demonstrated both seasonal trends and nighttime variations. In spring and autumn (Fig. 3b, d), the negative sentiment effect of blue light exposure generally diminished over time during night. Conversely, in summer and winter (Fig. 3c, e), blue light exacerbated negative sentiment, especially during earlier nighttime hours. Green light exhibited more complex, nonlinear effects that varied across seasons. In spring, the sentimental impact of green light followed a pattern of an initial decrease followed by an increase, with the most significant negative effect occurring late at night (Fig. 3b). In contrast, this trend inverted in autumn, showing an initial increase followed by a decrease, with the weakest negative sentiment during the same late-night period (Fig. 3d). These findings emphasized the critical role of seasonal and nighttime variations in shaping sentiment responses to ALAN exposure, suggesting the importance of seasonally-optimized and spatially targeted lighting strategies to mitigate negative effects and enhance public mental health.

Spatial distribution of ALAN-associated sentiment risks

To visualize how outdoor ALAN exposure influences sentiment across urban areas, we developed high-resolution sentiment risk maps. Using a logistic-regression-based probability model (see Methods), we quantitatively analyzed the relative probability of negative sentiment responses attributable to outdoor ALAN exposure. This analysis incorporated variations in wavelengths and brightness within a 200-meter radius, with the control of potential confounding variables. The relative risk coefficients for different wavelengths and overall brightness were calculated and weighted to aggregate as sentiment risk score (SRS) (see Methods). Furthermore, we categorized two types of zones influenced by ALAN, negative-sentiment mitigation zones ($SRS < 0.9$) and negative-sentiment enhancement zones

(SRS>1.1)²⁴. Notably, this analysis focused exclusively on the sentiment risks associated with ALAN exposure, independent of the functional attributes of the areas being studied.

The sentiment risk maps revealed pronounced geographical disparities in population-weighted negative sentiment risks across China, with risk hotspots concentrated in eastern cities (Fig. 4a). The cities with the highest sentiment risk were located in the Yangtze River Delta region, including Nanjing, Suqian, and Jinhua, and these regions also typically had a low proportion (<1%) of negative-sentiment mitigation zones. However, our analysis revealed no significant negative correlation nationwide between the proportion of negative-sentiment mitigation zones and population-weighted sentiment risk ($p > 0.1$). This suggested that in some cities, a larger proportion of the population resided in negative-sentiment mitigation zones, which effectively shielded residents from high-risk ALAN environments. This finding highlights the potential for nighttime lighting planning tailored to population distribution to mitigate public exposure to sentiment-aggravating lighting conditions.

To illustrate the profound intra-urban spatial heterogeneity of sentiment risk, we conducted detailed case studies on two representative megacities, Beijing and Shanghai, which revealed different spatial patterns. For instance, we saw contrasting patterns when examining two megacities, Beijing and Shanghai (Fig. 4b-e). In central Beijing, appropriate brightness and warm-toned high-pressure sodium lighting in streets and public spaces were generally associated with lower sentiment risk. Meanwhile, suburban areas of Beijing exhibited higher sentiment risk associated with cool-toned LED illumination. As a comparison, central Shanghai showed a pervasive elevation of sentiment risk, while suburban

Shanghai benefited from warmer streetlights, which were effective in mitigating sentiment risk. Notably, high-brightness lighting in commercial areas was consistently associated with elevated sentiment risk in both cities. These intra-urban variations caused substantial disparities in population exposure to sentiment risks. These findings underscored the importance of space-sensitive urban lighting design, with a comprehensive consideration of light intensity, color temperature, and spatial distribution to establish more balanced and emotionally supportive nightscapes, particularly in densely populated urban environments.

Urban lighting optimization strategies for sentiment risk mitigation

To explore practical strategies for mitigating ALAN-induced negative sentiment, we simulated three distinct urban lighting optimization scenarios, each of which targeted specific sentiment-modulating attributes identified in our analyses. These scenarios included: (1) the reduction of overall brightness (2) the adjustment of color temperature and (3) an integrated approach combining both (see Methods), representing actionable policy levers for urban planners.

The simulation outputs revealed that all three strategies significantly reduced sentiment risks, particularly in high-risk, densely populated eastern urban centers (see Fig. 5a-c). The brightness reduction strategy, which uniformly decreases light intensity by 50% in high-risk areas ($SRS > 1.1$) while maintaining spectral invariance, achieved an average 83.6% reduction in population-weighted sentiment risk nationwide (Fig. 5a). While brightness reduction was a commonly employed urban lighting approach, we found it only yielded a modest 60% average increase in negative-sentiment-mitigation locations nationwide. While effective in reducing risk in densely populated hotspots, brightness reduction alone exhibited limited efficacy in broader urban areas, and failed to shift the overall urban lighting

environment from negative-sentiment enhancing to mitigating (average SRS > 1.1, Fig. 5d).

In contrast, the color temperature adjustment strategy resulted in a substantial 89.7% average reduction in population-weighted sentiment risk and a 16.6-fold average increase in negative-sentiment-mitigation locations. More importantly, color temperature adjustment shifted the average urban sentiment risk profile from negative-sentiment-enhancing to negative-sentiment-mitigating dominance (average SRS = 0.8, Fig. 5d), with negative-sentiment-mitigating locations dominating 88% of cities.

The integrated strategy, combining brightness reduction and color temperature adjustment, yielded the most pronounced sentiment benefits, achieving an average 90% reduction in population-weighted sentiment risk and an 18-fold average increase in negative-sentiment-mitigating locations. These findings strongly suggested that brightness reduction alone was insufficient for fully reducing sentiment risk, and highlighted the critical, non-negligible role of color temperature adjustment in urban lighting optimization strategies.

Discussion

The escalating global burden of nighttime anxiety and depression, combined with the rapid expansion of urban lighting infrastructure, underscores the urgent need for a deeper understanding of how outdoor ALAN affects public sentiment and mental health. We, for the first time, quantitatively the association between individual sentiment expression and exposure to specific wavelengths of ALAN, representing the most comprehensive study of its kind to date. Unlike previous studies relying on coarse, city-level averages^{17,25}, our approach explicitly

accounted for the substantial spatial heterogeneity in ALAN distribution, which significantly impacted individual exposure. Meanwhile, the high-resolution characteristic of our data allowed us to capture previously undetectable low-intensity light sources, such as streetlights and building illumination²⁶⁻²⁸, thereby substantially reducing biases in estimating individual-level outdoor ALAN exposure. Furthermore, our study pioneers the exploration of wavelength-specific impacts of outdoor ALAN on sentiment, a critical dimension that has been largely overlooked in existing research. This research provides useful reference for evidence-based, sentiment-sensitive urban lighting policies to enhance public health, improve resident well-being, and support progress toward the Sustainable Development Goals (SDGs), particularly SDG 3 and SDG 11.

Our study substantially advances the current understanding of how outdoor ALAN exposure influences human emotions. Previous epidemiological research, primarily based on cohort surveys conducted within limited temporal and spatial contexts, established clear associations between ALAN exposure (majorly its timing and intensity) and increased risks of mood disorders and depression^{11,12,21}. Additionally, studies utilizing coarse-resolution, single-band satellite observations expanded the scope of investigation to broader urban populations, similarly identifying correlations between outdoor nighttime brightness and negative psychological outcomes^{17-19,25}. Rather than relying on city-level average data, which often suffer from spatial heterogeneity biases, edge effects, and incapability to detect low-intensity lighting sources^{29,30}, our research derived individual-level ALAN exposure estimates from new high-resolution SDGSAT-1 satellite. This methodological advancement ensured a more accurate representation of actual personal exposure to nighttime lighting. Furthermore, our study elucidated the differential impacts of specific wavelengths, a critical dimension overlooked in

previous research. We found that exposure to blue-rich and green-rich nighttime lighting significantly increased the risk of negative emotional states, whereas red-rich lighting exhibited minimal negative effects and, in certain contexts, even promoted positive emotions. These empirical findings align closely with existing experimental evidence demonstrating relationships between specific spectral compositions of light and emotional responses, as well as underlying neural mechanisms. Experimental studies demonstrated that blue light strongly activated melanopsin in intrinsically photosensitive retinal ganglion cells (ipRGCs), exerting pronounced effects on circadian rhythms and significantly suppressing melatonin secretion³¹⁻³³. Meanwhile, neural imaging research indicated that blue light exposure enhanced functional connectivity between the amygdala and dorsolateral prefrontal cortex (DLPFC), potentially altering emotional processing and responses³⁴. In contrast, our study found that the positive effect of red light was minimal or slightly attenuated. This was consistent with red light's position at the lowest end of the melanopsin sensitivity spectrum. By minimally activating ipRGCs, red light largely circumvented the melatonin suppression pathway and other direct pathways for negative effects, making it a more benign light source at night^{35,36}. The role of green light appeared more complex, which may explain the non-linear pattern we observed. While green light produced moderate melanopsin activation, emerging research has suggested its involvement in unique therapeutic pathways. For example, green light was shown to indirectly improve mood by modulating endogenous pain-inhibitory circuits³⁷. These findings strongly suggest that urban nighttime lighting strategies should minimize the use of blue-rich illumination to protect public emotional health.

Second, our study provides novel evidence of distance- and time-dependent patterns in the emotional impacts of outdoor ALAN exposure. Previous research

largely relied on average urban illumination levels or lighting measured at population centers^{17,25}, neglecting the complex associations between spectral characteristics, exposure distance, seasonal variations, and temporal dynamics. Our findings indicated that the emotional effects of red and green wavelengths significantly intensified at greater distances from the light source, possibly reflecting cumulative exposure or interactions with broader environmental contexts. This undocumented phenomenon underscores the necessity of incorporating exposure distance into assessments of ALAN's sentiment impacts. Interestingly, we observed that the emotional influence of blue light shifted from negative to positive with increased distances, potentially due to combined effects of reduced intensity, altered visual contexts, and psychological perception differences. Moreover, our research addressed a critical limitation of prior ALAN studies, which typically employed cross-sectional or short-term laboratory designs, thus failing to capture seasonal and nighttime temporal variations in emotional responses^{11,12}. Our analysis revealed pronounced seasonal and nighttime patterns in the emotional effects of nighttime lighting. Currently, urban lighting systems rarely account for seasonal variability, resulting in static illumination schemes poorly aligned with residents' physiological and psychological needs throughout the year. Therefore, future urban lighting strategies should incorporate adaptive adjustments in lighting intensity and spectral composition according to seasonal, environmental, and temporal contexts, thereby simultaneously fulfilling functional illumination requirements and optimizing public emotional health.

Finally, recent efforts to mitigate nighttime light pollution, often motivated by environmental and biodiversity protection, primarily focused on reducing brightness levels. While these initial steps were encouraging, specific regulations addressing ALAN exposure to alleviate adverse mental health effects remained

largely absent in most countries, and the critical role of color temperature was overlooked^{14,38}. The new world atlas of artificial night sky brightness highlighted the importance of improving color temperature for reducing light pollution². Although some studies suggested targeted adjustments to the correlated color temperature (CCT) of outdoor lighting to minimize negative effects on mental health, it remains unclear which specific urban areas are most vulnerable to sentiment risks from nighttime lighting, and to what extent targeted optimization could alleviate these risks. Our sentiment risk maps, for the first time, quantitatively revealed substantial spatial heterogeneity in ALAN-associated sentiment risks both within and across cities, highlighting how variations in brightness and color temperature caused uneven burdens of negative sentiment among urban populations. This fine-grained spatially explicit analysis provides essential data support for policymakers, enabling more precise identification of priority areas and targeted intervention strategies. Furthermore, our specially designed optimization scenario analysis quantitatively demonstrated that reducing brightness alone was insufficient to create urban nighttime environments conducive to positive sentiment. Instead, substantial additional sentiment benefits can be achieved through targeted optimization of lighting color temperature. This finding raises important considerations for the ongoing global transition toward LED-based urban lighting. While LED lighting reforms offer significant advantages in energy efficiency and carbon emission reduction, their characteristically blue-rich spectral composition may pose unintended risks to public emotional health³⁹. Therefore, our results underscore the necessity of balancing energy efficiency goals with careful consideration of lighting's psychological impacts by properly integrating color temperature optimization into future urban lighting strategies.

While our study provided unprecedented insights, several limitations warrant consideration. The limitations mainly arose from potential biases in the geolocation and demographic attributes of social media data, spatiotemporal uncertainties in measuring ALAN exposure, and inherent challenges in accounting for natural rhythms, lag effects, and causal inference. We provided a detailed discussion of these uncertainties in Supplementary Text S2.

Methods

Definition of urban entities

Instead of relying on administrative boundaries, this study utilized urban entities defined by urban boundaries, which represent contiguous built-up areas. These urban boundaries were obtained from the established Global Urban Boundary (GUB) dataset, derived from 30-meter resolution Landsat imagery and widely used for urban delineation⁴⁰. To ensure sufficient social media data within each unit, our analysis was restricted to urban entities exceeding 100 km² in area.

Geotagged social media data

This study collected 4.2 million geotagged posts from Weibo, a dominant social media platform in China (598 million monthly active users as of Dec 2023), covering 200 cities throughout 2023. This timeframe (year 2023) was specifically selected for two primary reasons. First, to mitigate the confounding influence of the COVID-19 pandemic on public sentiment⁴¹, necessitating the use of data after the main pandemic disruptions and lockdown (post-2022 in China). Second, to correspond with the availability of SDGSAT-1 nighttime light observations, which commenced in 2022 following the satellite's 2021 launch. The geotagged posts contain latitude and longitude coordinates, derived either from user-permitted location sharing or manual location tagging. Previous research demonstrated that institutional accounts (e.g., news media, celebrities, and private companies) could potentially introduce bias into public sentiment measurements⁴². Consequently, we eliminated institutional accounts from Weibo, including big "Vs" (the most influential celebrities), and exclusively utilized original posts from individual users.

ALAN data

ALAN data were acquired from the SDGSAT-1 satellite for 200 Chinese cities throughout 2023. SDGSAT-1 provides observations across three spectral bands: blue (424–526 nm), green (506–612 nm), and red (600–894 nm), enabling the investigation of wavelength-specific effects on sentiment. To ensure data quality and minimize atmospheric interference, only cloud-free nighttime images were utilized. The satellite’s overpass time for China (approx. 21:00–21:30 local time) preceded the typical posting times of the social media data by 1–3 hours. This offset was compounded by the necessity of using only cloud-free observations. This meant that a social media post was matched with the nearest available ALAN observation, and consequently, the date of the post did not always coincide with that of the corresponding ALAN data. While this temporal offset could potentially introduce bias in exposure measurements, particularly from transient sources, the impact is considered minimal because dominant, stable light sources (commercial, public) were captured, whereas more variable, lower-intensity sources (e.g., mobile) contribute less to the overall signal. Furthermore, our high-dimensional fixed-effects model explicitly controls for time-invariant spatial variations in average light levels, further mitigating potential bias from this temporal mismatch.

The utilized SDGSAT-1 Level-4A data required preprocessing to address potential inaccuracies stemming from sensor artefacts (e.g., striping, noise) and lack of radiometric calibration. Consequently, we applied a dedicated denoising algorithm^{28,43} and official radiometric calibration parameters (provided by the International Research Center of Big Data for Sustainable Development Goals) to correct these issues across the dataset. The final dataset provides calibrated nighttime radiance measurements in $\text{nW}/\text{cm}^2\text{sr}$. We validated the consistency between SDGSAT-1 and VIIRS nighttime light data for each observation pixel at the national scale. The results showed agreement in nighttime light detection

between the two datasets, with an overall Pearson correlation coefficient of 0.69 and a mean of 0.67 (Fig. S1). Our extensive validation, combined with existing studies, demonstrated that SDGSAT-1 data is suitable for national-scale analysis.

Climate and environmental data

To control for potential confounding effects of environmental conditions, we incorporated hourly meteorological data (temperature, precipitation, wind speed) from the ERA5-Land reanalysis dataset. These variables, commonly included in similar analyses^{20,23}, were extracted for the specific time and location of each social media post. Additionally, recognizing the established influence of air quality on sentiment²⁰, we included daily PM_{2.5} concentrations as a key indicator. These PM_{2.5} data were obtained from the China High Air Pollutants (CHAP) dataset, which is extensively validated against ground observations across China⁴⁴. Descriptive statistics for all variables included in the model are provided in Supplementary Table S6.

Population data

Population data utilized in this study were derived from the WorldPop dataset in 2023 for China. This dataset provided annual population distribution at 100-meter resolution across Chinese regions and has been extensively employed for population assessments within China. To ensure alignment with ALAN data, we resampled the population data to match the resolution of the ALAN.

Sentiment analysis

To quantify public sentiment across China, we employed natural language processing (NLP) to analysis daily Weibo posts, generating a structured sentiment dataset suitable for quantitative analysis. While traditional word-based NLP

methods struggle to capture contextual meaning shifts⁴⁵, deep learning approaches offer superior performance. Therefore, we utilized a BERT (Bidirectional Encoder Representations from Transformers)-based model, a state-of-the-art architecture that excels at capturing contextual semantics⁴⁶.

Based on BERT's capabilities, we implemented a RoBERTa (Robustly Optimized BERT Pretraining Approach) model within the Transformers framework for sentiment analysis. Specifically, we used the Chinese RoBERTa-Base model, pre-trained on diverse Chinese datasets, making it highly suitable for analysing Chinese social media text. This model variant demonstrates strong performance, particularly in processing longer texts and understanding nuanced context⁴⁷, and has been successfully applied in prior studies examining public sentiment related to urban environmental factors^{41,48}. The model classifies each post, assigning both a sentiment polarity (positive/negative) and a continuous sentiment score (-1 to 1). Processing the 4.2 million collected posts yielded a city-level daily sentiment dataset. The details of the model and its validation accuracy were provided in Supplementary Text S3. It is important to note that our approach captures momentary sentiment states expressed by individuals at specific times. By leveraging the real-time nature of social media, our method examines acute associations between environmental conditions and sentiment responses, rather than chronic health outcomes or the effects of long-term cumulative exposure.

To analyze the robustness of sentiment scores quantified by RoBERTa, we conducted various robustness checks (Supplementary Text S4). These assessments demonstrated the distinct advantages of the RoBERTa model and showed high consistency with results obtained using the established Chinese NRC Emotion Lexicon (Fig. S2). To further investigate the relationship between

sentiment expression and spatial context, we extracted 298 distinct Point of Interest (POI) categories from 2,580,285 geotagged posts and clustered them into six functional categories based on Google Mobility's behavioral classification: residential, workplaces, retail & recreation, parks, transit stations, and grocery & pharmacy. The results show that 60% of the posts were located within residential areas, followed by retail & recreation (17.6%) and parks (11.0%) (Table S7). We further extracted POIs directly related to road infrastructure (subway stations, bus stations, overpasses, bridges, roads, parking lots, and gas stations) from the Transit stations (2.6%) category and found that they accounted for less than 1% of all geotagged posts, indicating that the visual clustering of posts along road networks reflects the underlying spatial organization of urban land use rather than a positional bias in the data. We also examined the distribution of sentiment scores across different time periods and found that it remained highly consistent (Fig. S3). This suggested that natural nocturnal rhythms did not introduce systematic variations in the measured sentiment.

Statistical analysis

The key to quantifying the impact of ALAN exposure on sentiment expression lies in controlling for potential confounding variables in the model¹⁶. In this study, we employed a high-dimensional fixed effects panel regression model to quantify the independent effect of ALAN exposure on sentiment expression. This model has been widely used in previous research to control for various influencing factors and isolate the independent effects of the variables of interest, renowned for its robustness and reliability^{49,50}. Similar models have proven effective in estimating the influence of other environmental exposures, such as temperature fluctuations, on public sentiment²³, underscoring the suitability of this approach for our analysis. Specifically, we modelled the association between sentiment and overall NTL

517 intensity using equation (1), and wavelength-specific NTL exposures using
 518 equation (2).

$$\begin{aligned}
 &Sentiment_{i,t,p,y,w} \\
 &= \beta Brightness_{i,t,p,y,w} + \mu_p + \sigma_y + \rho_w + \delta X_{i,t,p,y,w} + \gamma A_{i,t,p,y,w} \\
 &+ \epsilon_{i,t,p,y,w}
 \end{aligned} \tag{1}$$

519

$$\begin{aligned}
 &Sentiment_{i,t,p,y,w} \\
 &= \sum_{k=1}^3 \beta_k Band_{k,i,t,p,y,w} + \mu_p + \sigma_y + \rho_w + \delta X_{i,t,p,y,w} + \gamma A_{i,t,p,y,w} + \epsilon_{i,t,p,y,w}
 \end{aligned} \tag{2}$$

520 In this model, $Sentiment_{i,t,p,y,w}$ represented the sentiment state of individual i at
 521 time t in province p , month y , and weekday w ; $Brightness_{i,t,p,y,w}$ denoted the
 522 brightness of light exposure for individual i at time t in province p , month y , and
 523 weekday w ; $Band_{k,i,t,p,y,w}$ represented the light exposure intensity for each spectral
 524 band; μ_p represented the fixed effects for province p ; σ_y captured the fixed
 525 effects for month y ; ρ_w accounted for the fixed effects of weekday w ; $X_{i,t,p,y,w}$
 526 denoted weather variables; $A_{i,t,p,y,w}$ represented air quality variables; and $\epsilon_{i,t,p,y,w}$
 527 constituted the error term.

528

529 To enhance model robustness and account for unobserved heterogeneity, we
 530 incorporated fixed effects at multiple levels. First, systematic differences across
 531 provinces could influence sentiment responses, so we incorporated provincial
 532 fixed effects to control for regional variations in environmental, policy, or
 533 socioeconomic factors that might affect sentiment. Second, monthly fixed effects
 534 were included to account for the impact of holidays and significant events, which
 535 could lead to fluctuations in sentiment expression. Finally, to address potential
 536 “weekend effects” on sentiment expression, we introduced weekday fixed effects,
 537 controlling for daily patterns in emotional responses. The rationale for employing
 538 these fixed effects in the model was discussed in detail in Supplementary Text S5

and Fig. S4.

To minimize the influence of confounding variables, we controlled for two sets of factors in the vector $X_{i,t,p,y,w}$. These included: (1) Meteorological variables (hourly temperature, precipitation, wind speed), given the documented influence of weather, particularly temperature, on expressed mood in China²³; and (2) Air quality, represented by daily average PM_{2.5} concentrations at the post location, a critical factor impacting well-being, especially in urban Chinese contexts²⁰. By controlling for these confounders, we ensure that the estimated effect of nighttime light exposure on emotion remains independent. Detailed descriptions of the control variables and their statistical summaries can be found in Supplementary Table S6.

To quantify the heterogeneous effects of nighttime light on emotions arising from variations in exposure distance, season, and time, we performed estimations according to equations (3) and (4), respectively. First, based on equation (3), we assessed how the estimated NTL effect varied when considering exposure within different spatial buffers around the post location (ranging from 100m to 500m). Second, employing equation (4) with a 200m exposure distance as the baseline, we examined heterogeneity across seasons (spring, summer, autumn, winter) and specific nocturnal time windows (20:00–00:00).

$$\begin{aligned} & \text{Sentiment}_{i,t,p,y,w,d} \\ &= \sum_{k=1}^3 \beta_k \text{Band}_{k,i,t,p,y,w,d} + \mu_p + \sigma_y + \rho_w + \delta X_{i,t,p,y,w,d} + \gamma A_{i,t,p,y,w,d} \\ &+ \epsilon_{i,t,p,y,w,d} \end{aligned} \quad (3)$$

$Sentiment_{i,t,p,y,w,s,m}$

$$= \sum_{k=1}^3 \beta_k Band_{k,i,t,p,y,w,s,m} + \mu_p + \sigma_y + \rho_w + \delta X_{i,t,p,y,w,s,m} + \gamma A_{i,t,p,y,w,s,m} \quad (4)$$

$$+ \epsilon_{i,t,p,y,w,s,m}$$

561

562 **Robustness checks**

563 Several checks were conducted to assess the robustness of the estimated ALAN-
 564 sentiment associations. First, we divided the entire sample into multiple subsets
 565 based on temporal and regional parameters, then examined whether the effects of
 566 ALAN remained consistent across various groups and conditions using equation
 567 (2). Second, to address potential confounding due to inter-correlations among
 568 spectral bands and explore possible synergistic or antagonistic effects, we
 569 incorporated pairwise interaction terms between the blue, green, and red band
 570 intensities into the regression framework. Third, to further explore potential non-
 571 linear effects of nighttime light exposure on sentiment expression, we added
 572 quadratic terms for brightness and for the three individual bands separately in
 573 equation 1 and equation 2, respectively. We also used county-level per capita GDP
 574 as an indicator of income and living conditions to examine the influence of
 575 socioeconomic factors. Finally, we tested the potential impact of spatial
 576 autocorrelation on the results. All robustness checks were described in detail in
 577 Supplementary Text S1.

578

579 **Quantification of sentiment risk**

580 In contrast to the independent effect of NTL quantified by high-dimensional fixed-
 581 effects models, sentiment risk quantifies the probability of negative sentiment
 582 responses occurring due to NTL exposure. This requires a shift from a continuous
 583 outcome to a binary one, allowing us to frame the association within a standard

risk assessment model. We employed conditional logistic regression to estimate the impact of nighttime light exposure on negative sentiment risk (equation (5)). This method provides an estimate of the odds ratio (OR) of negative sentiment responses under NTL exposure, a standard measure widely applied in modeling disease and sentiment risks²⁴. Given the 13% prevalence of negative sentiment in our dataset, the OR served as a robust indicator of association strength, even though its magnitude would slightly overestimate the true Relative Risk (RR). The model used for this risk score was based on a log-linear assumption, which acts as a robust first-order approximation. This modeling choice was appropriate and practical, given that our objective was to create a scalable index that captures the dominant, overall trend of the effect.

We categorized individual-level sentiment as the dependent variable (Y), classifying them into negative and non-negative sentiment using binary values of 1 and 0, respectively. Explanatory NTL variables included total brightness and individual spectral band intensities (blue, green, red) averaged within a 200m radius of each post location. Meteorological and air quality variables were included as controls (as described previously). Considering collinearity between total brightness and different bands, we incorporated L2 regularization into the logistic regression, a widely used form of ridge regression and a common approach to address collinearity issues.

$$\text{logit}\{P(\text{Sentiment}_i = 1)\} = \beta_1 \text{Brightness}_i + \sum_{k=2}^4 \beta_k \text{Band}_{k,i} + \delta X_i + \gamma A_i - \lambda \sum_{j=1}^4 \beta_j^2 \quad (5)$$

Where $P(\text{Sentiment}_i = 1)$ represented the probability of individual i experiencing negative sentiment; Brightness_i denoted the total nighttime light brightness within a 200-meter radius of individual i ; $\text{Band}_{k,i}$ indicated the nighttime light intensity in the specific spectral band k within a 200-meter radius of individual i ; X_i

represented all weather control variables for observation i ; and A_i represented air quality control variables for observation i .

It is important to note that while L2 regularization stabilized the model to generate a robust predictive sentiment risk, this came at the cost of biased coefficients. Given that our objective was to capture the relative contribution of each band to sentiment risk, the coefficients for the individual light variables in equation (5) should be interpreted with caution as part of a collective predictive model, rather than as precise, independent marginal effects. To this end, we conducted a sensitivity analysis in which we excluded the total brightness term from the model and used only the three spectral band intensities to predict sentiment. The results showed that the direction and statistical significance of the key spectral effects remained consistent, thereby validating the robustness of our overall conclusions (Table S8).

The regression coefficient for each nighttime light exposure-related explanatory variable reflects its contribution to the log-odds of negative sentiment. Therefore, for each location, the sentiment risk score (SRS) can be expressed as a weighted sum of nighttime light exposure values for each band and their corresponding regression coefficients (equation (6)). Based on this model, we were able to quantify the combined association of nighttime light exposure with the odds of negative sentiment for a given individual address. Regions with SRS exceeding 1.1 were classified as areas of negative-sentiment enhancement, while those with SRS below 0.9 were identified as areas of negative-sentiment mitigation²⁴.

$$SRS_i = \exp (\beta_1 Brightness_i + \beta_2 Band_1 + \beta_3 Band_2 + \beta_4 Band_3) \quad (6)$$

Where SRS_i represented the contribution of light exposure to sentiment risk for a given individual i , and β_1 , β_2 , β_3 , and β_4 were the coefficients from the fully

adjusted model (equation 5).

ALAN optimization scenarios

We established three optimization scenarios to compare the effectiveness of different lighting optimization measures in reducing negative emotional health risks associated with NTL exposure in urban environments. All optimization scenarios were simulated based on SDGSAT-1 data. The first was a brightness-priority scenario: this scenario was designed based on the established role of brightness in increasing negative sentiment risks, and in response to existing calls in the literature for reducing light brightness. We maintained the ratio of red, green, and blue bands constant while reducing light intensity by 50% in areas with an SRS greater than 1.1, aiming to mitigate the impact of overall brightness on increasing negative sentiment. The second was a color temperature-priority scenario: informed by existing research and American Medical Association (AMA), which advocate for setting the correlated color temperature (CCT) below 3000K, necessitating lower values for blue and green bands and higher values for the red band³⁹. Therefore, in the color temperature-priority scenario, we maintained the overall light intensity constant while reducing the values of the blue and green bands of nighttime light by 50% in areas with an SRS greater than 1.1. The third was an optimal scenario: for areas with an SRS greater than 1.1, we simultaneously reduced the overall light intensity by 50% and adjusted the color temperature in accordance with the color temperature-priority scenario.

Data availability

All the data used in this study are publicly available. The SDGSAT-1 datasets are available at (<https://www.sdgsat.ac.cn/>). Geotagged social media data used in this

study was obtained from Weibo and can be accessed at (<https://weibo.com/>). The ERA5-Land reanalysis dataset can be found at (<https://developers.google.com/earth-engine/datasets/catalog/>). The CHAP dataset can be found at (<https://doi.org/10.5281/zenodo.3539349>). The Global Urban Boundary dataset can be found at (<https://data-starcloud.pcl.ac.cn/zh>). WorldPop population data is available at (<https://www.worldpop.org/>).

Code availability

The code used to generate the results of this study is available at (<https://doi.org/10.5281/zenodo.17777725>).

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Author contributions

C.Z., M.M., Z.C. and J.W. conceived and designed the research; C.Z., M.M., J.H., K.Z., J.Y., F.Y., and Y.F. performed data analysis; C.Z., M.M., Wenchong Du, J.W. and Z.C. wrote the manuscript; and Weihua Dong, M.L. B.G. and Q.W. contributed

ideas to data analysis, interpretation of results or manuscript revisions.

Competing Interests

The authors declare no competing interests.

Figure Legends

Figure 1. Individual outdoor ALAN exposure and sentiment measurement. (a)

Conceptual diagram illustrating how satellite observations of nighttime light and social media were utilized to measure personal outdoor ALAN exposure and expressed sentiment. (b) Our workflow for analyzing the impact of outdoor ALAN exposure on sentiment expression. We quantified sentiment scores using Weibo social media posts and employed fixed-effects models to analyze the effect of nighttime light on sentiment expression while controlling for potential confounding factors.

Figure 2. Effects of ALAN exposure on sentiment. This figure illustrates the effects of nighttime light exposure measured at 200m on sentiment expression across all samples for (a) brightness, (b) red band, (c) green band, and (d) blue band. For each panel, total $n = 4,203,567$. The regression models incorporated provincial, monthly, and weekday fixed effects. Error bars represent standard deviation, and the measure of centre indicates the mean value. Further details are presented in Table S2.

Figure 3. The heterogeneous effects of outdoor ALAN exposure on sentiment. (a) The effects of nighttime light exposure measured at varying

distances on sentiment expression. As distance increased, the negative effects of green and blue light and the positive effects of red light all intensified. Total $n = 4,203,567$. Error bars represent standard deviation, and the measure of centre indicates the mean value. (b-e) Estimated effects of nighttime light exposure on sentiment from our main model run on samples stratified by season and time: (b) spring (March, April, and May), (c) summer (June, July, and August), (d) autumn (September, October, and November), and (e) winter (December, January, and February). All seasons included different time points between 20:00-24:00. Total $n = 1,466,530, 1,310,379, 629,868, \text{ and } 796,790$ for spring, summer, autumn, and winter, respectively. Error bars represent standard deviation, and the measure of centre indicates the mean value.

Figure 4. Geographical distribution of sentiment risks associated with ALAN exposure. (a) Nationwide distribution of sentiment risks associated with ALAN exposure. The size and color of the circles represented population-weighted sentiment risk and the proportion of negative-sentiment mitigation zones, respectively. (b) and (c) show the distribution of ALAN observed by SDGSAT-1 and the sentiment risks in Beijing, respectively. (d) and (e) show the distribution of ALAN observed by SDGSAT-1 and the sentiment risks in Shanghai, respectively. Maps were generated using ArcGIS Pro 3.1.6. The administrative boundaries were provided by National Catalogue Service for Geographic Information (<http://www.webmap.cn/>).

Figure 5. Sentiment risk mitigation under different lighting optimization scenarios. (a) Brightness reduction scenario, showing spatial distribution of sentiment risk reduction after uniformly decreasing light intensity by 50% in high-risk areas ($SRS > 1.1$) while maintaining spectral composition. Circle size

represents population-weighted sentiment risk reduction ratio (%), and color intensity indicates the percentage increase in locations that suppress negative sentiment. (b) Color temperature adjustment scenario, displaying spatial changes in sentiment risk after optimizing spectral composition without altering overall brightness. (c) Integrated scenario combining both brightness reduction and color temperature adjustment, demonstrating the most comprehensive mitigation strategy. (d) City-level population-weighted sentiment risk comparison across all optimization scenarios. Each line connects the same city under different lighting conditions. The horizontal dashed line represents the threshold between negative-sentiment-promoting (above) and negative-sentiment-suppressing (below) environments, illustrating how each strategy shifts sentiment profiles. Maps were generated using ArcGIS Pro 3.1.6. The administrative boundaries were provided by National Catalogue Service for Geographic Information (<http://www.webmap.cn/>).

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