Simulating Urban Green Space's Cooling Impact on School-age Children' Sleep Quality Using Diverse Planning Approaches

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Abstract
Despite the widespread use of urban green spaces (UGS) as a climate change mitigation strategy, their cooling effects have not been thoroughly studied for public health benefits. This study, conducted in Guangdong Province, a subtropical monsoon region in China's Great Bay Area, assesses four UGS scenarios with different trade-offs regarding their impacts on school-age children's sleep health. Introducing around 2.5 to 2.7 km^2 of UGS significantly lowers temperatures by up to 1.13 °C monthly, benefiting populations with varying risk levels. Prioritizing small UGS yields the most profound benefits, especially investing in existing ones. Emphasizing large UGS has limited benefits, with constructing new ones the least effective. Careful planning and design highlighting social benefits and equity are crucial for addressing heat-related health risks under climate change.

Keywords: Urban green space; Heat exposure, Planning; Sleep health; Simulation

1 Introduction

The escalating climate change exposes individuals to greater health risks (Ebi et al., 2021), particularly in densely populated urban areas of subtropical and tropical regions (Dong et al., 2024), where the urban heat island effect (UHI) combined with high humidity increases the risks of heat stress (Ho et al., 2025), non-communicable diseases such as cardiovascular and respiratory diseases (Liu et al., 2022), sleep disorders and mental illnesses (Cianconi et al., 2020; Rifkin et al., 2017).

Having the potential to confer physical and psychological benefits, urban green space (UGS) has been increasingly adopted as a climate change mitigation strategy (Sugiyama et al., 2018; Zhang et al., 2022). Apart from bringing psychological relief and promoting physical activities and social contacts (Lachowycz and Jones 2013; Shuvo et al., 2020), research also indicates that UGS mitigates heat exposure, improve thermal comfort and thus improve public health (Markevych et al., 2017).

However, this specific cooling pathway remain largely underexplored, especially regarding its associations with public health benefits (Huang et al., 2025; Sadeghi et al., 2022). Current research on UGS's cooling effect lacks systematic perspective that positions UGS in an extensive urban landscape with various intricately-influencing factors (Aram et al., 2019), thus failing to offer constructive prescriptions (Zhang et al., 2017 a). Moreover, simulations seldom consider the real-world planning practices that are embedded in the urban land use system (Li et al., 2022), leading to a fundamental gap between theoretical results and practical guidance.

Therefore, using Guangdong Province as a case site, this study examines the health benefits of UGS's cooling pathway through assessing the performances of different UGS planning scenarios. Results from air temperature simulations are linked with a large-scale survey on school-age children' s sleep health status. How different planning approaches are influencing their sleep health is evaluated to shed light on the common trade-offs between small-large and new-old UGS. Section 2 reviews the established findings and remaining debates. Section 3 illustrates the research strategy. Section 4 presents the results, and Section 5 conveys discussions and policy implications.

2 Literature review

2.1 Heat exposure's impact on school-age children's sleep health

Sleep health is closely related with all kinds of mental disorders (Hudson et al., 2020; Scott et al., 2016), yet has received less attention than diseases and death in the realm of health research. Research indicates that global warming is leading to increased thermal discomfort, night sweats, breathing difficulties, and disrupted sleep patterns (Obradovich et al., 2017; Zheng et al., 2019), resulting in individuals worldwide losing around two weeks of sleep each year (Minor et al., 2022). Sleep efficiency decreased by 10% in temperatures between 25 °C and 30 °C (Baniassadi et al., 2023), and interruptions and awakenings significantly increased when ambient temperatures exceeded 30 °C (Altena et al., 2023). Although air conditionings can mitigate outdoor heat exposure, they are typically used when temperatures rise to a relatively high degree; in their absence under mild and moderate exposure, indoor temperatures systematically surpass outdoor ones (Yan et al., 2022), causing significant sleep issues related to heat exposure (Lin and Deng, 2006).

Recently, the sleep issues of school-age children are receiving increasing attention, as the incidence of various sleep disorders among school-aged children, including sleep-related breathing disorders and circadian rhythm sleep disorders, may reach 30% to 40% around the world (Lim et al., 2023; Chen et al., 2021). School-age children are particularly prone to experiencing sleep disorders compared to adults, possibly due to their developing physiological and nervous systems that make them more sensitive to changes in thermal environment (Kansagra, 2020; Trosman and Ivanenko, 2024). Moreover, they are particularly sensitive to noise and artificial light (Wang et al., 2022) and indoor air quality (Fujii et al., 2015; Rahai et al., 2024), and the academic pressure they face may also make them more sensitive to the thermal environment (Qi et al., 2020; Steare et al., 2023). Since most current studies focus on vulnerable groups such as the elderly, the pregnant or outdoor workers (Baldwin et al., 2023; Gulia and Kumar, 2018), it holds theoretical and practical significance to examine the sleep health of school-age children and provide potential prescriptions.

2.2 UGS's health benefits and cooling capacity

UGS offers health benefits through various pathways, including emotional regulation, promoting physical activities and social contacts, as evident in extensive studies (McMahan and Estes, 2015; Lachowycz and Jones, 2013; Oliveira et al., 2014; Sallis et al., 2016). However, non-significant relationship between UGS and physical activities have also been reported (Triguero-Mas et al., 2015), partly due to some UGS's not being thermally comfortable or adequately designed for physical activities (Evenson et al., 2013). Additionally, UGS enhances air quality by absorbing, filtering, and decomposing harmful particles (Buccolieri et al., 2018; Ysebaert et al., 2021), yet concerns arise about the allergens and particles brought by UGS that may harm health (Osborne et al., 2017). Moreover, UGS confers public health benefits by reducing urban heat through evapotranspiration and shading[1](Probst et al., 2022; Wong et al., 2021). Research indicates that the temperature reduction contributed by UGS ranges from approximately 1 °C to 10 °C and even higher (Park et al., 2017; Rashid et al., 2014; Wu et al., 2012), further leading to profound decrease of air conditioning usage and promoting energy conservation (Zhang et al., 2014). Existing research has identified controversies regarding the size and layout of UGS. For example, some scholars highlight the extraordinary cooling effect of large UGS, pointing out UGS over 100 hectares can cool areas over several kilometers far (Du et al., 2017), while evidence also show that UGS as small as 0.49 to 2.04 hectares can generate a significant cooling effect of 1°C to 3 °C (Grilo et al., 2020). Some scholars highlight that a clustered pattern of UGS patches have greater cooling performances than a scattered pattern (Estoque et al., 2017; Rhee et al., 2014; Zhao et al., 2020), but there exist inconsistent findings (Zhou et al., 2011; Zhou et al., 2023). Some studies worry that UGS may increase humidity and thus hinder the cooling of the surrounding areas, yet studies from places such as Singapore and Malaysia have demonstrated UGS's profound cooling effect (Rashid et al., 2014; Shahidan et al., 2012).

However, current studies have not effectively linked UGS's cooling capacity to public health benefits through empirical investigations. Several gaps remain. First, Studies defining UGS boundaries often overlook the influence of the built environment, resulting in inaccurate definitions. Second, while some studies use simulation techniques to optimize UGS distribution for cooling effects (Zhang et al., 2017 b), they fail to include the real-world land use situations and leading to limited practical guidance. These ambiguities and gaps highlight the necessity of conducting location-based empirical research (Zhou et al., 2025).

2.3 UGS planning practices and equity debate

Recently, UGS has become a popular planning strategy aimed at improving public health (Sugiyama et al., 2018), as it is considered more economical in cost and can raise fewer concerns on environment and political sides than many other measures (Zhang et al., 2019). However, gaps remain between UGS research and planning practices. First, UGS is mainly provided by governments due to its competitiveness and non-exclusiveness as quasi-public goods (Chen et al., 2019) and thus less valued due to budget constraints (Chen and Hu, 2015; Lin et al., 2023; Wang,

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1 Evapotranspiration reduces ambient air temperature through converting liquid water into water vapor and exchanging sensible heat for latent heat, while the shade created by plant canopies blocks heat transfer and contributes to lowering temperatures, especially in humid regions through delaying the peak air temperatures during the day.

2015), leading to UGS relatively small, not appropriately designed and suitable for recreational activities (Jiao et al., 2017; Wolch et al., 2014). Furthermore, compulsory demands from the higher-level governments regarding UGS have not prompted local governments to intricately plan UGS. Instead, they struggle to meet minimal quantity requirement[2], disregarding spatial layout and interior design, as well as public participation (Miao, 2011; Yu and Padua, 2007). Additionally, that land developers placing high values of UGS construction turns them into private asses, exacerbating the inequalities in distribution and utilisation of UGS due to "green gentrification" (Liebelt et al., 2018; Shan et al., 2024). These practical obstacles embedded in the planning system hinder UGS from maximizing their potential to deliver comprehensive and equitable health benefits (Wang and Chan, 2019) and require more cautious planning interventions (De Haas et al., 2021; Kruize et al., 2019).

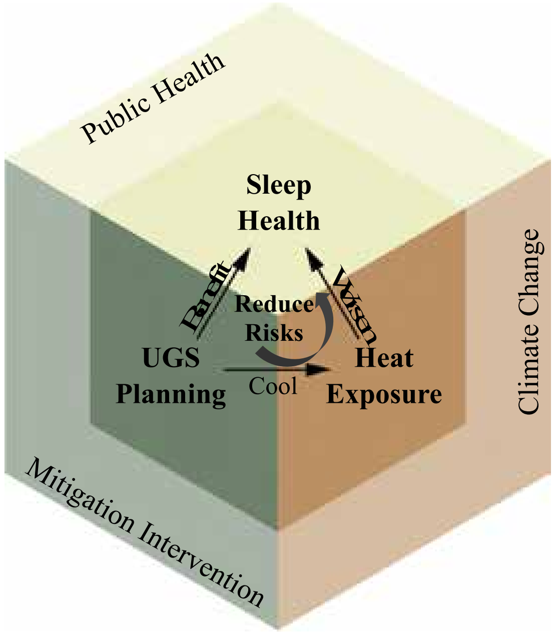

Figure 1 UGS's cooling pathway to mitigate climate change's impact on sleep health

3 Research strategy

3.1 Data source and research framework

This study focuses on Guangdong Province from the Great Bay Area of China, which features a subtropical and tropical monsoon climate zone (20°09'N to 25°31'N, 109°45'E to 117°20'E) with its average temperature between 19 °C and 23.5 °C and averagely over 30 °C during the summer, thus facing significant heat exposure-induced health issues (Ho et al., 2025).

Six cities from the Guangdong Province that cover both economically developed and developing cities were selected to conduct a survey of school-age children, including Guangzhou, Shenzhen, Foshan, Zhongshan, Zhuhai and Maoming (**Figure 2**). The six cities cover both the coastal and inland part, 41.50% of the impermeable area, 41.45% of the population, and 65.43% of the GDP of the entire Guangdong province[3], representative regarding climate and population. A large-scale survey was conducted across almost all months from 2016 to 2018[4], obtaining information on sleep health, home address and family's socioeconomic status from 131,412 school-age children in 105 randomly-selected primary and middle schools. The average atmospheric temperature within 500 meters of the residence is matched according to students' home address and used to represent heat exposure (Venter et al., 2020).

2 For instance, Guangzhou does not provide detailed definition and calculation method for the different requirements of UGS. Shenzhen sets the rate of green space for each district, which is a different indicator compare to Guangzhou. The planning documents do not specify the calculation method as well.

3 These percentages are calculated based on the 30m resolution land use data from 2016 to 2018, the 100m resolution population and GDP density data in 2019. Detailed data sources are in Table 1.

4 The protocol was approved by the Sun Yat-sen University Institutional Human Ethics Committee (Ethics Approval Number: 026).

This study comprises three stages (**Figure 3**). The first models the link between air temperature and sleep health and explores whether UGS has the potential to mitigate heat exposure's exacerbating influences on sleep disorders, with sampled school-age children as a focused group. The second constructs a prediction model for air temperature based on various factors, including planning interventions that can be linked with different planning approaches. The third applies the four UGS scenarios representing different trade-offs regarding small-large and new-old to established models in the first two stages, evaluating their nuanced potentials in improving school-age children's sleep health.

Multiple factors are included in the second stage (**Table 1**), including climate and geographic factors such as precipitation, relative humidity, wind velocity, solar radiation and digital elevation model (DEM) (Cristóbal et al., 2008; Yang et al., 2017), socioeconomic factors such as population and GDP density (Shen et al., 2020; Sun et al., 2018). Normalized difference vegetation index (NDVI) and land cover data are also included to link with planning interventions in different scenarios. Air temperature better represent people's perception of temperature exposure (Bernhard et al., 2015), yet land surface temperatures (LST) are also included as factors as recommended (Hu et al., 2019; Janatian et al., 2017).

Figure 2 Research sites[5]

5 The map of the Great Bay Area is from the Guangdong Provincial Department of Natural Resources, with review number Yue S (2022) No. 226, with the small islands on the sea omitted. The map of China is from the Ministry of Natural Resources, with review number GS (2023) No. 2765.

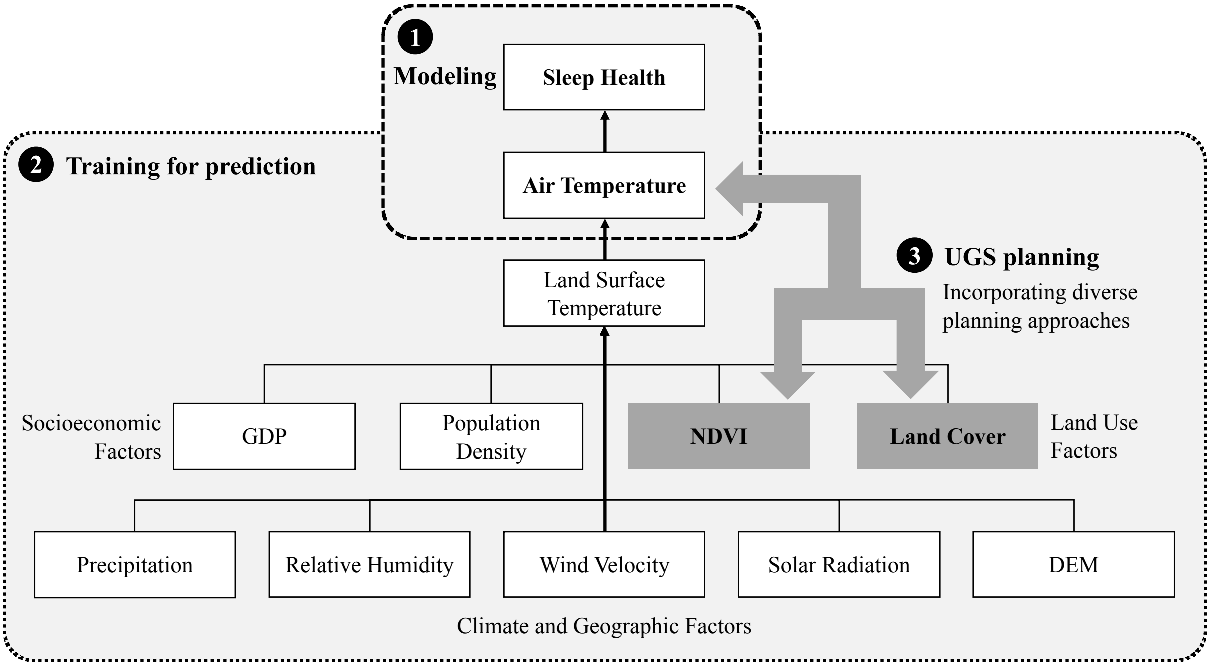

Figure 3 Research framework

Table 1 Source of data for heat exposure simulation

Data	Source	Spatial Resolution	Temporal Resolution
Air temperature		1km	monthly
Precipitation	National Earth System Science Data Centre, National Science & Technology Infrastructure of China (http://www.geo-data.cn)	1km	monthly
Relative Humidity		1km	monthly
Wind Velocity		1km	monthly
Solar Radiation		1km	monthly
NDVI		1km	monthly
DEM	National Tibetan Plateau Data Centre (Tang, 2019)	1km	2000, stable across years
Land Cover	(Yang and Huang, 2021)	30m	yearly, using 2016-2018
Population Density	China Resource and Environmental Science Data Platform (Xu, 2017a; 2017 b)	100m	every five years, using 2019
GDP Density		100m	every five years, using 2019
Land Surface Temperature	NASA's Land Processes Distributed Active Archive Centre (Wan et al., 2015)	1km	monthly

3.2 Model setting

3.2.1 Model between air temperature and sleep disorders

A logistic model is utilized to examine the impact of heat exposure on sleep health, considering sleep disorder indicators such as overall sleep disorder (SD), disorders of initiating and maintaining sleep (DIMS), and sleep hyperhidrosis (SH). Covariates include age, gender, body mass index (BMI), exercise time, secondhand smoke exposure, household income level, housing area per capita, presence of mold at home, proximity to main road or factory, and average NDVI in the neighborhood.

$$Prob(Y_i = 1|X_i, Z_i) = \Phi(\beta_0 + \beta_1 T_i + \theta G_i + Z_i \gamma + \varepsilon_i) \qquad (1)$$

where Prob(Y_i=1|X_i,Z_i) represents the probability of sleep disorders. R denotes the temperature exposure variable. G refers to the average NDVI of the surrounding neighborhood. Z represents the control variables.

A generalized structural equation model (GSEM) is used to test UGS's cooling pathway in mitigate heat exposure's adverse impact on sleep health. The formula (1) and (2) are estimated in a structed way (Yu et al., 2025).

$$T_i = \mu_0 + \mu_1 G_i + \varepsilon_i \qquad (2)$$

If both μ_1 and Δ_1 are significant, UGS's cooling pathway in mitigating heat exposure's adverse impact on sleep health is significant. If both μ_1 and Δ_1 are not significant, product-of-coefficients tests are performed. If Δ is nonsignificant, the full mediating effect is further verified. Otherwise, there is a partial mediating effect.

A natural cubic spline (NCS) method is used to detect the nonlinear impact.

$$Prob(Y_i = 1|X_i, Z_i) = \Phi(\beta_0 + \beta_1 ns_1(T_i) + \beta_2 ns_2(T_i) + \beta_3 ns_3(T_i) + \beta_4 ns_4(T_i) + \theta G_i + Z_i \gamma + \varepsilon_i) \qquad (3)$$

where $ns_1(T_i)$, $ns_2(T_i)$, $ns_3(T_i)$, $ns_4(T_i)$ indicate the functions generated using NCS method. Each disorder-specific model is determined using the lowest Akaike's Information Criterion (AIC) values that indicates the best fit across the three different knot specifications (Lee et al., 2020).

3.2.2 Model for predicting air temperature

A two-stage training approach using random forest method is adopted to construct an air temperature prediction model for each month across the survey time. UGS in this study is defined as all forest, shrub and grass within the "urban area"[6] (Sun et al., 2021) based on the land cover data of 30 m resolution (Yang and Huang, 2021), as employed by many other studies to exclude hard pavements and allow for the actual cooling effect from plants (Feltynowski et al., 2018; Kuang et al., 2021). The two-stage training method allows for the consideration of UGS impact on the environment through LST (Janatian et al., 2017), with marine areas omitted due to data unavailability. Urban areas and human habitats mostly situate to the southern area, allowing for the exclusion of the confounding effects from bordering regions. The importance of each factor and goodness of fit are reported in **Appendix Table 1**.

3.3 UGS scenarios

Four UGS scenarios are proposed based on the real-world practices and debates, including expanding current large UGS (s1), expanding current small UGS (s2), constructing new large UGS (s3), and constructing new small UGS (s4) (**Figure 4**). Expanding current UGS can be costly but beneficial for densely populated areas nearby. Building new UGS may be more feasible with lower costs, benefiting residents in the vicinity, although their impact may be limited if located in remote areas.

In China, local governments determine the UGS quota based on the total new urban land allocation set by higher

6 The urban area in this study is the minimum bounding rectangle based on the urban built-up area published by Sun et al. (2021) using the "Minimum Bounding Geometry" tool in GIS. This approach maximizes interconnected urban green spaces in close proximity while excluding rural and ecological conservation areas.

authorities, typically ranging from 5-30% of the annual new urban land. City-specific ratios between 5-30% is set for converting to new UGS, and the total amount of new UGS range from approximately 2.5 to 2.7 km^2, with the six sampled cities accounting for over 60% (**Table 2**).

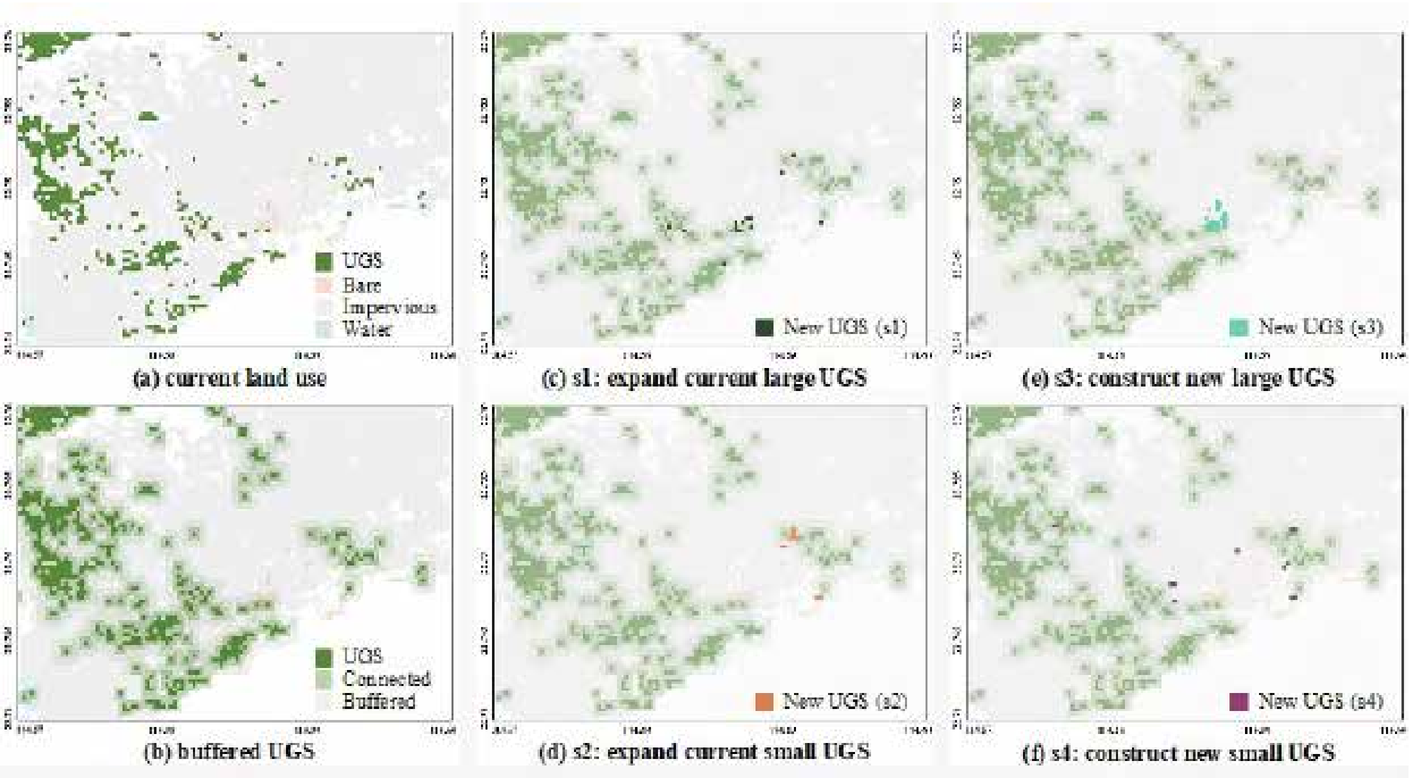

Figure 4 Simulation scenarios (Shenzhen example)

Table 2 The city-year-fixed total amount of new UGS (km^2)

	bare land			Increased UGS			Ratio
	2016	**2017**	**2018**	**2016**	**2017**	**2018**	
Foshan	4.028	4.193	4.233	1.209	1.258	1.270	30%
Guang-zhou	1.049	1.150	1.094	0.315	0.345	0.329	30%
Maoming	0.067	0.053	0.052	0.004	0.003	0.003	5%
Shenzhen	1.067	1.002	0.764	0.320	0.301	0.230	30%
Zhongshan	0.650	0.638	0.557	0.130	0.128	0.112	20%
Zhuhai	0.083	0.079	0.069	0.005	0.004	0.004	5%
Other	4.020	4.064	3.860	0.631	0.636	0.604	5-30%
Total	10.880	11.100	10.560	2.613	2.674	2.550	24%

4 Results

4.1 Modeling exposure-disorder relationship

Logistic models reveal that heat exposure significantly increases the risk of sleep disorders (SD, DIMS, SH) (**Table 3**, Model 1-3). lnNDVI significantly decreases of risks of sleep disorders. GSEM analysis examines the mediating role of UGS cooling effect on sleep health (**Table 4**), demonstrating a significant positive impact aligning with prior empirical evidence (Yu et al., 2025). The cooling pathway accounts for approximately 1% of the total effect using lnNDVI as a proxy.

The NCS method identifies the nonlinear impact of heat exposure (**Table 5**, Model 4-6). Each knot function shows significant estimated coefficients, especially ns(T)3 which falls around the moderate levels of exposure. The coefficients of lnNDVI are similar as those in normal logistic models. We focus on analyzing the predicted probabilities of experiencing sleep disorders rather than specific numerical results.

Table 3 Heat exposure's impact on sleep disorders using logistic egression

	Model 1 (SD)	**Model 2 (DIMS)**	**Model 3 (SH)**
T	0.013***	0.020***	0.017***
	(0.004)	(0.003)	(0.003)
lnNDVI	-0.539***	-0.448***	-0.506***
	(0.038)	(0.034)	(0.035)
Controls	Yes	Yes	Yes
N	108930	108930	108930
Pseudo R^2	0.019	0.013	0.061

Note: Robust standard errors are in the parentheses. * indicates statistical significance at the 0.1 level, ** indicates statistical significance at the 0.05 level, *** indicates statistical significance at the 0.01 level.

Table 4 UGS's cooling pathway in heat exposure's impact on sleep health

	SD	**DIMS**	**SH**
lnNDVI→T	-0.344***	-0.344***	-0.344***
	(0.036)	(0.036)	(0.036)
T→SLEEP	0.013***	0.020***	0.017***
	(0.004)	(0.003)	(0.003)
lnNDVI→SLEEP	-0.539***	-0.448***	-0.506***
	(0.038)	(0.034)	(0.035)
Indirect	-0.004***	-0.007***	-0.006***
	(0.001)	(0.001)	(0.001)
Total	-0.544***	-0.455***	-0.512***
	(0.038)	(0.037)	(0.034)
Indirect/Total	0.8%	1.5%	1.2%

Note: Robust standard errors are in the parentheses. * indicates statistical significance at the 0.1 level, ** indicates statistical significance at the 0.05 level, *** indicates statistical significance at the 0.01 level. All models included control variables.

Table 5 Heat exposure's nonlinear impact (NCS method)

	Model 4 (SD)	Model 5 (DIMS)	Model 6 (SH)
ns(T)1	0.882***	1.031***	1.005***
	(0.152)	(0.128)	(0.157)
ns(T)2	0.354***	0.410***	0.576***
	(0.126)	(0.097)	(0.128)
ns(T)3	1.497***	1.397***	1.903***
	(0.362)	(0.298)	(0.381)
ns(T)4	0.565***	0.564***	0.547***
	(0.132)	(0.089)	(0.118)
lnNDVI	-0.576***	-0.491***	-0.542***
	(0.040)	(0.035)	(0.036)
Controls	Yes	Yes	Yes
N	108930	108930	108930
Pseudo R^2	0.020	0.015	0.062

Note: Robust standard errors are in the parentheses. * indicates statistical significance at the 0.1 level, ** indicates statistical significance at the 0.05 level, *** indicates statistical significance at the 0.01 level. All models included control variables.

4.2 Simulating UGS's cooling potential

Figure 5 compares original and simulated temperatures in s1 within the built-up area, displaying monthly averages. The most significant cooling effect occurs in March and April, with a maximum decrease of 1.13 °C. Conversely, July and August show minimal cooling, with a potential increase of 0.04 °C, likely influenced by high humidity.

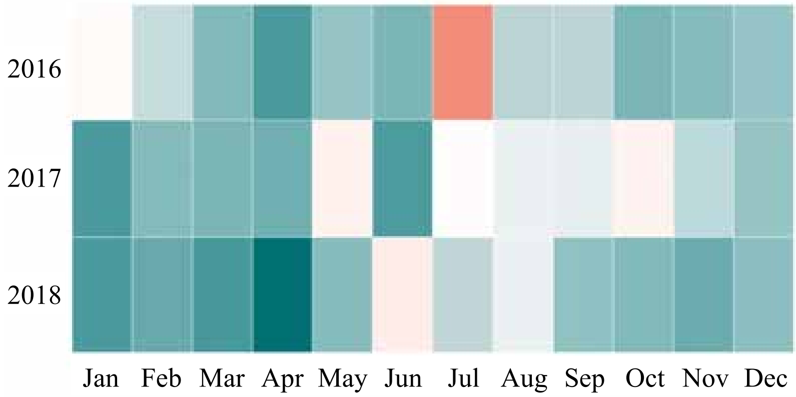

Figure 5 Temperature difference between the original and simulated (s1)

4.3 Simulating UGS's cooling impact on sleep health

Possibilities of developing sleep disorders are predicted based on the normal logistic and NCS models (Model 1-6). By incorporating simulated temperature exposures, new probabilities are generated for the four planning scenarios proposed in section 3.3. **Figure 6** presents the overall mean value and Gini coefficient. **Table 6** reports the t-test results of the mean value between four scenarios. **Figure 7** shows the decile-based probability changes, while **Table 7** reports the average risks of sleep disorders (measured using the NCS method) across different cities.

According to **Figure 6** and **Table 6**, Mean values from the NCS method are higher than those from normal logistic regression, with relatively lower Gini coefficients. Since prior research has highlighted that using a linear “exposure-response” relationship may underestimate health risks linked to high temperatures (Gasparrini et al., 2010), NCS results may provide a more reliable and accurate reflection of heat exposure’s real-world impacts. The mean values in s2 are significantly lower than in s1 and s3 according to the NCS method), suggesting that enhancing large UGS may not provide substantial health benefits through cooling. In contrast, mean values in s2 are higher than s1 and s3 in normal logistic regression due to potential underestimation at high temperatures. Gini coefficients in s2 and s4 are lower than in s1 and s3, with s4 showing a more balanced distribution of sleep disorder risks compared to s2, indicating that focusing on small UGS improvements may lead to more equitable outcomes.

In **Figure 7**, blue indicates a decrease in the average probability of sleep disorders compared to the original situation in the simulated scenario, while yellow signifies an increase. An unpaired t-test between the original and simulated scenarios reveals a significant improvement in the first decile group in the NCS model of SD. Introducing UGS shows potential to enhance sleep health for populations at low and high-risk levels, but may not have the same effect for those with moderate risk levels due to increased humidity in some areas. The NCS results, considering nonlinear relationships, show greater improvements, underscoring UGS’s ability to mitigate heat exposure’s negative effects. UGS’s cooling benefits are particularly advantageous for lower-risk groups (SD and SH), offering broad advantages across different risk levels. However, individuals in the extremely high-risk category (DIMS) may not experience significant improvements in sleep health, indicating complex factors beyond heat exposure may pose threats to DIMS.

In **Table 7**, the scenario with the lowest mean risk value for each city is highlighted in grey. Most cities show the greatest benefits from scenarios s2 and s4, with Foshan benefiting from scenario s4 across all three types of sleep disorders. Guangzhou and Zhuhai might derive the most benefit from scenario s1. Only a small number of cities appear to benefit from scenario s3.

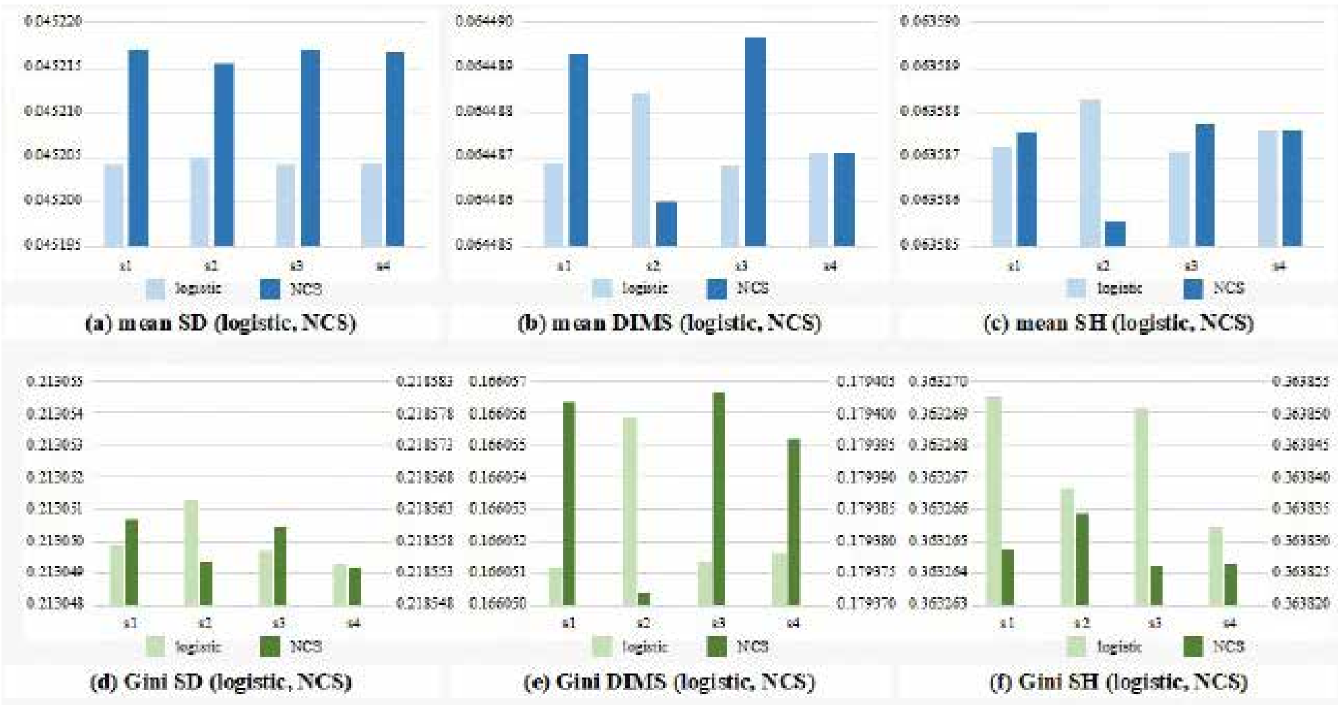

Figure 6 The mean and Gini coefficients of the risks of sleep disorders among four scenarios

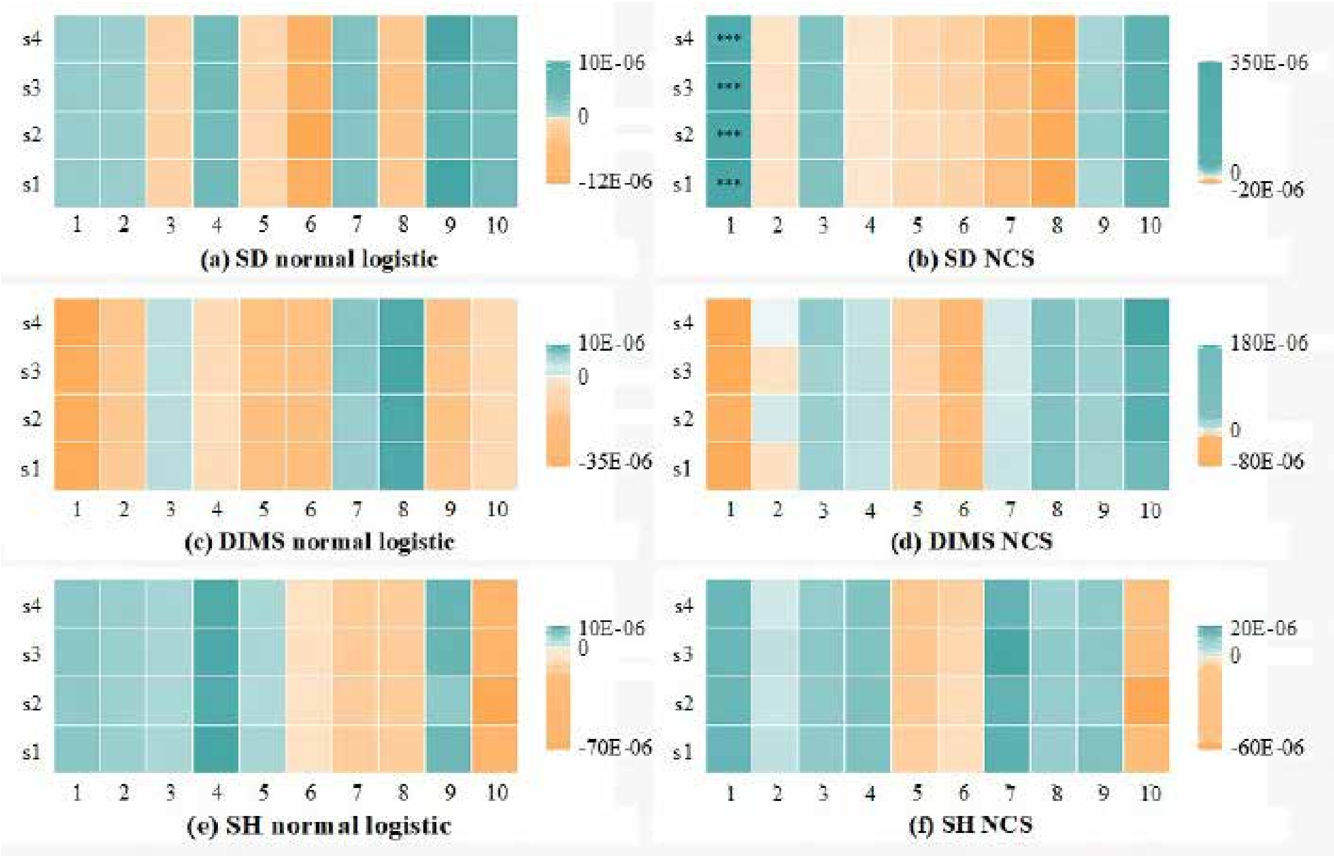

Figure 7 The differences between the current and simulated risks by levels among the four simulation scenarios

Table 6 T-test results of the risks of sleep disorders between the four simulation scenarios

group	l_sd	l_dims	l_sh	ns_sd	ns_dims	ns_sj
s1 - s2	-0.887***	-1.560***	-1.050***	1.600***	3.290***	2.000***
	(0.019)	(0.032)	(0.026)	(0.061)	(0.173)	(0.056)
s1 - s3	0.049***	0.070***	0.102***	0.044	-0.354***	-0.146***
	(0.007)	(0.013)	(0.010)	(0.027)	(0.080)	(0.022)
s1 - s4	-0.007	-0.030	0.076***	0.748***	2.030***	0.390***
	(0.011)	(0.019)	(0.017)	(0.040)	(0.117)	(0.035)
s2 - s3	0.936***	1.630***	1.150***	-1.560***	-3.640***	-2.150***
	(0.019)	(0.033)	(0.027)	(0.063)	(0.176)	(0.060)
s2 - s4	0.880***	1.530***	1.130***	-0.854***	-1.260***	-1.610***
	(0.018)	(0.031)	(0.026)	(0.063)	(0.176)	(0.057)
s3 - s4	-0.056***	-0.099***	-0.026*	0.704***	2.380***	0.536***
	(0.009)	(0.015)	(0.015)	(0.035)	(0.101)	(0.030)

Note: Due to the small numerical values, the reported results are shown after multiplying by , representing the key figures in scientific notation (E-06).

Table 7 The mean values of the risks of sleep disorders (NCS method) by cities

city	Foshan	Guangzhou	Maoming	Shenzhen	Zhongshan	Zhuhai
ns_sd						
p1	46032.8	46785.8	43376.2	44468.6	45425.2	43137.9
p2	46035.1	46786.6	43362.9	44467.9	45424.9	4 3137.8
p3	46031.3	46786.1	43377.4	44468.0	45425.0	43138.0
p4	46030.3	46785.7	43377.1	44467.9	45424.8	43138.4
ns_dims						
p1	65971.2	68181.4	67144.2	55384.2	63173.5	66310.5
p2	65978.7	68184.6	67111.9	55383.6	63172.8	66310.1
p3	65966.8	68183.6	67148.5	55383.4	63173.1	66310.5
p4	65963.3	68181.7	67138.7	55383.5	63172.7	66310.7
ns_sh						
p1	64160.4	56358.7	59075.8	75077.9	62735.7	73261.4
p2	64161.7	56359.2	59061.9	75077.5	62735.2	73261.2
p3	64160.0	56359.4	59076.9	75077.4	62735.4	73261.3
p4	64159.7	56359.0	59076.8	75077.3	62735.3	73261.9

Note: Due to the small numerical values, the reported results are shown after multiplying by , representing the key figures in scientific notation (E-06).

5 Discussion and policy implication

This study focuses on Guangdong Province which features a typical subtropical monsoon climate. Using a "marginal increase" approach, the research examines how UGS provide health benefits through cooling effects in the region. A monthly air temperature prediction model is developed, incorporating various factors and achieving a good fit above 0.95. Four UGS planning scenarios are proposed based on real-world practices. Simulation results are then used to assess the risks of three types of sleep disorders among school-age children in six sampled cities.

Results confirm that UGS serves as an effective strategy in mitigating climate change impacts on sleep health, and the cooling pathway significantly accounts for at least 1%. Introducing around 2.5 to 2.7 km^2 of UGS can effectively cool urban areas, with the most substantial temperature reduction of 1.13 °C in April 2018. Approaches highlighting small UGS have a more profound and significant positive effects on school-age children's sleep health than scenarios focusing on large UGS. Particularly, expanding existing small UGS in s2 shows the greatest potential for balanced and equitable outcomes. In contrast, s3 performs poorly in terms of health impact and equity.

Results indicate that UGS provides health benefits for population with both low and high risks, as shown in **Figure 7**. In other words, UGS not only serve to mitigate heat-related risks but also contribute to enhancing public health in a preventive way (Lachowycz and Jones, 2013; Zhang et al., 2022), emphasizing the importance of introducing and improving UGS to confer public health benefits. However, UGS may have negative impacts on populations with medium risk levels. In some cases, UGS in humid areas may increase humidity levels, impacting thermal comfort (Yu et al., 2025). The complex dynamics between humidity and temperature (Yang et al., 2024) jointly affect thermal comfort, and elevated humidity coupled with extreme high temperatures may exacerbate heat discomfort (Ho et al., 2025). UGS may not effectively mitigate risks at very high levels, highlighting the need for targeted investigations into factors beyond the thermal environment affecting sleep disorders.

The size of UGS matter a lot in planning practices. Contrary to the emphasis on large UGS in studies specifically focusing on the cooling effect (Shah et al., 2021), this study indicates that prioritizing small UGS may yield greater cooling-induced health benefits. Expanding and improving small UGS and creating new ones can provide broader access to cooling benefits for the population, consistent with previous findings (Yan et al., 2021). In contrast, expanding the large UGS in s1 shows limited health benefits, likely due to its placement in non-residential central urban areas (Aram et al., 2019). Similarly, constructing new large UGS in s3 is ineffective and unbalanced, as many remaining plots are in suburban areas, repurposed from factories, and far from residents, limiting their benefits. This study warns that practices in s3 may lead to underutilized UGS, wasting resources and should be avoided.

Although expanding small UGS may incur higher costs, its cooling and health benefits could be greater with better long-term social and economic outcomes. Instead of just "greening the city" (Wolch et al., 2014), it is highly recommended to implement strategic UGS placement and ongoing improvement of existing parks to maximize public health and ensure equity.

This study offers two main innovations. First, it integrates UGS's cooling capacity with public health benefits by quantitatively simulating the specific performances of UGS's cooling pathways. Second, the real-world quota-allocation practices in simulation scenarios are incorporated to compare the common trade-offs between large and small, new and old UGS, and thus provide constructive planning prescriptions. Limitations include non-random sampling, though participants are widely distributed across six cities. Moreover, due to data constraints, the spatial resolution is only 1 km. Future work aims to enhance accuracy and recommendations.

Appendix

Table 1 The importance of factors and goodness of fit for air temperature prediction models

Model	Precipitation	Humidity	Wind	DEM	Solar	GDP	POP	NDVI	Impervious	Water	Forest	Shrub	Grass	LST_day	LST_night	RMSE	R^2
201601	35363.94	43684.18	13424.62	125498.85	45718.74	218998.14	141624.08	15422.43	13309.03	4517.22	26662.74	961.07	1189.45	389790.23	148182.75	0.34	0.98
201602	16310.69	27920.15	9786.56	90532.63	39179.96	114464.10	48464.14	10196.53	4610.33	4454.43	18308.95	576.64	1039.13	271552.66	165117.24	0.32	0.98
201603	18292.19	40346.11	11996.80	193423.30	147938.25	87822.33	57716.45	11380.38	5318.96	4226.48	25172.44	706.26	992.73	48963.05	161734.56	0.34	0.98
201604	9199.94	12370.13	7095.24	78116.67	73401.34	24914.43	35873.24	6108.21	2357.79	1765.92	9760.67	491.24	686.61	26640.16	112754.93	0.34	0.97
201605	12472.40	13863.28	8467.91	131500.57	30474.93	28163.54	42348.30	7838.33	5533.29	2752.05	32023.33	651.12	886.85	31171.49	80592.10	0.32	0.96
201606	21645.90	15960.02	8887.78	115006.17	16644.14	16392.17	21265.87	11366.52	24761.30	2701.25	40342.21	732.72	912.86	21875.93	146323.68	0.34	0.96
201607	30851.60	11501.34	8658.54	92908.03	11979.96	18859.46	17586.64	13748.51	15273.86	3021.62	47347.42	1099.81	902.09	39356.29	180530.95	0.32	0.97
201608	22530.92	14980.69	8986.10	154277.60	17105.74	27522.31	39588.55	10134.15	7290.12	2989.30	31806.53	506.58	824.35	74665.74	134883.89	0.32	0.97
201609	20082.09	12331.22	9038.39	174488.71	20113.12	32779.10	26734.94	11097.87	11740.90	2906.36	49207.86	838.68	932.88	57383.75	137231.14	0.32	0.97
201610	18739.14	10721.12	9152.29	172468.58	27087.94	39938.77	56526.91	11075.62	8251.37	3974.55	39472.37	685.07	883.72	45220.17	90892.80	0.31	0.97
201611	11333.88	13779.81	9548.15	159384.35	137542.76	56770.09	154793.72	10976.55	9901.33	3600.00	20463.05	858.16	970.88	88261.08	116042.50	0.31	0.98
201612	16172.12	11967.01	7077.15	64573.26	31596.89	78807.30	96252.11	10663.17	5985.81	3975.06	21533.99	863.80	833.53	265450.35	407755.20	0.30	0.98
201701	15408.35	18853.97	8176.31	71798.39	55195.37	82970.98	46980.86	13530.92	8871.65	4484.19	16728.28	778.15	883.31	323424.62	176903.82	0.30	0.98
201702	12129.32	17063.68	7777.70	119544.93	46408.90	48404.75	55792.33	8846.88	6515.15	3695.82	19143.86	550.62	860.94	159689.82	205590.89	0.28	0.98
201703	30834.84	23617.34	14306.49	101626.71	185975.67	157993.65	244578.77	15086.65	7288.23	5080.66	23516.28	778.51	1086.56	150439.68	467201.61	0.32	0.99
201704	12576.18	13260.01	8324.72	157906.07	34129.87	57433.50	62565.13	8310.70	8705.37	2860.35	27651.06	721.70	768.58	57151.57	208497.19	0.28	0.98
201705	13253.38	11820.32	7785.82	137267.32	17566.92	23657.77	36572.98	8934.12	3726.58	3478.13	30299.38	709.72	882.51	33555.03	88876.23	0.31	0.96
201706	25274.65	11808.79	8996.60	74087.83	15512.69	23004.37	14829.88	8391.95	13010.55	3933.03	30692.97	550.69	870.66	15033.49	120632.85	0.38	0.95
201707	25189.83	19767.44	10382.29	107483.49	17817.81	22687.99	23268.05	22169.35	25975.38	2710.27	46220.85	701.83	829.46	21419.25	159529.28	0.34	0.96
201708	26104.16	15172.20	9759.19	139503.92	18059.31	34844.37	19714.15	25773.60	24454.64	3595.49	36555.13	863.60	934.05	55055.48	147046.02	0.32	0.97
201709	29364.18	10994.87	8122.21	148853.30	15803.18	27951.20	21860.34	17351.01	10713.27	2572.66	52679.06	704.48	911.59	42662.59	159217.55	0.30	0.97
201710	21818.96	10021.31	8697.40	180456.35	19713.64	34188.22	60620.58	11166.10	6062.99	4827.21	29394.63	855.09	875.44	62906.94	115435.91	0.31	0.97
201711	13012.98	15850.08	10530.59	125229.84	157519.67	55652.14	74489.74	11617.59	7954.31	3286.29	25432.00	1047.79	991.20	48688.36	197281.55	0.32	0.98
201712	16315.68	16260.96	8236.49	75852.12	40237.81	78470.52	68745.74	11737.13	7568.07	5681.33	13292.42	696.43	755.44	193824.26	421176.19	0.29	0.98
201801	23657.34	28493.27	11965.76	117832.81	104529.31	172583.19	126238.03	16719.29	5942.70	4087.38	28279.12	821.63	1155.07	135152.59	253793.52	0.33	0.98
201802	14574.70	20041.80	10530.51	119109.89	34425.23	93058.29	62011.02	11307.51	8943.92	2957.39	21600.50	566.94	832.99	81656.69	197288.41	0.31	0.98
201803	11047.04	15071.75	7928.69	182391.37	51255.06	74526.38	70537.28	10754.11	6019.40	2383.55	22624.47	499.69	723.27	146851.21	208413.59	0.27	0.98
201804	21032.61	19692.83	11786.22	165146.64	36321.38	40377.24	100268.02	16926.45	8389.24	3035.50	42690.06	1039.10	868.39	32222.78	121053.55	0.32	0.97
201805	39650.08	12473.18	9025.77	105845.40	16025.39	25619.09	16641.24	26456.78	13895.99	2768.13	52126.17	1138.29	920.93	21436.53	90539.90	0.35	0.95
201806	17774.68	12820.67	10473.76	159309.17	22942.07	22597.01	31965.23	15760.47	8921.36	3022.58	48556.20	1022.38	837.97	52279.72	180340.72	0.33	0.97
201807	16737.06	11612.05	9627.61	113620.83	15367.85	14944.71	21650.59	20625.22	18145.88	3138.64	29567.85	785.91	835.15	18408.09	108143.12	0.33	0.96
201808	36285.43	18166.92	18194.20	136684.36	22213.24	43693.76	30210.12	24837.88	27510.94	4121.60	61259.36	841.44	1127.33	37588.24	143804.58	0.42	0.95
201809	23308.35	10156.61	9250.09	176076.77	14592.48	31967.99	38389.07	27394.22	11632.96	2772.36	47380.46	887.99	832.56	25138.25	88686.10	0.32	0.97
201810	15247.43	9239.80	7118.63	155695.97	55143.62	47034.06	68741.16	13392.37	4817.60	3864.62	25387.07	697.69	786.12	55422.30	188148.06	0.30	0.98
201811	15327.92	14534.81	7467.25	86503.28	43681.16	68901.91	84686.50	9027.18	5213.19	2240.00	27365.38	541.70	754.90	192263.57	333902.23	0.29	0.98
201812	13326.98	13632.06	9143.38	64567.56	169642.39	94386.76	101507.52	11235.85	4494.81	2806.48	17205.33	793.37	831.75	371609.95	243380.54	0.30	0.99

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