Identifying Geospatial Factors Affecting Urban Heat Island (UHI) Intensity for Dhaka, Narayanganj and Gazipur District: A Case Study

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- Urban Heat Island;
- Geospatial Factors;
- Remote Sensing;
- Statistical Correlation;
- Urbanization

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Abstract: Amid adverse climate change, investigating the urban heat island (UHI) effect is vital for sustainable urban development in tropical and densely populated regions like Dhaka city and adjacent areas including Gazipur and Narayanganj city in Bangladesh, where unplanned urbanization, rapid industrialization, and declining green spaces are prominent. These challenges are particularly acute in tropical climates, where high temperatures and humidity can create severe heat stress conditions, affecting human health, energy consumption, and overall urban sustainability. The UHI effect can be optimized by regulating urban spatial forms. This study will focus on identifying the key factors such as impervious surface area ratio, soil area ratio, etc., driving the rise in surface temperature and the development of division-scale UHI in these areas. Utilizing remote sensing, the impact of 13 spatial factors on the intensity of surface urban heat island (SUHI) has been identified. Increased vertical development, imperviousness, and higher building density are positively correlated to SUHI. From Pearson's correlation matrix, it was observed that green infrastructure indicators and proximity to cooling elements have negative correlations with SUHI intensity. Building density (BD), building height (BH), and floor area ratio (FAR) have significant correlations ($r>0.8$) with each other. Additionally, higher values of variance inflation factor ($VIF>10$) suggested higher multicollinearity for normalized difference vegetation index (NDVI), impervious soil area ratio (ISF), and green space ratio (GSF).

1. Introduction

One of the biggest challenges of climate change is the rising air temperature and humidity, which has increased heat stress in many regions worldwide (Willett & Sherwood, 2012). In recent years, several areas have experienced record-breaking heatwaves, leading to a rise in heat-related deaths. This particular issue is especially severe in cities due to the Urban Heat Island (UHI) effect, which makes urban areas hotter than rural ones (Park et al., 2024).

Rapid urbanization has turned cities into heat traps by replacing natural landscapes with materials like asphalt and concrete, which absorb heat during the day and release it at night. Since urban areas have less vegetation, there is less evapotranspiration to help cool the air, making them significantly warmer. One of the main types of UHI is Surface UHI (SUHI), which refers to increased land surface temperatures in cities. SUHI is commonly studied through remote sensing because it provides broad spatial coverage (Fajary et al., 2024).

In Bangladesh, unplanned changes in land use and land cover (LULC), particularly in Dhaka, Narayanganj, and Gazipur, have created serious environmental challenges. Dhaka, the capital, has a population of 10.3 million and a high population density of 33,650 people per square kilometer, which increases urban heat effects. The city's average temperature is 26°C, but pre-monsoon heatwaves often raise daily maximum temperatures to around 34°C. Long-term studies show a steady rise in temperature (Tabassum et al., 2025). According to Imran et al., (2021), Dhaka's land surface temperature increased by 0.24°C per year from 1993 to 2020, while UHI intensity rose by 0.21°C per decade from 1995 to 2019. As urban growth and industrialization continue beyond Dhaka, the extent and impact of SUHI in the surrounding districts remain understudied.

Research on the UHI effect has progressed significantly, mainly in identifying its key influencing factors. However, there is still a lack of studies on three-dimensional (3D) spatial indicators, particularly in areas with unplanned urban growth and industrial expansion. A previous study by Xu et al., (2024) analyzed how both two (2D) and three (3D) dimensional urban characteristics influence SUHI in a planned urban area. Therefore, this study aims to examine SUHI intensity in Dhaka and its neighboring districts, Narayanganj and Gazipur (DNG), in 2024 and identifies the most governing factors by studying the correlation between both 2D and 3D parameters considered. The results will provide useful insights into recent SUHI trends and their causes, helping to improve urban thermal conditions in the DNG area and other rapidly developing urban areas.

2. Study Area

The combined area of DNG shown in Figure 1, is located between latitudes 23.30° N and 24.20° N, 90° E and 90.40° E longitudes. Previously Mahmud et al., (2024) found that Gazipur experienced the most significant increase in development, with a 5162.82% rise in new developments and an 1148.89% increase in built-up areas, followed by Narayanganj and Dhaka. Given that previous studies have linked LULC changes (Faisal et al., 2021) to land surface temperature (LST) variations in the Dhaka Metropolitan Area, the following sections will examine recent SUHI trends and identify the dominant contributing factors focusing on the combined DNG area.

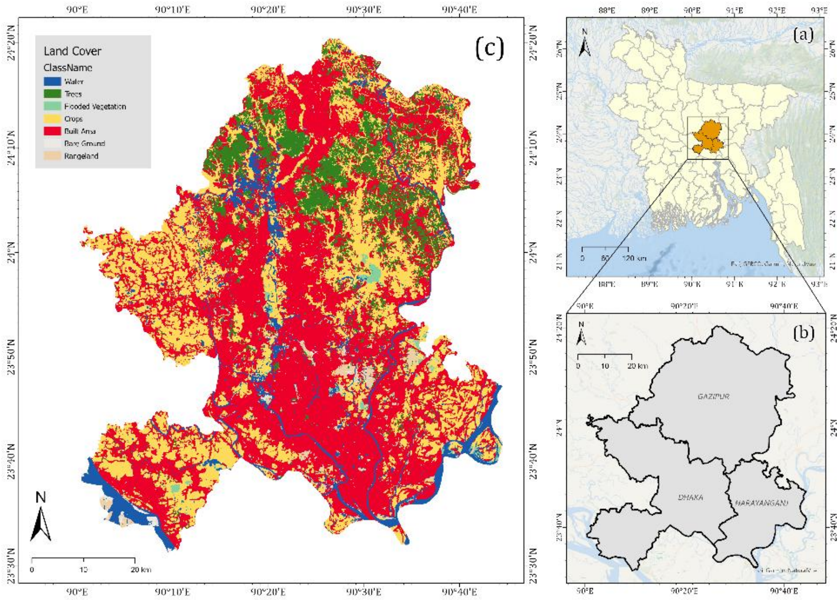

Figure 1 a) The map of Bangladesh highlighting the study area, b) focusing on the combined administrative boundary of Dhaka, Narayanganj, and Gazipur, and c) Land cover of the study area during the year 2024.

3. Methodology

3.1 Data sets

The differential in land surface temperature between urban and suburban areas is known as the Surface Urban Heat Island Intensity (SUHII) (Peng et al., 2012). For each study area, a single-channel approach utilizing the Landsat 9 Thermal Infrared Sensor (TIRS) and Band 11, along with the atmospheric correction method based on the radiative transfer equation, was employed to retrieve land surface temperature (LST). To enhance spatial resolution, the Kriging model and geostatistical methods were applied, downscaling the data to a 10-meter grid. Several key environmental variables were considered, including the Normalized Difference Vegetation Index (NDVI), Normalized Difference Built-up Index (NDBI), impervious surface fraction, vegetation fraction, and soil fraction, among others (J. Xu et al., 2020).

$$TOA(L) = ML \times Q(cal) + AL - O \tag{1}$$

$$BT = \frac{K_2}{\ln(K_1/TOA + 1)} - 273.15 \tag{2}$$

$$NDVI = \left(\frac{NIR - Red}{NIR + Red}\right) \tag{3}$$

$$PV = \left(\frac{NDVI - NDVImin}{NDVImax - NDVImin}\right)^2 \tag{4}$$

$$\varepsilon = 0.004 \times P_v + 0.986 \tag{5}$$

$$LST = \frac{T}{1 + (\lambda T/\rho) * \ln \varepsilon} - 273.15 \tag{6}$$

$$SUHII = LST_{urban} - LST_{subburban} \quad (7)$$

The Urban Heat Island Intensity (UHII) was computed using the definition provided in 7, which uses the equation to calculate the mean LST of an urban area minus the mean LST of the urban fringe area (Ferral et al., 2021). Furthermore, spatial factors shown in Table 1, were finalized based on previous literature to determine their correlation and influence on SUHI development.

Table 1: Overview of studied spatial factors influencing SUHI effect in the studied area

Indicator	Description	Data	Data Sources
Building density (BD)	The proportion of the total land area that is occupied by building footprints.	Google-Microsoft Open Buildings	Google-Microsoft Open Buildings - combined by VIDA, https://beta.source.coop/repositories/vida/google-microsoft-open-buildings
Building height (BH)	The vertical distance measured from the roof surface of a structure to the ground level outdoors.	Open Buildings 2.5D Temporal Dataset	
Water area ratio (WSF)	The proportion of the total area that is occupied by water bodies.	Esri Sentinel-2 10m Land cover, 2023	(Karra et al., 2021)
Green space ratio (GSF)	The proportion of the total area that is covered by vegetated or green spaces.		
Greenery rate (NDVI)	A spectral index derived from remote sensing data, calculated as the normalized difference between near-infrared and visible light reflectance, used to evaluate vegetation health and density.	Landsat 9 OLI	USGS earth explorer (https://earthexplorer.usgs.gov/)
Distance to the nearest water body (DTW)	The minimum distance between a segment and the nearest water body.	OpenStreetMap Road Network Dataset	Open Street Maps (https://www.openstreetmap.org/)
Distance to the nearest road (DTR)	The minimum distance between a segment and the nearest road.	OpenStreetMap Road Network Dataset	
Road density (RD)	The ratio of the total road length to the total area	OpenStreetMap Road Network Dataset	
Soil area ratio (LSF)	The proportion of the total area that is characterized by exposed or bare soil.		
Impervious surface area ratio (ISF)	The proportion of impervious area to the segment		
Topographic relief (TER)	The ratio of the average elevation of a specific segment to the mean elevation of the entire study area.	SRTM DEM-30m	USGS Earth Explorer (https://earthexplorer.usgs.gov/)
Relative elevation ratio (ELE)	The difference between the highest and lowest elevation points within a defined segment.		
Floor Area Ratio (FAR)	The ratio of the total ground coverage of buildings on a segment to the total area of that segment.	Open Buildings 2.5D Temporal Dataset	Google-Microsoft Open Buildings - combined by VIDA, https://beta.source.coop/repositories/vida/google-microsoft-open-buildings

3.2 Statistical parameters used for evaluation

In this study, to investigate the relationship between SUHI intensity and 13 indicators and to understand the multicollinearity among the independent variables before performing multiple regression analysis, Pearson's correlation matrices (PCM) and Variance Inflation Factor (VIF) were developed for the DNG study area.

Table 2 Statistical Metrics for Correlation and Multicollinearity Evaluation

Metric	Formula	Interpretation
PCM	$r = \frac{\mathrm{cov}\,(x,y)}{\sigma_x \sigma_y} = \frac{\frac{1}{N}\sum_{i=1}^{N}\,(x_i-\bar{x})(y_i-\bar{y})}{\sqrt{\frac{1}{N}\sum_{i=1}^{N}\,(x_i-\bar{x})2}\sqrt{\frac{1}{N}\sum_{i=1}^{N}\,(y_i-\bar{y})2}} = \frac{\sum_{i=1}^{N}\,(x_i-\bar{x})(y_i-\bar{y})}{\sqrt{\sum_{i=1}^{N}\,(x_i-\bar{x})2}\sqrt{\sum_{i=1}^{N}\,(y_i-\bar{y})2}}$	Correlation range: +1 (strong positive) to -1 (strong negative), with 0 indicating no correlation. Significant if > 0.5 (Wang et al., 2013)
VIF	$VIF_j = \frac{1}{(1-R_j^2)}$	Without multicollinearity, R_j^2=0 and VIF_j=1; with multicollinearity, $\mathrm{VIF}_j>1$ (Vu et al., 2015)

4. Results and Discussion

4.1 Relationship between LST and SUHI

Figure 2 shows the extracted Land surface Temperature using Landsat-9 images of 2024 and calculated Surface Urban Heat Island Intensity using equation (1 to 7).

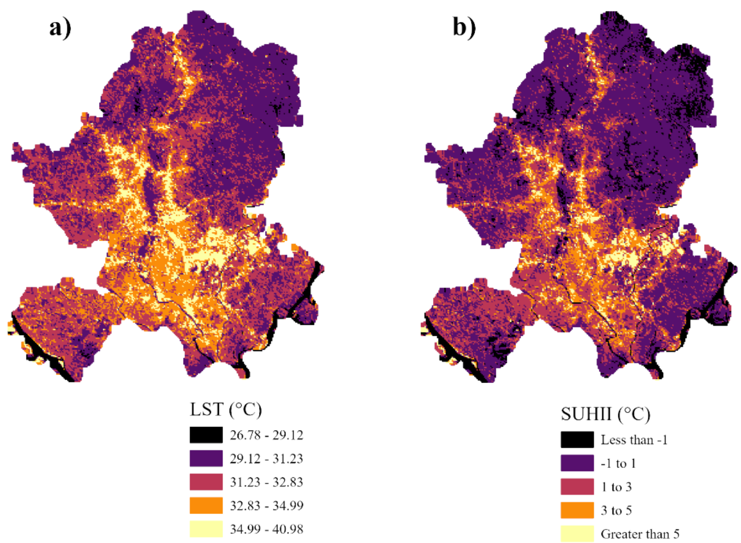

Figure 2: Extracted (a) Land Surface Temperature using Landsat-8 image and calculated (2) Surface Urban Heat Island intensity using extracted LST

4.2 Correlation evaluation using Pearson's Correlation Matrix

In Dhaka, higher building density, vertical development, and impervious surfaces positively correlate with SUHI, while green space indicators (GSF, NDVI) and proximity to cooling elements (DTR, DTW) show negative correlations. In Gazipur, SUHI is strongly correlated with

BD (+0.57), FAR (+0.52), BH (+0.45), and ISF (+0.44), whereas GSF (-0.40) and NDVI (-0.34) indicate cooling effects (Miah et al., 2024; Salam et al., 2024).

Like Dhaka and Gazipur, Narayanganj exhibits a positive correlation between SUHI and urbanization metrics (BD, BH, ISF), while green infrastructure indicators (GSF, NDVI) show negative correlations, reinforcing their cooling effect. These findings further support the role of urban structural factors in heat accumulation and the mitigating influence of natural features on temperature regulation (Haque & Uddin, 2025; Md. Razzakul Islam & Haque, 2022; Rashid et al., 2022).

From the Pearson correlation matrix (Figure 3), BD and BH show strong correlations with FAR, with values of 0.85 and 0.81, respectively. In contrast, GSF and ISF exhibit a negative correlation (r = -0.85). The inclusion of these variables together may weaken the regression analysis.

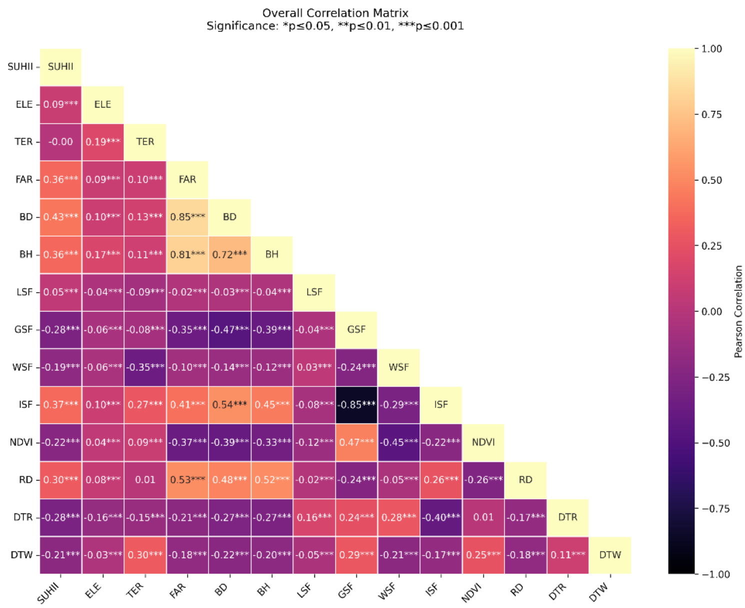

Figure 3: PCM for Dhaka, Gazipur and Narayanganj District (combined)

4.3 Correlation assessment using Variance Inflation Factor (VIF)

The high VIF values (shown in Figure 4) of >10 (NDVI:11.62, GSF:10.05, and ISF: 11.75) suggest significant collinearity among the vegetation indices and impervious surface indicators. Such multicollinearity indicates that these variables share overlapping information regarding their effect on SUHI, which may affect the stability and interpretability of regression coefficients. Moderate collinearity (5<VIF<10) has been found for TER (7.86), ELE (8.64), BH (4.64), BD (5.58), and FAR (6.04). While they provide essential insights into the urban structure, care should be taken in model selection to mitigate potential redundancy. Minimal collinearity (VIF <2.5) has been identified for LSF (1.05), WSF (1.60), RD (1.58), DTR (1.97), and DTW (2.24) which can be considered as relatively independent predictors in the SUHI prediction model (Kim, 2019; Mishra, 2017).

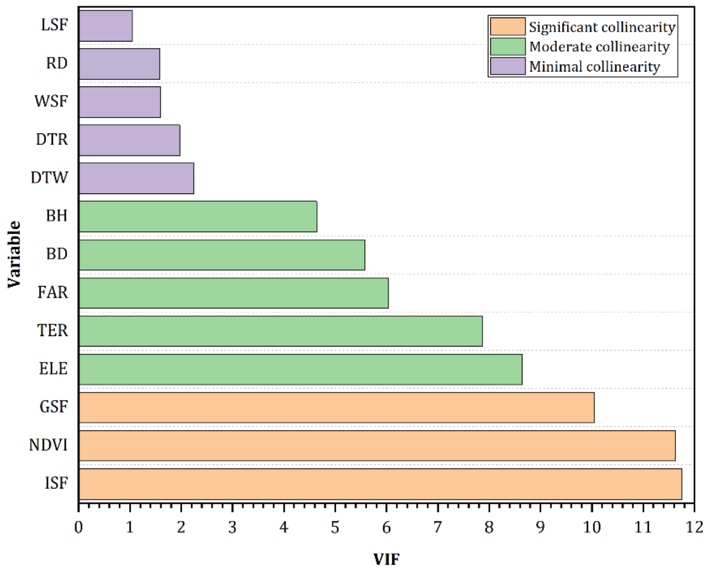

Figure 4: Variance Inflation Factor (VIF) for independent variables

5. Conclusion

This study highlights the notable impact of urban structural characteristics on the formation of Surface Urban Heat Islands (SUHI) across the combined DNG area. The findings reveal that higher BD, RD, FAR, BH, and ISF contribute positively to SUHI intensity, while GSF, DTW, NDVI, DTR, and WSF contribute to cooling urban areas. These results align with previous studies, reinforcing the importance of sustainable urban planning to reduce heat stress in rapidly growing cities. Moreover, to perform regression analysis for predicting SUHI with respect to the spatial factors, several recommendations can be made according to the results of Pearson's correlation and VIF values.

- LSF, WSF, RD, DTR, and DTW can be taken into the regression analysis without further assessment as they significantly correlated to SUHI and have less VIF value.
- For BH, BD, and FAR, principal component analysis can be performed before taking them to the regression analysis.
- Also, multiple combinations of NDVI, GSF, and ISF can be checked to overcome the autocorrelation and higher multicollinearity.

Reference

Faisal, A. Al, Kafy, A. A., Al Rakib, A., Akter, K. S., Jahir, D. M. A., Sikdar, M. S., Ashrafi, T. J., Mallik, S., & Rahman, M. M. (2021). Assessing and predicting land use/land cover, land surface temperature and urban thermal field variance index using Landsat imagery for Dhaka Metropolitan area. *Environmental Challenges*, *4*, 100192. https://doi.org/10.1016/J.ENVC.2021.100192

Fajary, F. R., Lee, H. S., Kubota, T., Bhanage, V., Pradana, R. P., Nimiya, H., & Putra, I. D. G. A. (2024). Comprehensive spatiotemporal evaluation of urban growth, surface urban heat island, and urban thermal conditions on Java island of Indonesia and implications for urban planning. *Heliyon*, *10*(13). https://doi.org/10.1016/J.HELIYON.2024.E33708

Ferral, A., Gili, A., Andreo, V., German, A., Beltramone, G., Bonansea, M., Pana, S., & Scavuzzo, M. (2021). Calculation of surface urban heat index from LANDSAT-8 TIRS data and its relation with land cover. *2021 19th Workshop on Information Processing and Control, RPIC 2021*. https://doi.org/10.1109/RPIC53795.2021.9648422

Haque, S. M. N., & Uddin, A. S. M. S. (2025). Identifying land use land cover change using google earth engine: a case study of Narayanganj district, Bangladesh. *Theoretical and Applied Climatology*, *156*, 94. https://doi.org/10.1007/s00704-024-05340-8

Imran, H. M., Hossain, A., Islam, A. K. M. S., Rahman, A., Bhuiyan, M. A. E., Paul, S., & Alam, A. (2021). Impact of Land Cover Changes on Land Surface Temperature and Human Thermal Comfort in Dhaka City of Bangladesh. *Earth Systems and Environment*, *5*(3), 667–693. https://doi.org/10.1007/S41748-021-00243-4/FIGURES/10

Karra, K., Kontgis, C., Statman-Weil, Z., Mazzariello, J. C., Mathis, M., & Brumby, S. P. (2021). GLOBAL LAND USE/LAND COVER WITH SENTINEL 2 AND DEEP LEARNING. *International Geoscience and Remote Sensing Symposium (IGARSS)*, *2021-July*, 4704–4707. https://doi.org/10.1109/IGARSS47720.2021.9553499

Kim, J. H. (2019). Multicollinearity and misleading statistical results. *Korean Journal of Anesthesiology*, *72*, 558–569. https://doi.org/10.4097/kja.19087

Mahmud, A. al, Sultana, N., & Habib, M. E. (2024). *Application of GIS for Spatio-Temporal Modeling of Land Use Change and Environmental Degradation in Dhaka, Narayanganj, and Gazipur: A 24-Year Study (1999–2023)*. https://doi.org/10.21203/RS.3.RS-5315528/V1

Md. Razzakul Islam, & Haque, Md. N. (2022). Identifying Urban Heat Effect through Satellite Image Analysis: Focusing on Narayanganj Upazila, Bangladesh. *Journal of Applied Science & Process Engineering*, *9*, 1223–1241. https://doi.org/10.33736/jaspe.4747.2022

Miah, M. T., Fariha, J. N., Jodder, P. K., Al Kafy, A., Raiyan, R., Usha, S. A., Hossan, J., & Rahaman, K. R. (2024). Urban Heat Island and Environmental Degradation Analysis Utilizing a Remote Sensing Technique in Rapidly Urbanizing South Asian Cities. *World*, *5*, 1023–1053. https://doi.org/10.3390/world5040052

Mishra, K. (2017). A Study of Multicollinearity in Estimation of Coefficients in Ridge Regression. In *Asian Journal of Technology and Management Research* (Vol. 07).

Park, K., Baik, J. J., Jin, H. G., & Tabassum, A. (2024). Changes in urban heat island intensity with background temperature and humidity and their associations with near-surface thermodynamic processes. *Urban Climate*, *58*, 102191. https://doi.org/10.1016/J.UCLIM.2024.102191

Peng, S., Piao, S., Ciais, P., Friedlingstein, P., Ottle, C., Bréon, F. M., Nan, H., Zhou, L., & Myneni, R. B. (2012). Surface urban heat island across 419 global big cities. *Environmental Science and Technology*, *46*(2), 696–703. https://doi.org/10.1021/ES2030438/SUPPL_FILE/ES2030438_SI_002.XLS

Rashid, N., Alam, J. A. M. M., Chowdhury, M. A., & Islam, S. L. U. (2022). Impact of landuse change and urbanization on urban heat island effect in Narayanganj city, Bangladesh: A remote sensing-based estimation. *Environmental Challenges*, *8*. https://doi.org/10.1016/j.envc.2022.100571

Salam, M., Islam, M. K., Jahan, I., & Chowdhury, M. A. (2024). Assessing the impacts of vegetation loss and land surface temperature on Surface Urban Heat Island (SUHI) in Gazipur District, Bangladesh. *Computational Urban Science*, *4*. https://doi.org/10.1007/s43762-024-00136-y

Tabassum, A., Hong, S. H., Park, K., & Baik, J. J. (2025). Simulating urban heat islands and local winds in the Dhaka metropolitan area, Bangladesh. *Urban Climate*, *59*, 102284. https://doi.org/10.1016/J.UCLIM.2024.102284

Vu, D. H., Muttaqi, K. M., & Agalgaonkar, A. P. (2015). A variance inflation factor and backward elimination based robust regression model for forecasting monthly electricity demand using climatic variables. *Applied Energy*, *140*, 385–394. https://doi.org/10.1016/J.APENERGY.2014.12.011

Wang, G. J., Xie, C., Chen, S., Yang, J. J., & Yang, M. Y. (2013). Random matrix theory analysis of cross-correlations in the US stock market: Evidence from Pearson's correlation coefficient and detrended cross-correlation coefficient. *Physica A: Statistical Mechanics and Its Applications*, *392*(17), 3715–3730. https://doi.org/10.1016/J.PHYSA.2013.04.027

Willett, K. M., & Sherwood, S. (2012). Exceedance of heat index thresholds for 15 regions under a warming climate using the wet-bulb globe temperature. *International Journal of Climatology*, *32*(2), 161–177. https://doi.org/10.1002/JOC.2257

Xu, D., Wang, Y., Zhou, D., Wang, Y., Zhang, Q., & Yang, Y. (2024). Influences of urban spatial factors on surface urban heat island effect and its spatial heterogeneity: A case study of Xi'an. *Building and Environment*, *248*, 111072. https://doi.org/10.1016/J.BUILDENV.2023.111072

Xu, J., Zhang, F., Jiang, H., Hu, H., Zhong, K., Jing, W., Yang, J., & Jia, B. (2020). Downscaling Aster Land Surface Temperature over Urban Areas with Machine Learning-Based Area-To-Point Regression Kriging. *Remote Sensing 2020, Vol. 12, Page 1082*, *12*(7), 1082. https://doi.org/10.3390/RS12071082