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Investigation of cooling effects of lakes during heatwaves: A case study of Dhaka City

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Abstract

The increasing frequency and severity of heatwaves pose a significant threat to urban resilience by profoundly altering urban microclimates. Urban lakes have recently gained recognition for their ability to mitigate these impacts by forming water cool islands, offering localized cooling in densely populated areas due to their higher specific heat capacity. However, the influence of altered urban microclimates by heatwaves on these cooling effects remains underexplored. This study investigates how urban microclimates affect the cooling effects of diverse lakes during both heatwave and non-heatwave periods, using Dhaka as a case study. The study was conducted using a combination of satellite imagery, meteorological data and land use information. A paired *t*-test was performed to examine the changes in cooling effects of urban lakes over a decade, while sensitivity analysis assessed parameter influences using gradient boosting regressors. The findings of the study are consistent with previous research, showing reduced cooling effects, differences in cooling intensity and distance and changes in relative humidity, wind speed and perceived temperature during heatwaves compared to non-heawave periods. Moreover, results indicate that wind speed and perceived temperature significantly affect the cooling intensity of lakes during heatwaves, with Class III lakes (larger in size) showing the highest correlation. Wind speed shows greater sensitivity to changes in cooling distance and gradient than to cooling intensity, indicating that variations in wind speed play a crucial role in shaping the cooling characteristics of lakes. These findings provide valuable insights for optimizing urban water resources and implementing nature-based solutions, enabling urban planners and policymakers to develop targeted strategies that enhance the cooling potential of urban lakes and improve resilience to extreme heat events.

KEYWORDS
heatwaves, meteorological factors, urban lakes, water-cooling effects

1 | INTRODUCTION

Heatwaves (HWs) have become a focal point in climate change research in recent decades due to their increased occurrence (Marx et al., 2021). In recent years, North America, Europe and Asia have witnessed a rising frequency of HW, which were once considered rare (Zachariah et al., 2023). The increasing frequency and severity of HW, combined with the urban heat island effect, present a significant threat to public health, infrastructure and the overall livability of cities (Filho et al., 2021). Research on multiple US cities found that heat exposure in urban cores during HW was significantly higher than during non-heatwave (NHW) conditions, with temperature differences ranging from 6 to 10°C (Hu et al., 2023; Luo et al., 2023). Therefore, urban planners and academic scholars are paying more and more attention to adaptation strategies to tackle this issue. Many studies have demonstrated that blue infrastructure can provide thermal benefits through the creation of urban cool islands (UCI). Water bodies, such as lakes, rivers, ponds and streams, can reduce surface temperatures through continuous evaporation and have a greater specific heat absorption capacity than other materials on the land surface (Jacobs et al., 2020; Kang et al., 2023; Wang & Ouyang, 2021; Wu et al., 2020; Yao et al., 2023; Zhang et al., 2021). Water bodies are important elements in urban landscape planning and design. Furthermore, they are crucial components of urban ecological systems on a citywide scale (Sun & Chen, 2012) though pollution in urban water bodies poses a significant environmental threat (Tran et al., 2023; Vasseghian et al., 2023; Vasseghian et al., 2024). However, the cooling effect of water bodies has received less attention than the vast number of studies on green spaces (Yu et al., 2020).

Initially, research efforts concentrated on investigating the cooling capabilities of water bodies by examining aspects such as cooling intensity, gradient and distance. Findings indicated that water bodies exhibit daytime cooling effects but may contribute to night-time warming over time (Du & Zhou, 2022). Subsequent studies explored the factors that influence water-cooling island effects, with many scholars identifying various determinants. These include the landscape pattern of the surrounding area, elevation, proportion of impervious surfaces, surrounding land cover, road density, proportion of built area and socioeconomic characteristics (Du & Zhou, 2022; Li et al., 2022; Wu et al., 2020; Yu et al., 2020).

Furthermore, the size, shape and geometry of water bodies were found to impact their cooling effectiveness, as larger water bodies with simpler and more regular shapes exhibit greater efficiency in cooling the urban environment (Du et al., 2016; Hong et al., 2023). There is a research gap in understanding the dynamics of the cooling effect of urban lakes during extreme HW events. Studies analysed elements of microclimate during the HW, where Ngarambe et al. (2020) concluded that wind speeds were relatively lower during HW periods than during NHW periods. Additionally, absolute humidity was substantially higher during HW periods than during NHW periods, contributing to the thermal stress experienced in urban environments (Ngarambe et al., 2020). Simultaneously, Qiu et al. (2021) concluded that the wind direction significantly affects the cooling impact of water bodies. These findings suggest that HWs may reduce the cooling capacity of urban lakes by altering the microclimate. However, there is no conclusive evidence to support this claim.

Given this context, the study aims to investigate the impact of urban microclimate on the cooling effect of lakes during HWs and NHWs events. The goal of the study is to provide answers to the following questions:

- Does urban microclimate affect the cooling effect of lakes during HWs?
- Which type of lake, based on geometric characteristics, experiences the greatest impact on its cooling effects from the urban microclimate?

The study focused on urban lakes in Dhaka as a case study; since one of the most noteworthy urbanizing regions in the world, the urban area of Dhaka has seen an average annual growth rate of 8% between 1991 and 2019 (Rahaman et al., 2023). Dhaka City of Bangladesh has experienced vast territorial expansion and infrastructural development in recent decades (Rashid et al., 2023). The rapid urbanization trend worldwide has raised considerable concerns regarding the occurrence of extreme heat events. Dhaka is no exception, having experienced a substantial temperature rise of approximately 3°C over the last two decades (Molla, 2024). An illustrative instance of this phenomenon occurred on 15 April, 2023, when Dhaka recorded a scorching maximum temperature of 40.4°C, marking it as the hottest day in the city in 58 years (The Daily Star, 2023). The study would contribute to the understanding of how urban microclimates influence the cooling effects of lakes, particularly during HWs. This research will fill a significant gap in urban climate studies, offering insights that can inform urban planning and climate resilience strategies.

2 | MATERIALS AND METHODS

2.1 | Study area

To investigate the cooling island effects of urban lakes, this study chose Dhaka, one of the most vulnerable cities to global climate change. Moreover, despite being ranked as the fourth most unsustainable megacity in a recent climate report (Bhuiyan, 2022), Dhaka is projected to become the world's sixth-largest megacity by 2030, with a population of 27.37 million (Morshed et al., 2017). Dhaka City, often referred to as the Dhaka Metropolitan Area (DMA), is positioned near the geographical midpoint of Bangladesh at 23 $\mathring{4}$3′0″N and 90 $\mathring{2}$4′0″E (Begum et al., 2021). The study area is bordered by four rivers: the Buriganga, Turag, Tangi and Balu. The city has a tropical climate influenced by the monsoon (Morshed et al., 2017), with a dry season from November to March and a rainy season from May to October. The area experiences an annual average temperature of 25.3°C (Hasan et al., 2023). The months of highest temperatures align with the rainy season, spanning from April to September, whereas the winter season, occurring between December and February, is characterized by cooler and drier conditions. Humidity levels remain consistently high throughout the year, reaching their peak during the monsoon season (June to October) (Bangladesh-Climatology, 2021); 7.96% of the total area is demarcated as water bodies, totaling 12161.33 ha in the recently prepared Detailed Area Plan of Dhaka (RAJUK & MoHPW, 2022). The capital development authority, Rajdhani Unnayan Kartripakkha (RAJUK), responsible for guiding the growth of Dhaka, has identified 64 lakes outlined in the plan (Figure 1) within the jurisdiction of DMA. These lakes, ranging from 0.25 to 24 ac, predominantly lie in the western part of the metropolitan area.

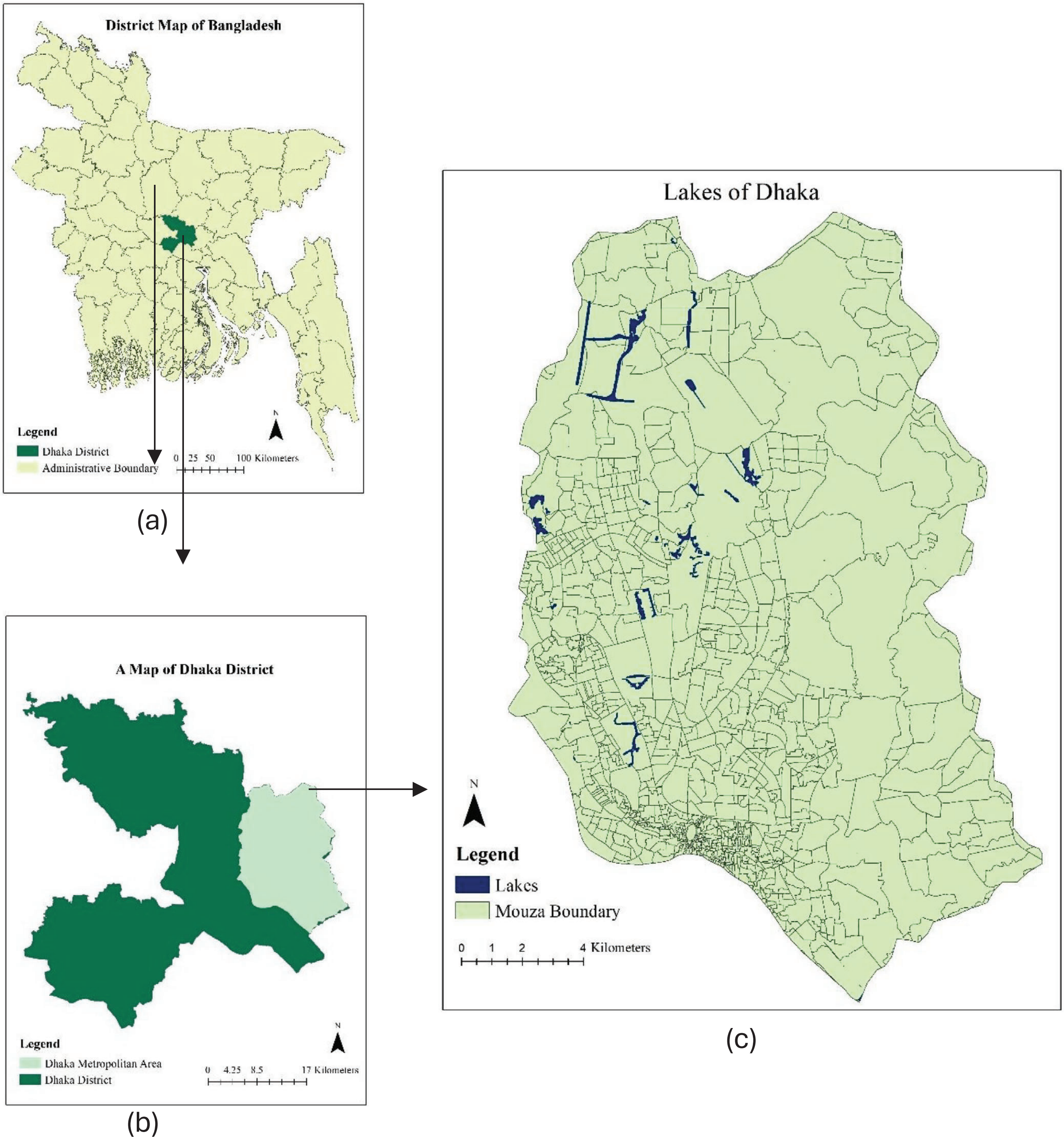

FIGURE 1 Location of study area: (a) Bangladesh; (b) Dhaka District; (c) study lakes in Dhaka.

2.2 | Data source

2.2.1 | Satellite data

Landsat 8 remote sensing data from the United States Geological Survey (USGS) Earth Explorer website was used to study the cooling island effect of urban lakes during HWs. This study chose satellite images from April 2013 and 2023. Based on the average maximum surface air temperature from 1990 to 2020 in Bangladesh, April marks the warmest month in Bangladesh (Figure 2) (Bangladesh-Climatology, 2021, Climate Change Knowledge Portal).

The Bangladesh Meteorological Department (BMD) defines a HW as a period with maximum daily temperatures of 36 degrees Celsius or higher for three consecutive days (Bangladesh Meteorological Department, 2024). Following this definition, the year 2013 was

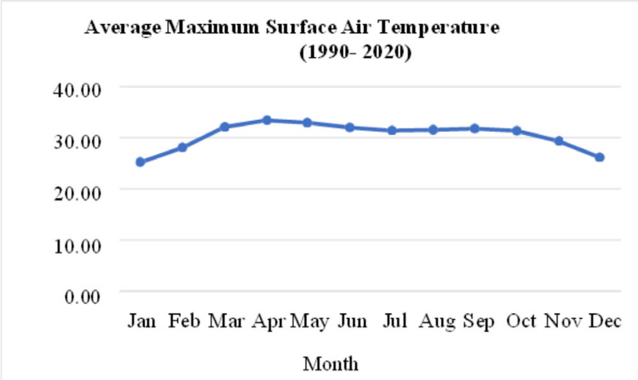

FIGURE 2 Month wise average maximum surface air temperature from 1990 to 2020 (*Source*: Bangladesh-Climatology, 2021, Climate Change Knowledge Portal).

chosen to represent NHW conditions because no HWs occurred during that year (Figure 3a). In contrast, 2023 was selected to represent HW conditions (Figure 3b). Additionally, the 2013 image was used as it is the earliest available satellite image captured by Landsat 8. Lastly, a key criterion in the image selection process was ensuring a cloud cover of less than 10%.

2.2.2 | Land use data

The shapefile containing the existing land use information for the DMA was obtained from the Capital Development Authority, RAJUK. For this study, specific areas designated as water bodies, particularly those identified as lakes, were extracted from the dataset.

2.2.3 | Meteorological data

Perceived Temperature, Wind Speed and Humidity data for 2013 and 2023 were collected from the BMD for April 15th for four weather stations including Dhaka, Mymensingh, Faridpur and Madaripur. These specific elements of microclimate were selected based on their previously established correlation with the HWs as one mentioned earlier in this study. Again, given that there was only one weather station in Dhaka, the Kriging interpolation technique was performed using ArcGIS to estimate the values for the mentioned factors for the whole DMA. The selection of these stations was motivated by their proximity to the Dhaka station, considering that they would have a more significant impact on the lakes' meteorological data in Dhaka compared to other stations.

2.3 | Research methodology

Figure 4 summarizes the sequential steps undertaken in this study.

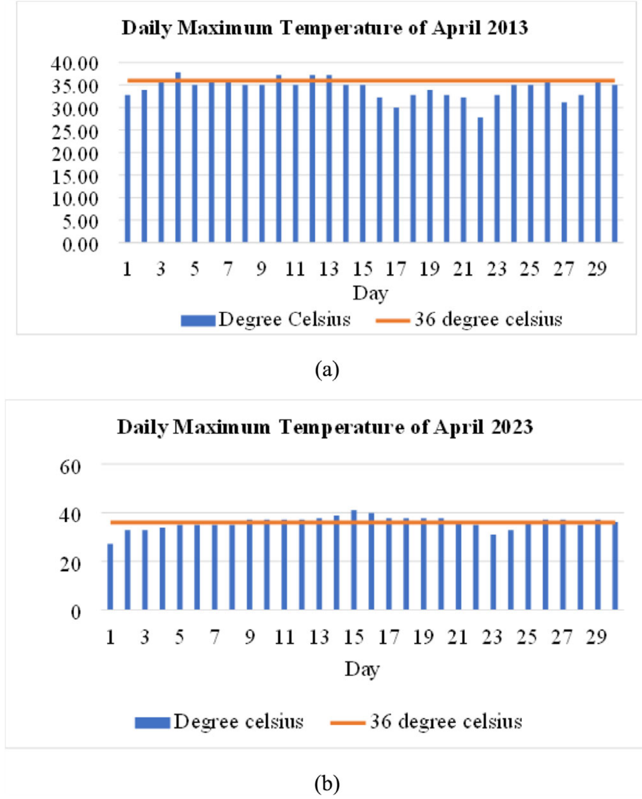

FIGURE 3 Daily maximum temperature of April (a) 2013, (b) 2023 (*Source*: Bangladesh Meteorological Department, 2023).

2.3.1 | Data extraction

- Physical Characteristics

The parameters chosen to assess lake characteristics included the water body's perimeter, area and Landscape Shape Index (LSI). The GIS field calculator tool was used to extract the lakes' area and perimeter. LSI is a quantitative indicator that reflects the spatial shape characteristics of patches in a landscape. The computation formula for the LSI (Patton, 1975) is given below:

$$LSI = \frac{P}{2\pi \times A}$$

where P is the perimeter of the water body (m), A is the area of the water body (m^2), and π is the circumference ratio.

- Land Surface Temperature (LST)

The LST was computed using the structured mathematical split-window (SW) algorithm. This algorithm utilizes the brightness temperatures of two thermal infrared (TIR) bands and the mean and difference in land surface emissivity to estimate the LST for a specific area. The algorithm is given in the Supporting information. The final LST result is depicted in Figure 5.

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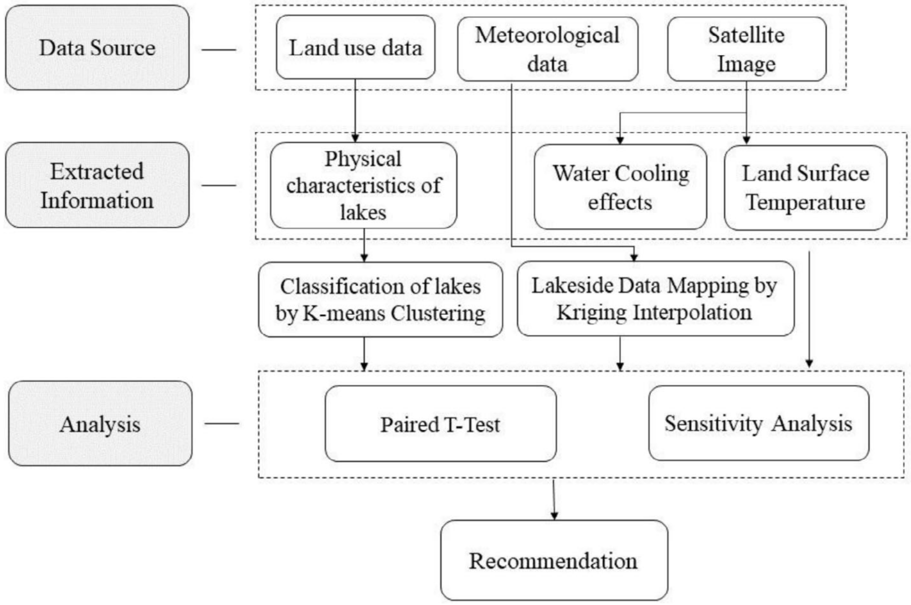

FIGURE 4 Workflow diagram of the study.

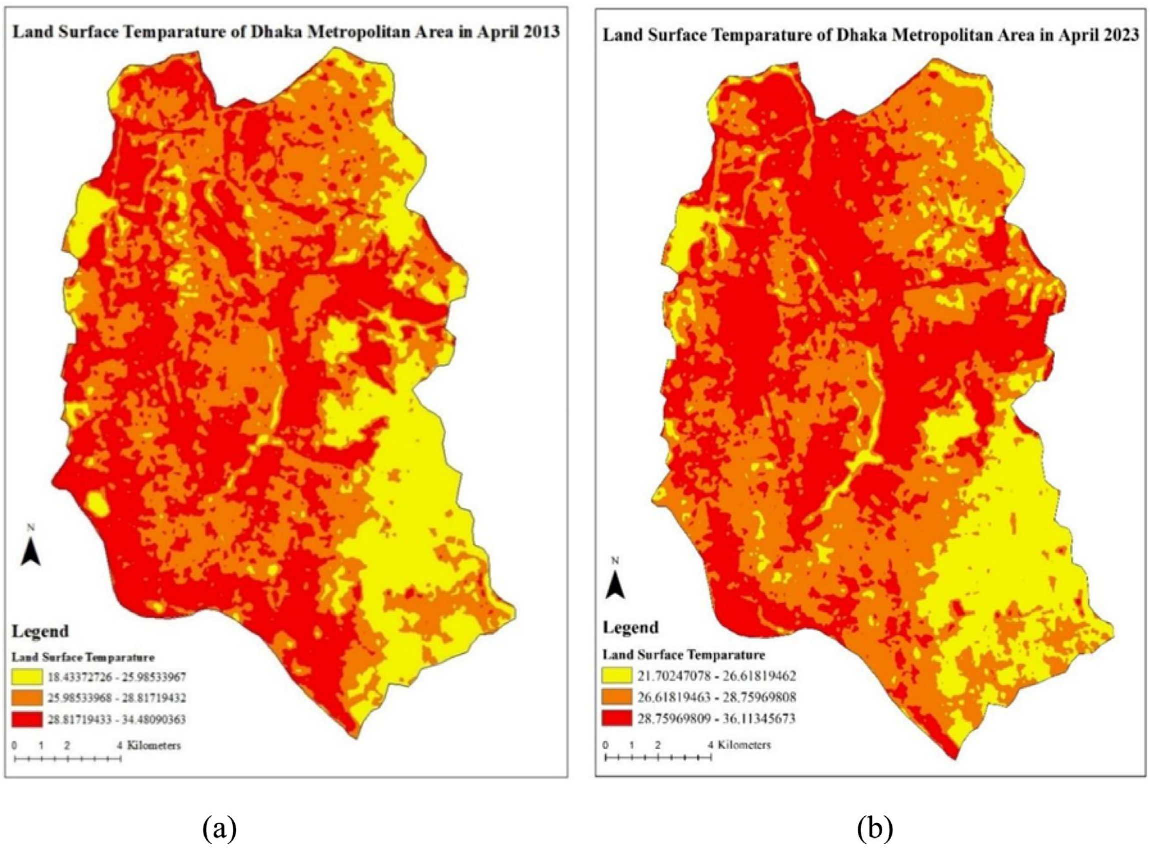

FIGURE 5 Land surface temperature of Dhaka Metropolitan Area in (a) 2013 and (b) 2023.

- Water-cooling Effect

The quantitative description of the Water Body Cooling Effect (WCE) involves three key aspects: Water Body Cooling Intensity (WCI), Water Body Cooling Distance (WCD) and Water Body Cooling Gradient (WCG).WCD is the difference in distance between the water's edge on the LST-offshore distance curve and the point of the first turning on the curve, indicated as Dpoint (Figure 6). WCI is the temperature difference between the water body's edge on the LST-offshore distance curve and the point of the first turning on the

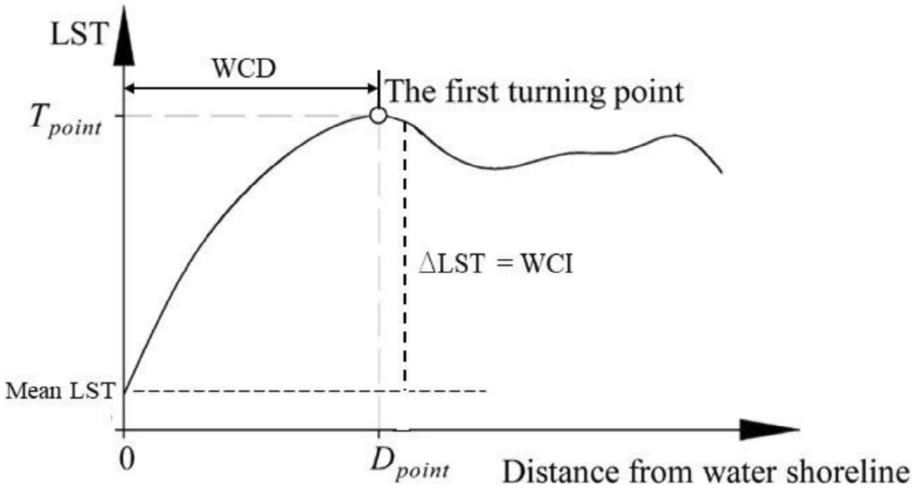

FIGURE 6 Illustration of land surface temperature (LST) change in littoral zones. *Source*: Reproduced from Du et al. (2016); Wang and Ouyang (2021).

curve. WCG is the average temperature drop per unit distance, calculated as WCI divided by WCD. Essentially, WCE demonstrates how bodies of water can absorb and retain heat energy from the surrounding air, exerting a cooling influence on their immediate vicinity.

2.3.2 | K-means clustering

The K-means clustering algorithm was used to classify urban lakes depending on their geometric characteristics. It is a popular unsupervised machine learning algorithm used for partitioning a dataset into distinct groups, or clusters, based on the similarity of data points (Nie et al., 2023). The primary objective is to group data points in a way that minimizes the within-cluster variance, with each cluster represented by its centroid. The process of the K-means clustering algorithm begins by initializing cluster centroids and then alternates between two steps until convergence. First, data points are assigned to the cluster whose centroid is closest, based on a distance metric such as Euclidean distance. The Euclidean distance is a commonly used definition of distance, which represents the real distance between two points in an *n*-dimensional space (Balaji et al., 2021). Second, the centroids are updated to the mean of the data points within each cluster. The algorithm repeats these steps until the centroids stabilize, signifying the formation of stable clusters.

$$d(X_i, C_j) = \sqrt{\sum_{k=1}^{n} (X_{ik} - C_{jk})^2}$$

Here, d (X_i, C_j) represents the Euclidean distance between a data point X_i and the centroid C_j with n being the number of features in the dataset. The elbow method is a crucial step in determining the optimal number of clusters (K) for a given dataset, and it is much more suitable for relatively small k values (Cui, 2020). It involves running the K-means algorithm for a range of K values and plotting the within-cluster sum of squares (WCSS), also known as the inertia, against the number of clusters. The inertia of a cluster is the sum of the squared distances between each data point in the cluster and the centroid of that cluster. Mathematically, for k number of clusters, the inertia (I_k) is calculated as follows:

$$I_k = \sum_{i=1}^{N_k} \sum_{j=1}^{n} (X_{ik} - C_{jk})^2$$

The elbow method identifies the point where the reduction in inertia starts to slow down, resembling an ‘elbow’ in the plot. The optimal K is often chosen at this elbow point, as it represents a balance between minimizing within-cluster variance and avoiding overfitting.

2.3.3 | Statistical analysis

Descriptive analysis was employed to explore the changes in the cooling island effects of urban lakes during 2013 and 2023. Paired *t*-test, a parametric test, was used in this study for inferential statistical analyses, as the variables were measured on a continuous scale and the number of observations in the dataset was more than 30 (64 lakes). The paired *t*-test was utilized to assess the significant difference in the cooling effects of urban lakes between the two specified years, as well as for the significant difference in meteorological factors, also known as microclimate factors. Furthermore, correlation matrices were constructed to ascertain the relationship between microclimate factors and cooling island effects across three distinct categories of urban lakes. These tasks were performed using the software RStudio.

2.3.4 | Sensitivity analysis

The clusters extracted from Section 2.3.2 are further investigated to check the influence of each parameter on each of the cooling impacts. The gradient boosting regressor model is used for doing the sensitivity analysis. The above-mentioned model is used for similar studies to model LST (Yu et al., 2020).

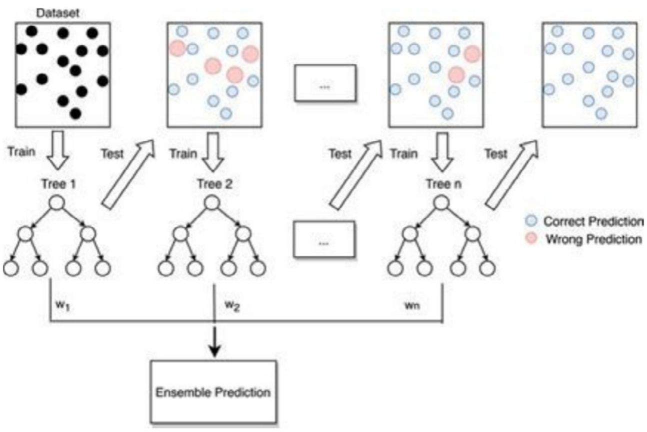

FIGURE 7 Workflow diagram of gradient boosting (Zhang et al., 2021).

As shown in the above Figure 7, the model works through iterative training from the primary approximation. Steps are described below:

- Initialization: The first weak learner is trained on the dataset, and its predictions are used as the initial approximation.
- Sequential training: In subsequent iterations, new weak learners are added to the ensemble, and each focus on the mistakes of the combined ensemble so far.
- Weighted combination: The predictions from all weak learners are combined, with each weak learner assigned a weight based on its performance. The weights are determined during the training process.
- Stopping criteria: The process continues until a specified number of weak learners are added or until the model reaches satisfactory performance. Overfitting is mitigated by early stopping or by limiting the depth of the weak learners.

3 | RESULT

3.1 | Temporal change of cooling effects of urban lakes

This section of the study provides an overview of the impact of HWs on the cooling effects of lakes in Dhaka. Three paired *t*-tests were conducted to determine whether there was a statistically significant mean difference in the cooling effects (Table 1) of the lakes between the years due to HWs in Dhaka. The results indicated no statistically significant difference in the cooling gradient between the two-time points (p-value $= 0.1999$) at a 95% confidence level. This indicates that there was no significant change in the cooling gradient between the years with HWs and those without. Conversely, notable differences were observed in the cooling intensity and the cooling distance between the 2 years, with a p-value of less than 0.001 and 0.02029, respectively, at the same confidence level.

3.2 | Temporal change of microclimate factors

This section of the study provides an overview of the impact of HWs on the microclimate factors in Dhaka. In the DMA, the temperature ranges in 2013 spanned from a minimum of 18.433°C to a maximum of 34.481°C (Figure 5a). Comparatively, in 2023, the temperature range expanded from a minimum of 21.7°C to a maximum of 36.11°C (Figure 5b). These changes indicate an expansion in temperature ranges and potentially signify the occurrence of HWs.

During this period, changes occurred not only in LST but also in microclimate factors. Three paired *t*-tests were executed to assess whether significant mean differences existed in the relative humidity, wind speed and perceived temperature of the lakes between HW and NHW periods in Dhaka. The analyses revealed marked differences (Figure 8) in wind speed, relative humidity and perceived temperature across the lakes between these years ($p < 0.001$, 95% confidence level).

3.3 | Change in water-cooling effects due to microclimatic influence during HWs

This section of the study comprises an in-depth exploration of how microclimate factors have shifted in their impact on water-cooling effects due to HWs on diverse lakes. Additionally, it analyses the degree of responsiveness of water-cooling effects to various meteorological factors.

3.3.1 | Classification results based on lake characteristics

Sixty-four water samples from the DMA were extracted from the land use shapefile, and their area, perimeter and shape index were determined. Based on these three parameters, which reflect the actual lake characteristics, the real classification of the 64 lakes was obtained through K-means clustering. Figure 9 shows the 'Elbow Curve' for different K values, and according to the curve, the best clustering can be obtained using $K = 3$. Therefore, this study considered the clustering results when $K = 3$ as the lake water classification, as shown in Table S1 of the Supporting information.

From Table S1, it can be seen that there are three classes of water bodies where Class I contains 19 water bodies with mostly the lowest area, perimeter and shape index values among the three classes of water bodies. Class II contains 31 water bodies. The area, perimeter and shape index values of this kind of lake are lower but slightly higher than those of the lakes in Class I. Class III contains 14 water bodies with mostly the largest values of area, perimeter and shape index.

Figure 10 shows the area, perimeter and shape index of the three lake sample classes. The average area values of Classes I–III water bodies were 11122.05, 33899.76 and 115219.83 m^2, respectively. But for the lake sample ID 45, despite having a lesser area

	Cooling intensity		Cooling distance		Cooling gradient	
	2013	2023	2013	2023	2013	2023
Min	0.417	0.0075	60	60	0.0023	0.000040
Mean	2.451	1.750	174.375	77.95312	0.0253	0.02009
Max	5.994	5.446	360	180	0.0908	0.07417

TABLE 1 Summary of the cooling effects of the lakes for the years 2013 and 2023.

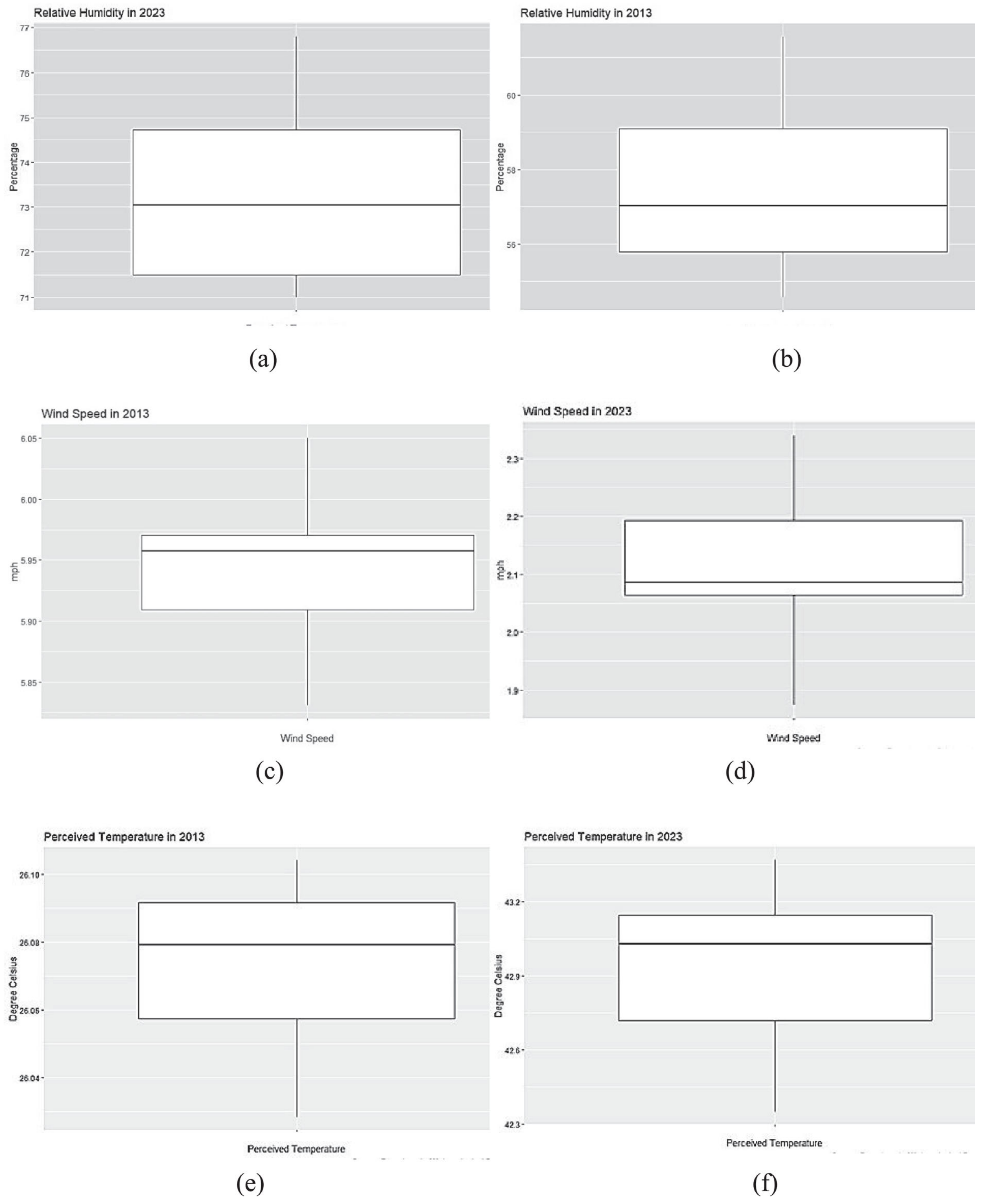

FIGURE 8 Comparison of relative humidity (a,b); wind speed (c,d), and perceived temperature (e,f) in 2013 and 2023 using boxplots.

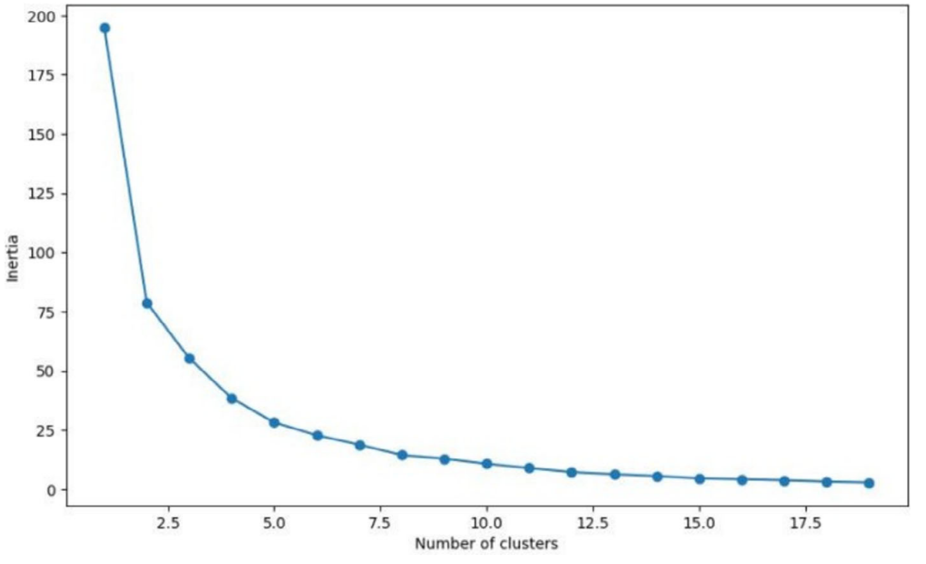

FIGURE 9 Elbow curve for K-means clustering.

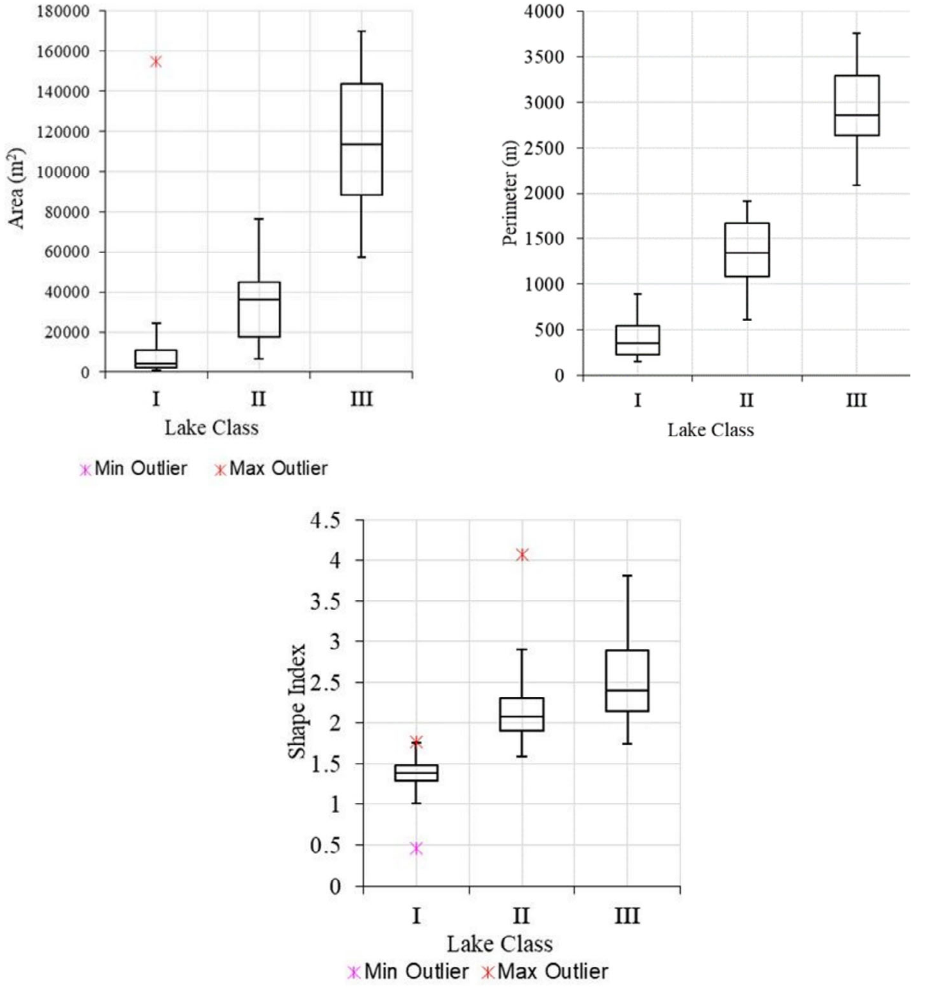

FIGURE 10 Distribution of area, perimeter and shape index between different lake classes.

(6908.05 m^2), it does not fall under the lake Class I due to its higher shape index (2.061) and relatively higher perimeter value (607.28 m). Similarly, for lake sample ID 1, despite having a much higher area (154779.87 m^2), it does not fall under lake Class III due to its smaller shape index (0.456) and perimeter value (636.49 m). These characteristics show that the distribution of various lakes under three classes was rational and had clear differences, indicating that the classification results can reflect different lake water bodies well.

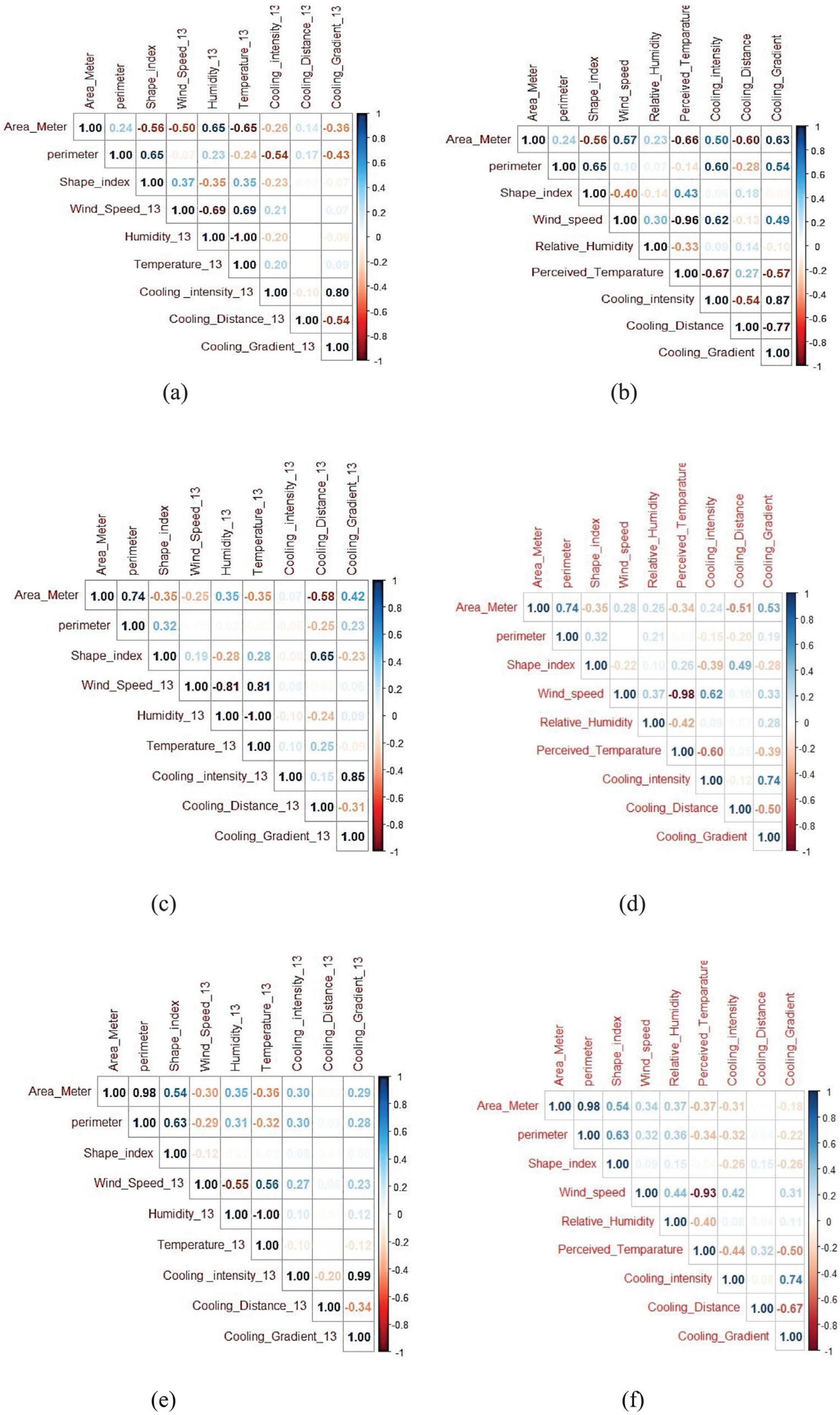

FIGURE 11 Correlation matrices for water-cooling effects and influencing factors for Class I (2013a, 2023b), Class II (2013c, 2023d) and Class III (2013e, 2023f) lakes.

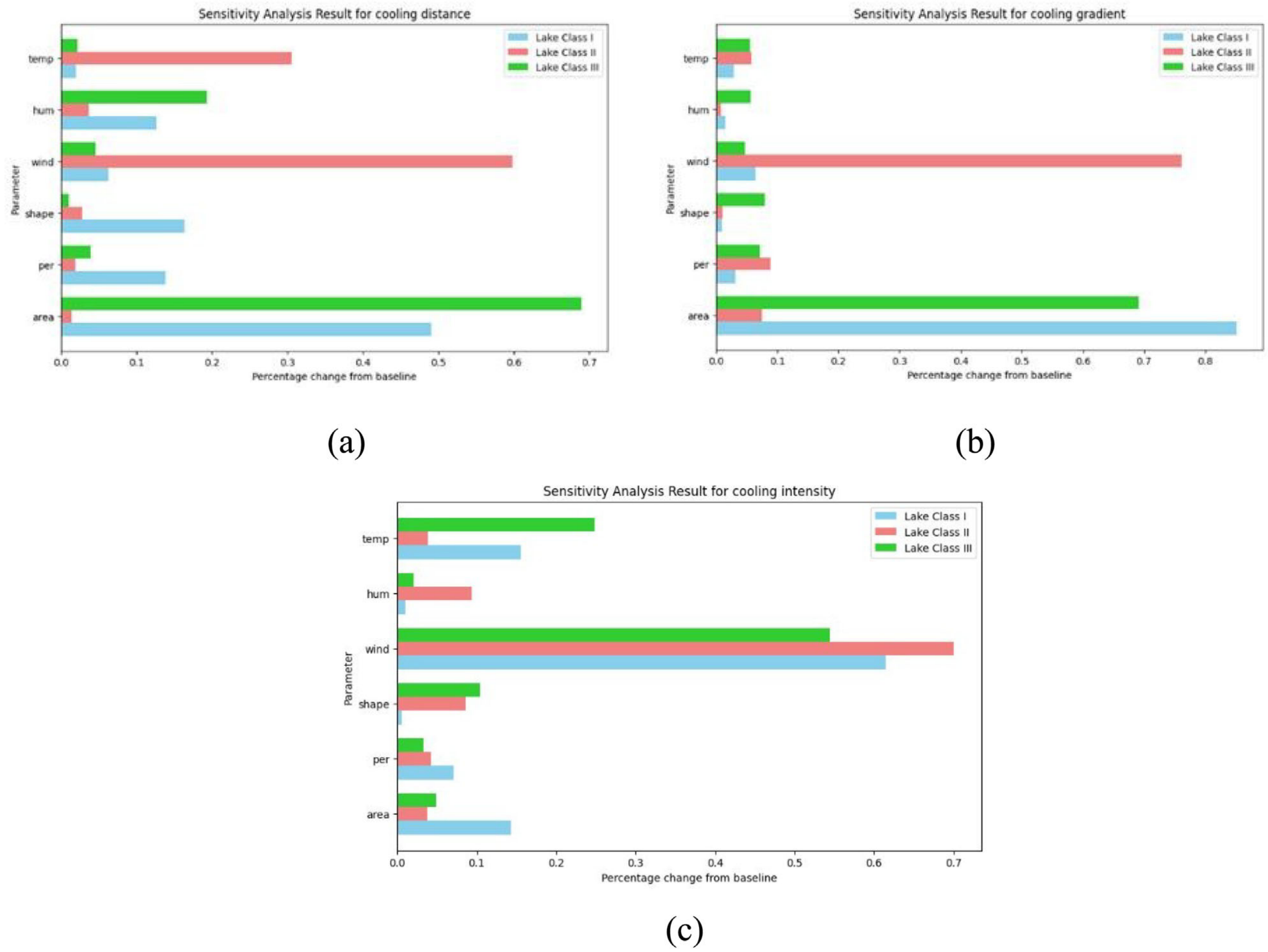

FIGURE 12 Sensitivity analysis result for 2023; (a) for cooling distance (b) for cooling gradient (c) for cooling intensity.

3.3.2 | Shifts in the impact of microclimatic factors

In the evaluation of water-cooling effects using three indices, notable variations emerge in cooling intensity and cooling distance between heat and non-heat periods (Section 3.1). Therefore, this analysis focuses specifically on these two indices.

The influence of meteorological factors on both cooling intensity and cooling distance remained insignificant for the small lakes of Class I in 2013. In 2023, wind speed showed a moderate positive correlation with cooling intensity, and perceived temperature showed a moderate negative correlation with cooling intensity, suggesting that higher temperatures reduce cooling intensity. The scenario is the same for Class II lakes. The cooling intensity of the Class II lakes appeared unaffected by meteorological factors during 2013. By 2023, a shift occurred: Wind speed showed a moderate positive correlation with cooling intensity, while perceived temperature showed a moderate negative correlation with cooling intensity (Figure 11). This suggests a newfound influence of meteorological factors on cooling effects in contrast to the earlier period. Aligned with the findings of Section 3.2, where meteorological factors varied significantly during heat and non-heat periods, the change in impact can be linked to HWs.

The impact of meteorological factors is more pronounced for Class III lakes compared to the other two classes. While the cooling effects of larger urban lakes in Class III showed no correlation with meteorological factors in 2013, by 2023, cooling intensity exhibited a strong correlation with wind speed and perceived temperature, with correlation values of 0.62 and 0.67, respectively (Figure 11).

3.3.3 | Sensitivity of the water-cooling effects on meteorological factors

The outcomes of the sensitivity analysis are shown in Figure 12. It indicates that water body area and wind speed exhibit greater sensitivity to changes in cooling distance and gradient compared to cooling intensity, which is more prone to variations in wind speed and temperature.

In the analysis of different clusters, it becomes evident that alterations in water body area exert a significant influence on both cooling distance and gradient within Class I lakes. Interestingly, the impact of the water body area appears to have a relatively minor effect on cooling intensity in this class. Contrary to this, wind speed emerges as the most influential factor, contributing to approximately 0.7% of the variation in cooling intensity. Moving to lakes under Class II, a distinct pattern shows where wind speed proves to be the most sensitive parameter across all cooling impact outputs. This suggests that, within this cluster, variations in wind speed play a crucial role in shaping the cooling characteristics of the lakes.

Class III lakes share certain similarities with that of Class I, where both water body area and wind speed exhibit high sensitivity to cooling distance and gradient. However, when it comes to cooling intensity, pivotal factors shift to wind speed (0.35%) and temperature (0.45%) within Class III. This underscores that cooling effects are influenced by many factors, and the importance of each factor varies depending on the group of lakes and the cooling impacts.

4 | DISCUSSION

4.1 | Understanding the influence of HWs

The findings of this study shed light on the critical role of the lakes in urban areas for cooling effects and their potential impact amidst rapid urban expansion. In cities like Dhaka, where there has been a substantial 19.12% expansion in city area and a 76.65% increase in inhabitants from 2001 to 2017 (Uddin et al., 2023), lakes of varying sizes hold promise in exhibiting considerable potential for cooling. However, the concentration of lakes primarily resides on the western side, and thus, utilization of these cooling benefits remains limited to a specific population subset, emphasizing the need for broader accessibility. As this investigation seeks to identify and understand the influence of HWs on water-cooling effects, a comparison was made between the cooling effects observed during the year of HWs and during NHW year. The findings suggest a significant reduction in cooling effects (Table 1) between the 2 years.

Numerous studies (Fiala et al., 2012; Steadman, 1979) have affirmed that HWs influence wind speed, relative humidity and perceived temperature. Ngarambe et al. (2020) noted a consistent trend of lower wind speeds during HW periods compared to NHW periods, aligning with the findings of the current study (Section 3.2). The analysis conducted on the correlation of meteorological factors (wind speed, relative humidity and perceived temperature) with the lakes was to establish a deeper connection between the decline in lake cooling effects and the occurrence of HWs. The well-established factors that influence the cooling effects include water surface area (Sun et al., 2020; Wu et al., 2020), shape index (Le Phuc et al., 2022; Sun et al., 2020; Wu et al., 2020), surrounding vegetation coverage (Jacobs et al., 2020; Le Phuc et al., 2022; Sun et al., 2020), waterfront green space type (Cao et al., 2022), surrounding building density (Sun et al., 2020) and percentage of impervious surface (Le Phuc et al., 2022). However, according to the results presented in Section 3.3.2, it was observed that while wind speed and perceived temperature did not significantly impact the cooling effects during NHW periods, their influence became evident for medium to large lakes (Class II and Class III) during HW periods. This suggests that HWs, which tend to reduce wind speed, play a crucial role in influencing the water-cooling effect. Since wind speed is positively correlated with cooling intensity, the reduction in wind speed during HWs ultimately results in a decrease in cooling intensity. Furthermore, within the realm of cooling effects, it was observed that meteorological factors have a comparatively lesser impact on cooling distance than they do on cooling intensity. One potential reason for this difference could be that cooling distance is more reliant on inherent physical characteristics of the water body, whereas cooling intensity is more susceptible to immediate atmospheric influences like wind speed and temperature fluctuations.

Furthermore, from the sensitivity analysis, it was found that not all parameters contribute equally to the cooling impact of Dhaka's lakes. Meteorological factors and landscape characteristics exhibit varying degrees of sensitivity to different cooling impacts. Among these factors, area, wind speed and perceived temperature stand out either individually or in combination as the most sensitive contributors to the lakes' cooling effects. The objective of this study is to identify the meteorological factors that have the most significant influence on either amplifying or diminishing the cooling effects of lakes. Given that the impact of such microclimatic factors is less explored in the study area, the findings are anticipated to offer valuable insights for potential interventions or strategies, contributing to informed planning.

4.2 | Policy suggestion

The following suggestions would contribute valuable insights for urban planners and policymakers in enhancing the resilience of Dhaka City to HWs through informed management of its urban water bodies:

- **Declaration of HWs as a disaster:** The Sixth Assessment Report (AR6) of the United Nations (UN) Intergovernmental Panel on Climate Change (IPCC) concluded the rise of the frequency and intensity of HWs with certainty, and these events are predicted to occur more frequently shortly (Intergovernmental Panel on Climate Change, 2023). Despite this, HWs are not currently categorized as official disasters in Bangladesh, unlike other Asian countries (South Korea and India). Along with the previous records of mortality, it is also evident from our study that HWs affect natural habitats as well. Thus, to effectively address the prevention and management of HWs, it is suggested to first designate them as a recognized disaster.
- **Distributed development of cooling resources:** Ensuring access to cooling benefits for all Dhaka residents through a balanced distribution of urban lakes is a priority. While creating new lakes within the administrative area of DMA might not be feasible due to land scarcity, proper planning for the new towns like Purbachol, Keraniganj and Narayanganj could integrate the potential for developing lakes to enhance cooling opportunities.
- **Research and innovation support:** Given the existing research gap in comprehensively addressing the interaction between HWs and

the potential of urban lakes, it is essential to allocate resources for conducting further research. This research should specifically focus on exploring the day–night variation of cooling effects, which stands as a limitation within the existing study.

- **Proper design and planning:** Since wind speed emerges as the most influential factor as per the sensitivity analysis, it becomes crucial to consider this factor when designing and planning lakes within urban areas. Additionally, the cooling effects of large-sized lakes of Class III demonstrate a higher correlation to meteorological factors in comparison to the other two Classes. Consequently, strategies should be taken for the existing large-sized lakes to increase the cooling effects.

5 | CONCLUSION

HW is considered a 'silent disaster' as it develops slowly, causing harm to living creatures worldwide. Consistent with the literature, this study has added evidence to ensure that urban lakes are valuable natural cooling agents to this disaster, offering localized relief from high temperatures within metropolitan areas. However, comprehending the interaction between urban microclimates and the cooling impact of water bodies is essential in light of the rising occurrence of HWs. This study examines the substantial influence of urban microclimate on the cooling effects of lakes during HWs and NHW events, focusing on urban lakes in Dhaka. The study utilizes a methodology that combines data from various sources and analytical tools, such as K-means clustering, Kriging interpolation, paired *t*-tests and sensitivity analysis. The findings clearly demonstrate that meteorological factors, including wind speed and perceived temperature, have a significant impact on the cooling intensity of lakes, and there are notable distinctions in relative humidity, wind speed and perceived temperature during HWs compared to NHW periods. The sensitivity analysis reveals that wind speed is the primary factor that affects the difference in cooling effects among different lake classes. The result emphasizes the significance of incorporating meteorological factors into the design and planning of urban water bodies in order to optimize their cooling advantages. Moreover, Class III lakes, characterized by their larger size, display the most profound response to meteorological factors. This implies that mitigation strategies should be taken for these types of lakes to increase the cooling effects.

This study has several limitations. The use of spatial interpolation in ArcGIS, based on data from four weather observation stations, to estimate meteorological factors for the DMA may introduce errors and reduce accuracy due to the limited number of stations. Additionally, the exclusive focus on daytime cooling effects overlooks nighttime conditions, where urban heat islands often have the most pronounced impacts. The comparison between 2013 and 2023 may also be insufficient to capture the full variability of HWs and urban climate dynamics, which can exhibit significant fluctuations over shorter periods. Despite these limitations, the study provides a foundation for further research. There is scope for future studies to address these gaps by incorporating more comprehensive datasets, including nighttime data, and extending the temporal scope to enhance the robustness and applicability of the findings.

DATA AVAILABILITY STATEMENT

The data analysed during the current study are available from the corresponding author upon reasonable request.

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Additional supporting information can be found online in the Supporting Information section at the end of this article.

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