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TEMPORAL ANALYSIS OF URBAN WATERLOGGING HOTSPOTS USING LANDSAT-DERIVED SPECTRAL INDICES – KOLKATA, INDIA

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ABSTRACT

Aim of the study

The aim of this study is the assessment of changes in land use and land cover (LULC) in Kolkata from 2010 to 2020 and how they affected urban waterlogging, employing satellite images and image classification methodologies.

Materials and methods

Landsat 7 satellite imagery and advanced image classification methods were used to identify and map five LULC categories: water bodies, built-up areas, barren land, scrubland, and cultivated land.

Results and conclusions

Built-up areas have expanded from 104.11 km² in 2010 to 142.80 km² in 2020, whereas scrubland, water bodies, and agricultural areas have decreased significantly. The study calculates waterlogging susceptibility using MNDWI and NDBI. Stratified sampling in QGIS was used to confirm the LULC classification accuracy, which increased from 73.73% in 2010 to 89.30% in 2020. Total 200 samples were used for this process, with 20 examples selected from each class. With Kappa coefficient of 0.564 (2010) and 0.859 (2020), the LULC classification has improved in accuracy and dependability. The Kappa value of 2010 (0.564) indicates moderate agreement between classified data and reference data, while the 0.859 (2020) value indicates high agreement and significant improvement of classification dependability. This shift from moderate to high classification dependability suggests that the 2020 LULC classification is more accurate and dependable, with less classification errors. According to hotspot research, eastern Kolkata and areas around the Hugli River are prone to waterlogging due to urban expansion and the loss of natural water retention facilities. Due to impermeable surface expansion, urbanized regions have seen a 114.75% increase in waterlogging. The study underlines the necessity for particular urban design and water management measures to decrease the harmful effects of waterlogging and improve the resilience of Kolkata's sensitive urban areas. These findings are crucial for sustainable urban development and flood avoidance.

Keywords: flood hotspots, waterlogging, normalized difference built-up index, modified normalized differential water index, hotspot analysis

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INTRODUCTION

Worldwide, urban waterlogging poses a significant challenge that has various social, economic, and environmental repercussions for cities. Investigating these incidences and understanding their impact has become a crucial area of study, often addressed through remote sensing approaches (Zotos et al., 2018). Remote sensing technologies like satellite imagery and geographic information system (GIS) provide invaluable tools for assessing and monitoring waterlogging in urban areas (Zhang et al., 2020). In India, cities like Delhi, Mumbai and Kolkata suffer water logging during monsoons, leading to breakdowns in transport systems, enormous financial losses, and outbreaks of waterborne diseases, such as dengue and malaria (Tiwari et al., 2025). By analysing satellite data, researchers can detect and track changes in land surface conditions, identifying areas prone to waterlogging, developing detailed elevation maps that allow for precise identification of topographic features contributing to water accumulation (Suhag et al., 2008). Furthermore, GIS enables the integration of diverse datasets, facilitating comprehensive analyses of factors, such as land use, drainage systems, and rainfall patterns. The impact of urban waterlogging extends beyond mere inconvenience, affecting infrastructure, public health, transportation, and the environment (Nematchoua et al., 2020). Through remote sensing, researchers can quantify the extent and duration of waterlogging events, assess damage to infrastructure, evaluate potential health risks from stagnant water, and understand the broader environmental implications, such as soil in degradation and habitat disruption (Maniatis et al., 2021). This information serves as a basis for developing effective mitigation and adaptation strategies, aiding urban planners and policymakers in making informed decisions to alleviate waterlogging issues (Ghosh and Mistri, 2020).

The problem of waterlogging has become widespread and persistent in several different regions of India, even though it is a country with a wide range of landforms and variable weather patterns (Comert et al., 2021). Waterlogging vulnerabilities have become a major concern for sustainable urban growth, with far-reaching implications for public safety, infrastructure, and economic stability (Uddin and Matin, 2021). Thus, understanding and fixing these vulnerabilities is crucial. Waterlogging vulnerabilities in India are caused by multiple reasons, including increased urbanization, outdated drainage systems, encroachment on natural water bodies, and deficiencies in urban design (Nozari et al., 2021. These issues all contribute to greater waterlogging vulnerabilities. The investigation of these components is essential for achieving a comprehensive understanding of the vulnerabilities associated with urban waterlogging in India and for designing strategies that are appropriate to the setting to successfully minimize associated risks (Radoglou-Grammatikis et al., 2021). Researchers have employed a wide range of methods, such as remote sensing, GIS, and hydrological modelling, to map and evaluate waterlogging hotspots (Kuang et al., 2021). These spatial analysis methods have made it possible to identify high-risk areas, which has made it possible to implement targeted interventions and improve urban planning projects (Zhang et al., 2024). In addition, research has been carried out to study the relationship between patterns of land use, soil qualities, and susceptibility to waterlogging. Hollenstein and Purves (2010) investigated the urban spatial structure of the metropolitan areas of London and Chicago (Basu and Pal, 2017). Recently, GIS data integration of groundwater and remote sensing images, and groundwater modelling have been adopted to approach waterlogging problems and manage drainage deficiency along the basins (Alam et al., 2006). Several gaps in the study of urban waterlogging warrant further investigation that requires studying urban waterlogging, including comprehensive data collection and standardized vulnerability assessment methodologies. This will result in better understanding of sector-specific impacts, evaluation of the effectiveness of mitigation measures, and promotion of interdisciplinary research (Zhou et al., 2021).

Prior studies assessed the risk of waterlogging using a hazard-exposure-vulnerability (H-E-V) model (Sahani et al., 2019) and climate risk (da Silva Costa et al., 2025). Urban flooding endangers basic infrastructure, agriculture, and social structures (Simarmata et al., 2021). Accurate and reliable prediction models are required for efficient water resource management, policy formation, and evacuation planning (de Caro et al., 2019). Waterlogging is difficult to predict due to the dynamic nature of climatic circumstances (Rahmani and Arsiun, 2016). Rainwater is a major contributor to urban waterlogging because it can raise the level of surface runoff, turning urban roadways into actual streams. Addressing rainwater accumulation with effective drainage systems and other measures can prevent or mitigate the impact of urban waterlogging in prone areas (Cao et al., 2021). Continuous and precise monitoring of waterlogging is essential for disaster prevention, providing with the public early warning information, identifying affected roads for targeted closure, and minimizing casualties and property damage (Wan et al., 2019). In urban areas, green spaces play a vital role in managing rainwater runoff. The incorporation of low impact development (LID) systems utilizing attached green spaces can effectively mitigate the impacts of waterlogging (Kuang et al., 2021). Heavy rain in Mumbai's Dadar region has resulted in massive waterlogging, causing numerous issues for commuters (Das et al., 2018). It was reported that the government did not take action (Mumbai, ANI, August 21, 2014, 11.57 am). As a result, more effective models that use less data as input have been suggested to evaluate the risks of urban waterlogging. Even though there has been a lot of research on urban storm waterlogging modelling, the hydrologic and hydrodynamic models both struggle with the complex and enormous amounts of difficult-to-access data related to topography, sewer conveyance, and infiltration conditions (Dasgupta et al., 2021; Kant et al., 2025). The expansion of urbanization necessitates an understanding of its consequences and the implementation of sustainable strategies in order to address the associated environmental and social impacts (Souza et al., 2020).

Studies have shown that LULC has changed during the past decade in Kolkata, related to such phenomena as the destruction of water bodies and the increase of developed land (Dutta et al., 2019). These studies demonstrate that urbanization has contributed to the waterlogging by eliminating wetlands and increasing impermeable surfaces, which is confirmed by the results of this study. Dutta et al. (2019) estimated that the loss of wetlands in eastern Kolkata was 0.33%, which increased waterlogging by 114.75%. This is a very similar trend and spatial pattern to the one observed in this study. Other studies have also acknowledged that the complex landscape of Kolkata (abounding in many small, shallow and seasonal water bodies within the urban sprawl) generates challenges for accuracy in LULC classification, especially for the water class. Although the user accuracy of water in some years is moderate at best, our results highlight that these LULC maps are still useful for waterlogging analysis, because the maps adequately capture the important hydrological components associated with flood risk. This view is also reflected in this study, and the previous study as well, supporting the argument for context-specific investigations and advanced classification methodology in various urban environments.

The literature does not only corroborate our major results about the urban expansion leading to the loss of water body and subsequently to waterlogging risk, it also validates the methodological approach and relevance of LULC dynamics analysis for flood management in Kolkata. There have been no big studies that have shown different trends in the region but on the contrary result shows that effective urban planning, sustainable development and better drainage infrastructure to deal with waterlogging in cities that are undergoing rapid urbanization, as is the case with Kolkata, is vital.

Kolkata has seen rapid urbanization and population increase, disrupting natural drainage with high-rise buildings. The population is expected to reach 20.1 million by 2025, and unorganized land use has clogged drains and sewers (Agonafir et al., 2021). The city's location in the lower Ganges Delta and height differences of 1.5–9 meters makes it favourable for the formation of tidal flats and mangrove forests. Monsoon season rainfall in Kolkata averages 1,836.5 millimetres, causing waterlogging (Turkar, 2010). For urban planning and growth, several issues must be addressed. Waterlogging and flooding in Kolkata are exacerbating, therefore efficient urban design that balances urbanization and environmental development is essential. Increasing settlement population density aggravates the situation (Ghosh and Das, 2017). LULC, normalized difference water index (NDWI), and normalized difference built-up index (NDBI), image band combinations, change detection, and image classification algorithms were used to create wasteland danger indicator thematic and spatial distribution change maps (Saha et al., 2022). Due to its flat topography and the meandering Hooghly River along its banks, it is particularly vulnerable to the adverse effects of heavy precipitation and inadequate drainage infrastructure. A thorough investigation into the factors that contribute to waterlogging in Kolkata has been carried out utilizing spatial analysis methods (Turkar, 2010). By analysing land use patterns, this research aims to pinpoint the areas where drainage systems have been compromised due to unregulated urbanization, encroachments on waterways, or inadequate infrastructure (Ackerman et al., 2014).

The purpose of this work is to investigate the susceptibility of Kolkata to flooding, and to establish a connection between the number of people living in slums and the requirement for storm protection measures. This research stands out for its thorough examination of the temporal aspects of urban waterlogging in Kolkata. It utilizes Landsat 7 data from 2010 and 2020 to provide a comprehensive analysis. The combination of NDBI and MNDWI offers a comprehensive perspective on urbanization and hydrological changes, allowing for accurate detection of areas prone to waterlogging. This research not only emphasizes the importance of addressing the issue of urban expansion and waterlogging, but also provides practical recommendations based on data for policymakers and urban planners to improve urban resilience.

MATERIALS AND METHODS

Study area

The capital of the Indian state of West Bengal, Kolkata is alternatively referred to as Calcutta. With a sprawling area of around 1851 square kilometres, the Kolkata Urban Agglomeration (KUA) is situated between the latitude of 22°00’19.00”N to 23°00’01.00”N and the longitude of 88°00′04.00”E to 88°00’33.00”E, as shown in Figure 1. As the third most populous metro-

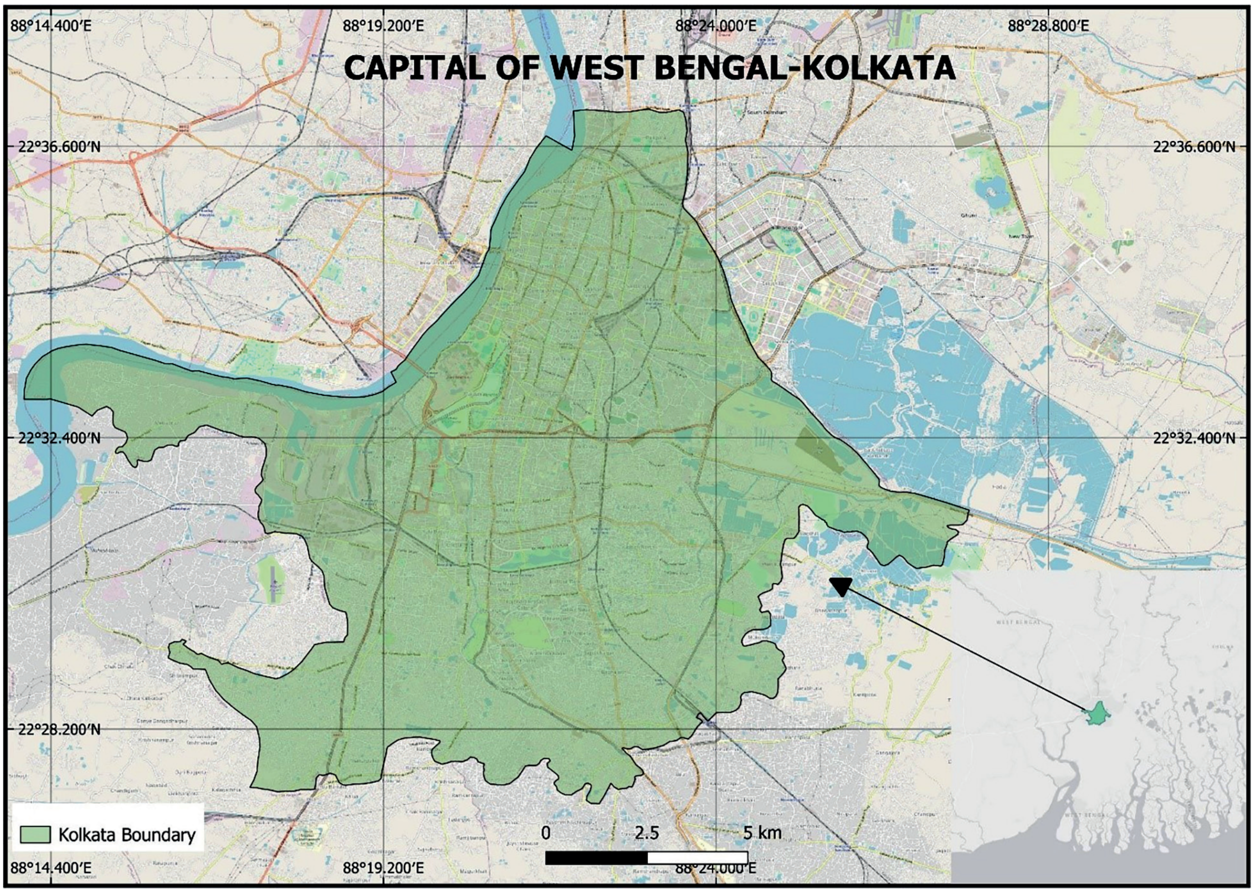

Fig. 1. Study area map of Kolkata urban agglomeration (source: Authors’ own elaboration)

politan area in India, Kolkata is home to over 14 million residents. It is the third-largest city in the country and encompasses an area of around 185 square kilometres (71 square miles), making it the third-largest city in terms of land area.

Kolkata is situated in the eastern portion of the Gangetic plain, and the Ganges River delta, which is rich in agricultural potential, forms the city's southern boundary. The majority of the city sits on very flat ground, with an elevation that is approximately 9 meters (30 feet) above mean sea level. The city of Kolkata has a tropical wet-and-dry climate, which means that summers are extremely hot and humid, while winters are mild. The proximity of this region to the Bay of Bengal, along with the impact of the southwest monsoon, causes a lot of precipitation. The monsoon season normally lasts from June until September, and is characterized by extended periods of heavy rainfall and sporadic instances of floods. The city of Kolkata receives roughly 1,582 millimetres (62 inches) of precipitation on an annual basis on average.

Temperatures in the city typically reach a high of 40°C during the afternoon in summer. The city also experiences high levels of humidity at this time of year. Conversely, winters have a more agreeable and moderate climate, characterized by fluctuations in temperature between 15 and 25°C throughout the season. Temperature and humidity levels in Kolkata fluctuate considerably over the year. Valuable to the history and commerce of Kolkata, the Hooghly River, a tributary of the Ganges, flows through the city. The Howrah Bridge, which connects Kolkata to its twin city, Howrah, is a prominent emblem of the city. The urban landscape is replete with vibrant markets, historical locations, and cultural hubs.

Data and methods

Flood risk of Kolkata, and the vulnerability of its slum residents, demands an extensive investigation. Initial hydrological and topographical assessments using GIS and remote sensing identify the flood-prone areas and evaluate the drainage systems. Historical flood data can reveal patterns and vulnerable locations based on previous disasters. Demographic studies are being done in these locations to estimate slum population density and distribution. This statistic compares flood-prone areas. Social vulnerability assessments examine the socioeconomic patterns, resilience, and coping abilities of populations at risk of floodings. Stakeholder engagements with local politicians and urban planners might indicate the needs and worries of people in slums. These collective studies identify high-risk slum areas using spatial vulnerability mapping, demographic correlations, and social resilience assessments. These measures can prioritize storm protection, synchronize infrastructure development, and fortify susceptible neighbourhoods to reduce Kolkata floods. Urbanization and waterlogging patterns in Kolkata were examined from 2010 to 2020.

Figure 2 shows how this study uses technical methods to assess Kolkata's LULC from 2010 to 2020. The USGS Earth Explorer acquires Landsat 7 ETM+ imagery for both years, focused on row/path 044/138 with minimum cloud cover (Table 1).

As a result of the scanline errors caused by the failure of the Scan Line Corrector (SLC), the imagery is corrected using the QGIS's 'Landsat Toolbox,' which utilizes interpolation to rectify missing data. Addressing the data gaps in Landsat 7 ETM+ (Marujo et al., 2020) images caused by the SLC failure is an important step in scanline correction. The essential parameters adopted in this procedure involve the input image, which is the Landsat 7 ETM+ image with SLC-off gaps in GeoTIFF format. In this study, scanline error correction was conducted with the Scanline Error Correction tool in QGIS. This tool was used to improve the quality of remotely sensed data by detecting and filling gaps related to scanline errors, usually by interpolating with a method such as nearest neighbour.

Table 1. Details of datasets used

Satellite image	Row path	No. of bands	Year of acquisition	Source
Landsat 7	044/138	9	2010	USGS
Landsat 7	044/138	9	2020	USGS

This formula interpolates missing pixel values using neighbouring valid pixels, generating a smoother and more continuous image. Temporal data from additional Landsat 7 images taken on different dates is necessary for data merging. To ensure effective merging, weighting factors are applied to these dates. Additional data can also be utilized to help fill in the missing information. These parameters and methods ensure that the gaps caused by the SLC-off issue are effectively filled, resulting in a corrected image suitable for further analysis.

The QGIS's 'Radiometric Calibration' tool was used to correct sensor and atmospheric distortions. Meanwhile in order to analyze land cover, the 'Build Virtual Raster' tool creates a multi-band composite image from bands 3 (Red), 4 (Near Infrared), and 5 (Shortwave Infrared). Machines learning can be applied to a variety of sources of information, such as satellite images, atmospheric data and historical weather and catastrophe data to make accurate results in weather prediction and natural disaster forecasting (Rawat et al., 2024). QGIS uses the 'Semi-Automatic Classification Plugin' for supervised classification. This process involves the following steps:

1) importing and defining the imagery of the area of interest,
2) drawing polygons for different land cover classes using high-resolution reference data,
3) setting up the classifier used like Random Forest,
4) running the classification to assign land cover categories to pixels,
5) generating 2010 and 2020 LULC maps.

Two spectral indices facilitate feature differentiation. The MNDWI highlights water bodies. The MNDWI is calculated by dividing the Green-SWIR band differences by their sum (Gašparović and Singh, 2023). While the NDBI identifies urban built-up zones, and it is calculated by dividing the NIR-SWIR band differences by their sum. Change detection uses QGIS 'Image Difference' tool to compare the 2010 and 2020 LULC maps. This tool quantifies decade-long land cover changes. A confusion matrix is created using ground truth data from high-resolution images. This calculates overall, producer, and user accuracy. Total accuracy represents the percentage of pixels in all categories classified correctly. The producer's accuracy (Equation 1) statistic measures the likelihood that a pixel sorted into a category corresponds to that category. In contrast, the user's accuracy metric evaluates each category's classification reliability. An accuracy assessment is essential for accurate change analysis and categorized data reliability. This method tests the precision of categorized outputs using statistics. The study tested 100 random locations for precision. Google Earth Pro data and field observations were used to verify these points. Equation 1 measures the producer accuracy, or the likelihood a pixel will be classified correctly. This metric is calculated using the following formula (Akbari et al., 2006):

$$PA = C_i / C_t \cdot 100 \tag{1}$$

where:

PA – producer accuracy,
C_i – correct sample location in the column,
C_t – total number of sample locations in the column.

User accuracy, as defined by Equation 2, is a crucial performance metric in the fields of remote sensing and image categorization. It is defined as the quotient obtained by dividing the number of accurately classified pixels within a specific category by the total number of pixels in that category. The computation process is as follows (Rawat et al., 2024):

$$UA = R_C / R_t \cdot 100 \tag{2}$$

where:

UA – user accuracy,
R_C – correct sample location in a row,
R_t – total number of sample locations in a row.

This metric reflects the accuracy with which the pixels are classified. An 80% user accuracy for forests means the classifier correctly identifies 80 out of 100 pixels as 'forest'. The classifier classifies pixels as forest with 80% accuracy. User accuracy assesses how often a categorization label matches the user's perception of the true category, demonstrating classification precision. The performance of the classification algorithm depends on overall accuracy (Equation 3). This measures the percentage of pixels categorized correctly across all categories. The pixels successfully detected by the error matrix are divided by the total pixels. This concept is mathematical (Rawat et al., 2024):

$$OA = A_C / A_t \cdot 100 \tag{3}$$

where:
- OA – overall accuracy,
- A_C – all correct classified samples from all classes,
- A_t – total number of samples from all classes.

Overall accuracy measures the performance of the classification algorithm across all categories by comparing correct classifications to analysed pixels. A classifier that detects 1,500 pixels in a 2,000-pixel error matrix has 75% accuracy. The categorization results and ROIs are compared to assess accuracy. It usually compares producer and user accuracy. T_i assess its performance the categorization should be compared to a map with randomly assigned values. Kappa coefficient is –1 to 1. The sample size needed per category to achieve 95% classification accuracy with a ±10% margin of error in the error matrix (Richards and Jia, 2006). This statistic assesses categorization's overall efficacy rather than category accuracy. A formula calculated Kappa coefficient as shown in Equation 4 (Foody, 2002):

$$\hat{k} = N\sum_{i=1}^{r} x_{ii} - \sum_{i=1}^{r}\left(x_{i+} \cdot x_{i+1}\right) / N^2 - \sum_{i=1}^{r}\left(x_{i+} \cdot x_{+1}\right) \tag{4}$$

where:
- N – sum of all observation in the matrix,
- r – number of rows in the error matrix,
- x_{ii} – number of observations in row i and column i (along the diagonal),
- x_{i+} – total of observations in row i (total to right of the matrix),
- x_{+i} – total of observations in column i (total at bottom matrix).

Finally, the MNDWI and NDBI variations are examined in waterlogging hotspot analysis. Continuously high MNDWI and significant NDBI results indicate waterlogging risk.

The NDBI was calculated using shortwave and near-infrared (Equation 5) (Razzakul Islam and Haque, 2022). The NDBI scales from –1 to +1, with values near –1 suggesting no buildup and values near +1 indicating dense buildup.

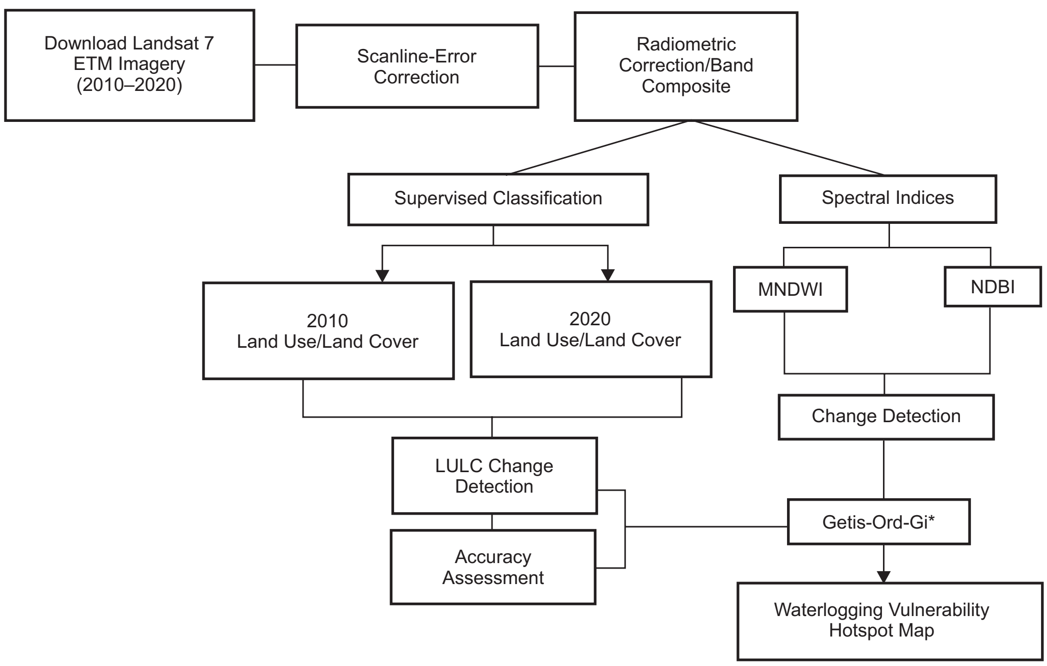

Fig. 2. Kolkata LULC and waterlogging hotspot analysis methodology (2010–2020) (source: Authors' own elaboration)

$$\text{NDBI} = (\text{SWIR} - \text{Red})/(\text{NIR} + \text{Red}) \quad (5)$$

The MNDWI effectively reduces land noise, vegetation, and soil noise, while enhancing open water feature (Gašparović and Singh, 2023). The water body extraction technology employs two bands: green and middle infrared. Water bodies are extracted from Landsat7 images using bands 2 and 4. The MNDWI excels in extracting water information in built-up land regions due to its ability to reduce or eliminate noise compared to the NDWI (Gašparović and Singh, 2023). MNDWI is derived from NDWI in which middle infrared is used instead of near-infrared, as shown in Equation 6. Efficiently distinguishing between open surface water and dry surfaces improves water body identification.

$$\text{MNDWI} = (\text{Green} - \text{SWIR})/(\text{Green} + \text{SWIR}) \quad (6)$$

Upon the computation of these indices, the raster maps undergo reclassification in order to streamline the data into useful groups. This stage is crucial for detecting substantial changes over a period of time. The classed raster data is subsequently transformed from raster to vector format, enabling more comprehensive geographic analysis. An analysis is conducted on the area undergoing change to discern the magnitude and characteristics of alterations in water bodies and developed regions.

After the detection process is completed, the Getis-Ord Gi* statistic is used to identify hotspots and cold spots that reach statistical significance. The Getis-Ord Gi* statistic can be expressed using the following formula (Roy et al., 2024):

$$G_i^* = \frac{\Sigma_j^n = {}_1 w_{ij} x_j - \bar{X} \Sigma_j^n = {}_1 w_{ij}}{\dfrac{\sqrt[S]{\left[n \Sigma_j^n = {}_1 w_{ij}^2 - \left(\Sigma_j^n = {}_1 w_{ij} \right)^2 \right]}}{n-1}} \quad (7)$$

where:

x_j – the attribute value for feature (j),
w_{ij} – the spatial weight between features i and j,
$\bar{X}$ – the mean of the attribute values,
S – the standard deviation,
n – the number of features.

The formula calculates the difference between the weighted sum of values in a neighbourhood and the expected value, allowing for comparison across locations. A positive Gi* indicates a hotspot, while a negative value indicates a cold spot (Equation 7). This helps to identify critical zones for intervention in Kolkata, where severe waterlogging incidents are clustered (Islam et al., 2022). The output includes a z-score and p-value, indicating the statistical significance of the clustering. This analysis is crucial for effective resource allocation and urban management in addressing waterlogging issues. The statistical measure facilitates the identification of clusters characterized by high values (hotspots) and low values (cold spots) by the comparison of the local sum of the attribute values with the anticipated sum. The obtained z-scores and p-values provide strong evidence of the statistical importance of these clusters.

An overlay study assesses the temporal variations in Kolkata's urban waterlogging hotspots and LULC. Overlay research evaluates temporal changes in Kolkata's urban waterlogging hotspots and LULC. The indices are reclassified to identify areas with buildings and water, then overlaid to find common waterlogging places. Comparing classified maps over two years can detect changes in LULC.

RESULTS

The National Remote Sensing Centre's Level-I classification scheme divided Kolkata's LULC into five categories: water bodies, built-up areas, barren land, scrubland, and agricultural land (Fig. 3). According to the study, the recent decade saw LULC patterns change significantly. The 2010 LULC map revealed 104.11 km^2 of built-up area, followed by scrubland (49.06 km^2), water bodies (20.72 km^2), agricultural land (7.59 km^2), and barren land (3.79 km^2). The results from 2020 stated 142.80 km^2 of built-up area, followed by 18.01 km^2 of water bodies, 11.79 km^2 of scrubland, 5.79 km^2 of agricultural land, and 3.91 km^2 of barren land. The area of scrubland, water bodies, and agricultural land dopped, while built-up areas and barren land increased.

The decrease in water bodies in eastern Kolkata, resulting from expansion of residential development on wetlands, has notably affected the city's drain-

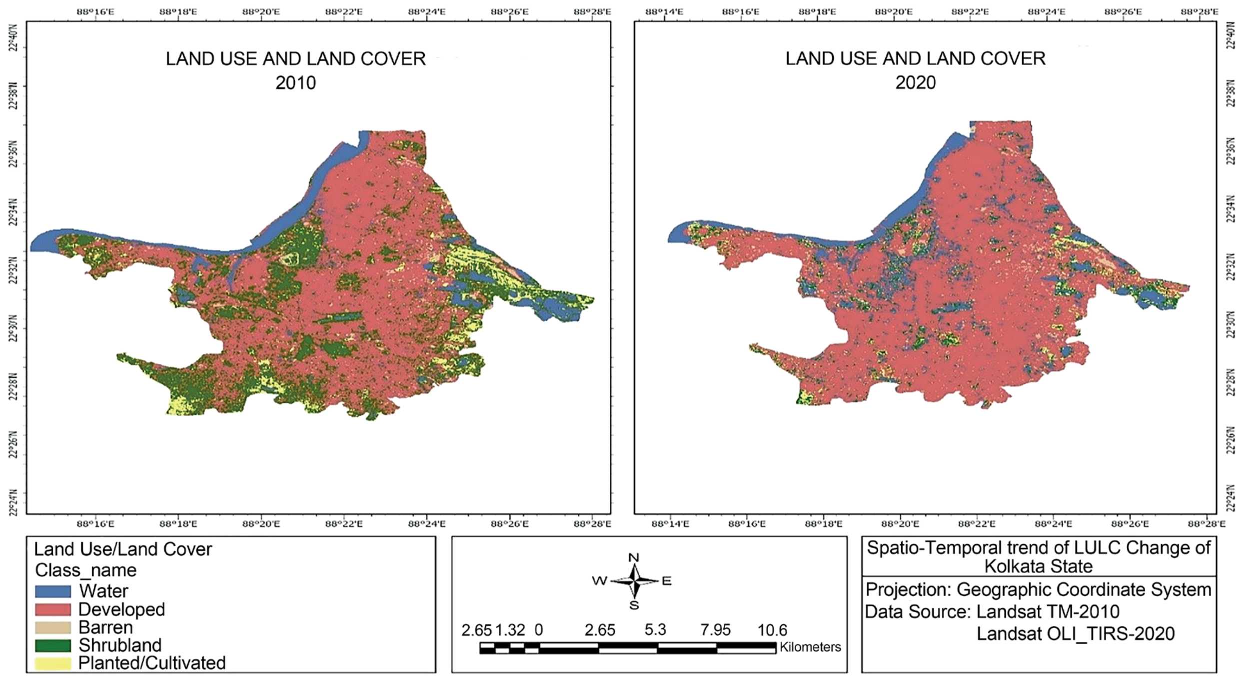

Fig. 3. Spatio-temporal trend of LULC change of Kolkata state (source: Authors' own elaboration)

age system and exacerbated its urban waterlogging issues. Approximately 33% of wetlands in eastern Kolkata have been lost over recent decades, leading to a 114.75% increase in waterlogging due to diminished natural water retention (Dutta et al., 2019). The increase of impermeable surfaces – urbanized areas rising from 104.11 km² in 2010 to 142.80 km² in 2020 – has inhibited drainage. This highlights the critical necessity for sustainable urban planning to address waterlogging (Ghosh and Mistri, 2018).

Stratified sampling accurately located each site in 2010 and 2020. For 2010 and 2020, accuracy equals 595/807 · 100 (Table 2) and 2913/3262 · 100 (Table 3), respectively. User accuracy was 92.16–39.47 in 2010 (Table 2) and 95.57–61.76 in 2020 (Table 3). Here, the lowest user accuracy for both years is 39.74% for water bodies, and 61.76% for agricultural land. The weak user accuracy of 39.74% for water bodies class can be partially attributed to Kolkata's distinctive urban landscape, with many small, shallow, and seasonally varying water bodies that are surrounded by built-up or vegetated areas. Although the statistical user accuracy for the water bodies class has been influenced, it would not cause the LULC map to lose its application value for the waterlogging research. Indeed, the classification effectively extracts the significant hydrological features related to waterlogging risk and offers a reliable basis for water accumulation patterns assessment throughout the city. Therefore, the findings are robust, and contribute to our understanding of the objectives of the study, indicating the need to conduct context-based investigation in complicated urban locations such as Kolkata.

For 2010 (Table 2), 60.26 of water bodies pixels are not identified, and for 2020, 38.24% of agricultural land pixels are not identified (Table 3). Classifying 595 and 2913 pixels for 2010 and 2020 is correct. Kappa coefficients of 0.564 in 2010 and 0.859 in 2020 are moderate and almost perfect, respectively. The Kappa value of 0.564 for the 2010 LULC map demonstrates the complexity of the landscape of Kolkata with a large number of natural and man-made water bodies (intermingled with urban and vegetated areas). Despite adding complexity and presenting a somewhat pessimistic outlook with respect to the predictive performance of the most well-known metrics, such complexity itself reinforces the richness of the data and the dynamic hydrological nature of the

Table 2. Confusion matrix of the LULC-2010 accuracy assessment

LULC Class	Water	Built-up	Barren Land	Scrub Land	Cultivated/ Planted	Total
Water	15	1	10	8	4	38
Built-up	0	435	18	13	6	472
Barren Land	0	11	35	0	0	46
Scrub Land	17	40	0	66	30	153
Cultivated/Planted	2	3	0	49	44	98
Total	34	490	63	136	84	807
PA [%]	44.12	88.78	55.56	48.53	52.38	
UA [%]	39.47	92.16	76.09	48.53	45.83	
Overall accuracy [%]		73.73				

Table 3. Confusion matrix of the LULC-2020 accuracy assessment

LULC Class	Water	Built-up	Barren Land	Scrub Land	Cultivated/ Planted	Total
Water	950	30	10	5	5	1000
Built-up	18	760	29	9	119	935
Barren Land	14	24	820	0	0	858
Scrub Land	4	11	6	278	0	299
Cultivated/Planted	7	52	0	6	105	170
Total	993	877	865	298	229	3262
PA [%]	95.67	86.66	94.80	93.29	45.85	
UA [%]	95.00	81.28	95.57	92.98	61.76	
Overall accuracy [%]		89.30				

urban environment. Crucially, the classification used in our study was specifically designed to facilitate waterlogging assessment such that spatial patterns most pertinent to water accumulation and drainage were accurately represented, even when multiple land cover types were present.

Increased Kappa value lead to improved accuracy in classifying data. The overall accuracy for 2010, as determined by the Kappa coefficient, is 73.33% (Table 2). Similarly, for 2020, the overall accuracy is 89.30% (Table 3), demonstrating a high level of correctness. Both the increase in overall accuracy and Kappa coefficient reflect a positive trend in the precision and reliability of land use classification in the past decade.

These baselines identify the greatest relative change observed during the study. Figure 4 includes positive numbers indicating a year with the lowest waterlogged area, land cover increasing, and negative values decreasing. From 0.12% to 2.43%, Kolkata flooded agricultural land fluctuated little (Fig. 4). The greatest variation was in water bodies, from 0.80% to 260.07%. Seasonal water levels variations, and land use changes around water bodies, may increase the

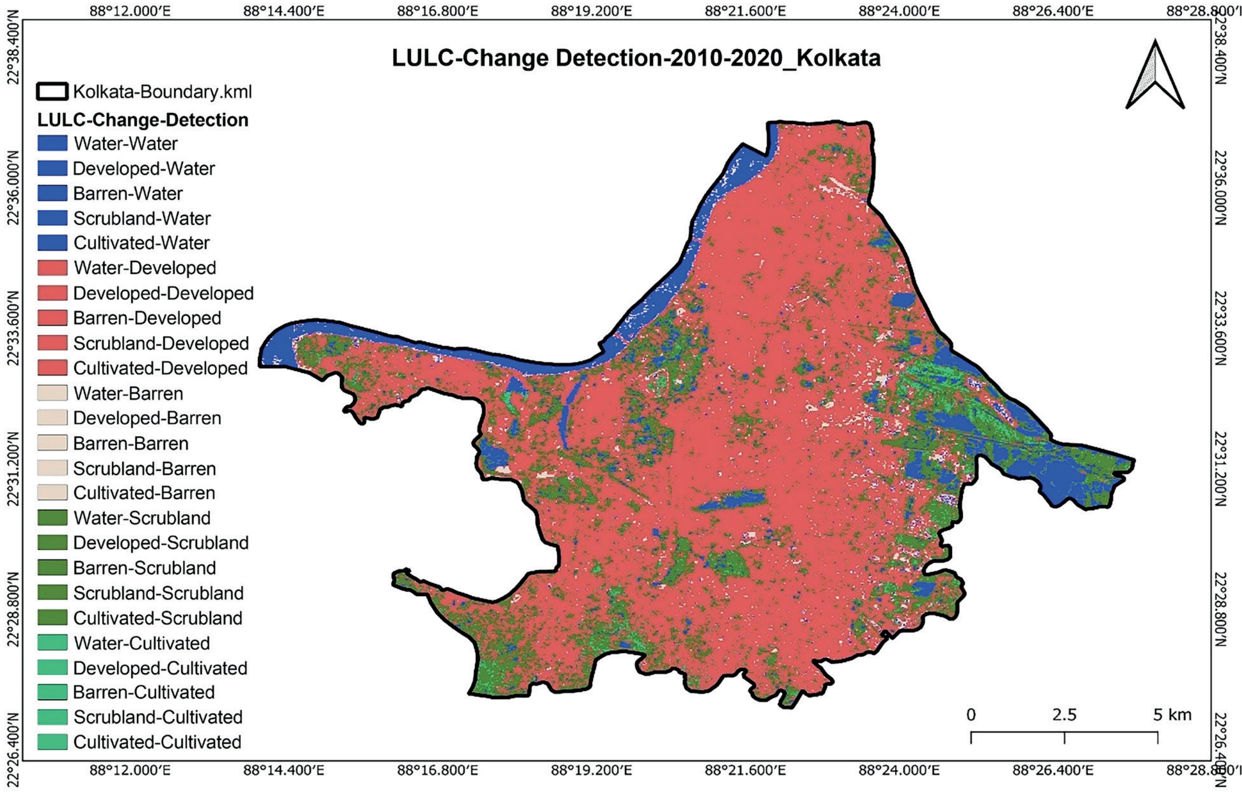

Fig. 4. LULC change detection 2010–2020 Kolkata (source: Authors' own elaboration)

unpredictability. Urban heterogeneity ranged from 0.53% to 114.75%.

Changes in LULC show major changes in water bodies, built-up areas, barren land, scrubland, and agricultural land due to environmental and anthropogenic influences. A major process involves the transformation of water bodies into built-up areas (1.45%) and scrubland (3.40%), which is caused by the appropriation of wetlands and other natural retention areas for buildings and urban expansion, especially in eastern Kolkata. This shift is driven by real estate development, which adopts wetlands for residential and commercial reasons, reducing their water retention capacity and causing waterlogging. The change from developed areas to scrubland (21.53%) points to the decay of urban infrastructure or abandoned buildings, which revert to wilderness due to poor maintenance or economic decline. Seasonal oscillations and water level variations contributed to the 260.07% rise in water bodies, showing a dynamic interaction between natural hydrological processes and human interventions like water management systems. Artificial water bodies for irrigation or flood control may also cause this volatility. Population growth, and rising infrastructure and housing needs have led to fast urbanization – built-up areas increased by 114.75%. Urban expansion often destroys natural landscapes, increasing impermeable surfaces and waterlogging. Another notable transition is from scrubland to built-up areas (2.56%), spurred by urban sprawl as marginal or underutilized lands are developed to suit the city's rising population. LULC fluctuates due to urbanization, real estate development, water management, and seasonality. Urbanization and economic pressures are the main causes affecting the landscape, although natural hydrological processes and human water management interventions also change land cover. While the rate of change in urbanized areas is 114.75%, water bodies exhibit seasonal or regulated changes, emphasizing the dynamic character of land use in urbanizing locations, like

Kolkata. City growth, infrastructure, and land use may alter these oscillations. This study emphasizes the consistency of waterlogged agricultural land versus water bodies and developed areas. Between 2010 and 2020, urbanized zones increased 114.75%, worsening Kolkata's waterlogging problem. Impermeable surfaces impede water absorption. Water bodies have increased 1.45%, although urban expansion is more significant, and may only create local waterlogging if drainage systems fails. Thus, waterlogging may develop due to 260.07% (Fig. 5) increase in water bodies area. Water bodies transforming into built-up areas (2.34%), barren land (0.19%), scrubland (1.66%), and agricultural land (0.80%) has little impact on waterlogging. It means that increase of water bodies and rapid urbanization cause major waterlogging. Kolkata's waterlogging incidents throughout time, with some years having more incidents than others. In 2010, there are few waterlogging cases, in 2017, there were many. Waterlogging incidents increased steadily from 2010 to 2020, with certain years seeing a significant increase.

Kolkata's urbanized regions range from –0.188 to 0.25 in 2010 and –0.24 to 0.16 in 2020, according to the NDBI (Fig. 6). Positive NDBI value indicate built-up areas, with higher values indicated denser urban structures. Negative values showed water bodies and agricultural land rather than buildings. The ranges have moderate building density, which reduces water infiltration and increases runoff causing waterlogging. The number of buildings increased significantly between 2010 and 2020, yet the greatest normalized difference built-up values changed from 0.25 in 2010 to 0.16 in 2020, indicating a modest construction density. The NDBI demonstrates that the built-up areas are common but agricultural land is rare. Understanding these trends helps identify waterlogging hotspots and developed mitigation methods.

The MNDWI and NDWI revealed landscape changes and waterlogging in Kolkata. The MNDWI metrics in 2010 ranged from –0.36 to 0.19 (Fig. 7), indicating aquatic and non-aquatic environments. Meanwhile, the NDBI values ranged from 0.18 to 0.25, indicating developed areas.

The NDBI values ranged from –0.24 to 0.16, whereas MNDWI registered urban growth and aquatic alterations. The MNDWI values are negatively correlated. In particular, densely built-up areas with high NDBI values have low MNDWI values, indicating less occurrence of water bodies. NDBI showed urban expansion from 2010 to 2020, whereas MNDWI shows water body decline (Fig. 7). Urbanization causes a drop of natural water discharge and decreases water absorption. Understanding how these variables are related is essential for analysing Kolkata's waterlogging vulnerability and developing effective solutions.

MNDWI indicates a significant reduction in water bodies, with areas experiencing decreases of up

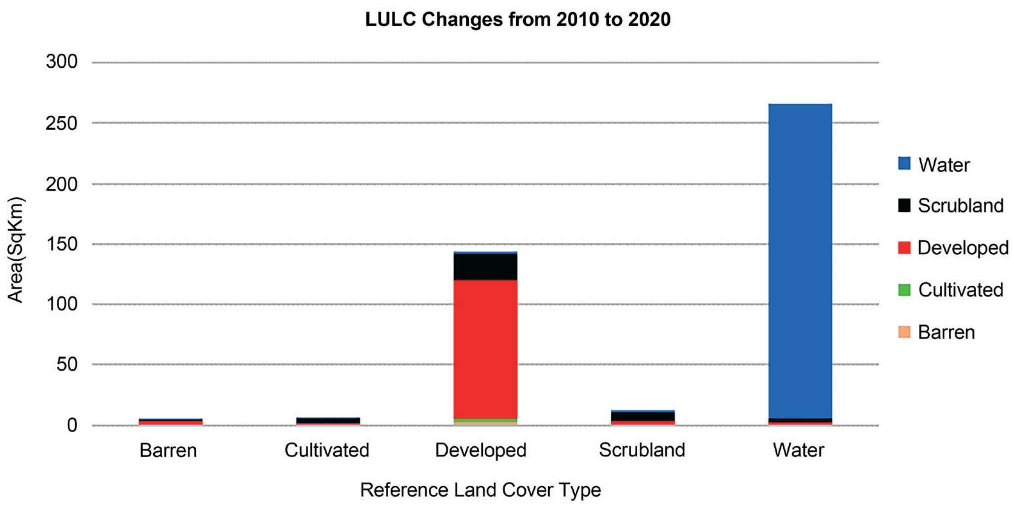

Fig. 5. Combined stacked graph showing LULC change detection, Kolkata 2010–2020 (source: Authors' own elaboration)

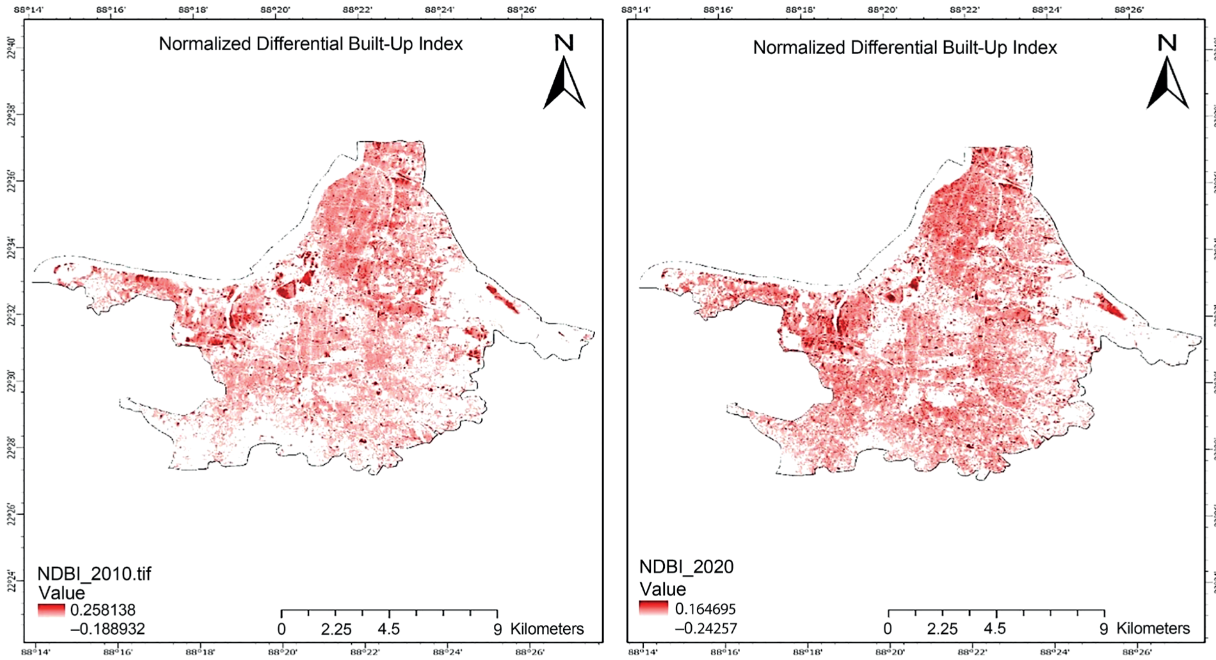

Fig. 6. Normalized difference built-up index, Kolkata 2010–2020 (source: Authors' own elaboration)

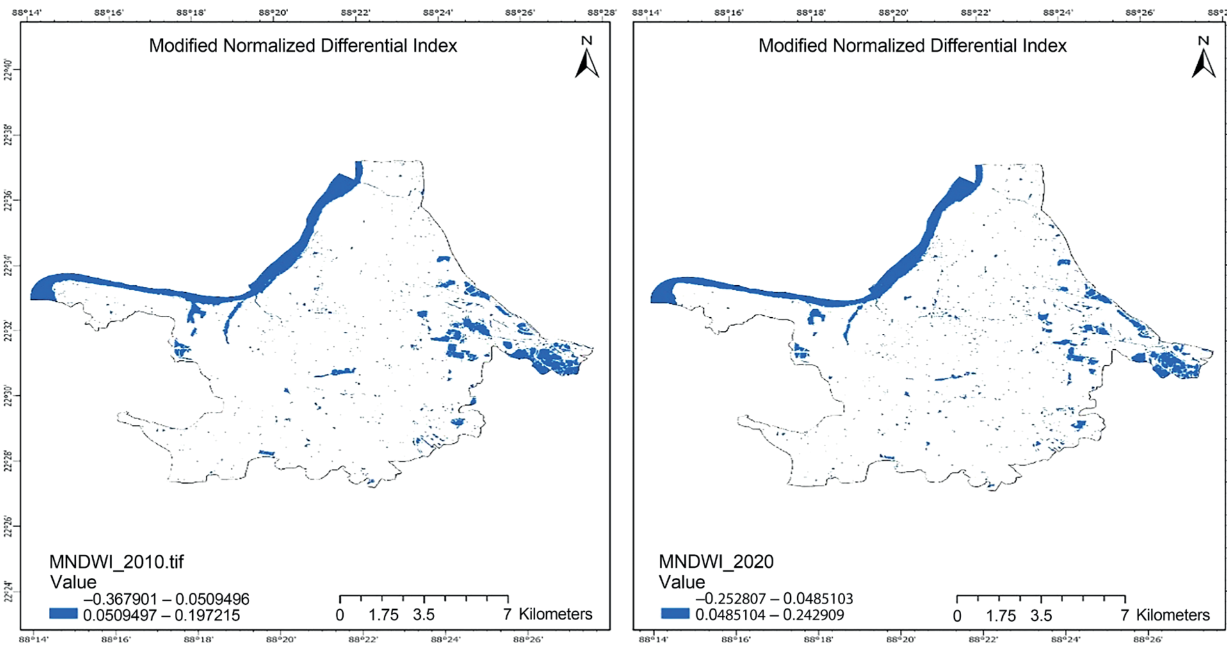

Fig. 7. Modified normalized difference water index, Kolkata 2010–2020 (source: Authors' own elaboration)

to –0.144, likely due to improved drainage systems and land use changes (Fig. 8). This reduction raises concerns about urban waterlogging, particularly in stable areas with water bodies that are vulnerable to extreme weather. Conversely, areas with increases in water bodies (>0.071) point to urbanization or altered precipitation patterns that have a potential of increased flooding risks.

Simultaneously, the NDBI data showed a marked increase in vegetation cover, especially in southern and eastern Kolkata, with significant growth exceeding 0.083 (Fig. 9). This increase can enhance air quality, mitigate the urban heat island effect, and improve biodiversity, while also aiding flood prevention through rainwater absorption. However, some regions have stable or declining vegetation, calling for harder conservation efforts.

Statistically, the analysis highlights a notable increase of 6.19 km^2 in area facing significant waterlogging and a moderate increase of 82.04 km^2 in areas at flooding risk. While 327.39 km^2 of water bodies remained stable, 22.09 km^2 saw a moderate decrease of risk, likely due to effective drainage strategies, as shown in Table 4. Kolkata experienced a substantial increase of built-up areas, 279.08 km^2, reflecting the ongoing extensive urban expansion, alongside a moderate increase of 63.24 km^2. However, 56.09 km^2 remained unchanged, and 28.98 km^2 experienced a moderate decrease in built-up areas, possibly linked to redevelopment. The interplay between urban development and water management underscores the necessity for strategic urban planning.

Figure 10 presents the final waterlogging index, which was produced by overlaying the LULC, MNDWI, and NDBI layers by a weighted overlay operation in GIS. A relative weight was assigned to each of these layers for the evaluation of waterlogging risk. Interval classification in the legend was also generated by the natural breaks (Jenks) and was used to group similar index values, improve representation of spatial variation and severity of waterlogging according to the criteria previously given. Integrating LULC with MNDWI and NDBI helps with the assessment of waterlogging risk in Kolkata. Eastern Kolkata, which

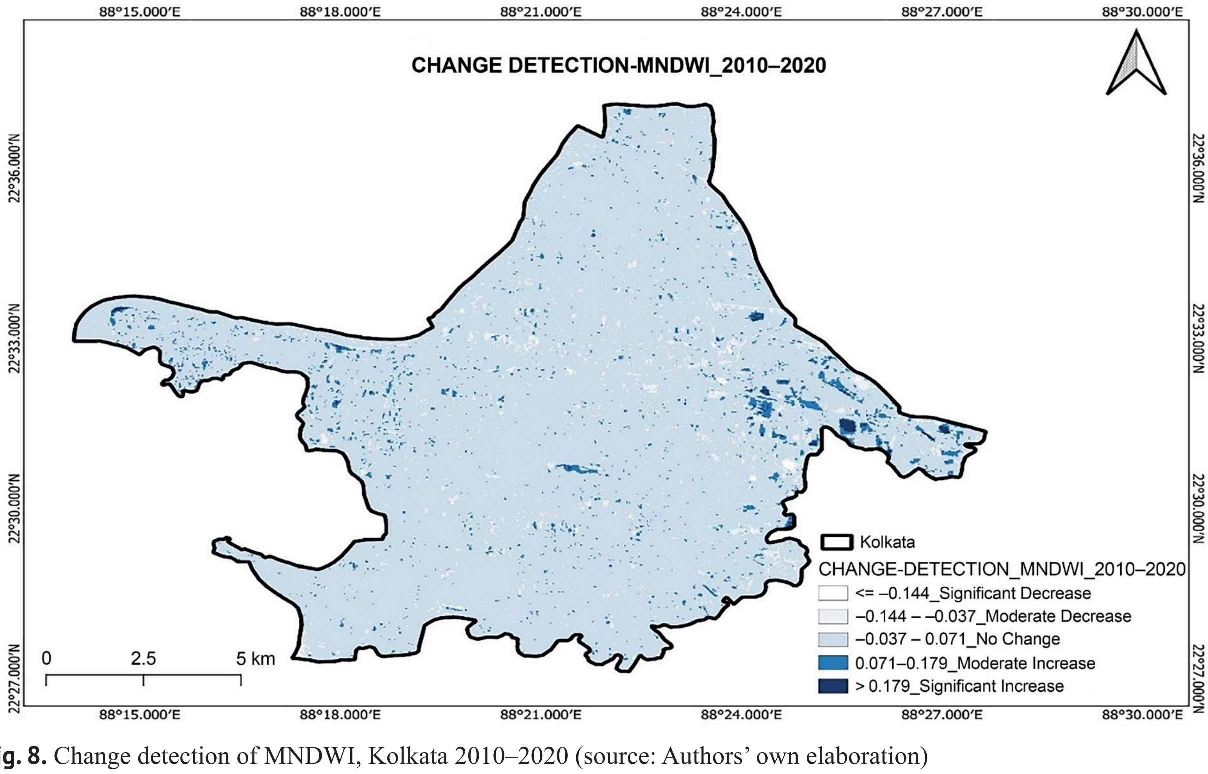

Fig. 8. Change detection of MNDWI, Kolkata 2010–2020 (source: Authors' own elaboration)

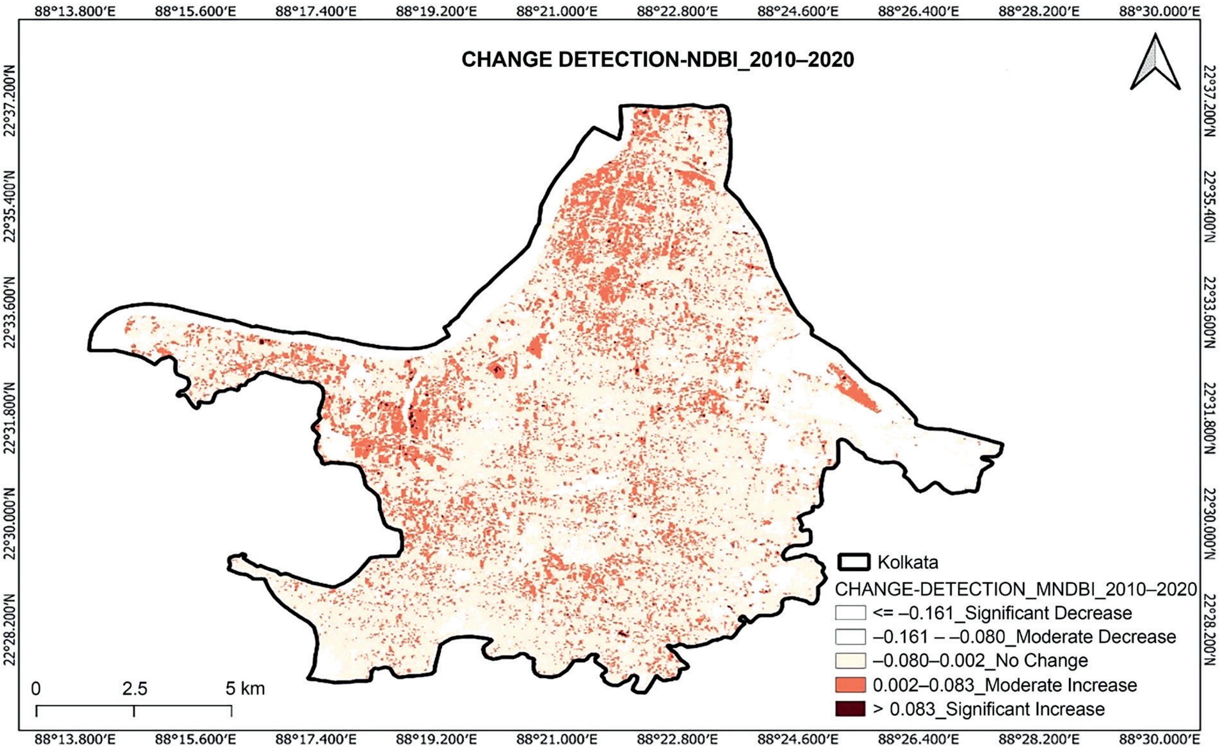

Fig. 9. Change detection of NDBI, Kolkata 2010–2020 (source: Authors' own elaboration)

Table 4. Area with changed MNDWI and NDBI 2010–2020

S. No.	MNDWI Change Detection Classes	Area [km^2]
1	Significant decrease	3.19
2	Moderate decrease	22.09
3	No change	327.39
4	Moderate increase	82.04
5	Significant increase	6.19

S. No.	NDBI Change Detection Classes	Area [km^2]
1	Significant decrease	13.50
2	Moderate decrease	28.98
3	No change	56.09
4	Moderate increase	63.24
5	Significant increase	279.08

urbanized from 2010 to 2020, is prone to waterlogging (Fig. 10). This phenomena impacts a large amount of agricultural land. Due to high population density and extensive farmland, drainage systems are flooded by natural water bodies and dense development, making this area vulnerable to flooding. Areas near Hugli River are high risk for waterlogging. Natural water bodies and lakes worsen this condition, with the index values from –0.005 to 0.119, and near to 0.119. Areas with the index values from –0.119 to –0.005 have moderate waterlogging depth due to frequent and significant water accumulation that harms living conditions and accessibility. These areas receive regular water accumulation but suffer few consequences. Regions with index values between –0.005 and –0.129 experience less water collection, possibly due to superior drainage or lower waterlogging risk. No or negligible waterlogging index values are below –0.129. The Getis-Ord Gi* statistic was applied to conduct the hotspot analysis to identify statistically significant clusters of high

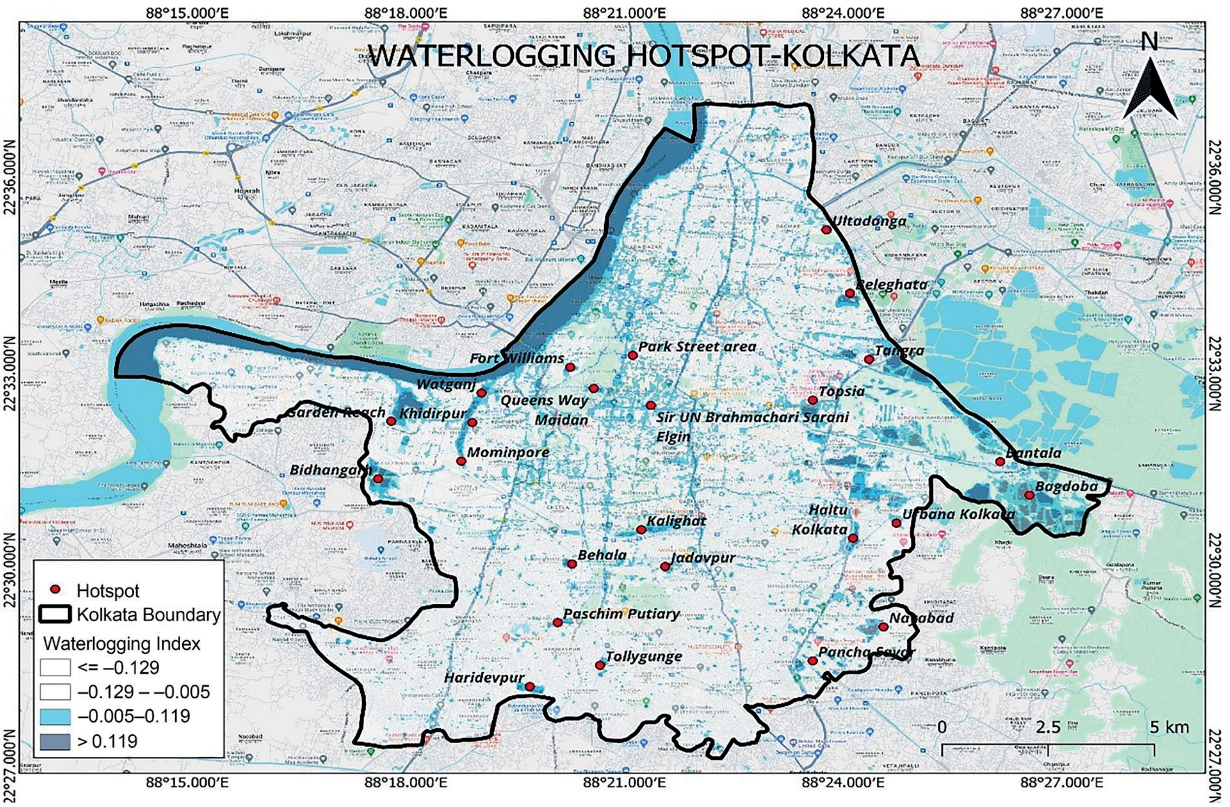

Fig. 10. Kolkata waterlogging hotspot map (source: Authors' own elaboration)

(hotspots) and low (cold spots) waterlogging risk. Here, hotspots were z-scores > +1.96 with P < 0.05, indicating a less than 5% probability that these clusters were due to chance. Cold spots where also found, with z-scores < –1.96 and p < 0.05. These cut-off points (at the 95% confidence level) guarantee that the hotspot map highlights only those locations with significant statistical evidence of clustering, enhancing the robustness and interpretability of the results in the context of Kolkata's intricate urban environment.

DISCUSSION

Waterlogging appears to be a major issue in densely inhabited areas, particularly on central and eastern Kolkata (Malik et al., 2020). These high waterlogging areas show how vulnerable urban inhabitants are without proper drainage system. Waterlogging prevents them from safe housing, basic utilities, and a decent standard of living. Thus, these areas require immediate support.

The study reveals that the Kolkata eastern section, areas along the Hugli River and ponds, is the most prone to waterlogging. Flooding is more likely in densely populated, agricultural land because natural water bodies and urban development overwhelm drainage infrastructure (Mulla et al., 2025). From low to extreme, the waterlogging index classifies the severity of potential waterlogging. These findings demonstrate the susceptibility of urban populations with limited resources, demonstrating the need for targeted interventions to improve living conditions, access to key services, and quality of life in high-risk areas. These recommendations include prioritizing waterlogging mitigation in areas with water bodies, analysing factors behind decreases in built-up areas, and developing a comprehensive urban plan that balances infrastructure growth with water management and green space promotion. By adopting sustainable practices, Kolkata can enhance its resilience against waterlogging and foster a more sustainable urban environment for its residents.

LULC analysis of Kolkata from 2010 to 2020 indicates key changes that are essential for understanding the relationship between urban expansion and waterlogging. The significant expansion of development, especially in eastern Kolkata, where urbanization has continued, is a primary factor contributing to the worsening of waterlogging problems. The urbanized area of the city expanded from 104.11 km² in 2010 to 142.80 km² in 2020, representing a 37.69% growth. This expansion has compromised natural water retention zones, including wetlands and water bodies, which have either diminished or been repurposed for real estate and infrastructural development. The decrease in water bodies – from 20.72 km² to 18.01 km² – correlates with the increase in impermeable surfaces, reducing the natural absorption capacity and elevating the surface runoff during precipitation events. The transformation of aquatic environments and arable land into urban areas has created more impermeable surfaces, diminishing water infiltration and exacerbating runoff, thus considerably contributing to urban flooding. The analysis indicates that areas formerly designated as scrubland or agricultural land are progressively being transformed into built-up areas: scrubland at a conversion rate of 2.56%, and agricultural land – 0.53%. Although these percentages appear minimal, their effect is amplified in heavily populated regions with already overburdened drainage systems. The 114.75% increase in waterlogging in urbanized areas underscores the strong correlation between urban expansion and the city's susceptibility to floods.

Water management challenges exacerbate this issue (Islam et al., 2022). Despite the fact that certain measures are being taken, for example recent establishment of artificial water bodies, which contributed to a 1.45% rise in water bodies, this is not enough to alleviate the issue of waterlogging. Urban development and insufficient water management systems have worsened the city's capacity to manage excess water. The MNDWI indicates substantial declines in water bodies, particularly in urban regions, implying a diminished capacity for water retention in the city, whereas the NDBI highlights the fast growth of built-up areas. The Kappa coefficient data reinforce the accuracy of these observations, with the 2020 coefficient rising to 0.859 from 0.564 in 2010, demonstrating enhanced classification reliability over time. The enhancement in classification accuracy indicates the efficacy of the land use mapping methodologies utilized in the study, alongside the significant alterations in LULC that transpired during the decade (Saket et al., 2024; Jodhani et al., 2025). The hotspot analysis delineates the areas most susceptible to waterlogging, specifically in eastern Kolkata and the vicinity of the Hugli River. These sites, having experienced considerable urbanization, are especially susceptible because of their low-lying terrain and nearness to natural water bodies. The proliferation of waterlogged areas and recognized hotspots illustrates the strain that the city's development is placing on its drainage infrastructure, especially in densely populated residential and agricultural sectors. The integration of remote sensing techniques with traditional field observations and modelling approaches improves our understanding of urban waterlogging dynamics, ultimately contributing to more resilient and sustainable urban development strategies. Waterlogging is further increased by low-lying topography, topographic depressions, and rising water tables.

Although this study has its limitation, it is nonetheless valuable for the understanding of the impact of land use changes on waterlogging in Kolkata. The classification accuracy of the water class was affected by the size and shape of water bodies, size and placement of gesture recognition technology, accuracy of the GPS unit, complexity of the environment which includes gradual changes from water to non-water surfaces. Variations in season, mixed pixels, and complex urban structure of Kolkata might also have affected the classification. Moreover, the accuracy assessment is dependent on existing reference data which is uncertain and the spatial resolution of ancillary data (drainage maps, ground surveys, etc.) might restrict the precision of waterlogging risk mapping. Future researches would be improved with higher resolution imaging, higher temporal frequency, and more field mass balance data, in order to increase the robustness of the results.

The study highlights the significance of natural hydrological processes and seasonal variations for the unpredictability of water levels in aquatic systems. The establishment of new water bodies, mostly via human interventions such as reservoirs or flood control systems, has resulted in fluctuations in the size of water bodies, accounting for a 260.07% variation in the region. Nonetheless, these initiatives have been inadequate in mitigating waterlogging, as the growing metropolitan areas persist in exerting pressure on the drainage systems. This study's findings highlight the pressing necessity for thorough urban planning solutions that tackle the rapid urbanization and significant water management issues in Kolkata. Implementing sustainable development methods, including the integration of green spaces, enhanced drainage systems, and more stringent limitations on the transformation of wetlands into built areas, is crucial for alleviating waterlogging effects and bolstering the city's flood resilience. In the absence of focused actions, Kolkata's urban population, especially in the eastern areas, will persistently confront escalating hazards connected with waterlogging and its concomitant socio-economic and environmental repercussions.

CONCLUSIONS

This study examines the significant correlation between accelerated urban growth and the rising incidence of urban waterlogging in Kolkata during the period from 2010 to 2020. The analysis of LULC changes indicates a notable increase in developed areas, especially in eastern Kolkata, resulting in a rise in impermeable surfaces and a decline in water bodies, scrubland, and agricultural land. The transformation of natural water retention areas into built-up areas has notably reduced the city's capacity to absorb and manage rainwater, intensifying waterlogging throughout the urban environment. Satellite-derived spectral indices, such as the MNDWI and the NDBI, offer significant insights into the spatial dynamics of urban waterlogging hotspots. The indices successfully pinpointed sites most susceptible to flooding, particularly in low-lying areas adjacent to the Hugli River, where urbanization has exacerbated the existing drainage infrastructure challenges. The results indicate a 114.75% increase in waterlogging rates in urbanized areas, while water bodies experienced fluctuations of up to 260.07%. This suggests the influence of both natural and anthropogenic factors on water retention and drainage patterns.

The research indicated an improvement in LULC classification accuracy over the decade, evidenced by the increasing Kappa coefficients, which imply a more dependable depiction of land cover alterations. Nonetheless, despite methodological advancements and comprehensive spatial analysis, the study highlights deficiencies in the city's water management systems. The establishment of artificial water bodies and related interventions has proven inadequate in addressing the rapidly growing issue of waterlogging, as unregulated urban expansion consistently surpasses the city's ability to manage surplus water. The study highlights the necessity for prompt and sustainable urban planning measures to address the effects of waterlogging. Enhancing drainage infrastructure, restricting encroachment on wetlands, promoting green space integration, and implementing water-sensitive urban design are essential strategies for mitigating Kolkata's flood vulnerability. Policymakers and urban planners should prioritize the mitigation of waterlogging hotspots, especially in eastern Kolkata, due to the significant risks posed to public health, safety, and infrastructure. The study's findings highlight the critical necessity for integrated urban planning and water management strategies to enhance resilience in Kolkata's urban regions. Sustainable urban development practices, supported by remote sensing and GIS technologies, can facilitate a balance between urban growth and environmental preservation, thereby promoting a more sustainable future for the residents of Kolkata. Failure to take prompt action will result in the worsening of socio-economic and environmental impacts of urban waterlogging, thereby threatening the long-term sustainability of the city.

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ANALIZA CZASOWA OBSZARÓW MIEJSKICH ZAGROŻONYCH PODTOPIENIAMI Z WYKORZYSTANIEM WSKAŹNIKÓW SPEKTRALNYCH UZYSKANYCH Z DANYCH LANDSAT: KALKUTA, INDIE

ABSTRAKT

Cel pracy

Celem niniejszego badania jest ocena zmian w użytkowaniu gruntów i pokryciu terenu (LULC) w Kalkucie w latach 2010–2020 oraz ich wpływu na podtopienia obszarów miejskich, z wykorzystaniem zdjęć satelitarnych i metodologii klasyfikacji obrazów.

Materiał i metody

W celu zidentyfikowania i sporządzenia mapy pięciu kategorii LULC: zbiorników wodnych, terenów zabudowanych, nieużytków, terenów zarośniętych i terenów uprawnych wykorzystano zdjęcia satelitarne Landsat 7 oraz zaawansowane metody klasyfikacji obrazów.

Wyniki i wnioski

Tereny zabudowane powiększyły się z 104,11 km² w 2010 r. do 142,80 km² w 2020 r., natomiast tereny zarośnięte, zbiorniki wodne i tereny uprawne uległy znacznemu zmniejszeniu. W badaniu obliczono podatność na zalanie wodą przy użyciu wskaźników MNDWI i NDBI. Do potwierdzenia dokładności klasyfikacji LULC wykorzystano stratyfikowane pobieranie próbek w QGIS, które wzrosło z 73,73% w 2010 r. do 89,30% w 2020 r. W procesie tym wykorzystano łącznie 200 próbek, po 20 z każdej klasy. Dzięki współczynnikowi Kappa wynoszącemu 0,564 (2010 r.) i 0,859 (2020 r.) klasyfikacja LULC uległa poprawie pod względem dokładności i wiarygodności. Wartość współczynnika Kappa z 2010 r. (0,564) wskazuje na umiarkowaną zgodność między danymi sklasyfikowanymi a danymi referencyjnymi, natomiast wartość 0,859 (2020) wskazuje na wysoką zgodność i znaczną poprawę niezawodności klasyfikacji. Przejście od umiarkowanej do wysokiej niezawodności klasyfikacji sugeruje, że klasyfikacja LULC z 2020 r. jest dokładniejsza i bardziej wiarygodna, z mniejszą liczbą błędów klasyfikacyjnych. Według badań hotspotowych wschodnia część Kalkuty i obszary wokół rzeki Hugli są podatne na podtopienia z powodu rozbudowy miasta i zaniku naturalnych zbiorników retencyjnych. W wyniku zwiększenia powierzchni nieprzepuszczalnej w obszarach zurbanizowanych odnotowano wzrost podtopień o 114,75%. Badanie podkreśla konieczność wprowadzenia specjalnych rozwiązań urbanistycznych i środków zarządzania zasobami wodnymi w celu zmniejszenia szkodliwych skutków podtopień i poprawy odporność newralgicznych części miasta Kalkuta. Wyniki tych badań mają kluczowe znaczenie dla zrównoważonego rozwoju miast i zapobiegania powodziom.

Słowa kluczowe: obszary zagrożenia powodziowego, podtopienia, znormalizowany wskaźnik różnicy zabudowy, zmodyfikowany znormalizowany wskaźnik różnicy wody, analiza obszarów zagrożenia