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Research article

Predicting changes in land use/land cover and seasonal land surface temperature using multi-temporal landsat images in the northwest region of Bangladesh

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HIGHLIGHTS

- Configurations of LULC and seasonal LST change in the Northwest region of Bangladesh were analyzed.
- Built-up area expansion contributed to increased summer and winter LST by 0.55 °C and 2.54 °C per decade from 1999–2019.
- Temperature increases have resulted in a significant decline in agricultural productivity over the last 30 years.
- Summer and winter LST simulations indicate that more than 50 % and 13 % will likely be in >35 °C by 2039.
- Prediction of LULC change and seasonal LST variation needs to be considered during urban development plans.

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ABSTRACT

Land use/land cover (LULC) variations are accelerated by rapid urbanization and significantly impacted global Land Surface Temperature (LST). The dynamic increase in LST results in the Urban Heat Island (UHI) effect. In this study, future LULC change scenarios, seasonal (summer & winter) LST variations, and LST distribution over different LULC classes were predicted using Landsat satellite images for 1999, 2009, and 2019 in Rajshahi District, Bangladesh. Cellular Automata (CA) and Artificial Neural Network (ANN) procedures were used to predict the LULC changes and seasonal LST variations for 2029 and 2039. In addition, Focus Group Discussions (FGDs) and Key Informants Interviews (KIIs) were conducted to identify the possible impacts of LULC change, LST shifts, and climate change on agricultural productivity and developed a sustainable land use management plan for the study area. Validation of the CA model demonstrated an excellent accuracy with a kappa value of 0.82. Similarly, the ANN model's validation using Mean Square Error (0.523 and 0.796 for summer) and Correlation coefficient (0.6023 and 0.831 for winter) values demonstrated a good prediction accuracy. The LULC prediction result indicated that the built-up area will be expanded by 58.03 km^2 and 79.90 km^2, respectively, from 2019 to 2029 and 2039. The predicted seasonal LST indicated that in 2029 and 2039, more than 23.30 % and 50.46 % of the summer and 3.02 % and 13.02 % of the winter seasons will likely be experienced LSTs greater than 35 °C. The results of public participation exposed that changes in LULC classes, variations in LST, and climate change significantly impact the regional biodiversity (loss of farmland and water bodies), reduce agricultural productivity, and increase extreme weather events (flood, heavy rainfall, and cold/warm temperature). This study provides the useful guidelines for agricultural officers, urban planners, and environmental engineers to understand the spatial configurations of built-up area enlargement and provide effective policy measures to conserve farming lands to ensure environmental sustainability.

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1. Introduction

Urbanization is a challenge for any country. Developed countries face fewer daunting challenges than developing countries because of rapid and unplanned urbanization [1, 2]. According to United Nations reports, the urban population will upsurge by more than 2.5 billion people by 2050, with Asia and Africa accounting for 90 % of the increase [3]. Therefore, the rapid population growth rate is speedily increasing and significantly impacting land use/land cover (LULC) in different parts of the world [4, 5, 6]. The change in LULC substantially affects the ecosystem and biodiversity, which significantly increases the land surface temperature (LST) and accelerates climate change risks [7, 8]. In addition, the LULC transformation progressively contributes to the arrangement of a warmer thermal condition resulting in creating the urban heat island (UHI) effect [9, 10, 11]. The UHI phenomenon harms social aspects, public health, and ecological sustainability [9, 12]. Thus, the changes in LULC and LST are necessary to assess in order to achieve systematic urban growth with a proper land use management plan for ensuring environmental sustainability at the city and regional level [1, 13, 14, 15, 16]. Analyzing historical LULC and LST pattern changes makes it possible to identify the issues associated with them easily. Likewise, based on the future prediction study, effective strategies need to be developed to mitigate the UHI effects by planned infrastructure development and conserving natural resources [14, 17, 18].

Bangladesh is facing rapid urbanization for the last three decades [19, 20]. Rajshahi district, located in Bangladesh's northwest region and known as an agrarian region, has also been undergoing speedy urbanization since the twenty-first century. From 6,63,000 in 1999 to 8,93,000 in 2019, the rapid population growth has altered the LULC configuration significantly in this region [3]. Between 1997 and 2010, nearly 14 % of agricultural land in this region was demolished, while infrastructure development continued to increase by 19.4 % [21, 22]. The unplanned transition of LULC classes are affecting ecological sustainability by the reduction of green covers and the increase of LST in this region. Additionally, recent city-level studies in this region discovered that unplanned urban expansion contributes significantly to LST increase [7, 23].

The application of Remote Sensing (RS) and the Geographic Information System (GIS) have provided opportunities to estimate LULC changes and the LST distribution in a particular region [24, 25, 26, 27, 28]. Several studies have described the LULC change and its impacts on LST using multi-temporal Landsat images [14, 18, 29]. Furthermore, because of UHI and LST have a close relationship, numerous studies have assessed these two using the RS database [12, 30]. Numerous methods and algorithms, i.e., Markov Chain (MC) [1, 15, 31, 32]. Cellular Automata (CA) [33, 34, 35], Logistic Regression (LR) [36], and Artificial Neural Network (ANN) [14, 37, 38] were used to predict the LULC and LST changes in several studies. Every method consists of its own strength and limitations. If variations in land cover are known, but there is no geographical dependence and distribution, the MC is preferred for the prediction [31, 35]. Depending on the prior position of cells in a region, the CA model specifies the position of cells in an array according to a set of transition laws [35]. The CA model is widely used for potential LULC simulation and predicts the future LULC change matrix by incorporating the past pattern of change [33, 34, 35, 39]. The main advantages of this model are that it focuses on historical trends and driving variables such as distance to highways, slope, and elevation [38]. Kappa coefficient values verify the consistency of the CA model [14, 32]. For LST prediction, the ANN concept is extensively used by researchers, which was first established to understand the dynamics of the human brain and its mechanisms [40, 41, 42, 43]. The ANN approach does not need any earlier information about the components, and the dynamic structure produces the basic process inside the framework to predict the future LST [40, 44]. The ANN is established on the multi-layered perceptron (MLP) protocol, which provides automated decisions for the effective representation of network parameters [14, 41, 44]. When it detects a pattern of changes from its neighboring pixels, it processes the data and produces a random low to high level accuracy output. Various useful parameters such as Normalized Difference Built-up Index (NDBI), Normalized Difference Bare Soil Index (NDBSI), Normalized Difference Vegetation Index (NDVI), latitude, longitude, and LULC maps can be used to predict the LST [13, 40, 41]. The NDVI is the weaker forecaster of LST, whereas the NDBI and NDBSI are comparatively more substantial parameters [40, 41]. One of the most significant advantages of the ANN is its ability to model complex and non-linear relationships if they are discovered. Unlike any other prediction model, the ANN does not impose restrictions on input parameters [22, 40, 45, 46]. Hypothesis-oriented indicators are unable to match with past trends, and for this reason, ANN is the finest fitted model to choose for LST simulation [1, 14, 40, 47].

Located in the Northeastern region of Bangladesh, Rajshahi District is an agricultural-based region and well-connected with all over Bangladesh. In the last decade, industrial growth, availability of better educational institutions and job opportunities have attracted people to migrate to this region. The growing pressure of the population accelerates the unplanned expansion in this region. Methods comprising the use of the CA and ANN algorithms can demonstrate useful findings in studying the short and long-term consequences of the LULC and LST change in this region. It can also support decision-makers and urban planners in abating the UHI effect. The current study is a regional scale study and the first of its kind in Bangladesh's northwest region, to determine the past (1999, 2009, and 2019) and future (2029 and 2039) trend of LULC and seasonal (summer and winter) LST change, as well as LST variation across different LULC classes, using novel approaches such as support vector machine (SVM) LULC classification algorithm, CA, and ANN prediction algorithms. Finally, this study engages the local community, people, and professionals to identify the impacts of LULC change, LST variation, and climate change on agricultural productivity and develop a sustainable land use management plan for this region.

2. Study area profile

Rajshahi district located in the northwestern region of Bangladesh, between 24°12′ to 24° 42′N latitude and 88°15′ to 88° 50′E longitude (Figure 1). The study area stands upon the northern bank of the river Padma. The region is a major commercial and educational hub of Bangladesh, with an area of about 2428 km^2 [19,48]. As it is an agricultural-based region, 1047 km^2 area consists of agricultural land followed by 780 km^2 bare land, 344 km^2 urban area, and 257 km^2 area represents water bodies in 2019 [7].

Various monsoons define this region's climate, bringing moderate rainfall, high humidity and temperature. Seasons in the region are divided into four distinct groups: winter (with low rainfall, high temperatures, and high humidity) from October to February; summer (with minimal rainfall, high temperatures, and high humidity) from March to June; and monsoon (with heavy rainfall, moderate temperatures, and high humidity) from July to September [14, 16, 49]. The high temperatures in the region varies between 30 °C and 40 °C in April and May. In December and January, the minimum temperature varies from 18 °C to 23 °C [3, 13, 18].

However, despite the fact that the district is known as an agrarian region, industrialization reaches a high point in this region following the completion of the Jamuna Bridge in 1998 [45,46]. This region has begun to experience rapid urbanization as a result of new job opportunities, which is primarily the result of unplanned rural-urban migration. The area's overall population in 2016 was 28,53,000 with a population density of 1,175 inhabitants per km^2 [50]. While the region had a population of 22,86,874 in 2001, the population density per km^2 was only 941 [18,43]. Land use history in this area indicates that over 7 % of agricultural land has been lost in the last two decades as a result of unplanned urbanization and development [18]. Additionally,

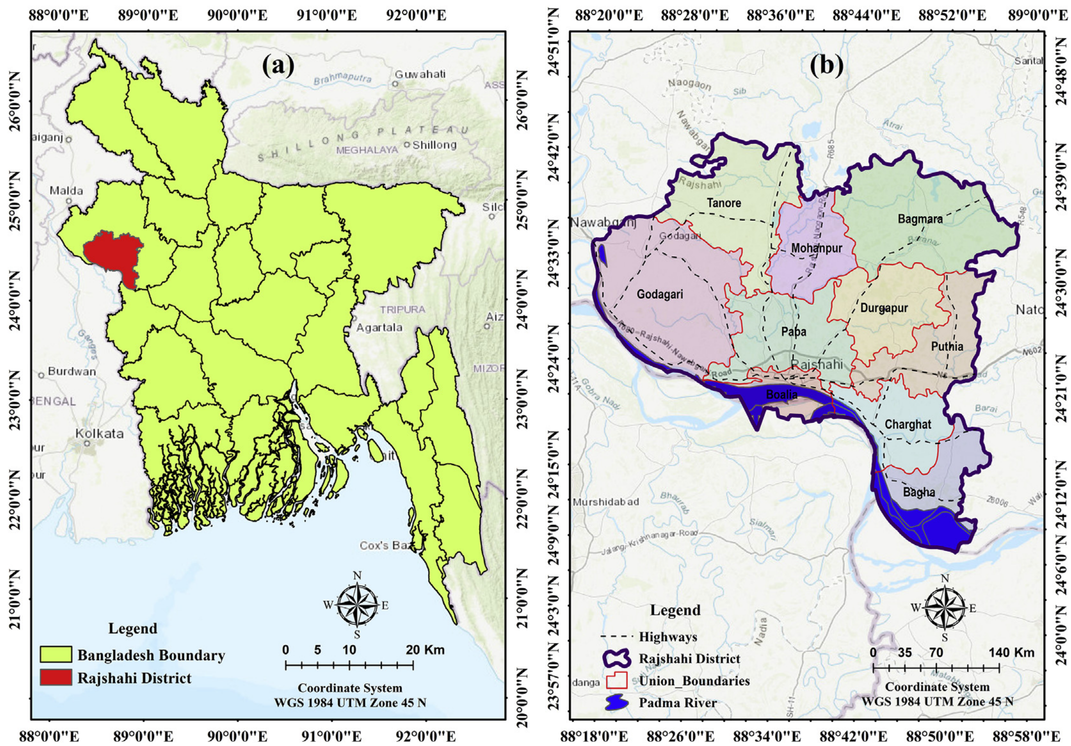

Figure 1. Location map of the study area a) Rajshahi district in Bangladesh b) Union boundaries and highways in Rajshahi district[1].

Table 1. Details information of downloaded satellite images.

Date (d/m/y)	Sensor	Cloud Cover	Path/Row
1999 (Summer) 28/03/1999	Landsat 5 TM	~1 %	138/043
1999 (Winter) 25/12/1999	Landsat 5 TM	~0 %	
2009 (Summer) 23/03/2009	Landsat 5 TM	~0 %	
2009 (Winter) 04/12/2009	Landsat 5 TM	~8 %	
2019 (Summer) 19/03/2019	Landsat 8 OLI	~9 %	
2019 (Winter) 30/11/2019	Landsat 8 OLI	~0 %	

Table 2. List of FGDs conducted in 10 unions in Rajshahi District.

Number	Focus Groups (community people and other stakeholders)	No. of FGDs	No. of Group Members
1.	Community people involved with agricultural productions and distribution, community leaders, councilors, and government officials were involved with Bagha, Charghat and Puthia union.	2	9
2.	Community people involved with agricultural productions and distribution, community leaders, councilors and government officials were involved of Durgapur and Bagmara union.	2	8
3.	Community people involved with agricultural productions and distribution, community leaders, councilors and government officials involved with agricultural production of Mohanpur and Tanore union.	2	8
4.	Community people involved with agricultural productions and distribution, community leaders, councilors, and government officials were involved with Mohanpur, Tanore and Godagari union.	3	10
5.	Community people involved with agricultural productions and distribution, community leaders, councilors and government officials involved with agricultural production of Boalia and Paba union.	1	7
Total		10	42

unplanned and haphazard urbanization and development activities have had a significant impact on the severity of the winter and summer seasons in recent years, resulting in negative impacts on the region's climate, livelihoods, and agricultural development [7].

3. Data & methodology

3.1. Data set and processing approach

The study was directed based on primary and secondary data. Primary data collected from field visits, Focus Group Discussions (FGDs), and Key Informants Interviews (KIIs). The secondary data comprise of multi-temporal Landsat 4–5 Thematic Mapper (TM) and Landsat 8 Operational Land Imager (OLI) satellite images obtained from US Geological Survey (USGS) website (https://earthexplorer.usgs.gov)

[1] Sources: Service Layer Credits for a) and b): Esri, HERE, Garmin, Intermap, increment P Corp., GEBCO, USGS, FAO, NPS, NRCAN, GeoBase, IGN, Kadaster NL, Ordnance Survey, Esri Japan, METI, Esri China (Hong Kong), OpenStreetMap contributors, and the GIS User Community.

Table 3. List of KIIs.

No	Key Informants	Organization
1	Chief Engineer	Rajshahi City Corporation, Rajshahi, Bangladesh
2	Town Planner	Rajshahi City Corporation, Rajshahi, Bangladesh
3	Environmental Development Officer	Rajshahi City Corporation, Rajshahi, Bangladesh
4	Town Planner	Rajshahi Development Authority, Rajshahi, Bangladesh
5	Project Director (Executive Engineer)	Barind Multipurpose Development Authority, Rajshahi, Bangladesh
6	Professor (Environmentalist)	University of Rajshahi, Rajshahi, Bangladesh
7	Professor (Agriculturist)	University of Rajshahi, Rajshahi, Bangladesh
8	Assistant Professor (Urban Planner)	Rajshahi University of Engineering & Technology, Rajshahi, Bangladesh
9	Additional Agriculture Officer	Department of Agricultural Extension, Rajshahi, Bangladesh
10	Agriculture Extension Officer	Department of Agricultural Extension, Rajshahi, Bangladesh
11	Agricultural Economist	Department of Agricultural Extension, Rajshahi, Bangladesh
12	Upazila Agriculture Officer	Department of Agricultural Extension, Rajshahi, Bangladesh
13	Monitoring And Evaluation Officer	Department of Agricultural Extension, Rajshahi, Bangladesh
14	Scientific Officer	Department of Agricultural Extension
15	Additional Deputy Director (Tuber Crops, Vegetable, and Spices)	Department of Agricultural Extension
16	Additional Deputy Director (Fruit & Flower)	Department of Agricultural Extension
17	Assistant Director	Department of Environment (DoE)
18	Research Officer	Department of Environment (DoE)
19	Divisional Forest Officer	Forest Department
20	NGO Representatives	BRAC and UNDP

Table 4. Questions of FGDs.

The FGDs questions aim to identify the possible impacts of LULC change, LST shifts, and climate change on agricultural productivity. The information will be collected for research purpose only.

FGDs questions
1. Do you have any knowledge of land use/land cover changes?
2. What are the possible impacts of LULC changes?
3. What are the positive and negative impacts of temperature change on agricultural production?
4. Do you know about climate change?
5. What are the possible impacts of climate change on temperature change and agricultural production?
6. Did you face any changes in Agricultural production due to climate change?
7. What are the impacts of climate change on the livestock and hydrology sector?
8. Can you suggest some effective strategies to overcome the impacts of LULC change, LST shifts, and climate change on agricultural productivity?
9. Who is responsible for taking these strategies?

where the scene path was 138 and row was 43 (Table 1) for the years, 1999, 2009 and 2019. The images had a spatial resolution of 30 m. The images were downloaded for the summer and winter seasons at 10 years intervals to assess the variation of LULC and summer and winter season LST in the study region. According to the Bangladesh Meteorological Department (BMD), the summer season starts in mid-April and ends mid-June in the study region. However, the summer effect felt early from mid-March. The winter season is starting from mid-December and extended to mid-February [51]. All the summer season images were downloaded for the same month and winter season images for a maximum one-month interval for avoiding seasonal variation. The images were downloaded in less than 10 % cloud coverage for ensuring better classification accuracy and surface temperature estimation. Table 1 contains information about the images obtained from the USGS online data portal.

3.1.1. Primary data collection

For primary data collection, a field visit was conducted in the study area in April 2019. Global Positioning System (GPS) was used to collect the

Table 5. Questionnaire for KIIs.

<table>
<tr><td colspan="3">Prediction of land cover and seasonal land surface temperature change using multi-temporal Landsat images in the northwest region of Bangladesh</td></tr>
<tr><td colspan="3">This interview aims to identify the possible impacts of LULC change, LST shifts, and climate change on agricultural productivity. The information will be collected for research purposes only.</td></tr>
<tr><td colspan="3">Introduction</td></tr>
<tr><td colspan="2" rowspan="2">Name:</td><td>Interview No:</td></tr>
<tr><td>Date (DD/MM/YYYY):</td></tr>
<tr><td>Current Position:</td><td colspan="2">Current Institution:</td></tr>
<tr><td colspan="3">Representative of (check all that apply):
○ Policy Makers ○ Local Community Leader ○ Environmentalist ○ Agricultural Officer ○ Urban Planner</td></tr>
<tr><td colspan="3">Impacts of LULC Change</td></tr>
<tr><td colspan="3">Observed any change in land Uses during the last 20 years? ○ Yes ○ No ○ I don't know</td></tr>
<tr><td colspan="3">In your opinion, is the change significant in Rajshahi region? ○ Yes ○ No ○ I don't know</td></tr>
</table>

What are the changes in land use you have noticed in past two years (check all the apply)?
○ Decrease in agricultural land ○ Increase of roads ○ Increase of buildings ○ Increase of industries
○ Increase in agricultural land ○ No change in infrastructures ○ Demolition of infrastructures

In your opinion, what will be the impact of this change in land use? ○ Positive ○ Negative ○ I have no idea

The consequences of land use change can be experienced in which aspects (check all that apply)? ○ Social ○ Economical ○ Environmental ○ Others; please specify: _______________	How? Explain your answer:

In your opinion, what will be the consequences of change in Land Use Land Cover (check all that apply)?
○ Less availability of farm lands ○ Soil erosion and degradation ○ Reduce land resource quality
○ Desertification ○ Hamper food productivity ○ Loss in water bodies ○ Loss in biodiversity
○ Increase in surface temperature & Greenhouse effect ○ Increase in surface runoff
○ Others: _________________________

____

Impacts of Temperature Change

Did you feel any change in seasonal temperature?	○ Yes ○ No	If yes, type of change: ________________________
In your opinion, can this change bring any positive impact in the agricultural sector?	○ Yes ○ No	Why do you think so?

What do you think about the negative impacts of temperature changes on agricultural productivity?	What is your suggestion in this regard?

Impact of Climate Change

What do you think about the relationship between regional economy & climate change?	○ Significant ○ Moderate ○ Neutral ○ I have no idea
What will be the consequences of climate change in Rajshahi Region according to your opinion (check all that apply)? ○ Impact on agricultural production ○ Impact on farm household income ○ Reducing water supply availability ○ Changes in livestock production ○ Affecting natural resources ○ Flooding agricultural lands ○ Others: ______________________	What is your suggestion to overcome the climate change effect? Do you have any additional suggestions regarding developing a sustainable land use management plan?

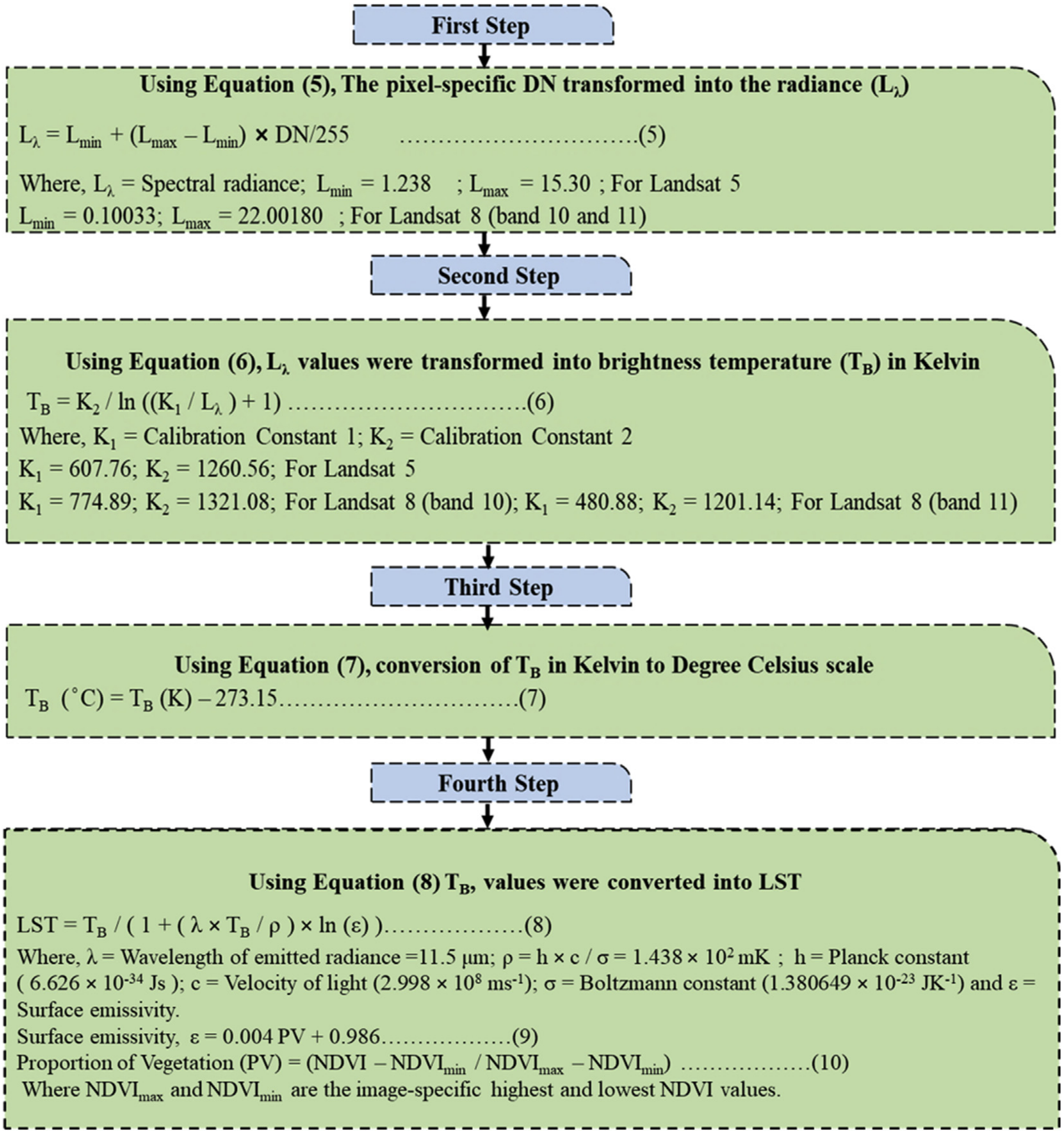

Figure 2. Process of seasonal LST estimation from Landsat TM and OLI thermal bands.

ground truth data for accuracy assessment of classified LULC maps. In addition, 10 FGDs (Table 2) and 20 KIIs (Table 3) were conducted from April 2019 to August 2019 to identify the possible impacts of LULC change and seasonal LST shifts on agricultural productivity and climate change. The questionnaires of FGDs and KIIs were demonstrated in Table 4 and Table 5. The FGDs were conducted in 10 unions of the Rajshahi district (Figure 1b). The locations of the FGDs were selected based on the area of the unions[2], the proportion of agricultural land, and the involvement of people in the agricultural sector in different unions of the Rajshahi district. Based on the output of the discussion, a sustainable future land use management plan was proposed for the study area. The KIIs and FGDs (8–10 participants) consisted of urban planners, agricultural officers, environmental engineers, policymakers, local community leaders, and decision-makers. Information and opinions regarding the impacts of LULC change on seasonal LST, influences of seasonal LST variations on the agricultural sector and climate change, and preparation of proposed land use management plan were collected during the FGDs and KIIs. The outputs from FGDs and KIIs have been discussed in section 4.8 and 4.9.

[2] Smallest unit of an administrative area.

3.1.2. Classification of LULC maps

Imagery from the Landsat satellite was classified into four broad LULC classes, including i) built-up area (industrial/residential/commercial area and transportation network); (b) agriculture land (green lands, agricultural lands, and vegetation); (c) water bodies (rivers, wetlands, reservoirs, canals, and streams; (d) bare land (fallow land, sand, playground, landfill sites, and vacant soil) for 1999, 2009, and 2019 using the SVM algorithm in ENVI 5.3 software. The SVM is a sophisticated supervised classification technique based on statistical learning theory which mostly results in accurate classification if the data are complex or noisy [45]. The images were analyzed based on their spectral and areal profiles to provide additional training information as well as background data from local and multiple secondary sources. The more sample data there are for each class, the more precise the classification will be.

3.1.3. Validation of classified LULC maps

Around 40 samples were collected for each LULC class in order to produce the LULC maps. The accuracy of the classified maps was evaluated through 100 field level and 300 Google Earth image random sampling ground truth data. For accuracy assessment, the overall accuracy (equation

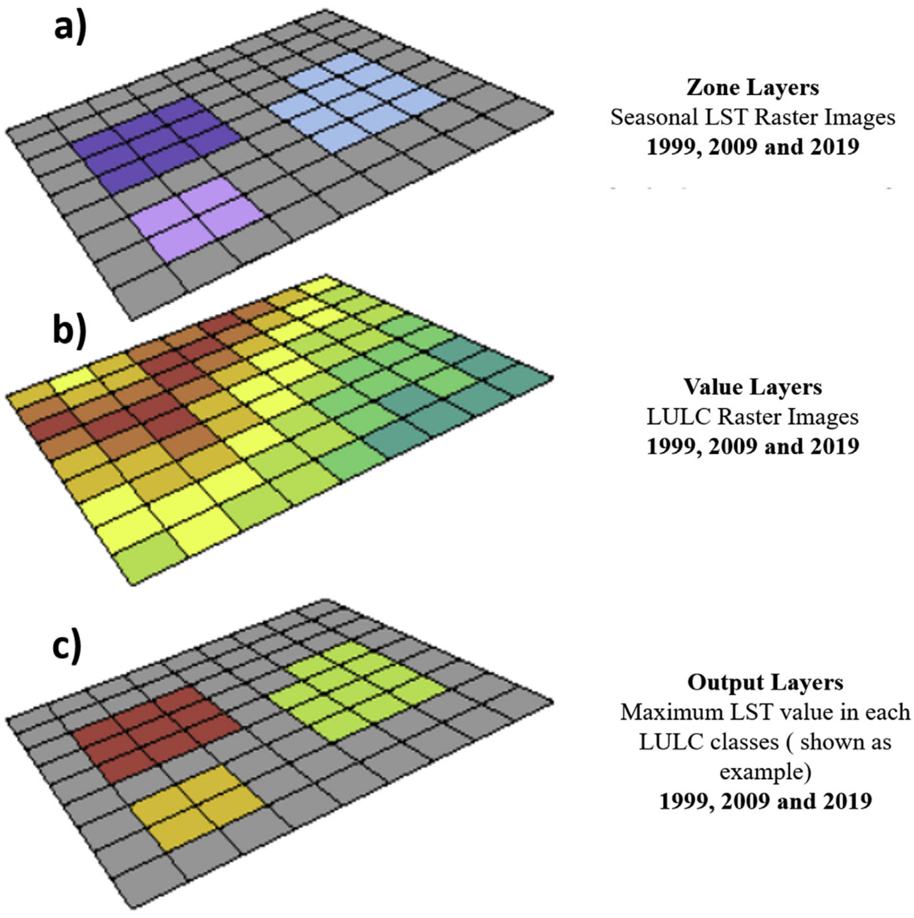

Figure 3. Zone (a), value (b), and output (c) layers in zonal statistics tool.

1), user accuracy (equation 2), producer accuracy (equation 3), and kappa statistics (equation 4) were calculated, and these are one of the best quantitative procedures for image classification accuracy [2].

The Landsat 8 has two thermal bands (band 10 and band 11) centred at 10.9 μm and 12 μm. Therefore, LST for Landsat 8 was estimated from both bands and then combined by using cell statistics to determine the final LST.

$$\text{Overall accuracy } = \frac{\text{Total number of corrected classified pixels (diagonal)}}{\text{total number of reference pixels}} * 100 \tag{1}$$

$$\text{User Accuracy} = \frac{\text{number of correctly classified pixels in each catagory (diagonal)}}{\text{total number of reference pixels in each category (row total)}} * 100 \tag{2}$$

$$\text{Producer Accuracy} = \frac{\text{number of correctly classified pixelxs in each category (diagonal)}}{\text{total number of reference pixels in each category (column total)}} * 100 \tag{3}$$

$$\text{Kappa Coefficient (T)} = \frac{\text{Total number of Sample*Total Number of Corrected Sample} - \sum(\text{col.tot*row tot})}{(\text{Total number of Sample})^2 - \sum(\text{col.tot*row tot})} * 100 \tag{4}$$

3.1.4. *Estimation of seasonal LST*

The seasonal (summer and winter) LST was estimated using Landsat thermal band images from 1999, 2009, and 2019. Landsat sensors accumulate thermal data and Digital Numbers (DN). For the available data, these DN were converted to LST with four steps process illustrated in Figure 2, using equations 5, 6, 7, and 8 [4,13,40,41,52,53].

3.1.5. *Variation of seasonal LST over LULC classes*

For estimating the summer and winter season LST distribution over different LULC categories, "zonal statistics tool as table" under spatial analyst tools was used in ArcGIS 10.6 software. This tool summarizes LULC classes' values within the zones of the seasonal LST dataset and reports the results into a table. After adding zone layers (Figure 3a) and

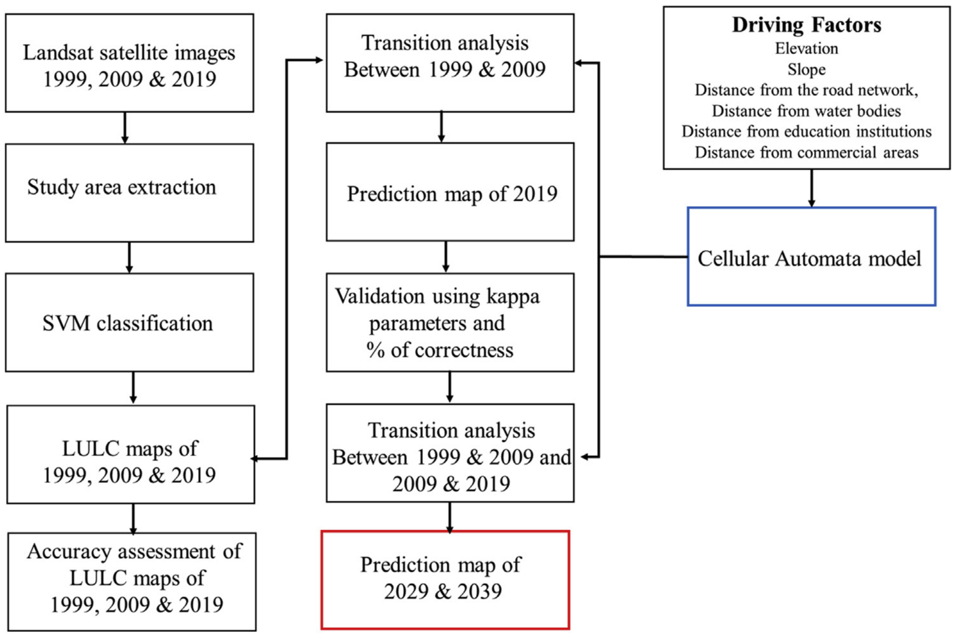

Figure 4. Flow chart of LULC change prediction using the CA algorithm.

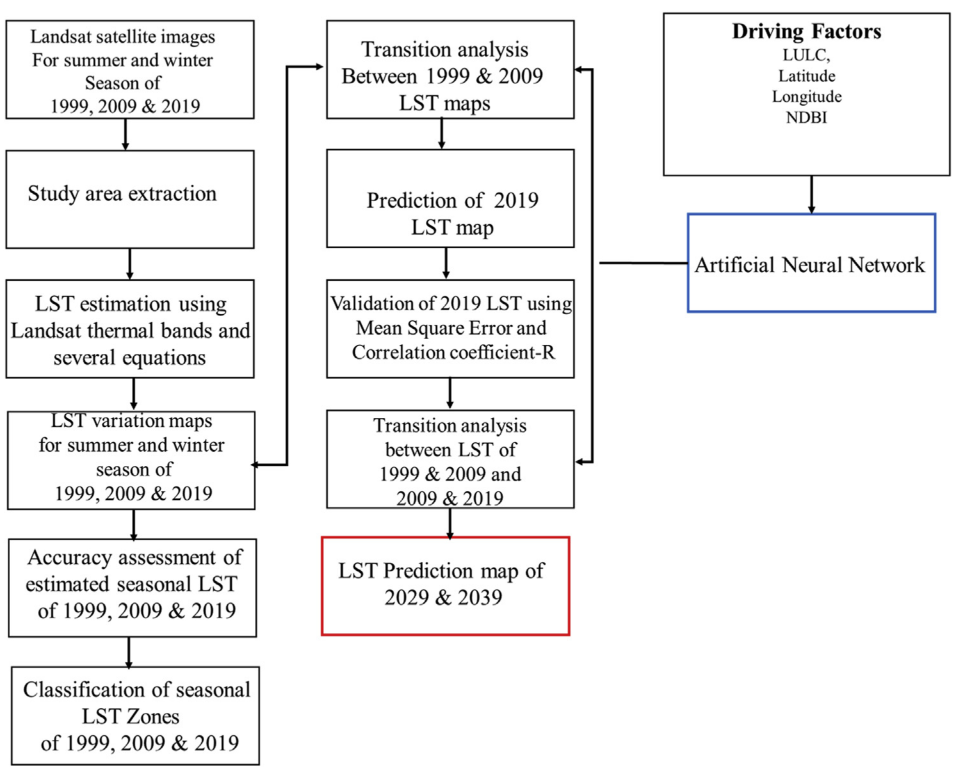

Figure 5. Flow chart of seasonal LST prediction using the ANN algorithm.

value layers (Figure 3b) to the zonal statistics tool, the layers generate output layers (Figure 3c) as a table, with all raster files converted to the same extension for an accurate representation of each LULC area falling within a different LST zone.

3.2. Predicting LULC change for the years 2029 and 2039

The CA model was used to identify the future LULC changing pattern in the study region using QGIS's MOLUSCE plugin. During prediction, the CA model considers all the static and dynamic aspects of changes in every LULC category and provides an excellent accurate result [32, 34, 35, 54]. The CA prediction model was based on dependent and independent variables. Elevation, slope, distance from the road network, water bodies, education institutions, and commercial areas were used as dependent variables, and classified LULC maps for the years 1999, 2009, and 2019 were used as independent variables in this study. In ArcMap 10.6, the Euclidian distance function and Digital Elevation - Shuttle Radar Topography Mission (SRTM) were used to measure dependent variables.

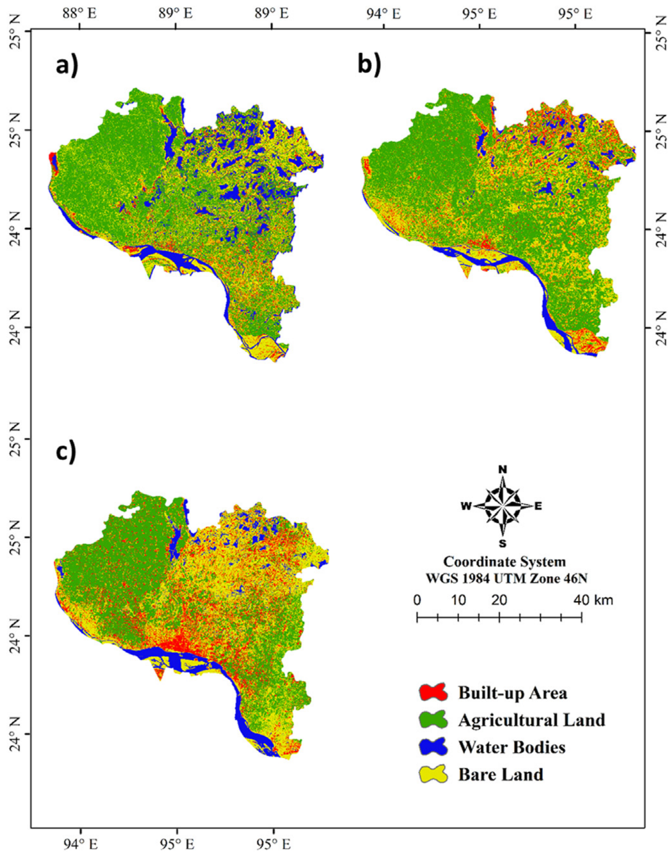

Figure 6. Classified LULC maps for years a) 1999 b) 2009 and c) 2019 estimated using SVM algorithm.

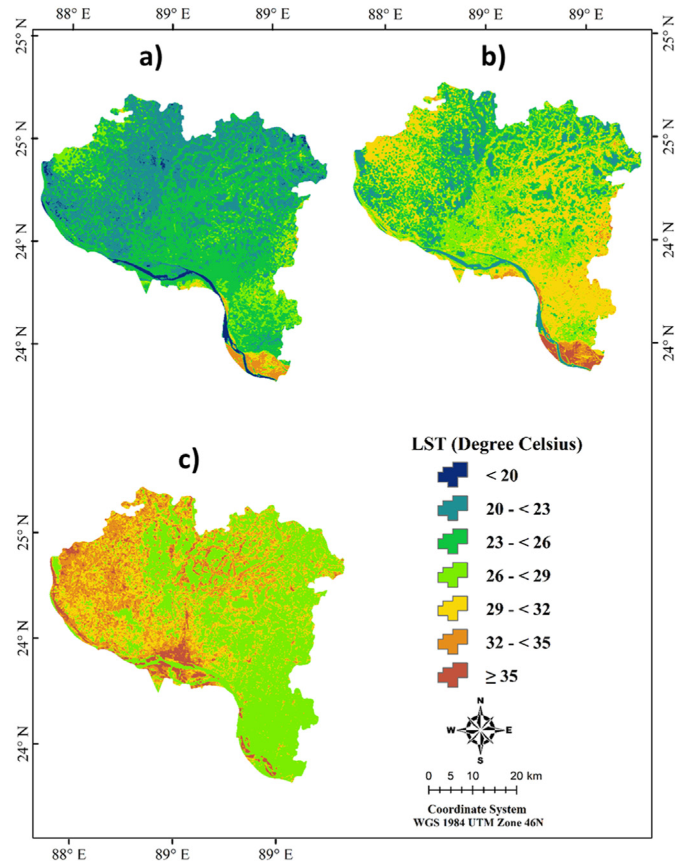

Figure 7. Spatial distribution of summer LST for years a) 1999 b) 2009 and c) 2019.

Table 6. Accuracy Assessment of classified LULC maps using SVM algorithm.

Classified Year	User Accuracy (%)	Producer Accuracy (%)	Overall accuracy (%)	Kappa Statistics (%)
1999	89.26	91.3	90.25	89.06
2009	91.26	88.57	89.36	90.87
2019	92.03	93.25	91.45	92.36

Table 7. Area distribution in km^2 of LULC classes and net change in percentage.

LULC	1999	2009	2019	Net Change (%)
Built-up Area	161.78	270.23	440.70	+7.81
Agricultural Land	1221.50	1108.91	926.18	-8.27
Water Bodies	295.24	206.80	125.67	-4.75
Bare Land	703.70	796.29	889.54	+5.20

Using a random sampling technique and setting a maximum iteration of 1000 cells (3 × 3) neighborhood pixels, these dependent variables developed the transition potential matrix. When the transition potential matrix was developed, the CA model then predicted future LULC maps of 2029 and 2039 in QGIS software. Before performing the prediction for 2029 and 2039, the model was validated using the CA model by predicting the LULC map of 2019 and compared it with the same year's estimated LULC map. Besides, the TerrSet software was used to validate the model by estimating multiple Kappa (K) parameters: $K_{location}$, K_{no}, $K_{location\ strata}$, $K_{standard}$, to evaluate the model accuracy. The validation module of the QGIS- was also used to measure the overall Kappa coefficients and accuracy percentage between the LULC classified and predicted map of 2019. The detailed procedure of LULC estimation and prediction is shown in Figure 4.

3.3. Predicting LST change for years 2029 and 2039

The seasonal LST was predicted for the years 2029 and 2039 using the ANN algorithm in MATLAB software. The ANN is an effective approach that helps in time series prediction using previous year datasets [37, 41]. In the first step, the ANN network receives the patterns, starts processing, and makes a random output with a low accuracy percentage. The ANN performs a self-computed feature by computing the gap between random low accurate output and intended output. The correction value was

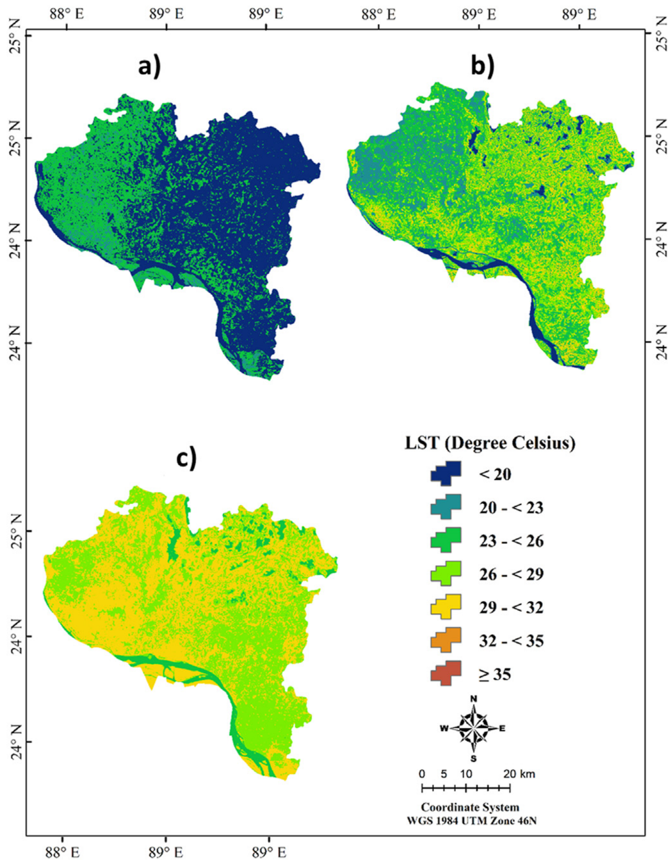

Figure 8. Spatial distribution of winter LST for years a) 1999 b) 2009 and c) 2019.

determined between the output layer and the hidden layers and even between the hidden layers and the input layers using the "Leveraging backpropagation" algorithm. The iterative cycle moves back and forth until an optimal error is achieved between the network output and the intended output [14, 15, 40, 55]. The detailed flow chart for estimating and predicting seasonal LST is illustrated in Figure 5.

For LST prediction, five layers (LULC images, NDBI, NDBSI, latitude, and longitude) were used as input supporting parameters, and LST images were used as output parameters. These supportive layers are essential as because they influence outcomes by allowing the network to manifest non-linear behavior. During this analysis, the initial learning rate (μ) was set at 0.1, and the rate of decay (β) was used to monitor it. The standard rate of decay ranges between 0 and 1 ($0 < \beta < 1$) [41,45]. The pixel value data were converted into discrete data for all the images to ensure better performance of the ANN model in QGIS software. The LST prediction included network development, the evaluation of network performance, network training, and prediction. A regression analysis was performed to determine how accurately the intended data set has represented the changes in the performance tests [36, 56]. The regression analysis provides the Mean Square Error (MSE) and Correlation Coefficient (R) values, which determine the network confidence [1, 13, 14, 40]. For validation of the ANN model, R and MSE values of 2019 for the summer and winter seasons were obtained.

3.4. Ethics

Consent was obtained from respondents prior to the FGDs and KIIs, and they remained anonymous. All contributors were informed of the study's specific objectives before beginning to complete the KIIs and FGDs questionnaire. Participants were only required to complete the questionnaire once, and they were free to stop it whenever they wanted. The relevant authority approved this study's ethical credentials (Rajshahi City Corporation, Rajshahi, Bangladesh). The privacy and confidentiality of the data were ensured. These KIIs and FGDs interviews were conducted according to established ethical guidelines of the concerned authority and the authors confirm that the respondents were informed of the study's specific objectives before beginning to answer the FGDs and KIIs questions.

4. Result and discussion

This section describes the results estimated from the methodology presented in section 3. The LULC changes, seasonal LST variations, distribution of LST over different LULC classes, prediction of future LULC and seasonal LST, and LST change impacts on agricultural productivity, and future sustainable land use management plan will be discussed in the following section 4.

4.1. Variation of past patterns of LULC (1999–2019)

The trend of changes in LULC classes estimated from Landsat images using the SVM algorithm for the years 1999 (Figure 6a), 2009 (Figure 6b), and 2019 (Figure 6c) are shown in Figure 6. The accuracy assessment of the classified LULC maps were measured using Kappa statistics, user accuracy, producer accuracy, and overall accuracy are

Table 8. Validation of summer season thermal bands estimated LST with weather station data.

Year	1999		2009		2019	
Source of estimated/recorded LST	Maximum	Minimum	Maximum	Minimum	Maximum	Minimum
LST estimated from thermal bands (°C)	35.83	19.5	36.06	21.5	40.37	26.95
BMD recorded air temperature (°C)	32.56	20.63	33.25	21.3	39.85	28.12
Deviation (°C)	-3.27	1.13	-2.81	-0.2	-0.52	1.17
Average Deviation (°C)	-1.07		-1.505		0.325	

Table 9. Validation of winter season thermal bands estimated LST with weather station data.

Year	1999		2009		2019	
Source of estimated/recorded LST	Maximum	Minimum	Maximum	Minimum	Maximum	Minimum
Remotely Sensed Estimated LST (°C)	24.54	16.1	30.85	19.95	31.32	23.09
BMD recorded air temperature (°C)	25	15.4	22.7	17.8	30.25	16.4
Deviation (°C)	+0.46	-0.7	-8.15	-2.15	-1.07	-6.69
Average Deviation (°C)	-0.12		-5.15		-3.88	

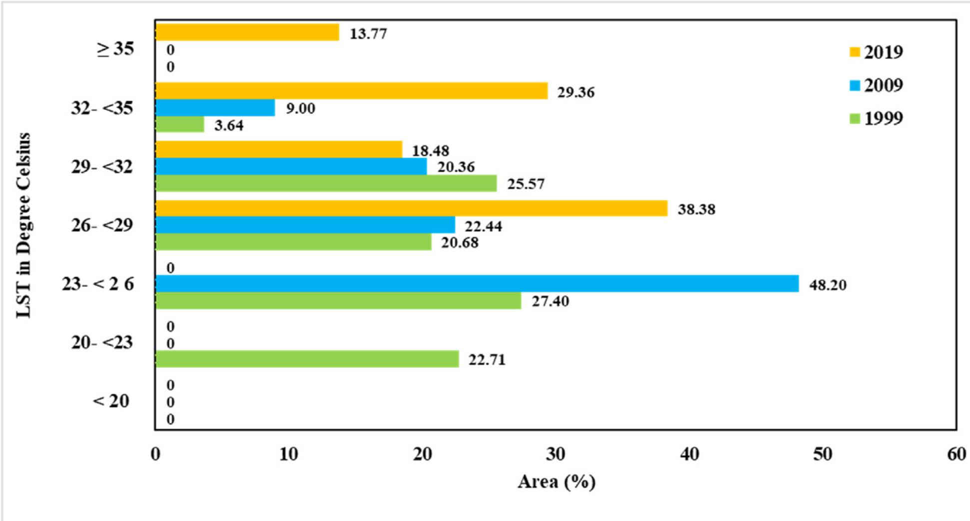

Figure 9. Zone wise summer LST distribution in the study area.

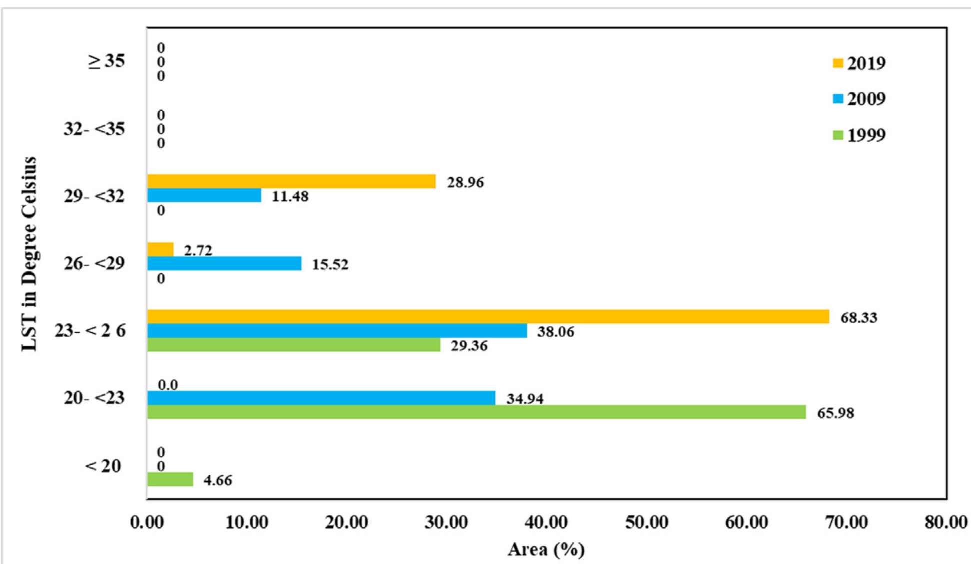

Figure 10. Zone wise winter LST distribution in the study area.

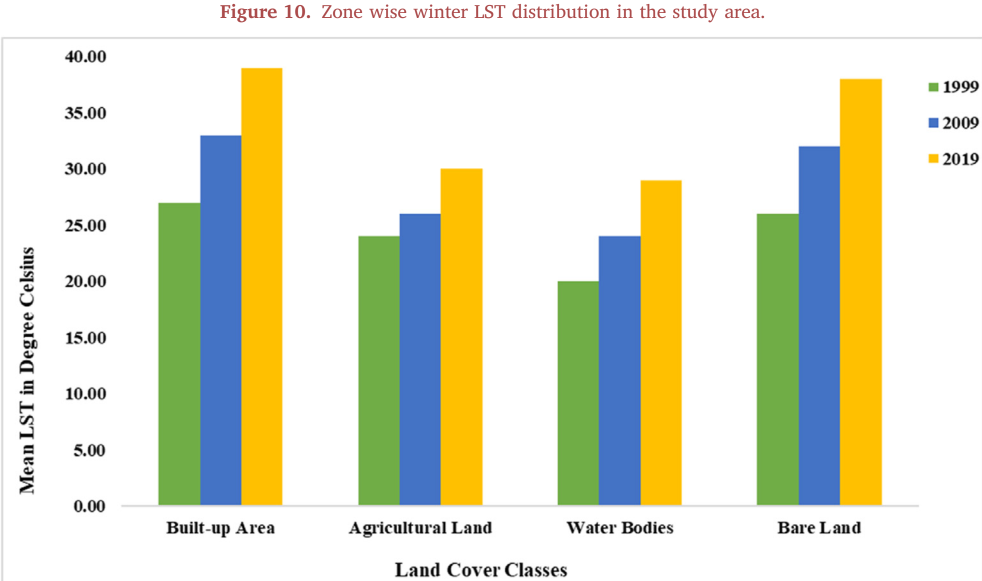

Figure 11. Mean distribution of summer temperature over different LULC classes from 1999-2019.

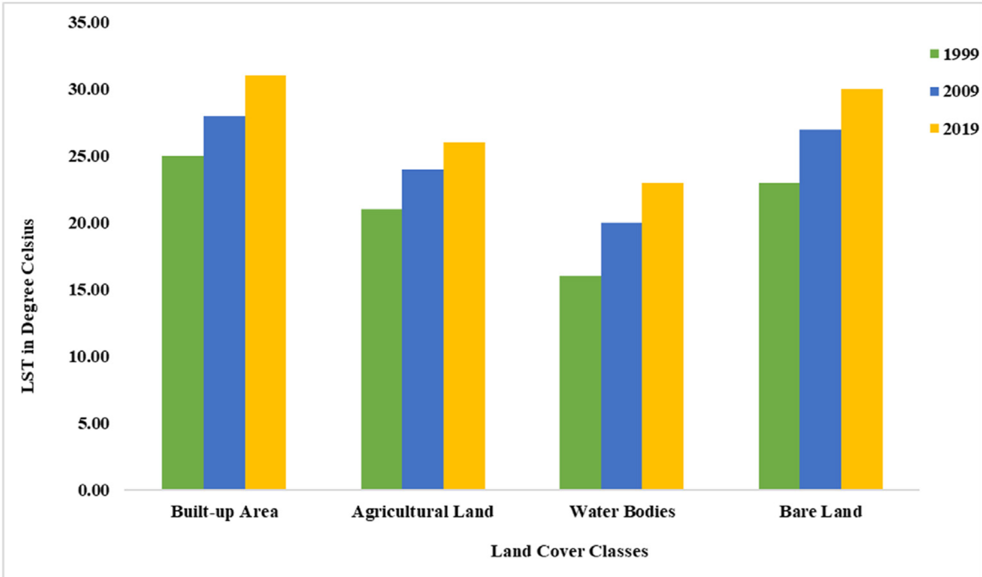

Figure 12. Mean distribution of winter temperature over different LULC classes from 1999-2019.

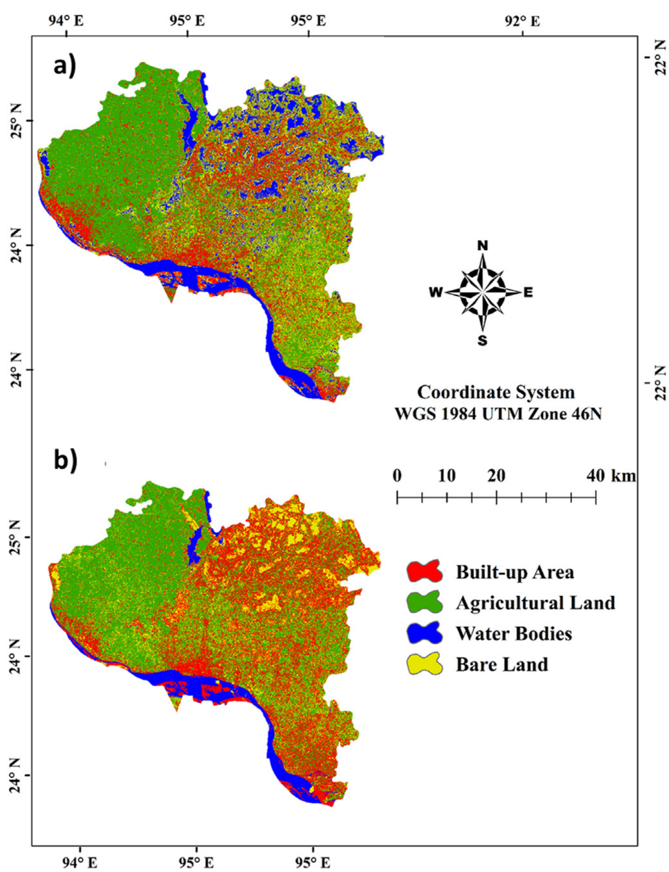

Figure 13. Predicted LULC maps using CA approach for years a) 2029 and b) 2039.

displayed in Table 6. The overall classification accuracy was recorded as 90.25 %, 89.36 %, and 91.45 % for 1999, 2009, and 2019, respectively. The accuracy results concluded that validation rates for all years were higher than 85 %, which displays excellent accuracy agreement [29].

In addition, to understand the extent of LULC changes, the area-wise distribution of LULC classes are presented in Table 7 from 1999 to 2019. Significant changes were noticed in the built-up area and agricultural land. The built-up area was 161.78 km^2 (6.79 %) in 1999, which was increased significantly by 440.70 km^2 (18.50 %) in 2019, with a net change of +7.81 %. Meanwhile, in 1999 agricultural land was 1221.50 km^2 (51.28 %), which was decreased to 926.18 km^2 (38.88 %) in 2019, resulting in a net change of -8.27 %. Noticeable changes were also observed for bare land and water bodies. Bare land, which covered 703.70 km^2 (29.54 %) in 1999, was increased by 889.54 km^2 (37.34 %) in 2019, displaying a +5.20 % net change. In 1999, water bodies covered 294.24 km^2 (12.39 %) area and were significantly reduced to only 125.67 km^2 (5.28 %) in 2019, leading to a -4.75 % net change (Table 7).

The data showed an unprecedented increase in the built-up area while a noticeable decrease in the amount of agricultural land and water bodies available for use. The primary reason for this is the rapid and unplanned urbanization that has taken place. Agriculture lands and water bodies were dynamically transformed into impervious infrastructures in order to meet the demands of a rapidly expanding population. Farmers are forced to cultivate their land more intensively as a result of the reduction in agricultural land, which increases the use of chemical fertilizers and pesticides, which contributes to pollution of the air, water, land, and other elements of the environment [57].

4.2. Changing pattern of seasonal LST

Thermal bands of Landsat images were used to estimate the seasonal (summer and winter) variation in LST distribution in the study region from 1999 to 2019. The illustration of summer and winter LST are shown in Figures 7 and 8.

For the years 1999, 2009, and 2019, the maximum and minimum summer LST values were 35.83 °C, 36.06 °C, 40.37 °C, and 19.5 °C, 21.5 °C, 26.95 °C, respectively (Table 8). Compared to the highest LST in 1999, the year 2019 showed a manifest increase by +4.54 °C. A significant deviation of +7.45 °C in the minimum LST can also be depicted from 1999 to 2019, which also indicated a rise in extreme temperature in the study region. Like the summer season, the winter season's LST distribution was also experienced remarkable changes during the study period. The maximum and minimum winter LST values were 24.54 °C, 30.85 °C, 31.32 °C, and 16.1 °C, 19.95 °C, 23.09 °C for the years 1999,

Table 10. Validation of CA model by TerrSet and QGIS software for the year 2019.

Prediction Year	CA model validation for LULC prediction using two modules					
	Kappa Parameters of TerrSet				QGIS-MULUSCE Plugin module	
	K-location	K-no	K-location Strata	K-standard	%-correctness	Overall Kappa Value
2019	0.83	0.85	0.79	0.81	86.42	0.79

Table 11. Area changes in LULC classes in the year 2029 and 2039.

LULC	Area in km^2			2019–2029		2019–2039	
	2019	2029	2039	Area Changes (%)	Net Change (%)	Area Changes (%)	Net Change (%)
Built-up Area	440.70	498.74	520.60	+2.44	+1.16	+3.35	+1.53
Agricultural Land	926.18	890.38	784.96	-1.50	-0.40	-5.93	-1.80
Water Bodies	125.67	114.43	72.21	-0.47	-0.98	-2.24	-7.40
Bare Land	889.54	878.68	1004.45	-0.46	-0.12	+4.82	+1.14

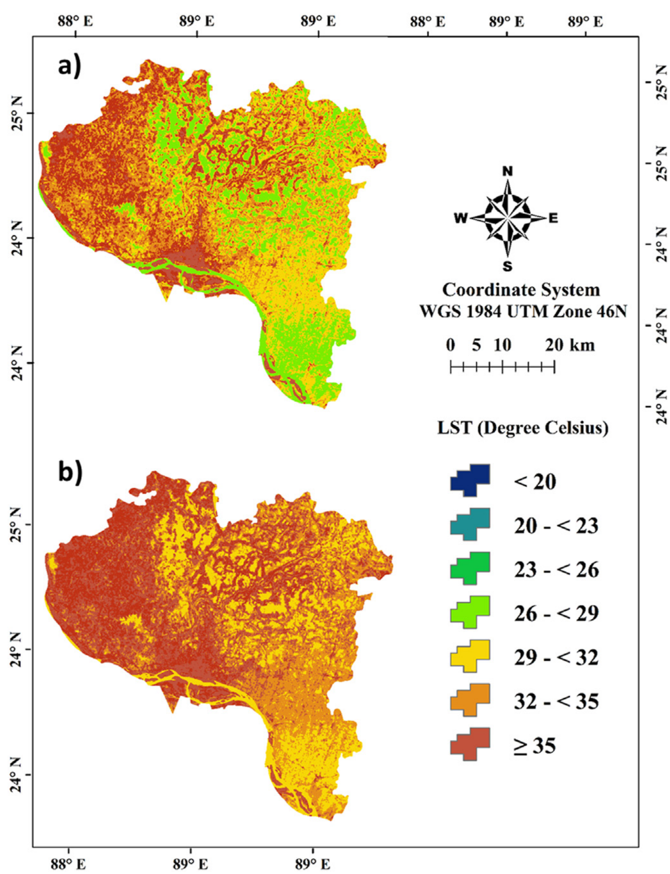

Figure 14. Predicted summer LST distribution map using ANN approach for years a) 2029 and b) 2039.

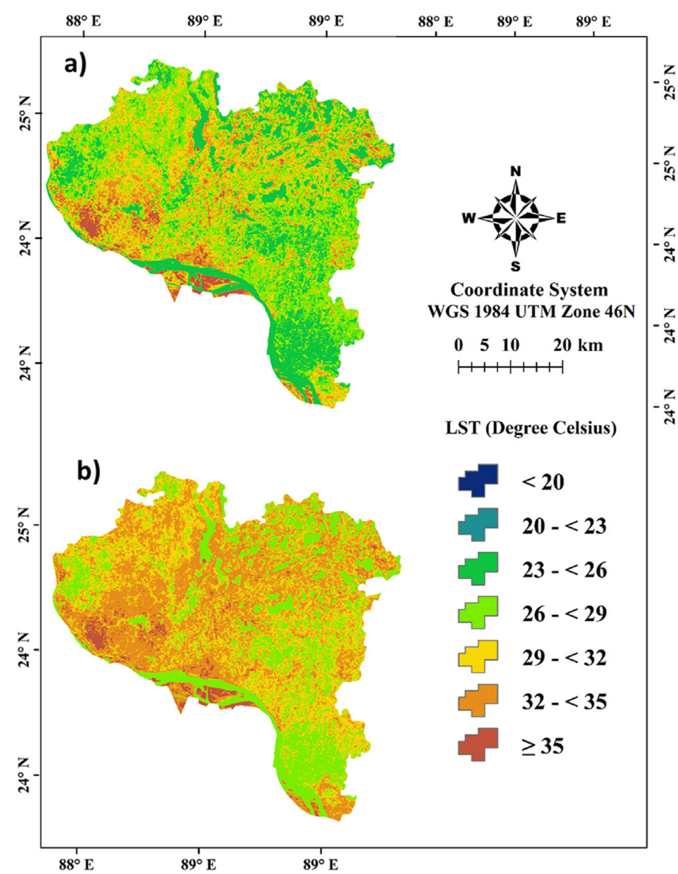

Figure 15. Predicted winter LST distribution map using ANN approach for years a) 2029 and b) 2039.

2009, and 2019, respectively (Table 9). Relative to the 1999 maximum LST, there was a significant rise of 6.78 °C in 2019. A substantial difference of +6.99 °C in the minimum LST can also be seen between 1999 and 2019, pointing towards uplift in the average temperature.

The summer season's LSTs distribution in the study area is shown in Figure 7 for the years 1999 (Figure 7a), 2009 (Figure 7b), and 2019 (Figure 7c). In 1999, 25.57 % (609.03 km^2) of the study area was experienced a high temperature between 29 °C - < 32 °C. Also, 9 % (214.36 km^2) of the study area came under the range of 32 °C - < 35 °C in 2009 and was increased to 29.36 % (699.42 km^2) in 2019. It is also evident that 13.77 % (328.11 km^2) of total area was demonstrated LST more than 35 °C in 2019 (Figure 9), suggesting an enormous rise in surface temperature in the study region. From the discussion, it can be concluded that the overall summer surface temperature was increased significantly from the last 20 years in the study area.

The Winter season's LST distribution in the study area is illustrated in Figure 8 for the years 1999 (Figure 8a), 2009 (Figure 8b), and 2019 (Figure 8c). In 1999, 2009 and 2019, around 29.36 % (699.33 km^2), 38.06 % (906.7 km^2) and 68.33 % (1627.59 km^2) of the area in study region were recorded the temperatures from 23 °C - <26 °C. No zone was recorded as more than 32 °C temperature because of the relatively cool weather in the winter season. However, 11.48 % (273.37 km^2) and 28.96 % (689.74 km^2) area were shown in the range of 29 °C - < 32 °C temperature in 2009 and 2019, respectively (Figure 10).

Table 12. ANN model validation by observed and predicted seasonal LST maps for 2019.

Prediction Year	ANN model Validation for LST prediction using MATLAB software		
	No of hidden layer	Mean Square Error (MSE)	Correlation coefficient-R
Summer 2019	5	0.63	0.84
Winter 2019	5	0.576	0.81

Table 13. Predicted summer and winter LST variation in the study area for the year 2029 and 2039.

LST in Degree Celsius	Summer Season				Winter Season			
	2029		2039		2029		2039	
	Area in km^2	Area in %	Area in km^2	Area in %	Area in km^2	Area in %	Area in km^2	Area in %
<20	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
20- <23	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
23- < 2 6	0.00	0.00	0.00	0.00	599.69	25.18	0.00	0.00
26- <29	339.10	14.24	0.00	0.00	799.66	33.57	599.69	25.18
29- <32	841.23	35.32	482.02	20.24	644.80	27.07	799.66	33.57
32- <35	646.91	27.16	698.31	29.32	266.07	11.17	672.67	28.24
≥35	554.98	23.30	1201.89	50.46	72.00	3.02	310.20	13.02
Total	2382	100	2382	100	2382	100	2382	100

Climate change, global warming, unplanned urbanization, and the loss of greenery and water bodies in the study region may all contribute to this seasonal LST increase [58, 59, 60]. Due to the significant increase in LST, water and crop yield availability will be reduced, which will increase the vulnerability of the study region to drought and extreme weather events [61]. Winters in the study region are becoming increasingly warm as a result of widespread climate change and global warming effects [20, 59, 60]. According to climate change experts and meteorologists, the winter season will be much warmer and shorter in the upcoming years than in previous years, as the temperature continues to rise on a daily basis [20]. Global warming also has an effect on the earth's ecosystem, eradicating numerous plant and animal species and wreaking havoc on the agricultural system through shorter growing seasons, decreased groundwater levels, and livestock shortages in the study region [51, 59, 62].

4.3. Validation of estimated seasonal LST

LST estimation using RS techniques requires weather-free and cloud-free images. The LST estimation of summer and winter seasons was performed using Landsat 4–5 TM and 8 OLI thermal bands for the years 1999, 2009 and 2019. Well-established equations were used to retrieve LST, however, it agonizes with certain limitations. Cloud coverage in an image can cause the values of LST analysis to be overestimated or underestimated. Additionally, none of the surface materials have a unique emissivity value in a particular area [7, 63, 64]. These issues may contribute to the incorrect calculation of LST values in the study area.

In order to validate the estimated LST summer and winter values from RS data, the maximum and minimum temperature data for 1999, 2009 and 2019 were collected from BMD (Tables 8 & 9). The deviations were determined using BMD-recorded weather station data. Whereas a negative deviation in LST indicates that the RS estimated value was greater than the recorded temperature, a positive deviation indicates that the RS estimated value was less than the recorded temperature.

The highest and lowest deviation was observed in the summer season for 1999's maximum and minimum temperatures: -3.27 °C and 1.13 °C. Besides, the deviated maximum and minimum values were -2.81 °C and -0.2 °C for 2009. For 2019, the maximum and minimum values were -0.52 °C and 1.17 °C, respectively. Overall, the summer season's average maximum and minimum deviations were -1.07 °C, -1.505 °C, and 0.325 °C for 1999, 2009, and 2019, as shown in Table 8.

In the winter season, the highest and lowest deviations were also observed for 1999's maximum and minimum temperatures, which were +0.46 °C and -0.7 °C. Hence, these maximum and minimum deviated values were -8.15 °C and -2.15 °C for 2009. For 2019, the maximum and minimum values were -1.07 °C and -6.69 °C, respectively. Overall, the winter season's average deviation was -0.12 °C, -5.15 °C, and -3.88 °C for 1999, 2009, and 2019, as shown in Table 9.

Taking all the limitations of RS-derived LST data into account, the small difference between estimated and recorded in LST can be accepted and used for further analysis, as well as the prediction of LST in the area of the study.

4.4. Variation of seasonal LST in different LULC class

Estimated mean seasonal LST distribution in different LULC classes were calculated using the zonal statistics tool in ArcGIS 10.6 software (Figure 11 & 12). For the summer season, the mean LST distribution in different LULC classes for 1999, 2009, and 2019 are presented in Figure 11. LST of the summer season was increased in every LULC class for the study period. In the built-up area and bare land, the LST values were increased significantly. Summer mean LST values for 1999 and 2019 in the built-up and bare land area were increased from 27 °C to 39 °C and 26 °C to 38 °C, respectively. In the last 20 years (summer 1999 to 2019), the mean LSTvalue was increased by 12 °C in both built-up and bare land areas. The LST distribution was also changed in agricultural land and water bodies. The estimation reveals that in summer 1999, the LST value for agricultural land was 24 °C, which was increased to 30 °C in 2019. In water bodies, the LST value was increased from 20 °C to 29 °C. The highest summer mean LST value was recorded as 39 °C (2019) in the built-up area, where the lowest value was recorded as 20 °C (1999) in water bodies (Figure 11).

The variation of the winter season's mean LST in different LULC classes is also demonstrated a significant change (Figure 12). Winter mean LST values for 1999 and 2019 in the built-up and bare land area were increased from 25 °C to 31 °C and 23 °C to 29 °C, respectively. The highest mean LST value was estimated in the built-up area as 31 °C for 2019, and the lowest LST value was recorded in water bodies as 16 °C for 1999. The highest change in winter LST value was 7 °C, which was noticed in both water bodies and agricultural land from 1999 to 2019 (Figure 12).

The variation of seasonal mean LST over different LULC types provides better insights about the contribution of the built-up area in LST

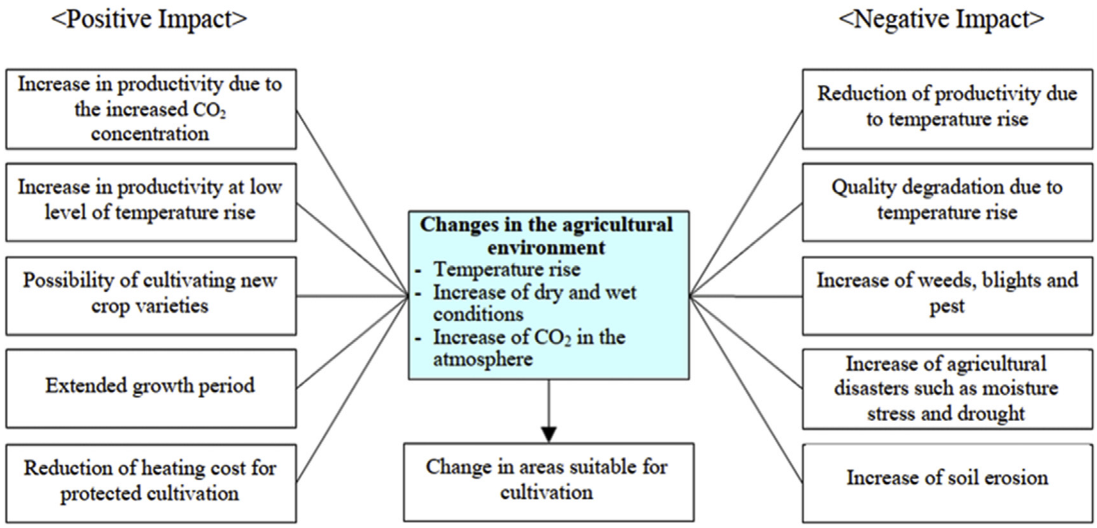

Figure 16. Impacts of temperature rise on agriculture in the study region.

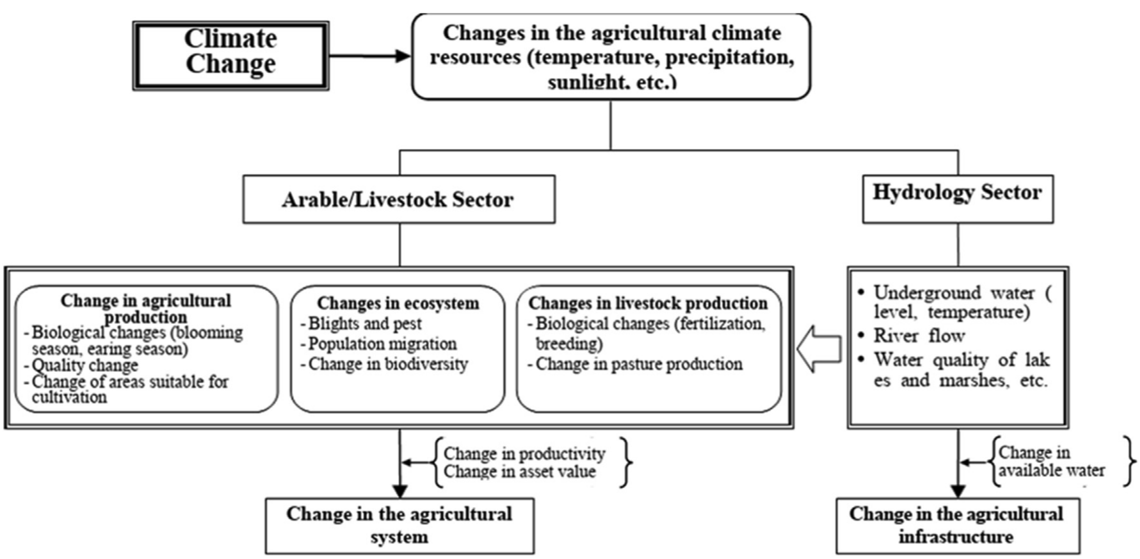

Figure 17. Climate change impact in agricultural resources in the study region.

increase by replacing the agricultural and water bodies into hardscape areas. Rapid urban development, climate change, and global warming significantly contribute to the temperature rise. Massive infrastructural development increases the proportion of impervious and paved surfaces, which retained more energy and radiated more heat [65, 66]. On the other hand, green space consists of penetrable layers and emitted less heat due to tree shading, which helps to reduce the heat [67].

4.5. Prediction of future LULC scenarios

The CA algorithm was used to predict the LULC change for 2029 (Figure 13a) and 2039 (Figure 13b) in the study area (Figure 13). The model was first predicted for the year 2019 using the 1999 and 2009 LULC maps. After achieving a stable rate of LULC changes, the model was reliable to predict future LULC patterns. The CA model validation was performed in two platforms, TerrSet, and QGIS. Both modules provide an excellent result for future prediction. The QGIS validation findings revealed that the percentage (%) of correctness and the overall Kappa value were 86.42 and 0.79. In the TerrSet, the kappa parameters, i.e., $K_{location}$, K_{no}, $K_{location\ Strata}$, and $K_{standard}$ values, were 0.83, 0.85, 0.79, and 0.81, respectively (Table 10). In the level of accuracy, the kappa values and percentage (%) of correctness values were acceptable for predicting future LULC maps [68].

Comparing the predicted LULC scenarios (2029 and 2039) to the 2019 result, it was revealed that almost 58.03 km^2 (2.44 %) and 79.90 km^2 (3.35 %) of the study area will be turned into built-up areas in 2029 and 2039, respectively. Hence, a significant decrease in agricultural land (-1.50 % and -5.93 %) and water bodies (-0.47 % and -2.24 %) were also identified in 2029 and 2039, respectively. The highest positive net change was estimated in built-up (+1.16 % and +1.53 %) areas, where the largest negative change was identified in water bodies (-0.98 % and -7.40 %) for the year 2029 and 2039, respectively (Table 11). Based on the consequence of LULC change, predicted LULC change reveals that the current trend could adversely affect the future environment by altering the study area's ecosystem, climate, and biodiversity.

4.6. Prediction of the future seasonal LST

In the study area, the seasonal (summer & winter) LST estimation showed a significant change from 1999 to 2019. Therefore, it is essential to predict future seasonal LST patterns to identify its likely possible impacts on climate change and ecosystems in the study region. The ANN algorithm was applied to predict the future seasonal summer (Figure 14a, b) and winter (Figure 15a, b) LST for the years 2029 and 2039 by analyzing the past patterns of LST. The comparison of predicted and observed LST for the year 2019 were revealed an excellent agreement that proved the ANN model's prediction accuracy. The MSE and R values for the summer and winter seasons were 0.63 & 0.576 and 0.84 & 0.81, respectively (Table 12), which signifies the strong correlation between observed and predicted seasonal LST.

Figures 14 and 15 showed the rising summer and winter LST trends in the study region for the years 2029 and 2039. Surface and air temperatures have a strong correlation with each other. Therefore, LST rising trend will directly affect the air temperature. In predicted summer 2029, about 23.30 % of the study area will likely to be in the high-temperature zone ($\geq$35 °C), and only 14.24 % area will be in the low-temperature zone (26 - <29 °C). The prediction also showed that more than 50 % of the study area will likely to be in the high-temperature zone ($\geq$35 °C), and 20.24 % area will be experienced under the zone of 32 - < 35 °C in summer 2039 (Table 13). Furthermore, similar to the summer predicted LST, Figure 15, represents the winter LST, which also demonstrates an increasing trend for the year 2029 and 2039. In winter LST, only 3.02 % and 13.02 % of the study area will likely to be experienced in the high-temperature zone ($\geq$35 °C), where 11.17 % and 28.24 % will be in the range of 32 - < 35 °C for the year 2029 and 2039, respectively (Table 13). Due to the fact that the predicted LST value was estimated using the trends of the previous year's (1999–2019) LST pattern, the prediction results also indicated a significant possible increase in the LST value for the years 2029 and 2039.

The increasing LST trend will affect the thermal capacity of LULC categories and contribute to the UHI effect [69]. The fifth IPCC assessment report directs that the Asian regions will face higher temperatures than the global average [60]. Global warming is mainly uplifted because of the intensification in urban area temperature compared to the rural area [70]. One effective way to mitigate the UHI, global warming, and greenhouse effects is by increasing green cover area through the plantation and preserving the agricultural land, which will ensure ecological stability and environmental sustainability in the study region.

4.7. Limitations of the CA and ANN models

While CA and ANN models provide an effective framework for evaluating and forecasting LULC and LST situations, the models are more accurate when the previous LULC and LST dynamics pattern remains consistent or stable. Therefore, the CA model is not always enough to make explicit spatial LULC predictions [54]. The ANN is occasionally referred to as a black box due to its limited ability to explicitly identify the relationship between influential variables [45]. The ANN model develops training samples after the input of layers, begins training by itself and finds the most influential factors without taking account of their relative relevance. There are no well-established criteria in the system for allocating each input parameter's specific weight depending on its importance [41]. Nonetheless, dynamic processes such as urbanization, loss of vegetation, and increased surface temperature cannot be forecast precisely because they are heavily dependent on human activities and rational decisions made at the regional to the municipal level.

Regardless of their shortcomings, dynamic models effectively establish assumptions of land cover and surface temperature changes in any location. As a result, techniques such as LULC, LST change, and prediction mapping are rapidly gaining recognition as highly effective tools for managing critical natural resources and mitigating environmental consequences, particularly in the developing world.

4.8. LULC change, LST shifts, and climate change impacts on the agricultural sector

4.8.1. Impacts of LULC change

Significant LULC changes have occurred in the Rajshahi region during the past 20 years. The total area of agricultural lands was decreased by 8.27 % from 1999 to 2019, while the built-up area was increased by 7.81 %. From the FGDs and KIIs, it was found that the changes in LULC classes create substantial negative impacts on socio-economic and environmental aspects in the study area. Considering the socio-economic impacts, conversion of farmland or agricultural land to infrastructure development decreases the number of lands available for food production. Soil erosion, desertification, and other soil degradation associated with intensive agriculture productivity reduce land resource quality and hamper food productivity. Categories of LULC changes, especially the loss of natural resources (agricultural land and water bodies), create environmental effects by adding loss in biodiversity, destroy habitats that support biodiversity, increase greenhouse effects and surface temperature, disturbs the hydrological cycle and increase surface runoff, soil erosion, and flooding. During the FGDs, participants also mentioned that one of the primary causes of water pollution in the study region is runoff from agricultural land, which contains fertilizer used by farmers during agricultural production. The participants suggested an effective policy measure while preparing the land use management plan (discussed in 4.9) to control water pollution for the increment of food productivity in the future.

4.8.2. Impacts of temperature change

The study area is an agrarian-based region, and variations in seasonal temperature have significant negative and positive impacts on crop yields. Seasonal temperature change have increased the atmospheric CO_2 and frequency/intensity of extreme weather events. The participants from FGDs and KIIs stated that crop productivity due to the fertilization effect induced by an increase in the concentration of CO_2 in the atmosphere, expansion of the available areas for growing the tropical and subtropical crops, development of two-crop farming due to an extended cultivation time and reduction of damage to winter crops by low temperatures are the main positive impacts of temperature rise. Besides, negative impacts of seasonal temperature rise include a decline in the number and quality of crops as a consequence of the low growth cycle for high-temperature rises, decrease in the sugar content and fruit store stability, poor coloring, rising weeds, and harmful insects in crops and decreasing soil productivity (Figure 16).

According to the Bangladesh Agricultural Development Corporation, "Boro rice" production will significantly be decreased from 13.5 % to 2.6 % in upcoming years, with an increase of 2 °C mean temperature in the study region. Due to the impact of climate change, Bangladesh is facing a 4 °C temperature increase in the last decades, resulting 28 % and 68 % reduction in rice and wheat production [20, 51]. Agriculture officers suggested that, in order to examine to what extent an increase in temperature affecting agricultural productivity in the study region, different experiments, simulations, and testing need to be carried out in laboratories as well as in the fields.

4.8.3. Impacts of climate change

Climate change is causing organic changes in the study area, such as fertilization and breeding in the livestock sector as well as influencing the growing pattern of pastures. During the FGDs and KIIs, a significant relationship was established between the regional economy (mainly depends on agricultural products) and climate change in the study area mentioned in Figure 17. It was found that the region's agricultural system is affected by a wide range of climate impacts, including agricultural production, farm household incomes, and asset prices, reducing the water supply available to agriculture. Because of the rapid development, the participants assumed that the study area would likely face a significant decrease in farmland, which substantially increases the climate change impact by affecting biodiversity and natural resources. The participants' statements can be validated by comparing the predicted LULC scenarios (2029 and 2039) with the 2019 result. Results revealed that almost 58.03 km^2 and 79.90 km^2 area would be turned into the built-up area with a significant decrease in agricultural land (-1.50 % and -5.93 %) in 2029 and 2039, respectively, in the study region (Table 11).

4.9. Future sustainable land use management plan

Effective land management is a proactive strategy for mitigating the negative consequences of natural land cover change and unplanned regional development. Government officials and policymakers must conduct an extensive study of current conditions and trend analysis of LULC changes on both spatial and temporal scales in order to develop a sustainable land use management plan. Measuring effective land use management practices frequently necessitates an accurate understanding of current and historical trends in LULC change. The trend analysis of LULC changes would aid in conserving natural resources and mitigating the adverse effects of these transformation in the study region. The following issues should be considered when preparing a regional-level land use management plan, based on the discussion during FGDs. The issues are as follows:

i. Ensuring the best possible use with restricting misuse and inappropriate use of bare land and water bodies.
ii. Safeguarding the gradual decreasing trend of agricultural land with strict rules and regulations to feed up the growing population, increase economic enlargement, and conserve biodiversity.
iii. Introducing and monitoring the zoning technique in order to make demarcation of natural resources (agricultural land and water bodies) according to rational criteria for effective utilization in various purposes.
iv. Preventing water and soil pollution for ensuring better agricultural productivity and environmental friendly land utilization.
v. Ensuring sustainable urban development by preparing a regional level master plan for planned and inclusive urbanization.
vi. Increasing plantation, green cover, and established artificial leaks to mitigate the seasonal heat weaves.

5. Conclusion

This study's main focus is to estimate and predict the land use transformation and their impacts on seasonal surface temperature variations in the agricultural-based region Rajshahi, Bangladesh. The analysis revealed that the study region has been going through a significant loss in agricultural land and expecting more in upcoming years. This study also identified the impacts of land cover change, temperature increase, and climate change on the agricultural sector using FGDs and KIIs. Finally, based on experts' opinions and considering the consequences of unplanned infrastructural development, reduction in green cover, and climate change, this study proposed a sustainable land use management plan for Bangladesh's northwest region.

The LULC analysis demonstrates a significant increase in the built-up area with a net increase of +7.81 % from 1999 to 2019. Meanwhile, agricultural land and water bodies were decreased by -8.27 % and -4.75 % from 1999 to 2019. More than 29 % and 28 % of the total area were recorded in the temperature range of 32 °C - < 35 °C and 29 °C - < 32 °C in 2019 in winter season, which was 3.64 % and 0 % in year 1999, respectively. The seasonal LST distribution over different LULC classes revealed that the highest temperature was recorded in the built-up area while the lowest temperature was recorded in water bodies and agricultural land for the studied years. The prediction of LULC and LST changes indicates alarming results for 2029 and 2039. More than 23 % (2029) and 50 % (2039) of the total area will likely be experienced high temperatures in the summer season of greater than 35 °C. For predicted winter LST, more than 3 % and 13 % of the area will likely be experienced in the high-temperature zone (≥ 35 °C) for 2029 and 2039, respectively, which is comparatively high considering the winter season.

Based on this study's results and discussion, Rajshahi's local government and urban planners can consider unplanned and haphazard development in and out of the city area and formulation of increasing LST as a burning issue of this region. The inclusion of these study outputs in a regional level master/development plan will make Rajshahi District ecologically and environmentally sustainable and able to mitigate the possible impacts of climate change and global warming on agricultural productivity and food security in this region. The study also focuses on the importance of agricultural land, green cover, and natural resources and conservation approach by proposed land use management plan to minimize the UHI effect to reduce the climate change impact. Further research may focus on human-environment interactions to better understanding the causes and consequences associated with urban growth, LULC transformation, and LST change. Urban growth, changes in land cover, and surface temperature in other Bangladesh cities should be reviewed and predicted for future sustainable development. The results will improve the understanding of city planners and policymakers in making a district-level sustainable land use management and development plan for ensuring environmental sustainability at the regional level.

Declarations

Author contribution statement

Abdulla - Al Kafy: Conceived and designed the experiments; Performed the experiments; Analyzed and interpreted the data; Contributed reagents, materials, analysis tools or data; Wrote the paper.

Abdullah-Al-Faisal: Performed the experiments; Analyzed and interpreted the data; Contributed reagents, materials, analysis tools or data; Wrote the paper.

Abdullah Al Rakib: Contributed reagents, materials, analysis tools or data; Wrote the paper.

Sumita Roy, Jannatul Ferdousi, Vinay Raikwar, Marium Akter Kona, S M Abdullah Al-Fatin: Contributed reagents, materials, analysis tools or data; Wrote the paper.

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Data availability statement

Data will be made available on request.

Declaration of interests statement

The authors declare no conflict of interest.

Additional information

No additional information is available for this paper.

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References

[1] A. Nurwanda, T. Honjo, The prediction of city expansion and land surface temperature in Bogor City, Indonesia, Sustain. Cities Soc. 52 (2020) 101772.
[2] M.S. Rahman, H. Mohiuddin, A.-A. Kafy, P.K. Sheel, L. Di, Classification of cities in Bangladesh based on remote sensing derived spatial characteristics, J. Urban Manag. (2018).
[3] W.B. UN, Bangladesh Population, Rajshahi, 2019.
[4] S. Pal, S. Ziaul, Detection of land use and land cover change and land surface temperature in English Bazar urban centre, Egypt. J. Remote Sens. Space Sci. 20 (2017) 125–145.
[5] A.-A. Kafy, M.N.H. Naim, G. Subramanyam, A.-A. Faisal, N.U. Ahmed, A. Al Rakib, et al., Cellular Automata Approach in Dynamic Modeling of Land Cover Changes Using RapidEye Images in Dhaka, Bangladesh, Environmental Challenges, 2021, p. 100084.
[6] M.N.H. Naim, A.A. Kafy, Assessment of Urban Thermal Field Variance Index and Defining the Relationship between Land Cover and Surface Temperature in Chattogram City: A Remote Sensing and Statistical Approach, Environmental Challenges, 2021, p. 100107.
[7] A.A. Kafy, A.-A. Faisal, S. Sikdar, M. Hasan, M. Rahman, M.H. Khan, et al., Impact of LULC changes on LST in Rajshahi district of Bangladesh: a remote sensing approach, J. Geograph. Stud. 3 (01/07 2020) 11–23.
[8] A.-A. Kafy, A. Al Rakib, K.S. Akter, Z.A. Rahaman, A.-A. Faisal, S. Mallik, et al., Monitoring the Effects of Vegetation Cover Losses on Land Surface Temperature Dynamics Using Geospatial Approach in Rajshahi City, Bangladesh, Environmental Challenges, 2021, p. 100187.
[9] A. Kafy, M. Hossain, A.A.N. Prince, M. Kawshar, M.A. Shamim, P. Das, et al., Estimation of land use change to identify urban heat island effect on climate change: a remote sensing based approach, in: International Conference on Climate Change (ICCC-2019), Dhaka, Bangladesh, 2019.
[10] A.-A. Kafy, M.S. Rahman, M. Islam, A. Al Rakib, M.A. Islam, M.H.H. Khan, et al., Prediction of seasonal urban thermal field variance index using machine learning algorithms in Cumilla, Bangladesh, Sustain. Cities Soc. 64 (2020) 102542.
[11] N.N. Dey, A. Al Rakib, A.-A. Kafy, V. Raikwar, Geospatial Modelling of Changes in Land Use/land Cover Dynamics Using Multi-Layer Perception Markov Chain Model in Rajshahi City, Bangladesh, Environmental Challenges, 2021, p. 100148.
[12] P. Fu, Q. Weng, Responses of urban heat island in Atlanta to different land-use scenarios, Theor. Appl. Climatol. 133 (2018) 123–135.
[13] S. Ullah, A.A. Tahir, T.A. Akbar, Q.K. Hassan, A. Dewan, A.J. Khan, et al., Remote sensing-based quantification of the relationships between land use land cover changes and surface temperature over the lower Himalayan region, Sustainability 11 (2019) 5492.
[14] A.A. Kafy, M.S. Rahman, A.A. Faisal, M.M. Hasan, M. Islam, Modelling Future Land Use Land Cover Changes and Their Impacts on Land Surface Temperatures in Rajshahi, Bangladesh, Remote Sensing Applications: Society and Environment, 2020.
[15] S. Mansour, M. Al-Belushi, T. Al-Awadhi, Monitoring land use and land cover changes in the mountainous cities of Oman using GIS and CA-Markov modelling techniques, Land Use Pol. 91 (2020) 104414.
[16] A.-A. Faisal, A.-A. Kafy, A. Al Rakib, K.S. Akter, V. Raikwar, D.M.A. Jahir, et al., Assessment and Prediction of Seasonal Land Surface Temperature Change Using Multi-Temporal Landsat Images and Their Impacts on Agricultural Yields in Rajshahi, Bangladesh, Environmental Challenges, 2021, p. 100147.
[17] A.F. Alqurashi, L. Kumar, P. Sinha, Urban land cover change modelling using time-series satellite images: a case study of urban growth in five cities of Saudi Arabia, Rem. Sens. 8 (2016) 838.
[18] R.M. Ramachandran, P.S. Roy, V. Chakravarthi, P.K. Joshi, J. Sanjay, Land use and climate change impacts on distribution of plant species of conservation value in Eastern Ghats, India: a simulation study, Environ. Monit. Assess. 192 (2020) 86.
[19] B. B. o. S. BBS, District Statistics, Ministry of Planning, Government of The People's Republic of Bangladesh2013, Rajshahi, 2011.
[20] UNB, Bangladesh Set to See Shorter, Warmer winter Again, The Business Standard, 2019. https://tbsnews.net/environment/bangladesh-set-see-shorter-warmer-winter-again-experts.
[21] M. Islam, M. Hassan, Land use changing pattern and challenges for agricultural land: a study on Rajshahi district, J. Life Earth Sci. 6 (2012).
[22] A.A. Kafy, N. Naim, M. Islam, A. Al Rakib, A.-A. Faisal, M. Sarker, Prediction of Urban Expansion and Identifying its Impacts on the Degradation of Agricultural Land, 2021, pp. 85–106.
[23] A.-A. Faisal, A.-A. Kafy, A. Al Rakib, K.S. Akter, D.M.A. Jahir, M.S. Sikdar, et al., Assessing and Predicting Land Use/land Cover, Land Surface Temperature and Urban thermal Field Variance index Using Landsat Imagery for Dhaka Metropolitan Area, Environmental Challenges, 2021, p. 100192.
[24] A.A. Kafy, M. Islam, S. Sikdar, T. Ashrafi, A.-A. Faisal, M. Islam, et al., Remote Sensing-Based Approach to Identify the Influence of Land Use/land Cover Change on the Urban thermal Environment: A Case Study in Chattogram City, Bangladesh, 2020.
[25] A. Faisal, A. Kafy, S. Roy, Integration of remote sensing and GIS techniques for flood monitoring and damage assessment: a case study of naogaon district," *Bangladesh*, J. Remote Sens. GIS 7 (2018) 2.
[26] A. Faisal, H. Khan, Application of GIS and remote sensing in disaster management: a critical review of flood management, in: International Conference on Disaster Risk Mitigation, 2018.
[27] A. Kafy, L. Ferdous, Pond filling locations identification using landsat-8 images in Comilla district, Bangladesh, in: 1st National Conference on Water Resources Engineering (Ncwre 2018), 2018.
[28] A.-A. Kafy, F. Abdullah Al, V. Raikwar, A.A. Rakib, M.A. Kona, J. Ferdousi, Geospatial Approach for Developing an Integrated Water Resource Management Plan in Rajshahi, Bangladesh, Environmental Challenges, 2021, p. 100139.
[29] H. Wang, Y. Zhang, J.Y. Tsou, Y. Li, Surface urban heat island analysis of Shanghai (China) based on the change of land use and land cover, Sustainability 9 (2017) 1538.
[30] A.A. Kafy, F. Abdullah Al, R.M. Shuvo, M.N. Huda Naim, M.S. Sikdar, R.R. Chowdhury, et al., Remote Sensing Approach to Simulate the Land Use/land Cover and Seasonal Land Surface Temperature Change Using Machine Learning Algorithms in a Fastest-Growing Megacity of Bangladesh, Remote Sensing Applications: Society and Environment, 2020, p. 100463.
[31] M.W.A. Halmy, P.E. Gessler, J.A. Hicke, B.B. Salem, Land use/land cover change detection and prediction in the north-western coastal desert of Egypt using Markov-CA, Appl. Geogr. 63 (2015) 101–112.
[32] C. Losiri, M. Nagai, S. Ninsawat, R.P. Shrestha, Modeling urban expansion in Bangkok Metropolitan region using demographic–economic data through cellular automata-Markov chain and multi-Layer perceptron-Markov chain models, Sustainability 8 (2016) 686.
[33] D. Ozturk, Urban growth simulation of Atakum (Samsun, Turkey) using cellular automata-Markov chain and multi-layer perceptron-Markov chain models, Rem. Sens. 7 (2015) 5918–5950.
[34] A.A. Al-sharif, B. Pradhan, A novel approach for predicting the spatial patterns of urban expansion by combining the chi-squared automatic integration detection decision tree, Markov chain and cellular automata models in GIS, Geocarto Int. 30 (2015) 858–881.
[35] I. Balogun, K. Ishola, Projection of future changes in landuse/landcover using cellular automata/markov model over Akure city, Nigeria, J. Remote Sens. Technol. 5 (2017) 22–31.
[36] J.J. Arsanjani, M. Helbich, W. Kainz, A.D. Boloorani, Integration of logistic regression, Markov chain and cellular automata models to simulate urban expansion, Int. J. Appl. Earth Obs. Geoinf. 21 (2013) 265–275.
[37] J.F. Mas, J.J. Flores, The application of artificial neural networks to the analysis of remotely sensed data, Int. J. Rem. Sens. 29 (2008) 617–663.
[38] B. Ahmed, M. Kamruzzaman, X. Zhu, M.S. Rahman, K. Choi, Simulating land cover changes and their impacts on land surface temperature in Dhaka, Bangladesh, Rem. Sens. 5 (2013) 5969–5998.
[39] X. Yang, X.-Q. Zheng, L.-N. Lv, A spatiotemporal model of land use change based on ant colony optimization, Markov chain and cellular automata, Ecol. Model. 233 (2012) 11–19.
[40] I.D. Maduako, Z. Yun, B. Patrick, Simulation and prediction of land surface temperature (LST) dynamics within Ikom City in Nigeria using artificial neural network (ANN), J. Remote Sens. GIS 5 (2016) 1–7.
[41] N. Shatnawi, H. Abu Qdais, Mapping urban land surface temperature using remote sensing techniques and artificial neural network modelling, Int. J. Rem. Sens. (2019) 1–16.
[42] D.L. Civco, Artificial neural networks for land-cover classification and mapping, Int. J. Geogr. Inf. Sci. 7 (1993) 173–186.
[43] A.A. Rakib, K. Akter, M.N. Rahman, S. Arpi, A.A. Kafy, Analyzing the pattern of land use land cover change and its impact on land surface temperature: a remote sensing approach in mymensingh, Bangladesh, in: 1st International Student Research Conference - 2020, Dhaka, 2020.
[44] L. Bodri, V. Čermák, Prediction of surface air temperatures by neural network, example based on three-year temperature monitoring at spořilov station, Studia Geophys. Geod. 47 (2003) 173–184.
[45] M. Van Gerven, S. Bohte, Artificial neural networks as models of neural information processing, Front. Comput. Neurosci. 11 (2017) 114.
[46] X. Yao, Evolving artificial neural networks, Proc. IEEE 87 (1999) 1423–1447.
[47] A.-A. Kafy, N.N. Dey, A. Al Rakib, Z.A. Rahaman, N.R. Nasher, A. Bhatt, Modelling the Relationship between Land Use/land Cover and Land Surface Temperature in Dhaka, Bangladesh Using CA-ANN Algorithm, Environmental Challenges, 2021, p. 100190.
[48] A. Clemett, M.M. Amin, S. Ara, M.M.R. Akan, Background Information for Rajshahi City, Bangladesh, 2006.
[49] M.I. Hossain, M.N. Bari, S.U. Miah, A.-A. Kafy, N.R. Nasher, Application of Modified Managed Aquifer Recharge Model for Groundwater Management in Drought-Prone Water-Stressed Barind Tract, Bangladesh, Environmental Challenges, 2021, p. 100173.
[50] A.F. Kafy, H.A.H. Khan, P.K. Sheel, Exploring the association of surface water body change and rapid urbanization in Rajshahi city Corporation (RCC) area using RS and GIS, in: 1st National Conference on Water Resources Engineering (NCWRE 2018), 2018.
[51] B.M.D. BMD, Country report: Bangladesh meteorological department (BMD). http://live3.bmd.gov.bd/2013.
[52] J.P. Connors, C.S. Galletti, W.T. Chow, Landscape configuration and urban heat island effects: assessing the relationship between landscape characteristics and land surface temperature in Phoenix, Arizona, Landsc. Ecol. 28 (2013) 271–283.
[53] B. Celik, S. Kaya, U. Alganci, D.Z. Seker, Assessment of the relationship between land use/cover changes and land surface temperatures: a case study of thermal remote sensing, FEB-FRESENIUS Environ. Bullet. 3 (2019) 541.
[54] I. Santé, A.M. García, D. Miranda, R. Crecente, Cellular automata models for the simulation of real-world urban processes: a review and analysis, Landsc. Urban Plann. 96 (2010) 108–122.

[55] S. Gopal, C. Woodcock, Remote sensing of forest change using artificial neural networks, IEEE Trans. Geosci. Rem. Sens. 34 (1996) 398–404.
[56] Z. Hu, C. Lo, Modeling urban growth in Atlanta using logistic regression, Comput. Environ. Urban Syst. 31 (2007) 667–688.
[57] M.M. Islam, A. Jannat, A.R. Dhar, T. Ahamed, Factors determining conversion of agricultural land use in Bangladesh: farmers' perceptions and perspectives of climate change, Geojournal (2019) 1–20.
[58] M. Alamgir, N. Khan, S. Shahid, Z.M. Yaseen, A. Dewan, Q. Hassan, et al., Evaluating severity–area–frequency (SAF) of seasonal droughts in Bangladesh under climate change scenarios, Stoch. Environ. Res. Risk Assess. (2020) 1–18.
[59] W. World Bank, Climate Change & Sustainable Report- Bangladesh, 2016.
[60] IPCC, Mitigation of climate change, in: Contribution of Working Group III to the Fifth Assessment Report of the Intergovernmental Panel on Climate Change, 1454, 2014.
[61] M.S. Hossain, M. Arshad, L. Qian, M. Zhao, Y. Mehmood, H. Kächele, Economic impact of climate change on crop farming in Bangladesh: an application of Ricardian method, Ecol. Econ. 164 (2019) 106354.
[62] Å. Kolås, L. Barkved, K. Edelen, K. Hoelscher, F. Jahan, H.B. Jha, Water Scarcity in Bangladesh, 2000.
[63] I. Dar, J. Qadir, A. Shukla, Estimation of LST from multi-sensor thermal remote sensing data and evaluating the influence of sensor characteristics, Spatial Sci. (2019) 1–19.
[64] M. Neteler, Estimating daily land surface temperatures in mountainous environments by reconstructed MODIS LST data, Rem. Sens. 2 (2010) 333–351.
[65] M.G.R. Fahad, A. Saiful Islam, R. Nazari, M. Alfi Hasan, G. Tarekul Islam, S.K. Bala, Regional changes of precipitation and temperature over Bangladesh using bias-corrected multi-model ensemble projections considering high-emission pathways, Int. J. Climatol. 38 (2018) 1634–1648.
[66] K.M. Rahman, L. Melville, D. Fulford, S.I. Huq, Green-house gas mitigation capacity of a small scale rural biogas plant calculations for Bangladesh through a general life cycle assessment, Waste Manag. Res. 35 (2017) 1023–1033.
[67] J. Djekic, P. Mitkovic, M. Dinic Brankovic, M. Igic, P. Djekic, M. Mitkovic, The study of effects of greenery on temperature reduction in urban areas, Therm. Sci. 2018 (2018) 122.
[68] R.G. Pontius Jr., M. Millones, Death to Kappa: birth of quantity disagreement and allocation disagreement for accuracy assessment, Int. J. Rem. Sens. 32 (2011) 4407–4429.
[69] S. Bonafoni, G. Baldinelli, P. Verducci, Sustainable strategies for smart cities: analysis of the town development effect on surface urban heat island through remote sensing methodologies, Sustain. Cities Soc. 29 (2017) 211–218.
[70] D.P. Roy, M.A. Wulder, T.R. Loveland, C.E. Woodcock, R.G. Allen, M.C. Anderson, et al., Landsat-8: science and product vision for terrestrial global change research, Rem. Sens. Environ. 145 (2014) 154–172.