Computing Urban blue green space and its impact on urban heat island and ecological index using multi sensor data at planned city Gandhinagar, Gujarat, India

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Abstract

Cities are experiencing considerable changes in regional landscape patterns and ecological structure. Hence, it is crucial to comprehend the spatial linkages between landscape patterns and ecological networks for optimal functioning of urban ecosystems. Urban heat island (UHI) is one of the most important sensitive parameters to understand the ecological vulnerability of cities. Gandhinagar, the green city of Gujarat, is showing a huge landscape transformation which has been assessed by remote sensing ecological index (RSEI) with multi-spectral satellite data for the year 2006, 2018 and 2022. We used the cellular automata land use simulation model to predict the landscape changes and Landsat data for ecological sensitivity to correlate the urban heat island effects in the city. The result shows an increase in 100% urban sprawl in the district since 2006 which led to surface urban heat island (SUHI) effect. The Land Use Land Cover change dynamics shows that 100 km^2 of agriculture land has been converted to built-up and wasteland. The accelerated change has been predicted with Artificial Neural Network model with MOLUSCE tool in QGIS. The results show further decreasing trend of agriculture land to be converted to commercial buildings and other classes. The ecological sensitivity of the green city has been calculated with four vital indices which are wetness, dryness, greenness, and heat index. Principal component analysis (PCA) is used to automatically assign the rank and weight of individual parameters based on their importance in index development. The PCA reveals that the ecological index RSEI of 2006 was better than 2018 and further improved in 2022 after the country shutdown in post covid.

Keywords: *Green city, Ecological sensitivity, SUHI, MOLUSCE (Modules for Land Change Evaluation), Cellular Automata, Remote Sensing Ecological Index*

1. Introduction

The world is currently experiencing widespread urban sprawl of about 168% between 2001 to 2018 with highest at Asia and Africa which is a key problem for sustainable development (Dewan et al. 2021; Ackerschott et al. 2023). These induced changes has vast implications on natural surfaces resulting in multiple environmental effects interwoven with sustainable development which are noticeable with local climate and biodiversity loss (Kong et al. 2019; Dewan et al. 2021). Consequently, land use is linked with Sustainable Development Goals of United Nation, particularly SDG-15 which is “Life on Land”. The goal demands to “protect restore and promote sustainable use of terrestrial ecosystems, sustainably manage forests, combat desertification, and halt and reverse land degradation”. In addition to the UN's defined international goals for land use, several nations have set particular targets as part of their sustainable development policies due to the significance of land use for sustainable development. There are a number of spatial planning-related strategies that could be used, including centralized systems, zoning, strategic planning, and land use allocations (Schmidt 2009; Jost et al. 2021). However, the international and national sustainability goals for land use are currently off course.

Urban population have become the key driver of changing global ecosystems by increasing anthropogenic impervious areas (Gong et al. 2020). Urbanization has led to landscape changes, degrades environmental livelihood (Hondula et al. 2014), pollute the ambient air and water quality (Adeyeri et al. 2017). Such conversions of natural lands cover to artificial impervious surfaces primarily asphalt and concrete leads to development of UHI phenomenon due to increase in land surface temperature (Ahmed et al. 2023). UHI is the most obvious effect of urbanization and a blatant indicator of environmental degradation which can be defined as the temperature difference between urban and rural surroundings as a result of human activity. Although human activities are the primary drivers of the UHI phenomena, other natural elements, such as geographic location like coastal, hilly or desert areas, seasonal variation as summer, monsoon and winter, climate type like semiarid, arid and humid, and topographical conditions, also have an impact. Additionally, the local weather conditions have an impact on the air temperature like cooling influence in coastal locations and heat waves in tropical and semi-arid regions (Zhou et al. 2020). Urban heat island effect is one of the most well-known effects of urbanization on local climate which exacerbate the energy consumption of the cities for cooling demands.

The land use simulation model is an efficient tool to forecast changes in land use and its consequences on increased temperature with thermal infrared remote sensing data (Purswani et al. 2022). The model simulation uses pre-requisite steps to identify drivers of land use change which include distance from urban center, roads, waterbodies, and elevation etc. With advancement of geomatics and resolution of remote sensing datasets, a number of land use simulation models are available which has been studied in detail by various authors (Chughtai et al. 2021; Gomes et al. 2021). These models are applicable in predicting rural development and urban growth with special attention to conservation areas and dynamics of shifting cultivation. Models help in urban planning, establishment of infrastructure, meeting transportation and utility demand, and the identification of risky zones. The techniques are also available for complex landscape settings and appropriate models for various earth's land surface like vegetation, urbanization, delta region, mountainous region, coastal zone, desertification, and watershed (Chughtai et al. 2021). Cheng et al used DINAMICA model to simulate the changes in Amazonian colonization border (Cheng et al. 2020). Cellular automata SLEUTH model was constructed to project global urban growth probability from 2020 to 2050 (Zhou et al. 2019). The remote sensing and GIS tools have cooperatively made the prediction easy to monitor from past to present and future. Many artificial neural networks have been found to be efficient to work with, for example, MLP-ANN based model with cellular automata simulation like MOLUSCE plugin. MOLUSCE tool was found to be popularly known for its flexible and accurate mapping.

The plugin includes several well-known algorithms, such as cross-tabulation methods, utility modules, and algorithmic modules, such as multi-criteria evaluation (MCE), weights of evidence (WoE), logistic regression (LR), and Monte Carlo cellular automata (CA) models (Muhammad et al. 2022). The MOLUSCE tool in QGIS is freely accessible and easily monitored which has been used for land use prediction and change detection study for the year 2030 in this study.

The study has been carried out in the tree capital of India, Gandhinagar which is the second planned city of India after Chandigarh and first smart city after GIFT city hub. Being in the close proximity to Ahmedabad, the city has expanded which has influenced the ability to sustain its ecosystem services. Thus, the aim of this study is to investigate the trend of change in land use with reference to already published study at Gandhinagar district its impact on LST causing surface heat island effect that might influence the ecological quality of the study area.

2. Datasets and Methods

2.1Description of the Study Area

The current research is performed at smart city Gandhinagar situated between Lat 22°56' and 23°36' and Long 72°23' to 73°05' (fig. 1). The district has four talukas with nine urban centers and 291 villages. The study region features a perennial river system and a semi-arid environment, which makes it dry for most of the year. The rainfall occurs in June to September, of which 95% is received from the southwest. According to IMD gridded data, the actual rainfall is 824mm during Jan to dec 2022 with 8% deviation from normal rainfall (Wris.gov.in). The maximum temperature during summer reaches up to 41ºC and sometimes affected by cold wave from western disturbances (Central Ground Water Board 2014). The relative humidity reaches 65% in monsoon and drops to 20% or less in the driest months (fig. 2). The population growth rate has been increasing to 12.5 % every decade since 2001 due to close proximity to Ahmedabad city. The district covers approximately 2137 km^2 which is 1.09% of Gujarat state with population of 1,934,537 as counted in December 2023 (uidai.gov.in). For accommodation of such huge population transformation, the city is expanding at the north and south direction mostly in the peripheral region towards Ahmedabad.

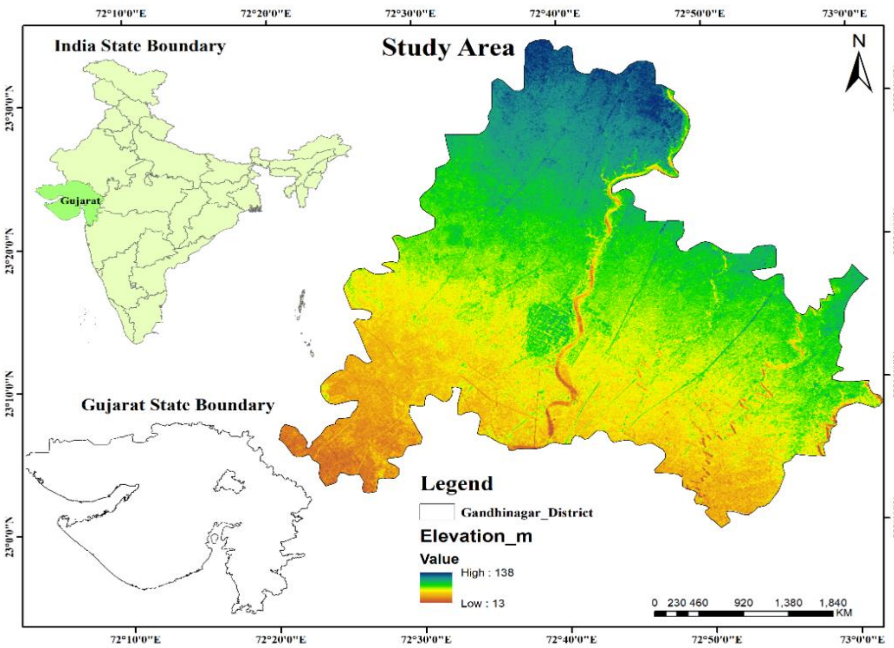

Fig. 1 Study area description and RGB images of district Gandhinagar

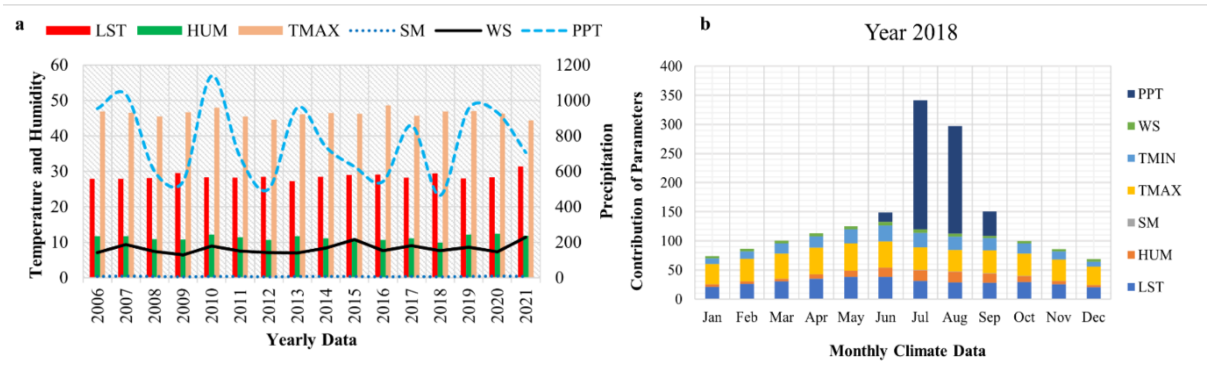

Fig. 2 Temporal Climate Data at Gandhinagar station and monthly contribution of individual parameters (LST- land surface temperature, HUM- humidity, Tmax- air temperature max, Tmin- air temperature min, SM- soil moisture, WS- Wind speed, PPT- precipitation)

a. Data

This study utilizes Landsat-TM, OLI, LISS-IV and climate data products for spatio-temporal monitoring of environment from 2006 to 2022 (Table 1). Landsat data level-2 products were obtained, then adjusted atmospheric and radiometric correction along with scan line error correction in Landsat-7. In order to get the consistent data, images are compared from both the years by uniformly selecting the May month at minimum cloud cover. The images are further layer stacked and clipped according to study area after pre-processing and respective indices were calculated afterwards. The land use classification is done using onscreen manual digitization with LISS-IV imageries. The LISS-IV dataset is provided by the National Remote Sensing Center (nrsc.gov.in), which has been comprehensively evaluated with first level of classification system at 90% accuracy status. Further dynamic modelling of land cover was performed in MOLUSCE tool of QGIS software based on multi-layer perceptron (MLP) neural network showing 0.59 kappa coefficient with 1000 iteration. The methodology of data processing and datasets used at their respective GIS software are further explained in fig. 3.

Table 1. Information of remote sensing data acquired at different time interval

Year	**Data type**	**Date**	**Path/Row**	**Cloudiness**
2006	Landsat TM	2006-05-16, 2006-05-06	148/44, 149/44	Less than 10%
2018, 2022	Landsat OLI	2018-05-25, 2018-05-16 2022-05-11, 2022-05-20	148/44, 149/44 148/44, 149/44	Less than 10%
2006	LISS-IV	2006-05-16, 2006-05-06	93/55-56	NA
2018	LISS-IV	2018-05-25,2 018-05-16	93/55-56	NA

2.3 Land use classification and accuracy assessment

Cloud free Resourcesat-2 LISS-IV images of the study area are acquired by NRSC at the Space Application Centre Ahmedabad at the dry season to avoid the seasonal fluctuation in LULC (Johansen et al. 2015). To enhance the quality of images, the data was pre-processed in ENVI 5.2 utilizing geometric, atmospheric, and radiometric correction. Before classification all the bands were layer stacked, mosaicked and subset in ERDAS IMAGIN software. The entire study area was classified using Onscreen digitization into four classes as Agriculture land, waterbody, Wasteland, and Built-up. The accuracy assessment is done using random point generation and validated in Google Earth showing 90% total accuracy which supports the results of true values with google earth data. For the overall accuracy percentage of matched number of sites to the total no. of sites has been calculated with the formula given below. The accuracy of individual land use classes is also calculated in the same manner.

$$Overall\ accuracy\ = \frac{Total\ number\ of\ correctly\ classified\ points}{total\ number\ of\ refrence\ points} * 100\ \textit{Eq. 1}$$

2.4 Calculation of remote sensing ecological index (RSEI)

The RSEI was first developed in 2013 to track the eco-environmental quality using the primary variables of greenness, wetness, dryness, and heat. The purpose of RSEI is to accomplice the convenient and fast results to visualize ecological environment. It can provide valuable information about the health status of ecosystem. The index has been utilized to observe the ecosystem of cities and monitor the urban environment which is calculated with equation 2.

$$RSEI = PCA(NDVI, TCW, NDBSI, LST)\ \textit{Eq. 2}$$

2.4.1 Green Index- Vegetation is an important part of terrestrial ecosystem which plays a significant role in various climatic phenomenon. Normalized Difference Vegetation Index can be calculated using NIR and RED bands of Landsat data which clearly indicates the vegetation coverage and nutritional information (Gao et al. 2022). The values generally range between -1 to +1, indicating poor and rich vegetation respectively.

$$NDVI = \frac{NIR-RED}{NIR+RED}\ \textit{Eq. 3}$$

2.4.2 Humidity/Wetness Index- The tasseled cap represents the environmental changes which describe the water and soil moisture. Wetness is represented by wet component of tasseled hat transformation which can be calculated by equation 4 and 5 (Crist 1985). The wetness index gives information of water content of soil and vegetation where constants vary according to dataset utilized.

$$WIETM = 0.0315\rho blue + 0.2021\rho green + 0.3012\rho red + 0.1594\rho nir - 0.6806\rho swir1 - 0.6109\rho swir2 \quad Eq.\ 4$$

$$WIOLI = 0.1511\rho blue + 0.1973\rho green + 0.3283\rho red + 0.3407\rho nir - 0.7117\rho swir1 - 0.4559\rho swir2 \quad Eq.\ 5$$

Where multiplication values are the coefficients and obtained from tasseled hat transformation of wetness index of Landsat TM and OLI with the literature (Crist 1985). $\boldsymbol{\rho}$blue, $\boldsymbol{\rho}$green…. are the bands of Landsat data.

2.4.3 Dryness Index- The ecological pattern of urban ecosystems is greatly influenced by LULC change within and beyond their boundaries. Among them, the change of ecological land to construction purpose is the notable physical feature, therefore build-up and soil index are used to represent the anthropogenic forces on environment. This index is characterized by built-up index (NDBI) and bare soil index (BSI). It represents no vegetation or negligible soil moisture which is due to replacement of natural land surface to built-up and bare soil. The expression of these indices are given in eq 6-8.

$$NDBI = SWIR - NIR/SWIR + NIR \quad Eq.\ 6$$

$$BSI = \frac{(SWIR+NIR)-(NIR+BLUE)}{(SWIR-NIR)+(NIR+BLUE)} \quad Eq.\ 7$$

$$NDBSI = \frac{NDBI+BSI}{2} \quad Eq.\ 8$$

2.4.4 Heat Index/LST- Urbanization alters the surface energy balance of urban ecosystem as compared to surrounding rural areas. Temperature not only affects the evolution of organisms, but also slight changes might be harmful to their development. In the following study heat index is calculated in terms of LST using band 10 in Landsat-OLI and band 6 in Landsat TM. The steps of LST calculation are differentiated into three sections: the conversion of atmospheric radiation brightness, the radiation brightness of ground through the atmosphere to satellite sensor, and energy reflected towards the ground as employed by various authors (Malik and Shukla 2018; Liu et al. 2021; Dutta et al. 2021). This study uses the LST calculation as done by Sukanya et al. 2022.

2.5 Standardization of indices and combination of indicators

Based on the above equation for various indices, we aimed to design the ecological index which allows the quick assessment of ecosystem quality. The quantitative interval of these four indices is different which are standardized by reclassification to get the values between 0 to 1 (eq. 14) (Carlson and Arthur 2000). The standardized images are run in PCA to get compressed multi-dimensional data with the relative importance of individual parameters and avoid impact of co-linearity between variables (Seddon et al. 2016). The weight or individual parameters are automatically assigned according to their contribution and prevent error in assigning weights in individual characteristics. ArcGIS PCA in spatial analysist tool is used to combine data into four bands PCA which is further calculated with eq. 15 to derive the final RSEI which falls between 0 to 1, the close values of RSEI to 1 entails the better ecological sustainability. The percentage eigen values and contribution of individual parameters is explained in table 3.

$$NDVIstd = \left(\frac{NDVI - NDVImin}{NDVImax - NDVImin}\right) \text{ Eq. 14}$$

$$RSEI = \left(\frac{PCA - PCAmin}{PCAmax - PCAmin}\right) \text{ Eq. 15}$$

2.6. Principal Component Analysis (PCA)

PCA explains the variability and reduces the dimensions of multiple datasets into a index values. It performs on a set of raster bands to give a single multiband raster output. Here the percentage variance identifies the amount of variance each eigenvalues captures which is useful to interpret the results of PCA. If very few eigenvalues are capturing the majority of variance, it is adequate to use this subset of bands in the analysis since they represent the majority of interaction within the dataset. The components having greater than 1 value are taken into consideration to understand the dominant parameter [Seddon et al. 2016, Campbell and Wynne 2011].

2.7 Surface Urban Heat Island effect

SUHI calculation was done as discussed in Sukanya et al, 2022. Two urban centers are identified in the study area, the city center Gandhinagar and Kalol taluka for comparision of the study.

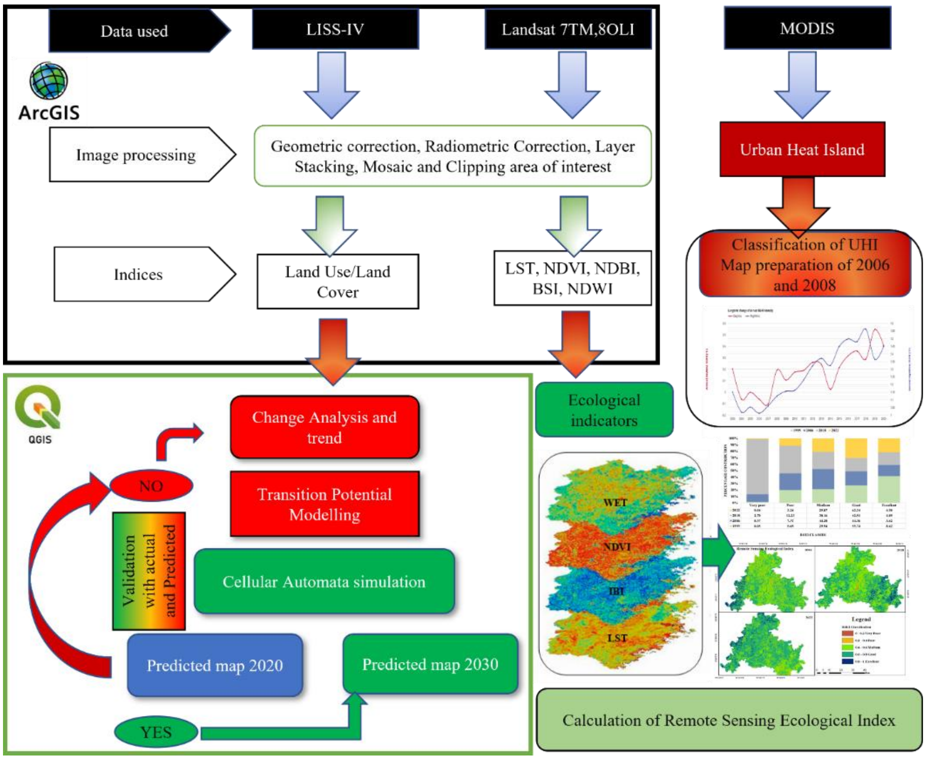

Fig. 3 Flow chart of selected dataset, applied Methodology and GIS platform to analyze the data

3 Results and Discussion

3.1 Change in LULC between 2006 to 2018 and projected expansion

The time series analysis of land cover change map has been presented (fig. 4-5). LULC statistics and transition patterns help to relate the forces behind the shifting of land use. The district has been classified under four major land use categories present in the study area which are Agriculture land, waterbody, built-up, and shrub land/wasteland. The most drastic change has occurred in built-up area which has expanded from 110 km^2 of land covered with residential and industrial area in 2006 to 181 km^2 in 2018. The maximum area was contributed by agriculture and bare land. The sides of the roads and construction of new roads are contributed by small scrubs. The river systems have been improved since 1995 as total area was occupied by only 38.4 km^2 of the area which has improved to 50 km^2. The extension of canal system at the north of the district has contributed to the increased water structure while at the same time small waterbodies disappeared due to increasing anthropogenic pressure. Hence after 2018, the waterbodies further decreased to 47.9 km^2 and predicted to decrease by 38.1 km^2 in 2030. The wasteland comprises 168 km^2 in 1995, while in 2006 it has increased to 294.6 km^2 and this area is continuously increasing to 350 km^2 and further the prediction map shows 484 km^2 in 2030. Agriculture, being the dominant class, has declined drastically from 1825 km^2 to 1456 km^2 till 2030 (fig. 4).

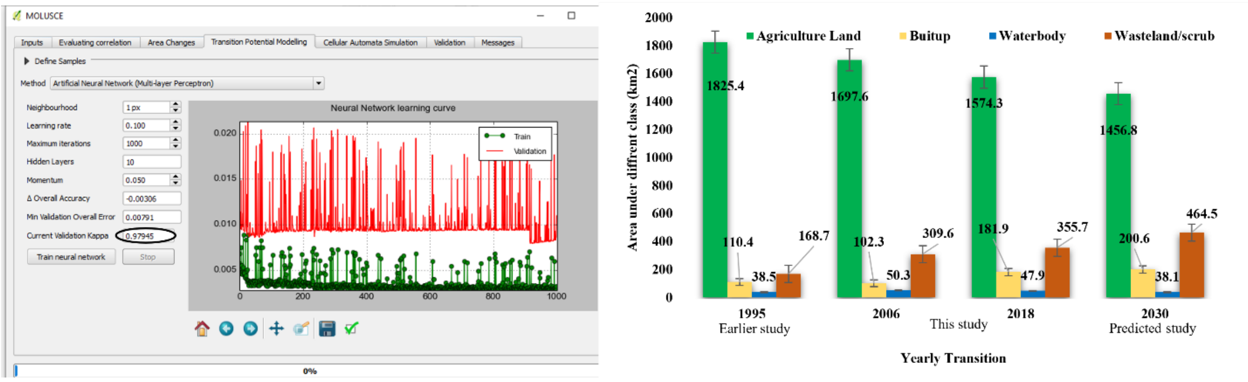

Fig. 4 Transition potential in MOLUSCE model and temporal variation of change in land use from 1995 to 2030

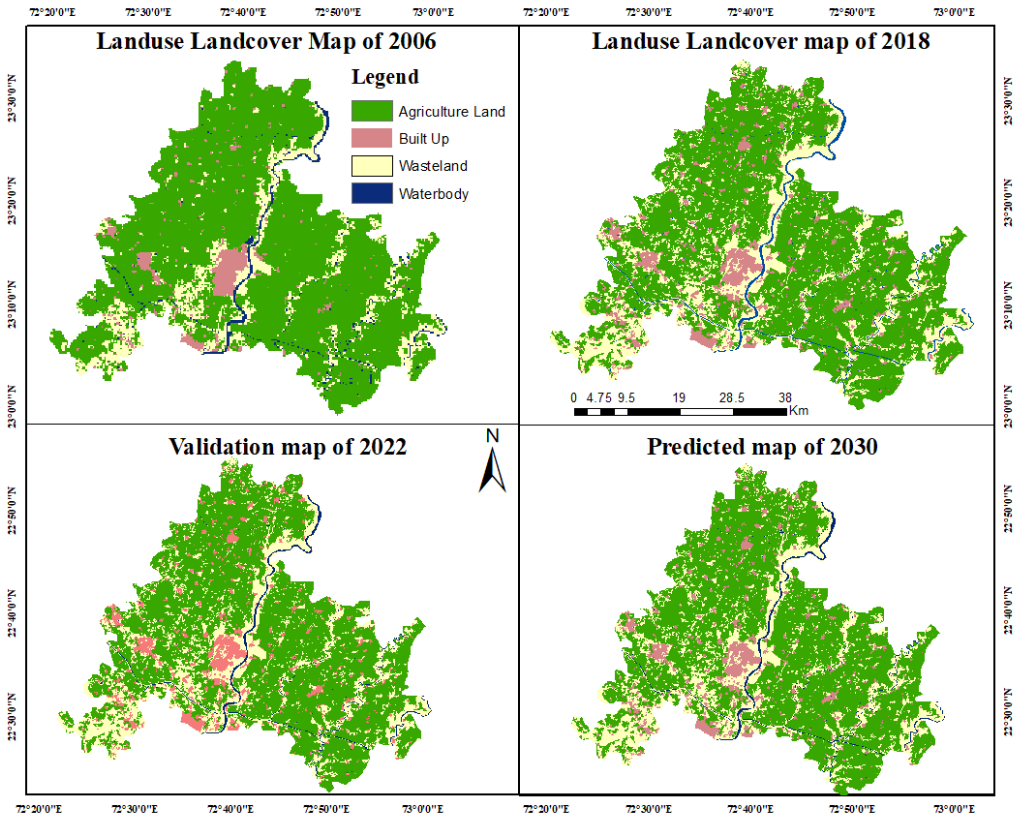

Fig. 5 Land use Land cover maps of two consecutive years with validation and prediction

3.2 Biophysical parameters of the study area

In this study we have computed vegetation in terms of NDVI, wetness as NDWI, dryness index as NDBSI and heat as LST as given in table 4. Fig. 6a explains the spatial variation of wetness index which is an important factor in RSEI because it helps in growth and productivity of ecosystem as plants require water to thrive. The index shows that there is a drastic decline was found in surface wetness after 2006 while a slight moisture has increased till 2022. The results are consistent with greenness index of area which falls between -0.24 to 0.77 in 2006 and -0.06 to 0.66 in 2018 with further increment till 2022 (fig. 6b). The positive values remark healthy vegetation and negative values are reflected by bare impervious land. The maximum value of NDVI is found to be 0.96 in 2022 due to limited destruction of natural resources after the covid lockdown. The overall results significantly explain that vegetation quality has declined due to changing natural landscape till now. On the other hand, the spatial variation of dryness index, which is the combination of built-up and soil index, also varies accordingly (fig. 7a). The values have increased from 0.61 to 0.7 and 0.8 till 2022 because of the declining vegetation and wetness of the area. Overall, these indices play a crucial role in obtaining the ecosystem quality of the study area.

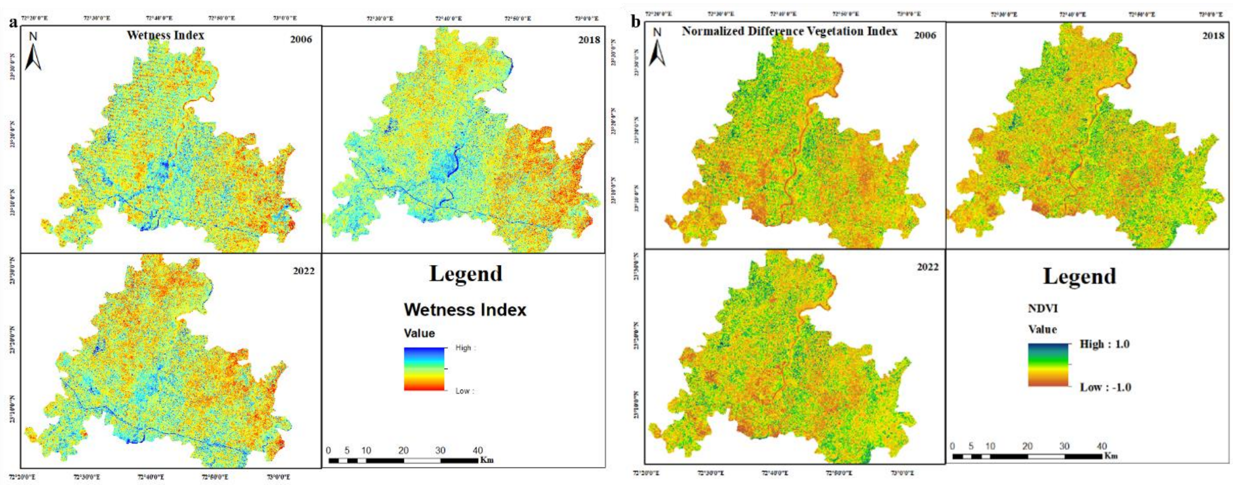

Fig. 6 Spatial maps of biophysical parameters a) Wetness index and b) Greenness Index

Table. 2 Statistics of minimum maximum mean of four indices used for ecological index

Parameters/Years	Min			Max			Mean			St Dv		
	2006	**2018**	**2022**	**2006**	**2018**	**2022**	**2006**	**2018**	**2022**	**2006**	**2018**	**2022**
Green Index	-0.24	-0.06	-0.15	0.77	0.66	0.96	0.26	0.26	0.29	0.09	0.07	0.08
Wet Index	-0.55	-0.41	-0.46	0.23	0.06	0.09	-0.2	-0.13	-0.1	0.04	0.03	0.04
Dry Index	-1.09	-0.64	-1.67	0.61	0.7	0.83	0.1	0.09	-0.26	0.15	0.09	0.19
Heat Index	20.26	30.7	30.15	50.79	49.6	48.67	38.07	41.19	42.04	3.17	1.93	2.98

3.6 Ecological sensitivity of the study area

In order to study the contribution of individual parameters (wetness, greenness, dryness and heat index) on RSEI values, Principal Component Analysis is done using ArcGIS 10.3. In table 2 the statistical data of individual components with their eigen values are given to understand the contribution of individual parameters on assessment of ecosystem quality. The factors which promote the quality of ecosystem were found to be degraded while unfavorable parameters like dryness and LST have increased to almost 50% in high and very high category (fig. 7). The greenness index has shrunk from 0.77 to 0.66 likewise the moisture content in the area was found slightly high at the central part where the river and canals are passing. The negatively affecting parameters, which are dryness and heat index, both have increased from 2006 to 2018 and further improved in 2022.

On the basis of these characteristics the remote sensing based ecological index has been developed. The descriptive analysis of the index shows that the ecosystem has been degraded since the area under poor RSEI values has drastically increased from 2006 to 2018 (fig. 12). At the same time the ecosystem has also improved due to the covid lockdown which has reflected at better ecosystem index in 2022. The values ranged between 0.0 to 1.05 and 0.0 to 1.21 during 2006 and 2018 respectively. Although the maximum values had increased from 1.05 to 1.21 with mean of 0.61 to 0.72 between 2006 to 2018 respectively but overall, the spatial extent has reduced. The effect of lockdown is also visible as improved ecosystem quality (RSEImean=0.88) was noticed in 2022. Few studies have also reported that natural resources were found to be rejuvenated at this time in Indian cities (Mishra et al. 2021; Joshi et al. 2022).

According to the technical criteria for good ecosystem quality, RSEI is divided into five classes that says <0.2 are very poor, 0.2-0.4 poor, 0.4-0.6 medium, 0.6-0.8 good and 0.8 to 1.0 are excellent (Gao et al. 2022). The spatial distribution map of RSEI shows that the central part of the study where all the major cities and villages are present have very poor ecological quality during both the study period. The area falling under very poor class increased from 7.8 km^2 to 58.3 km^2 which is due to increased built-up area. Likewise, the poor categories have also gained the area from 7.3 to 12.2%. The study area has undergone the construction of GIFT (Gujarat International Finance Tech) city and metro which has destroyed a vast natural resource and contributed to destruction of vegetation and wetness earlier in the area. The ecosystem has also improved due to plantation in the city as reported by GEER foundation, the RSEI values in Excellent class has gained almost 10 km^2 of area under this category proving the richness of vegetation due to tree plantation.

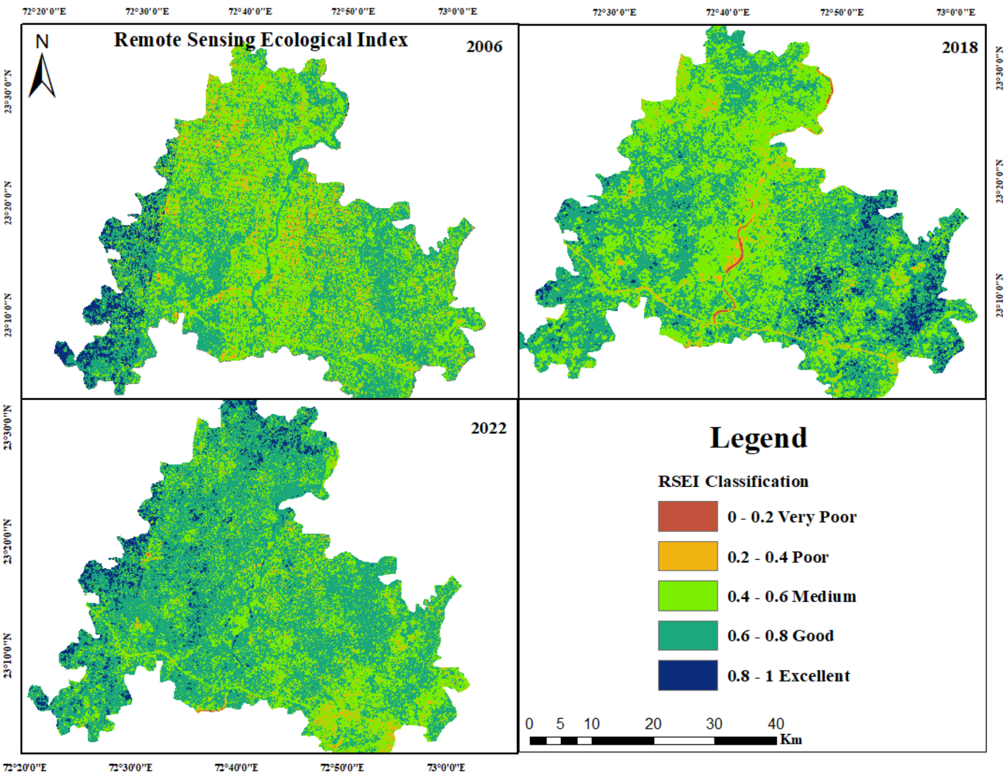

Fig. 7. Spatial Variation of Remote Sensing Ecological Index

5.0 Conclusion

This study examines the land cover changes in green city Gandhinagar that demonstrate a significant urban sprawl since the previous study carried out in the area. The primary changes in the land cover between 2006 and 2018 were decrease in agricultural land and an increase in built-up area. This behavior was mostly noticed at the southern area adjacent to Ahmedabad district and urban extension in Gandhinagar city. The land cover prediction based on CA-MLP showed satisfactory results for the district as kappa coefficient and percentage accuracy was 0.60 and 78% accuracy after 1000 iterations. The predicted map shows decreasing agriculture with minute changes in urban class while wasteland was increasing according to the prediction model till 2030. The result of increasing impervious surface is affecting LST which give rise to urban heat island effect. There is a significant increasing trend of LST of 2ºC during the summer season from 2006 to 2018 which is influencing the UHI of the district. The annual daytime and nighttime SUHI intensity of the district was found to be increased from 0.2 to 0.4 and 0 to 1.45 from 2003 to 2020 respectively which might influence the ecosystem of the urban dwellers. Further, till 2022 the improved surface temperature was noticed with improved biophysical factors like vegetation and wetness in the study area as an effect of post covid lockdown. The quality of urban ecosystem is identified using remote sensing ecological index by integrating four related indices important to human survival which are vegetation, wetness, dryness and heat index. The individual contribution of indices is noticed with principal component analysis. The vegetation richness was found to be degraded by 2018 as the classification shows that 44.2 km^2 of the area comes under rich vegetation while it was 84 km^2 during 2006. Likewise, the ecosystem quality was found to be decreased in medium and good quality classification while poor and very poor class has increased which clarifies that overall quality of ecosystem has degraded. This study shows that urban development has certain interferences on ecological environment therefore it is important to integrate ecological research to protect the sustainability of urban ecosystem. Hence effective urban green infrastructure planning and management are vital for creating sustainable, resilient, and inclusive cities to fulfill the Sustainable Development Goals by 2030.

Data Availability

All the data analyzed during the study are included in this research article.

Acknowledgement

The authors are thankful to the NRSC for providing the data & SERB for providing the fund (ECR/000202/2016).

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