Impact of land use and land cover change on the environmental quality of a region: A case of Ernakulam district in Kerala, India

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The increasing urbanisation trend over the decades has resulted in the rapid transformation of land use and land cover (LULC) patterns worldwide. One of the significant consequences of such an uncontrolled conversion process is on the environmental quality (EQ) of the regions, which needs to be addressed. Hence, the present study attempts to derive the environmental quality index (EQI) to measure the impact of LULC along a rapidly urbanising region. The study was divided into three phases. Firstly, the relevant variables were systematically identified from the literature and screened based on relevance, redundancy, context, and scale of the study. The variables then were finalised based on data availability and expert suggestions. The selected variables were grouped under bio-physical, LULC, and socio-economic domains. Secondly, using remote sensing and geographic information system (GIS) techniques, LULC analysis was performed and the bio-physical variables were processed. The LULC maps (with five classes: water body, settlements, hill, forest, and agriculture) were prepared for the study region for 2000, 2009, and 2019 from Landsat images using a supervised classification algorithm. The LULC analysis showed an increase in the settlement over the past two decades. The relationship between the bio-physical indicators, namely, land surface temperature (LST), normalised difference vegetation index, and normalised difference built-up index (NDBI), was also established to examine the general perception that the increase in urbanisation is one of the main causes for the increase in LST of a region. The correlation indicated that the LST increased with a reduction in vegetation area and growth in settlement areas. Finally, the EQI was constructed using the entropy method of weighting. The spatial mapping of the EQ of the region was obtained and planning interventions were discussed. The EQI map demonstrated that the areas with more industrial belts had poorer EQ compared with other areas. The study also revealed that the conversion of the land cover into different land use types has led to the poor EQ of the region. The insights from the study can help the planners, administrators, and policymakers to make informed decisions regarding the EQ of a region and future urban construction activities in an area.

Keywords:
spatial mapping,
remote sensing,
entropy method,
environmental quality index (EQI),
Regional environmental planning

Introduction

Environmental quality (EQ) and the quality of life positively influence each other (Moses et al. 2016). However, the quality of human life and the living environment have tremendously deteriorated with the increase in urbanisation worldwide (Sheela et al. 2014, Shimamoto 2019). This encroachment on the environment needs to be fixed, at least henceforth. An EQ Index (EQI) can be a possible primary tool to assess the environmental threats to an area. The Environmental Protection Agency researchers designed the EQI to present the overall EQ for the period 2000–2005 and its impact on public health for all the counties in the United States. Other studies, which primarily focus on any one particular domain of the environment or a bigger spatial resolution have also been conducted (Emerson et al. 2012). However, carrying out such studies at the regional as well as the local level and covering the heterogeneous components of the environment are needed (Musse et al. 2018). Through the construction of EQI, the residents of an area can be informed about the EQ of their place of living. A broader level comparison is possible among the different regions, which brings a sense of awareness among the community about the importance of maintaining the EQ. It can help policymakers, planners, and administrators to make way for an environment-friendly habitat. The common person can identify the areas with the best, average, and the least EQ, enabling him/her to propose and carry out suitable corrective actions. The EQI construction also finds its importance in the classification of regions into different clusters. The clusters can be further investigated in detail for the EQ performance at a local level for planning and implementing appropriate measures (Krishnan–Firoz 2020). The EQI spatial mapping can also be made as a mandatory process in the preparation of master plans and regional plans (Panagopoulos et al. 2016).

With the increase in sprawl and urbanisation in cities, LULC change detection has become the key objective of any urban planning study (Yuan 2008). In recent years, LULC distribution patterns have changed immensely. The decrease in agricultural lands and the rise in built-up areas are some of the visual evidence of modifications in LULC patterns (Deng et al. 2019). Changes in LULC of an area occur due to both natural and anthropogenic causes. In India, several studies have investigated the effects of LULC change over decades (Nayak–Mandal 2019, Kharol et al. 2013, Gogoi et al. 2019). Most of these studies are limited to metropolitan cities (Rose–Devadas 2009, Grover–Singh 2015, Dhar et al. 2019). However, high-quality research specifically relating to LULC change detection and its effects on EQ and land resources at a regional scale is relatively scant (Mishra et al. 2019). The development of remote sensing and GIS has played a vital role in mapping and studying these changes with more accuracy and in less time (Trinder–Liu 2020, Rawat–Kumar 2015).

Variable selection, weighting, and aggregation are the essential and challenging elements of EQI construction (Krishnan 2010, OECD 2008, Malakar–Mishra 2017). Both subjective and objective techniques for expressing the importance of the variables are available today. These include expert opinion (Krishnan et al. 2016), analytical hierarchy process (Ying et al. 2007), principal component analysis (Krishnan–Firoz 2020, Fernandez-Crehuet et al. 2019, Fathim–Firoz 2018), fuzzy evaluation technique (Asadi et al. 2017), and entropy method (Zou et al. 2006). The subjective methods have a drawback of getting influenced by the expert's knowledge and experience (Zhao et al. 2018). The entropy method is an objective way of assigning the weights to variables based on the observation entry of each variable (Zhao et al. 2018). According to the entropy method, the indicator that has more variation among the observations is assigned the highest weight (Zou et al. 2006). Unbiased relative variable weights can be obtained by using the entropy method as it eliminates subjectivity (Zardari et al. 2015). Hence, in the present study, the entropy method of weighting variables is used. Validation is important to develop any composite index (Dehdasht et al. 2020). The validation of a model and its sensitivity analysis are connected as both attempt to check the suitability of a specific model. Many scholars have employed the results from the sensitivity analysis to validate a model (Smith et al. 2008, Salciccioli et al. 2016).

In this study, we seek to address mainly three research questions: (1) With the increasing urbanisation rate in the region under study, has there been a considerable change in LULC over the past two decades? (2) Is the increase in urbanisation one of the reasons for the increase in LST. (3) Does the LULC change influence the EQ of a region? The first research question is addressed by conducting a LULC change analysis of the study region for the years 2000, 2009, and 2019. The second question is attempted to be answered by performing a correlation analysis of the LST with the normalised difference vegetation index (NDVI) and NDBI of the study region for the three years. The final question is to evaluate the influence of LULC change on the EQ of a region by constructing an EQI involving the LULC classes, bio-physical indicators, and socio-economic indicators. In the present study, the entropy method of weighting is used. Finally, EQI scores are represented in the form of a spatial map that can be used for making further interpretations and suggestions for improvement.

Materials and methods

Study region

The study region is Ernakulam, one of the districts[1] of the state[1] of Kerala, India (Figure 1). The rate of urbanisation in Kerala has increased from 25.9% in 2001 to 47.7% in 2011 (Praveen–Sajini 2018, Firoz et al. 2014, Kumar et al. 2020, Firoz–Kumar 2017), showing an increase of 92.72% in urban population during this period.

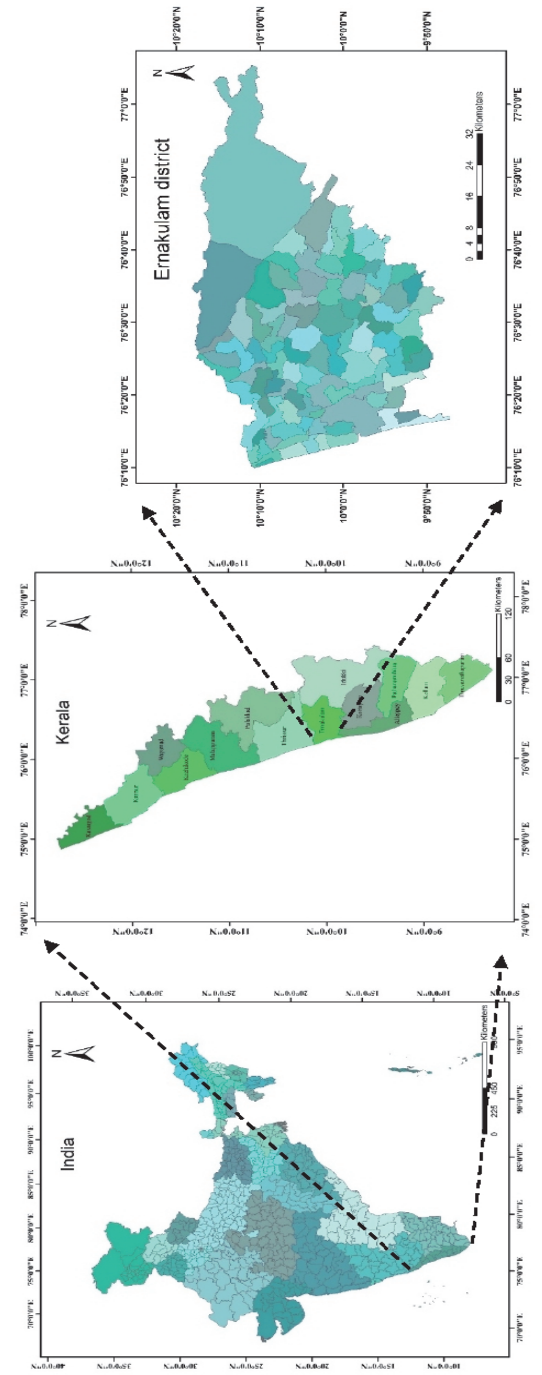
Ernakulam was taken as the case study region because of its highest decadal increase in urbanisation rate (68.07% according to the Census of India 2011 data) (Praveen–Sajini 2018). Kochi, which is the commercial, industrial, and financial capital of Kerala, is situated in this district and has the best connectivity through air routes, railways, and road networks, thus making it the most promising economically developed region. The effects of LULC transformations on the EQ was addressed by taking this case study, thereby rendering it truly representative for showcasing the impacts of urbanisation on the environment. The study region consists of 97 local bodies (LBs)[2], which are the units of analysis in the present work.

[1] India as a country is divided into states and union territories. Each state has its government elected separately (Census of India 2011). India has 28 states (as of 2020) and Kerala is one among them. The states within the country are divided into districts intended for administrative purposes, revenue collection, maintaining law and order etc. Kerala has 14 districts and each district is divided into subdistricts, which are known differently in diverse parts of the country, for example, Taluka, Tahsil, Blocks, Mandal (Census of India 2011).

[2] In India, LBs are the institutions of local self governance, constituted for local planning, development and administration in the rural and urban areas (Ministry of Statistics and Programme Implementation Government of India 2018, Krishnan–Firoz 2020).

Figure 1

Location of the study area



Variable selection

After the delineation/selection of the study area, the next step in the EQI construction (Figure 2) is the variable selection. The variable identification and selection were carried out in three different stages (Figure 3). Firstly, the relevant peer-reviewed articles were collected from the databases Science Direct and Google Scholar by using the keyword search, such as 'regional environmental quality', 'LULC', 'spatial mapping', and 'EQI'. The articles were first screened by reading their titles and abstracts (Feil et al. 2019, Ren et al. 2020) and only the relevant articles were studied in detail. Secondly, the comprehensive list of variables (variable list 1) associated with the EQ assessment and LULC analysis was identified and formed.

Figure 2

Methodology of the study

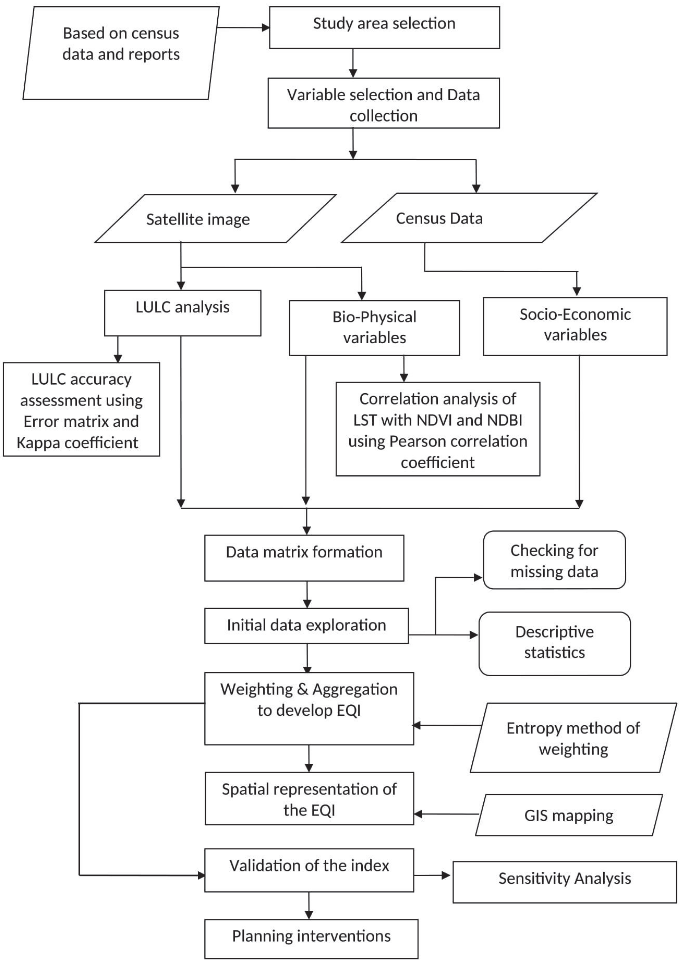
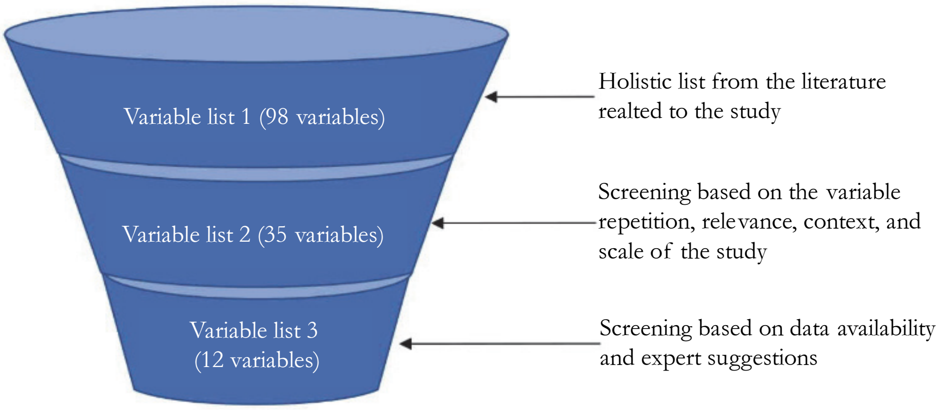


Figure 3

Variable screening procedure



Variable list 1 was only a comprehensive inventory of the variables that are commonly studied and addressed by scholars in the related areas of research. Hence, a systematic screening of the list was needed to represent the indicators specific to the topic and the scale of the study. Therefore, the variable list 1 was vetted based on its repetition (because many variables that shared the same meaning but designated differently were present), context and scale of the study (regional level), and the relevance. Thus, the variable list 2 was derived, which was grouped into three domains (bio-physical, LULC, and socio-economic domains). Finally, the variable list 3 was finalised (Table 1) based mostly on data availability and expert suggestions.

The first category, bio-physical variables, are most commonly used as proxy variables to indicate the importance of vegetation and the effect of built-up areas on EQ (Hadeel et al. 2011). The indices used in the bio-physical domain have the property of differentiating surface features (Mushore et al. 2018). The second category, which involves the LULC classes, is important to understand the effect of urbanisation in terms of change in land use patterns and conversion of land cover (Sun et al. 2020). LULC transformations have a great impact on the environmental sustainability of society (Yuan 2008). Finally, along with the LULC class and bio-physical variables, socio-economic variables were included to understand the interaction of people with the environment (Musse et al. 2018) because land use change directly influences the population. The regions with a higher population tend to have more economic importance (Hughes–Brundrit 1992, Kunte et al. 2014). Thus, any undesirable change in the land use pattern and causing environmental distress due to the anthropogenic activity leads to the devastation of the society (Mansur et al. 2016). Further, (Boori et al. 2014) reported that socio-economic actions are the main reason for environmental vulnerability.

Table 1

Variables selected for the EQ assessment

Sl. No:	Indicator	Variable Name	Variable Notation
1	Bio-physical	Land surface temperature	LST
2		Normalised difference vegetation index	NDVI
3		Normalised difference built-up index	NDBI
4	Land environment	% of the area covered by water body	Water
5		% of the area covered by settlements	Settlements
6		% of the area covered by forest	Forest
7		% of the area covered by hill	Hill
8		% of the area covered by agriculture	Agriculture
9	Socio-economic environment	Population density	PD
10		Household density	HHD
11		Percentage literate	Lit_percent
12		Workforce participation	Work_Part

Collection of data

Primary and secondary data were used in the study. The primary data comprised satellite images downloaded from the Earth Explorer interface developed by the United States Geological Survey (Mishra et al. 2019). Landsat 8 and Landsat 7 images were used (Dekolo et al. 2015) for deriving LULC classes and bio-physical variables (Table 2). To offer better analyses and interpretations, images with lower than 10% cloud cover were used. The secondary data, which included the socio-economic variables, were gathered from the Census of India website.

Table 2

Description of satellite images used in the study

Satellite	Sensor	Date of acquisition	Number of bands	Bands used	Spatial resolution (m)
Landsat 7	Enhanced Thematic Mapper Plus (ETM+)	28 January 2000	8	Bands 1–7	30
Landsat 7	ETM+	25 March 2009	8	Bands 1–7	30
Landsat 8	Operational Land Imager and Thermal Infrared Scanner	13 March 2019	11	Bands 1–7 (for LULC) Bands 10 and 11 (for LST)	30 100 m

LULC analysis

The details of the LULC classification are critical for the various aspects of urban planning. For example, LULC information is required for land development, regular monitoring and evaluation of land use, environmental planning and management, construction activities, and landscape development. LULC change has a large impact on the environmental status of a region or an area. When a particular type of land cover is converted into another land use type, then its effects tend to be accumulative (Yuan 2008). Hence, assessing the relationship between the LULC type and the EQ of a region is of utmost importance in the present urbanised world.

Studies over the past decades [e.g. (Hadeel et al. 2011, Rawat–Kumar 2015, Dhar et al. 2019)] have provided important information on the LULC changes in diverse parts of the world, including India, and have emphasised the changes in the environment and LULC patterns, stressing the increase in built-up areas over the decades. Kochi city entered the phase of economic growth in 2000 (Department of Town and Country Planning 2011). During 2008–2009, the tertiary sector in Kerala recorded the highest growth rate of 16.22% compared to the primary sector growth rate of 7.10% (Government of Kerala 2009). Recently, in 2017–2018, the agriculture and the associated sectors in Kerala registered a better growth rate of 3.64% when compared to the growth of 3.37% for entire India (Government of Kerala 2018). Considering all the above-mentioned facts and rationales, in the current study, the LULC change assessment was measured over the past 19 years (2000, 2009, and 2019) and the EQ was evaluated for the year 2019.

For the analysis, the satellite images were first pre-processed for geo-referencing, atmospheric correction, and radiometric correction (Hadeel et al. 2011) using ERDAS Imagine 2013 and ENVI 5.2 software. Initially, all the three satellite data were georeferenced to UTM Zone 43 N with WGS 1984 datum (Dhar et al., 2019). Landsat 7 images of 2000 and 2009 were imported to ERDAS Imagine 2013 software. Bands 1 to 7 were layer stacked and the study area was subsetted. The scan-line corrector of the Landsat 7 ETM+ sensor failed in 2003. Hence, the image acquired for 2009 had a few wedge-shaped gaps that needed to be filled before using it for further analysis (Chen et al. 2012). The focal analysis tool was used to fill the scan-line corrector gaps. Atmospheric correction (ATCOR) was applied for both 2000 and 2009 Landsat 7 images using the details, such as acquisition date, sensor name, and solar zenith, of the satellite data. The radiometric correction was performed for satellite images that included haze as the presence of haze decreases the accuracy of image interpretation and analysis (Makarau et al. 2013). Landsat 8 image of 2019 was imported to ENVI 5.2 software for image pre-processing. Initially, radiometric calibration was conducted, which included the conversion of digital number (DN) to top-of-atmosphere (TOA) radiance in band-interleaved-by-line format. The fast line-of-sight atmospheric analysis of hypercubes atmospheric correction was then performed. Next, the reflectance was rescaled to 0–1, the study area was subsetted, and inverse minimum noise fraction rotation was performed for the final surface reflectance.

The pre-processed Landsat images were opened in ArcMap10.5 software for the LULC classification. The supervised classification method was employed to categorise the pixels into suitable LULC classes. Maximum likelihood classification was adopted by collecting more than 100 training samples/regions for each class. Signature files for each class were created. The satellite images were categorised into five different LULC classes, namely, water body, settlements, forest, hill, and agriculture (Mishra et al. 2019, Ullah et al. 2019, Boori et al. 2014).

Accuracy assessment

Accuracy of the classified LULC was assessed by using an error matrix and Kappa coefficient (Hadeel et al. 2011, Dhar et al. 2019). An error matrix has quantitative data about the real and forecast LULC classes, as classified by a specific classification method. The assessment was based upon the predicted class by the system and the actual type of LULC present on the ground. The actual class was identified by conducting a field survey using the global positioning system (GPS) and Google Earth points.

The accuracy parameters included overall accuracy, user's accuracy, producer's accuracy, and Kappa coefficient (Patel–Kaushal 2010, Dhar et al. 2019). The overall accuracy is the percentage of correctly classified pixels and the total number of ground truth points (Dhar et al. 2019). The user's accuracy is the percentage of the correctly classified pixels in each class and the total number of pixels in the respective class (Grigoraş–Uriţescu 2019). The producer's accuracy is the percentage of the correctly classified pixels in each class and the total number of ground truth pixels of the respective class (Pal–Ziaul 2017). The Kappa coefficient is an indicator of the closeness of the classified image and the ground truth reality (Dhar et al. 2019) (Ullah et al. 2019). Coefficient values close to 1 represent a very good agreement between the classification and reality, whereas values close to 0 represent complete randomness (Dhar et al. 2019).

Extraction of LST, NDVI, and NDBI

For the extraction of LST, thermal bands 6 and 10 were used for Landsat 7 and Landsat 8, respectively. LST retrieval was carried out in ArcGIS 10.5. The process involved a series of steps (Li et al. 2016, Dhar et al. 2019, Grigoraş–Uriţescu 2019).

(i) Conversion of DN to at-sensor spectral radiance

The satellite image contains information in the form of DN. Hence, it was converted to at-sensor spectral radiance [equation (1)] using the spatial analysis tool in ArcGIS.

$$L\lambda = ML * Q_{cal} + AL \qquad (1)$$

where $L\lambda$ = spectral radiance at sensor's aperture (in W m^{-2} sr^{-1} μm^{-1}); ML = band-specific multiplicative rescaling factor from Landsat metadata; AL = band-specific additive rescaling factor from Landsat metadata; and Q_{cal} = Level 1 pixel value in DN.

(ii) Conversion of radiance into TOA brightness temperature

In the second step of extraction, thermal calibration was carried out, which involved the conversion of spectral radiance to TOA brightness temperature using equation (2).

$$TB = K_2 / \ln(K_1/L\lambda + 1) - 273.15 \quad (2)$$

where TB = TOA brightness temperature (°C); $L\lambda$ = spectral radiance at sensor's aperture (in W m^{-2} sr^{-1} μm^{-1}); and K_1, K_2 = Thermal conversion constants for the bands.

(iii) Conversion of TOA brightness temperature into LST

In the final step, the TOA brightness temperature was converted to LST using equations (3) and (4).

$$LST = TB/[1+(\lambda * TB/\rho) * \ln\varepsilon] \quad (3)$$

where LST = Land surface temperature (°C); λ = central band wavelength of the emitted radiance; $\rho = hc/\sigma$ (1.438×10^{-2} mK); and ε = surface emissivity. ε was calculated according to the following equation:

$$\varepsilon = 0.004 * P_v + 0.986 \quad (4)$$

where P_v = vegetation proportion.

P_v was calculated using the following equation:

$$P_v = [(NDVI - NDVI_{min})/(NDVI_{max} - NDVI_{min})]^2 \quad (5)$$

where NDVI = Normalised difference vegetation index; the extraction procedure is explained in the subsequent paragraph.

NDVI is an indicator of the vegetation of an area and its value ranges from −1 to 1. The values between −1 to 0 represent water bodies and those between 0.6 to 1 represent dense forests. NDVI was extracted from the Landsat image using near-infrared and red bands [equations (6) and (7)] (Li et al. 2016, Hadeel et al. 2011).

For Landsat 7, NDVI = float (Band 4 − Band 3) / float (Band 4 + Band 3) (6)

For Landsat 8, NDVI = float (Band 5 − Band 4) / float (Band 5 + Band 4) (7)

NDBI is an indicator to extract built-up pixels from satellite images. To extract NDBI from the Landsat images, shortwave infrared and near-infrared bands were used [equations (8) and (9)] (Hadeel et al. 2011). NDBI values also range from −1 to 1. Negative values represent water bodies and positive values represent built-up areas.

For Landsat 7, NDBI = float (Band 5 − Band 4) / float (Band 5 + Band 4) (8)

For Landsat 8, NDBI = float (Band 6 − Band 5) / float (Band 6+ Band 5) (9)

Relationship between NDVI and LST vs NDBI and LST

The variation of NDVI and NDBI with LST for all three years (2000, 2009, and 2019) was established statistically using the Pearson correlation coefficient (Dhar et al. 2019, Valkó et al. 2017). The relationship was graphically represented in the form of scatter plots (Deng et al. 2019). The correlation coefficient values vary between −1 to 1, indicating the negative or positive correlation between the two variables. Adjusted R^2 values were also calculated to measure the proportion of the dependent variable (i.e. LST) explained by the independent variables (i.e. NDVI and NDBI) (Pal–Ziaul 2017). Adjusted R^2 value ranges between 0 and 1, with higher values representing a good fit of the model (Pal–Ziaul 2017).

Construction of EQI

Variable selection and data collection were explained previously. For the data matrix formation, the LULC classes and bio-physical variables (LST, NDVI, and NDBI) were processed from satellite images as explained previously. The data were collected for each observation unit of the study area. Data exploration was carried out and weighting the variables was performed using the entropy technique. The weighted variables were aggregated and an EQ score/index was obtained for each unit. Finally, the obtained scores were mapped spatially with the GIS techniques, and the EQI map for the study region was created. The detailed explanation of each stage of index construction is explained in the subsequent sections.

Initial data exploration

In the present study, after completion of the extraction and collection of data for all the selected variables, the data matrix was created with the units of observations on the rows and the variables on the columns (Bartholomew et al. 2008). Initial data exploration is needed in any index construction to understand the behaviour and trends in the dataset (Gudivada 2017) (Krishnan–Firoz 2020). Missing data imputation, obtaining the descriptive statistics of the data, and normalising the data were included in the initial data exploration (OECD 2008, Hair et al. 2014, Firoz et al. 2015). Missing data imputation is required to avoid the incompleteness of the dataset before using it for analysis (Hair et al. 2014). The presence of missing data hampers the construction of a healthy index for the required purpose. The socio-economic variables had a few missing data, which were substituted with the average values of the corresponding variables (Nardo et al. 2005). Secondly, the descriptive statistics were calculated to describe the summary of the dataset (Almeida–García-Sánchez 2016, Gudivada 2017). The mean, standard deviation, coefficient of variation, minimum, and maximum were calculated for each variable using SPSS 16.0 software (Musse et al. 2018, Krishnan–Firoz 2020). Lastly, normalisation of the dataset is a prerequisite before aggregation of the variables (OECD 2008, Talukder et al. 2017) because the variables were collected or processed from different sources, implying a high probability of the variables having different units of measurement (Faisal–Shaker 2017). Therefore, the dataset should be converted into the same units for further analysis (Nardo et al. 2005) using the data standardisation technique (Talukder et al. 2017, Zuo et al. 2017).

Weighting and aggregation

After summarising the main characteristics of the dataset, the next step was to give weights to each variable. In this study, the objective method is selected for weighting. The entropy method of weighting, in which, the higher is the difference between the values of each variable, the higher is the preference given to the corresponding variable (Zhao et al. 2018), was introduced to calculate weights for each variable. The procedure for deriving weights using the entropy method was based on the studies by Lenjanat (2014), and Han et al. (2015). The linear method of aggregation was adopted for the aggregation of the weighted variables to derive the EQI for each LB (Lindén 2018). The EQI was normalised using the rescaling method [equation (10)] to obtain a uniform set of values for each LB in the entire study region (Talukder et al. 2017, Suarez-Alvarez et al. 2012). The normalised index was better represented in the form of a map, with different colour codes representing the quality of the environment.

$$\text{EQI of each unit} = (\text{EQI of each unit} - \text{Min. of EQI}) / (\text{Max. of EQI} - \text{Min. of EQI}) * 100 \tag{10}$$

Sensitivity analysis

Sensitivity analysis is important in spatio-temporal models (Javanbakht et al. 2021). The output model may be affected by various error sources, and thus, the accuracy of the model can be checked by using this analysis (Ghajari et al. 2018). In general, sensitivity analysis is of two types: local and global (Tate 2012). In the first type, the model input options are varied in percentage by changing them successively. By contrast, the latter assesses the model output variations by considering the full scale of the uncertainty of the input options (Lilburne–Tarantola 2009, Tate 2012). In the present study, the validation and the robustness of the model were carried out using local sensitivity analysis because the past data were not available to perform a real-time validation approach. The method involved increasing and decreasing the weights of all the 12 variables by 10% in succession (Ghajari et al. 2018) and examining the corresponding changes in the final EQI of each LB for each case. Therefore, in total, 24 iterations of sensitivity analysis were carried out for the entropy model. When the weight of a particular variable was increased or decreased by p%, its new value was calculated using equation (11) and the remaining variables were decreased or increased, respectively, using equation (12), so that the sum of all the weights remained 1 (Ghajari et al. 2018, Eldrandaly 2013).

$$W(v_m, p) = W(v_m, 0) + W(v_m, 0) * p, \; n \geq m \geq 1 \tag{11}$$

$$W(v_i, p) = [1 - W(v_m, p)] * W(v_i, 0) / [1 - W(v_m, 0)], \; i \neq m, \; n \geq i \geq 1 \tag{12}$$

where $W(v_m, p)$ is the new value of the m^th^ variable when it is changed by p%; $W(v_m, 0)$ is the weight of the m^th^ variable at its base run; $W(v_i, p)$ is the weight of the other variables when the m^th^ variable alone is changed; and $W(v_i, 0)$ is the weight of the other variable at its base run.

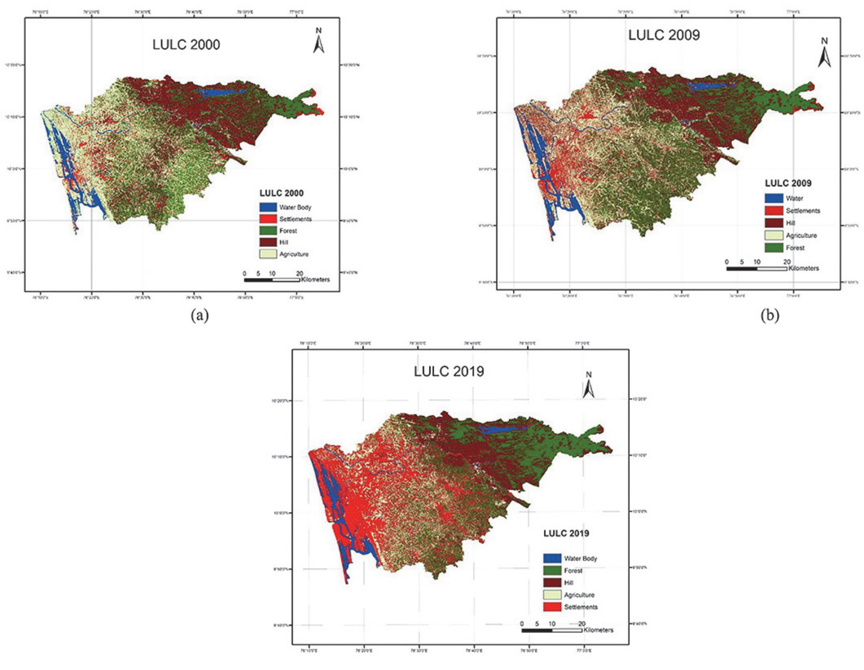
Results

LULC change detection and analysis

LULC classification of the study region for 2000, 2009, and 2019 was carried out using the maximum likelihood classification method (Figure 4). The study area was divided into five LULC classes, namely, water body, settlements, forest, hill, and agriculture. The percentage of area covered by each class (Figure 5) illustrated that the settlement areas were less prevalent in 2000. The area covered by agricultural land declined drastically from 29.83% in 2000 to 15.79% in 2019 (Figure 5). The decadal change in LULC classes (Figure 6) showed a very high positive change for the settlements. All other classes registered a negative change, with the agricultural class exhibiting the highest negative change.

Figure 4

LULC classification of the study region (a) 2000 (b) 2009 (c) 2019



(a) (b) (c)

Figure 5

Percentage of the area covered by each LULC class

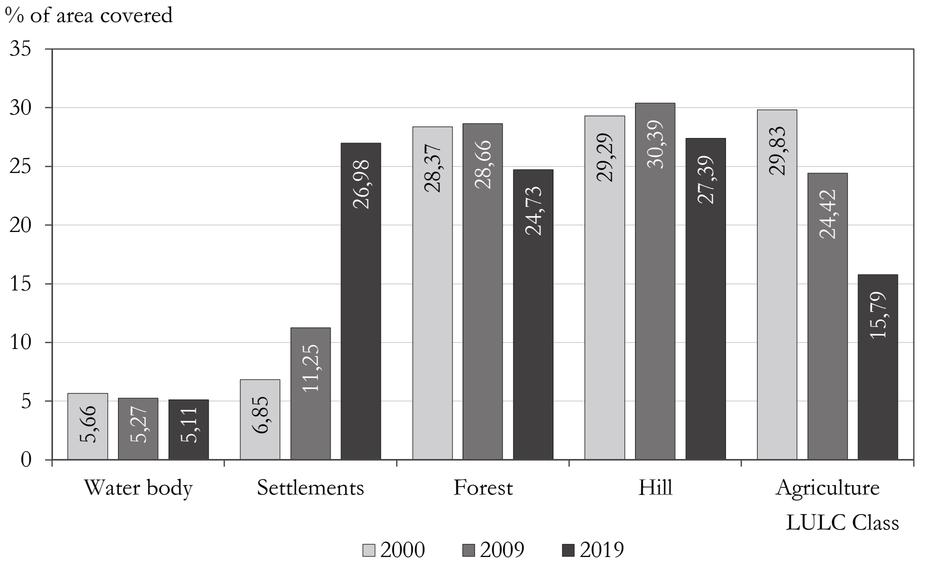
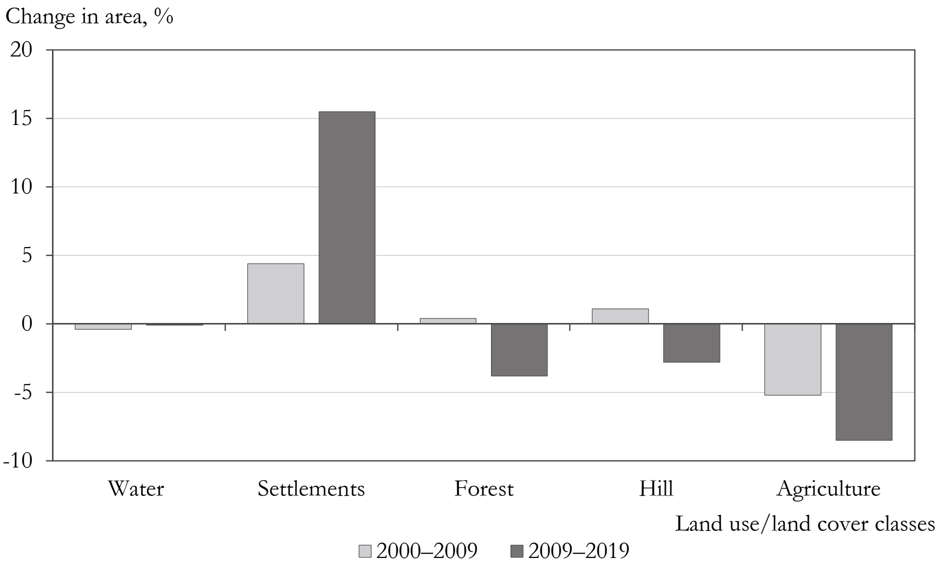


Figure 6

LULC change for 2000–2009 and 2009–2019



Accuracy assessment

Accuracy assessment was performed by comparing the classified LULC image with the ground truth observation (reference image). Stratified random sampling was adopted by selecting 250 random points on the ground (50 points per LULC class) using GPS survey (Figure 7) and Google Earth imagery (Congalton 1991, Haque–Basak 2017). The accuracy assessment was carried out for the year 2019 alone because of the non-availability of GPS points and clear Google Earth points for the years 2000 and 2009 (Mishra et al. 2019). Approximately 79% of overall accuracy was obtained in the LULC classification by employing the maximum likelihood method of supervised classification (Table 3). The Kappa coefficient was obtained as 0.74, which showed that the model reflects reality (Pal–Ziaul 2017).

Figure 7

Some of the locations of field survey using GPS

(a) (b)

(c) (d)

Table 3

Accuracy assessment of the classified image (2019)

LULC Class	Producer's Accuracy	Users' Accuracy	Overall Accuracy	Kappa Coefficient
Water body	100.00	86.00	79.20	0.74
Settlements	83.93	94.00		
Forest	75.00	66.00		
Hill	64.00	96.00		
Agriculture	84.38	54.00		

Extraction of LST, NDVI, and NDBI

Thermal bands of the Landsat images were employed for extracting LST, NDVI, and NDBI and were derived using red, near-infrared, and shortwave infrared bands, as explained previously. The spatial mapping of LST of the study region showed that the average temperature prevalent in the LBs had increased from 22.5°C in 2000 to 39°C in 2019 (Figure 8, Table 4). Similarly, the spatial distribution of NDVI and NDBI across the study region demonstrated that the vegetation percentage of the study region had decreased, whereas the settlement percentage had increased (Figure 9).

Figure 8

Spatial distribution of LST of Ernakulam district (a) 2000 (b) 2009 (c) 2019

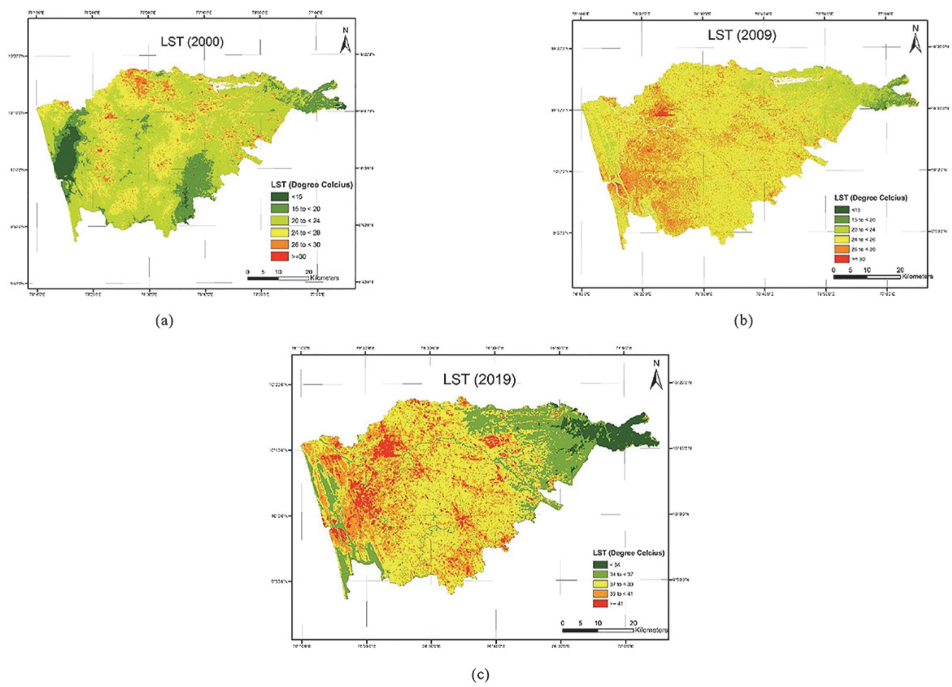
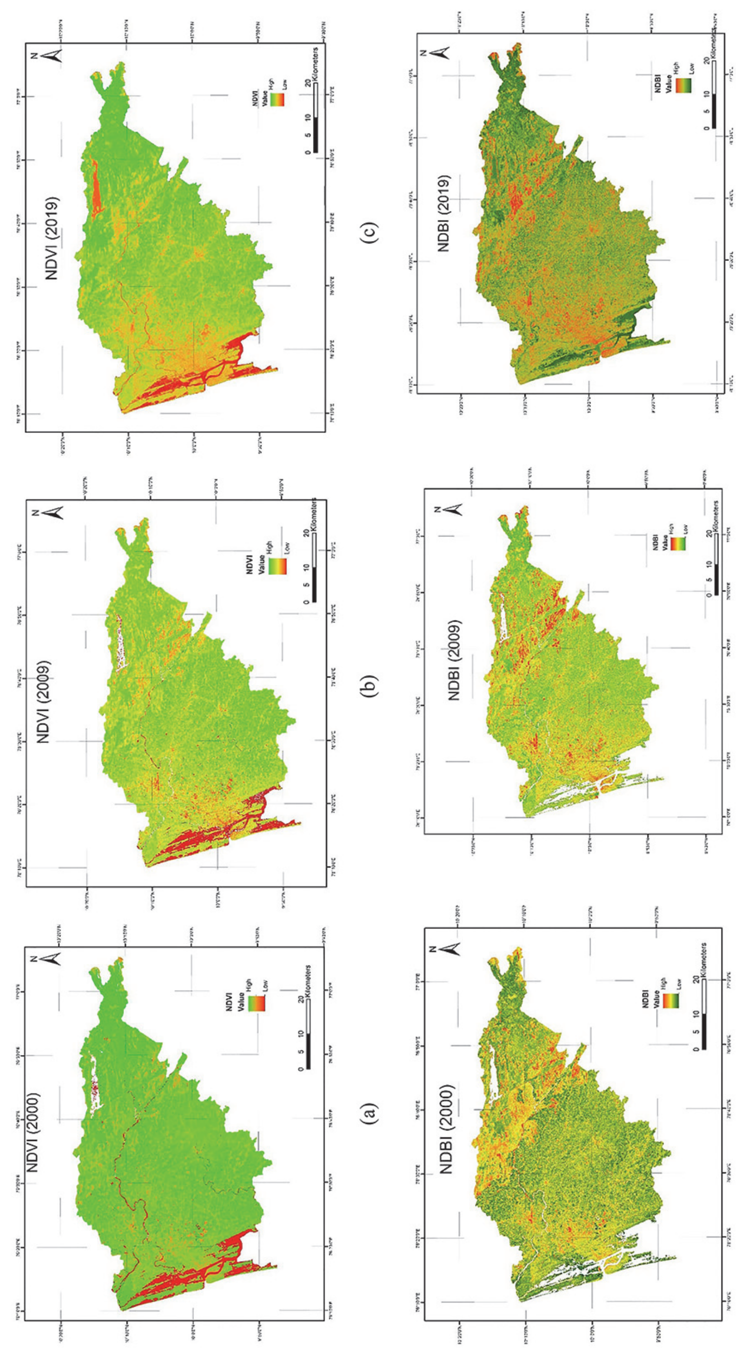


Figure 9

Spatial distribution of NDVI and NDBI of Ernakulam district for 2000, 2009, and 2019



Variation of LST with NDVI and NDBI

The relationship of LST with NDVI and NDBI is presented in Tables 4 and 5. The correlation between LST and NDVI was negative, whereas that between LST and NDBI was positive in all three years (Roy et al. 2020). The correlation indicated that LST increased with a reduction in vegetation area and growth in settlement areas. The variation is evident from the LULC change in the study area for the two decades, as explained previously. The correlation between the two groups of variables was better represented in the form of scatter plots (Figure 10 and Figure 11). Adjusted R^2 values recorded progress in both cases in the two decades, although the values indicate that NDVI and NDBI alone are not adequate to explain the variation in the LST.

Figure 10

Relationship between LST and NDVI in (a) 2000 (b) 2009 (c) 2019

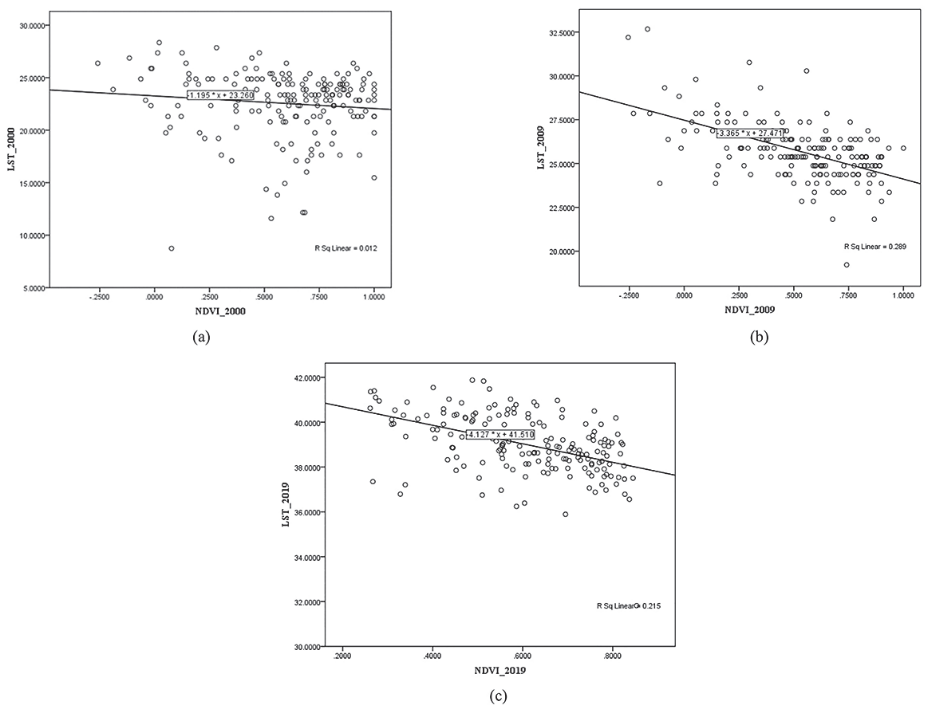


Figure 11

Relationship between LST and NDBI in (a) 2000 (b) 2009 (c) 2019

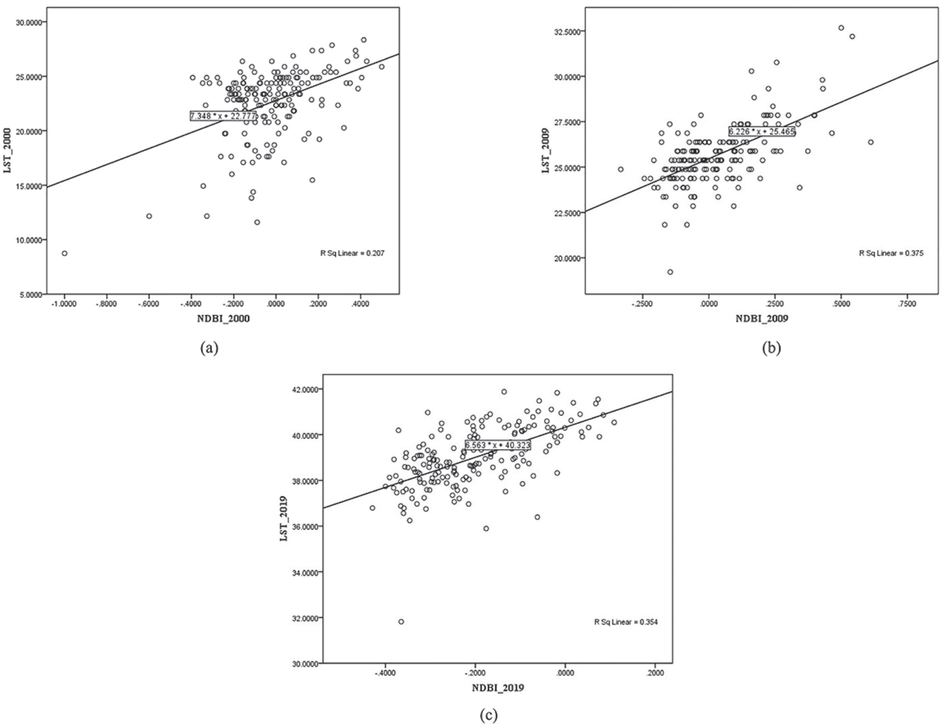


Table 4

Relationship between LST and NDVI

Year	Variable	No: of Observation	Mean	Standard Deviation	Pearson Correlation Coefficient	Adjusted R^2	Sig.
2000	LST	177	22.55	3.19	−0.108	0.006	0.00
	NDVI	177	0.59	0.28			
2009	LST	177	25.68	1.69	−0.538	0.285	0.00
	NDVI	177	0.53	0.27			
2019	LST	177	39.00	1.35	−0.464	0.211	0.00
	NDVI	177	0.61	0.15			

Table 5

Relationship between LST and NDBI

Year	Variable	No: of Observation	Mean	Standard Deviation	Pearson Correlation Coefficient	Adjusted R^2	Sig.
2000	LST	177	22.55	3.19	0.207	0.01	0.000
	NDBI	177	−0.03	0.19			
2009	LST	177	25.68	1.69	0.612	0.371	0.000
	NDBI	177	0.03	0.16			
2019	LST	177	39.001	1.35	0.595	0.35	0.000
	NDBI	177	−0.201	0.12			

Construction of EQI

The variables selected for the index construction were weighted based on the entropy method (Table 6). Water body had the highest weight among all the variables, the reason being the presence of large variations in the value among the observation units (i.e. LBs). The literacy rate of each observation unit does not vary much, and hence, it has the lowest priority among the variables.

Table 6

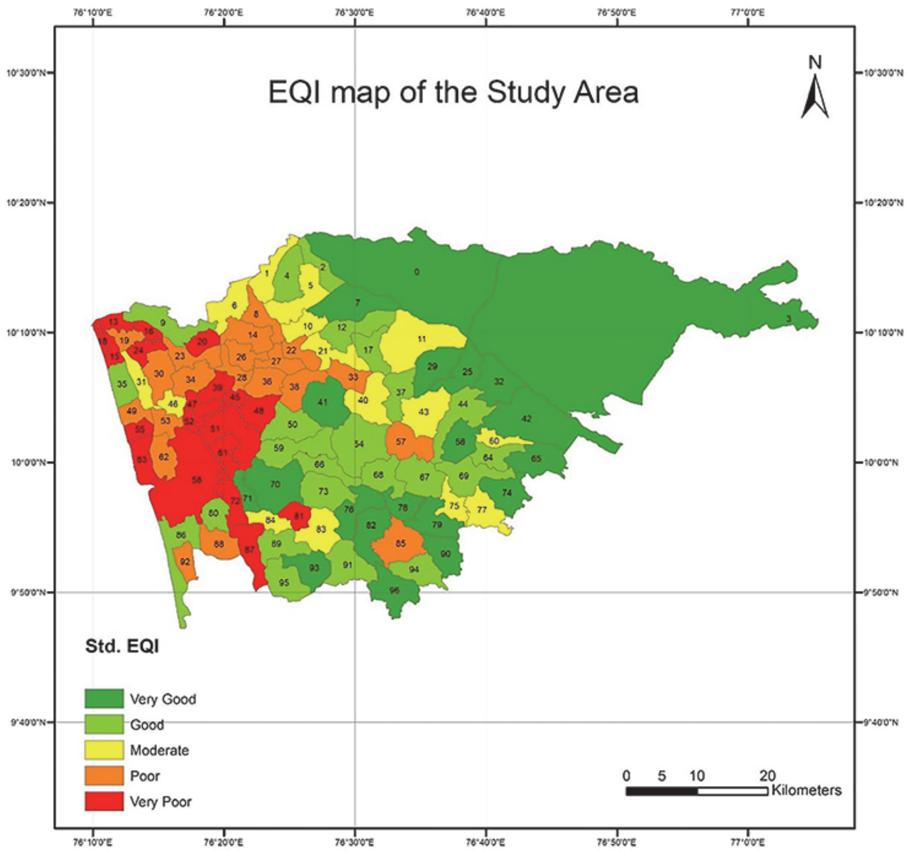
Weights derived for each variable using the entropy method

Variable	Weights derived
LST	0.030
NDBI	0.034
NDVI	0.025
Water	0.448
Settlements	0.041
Forest	0.234
Hill	0.019
Agriculture	0.064
PD	0.019
HHD	0.020
Lit_percent	0.016
Work_Part	0.049

The linear aggregation was adopted to combine the EQI for each observation. As the index values were in different units of measurement, these values were normalised using the rescaling method, as explained previously and equation 10. After normalisation, the index values were represented in the form of a map for ease in understanding the quality status of an area and to implement suitable remedial measures. The spatial map of the EQI of the study area (Figure 12) was categorised into five different classes according to the natural breaks classification method in ArcGIS (Nelson et al. 2015, Shao et al. 2015). The spatial distribution of the EQI (Figure 12) showed that about 40% of the LBs in the study region had poor and very poor EQ, which was distributed over much of the western part.

Figure 12

EQI map of the study area using the entropy method



Sensitivity analysis

As discussed previously, 24 iterations were carried out to check the robustness of the developed model. Table 7 summarises the sample results of the sensitivity analysis and shows the weights of the 12 variables when the variable LST alone was changed and the corresponding change in the EQI output model under the two criteria (+10% and −10%) as well as the base run (Eldrandaly 2013, Ilia–Tsangaratos 2016).

Table 7

Summary of sensitivity analysis

Percent Change	Variable	LST	NDBI	NDVI	Water	Sett-lements	Forest	Hill	Agricultur e	PD	HHD	Lit_ percent	Work_ Part
10%	Weight	0.0332	0.0337	0.0250	0.4465	0.0409	0.2336	0.0189	0.0637	0.0193	0.0196	0.0164	0.0485
	Change in the output model	0.0795	0.0827	0.0829	0.0857	0.0736	0.2230	0.0884	0.1103	0.0667	0.0713	0.0829	0.0793
Base run		0.0302	0.0338	0.0251	0.4479	0.0410	0.2343	0.0190	0.0639	0.0193	0.0197	0.0164	0.0487
−10%	Weight	0.0271	0.0339	0.0252	0.4493	0.0411	0.2350	0.0190	0.0641	0.0194	0.0197	0.0165	0.0488
	Change in the output model	0.0829	0.0829	0.0828	0.1878	0.1249	0.0651	0.0773	0.0773	0.1048	0.0881	0.0827	0.0863

The analysis demonstrated that when the weight is increased by 10%, the variables forest and population density (PD) had the highest and lowest variations, respectively. By contrast, when the weight was decreased by 10%, the variables water and forest showed the highest and lowest impact on the model, respectively. The amount of change that occurred in the model outputs was less than that applied to the input variable, thereby confirming that the model was not much sensitive to the input up to 10% variation in the weights of the variables (Ghajari et al. 2018). All the observations mentioned above indicated the robustness of the model.

Discussion

The LULC change analysis was performed for the study region for the years 2000, 2009, and 2019. Five classes of LULC, namely water, settlements, forest, hill, and agriculture, were analysed. The results illustrated that till 2000, the percentage of area covered by settlements was very low. Later, with the increase in construction and developmental activities, such as industrial setups, service sectors, metro rail, and the opening of the container terminal, the settlement percentage increased. By contrast, the agricultural area has drastically declined over the decades primarily due to increasing population density, the shift in the occupational structure of the people from the primary sector to secondary and tertiary sectors (Firoz et al. 2014, Firoz 2006), and the drop in the profitability of the agricultural yields (Shaharban–Shabana 2015).

The study further investigated some of the impacts of the LULC change in the study region by assessing the correlation between LST, NDVI, and NDBI. The results show that from 2000 to 2019, LST recorded a sharp increase in its Celsius values, mainly due to the increase in settlement patterns. The buildings and the development of other non-pervious surfaces have contributed to the rising temperature. At the same time, the NDVI and NDBI values showed a decreasing and increasing trend, respectively, for the same decadal change. The most evident reason for this change is the construction and development activities that occurred in the study region. Additionally, the correlation analysis confirmed that the LST increases with the increase in NDBI, whereas it decreases with the increase in NDVI (Roy et al. 2020). All the above observations led to the conclusion that the LULC changes in the study area over the past two decades have caused a significant amount of changes in the LST, which greatly affect the life of the human beings and other organisms.

The EQI spatial map of the study region showed that the identified poor and very poor EQ regions, which are distributed in the western part, have majority settlement characteristics, low NDVI, and high NDBI and LST values. Most of the industrial setups, ports, and container terminal are also situated here, which also contributes to the poor EQ of the region. The eastern part of the study region consists mainly of hills and forest areas, which primarily contribute to better EQ. The hills or natural resources restrict the construction or development activities, as evident from the research performed by Liu et al. (2017), which also reports similar results. In other words, the land cover types such as forests and hills have relatively better EQ than land use that is converted to settlements with increasing urbanisation in the region. Hence, it is clear from the study that LULC impacts the EQ of a region. The more the conversion of land cover to land use type suitable to the needs of human beings is, the higher the negative impact on the EQ.

Planning interventions

This study focused on the current impacts on the EQ of a region because of the increasing urbanisation trend by constructing an index. The analysis of LULC helps in the planning interventions at the city level. The present study can contribute to the knowledge of development control regulations, provision of better transportation corridors in the region, proper management of sprawl development, and diminution of urban heat island effect (Ullah et al. 2019). The use of remote sensing and GIS in the LULC detection and the EQI construction can act as pillars in creating an effective database for formulating planning measures in the future (Rahman–Kumar 2011). The research methodology used in this study can be utilised in spatial planning, which involves the LULC mapping, proper urban development, and effective working of the local self-government (Patra et al. 2018).

This study can also offer insight into the improvement in EQ and sustainability of coastal areas where these have been adversely impacted by the LULC changes (Ramachandran et al. 2005). The methodology adopted in the study can aid the coastal regulation zone rules in preventing the conversion of land for construction activities. By mapping the EQ of coastal areas, the actual ground level issues may also be considered, which helps in proper regional development (Nallathiga 2018). In areas that are similar to the study area with rural-urban continuum settlements, this model developed with proper sprawl analysis can be used to provide timely statistics for better urban planning interventions (Rahman–Kumar 2011). The EQI can act as an indicator to showcase the environmental status of an area so that the planners, administrators, and policymakers can suitably address the environmental issues. The categorisation of the study region depending on the EQI value aids in planning and implementing environmental actions and remedial measures (Xu et al. 2020). Domain-specific EQ mapping is also possible, which helps in identifying the domain that has a low contribution to the overall EQ of a region (Krishnan–Firoz 2020). The present study can also be adapted to other regions with the same or different collection of variables and weighting techniques to produce a spatial representation of the EQI of that region.

Conclusions

This study investigated the estimation of LULC change for the years 2000, 2009, and 2019 for the study region. The results presented a positive change for the settlement classes and negative changes for all the other classes, with the highest change in the agricultural category (from 29.83% in 2000 to 15.79% in 2019). The correlations of LST with NDVI and NDBI were tested and the results showed a negative relationship of LST with NDVI and a positive relationship with NDBI. The results help establish the general perception that the increase in urbanisation is one of the key reasons for the increase in LST of a region. The effect of LULC change on the quality of the environment was addressed by constructing the EQI using the LULC, bio-physical, and socio-economic variables. The entropy method of weighting the variables was used, prioritising them based on the presence of variation in the data among the observation units. The EQI of the units was represented spatially in the form of a map, which was categorised into five different classes of EQ, namely, very poor (19.6% of the LBs in the study region), poor (20.6%), moderate (15%), good (23.7%), and very good (20.6%). The spatial map indicated that the overall EQ of the study region was good. Approximately 35% of the entire population of the region reside in the areas of poor EQ. The spatial spreading of the EQI map illustrates that most of the western part of the study district has poor to very poor EQ when compared to the eastern and other parts. The present work confirms that the quality of the environment deteriorates with the conversion of the land cover into different land use types.

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Declaration of interests

The authors declare that they have no known competing financial interests or personal relationships that could have influenced the work reported in this paper.

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