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Article

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Regional urban environmental quality assessment and spatial analysis



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ABSTRACT

Rapid urbanization has resulted in sudden degradation of the environmental quality of urban settlements, which are difficult to measure and quantify. The present study attempts to provide an assessment of the environmental quality by developing environmental quality index (EQI) for the Ernakulam district in Kerala, India. The index values are spatially mapped to develop an environmental quality index map for the study area under five different classes namely, very poor, poor, moderate, good, very good. The EQI values are calculated for nineteen composite variables classified under three domains namely, ecological, meteorological, and socio-economic domains. A preliminary statistical analysis and detailed principal component analysis (PCA) were performed to construct the environmental quality index for the study region. This was followed by a spatial mapping and analysis to provide a better understanding of the status of the environmental quality to the local residents, environmental planners, regional scientists and policy makers. The results obtained from the analysis show that the study area has a low overall environmental quality. The region considered in this paper has highlighting features of various settlement patterns, population distributions, and land use distributions, which indicates a clear transition in the environmental quality index of different settlement units. Hence, by selecting this region and observing various number of indicators, the real effect of urbanization on the quality of the environment was projected. The systematic methodological procedure explained in this paper can be used elsewhere also, where the study area has similar characteristics as that of the area considered in this study. The outcome of the study is applicable for present and future urban planning, building construction, land and resource management for a sustainable environment.

1. Introduction

Urbanization may be referred to as the shift of population from rural areas to urban areas thereby increasing the urban population (Mcgranahan & Satterthwaite, 2014, Silva & Mendes, 2012). The shift in the population can be related to the better advantages available in the urban areas such as better healthcare facilities, education, housing, sanitation, transportation and communication facilities, business and employment opportunities, etc. The rate of urbanization is increasing at a rapid speed (Li, Li, Zhou, Shi, & Zhu, 2012, Ullah et al., 2019) in developing countries including India. With the increase in urban population, an increase in the requirement of land for several developmental and urban activities also increases (Rahman & Kumar, 2011). Sustainability of the cities is under severe threat since the urban environment is worsening all over India. Urban growth in terms of its population and economy

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regardless of the environmental carrying capacity would adversely affect the fundamental functions of the environment. Assessing the environmental quality thus helps to understand the range of quality of various elements suitable for human existence with a proper urban economic and social development (Gurram, Bulusu, & Kintada, 2015). Environmental quality evaluation thus becomes the most important part of efficient urban environment planning and management. It can be considered as a complex and abstract condition that varies continuously over the urban landscape (Nichol & Wong, 2009). The aim of the evaluation of urban environmental quality is not only to make the decision for supporting urban planning but to act as a bridge to link urban planners, environmental experts and other stakeholders (Gurram et al., 2015). The heterogeneity conditions which generate through the inter-relationship between ecological and socio-economic variables are difficult to understand since many are subjective. However, attempts are made to combine these variables through standard index generation procedures so that it can be used as a helping tool in sustainable urban planning measures (Musse, Barona, & Santana Rodriguez, 2018). Developing an Environmental Quality Index (EQI) for an area can be very useful at the same time a very effective way of communicating to the public about the quality of the environment in which they live. An index can give an idea of the environmental status of their area and can make comparisons with other areas taken under consideration, which will give them the realization of the present environmental threats and vulnerability. Hence, the present study attempts to develop an EQI incorporating the ecological, meteorological and socio-economic parameters.

The introduction section is followed by the research background, which includes the literature review of the environmental quality assessment in the various context, different tools and techniques widely used, and the variables and data sources available worldwide. Section 3 is the materials and methods comprising of the details about the study area, variable selection, and EQI construction procedures. Section 4 details the results from the analysis, followed by the inferences from the environmental quality assessment of the study area and suitable policy recommendations.

2. Research background

2.1. Scalar approach in environmental quality assessment

Various studies are conducted across the globe to evaluate the environmental quality of different areas and regions. The environmental problems are usually not limited to the administrative boundaries of the areas (Wei, 2011). But, there is a necessity to perform environmental studies at three different levels of analysis, namely, macro-, meso-, and micro-level (Wei, 2011). The macro-, meso-, and micro-level assessments are mainly performed at the global scale, national/regional scale and local/site-specific scale respectively (Higham, Bejder, & Lusseau, 2008). The micro-scale environmental quality assessment of an area can be useful in terms of reducing the contribution to the meso- and macro-scale environmental problems. But there is very little published research on the assessment of environmental quality at a micro-level of an area (Gurram et al., 2015). Most studies, namely (Anh Kim, Liou, Li, & Tran, 2016; Li, Zeng, Zhang, Yang, & Jiao, 2007; Rahman, Shi, & Chongfa, 2014), in the field of environmental assessment have only focused on macro and meso levels of analysis. The towns and cities in the developed countries are densely packed, thereby the living and working atmosphere of the inhabitants get reduced drastically. Very few studies have mapped such conditions in a combined way to address the environmental quality in an urban context (Nichol & Wong, 2009). The environment is a heterogeneous component, its evaluation requires a large set of data. But, most of the information required for the environmental evaluation is either unavailable or available in multiple scales (Musse et al., 2018). In developing countries like India, several steps are taken at the planning and policy level to address environmental issues (Centre for Energy, 2009). It is reported that many environmental issues are originated at the local level. Thus, these problems should be assessed properly and discussed with local-level authorities and stakeholders (Dutta, Bardhan, & Bhaduri, 2013). In India, very few studies have analysed the environmental quality problems for the appropriate environmental management (Gurram et al., 2015). The metropolitan cities of India, like Mumbai, Chennai, Delhi, etc. as well as other class I towns (according to Census classification of settlements in India) require an extensive assessment of the environmental quality because of the increase in population and rise in economic activities (Rahman & Kumar, 2011).

2.2. Tools and techniques for environmental quality assessment

To combine the heterogeneous indicators into a composite index in a meaningful way, assigning the weights to these indicators are essential (Nardo, 2005). Weights of each indicator signify their relative importance and have a high impact on the index construction (Lindén, 2018). Currently, different tools and techniques are used to make weights as well as to integrate the composite parameters into a single environmental quality index. Some of the currently used techniques are the Analytic Hierarchy Process (AHP) (Parry, Ganaie, & Sultan Bhat, 2018), Fuzzy Evaluation Technique (Phillis, Kouikoglou, & Verdugo, 2017), Geographic Information System (GIS) (Guite, 2019; Nelson, Grubestic, Sim, Rose, & Graham, 2015; Patra, Sahoo, Mishra, & Mahapatra, 2018), Geographically-Weighted Regression (GWR), Principal Component Analysis (PCA), etc. (Faisal & Shaker, 2017b). Principal Component Analysis, Factor analysis, and GIS overlay techniques are used in different domains for urban environmental quality evaluation (Faisal & Shaker, 2017b; Liu, Yue, Fan, Zhang, & Huang, 2017; Lo, 1997) as well as to demonstrate the possibility in surface water quality management study (Koçer & Sevgili, 2014; Voza, Vukovic, Takic, Nikolic, & Mladenovic-Ranisavljevic, 2015). Cluster analysis is a method used to classify the areas into different classes with homogenous character to improve environmental performance by developing more efficient and suitable policies (M. S. Rahman, Mohiuddin, Kafy, Sheel, & Di, 2019; Zuo, Hua, Dong, & Hao, 2017). Another technique known as the fuzzy logic was used by (Peché & Rodríguez, 2012), for designing and assessing the environmental quality indexes. Among these different weighting techniques, PCA is used in the present study, since it is a method that can be successfully employed in case of many independent variables, but no dependent variable.

2.3. Variables and data sources for environmental quality evaluation

To date, only a few attempts are made to evaluate the environmental quality of the areas incorporating multiple indicators (A. Rahman & Kumar, 2011). It is mainly due to the non-availability of data. With the recent advancements in remote sensing and GIS, improvements are made in the mapping of environmental quality of areas at a more detailed level comprising of multiple parameters (Amini Parsa & Salehi, 2016, Mohamed & Worku, 2019, Nichol & Wong, 2009). Several satellite images like Landsat series images, ASTER (advanced spaceborne thermal emission and reflection radiometer), IKONOS image, Quick bird image, etc. are available today at different spatial resolutions to make a detailed environmental quality assessment of the study area. With the developments in the field of remote sensing and GIS, identifying the spatiotemporal changes in the environment is also possible for the ecologists (He, Shen, & Zhang, 2018). However, due to the generation of uncertainties from anthropogenic disturbances as well as variation in spatial homogeneity, the reliability of the researches based on remote sensing for large scale use is weakened. (Hu & Xu, 2018). The environmental quality assessment is comprised of a heterogeneous set of indicators including bio-physical components (land surface temperature, normalized difference built-up index, normalized difference vegetation index, etc.) (Jain, Sannigrahi, Sen, & Bhatt, 2019, Musse et al., 2018), hydrogeochemical variables (calcium, sodium, sulphate etc.) (Batabyal & Chakraborty, 2015), air quality parameters (sulphur dioxide, nitrogen dioxide, particulate matter etc.) (Bayraktar & Turalioglu, 2005), socioeconomic variables (population density, household density, literacy per cent etc.) (Faisal & Shaker, 2017a, Faisal & Shaker, 2017b).

In Kerala (a region of India), where the study area is located, has a difference in settlement pattern, population distribution, land use distribution, etc. (Firoz, Banerji, & Sen, 2014). So, there is an urgent need to classify these areas based on the environmental quality index. Considering all these scenarios, the present study aims to address the research issues such as the factors influencing the environmental quality of an area, quantifying the complex set of indicators contributing to the environmental quality of an area and aggregating these heterogeneous sets of indicators. The environmental quality is assessed for the Ernakulam district (Fig. 1) in the Kerala state of India at a micro level or local body¹ level. Nineteen variables classified under three domains (ecological domain, meteorological domain, and socio-economic domain) are used for the environmental quality assessment for the year 2018. Principal component analysis (PCA) is applied to deduce the number of highly correlated variables into a smaller number of uncorrelated components without losing much of the information (Hu & Xu, 2018, Nichol & Wong, 2009). The weights are derived based on the values of the variance explained by each derived component (Musse et al., 2018). Finally, an environmental quality index map is developed for the study area.

3. Materials and methods

3.1. Study area

Ernakulam is the most urbanized district of Kerala, India as per the 2011 Census data (rate of urbanization was 68.1 per cent) with a total geographical area of 3063 km² and 7 sub-districts. The study area is shown in Fig. 1. It has good connectivity with other parts of the world via an international airport, main railway station, and major port. The large industrial belt and the commercial establishments in the district make it the most growth-oriented development region in the state of Kerala, India.

3.2. Methodology

The indicators and variables related to the environmental quality assessment were selected from the literature. PCA was adopted to derive the uncorrelated variables and to calculate the EQI for the study region. GIS tool was used to represent the spatial distributions of EQI of the study region. The consistency of the model was checked using regression analysis. The research design process included in the study is presented in the form of a flowchart (Fig. 2).

3.2.1. Variable selection and data sources

Initially, a holistic list of variables (variable list 1 containing 97 variables) related to the environmental quality assessment was prepared from the collected set of related journals, reports, and websites. A screening of the variable list 1 was done based on the overlap of the variables, relevance and the contextual importance of each variable and the variable list 2 was prepared (containing 43 variables). The finalized set of variables (containing 19 variables as given in Table 1) was derived by addition/deletion from the variable list 2 based on the availability of data for the variables and after an expert opinion and focus group discussion (FGD). The dataset used in this study was collected from different sources under three different domains (ecological domain, meteorological domain, and socio-economic domain) for the year 2018. The study consisted of both primary and secondary data sources. The variables in the ecological domain were processed from the satellite image (primary source). The variables of the meteorological and socio-economic domains were collected from the secondary sources of NASA Prediction of Worldwide Energy Resources site and Census of India website respectively (Table 1).

¹ Local bodies are institutions of the local self-governance, which look after the administration of an area or small community such as villages, towns, or cities (Statistical yearbook India, 2018).

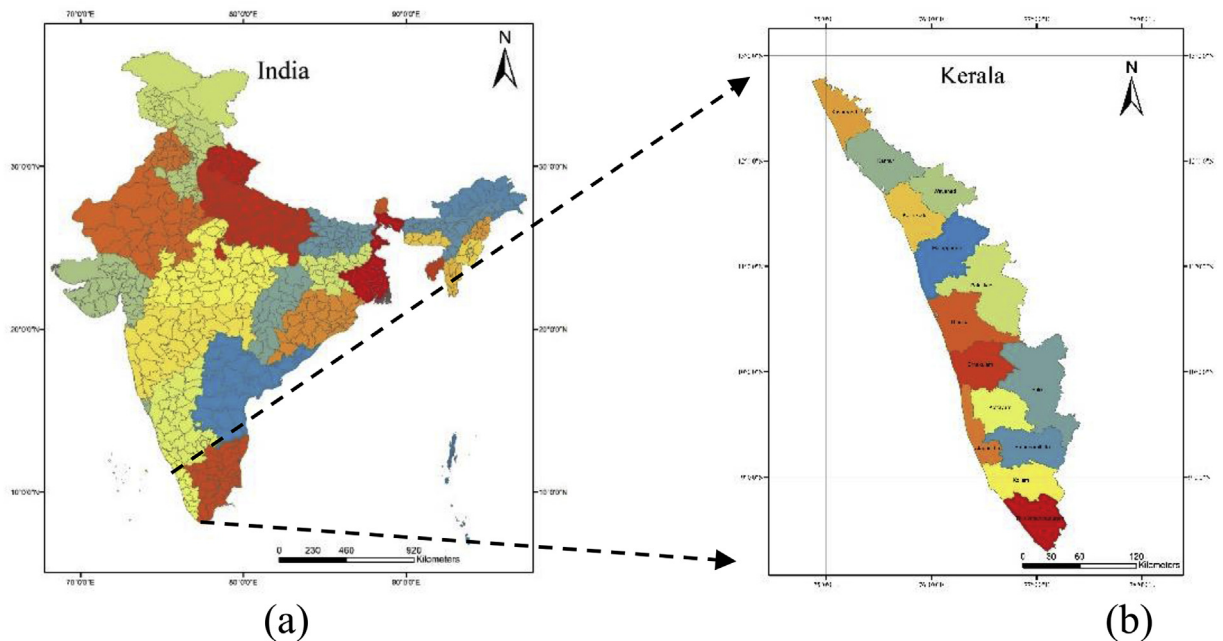


Fig. 1. Location of the study area.

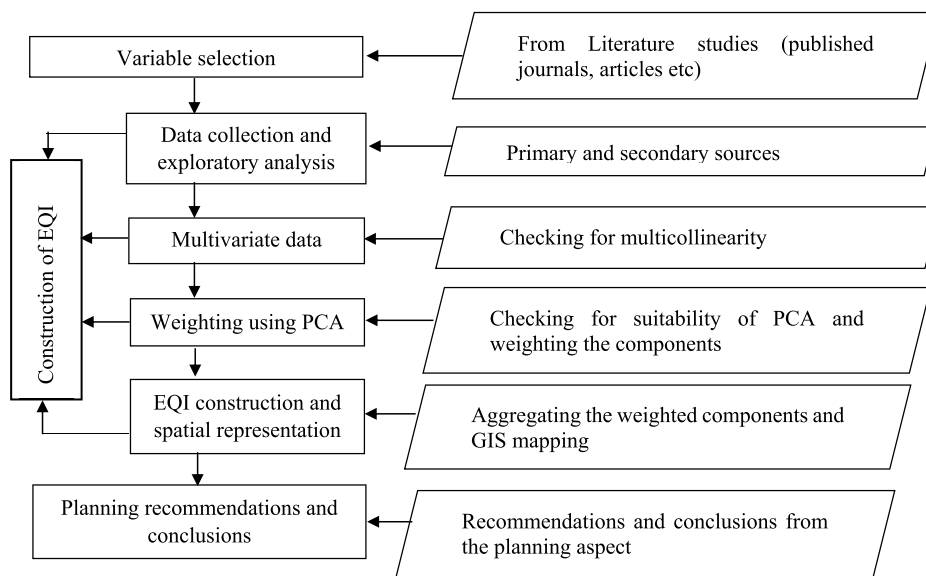


Fig. 2. Flow chart representing the research design process.

3.2.2. Construction of EQI

The environmental quality index for each local body in the study area was calculated by using a weighted linear combination. The weights were derived by using Principal component analysis (PCA). Before performing PCA, the nature and type of the collected data were explored. The following steps were performed in the construction of EQI.

- Imputation of missing data* – The data were checked to identify any missing values present. It was found that the census data was having some missing values. So, the missing value for each variable was replaced with the mean values of the corresponding variables.
- Initial data exploration* – Descriptive statistics were calculated for each variable to understand the basic features of the data (Musse et al., 2018). It was performed in SPSS software. These data were then checked for the presence of normality. Normality checking was done using the Shapiro Wilk test. The null hypothesis for the Shapiro Wilk test was that the data follow the normal

Table 1
Variables selected for the environmental quality assessment.

Variable (Unit)	Variable notation	Definition	Data Source and Pre-processing
Ecological domain			
rowheadLand surface temperature (°C)	LST	Radiative skin temperature of the land surface, as measured in the direction of the remote sensor.	Landsat 8 satellite image from the USGS website. (Ullah et al., 2019, Yue, Xu, Tan, & Xu, 2007)
Normalized difference vegetation index (Dimensionless)	NDVI	A ratio that represents the changes in the vegetation over time.	Geometric and atmospheric correction done (Huang et al., 2019).
Slope (%)	Slope	The measure of steepness or the degree of inclination of a feature relative to the horizontal plane.	SRTM DEM from the global data explorer.
Meteorological domain			
Precipitation (mm/day) (for April, June, and November)	Prec_Apr Prec_Jun Prec_Nov	Is any form of liquid or solid water particles that fall from the atmosphere and reach the surface of the Earth	NASA Prediction of Worldwide Energy Resources site (Sahoo, Dhar, & Kar, 2016)
Temperature (°C) (for April, June, and November)	Temp_Apr Temp_Jun Temp_Nov	A physical quantity expressing hot and cold.	
Wind speed (m/s) (for April, June, and November)	WS_Apr WS_Jun WS_Nov	The rate at which air is moving in a particular area.	
Relative humidity (%) (for April, June, and November)	RH_Apr RH_Jun RH_Nov	The amount of water vapor present in the air expressed as a percentage of the amount needed for saturation at the same temperature.	
Socio-economic domain			
Population density (Pop/sq.km)	PD	Measurement of population per unit area.	Collected from the census of India website (censusindia.gov.in)
Household density (HH/sq.km)	HHD	The total number of households per square kilometer.	
Percentage literate (%)	Lit_Percent	The total per cent of the population who can read and write.	
Workforce participation (%)	Work_Part	The number of people available for work as a percentage of the total population.	

distribution. The Shapiro Wilk test p-value should be greater than 0.05, for the data, to follow an approximately normal distribution. The data which are not normally distributed were undergone data transformation using the skewness and kurtosis shapes of the distribution.

- (c) **Multivariate analysis**- The transformed data were checked for the presence of multicollinearity using the Pearson correlation coefficient matrix in SPSS. For the suitability of running PCA, there should be at least some correlation between the variables ($r = 0.3$ or greater) (Joseph, William, Barry, & Rolph, 2014, Pallant, 2007). However, variables showing a very high correlation are also not recommended for the analysis. Few variables which had a correlation coefficient greater than 0.9 and which had a correlation of less than 0.3 were removed from further analysis (Pallant, 2007). The remaining variables were normalized using data standardization since the data had different units. It was done using the following formula (2) (Faisal & Shaker, 2017a):

$$z_i = \frac{x_i - \bar{x}}{\sigma} \quad (2)$$

- (d) **PCA**- Before running PCA for the data, the Kaiser Meyer Olkin (KMO) test was performed to know whether the data was suitable for PCA. KMO value should be higher than 0.5 to be adequate for running PCA (Joseph et al., 2014, Nardo, 2005). Also, Bartlett's Test of Sphericity was performed to test the null hypothesis stating that the correlation matrix is an identity matrix (Nardo, 2005). The p-value obtained should be significant (p-value < 0.05) (Pallant, 2007). Finally, PCA was performed on the data using SPSS using Varimax rotation.
- (e) **Weighting and Aggregation** – Weights were calculated for the new components using the percentage of variance. Weighted linear combination method was done using the following formula (3) (Musse et al., 2018):

$$\text{Non-standardized EQI for each unit} = w_1*FA1 + w_2*FA2 + w_3*FA3 + w_4*FA4 \quad (3)$$

where, w_1, w_2, w_3, w_4 – weights of each component and $FA1, FA2, FA3, FA4$ – factor scores for each component.

- (f) **EQI calculation and map generation** – The EQI value for each unit (local body) was standardized using the following formula (4) (Nardo, 2005):

Table 2

Coefficient of variation and Shapiro Wilk test result.

Variable	Coeff. of Variation (CV)	Statistic (Shapiro-Wilk test)	Type of transformation	Nature of Skewness and Kurtosis
LST	10.31	0.919	Box-Cox	Negatively skewed and leptokurtic
NDVI	30.91	0.889	Reflect and square root	
Slope	96.49	0.783	Logarithmic	Positively skewed and leptokurtic
Prec_Apr	9.97	0.824	Reflect and square root	Negatively skewed and platykurtic
Prec_Jun	17.98	0.659		
Prec_Nov	7.61	0.664	Square root	Positively skewed and platykurtic
RH_Apr	2.82	0.765	Reflect and square root	Negatively skewed and platykurtic
RH_Jun	20.25	0.248		
RH_Nov	3.39	0.775	Square root	Positively skewed and platykurtic
Temp_Apr	3.38	0.635	Reflect and square root	Negatively skewed and platykurtic
Temp_Jun	5.14	0.731		
Temp_Nov	6.29	0.727		
WS_Apr	36.94	0.786		
WS_Jun	31.21	0.827		
WS_Nov	34.33	0.810		
PD	64.36	0.902	Box-Cox	Positively skewed and platykurtic
HHD	65.04	0.895		
Lit_Percent	1.43	0.953	Reflect and square root	Negatively skewed and platykurtic
Work_Part	7.52	0.963	Logarithmic	Positively skewed and leptokurtic

$$\text{Standardized EQI for each unit} = \frac{\text{Index of unit1} - \text{Min. index}}{\text{Max. index} - \text{Min. index}} * 100 \quad (4)$$

Finally, the EQI map for each local body in the study area was developed in ArcGIS.

4. Results

4.1. Initial data exploration

The data was collected for the various parameters considered in the study area, and the initial exploration of the data was conducted to summarize the dataset. Even though the variability was more for socio-economic variables, especially population density and household density, the coefficient of variation was highest for the ecological component, slope (Table 2). The main reason being the fact that Kerala is having a large difference in the settlement pattern, population distribution, land use, etc (Firoz et al., 2014).

The normality of the data was tested using the Shapiro Wilk test. The p-values obtained for all the variables were less than 0.05 and thus were statistically significant (Table 2). Hence the null hypothesis was rejected, indicating that the data do not follow a normal distribution pattern. The data may have come from other identifiable distributions. The presence of outliers may also contribute to the misleading of the data from the normality.

Since none of the variables followed a normal distribution, all these were undergone data transformation. It was done based on the skewness and kurtosis shapes of the data. Based on this, different transformations were carried on the data, namely square root transformation, reflect and square root transformation, logarithmic transformation and Box-Cox transformation as given in Table 2. A trial and error approach is followed. After the data transformation, the data was again checked for normality, to confirm that the dataset follows a normal distribution.

4.2. Multivariate analysis

Multicollinearity of the data was checked for the 19 variables by calculating the Pearson correlation coefficients. The presence of multicollinearity affects the results of PCA. Out of the initial 19 variables, 7 variables (Prec_Nov, RH_Apr, RH_Jun, Temp_Jun, Temp_Nov, WS_Nov and HHD) were removed from further analysis. LST and the NDVI have a negative correlation because of the different land use land cover types present in the study area (Yue et al., 2007). The relative humidity for April and June are less correlated with the temperatures for the corresponding months. However, the case is different for November. The increasing frequency of the tropical cyclones during the post-monsoon season (October–November) contributes to the increasing rainfall (Krishnakumar, Prasada Rao, & Gopakumar, 2009). The precipitation is having a negative correlation with the air temperature during this season. The correlation coefficient between population density and household density was found to be very high. Both of these variables indirectly contribute to the population size per unit area. These values were high because of the high urbanization rate in Ernakulam district.

4.3. PCA

Before running PCA, normalization of the data was performed to consider them in the same unit. KMO test and Bartlett's test for

Table 3
KMO and Bartlett's test of sphericity.

Name of the test		Result
Kaiser-Meyer-Olkin Measure of Sampling Adequacy		0.634
Bartlett's Test of Sphericity	Approximate Chi-Square	2.12×10^3
	df	66
	Sig.	0.000

Sphericity were done on the transformed data before conducting PCA. The results from SPSS is shown in Table 3. KMO value was obtained as 0.634, which is adequate for running the PCA. The p-value obtained for Bartlett's test of Sphericity was 0.000, which is statistically significant and indicates that running PCA is valid for this data (Joseph et al., 2014).

The principal component analysis was used to reduce the number of correlated variables into uncorrelated components. The scree plot (Fig. 3) obtained from the analysis showed that the three components resulted in an Eigenvalue greater than 1 (Greenacre et al., 2008). PCA was performed on the data using Varimax rotation using these 3 components (Joseph et al., 2014). Table 4 shows that the variance percentage obtained for components 1, 2 and 3 are 45.61, 19.15 and 12.88 respectively. The model resulted in a cumulative percentage of variance as 77.64%. The rotated component matrix tabulated in Table 5 shows that the variables that load highly on component 1 are correlated to the meteorological variables. Similarly, components 2 and 3 have a high correlation with socio-economic and ecological variables respectively.

4.4. Weighting and EQI map generation

The weights for each component derived using the percentage of variance are presented in Table 4. These are calculated as the ratio of the percentage of variance to the cumulative percentage (Liang & Weng, 2011). The non-standardized index for each local body was calculated using the weights and corresponding factor scores derived from PCA using equation (3). The standardized index values for each local body was obtained using equation (4). The final environmental quality map for the study area was developed using ArcGIS software. Fig. 4 shows the final EQI map for each local body in the study area. Natural breaks classification method was used to categorize the entire study area in five different classes based on the EQI values: very good quality, good quality, moderate quality, poor quality and very poor quality (Brewer & Pickle, 2002, Nelson et al., 2015, Taohong Zou & Yoshino, 2017, Shao et al., 2016, Shao, Sun, Tao, Xiang, & Xian, 2015).

5. Discussions

5.1. Overall environmental quality assessment

The EQI map developed for the study area (Fig. 4) shows that the overall environmental quality of the area is poor. Only about 38% of the total number of local bodies comes under the class of “good” and “very good” quality, which is distributed over the central, eastern, northern and southern parts of the study area.

The consistency of the developed model is checked using regression analysis (Musse et al., 2018). In this case, the variables with the highest loading under each component are taken as the predictor variables and the EQI value is taken as the outcome variable. The regression analysis was carried out in SPSS software and the results are tabulated in Table 6. From the regression analysis, the R^2 value is obtained as 0.914, which shows that the developed model is good because they explain about 91% of the variance of the developed index. The p-value obtained for all the three predictors are less than 0.05, which is statistically significant. These results show that there is a linear regression relationship between the predictor variables and the outcome variables.

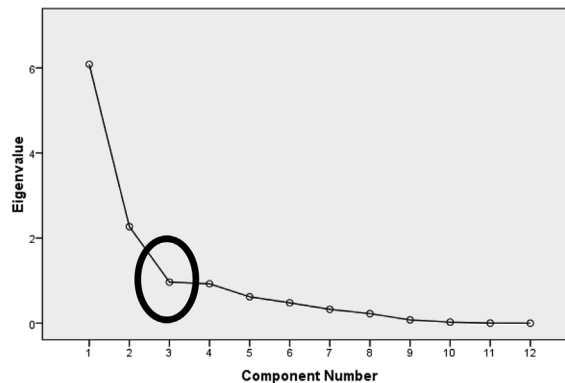


Fig. 3. Scree plot.

Table 4

Total variance explained.

Component	Rotation Sums of Squared Loadings			Weights Calculated
	Total	% of Variance	Cumulative %	
1	5.473	45.611	45.611	0.587
2	2.298	19.148	64.759	0.247
3	1.546	12.88	77.639	0.166

Table 5

Rotated component matrix.

Variable	1	2	3
Prec_Apr	0.894	0.03	−0.222
Prec_Jun	0.881	0.285	0.21
RH_Nov	0.958	0.209	0.115
Temp_Apr	0.847	0.295	0.245
WS_Apr	0.973	0.078	−0.106
WS_Jun	0.974	0.128	−0.007
Lit_Percent	0.173	0.446	0.162
Work_Part	−0.048	0.892	−0.033
PD	−0.276	− 0.841	−0.184
LST	−0.332	−0.018	0.816
NDVI	−0.194	−0.498	− 0.595
Slope	0.334	0.335	0.534

5.2. Environmental quality driving forces

As per the census 2011 data, the population of the local bodies (LB) having poor and very poor environmental quality is about 23,11,222 (total population of the study area is 29,53,048), i.e., more than thrice the population in moderate, good and very good environmental quality. The environmental quality of the area is affected mainly due to human interventions. Population density is one of the important factors indicating the quantum of human intervention. The sustainability of the cities is also witnessing severe threats. The effect of urbanization significantly increases the population which in turn drives the environmental quality to the worst conditions. For example, the western side of the study area has a high population density in the range of 3000–4760 pop/sq.km. These areas have very poor environmental quality. On the contrary, the eastern side of the study area have a very less population density below 500 pop/sq.km and have very good environmental quality.

Another factor that attributes to the poor environmental quality in some of the local bodies is the high land surface temperature values. Some of the LB situated on the western side and southern part of the study area have high LST values between 30 and 33 °C and have very poor environmental quality. One of the primary reasons for the increase in surface temperatures in the land-use change i.e.; conversion of agricultural lands to urban areas. It reduces the permeability of the surfaces due to the development of buildings and roads (Guo, Wang, Cheng, & Shu, 2012). For instance, in the study conducted by (Fathizad, Tazeh, Kalantari, & Shojaei, 2017), the land surface temperature in the year 1990, 2000 and 2010 for fair rangelands are 26.72, 30.06 and 30.95 °C respectively and for poor rangelands are 26.95, 32.83 and 34.49 °C respectively. Another factor responsible for the increase in land surface temperature is deforestation. Vegetation helps in evapotranspiration thereby absorbing the heat from the atmosphere (Yuan & Bauer, 2007). The study investigated by (Mwangi, Karanja, & Kamau, 2018) resulted that with an increase in land surface temperature from 1987 to 2002 reaching up to a maximum of 38.86 °C, there is a decrease in the maximum value of NDVI (0.535 in 1985 to 0.414 in 2002). The present study results that there is a negative correlation between LST and NDVI. In the study area, some of the LB have very low NDVI values, but very high LST. Also, there are other studies (Faisal & Shaker, 2017b, Guha, Govil, Dey, & Gill, 2018) that report a similar trend.

5.3. Component loadings

The relationship between the component and variables can be created using the component loadings (Musse et al., 2018). Component 1 has moderate to a strong positive correlation with the meteorological variables (precipitation, temperature, relative humidity, and wind speed). Hence this component is named as “meteorological component”. An increase in urbanization indirectly increases the score of this component, which decreases the environmental quality of the study area. Component 2 shows a negative correlation with the socio-economic variable, population density and moderate positive correlation with literacy percentage and workforce participation and hence named as “socio-economic component”. Environmental quality is improved with the increase in score value of component 2. Component 3, has a moderate positive correlation with the bio-physical variables such as LST and slope. On the other hand, it has a moderate negative correlation with NDVI. With the increase in the score of component 3, environmental quality reduces. This component is named as “bio-physical component”.

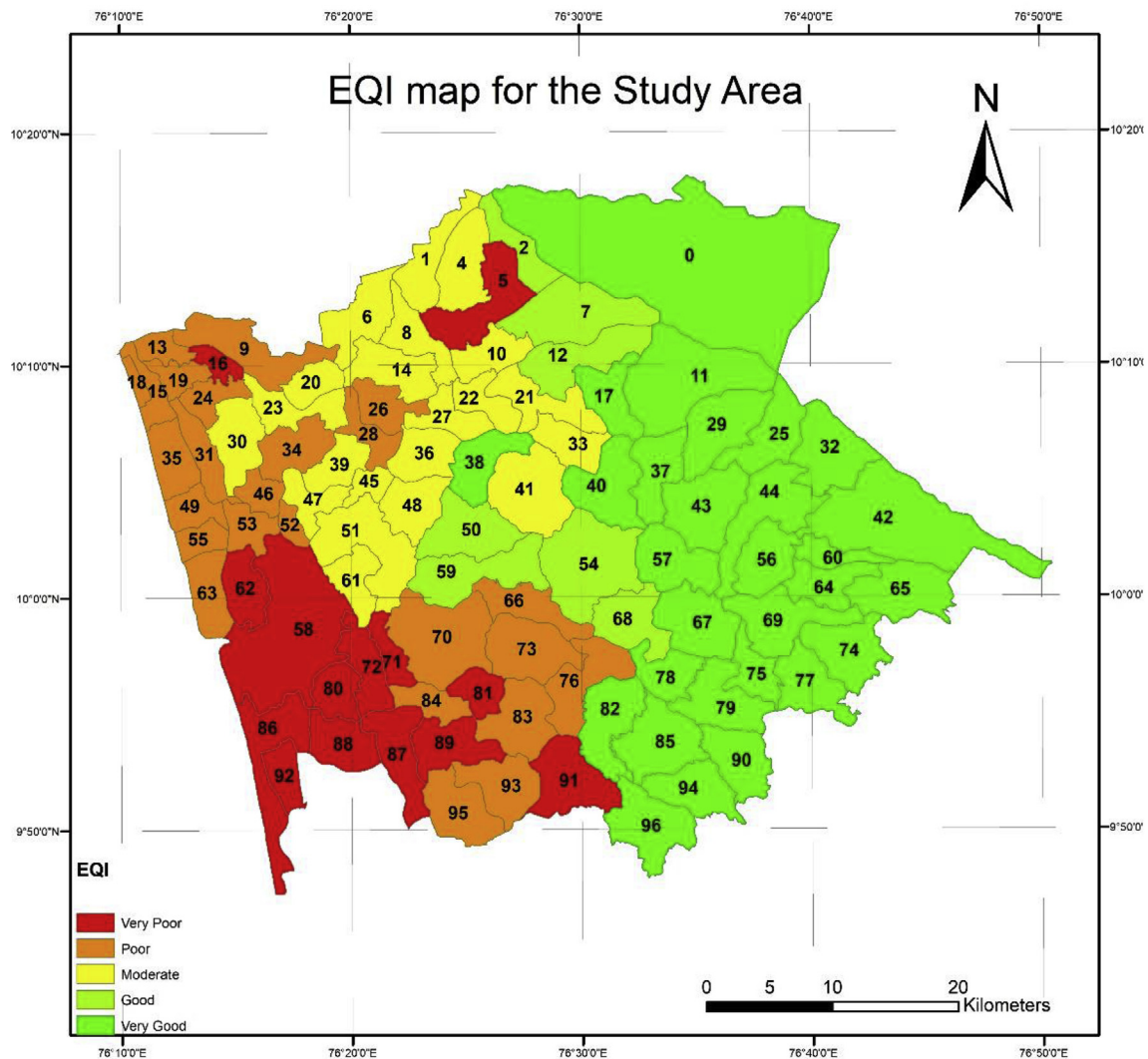


Fig. 4. EQI map developed for each local body in the study area.

Table 6

Regression analysis for checking model consistency.

Outcome Variable	Predictor Variables	R ²	Constant	Coefficient	Significance
EQI	WS_Jun	0.914	42.714	25.868	0.000
	Work_Part			4.825	0.000
	LST			5.242	0.000

5.4. EQI map of each component

The EQI maps for the scores of the components 1, 2 and 3 are represented in Figs. 5–7 respectively.

Meteorological component: As per Fig. 5, some of the LB which have high meteorological values are located in the western and southern parts of the study area. These areas have very poor environmental quality as per the analysis. On the other hand, the LB with low meteorological values have very good environmental quality and are located on the eastern side of the study area.

Socio-economic component: According to Fig. 6, the LB with very poor environmental quality are distributed randomly over the western side of the study area. They have high population density and low literacy per cent and workforce participation. On the contrary, some of the LB having low population density and high literacy per cent and workforce participation have good environmental quality.

Bio-physical component: Fig. 7 shows that the EQI map for the scores of component 3 has poor and very poor environmental quality

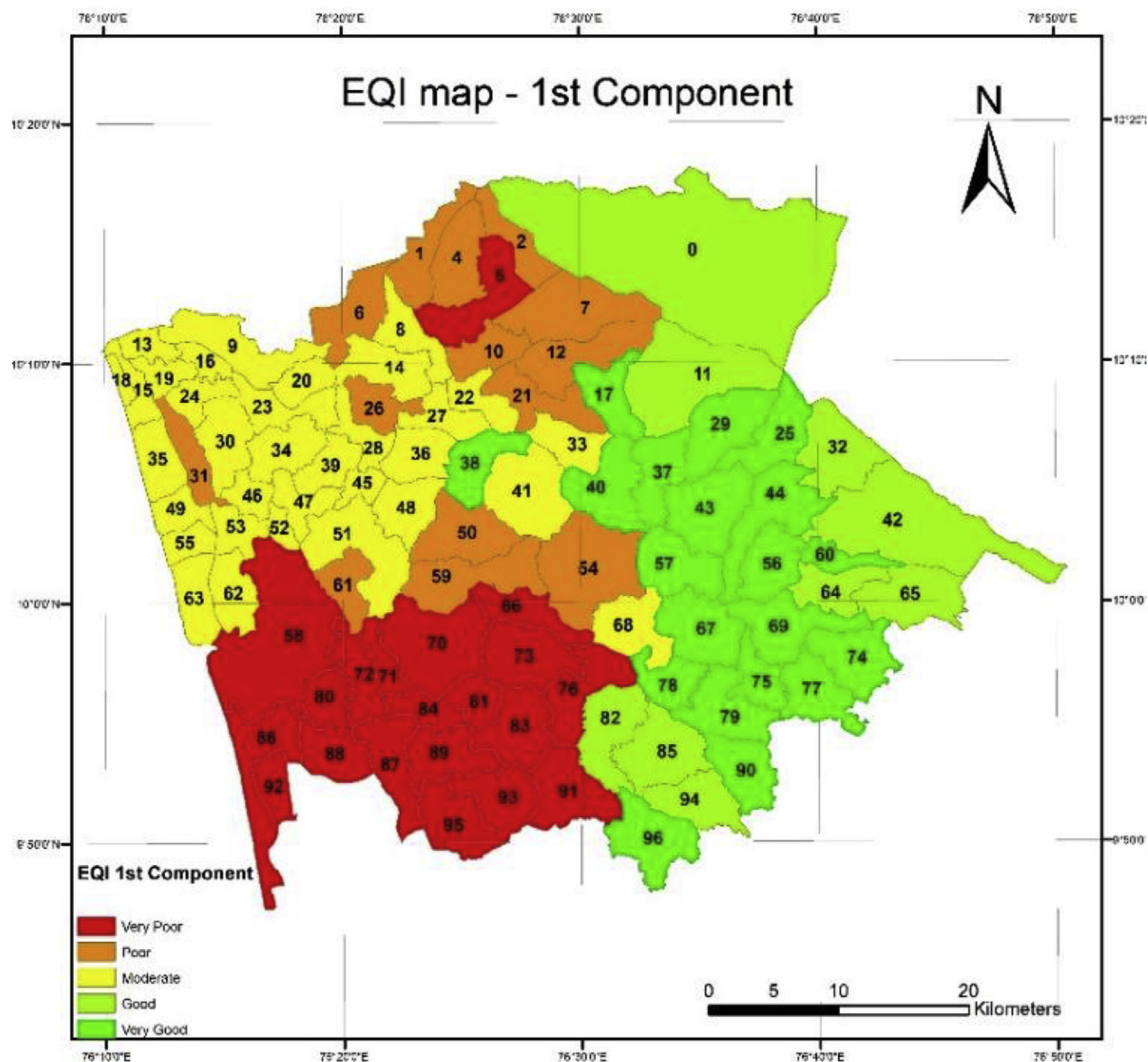


Fig. 5. EQI map developed for the scores of Meteorological Component.

mainly in the north-western part of the study area. These LB have high LST values, high slope values, and very low NDVI. Whereas, about 38% of the total number of local bodies in the study area has the good and very good environmental quality and have high NDVI and very low values of the slope.

6. Planning recommendations

The broad planning recommendations presented in the study are divided into two sections. Firstly, the study area was divided into five different classes of the environmental quality index by the proposed methodology. The classification helps the decision-makers to propose different methods to address the issue of the environmental quality within the study area (Zou & Yoshino, 2017). The areas with poor and very poor environmental quality are to be assessed with all sorts of planning measures and implementation strategies to improve the quality to the greatest possible manner. The policy and decision-makers are endowed with the knowledge of where to start with or give more priority of mitigation strategies to build up the environmental quality of the area. The officials can make sure that the areas with moderate environmental quality are not deteriorating the environmental quality in the future. As a step towards successful planning, the different domains can be first identified and the planning policy guidelines for each domain can be formulated separately so that each domain gets the maximum attention. The areas with good and very good environmental quality should be protected and appropriate development control regulations should be applied. The developed model can be used to foresee the intervention of trespassers to forestall the over-exploitation of natural resources and to safeguard the area from natural disasters and loss of lives. Planning measures should be taken and implemented by involving the residents of the areas so that the actual happening on the ground is also incorporated for a better environmental treat (Joseph, Wang, & Wang, 2014).

Secondly, the present study involves the classification of a region (macro-level) into sub-regions (Meso level) based on the

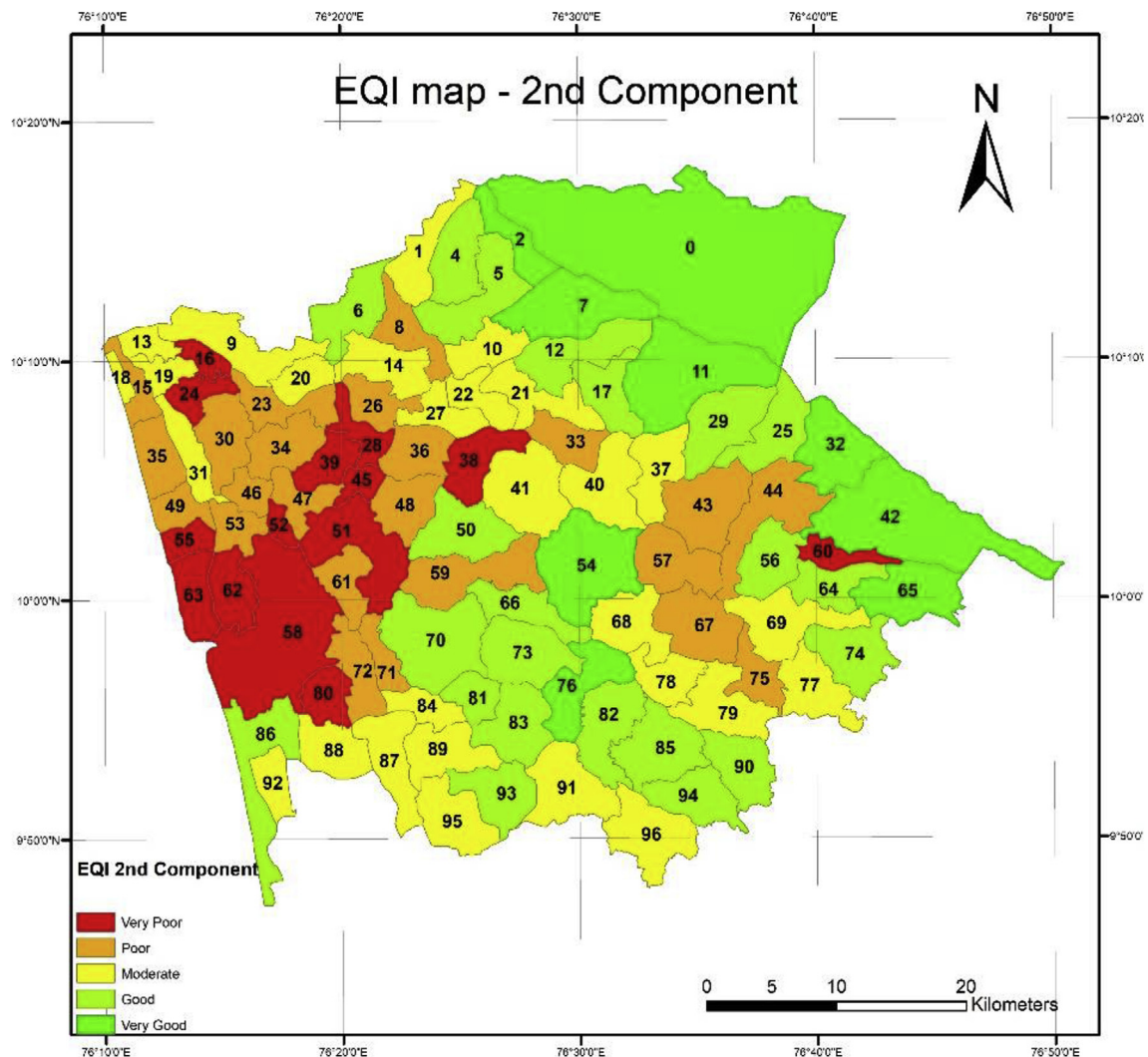


Fig. 6. EQI map developed for the scores of Socio-Economic Component.

homogeneity in environmental quality characteristics. If the same methodology, but a different set of specific variables are used to categorize the sub-regions further (to micro-level) within the different obtained environmental quality classes, several different combinations of differential settlements will be attained. For example, a zone which is classified with very poor environmental quality can be further analysed in a more detailed manner incorporating the same or differential variables, so that the micro-level assessment is possible. Such an assessment will be beneficial at a local level planning for implementation of measures to address the practical environmental problems of the residents of the area. The present study can be elaborated further by using the same methodology and different variables at a micro-scale for better evaluation of EQI at the local level. Environmental quality-based zoning of settlements is required in the context of the study area which will help the decision-makers and policymakers in implementing new guidelines regarding the future constructional and developmental activities. Zoning of the settlements based on the environmental quality provides an important path to enhance the environmental activities and helps to balance the urbanization trend, agricultural growth and environmental security (Xu et al., 2020). Preparation and regular updating of the EQI map of a region/sub-region/local body of an area and making it available in the online database can bring a sense of responsibility for protecting the environment among the citizens of the region. An EQI map generation also finds its suitability in the conventional planning of regional plans and master plans for cities (Panagopoulos, González Duque, & Bostenaru Dan, 2016).

7. Conclusions

The appropriate factors affecting the environmental quality of an area are identified and classified under three different domains: ecological domain, meteorological domain, and socio-economic domain using PCA. A micro-level assessment procedure is developed for calculating the environmental quality of the highly urbanized district of Kerala (Ernakulam), using the meteorological data,

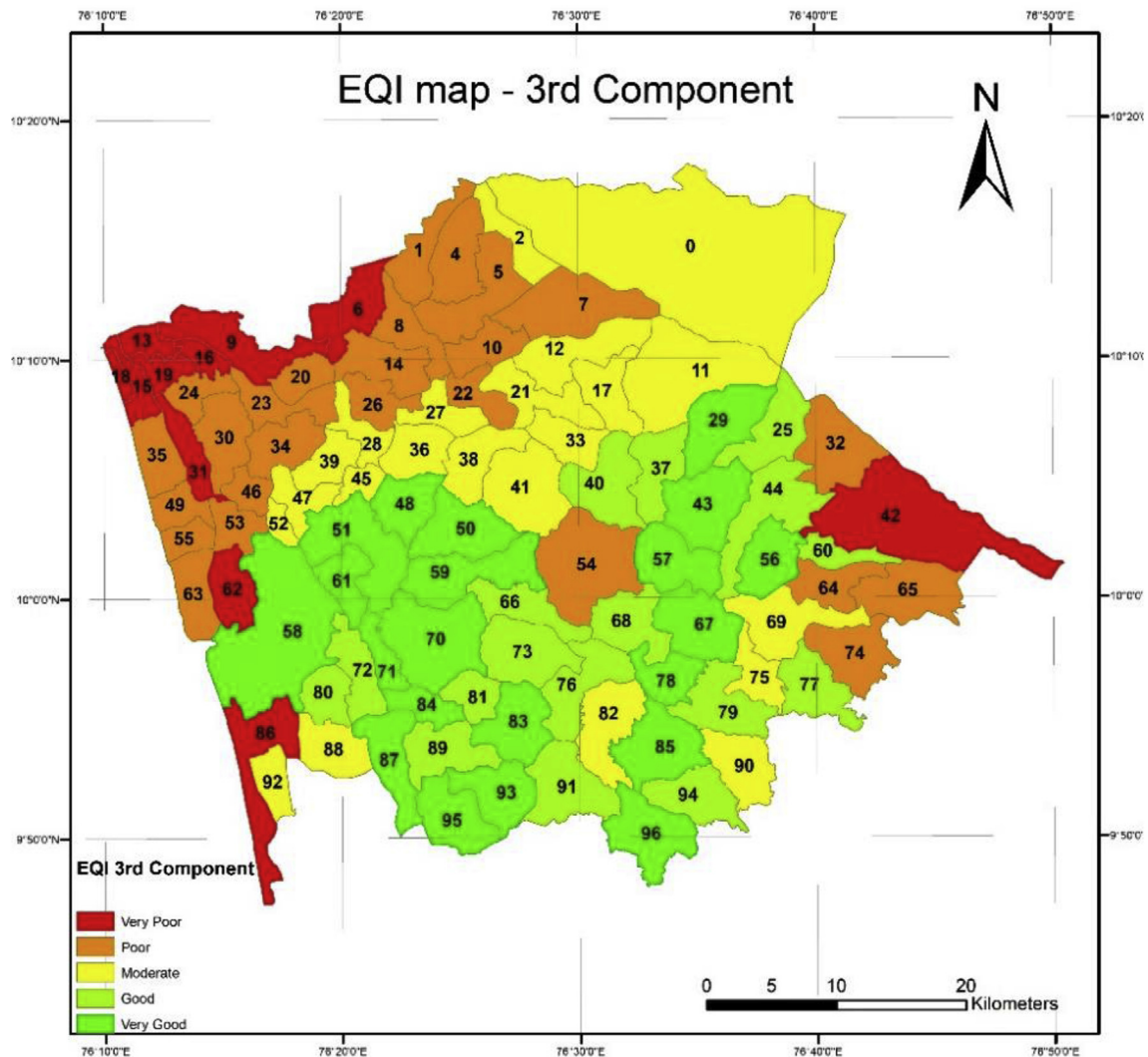


Fig. 7. EQI map developed for the scores of Bio-Physical Component.

satellite image processed data and socio-economic data. The same methodology can be used for evaluating the environmental quality of areas with similar conditions. GIS is an important tool which is used in most of the researches worldwide for the spatial analysis and to study the application of environmental management and sustainable development (Xie, Yao, & Liu, 2015, Vaz, Anthony, & McHenry, 2017, Vaz, 2018). The EQI map developed using GIS tool and categorized under the five different classes shows that the overall environmental quality of the study area is poor. The EQI classes delineated by PCA are as follows: (a) very poor (14% of the study area), (b) poor (26%), (c) moderate (22%), (d) good (7%) and (e) very good (30%). The spatial distribution of the environmental quality of the study area reveals that most of the western part has very poor quality and the eastern region obtained very good quality. About 23% of the total population of the study area live in areas with very poor environmental quality. The EQI maps of the components 1, 2 and 3 represent that 20, 15 and 12% of its respective LB comes under the class of very poor environmental quality.

The present model developed from the study is intended to give an overall framework to understand the systematic way of deriving the composite environmental index. Such an assessment can help the ecologists, urban planners and the policymakers to take necessary actions to safeguard the environment from future threats and thereby enhancing the quality of life of people. It can also help the residents of an area by creating awareness on the environmental quality of the place in which they live.

Declaration of competing interest

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

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