Remote Sensing Applications: Society and Environment 23 (2021) 100530

Contents lists available at ScienceDirect

Remote Sensing Applications: Society and Environment

journal homepage: www.elsevier.com/locate/rsase

Eco-environmental quality assessment based on pressure-state-response framework by remote sensing and GIS

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ARTICLE INFO

Keywords:
Ecological environmental quality
PSR framework
Remote sensing
GIS
RSEI
EI

ABSTRACT

Ecological environment quality assessment (EEQ) is an important parameter for sustainable development and sometimes it's more valuable during industrialization and urbanization progress of the region. This study compares remote sensing ecological index (RSEI) and ecological index (EI) and assesses EEQ with the most popular pressure-state-response (PSR) method based on a set of remote sensing and statistical indexes through a weight system in Samara region Russia. EI and RSEI framed from 15 toand 4 indicators respectively and in the PSR framework natural-human pressure and health state assessed based on 12 and 3 indicators respectively and in the last response index developed from pressure and state indicators. Results indicate that RSEI and EI showed very strong comparability in the ecological sense but EI reflect more effectively EEQ changes than RSEI. Finally this study explores all important effective indicators developed from remote sensing for eco-environment quality assessment, which provide a strong decision making base for sustainable development as well as provide a new and latest technological support for long term comprehensive mapping, monitoring and assessment of environment.

1. Introduction

The quality of the ecological environment is directly affected by local natural resources as well as human life. The eco-environment is at threat of dilapidation by the high amplification of human activities and consequently worldwide environmental change. Since the last two decades rapid growths of industrialization and urbanization have greatly affected land use/cover change, which influence regional degradation of climate and environmental changes (Abd Yang et al., 2020 & Yang et al., 2020). The worst thing is that this change speed is much faster than the self-reassembled speed of the ecosystem, which increases too much natural/human pressure and disturbance in the eco-environment as well as this is the main cause of its degradation. Therefore the study area faces a large number of problems such as air pollution, noise, traffic-jam, variation in temperature and humidity, uncertainty and difference in rain intensity etc. (Li et al., 2018; Janilci et al., 2018). This environmental ecological degradation is directly related with the growth of economic development of the region (Gao et al., 2019; Xinmin et al., 2020). A large number of research works have been carried out on eco-environment mapping and monitoring through remote sensing and GIS and a large number of methods have been developed to assess the ecosystem's spatial change. However, their methods usually focus on only one aspect of the eco-environment and then generate a single ecological factor for assessment (Liu et al., 2016; Zhiqiang et al., 2011; Brian et al., 2008) such as normalized difference vegetation index (NDVI), leaf area index (LAI), land use land cover (LULC) change, normalized difference water index (NDWI), and light index have been used for vegetation, biodiversity, water body, bare soil and city spatio-temporal change (choudhary et al., 2019; Kappas and Propastin 2012; Fu et al., 2013; Peijuan et al., 2011). Therefore presently this is a very important hot topic to quantitatively describe and estimate the spatio-temporal dynamics of eco-environmental quality in the study region for its sustainable development (Boori et al., 2015).

The PSR framework was initially developed for environmental policy making by organization of economic cooperation and development

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https://doi.org/10.1016/j.rsase.2021.100530
Received 11 November 2020; Received in revised form 22 April 2021; Accepted 23 April 2021
Available online 21 May 2021
2352-9385/

Abbreviations

AHP	Analytic hierarchy process
ANP	Analytic network process
IBI	Built-up index
DMSP	Defense Meteorological Satellite Program
DEM	Digital elevation model
EEQ	Ecological environment quality assessment
EI	Ecological index
ETM+	Enhanced Thematic Mapper
ER	Evaporation rate
ET	Evapotranspiration
FVC	Fractional vegetation cover
GIS	Geographical information system
GEMI	Global environmental monitoring index
LC	Land cover
LSM	Land surface moisture
LST	Land surface temperature
LULC	Land use land cover
LAI	Leaf area index
LI	Light index
NGOs	Non-governmental organizations
NDBSI	Normalized differential building and bare soil index
NDVI	Normalized difference vegetation index
NDWI	Normalized difference water index
OLI	Operational Land Imager
OECD	Organization of economic cooperation and development
PI	Pressure indicator
PSR	Pressure-state-response
PC	Principal component
PCA	Principal component analysis
RS	Remote Sensing
RSEI	Remote sensing ecological index
RI	Response indicator
SI	State indicator
SAVI	Soil adjusted vegetation index
NDMI	Soil humidity or soil moisture normalized difference moisture index
SI	Soil index
SEA	Strategic environmental assessment
TRI	Terrain roughness index
TN	Thematic Mapper
USGS	United states geological survey
FEWS NET	Famine Early Warning Systems Network

(OECD) (Huang et al., 2011; Bernhard and Harald 2008) for a single ecological index (EI) based on a set of remote sensing and statistical indexes through a weight system (Ludovic et al., 2011; Johnny and Heng 2008) e.g., analytic hierarchy process (AHP), analytic network process (ANP) etc. Basically three concepts were used to select ecological indicators. (1) all indicators regularly and accurate monitoring is not possible in an ecosystem due to their complicity, (2) all indicators have different characteristic, weights, values and their own long and short term effects in ecosystem, (3) mapping, monitoring and management of all indications lacked scientific ignorance in a defined protocells due to their different dimension effect and dissimilarities. Therefore it was necessary to understand all indicators individually, their complicity, integrity and ecological state to mapping and monitoring ecological response change (Hu and Xu 2019; Tomás et al., 2004; Patrício et al., 2016) under PSR framework. Sometimes the effective and duplicate indicators such as for vegetation and moisture content helps to assess sustainable development of ecological environmental mapping and monitoring. This research work categorized all indicators in three groups under PSR framework as a presser indicator, which represent human and natural pressure on environmental and natural resources quality and then make an environmental status and in last generate response (Huang et al., 2011). Therefore the response indicator has indicated undesirable changes in environment and natural resources due to pressure and state indicators.

Ecological environment quality (EEQ) assessment required a complete information about regional or site specific indicators in terms of their intensity and effectiveness, which effect on surrounding ecosystems (Schlevogt 2001; Mengshan et al., 2017; Hoa et al., 2018). In general for a regional level study of EEQ must be based on statistical data, LULC data, applying a widespread index method for qualitative analysis for a specific time period. A large number of researchers have been widely used analytic hierarchy process (AHP), NDVI, RSEI, strategic environmental assessment (SEA), land cover (LC) models to represent ecosystems which cover one to many parameters (Fulton 2010; Andrea et al., 2016). Moreover the weighted system of all selected indexes must be of subjective weights with the experience of expert's knowledge such as AHP (Boori et al., 2017; Zhao et al., 2016). It's not an easy task to uniform all ecological indicators due to their multi-dimensional intricacy and diversity. Therefore in the present time remote sensing and GIS is the most effective tool to study and analyze regional eco-environment (Taixia 2020; Wu et al., 2020; Boori et al., 2018) due to its multidimensional, multi-characteristics, regular and quick data availability. Thus this research work uses remote sensing derived ecological indicators for urgent need of accurate ecological condition assessment and to take immediate decision for its protection, preservation and recovery. This is only possible by remote sensing data as they are available with very high frequency, good quality, for any date, time and locations. Apparently, further research has been still needed to improve the objectivity of the databases, effectiveness of indicators, and procedures of monitoring and evaluation.

In this research work a remote sensing (RS) and geographical information system (GIS) based approach was developed to generate RSEI and EI and then compare their results and in last identify EEQ with the PSR approach in the study area. As soil, water, vegetation, biology and atmosphere are the key components for ecological response in an ecosystem. Soil texture, biological activities and chemical properties are effects on agriculture production, which could further affect the atmosphere by moisture, temperature, structure and texture contents (Baishali et al., 2018; Titova and Baltrėnaitė 2020). Water is a basic requirement for a society so water utilization, land use/cover, management or water resources are main factors in an ecosystem or its change (Leemhuis et al., 2017). Biological contents affect life activities of microorganisms and subsequently vegetation, atmosphere and agriculture production. Generally soil moisture and water resources bring changes in wetness, soil fertility later on vegetation type and quality of water environment, which affect plant growth and can lead by changes in greenness, soil temperature, land use/cover and further on heat, soil texture and in last dryness. Therefore any disturbance or change in any ecological indicator ultimately affects or disturbs the whole ecosystem, as all are directly or indirectly relevant.

2. Materials and data acquisition

2.1. Study area

Samara region is situated in the South-East of the Eastern European Plain in the middle flow of the greatest European river, the Volga, which separates the region in two parts of different size, Privolzhye and Zavolzhye. Study area (Fig. 1.) Samara known from 1935 to 1991 as Kuybyshev is the eighth-largest city in Russia and the administrative

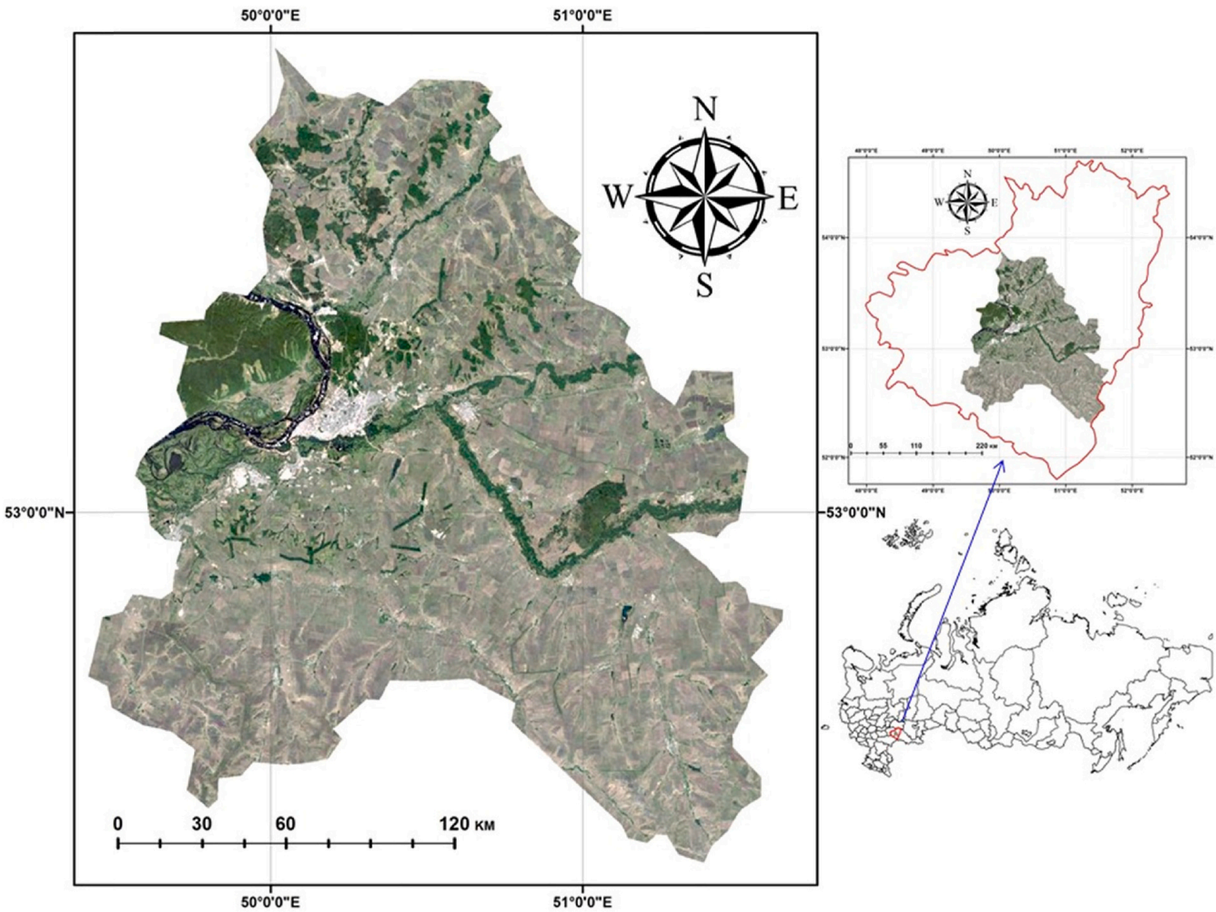

Fig. 1. Location map of the study area in Samara State, Russia (Image from google earth).

center of Samara Oblast. Geographical coordinates are 53° 12′10’’N and 50° 08′27’’E (Fig. 1). The region occupies an area of 53.6 square kilometers (0.31% of the territory of Russia) and forms a part of the Volga Federal District. It is situated in its southern part. The Volga acts as the city’s western boundary; across the river are the Zhiguli Mountains, after which the local beer (*Zhigulyovskoye*) is named. The northern boundary is formed by the Sokolyi Hills and by the steppes in the south and east. The region stretches from 335 km from the North to the South and for 315 km from the West to the East. The land within the city boundaries covers 46,597 ha hectares (115,140 acres). Population is 1,163,399 (2018 Census); 1,164,685 (2010 Census); 1,157,880 (2002 census); 1,254,460 (1989 Census). The metropolitan area of Samara-Tolyatti-Syzran within Samara Oblast contains a population of over three million. Formerly a closed city, Samara is now a large and important social, political, economic, industrial, and cultural center in European Russia. It has a humid continental climate characterized by hot summers and cold winters.

2.2. Data and pre-processing

2.2.1. Data

This research work used Landsat thematic mapper (TM), enhanced thematic mapper (ETM+) and operational land imager (OLI) data for the year of June 10, 10/06/2010, July 25, 25/07/2015 and August 20, 20/08/2020 respectively. All imageries were downloaded free of cost from Earthexplorer of united states geological survey (USGS) website with less than 10% cloud cover, mainly spring and autumn seasons from 169 path and 23 row. All missing and highly cloud covered data were replaced by one year before or after respectively. All sensors have 30 m spatial and 16 days temporal resolution. The details of all Landsat sensors are described in Table 1.

2.2.2. Pre-processing

All images were resampled by cubic method for high accuracy in ArcGIS software. Then geometric and atmospheric errors were removed and used filters for noise removal at pixel level. OLI images were rectified or projected in WGS-1984-UTM zone-39 N projection and then TM and ETM + images were registered based on OLI rectified images.

3. Method

Ecological responses were tried to identify in the study area by 15 ecological indicators under the PSR framework, in that following 12 indicators were pressure indicator and reaming 3 state indicators (Fig. 2):

Pressure indicators: global environmental monitoring index (GEMI), evaporation rate (ER) and land surface temperature (LST), soil adjusted vegetation index (SAVI) and normalized difference moisture index (NDMI), Land use/land cover (LULC) change, Road network, Railway network and light index (LI), normalized difference water index (NDWI), terrain roughness index (TRI) and digital elevation model (DEM).

State indicators: normalized difference vegetation index (NDVI), leaf area index (LAI), fractional vegetation cover (FVC).

Before ecological environment analysis all indicators were standardized from 0 to 1 range and rescale in terms of spatial and temporal resolution so that all indicators get similar weight and importance in the result (Wei et al., 2019; Yuanyuan et al., 2019).

Table 1
The band details of Landsat sensors.

Bands	Landsat TM		Landsat ETM+		Landsat OLI	
	Wavelength (μm)	Spatial Resolution (m)	Wavelength (μm)	Spatial Resolution (m)	Wavelength (μm)	Spatial Resolution (m)
1	0.45–0.52	30	0.45–0.515	30	0.43–0.45	30
2	0.52–0.60	30	0.525–0.605	30	0.45–0.51	30
3	0.63–0.69	30	0.63–0.69	30	0.53–0.59	30
4	0.76–0.90	30	0.775–0.90	30	0.64–0.67	30
5	1.55–1.75	30	1.55–1.75	30	0.85–0.88	30
6	10.41–12.5*	120	10.4–12.5*	60	1.57–1.65	30
7	2.08–2.35	30	2.08–2.35	30	2.11–2.29	30
8			0.52–0.9	15	0.50–0.68	15
9					1.36–1.38	30
10					10.6–11.2*	100
11	* Thermal bands				11.5–12.5*	100

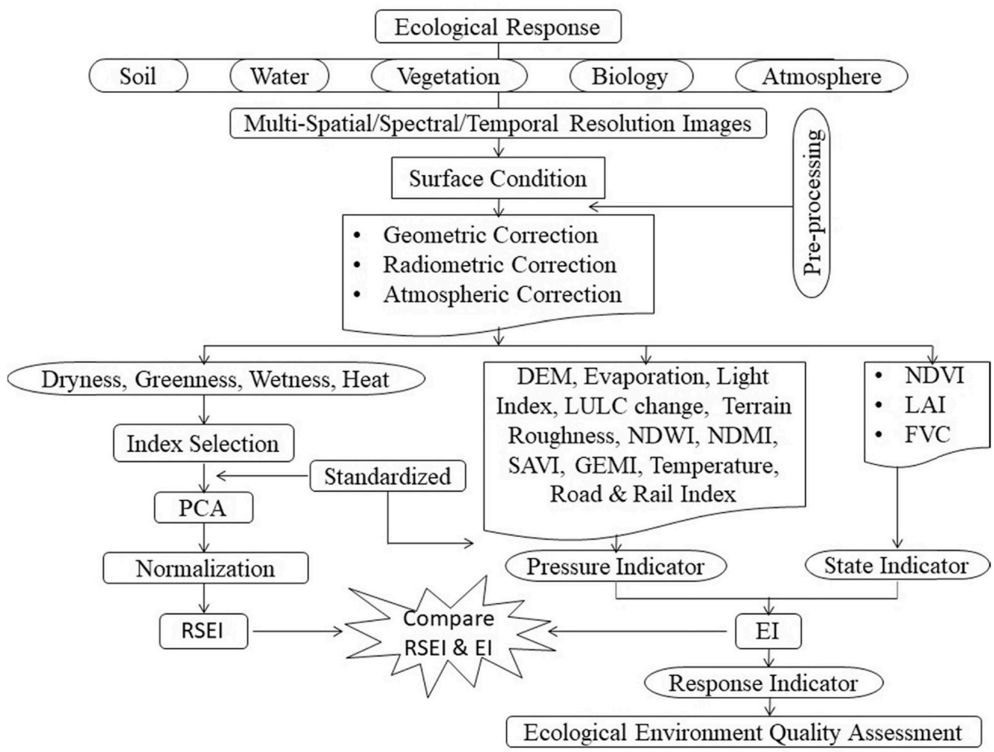

Fig. 2. Methodological chart for RSEI, EI and EEQ assessment based on PSR framework by RS-GIS.

3.1. *Indicators used*

3.1.1. *Wetness*

Wetness parameter express as land surface moisture (LSM) and can generated from Landsat OLI, TM, and ETM + images reflectance by follow Eqs. (1)–(3) respectively (Hu and Xu 2019; Huang et al., 2002):

$$LSM_{OLI} = 0.1511{*}B_{Blue} + 0.1972\ B_{Green} + 0.3283{*}B_{Red} + 0.3407{*}B_{NIR} - 0.7117{*}B_{SWIR1} - 0.4559{*}B_{SWIR2} \quad (1)$$

$$LSM_{TM} = 0.0135{*}B_{Blue} + 0.2021\ B_{Green} + 0.3102{*}B_{Red} + 0.1595{*}B_{NIR} - 0.6806{*}B_{SWIR1} - 0.6109{*}B_{SWIR2} \quad (2)$$

$$LSM_{ETM+} = 0.2626{*}B_{Blue} + 0.2141\ B_{Green} + 0.0926{*}B_{Red} + 0.0656{*}B_{NIR} - 0.7629{*}B_{SWIR1} - 0.5388{*}B_{SWIR2} \quad (3)$$

where B_{Blue}, B_{Green}, B_{Red}, B_{NIR}, B_{SWIRI}, and B_{SWIR2} is the reflectance values of the blue, green, red, near-infrared, and shortwave-infrared bands of the Landsat TM/ETM+ and OLI images, respectively.

3.1.2. *Greenness*

Normally NDVI is the best indicator to measure greenness and can easily measure by red and infra-red bands combination by following equation (4) (Liu and Shi, 2016):

$$NDVI = (B_{NIR} - B_{Red}) \ / \ (B_{NIR} + B_{Red}) \quad (4)$$

where, B_{NIR} and B_{Red} are referring to near-infrared and red bands reflectance. NDVI values existence in between −1 andto +1. Where +1 or close to it represents dense or healthy vegetation, close to 0 show barren lands and close to −1 represent no vegetation or water/ice/snow.

3.1.3. *Dryness*

Dryness represents by no vegetation or very less soil moisture in an open area and in cities by built-up areas. This research work used soil index (SI) and built-up index (IBI) to generate dryness index from different band combination of satellite images (Xu 2008; Essa et al., 2012) and call it normalized differential building and bare soil index

(NDBSI) as mentioned in Eqs. (5)–(7) respectively (Xu 2008; Essa et al., 2012; Hu and Xu 2019):

$$IBI = \{2\ B_{SWIR1} / (B_{SWIR1} + B_{NIR}) - [B_{NIR} / (B_{NIR} + B_{Red}) + B_{Green} / (B_{Green} + B_{SWIR1})]\} / \{2^* B_{SWIR1} / (B_{SWIR1} + B_{NIR}) + [B_{NIR} / (B_{NIR} + B_{Red}) + B_{Green} / (B_{Green} + B_{SWIR1})]\} \quad (5)$$

$$SI = [(B_{SWIR1} + B_{Red}) - (B_{Blue} + B_{NIR})] / [(B_{SWIR1} + B_{Red}) + (B_{Blue} + B_{NIR})] \quad (6)$$

$$NDBSI = (IBI + SI) / 2 \quad (7)$$

where B_{Blue}, B_{Green}, B_{Red}, B_{NIR}, B_{SWIRI}, and B_{SWIR2} is the reflectance values of the blue, green, red, near-infrared, and shortwave-infrared bands of the Landsat.

3.1.4. Temperature

Land surface temperature (LST) can generate by following equations from 8 to 10 (Estoque et al., 2017):

$$L_{\lambda} = gain^* DN + Bias \quad (8)$$

$$T_b = K_2 / \ln(K_1 / L_{\lambda} + 1) \quad (9)$$

$$LST = T_b / [1 + (\lambda T_b / \mathrm{P})\ In\varepsilon] \quad (10)$$

where L_{λ} is thermal band radiance; gain is thermal infrared gain value; bias is offset value. T_b is satellite generated brightness temperature and K_1, K_2 their thermal band's constants. All values can find from the referenced file of satellite data. λ and Ɛ are thermal band wavelength and emissivity respectively. Emissivity can calculate by following equation (11) (Sobrino et al., 2004):

$$\varepsilon = mP_v + n \quad (11)$$

where m is the bare soil emissivity (0.004) and n is vegetation coverage (0.986). P_v is vegetation proportion and can derive from NDVI as Eq. (12) (Carlson and Ripley 1997):

$$P_v = \left(\frac{NDVI - NDVI_{min}}{NDVI_{max} - NDVI_{min}}\right)^2 \quad (12)$$

3.1.5. Leaf area index (LAI)

There are many methods to generate LAI from remote sensing data but this research work used following empirical model (Baret et al., 2007) due to its simplicity and quickness and calculates LAI by following equation (13) based on NDVI value:

$$LAI = 0.57^* e^{2.33^* NDVI} \quad (13)$$

3.1.6. Fractional vegetation cover (FVC)

There are lots of methods to calculate FVC but Baret et al., (2007) is one of the best one, which is based of NDVI as following Eq. (14):

$$FVC = 1 - \left[(NDVI_{Veg.} - NDVI) / (NDVI_{Veg.} - NDVI_{Soil})\right]^{0.6175} \quad (14)$$

where FVC is fractional vegetation cover, normal pixel NDVI value, vegetation NDVI value (max NDVI) and bare soil NDVI vale (or min NDVI vale).

3.1.7. Elevation

This study used digital elevation model (DEM) for topographic features response. DEM was downloaded from USGS website at 30 m meter resolution.

3.1.8. Terrain roughness index (TRI)

This study used TRI terrestrial features response. TRI (Terrain Roughness or Ruggedness Index) was generated from DEM as following equation (15):

$$TRI = (Mean\ elevation - \mathrm{Min}elevation) / (Max\ elevation - \mathrm{Min}elevation) \quad (15)$$

3.1.9. Evapotranspiration (ET)

For climate change indication evaporation (ET) was used as this component is related with temperature and humidity in the environment and its change. ET data were acquired from USGS famine early warning systems network (FEWS NET) data portal.

3.1.10. Light index

A country's infrastructure and facilities such as light index can be used for analyzing human pressure on the ecosystem. High population density represents a high light index and its greater changes show more frequency of human activities. Light data was accessed from defense meteorological satellite program (DMSP), the Payne Institute for Public Policy under the Colorado School of Mines.

3.1.11. Rail and road network

A country's infrastructure and facilities such as road and rail networks can be used for analyzing human pressure on the ecosystem. High population density represents a higher density of road and rail network with higher frequency of transportation and its greater changes show more frequency of human activities. Road and rail network data were obtained from OpenStreetMap as it's globally available at free of cost and can be used for traffic situation and intensity. The obtained data was in line vector format so before using, it was converted into pixel raster format at 30 m resolution so that it was easily combined with reaming satellite data. In the study area road data includes primary (national highway), secondary (state highway), residential and local roads (including footpath & cycle way), while railway data includes Rails, metro, tram line and narrow-gauge.

3.1.12. Land use/cover

As land use/cove map is the baseline map for maximum types of studies and its changes directly affects the ecosystem so all three years LULC maps were used to access pressure indicators in the study region. In this research work supervised maximum likelihood classification approach was used in all three years (2010, 2015, & 2020) Landsat images and got following six major LULC classes: agriculture, forest,

Table 2
Grading index based on land cover.

Land use	Unused land, Forest, Water	Mangroves, Wetland	Agriculture	Settlements
Grades	1	2	3	4

mangroves, settlements, water and wetland. Therefore land use index was developed based on land cover and its intensity, effectiveness and importance in the ecosystem. High index represents extremely or peak utilized land and is unable to further utilization of land such as fully urbanization, where humans cannot use it further. The low index value shows the beginning of the land resource utilization like open land. Therefore land utilization grading index was developed as shown in Table 2 based on the AHP method.

3.2. PSR framework

In a pressure-state-response framework, pressure index refers to pressure on natural resources or ecosystems by social/artificial/human activities, whereas state index shows the health of ecosystems. Response index refers to changes in ecosystem due to pressure and state index. This research work derives ecological environmental quality (EEQ) assessment based on pressure, state and response index. The (1) Pressure factor was derived by 12 indicators, (2) State factor derived 3 indicators and (3) response indicator was calculated from difference between pressure and state indicator.

3.2.1. Pressure indicator (PI)

In this research work, natural ecosystems components such as land, water, atmosphere's exploitation, limitation were used to quantitatively measure pressure indicators. Therefore pressure indicators directly reflect natural resources conditions and human activities.

Based on Table 2 grading system, a pressure indicator was generated to analyze human activities interference or pressure on ecosystems from standardized data from 0 to 1 range with equal weight to all indicators in the study area as following equation (16).

$$°\mathrm{PI} = (\mathrm{GEMI} + \mathrm{ER} + \mathrm{LST} + \mathrm{SAVI} + \mathrm{NDMI} + \mathrm{LULC} + \mathrm{Road} + \mathrm{Rail} + \mathrm{NLI} + \mathrm{NDWI} + \mathrm{TRI} + \mathrm{DEM}) / 12 \quad (16)$$

hHere high values indicate high pressure so the worst situation of ecosystem and low value represent low pressure or less human activities means best ecological condition or best ecosystem situation (Table 3).

3.2.2. State indicator (SI)

State indicator represented by the health of the ecosystem, which is closely related to natural healthy vegetation conditions in the region. Vegetation changes also make an important role in global warming and biodiversity. Therefore in this study three major vegetation indexes or vegetation cove used for state indicator: NDVI, LAI and FVC. All are very significant with hydrology, ecology, regional change and can be accessed very simply and quickly (Wanjuan 2017). Therefore the state indicator was developed by a combination of NDVI, LAI and FVC from different bands of Landsat data.

Generally healthy ecosystems are represented by healthy natural phenomena such as NDVI, LAI, FVC, forest, mangroves, wetland and waterbody. Where there is not too much human interrelation, activities or disturbance in ecosystem, thus these land cover classes show healthy status of ecosystem and are defined as 1 otherwise its vice-versa as 0. To calculate the state indicator first all parameters were standardized from 0 to 1 range and then given equal weight as equation (17).

Table 3
Grades of pressure indicator.

Grades	I	II	III	IV	V
	Below standard	Low	Moderate	High	Extreme
Pressure indicator	0–0.2	0.2–0.4	0.4–0.6	0.6–0.8	0.8–1.0

Table 4
Grades of state indicator.

Grades	I	II	III	IV	V
	Poor	Fair	Moderate	Good	Excellent
State indicator	0–0.2	0.2–0.4	0.4–0.6	0.6–0.8	0.8–1.0

$$SI = (NDVI + LAI + FVC) / 3 \quad (17)$$

Higher SI value indicates better ecological condition and lower value represent poorer ecological condition (Table 4).

3.2.3. Response indicator (RI)

The response indicator was assessed by the geometric overlay method in between pressure indicator (PI) and state indicator (SI), which show net effect or balance situation from pressure and state condition. In other words, the response indicator can predict by pressure indicator minus state indicator as equation (18).

$$RI = PI - SI \quad (18)$$

Generally in a high pressure situation, response indicator will high, means a poor ecological situation, therefore a lot of changes in the ecosystem, so high responses were indicating high ecological disturbance or environmental change. On the other hand high state indicators show a low response indicator means high stable situation or good ecological condition and an established environment with very low or no change due to less human and natural pressure. Directly we can say low response indicators represent a stabilized ecosystem and sustainable development.

3.3. Calculation of RSEI

Remote sensing can provide a real-time data and large-scale monitoring and now widely used in the field of the eco-environment and has become an effective method for evaluating regional eco-environments. Xu (2013) proposed monitoring and evaluating the eco-environment by obtaining ecological indicators based on remote sensing technology in 2013, and it is remote sensing ecological index (RSEI).

RSEI can generate from following four remote sensing satellite data derived indicators: dryness, greenness, heat and moisture. All four indicators generally used to evaluate ecological condition because they are closely relate to ecological condition in an ecosystem and directly perceived by many researchers (Coutts et al., 2016; Seddon et al., 2016). First all four indicators must be standardize from 0 to 1 to remove the different dimensions and range values. Than a composite RSEI was derived from principal component analysis (PCA) for an objective and quantitative evaluation (Abson et al., 2012) as following Eq. (19):

$$RSEI = r_1PC_1 + r_2PC_2 + r_3PC_3 + \ldots\ldots\ldots r_iPC_i \quad (19)$$

where r_i is the contribution ratio of principal component (PC), and i is the quantity of PC that remains. The contribution ratio r_i is calculated as follows Eq. (20):

Table 5
Principal component analysis (PCA) for RSEI.

	2010				2015				2020			
	PCA1	PCA2	PCA3	PCA4	PCA1	PCA2	PCA3	PCA4	PCA1	PCA2	PCA3	PCA4
NDBSI	−0.0034	−0.2518	0.9661	0.05605	−0.00016	−0.0007	−0.00573	0.99998	−0.00018	−0.0028	−0.0092	0.9999
NDVI	−0.0009	0.9445	0.2579	−0.2032	−0.12566	0.91976	−0.37183	−0.0014	−0.015	0.9845	−0.1743	0.00117
LST	0.98161	0.0402	0.0031	0.1865	0.98949	0.14324	0.01992	0.00035	0.9998	0.01636	0.00563	0.0002
LSM	−0.1908	0.2069	−0.0023	0.9595	−0.07158	0.36542	0.92807	0.00559	−0.0084	0.1741	0.9846	0.00955
Eigenvalue	0.1483	0.0073	0.0071	0.0013	0.0124	0.0038	0.0005	0.00003	0.01007	0.0006	0.00028	0.00003
Eigv. %	90.35	4.497	4.326	0.8167	73.93	22.92	3.08	0.18	91.69	5.49	2.54	0.26
Accum.Eigv.	90.35	94.85	99.18	100	73.93	96.81	99.81	100	91.69	97.18	99.73	100

$$r_i = p_i \sum_{i=1}^{n} p_i \tag{20}$$

where p_i represent the eigenvalue of PC_i.

So RSEI for the year 2010, 2015 and 2020 were obtained from Table 5 by Eq. (21)–(23):

$$RSEI_{2010} = 0.9035PC_1 + 0.0449PC_2 + 0.0432PC_3 + 0.0081PC_4 \tag{21}$$

$$RSEI_{2015} = 0.7393PC_1 + 0.2292PC_2 + 0.0308PC_3 + 0.0018PC_4 \tag{22}$$

$$RSEI_{2020} = 0.9169PC_1 + 0.0549PC_2 + 0.0254PC_3 + 0.0026PC_4 \tag{23}$$

After getting all three years RSEI, it was classified into following five parts based on natural brakes in ArcGIS software as "POOR, FAIR, MODERATE, GOOD and EXCELLENT" to compare the whole study area to each other.

3.4. Calculation of EI

Based on AHP method, first assigned weight to all 15 indicators and then generate ecological index based on following equations (24) and (25) (Ludovic et al. 2011; Johnny and Heng, 2008):

$$\mathrm{EI} = \sum_{i=1}^{n} \mathrm{W* \ C} \tag{24}$$

where EI is an ecological indicator, w and c represents weight and standardized data.

$$EI = W^* \ C + \ldots\ldots n \tag{25}$$

So with the help of all ecological response parameters, we calculate EI as Eq. (26):

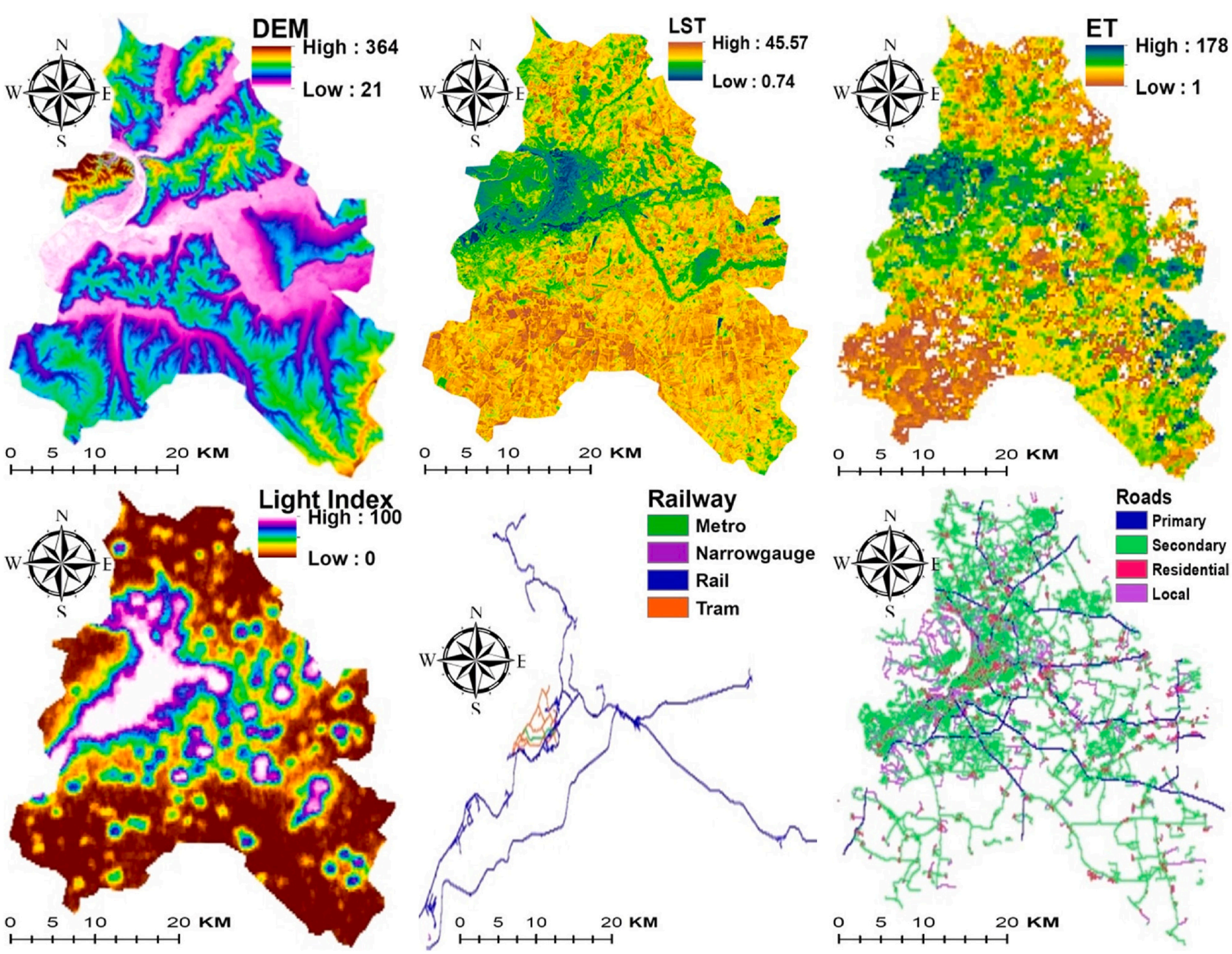

Fig. 3. Thematic layers for RSEI, EI and EEQ assessment based on PSR framework by RS-GIS.

$$\mathrm{EI} = \mathrm{W(environment)} + \mathrm{w(climate)} + \mathrm{w(soil\ moisture)} + \mathrm{w(greenness)} + \mathrm{w(LULC)} + \mathrm{w(artificial\ features\ \&\ energy)} + \mathrm{w(water\ content)} + \mathrm{w(landscape)} \tag{26}$$

where

Environmental parameter: *global environmental monitoring index (GEMI),*
Climate parameter: *evaporation rate (ER) and land surface temperature (LST);*
Soil moisture: *soil adjusted vegetation index (SAVI) and normalized difference moisture index (NDMI);*
Greenness: *normalized difference vegetation index (NDVI), leaf area index (LAI), fractional vegetation cover (FVC);*
Land use/land cover: *LULC change;*
Artificial features and energy: *Road network, Railway network and light index (LI)*
Water content: *normalized difference water index (NDWI);*
Landscape: *terrain roughness index (TRI) and digital elevation model (DEM)*,

Or in other words with the help of all 15 indicators and their weight based on AHP method, we calculate EI as following Eq. (27):

$$\mathrm{EI} = 0.35(\mathrm{GEMI}) + 0.31(\mathrm{ER} + \mathrm{LST}) + 0.30(\mathrm{SAVI} + \mathrm{NDMI}) + 0.25(\mathrm{NDVI} + \mathrm{LAI} + \mathrm{FVC}) + 0.22(\mathrm{LULC}) + 0.17(\mathrm{Road} + \mathrm{Railway} + \mathrm{LI}) + 0.15(\mathrm{NDWI}) + 0.10(\mathrm{TRI} + \mathrm{DEM}) \tag{27}$$

4. Results and discussion

The results represent constrictive analysis of Eco-environmental quality assessment (EEQ) under pressure-state-response (PSR) approach as well as changes and comparison in between RSEI and EI from 2010, 2015 and 2020 in the study area. The specific results were following:

4.1. Indicators characteristics

4.1.1. Elevation

The DEM topographic map shows variations of heights from 21 m to 364 m with 100 m average height in the study area (Fig. 3). The peak elevation was mainly located in Zhiguli Mountain area northwest center part of the study area. The lowest altitude was located at Volga and Samara rivers bank. Low altitude presents the upper, middle and south part of the study area from east to west direction. Normally high altitude shows more stable ecological conditions due to low socio-economic activities or low human pressure and activities. Therefore the west central part of the study area was the most suitable part for a stable environment and suitable ecology.

4.1.2. Temperature

The Samara region has very extreme cold winter weather and a very hot summer season. The average summer season temperature was variate from 0 to 45 °C (Fig. 3). The lower temperature mainly distributes to the northwest part of the study region, which was mainly covered by forest and plantation. South part of the study area shows high temperature as it's a plan area and has high socio-economic activities including large number of industries and cultivation as well as affected by terrain and high solar radiation. Therefore in the study area temperature gradually increased from northwest to south and east direction. In Russian climate context little bit high temperature from 20 °C to 40 °C is the most suitable temperature for species survival and vegetation richness.

4.1.3. Evapotranspiration (ET)

ET distribution was largely variate from 1 to 178 mm in the study area (Fig. 3). A higher evaporation was present in higher elevation, forest area and along the river and water bodies. It's especially located from center west to east direction. The average evaporation was around 90 mm and presents almost in all parts of the study areas in patches format except the southeast region. The lowest ET was present in the southwest and some patches in the north and other parts of the study region. Generally a very high evapotranspiration is not suitable for vegetation or stable ecology because it increases water stress condition in plants. But in Russian climate context due to extreme coldness, it creates favorable conditions for vegetation and ecology in a specific range as it makes a balanced moisture situation in the ecosystem.

4.1.4. Light index

Light index is the symbol of prosperity as well as indicating human activities with population density. City of Samara shows the highest light index and it gradually reduces from city center to outward. Some small towns and villages also show higher light index, which were within 150 km distance from the Samara city. In a general trend light index reduces with distance from any types of settlements (Fig. 3). Therefore higher socio-economic activities and rapid development is associated with higher light index and poor ecological condition. As higher human-socio-economic activities or higher human pressure are negative effects on a stable environment.

4.1.5. Rail and road network

The Samara region shows a very densely road network, as well as higher rail network and was centralized to the Samara city direction due to the state capital city in the region (Fig. 3). The density of road and rail network is directly related to higher population density, high human activities, and high socio-economic activities because higher road and rail network provide frequent transportation or convenient facilities for humans. But this higher transportation and socio-economic activities put a negative impact on the stability of ecology.

4.1.6. Land use/cover

Different earth surface objects NDVI curves show a certain change rule based on their phenological characteristics. In Russia November to march months, all ground covered by snow/ice. Thus in winter weather NDVI curves were close to 0 and in summer weather in between 0.1 andto 0.6 with peak value in July month (Fig. 4). Forest area shows

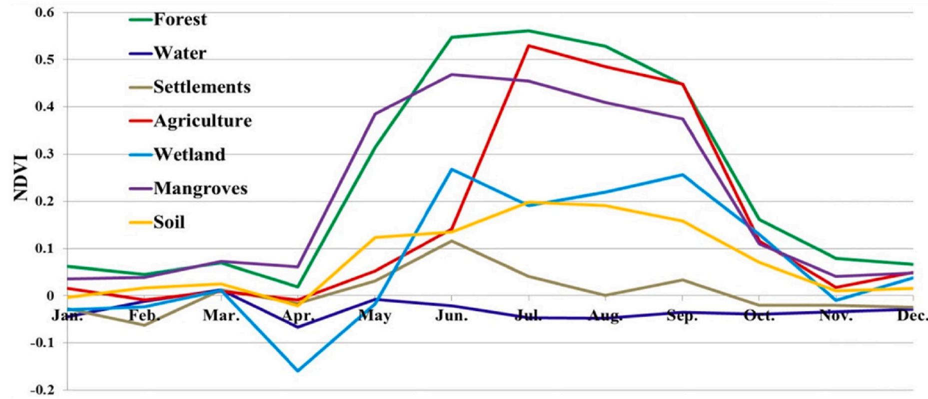

Fig. 4. NDVI time-series for different land cover features.

Table 6
Accuracy assessment based on land cover field data.

Accuracy	2010	2015	2020
User accuracy	86.5	87.2	92.4
Producer accuracy	87.3	91.6	93.2
Overall accuracy	85.8	90.2	91.7
Kappa coefficient	85.1	89.2	91.1

highest NDVI value, than agriculture, followed by mangroves and wetland. In April when snow/ice starts to melt mangroves show immediate reflection with growing and later on forest area but agriculture takes time for its first growth. This agriculture NDVI curve also represents Russian crop calendar phenology. Wetland shows negative value in April due to high water content and later positive value due to greenness. Settlements show low values of NDVI due to some plantation and grass and in the last water body have 0 to negative values (Fig. 4).

For accuracy assessment, two times fieldwork was done in summer 2017 and 2020, also taking help from ancillary data and maps. Some parts of the study area were inaccessible, such as the top of the mountains and valleys, so google earth images were very useful to identify features during accuracy assessment. In the field-work 50 random sample plots were selected for accuracy assessment. Normally 60% sample plots for each land cover class were used. Forest and agriculture classes were highly accurately classified; also in visual interpretation water class was identified very easily. But still, some pixels were misclassified such as rice crops miss classifying in-between wetland and agriculture classes due to moisture content. Some cloud cover areas were misclassified in the settlement area due to its cloudy white tone. The overall accuracy of the work was more than 86% with above 0.85 kappa coefficient (Table 6).

All three years land cover maps shown in Fig. 5. Agriculture, forest, mangroves, and wetland were the most important ecosystems in the study area. Central west part covered by forest and demarks with Volga

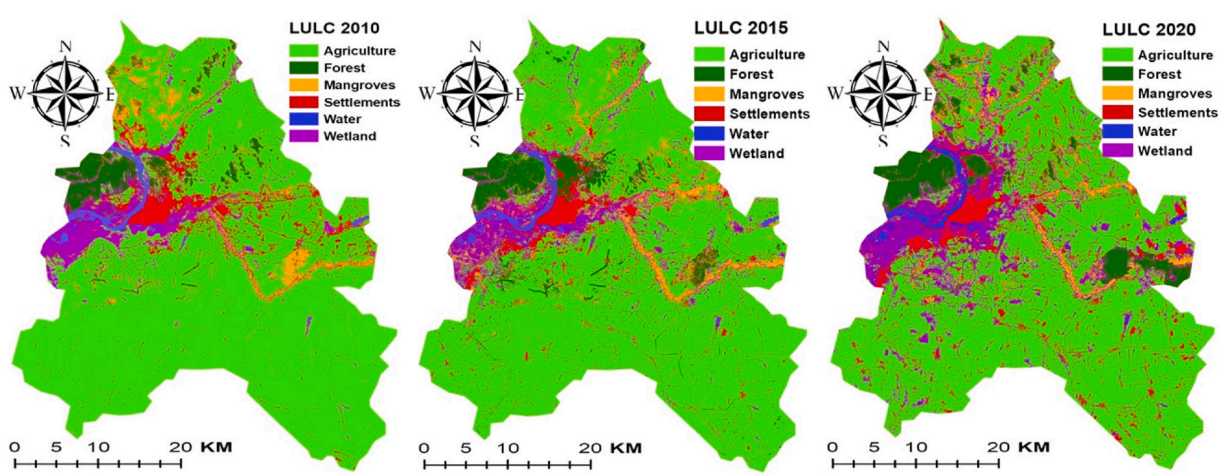

Fig. 5. Land use/cover map of the study area for the year of 2010, 2015 and 2020.

Table 7
Land use/cover classes area with changes from 2010 to 2020.

LULC	2010		2015		2020		Changes 2010 to 2020	
	Area km^2	Ratio %	Area km^2	Ratio %	Area km^2	Ratio %	Area km^2	Ratio %
Agriculture	10679.36	72.04	9710.85	65.50	9513.79	64.18	−1165.58	−7.86
Forest	703.96	4.75	732.33	4.94	1299.53	8.77	589.57	3.97
Mangroves	736.27	4.97	711.90	4.80	842.84	5.69	106.57	0.71
Settlements	1457	9.83	1462.32	9.86	1668.37	11.25	211.37	1.42
Water	182.54	1.23	189.02	1.28	200.32	1.35	17.78	0.11
Wetland	1065.55	7.19	218.20	13.61	1299.89	8.37	234.34	1.58

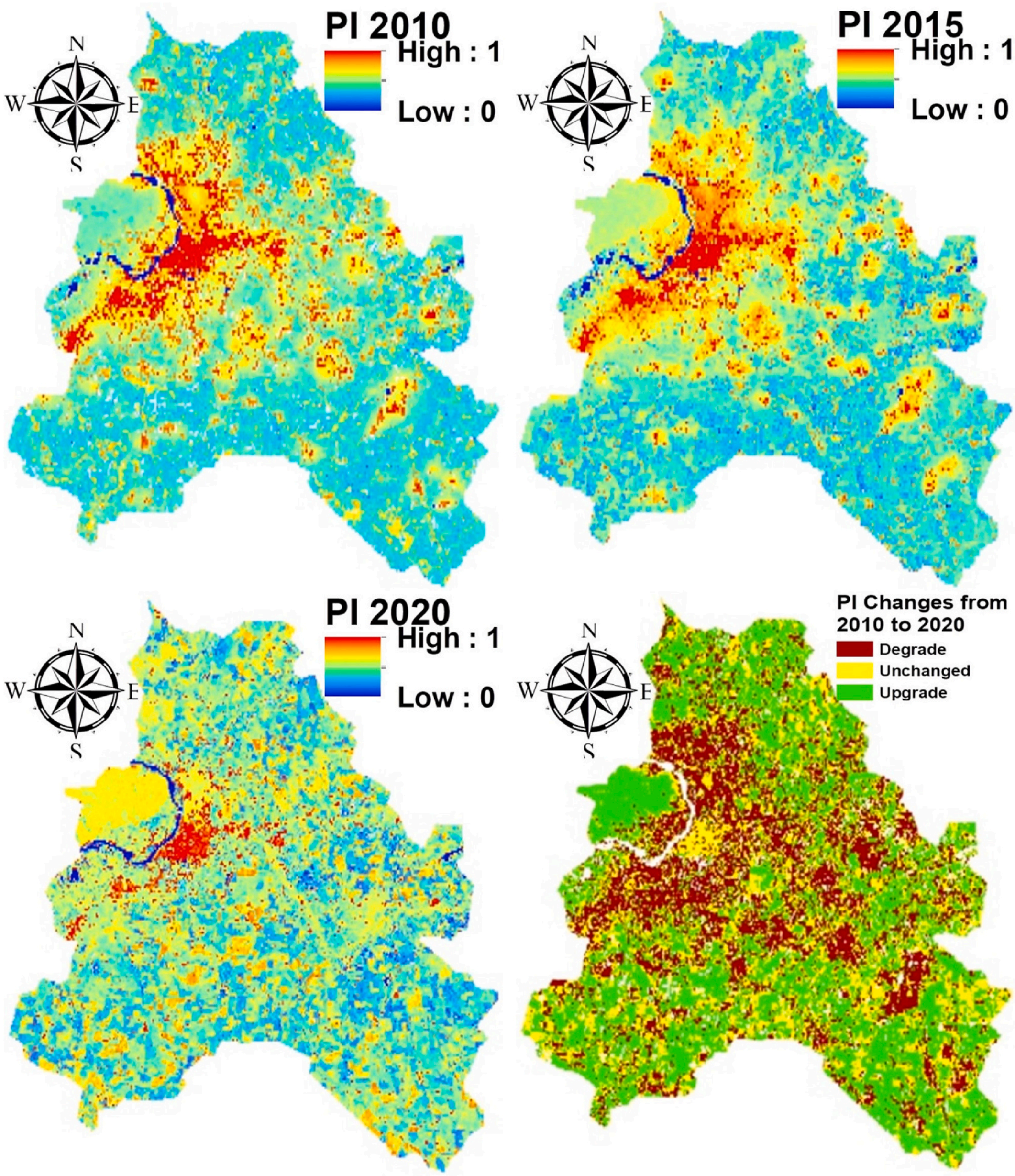

Fig. 6. Pressure indicator and its change map for the year of 2010, 2015 and 2020.

River, which was also associated with wetland. Samara and regional rivers pass from east to west direct in the medial of the study area and cover mangroves area. Central part covered Samara city and neighboring small towns and villages. Water bodies were found all over the study area in patches and the rest whole part of the study area covered by agricultural land (Fig. 5).

Agriculture was the biggest class in the study area and covers around 65% areas but from 2010 to 2020, it's reduced to −7.86% (Table 7). Forest and mangroves covered around 5% (700 km^2) area and during this decade both were increased 3.97% and 0.71% respectively. The

Table 8
Pressure indicators statistics in different stages with changes from 2010 to 2020.

PI	2010		2015		2020		Changes 2010 to 2020				
	Area km^2	Ratio %	Area km^2	Ratio %	Area km^2	Ratio %	Area km^2	Ratio %	Class	Area km^2	Ratio %
Bellow standard (0.0–0.2)	5814.81	40.97	3839.34	26.38	3077.42	21.21	−2737.39	−19.76	Degraded	3848.26	27.53
Low pressure (0.2–0.4)	3875.75	27.31	5549.99	38.14	5964.25	41.11	2088.5	13.80	Unchanged	3962.98	28.35
Moderate pressure (0.4–0.6)	1994.78	14.05	2677.41	18.40	3195.06	22.02	1200.28	7.97	Upgraded	6169.66	44.13
High pressure (0.6–0.8)	1583.91	11.16	1832.37	12.59	1647.85	11.36	63.94	0.20			
Extreme pressure (0.8–1.0)	923.62	6.51	653.83	4.49	624.06	4.30	−299.56	−2.21			
Max.	0.678		0.664		0.614						
Min	0.216		0.235		0.244						
Mean	0.368		0.414		0.39						
SD	0.056		0.051		0.036						

forest class increment showed the special governmental protection in the study area. Settlements covered around 1500 km^2 and continuously increased; the net change was 211.37 km^2 (1.42%). It's shown that the agriculture area was encroached by settlements during 2010–2020 (Table 7). In the first half wetland class was increased with very high speed almost 7% and in the next half from 2015 to 2020 reduced around 5% but overall from 2010 to 2020, it was increased 234.34 km^2 (1.58%), which represents wetland ecosystem preservation. Water class was almost stable around 10% of the study area (Table 7).

It observed that the urban ecosystem expanded on the agriculture ecosystem by industrial and residential construction. This high speed development puts a negative impact on stable ecosystems and influences environmental change. The natural ecosystem (forest and wetland) have been improved continuously, which provide a favorable condition to ecology. Over all in this decade the total negative effect (Agriculture −7.86% & Settlements 1.42%) was higher than total positive response (forest 3.97%, mangroves 0.71%, water 0.11%, wetland 1.58%) from 2010 to 2020. Therefore it's an alarming situation to start an unstable ecosystem.

4.2. General assessment of PSR

4.2.1. Pressure indicator

Pressure indicator was developed from 12 indicators/thematic layers (section 3.2.1) with given equal weight to all layers and get resulted PI map (Fig. 6).

Pressure indicator map showed that high socio-economic activities, development areas associated with extreme pressure such as cities, small towns and villages and far from these locations, pressure reduced gradually. Thus the center of the study area, which covered Samara city, close towns and neighboring villages within 150 km from the capital city showed extreme pressure. Below standard pressure area was continuously reduced and existing only on the water body or close to them (Fig. 6). Low and moderate pressure areas randomly increased and mainly distributed in forest and agriculture areas, while high pressure slightly increased in 2015 and later on miner reduced so not variate too much and existing close to settlements area. Extreme pressure areas also show the same behavior of below standard pressure and shrink continuously in all three years and in 2020, it was existent only in Samara City, nearing towns and in some small patches in some villages. This showed governmental protection and awareness to stabilize, preserve and protect of the ecosystem in the study area (Fig. 6).

PI maps shown that the maximum study area around 85% comes under the below standard to moderate pressure in all three years with moving from 0.0 to 0.6 pressure class (Table 8). High and extreme pressure covered around 15% with small variation in all three years. In comparing from 2010 to 2020 bellow standard and extreme pressure areas reduced −19.76% (−2737.39 km^2) and −2.21% (233.56 km^2) respectively (Table 8). The maximum change has occurred in the low pressure area, which increased 13.80%, during this decade the moderate pressure area has also increased 7.97%, while the high pressure area has negligible changes 0.20%. Over all in this decade 27.53% study area was degraded, while 28.35% area was unchanged but still 44.13% area was upgraded (Fig. 6).

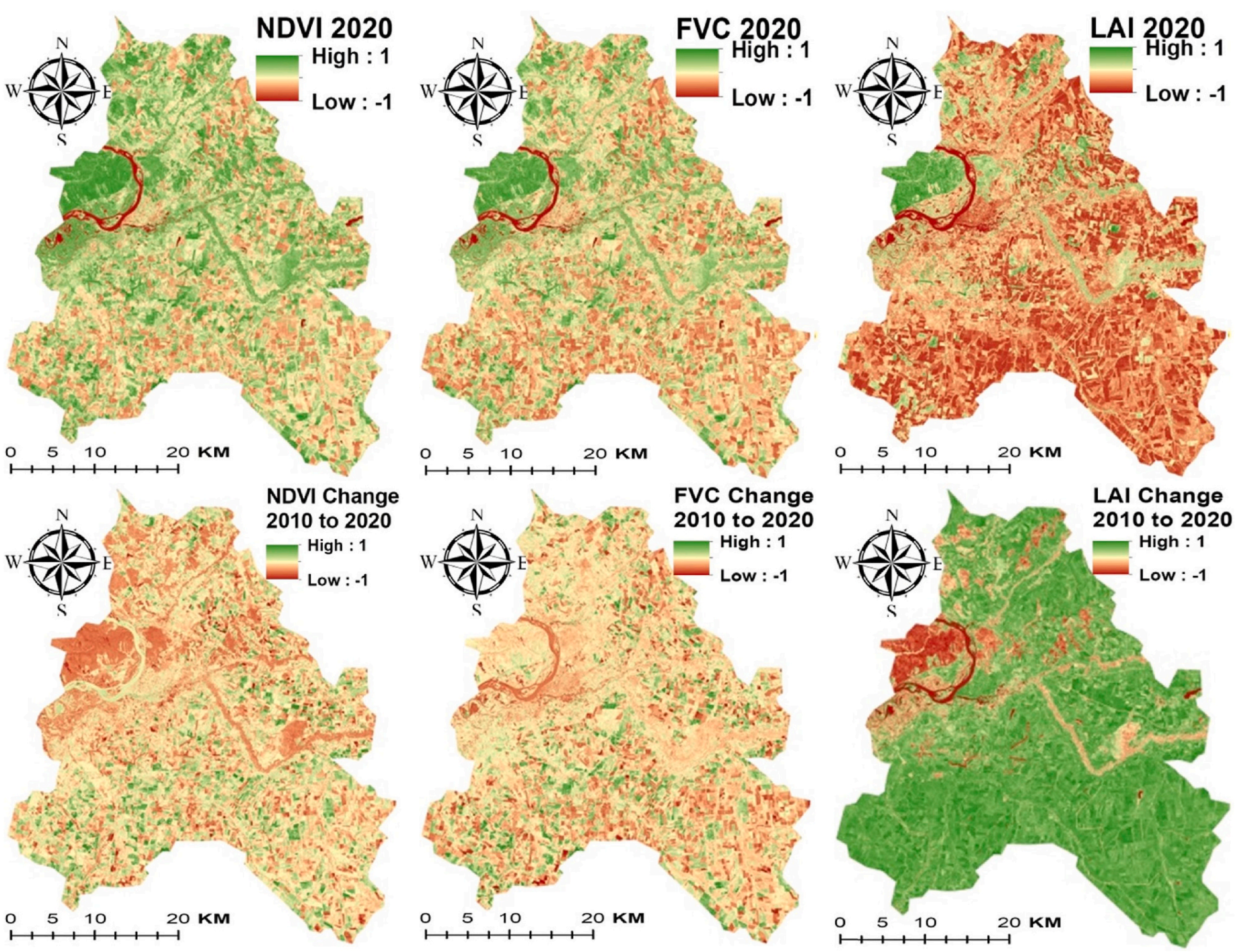

Fig. 7. NDVI, FVC and LAI map for the year of 2020 and their change map from 2010 to 2020.

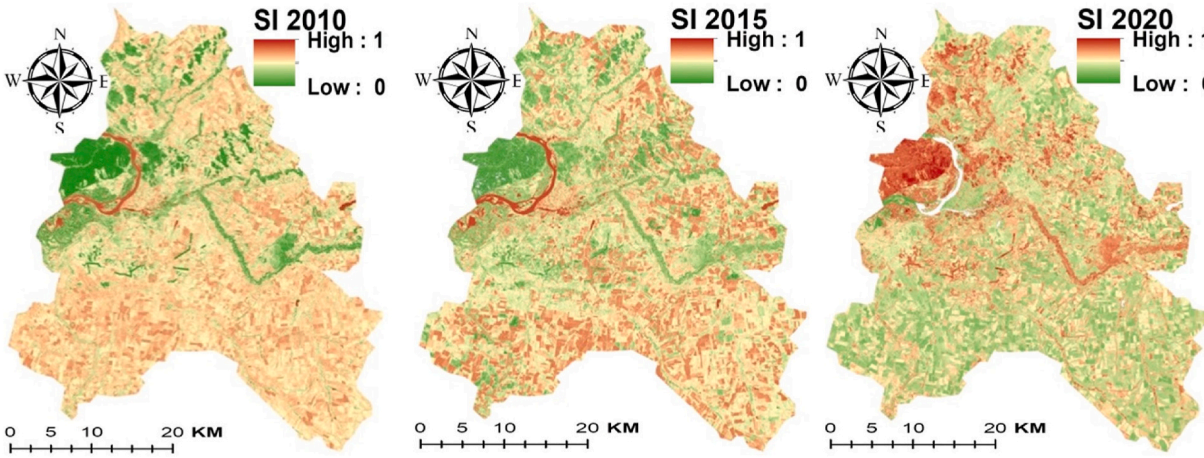

Fig. 8. State indicator map for the year of 2010, 2015 and 2020.

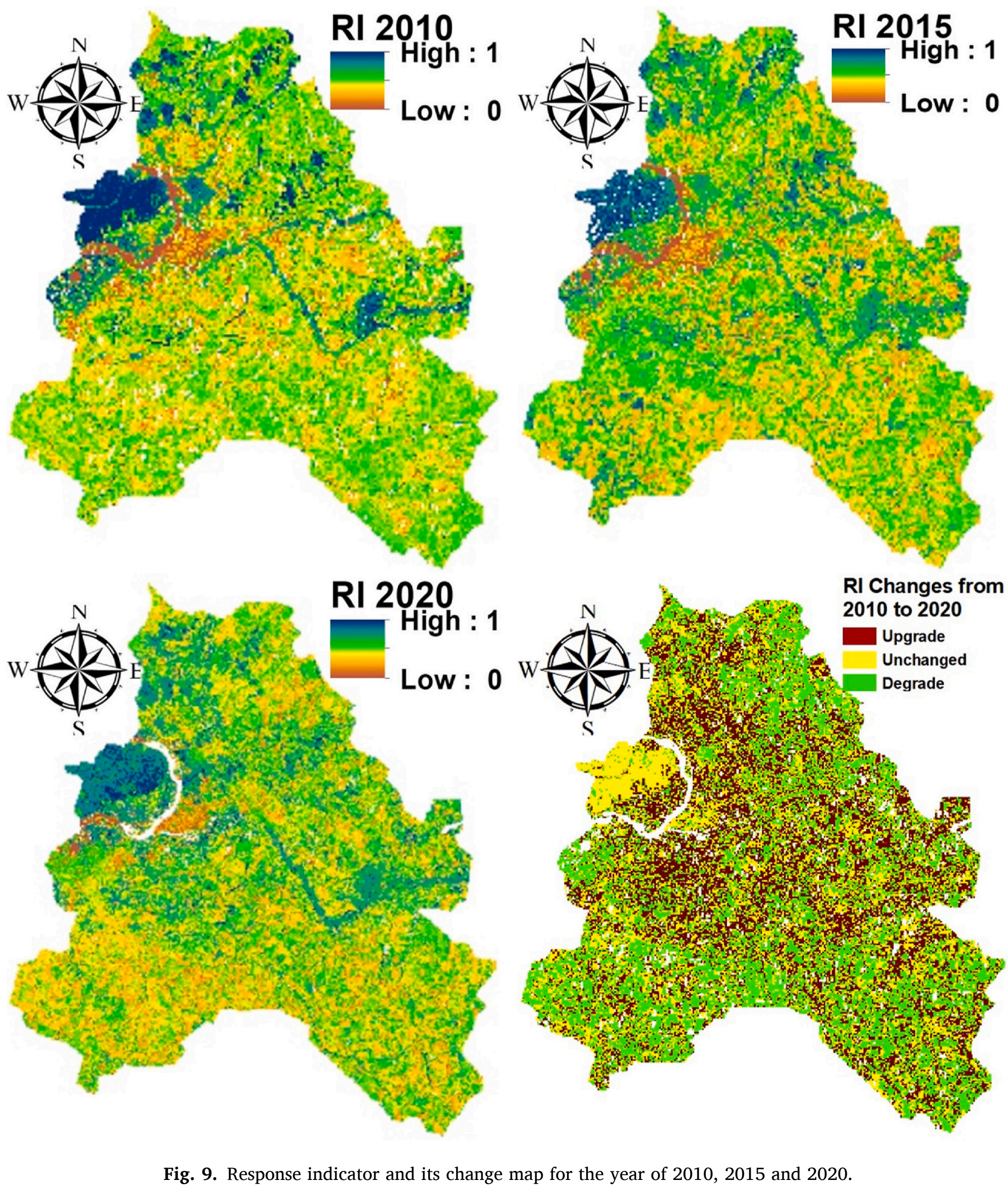

Fig. 9. Response indicator and its change map for the year of 2010, 2015 and 2020.

Table 9
Response indicators statistics in different stages with changes from 2010 to 2020.

RI	2010		2015		2020		Changes 2010 to 2020				
	Area km^2	Ratio %	Area km^2	Ratio %	Area km^2	Ratio %	Area km^2	Ratio %	Class	Area km^2	Ratio %
Bellow standard (0.0–0.2)	1103.86	7.81	999.95	6.92	2170.21	15.02	1066.35	7.21	Degraded	5095.29	32.59
Low response (0.2–0.4)	4499.00	31.83	3772.45	26.12	5103.44	35.33	604.44	3.50	Unchanged	4262.15	30.70
Moderate response (0.4–0.6)	5726.38	40.52	4879.82	33.78	2420.48	16.76	−3305.9	−23.76	Upgraded	4523.61	36.71
High response (0.6–0.8)	1505.66	10.65	3007.73	20.82	2796.34	19.36	1290.68	8.71			
Excellent response (0.8–1.0)	1297.90	9.18	1784.37	12.35	1955.13	13.53	657.23	4.35			
Max.	0.405		0.495		0.578						
Min	−0.528		−0.516		−0.353						
Mean	0.034		0.041		0.06						
Std.	0.113		0.155		0.138						

The maximum PI values gradually reduced (0.67, 0.66 & 0.61) which indicates that high pressure slightly reduced (Table 8). The minimum PI values continuously increased (0.21, 0.23, and 0.24) from 2010 to 2020, which represents that in low pressure areas, pressure were increased year by year, which means maximum changes comes in average pressure. While mean values increased randomly in first half and then slightly reduced in second half, which showed that maximum changes comes in medium level pressure but its high from 2010 to 2015 and in second half from 2015 to 2020, it was little bit less (Table 8).

4.2.2. State indictor

State indicator generated from NDVI, FVC and LAI and then derived changes from 2010 to 2020 as shown in Fig. 7. As Samara has a humid continental climate with extreme cold and heavy snowfall and hot summer, therefore during summer total vegetation was good to excellent condition with above 0.7 NDVI values. Northwest part and in the direction of east along to local rivers in the center of the study area covers forest so have higher NDVI values in comparison to south part, as it has agriculture land (Fig. 7). FVC and LAI also showed the same pattern of NDVI as both are indicators of healthy vegetation. Comparing all three years based on vegetation indexes, as it's also shown in Fig. 7, vegetation was continuously degraded due to extreme cold weather, high socio-economic activities and increased human pressure. From 2010 to 2015 NDVI values reduced little bit but in 2020, it was reduced dramatically even west central part forest area was converted dense to open forest.

If comparing NDVI, FVC, LAI changes from 2010 to 2020. FVC has less changed in comparison of NDVI and these changes were basically in the south part of the study area (Fig. 7). LAI has very highly changed except in the west central part of the forest area and along the rivers from 2010 to 2020.

The resulting state indicator map shows in Fig. 8 and it showed the combined effect of all vegetation indexes. In 2010 a low SI index was presented and it was distributed in the south part of the study area, while in 2015, it was higher than 2010. Comparing 2010 and 2015 maximum stability were in plan or agriculture land and low SI index in mountain forest areas. Later on in 2020 forest and north part of the study area showed higher SI index and south and east part showed low SI index which represent governmental protection in the natural resources and agriculture sector (Fig. 8). The 2020 SI map was just opposite of 2010, which showed high human pressure in the city and agricultural land due to market demand of production to compete with the demand of food. Therefore recent year's low SI index area needs to be more attention. The red color with higher SI values of the map in Fig. 8 showed a good ecological condition while green color with lower SI values indicates an unstable ecological situation.

4.2.3. Response indicator

Fig. 9 and Table 9 showed response indicator distribution in all three years and its changes from 2010 to 2020. High response indicators represent weaker, unhealthy and unstable ecological conditions under high human pressure and vice versa. Higher RI values indicate higher natural/human pressure/higher socioeconomic activities like urban expanses, industrial development, farming activities, which invite disturbance in ecosystems. Low RI values indicate low human interference in the ecosystem, like forest and water ecosystems and far from city center to outwards. Based on Fig. 9 RI maps show continuous upgradation of ecological condition as darkness of blue color tone reduced year by year. South part shows better ecological conditions in comparison of the northwest part of the study area. It means the agriculture or cultivation sector showed a lower RI index than forest area and some sites of socio-economic activities. But every year human pressure was reduced or in natural resources human interference was slowly reduced, thus RI values decreased and with that ecological stability was increased (Fig. 9). Generally change in lower RI value means disturbance in the ecosystem by intense human activities otherwise the ecosystem can convert in better condition with more natural resources.

RI change maps showed no changes in high RI zones or in natural forest resources from 2010 to 2020 (Fig. 9). The central part of the study area showed degradation in this decade. The south, northeast and west wetland area showed upgradation in this decade, which represents governmental protection and local people awareness about the environment for its preservation and protection.

The below standard RI class was almost stable from 2010 to 2015 but then increased 7.21% in 2020, which indicates upgradation of ecological condition, stable ecosystem or less environmental changes (Table 9). Low response class was first reduced from 31.83% to 26.12% and later on increased and reached 35.33% area with net change of 3.50% area from 2010 to 2020. The biggest change occurred in moderate response class, which continuously reduced and total change was −3305.9 km^2 (−23.76%). This reduction was shifted into below standard response class which means upgradation of ecology and second shift in high response class which means degradation of the ecological condition. This shift show that government was not protecting equally the whole study area as well as local people's awareness about ecology was not the same in the whole study area. High response and excellent response classes increased gradually from 2010 to 2020 as 8.71% and 4.35% respectively; therefore some specific locations were more concerned about the poor ecology in place of the whole study area. The total degradation of the study area was 32.59% (5095.29 km^2) and total upgradation was 36.71% (4523.61 km^2), while 30.70% (4262.15 km^2) area was unchanged from 2010 to 2020 (Table 9) thus overall around 4% net study area was going in worst situation. Based on these RI maps suitable policies must be implemented in these areas to make a favorable ecosystem, otherwise it will go in the worst situation.

As maximum values of RI (0.40, 0.49 & 0.57) continuously increased from 2010 to 2020, means high unstable ecological area was shifted in higher worst situation, and minimum RI values (−0.52, −0.51 & −0.35) also increased means high stable ecological condition area also shifted in unstable ecology or in worst situation (Table 9). While in all three years mean values increased (0.03, 0.04 & 0.06) which indicate that maximum changes come in average response areas and its quality gradually decreased (Table 9).

The response indicator under PSR framework developed by RS/GIS indicators is an important parameter to identify changes in ecology. It's

Table 10
Statistics of used factors from 2010 to 2020.

	2010					2015					2020				
	NDBSI	NDVI	LST	LSM	RSEI	NDBSI	NDVI	LST	LSM	RSEI	NDBSI	NDVI	LST	LSM	RSEI
Max.	1	1	66.93	0.455	1.09	1	1	49.97	0.807	1.03	1	1	39.6	0.403	0.96
Min.	−1	−1	17.02	−0.307	0.03	−1	−1	1.78	−0.638	0.16	−1	−1	4.32	−0.675	0.03
Mean	−0.014	0.3	37.04	−0.605	0.79	−3.58	0.29	35.3	−0.287	0.98	−1.79	0.0888	15.19	−0.227	0.82
S.D.	0.12	0.2	6.01	0.203	0.12	0.007	0.14	6.32	0.266	0.11	0.005	0.0561	1.58	0.900	0.1

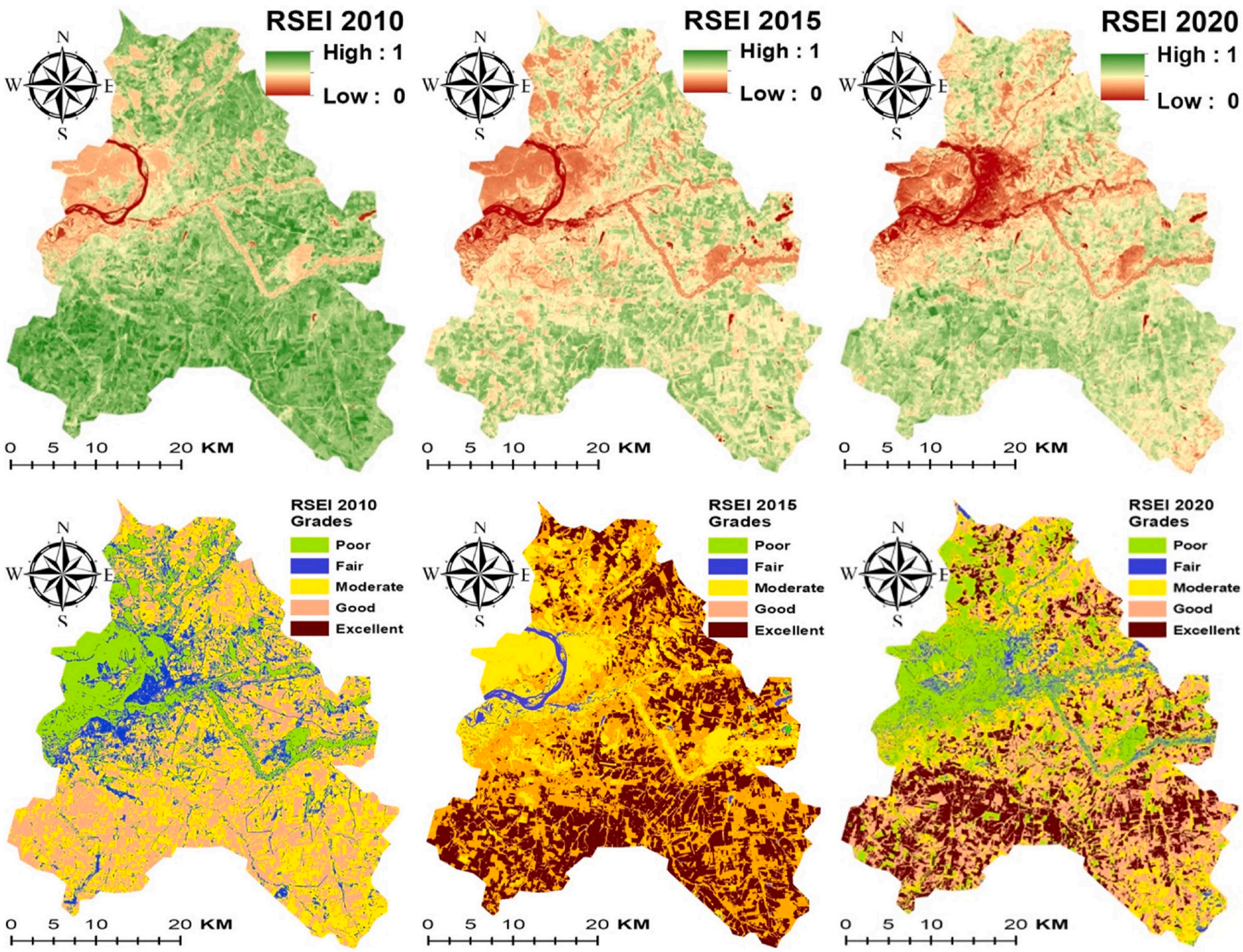

Fig. 10. RSEI maps for the year of 2010, 2015 and 2020.

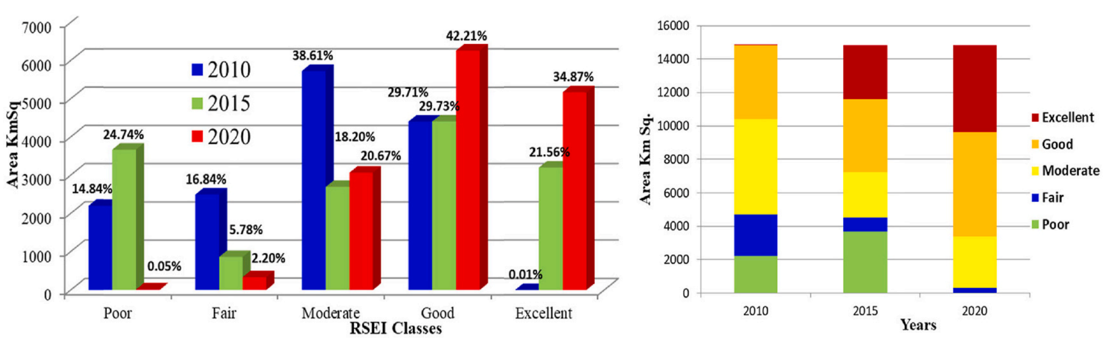

Fig. 11. The area change in each RSEI level for the year of 2010, 2015 and 2020.

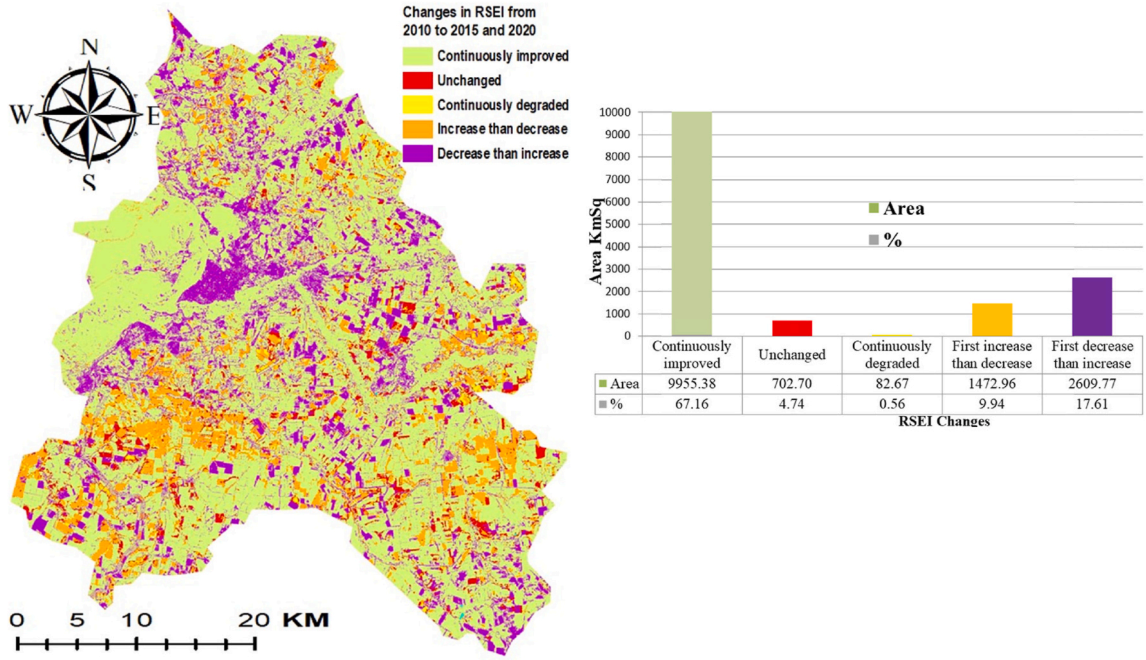

Fig. 12. Changes in RSEI between 2010 andto 2015 and then 2015 to 2020.

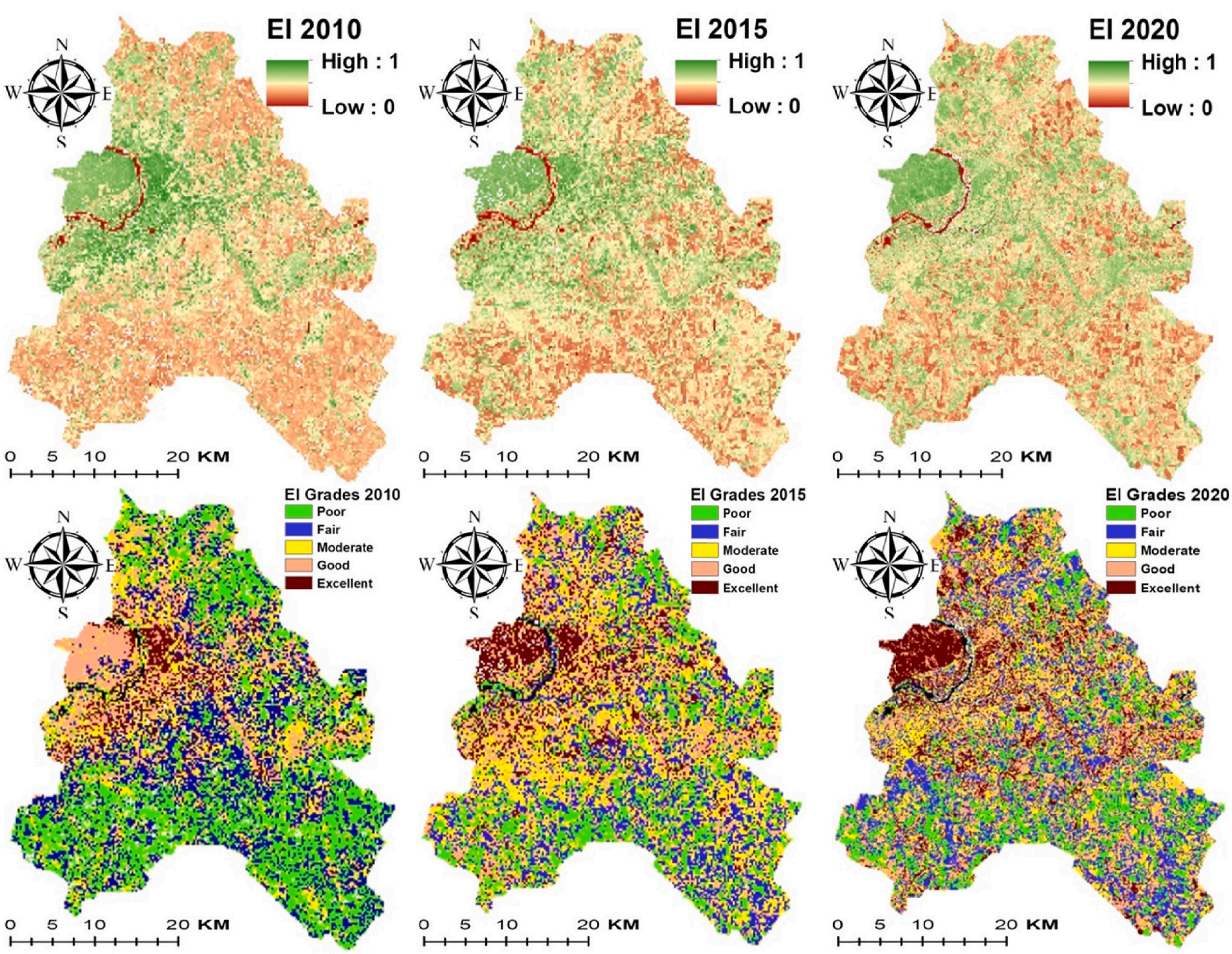

Fig. 13. EI maps for the year of 2010, 2015 and 2020, (A) stretch map of EI, (B) five levels of EI.

not only provide ecological condition information but can also use for non-governmental organizations (NGOs) or governmental decision making and policies for sustainable development. Indirectly, response indicator provides an areas growth or decay, economically or socially and helps to identify total evolution and changes in the region.

4.3. RSEI and EI

We calculate RSEI and EI as mentioned in the section 3.3 and 3.4 respectively.

4.3.1. RSEI

A high RSEI value represents a good ecological condition. Table 10 showed RSEI increased from 0.79 to 0.98 from 2010 to 2015, which indicates a better ecological situation. But in the second half from 2015 to 2020, it was reduced from 0.98 to 0.82, which indicates that ecological condition reduced or in a worse situation. If compared from 2010 to 2020, overall it was in a better situation as it shows RSEI increasing from 0.79 to 082. The variations in minimum value (0.03, 0.16 & 0.03) of RSEI have similar characteristics of mean value (0.79, 0.98 & 0.82) but in maximum values (1.09, 1.03 & 0.96), its continuously decreased, which indicate that high-quality RSEI condition was continuously reduced and low-quality RSEI condition was better in the first half and in the second half, it was reduced and reached, its earlier stage. It indicates that maximum variation was exist in the medial type of RSEI values, which show that favorable conditions (moderate to high temperature, moderate to low moisture, higher vegetation) of all factors have been recovered in the study period.

The spatial distribution of RSEI shows that the poor to moderate level of RSEI distributed in the Samara city and surrounding area with extension in drainage format to northeast direction (Fig. 10). Where vegetation and temperature were very low and moisture was very high. It's also indicating extremely unfavorable Russian cold weather. While in the medial part of the study area, where temperature and moisture were in moderate condition, it showed a high good level of RSEI. In the south part of the study area as well as some patches, where the temperature was increased from moderate to high and moisture was reduced from moderate to low, showed excellent RSEI condition (Fig. 10). As the maximum study area was covered by snow so when the temperature has been increasing, snow/ice starts to melt as well as moisture has started to decrease and this was the also most favorable condition for vegetation, therefore this situation represents the best RSEI situation in the region.

Fig. 11 indicates that from 2010 to 2015 fair and moderate RSEI condition area reduced dramatically and from 2015 to 2020 moderate, good and excellent classes increased. In this increment in 2020, the poor, fair and moderate area were not reached till the area covered in 2010 but good and excellent condition showed higher area covered in comparison of 2010. The good and excellent condition areas increased around 12% in this decade (Fig. 11). For the year of 2020 maximum area covered by good and excellent conditions, even in comparison to other two years excellent area was very high in this year, thus RSEI condition was best in the year of 2020.

Fig. 12 indicates that in this decade from 2010 to 2020 maximum area (9955.38 km^2, 67.16%) RSEI condition was improved and less than 1% area was continuously decreased. The continuously RSEI condition increasing area was forest and agriculture area. In comparing maps, high NDVI value was associated with the forest and agriculture area. This also indicates governmental protection and support in these areas. Generally vegetation or greenness and moisture content are highly required for a healthy environment. During this decade approximately 5 present area was unchanged which were some patches in the agriculture field and distributed in all around the study area.

The RSEI conditions in agriculture and open field/areas were first increased from 2010 to 2015 and then decreased from 2015 to 2020 around 1500 km^2 (10%) area. In city and small town as well as in the high socio-economic activities areas in first half RSEI was decried but later on in second half, its increased (26.9.77 km^2, 17.61%) because now government gives special attention in these sites such as making gardens and plantations (Fig. 12). Normally changes in vegetation or greenness due to *human-socio-economic* activities can relate to built-up area expansion and LST patterns. Therefore the government should make laws related to control built-up area sprawl under rapid urbanization to achieve the goal of sustainability. As the overall continuously decreasing area was very less which means samara administration trying to maintain good ecological conditions in the state with sustainable development.

4.3.2. EI

A higher EI values represents a favorable and stable ecological condition and vice versa. From 2010 to 2015 EI increased from 0.81 to 0.95, which indicates a better ecological situation. But in the second half from 2015 to 2020, it was reduced from 0.95 to 0.89, which indicates that ecological condition reduced or in a worse situation. Fig. 13 shows the EI map of the study area, where dark green color represents good ecological condition and dark red shows worst ecological condition (Fig. 13A). The resulting EI map was very much similar to vegetation maps as high NDVI value areas show good ecological condition and low NDVI, high temperature, high human pressure area showed low ecological condition.

The spatial distribution of EI maps showed that forest area or natural resources have excellent EI condition and its neighboring area showed excellent to moderate EI condition. Some cultivation and industrial areas showed fair to poor ecological conditions. South part of the study area was showed fair and poor ecology, where the north part shows moderate to excellent ecological condition. Center part of the study area and samara city comes under good to moderate ecological conditions which represent a mixed situation of governmental protection and awareness of the location population for ecology (Fig. 13B).

Fig. 14 indicates that from 2010 to 2020 good and excellent

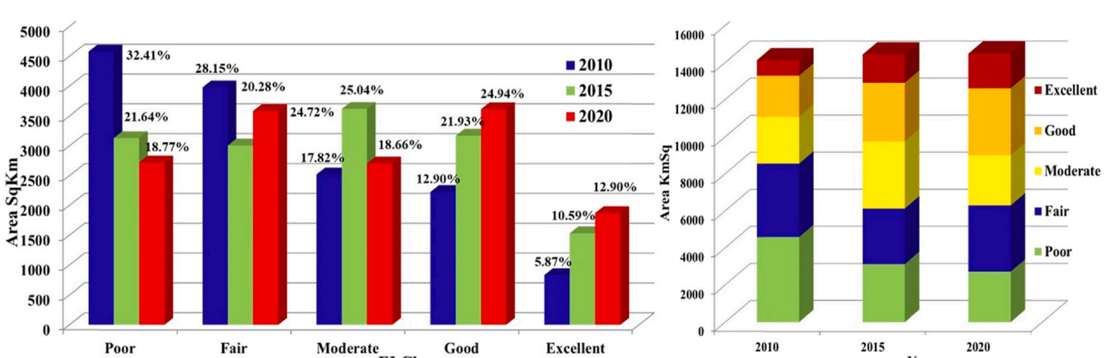

Fig. 14. The area change in each EI level for the year of 2010, 2015 and 2020.

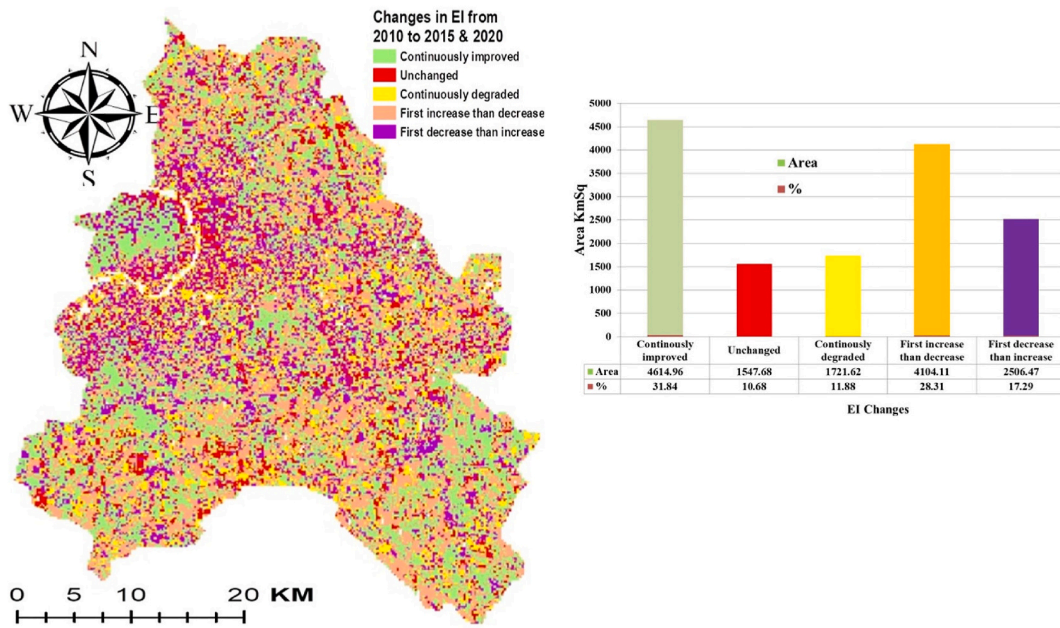

Fig. 15. Changes in EI between 2010 andto 2015 and then 2015 to 2020.

Table 11
Response indicators statistics in different stages with changes from 2010 to 2020.

	RSEI			EI		
	2010	2015	2020	2010	2015	2020
Maximum	1	1.003	1	0.999	1	0.999
Minimum	0	0.002	0.001	0	0	0
Mean	0.325	0.43	0.331	0.334	0.43	0.434
S.D.	0.095	0.103	0.044	0.138	0.143	0.154

ecological conditions gradually increased from 12.90% to 24.94% and 5.87%–12.90% respectively, while poor EI class continuously reduced from 32.41% to 18.77% from 2010 to 2020. The fair class first reduced and then increased but not reached till earlier years and moderate EI class first increased (17.82–25.04%) and then decreased in 2020 at 18.66%. In 2010 maximum area was covered by poor EI class, then fair, moderate, good and in last excellent class but in 2020, all classes have very much similar areas or with little bit difference (Fig. 14).

Fig. 15 indicates that in this decade maximum area (4614.96 km^2, 31.84%) was improved and 11.88% (1721.62 km^2) degraded, while 10.68% (1547.68 km^2) was unchanged from 2010 to 2020. The unchanged area was the lowest in all classes. The second highest class area was "first increase then decrease" class around 28.31%. The first decreased and then increased class area was 17.29% (25.0.47 km^2). The continuously increased area was distributed in forest and natural resources areas and continuously decreased area patches in all over the study area, while maximum unchanged area was distributed in the central part of the study area. First increased then decreased present in south and top north part, while first decreased then increased present in center part of the study area. The EI condition in agriculture and open field/areas were first increased from 2010 to 2015 and then decreased from 2015 to 2020 around 28.31% (4104.11 km^2). Some patches close to city and small towns/villages were first decreased and then increased as they were industrials sites and government have specially attention on them (17.29%), while maximum part of samara city and central part was unchanged.

4.3.3. Comparison of RSEI and EI

Based on the above mentioned 15 parameters this research work has figure out RSEI and EI and their changes for the year of 2010, 2015 and 2020. For the calculation of EI, AHP method was used to assign a weight to a thematic layer. For better comparison between RSEI and EI both results were standardized from 0 to 1 range. Results showed that RSEI and EI values are very much similar for all three years. If compare mean values of both indexes, it's similar or EI indexes values were little bit high, especially for the year of 2020 (Table 11). Here higher values represent more favorable ecological conditions. This concluded that EI shows better representation of the ecological conditions than RSEI.

Table 11 showed EI values increased 0.334 to 0.434 from 2010 to 2020, means better ecological conditions. In comparison from the first half (2010–2015) and second half (2015–2020), the ecological condition was really improved in the first half from 0.34 to 0.43 and in the second half, it was negligibly improved from 0.430 to 0.434 (Table 11). There were minor variations in high values in both EI and RSEI with similar patterns, which showed in high value ecological condition was improved in the first half but in the second half it was reduced till earlier year (2010) stage. Same pattern was shown for minimum values in RSEI but in EI it was stable in all three years. Its indicate that high values little bit reduced and convert into low quality values so overall it indicates that maximum variation was present in the medial type of EI and RSEI values, which showed that favorable condition (moderate to high temperature, moderate to low moisture, higher vegetation and low dryness) of all factors have been recovered in the study period.

Normally RSEI and EI have similarity because all four RSEI parameters (Greenness, wetness, dryness and temperature) were already included in the EI index. As RSEI greenness was represented in EI by NDVI, FVC and LAI. RSEI wetness was represented in EI by soil moisture (SAVI & NDMI) water content (NDWI). While RSEI dryness was defined in EI by LULC and artificial features and in last temperature was shown by LST. Thus EI has better results than RSEI as it used more environmental and natural parameters, which already included in RSEI four parameters.

In addition, the difference between EI and RSEI was that RSEI cannot evaluate properly in EEQ due to only four specific indicators. As RSEI results were based on PCA, it's indicated that temperature was the most dominant parameter, than NDVI, dryness and in last moisture content. Therefore RSEI maps were more representative of temperature content but EI maps were representing all 15 parameters.

4.4. General assessment of EEQ

This research work develops a RS based framework and constructs EI and RSEI to compare and monitor EEQ in the Samara Region, Russia. As EI more accurately represents the actual ecological condition in the study area due to more input indicators so for ecological environmental quality assessment EI maps were used in this study. The remote sensing and GIS technology is the most suitable tool to study EEQ due to multi-spectral, spatial and temporal resolution, working in all-weather condition, even at inaccessible locations, very quickly and cheaper with less manpower and efforts and providing real time information. Therefore based on time series remote sensing satellite data, this research work conducted in Samara region Russia for ecological sustainable development. As this work was done under PSR framework, where derive 15 indicators related to ecology and construct pressure indicator to identify actual human and socio-economic pressure, state indicator to balance the pressure and in last response indicator, which allow a quick and quantitative ecological environmental quality (EEQ) assessment. In EEQ assessment land use/cover change, natural and human pressure, natural environmental state and ecosystem health for EEQ response were used. Results showed that from 2010 to 2020, the population was increased and for this increased population; society required more housing facilities as well as food and other productions. Therefore the agriculture area was encroached for settlements and industries to compete this increased market demand, this encroachment also increased socio-economic activities, ultimately increasing socio-human pressure in the area and this pressure was not equally distributed in the study area. This intensive land exploration and high frequent human pressure have been the main cause of disturbance in the surrounding ecosystem. Thus in the study of EEQ, human-socio-economic activities must be analyzed. During this decade in 2010 pressure indicators were distributed in almost the maximum part of the study area but in 2020, it was centralized in the city area and only in big towns, which indicated good governmental policies for stable ecology and sustainable development.

In EEQ analysis state index was very important because SI neutralized the pressure. Therefore forest and natural vegetation play a major role in reducing environmental degradation and to make a stable ecological condition in the study area. During this decade forest, mangroves and wetland areas were increased to protect the ecology. Resulted maps also showed shifting of SI index from non-vegetation area to natural vegetation area from 2010 to 2020 to give more stability to regional ecology.

Under PSR framework response indicator easily identify any change in any ecosystem under different types of pressure. Thus an effective factor was developed in this research work with the help of RS/GIS to mapping, monitoring and management of ecological issue from regional to global level.

As this research work was done for the year of 2010, 2015 and 2020, so we identify the changes only these specific years. Therefore, to identify exact changing point or change tendency and main influence parameters, next time will study continuous years' time-series databases even monthly basis study for key change identification.

During this EEQ analysis, tried to calculate maximum possible parameters, which were relevant to topographic features, complex climate and natural conditions and main focus was given to the vegetation ecosystem as reducing pressure index and protecting ecology. We noticed that during the ecological monitoring period, the vegetation ecosystem was improved. Surrounding the samara city and central part of the study area, where the land exploration was relatively high due to specific human-socio-economic activities such as cultivation activities, urban development, therefore in this part of study area human pressure was increased and its bad effect on surrounding vegetation ecosystems health and natural environment. Therefore these areas show high human pressure, bad ecological condition and a higher response should draw more attention and regular ecological monitoring for its protection. In EEQ assessment, also identify specific locations, which were covered by governmental protection to protect ecology have less effect from human pressure than unprotected areas. Therefore need to make special policies for healthy and stable ecology and implement them properly in required areas. Thus the development of all factors in this research work are important for NGOs and governmental decision and policy making and support to sustainable development as all factors/parameter/indictors have broad aspects.

5. Conclusions

Based on remote sensing and GIS technology, this research work innovatively developed ecological indicators and constructs RSEI and EI under PSR framework further expanded spatio-temporal analysis of EEQ in the samara region, Russia and identify following key information: (1) RSEI and EI have very strong similarity but EI show better ecological condition than RSEI due to more used indicators, (2) The greenness and wetness showed positive response for healthy ecology, while dryness and heat/temperature have negative impact and vice versa, (3) Changes in mean values of EI reflect the EEQ patterns, (4) High human-socio-economic effect especially in urban and settlements areas put negative impact on ecological health, (5) Any positive response from natural resources such as crop growth, healthy and dense forest and less urban areas were the main pathway to improve EEQ. Overall EEQ assessment is critical to regional environment protection and sustainable development, as a new research topic, combining traditional ecology principals with remote sensing, GIS technology, landscape ecology and ecosystem service evaluation; it would have great sustainable development.

Author statement

M.S.B. & K.C.: Conceptualization; M.S.B.: Data curation; Formal analysis; Investigation; Methodology; Software; Visualization; Writing - original draft; A.K.: Project administration; Re-sources; Supervision; Funding acquisition; M.S.B.; K.C. & R.P.: Writing - review & editing.

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.

Acknowledgements

The research was supported by the Ministry of Science and Higher Education of the Russian Federation (Grant # 0777-2020-0017) and, was partially funded by RFBR, project number # 20-51-05008.

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