Integrating landscape ecological risk with ecosystem services in the Republic of Tatarstan, Russia

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Abstract

It is a novel approach to linking landscape ecological risk (LER) and ecosystem services (ESs) for environmental management and sustainable development, since it enables real-time decision-making. This study used 12 natural factors relevant to LER and 11 ESs factors to analyze spatio-temporal changes and establish a relationship between them in Tatarstan, Russia, for the years 2010, 2015, and 2020. The statistical tests (Global Moran's I, Getis-Ord Gi*), analysis of habitat vulnerability, and ecological loss in the ArcGIS platform reveal a consistent variance in factor clustering and pattern as well as the impact of governmental policies in the studied area. According to analysis findings, 2015 had the best ecological conditions of the three years because 44.79 % of the research area had decreased landscape ecological risk, which increased ecosystem services. Additionally, the results show that both maps have significant spatial disparities and that LER and ESs are negatively impacted by high human-socioeconomic activity. The integration of LER and ESs through the overlap of both maps provides a significant amount of spatial information for mapping, monitoring, management, and the protection of the fragile environment for sustainable landscape development and management.

Keywords: landscape ecological risk, ecosystem services, habitat vulnerability, spatiotemporal evolution, remote sensing, GIS.

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Introduction

Ecosystem services (ESs) are profits derived from an ecosystem [1, 2]. Due to poor management and excessive exploitation of natural resources, ESs is currently degraded [3]. The research on ESs is divided into two types of research: first, human policies and activities that affect the ecosystem in terms of structure and process; and second, their interference with the ecosystems provides benefits [4, 5]. In recent years, ESs investigations have become increasingly necessary for sustainable balancing situations at various landscape scales due to growing human dependence and demand on ecosystems [6, 7]. Land use and cover changes (LUCC) are the primary factors influencing ESs changes at any landscape scale; consequently, the greatest ESs changes are observed at high land use planning and development sites [1, 8, 9]. Given that LUCC is the primary factor contributing to ESs degradation, ESs research using the ESs concept has become more prevalent at a landscape scale in recent years [10, 11, 12].

Landscape ecological risk (LER) is assessed using the risk-bearing capacity of landscape-related ecological factors [13]. LER is determined by natural and human interference risk factors such as LUCC, industrialization, encroachment of forest or agriculture practices, etc. [14, 15]. Generally, LER provides decision-making guidelines for an area at a landscape scale with risk factors and ESs stability and management [16]. LER for a specific area at a specific landscape scale is typically represented by human interference in an ecosystem with LUCC and risk factors [17]. As a result, proper land use and coastal management are critical for a high-quality, stable ecosystem. A quality LER entails sustainable exploitation of the environment's natural resources and ecosystem [17]. Analysis of habitat vulnerability has become a prominent topic in LER studies in recent years because it illustrates the ecological response to human activity [18, 20]. In addition to reflecting land use land cover (LULC) habitat in a different way, it also creates relationships between hazards [20, 21]. As a result, lower habitat vulnerability ensures a stable ecosystem and high-quality LER.

The combination of LER and ESs is a rare combination that demonstrates ecological risk reduction guidelines by copying and resilience adaptive capacity with sustainable development [22, 23]. On the other hand, demonstrate human-socioeconomic links with ESs in an ecosystem as the endpoint of risk or reasonable risk reduction with future sustainable development. However, integrating LER and ESs for decision-making is a difficult process with a sustainable development approach, and considering ESs as an endpoint of risk in an ecosystem is not a simple task either [24, 25, 26]. Therefore, the goal of this research is to find answers to the following questions: is there a relationship between LER, ESs, and human-socioeconomic activities at the landscape scale; how to integrate LER and ESs in a sensitive area to reduce risk while increasing ESs; and how to integrate LER and ESs in a sensitive area to increase ESs.

1. Methodology and material

Fig. 1 depicts the methodological chart used in this study. First, collect satellite data, followed by human-socio-economic-ecological data from various sources for the republic of Tatarstan, Russia, for the years 2010, 2015, and 2020. LER and ESs were generated using 12 and 11 relevant and available datasets, respectively. The final results were then produced by integrating and overlapping both layers (Fig. 1).

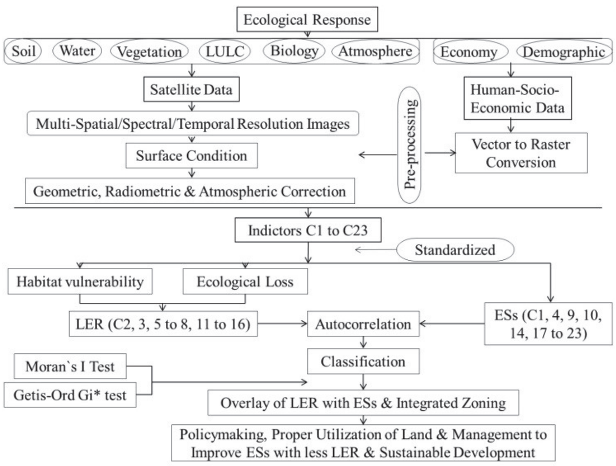

Fig. 1: Flowchart for Integrating LER and ESs for Proper Natural Resource Utilization, Management, and Sustainable Development

1.1. Study area

The Republic of Tatarstan is located in the heart of the East European plain, about 800 kilometers east of Moscow, Russia (Fig. 2).

1.2. Data and pre-processing

This study drew on a variety of data sources, including multi-spectral-spatial-temporal remote sensing (RS) data, elevation data, ground data, and human-socio-economic-ecological data (Tab. 1).

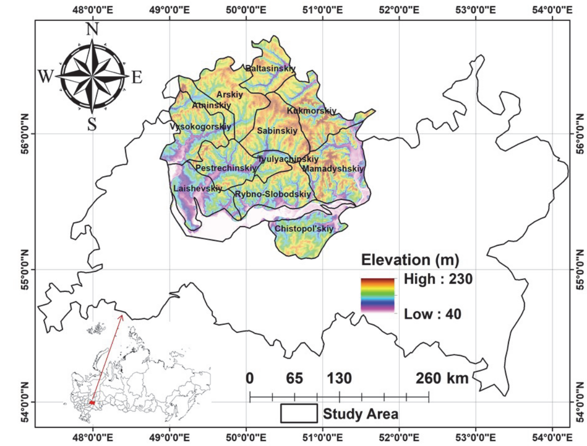

Fig. 2. Location map of the study area with elevation in the Republic of Tatarstan, Russia

Tab. 1. Complete details of all data used in this study, along with their sources

Data name	Attribute	Acquisition data	Source
Landsat ETM+ & OLI	16-Day temporal & 30 m spatial resolution	16/07/2010, 27/04/2015, 19/06/2020	Earth-Explorer USGS (https://earthexplorer.usgs.gov/)
MODIS 13Q1 NDVI	16-Day temporal & 250 m spatial resolution	07/12/2010, 13/08/2015, 12/08/2020	NASA LAADS DAAC (https://ladsweb.modaps.eosdis.nasa.gov/search)
MODIS 16A2 ET data	8-Day temporal & 500 m spatial resolution	04/07/2010, 20/07/2015, 17/06/2020	NASA LAADS DAAC (https://ladsweb.modaps.eosdis.nasa.gov/search)
MODIS 11A2 Temperature & Emissivity data	8-Day temporal & 1 km spatial resolution	20/07/2010, 28/07/2015, 12/07/2020	Earth-Explorer USGS (https://earthexplorer.usgs.gov/)
MODIS 15A2H LAI data	8-Day temporal & 500 m spatial resolution	20/07/2010, 12/07/2015, 20/08/2020	Earth-Explorer USGS (https://earthexplorer.usgs.gov/)
MODIS 17A2H GPP data	8-Day temporal & 500 m spatial resolution	12/07/2010, 12/07/2015, 20/08/2020	Earth-Explorer USGS (https://earthexplorer.usgs.gov/)
MODIS 12Q1 LULC data for HAI	8-Day temporal & 500 m spatial resolution	01/01/2010, 01/01/2015, 01/01/2020	NASA LAADS DAAC (https://ladsweb.modaps.eosdis.nasa.gov/search)
DEM	90 m spatial resolution	-	SRTM https://dwtkns.com/srtm30m/
AVHRR-NOAA VHI data	7-Day temporal & 1 km spatial resolution	12/07/2010, 12/07/2015, 20/07/2020	NOAA https://www.star.nesdis.noaa.gov/smcd/emb/vci/VH/vh_ftp.php
Road or topography data	shp	-	https://download.geofabrik.de/russia.html
Soil data	shp	-	https://soilgrids.org/
Socio-economic/ demographic data	shp	-	Official website of Tatarstan state (https://open.tatarstan.ru/reports/categories)

1.3. Indicators

This study employed a total of 23 indicators (Tab. 2). To produce ESs and LER maps for the study area, all indicators created in the RS/GIS platform were combined using a raster calculation module in ArcGIS software. Therefore, in order to create LER and ESs maps, each indicator has first been assigned a certain weight based on its importance, sensitivity, effect, or contribution to the LER and ESs (Tab. 2).

Tab. 2. A list of the indicators used, along with their weights

Factor	+/- impact	Importance	GMn	Wn
C1- Gross primary production (GPP)	+	5.5	1.04	0.043
C2- Population density (PD)	+	8.5	1.61	0.066
C3- Evapotranspiration (ET)	+	8	1.52	0.062
C4- Fertilizers	+	4	0.76	0.031
C5- Human activity index (HAI)	+	7.5	1.42	0.058
C6- Investment	+	9	1.71	0.070
C7- Land use land cover (LULC)	+	7	1.33	0.054
C8- Road density (RD)	+	4.5	0.87	0.036
C9- Soil moisture (SM)	-	4	0.76	0.031
C10- Water contamination (WC)	+	2	0.38	0.015
C11- Elevation	-	5	0.95	0.039
C12- Leaf area index (LAI)	-	6.5	1.23	0.051
C13- NDVI	-	6	1.14	0.047
C14- Precipitation	-	4	0.76	0.031
C15- Temperature	-	4	0.76	0.031
C16- Vegetation health index (VHI)	-	6	1.14	0.047
C17- Cattle	-	7	1.33	0.054
C18- Crop grain production (CGP)	+	6	1.14	0.047
C19- Milk production (MP)	+	4.5	0.85	0.035
C20- Soil classification (SC)	-	3	0.57	0.023
C21- Industrial production (IP)	+	8	1.52	0.062
C22- Livestock weight (LSW)	-	5	0.95	0.039
C23- Soil organic carbon (SOC)	-	3.5	0.66	0.027

Thus, all indicators were first paired [28] with each other (Tab. 4) as equation 1, and each indicator was assigned an arithmetic value between 1 and 9 (Tab. 3) based on its significance in comparison to other indicators with which it formed the pair (Tab. 4). To determine the weight of indicators, first establish judgment matrices (P) through pairwise comparison as shown in equations 1:

$$P=\begin{bmatrix} P11\,P12\ldots\ldots\ldots P1n \\ P21\,P22\ldots\ldots\ldots P2n \\ . \quad . \quad .. \\ . \quad . \quad .. \\ P1n\,P2n\ldots\ldots\ldots Pnn \end{bmatrix}. \tag{1}$$

Where P_{n} denote the n^{th} indicator with P_{nn} being the judgment matrix element.

In the resulting table, an arithmetic value of 9 indicates that a row indicator is much more significant than the corresponding column indicator with which it has been compared, while an arithmetic value of 1 means both indicators were equally significant as in table 3 [28, 29]. [28] suggests that fraction values are also possible, indicating that an indicator is less significant or important in comparison to the other compared indicator. For example, the values of 0.72, 0.47, and 0.50 (fertilizer row crossed with columns GPP, PD, and ER respectively in tab. 3) resulted after dividing value 4 (fertilizer) from 5.5 (GPP), 8.5 (PD), and 8 (ET) columns respectively in table 2, and by this way, all indicator values were calculated (Tab. 3) respectively. After completion of tab. 3, then to get results (Tab. 2 & 3), the normalized weight was calculated by the geometric mean method as following equations 2 and 3:

$$W_n=\left(GM_n\Big/\sum_{n=1}^{nf}GM_n\right). \tag{2}$$

Where the geometric mean of the i^{th} row of the judgment matrices is calculated as:

$$GM_n=n\sqrt{P1n\,P2n\ldots\ldots..PnNf}\ . \tag{3}$$

1.4. Assessment of landscape ecological risk (LER)

Primarily, LER is counted by vegetation, elevation, dryness, and population information. Landscape studies are fundamentally based on conceptual models such as vulnerability, risk assessment, exposer events, degraded/upgraded analysis, and evaluation [30], but this study used LUCC to better define LER and can be represented as equation 4:

$$LER=\sum\nolimits_{i=1}^{n}V_i\ .R_i\ . \tag{4}$$

Where LER is the landscape ecological risk, V_i and R_i is the habitat vulnerability and ecological loss of plot i respectively.

Tab. 3. Scale of relative importance

Definition	Equally important	Extremely less imp.	Strongly less imp.	Less important	Moderately less imp.	Moderately important	Strong important	Very strong imp.	Extremely important
Intensity importance	1	2	3	4	5	6	7	8	9

Tab. 4. Calculation of indicators weight (in combination with table 3)

	C1	C2	C3	C4	C5	C6	C7	C8	C9	C10	C11	C12	C13	C14	C15	C16	C17	C18	C19	C20	C21	C22	C23	GMn	Wn
C1	1	0.64	0.68	1.37	0.73	0.61	0.78	1.22	1.37	2.75	1.1	0.84	0.91	1.37	1.37	0.91	0.78	0.91	1.22	1.83	0.68	1.1	1.57	1.04	0.043
C2	1.54	1	1.06	2.12	1.13	0.94	1.21	1.88	2.12	4.25	1.7	1.30	1.41	2.12	2.12	1.41	1.21	1.41	1.88	2.83	1.06	1.7	2.42	1.61	0.066
C3	1.45	0.94	1	2	1.06	0.88	1.14	1.77	2	4	1.6	1.23	1.33	2	2	1.33	1.14	1.33	1.77	2.66	1	1.6	2.28	1.52	0.062
C4	0.72	0.47	0.5	1	0.53	0.44	0.57	0.88	1	2	0.8	0.61	0.66	1	1	0.66	0.57	0.66	0.88	1.33	0.5	0.8	1.14	0.76	0.031
C5	1.36	0.88	0.93	1.87	1	0.83	1.07	1.66	1.87	3.75	1.5	1.15	1.25	1.87	1.87	1.25	1.07	1.25	1.66	2.5	0.93	1.5	2.14	1.42	0.058
C6	1.63	1.05	1.12	2.25	1.2	1	1.28	2	2.25	4.5	1.8	1.38	1.5	2.25	2.25	1.5	1.28	1.5	2	3	1.12	1.8	2.57	1.71	0.070
C7	1.27	0.82	0.87	1.75	0.93	0.77	1	1.55	1.75	3.5	1.4	1.07	1.16	1.75	1.75	1.16	1	1.16	1.55	2.33	0.87	1.4	2	1.33	0.054
C8	0.81	0.52	4.5/8	1.12	0.6	0.5	0.64	1	1.12	2.25	0.9	0.69	0.75	1.12	1.12	0.75	0.64	0.75	1	1.5	0.56	0.9	1.28	0.87	0.036
C9	0.72	0.47	0.5	1	0.53	0.44	0.57	0.88	1	2	0.8	0.61	0.66	1	1	0.66	0.57	0.66	0.88	1.33	0.5	0.8	1.14	0.76	0.031
C10	0.36	0.23	0.25	0.5	0.26	0.22	0.28	0.44	0.5	1	0.4	0.30	0.33	0.5	0.5	0.33	0.28	0.33	0.44	0.66	0.25	0.4	0.57	0.38	0.015
C11	0.90	0.58	0.62	1.25	0.66	0.55	0.71	1.11	1.25	2.5	1	0.76	0.83	1.25	1.25	0.83	0.71	0.83	1.11	1.66	0.62	1	1.42	0.95	0.039
C12	1.18	0.76	0.81	1.62	0.86	0.72	0.92	1.44	1.62	3.25	1.3	1	1.08	1.62	1.62	1.08	0.92	1.08	1.44	2.16	0.81	1.3	1.85	1.23	0.051
C13	1.09	0.70	0.75	1.5	0.8	0.66	0.85	1.33	1.5	3	1.2	0.92	1	1.5	1.5	1	0.85	1	1.33	2	0.75	1.2	1.71	1.14	0.047
C14	0.72	0.47	0.5	1	0.53	0.44	0.57	0.88	1	2	0.8	0.61	0.66	1	1	0.66	0.57	0.66	0.88	1.33	0.5	0.8	1.14	0.76	0.031
C15	0.72	0.47	0.5	1	0.53	0.44	0.57	0.88	1	2	0.8	0.61	0.66	1	1	0.66	0.57	0.66	0.88	1.33	0.5	0.8	1.14	0.76	0.031
C16	1.09	0.70	0.75	1.5	0.8	0.66	0.85	1.33	1.5	3	1.2	0.92	1	1.5	1.5	1	0.85	1	1.33	2	0.75	1.2	1.71	1.14	0.047
C17	1.27	0.82	0.87	1.75	0.93	0.77	1	1.55	1.75	3.5	1.4	1.07	1.16	1.75	1.75	1.16	1	1.16	1.55	2.33	0.87	1.4	2	1.33	0.054
C18	1.09	0.70	0.75	1.5	0.8	0.66	0.85	1.33	1.5	3	1.2	0.92	1	1.5	1.5	1	0.85	1	1.33	2	0.75	1.2	1.71	1.14	0.047
C19	0.81	0.52	0.56	1.12	0.6	0.5	0.64	1	1.12	2.25	0.9	0.69	0.75	1.12	1.12	0.75	0.64	0.75	1	1.5	0.56	0.9	1.28	0.85	0.035
C20	0.54	0.35	0.37	0.75	0.4	0.33	0.42	0.66	0.75	1.5	0.6	0.46	0.5	0.75	0.75	0.5	0.42	0.5	0.66	1	0.37	0.6	0.85	0.57	0.023
C21	1.45	0.94	1	2	1.06	0.88	1.14	1.77	2	4	1.6	1.23	1.33	2	2	1.33	1.14	1.33	1.77	2.66	1	1.6	2.28	1.52	0.062
C22	0.90	0.58	0.62	1.25	0.66	0.55	0.71	1.11	1.25	2.5	1	0.76	0.83	1.25	1.25	0.83	0.71	0.83	1.11	1.66	0.62	1	1.42	0.95	0.039
C23	0.63	0.41	0.43	0.87	0.46	0.38	0.5	0.77	0.87	1.75	0.7	0.53	0.58	0.87	0.87	0.58	0.5	0.58	0.77	1.16	0.43	0.7	1	0.66	0.027

A higher population density has a negative impact on landscape ecological risk and always raises the LER risk level as human and socioeconomic activities increase. A human activity index can be generated by land-use type class score and area by following equation 5:

$$HAI = P.A / TA . \quad (5)$$

Where HAI is the human activity index, P land-use type score (tab. 5), A land-use class area, and TA is the total study area.

Tab. 5. Human activity index land use type and score [31]

Score	Land use type
1	Unused land, Shrub lands, Snow and ice
2	Water, Forest, grasslands, Savannas, Wetland
3	Crop land
4	Urban and built-up

A higher HAI put more strain on the terrain's ecosystem and had a negative impact on the landscape, such as higher investment rates and higher road density, which provide a potential site for landscape changes and the primary cause of land use and cover change. As a result, all of the above indicators have a positive impact on risk and thus have a higher weight (close to 9). Climate-related indicators such as evapotranspiration, temperature, and precipitation also affect landscape ecological risk by their variation, intensity, and time duration, thus considering creating an LER layer. Greenness or vegetation-related indicators such as leaf area index (LAI), normalized difference vegetation index (NDVI), and vegetation health index (VHI) increase stability in the ecosystem, reduce risk pressure, and try to maintain a balanced situation in an ecosystem.

1.4.1. Habitat vulnerability

According to [28], a habitat is a connection between the risk source and the risk recipient, and vulnerability is the level of sensitivity to it. As a result, habitat vulnerability demonstrates the sensitivity of risk receivers and their response to outside disturbance [18, 24]. Thus, habitat vulnerability represents human activities' impact on an ecosystem or its disturbance and quality reduction. Higher human-socioeconomic activity levels are typically correlated with higher habitat vulnerability, which suggests a lower-quality or unstable environment. If habitat vulnerability has a 0 to 1 value range, then 1 indicates the worst ecological condition. A total of 12 indicators were used to derive habitat vulnerability and they were categorized as (1) vegetation coverage by C12, C13, and C16 indicators; (2) topographic factors by C7, C8, and C11 indicators; (3) meteorology factors by C3, C14, and C15 indicators; and (4) demographic factors by C2, C5, and C6 indicators. Based on a literature review and earlier studies, 0.35, 0.30, 0.20, and 0.15 weights were assigned to vegetation coverage, topographic factor, meteorological factor, and demographic factor, respectively, via the expert scoring method [30, 31]. Finally, a habitat vulnerability thematic layer was created using the following equation 6:

$$V_i = \sum\nolimits_{i=1}^{n} W_i \ . f_i \ . \qquad (6)$$

Where V_i is the habitat vulnerability, W_i is the weight of the indicator, and f_i is the used indicator.

1.4.2. Ecological loss

Human-socioeconomic-economic-ecological activities have an impact on LUCC, which reflects changes in landscape structure and function [30]. An ecological loss (R_i) can be predicted based on actual ecological losses and natural system risk due to LUCC changes [30]. Equation 7 can therefore be used to predict the degree of ecological loss in a land parcel whose landscape structure has changed into a spatialized ecological risk as a result of human-socio-economic-ecological activities:

$$R_i = \sum\nolimits_{i=1}^{n} \frac{A_{ij}}{A_i} \ . S_i \ . \qquad (7)$$

$$S_i = aC_i + bN_i + cF_i \ . \qquad (8)$$

Where R_i is the degree of ecological loss of land parcel i, A_{ij} is the landscape type area j in land parcel i and A_i is the total area of land parcel i, S_i is the landscape disturbance index of landscape type i. C_i, N_i, F_i is the degree of landscape fragmentation, separation, and fractal dimensions respectively [19] and a, b, c are their weight respectively.

Based on natural characteristics and local conditions, the weights of landscape fragmentation degree, separation degree, and fractional dimension are 0.5, 0.3, and 0.2 via the expert scoring method, respectively [15, 16]. A total of 12 indicators were used to derive ecological loss and all were categorized as (1) landscape fragmentation degree by C5, C6, C11, C12, C13, and C16 indicators; (2) landscape separation degree by C3, C14 indicators; and (3) landscape fractal dimension by C2, C7, C8, and C15 indicators. A higher S_i index represents more unstable or lower quality ecosystems and, subsequently, higher ecological risk.

1.5. Assessment of ecological services (ESs)

The indicators relevant to ecological services were used to generate ESs maps, as shown in equation 9:

$$\begin{aligned} ESs = \big(&GPP + Fertilizers + SM + WC + Cattle + \\ &+ CGP + MP + SC + IP + LSW + SOC\big)/12 \ . \end{aligned} \qquad (9)$$

1.6. Integrating method to link LER & ESs

Previous research has demonstrated a clear link between LUCC and ESs changes since LUCC changes directly affect the environment by causing changes in temperature, precipitation, and vegetation [10, 11]. Meanwhile, LUCC is the most important factor in LER and the most important driver of ESs changes [22, 23]. However, for environmental management and sustainable development, it is critical to establish a link between LER and ESs at the landscape scale. As a result, LUCC is the critical factor in linking LER and ESs for a stable and healthy ecosystem. Thus, LUCC is considered a risk factor and a proxy of human-socio-economic activity and can generate income from habitat vulnerability and ecological loss.

1.7. Spatial autocorrelation in between LER & ESs

A correlation analysis was performed to determine the nature of the relationship between all individual indicators. No one can assume the type and nature of correlation-ship in between two individual indicators, whether they have a positive or negative relationship and how much they affect each other's and related variables, such as fertilizer effect on crop production and milk production related to cattle, and both have what type of relationship with industrial production without correlation analysis. A correlation matrix is required in order to comprehend the behavior of each individual indicator and how it affects other indicators.

1.8. Classification method

The natural break classification method was used to categorize the LER and ESs maps. In the ArcGIS natural break classification method, the entire value range was divided into the necessary number of classes with a similar range, for example, if the author needed five classes and the total data range was from 0 to 100, the division would be as follows: 0 – 20, 21 – 40, 41 – 60, 61 – 80, and 81 to 100. As a result of using natural break classification LER and ESs maps, the following five classes were obtained: potential, light, medium, high, and heavy level.

1.9. Overall approach

The ArcGIS overlay tool was used in this study to overlay LER and ESs layers and determine how they interact or affect each other at the pixel level in the study area. This information is helpful in determining management strategies and policymaking for particular locations in the research area based on regional circumstances. It is critical to identify which areas have high landscape ecological risk but low ecosystem services, and vice versa.

1.10. Statistics test

1.10.1. Global Moran`s I test

This study used Moran's I test to identify a spatial correlation between LER and ESs. Moran's I test values range from –1 to +1; a number close to 1 denotes a stronger spatial autocorrelation in the indicators utilized, and a value of -1 denotes the opposite.

Statistically, the Morans I test is explained by the following equation 10 [40]:

$$\mathrm{I} = \frac{n}{S_o} \frac{\sum\nolimits_{i=1}^{n} \sum\nolimits_{j=1}^{n} w_{i,j} z_i z_j}{\sum\nolimits_{i=1}^{n} z_i^2} \ . \qquad (10)$$

Where z_i is the I features attribute deviation from its mean value ($x_i - X$), $w_{i,j}$ is the weight of i and j feature, n

is the total number of features and S_o is the aggregate of all weights.

1.10.2. Hot Spot Analysis (Getis-Ord Gi*) test

A Getis-Ord Gi* statistics test was performed for all indicators in order to discover patterns in the feature. A higher value indicates a hot spot, while a lower value indicates a cold spot clustering based on neighboring features. A high z score with a small p-value indicates clustering of features with high and low values, but a close to zero value indicates no clustering.

Getis-Ord Gi* statistics were calculated by the following equation 11 [40]:

$$G_i^* = \frac{\sum_{j=1}^{n} w_{i,j} x_j - X \sum_{j=1}^{n} w_{i,j}}{S \sqrt{n \sum_{j=1}^{n} w_{i,j}^2 - \left(\sum_{j=1}^{n} w_{i,j} \right)^2 / n-1}} . \tag{11}$$

Where x_j is the j features attribute value, $w_{i,j}$ weight of the feature i, and j, n is the total number of features.

A positive and high z-score indicates a high-value clustering, indicating a hot spot. A cold spot is represented by a smaller and negative z-score, which represents a cluster of low values. In the Getis-Ord Gi* test, a high confidence level indicates a high possibility of that type of clustering.

2. Results

2.1. Landscape ecological risk (LER) assessment

Fig. 3 represents spatiotemporal changes in landscape ecological risk in the Republic of Tatarstan, Russia from 2010 to 2020. The landscape ecological risk value range was 0.85–7.39, 1.48–7.44, and 0.88–7.75 for the years 2010, 2015, and 2020, respectively, indicating that the highest ecological risk value was in 2020 and the lowest in 2010, but the smallest difference was present in 2015. As a result, the year 2020 represented the greatest risk in terms of LER, while the year 2010 was the safest, and the year 2015 had the least variation in landscape ecology. As a result of the average landscape ecological risk, the year 2015 had the best ecological balance ecological state out of the three. The resulting LER maps were classified into five risk levels: potential, light, moderate, high, and heavy, indicating different risk levels for specific management and strategy plans (Fig. 3).

The heavy level LER class was very low in all three years, but it gradually increased from 1.07 % to 1.66 % from 2010 to 2020 (Fig. 4). The high LER class increased from 10.58 % to 20.49 % in the first half from 2010 to 2015, nearly doubling the previous one, but decreased slightly in the second half to 17.57 % in 2020. In 2010, 2015, and 2020, the maximum study area was covered by the moderate type of landscape ecological risk at 50.01 %, 42.93 %, and 37.60 %, respectively. Additionally, the light LER class first decreases from 34.99 % to 27.14 %, then increases to 35.17 %. The potential class of LER covers a small area but steadily increases from 3.35 % to 8 % from 2010 to 2020. (Fig. 4).

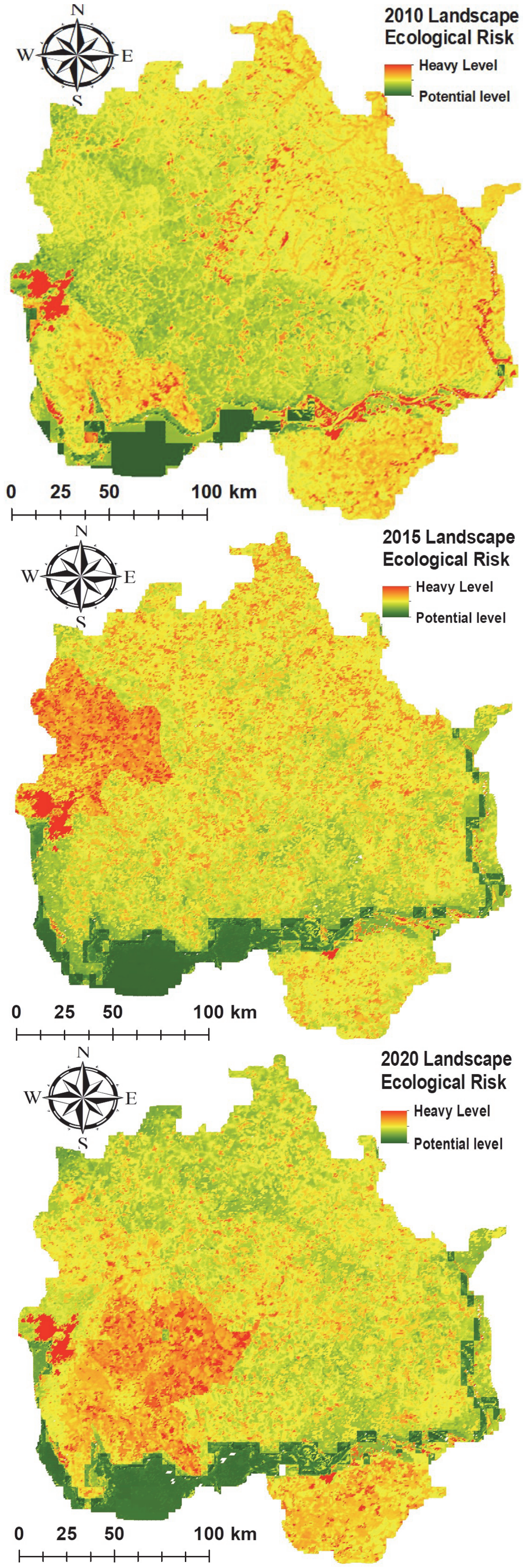

Fig. 3. depicts the spatial and temporal changes in LER in the Republic of Tatarstan, Russia, from 2010 to 2020

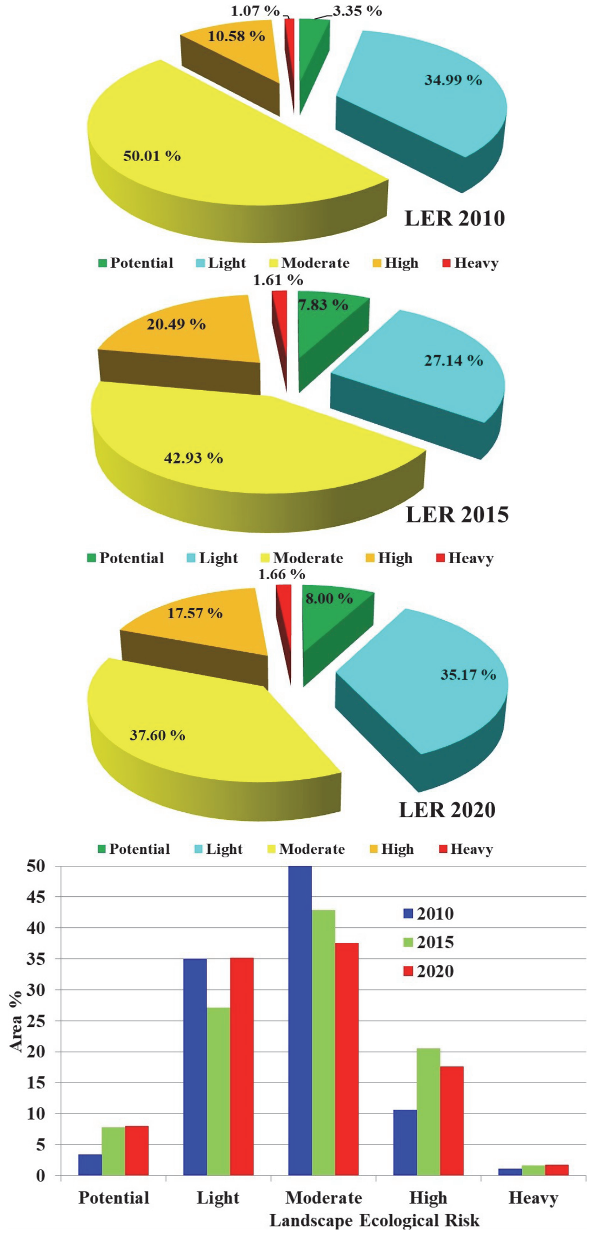

Fig. 4. Graphical representation of LER classes in Tatarstan, Russia from 2010 to 2020

2.1.1. Habitat vulnerability assessment

For the years 2010, 2015, and 2020, the habitat vulnerability value range was 0.39 – 1.67, 0.11 – 2.09, and 0.21 – 2.06, indicating that the highest variation, as well as the highest habitat vulnerability, was present in 2015. As a result, compared to 2010 and 2020, human and socioeconomic activity is higher in 2015. Fig. 5 shows that extreme human activities were present in Kazan throughout the three years. Higher human activities were present in the east part of the study area in 2010, which shifted to the north part of the study area in 2015, and later to the south part in 2020.

2.1.2. Ecological loss

For the years 2010, 2015, and 2020, the ecological loss value range was 0.62 – 3.18, 0.23 – 3.34, and 0.40 – 3.19, indicating that the highest variation, as well as the highest loss, was present in 2015. For all three years, fig. 6 shows that the highest ecological loss was found in Kazan city and its surrounding area, while the lowest ecological loss was found in the Volga and Kama river basins. The years 2010 and 2020 have more green color, whereas 2015 has more yellow color, indicating a greater ecological loss in 2015.

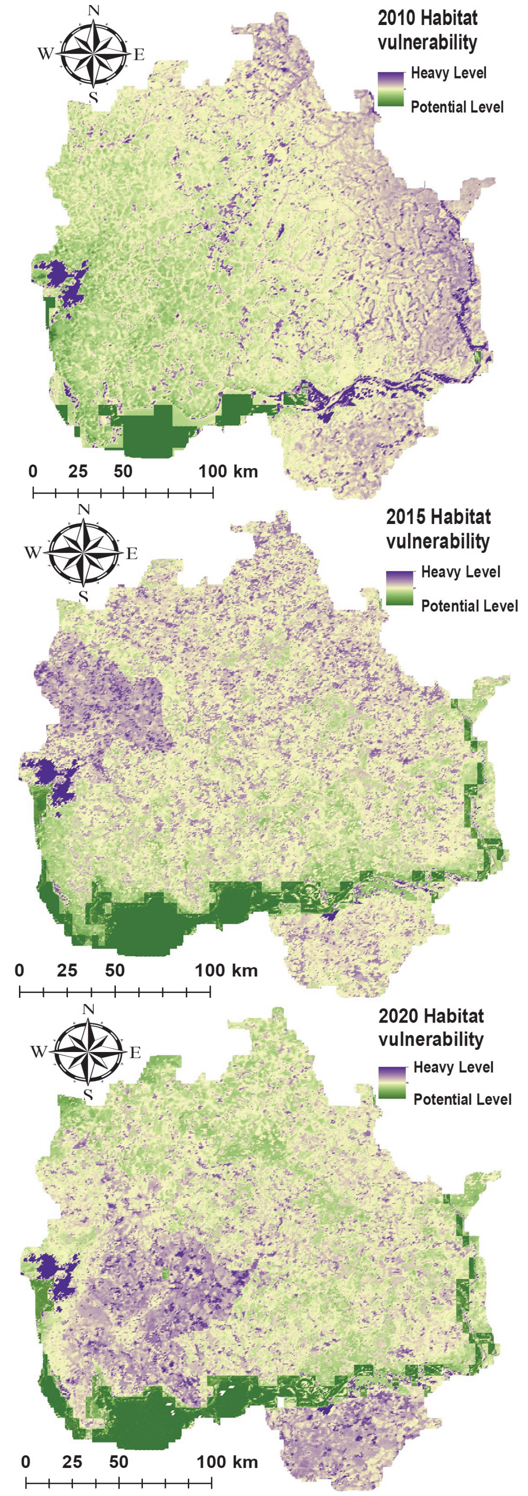

Fig. 5. Spatiotemporal changes in habitat vulnerability in Tatarstan, Russia from 2010 to 2020

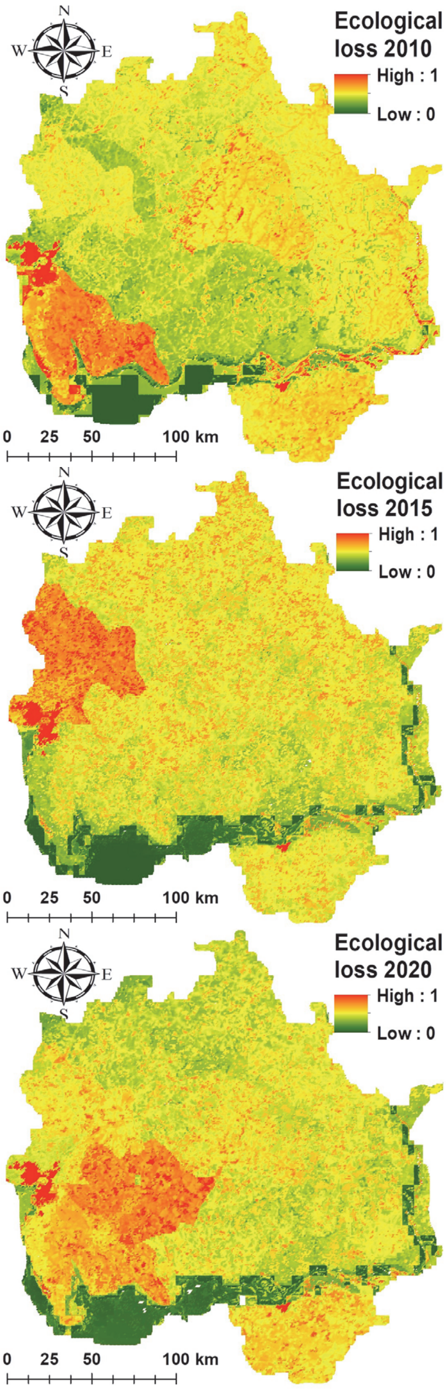

Fig. 6. Ecological loss maps of the Republic of Tatarstan, Russia from 2010 to 2020

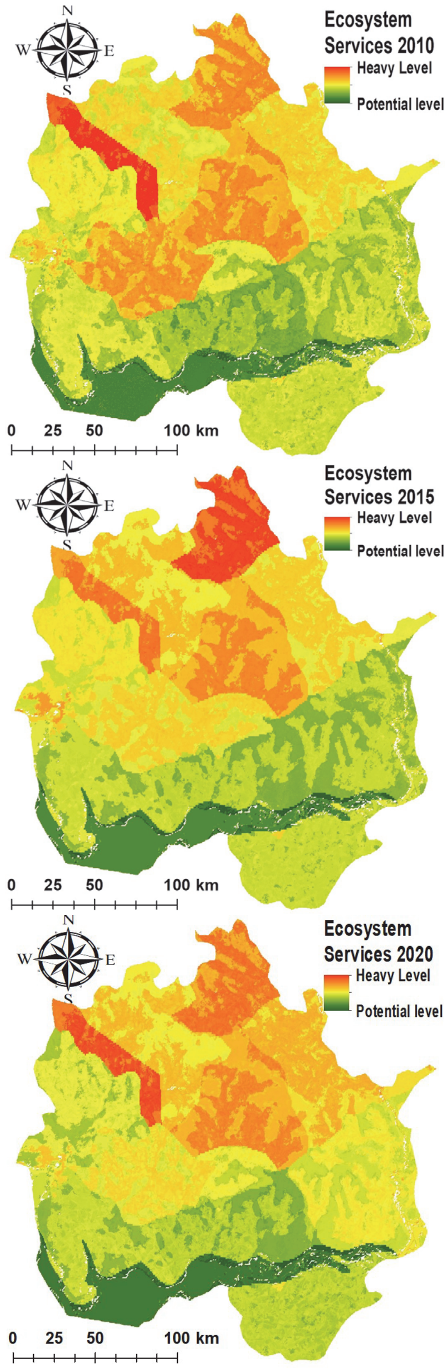

Fig. 7. Spatiotemporal changes of ESs in the Republic of Tatarstan, Russia from 2010 to 2020

2.2. Ecosystem services (ESs) assessment

For the years 2010, 2015, and 2020, the ESs value range was 0.85 – 8.39, 1.48 – 8.44, and 0.88 – 7.75, indicating that the highest variation in ecosystem services was present in 2010, with the highest in 2015 and the lowest in 2020. In the catchment areas of the Volga and Kama rivers, potential level services were proposed (Fig. 7). Potential for light-level ESs was found in the southern portion of the study area between 2010 and 2015, after which there was a center-to-east shift from 2015 to 2020.

Heavy level ESs were only 2.48 % in 2010 but drastically grew to 12.96 % in 2015 before slightly decreasing to 11.99 % in 2020 (Fig. 8). The high-level ESs class has steadily increased from 15.56 %, 29.42 %, and 32.60 % in 2010, 2015, and 2020, indicating an alarming situation but a high rate of ecosystem services. From 2010 to 2015, the moderate class of ESs increased from 28.40 % to 37.18 %, and then slightly decreased to 34.32 % in 2020. From 2010 to 2015, the light class decreased rapidly, from 41.29 % to 12.41, and then remained stable (Fig. 8). The potential class was also reduced slightly in the first half, and then stabilized in the second half.

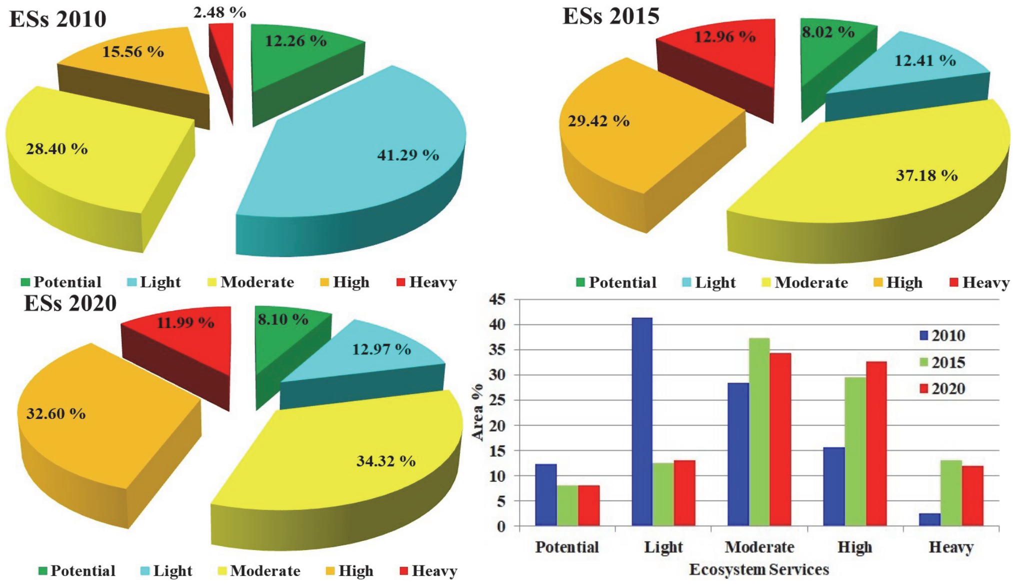

Fig. 8. Graphical representation of ESs in the Republic of Tatarstan, Russia from 2010 to 2020

Tab. 6. Shows the correlation between the LER and ESs indicators

2010	LER	GPP	Ferti.	SM	WC	Cattle	CGP	MP	SC	IP	LSW	SOC
LER	1.00	−0.15	0.23	−0.03	**−0.41**	0.24	−0.04	0.22	0.14	0.32	0.00	0.16
GPP	−0.15	1.00	−0.60	0.41	0.28	−0.44	0.06	−0.39	−0.35	−0.54	−0.22	−0.71
Ferti.	0.23	−0.60	1.00	−0.29	−0.11	**0.84**	−0.27	**0.85**	0.22	0.62	0.34	0.44
SM	−0.03	0.41	−0.29	1.00	0.15	−0.21	0.06	−0.19	−0.54	−0.31	−0.08	−0.22
WC	−0.41	0.28	−0.11	0.15	1.00	−0.29	0.14	−0.23	−0.15	−0.25	0.16	−0.19
Cattle	0.24	−0.44	**0.84**	−0.21	−0.29	1.00	−0.17	**0.98**	0.13	0.52	0.21	0.33
CGP	−0.04	0.06	−0.27	0.06	0.14	−0.17	1.00	−0.20	−0.03	0.08	−0.19	−0.03
MP	0.22	−0.39	**0.85**	−0.19	−0.23	**0.98**	−0.20	1.00	0.12	0.51	0.23	0.29
SC	0.14	−0.35	0.22	−0.54	−0.15	0.13	−0.03	0.12	1.00	0.29	0.07	0.18
IP	0.32	−0.54	0.62	−0.31	−0.25	0.52	0.08	0.51	0.29	1.00	0.44	0.39
LSW	0.00	−0.22	0.34	−0.08	0.16	0.21	−0.19	0.23	0.07	0.44	1.00	0.16
SOC	0.16	−0.71	0.44	−0.22	−0.19	0.33	−0.03	0.29	0.18	0.39	0.16	1.00
2015												
LER	1.00	−0.30	**0.41**	−0.24	−0.07	0.33	**0.50**	0.31	0.28	**0.49**	0.11	−0.14
GPP	−0.30	1.00	−0.54	0.35	0.38	−0.43	−0.63	−0.39	−0.33	−0.62	−0.20	−0.01
Ferti.	0.41	−0.54	1.00	−0.32	−0.39	**0.77**	**0.81**	0.70	0.28	0.65	0.34	−0.10
SM	−0.24	0.35	−0.32	1.00	0.13	−0.20	−0.30	−0.16	−0.36	−0.26	−0.10	−0.36
WC	−0.07	0.38	−0.39	0.13	1.00	−0.04	−0.17	−0.13	−0.22	−0.40	−0.16	−0.06
Cattle	0.33	−0.43	**0.77**	−0.20	−0.04	1.00	**0.83**	**0.96**	0.14	0.60	0.17	−0.07
CGP	0.50	−0.63	**0.81**	−0.30	−0.17	**0.83**	1.00	**0.75**	0.23	**0.77**	0.19	−0.11
MP	0.31	−0.39	0.70	−0.16	−0.13	**0.96**	**0.75**	1.00	0.12	0.59	0.17	−0.07
SC	0.28	−0.33	0.28	−0.36	−0.22	0.14	0.23	0.12	1.00	0.25	0.06	−0.06
IP	0.49	−0.62	0.65	−0.26	−0.40	0.60	**0.77**	0.59	0.25	1.00	0.25	−0.12
LSW	0.11	−0.20	0.34	−0.10	−0.16	0.17	0.19	0.17	0.06	0.25	1.00	−0.03
SOC	−0.14	−0.01	−0.10	−0.36	−0.06	−0.07	−0.11	−0.07	−0.06	−0.12	−0.03	1.00
2020												
LER	1.00	−0.27	0.26	0.10	−0.27	−0.03	**0.32**	−0.03	**0.30**	**0.44**	**0.40**	−0.15
GPP	−0.27	1.00	−0.59	−0.17	0.15	−0.37	−0.66	−0.30	−0.34	−0.56	−0.22	−0.01
Ferti.	0.26	−0.59	1.00	0.10	−0.04	**0.83**	**0.80**	**0.77**	0.22	0.47	0.27	−0.11
SM	0.10	−0.17	0.10	1.00	−0.09	0.07	0.16	0.05	−0.15	0.08	0.03	−0.24
WC	−0.27	0.15	−0.04	−0.09	1.00	0.27	−0.17	0.27	−0.11	−0.14	−0.05	−0.04
Cattle	−0.03	−0.37	**0.83**	0.07	0.03	1.00	0.60	**0.96**	0.08	0.31	0.20	−0.06
CGP	0.32	−0.66	**0.80**	0.16	−0.17	0.60	1.00	0.52	0.23	0.67	0.16	−0.12
MP	−0.03	−0.30	**0.77**	0.05	0.27	**0.96**	0.52	1.00	0.07	0.21	0.24	−0.05
SC	0.30	−0.34	0.22	−0.15	−0.11	0.08	0.23	0.07	1.00	0.26	0.05	−0.06
IP	0.44	−0.56	0.47	0.08	−0.14	0.31	0.67	0.21	0.26	1.00	0.20	−0.11
LSW	0.40	−0.22	0.27	0.03	−0.05	0.20	0.16	0.24	0.05	0.20	1.00	−0.04
SOC	−0.15	−0.01	−0.11	−0.24	−0.04	−0.06	−0.12	−0.05	−0.06	−0.11	−0.04	1.00

2.3. Correlation consequences between LER and ESs indicators

Tab. 6 shows the correlation between LER and various ESs indicators.

Tab. 7. shows the conversion of LER to ESs from 2010 to 2020

	2010	2015	2020
Lower LER to Higher ESs	25.75	43.12	45.50
Equal LER to Higher ESs	30.75	40.09	32.05
Higher LER to Lower ESs	37.84	12.25	17.74
Reaming/others	5.66	4.54	4.71

2.4. Zoning of LER with ESs

For all three years, ESs maps were integrated and overlaid on LER maps. Around 25 % of the study region, mostly in the north and east, is covered by lower LER with high ecosystem services (light to medium, high & heave 9.31 %, 6.01 %, 2 %, medium to high 8.43 %) in the year of 2010 (Fig. 9 & 10). This is the most suitable area as it has less landscape risk and provides high ecosystem services.

2.5. Statistical assessment

2.5.1. Global Moran`s Index test

All three LER and ESs maps were subjected to the Global Moran's I test, and all passed with positive autocorrelation, indicating a strong clustering pattern. The p-value for all six maps was statistically significant as 0.000 with a very high positive z-score, indicating that the null hypothesis can be easily rejected.

2.5.2. Getis-Ord Gi test*

All LER and ESs maps were examined hot/cold spot (Getis-Ord Gi*) statistics test after passing the Moran's I test to determine any local or regional clustering.

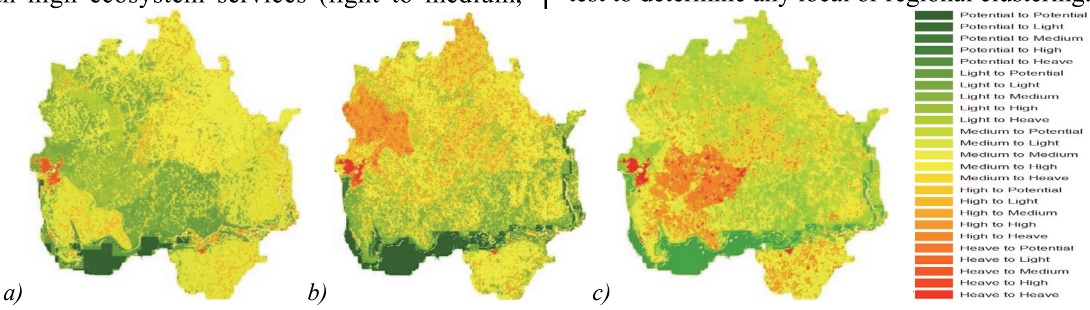

Fig. 9. Integration of LER with ESs maps in the Republic of Tatarstan, Russia from 2010 to 2020. a) 2010, b) 2020

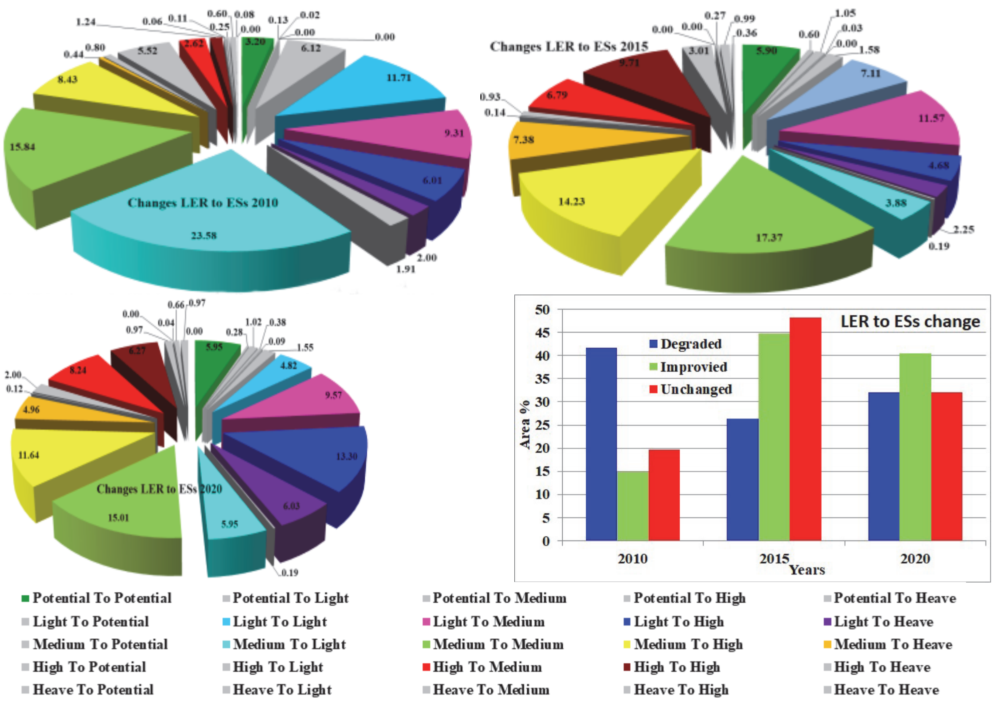

Fig. 10. Integration chart of ESs with LER in the Republic of Tatarstan, Russia from 2010 to 2020

Conclusion

The findings of this study suggest a good integration of landscape ecological risk (LER) and ecosystem services (ESs) for improved ecological function zoning, sustainable development, and management. This is the most effective use of a large number of indicators to determine the current state of the study area. It’s indicated that where there is high landscape ecological risk and provides a certain level of ecosystem services; it's useful to identify different ecological subzones for different management strategies. Linking LER and ESs provides a scientific foundation and a quantitative tool for the design and implementation of differentiated adaptive management to improve ESs and sustainable development. In all three years, the northwest part of the study area was highly sensitive due to high human-socioeconomic-ecological activity and should be protected immediately. To prevent any ecological risk, human activities, including farming, urbanization, and industrialization, should be continually monitored. Further land-use planning should prioritize environmental protection while causing the least amount of disruption to natural resources.

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