land

MDPI

Article

Environmental Assessment of Economic Activity Based on Analysis of Types of Permitted Use of Land Plots in the Russian Federation

Vasily Kovyazin [1], Elizaveta Bogdanova [1,*], Jana Volkova [2] and Vladimir Bogdanov [3]

[1] Department of Land Management and Cadasters, Empress Catherine II Saint Petersburg Mining University, 21st Line V.O., 2, St. Petersburg 199106, Russia; kovyazin_vf@pers.spmi.ru
[2] Department of Geodesy, Land Management and Cadasters, Saint Petersburg State University of Architecture and Civil Engineering, 2nd Krasnoarmeyskaya St., 4, St. Petersburg 190005, Russia; yavolkova@lan.spbgasu.ru
[3] Department of Land Management, Saint Petersburg State Agrarian University, St. Petersburg Highway, 2, Pushkin, St. Petersburg 196601, Russia
* Correspondence: elisaveta_b@mail.ru

Abstract

Intensive anthropogenic activity leads to ecosystem degradation, necessitating a shift from conventional management approaches towards proactive environmental risk assessment strategies. This study presents a quantitative methodology for calculating a Comprehensive Environmental Risk Indicator (CERI) based on the analysis of types of permitted use (TPU) of land plots in the Russian Federation. The methodology comprises three stages: determining a base risk weight for each TPU, statistically weighting impact factors using multiple regression analysis (MRA), and synthesizing the final CERI. This research identifies five key impact factors: industrial pollution, biogenic and agrogenic effects, landscape and resource changes, anthropogenic and household load, and specific risks and disasters. The results demonstrate that biogenic and agrogenic effects (weight 0.450) and specific risks and disasters (weight 0.398) are the most significant factors. Industrial pollution and landscape changes were excluded from the model due to multicollinearity. The model's R^2 (0.194) confirms its statistical validity as a foundational framework for macro-level risk evaluation. Further improvements could address limitations related to cadastral data variability and the integration of localized environmental parameters. The developed CERI was integrated into geographic information systems (GIS) to visualize risk gradients across land parcels. This study concludes that the use of statistically substantiated factor weights enables objective territorial zoning, facilitating a transition from subjective expert assessments to management based on actual environmental consequences.

Keywords: type of permitted use (TPU); environmental risk; multiple regression analysis (MRA); geographic information systems (GIS); impact assessment; land use

Check for updates

Academic Editors: Corrado Zoppi and Weiqi Zhou

Received: 17 March 2026
Revised: 23 April 2026
Accepted: 2 May 2026
Published: 7 May 2026

Copyright: © 2026 by the authors. Licensee MDPI, Basel, Switzerland. This article is an open access article distributed under the terms and conditions of the Creative Commons Attribution (CC BY) license.

1. Introduction

Recent studies indicate that intensive human economic activity, including industry, transport, and general urban expansion, is a primary driver of ecosystem degradation and habitat fragmentation, posing threats to local population health [1–3]. Modern environmental assessment in the context of urbanization, territorial development, and climate change requires comprehensive spatial analysis of anthropogenic impacts on the natural environment. The accumulation of hazardous chemical elements in soils, air, and dust,

originating from sources like roadside pollution or industrial emissions, necessitates both quantitative assessment of concentrations and evaluation of environmental and social risks [2,4]. In a broader context, research indicates that land-use change and increased urbanization lead to biodiversity loss and thermal degradation [5,6].

Scientific research emphasizes that effective action against climate threats requires interdisciplinary approaches capable of addressing their infrastructural components and their effects on social and environmental systems [7,8]. The lack of a systematic geospatial analysis of a territory results in inadequate environmental measures developed by industries, as they fail to consider territorial specifics. This leads to compromised ecosystem stability and disruption of ecological systems [9,10]. Thus, it is strategically important to develop a method that allows an objective assessment of adverse impacts based on specific territorial conditions. Given the fragility of ecosystems under the pressure of urbanization, accurate sustainability assessment requires an integrated approach that incorporates natural and climatic factors and relies on the development of reliable, integrated indicators adapted to local specifics [11]. Comprehensive analysis of land-use sustainability under urbanization and ecosystem fragility necessitates integrating natural and climatic data, moving beyond purely socio-economic factors. This requires developing multidimensional, reliable integrated indicators to create detailed and flexible, rather than universal, approaches to risk assessment [12–14]. Effective management of land resources and prevention of environmental threats require not only an analysis of the current state but also the use of predictive models to simulate future land-use scenarios and their ecological impacts [15]. The complexity of planning and assessing environmental projects arises from viewing them as dynamic processes rather than static scenarios, necessitating a flexible decision-making system [16].

Active government support stimulates the redistribution of land resources for new activities [17] and promotes the development of previously unused territories, creating a need for proactive management of the environmental consequences of land use. Currently, the global scientific community recognizes the necessity of developing proactive strategies aimed at achieving positive environmental outcomes, as classical management and assessment based on the “do no harm” principle are insufficient to counteract complex negative impacts [18,19]. The creation of integrated workflows for identifying and monitoring key environmental components, such as biodiversity and functional connectivity, is crucial to ensure the sustainability of natural and urban systems [20]. The effectiveness of environmental protection programs should be assessed based on a rigorous methodology where key indicators directly link the measured parameters to actual environmental consequences, minimizing discrepancies between formal goals and actual environmental improvement [21]. Considering that forecasting environmental impacts requires not only assessment of the current state but also comprehensive consideration of a variety of interrelated factors (from anthropogenic load to biogenic processes), the need to develop models capable of objectively weighing the contribution of each element to the overall risk is justified [22].

Intensive anthropogenic impact caused by various types of human economic activities leads to fragmentation and the disruption of ecosystem services [6,23]. Effective strategic planning requires consideration of spatial characteristics, as landscape structure and risk distribution are not uniform even within the same territory [24]. In this context, analyzing ecosystem services facilitates the rational integration of nature-based solutions into land-use patterns, enabling the prediction of their impact on ecosystem states [25].

The necessity of reducing the environmental burden is underscored by the requirement for rational industrial waste processing (e.g., recycling waste to create materials with improved characteristics [26]) and research into the use of optimal chemical solutions (e.g.,

for dust suppression of bulk materials [27]). When assessing technogenic risks associated with industrial types of permitted use (TPU), it is necessary to consider both negative aspects (pollution and landscape disturbance) and the potential to mitigate this impact through technological innovations. For example, methods for utilizing industrial by-products (such as CO_2) are actively being investigated in related industries, as a way to achieve dual benefits: increased efficiency and a reduced environmental footprint [28]. This highlights the need for flexible risk assessment that considers the entire industrial sector, because, as research indicates [29], significant achievements in reducing environmental impact have been observed in countries that have made moderate, realistic, scientifically based decisions. While these technological innovations provide specific pathways for risk mitigation, the CERI framework proposed in this study serves to establish the base weight of the TPU, representing the inherent environmental risk of a specific land-use category. Defining this baseline is a necessary prerequisite for proactive management; it allows for identifying the land-use types where industrial waste processing or carbon-utilization strategies are most critically needed. Thus, the proposed indicator acts as a diagnostic tool that links the legal status of land use with the potential demand for advanced environmental protection technologies.

In Russia, permissible economic activity is directly regulated by land relations. Land is classified into seven categories based on land plot purpose: agricultural land; settlement land; industrial land and land for other special purposes; land of specially protected natural areas; forest fund land; water fund land; and reserve lands. A land category serves as a general purpose, whereas a TPU clearly regulates permissible activities. Since a land plot can only be used in accordance with its TPU, a direct relationship exists between an established use type and its actual environmental impact on the territory. However, verifying compliance with permitted land use during economic activities remains a critical problem. The relevance of this problem is confirmed by studies that reveal significant discrepancies between the legally established purpose of green areas and their actual condition, often manifested in the illegal placement of facilities and degradation of vegetation cover, as indicated by the NDVI metric [30].

The negative impact of infrastructure facilities on land use must be assessed considering the combined effects of three groups of factors: restrictions on regulatory rights, territorial deficits, and environmental pollution. This requires the development of comprehensive compensation algorithms to ensure rational land use [31]. Thus, transitioning to a quantitative assessment of the potential risk inherent in the land-use type itself is a necessary step for proactive management.

Given the existing challenges and the urgent need to move towards proactive planning, an objective methodology for assessing environmental risk is required. Such a methodology should be based on TPU and multiple regression analysis (MRA) to correctly calculate weighting coefficients.

Despite the existence of various environmental assessment frameworks, current methodologies often suffer from two major limitations. First, they are predominantly qualitative, relying heavily on subjective expert scoring or manual indicators, which can lead to inconsistent results across different regions. Second, many existing models are restricted to localized field measurements or highly specific technical monitoring—such as the assessment of structural integrity within narrow construction risk zones [32]—making them difficult to scale or apply uniformly to large-scale national land-use systems. Furthermore, there is a lack of research that directly quantifies the environmental hazard inherent in the legal status of a land plot—its permitted use. This study fills these gaps by developing a quantitative, data-driven CERI framework. By utilizing a massive national dataset and applying multiple regression analysis (MRA) to derive objective weights, this research

replaces subjective judgment with a scalable and statistically substantiated framework for proactive risk management.

The aim of this study is to develop a quantitative methodology for calculating the Comprehensive Environmental Risk Indicator (CERI), empirically verified through regression modeling of impact factors.

To achieve this goal, the following tasks were accomplished:

Firstly, the base weight for various land-use types was determined based on the median risk values from the environmental control register; secondly, statistically significant negative impact factors were selected and their weights determined; thirdly, a Comprehensive Environmental Risk Indicator was developed and justified.

The novelty of this research lies in the development of a three-stage methodology for the environmental assessment of human economic activity: assessment of the basic risk of TPU, statistical weighing of factors of negative impact on the natural environment, and obtaining a comprehensive indicator of environmental risk.

2. Materials and Methods

2.1. Determination of a Base Weight of Permitted Use Types

The methodology for environmental assessment of economic activity, based on the analysis of land plot TPUs, comprises three main stages (Figure 1):

1. Determination of the base weight of the TPU based on the median value of objects' risks (Y).
2. Determination of the weights of the factors influencing the environment using multiple regression analysis (W_i).
3. Calculation of the Comprehensive Environmental Risk Indicator (CERI) by synthesizing influencing factors and the base weight of the TPU (Y).

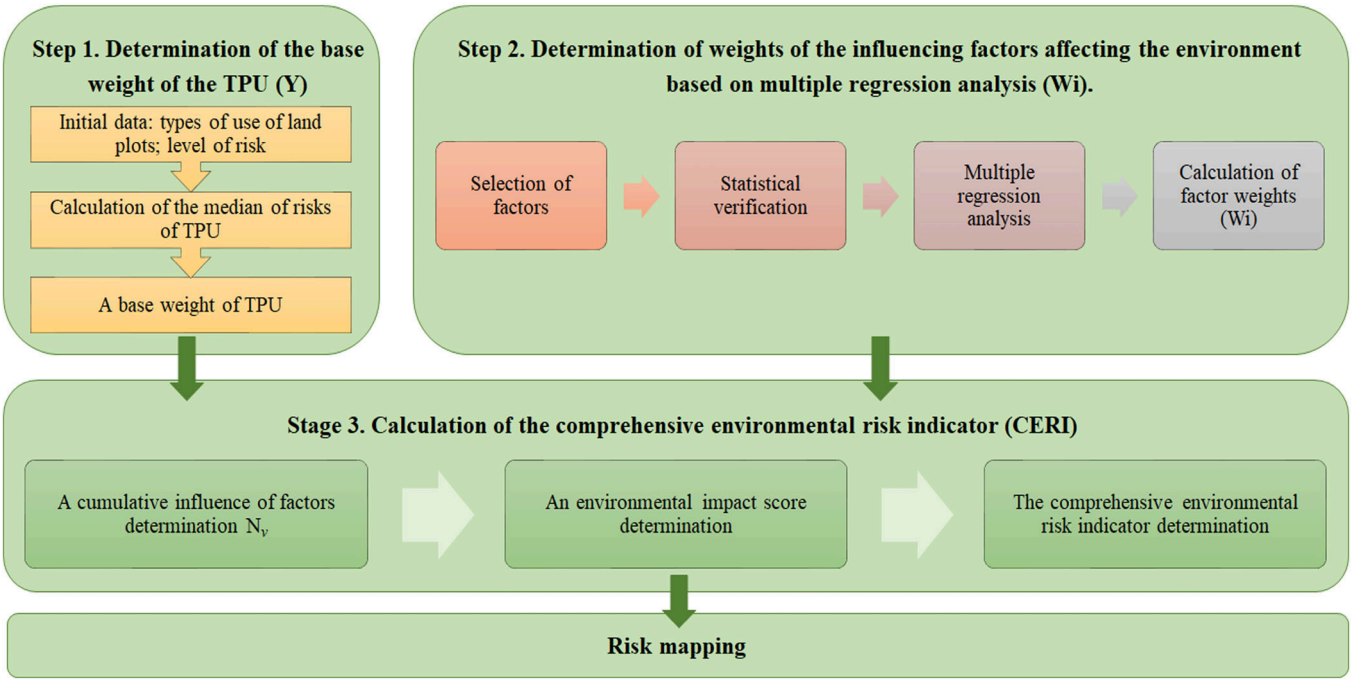


Figure 1. A three-stage methodology for the environmental assessment of human economic activity.

An important feature of this work is the federal scale of applicability of the developed method. Unlike local studies based on limited field data, the proposed methodology is based on all-Russian regulatory legal acts.

Input data for determining the base weight of TPU (Y) include: firstly, types of permitted use (legislation provides 171 types); secondly, registry objects whose environmental activities are monitored by the Federal Service for Supervision of Natural Resources. For this study, 1959 objects were selected across Russia, covering all TPUs, from the publicly accessible Register of Categorized Objects of the Federal Service for Supervision of Natural Resources (Rosprirodnadzor), established under the Federal State Environmental Supervision framework. This register can be accessed at: https://rpn.gov.ru/activity/supervision/objects/environment/ (accessed on 1 November 2025). The nature of control depends on the assigned risk level (Table 1).

Table 1. Interpretation of risk levels.

Risk Level	Description	A Numerical Interpretation of Risk Level *
Extremely high risk	Objects with the greatest potential for environmental damage, confirmed by recent serious regulatory actions.	6
High risk	Objects with high environmental impact that require frequent monitoring due to persistent violations or location in ecologically vulnerable areas.	5
Significant risk	Objects that have a significant but controlled negative impact on the environment	4
Medium risk	Objects with an average level of environmental impact, or facilities whose activities are limited only to waste transportation.	3
Moderate risk	Objects with minor impacts that are located in specially protected or water areas.	2
Low risk	Objects with minimal impact on the environment, which do not require frequent attention.	1
No risk *	Objects that do not have a proven environmental hazard and are not monitored.	0

* The "No risk" level is not included in the existing legislation, but it is introduced as part of this study. The numerical interpretation of risk converts qualitative risk levels into quantitative values for downstream analysis, modeling, or ranking.

This supervision approach is referred to as a "risk-based" approach, as it helps to differentiate the volume and frequency of state control. The higher the risk, the more often and thoroughly an object from the list will be checked.

The base weight of a TPU is calculated as the median risk level of registry objects associated with a particular type of permitted use, rounded up to the nearest whole number. A median was chosen as an outlier-resistant indicator. The example of calculating the base weights for registry objects is shown in Table 2.

Table 2. Calculation of the base weights for registry objects (fragment).

Land Plot Use Type	Name of An Object	Risk Level in the Registry	A Numerical Interpretation of Risk Level	Median	A Base Weight of TPU	Environmental Impact Interpretation
Cattle breeding	Farm	Medium risk	3	3	3	Overgrazing leads to soil erosion and destruction of vegetation cover. Manure concentration causes severe soil contamination with nitrogen compounds.
Fur farming	Farm	Significant risk	4	4	4	High concentration of toxic waste. Significant waste volumes lead to intense chemical and bacterial contamination, altering the soil landscape.

Table 2. *Cont.*

Land Plot Use Type	Name of An Object	Risk Level in the Registry	A Numerical Interpretation of Risk Level	Median	A Base Weight of TPU	Environmental Impact Interpretation
Fish farming	The production site of the fishing enterprise	Extremely high risk	6	3	3	Water contamination with feed residues and veterinary drugs, altering the species composition of aquatic flora and fauna.
Storage and processing of agricultural products	Mill	Moderate risk	2	2	2	Formation of organic waste and wastewater that can pollute water bodies.
Vehicle storage	Garage	Low risk	1	1	1	Risk of technical fluid leakage, polluting soil and groundwater.
Provision of public services	Boiler house (communal services)	Low risk	1	5	5	Ecosystem and acoustic landscape disturbance. Sewage treatment plant discharges poison water bodies. Boiler emissions worsen air quality, affecting vegetation. Household load and noise from pumping stations disrupt acoustic habitat conditions, scaring away wild animals. Gas leaks threaten local landscape stability.
Social Service Homes	Boarding house	Low risk	1	2.5	3	Household waste and wastewater require regular monitoring to prevent local environmental pollution negatively affecting soil flora.
Animal shelters	Animal Shelter	Moderate risk	2	1.5	2	The concentration of biological waste and wastewater creates a risk of severe soil pollution, as well as strong odors affecting wildlife.
Animal shelters	Fund for Animal Welfare	Low risk	1	1.5	2	The concentration of biological waste and wastewater creates a risk of severe soil pollution, as well as strong odors affecting wildlife.
Production activities	The territory of an enterprise	High risk	5	4	4	The potential for accidents with uncontrolled release of hazardous substances, which can lead to local environmental disasters, damage to flora and fauna.
Production activities	Industrial site	Significant risk	4	4	4	The potential for accidents with uncontrolled release of hazardous substances, which can lead to local environmental disasters, damage to flora and fauna.
Pulp and paper industry	Production of paperboard	High risk	5	4.5	5	Water poisoning and flora suppression. Wastewater discharge with chlorine and sulfur compounds is harmful to aquatic flora and fauna. Air emissions pollute and depress adjacent forest ecosystems.
Pulp and paper industry	Paper Factory	Significant risk	4	4.5	5	Water poisoning and flora suppression. Wastewater discharge with chlorine and sulfur compounds is harmful to aquatic flora and fauna. Air emissions pollute and depress adjacent forest ecosystems.
Railway transportation service	Railway service workshop	Medium risk	3	2.5	3	Soil pollution by petroleum products. Noise disrupts fauna habitats.

2.2. Selection of Factors and Statistical Verification

Within the scope of this study, it was determined that many risks can be categorized into five factors based on common impact mechanisms: industrial pollution (industrial facilities and transport); biogenic and agrogenic effects (agriculture and fish farming); landscape and resource changes (construction, mining, and logging); anthropogenic and household load (residential development and recreation); and specific risks and disasters (hazardous industries and accidents).

To characterize the impact of an object on a TPU, a classification method is employed. This involves: firstly, grouping all registry objects related to a single type of permitted use; secondly, establishing a relationship between the type of permitted use and one of the five factors using a binary variable: if the factor has an effect, set "1", if not—set "0"; thirdly, determining the contribution of an object to a TPU using Formula (1); and fourthly, estimating the impact of an object on a TPU (2) to obtain normalized contribution values on a scale from 0 to 100. Table 3 presents an example calculation for the TPU "fishing".

Table 3. Calculation method for the impact of an object on a TPU.

The Registry Objects with TPU "Fishing"	A Base Weight of TPU	Relationship Between TPU and Factors [1]					Contribution of An Object on a TPU					An Impact of An Object on a TPU				
		F1	F2	F3	F4	F5	F1	F2	F3	F4	F5	F1	F2	F3	F4	F5
The production site of the fishing enterprise	6	1	1	1	0	0	6	6	6	0	0					
Fish processing enterprise	5	1	1	1	0	0	5	5	5	0	0					
Fishing and Mariculture area	4	1	1	1	0	0	4	4	4	0	0					
Food industry enterprise (fish farming and processing)	2	1	1	1	0	0	2	2	2	0	0					
Cage trout farming	1	1	1	1	0	0	1	1	1	0	0					
Commercial fish farming site	2	1	1	1	0	0	2	2	2	0	0					
Fish hatchery	3	1	1	1	0	0	3	3	3	0	0					
Fish hatchery (Salmon)	3	1	1	1	0	0	3	3	3	0	0	7.31	9.57	8.25	0	0
Fish hatchery	3	1	1	1	0	0	3	3	3	0	0					
The production area of the fish hatchery	3	1	1	1	0	0	3	3	3	0	0					
Fish hatchery (Salmon)	3	1	1	1	0	0	3	3	3	0	0					
Fish hatchery	3	1	1	1	0	0	3	3	3	0	0					
Fish hatchery	2	1	1	1	0	0	2	2	2	0	0					
Total value							40	40	40	0	0					
Minimum value							0	0	0	0	0					
Maximum value							547	418	485	89	403					

[1] F1—industrial pollution; F2—biogenic and agrogenic effects; F3—landscape and resource changes; F4—anthropogenic and household load; and F5—specific risks and disasters.

The binary assignment of impact factors (B_j) to each TPU was performed based on a systematic analysis of the environmental impact characteristics described in official federal registers. A value of '1' was assigned if a specific land-use type was associated with the potential for a given impact factor (e.g., nitrogen loading for the biogenic factor), while '0' was assigned if no such association was established in the regulatory documentation.

$$C_i = \sum_{j=1}^{n} (R_j \cdot B_j) \quad (1)$$

where C_i—summarized contributions of objects to a specific factor for a given TPU; R_j—the individual risk level of the j-th object belonging to this TPU (as per registry data); B_j—a binary variable indicating the presence (1) or absence (0) of the factor's effect for the j-th object; and n—the total number of objects registered for the TPU.

$$X_i = \frac{C_i - C_{\min}}{C_{\max} - C_{\min}} \quad (2)$$

where X_i—an impact of an object on a TPU; C_i—summarized contributions of an object to a TPU.

2.3. Calculation of Factor Weights (W_i)

Multiple linear regression analysis (MRA) is employed to determine the unique contribution of each factor. MRA is chosen as the primary method because, unlike traditional Multi-Criteria Decision Analysis (MCDA) methods [1,33], it allows for the statistical determination of weights (W_i) based on actual data (Y), thereby minimizing the subjectivity of expert assessments [33]. The use of structured decision-making methods integrated with GIS is the most effective method for solving multi-criteria tasks related to the analysis of complex systems [34]. While geospatial methods (like DInSAR [28]) ensure high monitoring accuracy, our approach focuses on integrating multifactorial environmental risk into a comprehensive index.

Within the framework of this study, the dependent variable is the base weight of the TPU, and the independent variables are impacts of an object on a TPU. The MRA allows us to obtain regression coefficients (β_i) that reflect the unique contribution of each factor to the prediction of Y, eliminating the effect caused by the interrelationships between the factors.

Correlation analysis was performed for the primary filtering of the data array: a quantitative assessment of the relationship between the dependent variable and the factors allows for the identification of the most informative indicators of risk formation and excludes variables from the model that do not have sufficient explanatory power (see Section 3).

Factors can be interdependent and duplicate each other's information, which can lead to instability of regression coefficients. The inclusion of factors in the model was performed after a preliminary check for multicollinearity with a threshold value of 0.7 (see Section 3).

The weights of the factors are calculated by normalizing the absolute values of the regression coefficients and summing them to one, according to Formula (3), and are presented later in Section 3.

$$W_i = \frac{|\beta_i|}{\sum|\beta|} \tag{3}$$

where W_i—weights of the factors; β_i—regression coefficients.

2.4. Comprehensive Environmental Risk Indicator

The Comprehensive Environmental Risk Indicator (CERI) is calculated at the final stage of the methodology and represents a consolidated quantitative risk assessment. At the first stage, the cumulative influence of factors whose weights are statistically justified by MRA (Formula (4)) is determined. This value (N_v) reflects the weighted contribution of all external threats specific to this type of permitted use.

$$N_v = \sum (X_i \cdot W_i) = X_2 \cdot W_2 + X_4 \cdot W_4 + X_5 \cdot W_5 \tag{4}$$

where N_v—a cumulative influence of factors; W_i—weights of the factors; and X_i—a base weight of the TPU.

At the second stage, an environmental impact score (E_{TPU}) is calculated using Formula (5). This approach considers that the overall level of negative impact is determined not only by the potential of the TPU but also by the cumulative influence of factors.

$$E_{TPU} = Y \cdot N_v = Y \cdot \sum (X_i \cdot W_i) = Y \cdot (X_2 \cdot W_2 + X_4 \cdot W_4 + X_5 \cdot W_5) \tag{5}$$

where E_{TPU}—an environmental impact score; N_v—a cumulative influence of factors; Y—a base weight of the TPU; W_i—weights of the factors; and X_i—impacts of an object on a TPU.

It should be noted that the interaction between the base weight (Y) and the cumulative factor influence (N_v) in Formula (5) does not constitute double-counting of risk. While both parameters utilize the same regulatory dataset, they represent distinct dimensions of

environmental hazard. The base weight (Y) acts as a static normative benchmark, reflecting the median risk potential inherent to a land-use category. Conversely, the cumulative influence (N_v) is a dynamic coefficient that quantifies the relative intensity and distribution of specific impact factors (F2, F4, and F5) as determined by MRA. Multiplying these values allows the model to scale the intensity of risk factors relative to the category's fundamental hazard level, providing a more nuanced environmental impact score (E_{TPU}).

The Comprehensive Environmental Risk Indicator (CERI) is obtained using Formula (6). CERI ranges from 0 to 100 (Table 4) and serves as a composite indicator that includes both the inherent risk of the TPU and the cumulative multifactorial impact on the natural environment.

$$\text{CERI} = \frac{E_{TPUi} - E_{TPU\min}}{E_{TPU\max} - E_{TPU\min}} \cdot 100 \quad (6)$$

Table 4. CERI interpretation scale (based on quantiles).

A Level of Influence	Range of CERI Values	Risk Category	TPU Examples
I	0–1.8	Minimal impact	Viticulture, Apiculture, etc.
II	1.8–4.2	Low impact	Crop production, Provision of sports and entertainment events, etc.
III	4.2–8.5	Moderate impact	Sports facilities, Pipeline transport, etc.
IV	8.5–21.0	High impact	Livestock farming, Energy sector, etc.
V	>21.0	Critical impact	Public utility services, Petrochemical industry, etc.

A CERI interpretation scale has been developed to interpret the values of the Comprehensive Environmental Risk Indicator. Given the asymmetric distribution of the index, characterized by the dominance of low environmental risk values, the quintile method was used for classification (dividing all TPUs into five equal groups by frequency of occurrence). These threshold ranges are therefore data-derived and adapt dynamically to the distribution of CERI values across the national dataset, rather than being arbitrarily fixed.

This approach allows for statistically sound identification of activity clusters with varying degrees of environmental hazard: from minimal impact (Level I) to critical (Level V). Values of the indicator exceeding a threshold of 21% (on a scale of 0—100%) are statistically distinguished as abnormally high compared to 90% of other types of permitted use. This value acts as an objective cut-off point for the "Critical Impact" category (level V), which covers activities with the maximum potential for negative environmental impact. The use of this scale ensures transparency in the interpretation of results, allowing types of use to be ranked according to the intensity of their environmental impact across the country, where 100% corresponds to the maximum level of influence identified in the studied set of values.

Based on the developed scale, the CERI indicator acquires spatial relevance through integration into a geographic information system. To visualize the results, spatial data in the form of cadastral plans were sourced from the Unified State Register of Real Estate (USRRE). The map (Figure 2) was created by performing an attribute join between the calculated CERI values and the land parcel polygons. The link was established using the official 'type of permitted use' (TPU) attribute assigned to each cadastral plot. This allowed for the automated assignment of the corresponding risk level to each polygon within the GIS environment. These CERI values are mapped using quantile-based classification to visualize risk gradients and identify territories with the highest anthropogenic load.



Figure 2. Distribution of CERI in the Teriberka area, Murmansk Region.

Thus, CERI is transformed from a numerical index into a visual risk heatmap, enabling objective identification of territories with the greatest anthropogenic load and providing a basis for defining the boundaries of protected areas.

Statistical data processing was performed using Microsoft Excel 2021 (Microsoft Corp., Redmond, WA, USA). Spatial data analysis and visualization were conducted using the open-source software QGIS version 3.28 (Open-Source Geospatial Foundation, Beaverton, OR, USA).

3. Results

A primary correlation analysis of the data (Table 5) revealed the degree of relationship between the dependent variable and the selected factors. The analysis of the correlation coefficient indicated that factors F1 (industrial pollution) and F3 (landscape and resource changes) exhibited the strongest moderate relationship (r = 0.47), while factor F4 (anthropogenic and household load) showed a very weak relationship (r = 0.08). Interpretation of the obtained correlation coefficients (r = 0.34–0.47) requires consideration of the specifics of the subject area. From the perspective of applied land management and socio-environmental risks assessment, these values should be considered high and statistically significant, as they confirm that a single factor explains up to 22% of the variance in the base weight of the TPU (coefficient of determination = 0.22). This result confirms that the selected factors logically complement Y, rather than duplicate it.

Table 5. The result of the correlation analysis for five factors.

Factors	Correlation Coefficient (r)	Interpretation
F1 (industrial pollution)	0.47	Moderate
F2 (biogenic and agrogenic effects)	0.34	Moderate
F3 (landscape and resource changes)	0.47	Moderate
F4 (anthropogenic and household load)	0.08	Weak
F5 (specific risks and disasters)	0.36	Moderate

Despite F4 showing a weak linear relationship with the base weight of TPU, its exceptionally low cross-correlation with other factors (r = 0.40 with F5, r = 0.15 with F2) indicates that it reflects a unique, independent aspect of risk. Keeping F4 in the regression model allows us to take into account this specific, uncorrelated contribution to explaining the variability of the dependent variable.

Multicollinearity testing revealed high correlations between pairs F1/F3 (r = 0.997), F1/F5, and F2/F3 (Table 6). It was decided to exclude factor F1 (industrial pollution) because factor F5 (specific risks and disasters) is more complex and already includes characteristics of technogenic risks, emergencies, and the specifics of hazardous industries, thus covering a wider range of anthropogenic impacts. Similarly, the F3 (landscape and resource changes) factor is excluded from the model, since the component of landscape change underlying F3 (Landscape) is actually present in all the considered impact factors, being their common systemic feature. Thus, the following factors were selected for the MRA: F2 (biogenic and agrogenic effects), F4 (anthropogenic and household load), and F5 (specific risks and disasters).

Table 6. Results of multicollinearity testing for impact factors.

		An Impact of an Object on a TPU				
		F1	**F2**	**F3**	**F4**	**F5**
An impact of an object on a TPU	**F1**	1				
	F2	0.788	1			
	F3	0.997	0.773	1		
	F4	0.037	−0.141	0.033	1	
	F5	0.743	0.403	0.776	−0.080	1

The multiple linear regression analysis using the set of F2, F4, and F5 as independent variables yielded a statistically significant model with a coefficient of determination (R^2) of 0.194 (adjusted R^2 = 0.180), explaining 19.4% of the variance in the base weight of the TPU. An R^2 value explaining nearly 20% of the variance is substantial for multi-factor systems of this level of complexity. Environmental risks associated with land use represent a highly multifaceted system influenced by a wide array of variables, including natural conditions, anthropogenic pressures, economic activities, and socio-cultural aspects that are inherently difficult to capture fully within a single model. In such complex fields, achieving very high R^2 values (e.g., 0.70–0.80) is rarely feasible. While a significant portion of the variance remains influenced by factors outside the current regulatory scope, the model is sufficient as a high-level screening tool to provide a standardized, objective baseline for environmental risk assessment. Therefore, this model intentionally focuses

on the anthropogenic component as a critical and measurable subsystem of the larger environmental complex.

All three selected factors made a statistically significant contribution ($p < 0.05$) (Table 7). Normalization of the β coefficients by Formula (3) produced objective factor weights (Table 8).

Table 7. The results of the analysis of the coefficients of the regression model.

Factor	*p*-Value	Significance of the Factor	β Coefficients
F2 (biogenic and agrogenic effects)	0.00143	Significant	0.0233
F4 (anthropogenic and household load)	0.04631	Significant	0.0079
F5 (specific risks and disasters)	0.00041	Significant	0.0206

Table 8. Weights of environmental impact factors.

Factor	β Coefficients	Factor Weight (W_i)
F2 (biogenic and agrogenic effects)	0.0233	0.450
F4 (anthropogenic and household load)	0.0079	0.152
F5 (specific risks and disasters)	0.0206	0.398

The final multiple regression equation is described by Formula (7).

$$Y = 0.0233 \cdot X_2 + 0.0079 \cdot X_4 + 0.0206 \cdot X_5 \quad (7)$$

where Y—the base weight of the TPU; X_2—biogenic and agrogenic effects; X_4—anthropogenic and household load; X_5—specific risks and disasters; and 0.0233, 0.0079, and 0.0206—the standardized regression coefficients β_i.

The obtained weights reflect the independent influence of each factor on the prediction of the base weight, free from the effects of multicollinearity.

The CERI indicator was calculated using factor weights (W_i, Table 8) and the impacts of an object on a TPU (X_i) integrated with the base weight Y (Equations (4)–(6)). These calculations allowed us to obtain a ranked risk indicator for each TPU.

Similar to how an Environmental Safety Scheme integrates sources, corridors, and nodes [35], CERI provides the necessary structural framework that serves as a reliable tool for formulating recommendations on territorial management and optimizing protection regimes. CERI is an integral indicator suitable for thematic mapping of territorial vulnerability. The result of this thematic mapping is presented in Figure 2.

Figure 2 illustrates the spatial distribution of the integrated environmental risk indicator (CERI) in the territory of the rural settlement of Teriberka (Kola District, Murmansk Region), classified according to five influence levels. The map was generated using cadastral data from the Unified State Register of Real Estate (USRRE), with land-use boundaries corresponding to officially registered land parcels. CERI values were assigned to each parcel based on its registered type of permitted use (TPU). Visualization demonstrates that zones of "Critical" (Level V, >21.0) and "High" (Level IV, 8.5–21.0) impacts are mainly concentrated in the settlement's center and along transport corridors. Conversely, adjacent natural territories are characterized by "Minimal" (Level I, 0–1.8) or "Low" (Level II, 1.8–4.2) impacts, indicating a sharp gradient in environmental burden associated with concentrated human activity. Such site-level mapping effectively highlights the spatial heterogeneity of environmental risks, providing a clear basis for differentiated territorial management.

4. Discussion

4.1. Interpretation of Factor Weights

In contrast to the preliminary correlation analysis, where F1 (industrial pollution) and F3 (landscape and resource changes) initially exhibited strong relationships with the dependent variable and with each other (as detailed in Section 3), these factors were subsequently excluded from the multiple regression analysis due to high multicollinearity. Therefore, the discussion of factor weights focuses on the three factors that were retained in the regression model: F2 (biogenic and agrogenic effects), F4 (anthropogenic and household load), and F5 (specific risks and disasters).

The statistically justified weights obtained by MRA for these retained factors were distributed as follows: Factor F2 (Biogenic and agrogenic effects) received the highest weight (W_2 = 0.450), followed by F5 (specific risks and disasters, W_5 = 0.398). Factor F4 (anthropogenic and household load) received the minimum weight (W_4 = 0.152). This distribution highlights the key advantage of MRA: while correlation analysis indicated a joint change or strong interdependencies, the W_i weights reveal the unique, independent contribution of each factor to the variation in the base weight of the TPU, providing a more stable and interpretable model by addressing multicollinearity.

It should be emphasized that an R^2 value of nearly 0.20 is considered substantial for multi-factor socio-environmental systems of such complexity. Environmental risks associated with land use are influenced by a wide array of variables, including natural conditions, localized economic pressures, and even socio-cultural aspects that are inherently difficult to capture fully within a single predictive model. In such fields, achieving very high coefficients (e.g., 0.70–0.80) is rarely feasible due to the inherent stochasticity of environmental processes. Consequently, while the model does not capture every local nuance, it is sufficient for practical use as a robust preliminary diagnostic tool. Our model intentionally focuses on the anthropogenic component as a critical and measurable subsystem of this larger, complex system.

To improve the adequacy of vulnerability assessment and the development of sustainable strategies, it is necessary to move away from fragmented approaches and utilize integrated, hybrid analytical frameworks that link environmental, socio-demographic, and health-saving dimensions [36]. The justification for the advantages of a statistically weighted model (based on MRA) over traditional expert methods such as the Fuzzy Delphi or the Analytic Hierarchy Process (AHP) lies in the objectivity of weight derivation. While methods like Fuzzy Delphi or AHP rely on the subjective judgments of experts [33,37], the proposed method uses the predictive power of data to determine weights (β_i).

Studies on urban environmental quality demonstrate that its evolution is driven not only by technological advances but also by the growing demand for integrating multi-dimensional indicators (environmental and socio-economic) for adequate assessment of sustainability [38]. When assessing the functional potential of complex infrastructure facilities, the integration of multi-criteria decision-making with optimized neural networks provides a transition from subjective expert assessments to objective factor weighting based on the predictive power of data [33]. The concept of functional biodiversity requires that even systems focused on natural processes be designed taking into account human realities and requirements for quality and connectivity, rather than relying solely on spontaneous development [39].

4.2. Practical Significance

A key feature of the proposed methodology is its nationwide applicability, established by its foundation on federal regulatory acts and a comprehensive dataset derived from across Russia. The system of types of permitted use (TPU) and the risk categorization

framework are defined by federal legislation, ensuring legal standardization across the entire country. Crucially, the CERI calibration, including the base weights (Y) and factor weights (W_i), was performed using data from 1959 objects selected nationwide, representing all major TPUs. This approach ensures that the CERI index reflects a national standard, calibrated based on country-wide data.

The developed methodology transforms the qualitative assessment of TPU into a quantitative risk indicator (CERI) through a statistical model, representing a significant step forward compared to purely expert methods. As related studies indicate, to increase the accuracy of cadastral land valuation, it is necessary to use an integral quality indicator obtained through regression modeling of the relationship between the soil physico-chemical properties and market value, which allows for overcoming limitations associated with incomplete soil characteristics data [40].

Integrating CERI with geoinformation technologies enables the mapping of risks and the formation of objectively sound design solutions for defining the boundaries of protected zones within specially protected natural areas. Effective protection of natural areas requires an integrated approach that, based on an analysis of the extended radius of anthropogenic factors, allows for spatially zoning of adjacent territories and prioritization of facilities for applying protection regimes based on local risk levels [41]. In this context, the case study conducted in the Teriberka region (Figure 2) serves as a practical demonstration of applying the nationally calibrated CERI for spatial visualization and territorial risk zoning. This example illustrates the implementation and output of the methodology at a local scale.

5. Conclusions

The growth of urbanization and intensive economic activity exerts increasing pressure on natural systems, necessitating a transition from subjective assessments to objective methods for analyzing land-use environmental risk based on statistical data. Within the scope of this study, a mathematically sound framework has been developed that directly links types of permitted use of land plots with their ecological footprint.

In the course of this research, a three-stage methodology for determining the Comprehensive Environmental Risk Indicator (CERI) was developed and verified, providing an objective, quantitative approach to assessing risk nationwide. By integrating federal regulatory standards and utilizing a dataset encompassing 1959 objects across Russia, the CERI methodology offers a consistent framework applicable throughout the Russian Federation. The derived factor weights, determined using multiple regression analysis, highlight the significant contributions of biogenic effects and specific risks.

While the current model's explanatory power (R^2 = 0.194) indicates that a portion of environmental risk variance is influenced by highly localized or unquantified factors, its statistical significance firmly establishes the CERI as a valuable and objective baseline indicator for land-use risk across the Russian Federation. This foundational model serves effectively as a high-level screening tool for regional assessment, offering a robust starting point where comprehensive, site-specific data may be scarce. Future research will build upon this framework by integrating more granular local environmental data (e.g., geological, hydrological, and climatic conditions) and socio-economic variables. This will further enhance the model's explanatory power and enable a finer spatial resolution, moving towards even more precise, site-specific risk assessments.

The Teriberka demonstration illustrates the practical application of this nationally calibrated CERI, demonstrating its utility for spatial risk mapping and identifying territories with high anthropogenic loads. Thus, the CERI indicator serves as a robust tool for proactive and differentiated land management strategies at a national scale, transitioning from subjective assessments to data-driven decision-making.

https://doi.org/10.3390/land15050786

Author Contributions: Conceptualization, V.K. and V.B.; methodology, E.B.; formal analysis, E.B. and J.V.; investigation, E.B.; data curation, E.B.; writing—original draft preparation, E.B. and J.V.; writing—review and editing, V.K., V.B. and J.V.; visualization, E.B.; supervision, V.K. and V.B.; project administration, V.K. All authors have read and agreed to the published version of the manuscript.

Funding: This research was funded by the Ministry of Science and Higher Education of the Russian Federation, state assignment number FSRW-2026-0003 ("Study of the processes of integrated development of the Earth's interior and deep processing of geological resources"). The APC was funded by the authors.

Data Availability Statement: The datasets presented in this article are not readily available because the data are part of an ongoing study. Requests to access the datasets should be directed to the author.

Conflicts of Interest: The authors declare no conflicts of interest.

Abbreviations

The following abbreviations are used in this manuscript:

TPU	Type of permitted use
MRA	Multiple regression analysis
GIS	Geographic information systems
CERI	Comprehensive environmental risk indicator

References

1. Zhang, Y.; Liu, S.; Yu, P.; Liu, H.; Kong, F.; Jin, G.; Chen, Y. Non-Linear Impacts of Social and Ecological Drivers on Ecosystem Services: A Threshold Perspective. *Urban Sci.* **2025**, *9*, 390. [CrossRef]
2. Miletić, A.; Vesković, J.; Lučić, M.; Varol, M.; Crnković, D.; Potkonjak, N.; Onjia, A. Comprehensive Assessment of Heavy Metal(loid) Pollution in Agricultural and Urban Soils near an Oil Refining Facility: Distribution Patterns, Source Apportionment, Ecological Impact, and Probabilistic Health Risk Analysis. *Urban Sci.* **2025**, *9*, 415. [CrossRef]
3. Ivanov, A.V.; Smirnov, Y.D.; Lisay, V.V.; Borowski, G. Issues of the Impact of Granulated Sulfur Transportation on the Environmental Components. *J. Ecol. Eng.* **2023**, *24*, 86–97. [CrossRef] [PubMed]
4. Hayat, I.; Ali, W.; Muhammad, S.; Nafees, M.; Raziq, A.; Din, I.U.; Khan, J.; Iqbal, S. Contamination, Ecotoxicological Risks, and Sources of Potentially Toxic Elements in Roadside Dust Along Lahore–Islamabad Motorway (M-2), Pakistan. *Urban Sci.* **2025**, *9*, 225. [CrossRef]
5. Nguyen, C.T.; Downes, N.K.; Sitthi, A.; Losiri, C. Tourism-Induced Land Use Transformations, Urbanisation, and Habitat Degradation in the Phu Quoc Special Economic Zone. *Urban Sci.* **2025**, *9*, 11. [CrossRef]
6. Lei, C.; Phillips, M.; Li, X. Transition Characteristics and Drivers of Land Use Functions in the Resource-Based Region: A Case Study of Shenmu City, China. *Urban Sci.* **2025**, *9*, 520. [CrossRef]
7. Sádaba, J.; Luzarraga, A.; Lenzi, S. Designing for Climate Adaptation: A Case Study Integrating Nature-Based Solutions with Urban Infrastructure. *Urban Sci.* **2025**, *9*, 74. [CrossRef]
8. Massarelli, C.; Binetti, M.S. Improving Urban Resilience Through a Scalable Multi-Criteria Planning Approach. *Urban Sci.* **2025**, *9*, 309. [CrossRef]
9. Abedini, A.; Aram, F.; Khalili, A.; Mirzaei, E. Recognition and Evaluating the Indicators of Urban Resilient by Using the Network Analysis Process. *Urban Sci.* **2022**, *6*, 31. [CrossRef]
10. Sudarikov, S.M.; Yungmeister, D.A.; Korolev, R.I.; Petrov, V.A. On the possibility of reducing man-made burden on benthic biotic communities when mining solid minerals using technical means of various designs. *J. Min. Inst.* **2022**, *253*, 82–96. [CrossRef]
11. Miao, P.; Li, C.; Xia, B.; Zhao, X.; Wu, Y.; Zhang, C.; Wu, J.; Cheng, F.; Pu, J.; Huang, P.; et al. Incorporating Ecosystem Service Trade-Offs and Synergies with Ecological Sensitivity to Delineate Ecological Functional Zones: A Case Study in the Sichuan-Yunnan Ecological Buffer Area, China. *Land* **2024**, *13*, 1503. [CrossRef]
12. Mamitimin, Y.; Nuerla, A.; Abudushalamu, Z.; Huang, M. From Land Use Change to Ecosystem Service Sustainability: Multi-Scenario Projections for Urban Agglomerations in Arid Northwest China. *Urban Sci.* **2025**, *9*, 433. [CrossRef]
13. Wang, X.; Zhao, H.; Qian, J.; Li, X.; Cao, C.; Feng, Z.; Cui, Y. Sustainable Land Use Diagnosis Based on the Perspective of Coupling Socioeconomy and Ecology in the Xiongan New Area, China. *Land* **2024**, *13*, 92. [CrossRef]
14. Hernandez-Santin, C.; Amati, M.; Bekessy, S.; Desha, C. A Review of Existing Ecological Design Frameworks Enabling Biodiversity Inclusive Design. *Urban Sci.* **2022**, *6*, 95. [CrossRef]

15. Chen, Y.; Wang, W.; Yang, Z. Spatiotemporal Dynamics and Future Projections of Land Use and Land Cover Change in Shihezi City, Xinjiang, China. *Urban Sci.* **2025**, *9*, 356. [CrossRef]
16. Sopena Porta, M.P.; Pellicer, F. Urban Planning and Landscape Projects on Urban Riverbanks in Europe: Comparative Study of the Ebro River, Zaragoza, and the Isar River, Munich. *Urban Sci.* **2024**, *8*, 152. [CrossRef]
17. Nguyen, M.P.; Ponomarenko, T. State Incentives for Solar Energy in the Context of Energy Transition in Developed and Developing Countries. *Energies* **2025**, *18*, 1227. [CrossRef]
18. Birkeland, J. Nature Positive: Interrogating Sustainable Design Frameworks for Their Potential to Deliver Eco-Positive Outcomes. *Urban Sci.* **2022**, *6*, 35. [CrossRef]
19. Brunckhorst, D.J.; Trammell, E.J. Future Options Redundancy Planning: Designing Multiple Pathways to Resilience in Urban and Landscape Systems Facing Complex Change. *Urban Sci.* **2023**, *7*, 11. [CrossRef]
20. Massarelli, C. Developing a Calculation Workflow for Designing and Monitoring Urban Ecological Corridors: A Case Study. *Urban Sci.* **2024**, *8*, 169. [CrossRef]
21. Gordeev, R.V.; Pyzhev, A.I.; Syrtsova, E.A. Effectiveness of the Federal 'Clean Air' Project to Improve Air Quality in the Most Polluted Russian Cities. *Urban Sci.* **2025**, *9*, 18. [CrossRef]
22. Korshunov, G.; Mironenkova, N.; Poleshchuk, A. The topical methods of detecting spontaneous combustion sources in coal mines. *Min. Inf. Anal. Bull.* **2025**, *5*, 169–180. (In Russian) [CrossRef]
23. Castañeda-Chávez, M.d.R.; Carlón-Solís, B.; Soto-Estrada, A.; García-Saldaña, A.; Navarrete-Rodríguez, G. Fragmentation in the Environmental System of the Ecological Reserves in the Riparian Mangroves of Arroyo Moreno-Tembladeras Wetlands, Veracruz Mexico. *Urban Sci.* **2025**, *9*, 470. [CrossRef]
24. Vardopoulos, I.; Maialetti, M.; Scarpitta, D.; Salvati, L. Spatially Explicit Analysis of Landscape Structures, Urban Growth, and Economic Dynamics in Metropolitan Regions. *Urban Sci.* **2024**, *8*, 150. [CrossRef]
25. Semeraro, T.; Scarano, A.; Pandey, R. Ecosystem Services Analysis and Design through Nature-Based Solutions in Urban Planning at a Neighbourhood Scale. *Urban Sci.* **2022**, *6*, 23. [CrossRef]
26. Pashkevich, M.; Evdokimova, M. Finely-dispersed Wastes of Titanium Production as an Additive for Manufacturing of Building Materials. *Ecol. Ind. Russ.* **2025**, *29*, 2. (In Russian) [CrossRef]
27. Lisai, V.V.; Smirnov, Y.D.; Ivanov, A.V.; Borowski, G. Investigation of the effectiveness of the use of various substances for dust suppression during the transshipment of granular sulfur. *J. Min. Inst.* **2025**, *271*, 108–119.
28. Morenov, V.; Shchigolev, K. Assessment of the possibility of carbon dioxide utilization for enhanced oil recovery in oil field conditions. *Neft. Khozyaystvo Oil Ind.* **2025**, *4*, 76–81. [CrossRef]
29. Tsvetkov, P.; Andreichyk, A. The Analysis of Goals, Results, and Trends in Global Climate Policy Through the Lens of Regulatory Documents and Macroeconomics. *Sustainability* **2025**, *17*, 4532. [CrossRef]
30. Skachkova, M. Urban green infrastructure assessment: Identification of public green spaces misuse. *Geogr. Environ. Sustain.* **2024**, *17*, 4. [CrossRef]
31. Bykowa, E.; Voronetskaya, V. A Compensation Strategy for the Negative Impacts of Infrastructure Facilities on Land Use. *Sci* **2025**, *7*, 95. [CrossRef]
32. Skachkova, M.E.; Lepihina, O.Y.; Ignatova, V.V. Information support of monitoring of technical condition of buildings in construction risk area. *J. Phys. Conf. Ser.* **2018**, *1015*, 042056. [CrossRef]
33. Han, Y.; Huang, S.; Zhao, S.; Zhang, X.; Chen, Y.; Wu, Z.; Huang, Y.; Ren, W.; Peng, D. Assessment of Ecological Suitability for Highway Under-Bridge Areas: A Methodological Integration of Multi-Criteria Decision-Making and Optimized Backpropagation Neural Networks. *Urban Sci.* **2025**, *9*, 528. [CrossRef]
34. Kara, C.; Iranmanesh, A. Protection Boundary Development in Historical–Cultural Built Environments Using Analytical Hierarchy Process (AHP) and Geographic Information System (GIS). *Urban Sci.* **2025**, *9*, 173. [CrossRef]
35. Chen, S.; Ji, Z.; Lu, L. A Method for Identifying Key Areas of Ecological Restoration, Zoning Ecological Conservation, and Restoration. *Land* **2025**, *14*, 1439. [CrossRef]
36. Marković Vukadin, I.; Zovko, M.; Mandić, A.; Zovko, D. Climate Change, Nature-Based Tourism, and Aging: Assessing Vulnerability and Resilience in Urban and Natural Protected Areas—Semi-Systematic Review. *Urban Sci.* **2025**, *9*, 543. [CrossRef]
37. Mohamad Selamat, I.A.; Maruthaveeran, S.; Mohd Yusof, M.J.; Shahidan, M.F. A GIS-Based Multi-Tier Framework for Assessing the Ecological Potential of Urban Vacant Land. *Urban Sci.* **2025**, *9*, 218. [CrossRef]
38. Lima, L.B.; Franca Rocha, W.J.S.; Souza, D.T.M.; Lobão, J.S.B.; de Santana, M.M.M.; Cambui, E.C.B.; Vasconcelos, R.N. Urban Quality: A Remote-Sensing-Perspective Review. *Urban Sci.* **2025**, *9*, 31. [CrossRef]
39. Vogt, M. Functional Biodiversity for Urban Planning: Access to Mitigative Effects and Therapeutic Benefits of UGS. *Urban Sci.* **2025**, *9*, 372. [CrossRef]

40. Bykowa, E.; Banikevich, T. Relationship Between the Integral Indicator of Soil Quality and the Cadastral Value of Agricultural Lands. *Land* **2025**, *14*, 941. [CrossRef]
41. Kovyazin, V.; Bogdanova, E. Current State of Specially Protected Natural Areas of the Arctic of the Russian Federation. *Ecol. Ind. Russ.* **2025**, *29*, 4. (In Russian) [CrossRef]

Disclaimer/Publisher's Note: The statements, opinions and data contained in all publications are solely those of the individual author(s) and contributor(s) and not of MDPI and/or the editor(s). MDPI and/or the editor(s) disclaim responsibility for any injury to people or property resulting from any ideas, methods, instructions or products referred to in the content.