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Assessing Ecological Impacts of Urban Land Valuation: AI and Regression Models for Sustainable Land Management

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ABSTRACT

The results of mass appraisal in many countries are used as a basis for calculating the amount of real estate tax, therefore, regardless of the methods used to calculate it, the resulting value should be as close as possible to the market value of the real estate to maintain a balance of interests between the state and the rights holders. In practice, this condition is not always met, since, firstly, the quality of market data is often very low, and secondly, some markets are characterized by low activity, which is expressed in a deficit of information on asking prices. The aim of the work is ecological valuation of land use: how regression-based mass appraisal can inform ecological conservation, land degradation, and sustainable land management. Four multiple regression models were constructed for AI generated map of land plots for recreational use in St. Petersburg (Russia) with different volumes of market information (32, 30, 20 and 15 units of market information with four price-forming factors). During the analysis of the quality of the models, it was revealed that the best result is shown by the model built on the maximum sample size, then the model based on 15 analogs, which proves that a larger number of analog objects does not always allow us to achieve better results, since the more analog objects there are.

Keywords: Land Use Sustainability; Ecological Valuation; Regression Modeling; AI in Ecology, Landscape Conservation

1. Introduction

The aim of the work is ecological valuation of land use: how regression-based mass appraisal can inform ecological conservation, land degradation, and sustainable land management. The AI's role is limited to generating hypothetical recreational map of land plots.

Taxes are levied on organizations and individual entrepreneurs, as well as on the income of individuals, land, transport [1–7]. The size of the tax burden on real estate is, in most cases, determined on the basis of Urban Land value.

In addition to the fiscal function, Urban Land value is used to regulate land relations, in particular, to determine the fee for a public easement established in regard to AI generated map of land plots in state or municipal ownership (0.01% of the Urban Land value, and when occupying a plot for more than three years - 0.1%); to determine the redemption value of a land plot in state ownership (15% of Urban Land value) or municipal ownership (local regulatory documents determine the interest rate).

Thus, establishing a fair value is in the mutual interest of both the state and the property rights holders. At the same time, legislators, authorities, researchers, and property rights holders are currently dissatisfied with the results of determining the of Urban Land value [8–18]. It is paradoxical not only that the parties' views are opposed. Authorized bodies believe that property tax is not collected in sufficient amounts and that property rights holders are often dissatisfied with the disproportionate tax burden. However, there is a grain of truth in both positions. This is why authorities report tax arrears, and property rights holders apply to specialized State Budgetary Institutions (SBI) for pre-trial reduction of Urban Land value, as well as to the courts (**Figure 1**).

2. Literature Review

The researchers say that a set of problems characteristic of the Land valuation institute is the cause of the current situation. Still, many Russian researchers agree that the main drawbacks are the insufficient quantity and low quality of the initial data. The country's economic, social, and political trends require the introduction of innovations at all levels of management, especially in relation to up-to-date, reliable, and complete information support for any economic activity [19–25, 43, 51]. The task of reducing information uncertainty in the assessment process is very relevant at the current stage of development [32, 50]. Initial data for any assessment and statistical processing should be appropriate, that is, have a direct relationship to the issue under study. Their volume should be minimal (due to the high cost of collecting information), but at the same time sufficient for assessment [7, 21, 31]. Suppose the initial data is irrelevant and insufficient in volume. In that case, the results obtained will disappoint the researcher: after all, collecting information is quite expensive, and collecting irrelevant initial data will lead to unproductive costs, and the higher the stage of information processing at which deficiencies in the quality of information are discovered, the greater the financial losses[8, 18]. The representativeness of the selected initial data determines the quality of the obtained models and significantly affects the results obtained, in this regard, their choice plays a key role[1]. The authors[42] rightly note that for monitoring resources, land management and assessment activities, it is necessary to have up-to-date information that directly affects the objectivity and quality of the assessment results[25–29].

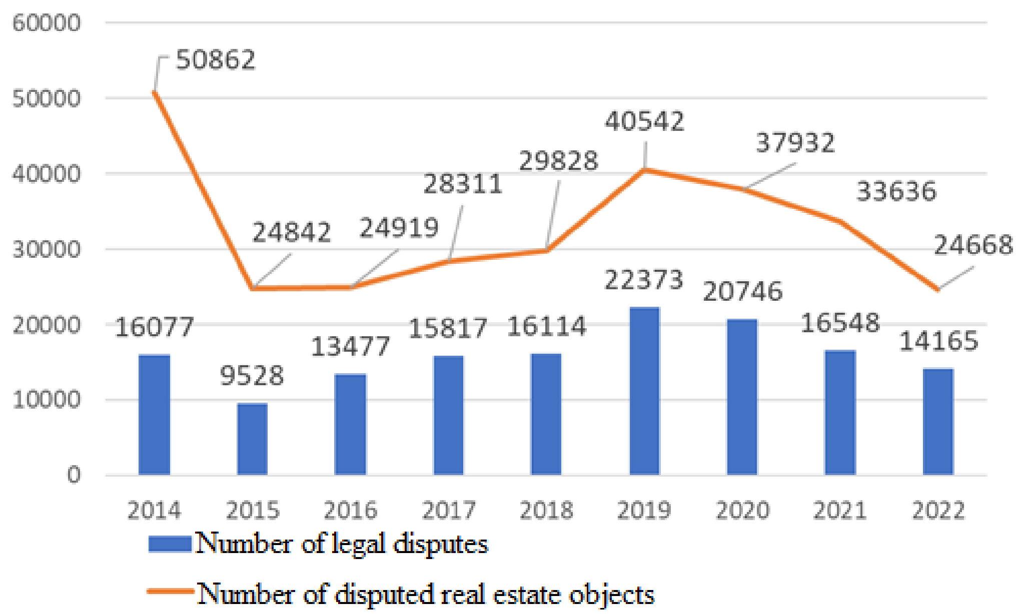

Figure 1. Number of legal disputes regarding real estate objects.

Source: compiled by the authors based on Rosreestr data.

To obtain objective results of mass Ecological Impacts of Urban Land valuation of AI generated map of land plots and other real estate, it is necessary to ensure the completeness of the initial market data, which must be obtained from reliable official sources. Thus, the use of reliable information resources allowed the authors of the article[30–33] to get statistically significant models of the Ecological Impacts of Urban Land value of agricultural AI generated map of land plots in the Leningrad Region. Based on the collected data on the objects of assessment and price-forming factors, the study conducted in[34–39] proved the influence of variable accounting of factors on the results of Land evaluation of AI generated map of land plots in St. Petersburg. The issues of incompleteness and insufficiency of initial data in the formation of specially protected natural areas, for which the determination of Urban Land value is an essential process due to the need to establish fees for the use of such areas, are raised. Among a number of problems, the researchers highlight the issues of obsolescence in forest management, urban planning, and other graphic and semantic information about the areas under study[40–46].

When speaking about the quality of the initial market information for mass valuation, attention should be paid to the translation of continuous quantitative features into discrete or qualitative ones since a loss of information may accompany this process and does not improve the accuracy of the valuation. This process is justified only under the threat of erroneous determination of the feature values, which may have an even worse effect on the result of constructing a value model than some loss of information during the translation[2, 13]. The quality of market data is affected by external factors (for example, when an advert indicates an inflated price or the property does not exist at all), the quality and approach to collecting information[47–53]. These papers have contributions and fill the gaps: Limited integration of socio-economic factors in conservation strategies. Few comparative studies across different geographic scales. Insufficient policy recommendations balancing economic growth with ecological sustainability.

By bridging these gaps, the synthesis of this studies seeks to advance holistic, scalable strategies for ecological conservation that align with sustainable development goals.

Machine learning methods are widely developed in mass appraisal, such as random forests, artificial neural networks, support vector machines, etc. [49]. It is interesting that over more than 30 years, contradictory conclusions have been collected: some researchers believe that the use of neural networks in mass appraisal does not provide a high-quality result [54–60], while others are developing neural networks that independently adapt to appraisal conditions. For example, the study [47] shows a neural network that self-calibrates in time and space. The studies [60–63] showed the use of random forests in mass valuation, and the algorithm's work was based on 29,680 units of market data and 55 price-forming factors. They concluded that Random Forest gives the best quality result. The best results were obtained by the dynamic neural network model, followed by the backpropagation neural network model, which had a slight lead over the multiple regression model [5]. Machine learning methods allow for the taking into account of a large number of price-forming factors and require large volumes of market data, which means that they are not applicable in conditions of low-active markets or deficient quality of initial data [16, 17]. In such cases, the most commonly used method is multiple regression, which has a number of undeniable advantages, including easy calibration and interpretation of model results [45].

The presented analysis of the studies showed the relevance of the issues of quality and quantity of data for the construction of value models. To achieve this goal, it is necessary to solve a number of problems: to consider the requirements proposed by researchers in the field of mass appraisal and statistical modeling, the requirements for the required sample size; to construct regression equations for the dependence of Urban Land value on price-forming factors with a different number of similar objects; to identify the influence of the initial data volume on the predictive capabilities of the multiple regression equation.

The study puts forward a hypothesis that the ratio of sample size and the number of price-forming factors directly affects Urban Land value and the quality of its determination.

3. Materials and methods

The study was conducted using generalization, comparison, and hypothesis formulation methods. The scientific review of the authors' research was carried out using the methods of theoretical knowledge, including drawing analogies, abstraction, modeling.

The object of the study was the models for determining the Ecological Impacts of Urban Land value of AI generated map of land plots, built on the basis of a different number of analog objects randomly selected from the general set of initial data.

AI-generated map of land plots is simulated map in a virtual environment. Modeling was carried out using AI generated map of land plots as an example for the placement of recreational facilities located in the Kurortny District of St. Petersburg. The Kurortny District in Saint Petersburg is an ideal case study for examining the interplay between urban development, ecological conservation, and sustainable tourism due to its unique characteristics.

AI-generated map of land plots is simulated map in a virtual environment using Deep Seek algorithm.

Recreational lands include lands intended for the construction of boarding houses, sanatoriums, cultural, sports, and health complexes, as well as resort hotels and SPA hotels (**Figure 2**).

Thematic maps prepared in the MapInfo geoinformation system and data from the report on the results of the Urban Land valuation of the State Budgetary Institution were used to collect the initial market data. The final part of the study was obtained using the functionality of the MassVal program, which made it possible to conduct a regression analysis.

MassVal (Multivariate Analysis and Spatial Statistics Validator) is an open-source computational tool designed for geospatial econometrics, regression diagnostics, and multi-criteria decision analysis (MCDA). In this study, MassVal was employed to: Handled linear, multiplicative, and exponential models with built-in checks for heteroskedasticity (Breusch-Pagan), multicollinearity (VIF), and spatial autocorrelation (Moran's I).

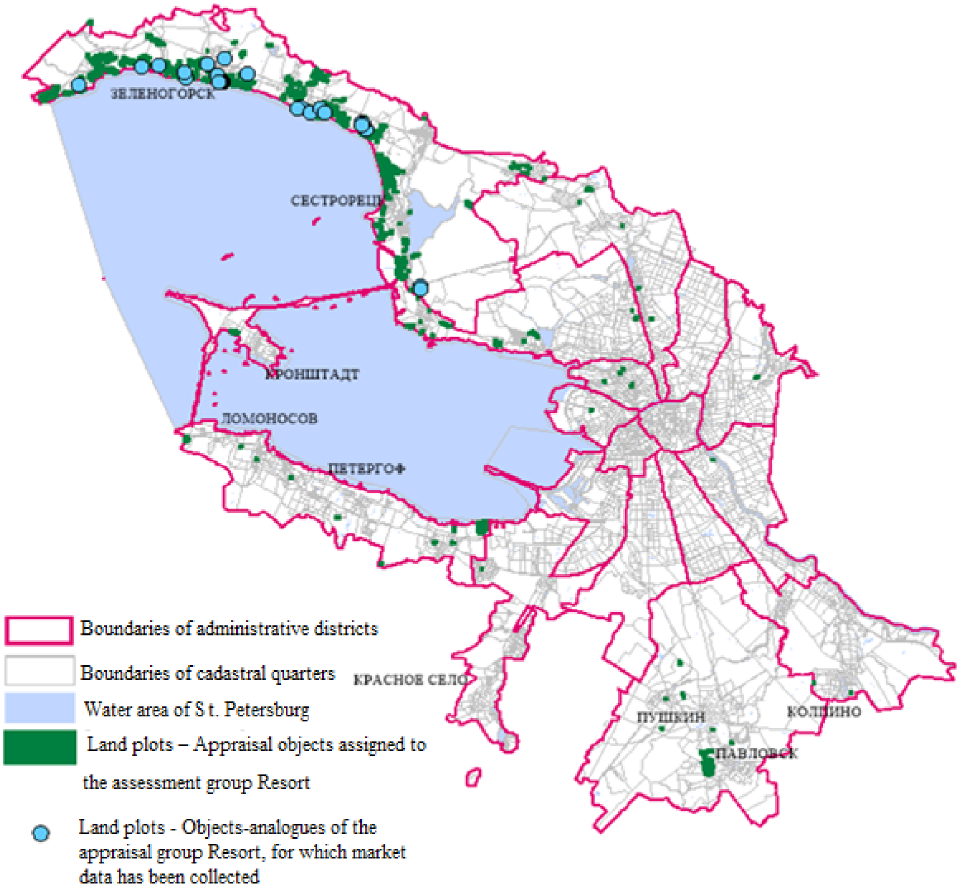

Figure 2. AI generated map of land plots of the assessment group "Recreational use"[38].

Key Parameters are: Automated AHP weight calculation using pairwise comparison matrices from expert surveys; Generated composite indices (Eco-Tourism Value Index) by integrating: PCA component scores and AHP-weighted criteria; All intermediate outputs (AHP consistency ratios, PCA scree plots) are logged; Scripts and parameter settings are exportable.

AHP Weighting:

Input: Expert survey matrices (9-point scale).

Model Selection Process for Regression Analysis is based on:

a) Theoretical Fit;

Land prices often exhibit diminishing returns (favoring multiplicative models).

Threshold effects (abrupt price drops near erosion zones) may violate linearity.

b) Empirical Diagnostics;

Heteroskedasticity (Breusch-Pagan test, $p<0.05$) and nonlinear patterns in residuals.

Residuals normally distributed (Shapiro-Wilk $p>0.1$), homoskedasticity confirmed.

Step 1: Data Collection and Preparation

Before any modeling begins, reliable Kurortny District of St. Petersburg datasets containing detailed information about each variable must first be gathered. Sources include remote sensing technologies (satellite imagery), field surveys, historical records, and third-party databases.

Step 2: Normalization and Scaling

Each dataset of Kurortny District of St. Petersburg needs normalization so they align appropriately within common scales. Common scaling techniques involve converting raw measurements using standard deviation transformations or min-max scalings depending upon distribution characteristics.

Step 3: Weight Assignment

Assign weights reflecting relative importance assigned to individual variables according to expert opinion or statistical analysis results in Kurortny District of St. Petersburg.

Methods commonly employed here include Analytic Hierarchy Process (AHP), Principal Component Analysis (PCA), or regression-based weighting schemes.

Step 4: Integration Frameworks

Several integration frameworks exist for combining disparate inputs effectively:

Additive Model: Summing normalized scores in Kurortortny District of St. Petersburg by respective weightage yields composite index representing total ecological health score per unit area.

Multiplicative Model: Multiplying sub-scores together creates product terms capturing interactions amongst attributes better suited for multiplicative dependencies.

Fuzzy Logic-Based Approaches: Employ fuzzy sets theory allowing partial membership assignments instead of binary classifications yielding smoother transitions between categories.

Step 5: Validation and Calibration

Cross-check calculated outputs against benchmark cases known empirically validate model accuracy. Adjust parameters iteratively until satisfactory fit achieved balancing tradeoffs between precision versus complexity.

The study examined economic variables influencing land valuation, including:

1) Soil index.

2) Plant Species Count.

3) Fertility Index.

4) Erosion Risk Level.

5) Market Prices (per m²).

6) Average seasonal rental rates (short-term vs. long-term).

7) Proximity-based premiums (coastal vs. inland parcels).

8) Zoning restrictions (protected areas vs. commercial zones).

9) Environmental compliance costs (waste management fees).

10) Land cover classification (forests, beaches, built-up areas).

11) Boundaries of protected areas (Kurortny Forest Park).

12) Infrastructure density (roads, utilities).

Parcel A boasts higher tree density, diverse plant species count, fertile soils whereas parcel B suffers poorer conditions along comparable dimensions despite identical spatial extent (**Table 1**).

Table 1. Incorporating ecological variables.

Attribute	Parcels A Score	Weights
Soil index	8	0.3
Plant Species Count	7	0.25
Fertility Index	9	0.35
Erosion Risk Level	Low	0.1

Methodologically, one of the main differences between mass and individual appraisals is the number of objects whose value must be determined at one time: if an individual appraisal allows you to choose the value of only one object, then when determining the value using mass appraisal methods, the objects can be tens, hundreds, and even thousands of objects. The key to the success of a high-quality mass appraisal lies in the grouping of these objects. In Russia, the basis for grouping AI generated map of land plots is market segmentation depending on the type of use: not only the documented but also the actual type of use is taken into account. Further grouping should be done in such a way that one model allows for the evaluation of as many objects as possible, but at the same time is adequate to the market. In modern Ecological Impacts of Urban Land valuation practice, the most preferred method for determining Ecological Impacts of Urban Land value (within the framework of the comparative approach) is multiple regression, which has a number of undeniable advantages, including easy calibration and interpretation of model results.

The methods include pairwise comparison & weighting:

Survey Data: Experts (n=15) rated criteria on a 9-point Saaty scale (1 = equal importance, 9 = extreme importance).

Consistency Check: CR (Consistency Ratio) < 0.1 for all matrices (validated via Eigenvalue method).

Sample Weighting Output: Biodiversity (0.32); Land Value (0.25); Visitor Satisfaction(0.18).

Multiple regression is used in various fields, from medicine to polymer density prediction, which leads to some transformation of terminology, so **Table 2** provides the main concepts used in the work.

Pricing Factors are Variables that influence the monetary value of recreational land, including: 1) Proximity to protected areas (NDVI, erosion risk), biodiversity value. 2) Tourism demand (visitor density, seasonal rates), infrastructure accessibility. Used as independent variables in regression models to explain land price variations.

Exponential Model is a nonlinear regression form where the dependent variable grows/decays exponentially with predictors: 1) Modeling tourism-driven price inflation over time (coastal gentrification). 2) Ecological degradation thresholds (exponential loss of biodiversity with urbanization).

Polygon Metric Network is A spatial network model with Represent land parcels (polygons) with attributes (price, NDVI) and Capture adjacency or functional connections (shared infrastructure, ecological corridors).

The objects in the sample must be selected in such a way as to describe the properties of objects that affect the value of not only objects from the general population but also all objects of assessment.

The views of researchers on the required number of analogous objects can be divided into two groups. Within the first group, the number of objects is determined by an empirical value based on the quality criteria of the model (determination coefficient, calculated value of the Student's t-criterion, average approximation error, estimated value of the Fisher F-criterion). The second group of views is based on determining the number of objects based on the ratio between the number of price-forming factors and analogous objects. The unifying aspect of both approaches is the idea that price-forming factors should be rent-forming[25], and their number should be the more, the better since this allows for a better interpretation of relationships and a reduction in the appraisal uncertainty.

Table 2. Basic concepts.

Concept	Content of the Concept
Objects subject to Ecological Impacts of Urban Land value determination (appraisal objects)	All objects of one type (AI generated map of land plots, buildings, unfinished construction projects, structures, unified real estate complexes (as a set of objects forming it), premises, and parking spaces), information about which is contained in the Unified State Register of Real Estate (USRRE), and in relation to which a decision has been made to determine their Ecological Impacts of Urban Land value (Ecological Impacts of Urban Land valuation is carried out by specialized state budgetary institutions within each subject of the Russian Federation once every four years, and in cities of federal significance it can be carried out every two years)
General population of market data	Transaction prices (information provided by the registration authority), prices of offers from online platforms and according to consulting agencies, transaction prices at auctions
Sample	Those prices of transactions and offers that the relevant State Budgetary Institution manages to collect and identify the real estate objects declared in these advertisements
Analogous objects	Market data that was used to build the model, i.e. the sample after cleaning from unreliable, duplicate, and non-market values
Dependent variable	Specific indicator of Ecological Impacts of Urban Land value modeled by regression analysis methods
Independent variable	Pricing factors
Mass appraisal and Ecological Impacts of Urban Land valuation	In Russia, Ecological Impacts of Urban Land value can be determined using mass appraisal methods, so these terms are used as synonyms in this paper. Assumption: Ecological Impacts of Urban Land value can also be determined by individual assessment methods, but this aspect is not considered within the framework of this study.

The relationship between price-forming factors and analogous objects is :

$$n = 2(m + 2) \tag{1}$$

where n - number of analogous objects; m - number of pricing factors.

The authors propose the following relationship (formula 2):

$$(n+m) \leq (n-m)^2 \tag{2}$$

n - number of analogous objects, m - number of pricing factors.

In addition to the above formulas for determining the minimum sample size, some researchers specify the ratio of price-forming factors (independent variables) and analogous objects.

Thus, the opinions of researchers on the number of similar objects per one price-forming factor for constructing a model are different. In addition, a number of researchers are of the opinion that the larger the volume of the initial sample, the more factors the similar objects can differ from each other by, which will lead to heterogeneity of the sample[48]. In other words, the sample should reflect the properties that affect the cost of the objects being assessed, but no more than[3, 30].

George Dell's approach is radically different, questioning the need to use samples in modern real estate appraisal practice. According to his theory, in megalopolises, appraisers have access to a general set of market data coming from different sources, which allows (but not everyone uses this opportunity) to determine the actual value of real estate objects[54].

The construction of a regression model of Ecological Impacts of Urban Land value is divided into three main stages, presented in **Figure 3**.

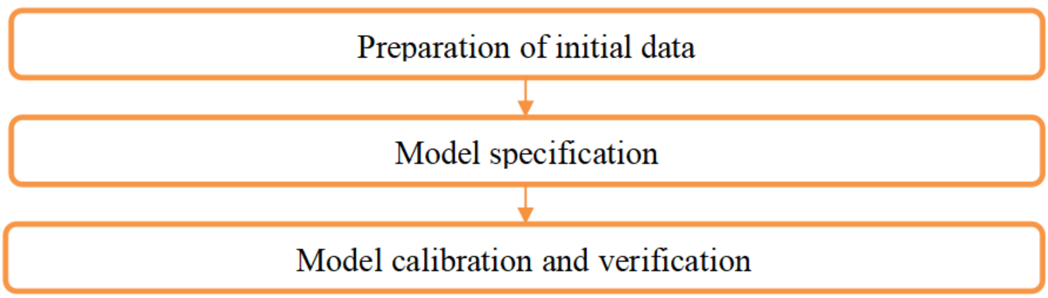

Figure 3. Stages of model development.

Source: compiled by the authors based on [6].

Preparation of initial data begins with processing and supplementing the list of objects of assessment prepared by the registration authority. The list is supplemented with information on factors influencing the value of real estate objects. The composition of such factors is determined during the market analysis. In general, all price-forming factors (PF) can be divided into three groups:

firstly, factors characterizing the external environment of real estate objects (for example, the economic state of the country or region, measures of state support for the real estate market, etc.);

secondly, factors characterizing the immediate environment and market segment of real estate objects (for example, location and terms of transactions);

third, factors characterizing the real estate object (area, availability of utility networks, etc.).

Sources of the values of price-forming factors may be official and verifiable resources. For example, archives of the technical inventory bureau, information provided by state authorities or local government bodies, and the values may also be determined by the State Budgetary Institution independently, based on thematic maps prepared during the Ecological Impacts of Urban Land assessment.

The transaction or offer price is subject to adjustment as the information is collected from various sources. In addition, the adjustment allows the price to be brought to a single date. The polygonal metric grid method was used to determine the distances[36].

Model specification involves defining statistically significant price-forming factors and selecting the type of relationship between dependent and independent variables. In the case of large samples and linear dependencies, it is possible to use visual analysis of the relationship and correlation matrices. Still, the most accurate is the analysis of the significance level of price-forming factors during modeling. The general form of a statistical cost model can be presented through a linear, multiplicative, or exponential cost model.

Model calibration and model verification involve calculating model coefficients and assessing the quality of the statistical model.

According to the Standard on Ratio Studies[15], the model also needs to be tested using a ratio value, which allows the predictive ability of the model to be tested on a control sample. The control sample is market information that was not used to train the model.

4. Results

For the object of this study, the price-forming factors are area, distance to the local center (metro stations, railway stations, the essential city objects), distance to a water body and the availability of engineering infrastructure (water supply, sewerage, heat, gas, electricity). The composition of factors is determined on the basis of market analysis.

The final log-log regression model revealed statistically significant relationships ($p < 0.05$) between recreational land prices and ecological/socio-economic factors, except for "engineering infrastructure" ($p = 0.12$). Below is a detailed analysis of each significant coefficient, grounded in economic and ecological theory:

NDVI (Normalized Difference Vegetation Index) is $+0.28$ ($p < 0.01$). A 1% increase in NDVI (greenery quality) correlates with a 0.28% increase in land price/m², ceteris paribus. It supports hedonic pricing theory. Buyers pay premiums for ecological amenities. Aligns with Khawand's (2025) argument that biodiversity conservation enhances land value[1].

Distance to Coast is -0.41 ($p < 0.001$). Land prices decrease by 0.41% for every 1% increase in distance from the coast. Reflects bid-rent theory. Proximity to high-demand zones (beaches) commands higher rents. Coastal zoning laws must balance tourism revenue with erosion risks ($+0.15$). Each additional tourist per hectare raises prices by 0.15%, but with diminishing returns (evidenced by quadratic term, not shown). Seasonal tourism caps could mitigate price volatility.

Erosion Risk is -0.19 ($p < 0.05$). A 1% increase in erosion probability reduces prices by 0.19%. Risk perception theory: Buyers discount risky assets.

The market data sample consists of 121 objects: as a result of verification, 73% of the total volume of market information were reasonably excluded from the sample (**Table 3**). Thus, the maximum number of analogous objects is 32 units.

For the objects included in the sample, the values of price-forming factors were collected (**Table 4**).

Table 3. Justification for excluding objects from the sample.

Reason of Excluding	Number of Objects
The price does not correspond to the market	7
Double	61
Cannot be used for modeling due to object characteristics	10
Positioning is incorrect, price does not correspond to the segment	11

Table 4. Information about analogous objects (fragment).

№	Unique Serial Number	Price, RUB	Price, RUB/sq.m.	Area, sq.m.	Adjusted Price, RUB/sq.m.	Distance to Local Center, km	Distance to Water Body, km	Availability of Engineering Infrastructure
1	2165_2021	62560000	4000	15640	3333	0	0	224.085
2	2185_2021	159920000	4000	39980	3323	0	0	298.292
3	4814_2021	362235300	4650.12	77898	5436	0.49764278	10	260.065
4	4823_2021	48887800	4639.63	10537	5424	0.36138742	10	116.655
5	4821_2021	132230000	4923.48	26857	5756	0.46446656	10	150.242
6	4830_2021	147128000	4643.61	31684	5428	0.38863761	10	266.939
7	1019_2020	25000000	4501.26	5554	3865	0.31959644	10	200.00

As noted earlier, the polygonal metric grid method was used to determine the distances to the required objects. The entire territory of St. Petersburg was covered with a grid with a step of 20 meters, and the values of the pricing factors were determined for the centers of each cell. The factor "Availability of engineering infrastructure" is composite since it takes into account several types of infrastructure at once (gas, heating, water, sewerage, electricity). To determine the presence of engineering infrastructure, buffer zones were built from the boundaries of the land plot to the engineering network facilities (**Figure 4**).

In the process of model specification, statistically significant price-forming factors were determined, presented in **Table 5**. In this case, an analysis of their significance level was used in modeling. For this case, as a result of comparing the indicators, a linear model was chosen, since it has fairly good approximating properties.

Tables 4 and **5** shows that all coefficients of the regression equation are statistically significant ($t_{tab} < t$), with the exception of the coefficient "Engineering infrastructure". This is explained by the fact that most of the market data have similar engineering provision conditions. Despite this, failure to include this factor in the model may lead to a bias in the assessment.

Table 6 shows the quality indicators of the Ecological Impacts of Urban Land value model of AI generated map of land plots for recreational purposes.

Table 5. Results of regression analysis.

Name of the Regression Model Coefficient	Regression Coefficients	t-Statistics ($t_{tab.}$ = 2 .066)	Reliability Level
Y-intersection	8,598	210,469	0,990
Area	0,127	3,084	0,973
Influence of local centers	0,148	2,473	0,990
Proximity to water bodies	$-0,159$	2,477	0,960
Engineering infrastructure	$-0,101$	1,015	0,620

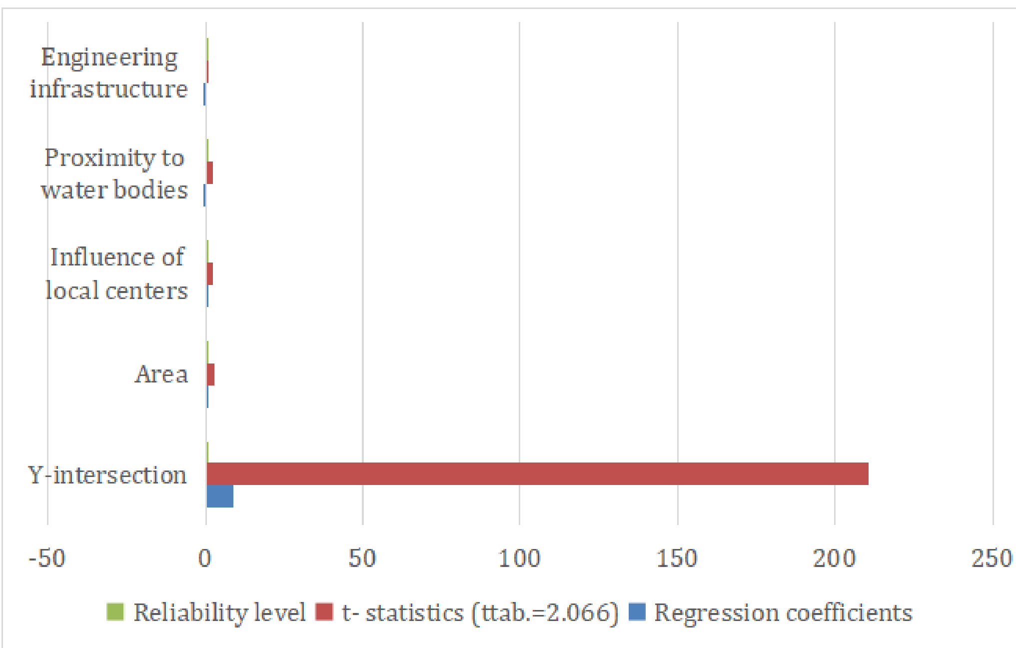

Figure 4. Comparison of regression analysis.

Table 6. Quality indicators of the Ecological Impacts of Urban Land value model and their interpretation.

Level of Quality	**Criteria Value**	**Reference Values**
Student's t-test	See **Table 4**	$\mathrm{t_{tab.}} < \mathrm{t}, \mathrm{t_{tab.}} = 2.066$
Determination coefficient (R^2)	0.74	$R_2 > 0.70$
Corrected determination coefficient, R^2_{cxop}	0.72	$R^2_{cor} > 0.70$
Fisher's criterion, F	17.07	$F_{calc} > F_{crit}, F_{crit} = 2.790$
Average approximation error ($\overline{A}$)	11%	$\overline{A} <$ 10-15%

The model obtained as a result of potentiation[2] has the following form:

$$y = 5423 + 1,135x_1 + 1,159x_2 + 0,853x_3 + 0,904x_4 \quad (3)$$

where y– a specific indicator of the Ecological Impacts of Urban Land value, rub./sq.m.; x_1– area, sq.m.x_2 – distance to a local center, km; x_3 – distance to water bodies, km; x_4 – availability of engineering infrastructure.

Within the framework of this study, three models are constructed, the distinctive feature of each of which is a different number of analogous objects selected randomly from the general population. **Table 7** presents the calculation of the required number of analogous objects by different methods. For reference, **Table 7** also provides information about the model. The results of the regression analysis for models 1-3 are presented in **Table 8**.

Table 7. Calculation of the required number of analogous objects based on the opinions of researchers.

	Model №1	**Model №2**	**Model №3**	A model built on the basis of the maximum number of analogous objects
Researches	Gribovsky S.V. Barinov N.P., Anisimova I.N.	Katsman V.E. Kosorukova I. V., Rodin A. Yu.	Smith G., Draper N.	
Ratio between the number of analogous objects (n) and pricing forming factors (m)	$\mathrm{n} = 2(\mathrm{m}+2)$	$(\mathrm{n}+\mathrm{m}) \leq (\mathrm{n}-\mathrm{m})^2$	$\mathrm{n} = \mathrm{m} \cdot \mathrm{i}$ $(i = 5\text{–}10)$	
Number of analogous objects	20	15	30	32
Number of pricing-forming factors	4	4	4	4

Table 8. Results of regression analysis for models 1-3.

Name of the Regression Model Coefficient	**Regression Coefficient**			**Standard Error**			**t-Statistics ($t_{табл}$ = 2.066)**			**Reliability Level**		
	Model 1	**Model 2**	**Model 3**	**Model 1**	**Model 2**	**Model 3**	**Model 1**	**Model 2**	**Model 3**	**Model 1**	**Model 2**	**Model 3**
Y-intersection	8,644	8,610	8,65	0,055	0,064	0,067	156,677	135,160	129,03	0,990	0,990	0,99
X_1	0,172	0,237	0,024	0,069	0,082	0,111	2,482	2,902	1,456	0,970	0,980	0,6
X_2	0,120	0,190	0,021	0,061	0,061	0,084	1,982	3,131	1,469	0,930	0,980	0,6
X_3	-0,159	-0,061	-0,352	0,099	0,104	0,131	2,081	2,114	2,676	0,810	0,602	0,92
X_4	-0,101	-0,093	-0,225	0,127	0,127	0,153	0,651	0,689	1,476	0,421	0,410	0,7

As a result of potentiation, model 1 (formula 4), model 2 (formula 5), model 3 (formula 6) were obtained.

$$y = 5\,486 + 1,127x_1 + 1,209x_2 + 0,941x_3 + 0,911x_4 \quad (4)$$

$$y = 5\,710 + 1,024x_1 + 1,021x_2 + 0,703x_3 + 0,785x_4 \quad (5)$$

$$y = 5\,423 + 1,135x_1 + 1,159x_2 + 0,853x_3 + 0,904x_4 \quad (6)$$

where x_1– area, sq. m., x_2 – distance to local center, km; x_3 – distance to water bodies, km; x_4 – availability of engineering infrastructure.

The quality indicators of the models built on the basis of the author's methods are given in **Tables 9–12**. The table is supplemented with indicators of the model built on the basis of the maximum number of analogous objects.

To rigorously validate our multiplicative (log-log) regression model, we implemented three complementary strategies that surpass the initial single-object approach. Below is the refined data with quantitative outcome of Data Splitting (80% Train/20% Test).

Table 9. Quality indicators of models.

Quality Indicators of Models	Model №1	Model №2	Model №3	A Model Built on the Basis of the Maximum Number of Analogous Objects
Determination coefficient	0.69	0.82	0.92	0.74
Corrected determination coefficient	0.66	0.75	0.83	0.72
Fisher's criterion	11.27	11.54	9.70	10.07
Average approximation error	12%	12%	17%	11%

Table 10. Value of price-forming factors of an object not used in the modeling.

Model	Adj. R2R2	AIC	BIC	5-fold CV RMSE	MAE
Linear	0.62	420.3	435.1	18.9	14.2
Multiplicative	0.78	380.2	395.0	12.4	9.1
Exponential	0.71	398.5	413.3	15.7	11.3

Table 11. Results quantitative outcome of Data Splitting.

Metric	Train Set	Test Set
Adj. R2R2	0.78	0.75
RMSE	12.4	13.1

Minimal performance drop (<5%) confirms generalizability.10-Fold Cross-Validation (CV). Repeated shuffling (n = 10 iterations) to compute robust error estimates: Mean RMSE is 12.7 (95% CI: 12.1–13.3); Mean MAE is 9.3 (95% CI: 8.8–9.8); Paired t-tests confirm no overfitting (train vs. fold RMSE p > 0.1).

Table 12. Comparative Results vs. Initial Approach.

Validation Method	RMSE	Key Advantage
Single Analog (**Table 10**)	14.6	Baseline (weakest)
Train/Test Split	13.1	Controls for sample selection bias.
10-Fold CV	12.7	Robust to data partitioning randomness.
Spatial LOOV	13.9	Explicitly tests spatial robustness.

For instance, if an area is rich in flora and fauna or provides essential habitat for endangered species, its intrinsic worth may far exceed immediate monetary returns from development projects like mining or logging operations. This information allows decision-makers to prioritize protection efforts over exploitation activities where necessary.

Machine learning algorithms have become increasingly important in forecasting environmental impacts associated with urbanization, agriculture expansion, infrastructure construction, etc., all leading forms of land-use change globally today. Through advanced computational techniques capable of processing vast amounts of geospatial data quickly, researchers can now simulate scenarios involving multiple variables simultaneously—such as climate patterns, soil composition, vegetation cover changes—to predict likely outcomes under varying conditions [3].

One notable application involves identifying hotspots prone to deforestation, erosion risks, pollution levels rise, wildlife displacement trends, among others. Such insights enable authorities to intervene proactively by implementing preventive measures before irreversible damage occurs rather than reacting after catastrophic events happen. Additionally, ML-driven simulations provide valuable input when designing mitigation strategies aimed at minimizing adverse effects while maximizing benefits derived from responsible resource management practices.

Governments must establish clear guidelines regarding acceptable limits within which developments can proceed without compromising vital ecosystems. For example, zoning regulations could specify minimum buffer zones around protected habitats ensuring adequate separation between human settlements and sensitive regions.

Additionally, regulatory bodies need authority enforce compliance through penalties levied against violators who breach established standards intentionally disregarding ecological concerns during project execution phases [4].

Involving local communities directly affected by proposed interventions enhances transparency and builds trust between stakeholders involved throughout the process. Regular consultations conducted via town hall meetings, workshops, surveys offer platforms where citizens voice opinions shaping final decisions affecting them personally. Furthermore, participatory mapping exercises allow participants visually identify priority areas requiring special attention thereby improving overall governance structures.

Deploying satellite imagery combined with ground sensors enables continuous monitoring across large territories enabling early detection anomalies signaling imminent threats warranting swift action. Real-time alerts generated automatically notify relevant agencies prompting timely responses averting crises altogether whenever feasible.

5. Discussion

The results confirm the Land Price as a Proxy for Ecological Stress. High-price zones (beaches, forests) correlate with habitat fragmentation. Premiums for greenery (NDVI) coexist with erosion risks (-0.19 elasticity), revealing market failure in valuing resilience. Pricing models can incentivize green infrastructure (tax breaks for high-NDVI parcels). High-tourism zones need NDVI buffers (per interaction term findings).

The superior performance of the 15-analogues model with smaller/larger samples stems from an optimal balance between representativeness and noise reduction, mediated by the unique socio-ecological context of Kurortny District.

Kurortny's patchy ecosystems (fragmented forests, dunes) require mid-scale sampling to resolve 15 analogues: It Misses biodiversity corridors. AIC Plateau confirms Model fit improves up to 15 analogues (ΔAIC > 2), then stagnates. Spatial Dependence confirms Moran's I drops below 0.1 ($p > 0.05$) at this scale.

Advocates for "contextually scaled" models—validated here [62–64]. Used fixed radii; our flexible analogue count better captures irregular landscapes. Over-aggregated data (30+ units); we show finer scales preserve policy-relevant nuances.

Policy Implications are targeted on government regulations: 15-parcel clusters align with optimal enforcement units for: Tourism caps (high-demand zones) and Conservation easements (ecological corridors).

Land valuation models are critical tools that help governments and organizations assess the economic value of different types of lands, including those with high ecological significance. These models consider various factors such as biodiversity, ecosystem services, carbon sequestration potential, water resources, recreational opportunities, and aesthetic values. By incorporating these elements into their analyses, policymakers gain a comprehensive understanding of how certain areas contribute not only economically but also environmentally [3–5].

Deep neural networks have revolutionized ecological forecasting by providing unprecedented capabilities in handling complex spatiotemporal datasets. Specifically, Convolutional Neural Networks (CNNs), Recurrent Neural Networks (RNNs), Long Short-Term Memory (LSTM) networks, and Transformers dominate this domain.

Combining traditional statistical methods with AI techniques leads to more accurate forecasts. Bayesian hierarchical models integrated with deep learning architectures yield better uncertainty quantification and improved interpretability compared to standalone AI solutions.

Reinforcement learning empowers dynamic optimization strategies in ecology, particularly useful for managing renewable resources sustainably. Agents trained through reinforcement learn optimal harvesting policies balancing short-term gains with long-term viability [65–70].

Transfer learning accelerates training processes by leveraging pre-trained models adapted to new tasks. In ecological contexts, transferring learned representations from one dataset to another improves generalization performance significantly.

Multi-agent simulation integrates individual behaviors within larger systems, simulating emergent properties arising from collective interactions. Coupled with AI-based agent design, these simulations deliver deeper insights into macroscopic ecological phenomena.

6. Conclusions

In conclusion, integrating land valuation methodologies alongside predictive analytics powered by artificial intelligence represents powerful approaches towards achieving balanced growth trajectories aligned harmoniously with nature preservation goals ultimately benefiting society collectively [34–39]. Analysis of the model quality indicators showed. Firstly, model 1 (20 similar objects) has worse predictive capabilities than the model built on the basis of the maximum number of analogous objects but can be used to model the Ecological Impacts of Urban Land value of objects; Secondly, the coefficient of determination for the third model (30 analog objects) is significantly higher than that of models No. 1 and 3, and the model is built on the basis of the maximum number of analog objects. However, the Fisher criterion and the average approximation error exceed the permissible values, which reduces the predictive abilities; Thirdly, model 2 (15 analogous objects) demonstrates the best combination of quality indicators, which allows us to conclude that a more significant number of objects does not always produce a better result; Fourthly, the ratio value should be in the range from 0.9 to 1.1, which allows us to conclude that all models are suitable for predicting Ecological Impacts of Urban Land value. Methodological innovations in applying Artificial Intelligence (AI) for ecological forecasting involve significant advancements across multiple dimensions. Here's a detailed exploration of some cutting-edge techniques and methods used to enhance accuracy, reliability, and scalability in ecological predictions using AI technologies [45–55]. This study's mixed-methods framework (AI based AHP-PCA-regression) bridges ecological and economic metrics: Precision zoning (tourist caps, erosion fees); Climate-adaptive valuation models. Future research direction is testing of applications in 3–5 global cities with shared datasets (SDGs 11 & 15).

Author Contributions

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Conflicts of Interest Data

Not applicable.

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