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MAPPING ENVIRONMENTAL AND SOCIO-ECONOMIC LANDSCAPE: A DISCRIMINANT ANALYSIS OF SUSTAINABLE REGIONAL DEVELOPMENT OF UKRAINE

Abstract. *This study investigates the regional disparities in environmental conditions and socio-economic development in Ukraine. Utilizing discriminant analysis, the research classifies Ukrainian regions according to a set of key ecological and economic variables: carbon dioxide emissions, nature reserves and national parks, gross regional product, return water discharges, waste generation, and environmental protection expenditures. The analysis identifies distinct regional groupings based on these indicators, revealing significant differences in environmental burden and economic output across the country. Furthermore, the study identifies the specific variables that most effectively discriminate between these regional groups, highlighting the factors driving environmental challenges in some areas and more sustainable patterns in others. The findings offer valuable insights for policymakers seeking to develop targeted environmental policies and promote sustainable development strategies that account for the diverse regional contexts within Ukraine.*

Keywords: *Time-series data, Discriminant analysis, Regional development, Economic policy, Region, Model, Multidimensional analysis, Ecology, Economy, Environmental Policy, Sustainable development.*

1. Introduction

In the current context of global climate change and increasing anthropogenic pressure on the environment, the issue of harmonizing economic development with environmental safety has become particularly urgent. Ukraine, as a country with substantial industrial potential, simultaneously faces serious environmental challenges, including excessive emissions of pollutants into the atmosphere, irrational use of natural resources, high volumes of waste generation, and pollution of water bodies. These issues highlight the need for an in-depth analysis of the spatial heterogeneity of the country's environmental situation and its relationship with the socio-economic development of the regions.

The uneven distribution of industrial capacity, population welfare, and environmental load across Ukraine's regions necessitates the application of quantitative analytical methods to identify key patterns and relationships in various sectors of the economy. This, in turn, demands priority attention in the formulation of state environmental policy. In this context, multivariate statistical methods — such as cluster analysis, discriminant analysis, correlation-regression analysis, and factor analysis — are of particular importance. These methods allow for the classification, grouping, and examination of relevant objects based on multiple variables, and help identify the most significant factors underlying regional differences.

In Ukraine, increasing environmental pressure has long been observed in specific regions, especially those with a strong industrial base such as Donetsk, Dnipropetrovsk, Zaporizhzhia, and Kharkiv. According to the State Statistics Service, these regions significantly exceed national averages in carbon dioxide emissions, waste generation, and return water discharges into surface water bodies. In contrast, the western and northern regions exhibit lower levels of environmental load, which points to substantial regional disparities in environmental management and policy implementation.

The relevance of this topic is also driven by the need to support sustainable territorial development, which integrates economic efficiency, social equity, and environmental sustainability. The use of discriminant analysis, among other analytical methods, enables the identification of commonalities and differences between regions based on environmental and economic indicators, and contributes to the formulation of scientifically grounded recommendations for improving regional environmental policy.

Several studies have explored the interplay between economic development and environmental sustainability. For instance, [1] analyzed regional economic development from a sustainability perspective using a hybridized algorithm, highlighting the importance of considering sustainability in regional economic assessments. [2] also assessed regional sustainable development through the integration of nonlinear principal component analysis and Gram Schmidt orthogonalization, offering a methodological approach that aligns with the quantitative focus of the present study.

Research has also focused on the factors influencing regional development. [3] examined regional development in Romania, providing empirical evidence on factors relevant to a prosperous and sustainable economy. [4] contributed to this area by analyzing the time-series factor decomposition of socio-economic impulses and urbanization trends in a European region, offering insights into the drivers of regional growth.

The spatial dimension of economic and environmental factors has been a key area of investigation. [5] conducted a spatiotemporal and multiscale analysis of the coupling coordination degree between economic development equality and eco-environmental quality in China, demonstrating the importance of spatial analysis in understanding regional dynamics. [6] also explored regional economic disparities in Europe using time-series clustering, further emphasizing the significance of spatial considerations. [7] assessed unbalanced development by jointly examining regional disparities in socio-economic and territorial variables in Italy. [8] contributed to this perspective by examining patterns of sustainability across Europe using a multivariate and spatial assessment.

The relationship between economic growth and environmental impact has been examined in several studies. [9] explored the impact of economic growth on the environment, providing an overview of trends and developments in this area. [10] focused on ecological sustainability in the Belt and Road region, evaluating and predicting ecological environment dynamics. [11] conducted a data-driven analysis of regional resources and environmental carrying capacity, offering a quantitative approach to assessing regional sustainability.

Specific studies have also addressed the situation in Ukraine and surrounding regions. [12] utilized a canonical discriminant model to assess environmental security threats. [13] examined the theoretical aspects of regional sustainable development in the EU and Ukraine. [14] discussed geopolitical realities and regional development perspectives in Ukraine. [15] analyzed the economic growth of Ukraine's regions in conditions of disproportional regional development. [16] proposed an intelligent environmental plan for sustainable regionalization policies in Ukraine. [17] explored disparities and resilience in Ukrainian regional labor markets. [18] focused on economic modeling of sustainable rural development under conditions of decentralization in Ukraine.

Additionally, researchers have employed various modeling techniques relevant to the analysis of regional data. [19] used a PCA–VAR model to study the interaction between society, economy, and the environment. [20, 21] have contributed to time-series forecasting, which can be relevant in the context of regional economic and environmental data analysis. [22] explore renewable energy and regional integration, [23] examine environment-society-economy relations, [24–25] discuss advanced computational methods, [26] analyze food security resilience, [27] export activities, [28] business innovations and [29] green taxation.

2. Materials and Methods

Discriminant analysis is one of the key methods in multivariate statistics, used for classifying objects by assigning them to predefined groups based on an optimal rule. A typical example is grouping enterprises into several homogeneous categories based on indicators of their production and economic performance.

A key feature of discriminant analysis is that the researcher knows in advance how many groups are to be formed and what characteristics these groups possess. It is also known that each object belongs to one of the defined groups, although the specific group for a given object is initially unknown.

Discriminant analysis enables researchers to:

Identify structural differences between groups of objects;

Determine the most informative variables that significantly influence group membership;

Construct discriminant functions to classify new objects based on established criteria;

Test hypotheses regarding differences in mean values across groups.

The standard procedure for conducting discriminant analysis includes the following stages:

Preliminary grouping of objects — For analysis to be conducted, each object must be assigned to a known group (e.g., "ecologically loaded regions," "moderately loaded," or "environmentally stable"). This grouping is often achieved through clustering methods, such as k-means clustering.

Calculation of discriminant functions — Based on input data, discriminant functions are constructed as linear combinations of indicators that best differentiate between the groups.

Evaluation of model quality — Model performance is assessed using Wilks' Lambda, coefficients of determination, and classification accuracy (including reclassification tests).

Interpretation of results — The coefficients of the discriminant functions and the significance of individual variables are analyzed to identify the key factors influencing regional differentiation.

To conduct the discriminant analysis of Ukraine's regions, official ecological and economic statistical data were used. The primary sources of information were the statistical publications "Environment of Ukraine — 2020" and "Gross Regional Product — 2020", issued by the State Statistics Service of Ukraine.

Within the framework of the study, six regional ecological and economic indicators were selected (Table 1). These indicators were chosen for their ability to most accurately reflect the relationship between economic activity and environmental conditions across different regions of the country. All selected variables are quantitative, fully meeting the requirements for discriminant analysis. Moreover, they hold practical significance for analyzing spatial disparities in regional development.

Together, these indicators provide a multi-faceted perspective on the ecological and economic interactions within Ukraine's regions. Their combination offers a solid foundation for discriminant analysis, aiming to identify groups of regions with similar characteristics and to develop recommendations for optimizing regional environmental and economic policy.

Data were collected and processed for 24 regions of Ukraine and the city of Kyiv for the year 2020. The data were compiled into a unified table, normalized, and prepared for further statistical analysis to ensure comparability.

After that, the data was normalized using the minimax method according to the formula:

$$X_{norm} = \frac{X - X_{\min}}{X_{\max} - X_{\min}}. \quad (1)$$

First, we applied the k -means cluster analysis method, and then we tried to perform the classification subjectively, dividing the regions of Ukraine into 3 conditional groups with the level of environmental pollution, such as "low", "medium ", "high".

After implementation received such results (Table 2)

To evaluate how effectively the selected factors in the model (number of reserves, GRP, surface water discharge, waste generation, and environmental protection expenditures) distinguish between the identified

Table 1

Input data of the model

Variable	Description
carbon dioxide emissions into the atmosphere from stationary sources of pollution	reflects the level of industrial activity, the energy intensity of the economy, and the overall environmental situation in a region
nature reserves and national parks	reflects the ecological orientation of regional policy and indicates the presence of protected natural areas
Gross Regional Product (GRP)	the primary measure of regional economic activity
volume of return water discharged into surface water bodies	reflects the level of pressure on water resources, the efficiency of wastewater treatment, and environmental risks related to water use within the regio
waste generation	highlights the overall resource intensity of economic activity and enables assessment of the efficiency of regional waste management systems
environmental protection expenditures	reflects the intensity and effectiveness of environmental policy in the region

Source: prepared by authors

Table 2

Clustering regions of Ukraine be ecological and economic development

Cluster	Regions	Characteristics
Cluster A	Vinnytsia, Zhytomyr, Kropyvnytskyi, Luhansk, Poltava, Khmelnytskyi	– CO_2 emissions: low level (1954.32, –55.2% from average) – Reserves: low level (1.50, –48.6% from average) – GRP: low level (105074.67, –37.8% from average) – Water discharge: very low level (48.00, –76.7% from average) – Formation waste: medium level (16877.63, –8.7% from average) – Security costs: low level (537.57, –67.5% from average)
Cluster B	Volyn, Transcarpathian, Ivano-Frankivsk, Kyiv, Lviv, Mykolaiv, Odessa, Rivne, Sumy, Ternopil, Kharkiv, Kherson, Cherkasy, Chernivtsi, Chernihiv	– CO_2 emissions: low level (2470.52, –43.4% from average) – Reserves: high level (3.80, 30.1% of average) – GRP: low level (120305.60, –28.8% from average) – Water discharge: low level (117.67, –43.0% from average) – Formation waste: very low level (1069.51, –94.2% from average) – Security costs: low level (675.00, –59.2% from average)
Cluster C	Dnipropetrovsk, Donetsk, Zaporizhia, Kyiv	– CO_2 emissions: very high level (15073.92, 245.5% of average) – Reserves: low level (1.75, –40.1% from average) – GRP: very high level (446748.50, 164.5% of average) – Water discharge: very high level (776.75, 276.3% of average) – Formation waste: very high level (86266.25, 366.4% of average) – Security costs: very high level (6995.45, 323.1% of average)

Source: prepared by authors

regional groups, we use Wilks' Lambda. This metric is automatically calculated using built-in formulas in the Statistica software. Wilks' Lambda ranges from 0 to 1, where a value of 0 indicates complete separation between groups, and a value of 1 suggests no distinction at all. In our case, Wilks' Lambda is 0.055, indicating that the selected factors discriminate well among the groups.

During discriminant analysis, an approximate value of Fisher's F-test is also calculated. Like Wilks' Lambda, this value is obtained using Statistica's built-in functions. The F-test helps determine whether the influence of the studied factors is statistically significant. It compares the differences between group means for each variable. The result is then compared with a critical value from statistical reference tables. In our study, the calculated F-value is 11.65, which exceeds the tabulated value, confirming the significance of the factors' impact.

The significance level, or p-value, reflects the reliability of the results. In our analysis, the p-value is close to 0, indicating an extremely low probability of error. Results are considered statistically reliable if the p-value is less than 0.05, meaning the chance of error does not exceed 5%.

Among the selected variables, the number of reserves and national parks, along with environmental protection expenditures, had the greatest impact on regional classification. The first variable shows a low Wilks' Lambda value (0.098549) and a high level of statistical significance ($p = 0.005906$), confirming its strong contribution to group differentiation. A similar result is observed for environmental protection expenditures, which also demonstrate statistical significance ($p = 0.022279$) and a moderately low Wilks' Lambda value (0.085032). These two indicators are therefore the most influential in distinguishing between regions.

In contrast, Gross Regional Product (GRP) was found to be statistically insignificant for distinguishing between groups. It has a very high p-value ($p = 0.895603$) and a Partial Lambda value close to 1 (0.987824), indicating minimal contribution to the discriminant model.

Indicators such as surface water discharge and waste generation had p-values close to 0.1. While their contribution is weaker than the two aforementioned indicators, they still demonstrate sufficient statistical significance to be included in the model.

Next, the Mahalanobis distances from each Ukrainian region to the centroids of the three identified groups are examined.

These groups are provisionally labeled A, B, and C, with approximate group sizes of $p = 0.24000$, $p = 0.60000$, and $p = 0.16000$, respectively. The Mahalanobis distance is measured in squared units and is used to classify each region — the smaller the distance to a group's centroid, the higher the likelihood that a region belongs to that group. For example, the Vinnytsia region, which belongs to Group A, is correctly classified by the model, as it has the smallest distance to that group. A similar case is observed with the Volyn region, which belongs to Group B and is also correctly classified.

An interesting case is the Luhansk region. Although it was originally assigned to Group A, the model classifies it as closer to Group B. This is supported by the relatively small distance to Group B's centroid (3.19450), although the distance to Group A's centroid is even smaller (1.77007). The misclassification, marked with an asterisk, may reflect mixed characteristics or suggest that the initial cluster assignment did not fully correspond with the underlying data structure. This means that, based on the selected environmental and economic indicators, the model perceives Luhansk region as more similar to Group B.

Table 3

Discriminant function coefficients

Variabla	A	B	C
nature reserves and national parks	7.89	20.28	16.36
Gross Regional Product (GRP)	4.55	4.66	10.24
volume of return water discharged into surface water bodies	2.32	1.47	30.46
waste generation	5.38	-16.69	-67.21
environmental protection expenditures	-3.63	28.79	126
constatnt	-2.53	-6.85	-38.34

Such classification discrepancies — especially in cases like Luhansk — may stem from the limitations of the initial clustering process. While clustering automatically assigned regions to groups (e.g., Group A), this does not guarantee a strong similarity among the group's members. Discriminant analysis reveals that, for the selected indicators, Luhansk exhibits greater alignment with Group B. Therefore, this inconsistency may point not only to a classification error but also to potential shortcomings in the earlier clustering stage.

Next, we construct a table of classification functions (Table 3), which is used to determine which of the three groups (A, B, or C) each observation (in this case, a region) belongs to, based on the values of the selected variables.

Each function — corresponding to groups A, B, and C — is a linear equation in which each variable is multiplied by a specific coefficient, and a constant is added to the sum. A region is assigned to the group for which the value of the classification function is the highest.

For example, the classification function for group A has the following form:

$$U = 7.89400 \times (\text{reserves and national parks}) + \\ + 4.55148 \times (\text{GRP}) + 2.32344 \times (\text{water discharge}) + \\ + 5.38244 \times (\text{waste generation}) — 3.63257 \times (\text{environmental protection expenditures}) — 2.52756$$

Similar equations are constructed for groups B and C, each with its own set of coefficients. For instance, the function for group C assigns significantly higher weights to environmental protection expenditures (126.0059) and return water discharge (30.4562), while the coefficients for waste generation and GRP are negative. This suggests that regions with high environmental protection spending and high volumes of return water are more likely to be classified into group C.

The variable 'reserves and national parks' shows the highest coefficient in the classification function for group B (20.2774), indicating that a larger share of protected areas strongly increases the probability of a region being classified into this group. This variable is also influential in group C (coefficient = 16.3637), though to a lesser extent, while in group A, the coefficient is much lower (7.8940), indicating a comparatively weaker influence.

The coefficients for the 'Gross Regional Product (GRP)' variable suggest that higher levels of economic activity increase the likelihood of a region being classified into group C (coefficient = 10.2381). In contrast, GRP has a more moderate and nearly equal influence in groups A and B (4.5515 and 4.6643, respectively). This implies that group C includes regions with the highest levels of economic development.

A particularly notable result is seen with the variable 'return water discharge to surface water bodies.' Its coefficient in the group C function (30.4562) is significantly higher than in groups A (2.3234) and B (1.4743). This suggests that high levels of polluted water discharge are a strong distinguishing feature of regions in group C and may indicate severe environmental challenges.

An even more distinct pattern is seen with the 'waste generation' variable. For group A, the coefficient is positive (5.3824), indicating that high levels of waste are associated with classification into this group. However, for groups B and C, the coefficients are negative (–16.6903 and –67.2139, respectively), meaning that an increase in waste generation decreases the likelihood of a region being classified into these groups — especially group C.

The variable 'environmental protection expenditures' also stands out. In the classification function for group C, it has an exceptionally high coefficient (126.0059), confirming its dominant influence. This

Table 4

Classification matrices

Group	Percent Correct	A P = 0.24	B P = 0.6	C P = 0.16
A	83.33	5	1	0
B	100	0	15	0
C	100	0	0	4
Total	96	5	16	4

means that regions with high environmental spending are most likely to belong to group C. Although this variable also has a positive influence in group B (28.7987), it is considerably less pronounced. Interestingly, the coefficient for group A is negative (–3.6326), which may indicate that environmental spending in these regions is relatively low or not a defining characteristic for classification into this group.

Overall, these classification functions form the foundation of a discriminant model that can be used to classify new observations. By plugging in the values of the selected variables, one calculates the values of all three functions, and the region is then assigned to the group with the highest score.

The classification matrix (Fig. 7) presents the results of the discriminant analysis for three groups: A, B, and C. The rows represent the actual (observed) classifications, while the columns show the predicted classifications.

In terms of classification accuracy, Group A achieved 83.3% accuracy (5 out of 6 observations correctly classified), while Groups B and C both showed perfect classification rates of 100% (all 15 and 4 observations, respectively, correctly classified). Overall, the model achieved a high accuracy rate of 96%, with 24 out of 25 regions correctly classified.

The a priori probability distribution for the groups is as follows: Group A — 0.24 (24%), Group B — 0.60 (60%), and Group C — 0.16 (16%).

Only one observation was misclassified: one region from Group A was incorrectly assigned to Group B. In general, the discriminant model demonstrates excellent performance, with perfect classification for Groups B and C and only one misclassification in Group A.

Group A primarily includes central Ukrainian agricultural regions, with high membership probabilities for Poltava (0.99), Kirovohrad (0.98), Vinnytsia (0.87), Zhytomyr (0.62), and Khmelnytskyi (0.53). These regions share similar socio-economic characteristics and economic structures.

Group B is the largest cluster, comprising 15 regions mainly located in western, northern, and parts of southern Ukraine. This group demonstrates strong internal homogeneity, with particularly high posterior probabilities observed for Kherson (0.99), Ivano-Frankivsk (0.999), Lviv (0.999), and Kharkiv (0.994).

Group C includes the most industrialized and urbanized regions (Dnipropetrovsk, Donetsk, Zaporizhia, and the city of Kyiv) all of which are classified with a maximum posterior probability of 1. This group is characterized by high urbanization levels and concentrated industrial activity.

As previously mentioned, the Luhansk region is the only case of misclassification. Although formally assigned to Group A, it shows a higher posterior probability for Group B (0.55 vs. 0.45), indicating its transitional position between these two clusters.

It is also worth noting the Khmelnytskyi region, where the posterior probabilities for Groups A and B are nearly equal (0.53 vs. 0.47). This suggests that Khmelnytskyi may occupy a borderline position between the two regional groupings.

4. Conclusions

The conducted research enables the evaluation of the spatial heterogeneity of ecological and economic development across the regions of Ukraine using cluster and discriminant analysis methods. The results confirm the presence of significant differences between regions in terms of technogenic load, environmental costs, and environmental protection activities. The model demonstrated high classification accuracy (96%) and a significantly lower Wilks' Lambda value (0.055), indicating its high discriminatory power.

Key variables distinguishing the clusters include environmental protection costs and the quantity of reserves and national parks. Their significance underscores the importance of a comprehensive ecological policy and financial support for environmental protection activities as determining factors of a region's ecological and economic profile.

The normalization of variables using the minimax method complicates the direct numerical interpretation of the coefficients in the discriminant functions. However, it allows for an assessment of their influence based on the sign: a positive value indicates an increased probability of assigning a region to a specific cluster as the relevant indicator grows, while a negative value indicates a decrease in such probability. This interpretation enabled the identification of characteristic traits for each group of regions. For instance, regions with high environmental protection costs and significant water discharge were classified as clusters with increased technogenic load, while waste generation had a lesser impact.

The application of discriminant analysis in this study identified distinct regional patterns in Ukraine, characterized by significant differences in environmental conditions and socio-economic development. By classifying regions based on key indicators, the research demonstrates the spatial heterogeneity of Ukraine's environmental challenges, including disparities in air and water pollution, waste management, and the distribution of protected areas, as well as the uneven distribution of economic development as reflected in gross regional product. These results emphasize that addressing these regional disparities is crucial for the effective formulation and implementation of environmental policies. A one-size-fits-all approach will be insufficient; instead, policies must be tailored to the specific circumstances of each region. This will involve not only mitigating environmental damage in heavily impacted areas but also promoting sustainable practices and resource management in regions with lower levels of environmental stress. Such a nuanced approach is essential for guiding Ukraine towards a more equitable and ecologically responsible path for its future development.

In conclusion, the analysis results confirm the rationale for applying multidimensional methods to study the spatial structures of ecological and socio-economic development. This creates a foundation for scientifically grounded improvements in regional ecological policies. The focus should shift from abstract economic growth to more efficient management of natural resources, the development of environmental protection infrastructure, and pollution control strategies.

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КАРТУВАННЯ ЕКОЛОГІЧНОГО ТА СОЦІАЛЬНО-ЕКОНОМІЧНОГО ЛАНДШАФТУ: ДИСКРИМІНАНТНИЙ АНАЛІЗ СТАЛОГО РЕГІОНАЛЬНОГО РОЗВИТКУ УКРАЇНИ

Анотація. *Це дослідження вивчає регіональні диспропорції в екологічних умовах та соціально-економічному розвитку України. Використовуючи дискримінантний аналіз, дослідження класифікує українські регіони відповідно до набору ключових екологічних та економічних змінних: викиди діоксиду вуглецю, природні заповідники та національні парки, валовий регіональний продукт, скиди зворотних вод, утворення відходів та витрати на охорону навколишнього середовища. Аналіз виявляє чіткі регіональні угруповання на основі цих індикаторів, демонструючи значні відмінності в екологічному навантаженні та економічному виробництві по всій країні. Крім того, дослідження ідентифікує конкретні змінні, які найбільш ефективно дискримінують між цими регіональними групами, висвітлюючи чинники, що спричиняють екологічні проблеми в одних областях та більш стійкі моделі в інших. Отримані результати пропонують цінні відомості для політиків, які прагнуть розробити цільову екологічну політику та сприяти впровадженню стратегій сталого розвитку, що враховують різноманітні регіональні контексти в Україні.*

Ключові слова: *часові ряди, дискримінантний аналіз, регіональний розвиток, економічна політика, регіон, модель, багатовимірний аналіз, екологія, економіка, екологічна політика, сталий розвиток, еколого-економічний.*