This study investigates the process of building a stable methodological basis for assessing environmental risks in regions. The possibilities of using integrated indicators of environmental risks have been considered, which are a useful tool for summarizing complex information. However, their interpretation should be especially cautious during periods of social upheaval. The combination of a quantitative index with a qualitative analysis is necessary for a complete and adequate assessment of environmental safety for such periods.

This work analyzes the methodological robustness of composite indices of environmental safety of regions under war-time conditions using Ukraine as an example. The influence of the choice of normalization methods, weighting schemes, and processing of missing data on the results of integrated ranking was studied. It is shown that under crisis conditions the semantics of key social-ecological indicators undergoes qualitative changes, as a result of which conventional interpretations of their dynamics become incorrect.

A comparative analysis of combinations of normalization and weighting of indicators for calculating the integrated index of environmental safety of regions in Ukraine over 2021–2022 was conducted. It was found that the rank approach in combination with equilibrium weighting is methodologically unstable under crisis conditions and leads to inversions in regional ranking. An algorithm for calculating the index has been proposed, which involves checking the stability of regional indicators for the completeness and reliability of statistical data, which increases the adequacy of environmental risk assessment during the conflict period. This is particularly important for Ukraine but is also relevant for other countries experiencing or recovering from conflict.

The findings make it possible to increase the readiness of an environmental monitoring system for emergencies, as well as contribute to the construction of a robust methodological base for assessing environmental risks

Keywords: environmental safety, environmental risk indices, environmental indicators, military conflict zones

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RESILIENCE OF COMPOSITE ENVIRONMENTAL SAFETY INDICES UNDER WARTIME CONDITIONS: SENSITIVITY TO METHODOLOGY AND THE IMPACT OF STATISTICAL DISTORTIONS

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1. Introduction

Composite indices (CIs) are important levers in the field of sustainable development, environmental management, risk assessment and forecasting, policy development, implementation, and evaluation. The purpose of composite indices is to collect diverse indicators, analyze them in one selected plane, and then compare the results on interregional, interstate, or time scales [1–3]. Examples of composite indices on a global scale are Environmental Performance Index (EPI), Human Development Index (HDI), Global Innovation Index (GII). The Environmental Safety Index is another example of CI on an interregional (national) scale.

The advantages of composite indices include the following:

– combination and interpretation of diverse information, which makes it possible to take into account various factors, in particular demographic, technogenic, natural [1, 4];

– ranking according to certain criteria, which focuses on the critical states of objects, territories, etc. [5, 6];

– providing justifications for devising effective strategies and making decisions [2, 7].

Due to the listed advantages, composite indices are standard practice in environmental management. In particular, more than 400 integrated indices are used in the world in the field of environmental management [4].

Despite their global recognition, composite indices have certain limitations, in particular:

– vulnerability to weighting factors: even minor fluctuations in weighting coefficients significantly change the results of the composite index; often the values of weighting coefficients do not fully assess the real impact on the risk or state of the environment [5];

– normalization and scaling: the choice of method (for example: ranking, minimum-maximum, Z-score) affects sensitivity; interregional differences also introduce their own specificity [1, 8, 9];

– loss of semantic depth (meaningfulness): when combining diverse information as a result of the analysis, there is a risk of losing key deviations in specific components [2, 10];

– insensitivity to missing or fabricated data: the proposed approaches to processing missing or falsified data may increase the index of territories with missing statistics [10, 11].

The existence of a number of systemic limitations in generally accepted methodologies for assessing integrated indicators necessitates devising new approaches to analysis, interpretation, and integration of data. Therefore, research into designing composite indices and their adaptation under conditions of military conflicts is relevant and of great importance for assessing and forecasting risks at the regional, national, and international levels.

2. Literature review and problem statement

Integrated indicators of environmental safety are important tools for assessing regional and national environmental threats. They are able to accumulate and process diverse indicators into a generalized assessment or rating/rank, which further contributes to the adoption of management environmental decisions. However, methodological criticism of integrated indices of environmental safety remains relevant even in peacetime. Studies [6, 9] prove that changing the method of normalization, weighting or aggregation significantly affects the value of the index. In peacetime, these changes fluctuate within the limits of permissible error. However, during wartime, when data are partially or completely absent or radically changed, fluctuations can go beyond the limits of permissible errors. And this completely changes the analytical picture. In particular, studies indicate a high sensitivity to the choice of normalization, weights, and aggregation scheme [4], low transparency in reflecting the importance of individual indicators, even if formally given equal weights [5], vulnerability to distortion due to missing or questionable data [11].

Under normal circumstances, these features of the methodology can reduce the analytical accuracy of the calculated index but in war conditions they become critical. The full-scale war in Ukraine led to significant disruptions in the statistical system, demographic and environmental changes. All these changes are reflected in the correctness of the final values of the indices. Among the main violations that affect the index assessment, the following are distinguished:

– loss or falsification of statistical data in combat zones;

– change in the value of indicators (for example, a decrease in emissions does not indicate an improvement in the environmental situation, but rather confirms the destruction of industrial facilities [12];

– a significant increase in mortality, which reflects the direct consequences of military operations, and not background chronic risks [13];

– absolute or partial absence or unreliability of statistical data in regions that are under occupation or have suffered major destruction. These “gaps” concern both environmental (emissions, waste, emergencies) and demographic indicators (mortality, population). Artificially filling such “gaps” (for example, introducing average values or conditional minimums-maximums) can radically change the ranking of regions [10].

The above main violations raise doubts about the ability of standard composite indices to correctly assess the state of environmental security under non-standard, extreme conditions. In this regard, new approaches are needed that would be able to take into account structural uncertainty and loss of source data. An important aspect of the adapted methodology should be the ability to perform sensitivity analysis to changes in weights, normalization, and the structure of indicators under conflict conditions, institutional degradation, or catastrophic events.

In Ukraine, one of the most common models for a comprehensive assessment of the environmental safety of regions is the environmental safety index [14]. This methodology has been used for decades to compile reports of state administration bodies and analytical reviews. The main advantage of this methodology is its simplicity and formality in the presence of available source data. However, this methodological approach has certain critical limitations in the absence, instability, and violation of source data. It was the limited application of this methodology under conflict conditions or catastrophic events that motivated our study.

The authentic methodology involves selecting several main indicators that characterize the environmental situation in the regions, such as:

– mortality rate of the population (per 100 thousand people);

– number of emergencies (Es) of technogenic and natural nature;

– atmospheric pollution index (API);

– volume of waste generation of hazard classes I–IV (t);

– share of forest cover of the region (%).

The algorithm for determining the values of the Environmental Safety Index includes:

– collection of official regional statistics;

– normalization of each indicator by ranking, as a result of which each region is given a place from 1 (worst indicator) to 24 (best);

– calculation of the total rank score by calculating the values of all five components for each region;

– compilation of the overall regional rating by increasing the total score.

When calculating the total ranking score for each component, its weight coefficient is taken into account, usually established by an expert. The weight coefficient characterizes the contribution of each component to the overall picture of the region. However, a balance between all five components is often assumed.

The calculation of the environmental safety index [14] is based on a number of assumptions, including the following:

– linearity of scaling: all indicators are comparable on the rank scale, regardless of their physical nature or units of measurement;

– equal importance of all components, regardless of the specificity of the region;

– availability and reliability of statistical data, absence of “gaps” in reporting.

In peacetime, these assumptions are absolutely normal simplifications. In wartime, they are critical, leading to serious distortions, in particular:

– regions from which statistical data do not come can receive artificially high ranks;

– a decrease in emissions/waste or a decrease in mortality may not indicate improvement, but a lack of reporting;

– the aggregate rank is insensitive to sharp shifts in key variables due to the lack of weighting or normalization by distribution [7, 15].

Thus, under the conditions of war in Ukraine, environmental safety indices were trapped in a critical methodological situation. This methodology was devised for conditions of relative stability of the data collection system, predictability of demographic changes and inertia of environmental trends. However, the war caused:

– a sharp increase in mortality because of hostilities;

– mass migration of the population, which significantly changed the demographic situation of almost all regions;

– destruction of civilian infrastructure;

– destruction of industrial facilities and, as a result, a decrease in emissions in zones of occupation and active hostilities;

– lack of regional statistical data.

The issue of the impact of wars and armed conflicts on the environment is widely considered in international publications. However, discussion of the issue related to interpreting environmental and demographic statistics in conflict zones is much less common in the literature. Most publications focus on two interrelated aspects: the long-term environmental consequences of war and the complexity of their adequate statistical measurement.

In particular, in work [16] it is shown that the consequences of armed conflicts are the degradation of ecosystems, which persist for years even after the end of active hostilities. The authors emphasize that a significant part of these negative consequences, unfortunately, remains underreported or partially reflected in statistical reports due to the lack of resources for systematic measurements. This paper emphasizes that under war-time conditions, official statistical data, in particular the ecological component, cannot be interpreted in the same way as in periods of stability.

The studies reported in [13] once again demonstrate the long-term consequences of civil wars for the health of people after the end of hostilities. It is shown that conflicts lead to a significant increase in mortality and disability rates, which are not limited to the period of active hostilities. The mortality rate of the population in countries that have experienced war characterizes both long-term socio-economic and environmental factors and direct military consequences. And this complicates the use of this indicator as a stable indicator of environmental risk.

Works on social vulnerability to natural and man-made threats, for example [17], emphasize that the quality and completeness of statistical data significantly deteriorate precisely where the risks are highest. The paper discusses the problem of vulnerability of a community that is in a state of "double burden": on the one hand, the population suffers from dangerous events, on the other hand, the population of the region has a worse monitoring and accounting infrastructure. This provision is important for assessing the state of Ukrainian regions, in which frontline and occupied territories are characterized by a high level of risk with virtually no statistical infrastructure.

Review publications on composite indices and their stability [11, 12] emphasize that any crises and conflicts in countries can radically change both the values of indicators and their interpretation. Work [12] on the lack of formation of rating systems of composite environmental indices shows that even in peacetime, minor methodological changes can significantly change the ranks of countries or regions. Paper [11] states that the processing of statistical information with some missing data and the choice of an aggregation scheme could lead to compiling unreliable ratings sensitive to minor changes in input information.

Thus, our review of the literature demonstrates that armed conflicts:

– worsen the state of the environment and health of the population for a long time [13, 16];

– destroy or weaken monitoring systems, which leads to incomplete, contradictory statistical data or their absence [17];

– make standard composite indices particularly vulnerable to semantic shifts, missing data, and methodological adjustments [6, 10–12].

These findings provide a scientific basis for research focusing on the robustness of the integrated index of environmental safety in the face of incomplete, distorted, and content-altered statistics.

3. The aim and objectives of the study

The purpose of our work is to assess the resilience of the environmental safety index to structural disruptions caused by the war and to formulate approaches to its adaptation under conditions of high uncertainty. This will make it possible to increase the readiness of the environmental monitoring system for emergencies and contribute to the formation of a more stable methodological basis for assessing environmental risks.

To achieve the goal, the following tasks were set:

– to recreate the environmental safety index using the example of 24 regions of Ukraine for 2021 and 2022 based on available open data;

– to check the sensitivity of regional ranking to the choice of normalization method, weighting scheme, and scenarios for filling in missing data.

4. Materials and methods

4. 1. The object and hypothesis of the study

The object of our study is the process of forming a more stable methodological basis for assessing the environmental risks of regions.

The principal hypothesis assumes that the selection of normalization and weighting systems for assessing the environmental safety index could make it possible to level the vulnerability of integrated indicators and ensure high sensitivity of the system to deviations and increase the accuracy of predicting environmental risks.

Assumptions adopted: the selected number of indicators is representative, and their values are reliable; however, changing the normalization methods or weighting coefficients can significantly change the values of the environmental safety indices.

Simplifications accepted: the list of indicative indicators is deliberately limited; the emphasis was on determining the nature of change in the index under conditions of variability of the methodology, and not on establishing the absolute value of environmental damage.

4. 2. Description of the source data: regional indicators of Ukraine for 2021–2022

The empirical basis of our study was statistical data on the regions of Ukraine for 2021 and 2022. The statistical data were grouped in a format compatible with the methodology for calculating the environmental safety index [14]. The list of indicators was selected in such a way as to ensure comparability with the established Ukrainian practice of integrated assessment of environmental safety and at the same time allow the application of modern approaches to the analysis of composite indices [1, 4, 18].

The study used statistical data on the administrative regions of Ukraine for which official statistics are available for all (or most) of the selected indicators over 2021–2022. The analysis of statistical data was carried out both for regions that were not subjected to ground occupation, and for frontline and partially occupied regions. The basic indicators that were taken into account to determine the index of environmental safety of regions included mortality rate, number of emergencies, air pollution index, volume of hazardous waste generation, share of forest cover.

For clarity, the resulting classification of regions by level of completeness and reliability of data is displayed on a map in Fig. 1.

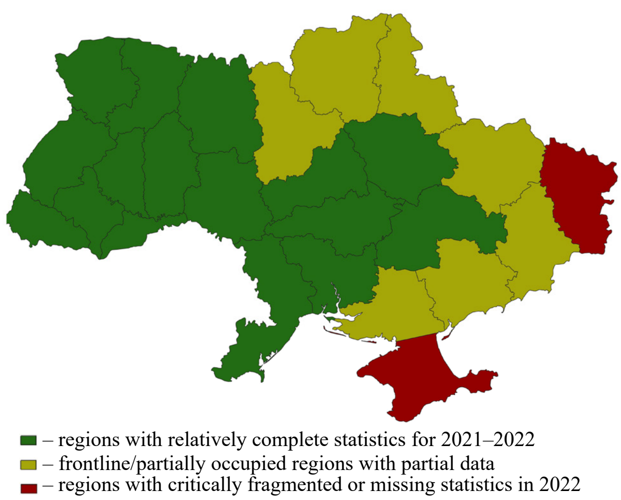

Fig. 1. Classification of regions in Ukraine by completeness and reliability of statistical data for 2021—2022

The first group of regions covers administrative territories for which relatively complete and consistent statistical information is available for 2021–2022. The second group includes frontline and partially occupied regions where "gaps" or anomalous values of individual indicators for 2022 are observed but general statistical data are preserved. The third group includes regions with partial or practically absent statistics for 2022. It is the situation with the third group of regions that necessitates the development of special imputation scenarios and a separate sensitivity analysis. The concept of "imputation" is understood as a technological operation implying determining and entering values for specific data elements for which answers are missing or cannot be used [19].

To fulfill the tasks set in our work, it was this three-level classification that was used to devise alternative scenarios for processing statistical data and interpreting the stability of the composite index.

In the study, the research was carried out on the basis of statistical data for two consecutive characteristic years:

– 2021 is a conditionally "pre-war" base period with more stable statistical characteristics;

– 2022 is the first year of a full-scale war, which was accompanied by significant changes in demographic, environmental, and institutional indicators.

The studied period allows us to take 2021 as a reference year for assessing the standard functioning of the composite index, and 2022 is considered as a test of its resistance to extreme disturbances.

The list of indicators was compiled in accordance with the logic of calculating the environmental safety index. The set of indicators was focused on five key components:

– population mortality – an integrated demographic indicator that indirectly reflects the socio-economic and ecological environment, and in wartime is particularly sensitive to military losses and errors in registering mortality);

– the number of emergencies, which reflects officially recorded cases of extreme risk, however, in wartime this value depends not only on the frequency of events but also on the ability to classify and register them;

– the atmospheric pollution index, which in peacetime characterizes the total load on atmospheric air from stationary and mobile sources. During armed conflicts, a decrease in the value of this indicator can be due to both a decrease in the industrial capacity of enterprises and the total destruction of industrial facilities (which has a fundamentally different interpretation);

– the volume of hazardous waste generation (classes I–IV), which indirectly reflects the anthropogenic load on the environment. In wartime, due to insufficient or lack of systematic accounting, official figures may be underestimated, while the actual generation (in particular, construction, military, and technogenic waste) increases;

– the share of forest cover in the region is a relatively static indicator that changes little in the short term, used as a "buffer" or protective factor in the environmental safety index.

In our work, all the listed indicators were aggregated as annual values by region, and then converted into dimensionless values (ranks, risks of the corresponding categories), according to the methodology from [14]. Based on the results, the values of the composite index were determined in accordance with the general approaches to building composite indicators described in international recommendations [1, 3, 4, 18].

4. 3. Initial indicators and their direction of influence

In the study, five statistical indicators were used for each region of Ukraine r and year $t \in \{2021, 2022\}$:

– mortality rate, people per 100 thousand ($M_{r,t}$);

– number of emergencies ($E_{r,t}$);

– air pollution index ($A_{r,t}$);

– volumes of hazardous waste generation of classes I–IV ($W_{r,t}$):

– share of forest cover in the region, % ($F_{r,t}$).

The indicators M, E, A, W are interpreted as "negative" (i.e., their increase means higher risk), while the indicator F is "positive" (i.e., its increase means lower risk). This approach corresponds to the initial logic of the method and established practices in the field of composite indices [1, 3].

In order to unify the scale of influence of each indicator, rank normalization was applied, which is typically used in the methodology for calculating the environmental safety index. For each indicator $j \in \{M, E, A, W, F\}$, the regions were ordered by increasing risk: for indicators *M*, *E*, *A*, *W*, the worst value received rank 1, the best – 24.

In the baseline scenario, all five indicators are assumed to be equivalent

$$w_M = w_E = w_A = w_W = w_F = \frac{1}{5}, \quad (1)$$

where *w* is the weighting coefficient of a separate indicator.

The equilibrium weighting option reflects standard Ukrainian practice and corresponds to the generally accepted equilibrium scheme in international integrated indices [7, 15]. At the same time, such a model could increase the sensitivity of the index to unstable indicators [4, 12]. This is the issue that our work deals with.

The composite index of environmental safety for region *r* in year *t* was determined as

$$K(r,t) = \sum_{j \in \{M,E,A,W,F\}} w_j R_j(r,t), \quad (2)$$

where *w* is the weighting factor;

R is the risk of the corresponding category.

The calculated value $K(r, t)$ is an averaged rank indicator. According to the logic of the basic methodology: the higher the value of the composite index of environmental safety, the "safer" the region is.

Based on the obtained values of the $K(r, t)$ indices, a ranking of regions was formed for each year. Further analysis of the obtained results focused not so much on absolute values but on the spatial distribution of the index and changes in the positions of regions over the years.

For visual interpretation of the analysis results, the $K(r, t)$ indices were represented in the form of map diagrams.

4. 4. Alternative normalization techniques and weighting procedures

The professional literature [1, 4, 7, 8, 12, 15, 18] emphasizes that the choice of the normalization technique and weighting procedure is one of the main sources of uncertainty and potential distortions when determining composite indices. To assess the dependence of results from calculating the environmental safety index on the adopted calculation techniques, we built a matrix of three normalization methods (*N*1, *N*2, *N*3) and three weighting procedures (*W*1, *W*2, *W*3). That is, a total of nine options for each year (2021, 2022).

The results for all regions of Ukraine by year were represented in the form of two summary tables, in which each column characterizes a separate option of the form $N^* + W^*$. The index values in each scenario were linearly transformed to the range [1, 24], which ensures their comparability with the "reference" value of the environmental safety index [14], which is also interpreted as the average rank of the region.

For each indicator for each year, three alternative normalization approaches were applied.

The simplest normalization approach is rank normalization (basic configuration) (*N*1). This option is consistent with the classical method for calculating the environmental safety index. For each indicator *j*, the regions are ordered in order of increasing risk. For "negative" indicators (*M*, *E*, *A*, *W*), the region with the worst value receives rank 1, with the best value – rank *R* (according to the number of regions with initial data). For a "positive" indicator (*F*), the order is reversed: the largest share of forests corresponds to rank *R*, the smallest – to rank 1.

In further calculations, the ranks were used as normalized values. Due to the simplicity and independence of values from units of measurement, this approach is widely used to determine composite indices [1, 2].

Under the second normalization scenario – linear min-max normalization (*N*2) – the initial values of indicator $x_j(r, t)$ are scaled linearly within each year. For "negative" indicators, the following calculation is used

$$x_j'(r,t) = 1 + (R-1)\frac{x_j(r,t) - \min x_j}{\max x_j - \min x_j}, \quad (3)$$

where min x_j and max x_j are the minimum and maximum values of the indicator among all regions in the corresponding year;

$R = 24$ is the number of regions.

For "positive" indicators, the inversion is used

$$x_j'(r,t) = 1 + (R-1)\frac{\max x_j - x_j(r,t)}{\max x_j - \min x_j}. \quad (4)$$

Thus, all normalized values of indicators immediately appear on the scale [1, 24] with the same direction of interpretation as in the first case – rank normalization. Linear normalization preserves information about the relative distances between regions but is sensitive to the extreme values of indicators [1, 12, 15].

The third normalization scenario – standardization followed by linear transformation (*N*3) is based on standardized deviations from the mean. First, Z-scores are determined for each indicator

$$z_j(r,t) = \frac{x_j(r,t) - \mu_j}{\sigma_j}, \quad (5)$$

where μ_j and σ_j are the mean and standard deviation of indicator *j* among all regions in a fixed year, respectively.

For "positive" indicators (*F*), the sign of the Z-score is inverted.

The obtained Z-scores ($z_j(r, t)$) are linearly transformed into the range [1; 24] using min-max formulas similar to scenario *N*2. This normalization scenario allows for taking into account deviations from the mean value of the indicator, and this is useful for data analysis under critical conditions [1, 3, 8].

Simultaneously with normalization, weighting procedures were varied for the five components of the index. Each scheme corresponded to one of the options highlighted in papers on the problems of weight selection [4, 7, 9, 15].

In the basic weighting procedure – equilibrium weighting (*W*1) – all components are assumed to be equal (1). This scheme is considered the simplest and is often perceived as a "neutral" choice. In fact, this approach sets the normative assumption that all indicators are of equal importance [7, 15].

According to the second weighting procedure – ecologically oriented normative weighting (*W*2) – the weights are chosen in such a way as to strengthen the contribution of indicators that directly characterize the anthropogenic load on the environment (air pollution, hazardous waste generation) and weaken the influence of indicators sensitive to military losses, for example, demographic:

$$w_M = 0.10,\quad w_E = 0.15,\quad w_A = 0.30,$$

$$w_W = 0.30,\quad w_F = 0.15. \tag{6}$$

This scheme reflects an attempt to reduce semantic bias under wartime conditions, associated, in particular, with increased mortality, the complexity of registering emergencies, and changes in the proportion of forest cover in the region. In addition, this scheme is consistent with recommendations for policy-driven weights [1, 7, 20].

The third weighting procedure, weighting based on indicator variation (*W*3), refers to "real" weighting methods [4, 8, 15]. For each indicator *j* within a year, the standard deviation σ_j between regions (on normalized values) is calculated

$$\sigma_j = \sqrt{\frac{1}{R-1}\sum_r \left(x'_j(r,t) - \mu'_j\right)^2}, \tag{7}$$

where μ_j is the average normalized value of the indicator.

The weights are determined proportionally to variance

$$w_j = \frac{\sigma_j}{\sum_k \sigma_k}. \tag{8}$$

Therefore, indicators that differentiate regions more strongly receive greater weight, and indicators with small spatial variation have a smaller contribution to the final index.

For each combination of normalization N_m and weighting W_n (*N*1–*N*3×*W*1–*W*3), the integrated index for region *r* in year *t* is defined as

$$K^{(m,n)}(r,t) = \sum_{j\in\{M,E,A,W,F\}} w_j^{(n)} x_j'^{(m)}(r,t), \tag{9}$$

where $x_j^{(m)}(r,t)$ – normalized values of indicators in scenario N_m, $w_j^{(n)}$ – weights in scheme W_n.

Since for different combinations $K^{(m,n)}(r,\ t)$ can have different ranges, for each year separately these values are linearly scaled [1, 24]

$$\tilde{K}^{(m,n)}(r,t) = 1 + (R-1)\frac{K^{(m,n)}(r,t) - \min\limits_r K^{(m,n)}(r,t)}{\max\limits_r K^{(m,n)}(r,t) - \min\limits_r K^{(m,n)}(r,t)}. \tag{10}$$

This operation ensures direct comparability of all combinations among themselves and with the basic environmental safety index, which is represented as an "average rank".

Based on the obtained values $\acute{K}^{(m,n)}(r,\ t)$ for each region, the minimum and maximum index values among the nine combinations are determined, as well as the width of the interval of possible estimates. These intervals were also visualized in the form of map diagrams.

Thus, the matrix of normalizations and weights allows us to systematically assess the sensitivity of regional ratings to methodological decisions and quantitatively measure the stability of the environmental safety index in peace and war.

Subsequently, these intervals were used as initial information for stability analysis and raising the issue of the admissibility of using "conventional" composite indices under conditions of deep structural disturbances.

4. 5. Sensitivity analysis of the composite index

Since the composite index of environmental risk is determined on the basis of a number of methodological decisions (normalization scheme, weighting system), it is important to assess how stable the obtained index values and the ranking of regions are to changes in these decisions.

For each year *t*, a basic normalization and weighting procedure is selected, denoted as s_0. In our work, such a base is the combination *N*3 + *W*3, which is considered the most adequate. The following notations were used for calculations:

– $i = 1,\ldots n$ – regions of the country ($n = 24$);

– $s \in S$ – index construction scheme (a specific pair of "normalization-weights");

– $R_i^{(s,t)}$ – composite index value for region *i* in year *t* according to scheme *s*;

– $r_i^{(s,t)}$ – rank of region *i* in year *t* according to scheme *s*, where rank 1 corresponds to the worst state (highest risk), and rank *n* – to the best state.

The ranks for each combination are determined by ordering $R_i^{(s,t)}$ across all oblasts

$$r_i^{(s,t)} = \mathrm{rank}\left(R_i^{(s,t)};\left\{R_1^{(s,t)},\ldots,R_n^{(s,t)}\right\}\right). \tag{11}$$

Since the analysis is consequently performed for a fixed year *t*, the index *t* is omitted in the formulas for brevity.

To assess how much a change in scheme *s* (fixed pair of "normalization-weights") affects the overall order of the regions, the Spearman rank correlation coefficient between the rank vector according to scheme *s* and the base scheme s_0 is used. This approach is termed the Spearman correlation between schemes (global sensitivity).

Let

$$\mathbf{r}^{(s)} = \left(r_1^{(s)},\ldots,r_n^{(s)}\right),\quad \mathbf{r}^{(0)} = \left(r_1^{(s_0)},\ldots,r_n^{(s_0)}\right). \tag{12}$$

For each scheme $s \in S$, $\{s_0\}$, the global index of ranking sensitivity to the transition from the base scheme to the given scheme *s* (ρ_s) is calculated in the following order:

$$d_i^{(s)} = r_i^{(s)} - r_i^{(s_0)}, \tag{13}$$

$$\rho_s = 1 - \frac{6\sum_{i=1}^{n}(d_i^{(s)})^2}{n\left(n^2-1\right)}. \tag{14}$$

Values of ρ_s close to 1 indicate almost complete preservation of the order of oblasts, while values far from 1 or negative indicate a significant change in the ranking order.

For each year *i* and for all schemes *s*, global ranking sensitivity indices (ρ_s) were determined, which allowed us to compare groups of normalizations and weighting procedures with each other.

In order to characterize the sensitivity of individual oblasts, an analysis of the change in their ranks is carried out when moving from the base scheme s_0 to all other schemes *s*. This approach is termed the change in rank by oblasts (local sensitivity).

For each oblast *i* and scheme $s \neq s_0$, the absolute difference in rank is determined

$$\Delta r_i^{(s)} = \left|r_i^{(s)} - r_i^{(s_0)}\right|. \tag{15}$$

Based on the obtained values, two generalized indicators are calculated:

– maximum rank change for oblast i

$$\Delta r_{i,\max} = \max_{s\in S\setminus\{s_0\}} \Delta r_i^{(s)}, \tag{16}$$

which shows how far an oblast can deviate from its position in the baseline scheme in the worst case;

– the average absolute rank change for oblast i

$$\Delta \overline{r}_i = \frac{1}{|S-1|}\sum_{s\in S\setminus\{s_0\}} \Delta r_i^{(s)}, \tag{17}$$

which characterizes the "typical" magnitude of rank change when searching through all the considered schemes.

Oblasts with small values $\Delta r_{i,\max}$ and $\Delta \bar{r}_i$ are considered relatively stable with respect to the choice of methodology. Oblasts with large values of these indicators are the most sensitive to changes in normalization and weights.

To build maps, the geoinformation software QGIS (USA) was used, which allows one to attach tabular data to a polygonal layer of oblasts and perform thematic mapping with selected classification schemes and color scales.

5. Results of research on assessing the resilience of the environmental safety index to structural disruptions caused by the war

5. 1. Reconstruction of the environmental safety index for regions of Ukraine for 2021 and 2022

Composite indices, as tools for aggregating complex multidimensional information, always depend on a number of critical methodological decisions. Three of them (normalization, weighting system, and missing value handling) have a particularly significant impact on the final form of the index. Under conditions of disruption of the stability of the data collection system, these components become a source of potential misinterpretation or even manipulation of results.

The full-scale war that began in 2022 significantly affected key environmental indicators in the regions of Ukraine. Compared to 2021, 2022 saw a sharp increase in negative phenomena and violations in the environment, which was reflected in statistical indicators. In particular, mortality in many oblasts has increased due to direct combat losses of civilians and deterioration of living conditions. Although national mortality data may be distorted by mass migration and incomplete registration in occupied territories, the trend towards an increase in mortality rates in regions of active hostilities is obvious. For example, in frontline oblasts, the number of civilian deaths in 2022 was estimated in the thousands, which significantly exceeds pre-war figures. At the same time, the demographic situation in relatively safe western regions has stabilized or even improved somewhat due to the influx of internal refugees, which partially offset war losses in the Ukrainian context.

The volumes of industrial and other emissions of pollutants have changed significantly. As a result of the shutdown or destruction of many enterprises in the combat zone, total industrial emissions into the atmosphere have decreased sharply. Thus, according to operational estimates, emissions from stationary sources (thermal power plants, factories, etc.) in 2022 decreased by tens of percent compared to 2021 [21, 22]. For example, the volumes of emissions from the thermal power industry and large boiler houses decreased by approximately 40%, reflecting the shutdown of industry in the east of the country. In industrially developed oblasts, such as Donetsk, Luhansk, Zaporizhia, the volumes of registered air pollution decreased particularly sharply – in some places up to half of the 2021 level. This is explained by both positive effects (reduction in emissions due to the shutdown of factories and transport) and negative ones – part of the reduction may be false since statistical accounting in the occupied territories was impossible. At the same time, in relatively safe central and western oblasts (for example, Vinnytsia, Cherkasy, Khmelnytskyi), the level of emissions remained close to the pre-war level or even increased slightly due to the relocation of production and an increase in the load on local thermal power plants.

Another striking trend was the reduction in forest area and the deterioration of the forest fund. Military actions led to large-scale forest fires and the destruction of green spaces, especially in the east and south of the country. According to available data, in 2022 the area of forests affected by fires increased several times compared to 2021: from several thousand to over 180 thousand hectares [23, 24]. It was recorded that in 2022, 25 times more forest fires occurred than in the previous year. This led to enormous losses of forest cover, especially in Luhansk, Donetsk, Kharkiv, and Kherson oblasts, where forests burned as a result of shelling and hostilities. For example, significant parts of the forest massif in Luhansk oblast around Siversky Donets burned down, and in Kharkiv oblast, fires devastated forest park areas near Izyum and Chuhuiv. In addition, the area of the nature reserve fund in the occupation zones (reserves, national parks) also suffered losses. Some territories were damaged by military equipment or mined, which makes their proper protection impossible.

Other environmental indicators also responded to the military upheavals. In particular, waste management indicators deteriorated: in 2022, the share of waste disposal and recycling in front-line regions significantly decreased. Due to the destruction of infrastructure and the evacuation of the population, the percentage of waste disposal decreased, and natural landfills near the destroyed cities (Mariupol, Severodonetsk) created additional environmental risks.

The quality of water resources also deteriorated locally. Damage to sewage treatment plants and hydraulic infrastructure led to emergency discharges of wastewater [21, 22]. It was recorded that in 2022, in some regions, the volume of return water discharges decreased several times compared to 2021, which rather indicates the shutdown of enterprises than an improvement in water quality.

In general, Table 1 summarizes the change in average values of key environmental indicators between 2021 and 2022. It shows that mortality rates increased, while officially recorded emissions and waste generation fell significantly; other indicators show changes that vary by region depending on the degree of war impact.

Based on the above input data, a basic composite index of environmental risks (1), (2) [14] was calculated for each region in 2021 and 2022 (Fig. 2, 3). The base scenario is considered to be the integrated index calculated using the adopted methodology (normalization of indicators and weights) without taking into account special adjustments for military factors.

The values of this index underwent noticeable changes between the two years (Fig. 2, 3), reflecting both the objective deterioration of the environmental situation and statistical effects associated with incomplete data.

Table 1

Changes in key environmental indicators in 2022 compared to 2021: mortality per 100,000 population [19]; number of emergencies [23]; air pollution index (API) [19]; waste volume [19]; forest cover [24]

Oblast	Mortality per 100,000 population, people		Emergencies, units		Air pollution index (API)		Volume of waste, t		Forest cover, %	
	I	II	I	II	I	II	I	II	I	II
Kyiv	1312	3752	8	6	8.6	7.6	4764	3555.2	22.2	22.2
Transcarpathia	467	1280	4	11	4.7	4.9	139.1	144.4	51.4	51.4
Rivne	467	1268	6	7	6.8	5.8	719.3	569.4	36.4	36.4
Volyn	552	1287	10	1	7.3	8.0	515.8	562.2	31	31
Ivano-Frankivsk	743	1351	10	2	3.5	3.2	790.5	650	41.0	41.0
Chernivtsi	734	1320	4	2	3.0	3.0	171.2	155.7	29.2	29.2
Lviv	825	1381	7	1	7.2	7.0	3212.2	2492.2	28.5	28.5
Vinnytsia	1136	1651	6	2	6.8	5.4	1108.9	731.6	13.1	13.1
Ternopil	936	1432	5	3	4.2	4.0	380.0	315.6	13.3	13.3
Dnipro	1462	1915	6	4	12.8	11.9	321735	139917	5.6	5.6
Odesa	984	1424	3	5	12.5	14.2	370.1	195.1	6.1	6.1
Khmelnitsky	1206	1628	4	2	3.7	3.5	752.9	801	12.8	12.8
Zhytomyr	1284	1693	4	3	4.2	3.8	421.1	375.6	33.6	33.6
Poltava	1445	1846	5	2	5.4	6.4	121823	40541	8.6	8.6
Cherkasy	1389	1788	4	1	7.4	5.4	1301.4	1330	15.1	15.1
Kirovohrad	1491	1841	3	6	4.3	4.5	488.0	461.0	6.7	6.7
Chernihiv	1661	1985	6	3	3.6	3.2	456.2	245.8	20.9	20.9
Mykolaiv	1315	1624	11	5	8.5	10.0	2498.5	572.5	4.0	4.0
Sumy	1485	1745	3	4	6.8	6.7	922.1	437.0	17.8	17.8
Kharkiv	1523	1480	8	4	3.4	3.2	1249.1	635.8	12	12
Zaporizhzhia	1596	1268	6	3	8.0	6.7	5593	1724.6	3.7	3.7
Kherson	1302	776	11	1	7.8	7.0	122.6	3.3	4.1	4.1
Donetsk	877	348	9	8	15.7	10.2	23467.9	7171.6	6.9	6.9
Luhansk	714	122	2	3	5.9	6.7	269.7	0.0	11.0	11.0

Note: I – 2021; II – 2022.

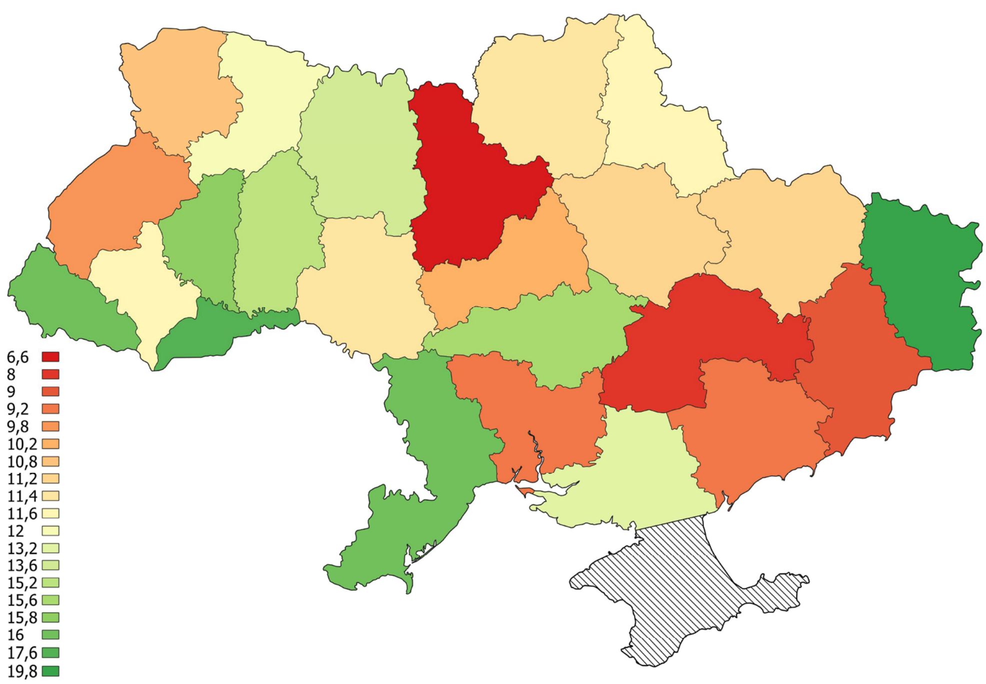

Fig. 2. Geographic distribution of the basic environmental safety index in 2021

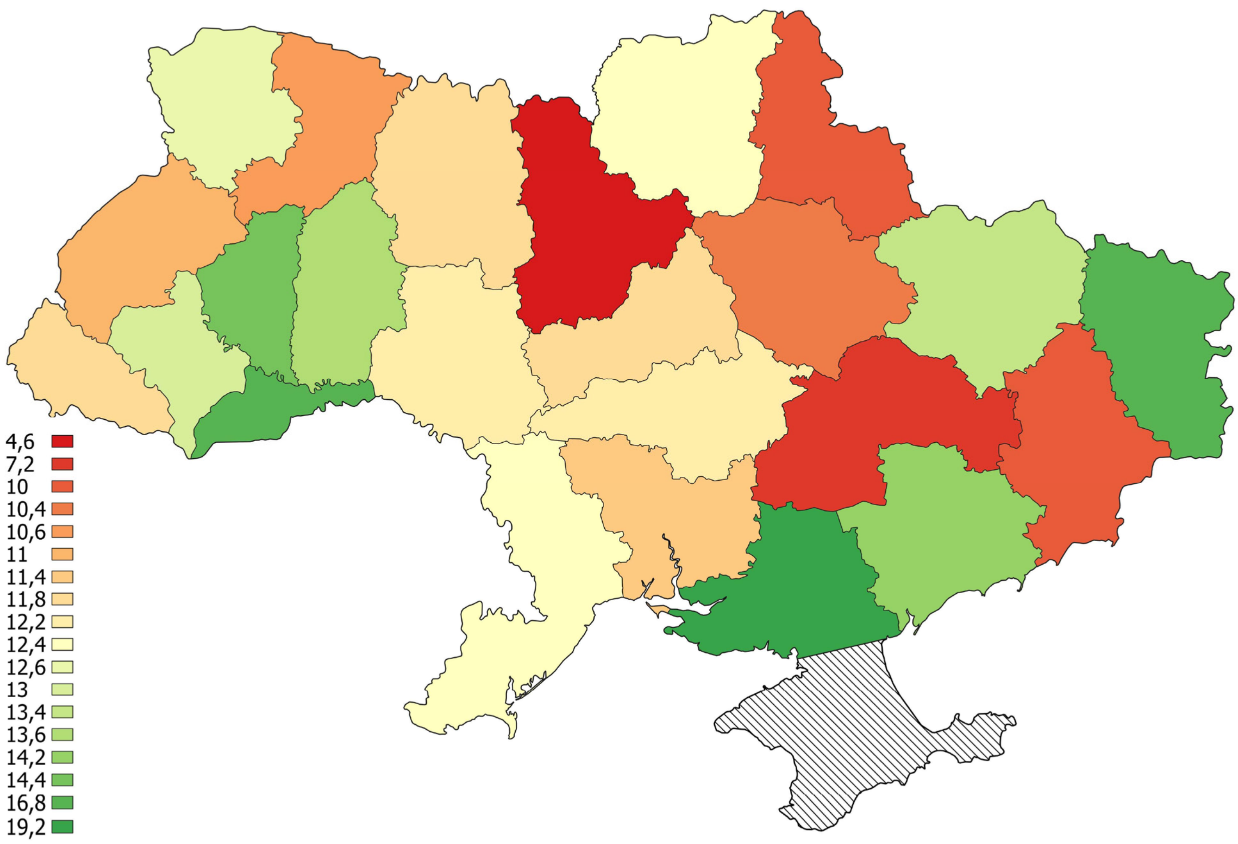

Fig. 3. Geographic distribution of the basic environmental safety index in 2022

5. 2. Checking the sensitivity of regional ranking to the choice of normalization method, weighting procedure, and scenarios for filling in missing data

The construction of a composite index involves certain methodological settings that may affect the final values and the ranking of regions. In our study, the integrated index of environmental safety was calculated using different scenarios of data normalization and indicator weighting to check the stability of the results. Three approaches to normalization were applied: rank ($N1$), linear ($N2$), and standardization ($N3$), as well as three indicator weighting procedures: equilibrium ($W1$), environmentally oriented (increased weights for critical eco-indicators, $W2$), and based on indicator variation (weights proportional to the statistical dispersion of the indicator, $W3$). In total, nine combinations of index calculation methods were considered for the available data. The results of calculations (1)–(10) of composite indices using different approaches are given in Tables 2, 3.

Based on our results, a visualization (Fig. 4, 5) of the ranges of variations in the composite index of environmental safety for each region was prepared using the geoinformation software QGIS (USA). The background color reflects the width of the interval [min $\acute{K}$; max $\acute{K}$] as an indicator of the sensitivity of the index to the choice of methodology. The caption on the polygons contains the minimum and maximum values of the interval for each oblast.

The index sensitivity to the choice of methodology ([min $\acute{K}$; max $\acute{K}$]), displayed in color, indicates how far the index estimates can diverge depending on the chosen methodology. The darker the shade, the higher the index sensitivity to methodological assumptions.

In the subsequent analysis, the Spearman rank correlation coefficient (12)–(14) was used to quantify the impact of different combinations of normalization (N1–N3) and weighting (W1–W3) on the spatial distribution of the integrated index in 2022. For each combination "normalization-weighting", the Spearman correlation coefficient (ρ_s) was calculated for the normalization–weighting pairs between the ranks of the oblasts according to the corresponding scheme and the ranks according to the basic configuration of the index (Table 4). Values close to +1 indicate almost complete preservation of the order of the regions, values close to 0 indicate a significant restructuring of the ranking, and negative values indicate a partial or almost complete inversion of the ranking. As a "zero" pair, a combination of standardization with weighting based on the variation of indicators was chosen as the most interpretatively adequate. Such a combination, in our opinion, is the combination $N3 + W3$.

The calculation of ranks according to the Spearman methodology was carried out according to the algorithm (15)–(17).

Based on the results , a visualization of the variation in the Spearman ranking was prepared using the geoinformation software QGIS (USA) for nine normalization and weighting scenarios for the oblasts of Ukraine in 2022 (Fig. 6), namely the results of the maximum and average deviations in the ranking results.

The background color indicates the maximum deviation $\Delta r_{i,\max}$. The legend on the polygons highlights the average $\Delta \bar{r}_i$ value for each oblast.

Table 2

Values of the composite index of environmental safety for oblasts of Ukraine under different combinations of normalization and weighting (2021)

Normalization	N1	N1	N1	N2	N2	N2	N3	N3	N3
Weighting	W1	W2	W3	W1	W2	W3	W1	W2	W3
Kyiv	6.6	5.8	6.6	11.7	9.6	11.8	12.2	10.2	13.0
Transcarpathia	16.0	16.7	15.8	1.7	1.8	1.7	2.6	2.7	2.7
Rivne	12.0	11.6	11.9	5.1	4.9	5.0	5.9	5.7	6.0
Volyn	10.8	10.6	10.7	8.3	7.4	8.2	8.9	8.1	9.3
Ivano-Frankivsk	11.6	12.9	11.5	6.6	4.8	6.8	7.3	5.6	7.9
Chernivtsi	17.6	19.1	17.4	4.4	3.0	4.4	5.2	3.9	5.5
Lviv	9.8	8.9	9.7	8.0	6.9	8.0	8.7	7.6	9.1
Vinnytsia	11.4	11.0	11.4	10.1	8.0	10.2	10.7	8.7	11.3
Ternopil	15.8	16.6	15.7	7.8	5.7	7.8	8.5	6.5	8.9
Dnipro	8.0	6.2	8.1	19.2	19.8	17.9	19.4	20.0	19.1
Odesa	16.0	14.7	15.9	10.8	10.2	10.4	11.3	10.8	11.6
Khmelnitsky	15.2	15.7	15.1	8.2	5.6	8.4	8.9	6.4	9.5
Zhytomyr	13.6	15.0	13.4	6.6	4.5	6.8	7.3	5.3	7.9
Poltava	11.2	10.6	11.2	12.6	10.5	12.3	13.0	11.0	13.4
Cherkasy	10.2	9.7	10.1	10.1	7.9	10.2	10.7	8.6	11.3
Kirovohrad	15.6	16.5	15.5	9.6	6.6	9.8	10.2	7.3	11.0
Chernihiv	11.4	14.2	11.3	10.2	6.6	10.6	10.8	7.4	11.8
Mykolaiv	9.2	8.3	9.4	15.1	12.1	15.2	15.5	12.6	16.4
Sumy	11.6	11.8	11.4	9.5	7.2	9.6	10.1	7.9	10.7
Kharkiv	11.2	13.1	11.2	11.6	7.7	11.9	12.1	8.4	13.1
Zaporizhzhia	9.2	8.3	9.3	13.4	10.4	13.6	13.9	11.0	14.7
Kherson	13.2	14.0	13.4	14.7	11.6	14.9	15.1	12.1	16.1
Donetsk	9.0	6.5	9.1	15.0	14.7	14.5	15.4	15.1	15.7
Luhansk	19.2	18.6	19.0	6.2	5.2	6.0	6.9	6.0	7.1

Table 3

Values of the composite index of environmental safety for the oblasts of Ukraine under different combinations of normalization and weighting (2022)

Normalization	N1	N1	N1	N2	N2	N2	N3	N3	N3
Weighting	W1	W2	W3	W1	W2	W3	W1	W2	W3
Kyiv	6.4	4.9	4.6	12.2	9.5	11.7	12.7	10.1	12.5
Transcarpathia	11.8	13.6	11.7	7.2	5.6	7.0	7.9	6.4	7.9
Rivne	10.6	10.8	10.5	7.1	5.9	7.2	7.8	6.6	8.0
Volyn	12.6	11.4	12.2	5.8	5.6	5.8	6.5	6.3	6.7
Ivano-Frankivsk	13.0	13.6	12.6	3.3	2.1	3.0	4.1	3.0	4.0
Chernivtsi	16.8	18.5	16.4	4.3	2.8	4.3	5.1	3.7	5.2
Lviv	11.0	9.3	10.6	5.8	5.3	5.8	6.5	6.0	6.7
Vinnytsia	12.2	12.2	11.9	7.4	5.8	7.6	8.1	6.6	8.5
Ternopil	14.4	15.6	14.2	7.0	5.1	7.2	7.7	5.9	8.1
Dnipro	7.2	5.7	7.2	17.0	18.6	16.8	17.3	18.9	17.5
Odesa	12.4	11.8	12.4	13.0	12.9	13.7	13.5	13.4	14.5
Khmelnitsky	13.6	13.9	13.3	6.6	4.6	6.7	7.3	5.4	7.6
Zhytomyr	11.8	13.9	11.5	5.2	3.6	5.0	6.0	4.5	5.9
Poltava	10.4	9.7	10.2	9.9	9.0	9.9	10.5	9.6	10.8
Cherkasy	11.8	11.7	11.4	6.9	5.5	7.0	7.6	6.2	7.9
Kirovohrad	12.2	13.7	12.2	9.8	7.3	10.1	10.4	8.0	10.9
Chernihiv	12.4	15.2	12.1	6.6	4.4	6.5	7.3	5.2	7.4
Mykolaiv	11.4	10.4	11.5	11.7	10.5	12.2	12.2	11.1	13.0
Sumy	10.0	10.9	9.9	8.6	7.1	8.7	9.2	7.8	9.6
Kharkiv	13.4	14.3	13.3	7.3	5.1	7.5	8.0	5.9	8.4
Zaporizhzhia	14.2	11.9	14.1	8.9	7.5	9.4	9.5	8.2	10.3
Kherson	19.2	17.8	18.9	7.3	6.6	8.0	8.0	7.3	8.8
Donetsk	10.0	7.3	10.1	11.5	11.0	12.4	12.0	11.6	13.2
Luhansk	16.8	16.4	16.6	6.6	6.1	7.4	7.3	6.9	8.3

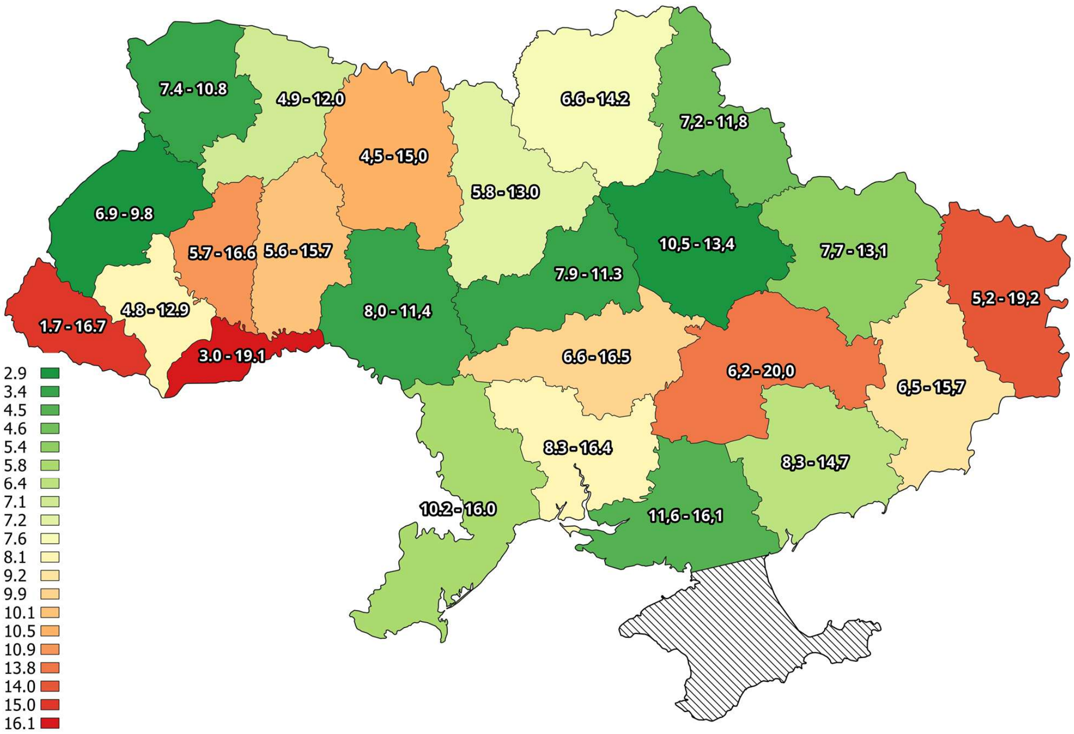

Fig. 4. Range of variation in the composite index of environmental safety under nine normalization and weighting scenarios for the oblasts of Ukraine in 2021

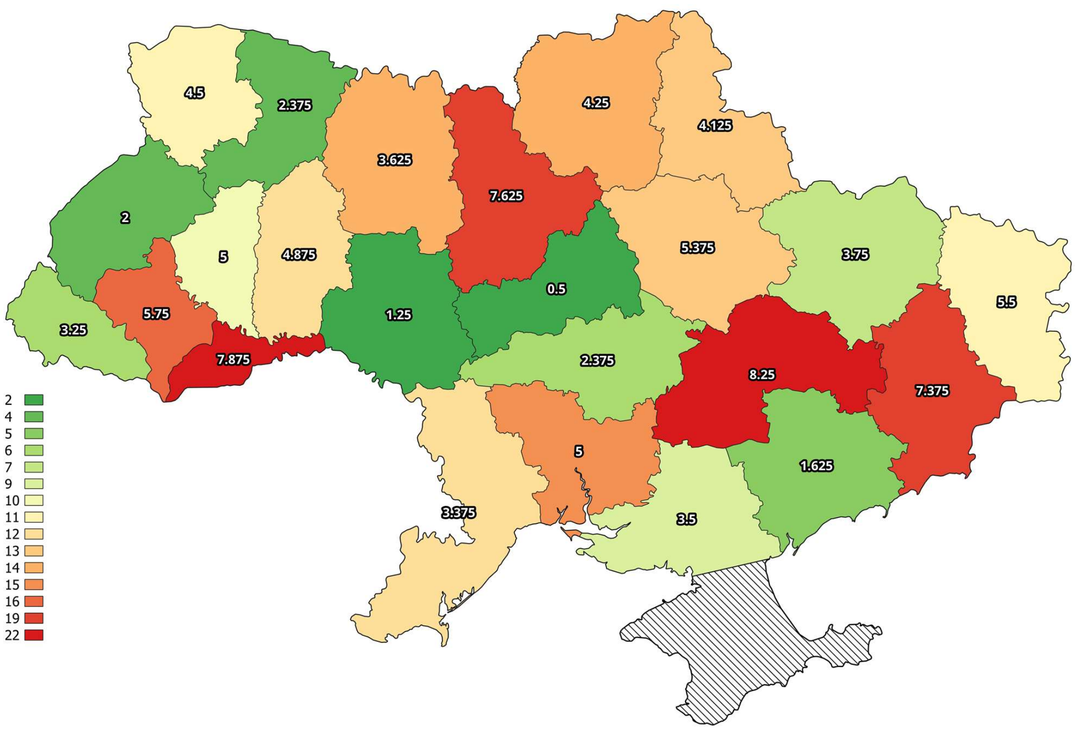

Fig. 5. Range of variation in the composite index of environmental safety under nine normalization and weighting scenarios for the oblasts of Ukraine in 2022

Table 4

Spearman correlation coefficient matrices for normalization-weighting pairs in 2022

$N \backslash W$	$W1$	$W2$	$W3$
$N1$	–0.41	–0.48	–0.33
$N2$	0.98	0.94	1
$N3$	0.98	0.94	–

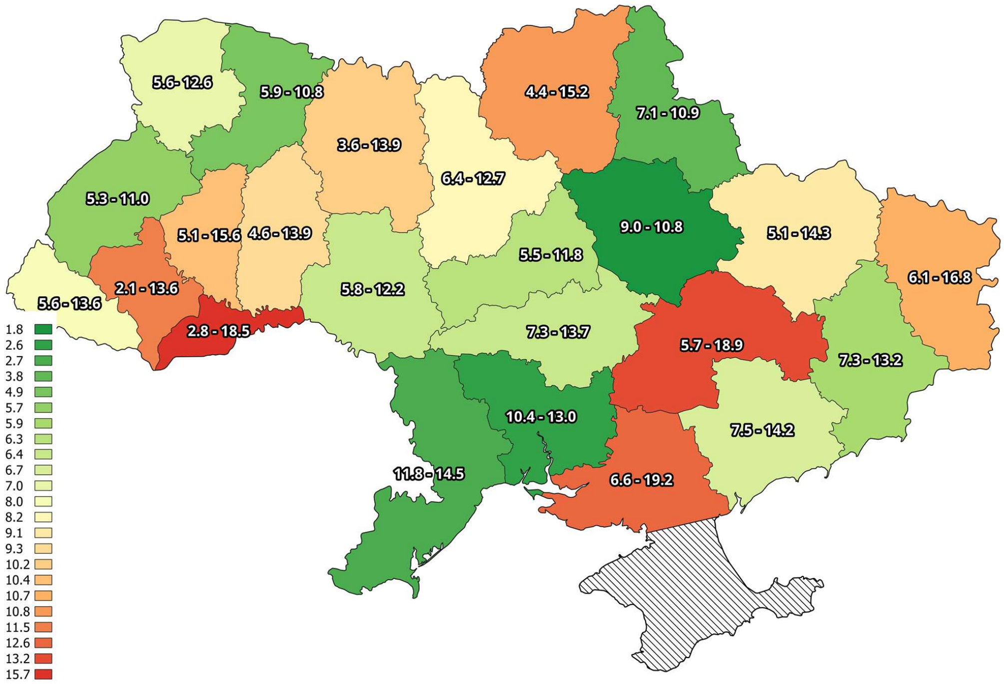

Fig. 6. Visualization of the variation in Spearman's rank under nine normalization and weighting scenarios for the oblasts of Ukraine in 2022

6. Discussion of the results of research into the processes of treating sodium chloride solutions by electrodialysis

The goal of normalization is to establish all indicators that can be compared on a scale regardless of their physical units (tons, %, people/100 thousand, etc.). Three approaches are most often used:

1. Ranking: simple, interpretable, but loses the distributions and the meaning of the distance between values.
2. Minimum-maximum normalization: gives values in the range [0; 1] but is sensitive to extreme values.
3. Z-normalization (standardization): takes into account the mean and standard deviation but is more difficult to interpret by non-specialists.

The choice of method affects the distribution of weight between regions and determines which areas will be "better" or "worse" at the same initial values [1, 4, 15]. In situations where some regions have missing or abnormally low or high values, the ranking results can be radically distorted.

The weights, in turn, determine the contribution of each component to the overall score. Here, too, there are three main approaches:

1. Equilibrium weighting: most common but does not reflect the real importance or stability of the indicators.
2. Expert weighting: subjective and not always transparent.
3. Statistical weighting: formally objective, but sensitive to the choice of variables and scales [7, 8].

Different approaches to weighting may lead to inversions in ranking, especially when one or two indicators are prone to high variance in values due to structural disturbances (e.g., a mortality spike or complete disappearance of data from a region) [4–6].

The issue of missing data is a key problem for indices in crisis settings. Standard methods for filling in missing data include:

– ignoring: removing regions or indicators with missing values leads to loss of coverage;

– replacing with means or a mode: it simplifies processing but masks structural breaks;

– imputation through decomposition or multi-imputation: complex, but effective with sufficient sampling [11].

Under wartime conditions, missing data is not accidental, but is associated with geopolitical events (occupation, destruction, blocking of infrastructure). If this is not taken into account when filling out statistical reporting, the index begins to work against logic. For example, an oblast without emissions statistics looks like an environmentally safe one, while regions with artificially low mortality due to undercounting occupy better positions in the ranking.

Given these factors, the stability of the composite index depends not only on the input data but also on all intermediate decisions.

Most composite indices, in particular environmental ones, are based on the assumption that changes in indicator values have a stable interpretation over time. For example, an increase in mortality is usually interpreted as a sign of a worsening socio-ecological situation, and a decrease in industrial emissions is the result of a more effective environmental policy. In wartime, this assumption is violated: the semantics of key indicators change, and they cease to reflect the same phenomena as in peacetime.

In the methodology for calculating the environmental safety index [14], total mortality of the population is used as an integrated indicator of demographic and indirect environmental burden. In peacetime, increased mortality may be associated with chronic diseases, environmental pollution, the quality of medical care, socio-economic conditions, etc. During a full-scale war, a significant proportion of deaths is due to hostilities, shelling, destruction of civilian infrastructure, and official registration of deaths in frontline and occupied territories is incomplete, fragmentary, or, at best, provided with a delay.

Therefore, the same numerical mortality rate in 2021 and 2022 has a different nature and content. Using such an indicator without taking into account the change in context leads to the fact that the index supposedly captures "environmental risk", although in fact it reflects military losses.

Indicators of pollutant emissions, hazardous waste generation, and energy consumption are conventionally considered as indicators of anthropogenic environmental burden. A decrease in these values in peacetime is most often interpreted as a result of the transition to cleaner technologies, modernization of production, and increased environmental control [1, 20]. In wartime, a decrease in emissions is often a consequence of the shutdown of enterprises, the destruction of industrial and energy infrastructure. A decrease in officially declared waste volumes may be associated with a loss of reporting or the inability to record them, rather than with a change in disposal technologies.

Under such conditions, an index that treats lower emissions as an unconditionally "better" state is semantically wrong. It "rewards" areas where industry has been destroyed and may underestimate risks where the actual analytical load on the environment has not changed for the better but simply ceased to be measured.

The number of registered emergencies also undergoes semantic changes. Under stable conditions, this indicator reflects the frequency of natural, man-made, and social incidents. During wartime, the classification of events changes and some phenomena may be recorded according to other standards, for example, as military events, rather than emergencies. At the same time, some incidents are not registered at all due to the destruction of institutions, the evacuation of personnel, or the lack of communication.

As a result, a decrease in the number of registered emergencies does not necessarily reflect a decrease in real risk but may be a consequence of an information vacuum.

Thus, when a composite index aggregates indicators with "broken" semantics, three typical consequences arise:

– false positive signals: regions with the greatest destruction of industry or loss of statistics can artificially improve their positions in the ranking, since they formally demonstrate lower emissions, waste or the number of emergencies;

– false negative signals: regions that have retained statistical capacity and continue to fully report may look "worse" compared to territories without data.

– incomparability over time: the same values of the indicator before and after the start of the war are no longer comparable; the index loses the ability to correctly track dynamics [2, 10, 12].

Thus, under wartime conditions, the problem of composite indices goes beyond statistical error alone. It is about a qualitative change in the content of the indicators.

The proposed algorithm for calculating the integrated index of environmental safety, in contrast to conventional calculation methods with full statistical data, includes a stage of checking the stability of the indicator under conflict conditions. In addition, the proposed classification of regions by the completeness and reliability of statistical data allows the use of imputation schemes, which is not provided for in standard methods.

Our approach to calculating the integrated rating is attractive for conditions of instability or the presence of conflict in a region. However, it has limitations, in particular, the necessary reference stable period for comparing stability.

Calculations of integrated indicators of environmental safety using various algorithms were carried out on the basis of statistical data on key environmental indicators (Table 1). A comparative analysis of the results on the reproduction of the environmental safety index for the regions of Ukraine for 2021 and 2022 (Tables 2, 3, Fig. 3, 4) revealed that in most regions the index values remained relatively stable or decreased, which is an expected result against the background of large-scale social, economic, and environmental upheavals caused by a full-scale war. However, in a number of front-line or affected regions, the environmental safety index unexpectedly increased, which may indicate paradoxical effects of data loss, structural shifts, or methodological instability.

The most pronounced increase in the index (i.e., improvement under conditions in terms of index calculations) was recorded in the following regions:

– Kherson oblast: the index increased from 13.2 to 19.2 (+6.0);

– Zaporizhia oblast: +5.0 (from 9.2 to 14.2);

– Kharkiv oblast: +2.2 (from 11.2 to 13.4);

– Chernihiv oblast: +1.0 (from 11.4 to 12.4);

– Donetsk oblast: +1.0 (from 9.0 to 10.0).

These improvements do not necessarily indicate a real improvement in the state of the environment but rather demonstrate the effects of "anomalous cleaning" of the index due to the disappearance or decrease in data in areas of active hostilities.

Therefore, as can be seen from the above "increases" in index values, hostilities can paradoxically formally improve the value of the integrated environmental index, if special measures are not taken to process fragmentary or unreliable data. The environmental safety index turned out to be not fully resistant to structural shocks. It does not take into account new types of threats (mining, radiation risks, uncontrolled emissions), does not reflect the "dark zone" of statistics in occupied territories and maintains formal equilibrium even with catastrophic deterioration of the situation. This directly confirms the need to adapt the indexing methodology to war conditions, including rethinking the normalization, weighting, and validation of data.

For this purpose, integrated environmental safety indices were calculated under different scenarios of data normalization and indicator weighting.

As can be seen from Fig. 4, in 2021, for most central and southern oblasts, the width of the interval is limited to a few points. The index varies within approximately 3–6 positions on a 24-point scale. This means that for different $N_m \times W_n$ combinations, such regions maintain index values close in magnitude and will not "jump" between extreme risk groups. In contrast, for a number of western (Transcarpathian, Chernivtsi) and eastern/industrial oblasts (in particular, Dnipropetrovsk, Luhansk), the intervals reach 14–16 points, i.e., an oblast can move almost from the minimum to the maximum values of the scale depending on the normalization method and weights. It is these regions that form the "centers" of maximum methodological uncertainty in the pre-war 2021.

In 2022 (Fig. 5), the spatial pattern is generally preserved, but a certain "narrowing" of ranges is observed in a significant part of the territory. The southern (Odesa, Mykolaiv) and most of the central oblasts demonstrate very narrow intervals (approximately 2–3 points), which indicates a high consistency of the scenarios even under conditions of military unrest. At the same time, some oblasts, primarily Chernivtsi, Dnipropetrovsk, and Zaporizhia, retain very large ranges (over 12–15 points). This means that for them, the choice between rank, linear, or Z-normalization and between different weighting procedures can radically change the position of the region in the all-Ukrainian rating.

As the results of our study demonstrate (Fig. 2–5), conventional equivalent techniques for determining the integrated index under war-time conditions are indeed too sensitive to the absence and instability of indicators. In particular, normalization techniques and weighting procedures significantly change the ranks of regions, especially those located in conflict zones. Our results confirm the conclusions by scientists whose publications were reviewed above.

Calculation of local sensitivity indicators showed that the stability of the ranking differs significantly between regions (Fig. 6). The maximum deviation of rank $\Delta r_{i,\max}$ (16) in 2022 varies from 2 to 22 positions of the 24-level scale (Fig. 6), while the average deviation $\Delta \bar{r}_i$ (17), reflected by numerical captions on the map (Fig. 6), for most oblasts is within 1–5 positions.

The group of relatively stable regions is formed primarily by a part of the western, central, and southern oblasts, where the maximum change in rank under all scenarios does not exceed 6–7 positions, and the average is about 1–3. For these oblasts, the transition from the basic scheme $N3 + W3$ to alternative combinations of normalization and weighting changes their place in the overall rating only slightly. The regions remain in the same risk group, and local fluctuations in rank are rather technical in nature.

In contrast, a number of border western and frontline eastern/industrial oblasts demonstrate very high local sensitivity. For them, the maximum deviation in rank reaches 16–22 positions, and the average values Δr_i are 6–8 ranks. This means that under some scenarios of the methodology, such regions fall into the group with the highest environmental risks, while under others, they move to the middle or even relatively "safe" part of the rating. In fact, for these oblasts, the choice between rank, linear, or Z-normalization, and between different weighting procedures is decisive for their position in the all-Ukrainian ranking.

The Spearman coefficient matrix for 2022 (Table 4) confirms that the key source of distortion in the ranking is precisely the basic variant of the methodology – a combination of rank normalization with equilibrium weighting ($N1 + W1$).

For all three weighting procedures, in the case of $N1$, the correlation coefficients with the basic configuration $N3 + W3$ are negative and significant in magnitude (from −0.48 to −0.33). This means that the use of rank normalization fundamentally changes the order of regions. Namely, oblasts that belong to the group with the highest risk in the basic scheme are often shifted to the "safe" part of the rating under the $N1$ scenarios, while relatively stable western and central regions may occupy worse positions. That is, under war-time conditions, the classic version of calculating the environmental safety index ($N1 + W1$) [14] actually "reverses" the logic of the assessment, creating the illusion of improvement precisely where the real ecological risk has increased the most.

In contrast, for metric normalizations $N2$ and $N3$, a very high positive correlation with the baseline is observed: $\rho_s \approx 0.98$ for $W1$, $\rho_s \approx 0.94$ for $W2$, and for the combination $N2 + W3$, the correlation with $N3 + W3$ is 1, i.e., the ranks of the oblasts completely coincide. This shows that, while maintaining the same weighting logic, changing the min–max normalization to Z-standardization (or vice versa) has almost no effect on the spatial distribution of the index, while switching to a purely rank approach ($N1$) destroys this distribution. The influence of the weights themselves within $N2$–$N3$ turns out to be secondary: transitions $W1 \rightarrow W2 \rightarrow W3$ change ρ_s by only a few hundredths, while the $N1 \rightarrow N2$ / $N3$ change alters both the sign and the order of the correlation values.

As a result, the global analysis according to Spearman reveals that under combat conditions, it is the rank normalization option ($N1$) with any type of weighting ($W1$, $W2$, $W3$) that becomes methodologically unacceptable. It gives a ranking that contradicts both more robust metric schemes and the actual picture of environmental risks in frontline and affected regions.

Thus, under war-time conditions, the role of expert interpretation has increased along with quantitative indicators. Our study has confirmed that a purely quantitative approach in a crisis period is insufficient. Indicators should be interpreted taking into account non-statistical factors. For an adequate assessment of environmental risks, a combination of an integrated index with a qualitative analysis of the situation (expert assessments, contextual information), as well as the introduction of backup mechanisms for collecting data under emergency conditions, is required.

It should be noted that the calculation of the integrated indices was performed based on data from 2021 (stable period) and 2022 (period of hostilities), and the potential for their long-term forecasting and extrapolation is limited. However, the results could be used as a basis for short-term forecasting.

The proposed approach to determining composite indices could be applied by government agencies to optimize the collection and quality control of environmental data, assess the level of environmental safety under crisis conditions, and prioritize environmental restoration measures.

As mentioned above, the issue of the limitations of the application of conventional methods for determining composite indices was discussed in the international community in the early 2000s [1, 2, 9] and continues to be discussed in modern scientific papers [25–28]. Therefore, our studies are of interest to world analysts due to the methodological adaptation of the determination of the composite index of environmental safety for any crisis conditions that lead to the loss or distortion of statistical data. The proposed approach could allow for assessments of the level of environmental safety not only in zones of military conflicts but also in regions suffering from natural and man-made disasters. The adapted composite indices could provide an indisputable basis for decision-making by international organizations in the field of global environmental monitoring and humanitarian assistance.

The disadvantage of the study is the "blind" use of statistical data, which may have already been previously transformed due to the absence or inferiority of the original data. To eliminate such a disadvantage, an expert assessment with adequate interpretation of the original data is required. Another disadvantage of the proposed approach is a certain limitation of the list of indicators involved. Probably, in the future, the expansion of the set of original parameters could be implemented using remote sensing.

In the future, to build on such studies, it is advisable to design a dynamic, sensitive environmental monitoring system with subsequent expert analysis of the obtained data, taking into account the specificity of the region.

7. Conclusions

1. The full-scale war in Ukraine has significantly affected the components of the integrated index of environmental safety of regions. The index values for 2022 differ significantly from the corresponding values for 2021, reflecting both the real negative consequences of hostilities for the environment and data distortions due to interruptions in statistical observation. The most dramatic anomalies in the indicators were recorded in the eastern and southern oblasts directly affected by the war. In particular, in the regions of hostilities, the official volumes of pollutant emissions and the number of registered emergencies in 2022 decreased sharply (in some places to half the level of 2021), which led to an artificial increase in the integrated index of environmental safety. That is, the relatively better environmental ratings of a number of front-line oblasts in 2022 do not reflect a real improvement in the state of the environment but are caused by failures in data collection. Regions not affected by active hostilities demonstrate more gradual and logical changes in the index. The safest oblasts in environmental terms before the war remained in the top ranks of the rating in 2022 (for example, traditionally prosperous western regions retained high positions regardless of the calculation scenario). In contrast, significant permutations occurred in the group of medium and relatively disadvantaged regions. The places of individual oblasts in the 2022 rating strongly depend on the chosen methodology for calculating the index, especially for conflict zones.

2. According to the results of our sensitivity analysis, changing the data normalization methods has almost no effect on the ranking order of regions. Different normalization methods (min-max, z-standardization, etc.) give a high mutual correlation of ranks. At the same time, revising the weighting coefficients and different approaches to filling in missing data significantly affect the integrated index, reducing the correlation of rankings with the baseline scenario. This means that methodological assumptions (especially regarding wartime data) can significantly change the assessments of the environmental safety of regions. The composite index of environmental safety (in its conventional form, with a fixed set of indicators and weights) has shown limited resilience to shock events caused by war. Violations of the normal data collection regime and extreme values of indicators lead to the fact that without adaptation of the methodology, the integrated index may generate false signals about the state of regions. That is, the current index model requires adjustment and flexibility to remain informative under conditions of radical changes in the socio-ecological system.

Conflicts of interest

The authors declare that they have no conflicts of interest in relation to the current study, including financial, personal, authorship, or any other, that could affect the study, as well as the results reported in this paper.

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Data availability

All data are available, either in numerical or graphical form, in the main text of the manuscript.

Use of artificial intelligence

The authors confirm that they did not use artificial intelligence technologies when creating the current work.

Authors' contributions

Yevhenii Bulhakov: Methodology, Software, Data curation, Writing – original draft, Visualization; **Viacheslav Hnatiuk**: Formal analysis, Investigation, Resources; **Tetyana Shabliy:** Conceptualization, Validation, Project administration, Writing – review & editing, Supervision.

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