

DOI: <https://doi.org/10.26565/1992-4259-2025-33-12>

UDC: 504.064:556.5:519.876.5(477)

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ENTROPY-WEIGHTED MODEL FOR ASSESSING THE ENVIRONMENTAL SAFETY OF SURFACE WATERS IN UKRAINE

Purpose. To develop and test an adaptive entropy-weighted model that allows eliminating the subjectivity of traditional index-based methods and accounting for the spatiotemporal variability of hydrochemical parameters to improve the efficiency of river basin environmental safety management.

Methods. The methodology is based on calculating the Entropy-Weighted Water Quality Index (EWQI), where the weight of each physicochemical parameter is determined using Shannon entropy

Results. Observation data from over 540 monitoring points within the main river basins of Ukraine for five seasonal phases of the hydrological cycle were analyzed with cartographic visualization of the calculation results. A clear dependence of water quality on the hydrological regime was established. The best ecological status was recorded in the winter and spring periods (Danube and Vistula basins) due to the natural dilution of pollutants. Critical deterioration of quality is observed during the shallow-water and autumn periods, when pollution indices reach extreme values, especially in the basins of the Southern Bug, and rivers of the Black Sea and Azov Sea regions (classes "very dirty" and "extremely dirty" water). Spatial analysis localized the zones of highest anthropogenic risk, confirming the inefficiency of river self-purification in industrially burdened regions during the low-flow period.

Conclusions. The proposed model demonstrated high sensitivity to seasonal changes and anthropogenic load. It provides a scientific basis for transitioning to adaptive water resource management, allowing for the prioritization of water protection measures and the optimization of the monitoring system according to periods of maximum ecological risk.

KEYWORDS: *Entropy-weighted model, surface water quality, EWQI, environmental safety, seasonal dynamics, river basins*

Як цитувати: Bezsonnyi V. L. Entropy-weighted model for assessing the environmental safety of surface waters in Ukraine. *Вісник Харківського національного університету імені В. Н. Каразіна. Серія «Екологія»*. 2025. Вип. 33. С. 166-187. DOI: <https://doi.org/10.26565/1992-4259-2025-33-12>

In cites: Bezsonnyi, V. L. (2025). Entropy-weighted model for assessing the environmental safety of surface waters in Ukraine. *Visnyk of V.N. Karazin Kharkiv National University. Series Ecology*, (33), 166-187. <https://doi.org/10.26565/1992-4259-2025-33-12>

Introduction

Ensuring the environmental safety of surface water basins represents one of the most pressing global and national challenges of the 21st century. Water resources play a crucial role in maintaining ecological balance, human well-being, and sustainable development. However, the intensification of anthropogenic pressure, the consequences of climate change, and the degradation of natural ecosystems significantly reduce the ability of hydrological systems to

self-regulate. These processes cause a progressive deterioration in water quality, the disruption of aquatic ecosystems, and growing risks for human health and the environment.

At the global level, the issue of water safety is directly connected to achieving the United Nations Sustainable Development Goals (SDGs), particularly Goal 6 – “Clean Water and Sanitation” and Goal 12 – “Responsible Consumption and Production”. According to UN

reports, nearly 40% of the world's population already experiences water scarcity, while more than 1.7 billion people living in river basins require improved access to safe water resources. Approximately 783 million individuals still lack access to clean drinking water, directly affecting their quality of life, public health, and socio-economic stability. These figures illustrate the urgent need to strengthen mechanisms for the sustainable management of water basins and to enhance the resilience of aquatic ecosystems against technogenic and climatic stressors.

For Ukraine, the problem of surface water quality and basin-scale ecological safety has acquired critical importance. The country's river systems, including the Dnipro, Dniester, Southern Bug, and others, are exposed to continuous impacts from industrial, agricultural, and urban sources. In the framework of the national environmental monitoring program "EcoThreat," more than 540 observation points operate across the main basins. The monitoring results indicate systematic exceedances of permissible concentrations of pollutants – including nitrates, phosphates, pesticides, and heavy metals (Pb, Cd, Zn, Cu, Cr) – in numerous regions. The cumulative environmental and economic losses caused by violations of water protection regulations exceeded 21 million UAH in the first half of 2024 alone. These data highlight the scale of the anthropogenic burden on aquatic ecosystems and the insufficient efficiency of existing monitoring and control systems.

The scientific and practical problem lies in the absence of a unified, adaptive, and scientifically grounded methodology capable of assessing the ecological safety of surface waters under conditions of spatio-temporal variability. Traditional assessment approaches often fail to account for the seasonal dynamics of hydrological processes and the heterogeneity of technogenic influences, resulting in a fragmented understanding of the real ecological state of river basins. Furthermore, existing models frequently rely on expert-based weighting of indicators, which introduces subjectivity and reduces the reliability of water quality indices.

Given these limitations, it becomes necessary to develop quantitative tools for assessing water quality and ecological safety that can objectively capture the variability of hydrochemical parameters across both spatial and temporal dimensions. From a scientific standpoint, this task corresponds to the formation of an information–entropy framework for environmental safety management, where entropy serves as a measure

of uncertainty and disorder within ecological systems. Such an approach allows one to evaluate the structural complexity and stability of aquatic environments and to detect deviations caused by technogenic activities.

From a practical perspective, the implementation of an entropy-weighted water quality model offers substantial potential for improving environmental governance. It provides the basis for data-driven management decisions, prioritization of high-risk territories, and optimization of monitoring networks. The results of such analyses can be directly used for planning preventive measures, adjusting technological processes in industry and agriculture, and enhancing the efficiency of water protection programs at both regional and national levels.

Therefore, the general problem can be formulated as follows:

To ensure the ecological safety of Ukraine's surface waters under growing technogenic and climatic pressures, it is essential to develop an integrated, entropy-based model for assessing and forecasting the state of aquatic ecosystems, enabling effective management and mitigation of environmental risks.

The solution to this problem is significant not only for Ukraine but also for other regions facing similar challenges of water resource degradation. It contributes to the global scientific discourse on entropy-driven environmental modeling, risk-based water management, and sustainable basin governance – forming the theoretical and methodological foundation for modern systems of technogenic–ecological safety.

A comprehensive review of contemporary scientific publications indicates that improving the efficiency of surface water quality assessment requires the integration of analytical methods, digital data processing technologies, and a systematic approach to interpreting monitoring results. In current scientific practice, there is a clear trend toward transitioning from descriptive to quantitative and analytical models that enable tracking the spatial and temporal variability of pollution, considering both anthropogenic and natural factors.

The origins of the index-based approach to water quality assessment date back to 1965, when Horton proposed the first empirical model of an integrated index that combined a set of hydrochemical parameters into a single numerical indicator [1–6]. Subsequently, this methodology became the foundation for more sophisticated indices that incorporated weighting coefficients and regulatory limits. However, classical

methods based on fixed or expert-assigned weights often fail to reflect the actual dynamics of indicators and overlook the spatial variability of aquatic systems. Therefore, modern researchers increasingly employ entropy-weighted indices, which are characterized by higher accuracy, sensitivity, and stability when analyzing seasonal and regional changes in water quality [7–9].

Within the information-entropy framework, entropy is regarded as a quantitative measure of uncertainty or disorder in the distribution of chemical substance concentrations in the aquatic environment. It reflects the degree of ecosystem destabilization and allows the evaluation of its structural order. The higher the entropy of a given parameter, the greater its contribution to the overall assessment of the water body's condition [7–9]. Thus, the entropy-based approach offers opportunities to develop integrated models of environmental safety that can adequately respond to changes in natural and anthropogenic conditions.

The foundational basis for creating such models is the Water Quality Index (WQI), which encompasses a set of physicochemical parameters—from pH and dissolved oxygen to mineralization and biochemical oxygen demand [10, 11]. In traditional approaches, all parameters were considered equally significant, whereas in modern entropy-weighted models, each parameter is assigned an individual informational weight calculated based on its entropy. This ensures objectivity and mathematical consistency in assessment.

The use of entropy as a weighting criterion eliminates the subjectivity of expert judgment and reflects the actual variability of each parameter within spatial and temporal contexts [12]. Parameters exhibiting higher variability receive greater weight in the final integrated index, as they carry more information about the system's state. This principle substantially increases the reliability of assessing the ecological safety of river basins compared to classical index-based methods [13].

The calculation of the entropy-weighted water pollution index (EWQI) involves normalizing the parameter values, determining their entropy-based weights, and aggregating them into a single integrated indicator. This method has demonstrated high efficiency in several international studies. For instance, in [14], the EWQI was first applied to assess groundwater quality in the Lenjanat region (Iran), where it was shown that the use of entropy-based weights enhances the model's sensitivity to hydrochemical

variations. Similar results were obtained in India [15], where the index was applied for the spatial analysis of ionic water composition.

In African countries, the methodology has also demonstrated high informational value: in the city of Ibadan (Nigeria), nitrates and heavy metals were identified as the most significant factors contributing to the deterioration of drinking water quality [16]; in South Africa, the entropy-weighted approach was applied to study seasonal variations in surface waters using data from Google Earth Engine and Sentinel-2 satellite imagery [17]. Studies [18–20] confirmed that integrating entropy analysis with spatial modeling and autocorrelation indices allows for more accurate mapping of pollution levels and identifying zones of elevated ecological risk.

Considerable attention has also been given to assessing anthropogenic pressure on water bodies. In the Indian state of Telangana, it was shown that parameters associated with economic activity have the highest entropy significance, indicating a direct correlation between anthropogenic impact and the destabilization of aquatic environments [21]. Further studies [22–25] expanded the application of the EWQI for systematic water quality assessment in domestic and industrial sources, confirming the universality of the method and its adaptability to different climatic and socio-economic regions.

On the African continent, study [26] analyzed the seasonal and spatial variability of hydrochemical parameters in the mangrove estuary of the Nyong River (Cameroon). The use of multivariate statistical analysis enabled the identification of characteristic seasonal pollution patterns, confirming the connection between natural hydrological dynamics and anthropogenic influences. A similar approach was implemented in study [27], which examined the impact of land use structure on the water quality of Lake Muhazi (Rwanda). The combination of GIS analysis, cartographic modeling, and water quality indices made it possible to trace spatial contrasts in pollution and identify the main sources of impact associated with urbanized and agricultural territories.

In southern Nigeria [28], a comprehensive assessment of surface water conditions was carried out using factor and cluster analysis integrated with entropy weighting. The results confirmed the advantages of combining informational-entropy weighting with multivariate statistical methods for classifying water types and identifying the main factors of technogenic pollution. Study [29] developed a water quality

assessment model for the confluence of the Wei and Huang He rivers (China), which integrates the entropy-weighted index (EWQI), principal component analysis, and geospatial visualization. This allowed for the identification of pronounced seasonal differentiation in pollution levels and the localization of critical impact zones.

Of particular interest are studies that demonstrate the transfer of digital technologies into environmental monitoring. Study [30] examined big data processing algorithms originally developed for economic processes but adapted by the authors for analyzing ecological systems. These algorithms allow for the consideration of spatiotemporal variability and enable real-time modeling of water quality. Similarly, study [31] proposed constructing uncertainty zones in multidimensional risk spaces, which allows classifying river basins by levels of ecological hazard using entropy-weighted indicators.

Study [32] advances a systems approach to dynamic analysis of complex systems, emphasizing the identification of structural transformations in sustainable development processes. Transferring this methodology into hydro ecological research makes it possible to better understand the mechanisms of seasonal dynamics in aquatic ecosystem functioning, especially under anthropogenic stress. Similar ideas are reflected in study [33], which developed theoretical and methodological foundations for spatial planning that account for temporal variability in natural and technogenic parameters. For the present research, this is crucial, as it provides justification for including seasonally weighted water quality indices in strategic basin management models.

An important contribution to modern environmental monitoring methodology was made in study [34], which analyzed the potential of machine learning and predictive analytics for forecasting post-crisis trends. Applying similar algorithms in water research opens opportunities for predicting water quality dynamics under seasonal and anthropogenic influences, forming the basis for adaptive water resource management strategies.

A study directly relevant to integrated water resource assessment [35] implemented a multiparametric analysis of water supply sources considering ecological risk indicators. The authors emphasized the importance of accounting for spatiotemporal variability to adequately evaluate seasonal fluctuations in water conditions. A comparable approach was used in modeling the oxygen regime of reservoirs [36], which revealed dependencies of biochemical oxygen demand

(BOD₅) on temperature and seasonal parameters – key factors in entropy-weighted index calculations.

The application of thermodynamic concepts to explain degradation processes in aquatic ecosystems was proposed in study [37], introducing the concept of anti-entropy as an indicator of ecological system stability. This approach is promising for long-term water monitoring and identifying trends in ecosystem degradation. Review [38] highlighted the importance of optimizing the spatial placement of monitoring points using informational-entropy criteria, which increases the accuracy and representativeness of tracking spatiotemporal changes in water quality.

A particularly relevant direction for Ukraine is represented by study [39], which examined the impact of military actions on aquatic ecosystems. The authors found that during armed conflicts, eutrophication levels rise, and seasonal pollution dynamics intensify, necessitating adaptive environmental monitoring strategies in crisis conditions. Specifically, for Ukrainian conditions, study [40] conducted the first practical application of the entropy-weighted methodology to assess water quality in the Dnipro River. The results revealed substantial differences between cold and warm seasons, confirming the high sensitivity of the method to seasonal dynamics.

The problem of domestic and industrial wastewater impact on water bodies was analyzed in study [41], which demonstrated that ecological risk levels significantly increase during warm seasons due to intensified biochemical processes and higher concentrations of organic compounds. Study [42] carried out an integrated assessment of pollution in the Dnipro Reservoir, identifying the main sources of nitrogen and organic compounds that form critical pollution hotspots. The assessment of ecological safety components in the Siverskyi Donetsk basin [43] emphasized the importance of oxygen regime parameters – dissolved oxygen and biochemical oxygen demand – as key indicators of long-term water quality changes.

Summarizing the analysis of studies [26–43], it can be concluded that in most cases, the entropy-weighted approach has proven highly effective in revealing seasonal and spatial patterns of water quality variation. At the same time, Ukraine still lacks comprehensive models that integrate entropy weighting, spatial analytics, and multiparametric monitoring. Therefore, the development of an adaptive entropy-weighted model for assessing the environmental safety of surface waters, based on open data and modern

analytical methods, represents a relevant and important scientific-practical task in the field of water resource management and ensuring ecological sustainability.

An in-depth analysis of scientific sources and practical experience in water resource assessment has shown that modern methods of environmental monitoring require improvement in terms of integration, objectivity, and adaptability to seasonal and spatial variations. Traditional index-based approaches, which rely on fixed or expert-defined weighting coefficients, do not always reflect the real dynamics of water quality formation under complex anthropogenic influences. Furthermore, the absence of unified algorithms capable of automatically processing large volumes of hydro chemical data limits the efficiency of management decisions in the field of basin environmental safety.

Under these circumstances, the development of scientifically grounded approaches that combine informational-entropy principles, digital data analysis technologies, and integrated environmental risk indicators becomes particularly important. Such an approach ensures a quantitative assessment of the complexity, instability, and spatial variability of aquatic systems, forming the foundation for adaptive models of surface water management.

The aim of the study is to develop and test an entropy-weighted model for assessing the environmental safety of surface waters in Ukraine, which enables the quantitative evaluation of seasonal and spatial dynamics of hydrochemical parameters, the identification of zones of increased anthropogenic risk, and the formation of a scientifically justified basis for improving the effectiveness of the monitoring system.

The study utilized data from the national surface water quality monitoring system provided by the State Agency of Water Resources of Ukraine. The information base includes over 540 observation points located within the country's main river basins – Dnipro, Danube, Dniester, Don, Vistula, Southern Bug, as well as the rivers of the Black Sea and Azov Sea regions. This spatially extensive network allowed for the coverage of diverse aquatic ecosystems and the identification of territorial patterns of water quality formation.

The analysis considered five seasonal phases of the hydrological cycle – winter, spring, low-water (mezheny), shallow-water, and

To achieve this aim, the following objectives were defined:

1. Systematize scientific and methodological approaches to the assessment of surface water quality and basin environmental safety.

2. Develop an algorithm for calculating the entropy-weighted water pollution index (EWQI) that accounts for the actual variability of hydro chemical indicators.

3. Conduct a seasonal and spatial analysis of surface water quality using entropy-weighted coefficients.

4. Identify critical areas with high levels of anthropogenic pressure and assess environmental risks.

5. Develop recommendations for improving observation systems and decision-making processes in water safety management, considering seasonal variations.

The scientific novelty of the study lies in the formation of an adaptive entropy-weighted model that integrates quantitative entropy analysis with spatiotemporal monitoring data, enhancing the precision and sensitivity of surface water quality assessment. The practical significance of the results lies in their potential application for optimizing monitoring networks, assessing ecological risks, and developing regional strategies for sustainable water resource management.

Thus, the implementation of these objectives provides the basis for a new approach to evaluating the environmental safety of Ukrainian river basins, ensuring objectivity, flexibility, and reproducibility of results while minimizing subjective influence on environmental decision-making.

Methods

autumn periods – ensuring the reflection of the natural dynamics of hydro chemical processes.

The assessment of surface water quality was performed using ten key physicochemical indicators that characterize the hydro chemical stability and ecological safety of aquatic systems: pH, dissolved oxygen, biochemical oxygen demand (BOD₅), chemical oxygen demand (COD), ammonium nitrogen, nitrates, phosphates, total iron, total hardness, and total mineralization.

The selection of these indicators is justified by the methodological recommendations of the World Health Organization (WHO), the provisions of EU Water Framework Directive 2000/60/EC, and the requirements of current

Ukrainian environmental legislation, ensuring the comparability of results with international water quality assessment practices.

Calculation of the Entropy-Weighted Water Quality Index (EWQI) was performed in several sequential stages [7–9] (Table).

1. Formation of the initial observation matrix, which included the measured values of water samples and the corresponding parameters (1):

$$X = \begin{bmatrix} x_{11} & x_{12} & \dots & x_{1n} \\ x_{21} & x_{22} & \dots & x_{2n} \\ \vdots & \vdots & \ddots & \vdots \\ x_{m1} & x_{m2} & \dots & x_{mn} \end{bmatrix} \quad (1)$$

where (x_{ij}) is the concentration of the i -th substance for the j -th sampling point (mg/dm³).

2. Construction of the normalized matrix, where each evaluated parameter is expressed in dimensionless form to eliminate errors caused by different measurement units (2):

$$Y = \begin{bmatrix} y_{11} & y_{12} & \dots & y_{1n} \\ y_{21} & y_{22} & \dots & y_{2n} \\ \vdots & \vdots & \ddots & \vdots \\ y_{m1} & y_{m2} & \dots & y_{mn} \end{bmatrix} \quad (2)$$

where (y_{ij}) is the normalized value of the i -th substance for the j -th sampling point.

The normalized value of a parameter is determined by:

$$y_{ij} = \frac{x_{ij} - (x_{ij})_{\min}}{(x_{ij})_{\max} - (x_{ij})_{\min}} \quad (3)$$

For dissolved oxygen, where higher values indicate better quality, normalization is performed inversely:

$$y_{ij} = \frac{(x_{ij})_{\max} - x_{ij}}{(x_{ij})_{\max} - (x_{ij})_{\min}} \quad (4)$$

3. Calculation of information entropy (E) for each parameter using the Shannon entropy formula (5):

$$E_n = - \left(\frac{1}{\ln n} \right) \sum_{i=1}^m V_{ij} \ln V_{ij} \quad (5)$$

where n is the number of sampling points, and (V_{ij}) is the probability of occurrence of the normalized value (v_{ij}) for parameter j in the i -th sample:

$$V_{ij} = \frac{v_{ij}}{\sum v_{ij}}. \quad (6)$$

4. Determination of entropy weights (W), where parameters with lower entropy (i.e., less disorder) receive higher weights:

$$W_j = (1 - E_j) / \sum_{j=1}^t (1 - E_j). \quad (7)$$

Parameters with lower entropy indicate more structured and less random systems and thus carry more information for assessing water quality.

5. Aggregation of entropy weights and quality scores into the entropy-weighted water quality index (EWQI):

$$EWQI = \sum_{j=1}^n W_j U_j, \quad (8)$$

where (EWQI) is the entropy-weighted water quality index, and (U_j) for each parameter is defined as the ratio of the observed value (I_j) to the corresponding standard value (S_j) :

$$U_j = \left(\frac{I_j}{S_j} \right). \quad (9)$$

Table

The calculated EWQI values were classified according to a seven-class water quality scale.

Class	Water Quality Description	EWQI Range
I	Very clean	≤ 0.3
II	Clean	$0.3 < EWQI \leq 1$
III	Moderately polluted	$1 < EWQI \leq 1.5$
IV	Polluted	$1.5 < EWQI \leq 2$
V	Dirty	$2 < EWQI \leq 4$
VI	Very dirty	$4 < EWQI \leq 8$
VII	Extremely dirty	> 8

For calculations, the upper limit of Class II water quality was adopted as the reference standard according to DSTU 4808:2007

“Sources of centralized drinking water supply. Hygienic and environmental requirements for water quality and sampling procedures”.

Results

River basins that provide drinking water to the population and play a crucial role in

forming ecosystem services require scientifically grounded and technologically efficient

management approaches aimed at maintaining their ecological stability and safety. Achieving this goal involves not only recording pollutant concentrations but also understanding the structural order of the system, its self-regulation capacity, and its response to anthropogenic influences.

Applying the concept of entropy as a quantitative measure of uncertainty and disorder makes it possible to assess the level of destabilization of hydro ecosystems and determine which parameters have the most significant influence on the overall ecological state of the basin. This approach provides a deeper understanding of the degradation processes in aquatic environments, allowing for the identification of high-risk zones and factors that reduce ecological stability.

Based on the methodology for determining the entropy-weighted water quality index (EWQI), calculations were performed for each monitoring station using surface water monitoring data provided by the State Agency of Water Resources of Ukraine. Integrated EWQI values were obtained for each river basin, reflecting the spatial and seasonal dynamics of water quality and the level of anthropogenic load.

The results of the analysis of the entropy-weighted water pollution index (EWQI) across major river basins of Ukraine and seasonal periods were visualized in Figure 1, which illustrates both inter-basin and seasonal contrasts in

the indicators of surface water environmental safety.

In the spring season, the cleanest waters were recorded in the Danube basin (EWQI = 0.33; “clean water”), while the Southern Bug basin showed the highest level of pollution (EWQI = 1.58; “polluted water”). During the winter period, the Danube once again demonstrated the best water quality (EWQI = 0.28; “very clean water”), whereas the Southern Bug was characterized by a high pollution level (EWQI = 2.33; “dirty water”).

In the low-flow phase (mezhin’), most river systems exhibited a moderate level of contamination. The lowest EWQI values were observed in the Danube (EWQI = 0.48; “clean water”), while the highest occurred in the Dniester (EWQI = 1.37; “moderately polluted water”). During the shallow-water period, the maximum pollution levels were detected across all basins. In particular, the Southern Bug (EWQI = 13.54) and the Azov rivers (EWQI = 12.39) were classified as “extremely dirty waters.” In the autumn season, high pollution levels persisted, especially in the Black Sea (EWQI = 14.23) and Southern Bug basins (EWQI = 11.60), both remaining in the “extremely dirty” category.

Overall, the lowest EWQI values were typical of the winter and spring seasons, whereas the highest pollution levels occurred during the shallow-water period, when reduced water discharge led to the concentration of contaminants.

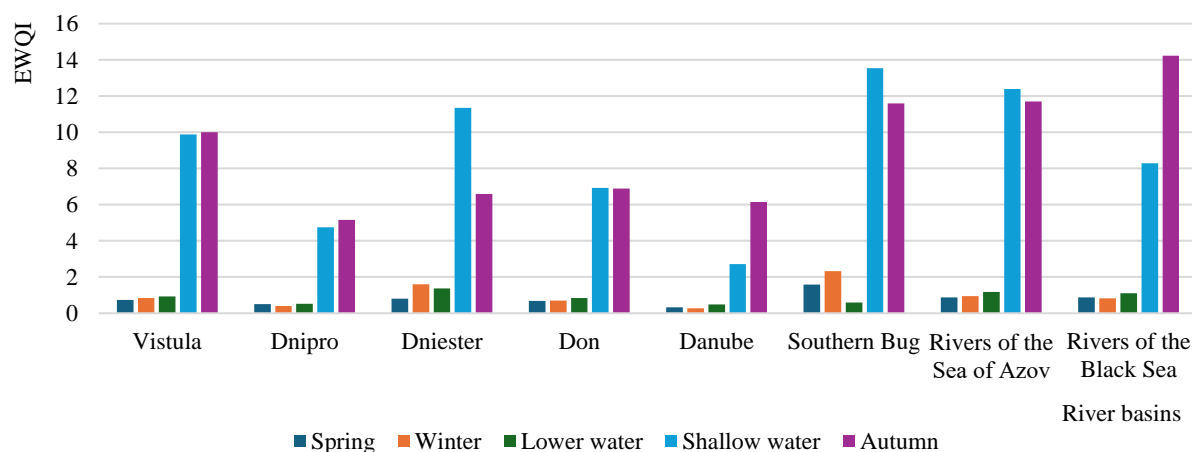


Fig. 1 – Distribution of average values of the entropy-weighted water pollution index (EWQI) across river basins and seasonal periods

The cleanest rivers were the Danube and, to a lesser extent, the Dnipro, which maintained consistently low EWQI values even during

periods of general water quality deterioration. The most polluted basins included the Southern Bug, the Black Sea, and the Azov regions,

particularly during the autumn and shallow-water periods.

Thus, the seasonal factor plays a decisive role in shaping surface water quality, as changes in hydrological conditions directly influence the degree of anthropogenic impact. Elevated pollution levels during low-water phases highlight the

need for enhanced monitoring and the implementation of adaptive water quality management strategies, particularly for the Southern Bug and Black Sea basins. To visually represent the spatial and seasonal patterns, maps of average EWQI distribution were constructed (Fig. 2–6).

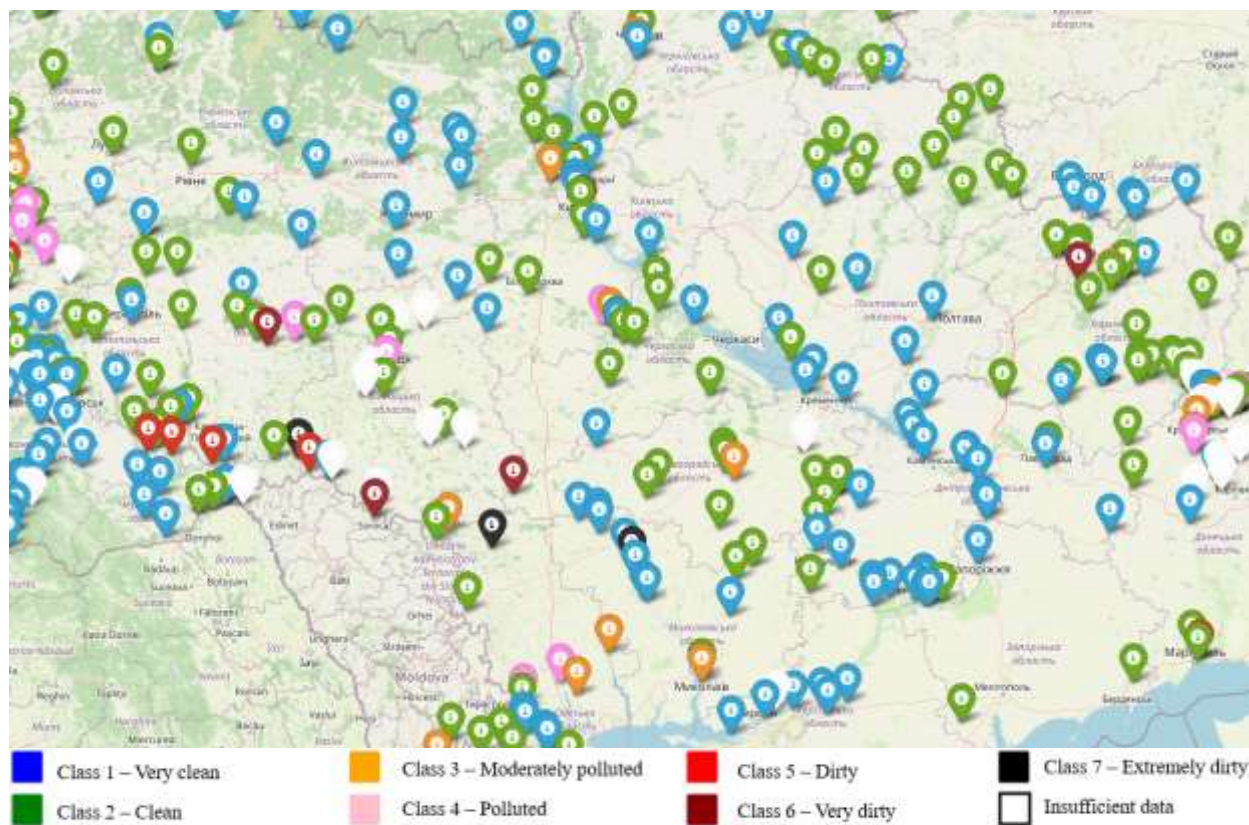


Fig. 2 – Fragment of a map of the spatial distribution of the entropy-weighted water pollution index for the winter period

The map of the spatial distribution of the entropy-weighted water pollution index (EWQI) for the winter period (Figure 2) illustrates the quality of surface waters within Ukraine's river basins according to a classification system comprising seven pollution grades – from “very clean” (blue) to “extremely dirty” (black).

The results of the spatial analysis reveal a clear differentiation of water quality depending on the basin and geographical location. The highest water quality is observed in the Danube basin, where EWQI values are the lowest, corresponding to classes I–II (“very clean” and “clean” water). The northern regions of Ukraine also demonstrate predominantly low EWQI values (classes I–II), indicating a minimal level of anthropogenic impact.

Zones with moderate pollution levels include the Dniester and Don basins, where water quality mainly corresponds to classes III–IV (“moderately polluted” and “polluted”). The most problematic regions are the Black Sea and Azov basins, characterized by high EWQI values corresponding to classes VI–VII (“very dirty” and “extremely dirty” water). Elevated pollution levels are also noted in the Southern Bug basin, reflecting the significant influence of human activity. The spatial distribution map of EWQI for the spring period (Fig. 3) shows an improvement in the ecological condition of surface waters compared to other seasons. This improvement is primarily due to increased water discharge resulting from snowmelt and spring floods, which dilute pollutant concentrations

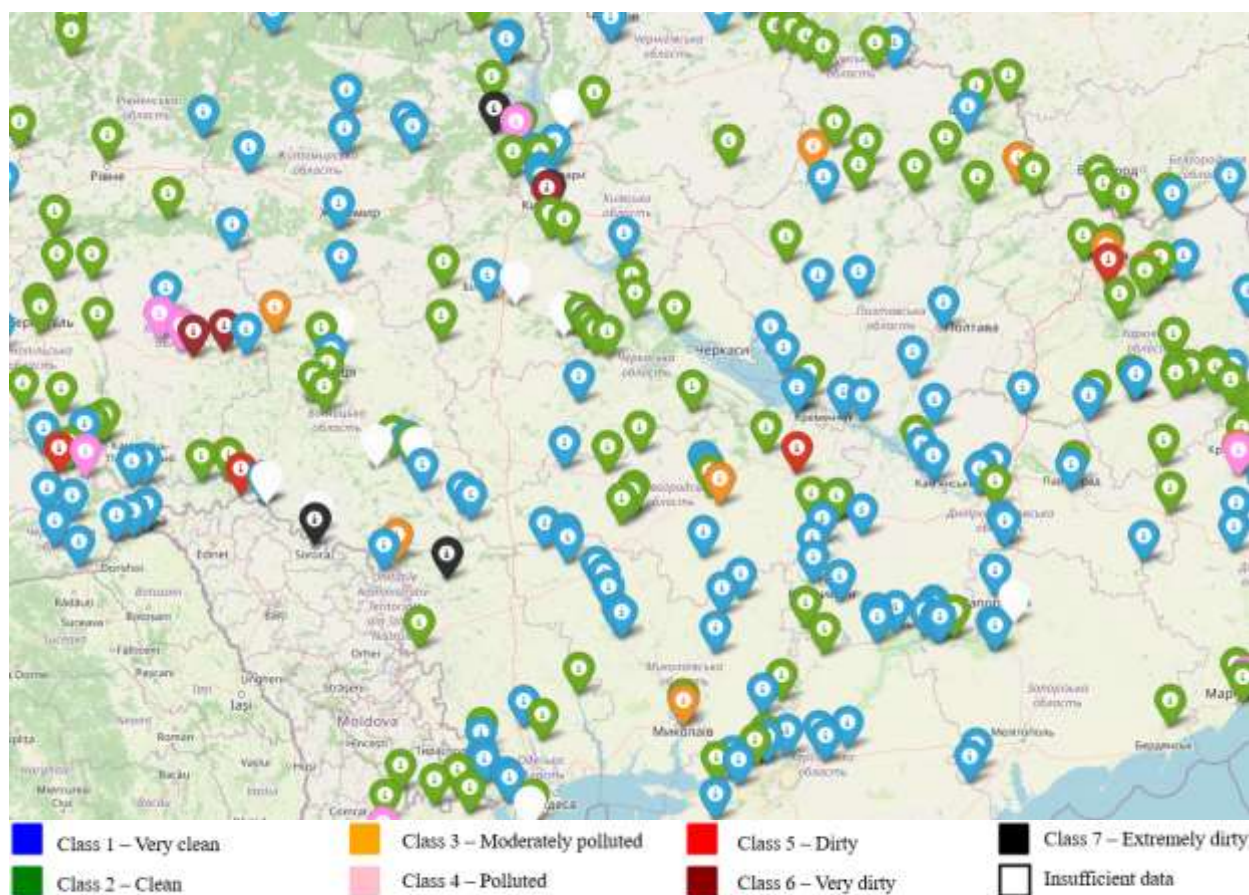


Fig. 3 – Fragment of a map of the spatial distribution of the entropy-weighted water pollution index for the spring period

and lead to a temporary enhancement of the hydrochemical characteristics of aquatic ecosystems.

However, the level of water quality remains spatially heterogeneous and largely depends on geographical location and basin affiliation.

Regions with the best water quality indicators (classes I–II – “very clean” and “clean water”) include the Danube basin, where blue and green shades dominate on the map, indicating low EWQI values. This can be explained by a lower concentration of industrial facilities, high water exchange rates, and favorable natural conditions. Similarly, the western river basins, such as the Vistula and Dniester, contain a significant number of monitoring points that also correspond to classes I–II, indicating clean or very clean water.

Areas with a moderate level of pollution (classes III–IV – “moderately polluted” and “polluted water”) cover the central part of Ukraine. In the Dnipro and Don basins, an increased number of yellow and pink markers (classes III–IV) are observed, indicating

localized anthropogenic impacts related to agricultural activities, industrial enterprises, and urbanized areas. In the Black Sea and Azov rivers, individual sites exhibit moderate pollution levels, likely due to dispersed wastewater discharges and the limited self-purification capacity of small watercourses.

Zones with high pollution levels (classes V–VII – “dirty,” “very dirty,” and “extremely dirty water”) primarily include the Southern Bug basin, where red and black markers on the map highlight areas of significant anthropogenic pressure. This is likely caused by high industrialization, urbanization, and intensive agricultural runoff. In some parts of the Azov basin, extremely high EWQI values (black color) have been recorded, indicating a critical condition of aquatic ecosystems in these regions.

During the spring period, overall water quality improves across most regions due to the dilution of pollutants by floodwaters. This trend is clearly visible in the Danube, Vistula, and partially Dniester basins, where contaminant concentrations decrease significantly. However, the

Southern Bug, Black Sea, and partially Dnipro basins remain the most problematic, as even spring floods cannot offset the effects of anthropogenic pollution sources.

The spatial distribution map of EWQI for the low-flow period (Fig. 4) illustrates the specific seasonal characteristics of surface water conditions during the lowest-water phase, when the natural self-purification capacity of river systems reaches its minimum.

Regions with the highest water quality (classes I–II – “very clean” and “clean water”) include the Danube basin, where most points on the map remain blue and green, indicating a consistently clean water condition. This confirms the ecological resilience of the hydrological system even under conditions of reduced water flow.

In the western part of Ukraine, particular the Vistula basin, a similar trend is observed: rivers in this region mostly belong to classes I–II, reflecting a low level of anthropogenic

impact. In the northern section of the Dnipro basin, low EWQI values are also recorded, corresponding to “clean” or “moderately clean” water classes.

Regions with a moderate level of pollution (classes III–IV – “moderately polluted” and “polluted water”) include the Dniester basin, which, compared to other areas, shows an increase in yellow and pink markings on the map, indicating rising pollution levels. A similar situation is observed in the Don and Black Sea basins, where classes III–IV dominate, suggesting notable anthropogenic pressure and accumulation of pollutants resulting from decreased water discharge.

Areas with high pollution levels (classes V–VII – “dirty,” “very dirty,” and “extremely dirty water”) include the Southern Bug basin, where red and black markers indicate a critical ecological condition. The main causes are the high concentration of industrial facilities, urbanization,

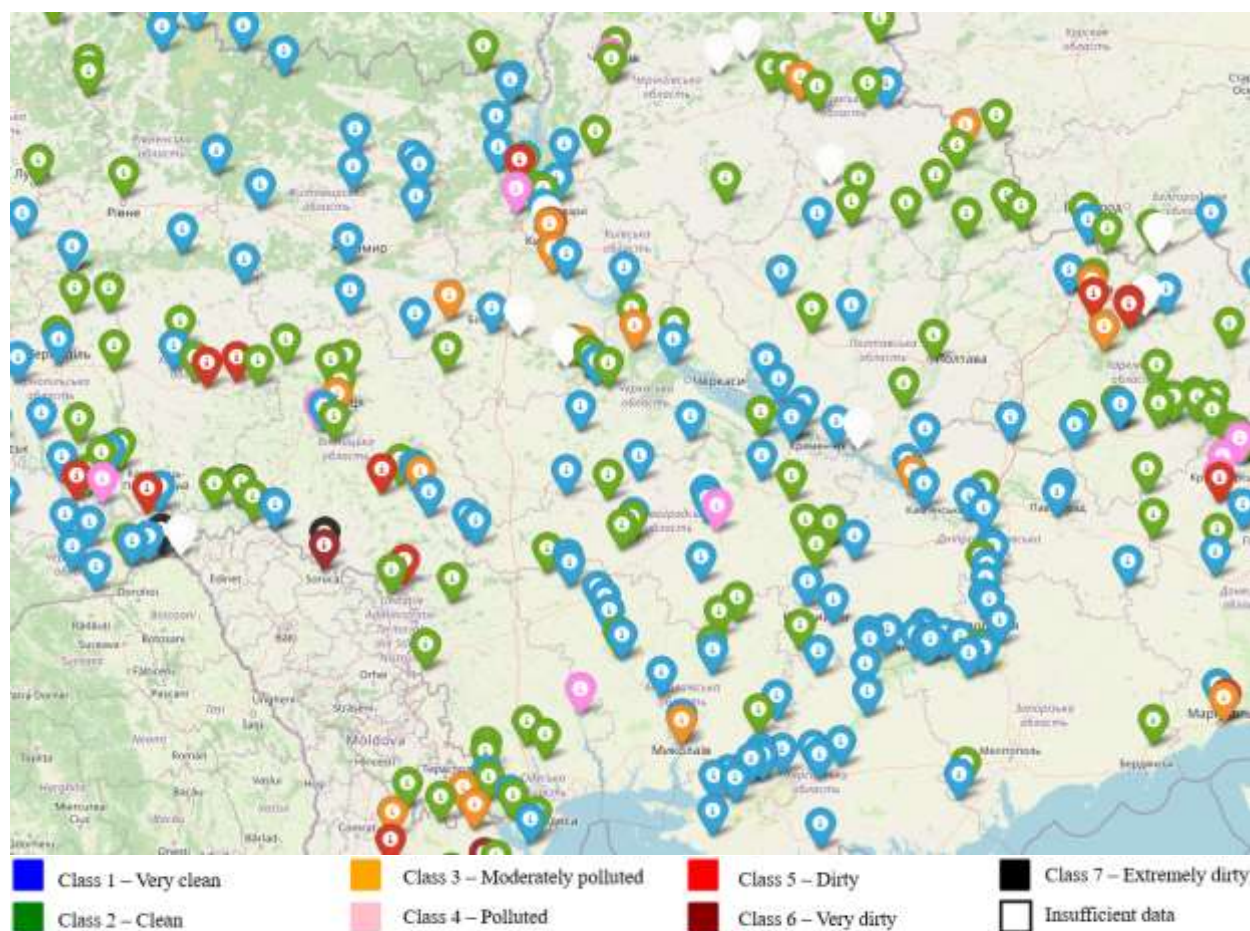


Fig. 4 – Fragment of a map of the spatial distribution of the entropy-weighted water pollution index for the low water period

and agricultural runoff. Some sites within the Black Sea river basin show elevated EWQI values, confirming significant anthropogenic stress. In certain Azov river sections, extreme EWQI values (class VII) are recorded, indicating an extremely critical state of the aquatic environment.

During the low-flow period, water quality deteriorates across nearly all basins due to reduced discharge and the corresponding increase in pollutant concentrations.

The spatial distribution map of EWQI for the shallow-water period (Fig. 5) reflects the most strained ecological state of water resources, caused by minimal river flow volumes. This period shows maximum pollution levels across most regions of Ukraine.

Basins with relatively favorable indicators (classes I–II – “very clean” and “clean water”) include the Danube basin, where blue and green areas persist only in limited sections, indicating relative ecological stability even under low-water conditions. The Vistula basin also exhibits a moderately good water quality, attributed to lower industrial density and limited anthropogenic impact.

Regions with moderate pollution (classes III–IV) include the Dniester basin, where yellow

and pink markers predominate, signaling a moderate contamination level likely caused by a reduction in the river’s self-purification capacity during periods of low flow. In the Dnipro and Don basins, water quality indicators also deteriorate but remain within classes III–IV, suggesting a stable yet tense ecological condition.

Regions with a high level of pollution (classes V–VII – “dirty,” “very dirty,” and “extremely dirty water”) primarily include the Southern Bug basin, where numerous red, dark red, and black markers on the map indicates a critically high level of water contamination. The main contributing factors are industrial activities, agricultural runoff, and the insufficient efficiency of wastewater treatment facilities.

In the Black Sea and Azov basins, classes VI–VII dominate, reflecting extremely polluted water. This condition signifies a catastrophic overload of aquatic ecosystems, caused by intensive economic activity, urbanization of coastal areas, and the low self-purification capacity of watercourses.

The Dnipro basin also demonstrates elevated EWQI values, confirming a significant an-

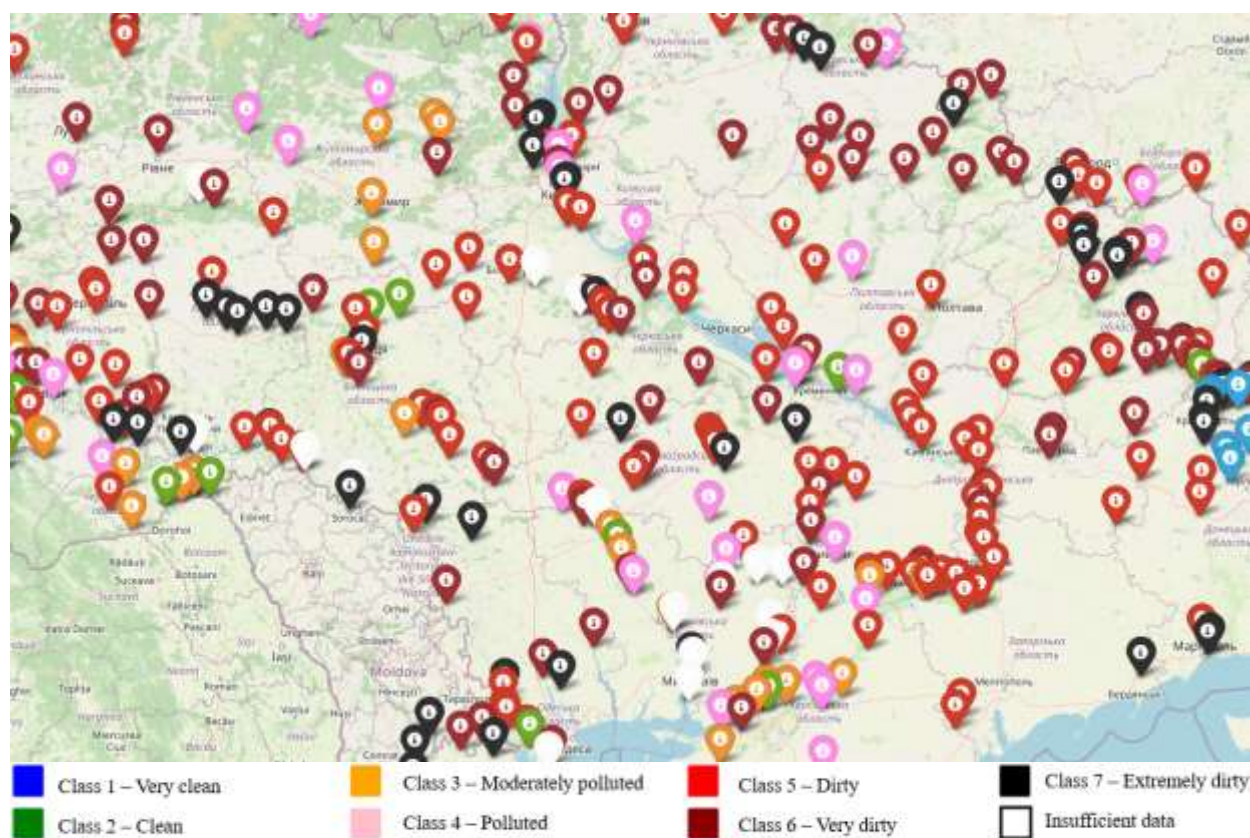


Fig. 5 – Fragment of a map of the spatial distribution of the entropy-weighted water pollution index for the shallow water period

thropogenic impact associated with industrial discharges, wastewater effluents, and the accumulation of pollutants in bottom sediments. Particularly critical conditions are observed in small and medium-sized rivers, where low water levels lead to a concentration of contaminants, severely deteriorating the ecological state of water bodies.

The spatial distribution map of EWQI for the autumn period (Fig. 6) illustrates the state of surface water quality in Ukraine at the end of the hydrological cycle, when – following the summer low-water phase – river flows have not yet reached their minimum but the dilution capacity for pollutants is already reduced. The analysis of the data reveals pronounced regional contrasts in pollution levels, formed under the combined influence of natural factors (hydrological regime, climatic conditions) and anthropogenic pressures (industrialization, agriculture, and urban development).

Regions with the highest water quality (classes I–II – “very clean” and “clean water”)

cover the western part of Ukraine, primarily the Danube and Vistula basins. These areas show the highest concentration of blue and green markers, indicating a high ecological status of water resources. Such stability is attributed to low anthropogenic pressure, the effectiveness of natural self-purification processes, and favorable hydro-climatic conditions of the region. Isolated zones with clean water are also observed in the central and northern parts of the Dniro basin, where pollution levels remain relatively low due to natural water circulation and lower industrialization of the area.

Regions with a moderate level of pollution (classes III–IV – “moderately polluted” and “polluted water”) include the Dniester and Dniro basins, where numerous yellow and pink markers indicate medium contamination levels. This condition results from a combination of natural hydrological factors and localized anthropogenic influences, such as agricultural activity, surface runoff of fertilizers, and

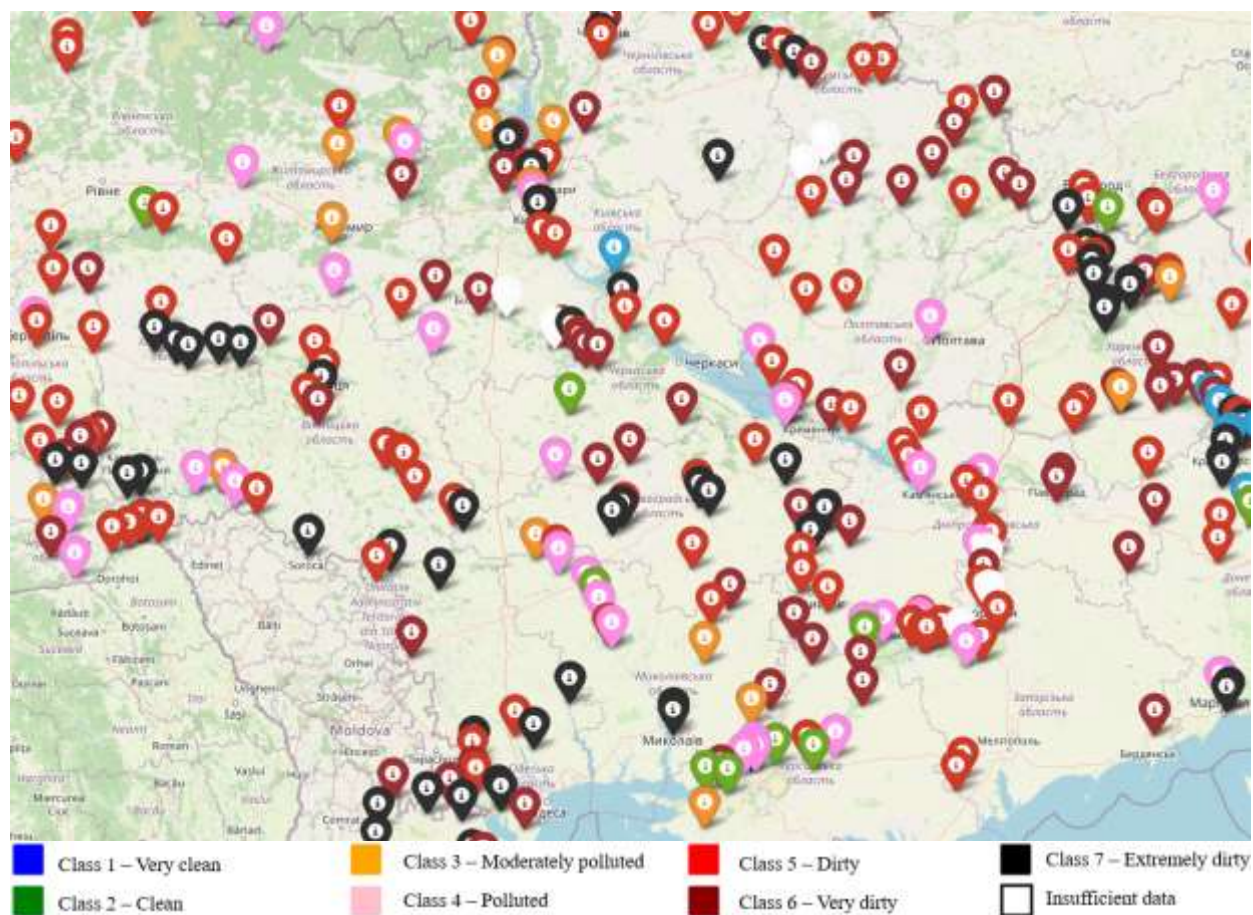


Fig. 6 – Fragment of a map of the spatial distribution of the entropy-weighted water pollution index for the autumn period

insufficiently treated wastewater. A similar pattern is found in some parts of the Black Sea and Azov river basins, where moderate pollution levels are typical for zones of intensive agricultural production.

Areas with critical water quality indicators (classes V–VII – “dirty,” “very dirty,” and “extremely dirty water”) include the Southern Bug basin, where red, dark red, and black markers dominate, reflecting high concentrations of pollutants. This basin is considered one of the most vulnerable in Ukraine due to intense industrial pressure, urbanization, and agricultural pollution. High pollution levels are also recorded in the Black Sea and Azov basins, where numerous zones with “very dirty” and “extremely dirty” water are caused by excessive

fertilizer use, erosional runoff from farmlands, and inefficient wastewater treatment systems.

In the eastern regions of Ukraine, particularly in the Don and eastern Dnipro basins, a large number of areas fall into pollution classes VI–VII, associated with industrial zones, a high concentration of point-source discharges, and the accumulation of technogenic substances in bottom sediments.

The autumn period marks the initial phase of pollutant accumulation, serving as a precursor to further water quality deterioration during the winter and low-flow (*mezheny*) seasons, when hydrological processes slow down and the dilution of pollutants becomes minimal.

Discussion

The analysis of the spatial distribution of the entropy-weighted water pollution index (EWQI) revealed distinct patterns of seasonal and regional variability in the quality of surface waters across Ukraine.

During the winter period, most river basins demonstrate the best ecological condition: EWQI values remain low, particularly in the western regions (Danube, Vistula) and in the upper reaches of the Dnipro basin. This is attributed to a stable hydrological regime and low anthropogenic pressure.

In spring, water quality generally improves due to increased flow, snowmelt floods, and dilution of pollutants. The Danube and Vistula basins show the best indicators (classes I–II), confirming the effective self-purification capacity of aquatic ecosystems. Meanwhile, in the central regions and the lower Dnipro, localized zones of elevated pollution appear, linked to intensive agriculture and urban runoff.

During the low-flow (*mezheny*) period, as river discharge decreases, EWQI values rise, indicating a deterioration in water quality and a growing contrast between basins. The entropy-weighted index effectively differentiates pollution levels, capturing even minor variations in contaminant concentrations.

The worst ecological conditions are observed during the shallow-water period, when river volumes reach their minimum and dilution processes almost cease. At this time, EWQI reaches its highest values in the Southern Bug, Black Sea, and Azov basins, dominated by

classes VI–VII – indicative of critical water ecosystem states. High pollutant concentrations result from the accumulation of industrial and domestic effluents, as well as intensive agricultural loads.

In autumn, pollution levels remain high but do not reach the extreme peaks typical of the shallow-water season. Spatial contrasts persist: the western basins (Danube, Vistula) remain the cleanest, while the Southern Bug, Black Sea, and Azov basins show the highest contamination levels throughout the year, indicating persistent sources of anthropogenic pressure.

The highest EWQI values are typical of the autumn and shallow-water periods, when reduced flow contributes to pollutant concentration. The most polluted basins are the Dniester, Southern Bug, and Dnipro, where extreme EWQI values are recorded in areas directly affected by industrial and agricultural discharges.

During winter, critical EWQI values are observed in the Southern Bug (31.67), Dniester (66.66), and Dnipro (6.29) basins, particularly near industrial facilities and discharge channels. In spring, the index increases due to floodwaters washing pollutants from soils, with the highest levels in the Southern Bug (41.69), Dniester (12.58), and Dnipro (8.51) basins. During the *mezheny* period, water quality worsens – the Dniester (34.21) and Danube (24.48) show critical conditions due to industrial discharges, while the Dnipro (22.51) and Southern Bug (13.43) maintain consistently high values.

The shallow-water period records the

poorest ecological conditions: maximum EWQI values in the Dniester (167.57), Dnipro (75.67), and Southern Bug (327.23) basins exceed permissible pollution limits. The main factors include industrial discharge channels, agricultural runoff, and untreated domestic wastewater. In autumn, pollution remains high, especially in the Southern Bug (65.03), Dniester (64.13), and Dnipro (58.26) basins, influenced by large industrial facilities, such as the Mykolaiv TPP.

Summarizing the results, the key problematic basins can be identified as follows: the Southern Bug, with the highest EWQI values across all seasons (up to class VII); the Dniester,

with persistently high contamination near wastewater treatment zones; and the Dnipro, significantly affected by industrial discharges and thermal water return flows. On the Danube, pollution is recorded mainly during the *mezhen-nyi* and shallow-water periods, particularly near Lake Katlabukh.

The dynamics of EWQI and changes in water quality classes for the main rivers – Southern Bug, Dniester, and Siverskyi Donets – are shown in Figures 7–12, illustrating the seasonal fluctuations in pollution levels and the impact of technogenic factors on Ukraine's surface waters.

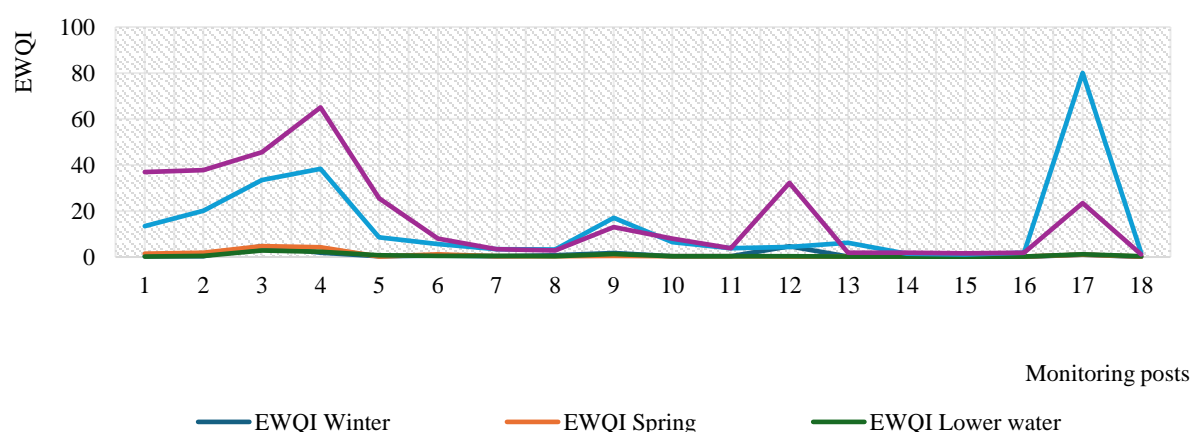


Fig. 7 – Variation of the Entropy-Weighted Water Quality Index (EWQI) based on monitoring results for the Southern Bug River

For the Southern Bug River (Fig. 7–8), the EWQI values demonstrate a pronounced seasonal variability in water quality. The lowest average index is recorded during the low-flow period (0.684), while the highest value occurs in autumn (17.443). The standard deviation indicates a substantial variability of the water quality index, particularly during the shallow-water and autumn periods, reflecting significant differences between individual monitoring stations.

In the winter and spring seasons, a greater proportion of measurements correspond to higher water quality classes (classes 1–2). In contrast, during the low-flow and shallow-water phases, the distribution shifts toward lower classes, with a sharp increase in the proportion of measurements classified as class 7, indicating extremely polluted water conditions.

The autumn period is characterized by high EWQI values, with the majority of meas-

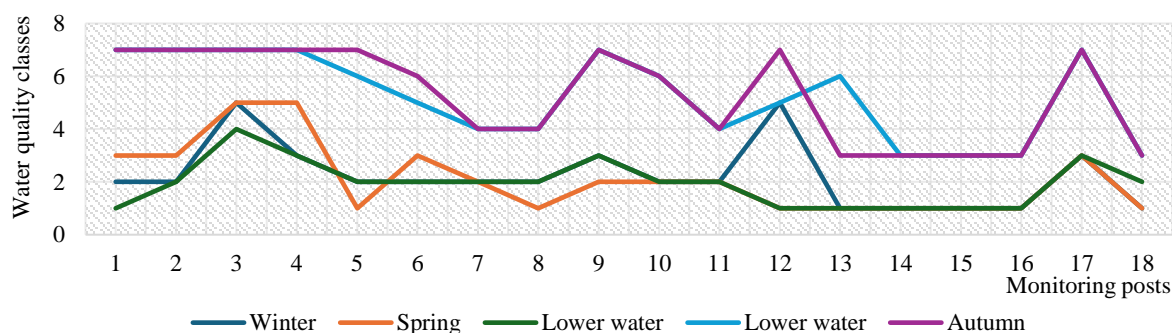


Fig. 8 – Variation of water quality classes based on monitoring results for the Southern Bug River

urements falling into classes 6 and 7, indicating a significant deterioration in the ecological condition of the river. The results confirm that the water quality of the Southern Bug River fluctuates considerably throughout the year, with the worst indicators observed in autumn, when the chemical composition of the water is strongly influenced by seasonal processes, surface runoff, and agricultural pressures.

For the Dniester River (Fig. 9), the EWQI values exhibit a clearly defined seasonal variability in water quality, with the highest index recorded in winter (4.233). The standard deviation reflects a substantial variability of the

index, particularly during the winter period, indicating noticeable spatial differences in pollution levels among individual monitoring sites within the river basin.

During the winter and spring periods, the majority of measurements correspond to the higher water quality classes (classes 1–2), with the largest number of observations falling into class 1 (Fig. 10), indicating a favorable ecological condition of the river at that time.

In contrast, during the shallow-water and autumn periods, there is an increase in the proportion of measurements corresponding to lower water quality classes (class 3 and above). Par-

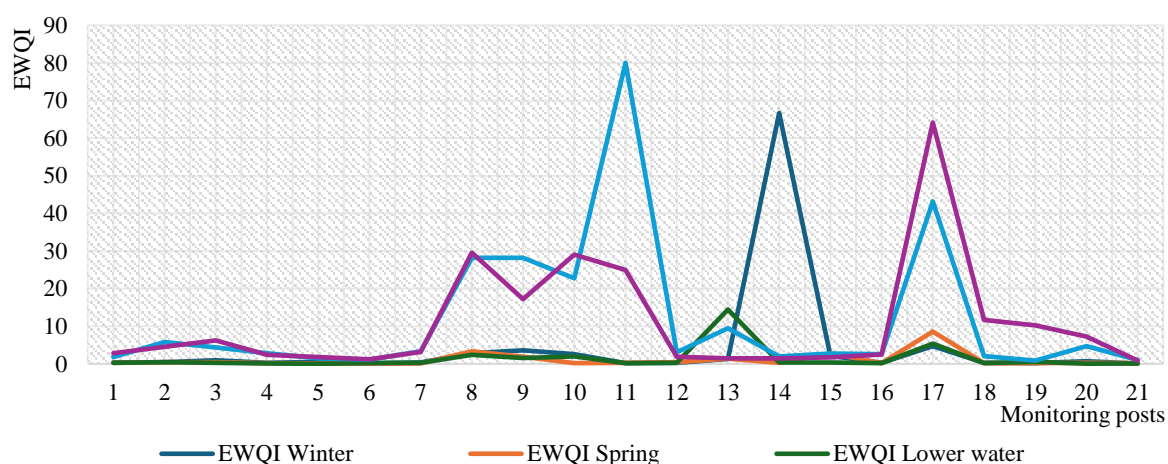


Fig. 9 – Variation of the Entropy-Weighted Water Quality Index (EWQI) based on monitoring results for the Dniester River

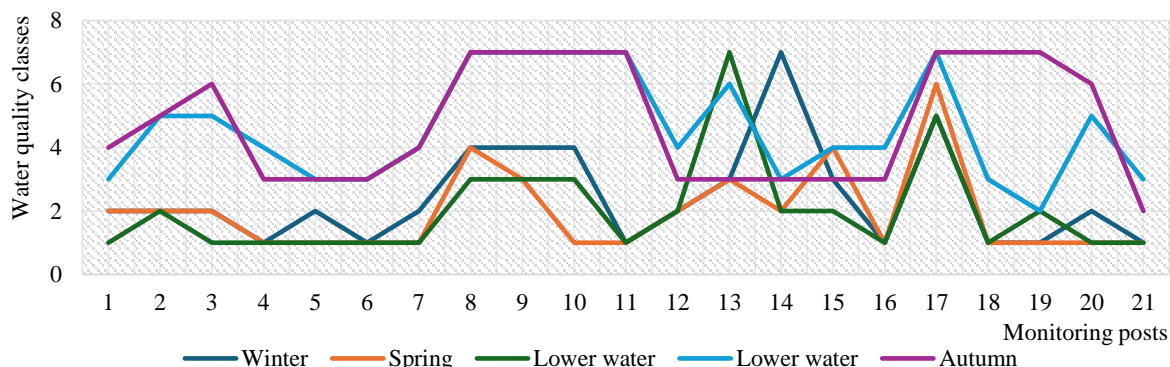


Fig. 10 – Variation of water quality classes based on monitoring results for the Dniester River

ticularly notable is the growth in the number of points belonging to classes 3 and 7, which indicates a deterioration in water quality and the presence of localized pollution events. The obtained results indicate that the Dniester River exhibits a pronounced seasonal variability in water quality, with a deterioration of conditions during the shallow-water and autumn periods.

Particularly notable is the high variability of EWQI values in winter, which can be attributed to the specific hydrological regime of the river and the influence of local anthropogenic factors, such as wastewater discharges and industrial pressure.

For the Siverskyi Donetsk River (Fig. 11), the average EWQI values show that the highest

water quality occurs in winter (0.446) and spring (0.498). During the summer low-flow period, water quality deteriorates (0.647), and a significant increase in pollution levels is recorded during the shallow-water (5.940) and autumn (6.266) seasons. The standard deviation values indicate a homogeneous water environment in winter and spring, whereas during shallow-water and autumn periods, an increased variability is observed, reflecting the presence of local pollution sources and the uneven distribution of anthropogenic impacts.

During the winter and spring periods, the

majority of measurements correspond to class 2 water quality, indicating a relatively high ecological condition of the river (Fig. 12).

In contrast, during the shallow-water and autumn periods, there is a significant deterioration in water quality, with most values falling into classes 5 and 6, which reflects an increase in pollution levels and a decline in the natural self-purification capacity of the aquatic ecosystem.

The obtained results indicate a distinct seasonal dynamic of water quality: the best conditions are observed during the cold period of the year (winter and spring), while during the

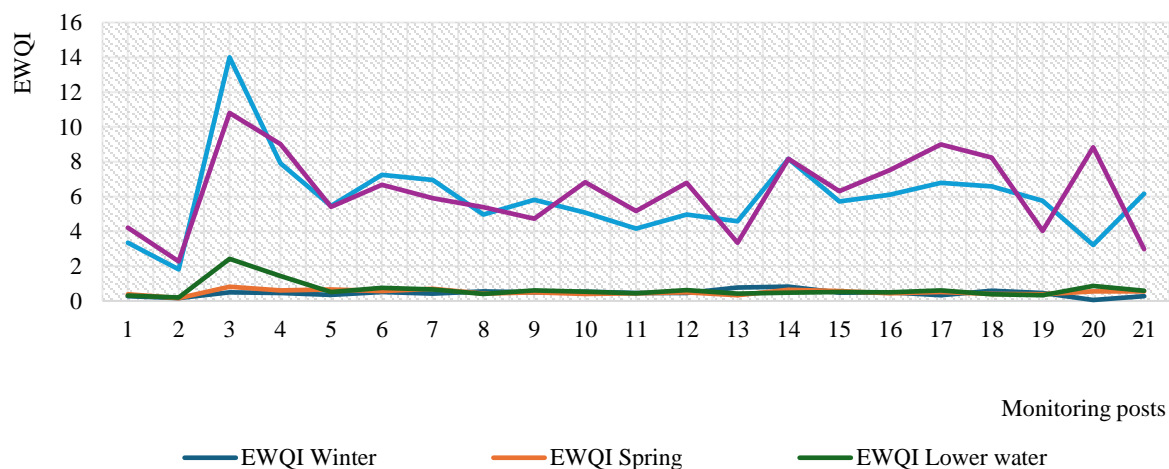


Fig. 11 – Variation of the Entropy-Weighted Water Quality Index (EWQI) across monitoring stations of the Siverskyi Donets River

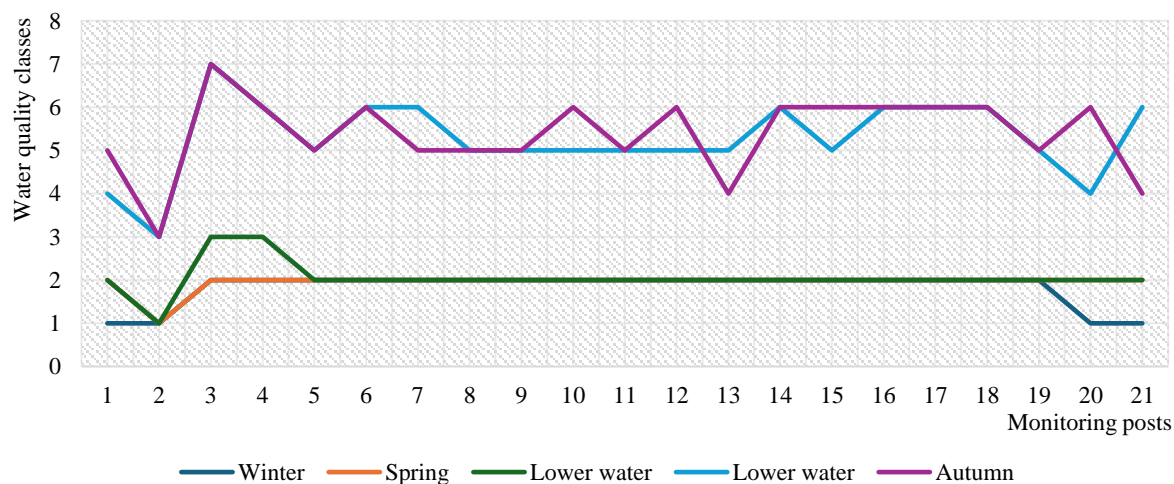


Fig. 12 – Variation of water quality classes based on monitoring results for the Siverskyi Donets River

warmer months (shallow-water and autumn) there is a notable deterioration in water quality.

The most critical periods are shallow-water and autumn, when low water levels, higher

temperatures, and intensified anthropogenic pressure lead to an increase in pollutant concentrations, significantly reducing the ecological safety of river ecosystems.

Conclusions

The study achieved its main objective – the development and testing of an entropy-weighted model for assessing the environmental safety of surface waters in Ukraine, which made it possible to quantitatively evaluate the seasonal and spatial variability of water quality within the country's major river basins.

The results demonstrated a distinct seasonal dynamic in the quality of surface waters. The best indicators were recorded in spring (EWQI = 0.65) and winter (EWQI = 0.77), reflecting a relatively high water quality due to dilution of pollutants and reduced anthropogenic pressure. During the low-flow period, the average EWQI value was 0.71, indicating an acceptable ecological condition.

In contrast, during the shallow-water (EWQI = 6.69) and autumn (EWQI = 6.89) periods, a sharp decline in water quality was observed, caused by low discharge, increased temperature, and pollutant accumulation. These seasons present the greatest ecological risks for

aquatic ecosystems, particularly in the Southern Bug, Black Sea, and Azov Sea river basins, which remain the most critical areas in terms of technogenic load and pollution.

The comparative analysis revealed that the entropy-weighted water pollution index (EWQI) is a more sensitive and informative tool than traditional index-based methods, as it accounts for the spatio-temporal variability of parameters. This approach significantly improves the accuracy of identifying local risk zones and creates a foundation for optimizing environmental monitoring systems.

Thus, the entropy-weighted model for water quality assessment can serve as a scientifically grounded instrument for managing the environmental safety of Ukraine's river basins, contributing to the implementation of sustainable development goals, the rational use of water resources, and the reduction of anthropogenic impacts on the environment.

Conflict of Interest

The author declares no conflict of interest regarding the publication of this manuscript. Furthermore, the author has fully adhered to ethical norms, including avoiding plagiarism, data falsification, and duplicate publication.

The work does not use artificial intelligence resources.

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The article was received by the editors 28.10.2025
The article is recommended for printing 05.12.2025

The article was revised 30.11.2025
This article published 30.12.2025

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ЕНТРОПІЙНО-ЗВАЖЕНА МОДЕЛЬ ОЦІНЮВАННЯ ЕКОЛОГІЧНОЇ БЕЗПЕКИ ПОВЕРХНЕВИХ ВОД УКРАЇНИ

Мета. Розробка та апробація адаптивної ентропійно-зваженої моделі, що дозволяє усунути суб'єктивність традиційних індексних методів та врахувати просторово-часову мінливість гідрохімічних показників для підвищення ефективності управління екологічною безпекою річкового басейну.

Методи. Методологія базується на розрахунку ентропійно-зваженого індексу якості води (EWQI), де вага кожного фізико-хімічного параметру визначається за допомогою ентропії Шеннона.

Результати. Проаналізовано дані спостережень понад 540 пунктів моніторингу в межах основних річкових басейнів України для п'яти сезонних фаз гідрологічного циклу з картографічною візуалізацією результатів розрахунків. Встановлено чітку залежність якості води від гідрологічного режиму. Найкращий екологічний стан зафіксовано в зимовий та весняний періоди (басейни Дунаю, Вісли) завдяки природному розбавленню забруднень. Критичне погіршення якості спостерігається у маловодний та осінній періоди, коли індекси забруднення досягають екстремальних значень, особливо в басейнах Південного Бугу, річок Причорномор'я та Приазов'я (класи «дуже брудна» та «надзвичайно брудна» вода). Просторовий аналіз локалізував зони найвищого антропогенного ризику, підтвердивши неефективність самоочищення річок у промислових навантажених регіонах під час межени.

Висновки. Запропонована модель продемонструвала високу чутливість до сезонних змін та антропогенного навантаження; забезпечує наукове підґрунтя для переходу до адаптивного управління водними ресурсами, дозволяючи пріоритизувати водоохоронні заходи та оптимізувати систему моніторингу відповідно до періодів максимального екологічного ризику.

КЛЮЧОВІ СЛОВА: ентропійно-зважена модель, якість поверхневих вод, EWQI, екологічна безпека, сезонна динаміка, річковий басейн

Конфлікт інтересів

Автор заявляє, що конфлікту інтересів щодо публікації цього рукопису немає. Крім того, автор повністю дотримувався етичних норм, включаючи плагіат, фальсифікацію даних та подвійну публікацію.

В роботі не використано ресурс штучного інтелекту.

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Стаття надійшла до редакції 28.10.2025
Стаття рекомендована до друку 05.12.2025

Переглянуто 30.11.2025
Опубліковано 30.12.2025