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Information and analytical technologies for decision support in environmental monitoring systems of amalgamated territorial communities

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Abstract. The relevance of this study is conditioned by the increasing need to improve the effectiveness of environmental monitoring of amalgamated territorial communities in the context of growing anthropogenic and military impacts on the environment. The purpose of the study was to create an integrated decision support system for environmental monitoring, which allows combining data from different sources, continuously monitoring the state of ecosystems, predicting changes, and quickly responding to environmental threats. In the course of the research, a systematic approach, mathematical modelling of ecosystem dynamics, the least squares method for identifying model parameters based on limited data were applied, including cloud technologies, the Internet of Things, crowdsourcing platforms, and sensor networks for collecting and processing information were introduced. Data integration was carried out from government, public and departmental sources, which provided comprehensive coverage of various types of environmental impacts. The main results of the study were: development of a multi-level organisational structure of the monitoring system, construction of discrete and continuous mathematical models for assessing and predicting the state of ecosystems, implementation of recurrent algorithms for adapting models to changes in the environment. The system helped to ensure constant monitoring of industrial, agro-industrial and military-anthropogenic impacts, identify potential threats in a timely manner, assess their impact, and make informed management decisions to reduce environmental risks. The developed decision support system helps to effectively manage environmental risks, contributes to improving environmental safety and sustainable development of amalgamated territorial communities. The integration of advanced information technologies, mathematical models and public involvement in the monitoring process creates a new paradigm of environmental management in crisis conditions

Keywords: Internet of Things; military impact; crowdsourcing; mathematical modelling; anthropogenic load; risk management; cloud technologies

Introduction

Environmental monitoring in amalgamated territorial communities (ATC) defined a key role for sustainable development and environmental protection. The problem of insufficient coordination between the international, state, local, public, and departmental levels was identified, which made it difficult to respond to threats in a timely manner, especially due to the growing anthropogenic and military burden. Public monitoring was recognised as important for the implementation of the right to a safe environment and the detection of violations. The relevance of the study was

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justified by the need to create an integrated decision support system (DSS) for combining information, continuous monitoring, forecasting, and rapid response in ATC. Global experience and current scientific paradigms were used for effective monitoring and implementation of advanced DSS.

A. Popov (2024) focused on the analysis of advanced regional environmental monitoring systems using cloud and Internet of Things technologies. The study examined the level of development of integrated information systems for collecting, processing, and managing eco-data. The advantages are the use of the Internet of Things with multisensory systems for instant collection and processing of large amounts of information in real time. Due to its modular architecture, systems are flexible, scalable, and integrated with other technologies. However, the complexity of integrating heterogeneous data and technologies, and the dependence of model accuracy on information quality, remain problems. It is also important to ensure compatibility and standardisation of components for effective interaction of the system.

The study by A. Bonfante *et al*. (2024) detailed the development of a geospatial DSS to support EU authorities in implementing climate change adaptation policies. The tool combines spatial and non-spatial data, works at various scales from municipality to Europe, and includes advanced climate models for assessing anomalies and crop adaptation. The advantages were openness, free access, flexible architecture, working with large amounts of data, fast visualisation and report generation. The disadvantages were the complexity of implementation due to the need for high-quality information and technical training of users, and significant efforts to standardise and compatibility of system components. S. Xu (2024) combined the development of artificial intelligence-based DSS for sustainable urban planning in smart cities. The system analyses big data, models scenarios, and optimises resources to improve energy and water efficiency, develop public gardens, and transport infrastructure. The advantages were an integrated approach, integration of various data and technologies to improve environmental sustainability, and forecasting long-term impacts and optimising resources. The disadvantages were dependence on data quality, which affects the accuracy of forecasts, the difficulty of integrating with existing infrastructure due to different standards, and the need for significant investment in technology and training of specialists.

The study by J. Haqbeen *et al.* (2021) focused on involving residents, particularly women and minorities, in identifying problems and finding solutions for local authorities. The study demonstrated how digital tools promote equal participation of citizens in urban planning, even in times of crisis. The advantages were the involvement of different segments of the population, reducing bias in discussions, and creating a platform for dialogue between society and the authorities. The system collects and organises proposals, increasing the transparency and effectiveness of strategic planning. The disadvantages were the need to improve digital literacy, ensure confidentiality, and the need to support the authorities and adapt to socio-cultural conditions, which makes it difficult to scale and stability the system.

B. Orlove *et al*. (2020) reviewed climate decision-making processes. The researchers tracked the development of the industry from politics to the analysis of various stakeholders – the private sector, community organisations, and indigenous communities, with a focus on cognitive and deliberative processes. Special attention was paid to the influence of the social environment, scientific knowledge, and conceptual framework. The advantages were an interdisciplinary approach that combined psychological and rational aspects, and the use of non-climatic narratives and the concept of urgency to encourage change. The disadvantages were the complexity of performance assessment due to multidimensional processes, the lack of empirical data, the difficulty of interaction between participants and the limited integration of scientific data into practice, which makes it difficult to achieve climate policy goals.

A. Sadeghi-Niaraki *et al*. (2020) combined information from citizens with geoinformation technologies and multi-criteria analysis to improve pollution monitoring and decision-making in waste management. The researchers highlighted the advantages of the system – improving the accuracy and detail of data due to the participation of local residents as human sensors, and the effectiveness of management decisions and the development of environmental consciousness. The disadvantages were the heterogeneity and subjectivity of data, the complexity of verification and integration, the dependence of performance on the activity of the population, digital technologies, and infrastructure for collecting and analysing information. A.J. Constable *et al*. (2022) conducted an analysis of decision support tools in the field of climate risk management. Systematisation of methods, consideration of the political, social and cultural context, and involvement of interested parties were noted. The lack of a universal tool, complexity of integration in multi-level systems, uncertainty of goals and limited quality data were revealed. The importance of a flexible, context-sensitive approach, and an iterative decision-making process was emphasised.

Recent research in systems ecology and decision support information technologies has shown the effectiveness of mathematical models of ecosystem dynamics, expert systems, the Internet of Things, cloud technologies, and crowdsourcing for integrated environmental monitoring. Despite the numerous systems at different levels, there are problems of interaction between them and modelling the impact of anthropogenic and military factors, which requires further study. The issues of identifying model parameters based on limited data and integrating multi-level monitoring systems were not sufficiently investigated. The purpose of the study was to develop and substantiate an integrated decision support system for environmental monitoring of amalgamated territorial communities using advanced information technologies, modelling ecosystem dynamics, and identifying parameters based on limited data to improve the effectiveness of environmental risk management.

Materials and Methods

The study was conducted in accordance with the principles of scientific correctness, reproducibility, and transparency. The key stages of scientific research were the analysis of current approaches to environmental monitoring and decision support systems; formalisation of necessary requirements for an integrated multi-level monitoring system; development of mathematical models of ecosystem dynamics; identification of model parameters based on a limited amount of data; creation of an organisational and technical structure for information support of the decision support system. To achieve this goal, a systematic approach was applied, focused on the analysis of monitoring levels (state, local, public, departmental), which contributes to the comprehensive consideration of interaction between participants in environmental control. The rationale for choosing modelling methods was explained by the need to recreate complex processes in terrestrial ecosystems under anthropogenic and military pressure. For this purpose, linear and nonlinear differential and difference equations were used to describe the dynamics of organic matter reserves (Chapin *et al.*, 2012), and the least squares method for identifying model parameters based on available environmental data (Lysenko *et al.*, 2017). To improve the accuracy of prediction, recurrent parameter estimation algorithms were used (Slabospytsky, 2008), which ensured the adaptation of models to changes in the environment. Recurrent algorithms for estimating ecosystem parameters are a type of algorithm that uses previous values or the state of the ecosystem to calculate the current value.

The information base of the decision support system was developed based on integrating data from various sources: state and public environmental monitoring networks, crowdsourcing platforms, wireless sensor systems, and open databases (Füller *et al.*, 2021). For data collection, storage and processing, cloud technologies for the development of multidimensional databases, the Internet of Things for the development of intelligent sensors, automated workplaces for conducting expert assessments of the parameters of the impact of anthropogenic and military loads on ecosystems, local area networks and server capacities for decision support systems (Killen *et al.*, 2022). The criteria for developing a sample for the empirical part of the study were based on the representativeness of data on various types of load on ecosystems (anthropogenic, agro-industrial, military) and the availability of high-quality information for modelling. The experimental base of the study covered data from open state and public sources of environmental monitoring (Ecodozor, n.d.; Ecozagroza, n.d.), and simulation results at test sites (dedicated locations for monitoring background monitoring parameters) that reflect typical environmental impact scenarios.

The dynamics of organic matter reserves in the biogeocoenosis was described by a system of discrete equations that consider changes in organic mass reserves in various components of the ecosystem over a certain period of time:

$$\begin{cases} P(i+1) = P(i) + \Delta_P(i,\ i+1) - \Delta_G(i,\ i+1); \\ G(i+1) = G(i) + \Delta_G(i,\ i+1) - \Delta_S(i,\ i+1); \\ S(i+1) = S(i) + \Delta_S(i,\ i+1) - \Delta_S^*(i,\ i+1), \end{cases} \quad (1)$$

where $i \in N$ – discrete time; $\Delta_P(i, i+1)$, $\Delta_G(i, i+1)$, $\Delta_S(i, i+1)$ – respectively, an increase in aboveground phytomass, precipitation, and litter in the time interval from i to $i+1$; $\Delta_S^*(i, i+1)$ – reduction of litter in the time interval from i to $i+1$.

The sampling interval is assumed to be one year, and the countdown began with the period when plants reach their maximum development – this is usually the end of May or the beginning of June. In order to construct a continuous mathematical model, the following dependencies were used:

$$\dot{P}(t) \cong \frac{P(i+1)-P(i)}{1\ year} = P(i+1) - P(i); \quad (2)$$

$$\dot{G}(t) \cong \frac{G(i+1)-G(i)}{1\ year} = G(i+1) - G(i); \quad (3)$$

$$\dot{S}(t) \cong \frac{S(i+1)-S(i)}{1\ year} = S(i+1) - S(i). \quad (4)$$

Given that in the first approximation, the increments $\Delta_P(i, i+1)$, $\Delta_G(i, i+1)$, $\Delta_S(i, i+1)$, $\Delta_S^*(i, i+1)$ are proportional to $P(i) + S(i)$, $P(i)$, $G(i)$, $S(i)$, respectively, a system of equations is derived:

$$\begin{cases} P(i+1) = a_{11}P(i) + 0G(i) + a_{13}S(i); \\ G(i+1) = a_{21}P(i) + a_{22}G(i) + 0S(i); \\ S(i+1) = 0P(i) + a_{32}G(i) + a_{33}S(i); \end{cases} \quad (5)$$

$$a_{11} = 1 + \frac{\Delta_P(i,i+1)}{P(i)+S(i)} - \frac{\Delta_G(i,i+1)}{P(i)} \cong const_1;\ a_{12} = 0; \quad (6)$$

$$a_{13} = 1 + \frac{\Delta_P(i,i+1)}{P(i)+S(i)} \cong const_2; \quad (7)$$

$$a_{21} = \frac{\Delta_G(i,i+1)}{P(i)} \cong const_3; \quad (8)$$

$$a_{22} = 1 - \frac{\Delta_S(i,i+1)}{G(i)} \cong const_4;\ a_{23} = 0;\ a_{31} = 0; \quad (9)$$

$$a_{32} = \frac{\Delta_S(i,i+1)}{G(i)} \cong const_5; \quad (10)$$

$$a_{33} = 1 - \frac{\Delta_S{}^*(i,i+1)}{S(i)} \cong const_6; \quad (11)$$

In matrix form, equation (5), considering external influence, has the following form:

$$\begin{bmatrix} P(i+1) \\ G(i+1) \\ S(i+1) \end{bmatrix} = \begin{bmatrix} a_{11} & 0 & a_{13} \\ a_{21} & a_{22} & 0 \\ 0 & a_{32} & a_{33} \end{bmatrix} \begin{bmatrix} P(i) \\ G(i) \\ S(i) \end{bmatrix} + \begin{bmatrix} W_1(i) \\ W_2(i) \\ W_3(i) \end{bmatrix}, \quad (12)$$

where $W_n(i)$, $(n = \overline{1,\ 3})$ – external influences, including test factors.

Data from open state and public sources of environmental monitoring (Ecodozor, n.d.; Ecozagroza, n.d.) were used to determine the indicators of anthropogenic and military loads $W_n(i)$, $(n = \overline{1,\ 3})$. Vector equation (12) provided a discrete model of the dynamics of organic matter reserves. The continuous model took the form:

$$\begin{bmatrix} \dot{P}(t) \\ \dot{G}(t) \\ \dot{S}(t) \end{bmatrix} = \begin{bmatrix} {a_{11}}^{-1} & 0 & a_{13} \\ a_{21} & {a_{22}}^{-1} & 0 \\ 0 & a_{32} & {a_{33}}^{-1} \end{bmatrix} \cdot \begin{bmatrix} P(t) \\ G(t) \\ S(t) \end{bmatrix} + \begin{bmatrix} W_1(t) \\ W_2(t) \\ W_3(t) \end{bmatrix}. \quad (13)$$

The vector of unknown parameters was denoted as $X^T = [a_{11}, a_{13}, a_{21}, a_{22}, a_{32}, a_{33}] = [X_1, X_2, X_3, X_4, X_5, X_6]$ and assumed $W_n(i) \equiv 0$, ($n = 1, 2, 3$), in which case, a system of equations was obtained to identify these parameters:

$$\begin{cases} P(i+1) = P(i) \cdot X_1 + S(i) \cdot X_2 + 0 \cdot X_3 + 0 \cdot X_4 + 0 \cdot X_5 + 0 \cdot X_6; \\ G(i+1) = 0 \cdot X_1 + 0 \cdot X_2 + G(i) \cdot X_3 + S(i) \cdot X_4 + 0 \cdot X_5 + 0 \cdot X_6; \\ S(i+1) = 0 \cdot X_1 + 0 \cdot X_2 + 0 \cdot X_3 + 0 \cdot X_4 + G(i) \cdot X_5 + S(i) \cdot X_6; \\ P(i+K+1) = P(i+1) \cdot X_1 + S(i+1) \cdot X_2 + 0 \cdot X_3 + 0 \cdot X_4 + 0 \cdot X_5 + 0 \cdot X_6; \\ G(i+K+1) = 0 \cdot X_1 + 0 \cdot X_2 + G(i+1) \cdot X_3 + S(i+1) \cdot X_4 + 0 \cdot X_5 + 0 \cdot X_6; \\ S(i+K+1) = 0 \cdot X_1 + 0 \cdot X_2 + 0 \cdot X_3 + 0 \cdot X_4 + G(i+1) \cdot X_5 + S(i+1) \cdot X_6, \end{cases} \quad (14)$$

where K – time shift, $K \in N$.

Since a limited number of measurements are available at the initial stage of studying the terrestrial ecosystem of the ATC, it is sufficient to solve a system consisting of six linear equations and containing six unknown variables to determine the vector of unknown parameters. In this case, the least squares method was used in the recurrent form (Mokin *et al.*, 2010), but only after the amount of data collected has increased. The obtained values of the parameters of the mathematical model of the ecosystem should be considered as a primary approximation – that is, as an initial condition that will be used in the future for the recurrent application of the least squares algorithm. This approach allows gradually refining the model parameters as the amount of incoming information increases, and increases the accuracy of subsequent calculations. To confirm the correctness of the hypothesis put forward in relation to the mathematical model in the form (5), the following conditions were used: $a_{12} = a_{23} = a_{31} = 0$:

$$\begin{cases} P(i+\tau) - \hat{a}_{11} P(i+\tau) - \hat{a}_{13} G(i+\tau) \cong 0; \\ G(i+\tau) - \hat{a}_{21} P(i+\tau) - \hat{a}_{22} G(i+\tau) \cong 0; \\ S(i+\tau) - \hat{a}_{32} G(i+\tau) - \hat{a}_{33} G(i+\tau) \cong 0, \end{cases} \quad (15)$$

where τ – time shift; $\hat{a}_{11}, \hat{a}_{13}, \hat{a}_{21}, \hat{a}_{22}, \hat{a}_{32}, \hat{a}_{33}$ – estimation of the values of the parameters of the mathematical model (12).

Given the limited number of experimental data available for calculating estimates of model parameters (12), it was necessary to apply the simplest and most efficient algorithm for determining the parameters of the system of difference equations (5). This algorithm was based on relations (6)-(11), which established a relationship between the estimates of system parameters (12) and the increments of the corresponding biomass. First, equation (1) was solved with respect to changes $\Delta_P(i, i+1), \Delta_G(i, i+1), \Delta_S(i, i+1)$, using values $P(i)$ and $P(i+1)$ known from observations, and it was assumed that the desired values $\Delta_S^*(i, i+1) = K_S S(i)$, $KS \in [0; 1]$ of the system parameters (12) were found. The parameters of this model were calculated based on real experimental data and were shown in Table 1, which ensured its compliance with the actual characteristics of ecosystems.

Table 1. *Model adequacy check*

Data type			1970			1971			1972		
Data on the dynamics of organic matter reserves in the biogeocoenosis of reed grass meadow, [g/m²]			*P*(*i*)	*G*(*i*)	*S*(*i*)	*P*(*i*)	*G*(*i*)	*S*(*i*)	*P*(*i*)	*G*(*i*)	*S*(*i*)
			154	124	121	240	190	145	295	204	245
Simulation modelling: 1970 – initial conditions, 1971, 1972 – forecast	linear model	continuous	154	124	121	234	182	136	318	262	218
		discrete	154	124	121	226	166	150	325	250	200
	nonlinear model	continuous	154	124	121	144	122	144	144	122	150
		discrete	154	124	121	134	130	156	144	110	166

Note: *accuracy of experimental data ±15%*
Source: *V. Smith (1988), F.S. Chapin et al. (2006)*

These experimental results remain relevant and can be used in contemporary research. To identify the parameters, not only data taken from scientific sources were used, but also the results of specially conducted experimental observations. The initial values of the parameters were determined based on the analysis of the first two columns of the corresponding table, and considering the accepted litter loss coefficient, which is shown in Table 2, which allows more accurately reproducing the real conditions of the ecosystem functioning.

Table 2. *Performance improvement indicators*

Natural environment (number of model components)		Conceptual objectivity, score	Pragmatic objectivity (1-10 years), %									
			1	2	3	4	5	6	7	8	9	10
Phytocoenosis	Before	Green phytomass – 1.	K_{ph}	K_{ph}	K_{ph}	1.5 K_{ph}	1.5 K_{ph}	1.5 K_{ph}	2 K_{ph}	2 K_{ph}	2.5 K_{ph}	3 K_{ph}
	After	Green phytomass, litter – forest floor – 3 (prevails).										

Table 2. Continued

Natural environment (number of model components)		Conceptual objectivity, score	Pragmatic objectivity (1-10 years), %									
			1	2	3	4	5	6	7	8	9	10
Zoocoenosis	Before	–	1.5 K_z	1.5 K_z	1.5 K_z	2 K_z	2 K_z	2 K_z	2.5 K_z	2.5 K_z	3 K_z	3 K_z
	After	Divichky target range – 16. Yavoriv military base – 18 (prevails).										

Note: *the level of reduction in the current estimate error – less than 30%. Provided that pollution has led to a decrease in green phytomass growth by reducing the coefficient of organic matter transfer from litter to phytomass by only K_{ph} %, or by slowing down the transfer of lower-level consumer biomass to higher-level biomass by K_z %*
Source: *A. Lysenko et al. (2017)*

A special observation algorithm based on the Lewinberger observer was used to assess and predict the state of organic matter in the ecosystem. The parameters of this algorithm were optimised using the standard error minimisation criterion, which ensured stable operation of the algorithm even in cases of significant errors in the measurements of green phytomass (Chapin *et al.*, 2012). The parameters of the continuous model were calculated in the same way as for the discrete model, using the same relations. The model parameters were calculated using experimental data and the corresponding equations (17)-(27). Based on the system of balance equations (1), a system of nonlinear difference equations (16) was formed, which describe in detail the dynamic changes in the main components of the ecosystem. This model considered complex interactions between elements of the biogeocoenosis, which helped to more accurately reproduce the processes that occur in the natural environment, especially in conditions where the influence of anthropogenic or other external factors is significant.

$$\begin{cases} P(i+1) = a_1 \cdot P(i) + a_2 \cdot P(i) \cdot S(i) + a_3 \cdot P^2(i) + W_1(i); \\ G(i+1) = b_1 \cdot P(i) + b_2 \cdot G(i) + b_3 \cdot S(i) + b_4 \cdot P^2(i) + b_5 \cdot G^2(i) + W_2(i); \\ S(i+1) = c_1 \cdot P(i) + c_2 \cdot G(i) + c_3 \cdot S(i) + c_4 \cdot G^2(i) + c_5 \cdot S^2(i) + W_3(i); \end{cases} \quad (16)$$

$$a_1 = 1 + \frac{\Delta_P(i,i+1)}{P(i)+P(i)\cdot S(i)} - \frac{\Delta_G(i,i+1)}{P(i)}; \quad (17)$$

$$a_2 = \frac{\Delta_P(i,i+1)}{P(i)+P(i)\cdot S(i)}; \quad (18)$$

$$a_3 = -\left(\frac{\Delta_G(i,i+1)}{P(i)}\right)^2; \quad (19)$$

$$b_1 = \frac{\Delta_G(i,i+1)}{P(i)}; \quad (20)$$

$$b_2 = 1 - \frac{\Delta_S(i,i+1)}{G(i)};\ b_3 = 0; \quad (21)$$

$$b_4 = \left(\frac{\Delta_G(i,i+1)}{P(i)}\right)^2; \quad (22)$$

$$b_5 = -\left(\frac{\Delta_S(i,i+1)}{G(i)}\right)^2;\ c_1 = 0; \quad (23)$$

$$c_2 = \frac{\Delta_S(i,i+1)}{G(i)}; \quad (24)$$

$$c_3 = 1 - K_S; \quad (25)$$

$$c_4 = \left(\frac{\Delta_S(i,i+1)}{G(i)}\right)^2; \quad (26)$$

$$c_5 = -K_S^{\,2},\ W_n(i);\ (n = 1, 2, 3) \text{ – external influence.} \quad (27)$$

To calculate the coefficients in equations (16), the formulas given in the range (17)-(27) were used. In this process, they relied on changes $\Delta_P(i, i+1)$, $\Delta_G(i, i+1)$, $\Delta_S(i, i+1)$, which were obtained by solving the system of equations (1). These changes were calculated based on the observed values of P(i) and P(i + 1), while considering the assumptions that $\Delta_S^*(i, i+1) = K_S S(i)$, $K_S \in [0; 1]$. The continuous model took the form:

$$\begin{cases} \dot{P}(t) = (a_1 - 1) \cdot P(t) + a_2 \cdot P(t) \cdot S(t) + a_3 \cdot P^2(t) + W_1(t); \\ \dot{G}(t) = b_1 \cdot P(t) + (b_2 - 1) \cdot G(t) + b_3 \cdot S(t) + b_4 \cdot P^2(t) + b_5 \cdot G^2(t) + W_2(t); \\ \dot{S}(t) = c_1 \cdot P(t) + c_2 \cdot G(t) + (c_3 - 1) \cdot S(t) + c_4 \cdot G^2(t) + c_5 \cdot S^2(t) + W_3(t). \end{cases} \quad (28)$$

A nonlinear computer simulation model was created based on a discrete model, the parameters of which were calculated using experimental data presented in Table 1. For this purpose, the corresponding dependencies were used, which are defined by equations (17)-(27). Simulation estimation and prediction of the development over time of the state vector of a nonlinear discrete system describing changes in the content of organic matter was carried out on the condition that the initial parameters of the system were unknown, and the components of the model can vary up to 20% of the nominal values. The parameters of the continuous model were calculated based on experimental data using the corresponding dependencies defined by equations (17)-(27).

Results and Discussion

Analysing the work of the territorial community in the field of environmental monitoring, certain doubts arise as to how effectively the coordination and integration of different levels of observation – from international to state, local, public and departmental – is taking place. At the international level, there are systems for assessing the environmental condition specified in the Resolution of the Cabinet of Ministers of Ukraine No. 391 (1998), which operate under the leadership of such organisations as the United Nations, UNESCO, and UNEP. Simultaneously, at the local level, monitoring is carried out by various structures: state bodies, municipal services, specialised divisions of the communities themselves, and industrial and agricultural enterprises that conduct their own departmental environmental control. Special attention should be paid to public monitoring, which plays an important role in the implementation of citizens' right to a safe environment (Morshch & Savchenko, 2018; Alvarez-Risco & Del-Aguila-Arcentales, 2021) and helps to identify violations of environmental laws (Donnelly *et al.*, 2014).

Due to the dispersion and lack of interaction between these different actors, doubts arise whether the existing system is able to respond in a timely and comprehensive manner to environmental threats, especially in the face of growing anthropogenic and military load on the environment. It is these challenges that highlight the urgent need to create a specialised decision support system (Fig. 1), which would be able to combine all information flows, ensure continuous monitoring of sources of industrial, agro-industrial, and military-anthropogenic load, and assess the impact of these factors on the ecosystem, predict possible changes in the natural environment and promote rapid response to emergencies (Morshch & Savchenko, 2018). Special attention was paid to formalising the structure of a multi-level monitoring system, building discrete and continuous models of the dynamics of organic matter reserves in terrestrial ecosystems, and developing recurrent algorithms for estimating parameters to improve the accuracy of scientific forecasts in difficult conditions of anthropogenic and military loads.

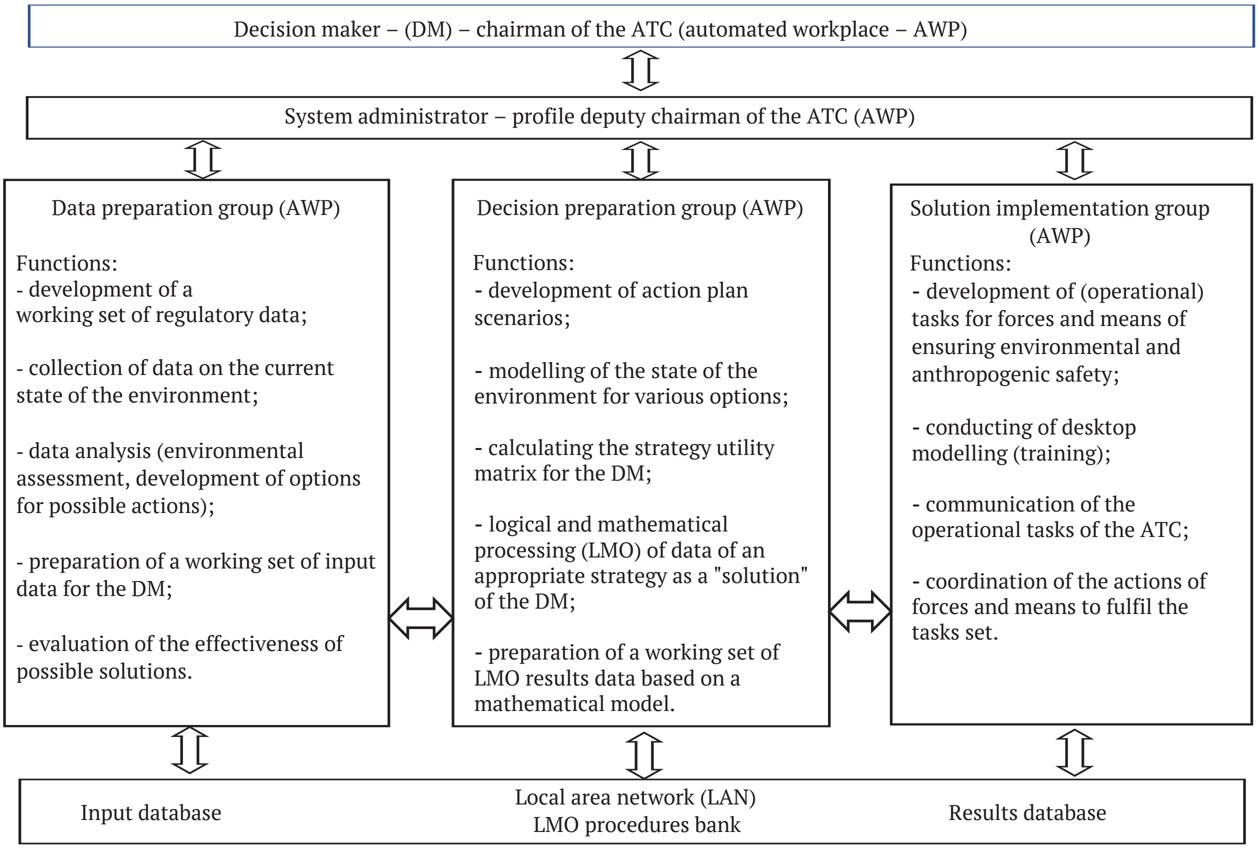

Figure 1. *General block diagram of the DSS for environmental monitoring of the environment*
Source: *developed by the authors*

The main functions of such a decision support system include:

1. Continuous monitoring of industrial anthropogenic load (IAL), agro-industrial anthropogenic load (AIAL) and military anthropogenic load (MAL) (Chumachenko *et al.*, 2022).

2. Assessment of the physical state of the environment and natural processes occurring in it.

3. Forecasting changes in the environmental situation and assessing the potential consequences of these changes.

4. Improving the speed and quality of user information services at various levels of management, in accordance with DSTU 9001:2001 (2001).

5. Support of the adoption of informed and scientifically balanced management decisions aimed at reducing emissions and discharges of harmful substances into the environment.

6. Ensuring safety and comfortable living conditions for residents of amalgamated territorial communities.

The development and further implementation of such an DSS is an extremely necessary step to improve the effectiveness of environmental monitoring in AHS. This will help to identify potential threats that may negatively affect the environment in a timely manner, assess their impact, and take appropriate measures to protect nature and public health. According to advanced approaches to system ecology, for modelling biocoenoses in terrestrial ecosystems, the structure of mathematical models of biotopes can be represented by three main species. Firstly, these are linear scalar equations, which can be either ordinary differential or difference equations. They are used to describe the process of succession – that is, the gradual development and change of communities of organisms over time. Secondly, there are linear multidimensional equations that can also be differential or differential. These models are designed to reflect the dynamics of processes in biotopes where anthropogenic impact is minimal or completely absent, for example, in areas free of external factors, such as zoocoenoses. And thirdly, nonlinear logistic equations are applied, which can be either differential or difference. They are designed specifically for modelling phenomena in biotopes that are exposed to significant anthropogenic or military loads.

These types of models are used not only to estimate the current state of the ecosystem, but also to simulate forecasting, i.e., to analyse the current state of an object and model its behaviour in the future (Ivanyuta & Kachynskyi, 2012). Model parameters were estimated using the least squares method, which is used over a sliding time interval that can last up to 20 years (Dubovoy, 2012). Forecasting, in turn, is possible for a period of 10-12 years ahead, which allows assessing the potential consequences of changes in the system. For discrete models, the sampling period T_0 is taken as one year. At the initial stage, several years are allocated to obtain an initial approximation of the parameters, which ensures the accuracy of further calculations. In order to assess and predict the state of terrestrial ecosystems, a special computer simulation model was created (Fig. 2), which reproduces the key processes of the organic matter cycle in nature.

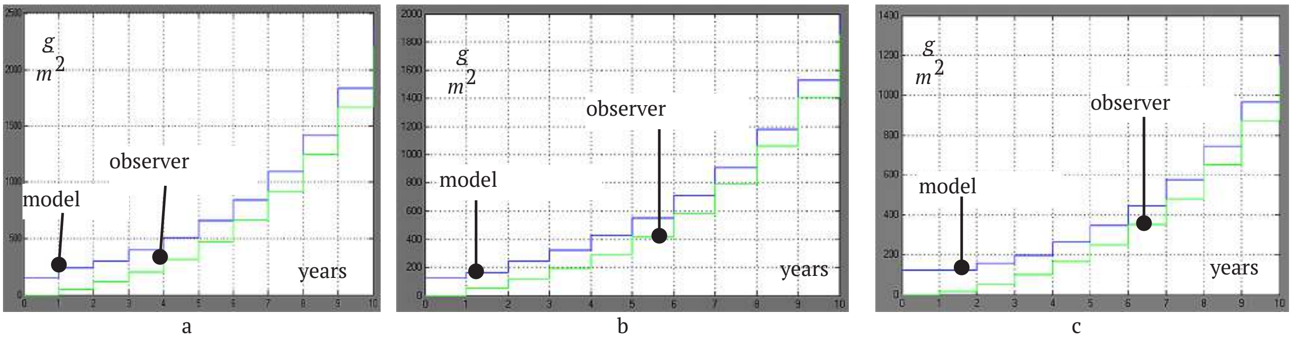

Figure 2. *Results of modelling simulation estimation and forecasting of the dynamics of the state vector of a linear discrete system of organic matter reserves*

Source: *a – green phytomass; b – litter; c – forest floor*

Source: *developed by the authors*

Verification of the model showed that if the initial parameters are the same, the forecast error for the first and second years does not exceed 10% of the actual values obtained during measurements. The conducted modelling showed that even if there are sufficiently large errors in the measurements of green phytomass – up to 30% – after four years, the error in assessing the state of all components of the model does not exceed 10%. This indicates the high ability of the chosen approach to correction and adaptation. In addition, it was found that all components of the model change in a consistent manner, regardless of the type of external perturbations. This result confirmed the expediency of focusing monitoring on green phytomass during its maximum growing season. With this approach, it is possible to obtain representative and reliable information about the overall state of the ecosystem, even if the amount of data available is limited.

It is also worth noting that advanced methods of remote sensing of the Earth greatly facilitate the collection of data on green phytomass. This makes regular monitoring of ecosystems more accessible and efficient, eliminating the need for complex and time-consuming field measurements. Simulation prediction based on a continuous linear model and Lewinberger observers confirmed the conclusions obtained for the discrete case (Fig. 3). This indicates the consistency of both models and the chosen approach as a whole, and their reliability and suitability for long-term forecasting of the state of terrestrial ecosystems. Comparison of the simulation results with actual experimental observations showed that the error can reach approximately ±45%, which is significantly higher than the accuracy shown by the linear model. A nonlinear computer simulation model was created based on a discrete model, the parameters of which are shown in Figure 4.

The results of a simulation experiment conducted using a nonlinear model together with the Lewinberger observer confirmed the same conclusions as previously obtained for the linear model. The initial values of the feedback matrix parameters in the observer were determined based on a linear model, which helped to move smoothly and efficiently to the application of a more complex nonlinear model. The simulation results showed high accuracy and reliability of this approach. Choosing between using a linear or nonlinear model requires a step-by-step and careful approach that considers the length of the observation period (at least 10 years) and the amount of experimental data available (Van Veen & Paul, 1981). This is necessary to ensure reliable identification of model parameters and obtain reliable results. The parameters of the continuous model are illustrated in Figure 5. The results showed that the continuous model confirms the consistency and reliability of the discrete model, which emphasises the effectiveness of both approaches in reflecting the dynamics of the processes under study. This suggests that both models are useful tools for analysing and predicting changes in systems associated with organic matter reserves.

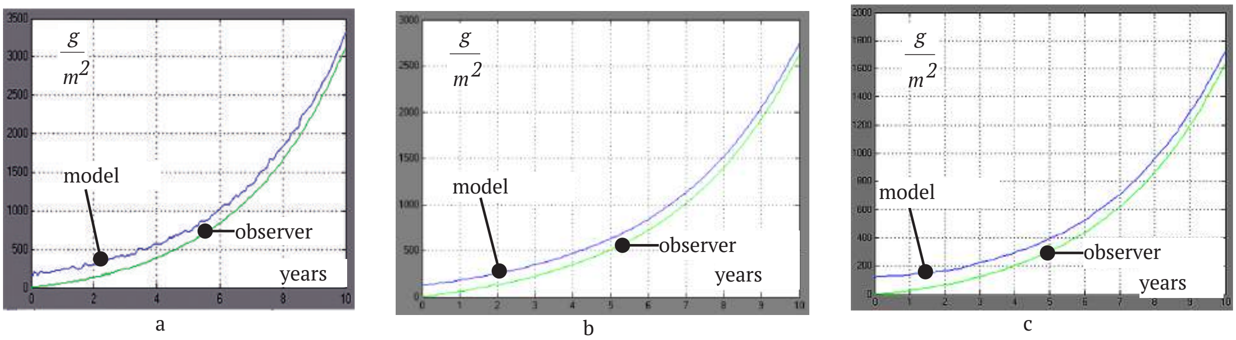

Figure 3. *Results of modelling simulation estimation and forecasting of dynamics of organic matter reserves of a linear continuous system*

Note: *a – green phytomass; b – litter; c – forest floor*

Source: *developed by the authors*

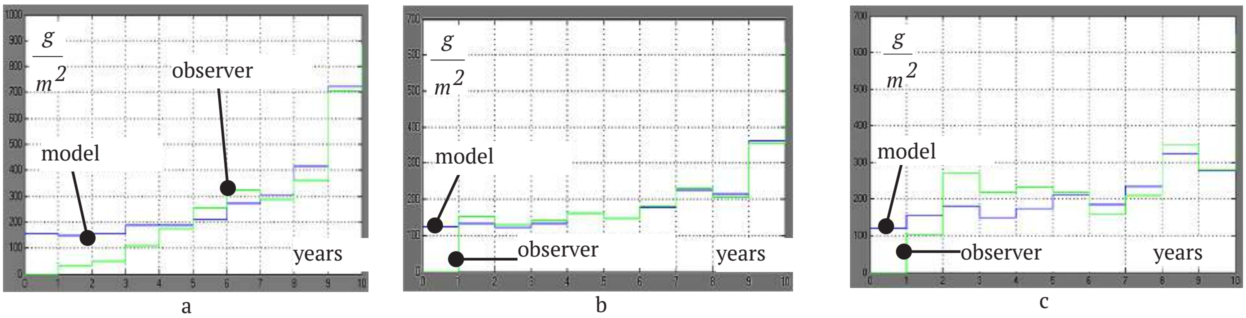

Figure 4. *Results of modelling simulation estimation and forecasting of the dynamics of the state vector of a nonlinear discrete organic matter system*

Note: *a – green phytomass; b – litter; c – forest floor*

Source: *developed by the authors*

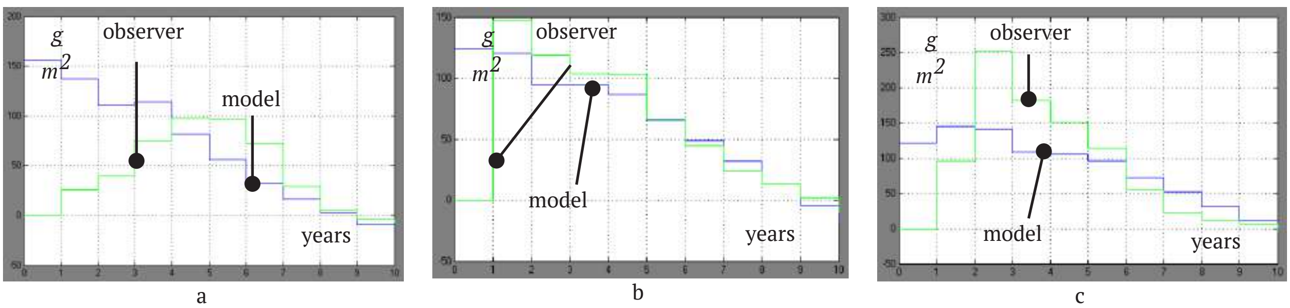

Figure 5. *Results of modelling simulation estimation and forecasting of the dynamics of the state vector of a nonlinear continuous organic matter system*

Note: *– a – green phytomass; b – litter; c – forest floor*

Source: *developed by the authors*

As part of this study, an integrated DSS designed for environmental monitoring in ATC was developed and tested. The key concept was to combine a variety of data sources – from official government resources to public and departmental initiatives – to ensure continuous collection of information on environmental impacts. The main focus was on tracking anthropogenic, agricultural, and military loads, and the ability of the system to quickly respond to environmental risks that arise within the community. Comparing the obtained data with the methods described by E. Levin *et al*. (2023), a significant correlation was observed. Namely, they stressed the importance of implementing cloud platforms, the Internet of Things, and the use of semantic web services. Instead, the study by B. Varer & V. Mokin (2025) focused on artificial intelligence, namely, the use of large language models for building cognitive maps and modelling systems without the participation of experts, that is, on the analytical and predictive part of the DSS, especially in conditions of a lack of high-quality input data. These tools help to improve the flexibility, scalability, and integration capabilities of the system with other advanced solutions. Both in this study and in the paper by E. Levin *et al*., a similar problem was identified: difficulties in integrating different types of data and technologies, and a high dependence of the accuracy of models on the quality of source information. Therefore, the issue of compatibility and standardisation of all components of the system was defined as a key requirement for ensuring its performance.

Paying attention to the study by A. Bonfante *et al.* (2024), similar strategic approaches using geospatial data were observed, and the DSS architecture was designed on a multi-layered basis. In the proposed system, like A. Bonfante *et al.*, used advanced models for predicting the ecological state, in particular climate algorithms. However, if A. Bonfante *et al.* focused on supporting EU authorities in implementing climate change adaptation policies, this study aimed to integrate monitoring at various levels – state, local, public, and departmental – in the context of anthropogenic and military tensions, which is particularly important for Ukraine. S. Xu (2024) considered the use of artificial intelligence in DSS for sustainable urban development, when adaptive models, fuzzy logic, and specialised algorithms were used in this study to improve the accuracy of diagnostics and forecasting of the environmental situation. Similarly to C. Xu, the current study confirmed that the quality of input data and the complexity of integration with the existing infrastructure remain significant obstacles to the widespread use of such systems.

Separately, it is necessary to emphasised the focus on involving ordinary citizens in environmental monitoring as part of the current study. This fully correlated with the approaches outlined by J. Haqbeen *et al*. (2021). The above system, like the current study, contained crowdsourcing mechanisms and the practice of cooperation with public associations. This contributed to the receipt of detailed information, accelerated identification of problems, and the development of environmental consciousness among the population. Simultaneously, certain difficulties have arisen, in particular, those related to the heterogeneity and subjectivity of data, and the need to improve digital literacy and ensure the protection of information.

Comparing the results obtained with the study by G. Anjum & M. Aziz (2025), it was found that both papers emphasised an interdisciplinary approach to environmental strategies. Attention was paid not only to technical aspects, but also to cognitive, social factors, and the importance of scientific data and conceptual frameworks for improving the effectiveness of policy decisions. Similar to G. Anjum & M. Aziz, the problems of comprehensive system performance assessment and the lack of convincing empirical data remained significant obstacles. A.J. Lynch *et al*. (2022) highlighted the key role of a flexible, situation-oriented approach and iterative decision-making process in climate risk management. This approach was also implemented in the present study: systematisation of various methods, considering the political, social, and cultural context, and the involvement of all interested parties became the foundation for the development of an effective DSS.

Summing up, the study showed the effectiveness of the created integrated DSS for environmental supervision of ATC. This is fully consistent with current global practices in this area. To improve the operation of the system, the need to address issues of standardisation, ensuring the quality of information, improving digital awareness of users and adapting models to the specifics of each community was clarified. The experience of Ukrainian and foreign experts has shown that the best results are achieved through a combination of various scientific approaches, the use of advanced information technologies, and the active involvement of the public in the process of environmental monitoring, which will ultimately contribute to the sustainable development of territorial communities.

Conclusions

The present paper offered a scientifically based concept of multi-level DSS for environmental monitoring of ATC. This system considered the current challenges faced as a result of anthropogenic accidents and military operations, which significantly affect the state of the environment. The organisational and technical structure of the DSS was developed, which combined automated workstations, local area networks, cloud services, crowdsourcing platforms, sensor systems, and data from open sources. The use of mathematical models for local monitoring of the dynamics of organic matter reserves with the ability to identify parameters even with limited data is also justified, which allows performing operational analysis of the state of ecosystems and predicting the long-term consequences of anthropogenic and military factors.

Simulation simulations conducted as part of the study demonstrated high accuracy in estimating changes in terrestrial ecosystems. The results also determined the effectiveness of management decisions aimed at reducing the negative impact on the environment. Integrating data from multiple sources – government, public, sensor networks, and crowdsourcing platforms – increases responsiveness to environmental threats. In addition, such integration promotes transparency and accessibility of environmental information to government agencies and the public. An important aspect is the proven possibility of public involvement in environmental control through digital platforms, which, in turn, increases environmental awareness and contributes to the democratisation of the decision-making process.

In the course of the study, the effectiveness of using recurrent algorithms for identifying model parameters was confirmed. This is extremely useful in cases where environmental data is limited or fragmented, which is a typical problem for territorial communities, especially in times of crisis. The proposed methodology allows adapting decision support systems to the specific conditions of each territory, considering local features of the load on ecosystems, and the availability of information resources. Practical testing of the system at test sites has shown its ability to scale and integrate with existing national and international monitoring platforms.

Further research will focus on implementing artificial intelligence techniques to improve the accuracy of predictions. It is also planned to expand the functionality of the decision support system for emergency risk management, integration with national and international monitoring platforms. In addition, it is planned to develop adaptive algorithms for analysing large amounts of environmental data. Further development of this system is aimed at improving the effectiveness of environmental monitoring, ensuring timely response to environmental threats, and promoting scientifically sound management decisions at the local community level.

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Conflict of Interest

None.

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Інформаційно-аналітичні технології підтримки прийняття рішень у системах екологічного моніторингу об'єднаних територіальних громад

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Анотація. Актуальність цього дослідження зумовлена дедалі більшою необхідністю покращення ефективності екологічного моніторингу об'єднаних територіальних громад в умовах зростання техногенного та військового впливу на навколишнє середовище. Метою роботи було створення інтегрованої системи підтримки прийняття рішень для екологічного моніторингу, що дозволяє об'єднувати дані з різних джерел, здійснювати безперервний контроль за станом екосистем, прогнозувати зміни та оперативно реагувати на екологічні загрози. У процесі дослідження застосовано системний підхід, математичне моделювання динаміки екосистем, метод найменших квадратів для ідентифікації параметрів моделей на основі обмежених даних, а також впроваджено хмарні технології, Інтернет речей, краудсорсингові платформи та сенсорні мережі для збору й обробки інформації. Інтеграція даних здійснювалася з державних, громадських та відомчих джерел, що забезпечило комплексне охоплення різних типів навантаження на довкілля. Основними результатами дослідження були: розробка багаторівневої організаційної структури системи моніторингу, побудова дискретних і безперервних математичних моделей для оцінки та прогнозування стану екосистем, впровадження рекурентних алгоритмів для адаптації моделей до змін у середовищі. Система дозволила забезпечити постійний моніторинг промислового, агропромислового та військово-техногенного впливу, своєчасно виявляти потенційні загрози, оцінювати їхній вплив і приймати обґрунтовані управлінські рішення для зниження екологічних ризиків. Розроблена система підтримки прийняття рішень дозволяє ефективно управляти екологічними ризиками, сприяє підвищенню екологічної безпеки та сталому розвитку об'єднаних територіальних громад. Інтеграція сучасних інформаційних технологій, математичних моделей та залучення громадськості до процесу моніторингу створює нову парадигму екологічного управління в кризових умовах

Ключові слова: Інтернет речей; воєнний вплив; краудсорсинг; математичне моделювання; техногенне навантаження; управління ризиками; хмарні технології