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INTEGRATING ARTIFICIAL NEURAL NETWORKS AND GEOGRAPHIC INFORMATION SYSTEMS FOR ENVIRONMENTAL DATA ANALYSIS AND PREDICTION

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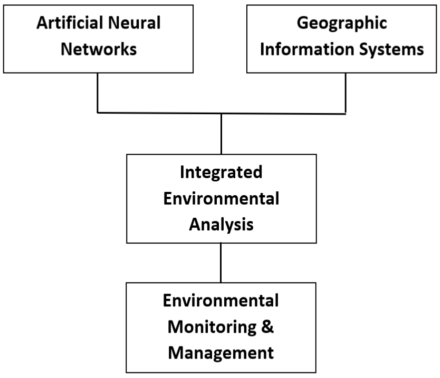
Graphical abstract



Abstract

The relevance of the research lies in the need to apply modern methods of spatial environmental data analysis, particularly artificial neural networks with geographic information systems, to address global environmental issues like climate change, biodiversity loss, and resource degradation. The study aimed to investigate the potential of artificial neural networks and geographic information systems for analysing spatial environmental data, addressing the development of effective methods for processing and interpreting environmental information. The research developed methods for integrating artificial neural networks and geographic information systems to monitor ecosystems, assess environmental risks and improve environmental sustainability. Modern deep learning methods, including convolutional and recurrent neural networks, along with geographic information systems for visualization and modeling, enhance the analysis of environmental changes, pollution prediction, and natural resource management. The results show that the integration of these technologies helps to effectively solve environmental monitoring tasks, including controlling water and air pollution, studying the impact of climate change on ecosystems and predicting agricultural sustainability. The study emphasised the need to continue developing and applying artificial neural networks and geographic information systems to solve environmental problems and ensure sustainable management of natural resources and environmental protection.

Keywords: geographic information systems, machine learning, deep learning, environmental monitoring, and big data processing.

1.0 INTRODUCTION

Analysing spatial data on the environment is substantial in the context of sustainable development, ecology and nature management. Spatial data collected through remote sensing, unmanned aerial vehicles and Geographic information systems (GIS) can be used to analyse the dynamics of changes in natural processes and make informed management decisions. However, the volume and complexity of such data require the use of modern methods of processing and analysis, among which artificial neural networks (ANNs) occupy a special place. The research relevance is determined by global environmental challenges such as climate change, biodiversity loss and natural resource degradation. Traditional methods of analysis are often insufficient to identify hidden patterns, which limits the possibilities of forecasting and modelling. The use of ANNs in combination with GIS technologies creates new perspectives for solving these problems due to the ability of ANNs to effectively process big data, learn from complex patterns and adapt to new conditions. The challenge is to integrate Internet Map Server (IMS) and GIS technologies for spatial data analysis, which requires solving several technical and methodological issues. There is also a need to optimise neural network algorithms to process geospatial data that have unique characteristics, such as spatial autocorrelation and heterogeneity. In the context of spatial data analysis, ANNs are used for classification, clustering, prediction and anomaly detection. At the same time, GIS technologies provide tools for processing, storing and visualising spatial information. The combination of these approaches allows for the development of integrated systems capable of integrating data from various sources and providing informed decision-making recommendations.

Since the 2020, the use of artificial neural networks and GIS technologies to analyse spatial data has been actively explored in the scientific community. Many authors confirm the promising nature of these methods and identify the key areas of their application. Mishra 2019 *et al.* [1] emphasised the effectiveness of ANNs in the task of landscape classification using remotely sensed data. The author noted that deep neural networks outperform traditional machine learning algorithms in terms of accuracy in recognising land cover types. Hossain and Sajib 2019 [2] investigated the application of convolutional neural networks (CNNs) for monitoring urbanisation, demonstrating that the integration of data from GIS significantly improves the accuracy of predicting changes in the urban environment. Guo *et al.* 2022 [3] analysed the spatial dynamics of biodiversity. The author successfully applied recurrent neural networks (RNN) to model ecosystem changes based on satellite image time series. A similar problem was considered by Alexakis *et al.* 2019 [4] in a study on a hybrid approach combining neural networks and geostatistical analysis algorithms to predict soil degradation. The results demonstrated that combined methods could provide more accurate and reliable predictions.

Khoirunisa *et al.* 2021 [5] analysed the application of GIS and neural networks for flood risk analysis. The author developed a model based on LSTM (Long-Short-Term Short-Term Memory), which can be used to predict flood zones with a high level of detail. Guha *et al.* 2022 [6] confirmed these conclusions, demonstrating the advantages of using neural networks in the tasks of emergency response to natural disasters. Of particular interest is the study by Barrile *et al.* 2022 [7], which explored the oriented use of unmanned aerial vehicle (UAV) data combined with GIS for farmland surveillance, including the use of transformers to analyse UAV images. This approach predicted crop yields with high efficiency, addressing the influence of climatic factors. Omeka *et al.* 2024 [8] also addressed agriculture, investigating how GIS-based neural networks can help optimise the use of water resources. Amato *et al.* 2020 [9] developed climate change prediction models based on spatial-temporal data. The study employed hybrid neural networks that combine the properties of convolutional networks (CNN) to analyse spatial data and recurrent networks (RNN) to account for temporal dependencies. Integration of models with GIS allowed the authors to develop tools for forecasting temperature, precipitation and other climatic factors with high detail, which is especially relevant for regions with increased climatic vulnerability. Moreover, Deekshith 2020 [10] developed tools for data visualisation and interpretation. The author emphasises the importance of creating intuitive interfaces that will allow specialists to easily use the analysis results for natural resource management.

Despite significant progress, there are still areas that require further research. Adaptation of neural network architectures to process unique characteristics of geospatial data, such as spatial autocorrelation and heterogeneity, has not been sufficiently explored. Limited attention has been paid to developing methods to combine data from different sources (e.g., satellite imagery, UAV data, sensors) into a single analysis model. There are gaps in the development of intuitive interfaces for visualising results, which limits the practical application of the developed methods.

The study aimed to develop approaches to the integration of artificial neural networks and GIS technologies for the analysis of spatial environmental data, addressing the unique features of these data and contributing to the accuracy, interpretability and practical applicability of the results.

The objectives of the study were to develop methods for adapting neural network architectures to work with spatial data, considering their autocorrelation and heterogeneity. Furthermore, the study analysed the possibilities of integrating data from various sources (satellites, UAVs, sensors) into a single analytical system.

2.0 METHODOLOGY

This study integrates ANNs and GIS to address modern environmental challenges such as climate change, biodiversity loss, and pollution. ANNs, including CNNs and RNNs, are used for processing complex data, including satellite imagery and time series data like temperature, water levels, and pollutant spread. CNNs excel in land cover classification and pollution detection, while RNNs, particularly LSTM models, provide accurate long-term predictions and anomaly detection. GIS technologies complement ANNs by managing and visualizing spatial data, creating thematic maps, and integrating various data sources. This integration allows for spatial-temporal modeling, combining time-dependent and location-dependent data to effectively address environmental issues like deforestation and pollution spread. GIS and ANN together enhance decision-making and provide real-time insights for better environmental management.

The study demonstrates these technologies' application in monitoring forest ecosystems and assessing the impact of climate change on agriculture. It also extends to pollution monitoring, with an example from Albania, showing how GIS and ANN can detect environmental risks such as air and water pollution. Similar challenges in oil-producing regions like Kazakhstan, Nigeria, and Venezuela further emphasize the global relevance of this methodology. The study suggests that integrating GIS and ANN is crucial for developing sustainable practices in the oil industry and improving environmental monitoring worldwide. These technologies offer valuable tools for resource management, climate change mitigation, and biodiversity preservation.

One of the key parameters affecting the integration of ANN and GIS is the quality and type of data used for analysis. Since ANN requires large amounts of data for training and accurate predictions, the quality of this data, particularly its accuracy, granularity, and quantity, is of paramount importance. The use of high-quality geospatial data from GIS allows the creation of accurate thematic maps that ANN can use to detect and predict changes in natural systems. For tasks such as monitoring landscape changes or water pollution, GIS provides georeferenced data such as the coordinates of pollution sites, land cover types, or changes in climatic conditions. This data can then be integrated into ANNs to detect patterns, classify areas, or predict environmental changes.

Deep learning algorithms, including CNNs, recurrent neural networks (RNNs) and their hybrid combinations, were used to process multidimensional and spatial and temporal data. CNNs were used to analyse satellite images and remote sensing data to classify land cover types, identify areas of forest degradation and assess water pollution. U-Net and Residual Network (ResNet) models adapted for environmental tasks were used for data classification and segmentation.

RNNs, including LSTM architectures, were used to predict the dynamics of environmental parameters based on time series of data, such as temperature changes, water levels and the spread of pollutants. These models addressed temporal dependencies and provided accurate forecasting of long-term changes.

GIS technologies were used to process and visualise spatial data. GIS tools were used to process geo-referenced data, create thematic maps, such as maps of environmental risk zones, and integrate data from various sources. Spatial databases were used for data management, enabling long-term monitoring of environmental parameters.

The integration of GIS and IMS provided an integrated approach to environmental monitoring. In the first stage, data from various sources, including satellite imagery, drone data and meteorological measurements, were integrated into a single system using GIS. In the second stage, the data was processed using an ANN, which included classification, anomaly detection and forecasting of changes. The results of the analysis were again integrated into the GIS to create visualisations and support decision-making.

As an example, monitoring forest ecosystems involves processing satellite images using CNNs to identify areas of deforestation and forest degradation. Data on temporal changes were then analysed using RNNs to predict further changes. Integration of this data into GIS enabled the creation of interactive maps indicating critical areas requiring immediate action.

Research on the impact of climate change on agriculture includes an analysis of climate change, such as rising temperatures, changes in precipitation and extreme weather events, and their impact on crop yields and production in different regions of the world. It assesses the main crops exposed to climate risks and develops adaptation measures to minimise damage, such as the use of resistant varieties, improved irrigation, agroforestry, precision agriculture and protection against extreme weather events. The research uses climate models, satellite data and reports from international organisations to identify trends and offer recommendations for sustainable agricultural development in the face of climate change.

3.0 RESULTS

3.1 Application Of Artificial Neural Networks And Geographic Information Systems In Monitoring And Forecasting Changes In Natural Systems

Modern environmental challenges are highly complex and multifaceted, including monitoring changes in natural systems, predicting environmental risks and managing natural resources. Artificial neural networks and geographic information systems play a key role in solving these problems by providing tools for analysing, interpreting and visualising large amounts of data. ANNs based on the principles of deep learning are capable of efficiently processing complex and multidimensional data. Their application in ecology can be used to detect hidden patterns, classify objects and phenomena, such as land cover types or forest degradation zones, and predict the dynamics of climate parameters or the spread of pollutants. In addition, neural networks efficiently process data from various sources, including satellite images, drones and sensors, to integrate heterogeneous information.

GIS technologies, in turn, are beneficial for storing, analysing and visualising spatial data [11]. They are used to analyse data in a geo-referenced manner, create thematic maps, such as environmental risk zones, and integrate with forecasting models. GIS also provides management of large spatial and temporal databases, which is important for the long-term monitoring of environmental changes [12].

Integrating GIS into research can involve combining different types of data, such as satellite imagery, land cover data, climate data and pollution information. Importantly, this approach requires the consideration of multiple data layers, each of which is responsible for a specific characteristic of an ecosystem or natural process. For instance, layers can be used to represent the topography of the area, the distribution of water resources, levels of air and soil pollution, and changes associated with anthropogenic activities. This data can be used to create thematic maps, such as pollution maps, climate change forecasts, and high-risk areas for agriculture and ecosystems. This approach provides a comprehensive understanding of the changes taking place in natural systems and helps to make more informed management decisions aimed at environmental protection and sustainable use of natural resources.

The synergy between ANNs and GIS creates unique opportunities for solving environmental problems [13]. The combination of deep learning methods with spatial data allows for spatial-temporal modelling, where ANNs analyse time series and GIS adds a spatial component. This is especially beneficial for processing large amounts of environmental data, such as satellite images or sensor data, which cannot be analysed effectively using traditional methods. Integrating the results of the analysis into a GIS simplifies their visualisation and makes the conclusions accessible to decision-makers. Thus, ANN and GIS technologies are central to addressing modern environmental challenges by providing tools for accurate analysis, forecasting and sustainable management of natural resources.

The integration of artificial neural networks and geographic information systems is a powerful tool for addressing contemporary environmental challenges. Thanks to their ability to process large volumes of complex and multidimensional data, ANNs enable the identification of hidden patterns, the classification of objects, and the prediction of changes in natural systems. In turn, GIS provide opportunities for storing, analyzing, and visualizing spatial data, which facilitates the creation of thematic maps and integration with forecasting models. The combined use of these technologies makes it possible to more accurately assess environmental processes, predict risks, and make informed management decisions for the sustainable use of natural resources and protection of the environment.

3.2 Methods And Algorithms For Data Analysis And Forecasting Of Environmental Changes

Artificial neural networks have proved to be efficient in environmental monitoring tasks, enabling analysis of complex multidimensional data, automating processing processes and providing accurate forecasts. Their application covers a wide range of tasks related to environmental monitoring, forecasting changes and detecting anomalies [14]. One of the key tasks where ANNs are used is the classification of environmental objects based on remote sensing data. For instance, CNNs are used to classify land cover types and identify areas of forest degradation or changes in urbanised areas. Such models can process satellite images or drone data, analysing them with high accuracy and speed [15].

Predicting changes in ecosystems is another important area of application for ANNs. RNNs, including architectures such as LSTM, are used to analyse time series of data, such as temperature, water levels or the spread of pollution. These models can consider the temporal dependence of events, which makes them indispensable for making long-term forecasts. ANNs are also used in anomaly detection tasks, such as detecting pollution in water or air. For this purpose, auto-encoders are used, which are trained on normal data and then identify deviations associated with a violation of the ecological balance. Such approaches are particularly useful in operational monitoring systems where it is necessary to respond quickly to changes.

The combination of the ANN with data from various sources, including satellites, sensors and meteorological stations, allows for the integration of heterogeneous data into single models. This greatly enhances analysis capabilities and provides a more complete understanding of environmental processes. For example, hybrid architectures that combine CNNs and RNNs allow for both spatial and temporal aspects of data to be considered, creating comprehensive forecasts [16]. In addition, ANNs help automate monitoring processes, reducing dependence on manual data processing. This makes environmental monitoring more efficient and affordable, especially in regions with limited resources. Thus, the use of ANN in environmental monitoring tasks allows not only to increase the accuracy and speed of data analysis but also to offer new approaches to solving complex environmental problems. These technologies play an important role in the development of sustainable environmental management systems.

Geographic information systems are efficient in spatial analysis, enabling the processing, visualisation and analysis of geospatial data. These systems are used in a variety of areas, including environmental monitoring, land use planning, natural resource management and risk assessment. One of the key functions of GIS is the processing of georeferenced data [17]. This includes creating, storing and managing spatial databases that contain information about objects such as water bodies, forests, settlements and transport infrastructure. GIS provides a wide range of tools for working with this data: filtering, editing, merging and transforming it [18].

An important aspect of GIS is the ability to analyse spatial data. The systems support a wide range of analytical operations, including spatial matching, buffering, terrain modelling and visibility analysis [19]. For instance, GIS can be used to identify flood risk zones, calculate deforestation areas, or analyse spatial autocorrelation. These capabilities are particularly valuable in environmental studies where spatial relationships between phenomena need to be addressed.

GIS is also used to create and visualise maps that make complex information easier to understand [20]. Thematic maps can present data on air pollution, temperature changes or species distribution in an intuitive way [21]. This makes GIS an indispensable tool for communicating information to specialists and the public, as well as for making management decisions. Another important function of GIS is the integration of data from various sources. For example, satellite images, remote sensing data, ground measurements and socio-economic indicators can be combined into a single analytical system. This provides a comprehensive approach to the study of environmental problems.

Modern GIS systems extensively use machine learning and artificial intelligence technologies [22]. This allows for the automation of data processing and analysis processes, such as image classification, change prediction and anomaly detection. For instance, GIS systems can integrate the results of artificial neural networks, providing a spatial context for analytical conclusions [23, 24]. Thus, GIS technologies play a key role in spatial analysis. They provide access to vast amounts of geographic information, provide tools for in-depth data analysis and visualisation, and help develop innovative solutions for managing natural resources and solving environmental problems.

The impact of climate change on agriculture is one of the most debated and pressing issues of our time. Extreme climatic events such as droughts, floods, rising temperatures and changing precipitation patterns are increasingly affecting agricultural production in different regions of the world [25]. These changes not only affect yields but also change agronomic practices, which requires effective adaptation measures to ensure food security and agricultural sustainability.

Crops and production methods are exposed to climate change risks in different ways depending on the region. In some countries, rising temperatures lead to droughts, while in others they cause excessive rainfall and flooding. Understanding the impacts of climate change on agriculture in different parts of the world over the last decade is key to developing effective adaptation strategies and mitigation measures. Table 1 provides an overview of the impacts of climate change on agriculture in different regions of the world and suggests possible adaptation measures.

Table 1 The impact of climate change on agriculture in different regions of the world

Region	Major climate changes	Impact on agriculture	Main crops	Adaptation measures
North America	Rising temperatures, more extreme weather events	Reduced yields due to droughts and rising temperatures, threat of hurricanes and tornadoes	Wheat, corn, soya	Introduction of resistant varieties, improved irrigation, protection from extreme weather conditions
South Asia	Sea level rise, increased monsoon rains	Threats of flooding, rising groundwater levels, reduced yields of rice and other crops	Rice, wheat, sugar cane	Construction of protective dams, change of crop patterns, improvement of irrigation methods
Sub-Saharan Africa	Droughts, rising temperatures, changes in precipitation patterns	Lack of water, reduction of arable land, lower grain and legume yields	Cassava, maize, millet, sorghum	Development of water-saving technologies, crop rotation, and increasing crop resilience
South America	Wetting and droughts, rising temperatures, increased storms	Crop losses due to droughts and floods, changing conditions for coffee and cocoa cultivation	Coffee, cocoa, soya, corn, sugar cane	Use of resistant varieties, agroforestry, improved water management
Europe	Rising temperatures, increased frequency of heatwaves, more intense and unpredictable rainfall, and an increasing number of extreme weather events, including floods and storms.	Reduced wheat yields, risk of over-humidification, changes in sowing and harvesting dates	Wheat, barley, grapes, olives	Modernisation of agriculture, development of precision farming, use of resistant varieties
Australia and Oceania	Frequent droughts, rising temperatures, reduced precipitation	Reduced yields due to droughts, threats to livestock, and changes in the timing of grain growing	Wheat, barley, grapes	Use of resistant varieties, improvement of water supply technologies, transition to sustainable farming methods
China	Droughts, rising temperatures, increase in extreme weather events	Crop losses due to water shortages, threats to rice fields, reduced grain productivity	Rice, wheat, corn	Development of sustainable technologies in agriculture, redistribution of water resources, modification of varieties

Source: [26-28].

Following the abovementioned table, the impact of climate change on agriculture varies considerably across the world, depending on geography and climate conditions. In some countries, climate change is leading to an increase in the number of droughts, which in turn is reducing yields of important crops such as wheat and corn [29, 30]. In other regions, on the contrary, increased humidity and frequent flooding are damaging agriculture, leading to crop destruction and agricultural land degradation. The grouping of regions is based on geographical continents and subregions, such as North America, South Asia, Sub-Saharan Africa, South America, Europe, Australia, and Oceania, as well as China. This grouping is determined by specific climate changes and their impact on agriculture, which vary depending on the geographical and climatic conditions of each region. Different regions have unique climatic characteristics that manifest themselves in different ways — rising temperatures in some regions lead to drought, while in others they cause excessive rainfall and flooding. In addition, regions also differ in their typical crops, such as wheat, corn, rice, coffee, and soybeans, which also influences adaptation strategies. Thus, the grouping is based on geographical location and climatic conditions, which determine the varying impact of climate change on agriculture.

Adapting to these changes requires a range of measures, including the introduction of resilient crop varieties, improved irrigation methods, and the use of innovative agricultural technologies. It is also important that governments take measures to improve water management and develop strategies to minimise the impact of extreme weather events on agricultural production. In summary, climate change is a substantial threat to global agriculture, and it is necessary to continue to research and implement adaptation strategies aimed at reducing the negative impacts on food security and the sustainability of agricultural production.

Modern challenges in environmental monitoring require the use of innovative technologies capable of processing large amounts of spatial data quickly and accurately. Geographic information systems and artificial neural networks have already proven to be efficient in addressing these problems. GIS provides visualisation and analysis of spatial data, while ANNs allow for the identification of complex relationships, classification of objects and forecasting of changes [31]. The integration of these technologies opens new opportunities for monitoring various types of pollution, especially in conditions where traditional methods of data analysis are not effective enough. This is especially relevant for various ecosystems that are affected by anthropogenic factors such as urbanisation, industrial pollution, climate change and intensive use of natural resources.

Table 2 provides an overview of the use of GIS and ANN for pollution monitoring in different ecosystems. It discusses the main types of pollution, data sources, optimal algorithms for Internet Information Services (IIS), practical examples of technology applications and the benefits of their integration for each ecosystem. This analysis contributes to a deeper understanding of the importance of these technologies in solving environmental problems and assesses their potential for sustainable management of natural resources.

Table 2 Integration of GIS and ANN in monitoring the pollution of various ecosystems: Approaches and benefits

Ecosystem type	Types of contamination	The algorithms used by the ANN	Examples of use	The benefits of integrating GIS and ANN
Marine ecosystems	Oil pollution, plastic waste, eutrophication	CNN for image classification	CNN for image classification	High accuracy in determining contamination zones and their dynamics
Forest ecosystems	Air pollution, acid precipitation	RNN for time series analysis	Monitoring of SO_2 and NOx emissions, forecasting the effects of pollution	Real-time change detection, spatial detail
Urban ecosystems	Air pollution, waste, heat pollution	Hybrid models (combination of CNN and RNN)	Heat island analysis, air emissions control	Ability to model scenarios and forecast emissions
Agricultural zones	Pesticide and nitrate pollution	Auto-encoders for anomaly detection	Controlling pesticide use, predicting pollution migration	Precise identification of local problems, spatial analysis

Source: [32-34].

GIS and ANN are being used to monitor pollution in various ecosystems [35]. This approach can not only process huge amounts of data but also identify complex relationships that are difficult to detect with traditional methods of analysis. For marine ecosystems, for instance, the use of satellite data with the help of GIS can be used for effective monitoring of oil spills, microplastics and other pollutants, which is particularly important for preventing long-term damage to marine life. In forest ecosystems, GIS and GIS can help monitor changes in vegetation and biodiversity, as well as analyse the impact of pollutants such as acid rain and industrial emissions.

Urban and agricultural ecosystems also benefit from the use of these technologies, as they allow for the control of air, water and soil quality, which is important for human health and the health of ecosystems in general. With the help of Internet of Things (IoT), it is possible to predict the effects of pollution and develop more effective measures to minimise them [36, 37]. Thus, the integration of GIS and ANN into pollution monitoring is substantial in ensuring sustainable development and environmental protection. It allows not only to respond promptly to current environmental threats but also to develop strategies for the long-term management of natural resources and improve the quality of life and biodiversity.

The use of GIS and ANN to assess and manage risks associated with ecosystem services is a central part of modern environmental monitoring and natural resource management. Ecosystem services are processes occurring in ecosystems that provide vital benefits for humanity, such as clean water, air, agricultural products, climate regulation and biodiversity conservation [38]. However, various anthropogenic and natural factors can threaten these services, making it necessary to use high-tech approaches to assess and manage the risks associated with their loss or degradation.

Geographic information systems provide the capabilities for mapping, analysing and visualising spatial data, which is essential for assessing ecosystem services. GIS can be used to integrate data on various natural and anthropogenic factors, such as ecosystem types, water bodies, air and soil quality, and the impact of human activities [39]. GIS can assess the state of ecosystems, identify risk areas and predict possible changes in ecosystem services that may be caused by, for example, climate change, urbanisation or pollution.

Artificial neural networks can process complex datasets, identify hidden relationships and make predictions based on huge amounts of information. In the field of ecosystem services, such networks can be used to predict losses associated with the deterioration of water bodies or the reduction of biodiversity [40]. Neural networks can also be used to analyse the impact of various factors, such as climate change or land use changes, on ecosystems, and to model various possible scenarios of the impact of these factors. Artificial neural networks and geographic information systems are effectively used to analyze and predict environmental changes. ANNs, such as convolutional and recurrent networks, allow data classification and prediction of changes in ecosystems, while GIS provide visualization and analysis of spatial data. The integration of these technologies improves the monitoring of environmental processes and enables the development of strategies for sustainable natural resource management and ecosystem conservation.

3.3 Integration Of Geographic Information Systems And Artificial Neural Networks For Pollution Monitoring And Ecosystem Management

The integration of GIS and ANN can be beneficial for integrated risk assessment and management of ecosystem services. GIS provides mapping and spatial analysis of data, while ANN can use this data to build predictive models and make decisions. This integration helps to assess risks to ecosystem services in real-time, develop strategies to minimise ecosystem service losses and create projections for different ecosystem change scenarios.

Examples of applications of this integration include water resources monitoring, where GIS can be used to track the condition of water bodies, and where ANN can help predict the impact of climate change on water availability. GIS and ANN are also used to assess the impact of climate change on agriculture, allowing to predict the risks of drought, floods or temperature rise and develop adaptation strategies [41]. In forest ecosystems, GIS helps to monitor the condition of forests, while GIS analyses data on deforestation, forest fires and pollution, predicting future threats and suggesting ways to restore ecosystems.

Thus, the use of GIS and ANN to assess and manage ecosystem service risks can efficiently monitor natural resources, predict threats and develop optimal measures to protect ecosystem services. This contributes to a more sustainable management of natural resources and the preservation of ecosystem services for future generations.

The oil industry is a substantial sector of the Albanian economy but significantly addressing the environment. The main environmental problems associated with oil production and refining are air, water and soil pollution, as well as significant greenhouse gas emissions. Given the growing focus on environmental safety, assessing the extent of pollution caused by the oil sector is an important step in developing effective measures to reduce the negative impact on the environment.

Table 3 presents the key environmental indicators that characterise the level of pollution caused by the oil sector in Albania. These data are based on information obtained from international environmental and energy reports and reflect the scale of the problem.

Table 3 Analysis of pollution caused by the oil sector in Albania

Metric	Value/Range	Note
Air pollution (Particulate Matter (PM) 2.5, µg/m³)	25-40 µg/m³	The data are for regions with refineries in Southern Europe.
Lead content in soil (Pb, mg/kg)	50-150 mg/kg	Assessment of soil contamination in oil regions; data specific to industrial impact zones
Pollution of water resources by oil products (TPH, ppm)	0.2-1.0 ppm	Monitoring of coastal zones and water bodies near oil facilities in Albania.
Annual Carbon Dioxide (CO_2) emissions from the oil sector (tonnes/year)	0.5-1.2 million tonnes per year	Estimation of emissions for the last reporting period; the data can be used to assess the climate impact.
Oil production (barrels/day)	100-250 bpd	Data for the last reporting period; can be used to assess the scale of production activities of the oil sector.

Source: compiled by the authors based on [42-44].

The analysis of environmental indicators shows a significant level of pollution from the oil industry in Albania. The primary issues are high levels of PM2.5 air pollution, which exceed World Health Organisation (WHO) recommended standards and can cause respiratory diseases, accumulation of heavy metals in the soil near oil fields, which poses a threat to agriculture and the local population, and water pollution by oil products, which negatively affects biodiversity. In addition, significant CO_2 emissions contribute to climate change and require decarbonisation measures.

Similar environmental challenges are faced by other oil-producing countries in the region. In Kazakhstan, for example, the oil and gas industry has led to high levels of air pollution, particularly in industrial regions such as Atyrau and Tengiz, where oil extraction and refining activities cause elevated concentrations of sulfur dioxide and particulate matter. These pollutants have detrimental effects on human health, leading to an increase in respiratory and cardiovascular diseases. In Nigeria, the Niger Delta region is notorious for its oil spills, gas flaring, and widespread deforestation caused by oil extraction activities. These environmental impacts result in the contamination of local water sources, loss of biodiversity, and health problems for local populations, especially in rural communities that rely on natural resources for their livelihoods. In South America, particularly in Venezuela and Ecuador, oil extraction has caused significant environmental damage, including water and soil contamination from oil spills and the release of harmful gases. These pollutants have long-term consequences for the ecosystem, affecting agriculture, water quality, and human health, particularly in regions heavily dependent on oil production.

Reducing the environmental burden of the oil sector is possible through modernization of production, introduction of environmentally friendly technologies, and strengthening pollution control [45, 46]. Further research and government programmes, such as those implemented in Norway with its focus on green technologies and stricter environmental regulations for oil extraction, can help develop a strategy for sustainable development of the oil sector with minimal environmental impact. These efforts are crucial not only for Albania but also for other nations facing similar environmental challenges due to the oil industry.

The integration of GIS and ANN is an important tool for risk assessment and ecosystem service management. The combination of GIS and ANN allows for effective monitoring of natural resources, forecasting threats, and developing strategies to protect ecosystems. These technologies also contribute to the development of adaptation strategies to climate change and the conservation of biodiversity, particularly in aquatic, forest, and agricultural ecosystems. They are also important for assessing and reducing the negative impact of sectors such as the oil industry on the environment. As a result, the integration of these technologies supports the sustainable use of natural resources and the preservation of ecosystem services for future generations.

4.0 DISCUSSION

The article presents a valuable analysis of the use of ANN and GIS for environmental monitoring and forecasting changes in natural systems, as well as for sustainable management of natural resources. The authors highlight the importance of integrating these two technologies to address pressing contemporary environmental issues such as climate change, environmental pollution, and biodiversity loss. This approach not only enhances the accuracy of environmental monitoring but also enables the development of effective adaptation strategies to mitigate the negative impacts on the environment.

This aligns with the growing body of research that underscores the transformative potential of these technologies in addressing global environmental challenges. For example, studies by Ortiz *et al.* 2021 [47] emphasize the increasing significance of advanced technologies in managing environmental data and supporting the prediction of ecological changes. The author noted that an effective solution to these challenges requires the use of advanced technologies, in particular, artificial neural networks and geographic information systems. The author addressed the potential of these technologies to process large amounts of environmental data and create models that can predict environmental changes and support sustainable management of natural resources. A comparison of the current results and the author's work shows that both studies converge in recognising the importance of INS and GIS for environmental data analysis. However, the author emphasises the global context and strategic importance of these technologies, while the current study prioritises specific methods and their implementation in specialised environmental projects.

One of the significant advantages of using ANNs in environmental monitoring is their ability to process large volumes of complex and multidimensional data, such as satellite images, and data from unmanned aerial vehicles and sensors. This is especially important when solving problems related to the classification of natural objects and predicting changes in ecosystems. For example, CNNs can be used to classify land cover types, which allows tracking changes in vegetation, and recurrent neural networks can be used to analyse time series data, such as temperature fluctuations or water level dynamics. These approaches significantly improve the accuracy of forecasts, which is important for developing strategies for sustainable management of natural resources. Carranza-García *et al.* 2019 [48] studied the use of convolutional neural networks for analysing satellite data and classifying land cover types. The author analysed changes in vegetation, agricultural land, and urbanised areas. The proposed model demonstrated a classification accuracy of up to 85%, but the author did not include spatial and temporal aspects, limiting himself to image processing. The current results integrate CNN with ANN for spatial modelling, which allows for temporal changes and extends the application of the technology. Atik and Ipbuker 2021 [49] addressed the use of convolutional neural networks for analysing satellite data and classifying land cover types. The author developed a CNN architecture specially adapted for processing multispectral images, such as data from Sentinel-2 and Landsat-8 satellites. The main goal was to create a model capable of distinguishing between key land cover categories, including forests, agricultural land, water bodies and urbanised areas. The author's approach and the approach in the current study both apply modern data processing and augmentation techniques to improve model reliability.

Furthermore, IoTs are substantial in detecting anomalies and predicting environmental risks, such as air or water pollution. The use of auto-encoders to analyse normal data and detect deviations facilitates a rapid response to environmental disruptions. Such monitoring is becoming especially relevant in the context of climate change when an increase in the frequency of extreme weather events requires timely solutions to prevent disasters. Russo *et al.* 2020 [50] emphasised the importance of using auto-encoders to detect anomalies in environmental data. The author noted that this approach is particularly effective for analysing air and water pollution data, as well as for predicting risks associated with extreme weather events. The findings are consistent with the current ones in terms of the high accuracy of identifying abnormalities and the importance of responding quickly to environmental threats. However, in contrast to the current results, the author emphasises that autoencoders work better with small data sets with a high degree of detail, while the current study determined that they are effective on larger, less detailed data. Wei *et al.* 2023 [51], studying the use of auto-encoders in environmental monitoring, focuses on their application to detect anomalies in air and water pollution data. The author conducted a series of experiments where auto-encoders are used to analyse data with a high degree of detail, such as pollutant concentrations measured in real-time using sensors. The author emphasises that the accuracy of auto-encoders in detecting deviations from normal values allows not only to respond quickly to threats but also to predict the development of extreme events, such as an increase in pollution levels after intense rainfall or sudden changes in water temperature.

On the other hand, GIS provide powerful tools for storing, analysing and visualising spatial data. GIS allows for the integration of heterogeneous data, such as pollution monitoring results, climate change and anthropogenic impacts, and provides tools for creating thematic maps that help in decision-making. The interaction between ANN and GIS is particularly effective when analysing spatial and temporal data, as ANN can analyse temporal aspects of change, while GIS can analyse spatial aspects. This synergistic interaction allows for the creation of models that consider both temporal and spatial dependencies, which is important for accurate forecasting of changes in ecosystems. Himeur *et al.* 2022 [52] highlights the advantages of using GIS to integrate spatial data with the results of environmental monitoring. The author also emphasises the importance of the synergy of GIS and ANN in analysing spatial and temporal dependencies. According to him, such models are particularly effective for predicting changes in ecosystems with high spatial and temporal dynamics, such as in areas of seasonal ice melt. A comparison of results shows that the author's conclusions about the synergy of ANN and GIS coincide with those of the current study, including the use of ANN for temporal analysis and GIS for spatial analysis. However, the author focuses on the application of these technologies in highly specialised tasks, such as the study of polar regions, while current research is focused on a wider range of ecosystems, including urban areas.

An example of successful integration of these technologies is pollution monitoring in marine, forest and agricultural ecosystems. With the help of ANN and GIS, pollution zones can be precisely identified, their dynamics analysed and the effects on ecosystems predicted [53]. Such technologies help to monitor oil pollution in marine ecosystems or changes in water quality in freshwater bodies. In agricultural zones, it allows the migration of pollutants such as pesticides or nitrates to be predicted, thus contributing to better agricultural risk management. Lu *et al.* 2020 [54] demonstrated successful examples of using ANN and GIS for monitoring and analysing pollution in different ecosystems. The author emphasises that in marine ecosystems, neural networks can track the dynamics of oil slicks using satellite image data, and in forest ecosystems, can identify areas with high levels of air pollution. In agricultural areas, the author believes the use of ANNs helps predict the movement of pesticides in soil and water systems to minimise environmental damage. A comparison of research results demonstrates that the author's approaches to integrating ANN and GIS for pollution analysis are consistent with those proposed in the current study. However, in contrast to the current findings, the author emphasises methods for predicting pollutant migration rather than real-time monitoring. In addition, the study emphasises the regional level of analysis, while the current study covers both local and global ecosystems.

However, despite the significant advantages of ANN and GIS, there are several challenges associated with their integration. One of the main ones is the need to process and analyse huge amounts of data, which requires powerful computing resources and highly qualified specialists. In addition, different types of data may have different accuracy and resolution, which creates difficulties in integrating them into a single analytical system. Despite these difficulties, the integration of ANN and GIS provides new opportunities for comprehensive monitoring and management of environmental risks. Yariyan *et al.* 2020 [55] analysed the problems of integrating ANN and GIS, noting that one of the main obstacles is the need to process heterogeneous data sets with different accuracy. The author stresses that the incompatibility of data formats and limited computing power can slow down the analysis process, especially when working with highly detailed satellite images. The author suggests the use of cloud platforms and distributed computing to improve integration efficiency, and the development of standards to harmonise input data. Research results comparison demonstrates that the author's conclusions confirm current observations about the difficulty of processing and integrating data of different formats and resolutions. However, the emphasis on the use of cloud technology as a key solution is somewhat different from the current approach of optimising existing data processing algorithms to improve their efficiency. Furthermore, the current results highlight the human factor – the need to train specialists to operate with such systems.

Wong *et al.* 2021 [56], Shtovba and Shtovba 2024 [57]. investigates the effects of industrial pollution on forest ecosystems using ANN to analyse data on acid rain, air pollution and soil degradation. The author RNN to analyse time series data and predict further changes in forest ecosystems. The author did not analyse GIS, focusing only on monitoring data. Thus, the use of ANN and GIS in environmental monitoring and natural resource management holds great promise for solving complex environmental problems. These technologies can improve the accuracy of forecasts, improve responsiveness to changes in ecosystems, and enable sustainable management of natural resources. It is important to continue to develop methods for integrating these technologies to better address environmental challenges in the face of global change. Zeshan *et al.* 2021 [58], Nosach 2024 [59] discussed the prospects of using ANN and GIS to solve global environmental problems. The author argues that the integration of these technologies contributes to a more accurate prediction of changes in ecosystems and allows for rapid response to environmental threats. The researchers emphasise that the combination of ANN and GIS is key for the transition to sustainable management of natural resources, especially in the face of the growing challenges of climate change. The author also highlights the need for an interdisciplinary approach that brings together ecologists, programmers and data scientists to develop more adaptive and robust models. Comparing the findings with current results, a common understanding of the key role of ANN and GIS in solving environmental challenges is notable. At the same time, the author emphasises more on the need for interdisciplinary collaboration, while current research focuses on improving the technical aspects of integrating these technologies.

The scientific novelty of the study is the presentation of a comprehensive approach to the analysis of environmental processes, combining LRS methods for processing large amounts of data and GIS for their visualization and analysis of spatial aspects. The authors emphasize the ability of LSS to reveal hidden patterns in data, which allows not only to classify various ecological objects, but also to predict the dynamics of changes in such important areas as land cover, forest degradation, and water pollution. At the same time, the use of GIS provides a reliable basis for creating integrated models that take into account not only data on nature, but also socio-economic factors that affect ecosystems.

The practical significance of this study lies in its potential to improve natural resource management. Identifying and classifying environmental threats, such as pollution, water scarcity, or changes in agricultural systems, allows for a rapid response to them and ensures more effective resource use planning. At the same time, the authors emphasize the importance of adapting agriculture to climate change, such as rising temperatures or changes in precipitation patterns. They also justify the need to use innovative technologies to predict these changes and plan adaptation measures that will ensure the stability of agricultural production.

Future research in this area may focus on improving LMS models, which will improve the accuracy of forecasts, particularly when predicting long-term changes in natural systems. It is also important to integrate new data sources, such as sensors and satellite imagery, which can significantly improve the effectiveness of real-time monitoring. Another area for future research is the optimization of algorithms for processing large amounts of data, which will significantly reduce processing time and improve decision-making efficiency.

5.0 CONCLUSIONS

Modern environmental challenges, including monitoring changes in natural systems, predicting environmental risks and managing natural resources, require innovative approaches to analysing, interpreting and visualising large amounts of data. Artificial neural networks' have demonstrated their effectiveness in processing complex and multidimensional data, allowing them to identify hidden patterns, classify objects such as land cover types or forest degradation zones, and predict the dynamics of climate parameters or the spread of pollutants. These technologies successfully integrate data from a variety of sources, including satellite imagery, sensors and unmanned aerial vehicles, to provide a more complete understanding of environmental processes.

Geographic information systems, in turn, is highly beneficial in analysing spatial data. They can address the geographical location of information, which is especially important for the creation of thematic maps, such as environmental risk zones, as well as the management of large spatial and temporal databases. Data visualisation using Geographic information systems greatly simplifies the interpretation of the results and makes them accessible to decision-makers.

The synergy of artificial neural networks and Geographic information systems, which creates unique opportunities for spatial and temporal modelling, was emphasised. For instance, the use of deep learning to analyse time series in combination with spatial Geographic information systems data allows for a comprehensive analysis, addressing both temporal and spatial aspects of changes in ecosystems. This is especially true when processing large amounts of data, such as satellite images, sensors and weather station data, which are traditionally difficult to analyse.

Environmental pollution by the oil sector is manifested in several ways. The concentration of PM2.5 in the air varies from 25 to 40 μg/m³, the content of lead in the soil ranges from 50 to 150 mg/kg, and the pollution of water resources by oil products is between 0.2 and 1.0 ppm. Annual CO_2 emissions range from 0.5 to 1.2 million tonnes, and oil production is 100 to 250 barrels per day. These data indicate the significant environmental impact of the oil industry in the region and highlight the need for more effective environmental protection measures.

The study demonstrated that the integration of artificial neural networks and Geographic information systems can be used to develop hybrid models for predicting environmental risks, modelling the effects of climate change, tracking pollution and assessing the impact of anthropogenic factors on ecosystems. This approach improves the accuracy and speed of analysis, automates monitoring processes and promotes sustainable management of natural resources. Thus, the use of artificial neural networks and Geographic information systems is central to solving modern environmental problems by providing effective tools for monitoring, analysing and forecasting environmental changes. The limitations of the study are related to the availability of data on some ecosystems, as well as the need for high-quality spatial and temporal data to build accurate models. Further research will focus on improving big data processing algorithms, integrating with real-time data, and extending the models to more accurately predict environmental change.

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Conflicts of Interest

The author(s) declare(s) that there is no conflict of interest regarding the publication of this paper

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