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Research and applications of artificial neural networks in spatial analysis: Review

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Abstract

The conducted review presents the possibility of using artificial neural networks in sectors related to environmental protection, agriculture, forestry, land uses, groundwater and bathymetric. Today there is a lot of research in these areas with different research methodologies. The result is the improvement of decision-making processes, design, and prediction of certain events that, with appropriate intervention, can prevent severe consequences for society. The review shows the capabilities to optimize and automate the processes of modeling urban and land dynamics. It examines the forecasts of assessment of the damage caused by natural phenomena. Detection of environmental changes via the analysis of certain time intervals and classification of objects on the basis of different images is presented. The practical aspects of this work include the ability to choose the correct artificial neural network model depending on the complexity of the problem. This factor is a novel element since previously reviewed articles did not encounter a study of the correlation between the chosen model or algorithm, depending on the use case or area of the problem. This article seeks to outline the reason for the interest in artificial intelligence. Its purpose is to find answers to the following questions: How can artificial neural networks be used for spatial analysis? What does the implementation of detailed algorithms depend on? It is proved that an artificial intelligence approach can be an effective and powerful tool in various domains where spatial aspects are important.

Introduction

Given the diversity of artificial intelligence-based data processing algorithms in recent times and the tendency to generalize complex parametric models, it can be assumed *a priori* that research in spatial analysis will be largely based on the application capabilities of artificial neural network methods. Neural networks enable the control of complex problems of multidimensionality, which is much more difficult when using other traditional methods. Undoubtedly, the main advantage of using these methods is their ability to discover complex relationships between different datasets and to find and explore hidden features in the data (Guzy et al., 2021).

The topic of neural networks belongs to an interdisciplinary field of research, which has received widespread attention mainly due to its predictive ability. As a result of the learning process, the network can acquire predictive capabilities without the need for clear hypotheses and indicating the relationship between input data and predicted results (Fischer, 2006). Artificial neural networks have become an excellent computational tool for several reasons. One of them is the ability to perform parallel computations, which results in a significant acceleration of the computational process. Another advantage is the universality of algorithm development without the need to concretize problems. Neural networks allow one to control a complex multidimensional problem, which is much more difficult to do with other conventional methods (Haduch, 2012).

Neural networks have some natural capabilities that are missing in traditional analysis approaches. The enormous number of inter-neuron links makes the network robust to errors that occur in some connections. Another feature of the network is its ability to learn and generalize the acquired knowledge. Trained on a limited set of learning data, it can associate the acquired knowledge and exhibit the expected operation on data not involved in the learning process (Osowski, 2013). Due to the great interest in the topic, the concept of artificial neural networks has strongly evolved. In recent years, tremendous advances in data mining have created the need for new, unconventional methods. Any spatial analysis requires a high level of expertise, which is based on combining certain algorithms, augmenting sets, and integrating data.

This paper focuses on presenting artificial neural networks as a tool for solving geoinformatics problems. The conducted study presents the possibility of using ANNs in sectors related to environmental protection, agriculture, forestry, land management, and civil engineering. The result of the application of these techniques is the improvement of decision-making processes, design, and prediction of certain events that, with appropriate intervention, can prevent natural disasters. The purpose of this paper is, thus, to systematically investigate existing approaches to implementing ANN in spatial analysis in various fields.

After reviewing the existing review articles, it was noticed that they were fragmented. Despite the exhaustive information in a particular area, it is often noted that there is a lack of some element linking theory to practice, expanding the use cases of ANNs. Therefore, this study presents a comparison of modern models, methods, and techniques for various geospatial applications, which is the main contribution of this work. A breakdown of the models, i.e., classification, regression, prediction, and the most common algorithms (e.g., MLP or SVP) that are dependent on the use case, is presented. The practical aspects of this work include the ability to choose the correct artificial neural network model depending on the complexity of the problem.

Analysis of existing review articles

Recently, we have seen an increase of interest in artificial intelligence in spatial analysis; the reviews previously completed by researchers focus on some well-defined categories. The most common application of ANNs is remote sensing and photogrammetry by Mas and Flores (Mas & Flores, 2008) and Kolar et al. (Kolar, Benavidez & Jamshidi, 2020). Samaras et al. (Samaras et al., 2019) conducted a solid literature review focusing on the use of deep learning for the detection of unmanned aerial systems. They present several detection methods, commenting on the advantages and disadvantages of each method. Moreover, they point out that the data acquisition process can be performed from different altitudes: ground, air, and space, which depend on the sensors used. Radar, electro-optical, thermal, and acoustic sensors were mentioned.

Wu and Silva (Wu & Silva, 2010) provided an overview relating to the use of artificial intelligence for urban and land dynamics modeling processes. The purpose of this article was to increase the understanding of how artificial intelligence approaches urban and land dynamics modeling processes and how researchers can structure this knowledge and select appropriate approaches in their models. Niu et al. (Niu et al., 2016) conducted a review on whether artificial intelligence is applicable in earth science, covering a wide range of fields such as geographic information sciences, geography, earth sciences, and environmental sciences.

A review by Machiwal et al. (Machiwal et al., 2018) presented the application of artificial intelligence in groundwater quality assessment and protection. This paper focused on applications of time series modeling, multivariate geostatistical analysis, and artificial intelligence techniques applied to groundwater quality assessment and aquifer vulnerability assessment. The findings from this article were that statistical integration and techniques with enhanced GIS capabilities could be used to accurately interpret hydrogeologic processes occurring within aquifer systems.

Similarly, a review of single and hybrid artificial intelligence models for river water quality prediction has emerged (Rajaee, Khani & Ravansalar, 2020; Mustafa et al., 2021). As a result of the need for accurate river water quality predictions, researchers have been encouraged to explore new, unconventional artificial intelligence-based models. A review of this work is undertaken in terms of predictor selection, data normalization, data partitioning into the training set and test set, and modeling performance, among others.

The use of artificial intelligence in earth science-related research was presented by Siti et al. (Siti Khairunniza Bejo et al., 2014), in which a review of articles relating to crop yield prediction was presented. Huang et al. (Huang et al., 2010) provided a fair summary in which they highlighted 348 articles and reports where ANNs are used in agricultural and biological engineering. Chen et al. (Chen et al., 2013) conducted a review of the advances in artificial intelligence applied to civil engineering, in which a summary of the methods and techniques developed included neural networks, fuzzy systems, expert systems, and inference, among others. The research area includes structural optimization using evolutionary algorithms, damage detection, and performance prediction of civil infrastructure using neural networks.

Also noteworthy is the review by Nikparvar and Thill (Nikparvar & Thill, 2021), who, by undertaking a fair analysis of the articles, presented to what extent spatial data affects the performance of machine learning, what are the best practices in this area, and where is the potential for future research. They presented two approaches, in which the first is to generate new spatial features and process them with traditional non-spatial learning methods. The second approach, on the other hand, used dedicated algorithms such as decision trees and random forests, support vector machines (SVM), neural networks, and deep neural networks (DNN). Each algorithm is briefly described, indicating the principle of operation and the problems encountered during use. Many of these methods have been successfully used in applications ranging from point cloud classification to trajectory analysis and pattern recognition in satellite images.

This literature review begins with the 1990s. The complete analysis consisted of more than 150 articles, several high-end monographs, dissertations, and scientific books. Articles were analyzed with a high impact factor, published by: Elsevier, IEEE, MDPI, Taylor & Francis, and IET. Figure 1 presents

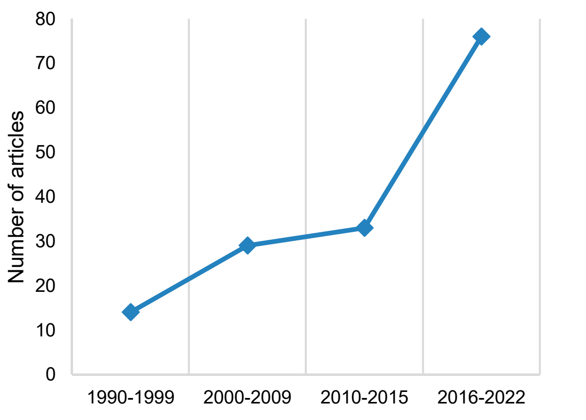

Figure 1. Number of analyzed articles versus years published

a graph showing the number of articles reviewed relative to the years in which the research was published. As assumed in the introduction, artificial neural networks are gaining popularity in spatial analysis every year. Confirmation for these words is provided by the following observation, from which a significant upward trend can be observed.

Artificial neural networks in spatial analysis

In practical solutions, neural networks are usually the element of the decision-making process, passing the executive signal to the next parts controlling the process. The functions performed by the network can be grouped into three basic groups: classification, regression, and prediction. In classifying and recognizing objects, the network learns the basic features of these patterns, such as the geometric representation of the pattern's pixel layout, the distribution of principal components, or other properties of the pattern. In the learning stage, the variations found in different patterns are highlighted as a basis for decision making, assigning them to the appropriate class. In the prediction domain, the task of the network is to determine the future responses of the system based on a sequence of past values. Regression, on the other hand, is used to estimate continuous or ordered values using regression techniques. This technique is used for forecasting, modeling time series, and finding a causal relationship between variables.

Multi-criteria analysis relies on a set of diverse criteria to support certain decisions. Probably due to the fact that ANNs use diverse data in the modeling process, they are the most frequently used tool in this area of research for various complex problems.

Landslide problems

Pham et al. (Pham et al., 2017) in their paper presented a landslide problem where the main aim of this research is to evaluate and compare the performance of landslide models using ANNs techniques to assess the susceptibility to this phenomenon. In a similar way, in a previous publication (Yilmaz, 2009), research was conducted in the area of Turkey. The results obtained are the same, and the usefulness of ANNs for creating this type of map is confirmed. However, problems relating to the network training process are indicated. Due to the large amount of data, the training stage is time-consuming. However, according to the author, in analyses composed of various data or studies on large areas, the problem related to time-consuming calculations will always occur. As is known, landslides are natural phenomena that occur independently of human activities. Therefore, methods are sought to reduce the occurrence of potential damage and losses. Maps showing areas prone to this phenomenon are certainly helpful to planners.

A different approach to a similar topic was demonstrated by Lee et al. (Lee et al., 2003). In the area of South Korea, the location of landslides was identified using ANNs based on the interpretation of aerial photographs and a spatial topographic database. Factors related to landslides were extracted from the spatial database, including slope, curvature, and soil texture. The results of the analyses performed with the ANNs application were verified with the landslide location data. The result was satisfactory; there was a correspondence that occurred between the susceptibility map and the existing data.

In a similar way, ANNs have been applied in the area of Malaysia, where landslides are one of the most important problems (Pradhan, Lee & Buchroithner, 2010). Studies relating to landslides have also been conducted in Brazil (Bragagnolo, da Silva & Grzybowski, 2020). Zhu et al. (Zhu et al., 2020), who studied this problem, proposed an innovative model. According to them, the use of conventional machine learning models results in a limited performance of landslide susceptibility prediction. This is because landslide objects are generally uncorrelated or nonlinearly correlated. Their results showed that, compared to existing conventional algorithms such as multilayer perception, logistic regression and decision tree, the authors' proposed novel cascade-parallel LSTM-CRF model had a higher landslide prediction rate.

Forestry problems

Another area that relates to multi-criteria analysis is the forestry sector. Sunil et al. (Sunil et al., 2021) used ANNs to predict the spatial probability of deforestation. Through rapid population growth, followed by the rapid development of settlements, agricultural land, and roads, several regions of the world have contributed to the depletion of forest land. The results obtained in this research indicated that, by using different ANNs models, an accurate map of deforestation probability could be prepared. Delineating such areas using traditional methods would be time consuming and expensive, especially over large areas. The results are expected to be an effective tool for environmental planners and forest managers. This process is closely correlated with certain natural and anthropogenic factors. The findings may be valuable for deforestation forecasts in other regions with similar geo-environmental conditions.

The next example relating to deforestation is the article by Mas et al. (Mas et al., 2004). This study was designed to predict the distribution of tropical deforestation. Using Landsat images from 1974, 1986, and 1991, digital deforestation maps were generated to indicate the location of such areas and the persistence of forests. Various spatial variables, such as proximity to roads and settlements, forest fragmentation, elevation, slope, and soil type, were overlaid on the maps to determine the relationship between deforestation and these variables. da Silva et al. (da Silva et al., 2014) in their study used artificial neural network techniques to map land cover and check the correlation with biophysical parameters of tropical forests in eastern Amazonia.

Land use problems

In addition to forests, ANNs find extensive applications in forecasting land use and land use changes. Such changes are influenced by a variety of social, political, and environmental factors. For example, Pijanowski et al. (Pijanowski et al., 2002) used the integration of GIS with ANNs to investigate how factors such as roads, highways, streets, rivers, and lakes can influence urbanization patterns in a designated area. The authors made an important conclusion that non-spatial aspects are very important in such studies, giving the example of a demographic factor such as age. Further research on this topic should be expanded to include the indicated elements. Cao et al. (Cao, Dragićević & Li, 2019) examined how the use of recursive neural network models handles the prediction of land use changes over short periods of time. For training, they used land use data from 1996, 2001, 2006, and 2011 DL models to enable a short-term forecast for 2016. This study showed that RNN models provide a set of valuable tools for short-term forecasting activities that can inform and complement the traditional long-term planning process.

As is known from earlier phrases, crops are an important economic component. Niedbała et al. (Niedbała et al., 2019) proposed a combination of quantitative and qualitative data to build three independent predictive models from which canola oil yields were simulated. Hagenauer's paper (Hagenauer, Omrani & Helbich, 2019) presented a comparison of 38 machine learning models to investigate land consumption rates, i.e., the transition of landscapes to built-up areas. Models were developed based on the years 2009–2015 in Germany, while predictions were made for the years 2015–2021. To evaluate the effectiveness of the approach, mean absolute error, mean squared error, and coefficient of determination were measured for the analyses using cross-validation. Models that performed the worst on a given task were indicated. Reades et al. (Reades, De Souza & Hubbard, 2019) addressed the modeling of some complex socio-spatial processes. They are shown to analyze existing patterns and processes of socio-economic change in London boroughs, based on the 2001 and 2011 censuses, which are then used to predict areas where population growth or decline is most likely to occur by 2021.

Bathymetric problems

Another use case study for ANNs is in aquatic areas. Accurate bathymetric mapping for shallow areas is essential for coastal and marine engineering applications. Most commonly, traditional survey techniques using bathymetric sensors or LiDAR scanning of the water surface are used to produce high-quality bathymetric maps. However, the indicated techniques are very expensive, hence the motivation to create proprietary ANN-based methods. Makboul et al. (Makboul et al., 2017) in their study evaluated the performance of artificial neural networks in estimating bathymetry in the eastern port of Alexandria. This area is characterized by shallow water with low turbidity and a muddy seafloor. The depth estimation is based on ANNs fitting algorithms using the logarithms of the reflectance values of multispectral bands using Landsat-8 multispectral images. The images in the first phase are corrected for effects due to atmospheric conditions and solar reflectivity. The bands are then calibrated using reference measurements obtained with GPS and a single beam echosounder. The results of this study indicated that ANNs have an improved ability to estimate bathymetry using remote sensing data.

A similar study was conducted in the coastal area of one of the islands of Saudi Arabia (Kaloop et al., 2022), which proposed two new hybrid ANN models for bathymetric modeling. Their performance was investigated using satellite images and depth values of the study area obtained from direct measurements. The results showed that the developed method could accurately determine bathymetry for shallow water areas with depths up to 30 m. Satellite bathymetry can be an excellent fast, and inexpensive alternative to traditional methods of mapping shallow areas.

A different approach was demonstrated by Moses et al. (Moses et al., 2013), who developed bathymetry for a selected lake system from satellite imagery (IRS P6-LISS III). Water depth measurements were taken for 17 months at different points in the lake. The conclusion of this study was that, for a shallow lake with less depth, the difference between the actual and predicted value was significant, indicating the disadvantage of using ANNs. In contrast, as the depth increases for shallow lakes, the prediction accuracy of ANNs increases.

A different conclusion was reached by researchers in another paper (Elshazly et al., 2021), in which satellite images were used to determine the bathymetry of Lake Manzala (Egypt). The results showed that the proposed approach works effectively for the studied body of water. The authors suggested that such methodologies should be used to determine bathymetry, especially in shallow lakes, to save effort and monitoring costs. Seafloor modeling has also been addressed by Nagamani et al. (Nagamani et al., 2012); their study presented the use of ANNs to spectrally distinguish different seafloor types while estimating shallow water depths. Mapping of coastal bathymetry from satellite imagery using ANN has also appeared for the shallow turbid water areas in Saint-Malo (Collin, Etienne & Feunteun, 2017). Keohane and White (Keohane & White, 2022) developed the chimney identification tool (CIT), which, using convolutional neural networks (CNNs), classifies bathymetry acquired from an autonomous water vehicle with a 1 m grid to identify the location of hydrothermal vents. They indicated that this is the first application of these methods to hydrothermal systems, making it possible to study their correlation with geology, lithosphere cooling, and deep-sea biogeography.

Groundwater problems

The next example of using ANNs in the field of advanced geospatial modeling is the groundwater problem. Lovedee-Turner and Murphy (Lovedee-Turner & Murphy, 2018) used ANNs to map groundwater potential. They further indicated that integrated models built from various machine-learning techniques are the most effective. Some modeling techniques have some drawbacks, for example, lack of applicability in regions with data scarcity. The use of composite algorithms precludes many of the problems encountered with single techniques.

For the most destructive natural hazards and flooding, ANNs are used with effectiveness. Every year, severe damage is caused due to this natural phenomenon, resulting in economic losses and increased mortality.

Kia et al. (Kia et al., 2012) developed a flood model using various flood factors using ANNs and geographic information system (GIS) techniques to model and simulate flood-prone areas in the Malaysian Peninsula. With satisfactory results, the information obtained can be used in the planning of new protective infrastructure. One of the other countries in the world that also faces the problem of flooding is Iran, especially in urban catchments. Bejo et al. (Bejo et al., 2014) had the goal of presenting the possibility of ANNs' prediction of water discharge values on the basis of a diverse dataset, which includes GIS spatial analysis, hydrometric station data, and satellite images, among others. The results obtained in this study can be used in future environmental planning at the local scale as a means to improve the management of environmental hazards and crises. The referenced study demonstrated that the integrated use of GIS spatial analysis function with neural network algorithm is one of the high-performance methods to predict the potential of natural disasters such as floods.

A similar problem was addressed by Sahoo (Sahoo & Bhaskaran, 2019), who conducted a study in the Indian area. The obtained results are encouraging, demonstrating the effectiveness of the ANN model in real time. Thus, according to the author, the presented approach will be applicable for disaster risk reduction during tropical cyclone activity and the resulting unwanted floods. Within Ethiopia, Tamiru and Dinka (Tamiru & Dinka, 2021) used GIS-ANN to assess the flood risk zone for this city and its floodplain, where historical flood data from 2006 was used for the training process.

Environmental changes examples

An example of using an artificial neural network to predict seismic damage of multi-story buildings based on earthquake intensity is worth mentioning (Wang, Gao & Xin, 2010). An example of the use of ANNs in discovering geographic information is provided in the article by Rizeei et al. (Rizeei et al., 2019), in which ANNs models were used to determine the tar hazard over a specific region. The developed hazard map can be used as an aid for drilling new boreholes. As a result, it avoids locations where there is a potential tar hazard.

In today's trend of obtaining energy from renewable sources, it is worthwhile to search for the application potential of ANNs in connection with solar energy. Following this thought, Anwar and Deshmukh (Anwar & Deshmukh, 2018) investigated the prediction and evaluation of solar radiation across India. Geographic (i.e., latitude, longitude, and altitude) and meteorological (temperature, sunshine duration, relative humidity, and precipitation) data from the NASA geosatellite database for 22 years was used to train and test the network. Average solar radiation was used as the output of the network. Based on the developed model, solar radiation of major cities and solar energy potential can be estimated. Within Indonesia, Rumbayan et al. (Rumbayan, Abudureyimu & Nagasaka, 2012) also studied solar radiation potential, additionally visualizing solar irradiance by province as a solar map for the whole country. They proposed average temperature, average relative humidity, average sunshine duration, average wind speed, average precipitation, geographical coordinates, and month during the year as input datasets. An important motivation for this study was that, through the vast area of the islands, Indonesia has a limited number of weather stations that record the availability of solar radiation. The results from this study showed that the used ANNs method could be an alternative option for data estimation. Applications are also possible in solar power systems.

Zheng et al. (Zheng et al., 2021) used deep convolutional neural networks (DCNNs) to segment clouds and snow in satellite images. This is a useful operation for image analysis and interpretation. Atmospheric conditions negatively affect the quality of satellite images, and therefore, the resulting procedure greatly facilitates analyses based on this kind of data. Similar tools were used by Sun et al. (Sun et al., 2022), who created a proprietary algorithm using a hybrid multi-resolution and transformer semantic extraction network (HMRT) to classify buildings and roads from remote sensing images. This procedure is very important in the area of land cover monitoring, which translates to aiding urban planning.

Results

Table 1 presents the breakdown of each article by use case, the model used, the algorithm implemented, and the country in which the research was completed. The use cases are generally extremely numerous, most of them dealing with problems

Table 1. Division according to the data type used

References	Use case	Model	Algorithm	Country
Pham et al., 2017; Yilmaz, 2009; Lee et al., 2003; Pradhan, Lee & Buchroithner, 2010	Assessment of susceptibility to landslides	Regression; classification; prediction	MLP	India, Turkey, South Korea, and Malaysia
Bragagnolo, da Silva & Grzybowski, 2020	Landslide susceptibility mapping	Classification	MLP (backpropagation)	Brazil
Zhu et al., 2020	Modeling of susceptibility to landslides	Regression	RNN	China
Saha et al., 2021	Forecasting areas of deforestation	Prediction	MLP	India
Mas et al., 2002	Predicting the spatial distribution of tropical deforestation	Prediction	MLP	Mexico
Pijanowski et al., 2002; Cao, Dragićević & Li, 2019	Forecasting changes in land use	Prediction	MLP and RNN	USA and Canada
Moses et al., 2013	Predicting the depth of the lake	Prediction	MLP (backpropagation)	India
Elshazly et al., 2021	Bathymetry mapping	Regression	Decision tree (DT) and SVM	Egypt
Nagamani et al., 2012	Seabed classification	Classification	MLP	India
Collin, Etienne & Feunteun, 2017	Coastal bathymetry	Prediction	MLP	France
Kia et al., 2012	Predicting a flood	Prediction	MLP	Malaysia
Sahoo & Bhaskaran, 2019	Forecasting a storm wave and coastal flooding	Prediction	MLP	India
Anwar & Deshmukh, 2018	Detecting solar energy potential	Prediction	MLP (backpropagation)	India
Rumbayan, Abudureyimu & Nagasaka, 2012	Detecting solar energy potential	Prediction	MLP	Indonesia
Rizeei et al., 2019	Groundwater potential mapping	Regression	MLP, LR, and SVM	South Korea
Mollalo et al., 2019	Distribution of tuberculosis	Prediction	MLP	USA
Kogut et al., 2022	Classification of point clouds characterizing the water surface, seafloors, and seafloor objects	Classification	MLP	Germany
Kogut & Słowik, 2021	Classification of airborne bathymetric scanning data to detect objects at the seabed	Classification	MLP	Germany
Reades, De Souza & Hubbard, 2019	Urban gentrification	Prediction	Random forests	Great Britain
Włodarczyk-Sielicka & Lubczonek, 2019	Reduction of bathymetric data	Regression	RBF and Kohonen	Poland
Niedbała et al., 2019	Yield prediction of rapeseed	Prediction	MLP	Poland
Frohn & Arellano-Neri, 2005	Classification of land cover	Classification	Decision tree (DT)	USA

relating to separate natural disasters that are beyond our control; hence, predictive capabilities are an important aspect.

In summary, Figure 2 presents a graph showing the ratio of models used, i.e., regression, classification, and prediction in the analyzed articles on multi-criteria analyses. It is indisputable to observe that the predictive capabilities of artificial neural networks are used the most in spatial analyses. The whole popularity of ANNs in this aspect is due to the fact that it is possible to predict certain phenomena. On the basis of temporal patterns, it is feasible to forecast the changes that occur. The outcomes from such a process undoubtedly facilitate the work of many important state institutions and support the making of important decisions. In the case of regression and classification, the division is equal. There is also interest in these functions, but not as much as in prediction. Predictive capabilities are most often based on various types of imagery acquired at the turn of various time periods.

Figure 3 shows the breakdown of the algorithms used in the multi-criteria analyses. Referring to the graph relating to the algorithms for the classification

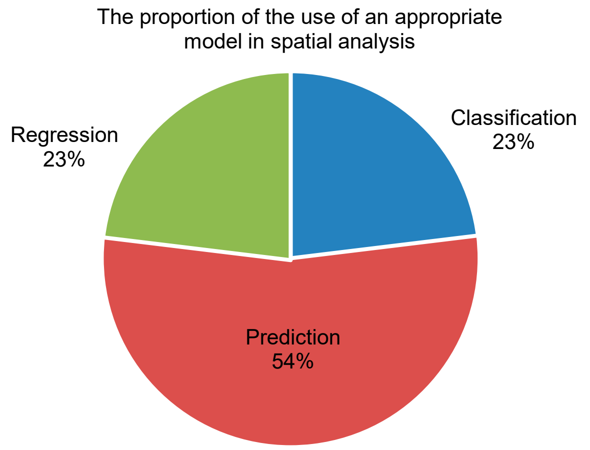

Figure 2. Graph showing the use of prediction, classification, and regression in the analyzed articles

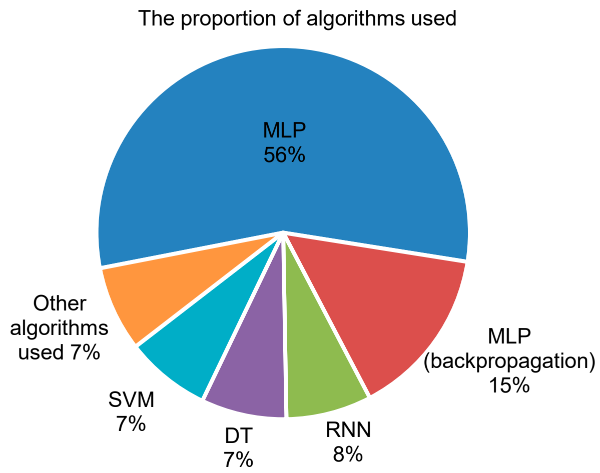

Figure 3. Graph showing the proportion of algorithms used in the multi-criteria analysis: MLP – multilayer perceptron; DT – decision tree, RNN – recurrent neural network; SVM – support vector machine

of objects found in the images, a significant change can be seen. First of all, convolutional neural networks did not appear. The MLP algorithm, which was previously a minority, is one of the most used solutions in this case. It is also noteworthy that there is a broader spectrum of algorithms used.

Discussion

This paper focuses on the implementation of artificial neural networks in spatial analysis with respect to the models used and because of the algorithm used. The problematic areas, including a need to improve the work or support certain decisions, are also analyzed. It is clear that in areas prone to destructive natural hazards, researchers are looking for solutions that could inhibit certain activities. As is known, these natural phenomena occur independently of human actions. It is, therefore, necessary to search for methods that reduce the occurrence of potential damage and losses and anticipate certain phenomena in advance to be able to intervene in time. Thus, articles with predictive models for mapping landslides or floods in India or Malaysia are often noted. Due to such natural disasters, many people die, and urbanized areas are destroyed, which translates into a lack of shelter and housing for many residents. These vital problems are a great motivation for creating this type of analysis.

In European countries and the USA, the research motivation is different; research efforts are directed towards various process automation. It seems important to improve conventional measurement methods to save time and improve the accuracy of traditional modeling and analysis tools. Hence, we observe the emergence of more hybrid models, where there is an integration of different algorithms and some data fusion to improve accuracy.

The choice of the optimal method is mostly determined by the availability of data necessary for model parameterization. Traditional methods usually represent a holistic approach to the issue in question, which requires comprehensive knowledge and recognition of the exact data or object under study. This review does not include such issues as the mathematical complexity of the models, the system load, or the number of learning samples since testing data in the implementation of artificial neural networks were not covered. In future, it would be worthwhile to develop research in the direction of checking the above issues since this may provide even better insights into the application of the algorithms in question. Sometimes we have some limited datasets, which could preclude the application of some algorithms. It is also worth focusing on the implementation of hybrid models and the fusion of data from different sensors to improve the results. Usually, by combining several methods, we eliminate the disadvantages of one, which translates into even more satisfying results.

Conclusions

This paper presents a review of the literature on the use of artificial neural networks in spatial analysis. The review shows that neural networks are increasingly used in spatial analysis, thus increasing the spectrum of applications and techniques employed. Researchers, in their studies, are attempting to combine and use unconventional methods to provide better results and improve their work.

Based on this review, it is seen that many advantages of applying artificial neural networks can be formulated. This starts with the fact that no prior knowledge of the structure and relationships between the parameters used in the ANNs architecture is required. Artificial neural networks have the ability to predict nonlinear and complex processes without an understanding of the relationship between the input and output data. The learned networks used tend to have relatively low computer requirements compared to other modeling tools. No specialized knowledge of the problem is required to achieve a satisfactory result. Some models have the ability to be self-organizing. Effective results are obtained when the integration of data acquired from heterogeneous sensors is introduced. The use of combined algorithms excludes many problems that can be encountered with single techniques. Another very interesting relationship is that it is possible to use data from different time periods and, on the basis of prediction abilities, we can model certain phenomena that may happen in the future. With this in mind, it can be assumed that the research conducted in the field of spatial analysis will be largely based on the application capabilities of artificial neural network methods.

At the beginning of this paper, a research question was posed: Why is there a growing trend relating to artificial intelligence today? As emerged from this review, it is an increasingly current direction. It is important to emphasize the significant importance of ANNs, especially in safety-critical analyses such as predicting landslides, floods, fires, or other destructive elements of nature. Assistance and rapid diagnosis are required to ensure the safety of the public. Another nagging question is: How can artificial neural networks be used for spatial analysis? The answer to this question cannot be given in a short sentence because the whole study above indicates many various implementations; the cross-section of this research is highly extensive. This review attempts to assert that artificial intelligence should be treated as a versatile tool in science. It is anticipated that, in future, it will become an indispensable practical ingredient for improved results. Based on this review, it is worth undertaking research to use and improve artificial intelligence methods in the water area sector. Future research plans to conduct a comparative analysis of applied algorithms used in bathymetry, among other factors. This could be achieved by identifying strengths and weaknesses and matching the optimal areas of application.

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