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New Approaches to Determining Carbon Capture Potential

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Abstract: Climate change and global warming are among the most important environmental issues and require sufficient and urgent global action to protect the Earth for future generations. One of the main approaches used to reduce CO_2 emissions and mitigate the worst impacts of climate change is carbon capture technology. Carbon capture technologies have the potential to capture carbon from the atmosphere and convert it into fuels that can be used in environmentally friendly energy production. Innovative technologies can increase the potential for carbon capture, which can play an important role in combating climate change. A better understanding of the mechanisms that extract, store and release carbon from the atmosphere will allow us to make more accurate predictions for assessing carbon capture potentials. There have been many efforts by scientists, industry sectors and policy makers in the search for new technologies to reduce greenhouse gas emissions and achieve net zero emissions targets. Research and development work to create new technology involves complex processes and requires a digital system to optimize big data forecasting as well as reduce production time. A mathematical and statistical approach such as machine learning plays an important role in solving research problems, providing fast results and cost-effective tools for predicting big data. Effective policies and international cooperation for carbon capture can increase the potential for carbon capture. New policies and cooperation models can incentivize investment in carbon capture projects, which can increase potential. These new approaches can be used to better understand the potential for carbon capture and develop effective solutions to tackle climate change. However, work in this area is still ongoing and more research and development is needed in the future.

Keywords: Carbon capture, Climate change, Machine learning.

1. INTRODUCTION

In ecosystems on earth, living and non-living elements are interconnected by three basic functions such as energy transfer, chemical cycles, and population controls and these three functions constitute the basis for the quantitative functioning of ecosystems (Odum, 1989). Each element in the ecosystem, which has certain functions, is in balance within itself and with other elements. Disruption of this balance leads to disruptions in the functioning of the whole system and may threaten the existence of the system. Carbon (C), which is widely found in nature, is one of the common and basic elements of all living organisms. Carbon, which has high bonding properties compared to many elements, is found both singly and in compounds in nature. Due to its properties, carbon, which is found in living and non-living structures from photosynthesis process to glucose structure, has become an increasingly important environmental component since it has caused global warming in the last century.

The carbon cycle is nature's method of recycling carbon atoms. Plants, the nexus of the carbon biogeochemical cycle in terrestrial ecosystems, play a vital role in the global carbon cycle. Green plants can absorb atmospheric CO_2 through photosynthesis and forests therefore act as a large and permanent carbon sink (Pan et al., 2011). Plants are also the primary pathway for transferring CO_2 to soil through their roots and fallen leaves (Felzer et al., 2005; Sitch et al., 2007; Ainsworth et al., 2012). Meanwhile, carbon flows back into the atmosphere from vegetation through the release of volatile organics from leaves (Guenther et al., 2012) and the release of CO_2 from the decomposition of soil organic matter and plant debris (Krishna & Mohan, 2017; Chen & Chen, 2018). As climate and environmental conditions greatly influence the physiology of plants, there is a growing concern that global warming and changing atmospheric compositions are disrupting the carbon cycle, crop yields and biodiversity (Feng et al., 2019, 2022; Agathokleous et al., 2020; Chaudhry & Sidhu, 2022).

Efforts to achieve post-industrial economic development goals, the use of ecosystem products as free natural capital, and improper land use policies lead to high CO_2 emissions from the terrestrial ecosystem to the atmospheric system.

Carbon dioxide that cannot leave the atmosphere can be trapped in the forest biomass, from the root and stem structures of woody and herbaceous annual and perennial plants on the earth to the leaf and bark contents. For this reason, green wealth is one of the most important sink areas that provide a high rate of absorption of free travelling carbon gas in the world. The sequestered carbon dioxide gases are stored in different ways in the genetic structures of all herbaceous and woody individuals in the forest ecology (Ataf, 2017).

The gradual increase in the rate of CO_2 in the earth's atmosphere causes global (worldwide) climate change and temperature increase together with other gases that cause greenhouse effect. Research on the causes of global climate change has shown that the effect of CO2 on this phenomenon is 55-80% (Asan, 1995). As it is known, all plants produce organic matter by taking CO_2 from the air through photosynthesis and then convert it into other organic matter through a series of chemical reactions. Since CO_2 uptake increases with the number of leaves in plants and forests have the highest number of leaves compared to other plant communities, CO_2 consumption occurs mostly in forests. Due to this fact, the protection of forest areas on earth and their expansion through afforestation is recommended by many researchers as the most effective method to delay global climate change.

Forests, which are the largest sink areas on the globe, are important sources where carbon gases affecting climate changes are sequestered. Thanks to their structural abilities, forest assets with their above- and below-ground components, annual and perennial herbaceous and woody structures provide the absorption of carbon gas travelling freely in the earth. For this reason, it is understood that more carbon gas is sequestered in areas where photosynthesizing organisms are dense (Kahyaoğlu et al., 2019). The forest ecosystem, which contains 76-78% of the carbon gas sequestered in land areas on the globe, is one of the major sink areas that have an important place in the fight against global warming.

Greenhouse gas emissions are causing serious global climate change and CO_2 emissions urgently need to be stopped. Carbon capture and storage is emerging as the last guaranteed technology to reduce carbon emissions and has the potential to be an important option to reduce the greenhouse effect in the future. Machine learning (ML), one of the fastest developing areas of smart technology today, is considered as an important way to realise demand forecasting based on computer science and data statistics.

Nowadays, machine learning is applied to the development of prediction systems using experience, especially in highly complex systems that are difficult to model with deterministic methods (Kubat, 2017). Machine learning provides techniques that can automatically generate computational models directly as a closed-form input-output relationship, based on this available data, and maximize a performance criterion depending on the problem (Bhatnagar, 2020).

Recently, the developed machine learning methods are a promising development direction due to their ability to effectively combine remote sensing products with ground observation data. The data-driven machine learning method can preserve the effective information of remote sensing products and sample observation data, extract the complex non-linear relationship between input and output variables, and achieve the goal of combining different data scales; thus, it has a high degree of flexibility and data adaptability (Ali et al., 2015). Data-driven approaches based on machine learning can extract new knowledge from data, which can provide a new understanding of new mechanisms. Research has also proven that machine learning methods are more successful in predicting ecosystem carbon sinks compared to traditional statistical methods (Wood, 2023). A carbon sink estimation method that uses machine learning as a bridge to combine remote sensing products and ground observation data is an effective solution to reduce estimation uncertainty.

The effects of global climate change are increasing and the increase in greenhouse gas concentrations in the atmosphere is accelerating this process. Therefore, the protection and restoration of ecosystems with high carbon sequestration capacity is of great importance. Forests play a critical role in the Earth's carbon cycle and biodiversity, and therefore determining their carbon sequestration potential is an important research topic. In this study, we will discuss new approaches used in addition to traditional methods to determine the carbon sequestration potential of forests.

2. TRADITIONAL CARBON ESTIMATION METHODS

Traditional carbon sequestration estimation methods are used to predict how carbon will be sequestered in relation to natural resources. These methods use different mathematical models and data analysis techniques to determine the carbon storage capacity of forests, farmland, water systems and other ecosystems. These methods provide an important tool in the design and management of carbon sequestration projects.

The methods commonly used to calculate carbon stocks in forests are common tree inventories and estimation formulae. These methods estimate carbon values using parameters such as tree diameter, height, and density.

Traditional carbon sequestration estimation methods are used in the development of ecosystem-based strategies to reduce carbon emissions. These methods suggest various interventions including crop rotations of forests and sustainable agricultural practices of soils. They also promote the conservation and restoration of ecosystems with high carbon storage potential. However, these methods have some limitations and often face difficulties in providing sufficient accuracy. Mathematical models need to be based on sufficient data for specific ecosystems. This lack of data can reduce the accuracy of predictions and create uncertainty about the effectiveness of projects. Furthermore, climate changes can also be difficult to predict, which can affect the reliability of predictions.

3. NEW APPROACHES AND TECHNOLOGIES

In recent years, developing technologies and advanced analysis methods have led to the emergence of new approaches to determine the carbon sequestration potential of forests.

3.1. Remote Sensing Methods

Remote sensing methods are frequently used to determine the carbon sequestration potential of forests. Remote sensing is a technique for determining the properties of objects using data collected through remote sensors and instruments. Remote sensing techniques can be used to estimate the carbon stock in forest cover through aerial and satellite imaging systems. High resolution satellite data allow the development of models that determine the relationships between plant biomass and carbon stock. Furthermore, the use of artificial intelligence algorithms and computer vision analyses increases the potential to automatically identify trees and estimate carbon stocks.

The most widely used technique in remote sensing methods is, roughly speaking, the analysis of remote images of the earth. In this analysis, some important data are used to determine the carbon sequestration potential of forests. For example, parameters such as vegetation density, leaf area index and chlorophyll content are used to provide information on the carbon sequestration capacity of forests.

In previous studies, valuable information on the biological characteristics and carbon stocks of forests has been obtained using remote sensing methods such as satellite images and aerial photographs. The colour in satellite images is used to obtain spectral data to determine parameters such as photosynthetically active radiation of vegetation and vegetation density. In addition, mapping of parameters such as climate data, soil properties and vegetation structure used to estimate the carbon sequestration capacity of forests is also carried out by remote sensing methods.

Remote sensing methods are very valuable tools to determine the carbon sequestration potential of forests. These methods provide more information about the ecosystem services of forests and their role in combating climate change and contribute to the sustainable management of forests. Therefore, the use of remote sensing methods to determine the carbon sequestration potential of forests is an important research area.

3.2. Artificial Intelligence

Determining the carbon sequestration potential of natural forests is of great importance in combating climate change and is a research area of activity among forestry experts. In this field, artificial intelligence methods have emerged as advanced analytical tools used to determine the carbon sequestration potential of natural forest ecosystems. Artificial intelligence methods are used to perform several complex operations such as analyzing large data sets, identifying carbon sequestration characteristics, and estimating the emissions of forest ecosystems.

Machine learning, an artificial intelligence method, plays an important role in determining the carbon sequestration potential of natural forests. Machine learning methods analyse large data sets to identify factors associated with carbon sequestration and use these factors to estimate the carbon sequestration potential of forest ecosystems. These methods use learning algorithms to identify plant species and other ecosystem components in the forest and estimate their carbon sequestration capacity.

3.3. Machine Learning (ML) Methods

3.3.1. Decision tree (DT)

Decision Tree algorithm is one of the data mining techniques, also known as decision trees. Decision Tree refers to a tree structure that makes meaningful decisions using a given data set. This algorithm works by dividing the dataset into small subsets and applying classification methods on each subset.

Decision tree structure:

Decision Tree has a structure consisting of many inner nodes and leaf nodes. Each internal node represents a decision point, while each leaf node represents a classification. Decision points are determined based on the characteristics of the dataset and partitioning operations are performed at each level. In this way, the decision tree divides the dataset into smaller subsets and performs more detailed classifications on each subset (Figure 1).

How the algorithm works:

To create a Decision Tree, training data is needed first. Training data refers to the features or attributes associated with a particular target variable (class). The algorithm is used to classify an unknown data sample, taking these features into account. The decision tree building process includes the steps of partitioning the dataset according to the best indivisibility criteria, selecting the most effective decision node and building the structure of the tree, respectively. These steps are important for the correct classification of the dataset.

Decision Tree is a machine learning algorithm and can be used in many different fields. Carbon estimation is one of these areas.

Carbon forecasting aims to estimate the carbon emissions of an organization or a country. Decision Tree is a tree structure consisting of interconnected "decision" nodes used to estimate this carbon emission.

The use of Decision Tree in carbon forecasting can be highly effective for extracting insights from complex data structures and predicting trends. Since there are many factors affecting carbon emissions, the Decision Tree algorithm can analyses these factors and make predictions about how carbon emissions may be in the future.

As a result, the use of Decision Tree in carbon forecasting can be an effective tool for environmental sustainability and carbon emission management. However, it is important to consider factors such as data quality and accuracy of the model.

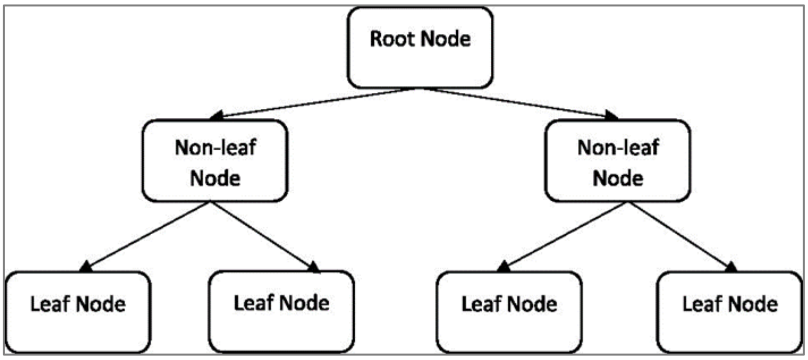

Figure 1. Decision tree layout.

3.3.2. Random forest (RF)

Random Forest is a flexible, easy-to-use machine learning algorithm that often produces a large result, even without hyperparameterisation. It is also one of the most widely used algorithms because of its simplicity and because it can be used for both classification and regression tasks. In recent years, the development and popularity of machine learning methods has led to many methods that can provide benefits in modelling. However, only a few of them have been preferred or proposed by researchers. Among these methods, discriminant analysis (DA), logistic regression analysis (LR), generalized additive model (GAM), classification and regression tree technique (CART), maximum entropy approach (MAXENT), genetic algorithms for rule set prediction (GARP) and random forest (RF) are the most common ones. Among the mentioned methods, except RF, the others have been frequently used until recent years, while RF method has started to be preferred more frequently especially with the widespread use of R programmed (Austin, 2007; Özkan et al., 2015; Beaumont et al., 2016, Mert et al., 2016).

Operation of random forest algorithm:

Before understanding how random forest works, we should look at the ensemble technique. Ensemble simply means combining multiple models. Therefore, a collection of models is used to make predictions rather than a single model.

Enseble uses two types of methods:

a) Bagging: Creates a training subset different from the sample training data with replacement and the final output is based on majority voting. For example, Random Forest.

b) Boosting: Combines weak learners into strong learners by building sequential models such that the final model has the highest accuracy. For example, ADA BOOST, XG BOOST

Bagging: Bagging, also known as Bootstrap Aggregation, is the enseble technique used by random forest. Bagging randomly selects a sample from the data set. Therefore, each model is generated from the samples provided by the Original Data (Bootstrap Samples) by substitution, known as row sampling. This step of row sampling with replacement is called bootstrap. Each model is now trained independently, which produces results. The final output is based on majority voting after the results of all models are combined. This step, which involves combining all results and producing output based on majority voting, is known as aggregation (Figure 2).

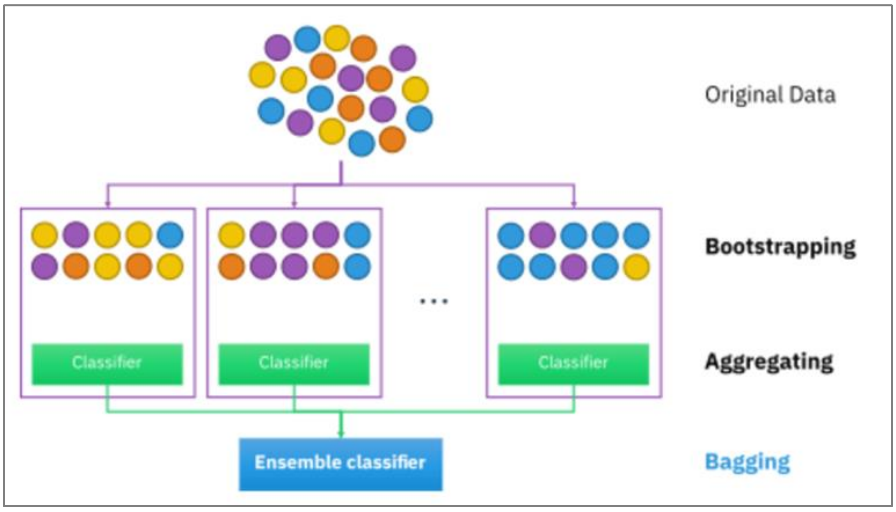

Figure 2. Bagging technique.

Steps in the random forest algorithm:

Step 1: Random Forest n random records are taken from the dataset with k records.

Step 2: Separate decision trees are created for each sample.

Step 3: Each decision tree will produce an output.

Step 4: The final output is evaluated based on majority vote or average for classification and regression respectively (Figure 3).

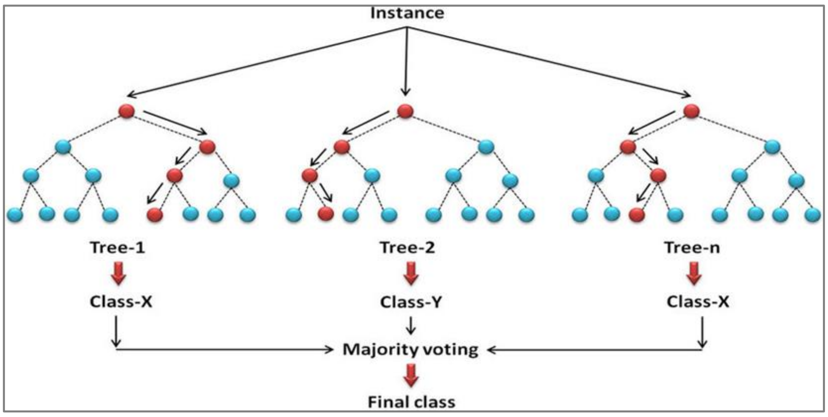

Figure 3. Random Forest algorithm setup.

Random Forest is a machine learning algorithm that can be used in carbon forecasting. In carbon forecasting, a set of measurements, such as carbon emissions in the atmosphere, need to be correlated with environmental and climatic factors.

The Random Forest algorithm is an ensemble model consisting of many trees, and each tree is trained on random subsets of the data set. To estimate carbon, this algorithm is used to build a model that considers various environmental factors such as soil type, vegetation cover, climate data as well as previous carbon measurements.

The Random Forest model learns a relationship that determines the effects of these different factors on carbon levels. Then, when you give new data as input to the modelling, the Random Forest model can estimate carbon based on this input.

In this way, the Random Forest algorithm can create a carbon prediction model that considers complex environmental and climatic influences. This model can be used for many different purposes, such as estimating carbon emissions, monitoring carbon emissions, or evaluating policies related to climate change.

Difference between decision trees and random forest:

- In the random forest algorithm, the process of finding the root node and dividing the nodes is random.
- As the number of trees increases, the rate of obtaining a precise result increase.
- The random forest algorithm reduces the problem of overlearning if there are enough trees. It requires little data preparation (Figure 4).

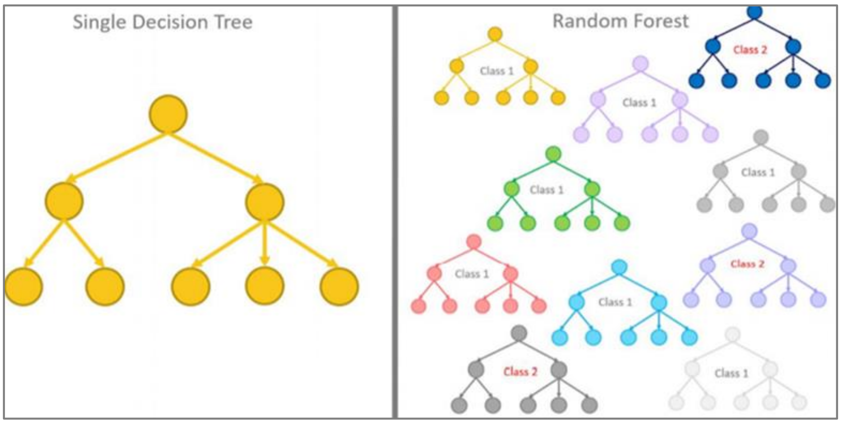

Figure 4. Decision tree and random forest difference.

3.3.3. Artificial neural networks (ANN)

Artificial neural networks (ANN), one of the most preferred models in big data, is a type of technology created by imitating the biological nervous system. ANN can be considered as a collection of systems in which neurons transmit messages between each other.

A simple neural network consists of interconnected artificial neurons. Mimicking the principle of the human brain, each neuron receives various inputs to combine them, process them and eventually produce an output. (Figure 5) ANNs are very powerful and popular tools in data mining and business analytics. Since ANNs are applicable to prediction, classification and clustering and are used in a wide variety of industries, they have proven to be useful. The most important feature of ANNs compared to other algorithms is their ability to learn highly complex relationships in data (Gaur, 2012).

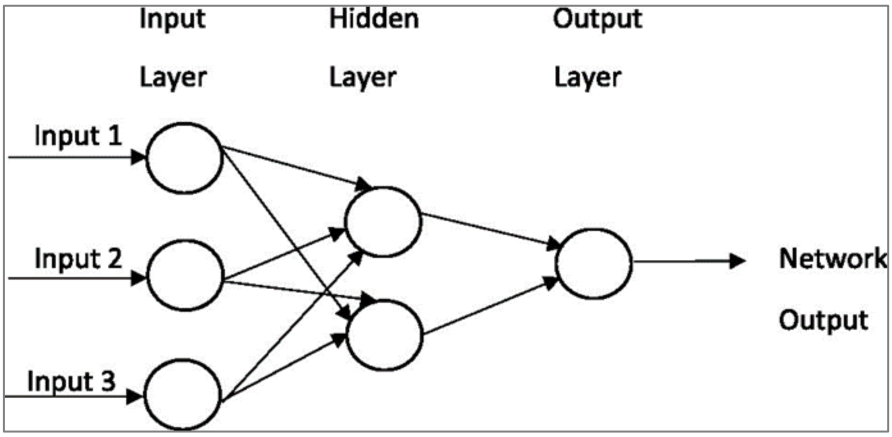

Figure 5. Neural network architecture.

The prediction phase of neural networks has two phases: training and learning. In the training phase, the network is trained using historical data containing information about the input and output. After the training phase, the model is subjected to learning on test data. In this phase, the network travels between input and output to update the weights and errors. In general, the learning phase can be considered as an optimization process and hence this minimization process continues until an acceptable error level is reached.

Artificial neural networks (ANN) are another artificial intelligence method used to determine carbon sequestration potential. Artificial neural networks can be used effectively in carbon estimation thanks to their ability to analyze complex data sets (Tsai & Kuo, 2013). These networks improve the ability to predict carbon emissions by learning based on training data sets with many input parameters. This method models the complex relationships related to the carbon cycles of forest ecosystems and estimates the carbon sequestration potential of forests.

3.3.4 Convolutional neural networks (CNN)

Convolutional neural networks are an artificial neural network model used to perform high-performance processing on images and visual data and to solve computer vision problems with deep learning algorithms. Therefore, it can also be used in solving some environmental or climatic problems such as carbon estimation (Figure 6).

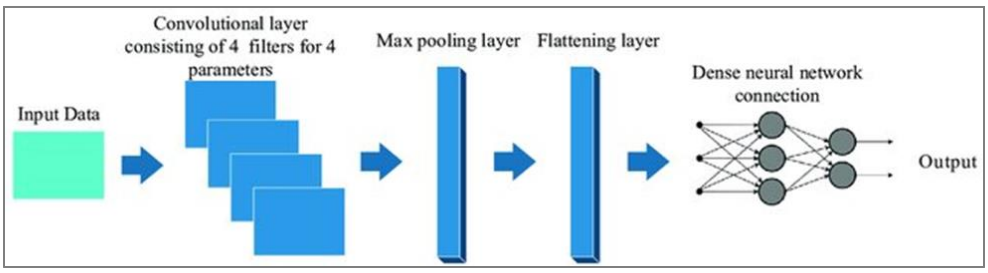

Figure 6. Convectional neural network structure.

When trained on environmental data sets, convectional neural networks can analyse images of various parameters affecting CO_2 emission and find patterns to predict these parameters. For example, factors such as the settlement of forests, agricultural areas, power plants, industrial plants, and vehicle traffic affect CO_2 emissions. CNNs can extract patterns to predict future carbon emissions by analyzing images of these factors and using previous carbon emission data.

However, the accuracy and reliability of such predictions depend on the quality and diversity of the data sets used, the training process of the model and other factors. In an important topic such as carbon prediction, it can be combined with other methods or combined with various machine learning techniques to improve accuracy.

4. CONCLUSION

Forests play an important role in combating global climate change, and understanding carbon cycles, identifying, and monitoring their carbon sequestration potential is fundamental to this endeavor. In addition to traditional methods, new approaches are increasingly being used to determine the carbon sequestration potential of forests. Technologies such as remote sensing and artificial intelligence have great potential in the processes of estimating and monitoring the carbon stock of forests.

Remote sensing methods are an important tool in determining the structure and dynamics of forest ecosystems and estimating their carbon sequestration potential. Therefore, the use of remote sensing methods should be encouraged for the assessment and conservation of carbon stocks in forests.

In conclusion, artificial intelligence methods in the field of forestry play an important role in the process of determining the carbon sequestration potential of natural forests. Methods such as machine learning, artificial neural networks and genetic algorithms are used in data analysis and modelling processes to estimate the carbon sequestration capacity of forest ecosystems. These advanced analytical tools are recognized as an important tool in combating climate change and developing sustainable forestry practices.

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