http://silvaworld.org
SilvaWorld
e-ISSN: 2822-6127
PRENSIP
https://prensip.gen.tr

REVIEW ARTICLE

The Role of Artificial Intelligence and Remote Sensing Technologies in Forest Ecosystems and Their Importance in Determining Carbon Capture Potential

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ARTICLE INFO

Article History
Received: 13.03.2024
Accepted: 20.03.2024
First Published: 31.03.2024

Keywords
Artificial intelligence
Carbon capture
Machine learning
Remote sensing

ABSTRACT

Climate change and global warming are among the most pressing environmental issues requiring urgent and adequate global action to protect future generations worldwide. One of the key approaches used to reduce CO_2 emissions and mitigate the worst effects of climate change is carbon capture technologies. 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 enhance carbon capture potential, which can play a significant role in combating climate change. Better understanding of mechanisms for capturing, storing, and releasing carbon from the atmosphere allows for more accurate assessments of carbon capture potentials. Scientists, industries, and policymakers are making significant efforts to explore new technologies to reduce greenhouse gas emissions and achieve net-zero emission goals. Development of new technologies involves complex processes and requires a digital system to optimize big data forecasting and reduce production time. Mathematical and statistical approaches play a crucial role in solving research problems, providing fast results and cost-effective tools for predicting large datasets. Effective policies for carbon capture and international cooperation can enhance carbon capture potential. New policies and collaboration models can incentivize investment in carbon capture projects, thereby increasing their potential. These new approaches can be used to better understand carbon capture potential and develop effective solutions to combat climate change. However, research in this field is still ongoing, and further research and development will be needed in the future.

Please cite this paper as follows:

Güler, S. (2024). The role of artificial intelligence and remote sensing technologies in forest ecosystems and their importance in determining carbon capture potential. *SilvaWorld*, *3*(1), 44-51. https://doi.org/10.61326/silvaworld.v3i1.248

1. Introduction

Ecosystems are defined as complex structures formed by the interaction of living and non-living components. This interaction occurs around three fundamental functions: energy transfer, chemical cycles, and population controls (Odum, 1989). Energy transfer initiates with the utilization of sunlight by plants through photosynthesis and continues by being transferred among organisms in food chains. Chemical cycles involve the transformation of elements through biological, geochemical, and atmospheric processes. Population controls regulate the growth and decline of populations because of interactions between species. Each element within the ecosystem has specific functions and maintains equilibrium with other elements while fulfilling these functions. For instance, plants absorb CO_2 from the atmosphere through photosynthesis, while animals consume oxygen and produce CO_2. This equilibrium preserves the functionality of the ecosystem. However, disturbances to this balance can lead to disruptions in the functioning of the entire system, threatening its existence.

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Carbon (C) is a ubiquitous and fundamental element found in nature, shared by all living organisms. Carbon is crucial as a building block of biological molecules and is present in both living and non-living structures, ranging from the glucose produced in photosynthesis to various organic and inorganic compounds. Particularly, carbon in the form of CO_2 in the atmosphere has contributed to environmental issues such as global warming and climate change with its increasing levels over the past century. Carbon exhibits a high affinity for bonding compared to many other elements and can be found in nature both in its elemental form and in compounds. Carbon present in organic compounds forms the structure of living organisms, while it can also be found in inorganic compounds such as carbonates (Mirici & Berberoğlu, 2020).

The carbon cycle is the process of recycling carbon atoms in nature, and in this process, plants in terrestrial ecosystems play a significant role. Plants absorb carbon dioxide from the atmosphere through photosynthesis, particularly in large areas such as forests, creating a significant carbon sink (Pan et al., 2011). Additionally, plants contribute to the carbon cycle by transferring CO_2 to the soil through their roots and fallen leaves (Felzer et al., 2005; Sitch et al., 2007; Ainsworth et al., 2012). However, carbon can be released back into the atmosphere from plants through the emission of volatile organic compounds from their leaves and the decomposition of soil organic matter and plant litter (Guenther et al., 2012; Krishna & Mohan, 2017; Chen & Chen, 2018). Factors such as climate and environmental conditions affecting plant physiology, as well as factors like global warming and changes in atmospheric composition, can significantly impact the carbon cycle, crop productivity, and biological diversity in a concerning manner (Feng et al., 2019, 2022; Agathokleous et al., 2020; Chaudhry & Sidhu, 2022).

The efforts to achieve post-industrial economic growth targets, coupled with the unrestricted use of products within ecosystems as natural resources and flawed land use policies, result in high levels of CO_2 emissions from terrestrial ecosystems to atmospheric systems. Throughout the process of retaining the generated carbon dioxide in the atmosphere, it can be stored in various parts of woody and herbaceous plants, ranging from root and stem structures to leaf and bark contents. Therefore, green areas serve as significant regions that absorb a high amount of freely circulating carbon gas on Earth. The retained carbon gases are stored in the genetic structures of all plants within forest ecology in different manners (Ataf, 2017).

The increase in CO_2 levels in the Earth's atmosphere, along with other greenhouse gases, leads to global climate change and temperature rise. Research indicates that global climate change is attributed to CO_2 effects ranging from 55% to 80%. Plants absorb atmospheric CO_2 through photosynthesis to produce organic matter. Forests, having the highest leaf area compared to other plant communities, are where CO_2 is predominantly consumed. Hence, the preservation and expansion of forested areas on Earth's surface through afforestation are recommended as the most effective methods to delay global climate change.

Forests are the largest sink areas and significant reservoirs where carbon gases are sequestered. With their structural features and both above and below-ground components, forests containing annual and perennial herbaceous and woody plants facilitate the absorption of free carbon gas. Therefore, areas with dense populations of photosynthetic organisms are observed to sequester more carbon gas. The forest ecosystem, which contains 76-78% of the carbon gas sequestered in terrestrial areas, plays a crucial role in combating global warming (Kahyaoğlu et al., 2019).

Greenhouse gas emissions led to severe global climate change, and urgent reductions in CO_2 emissions are necessary. Carbon capture and storage represent highly reliable technologies for reducing carbon emissions and hold potential for reducing the greenhouse effect in the future. Machine learning (ML) is one of the fastest-growing areas of intelligent technology today, regarded as a significant tool for performing demand forecasting based on computer science and data statistics.

Machine learning is applied in the development of prediction systems, particularly in highly complex systems where modeling with deterministic methods is challenging, using past experiences. These techniques provide a closed-form input-output relationship that automatically generates and manages computational models based on existing data, maximizing a performance criterion depending on the problem.

Recently developed machine learning methods show promising progress due to their ability to effectively integrate remote sensing products with ground observation data. Data-driven machine learning methods can preserve the effective information of remote sensing products and sample observation data, extract complex nonlinear relationships between input and output variables, and achieve the goal of merging different data scales, providing high flexibility and data adaptability. Data-driven approaches based on machine learning can extract new information from data and develop insights about new mechanisms. Research also indicates that machine learning methods are more successful in predicting ecosystem carbon sinks compared to traditional statistical methods. In this context, using machine learning methods as a bridge to integrate remote sensing products with ground observation data offers an effective solution to reduce prediction uncertainty.

The impacts of global climate change are increasingly evident, with the rise in greenhouse gas concentrations in the atmosphere accelerating this process. Therefore, the preservation and restoration of ecosystems with high carbon capture capacity are of paramount importance. Forests play a critical role in the carbon cycle and biological diversity worldwide, making the determination of carbon capture potentials a significant research topic. In this study, we will explore novel approaches beyond traditional methods, utilizing machine learning to determine the carbon capture potential in forests.

2. Determination of Carbon Capture Potentials of Forests through Traditional Methods

The carbon capture potentials of forests are typically determined through traditional methods such as long-term data collection, field measurements, and statistical analyses. These methods involve a detailed analysis process that considers biological and physical characteristics of forests as well as soil, climate, and other environmental factors. Environmental factors are given in Table 1.

Table 1. Environmental factors.

Soil properties	Climate conditions	Vegetation and biodiversity	Topography
Soil form	Rainfall regime	Species diversity	Land slope
Organic matter content	Heat	Growth rates of trees	Height
pH	Moisture	Ages	Water drainage
Depth	Wind speed	Densities	Aspect

2.1. Field Measurements and Statistical Analyses

The process of determining carbon capture potentials in forests begins with field measurements. These measurements typically encompass factors determining forest structure such as tree species, age, diameter, height, and density, as well as soil properties like organic matter content. The collected data is processed through statistical analyses and utilized to estimate the carbon storage capacity of forests. These analyses are crucial for understanding the quantity and distribution of carbon stocks in forests.

2.2. Biophysical Models

Another traditional method used to determine the carbon capture potentials of forests is the use of biophysical models. These models simulate the carbon cycle of forest ecosystems and assess the impacts of various factors (e.g., climate change, soil properties, plant species, etc.) on carbon storage. These models typically rely on processes such as tree growth rates, photosynthetic activity, organic matter decomposition, and use mathematical formulas to predict carbon capture potentials.

2.3. Soil Analyses

Since soil is a crucial component of carbon storage, soil analyses are also important in determining the carbon capture potentials in forests. These analyses typically involve determining the physical and chemical properties of soil samples. Factors such as soil organic carbon content, soil texture, pH, and nutrient elements influence the carbon storage capacity of forest soil. These data are used to evaluate the carbon storage potentials of forests in the soil.

Overall, the determination of carbon capture potentials of forests is a complex process involving various data collection and analysis methods. Traditional methods typically rely on direct field studies, while the use of modern technologies enables broader coverage and more precise predictions. These methods play a crucial role in the sustainable management of forest resources and in combating climate change.

3. New Approaches and Technologies

Determining the carbon capture potential of forests is crucial for environmental conservation and combating climate change. In addition to traditional methods, evolving technologies and advanced analysis techniques provide new and effective approaches for assessing this potential. Next-generation remote sensing technologies, such as high-resolution imagery and laser scanning tools, offer the opportunity to analyze the structural characteristics of forests in detail. These technologies can be utilized to determine the biophysical properties of forests, tree density, species diversity, and age distribution. Furthermore, advanced analysis methods like machine learning and artificial intelligence play a significant role in predicting carbon storage potential in forests by processing large amounts of data. These methods can model the complex relationships between forest structural characteristics and carbon stocks and forecast future changes. However, it is essential to consider environmental factors such as local climate data and soil properties. These data are crucial for understanding the effects of forest ecosystems on the carbon cycle and identifying potential carbon storage areas. Evolving technologies and advanced analysis methods offer new and effective approaches for determining carbon capture potential in forests. These approaches could be a significant step for environmental conservation and combating climate change, contributing significantly to the sustainable management of forests.

3.1. Remote Sensing Methods

In recent years, remote sensing methods have become a significant research area for determining the carbon capture potential of forests. Remote sensing enables the analysis of the structural and biophysical characteristics of forests through technologies such as high-resolution images and laser scanning collected from satellites and aircraft (Zhang et al., 2019). With these technologies, important features of forests such as tree density, species diversity, age distribution, tree height, and total carbon stock can be directly measured.

Remote sensing is a technique used to determine the properties of objects using data collected by remote sensors and devices. Remote sensing techniques can be used to estimate carbon stock in forest cover through aerial and satellite imaging systems. High-resolution satellite data allows for the development of models that identify relationships between plant biomass and carbon stock. Additionally, the use of artificial intelligence algorithms and computer vision analyses enhances the potential for automatically identifying trees and predicting carbon stocks.

Remote sensing data can be collected over larger areas and more rapidly compared to traditional field measurements, allowing for the creation of more comprehensive carbon inventories. Furthermore, remote sensing techniques can be used to monitor forest dynamics over time and understand changes in carbon storage potential. Therefore, remote sensing methods are considered an important tool for determining the carbon capture potential of forests and developing sustainable forest management strategies.

3.2. Artificial Intelligence Methods

Climate change stands out as a prominent environmental threat on a global scale, and determining the carbon capture potential of natural ecosystems is a crucial step in combating this threat. Experts in the field of forestry are working in various research areas to better understand and enhance the carbon capture capacity of natural forests. In this context, artificial intelligence (AI) methods emerge as advanced analytical tools.

Artificial intelligence methods such as machine learning are effectively utilized in complex processes such as analyzing large datasets, identifying carbon capture properties, and predicting carbon emissions from forest ecosystems. Machine learning algorithms are particularly important in determining the carbon capture potential of forests. These algorithms process large datasets to identify factors associated with carbon capture in forests and use these factors to predict carbon storage capacity. Additionally, machine learning methods use learning algorithms to identify plant species and other ecosystem components in forests and predict their carbon capture capacities.

In this context, artificial intelligence methods emerge as effective tools in forestry for carbon management and combating climate change. The use of artificial intelligence techniques in determining the carbon capture potential of natural forest ecosystems can contribute to the development of forestry policies and the creation of sustainable forest management strategies.

3.3. Machine Learning (ML) Methods

Determining the carbon capture potential of forests is of critical importance for environmental conservation and combating climate change. In this context, machine learning (ML) methods play a significant role in analyzing large datasets and deciphering complex relationships (Mitchell, 2014; Yan et al., 2021). ML methods can provide faster and more accurate results compared to traditional methods in predicting the carbon capture potential of forest ecosystems.

Machine learning can identify factors associated with carbon capture by analyzing large datasets and use these factors to predict the carbon capture potential of forest ecosystems. These methods can be effective in identifying plant species and other ecosystem components in forests, predicting carbon storage capacity, and monitoring changes in the carbon cycle.

ML methods offer various approaches in determining the carbon capture potential of forests. Among these approaches are various algorithms such as support vector machines, decision trees, random forests, and deep learning. These algorithms can be used to analyze factors influencing carbon storage capacity in forests and predict the carbon capture potential of forest ecosystems.

3.3.1. Decision tree (DT)

Decision trees are a popular machine learning algorithm used for both classification and regression tasks. They work by recursively partitioning the data into subsets based on the values of input features, maximizing the homogeneity of resulting subsets at each split. This process continues until a stopping criterion, such as reaching maximum tree depth or minimum number of samples in a node, is met.

One of the most significant advantages of decision trees is their interpretability. The resulting tree structure is easy to understand and can be visualized, facilitating explanation of the logic behind predictions. Additionally, decision trees can handle both numerical and categorical data and are robust to outliers and missing values. However, decision trees tend to overfit, especially when allowed to grow very deep. Techniques such as pruning and adjusting maximum tree depth or minimum samples per node can be used to mitigate this issue. Additionally, ensemble methods like random forests and gradient boosting can be employed to combine multiple decision trees for enhanced performance.

In summary, decision trees are versatile and interpretable models widely used in various machine learning applications. While they have limitations such as overfitting, these can be alleviated with proper tuning and ensemble techniques, making decision trees a valuable tool in predictive modeling.

3.3.1.1. determining carbon capture potential of forests: decision trees

Determining the carbon capture potential of forests is crucial for forestry management and climate change strategies. In this context, machine learning methods such as decision trees can be effective tools for predicting the carbon storage capacity of forest ecosystems (Işık et al., 2024).

Decision trees are modeling techniques that represent complex relationships in the dataset as simple decision rules. When decision trees are used to determine the carbon capture potential of forests, the impact of various factors (such as plant species, soil properties, climate data) on carbon storage capacity can be examined. Decision trees offer several advantages. Firstly, they are easy to explain and interpret since the tree structure is represented in a human-understandable format. Additionally, decision trees can tolerate missing values in the dataset and can work with both categorical and numerical data.

When using decision trees in the process of determining the carbon capture potential of forests, careful preparation of the dataset and proper training of the model are important. Selecting the right features and avoiding overfitting can improve the accuracy of predictions. Decision trees are an effective machine learning method that can be used in the process of determining the carbon capture potential of forests. This method can support decision-making processes in forestry and contribute to the development of sustainable forest management strategies.

3.3.2. Random forest (RF)

Random Forest (RF) is a powerful ensemble learning method used for both classification and regression tasks. It is based on the concept of decision trees but enhances them by reducing overfitting and improving prediction accuracy.

In the Random Forest model, multiple decision trees are independently trained on random subsets of the training data and random subsets of features. During training, each tree is constructed by selecting a random subset (with replacement) of the training data and considering only a random subset of features at each split. This randomness helps reduce overfitting by decorrelating individual trees. To make predictions, each tree in the forest independently predicts the target variable, and the final prediction is determined by aggregating the predictions of all trees. For regression tasks, this aggregation is typically done by taking the average of individual tree predictions, while for classification tasks, it can be done by taking the majority vote.

Random Forests offer various advantages over single decision trees. They are resilient to overfitting and handle high-dimensional data well. Additionally, they provide estimates of feature importance that can be useful for feature selection and interpretation. Moreover, the implementation of Random Forests is relatively straightforward, and they can handle both numerical and categorical data without requiring preprocessing. Overall, Random Forest is a versatile and powerful machine learning algorithm widely used in practice due to its high performance, robustness, and ease of use.

3.3.2.1 determining forest carbon capture potential: random forest (RF)

Ensemble learning methods like Random Forests have become significant research avenues in recent years for determining the carbon capture potential of forests (Gozukara et al., 2023). Random Forests rely on the principle of training each tree on a random subset of the data using multiple decision trees to make predictions. This way, each tree constructs its unique learning model, and then these models are aggregated to obtain a stronger and more stable predictive model.

When Random Forests are used to determine the carbon capture potential of forests, various input features (e.g., plant species, soil composition, climate data) are considered, and the impact of these features on carbon storage capacity is analyzed. Each decision tree predicts carbon storage potential using different combinations of these features. Then, predictions obtained from all trees are aggregated to make a collective prediction.

The success of Random Forests in determining forest carbon capture potential can be evaluated from multiple perspectives. Firstly, this method provides higher prediction accuracy compared to a single tree because predictions from multiple trees are combined. Additionally, Random Forests enable feature selection to assess the importance of each feature and build the most effective predictive model.

In conclusion, ensemble learning methods like Random Forests offer an effective and reliable approach for determining the carbon capture potential of forests. These methods support decision-making processes in forestry and contribute to the development of sustainable forest management strategies.

3.3.3. Artificial neural networks (ANNs)

Artificial Neural Networks (ANNs) are a form of artificial intelligence technology that encompasses mathematical models and algorithms inspired by the functioning of biological neural networks. ANNs are used to describe complex data relationships, discover patterns, and make predictions. They consist of interconnected artificial neurons or units called neurons. Each neuron receives input data, multiplies these inputs by weights, passes them through an activation function, and then produces an output. The overall output of the network is obtained by appropriately combining the outputs of each neuron (Sazli, 2006).

ANNs have a wide range of applications. For instance, ANNs used in classification problems are successfully employed in various fields such as image recognition, text classification, and medical diagnosis. Additionally, ANNs used in regression problems are effective in areas such as stock price prediction, weather forecasting, and market demand prediction.

The training of ANNs is typically an iterative process carried out with real data. The data set is fed into the network, the network's predictions are compared with the actual values, and then the model parameters (weights and biases) are updated to reduce errors. This process is repeated to enable the network to make accurate predictions, and the overall performance of the network improves.

Artificial Neural Networks are considered powerful and flexible tools for identifying patterns and making predictions in complex data sets. However, training and computation processes of the network can be time-consuming, especially when working with large data sets, and may encounter some issues like overfitting. Therefore, careful design and training of ANNs are crucial.

3.3.3.1. determining forest carbon sequestration potential: artificial neural networks

Artificial Neural Networks (ANNs) are machine learning models with the ability to learn from complex datasets. The use of ANNs in determining the carbon sequestration potential of forests may involve analyzing information from various data sources and creating models to predict carbon sequestration potential in forests (Nandy et al., 2017). Here are some general approaches where ANNs could be used in this process:

Data Collection and Preparation: The first step in utilizing ANNs typically involves appropriate data collection and preparation. Various factors such as climate data, soil properties, plant species, and forest structure can be among the data used to determine the carbon sequestration potential in forests. ANNs can process and analyze this data.

Model Development and Training: ANNs can learn complex relationships from such data and develop models to predict the carbon sequestration potential in forests. These models can be trained to predict the carbon storage capacity in a particular forest ecosystem.

Validation and Adjustments: It is important to evaluate the accuracy of the models created by ANNs and adjust as necessary. This process may involve various validation techniques to determine how well the model performs on real-world data.

Application and Prediction: The developed models by ANNs can be used to predict the carbon sequestration potential in a specific forest ecosystem. These predictions can play a significant role in the formulation of forestry policies and strategies such as carbon trading.

Continuous Updating and Improvement: Forest ecosystems change over time, so it is important to continuously update and improve the models used by ANNs. This may involve adding new data and ensuring that the model adapts to changing conditions.

The use of ANNs in determining the carbon sequestration potential of forests can contribute to the sustainable management of natural resources and play a significant role in combating climate change. This approach can assist in making informed and efficient decisions in forest management (Tsai & Kuo, 2013).

3.3.4. Convolutional neural networks (CNNs)

Convolutional Neural Networks (CNNs) are deep learning models that have been particularly successful in areas such as image processing and recognition. They are designed to process unstructured and high-dimensional datasets, especially visual data, and have a structure that is optimized for image processing (Taye, 2023).

The fundamental components of CNNs include convolutional layers, activation functions, pooling layers, and fully connected layers. Convolutional layers learn different features of an input image by moving filters (kernels) over the input image. Activation functions enhance the learning ability of the network by activating the outputs at each layer. Pooling layers reduce the output size, thereby reducing computational costs and improving the network's generalization ability. Fully connected layers combine all feature maps to obtain the output of the network."

CNNs have achieved significant success in many applications, particularly in image classification, object detection, facial recognition, land classification, and medical image processing. Especially in competitions conducted on large datasets such as ImageNet, they have shown significantly better performance compared to traditional methods.

The key to the success of CNNs lies in the use of learnable filters and shared weights between layers. These features enhance the network's ability to generalize overall features and learn specific characteristics.

3.3.4.1. determining forest carbon sequestration potential: convolutional neural networks

An advanced approach for determining the carbon sequestration potential of forests involves the use of Convolutional Neural Networks (CNNs). CNNs are one of the widely used deep learning methods, particularly in the field of image processing. However, the success of this model in determining the carbon sequestration potential in forests depends on the quality of the dataset and, especially, the proper selection of input data.

The working principle of CNNs is like ANN in terms of determining the carbon capture potential in forests.

The use of CNNs in determining the carbon capture potential in forests can be a valuable tool for the sustainable management of these valuable natural resources. However, careful data collection, preprocessing, and model training are required for the accuracy and reliability of the model.

There are many advantages and disadvantages between traditional machine learning methods and deep learning (such as CNN). The main advantages and disadvantages of these two approaches are given in the table below (Table 2).

Table 2. Key advantages and disadvantages between traditional machine learning methods and deep learning (such as CNN).

Traditional Machine Learning Methods (Random Forest, Decision Trees)		**Deep Learning (CNN)**	
Advantages	**Disadvantages**	**Advantages**	**Disadvantages**
High interpretability	May be inadequate to model complex relationships	Automatic feature extraction	High computing power requirement
Less computational complexity	May have difficulty modeling nonlinear relationships	Modeling complex relationships	Large data sets requirement
Less dependence on data	Tendency to overfitting	Superior performance on large data sets	Interpretability challenge

The advantages and disadvantages of both approaches may vary depending on their specific requirements and the amount of data available. Therefore, it is important to consider your problem area and available resources when choosing the most appropriate method.

4. Conclusion

Determining the carbon capture potential of forests with new methods emerges as a significant step in forestry and climate change mitigation. The utilization of innovative technologies such as artificial intelligence and data science, alongside traditional methods, enables us to achieve more accurate and comprehensive results. Through these new methods, it becomes possible to better understand the interaction of various factors, predict carbon capture capacity, and identify potential areas for improvement. Therefore, the adoption of new methods to determine the carbon capture potential of forests can contribute to the more effective development and implementation of forestry policies and carbon trading strategies. This, in turn, can promote sustainable forestry practices and facilitate the discovery of more effective solutions in combating climate change.

Acknowledgment

Sümeyye GÜLER is a doctoral candidate in the Sustainable Forestry Program supported by the Higher Education Council's 100/2000 Scholarship at Kastamonu University, Institute of Science.

Declaration

An earlier version of this article was presented at the 3rd International Congress on Engineering and Life Science held by Karadeniz Technical University in Trabzon (20-22 September, 2023) and was published as a full text.

Conflict of Interest

The author has no conflict of interest to declare.

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