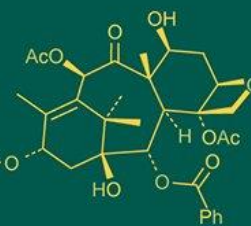
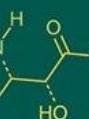
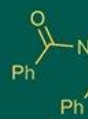


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Artificial intelligence and machine learning in sustainable forest management: Applications, challenges and future perspectives

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Abstract

Forest ecosystems provide essential biological, environmental and socio-economic activities including biodiversity conservation, carbon sequestration, watershed protection and sustainable wood production. "Sustainable forest management is facing unprecedented problems due to rapid deforestation, climate change, forest degradation, exotic pests and increasing wildfire frequency. Recent advances in Artificial Intelligence (AI) and Machine Learning (ML) have transformed forest monitoring and decision-making by enabling the automatic processing of large and complex data collected thru satellites, unmanned aerial vehicles (UAVs), LiDAR, Internet of Things (IoT) sensors, and field observations. In this review, we discuss current works that have used AI and ML approaches to forest management, including forest inventory, species classification, wildfire prediction, pest and disease detection, biodiversity monitoring, carbon stock estimation, and illegal logging monitoring. The study also discusses prominent algorithms including Random Forest, Support Vector Machine, Artificial Neural Networks, Convolutional Neural Networks, Long Short-Term Memory networks, Gradient Boosting, and ensemble learning techniques. The study also analyzes the current limitations including data sparsity, model interpretability, processing cost and transferability across different forest ecosystems. Finally, future research opportunities including explainable AI, digital twins, federated learning, edge computing and multimodal data fusion are discussed. The report provides a broad overview of AI-enabled solutions for sustainable forest management for researchers, policy makers and forest managers and identifies intriguing directions for further research.

Keyword: Artificial intelligence (AI), machine learning (ML), sustainable forest management, forest monitoring, remote sensing

Introduction

Forests are among the world's most valuable natural ecosystems, providing vital ecological, economic and social services. They are important carbon sinks that play a role in climate change mitigation, influence global climate processes, preserve soil and water resources, and maintain biodiversity. Forests provide timber, non-timber forest products and ecosystem services on which millions of people rely for their livelihoods. The Global Forest Resources Assessment estimates that the world's forests cover about 4.06 billion hectares, but forests are still under high pressure from deforestation, degradation, conversion of forest land, climate change and increasing frequency of natural disturbances (FAO, 2020). These challenges have heightened the demand for advanced technologies that can enhance forest monitoring, assessment and management. Forest management has traditionally been based on field inventories, expert knowledge and traditional statistical approaches. Field based measurements provide accurate information on forest structure, species composition and biomass, but are often expensive, timeconsuming and difficult to apply over large and inaccessible areas. The increasing spatial extent and complexity of forest ecosystems demand innovative approaches that are able to deliver fast, accurate and continuous information. Recent advances in remote sensing, GIS, AI and ML have opened new opportunities for improving forest management practices by allowing automated data processing and predictive analysis. Artificial Intelligence (AI) is a term that covers computational techniques allowing machines to execute tasks that require human intelligence such as learning, pattern

recognition, reasoning and decision making. Machine Learning (ML), a major branch of AI, allows computer systems to learn relationships from existing datasets and to make predictions without being explicitly programmed. Deep Learning (DL), a more advanced form of machine learning based on multilayer artificial neural networks, has demonstrated exceptional capabilities in processing complex and high-dimensional datasets, in particular images and spatial information. (LeCun *et al.*, 2015; Goodfellow *et al.*, 2016) ^[10, 15]. These developments had a major impact on environmental sciences, including forestry, by providing powerful methods for the analysis of large-scale ecological datasets. One of the important aspects in forest management is the combination of AI with remote sensing. Satellite systems such as Landsat, Sentinel and MODIS generate large amounts of multispectral and temporal data. To extract valuable ecological information from this data, sophisticated analytical methods are needed. Machine learning algorithms, including Random Forest, Support Vector Machines, Artificial Neural Networks and Gradient Boosting, have improved the classification and interpretation of remote sensing data by revealing complex relationships between spectral features and forest conditions. (Belgiu & Drăguț, 2016) ^[3]. These approaches have demonstrated higher accuracy and flexibility compared with traditional statistical classification methods.

The development of deep learning methods has greatly benefited remote sensing-based forest monitoring. Deep neural networks, and in particular convolutional neural networks (CNNs), can automatically extract spatial and spectral features from high-resolution imagery. Deep learning models learn hierarchical representations from data as opposed to traditional approaches that require manual feature selection. This has led to improved performance in tasks such as forest classification, tree detection, and disturbance mapping. (Zhu *et al.*, 2017) ^[27]. Deep learning techniques have demonstrated increasing success in recent years for vegetation mapping, forest structure analysis and ecosystem monitoring due to their power to capture complex spatial patterns (Ma *et al.*, 2019) ^[16]. One of the most important components of sustainable forest management is forest inventory. Correct estimation of forest parameters such as tree density, species distribution, canopy height and biomass is needed for conservation planning and resources management. Field-based sampling inventories of forests are reliable measurements, but are constrained by high operational costs and limited spatial coverage. The integration of LiDAR, hyperspectral imagery, UAV data, and machine learning algorithms has enhanced the efficiency of forest inventory by allowing automated estimation of forest attributes. Deep learning based methods have demonstrated promising results for individual tree detection and forest structure analysis using high-resolution remote sensing imagery. (Zhang *et al.*, 2016) ^[26]. Climate change effects on temperature, precipitation and vegetation are increasing the frequency and severity of disturbances to forest ecosystems from wildfires, insect outbreaks, droughts and diseases. These disturbances require early detection and prediction for effective management. Machine learning has been successfully applied to wildfire susceptibility mapping, prediction of fire occurrence and real-time fire detection by remote sensing, with artificial intelligence models using environmental variables, historical data, satellite observations and meteorological information to predict

risks. (Khan *et al.*, 2021) ^[14]. Monitoring forest health is one of the crucial areas where Artificial Intelligence (AI) technology may provide significant advantages, detecting illnesses, parasite infestations and invasive species early is important since these dangers may have considerable economic and ecological impacts. Traditional monitoring systems sometimes only detect forest degradation when evident signs are present, often leading to a delay in management. Conversely, AI-based approaches use hyperspectral images and machine learning algorithms to identify small changes in the vegetation characteristic values that reflect stress conditions. It is interesting to note that deep learning models are very good in the detection of complicated patterns related to plant health and hence in the improvement of the early warning systems of forest managers. This technology offers a proactive strategy for forest vitality preservation and, therefore, a prompt realization of management choices to minimize projected losses (Kattenborn *et al.*, 2021) ^[13].

Biodiversity conservation is a critical objective of sustainable forest management. Forests contain a large proportion of global terrestrial biodiversity, but monitoring species distribution and ecosystem changes remains challenging due to the complexity and scale of natural environments. Artificial intelligence has expanded the capability of ecological monitoring through automated species identification, camera trap image analysis, acoustic monitoring, and habitat suitability modeling. Deep learning-based computer vision methods have demonstrated considerable potential for identifying species and analyzing ecological patterns from large datasets (Christin *et al.*, 2019) ^[6]. Machine learning and artificial intelligence also have an important role in forest carbon estimation and climate change research. Precise estimation of forest biomass and carbon stocks is vital for carbon accounting, climate policies and international forest conservation programs. In remote sensing, spatial prediction of biomass distribution can be realized through the integration of satellite observations, field measurements, and environmental variables using machine learning algorithms. More recently deep learning methods have increased the capability to analyze complex interactions within Earth system processes, supporting a better understanding of carbon dynamics and ecosystem responses. (Reichstein *et al.*, 2019) ^[21]. Another new use of AI in forest management is the detection of illegal logging and forest degradation. Many of the affected areas are remote and large, making it difficult to monitor illegal harvesting activities using conventional approaches. Besides satellite imagery, machine learning algorithms can be used to recognize changes in forest cover and identify suspicious patterns of anthropogenic disturbances. Remote sensing-based approaches have been shown to be effective for monitoring global forest loss and for supporting conservation efforts (Hansen *et al.*, 2013) ^[11]. Similarly, advanced satellite monitoring technologies are continuously improving the operational forest surveillance capabilities. (Wulder *et al.*, 2018) ^[24]. These advances notwithstanding, there remain many challenges to widespread use of AI-based forest management systems. One key limitation is the availability and quality of training datasets. Models using machine learning require large and representative datasets, but forest ecosystems differ considerably from one geographic region to another, making the transfer of the models challenging. In addition, many deep learning models

are “black-box” systems with complex structures, with the rationale behind the predictions hard to interpret. Therefore, Explainable Artificial Intelligence (XAI) approaches are gaining more and more importance to increase transparency, reliability and acceptance of AI-based decisions in environmental management. (Arrieta *et al.*, 2020) [2]. The integration of multiple data sources is an important future direction of intelligent forest management. AI-based data fusion approaches can contribute to the integration of satellite imagery, UAV observations, LiDAR measurements, climate information, and ground observations to obtain more comprehensive and more accurate assessment of the forest condition. Progress in cloud computing, Internet of Things (IoT), edge computing and digital modeling are expected to enhance real-time forest monitoring and decision-support systems.

Review methodology (Prisma approach)

Study Design and Review Framework

This review was performed under the Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) framework, which establishes a transparent, systematic and reproducible method for identification, screening, evaluation, and synthesis of scientific literature related to Artificial Intelligence (AI) and Machine Learning (ML) applications in forest management. PRISMA is regarded as a standard guideline for systematic literature review and provides a structured approach that improves the quality of reporting for evidence-based review and thus improves the reliability and credibility of research results in this field. (Moher *et al.*, 2009; Page *et al.*, 2021) [17, 19]. Introduction Artificial Intelligence (AI) is helping to improve forest management. This study provides a systematic review of the key contributions based on the PRISMA method. It presents the state-of-the-art knowledge, analyzes the technological trends and identifies the research gaps in the use of AI, ML and deep learning for forest monitoring, inventory assessment, wildfire prediction, biodiversity conservation, forest health monitoring, carbon estimation and illegal logging detection. The review emphasizes the value of artificial intelligence (AI) technologies for enhancing forest management practices and calls for further research in less explored areas.

literature search strategy

The relevant scientific studies focusing on the applications of Artificial Intelligence (AI) and Machine Learning (ML) in forest management were identified thru a comprehensive literature search. The literature search was conducted using a systematic approach based on the principles of the PRISMA framework to ensure transparency, reproducibility, and accuracy of the study selection. Peer-reviewed research articles and review papers were collected from various international academic databases which include Scopus, Web of Science, Google Scholar, ScienceDirect, SpringerLink, and IEEE Xplore. Due to the interest in the early application of machine learning techniques in forestry, the search was performed for publications from 2000 to 2026.

A comprehensive keyword strategy was created so as to search on the applications of Artificial Intelligence (AI) and Machine Learning (ML) in forestry ecosystems. Boolean operators such as AND and OR were also successfully utilized to combine the various primary search terms needed

for this strategy. The key words were: “Artificial Intelligence”, “Machine Learning”, “Deep Learning”, “Forest Management”, “Forestry”, “Forest Monitoring”, “Remote Sensing”, “GIS”, “LiDAR”, “UAV”, “Forest Inventory”, “Wildfire Prediction”, “Forest Health Monitoring”, “Biodiversity Conservation” and “Carbon Estimation”. Researchers could use different combinations of these keywords to retrieve studies focusing on the specific uses of AI and ML in forest management. Examples of search strings were ("Artificial Intelligence" OR "Machine Learning" OR "Deep Learning") AND ("Forest Management" OR "Forestry") and ("Remote Sensing" AND "Machine Learning" AND "Forest Monitoring") useful for the identification of relevant publications. This strategic strategy also provided a targeted search that addresses specific applications and challenges in forest ecosystem management, in addition to the quality of literature retrieval. The first search included studies on forest classification, vegetation mapping, biomass estimation, forest disturbance detection, wildfire modeling, species identification, and conservation. Articles were imported into a reference management system and duplicates were removed. Titles, abstracts and keywords were screened for relevance to the review’s objectives, after which the full-text of eligible studies were assessed for methodological quality, contribution to research and applicability to AI-driven forest management. Only studies that applied AI, machine learning or deep learning techniques in the forest-related contexts were selected for final analysis. This systematic search strategy has ensured the inclusion of relevant high quality literature that highlighted the recent advances in the AI applications for sustainable forest management.

Inclusion and exclusion criteria

Inclusion criteria

The studies reviewed were chosen according to a number of rigorous criteria. They should be published in peer-reviewed journals or accepted sources of academics for credibility. Second, the studies needed to be explicitly related to the roles of Artificial Intelligence (AI), Machine Learning (ML), or Deep Learning (DL) in forest research. Also, the selected research should cover practical applications relevant to forest management such as but not limited to inventory assessment, forest data classification, and forecasting for wildfires. Another important element was the use of specific computational techniques such as Random Forest algorithms or Neural Networks, which are part of the analysis. In addition, full methodologies were required to ensure transparency and replicability of the studies. Lastly, to ensure a consistent standard, the literature reviewed was required to be published in English.

Exclusion criteria

Studies that failed to meet the defined research objectives were excluded from the review. Articles were excluded if they (1) focused on artificial intelligence concepts without application to forest ecosystems or environmental management; (2) investigated agricultural crops, urban vegetation, or other non-forest ecosystems with no direct relevance to forestry; (3) did not apply machine learning, deep learning, or other AI-based methods; (4) showed duplicate publications in multiple databases; (5) were review articles, editorials, opinion papers, book chapters, technical reports, or conference abstracts with no sufficient

research methodology; (6) did not provide clear descriptions of datasets, analytical methods, or validation procedures; or (7) were not available in English.

Literature screening and selection process

The literature selection process was based on the four main stages of the PRISMA framework:

Step1: Identify

In the identification step, publications that were relevant were retrieved from selected databases by using pre-defined search keywords. All identified records were imported into a reference management program and duplicates were removed.

Step2: Review

Titles and abstracts of the identified studies were screened for relevance with AI applications in forest management. Studies that did not clearly fit the research objectives was excluded.

Step3: Determine-eligibility

The full texts of potentially relevant studies were read in detail. Articles were evaluated based on their methodological quality, relevance, application of AI technique, and contribution to forest management research.

Step 4: Last inclusions

The most relevant studies were selected after full screening for qualitative synthesis. These studies were major applications of AI and ML in forestry such as forest mapping, biomass estimation, wildfire forecasting, forest health assessment, biodiversity monitoring and conservation planning.

Artificial intelligence and machine learning techniques used in forest management

Artificial intelligence (AI) and machine learning (ML) are revolutionizing forest management thru the automation of analysis and decision making using complex ecological datasets. Current systems for monitoring forests use a variety of technologies to collect massive amounts of data including satellite imagery, unmanned aerial vehicles (UAVs), LiDAR sensors, field observations and environmental monitoring networks. Traditional statistical methods often fail to handle these high-dimensional and nonlinear datasets, but AI and ML methods are capable of identifying unseen patterns, improving prediction accuracy, and strengthening real-time decision making in forest management. (LeCun *et al.*, 2015; Ghamisi *et al.*, 2019) ^[9, 15]. Machine learning methods for forestry can be generally grouped into supervised, unsupervised, semi-supervised learning and deep learning. The supervised learning

methods are trained with labeled datasets, and are commonly used for forest classification, biomass estimation, species mapping, and disturbance detection. The unsupervised learning methods identify the inherent patterns in the datasets without predefined labels, and are often used for clustering and exploratory analysis. Deep learning methods, based on multi-layer neural networks, have recently attracted much attention for their ability to automatically learn complex features from large-scale remote sensing data. (Zhu *et al.*, 2017) ^[27].

Random forest (RF)

Random Forest (RF) is a popular and dominant machine learning algorithm in forest management, which is known for its high classification accuracy, robustness and ability to handle large data sets with many variables. RF is an ensemble learning method that combines multiple choice trees to improve the predictive performance of the model and to control overfitting. For each decision tree, a subset of the training data and a subset of the predictor variables are randomly selected to build the decision tree. Finally, the RF model predicts based on the majority voting in classification tasks or averaging in regression problems. Therefore, it is an effective tool in many analytical scenarios. (Breiman, 2001) ^[4].

RF has been widely applied in forestry for land-cover classification, forest type mapping, biomass estimation, tree species identification, and forest disturbance monitoring. The algorithm works very well with remotely sensed data because it can integrate spectral, environmental and topographic variables. Random Forest has been one of the most widely used algorithms in remote sensing studies because of its flexibility and reliable performance (Belgiu and Drăguț, 2016) ^[3].

Support vector machine (SVM)

Support Vector Machine (SVM) is a supervised machine learning algorithm that finds an optimal hyperplane in the multidimensional feature space to separate the different classes. SVMs work well for classification problems with small training sample size and high dimensional data. The kernel functions such as radial basis function (RBF), polynomial and linear functions are used by the algorithm to convert complicated nonlinear relations into separable patterns. SVM has been applied in the forest management for forest cover classification, vegetation mapping, species discrimination and forest disturbance detection. Remote sensing datasets suffer from complicated spectral variations and SVM can effectively distinguish different forest conditions by maximizing the separation between classes. SVM has performed even better than traditional classification methods with limited training samples (Mountrakis *et al.*, 2011) ^[18].

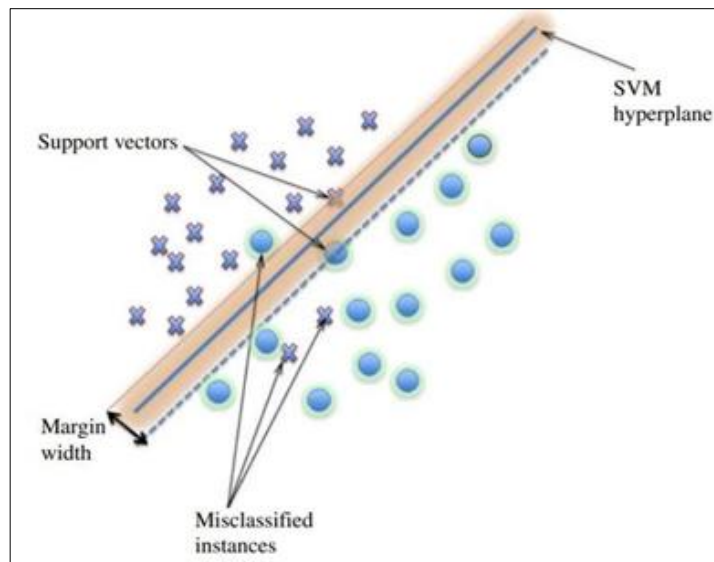


Fig. 1: Linear support vector machine example. Source: adapted from Burges (1998) [5].

Artificial neural networks (ANN)

Artificial Neural Networks (ANNs) are composed of interconnected neurons that learn relationships between inputs and outputs during the training process. They are good at capturing complex non-linear relationships and therefore are useful for ecological modeling and environmental prediction. In forest management ANNs are used for biomass estimation, vegetation classification, fire risk prediction and ecosystem modeling. They are as good as the data they are trained on, the architecture of the network, and the parameters they are optimized for. These factors affect how well they work in real-life situations.

Convolutional neural networks (CNNs)

have been one of the most successful deep learning

architectures for image based applications. Convolutional layers are used in CNNs to automatically extract spatial features from images, avoiding the need for manual feature selection. This makes CNNs particularly useful for analyzing high-resolution satellite imagery, UAV images and aerial photographs. CNNs have been applied in individual tree detection, forest species classification, canopy structure analysis, disease identification and forest change detection in forest management. Zhang *et al.* (2016) [26], demonstrated that deep learning approaches can be successfully applied for individual tree detection from high resolution remote sensing imagery. The accuracy of the vegetation mapping has also been improved by CNN-based methods as they can identify the complex spatial patterns within forest landscapes (Kattenborn *et al.*, 2021) [13].

Basic functioning and structure of CNNs

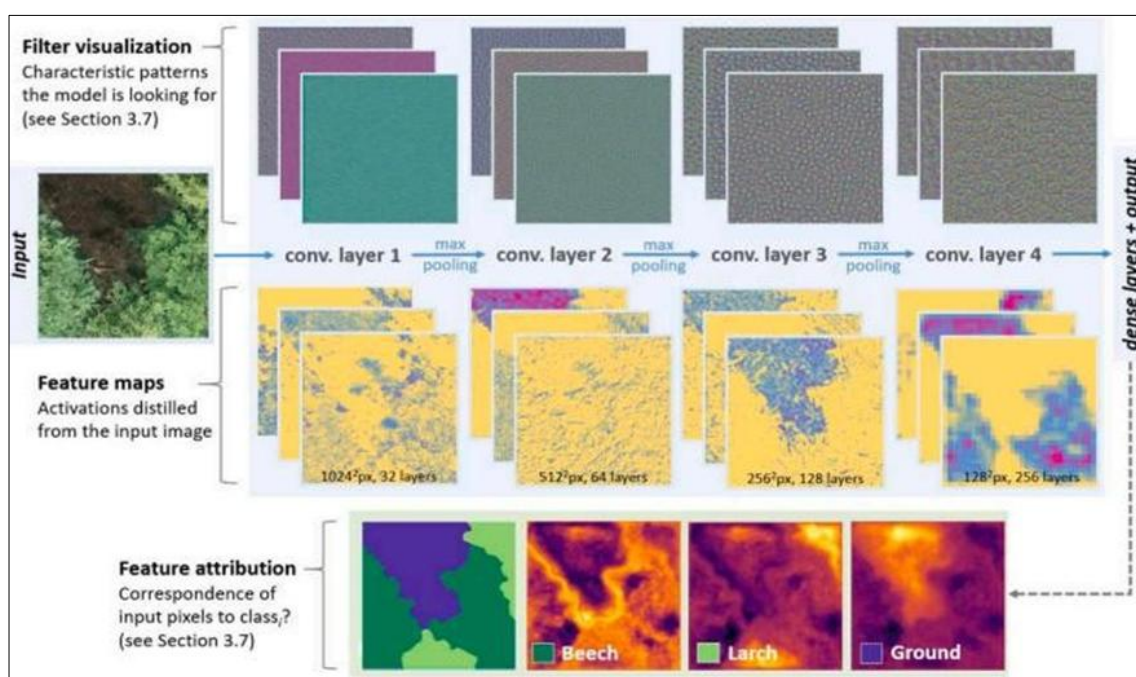


Fig 2: Scheme of a CNN composed of four convolutional layers and subsequent pooling operations trained for tree species classification

The visualization of convolutional filters (top) indicate characteristic patterns the CNN is looking for and were

derived by gradient ascent; a technique revealing artificial images maximizing each filter's activation. The feature

maps (center) are the dot-product of the preceding layer and individual filters. Feature attribution maps. Source (Kattenborn *et al.*, 2021) ^[13].

Recurrent neural networks (RNN) and long short-term memory (LSTM)

Recurrent Neural Networks (RNNs) are a special type of neural networks that are designed to work with sequential data and can remember data from previous inputs. Long Short-Term Memory (LSTM) networks are a popular variant of RNNs which solve some of the problems with learning long-term dependencies. This ability makes LSTMs a very effective tool for processing time-series data including data obtained from satellite imaging and environmental monitoring systems.

LSTM has been successfully applied in forestry for a number of predictive tasks such as predicting forest dynamics, monitoring changes in vegetation, assessing the impacts of drought and estimating fire risk. The LSTM models are useful in tracking the slow changes in the ecosystem over time and also in predicting potential conditions of forested areas since they can effectively analyze temporal relationships by leveraging historical climate data and remote sensing information. Their ability to interpret sequential data gives important information about ecological trends and possible future events in forest environments.

Gradient boosting and extreme gradient boosting (xgboost)

Gradient Boosting algorithms are a class of ensemble machine learning algorithms that leverage multiple weak prediction models to build a stronger predictive model. Extreme Gradient Boosting (XGBoost) is an optimized gradient boosting which offers better computational efficiency and model accuracy. These algorithms have been increasingly used in forest management for biomass estimation, habitat suitability modeling, wildfire prediction and ecological forecasting. XGBoost does a good job on structured data with many environmental variables and can identify the key drivers of forest conditions.

Deep learning and transformer-based models

Recently, deep learning has advanced with the creation of more sophisticated architectures, such as Transformer models. These models were first designed for natural language processing, but are now increasingly used in remote sensing and environmental applications. Transformers use attention mechanisms to identify relationships between different parts of large datasets and have proven to achieve superior performance in image analysis and temporal modeling. We are exploring advanced deep learning models for large scale forest mapping, for analysis of multi-temporal satellite images, for automated biodiversity monitoring and for climate impact assessment within the framework of forest management. These approaches provide a potential for the development of intelligent forest monitoring systems that can process heterogeneous data sources.

Unsupervised and semi-supervised learning approaches

Techniques of unsupervised learning such as K-means and hierarchical clustering can be useful for the detection of

patterns in forest datasets where labeled samples are not available. Especially powerful are these methods for analyzing vegetation pattern, classifying ecosystems and detecting anomalies. Semi-supervised learning, however, is to use labeled and unlabeled datasets and can improve the model performance when there are not many labeled datasets. Recently, hybrid and ensemble AI approaches that combine multiple algorithms have been highlighted in the forest management research to improve the prediction accuracy and reliability, providing promising solutions for large-scale forest monitoring applications where collecting labeled data is expensive and time-consuming.

Integration of multiple ai techniques

Recent studies on forest management focus on hybrid and ensemble AI approaches, which integrate several algorithms, e.g., coupling Random Forest with deep learning and combining CNNs with LSTM networks. The goal is to enhance the accuracy and reliability of prediction. The integration of AI with emerging technologies such as UAVs, LiDAR, IoT sensors and cloud computing is expected to improve forest monitoring by enabling automated decision making and sustainable management strategies.

Applications of artificial intelligence and machine learning in forest management

Artificial Intelligence (AI) and Machine Learning (ML) have transformed forest management by enabling better monitoring, analysis, and prediction of changes in forest ecosystems; They have been integrated with technologies such as remote sensing, GIS, LiDAR, UAVs and environmental sensors, which has improved the accuracy and efficiency of forest assessments. AI methods can evaluate big data and discover intricate ecological patterns, which can help in making sustainable decisions, and they are superior to traditional methods. Its main applications are forest inventory, mapping, biomass estimation, prediction of wildfires, health monitoring, biodiversity conservation, carbon assessment and detection of illegal logging. (Reichstein *et al.*, 2019) ^[21].

Forest inventory and biomass estimation

Forest inventory is a fundamental part of sustainable forest management, because it provides the basic information about tree density, species diversity, canopy structure and biomass to make effective conservation strategies. Traditional forest inventory methods, although accurate, are often costly and labor-intensive, limiting their practicality for large-scale assessments. Recently, artificial intelligence (AI) and machine learning (ML) technologies, along with remote sensing capabilities, have emerged as efficient alternatives to collect and analyze forest data over large areas. Algorithms such as Random Forest, Support Vector Machine, and Convolutional Neural Networks are used to process different types of remote sensing data such as satellite imagery, Light Detection and Ranging (LiDAR), and Unmanned Aerial Vehicle (UAV) data. "Using these sophisticated analytical methods, researchers can accurately predict important forest characteristics. Importantly, the integration of LiDAR with these algorithms enables a more detailed 3D analysis of forest structures that greatly improves biomass estimation and allows for the identification of individual trees. (Zhang *et al.*, 2016) ^[26].

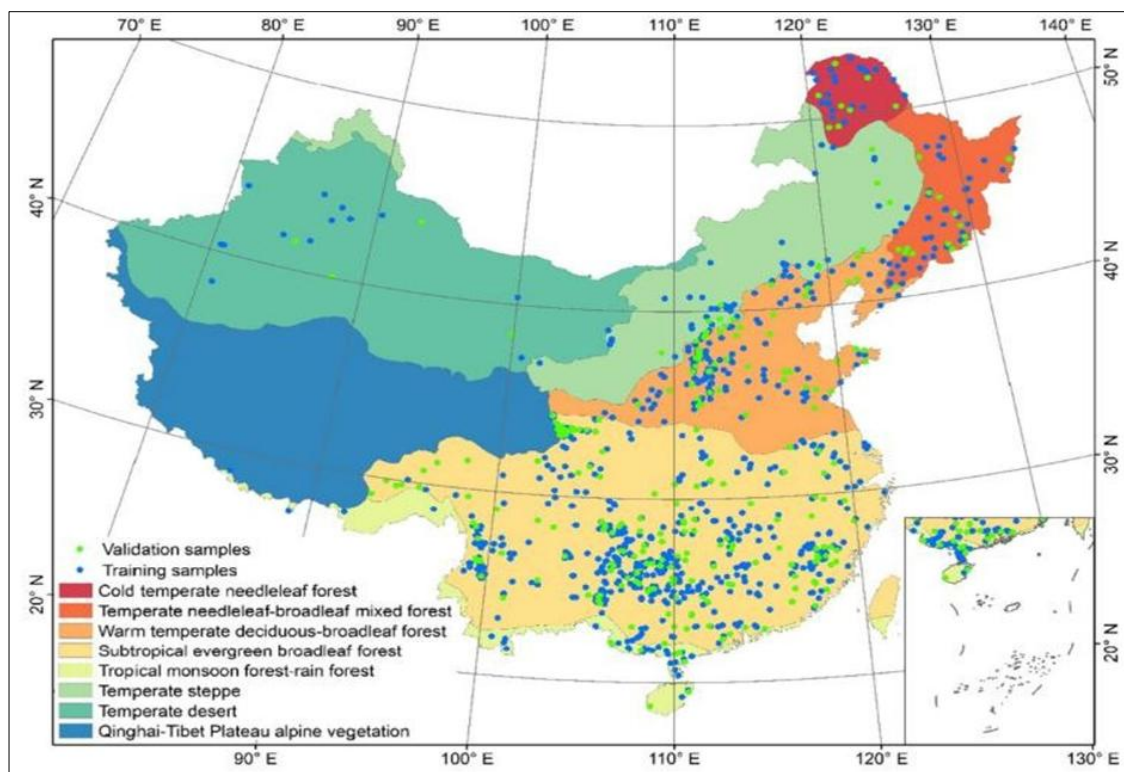


Fig 3: Geolocations of collected ground inventory data and corresponding vegetation zones from Hou (2001)

The collected ground inventory data were divided into validation samples (green dots) and training samples (blue dots), at a ratio of 1:3. (For interpretation of the references

to color in this figure legend, the reader is referred to the web version of this article.)

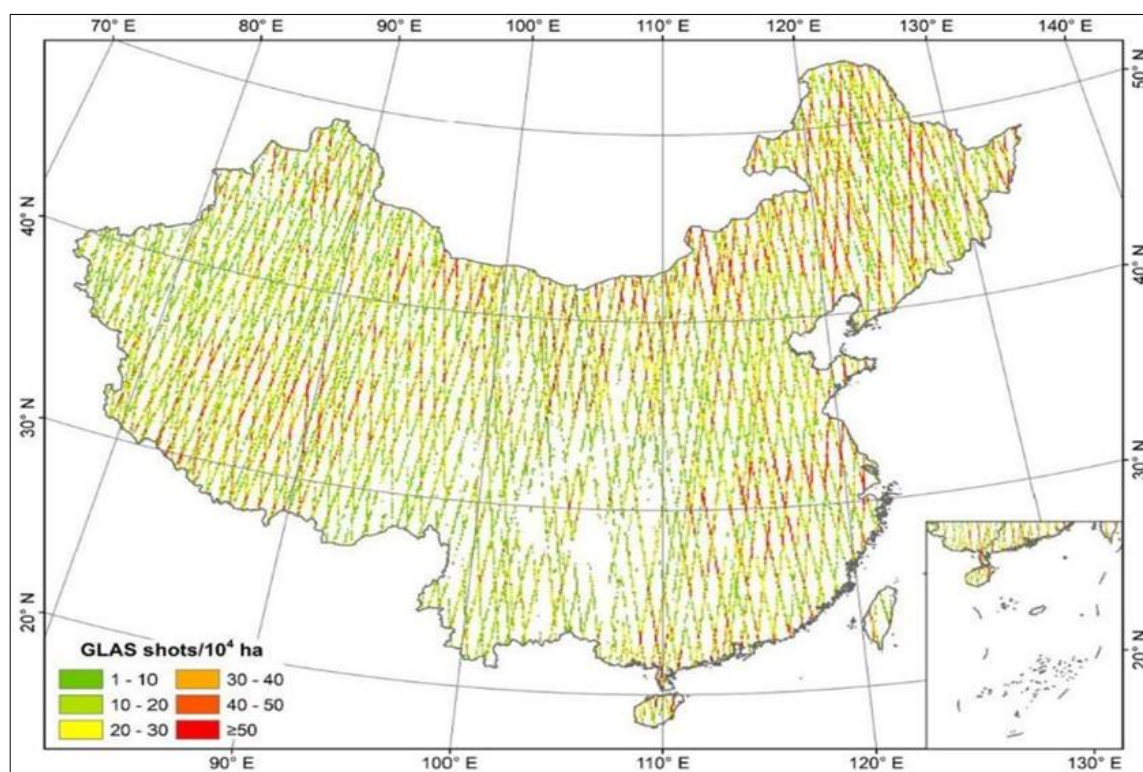


Fig 4: Densities of filtered GLAS shots (per 104 ha) used in AGB mapping procedure

Estimation of biomass based on machine learning techniques is important for climate change research because forest biomass stores a large amount of carbon on the globe. AI models can be used to integrate different data types such as satellite imagery, climate data, topographic information

and on-the-ground field measurements. This multi-faceted approach allows for developing accurate biomass maps that can be used at regional to global scales improving our understanding and management of forest carbon dynamics. (Zolkos *et al.*, 2013) ^[28].

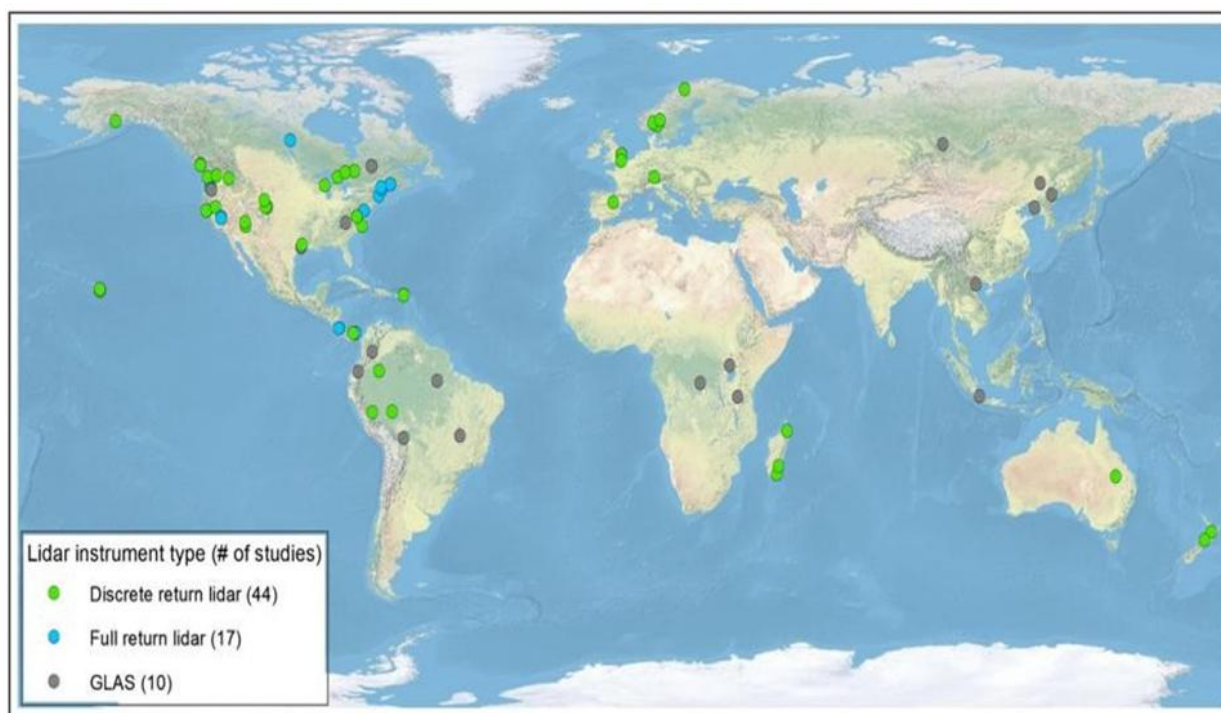


Fig 5: Locations of studies from which data were extracted for the meta-analysis. If a study evaluated multiple locations, all sites are included in the map (Baccini *et al.*, 2012; Supplementary material, Table S1). Base map from Esri ArcGIS online

Remote sensing-based forest mapping and monitoring

Remote sensing has become an important source of information for monitoring forests, because it provides the possibility of continuous observation over large and inaccessible regions. However, the extraction of useful information from satellite images is not a straightforward task due to variations in vegetation characteristics, atmospheric conditions and landscape complexity. AI and

ML algorithms have improved remote sensing-based forest mapping by automating land cover types classification, forest boundary detection, and forest ecosystems change detection. Traditional classification methods are usually based on the manually selected features, while deep learning models can automatically extract complex spectral and spatial features from the images (Zhu *et al.*, 2017) [27].

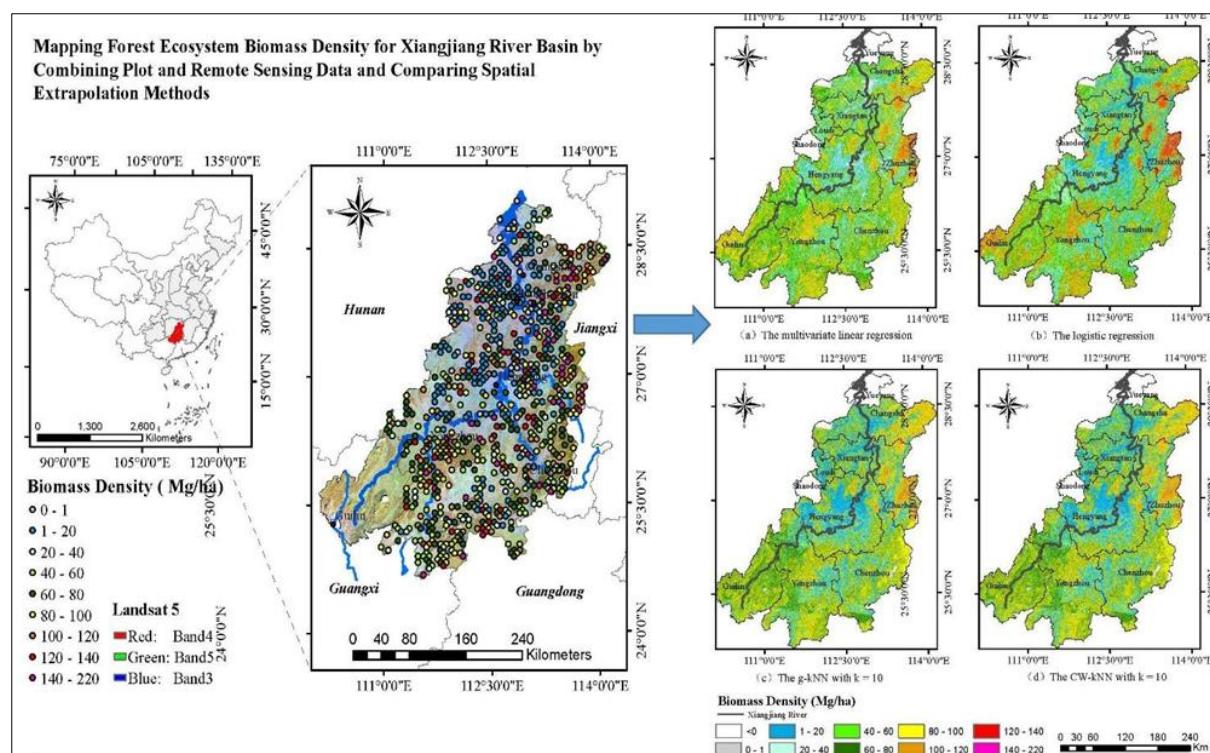


Fig 6: Mapping Forest Ecosystem Biomass Density For Xiangjiang River Basin By Combining Plot And Remote Sensing Data And Comparing Spatial Extrapolation Methods source ; (Zhu *et al.*, 2017) [27].

Random Forest and Support Vector Machine algorithms have been widely used for forest/non-forest classification, vegetation mapping and land-cover change detection. Deep learning methods, e.g., CNNs, have further improved classification accuracy by considering spatial patterns in high resolution satellite and UAV imagery. These technologies enable ongoing surveillance of forests and early detection of deforestation, degradation and ecosystem recovery.

AI-assisted analysis of satellite data is gaining importance in global forest monitoring systems.

(Hansen *et al.*, 2013) ^[11].

Forest fire prediction and detection

Wildfires are among the most destructive disturbances to forest ecosystems. Rising temperatures, increasing drought periods and climate variability have all contributed to the increase in frequency and severity of wildfires around the world. The early prediction and rapid detection of forest

fires is essential to minimize environmental and economic losses. AI and ML techniques have been introduced as promising tools for wildfire risk assessment, fire behavior prediction and real-time detection, several variables, including temperature, rainfall, humidity, vegetation conditions, wind speed, topography, and historical fire data are used by machine learning algorithms to predict the probability of wildfires. Random Forest, Artificial Neural Networks, Support Vector Machines and Gradient Boosting algorithms have been employed in wildfire susceptibility mapping. Such models can help to identify high-risk areas and support preventive forest management strategies. Deep learning models applied to satellite imagery and UAV data can automatically detect smoke, flames and burned areas in early stages, Convolutional Neural Networks have shown promising potential for image based wildfire detection thanks to their ability to learn visual patterns associated with smoke and fire phenomena. (Jain *et al.*, 2020) ^[12].

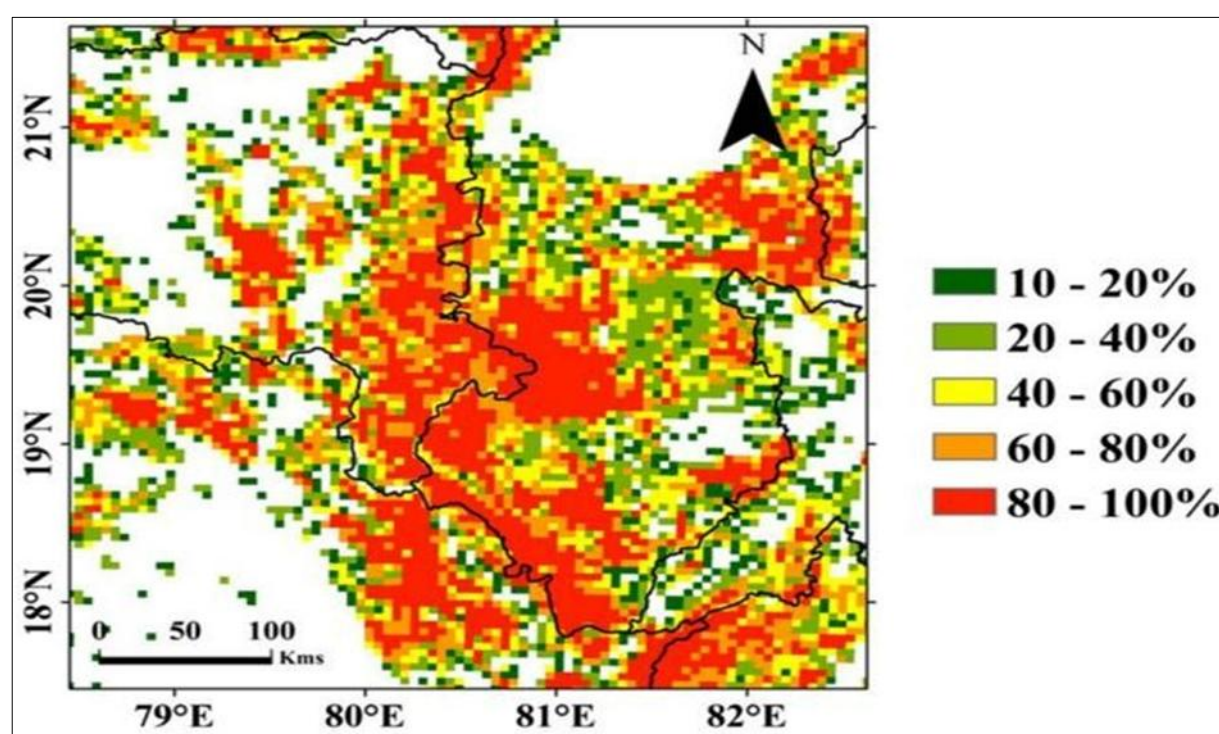


Fig 7: ISRO forest fraction cover (%) data set at 5 km spatial resolution (Reddy *et al.*, 2016) ^[20], extracted over central India domain (latitude: 17.5°- 21.5°N and longitude: 78.5°–82.5°E)

Forest health monitoring and pest/disease detection

Early identification of stress is crucial to help limit ecological damage, as biological threats to forest ecosystems include invasive species and insect outbreaks. Traditional field surveys find damage too late to allow intervention. The utilization of satellite imagery, hyperspectral data and

machine learning in AI-based monitoring for early detection of vegetation changes is discussed. Vegetation indices and deep learning models, in particular CNNs, effectively classify damaged vegetation and identify stress patterns, providing forest managers with timely information for specific measures. (André, *et al.*, 2022).

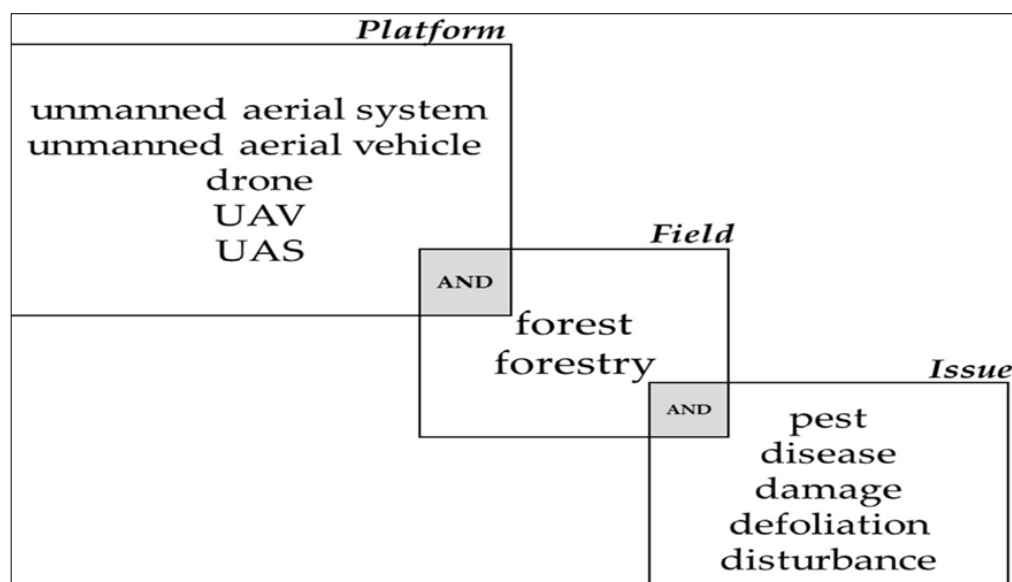


Fig 8: Search query design (“Platform” AND “Field” AND “Issue”) used. Source: André, *et al.*, 2022)

Biodiversity monitoring and wildlife conservation

The conservation of biodiversity is a key element of sustainable forest management. However, the complexity of ecosystems and the difficulty of monitoring rare species challenge their implementation. Artificial intelligence (AI) tools improve biodiversity assessment through automated species identification, analysis of camera traps, acoustic monitoring, and habitat modeling. Deep learning models can effectively analyze wildlife images for species identification in computer vision. Machine learning predicts species distribution and habitat suitability by incorporating various environmental factors. (Christin *et al.*, 2019) ^[6].

Carbon stock estimation and climate change assessment

Forests are vital in global climate regulation through sequestration of carbon. Therefore, accurate estimation of carbon stock is important for climate mitigation and sustainable policies. Traditional methods are based mainly on field measurements, which are spatially constrained. Conversely, artificial intelligence and machine learning (ML) models enhance these estimations by integrating field data with satellite images and LiDAR data. Machine learning can identify nonlinear relationships between forest attributes and carbon storage, while deep learning can enhance carbon mapping with large remote sensing data. (Reichstein *et al.*, 2019) ^[21].

Illegal logging detection and forest protection

Illegal logging is a leading cause of forest degradation and loss of biodiversity, especially in the tropics, where remoteness and difficulties of access make monitoring problematic. AI-powered forest watch systems rely on satellite images, sound sensors, UAV monitoring and machine learning algorithms to detect illegal activities. These standard models based on machine learning can be used to assess forest cover change over time, revealing patterns that are associated with logging. Remote sensing technology allows for constant surveillance, enabling quick responses from conservation groups and government agencies to illegal activities. Automated detection methods decrease reliance on manual monitoring and increase forest protection efficiency (Hansen *et al.*, 2013) ^[11].

Challenges and limitations of artificial intelligence and machine learning in forest management

Despite the great potential of Artificial Intelligence (AI) and Machine Learning (ML) to improve forest management practices, their broad adoption is hampered by several technical, operational, and methodological challenges. Forest ecosystems are complex, dynamic and geographically diverse, and as such, developing accurate and transferable AI models is a challenge. High-quality and representative datasets are basic requirements for building reliable AI and ML models. However, the availability of enough training data remains one of the major challenges in forest applications. Machine learning algorithms, especially deep learning models, need lots of labeled data to train well. In forestry, acquiring labeled datasets frequently necessitates large-scale field inventories, expert analysis. Challenges including data accessibility, model explainability, computational demands, standardization, and field application need to be tackled to utilize AI-based approaches for sustainable forest management.

Data availability and quality limitations artificial intelligence (AI) and machine learning (ML) models rely heavily on high-quality and representative datasets. But this necessity is one of the biggest obstacles in the forest applications: the lack of sufficient training data. Training machine learning algorithms, particularly algorithms that use deep learning, requires large amounts of labeled data. The acquisition of such labeled datasets in the domain of forestry is usually complex and demanding, requiring often lengthy field surveys, expert interpretations and long-term monitoring, which can be costly and time consuming. Moreover, the forest ecosystems are characterized by high heterogeneity due to such factors as climate, soil properties, vegetation types, and management practices. This variability implies that models developed in one geographic region may not generalize well to other regions with differing environmental characteristics. Consequently, the absence of globally standardized forest data constitutes a significant barrier to the development of universal AI models capable of efficiently monitoring forests under different circumstances (Zhu *et al.*, 2017) ^[27].

Model generalization and transferability

One major challenge in artificial intelligence-based forest management is the transferability of models from one forest ecosystem to another. Differences in species composition, environmental conditions, disturbance regimes and management practices can result in inaccuracies. For example, an AI model trained on data from temperate forests may not generalize well in tropical or boreal forests. Deep learning models have been proved to have high accuracy in some specific training scenarios. But the performance can be deteriorated when the environment is unknown. This is the domain adaptation problem. This limitation has to be overcome for largescale forest monitoring and developing flexible models that can capture different ecological conditions is a major research focus (Reichstein *et al.*, 2019) ^[21].

Lack of model interpretability and explainability

Many state-of-the-art artificial intelligence algorithms, especially deep learning models, are “black-box” systems and it is difficult to understand how they make decisions even when their prediction accuracy is good. This opacity creates serious problems in areas like forest management, where AI-based decisions can impact conservation strategies, resource management, and ecosystem preservation. In an attempt to tackle this, methods of Explainable Artificial Intelligence (XAI) have been engineered to increase the comprehension of AI predictions by pointing out important variables that influence the model’s output. For example, XAI is able to explain which factors such as climate conditions, vegetation characteristics, or topography are important for predicting forest disturbance events. This is supported stating that increasing the interpretability of these models, can give stakeholders such as forest managers, researchers and policymakers, even more confidence in AI predictions. Arrieta *et al.* (2020) ^[2].

Computational requirements and infrastructure challenges

Sophisticated AI techniques, especially deep learning architectures, require a highperformance computer to process data, develop models and generate predictions. Extensive forest surveillance is based on analysis of massive datasets from satellites, LiDAR technology, unmanned aerial vehicles and ecological sensors. This requires powerful computer infrastructure, large storage capacities and specialized technology know how. Many forestry bodies in poor countries lack enough computers and trained staff. The high costs of hardware, software and data maintenance may hinder practical implementation of AI-driven forest monitoring systems. The best alternatives for this are cloud computing services and open source artificial intelligence frameworks. These can minimize the infrastructure requirements and make it more accessible.

Data integration and standardization issues

Modern forest management is becoming more and more data driven by using multiple sorts of data like satellite imaging, LiDAR, data acquired by UAVs, field measurements, climatic data and ecological data bases. However, these datasets are usually heterogeneous in spatial resolution, temporal frequency, measurement technique, and

data format. Integrating disparate data sets needs complex data fusion techniques and standardized processing frameworks. Inconsistent techniques could lead to decreased model accuracy and may limit the comparability of outcomes across research.

Uncertainty assessment and model validation

Accurate projections and a thorough knowledge of model uncertainty are necessary for reliable forest management decisions. However, many AI studies are concerned on boosting prediction accuracy without proper uncertainty evaluation. Sources of error can be due to the constraints of the training data, sensor measurements, variability in the environment or assumptions of the model. Rigorous validation methods should be applied to AI model performance, including independent datasets, cross-region testing, and long-term monitoring. Uncertainty analysis should be included into AI-based forest management systems to enable ethical decision-making.

Ethical and governance issues

Ethical and governance challenges can arise with AI use in environmental management. Large-scale forest monitoring entails the collection and analysis of large amounts of environmental data which may include information on indigenous people, land tenure and resource usage. This includes ethical data management, privacy protection and fair access to advanced artificial intelligence (AI) technology. Moreover, artificial intelligence technologies should enhance human decision making instead of replacing expert knowledge entirely. Local biological knowledge and professional experience are still key elements of efficient forest management. “A balanced approach that balances AI capabilities with human expertise can get better results on sustainability.”

5.8 Limited Adoption in Operational Forest Management despite the progress in research, the practical use of artificial intelligence (AI) tools by forest authorities and managers is still limited. Many AI solutions are still developed at experimental scales and are not yet incorporated into ordinary forest management operations. The challenges are: lack of technical skills, lack of funds, lack of institutional backing, and difficulty in moving from research models to operational tools. For its successful implementation, we need better coordination between researchers, technology developers, government agencies and forest managers.

Future improvements to overcome current challenges

Several emerging approaches may help overcome current limitations in AI-based forest management. These include:

1. Explainable AI (XAI): Improving transparency and trust in AI predictions.
2. Transfer learning: Allowing models trained in one region to adapt to new forest environments.
3. Federated learning: Enabling collaborative model development without sharing sensitive datasets.
4. Edge computing: Supporting real-time analysis directly from field sensors and UAV platforms.
5. Digital twins: Creating virtual representations of forest ecosystems for simulation and prediction.
6. Multimodal data fusion: Combining satellite, LiDAR, UAV, and field data for improved accuracy.

Future research directions and emerging opportunities of artificial intelligence and machine learning in forest management

The fast development of AI and ML technologies has opened up new possibilities to enhance the monitoring, protection and sustainable management of forests. AI-based approaches have shown promising promise in forest inventory, remote sensing analysis, wildfire prediction, biodiversity assessment, and carbon calculation. However, there are still certain constraints in terms of data availability, model reliability, and practical implementation. Future work should aim at establishing more accurate, interpretable and tunable AI models to assist long-term forest management in the face of changing climatic conditions.

Explainable artificial intelligence for transparent decision-making

One of the key future objectives of AI-based forest management is the development of Explainable Artificial Intelligence (XAI) techniques. Advanced deep learning models typically reach great prediction accuracy, but they are sophisticated "black-box" systems and it is difficult to grasp how the conclusions are made. Transparency is important in practical forestry applications, as AI predictions may inform decisions on conservation planning, wildfire response, carbon management, and policy. Future research could incorporate XAI techniques with machine learning algorithms to uncover crucial environmental aspects influencing predictions and boosting user confidence. Explainable models allow us to quantify the influence of climatic variables, vegetation traits and topographical variables in wildfire risk assessment or biomass calculation. More interpretable models will improve adoption of artificial intelligence (AI) tools by forest managers and policy makers (Arrieta *et al.*, 2020) ^[2].

Integration of multisource remote sensing and environmental data

Future AI-based forest management systems will be dependent on multi-source data integration of satellite imaging, LiDAR, UAV observations, hyperspectral sensors, climate information, and field measurements. Data sources individually often provide limited information, but the combination of diverse datasets can provide a fuller picture of forest ecosystem conditions. Multimodal machine learning methods can enhance forest monitoring by combining spatial, spectral and temporal information. For example, fusion of LiDAR and satellite imagery can improve estimates of forest structure and biomass, and combination of climate and vegetation measurements can improve forecast of drought and wildfire hazards. Future research should focus on the development of effective data fusion methods able to handle huge and diverse ecological datasets.

Development of advanced deep learning and foundation models

Recent advances in deep learning have led to large-scale foundation models that can learn complicated patterns from enormous datasets. These algorithms can revolutionize forest monitoring by decreasing the need for manually labeled datasets and boosting model performance across different ecosystems. Future work should explore the construction of forest-specific foundation models that are

trained on global satellite images, LiDAR datasets, and ecological information. The models might underpin a range of applications, including automated mapping of forests, identification of species, detection of disturbances and assessment of climatic impacts. Better transfer learning methodologies will also help to adapt AI models established in one region to other forest ecosystems.

Digital twins and intelligent forest management systems

Digital twin technology is an emerging opportunity for building dynamic virtual models of forest ecosystems. Digital twins utilize artificial intelligence algorithms and real-time data from remote-sensing platforms, IoT sensors, and ecological databases to model forest status and predict possible changes in the ecosystem. In future applications, decision support thru evaluation of different forest management strategies with AI-based digital twins before implementation is possible. These systems could help predict climate change impacts, optimize restoration efforts, monitor forest health, and improve resource management. Digital forest models offer huge potential for adaptive forest management.

AI integration with IOT and autonomous monitoring Systems

Integration of AI with Internet of Things (IoT) technology can permit the continuous and real-time monitoring of forests. Sensor networks built in forest environments can collect information relating to temperature, humidity, soil moisture, vegetation status and climatic variables. Artificial intelligence algorithms can analyze these data streams to detect aberrant situations and provide early warnings of wildfire, drought stress and pest outbreaks. Therefore, future research should be directed to find low-cost and energy-efficient sensor systems for distant forest areas. The integration of IoT networks with satellite and UAV-based observations can lead to complete monitoring systems that can provide real-time information to forest managers.

Climate change adaptation and predictive forest modelling

Climate change is one of the major concerns faced by forest ecosystems globally. Increasing temperatures, shifting precipitation patterns and extreme weather events are affecting forest productivity, species distribution and disturbance regimes. Opportunities for predicting future ecosystem reactions and supporting climate adaption methods are offered by AI and ML models. Climate projections, remote sensing observations and biological data should be incorporated into future AI models to predict changes in forest composition. A lack of high-quality datasets remains a major impediment to AI applications in forestry. Future development will depend on greater data sharing among academic institutions, government agencies and conservation organizations. Open access data sets on carbon storage, likelihood of wildfire, and ecosystem resilience. Such forecasting techniques can help policymakers establish viable plans for climate-smart forest management.

Collaborative ai development and open data sharing

The lack of quality datasets continues to be a major bottleneck in the applications of AI in forestry. Better data sharing among research institutions, government agencies

and conservation groups will help build the future. Datasets from open access that include satellite imagery, LiDAR measurements, forest inventories, and biodiversity observations will help to develop AI models that are more reliable and generalizable. New trends such as federated learning may even enhance collaboration by enabling organizations to develop AI models without sharing sensitive datasets directly at all. This approach could encourage international cooperation on large-scale forest monitoring, while protecting data security.

Future role of ai in sustainable forest management

In the future forest management will be more and more AI-based decision support systems combining monitoring, prediction and management recommendations. Such systems can aid in planning forest restoration, conservation of biodiversity, carbon accounting and sustainable use of resources. But to succeed, it needs to be executed with AI researchers, ecologists, forest managers, and policymakers collaborating. AI should be viewed as a supporting technology for human expertise, not as a replacement for ecological knowledge and field-based decision-making, combining advanced computational techniques with traditional forest management approaches will be critical for sustainable and resilient forest ecosystems.

Conclusion

Artificial Intelligence (AI) and Machine Learning (ML) are powerful tools to improve forest management today, by providing effective ways for monitoring ecosystems. These technologies are used in different fields of forestry, such as forest inventory, biomass estimation, wildfire prediction and biodiversity assessment. Algorithms such as Random Forest and Convolutional Neural Networks provide robust analysis of complex ecological data and improve accuracy of assessments compared to traditional methods. However, challenges remain including the need for quality training datasets and interpretability of AI models. Future work should be on the development of explainable AI and the integration of novel technologies such as the Internet of Things and digital twins to promote sustainable forestry practices, AI and ML are useful tools to address forest management problems and create resilient ecosystems.

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