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ORIGINAL RESEARCH ARTICLE

Artificial intelligence and machine learning applications in forest management and biodiversity conservation

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ABSTRACT

The recent progress in data science, along with the transformation in digital and satellite technology, has enhanced the capacity for artificial intelligence (AI) applications in the forestry and wildlife domains. Nevertheless, the swift proliferation of developmental projects, agricultural, and urban areas pose a significant threat to biodiversity on a global scale. Hence, the integration of emerging technologies such as AI in the fields of forests and biodiversity might facilitate the efficient surveillance, administration, and preservation of biodiversity and forest resources. The objective of this paper is to present a comprehensive review of how AI and machine learning (ML) algorithms are utilized in the forestry sector and biodiversity conservation worldwide. Furthermore, this research examines the difficulties encountered while implementing AI technology in the fields of forestry and biodiversity. Enhancing the availability of extensive data pertaining to forests and biodiversity, along with the utilization of cloud computing and digital and satellite technology, can facilitate the wider acceptance and implementation of AI technology. The findings of this study would inspire forest officials, scientists, researchers, and conservationists to investigate the potential of AI technology for the purposes of forest management and biodiversity conservation.

Keywords: natural resources; forest; biodiversity conservation; artificial intelligence; machine learning

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1. Introduction

Artificial intelligence (AI) is a broad field of computer technology focused on creating intelligent computers that can enhance, automate, and expedite important daily operations that usually rely on human intelligence[1]. The process entails extracting patterns, forecasting future states, and identifying abnormalities[2]. The advancements in AI have led to its widespread implementation across various sectors, including e-commerce, social networks, agriculture, environmental sustainability, education, healthcare, tackling manipulation of data, social care, urban design, public safety, transport, and environment conservation[3]. This also includes its application in forest and wildlife subdivisions[4–7]. The advancements have been propelled by various factors. Firstly, the rapid availability of information has increased, providing an opportunity to generate influential insights and facilitate decision-making[8]. Secondly, the costs of data storage and computing have decreased due to the availability of cloud technologies. This enables us to develop intricate solutions on a large scale, thereby expediting experimentation and research[9]. Lastly, the availability of comprehensive data sources, such as high-resolution satellite imagery, sensors and telemetry technologies, drone and camera technologies, and people-centric data sources (social networks, citizen science, and other open data sources), further contributes to these advancements[10]. Nevertheless, the influence of AI technology has been unequal, primarily favoring industries with significant economic returns, while having fewer applications in forestry and biodiversity conservation[11–16]. Despite the fact that the application of AI in forest and natural resources management began thirty years ago, the research and implementation of AI technology in the forestry sector has been slower compared to other industries like health, transportation, and agriculture.

Approximately 30% of the Earth's land area is covered by forests, making them the most prevalent ecosystems on land and home to 90% of the planet's biodiversity[17]. Forests play a crucial role in maintaining the normal functioning of our planet by providing essential functions for supporting life, including protective functions and environmental services[18]. They contribute to the purification of the atmosphere by stabilizing greenhouse gases, ensuring the presence of clean and breathable air[19]. Additionally, they have the capacity to absorb a significant portion of the yearly global atmospheric CO_2 emissions, amounting to approximately 30%, which is equivalent to 2 billion tons per year[20]. They have a significant impact on worldwide food security by providing assistance to pollinators, natural enemies of agricultural pests, and the hydrological cycle[21]. They serve as a significant reservoir of medicinal flora and contribute around 40% of the world's sustainable energy in the form of biofuels[22]. Wetlands play a crucial role in maintaining the hydrological balance of different ecosystems and enhancing their ability to withstand catastrophic events like floods and droughts[23]. Furthermore, around 1.6 billion individuals rely on forests as their primary source of sustenance[24].

Regrettably, forests are confronted with numerous issues. Worldwide, forests are experiencing swift deterioration as a result of the exploitation for timber, development of agriculture, and urbanization[25]. The effects of climate change, such as wildfires, are exacerbating the process of worldwide forest degradation[26]. Over the past 25 years, a total of 129 million hectares of forest land has been destroyed worldwide, leading to a decrease in the global carbon store of 17.4 billion of tons[27]. It is anticipated that the ongoing global pattern of forest degradation and carbon depletion will persist in the foreseeable future. Although the forest sector continues to utilize traditional strategies for managing the benefits and hazards associated with forests, it is important to acknowledge the potential advantages and challenges they present. Indeed, it is among the limited industries that exhibit a sluggishness in embracing innovative technology. For instance, in numerous nations, forest authorities continue to employ traditional methods of pen and paper to carry out forest inventories. Traditional approaches have several disadvantages, such as the inclusion of subjective opinions, the deceleration of data gathering and processing, and the lack of scalability of the methodology. Unlike the forestry sector, other industries such as agriculture, which is a major contributor to deforestation, have quickly adopted technology alternatives[28]. Precision agriculture employs robotic systems to perform tasks such as weed removal, fertilizing, and pesticide application, resulting in increased crop productivity per unit of land.

Forests, unlike agricultural systems, are characterized by their dynamic nature, necessitating appropriate management, particularly as numerous countries are presently seeking methods to accomplish transformative change in order to fulfill their nationally determined contributions (NDCs). Technology may effectively address the limitations of traditional methods of data gathering and analysis, thereby playing a critical role in enhancing forest management and conservation. Access to large and high-quality datasets, Internet-of-Things (IoT) network infrastructure, advanced technology such as high-resolution cameras, satellite technology, sensors, drones, and unmanned aerial vehicles (UAVs), as well as computational space and storage, are essential requirements for the development and implementation of AI in any field. The need to access a mix of these criteria has driven research on AI applications in various fields of biodiversity protection and forestry. These domains include forest inventory, detection of illicit animals, timber trafficking, and felling (**Figure 1**). Moreover, these research endeavors have fundamentally transformed the immediate implementation of AI technology in the fields of biodiversity conservation and forestry. This is evidenced by the growing number of start-ups that utilize AI technology in these sectors.

The forest industry would greatly profit from technology's natural capacity to facilitate and embrace innovation across different regions and scales, and at a considerably accelerated rate. Hence, the objective of this review article is to offer an in-depth overview of the implementation of artificial intelligence in the forest industry and the preservation of biodiversity. Furthermore, this review study examines the difficulties encountered in the forest industry, the preservation of biodiversity, and the applicability of advanced AI technology in addressing these concerns. The findings of this study would inspire forest officials, scientists, researchers, and conservationists to investigate the potential of AI technology for the purposes of forest management and biodiversity conservation.

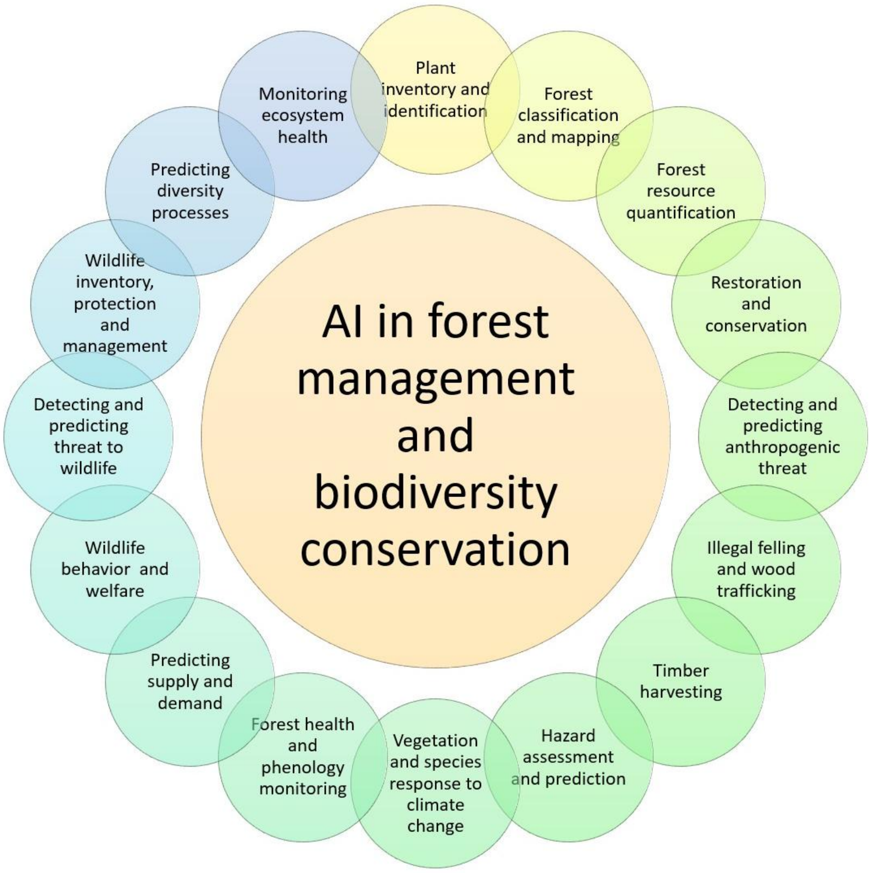

Figure 1. Overview of AI in forest management and biodiversity conservation.

2. AI-based start-ups and non-profits in biodiversity conservation and forestry

Ensuring both the preservation and sustainable exploitation of forest resources is a challenging endeavor, especially due to the absence of openness and the ongoing corruption in the forestry sector. The incidence of illicit activities, such as unauthorized logging, widespread deforestation, and the illicit sale of timber, has escalated throughout the years. Although technology is not a panacea, it can undeniably aid in preventing illicit actions, hence enhancing transparency in the forestry sector and facilitating efforts to combat climate change by promoting sustainable practices. The subsequent sections delineate the economic markets for AI applications in the forestry sector and the resultant proliferation of promising AI technology start-ups and non-profit organizations worldwide. These entities strive to digitize forests, enhance forest management, mitigate escalating CO_2 levels, safeguard endangered animal species, combat wildlife trafficking and illegal trading, facilitate wildlife census alongside monitoring, and automate taxonomic recognition and classification of plants and animals by embracing digital advancements[29–41].

The utilization of AI in the forestry industry is anticipated to make a substantial economic impact, particularly in the precision forestry market. This market was valued at USD 3.9 billion in 2019 and is forecast to grow to USD 6.1 billion by 2024. The primary factors fueling the growth of the precision forestry market include the escalating mechanization in emerging countries across Europe, Asia Pacific, and Africa for logging operations, the surging construction activities, the rising demand for timber from sawmills, the declining cost of forestry mapping technologies, and the adoption of advanced monitoring and surveillance technologies. Additionally, there is a concerted effort to combat illegal logging and deforestation, and governments are increasingly supporting the digitalization of forest resources.

Furthermore, the AI technology market is anticipated to expand in the near future in areas such as inventory and logistics management, fire detection, digital mapping of forests for biomass, and the assessment of carbon and timber resources. The forestry sector's potential for AI technology market growth has motivated numerous start-up companies and non-profit organizations to utilize AI-powered technology in addressing various issues. These include identifying human-caused threats to forests such as deforestation and illegal logging, assessing and predicting hazards like fires, pests, diseases, storms, and floods that can damage forests, restoring and reforesting areas, quantifying and mapping forest resources such as classifying forests, estimating real-time forest cover, carbon stock, biomass, and timber resources, tracking illegal wood trafficking, as well as monitoring the health and phenology of forests. The majority of these start-ups and non-profit organizations are situated in developed nations such as the United States, Europe, Canada, Australia, and South Africa. With the exception of Brazil, the majority of developing nations that possess biodiverse tropical forests have been sluggish in their embrace of AI technologies.

3. AI and ML for forest management and biodiversity conservation

3.1. Combating deforestation and illicit logging

Artificial Intelligence (AI) and Machine Learning (ML) techniques, in conjunction with spatial analysis, have been employed to forecast and track deforestation rates worldwide[42–44]. An example of an organization tackling the issue of deforestation is “Rainforest Connection”. The startup is repurposing obsolete mobile devices, harnessing solar energy to operate them, and affixing them to the uppermost branches of trees to capture the sounds produced by chainsaws in the forest. The recordings/data are transmitted to cellular towers and subsequently to the base station, where Google’s TensorFlow, an AI and ML framework, is employed to discern and recognize the sound of chainsaws amidst other noises. After being discovered, this information, along with the location data of the placed sensors, is shared with forest managers. This enables them to conduct more investigations and take necessary actions to identify and prevent unlawful tree felling. Furthermore, several startup enterprises and non-profit organizations, such as Outland Analytics, Global Forest Watch, Terramonitor, and Future Forest Map project, employ open-source satellite data and AI technologies to accurately map and continuously monitor deforestation in real time. Outland analytics use AI algorithms for audio identification to identify the sounds of chainsaws or unauthorized cars. It promptly provides real-time alerts via email to officials, enabling effective management of environmental crime. Terramonitor and Satelligence utilize a comprehensive database of daily satellite imagery captured by numerous satellites, coupled with artificial intelligence, to generate cost-effective satellite data for the purpose of natural area management. This data is employed to monitor deforestation and assess the overall health of forests in real-time. **Figure 2** depicts utilizing outdated mobile devices to detect and monitor the activities of unauthorized loggers.

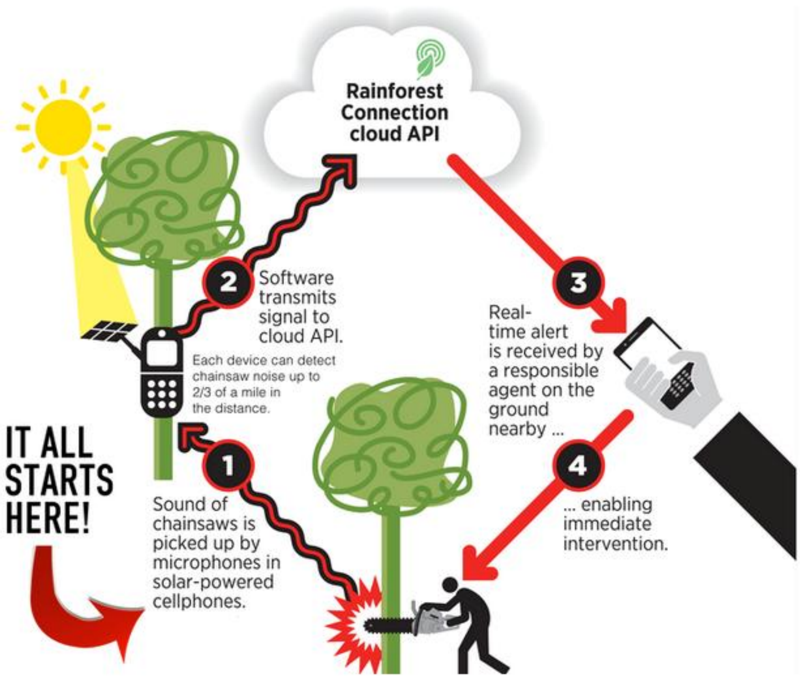

Figure 2. Unauthorized loggers are detected and monitored using old mobile devices.

The World Resources Institute, in conjunction with the Central Africa Regional Program for the Environment (CARPE), employed spatial modeling and AI to comprehensively analyze the factors that contribute to deforestation in the Democratic Republic of Congo (DRC). Additionally, this study aimed to accurately map the areas where future forest loss is very probable. According to their analysis, the most significant variables contributing to forest loss were human activities like shifting agriculture and the existence of highways, with precipitation as a meteorological variable also playing a role. Moreover, the data indicated that forests in close proximity to agricultural areas are particularly susceptible to destruction. Their findings can assist the authorities in the DRC in making proactive land use decisions that redirect the push for development away from forests with significant economic potential.

3.2. Estimating carbon, biomass, and inventorying forests

Several firms are utilizing publicly accessible and exclusive high-resolution satellite images, along with other datasets, to generate intricate maps of forests and landcover[45,46]. As an illustration, SilviaTerra integrates publicly accessible, detailed satellite images with data collected by the US forest department through field surveys. This combination is used to create a forecasting model that accurately assesses the state of forests at a scale of 15 m × 15 m. The data encompasses crucial details regarding the height, kind, and diameter of trees. This information is already being utilized by numerous forestry and conservation organizations to educate and shape their strategic initiatives. The Chesapeake Bay Conservancy collaborated with Esri and the Microsoft Azure team to utilize ML libraries in order to create a meticulously accurate landcover map of the region, with a resolution of one square meter. With the method and mechanics now accessible, it is possible to create a comprehensive landcover map for either the entire United States or other regions of the world, by making some necessary adjustments. A Portuguese start-up called 20tree.AI utilized remote sensing, big data, and cloud computing, alongside AI to conduct real-time forest inventory and monitoring. The Finnish forest center utilizes Geographic Information System (GIS) data, imagery sources, weather and climate data, and AI to obtain precise assessments of forest stands while improving the prediction of forest inventory. CollectiveCrunch, a profit-oriented company with headquarters in Germany and Finland, has created an AI platform called “Linda Forest” that surpasses conventional approaches in accurately predicting the wood mass, wood species, and overall wood grade of specific locations. Linda Forest utilizes various data sources, including the very high resolution (VHR2) image of Europe from the Copernicus Land Monitoring Service, Sentinel-2 images for growth modeling, and Copernicus Climate Change Reanalysis data for microclimate modeling and future development predictions, to precisely assess the wood mass and wood quality in the standing forest of the specific area of interest. Based on this information, organizations can then calculate the optimal utilization of resources for the production alongside consumption of wood-based goods.

Approximately 11% of the world's carbon emissions are attributed to deforestation and forest degradation, surpassing the carbon emissions of the total worldwide transport sector and ranking second only to the energy sector. Reducing Emissions from Deforestation and forest Degradation (REDD+) is a method created by Parties to the United Nations Framework Convention on Climate Change (UNFCCC) to decrease emissions resulting from deforestation alongside forest degradation. The program aims to establish monetary worth for the carbon stored in forests by providing incentives to developing nations to decrease emissions from wooded areas and allocate resources towards sustainable development with low carbon footprints. Nevertheless, the process of developing efficient REDD+ policies, evaluating their greenhouse gas (GHG) effects, and connecting them with the appropriate financial compensations is a demanding and intricate endeavor. The application of AI and ML methods has demonstrated significant promise in accurately mapping and monitoring the levels of CO_2 stock along with various ecosystem services inside forest environments[31]. Start-ups like GainForest and Panchama utilize AI technologies to address intricate challenges. GainForest uses extensive quantities of unannotated satellite images, a predictive model for video analysis, game theory, and ML-based Measurement, Reporting, and Verification (MRV) procedures to oversee and anticipate deforestation, as well as develop carbon payment systems. Similarly, Panchama uses ML algorithms to accurately assess the size, volume, and carbon density of individual trees by analyzing a combination of satellite, drone, alongside Light Detection and Ranging (LiDAR) photos. Non-profit organizations like the Erol Foundation, the Center for Global Discovery, and Conservation Science (GDCS) at Arizona State University (ASU), and non-profit Planet.Inc utilizes computer vision models, LiDAR, and satellite imagery with a resolution of 3–5 m to measure and map carbon stock and emissions in the Peruvian forest. This approach is both efficient and cost-effective, providing detailed and frequent data. Forest aboveground biomass assessment utilizing remote sensing techniques is illustrated in **Figure 3**.

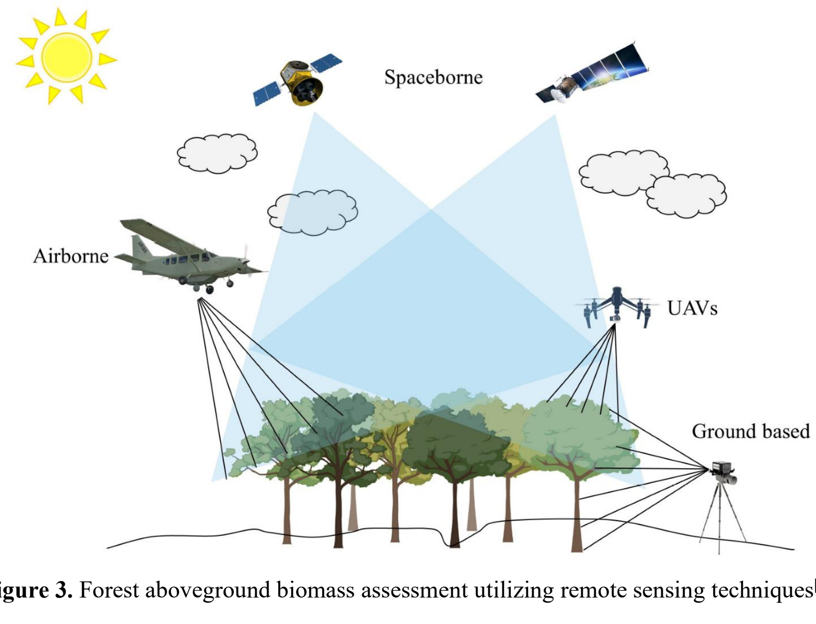

Figure 3. Forest aboveground biomass assessment utilizing remote sensing techniques[47].

3.3. Afforestation and reforestation automation

AI can be applied to reforest newly deforested areas, facilitating the planting of an additional 1.2 trillion trees worldwide[48]. This has the capacity to sequester hundreds of gigatons of CO_2 from the atmosphere[48]. Three emerging companies, including Droneseed, Dendra, and Land Life, are developing innovative products to tackle this pressing issue. Droneseed is a company that has created a cutting-edge device known as the seed vessel, which transports seeds of specific species. This product aids in the rapid and secure protection and germination of the seeds upon planting. The company utilizes drone swarms, consisting of four to five drones that are authorized by the FAA for heavy lifting. These drones are capable of carrying a weight of approximately 57 lbs. Their purpose is to scan the designated study area in order to detect favorable conditions for planting, such as moisture availability. Once proper conditions are determined, the drones release seed containers. This technique has several advantages compared to manual forestry methods. It allows for quicker seed dissemination and can cover a wider area than hand planting. Additionally, it permits the efficient monitoring and measurement of regeneration progress through the use of drones. By offering a comprehensive overview, it also facilitates the identification of precise locations of problematic regions where targeted interventions can be implemented to attain improved outcomes.

The Oregon branch of The Nature Conservancy has partnered with Droneseed to rehabilitate rangeland in Oregon that has been disrupted by exotic species. Dendra, a UK-based start-up, employs AI-driven automation as well as digital intelligence to locate appropriate planting sites. They distribute seedpods with preferred species of seeds and nutrients to facilitate germination. Amsterdam-based start-up, Land Life, employs many cutting-edge technologies including GPS, satellite imaging, an automated driller, Cocoon (a seedling support technology), alongside AI technology to carry out large-scale replanting and analyze the success of forestry efforts.

3.4. Risk assessment and forecast

The forestry sector is seeing transformative changes in the collecting of inventory data due to technology advancements. These advancements have resulted in innovative methods for gathering and processing precise, detailed data that will greatly enhance our ability to manage forests and conservation efforts. For instance, there is a significant amount of data in paper format from previous forest monitoring efforts, which can be digitized using technologies such as Optical Character Recognition (OCR) as well as Natural Language Processing (NLP). Once the data is in a digital format, it may be inputted into various analytical programs to perform analysis. Internet-of-Things (IoT) devices, equipped with sensors, can be deployed in forests to collect data on temperature, moisture levels, and other variables. This enables the acquisition of up-to-date information on forest operations and conditions. The data is currently being utilized to construct prognostic models for the purpose of recognizing and gaining a deeper understanding of forest health and various threats such as deforestation, wildfires, drought, pests, outbreaks of diseases, soil conditions, storm damage, as well as other disturbances in the forest ecosystem[49–56]. Terrafuse, a Canadian start-up, employs physics-enabled AI models to comprehensively analyze climate-related risk at a hyperlocal scale. Terrafuse utilizes historical wildfire data, and numerical simulations, alongside satellite imagery on Microsoft Azure to accurately predict the likelihood of wildfires occurring in any given place. Additionally, it calculates the temporal fluctuations in carbon density resulting from fire, deforestation, and various other catastrophic events.

In addition, scientists at Columbia University are employing AI technologies to comprehend the impact of Hurricane Maria on the woods of Puerto Rico. Scientists want to comprehend the impact of tropical storms, which could exacerbate due to climate change, on the distribution of tree species in Puerto Rico. In 2017, NASA conducted an aerial survey of Puerto Rico, capturing highly detailed shots of the tree canopies. By utilizing these images and employing AI technology, scientists want to examine the tree species that were devastated by the hurricane and those that managed to endure. This analysis will enable them to forecast trends linked to forthcoming hurricanes.

3.5. Locating illegal wood trafficking

The illicit trade of timber is regarded as equally profitable as the illicit traffic of wildlife. Interpol reports that the illicit timber industry has an estimated annual value ranging from USD 50 billion to 150 billion. The illicit trade of lumber not only exacerbates deforestation, resulting in substantial carbon depletion, but also poses a severe threat to various endangered tree species, including rosewood, dipterocarps, and mahogany. The illicit trafficking of timber reduces worldwide timber prices by 7% to 16%, resulting in yearly income losses of up to USD 5 billion for source nations. This serves as a substantial motivation for governments to take action. Therefore, in order to safeguard forests from unauthorized logging and regulate the lawful utilization of timber on a global scale, it is imperative to establish a tracking system capable of monitoring illicit timber activities[57]. Timbeter is an Estonian start-up that combats illegal logging and timber trafficking by utilizing the world's most extensive database of photometric measurements of roundwood and AI for online monitoring of individual shipments and stacks of roundwood. Xylene, a German start-up, employs an amalgamation of space technology, blockchain, supply chain mapping, autonomous data collected by IoT devices, as well as Earth Observation alongside AI technology to monitor the wood supply chain in real-time.

3.6. Ecology and biodiversity monitoring

The conservation community frequently aims to enhance forest attributes that impact the abundance and variety of animal species within the forest. Therefore, it is crucial to comprehend which treatments are effective in achieving this goal. AI technology is proving to be beneficial in facilitating such interventions[58]. Researchers from The Nature Conservancy and its affiliated organizations have devised an innovative method of automated soundscape monitoring to assess the effect of conservation efforts on biodiversity. In order to comprehend the reactions of species to disturbances such as recent deforestation and poaching, researchers devised miniature sound recording devices and strategically placed them around different areas of the forest. The researchers captured the sounds of the forest, known as a soundscape, and subsequently examined it to discern different species' vocalizations and patterns of activity during different hours of the day and seasons of the year. A global platform is being developed to hold data collected from diverse conservation projects worldwide. This platform will also offer analytical services to examine these datasets and get insights into the advantages of conservation actions. This technology has diverse implications for comprehending how organisms respond to disruption or gain from interventions. ML has been employed to classify vibration patterns from approaching trains in order to provide timely alerts to wildlife in Banff National Park, Canada. This is particularly important as train collisions have been a significant cause of death for grizzly bears (Ursus arctos horribilis). Implementing these categorizations to activate auditory and visual alerts prior to the arrival of trains, animals were seen vacating the railway track 29%–62% sooner than they would have otherwise[59].

In addition to sound recognition, the extensive utilization of pictures in wildlife monitoring has resulted in a compelling application for AI-driven automation in species identification. Imagery can be acquired using automated camera traps that are activated by heat and motion. The extensive deployment of such devices may yield millions of photos or video clips. Due to the vast quantity of data, analyzing and extracting information on species of conservation significance may prove to be a difficult task. Utilizing AI for this task can lead to precise categorization of species. As an illustration, in the Serengeti habitat, a group of 48 species was categorized utilizing this particular method. Comparable techniques have also been employed in the recognition of individual animals. For instance, the distinctive markings on the fur of tigers (*Panthera tigris*) have been utilized for the purpose of identifying individual animals. Shi et al.[60] created a convolutional neural network (CNN) with the purpose of recognizing and distinguishing individual tigers. Being able to distinguish between different species and individual organisms has significant consequences for biodiversity monitoring, as well as for conservation efforts aimed at reducing conflicts between humans and wildlife. Automated cameras equipped with image analysis software could be used to provide farmers with timely alerts regarding the presence of elephants (*Elephas maximus*) in agricultural fields and settlements. Moreover, these methods can be utilized to identify individual tigers that have become accustomed to humans, hence heightening the likelihood of conflicts. An essential condition for deploying such systems in practical settings is the swift categorization and transmission of information. Ideally, this can be achieved using on-device processing, but the initial setup cost may be high. Moreover, the absence of cellular infrastructure in isolated wooded regions can impede the transmission of information.

3.7. Supply-demand balance

Due to the increasing worldwide population, there is a significant demand for both wood and non-timber forest products. Hence, the global forestry industry is currently grappling with unpredictable demand, heightened supply risks, and escalating competition intensity. Hence, an imperative exists for the implementation of intelligent supply chain management to address supply and demand challenges within the forestry industry[61]. AI has the potential to be applied in the field of supply chain management, which is an emerging management philosophy. For more than two decades, aiTree Ltd. in Canada has been dedicated to utilizing AI algorithms to address demand and supply challenges in the forestry industry through systematic technology. The aiTree has implemented its Forest Simulation Optimization System (FSOS) in British Columbia, Canada to address demand and supply challenges in the forestry industry. A forest is required to fulfill several needs such as providing habitat for species, promoting biodiversity, maintaining water quality, enhancing visual aesthetics, storing carbon, producing timber, and making economic benefits. FSOS emphasizes both the extraction of resources from the forest and the generation of new creations inside the forest. Designing a forest is a complex task due to the continuous growth and mortality of trees, requiring the consideration of several factors annually for a span of more than 400 years. FSOS is an exemplary case that leverages artificial intelligence, big data, along with cloud computing techniques to address intricate demand and supply issues.

3.8. Forest hydrology

An essential component of forest management is comprehending its connections with watershed/forest hydrology, as it influences nutrient cycling, precipitation inputs, and surface as well as subsurface flow networks that sustain forest development and downstream water quality. The collection of data on ecohydrological factors is expanding due to advancements in technology for instance high-performance sensors, smartphones, autonomous cars, remote sensing, and GIS. This data is becoming more voluminous and complex. The study of ecohydrology, specifically forest hydrology, is utilizing advanced technologies like AI and ML to harness the full potential of data and gain novel insights concerning ecohydrological processes[62]. AI/ML techniques have been employed to calculate and simulate the amount of rainwater intercepted by forest canopies, the water content of canopies, the spatiotemporal patterns of soil moisture in vegetated regions, the evapotranspiration of land on a global and regional scale, the efficiency of water usage in terrestrial ecosystems, the storage of water in vegetation, the estimation of terrestrial and groundwater storage utilizing vegetation cover as an indicator, as well as the assessment of water stress in plants[63–71]. The proliferation of large hydrologic datasets obtained via remote sensing and data compilation has facilitated the integration of ML techniques into land surface modeling. This modeling approach replicates several land surface processes, including the distribution of water between the land and the atmosphere, such as groundwater dynamics[72].

The utilization of big data and AI/ML has been on the rise for forecasting severe geoclimatic occurrences like droughts, floods, and landslides, which have significant consequences for forest management[73]. Currently, there are ongoing efforts to enhance the forecasting of extreme ecohydrological events on land (such as extreme evapotranspiration, streamflow, soil moisture, and terrestrial water storage) over periods ranging from seasons to decades. This is being done through the utilization of integrated modeling techniques based on AI[74]. Collectively, these technological advancements, data analysis, and modeling are gradually revolutionizing our capacity to comprehend forest and watershed hydrology, with significant consequences for policy and management. The utilization of AI/ML techniques in forest hydrology appears to be restricted to scientific investigation and has not yet been implemented for widespread conservation and management purposes. The utilization of these methodologies holds significant potential for enhancing decision support in the management of forest hydrology.

3.9. Water resource conservation and marine biodiversity

The utilization of AI in the preservation of aquatic alongside marine biodiversity as well as water resources has garnered considerable research interest in the past decade. Artificial Intelligence (AI) and Machine Learning (ML) models have been employed to forecast stream flow[75], assess water quality[76–81], detect water pollution alongside toxicology[82,83], anticipate changes in aquatic and marine biodiversity[84–86], predict species distribution and map habitats[87,88], as well as recognize and classify marine and aquatic species[89–97]. The aforementioned AI research in aquatic alongside marine biodiversity as well as water resource conservation emphasizes the crucial role of AI in developing innovative technology to discover previously unknown aspects of conservation and potential risks to the structures and functions of aquatic and marine ecosystems. This, in turn, facilitates efficient monitoring alongside conservation of aquatic together with marine biodiversity, as well as the management of water resources. This newfound knowledge will specifically tackle various significant obstacles pertaining to aquatic alongside marine ecosystems, encompassing proficient management of water resources, preservation of biodiversity, establishment of a digital portrayal of freshwater and ocean ecosystems, and dissemination of data, knowledge, as well as technology to all stakeholders.

4. Challenges to AI-based forest and biodiversity conservation systems

4.1. Lack of awareness

Stakeholders, including forest managers, politicians, and civil society, frequently lack understanding regarding the availability and suitability of technologies. This is partially attributed to the intrinsic intricacy of these emerging technologies, which can result in a lack of interest. Conversely, the utilization of terminology like AI can sometimes generate impractical anticipations for solutions. Hence, enhancing the proficiency of stakeholders in the proper utilization of these technologies is a crucial measure in implementing them in practical situations. Robust case studies and pilot demonstrations play a crucial role in fostering comprehension and establishing practical expectations.

4.2. Poor ethics and protection

The utilization of technologies like has various potentialities for abuse. Robust safeguards are essential for employing such technology in regions inhabited by highly vulnerable communities, including indigenous tribes or communities reliant on forests. It is necessary to establish clear definitions and adhere to principles involving free, prior, and informed consent, data security, as well as allowed applications. Capacity development of communities in places where these technologies are used is necessary to assure fairness in outcomes, in addition to the establishment of such standards.

4.3. Unsuitable for difficult environment

Technologies deployed in challenging field circumstances must possess sufficient robustness to operate reliably for significant durations. Challenges like climatic and meteorological conditions, animal damage, alongside vandalism pose significant obstacles for these systems[97]. Insufficient preparation for such circumstances can result in equipment malfunctions, thereby eroding confidence in the concept as a whole. Strategic planning is crucial due to the substantial financial investments and ongoing expenses associated with these technologies. In addition, insufficient infrastructure in the field, for instance unreliable connectivity, can hinder the dependability of equipment.

4.4. Low commercial flexibility

Enthusiasts as well as small startup enterprises now lead the application of AI in the forest sector[98]. The absence of a robust market constrains the potential investments that can be allocated to the industry, thereby resulting in insufficient expansion. Moreover, the division of resources among tiny rivals working on comparable applications may impede the widespread economic advancement of AI technology. These limits can also hinder the creation of interfaces that are easy for users to interact with, resulting in AI models being stored in repositories like GitHub but not utilized by professionals.

4.5. Uncertainties regarding AI

While AI technology has promise for applications in forestry and biodiversity conservation, it is crucial to assess the dependability and effectiveness of AI and ML systems prior to their practical use[99–103]. Artificial Intelligence (AI) and Machine Learning (ML) models' predictions may lack reliability due to the uncertainty stemming from data as well as expertise[104–106]. In the absence of a sufficient quantity of tagged photos of natural forest, plantations, along with reforestation regions, AI and ML algorithms would struggle to distinguish between these distinct types of areas, particularly in species-rich tropical forests. Hence, the dependability of the results generated by AI and ML models relies on a substantial quantity of training and testing data, as well as expert expertise.

5. Conclusions

On a global scale, it is necessary for forestry practices to align with sustainable development goals. These goals aim to preserve forests as carbon sinks alongside biodiversity habitats, as well as to maintain and nurture forests as green infrastructure. The implementation of growing technical innovations to oversee, supervise, and preserve the forest along with its resources is facilitating the attainment of sustainable development objectives in the sector. Internationally, a growing number of nations are embracing smart forest and precision forestry methods, which employ advanced technology such as digital systems, satellite imagery, sensors, and artificial intelligence to effectively manage, safeguard, and responsibly exploit forest resources. Nevertheless, the implementation of these advancements is primarily restricted to industrialized nations and a select few emerging nations that actively manage forests for economic gain. Conversely, in cases where forests are primarily managed for the non-commercial objectives of biodiversity protection, carbon storage, and rural life improvement, the integration of cutting-edge technologies in forest management has been sluggish.

Obstacles and constraints, such as the lack of high-quality data or restricted access to existing large datasets, along with technical and computational difficulties associated with utilizing technologies like AI (for example, making them accessible to a broader audience), have led to a restricted implementation of these technologies in the forest industry. Hence, in order to enhance the advantages and availability of technologies such as AI in the forest industry, this study proposes the implementation of the following measures:

- Interdisciplinary collaborations among forestry professionals, forest ecologists, conservation specialists, forestry authorities, academicians in the forestry sector, alongside technologists are crucial for promoting the widespread use of AI technology in forestry applications. For instance, initiatives such as Microsoft and Google's "AI for Earth Innovation" bring together researchers alongside conservationists to integrate AI solutions in nature conservation efforts. These initiatives provide technical assistance, infrastructure, and training.

- Affordable and efficient computing resources, such as cost-effective cloud-based solutions for online data processing and storage, have the advantage of requiring low investment and hardware upkeep.

- The ongoing growth of data collection capabilities includes the utilization of emerging technologies such as wireless sensor networks, digital recording devices, drones, camera technology, as well as crowd-sourced data approaches like citizen science. Additionally, algorithms are being developed to extract data from social media and other online sources.

- Creation of computationally efficient algorithms for rapid analysis of large-scale data.

Moreover, these advancements possess immense capacity to facilitate revolutionary alterations in our approach to forest management, biodiversity preservation, and the establishment of suitable conservation strategies.

Conflict of interest

The author declares no conflict of interest.

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