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Review

Potential for Artificial Intelligence (AI) and Machine Learning (ML) Applications in Biodiversity Conservation, Managing Forests, and Related Services in India

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Abstract: The recent advancement in data science coupled with the revolution in digital and satellite technology has improved the potential for artificial intelligence (AI) applications in the forestry and wildlife sectors. India shares 7% of global forest cover and is the 8th most biodiverse region in the world. However, rapid expansion of developmental projects, agriculture, and urban areas threaten the country's rich biodiversity. Therefore, the adoption of new technologies like AI in Indian forests and biodiversity sectors can help in effective monitoring, management, and conservation of biodiversity and forest resources. We conducted a systematic search of literature related to the application of artificial intelligence (AI) and machine learning algorithms (ML) in the forestry sector and biodiversity conservation across globe and in India (using ISI Web of Science and Google Scholar). Additionally, we also collected data on AI-based startups and non-profits in forest and wildlife sectors to understand the growth and adoption of AI technology in biodiversity conservation, forest management, and related services. Here, we first provide a global overview of AI research and application in forestry and biodiversity conservation. Next, we discuss adoption challenges of AI technologies in the Indian forestry and biodiversity sectors. Overall, we find that adoption of AI technology in Indian forestry and biodiversity sectors has been slow compared to developed, and to other developing countries. However, improving access to big data related to forest and biodiversity, cloud computing, and digital and satellite technology can help improve adoption of AI technology in India. We hope that this synthesis will motivate forest officials, scientists, and conservationists in India to explore AI technology for biodiversity conservation and forest management.

Keywords: forest; artificial intelligence; forest resource management; machine learning; biodiversity conservation

1. Introduction

Artificial intelligence (AI) is a wide-ranging branch of computer technologies concerned with building smart machines capable of augmenting, automating, and accelerating key day-to-day tasks that typically require human intelligence. It involves extracting patterns, predicting "future states", and detecting anomalies. The computational, technological and research breakthroughs in the field of AI have promoted a rise of their application in every field (e-commerce, social network, agriculture, education, environmental sustainability, healthcare, combating information manipulation, social care and urban planning, public safety, transportation, environment conservation, and many more) including forest and wildlife sectors [1–8]. The advancements have been driven by the following factors:

(1) the pace with which information is available has increased—creating the opportunity to drive impactful insights and decision-making; (2) the costs of data storage and computing have dropped due to availability of cloud technologies—allowing us to build complex solutions at scale to accelerate experimentation and research; and (3) availability of holistic data sources due to availability of (a) high-resolution satellite imagery, (b) drone and camera technologies, (c) sensors and telemetry technologies (IoT), and (d) people-centric data sources (social networks, citizen science, and other open data sources). However, the impact of AI technology has been uneven, mostly benefiting high economic return sectors, with fewer applications for forestry [9,10] and biodiversity conservation [11–14]. Though, application of artificial intelligence (AI) in forest and natural resources management started three decades before [15], the research and adoption of AI technology in the forestry sector lagged behind other fields such as health, transportation, and agriculture [3].

Forests cover approximately 30% of global land area and are dominant terrestrial ecosystems harboring 90% of terrestrial biodiversity [16,17]. Forests are vital for proper functioning of our planet as they provide several critical functions for sustaining life, such as protective functions and environmental services. For instance, they provide clean, breathable air by stabilizing greenhouse gasses in the atmosphere, and they absorb as much as 30% (2 billion tons/year) of annual global atmospheric CO_2 emissions [18]. They play a major role in global food security by supporting pollinators, natural predators of agricultural pests, and the hydrological cycle. They are an important source of medicinal plants and supply about 40% of global renewable energy (biofuels) [19]. They are critical for hydrological integrity of various ecosystems and contribute to people's and the ecosystem's resilience to extreme events such as floods and droughts. To add to that, about 1.6 billion people depend on forests for their livelihood [20].

Unfortunately, forests also face many challenges. Globally, forests are undergoing rapid degradation due to exploitation for timber, agriculture expansion, and urbanization. Impacts of climate change, such as wildfires, are further contributing to global forest degradation [21]. In the last 25 years, 129 million hectares of forest area were lost globally, resulting in a reduction of global carbon stock by 17.4 Gt [22]. It is predicted that the current global trend of forest decline and carbon loss will continue in the near future [19]. Despite the benefits the forest provides and the kind of threats it is experiencing, the forest sector is still using traditional techniques to manage them. In fact, it is one of the few sectors where adoption of new technology is slow [23]. For example, in many countries including India, forest officials still use pen and paper to conduct forest inventories. Such traditional methods pose many drawbacks, like the introduction of personal bias, slowing data collection and analysis, and lack of scalability of the approach [24]. In comparison to the forestry sector, other sectors like agriculture—one of the prominent drivers of deforestation—have embraced technological solutions at a rapid pace [25]. Precision agriculture is a result of companies like sagarobotics.com, and farm.bot which use robots for precise de-weeding, precise fertilization, or pesticide applications, as they contribute to higher yields per acres.

Unlike agricultural systems, forests are dynamic in nature, and so they need to be managed accordingly, especially when many governments are currently identifying ways to achieve transformational change to meet their nationally determined contributions—NDCs [19]. This is where technology can play a significant role by filling the gaps/drawbacks of traditional approaches of data collection and analytics, which is crucial for effective forest management and conservation. The forest sector will benefit significantly by technology's inherent ability to support innovation and adopt innovation to various geographies and at various scales, and at a much faster pace.

This synthesis article discusses the scope of artificial intelligence and its applications to the Indian forest sector and biodiversity conservation with following objectives: (1) provide a global overview of AI application in the forest sector and biodiversity conservation, and (2) discuss challenges in the Indian forest sector, biodiversity conservation, and relevance of innovative AI technology to solve those challenges.

2. Materials and Methods

We identified published literature and reports that addressed the application of artificial intelligence (AI) and machine learning algorithms (ML) for biodiversity conservation, forest management, and related services across the globe and in India using a systematic literature search. To establish a database, we searched the ISI Web of Science (http://webofknowledge.com, accessed on 3 August 2021) and Google Scholar (https://scholar.google.com/, accessed on 18 June 2021) for peer reviewed journal articles published since 1980. Literature/reports published by the industry, nonprofit organizations, and government organizations were also considered. We used a different combination of keywords such as AI and ML application in: biodiversity conservation, wildlife conservation, forestry, illegal logging, plant inventory and identification, forest classification and mapping, wildlife identification and monitoring, forest restoration and conservation, aboveground carbon stock, forest health and phenology monitoring, detecting, and predicting anthropogenic threat to forest, etc. (Table S1). The initial search yielded 900 peer-reviewed studies after removing duplicates (300 studies), of which we excluded 628 studies by reading title and abstract, as they did not qualify the objective of our study. We reviewed full texts of the remaining 272 publications to find studies that reported application of AI and ML in forest management and their related services across the globe and in India.

We only included studies that reported application of AI and ML at least in one of the areas related to forestry, biodiversity research, and conservation as mentioned in Table S1. We gave priority to primary studies to avoid the duplication. Following the mentioned search and criteria for literature selection, we finally selected 172 studies to include in the review. Additionally, we also collected data on AI-based startups and non-profits in forestry, and biodiversity conservation from published reports, literature, blogs, and from google search.

3. Results and Discussion

3.1. Global Overview of AI Research and Application in Biodiversity Conservation and the Forest Sector

One of the main pre-requisites for developing and applying AI in any field is access to high-volume and high-quality datasets, network infrastructure of the Internet-of-Things (IoT), advanced technology (high resolution camera, satellite technology, sensors, drones, and unnamed aerial vehicles (UAVs)), and computational space and storage. Access to a combination of these requirements has motivated AI application research in many domains of biodiversity conservation and forestry, ranging from forest inventory and detecting illegal wildlife and timber trafficking and felling [6,26,27] (Figure 1 and Table S1). Further, these research efforts have revolutionized real-time application of AI technology in biodiversity conservation [28–30] and forestry sectors [9,10,31], as indicated by an increasing number of related AI-technology-based start-ups (Table S2).

3.2. The Growth of AI-Based Start-Ups and Non-Profits in Biodiversity Conservation and the Forest Sector

Balancing preservation with sustainable utilization of forest resources is a daunting task, particularly given the lack of transparency and the persistent corruption in the forestry sector. Unlawful practices such as illegal logging, deforestation and illegal timber trade have increased over time. While technology cannot solve all the problems, it can certainly contribute to prevention of such unlawful practices, ultimately improving transparency in the forestry sector and even helping tackle climate change through sustainable practices. In the following section, we describe economic markets for AI applications in the forestry sector and how such economic growth has led to a number of promising AI technology start-ups and non-profits all over the globe, that aim to digitize forests, improve forest management [7,32–34], combat rising levels of CO_2 [35–38], protect endangered animal species [39,40], prevent wildlife trafficking and illegal trading [41–44], help in wildlife census and monitoring [27,45–47], and automate taxonomic identification and classification of animals and plants, ect. [48–53] by embracing digital advancements (Table S2).

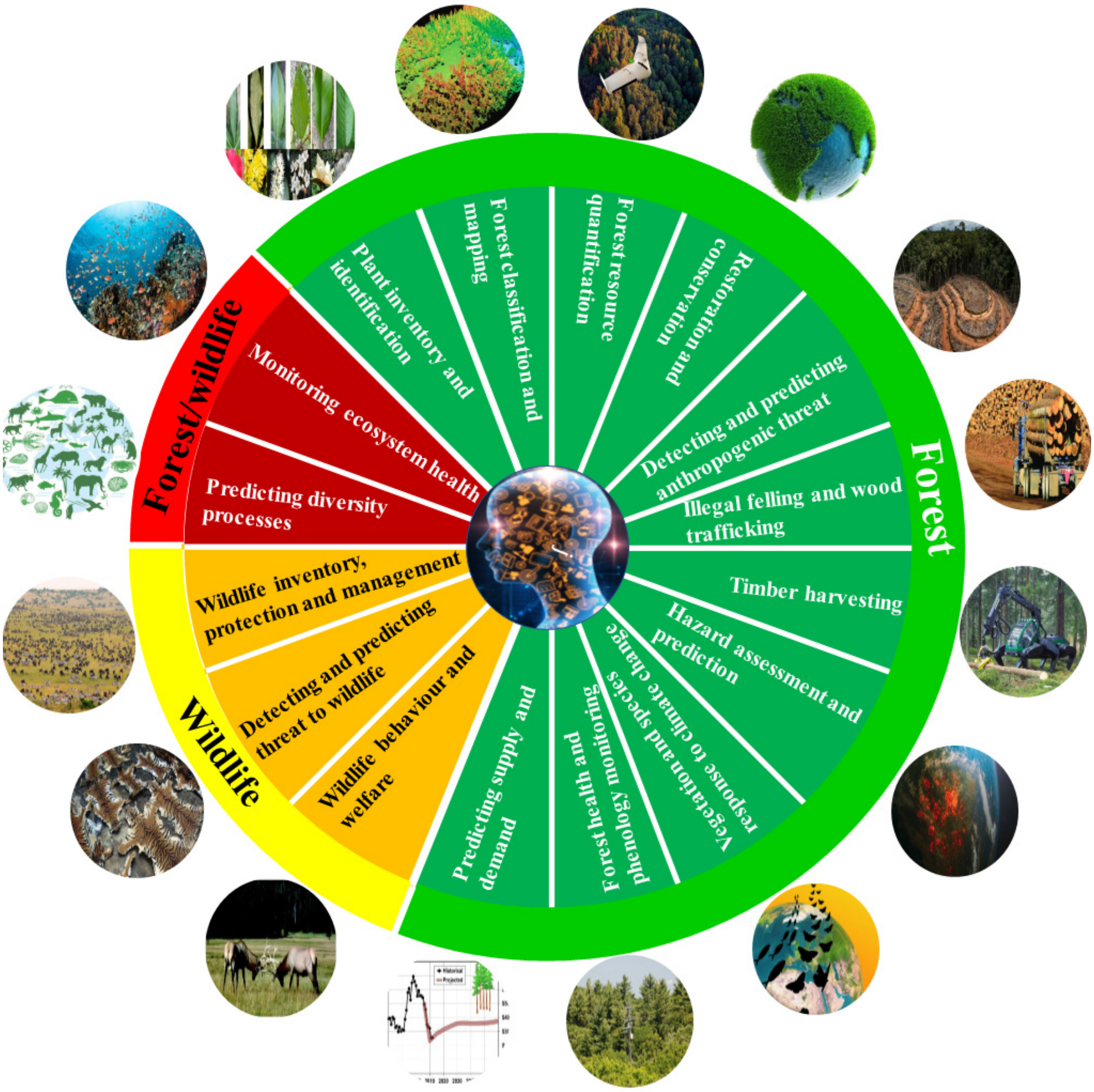

Figure 1. The overview of artificial intelligence application in forest and wildlife sector. Refer to Table S1 for details and reference related to respective sector 3.3. The economic market for AI-based forestry start-ups.

AI applications in the forestry sector are expected to significantly contribute to the global economy primarily through the precision forestry market which was worth USD 3.9 billion in 2019 and is projected to reach USD 6.1 billion by 2024. The major drivers of the precision forestry market are increasing mechanization in emerging countries of Europe, Asia Pacific, and Africa for logging operations, rising construction activities, growing demand for timber from sawmills, decreasing cost of forestry mapping technologies, and advanced monitoring and surveillance technologies, as well as the push to drive prevention of illegal logging and deforestation, and increase government support towards digitalization of forest resources.

Additionally, the AI technology market in inventory and logistics management, fire detection, digital mapping of forest for biomass, and carbon and timber resources is also expected to grow in the coming years. Such promising AI technology market growth relevant to the forestry sector has encouraged multiple start-up companies and non-profits to use AI-powered technology to tackle a wide range of problems such as detecting anthropogenic threats to the forest (deforestation, illegal felling), hazard assessment and prediction (fire, pest, and disease prediction and detection; predicting storm and flood damage to forest), restoration and reforestation, forest resource quantification and mapping (forest classification, estimating forest cover in real time, estimating carbon stock, and biomass and timber resource), tracking illegal wood trafficking, and monitoring forest health and phenology (Table S2). Most of these starts-ups and non-profits are located in developed countries such as the USA, Europe, Canada, Australia, and South Africa. Except Brazil, most developing countries which hold biodiversity-rich tropical forests are very slow in adoption of AI technology (Table S2).

3.3. AI and ML Application in Managing Forests and Their Resources, and Biodiversity Conservation

3.3.1. Addressing Challenges of Deforestation and Illegal Felling

AI and machine learning algorithms coupled with spatial analysis have been used to predict and monitor deforestation rates across the globe [54–59]. For instance, Rainforest Connection (https://rfcx.org/, accessed on 26 June 2021) is working to address the challenge of deforestation. The company is using old, discarded cellphones, powering them with solar power, and installing them on the treetops to record chainsaw sounds from the forest. These recordings/data are sent to cellphone towers and then to the base station where Google's AI and machine learning library called TensorFlow is used to identify and detect chainsaw noise over others. Once identified, this information along with location information of installed sensors is then shared with forest managers so that further due diligence can be carried out to identify and stop illegal tree felling. Similarly, other startup companies and non-profits such as Outland Analytics, Terramonitor, Global Forest Watch, and Future Forest Map project also make use of open-source satellite data and AI technology to map and monitor deforestation in real time. For example, Outland analytics makes use of audio recognition AI algorithms to detect chainsaw sounds or unauthorized vehicles and sends real-time alerts via email to officials to efficiently manage environmental crime. Terramonitor and Satelligence use a database of satellite images collected every day by multiple satellites and AI to create low-cost satellite data for natural area management and to monitor deforestation and forest health in real time (Table S2).

The World Resources Institute in collaboration with Central Africa Regional Program for the Environment (CARPE) used spatial modeling and AI to understand what factors influence deforestation in the Democratic Republic of Congo and to map where future forest loss is most likely to occur. Their analysis suggests that human presence factors such as shifting cultivation, and the presence of roads, had highest influence on forest loss followed by climatic variable precipitation. Further, analysis suggested that forests near to farmland are most vulnerable to deforestation. Their study can help DRC authorities to proactively make land use decisions that shift development pressure away from high-value forests.

3.3.2. Forest Inventory, Mapping, Carbon, and Biomass Estimation

Various startups are also making use of openly available and proprietary high-resolution satellite imageries and combining them with various other datasets to produce highly detailed maps of forests and landcover [60–63]. For example, SilviaTerra combines openly available high-resolution satellite imagery with field survey data from the US forest department to develop a predictive model that estimates forest conditions at a 15 m $\times$ 15 m resolution. The data contains information about tree height, type, and diameter, for example, which is being used by various timber and conservation organizations for guiding their plans (https://silviaterra.com/bark/index.html, accessed on 26 June 2021). Chesapeake Bay Conservancy teamed with Esri, and the Microsoft Azure team used machine learning libraries, to develop a highly detailed (one square meter resolution) landcover map of the region (https://chesapeakeconservancy.org/, accessed on 26 June 2021). Now, that the algorithm and mechanics are available, with some modification, to develop a detailed landcover map either for the entire US or other parts of the globe. 20tree.AI, a start-up in Portugal, made use of remote sensing, big data, cloud computing, and artificial intelligence for real-time forest inventory and monitoring. The Finnish forest center makes use of GIS data, imagery sources, climate and weather data, and AI for accurate measurements of forest stands and to better predict forest inventory. Similarly, CollectiveCrunch a for-profit company based in Germany and Finland has developed an AI platform dubbed as “Linda Forest”, that predicts wood mass, wood species, and wood quality of target areas far more accurate than any existing conventional methods. Linda Forest uses multiple sources of data, such as 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 growth predictions, to accurately estimate wood mass and wood quality in standing forest of the target area. Using this information, companies can then estimate resource-efficient production and consumption of wood products.

Deforestation and forest degradation account for approximately 11% of carbon emissions, more than the entire global transportation sector and second only to the energy sector. Reducing emissions from deforestation and forest degradation (REDD+) is a mechanism developed by Parties to the United Nations Framework Convention on Climate Change (UNFCCC). It creates a financial value for the carbon stored in forests by offering incentives for developing countries to reduce emissions from forested lands and invest in low-carbon paths to sustainable development. However, designing effective REDD+ policies, assessing their GHG impact, and linking them with the corresponding payments, is a resource-intensive and complex task. AI and machine learning techniques have shown a high potential in mapping and monitoring CO_2 stock and other ecosystem services in forests [35–38]. Start-ups such as GainForest and Panchama make use of AI technology to solve such complex tasks. GainForest uses large amounts of unlabeled satellite imagery, a video prediction model, game theory, and machine-learning-based Measurement, Reporting, and Verification (MRV) processes to monitor and forecast deforestation and design carbon payment schemes. Similarly, Panchama uses machine learning on a combination of satellite, drone, and lidar images to precisely estimate individual tree size, volume, and carbon density. Non-profit collaboration such as for Erol Foundation, the Center for Global Discovery, and Conservation Science (GDCS) at ASU and non-profit Planet.Inc use computer vision models, LiDAR, and satellite imagery at 3–5 m resolution for automatic and cost-effective direct measurement and mapping of carbon stock and emission at high resolution and high frequency in the Peruvian forest.

3.3.3. Automated Reforestation and Afforestation

Another example of AI application is reforestation of recently deforested areas that can promote the planting of 1.2 trillion more trees on the planet [64]. This has the potential to absorb CO_2 from the atmosphere in the order of hundreds of gigatons [64]. Three start-ups, Droneseed, Dendra, and Land Life, are creating products to address this challenge. Droneseed is a company which has developed an innovative product called the seed vessel that carries seeds of desired species, helping to protect and germinate faster once planted. The company deploys drone swarms and FAA heavy lift certified a group of four or five drones that carry weight of about 57 lbs, scan the study area to be planted to identify suitable conditions for planting-like moisture availability, and drop seed vessels. This technology provides numerous advantages over manual reforestation method because it enables faster dispersal of seeds, and it can cover a larger area than planting by hand; most importantly, it also provides the ability to quickly monitor and measure the status of reforestation using drones. As it provides a bird eye view, it also helps to identify exact locations of problematic areas where appropriate interventions could be done to achieve better results (https://www.droneseed.com/, accessed on 26 June 2021).

The Nature Conservancy’s Oregon chapter has teamed up with Droneseed to restore rangeland that was disturbed by invasive species in Oregon (https://uavcoach.com/droneseed-oregon/, accessed on 26 June 2021). A similar start-up in UK called Dendra uses AI-based automation and digital intelligence to identify suitable planting areas to disperse seedpods filled with seeds of desired species and nutrients to support germination.

Land Life, a start-up in Amsterdam, uses multiple technologies such as GPS, satellite imagery, an automated driller, Cocoon (a seedling support technology), and AI technology for mass-scale reforestation and monitoring reforestation success.

3.3.4. Hazard Assessment and Prediction

Another area where technological advances are bringing transformational changes to the forestry sector is through the collection of inventory data. Such advances have led to novel ways of collecting and preparing highly accurate, high-resolution data that will significantly improve the way we are managing forests and conservation activities. For example, a lot of data exists in paper format from past forest monitoring, which technologies like Optical Character Recognition (OCR) and Natural Language Processing (NLP) can digitize. Once the data is available in digital format, they can be fed into several analytical algorithms for conducting analyses. Internet-enabled sensors (Internet of Things devices), that can measure temperature, moisture, etc., when installed in forests, provide near-real-time information about forest activities and conditions. Such data are being used to develop predictive models for identifying and getting insights into forest health and threats like deforestation [55–59], drought [65,66], wildfires [67–69], pests, diseases outbreak [70–72], soil health, storm damage, and other forest disturbances [71]. Terrafuse, a start-up in Canada, uses physics-enabled AI models to understand climate-related risk at the hyperlocal level. Terrafuse leverages historical wildfire data, numerical simulations, and satellite imagery on Microsoft Azure to model wildfire risk for any location. It also estimates temporal change in carbon density because of fire, deforestation, and other calamities.

Further, researchers in Columbia University are using AI technology to understand the effect of Hurricane Maria on Puerto Rico forests. Researchers want to understand how tropical storms, which may worsen with climate change, affect the distribution of tree species in Puerto Rico. In 2017, a NASA flyover of Puerto Rico yielded very high-resolution photographs of the tree canopies, using this images and AI technology, scientists hope to analyze which tree species were destroyed and which withstood the hurricane to predict patterns associated with future hurricanes.

3.3.5. Tracking Illegal Wood Trafficking

The illegal timber trade is considered as lucrative as the illegal wildlife trade. According to Interpol, the illegal timber trade is worth USD 50 billion to 150 billion annually. The supply of illegal timber not only contributes to deforestation (leading to significant loss of carbon) but also threatens many rare tree species such as rosewood, dipterocarps and mahogany. Illegal timber trade lowers global timber prices by 7 to 16%, costing source nations up to USD 5 billion as losses in annual revenue and providing a significant incentive for governments to act. Thus, to protect forests from illegal felling and to guide legal timber use globally, there is a need for a system which can track illegal timber [73]. Timbeter is a start-up in Estonia, which uses the world's largest database of photometric measurements of roundwood and AI for online tracking of roundwood to individual shipments and piles to fight illegal logging and timber trafficking. Xylene, a start-up in Germany, uses a combination of space technology, blockchain and supply chain mapping, automatic data gathered by IoT devices, and Earth Observation and AI technology to track the wood supply chain in real-time.

3.3.6. Monitoring Ecosystem Health and Biodiversity Conservation

The conservation community often seeks to promote forest characteristics that influence richness and diversity of fauna in the forest, making it critical to understand what interventions are successful, and AI technology is helping in such interventions [11–14]. Scientists from The Nature Conservancy and its partner organizations have developed a novel way of automated soundscape monitoring to evaluate the impact of conservation actions on biodiversity. To understand how species respond to disturbances like recent deforestation or poaching, they developed tiny sound recorders and installed them across various locations in the forest. They recorded sounds of the forest, referred to as a soundscape, which was then analyzed to identify various species sounds, and activity across various times of the day and various periods of the year. They are developing a global platform to store such data from various efforts across the globe and provide analytical services to analyze these datasets to understand benefits of conservation interventions. Such technology has various implications for understanding how species react to disturbance or benefit from interventions [13]. Classification of vibration patterns from oncoming trains using machine learning has also been used in providing early warning to wildlife in Banff National Park, Canada, where train strikes have been a major source of mortality for grizzly bears *Ursus arctos horribilis* [74]. By using such classifications to trigger sound and light-based alarms before trains reached the location, animals were found to leave the track 29–62% earlier than they would have otherwise done [74].

Apart from sound recognition, the widespread use of imagery in wildlife monitoring has led to a strong use-case for AI-based automation for identification of species [48–53] (Tables S1 and S2). Imagery may be obtained, for example, through automated camera traps, which are triggered by heat and motion. Millions of photographs or video clips may result from the widespread deployment of such devices. Given the massive amount of data, this may make it challenging to analyze and extract data on species of conservation importance. The application of AI to this problem can result in accurate species classification. For example, in the Serengeti ecosystem, a community of 48 species was classified using such an approach [27]. Similar methods have also been applied in the identification of individual animals. For example, the strip patterns of tigers, (*Panthera tigris*) have been used to identify individuals [75]. Based on this, Shi et al. [76] developed a convolutional neural network (CNN) to identify individual tigers. The ability to identify both species and individuals has important implications for monitoring biodiversity, but also in conservation applications such as mitigating human-wildlife conflict. For example, farmers could be provided with early warning on the entry of elephants (*Elephas maximus*) into crop fields and villages by combining automated cameras with image analysis software. Similarly, individual tigers that become habituated to humans, increasing risk of conflicts, can be identified using such systems. A key requirement in implementing such systems in the field is rapid classification and information transfer, for this computation on the device itself is ideal but can be expensive to set up. Further, the lack of mobile towers in remote forested areas can hamper information transfer.

3.3.7. Solving Supply and Demand Problem

With rising global population, there is high demand for timber and non-timber forest products. Therefore, the forestry sector, globally, is facing demand uncertainty, higher supply risk, and increasing competitive intensity. Thus, there is a need for smart supply chain management to solve supply and demand problems in the forestry sector [77,78]. One area of AI's potential application is the emerging management philosophy of supply chain management (SCM). The aiTree Ltd. in Canada, for over 20 years, has been focusing on systematic technologies to solve demand and supply problems in the forestry sector with AI algorithms. The aiTree has applied its typical application Forest Simulation Optimization System (FSOS) in British Columbia, Canada to solve demand and supply problems in the forestry sector. The demands from a forest include wildlife habitat, biodiversity, water quality, visual quality, carbon storage, timber production, and economic contributions. FSOS focuses on both "what we can take from the forest" and "what we can create in the forest". Forest design is a complicated problem because the trees are growing and dying, and all the values must be considered every year for over 400 years. FSOS is a good example that uses AI, big data, and cloud computing technologies to solve the complicated demand and supply problems.

3.3.8. Forest Hydrology

One of the most critical aspects of forest management is understanding its linkages with watershed/forest hydrology, as it drives nutrient cycling, precipitation inputs, and surface and subsurface flow networks that support forest growth and downstream water quality [79]. With improvements in technologies such as high-performance sensors, smart phones, autonomous vehicles, remote sensing, and GIS, increasing volume and complexity of data on ecohydrological parameters are being collected. Tools such as AI and ML are being applied in the field of ecohydrology, including forest hydrology, to fully realize the potential of these data and obtain new insights into ecohydrological processes [80]. For instance, AI/ML methods have been used to estimate and model precipitation interception by forest canopies [81,82], canopy water content [83], spatiotemporal behavior of soil moisture in vegetated areas [84–86], global [87] and regional [88] terrestrial evapotranspiration, water-use efficiency in terrestrial ecosystems [89], vegetation water storage [90], terrestrial/groundwater storage [91] using vegetation cover as an indicator [92], and plant water stress [93]. The recent growth of big hydrologic data through remote sensing and data compilation has also fostered the adoption of ML in land surface modeling which simulates land surface processes including partitioning of water between land and atmosphere, such as in groundwater dynamics [94]. Big data and AI/ML have been increasingly used to predict extreme geoclimatic events such as droughts, floods, and landslides [95], which have direct implications for forest management. More recently, efforts are being made to improve prediction of terrestrial ecohydrological extremes (TEE) (e.g., the extremes of evapotranspiration, soil moisture, streamflow, and terrestrial water storage) at seasonal to decadal scales using AI-based integrated modeling [96]. Taken altogether, these advances in technology, data interpretation, and modeling are slowly transforming our ability to understand forest and watershed hydrology [97] and have important policy and management implications [80]. Use of AI/ML methods for forest hydrology, however, seem to be limited to scientific research and are yet to be applied for conservation and management at a large scale. These methods have a tremendous potential for better decision support in forest hydrology management.

3.3.9. Aquatic and Marine Biodiversity and Water Resource Conservation

Artificial intelligence (AI) applications in aquatic and marine biodiversity and water resource optimize the conservation of aquatic and marine flora and fauna and water resources and attracted significant reserch attention since last decade. For instance, AI and ML models have been used to predict stream flow [98–103], water quality [104–125], water pollution and toxicology [126–132], aquatic and marine biodiversity diversity prediction and extinction [133–149], predicting species distribution and habitat mapping [150–164], and marine and aquatic species recognition and classification [165–183]. Above mentioned AI research in aquatic and marine biodiversity and water resource conservation highlight that AI will be key to developing new technology to uncover new aspects of conservation and potential threats to aquatic and marine ecosystems' structures and functions, thereby informing effective monitoring and conservation of aquatic and marine biodiversity and managing water resources. This new knowledge will directly address several of the key challenges identified for the aquatic and marine ecosystems, from effective water resource management and biodiversity conservation, to creating a digital representation of the freshwater and ocean ecosystems and delivering data, knowledge, and technology to all.

3.4. Status of Indian Forests and Need of AI Technology

Indian forests are an important defining feature of the country's landscape that hold both cultural and biological importance [184]. India's wide range of climate, geography, and culture is unique among biodiversity-rich nations and is known for its diverse forest ecosystems and megabiodiversity. It ranks as the 10th most forested nation in the world [19] with 24.56% (81Mha) of its geographical area under forest and tree cover [185]. Out of 34 global biodiversity "hot spots," four are located in India, namely, the eastern and northeastern Himalayas, Indo-Burma (North-east India), Sundaland, and Western Ghats [186]. Being one of the 17 megadiverse countries, with only 2.4% of global land area, India accounts for 7 to 8% of recorded species in the world [98]. In addition, Indian forests provide many ecosystem services and livelihoods to people. Approximately 275 million people of India live in the fringes of forest and earn the bulk of their livelihood from forests [187]. It is estimated that Indian forests sequester 5.84–7.39 Gt of carbon every year [188].

Despite their cultural, economic, and ecological importance, Indian forests face many adverse challenges.

- About 85% of forest area is publicly owned and 15% privately owned [19]. Most of the public forests are administered by the government, and some of them by communities and indigenous groups, and only around 27% of publicly owned forest is protected in 2019, compared to 31.63% in 2003. Further, 14% of tree cover assumes unclassified status (Table 1), indicating that Indian forests suffer from low protection status.
- Of the approximately 81 Mha of forest, 9928 Mha are dense primary forests, 30.847 Mha are moderately dense forests, 40,775 Mha are open forests, and 9503 Mha consists of agroforestry, social forestry, and plantations [185]. The forest cover data from 2003 to 2019 suggests that there is a consistent increasing trend in open forest and a decrease of dense forest cover with the gain of 1,917 Mha of open forest and loss of 2599 Mha of moderately dense forest (Table 1), indicating a continuous degradation of dense forest in India.
- Further, Indian forests suffer from low growing stock. The data from 2003 to 2019 suggest that there is an loss of 507,944 million cubic meters of growing stock in forests, whereas trees outside forests show a gain of 0.61 million cubic meter, suggesting that Indian forests are poorly managed (Table 1).
- Illegal logging and trade of high-value timber is a major problem in many parts of the country. In 2009, the Ministry of Environment and Forests estimated that 2 million m^3 of logs were illegally felled per year. Underlying this logging are several uncertainties relating to legal rights to harvest, tax, perform timber harvesting activities, third parties' rights, and trade and transport.
- As India is one of the world's largest importers of wood-based products, it is also a major consumer of illegal timber. The volume of illegal imports has increased, and in 2012, almost 20% of timber imports were estimated to be illegal [189].
- India's population and economic growth in the last several years has raised several concerns in terms of its present and future resource demands for timber and non-timber material and energy needs from the forest. With 18% of global livestock and 17% of the human population on 2.4% of the world's land area, the Indian forest faces immense biotic pressure. Around 30% of fodder needs for cattle and 40% of domestic fuel wood needs directly come from these forests. Despite protection status, 87% of national parks experience grazing. Further, in eastern and northeastern India, around 1.2 Mha of forest land is under shifting cultivation. Therefore, there is high anthropogenic and other biotic pressure on Indian forests.
- Moreover, the Indian forest sector still depends on resource-intensive and time-consuming traditional forestry practices to manage and protect forests. Compared to the wildlife sector, the forestry sector in India has been slow in adapting innovative technology, which can bring transformative change in conservation and management of forests and their resources.

While these challenges persist in the Indian forest sector, they coincide with an era in which there is unprecedented innovation and technological change. The rapid advancement in AI technology supported by the Internet of Things (IoT), open-source big data, unmanned aerial vehicles (UAVs), high-resolution satellite images, sensors, and cheaper computing, is a boon to the Indian forestry sector for solving many of its challenges. Given the similar nature of problems plaguing tropical forests globally and in India (such as deforestation, encroachment for farming, forest degradation to extract timber and non-timber resources, illegal logging, illegal timber import and export, and inefficient supply chain management), AI technologies being developed for the forestry sectors in other countries and related learnings can also be applied for improving forest management in India (Table S2).

Table 1. Status of forest in India from 2003 to 2019.

Forest Resource Variable	2003	2005	2009	2011	2013	2015	2017	2019	Net Change between 2003 to 2019 (In Million ha)	% Change between 2003 to 2019
Very dense forest (in million ha)	5.452	5.457	8.351	8.347	8.35	8.59	9.816	9.928	4.476	45.08
Moderately dense forest (in million ha)	33.406	33.265	31.901	32.074	31.875	31.537	30.832	30.847	−2.599	−8.43
Open forest (in million ha)	38.858	38.722	40.252	40.421	40.225	31.54559	40.648	40.775	1.917	4.7
Tree cover (in million ha)	9.99	9.166	9.277	9.084	9.127	9.257	9.382	9.503	0.487	4.87
Growing stock in forest (million cubic meter)	4781.414	4602.04	4498.66	4498.731	4173.362	4195.057	4218.38	4273.47	−507.944	−10.62
Growing stock in trees outside forest (million cubic meter)	1632.338	1616.24	1599.57	1548.427	1484.684	1573.34	1603.997	1642.29	9.952	0.61
Reserve forest (in million ha)	39.99	41.903	43.05	42.25	42.9	42.5	43.47	43.49	3.5	8.60%
Protected forest (in million ha)	23.84	21.661	20.62	21.39	22.66	20.94	21.94	21.9	−1.94	8.80%
Unclassified forest (in million ha)	13.63	13.4	13.27	13.3	13.4	13.01	11.39	11.37	−2.26	19.80%

Note: Data for the table was assembled from India State of Forest Report, 2003–2019 (https://fsi.nic.in/forest-report, accessed on 15 August 2021).

3.5. Barriers to Adoption of AI-Based Systems for India's Forests and Biodiversity Conservation

3.5.1. Inadequate Awareness

There is often a lack of awareness among stakeholders (such as forest managers, policymakers, and civil society) on the availability and applicability of technologies. This is partly due to the inherent complexity of these new technologies, which may lead to disinterest. On the other hand, the use of terms such as artificial intelligence may also create unrealistic expectations for solutions. Therefore, building the capacity of stakeholders on the appropriate use of these technologies is an important step in applying them in the field. Strong case studies and pilot demonstrations are important in building both understanding and realistic expectations.

3.5.2. Lack of Ethical Standards and Safeguards

The use of technologies such as AI brings with it several possibilities for misuse. When using such technologies in areas with particularly vulnerable communities, such as indigenous groups or forest-dependent communities, safeguards need to be especially strong. Concepts such as free, prior, and informed consent, data security, and permitted applications need to be defined and followed. Such standards also need to be accompanied by capacity development of communities in areas where such technologies are deployed, to ensure equity in outcomes.

3.5.3. Limited Suitability to Harsh Field Conditions

Technologies that are implemented under the harsh conditions of the field need to be robust enough to function over meaningful timeframes. Climatic and weather conditions, animal damage, and vandalism are key challenges for such technologies. Inadequate planning for such conditions may lead to equipment failures, thereby also undermining trust in the concept itself. Such planning is particularly important given the high capital and running costs of such technologies. Further, inadequate supporting infrastructure in the field, such as unstable connectivity, may limit the reliability of equipment.

3.5.4. Limited Commercial Scalability

Applications of AI in the forest sector in India are currently driven by enthusiasts and small startup companies. The lack of a strong market limits the investments that can be made in the sector, in turn leading to inadequate scaling. Further, the fragmentation of efforts among small competitors working on similar applications may hinder the large-scale economic development of AI technology. Such limitations may also prevent the development of user-friendly interfaces, leading to AI models being deposited in repositories such as GitHub but not being used by practitioners.

3.6. Uncertainties Associated with AI

Though, AI technology has potential applications in forestry and biodiversity conservation, it is increasingly important to evaluate the reliability and efficacy of AI and ML systems before they could be applied in practice. Because the predictions made by AI and ML models may not be always reliable due to uncertainty associated with data and expert knowledge. For example, the AI and ML algorithms will not be able to differentiate plantations from reforestation areas and natural forest, especially in a species-rich tropical forest, if there is no good number of labeled images of natural forest, plantations, and reforestation areas. Thus, the reliability of output produced by AI and ML models depends on large amount of training and test data and expert knowledge.

4. Conclusions

Globally, there is a need for forestry practices to contribute to sustainable development goals that attempt to conserve forests as carbon sinks and biodiversity habitats, and to sustain and cultivate forests as green infrastructure. The emerging technological innovation to manage, monitor, and conserve the forest and its resources is helping the sector achieve sustainable development goals. Globally, there is an increasing number of countries adapting smart forest and precision forestry techniques which make use of technological innovation in digital, satellite, sensors, and AI technology to manage, protect, and sustainably utilize forest resources. However, adoption of these innovations is mostly limited to developed countries and a few developing countries where forest is managed for commercial purposes. On the other hand, for countries like India, where forests are mostly managed for non-commercial purpose of biodiversity conservation, storing carbon, and benefiting rural livelihood, the adaption of innovative technologies in the forest sector has been slow.

Challenges or limitations, such as (1) the unavailability of better data or limited access to available big data, and (2) technical and computation challenges of using technologies like AI (e.g., accessibility to the wider community), have resulted in a limited application of these technologies in the Indian forest sector. Therefore, to make technologies like AI more beneficial and accessible to the Indian forest sector, we suggest the following actions:

1. Interdisciplinary collaborations between forestry practitioners, forest ecologists, conservation practitioners, forestry officials, academicians working in the forestry sector, and technologists will be important in facilitating long-term adoption of AI technology for forestry sector applications (for example, corporations like Microsoft and Google initiative's "AI for earth innovation" bringing together researchers and conservationists to incorporate AI solutions into nature conservation by providing technical support, infrastructure, and training [190]),
2. Cheap and cost-effective computational resources for both data analysis and storage (e.g., cheaper cloud-based options for online data analysis and storage) will have an advantage of minimal investment and hardware maintenance [191].

3. Continued expansion of data collection capabilities (for example, emerging technologies such as the wireless sensor networks, digital recording devices, drones and camera technology, and crowd-sourced data approaches like citizen science, development of algorithms to extract data from social media, and other online sources), and
4. Development of computationally less intensive, fast processing algorithms to analyze big data.

Further, these developments will have tremendous potential to drive transformational changes in the way we manage our forests, biodiversity, and design appropriate conservation measures.

Supplementary Materials: The following supporting information can be downloaded at https://www.mdpi.com/article/10.3390/su14127154/s1. Table S1: Summary of AI and machine learning application research in biodiversity conservation and forest sector; Table S2: AI start-up companies and non-profits in biodiversity conservation and forest sector.

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Abbreviations

AI	Artificial intelligence
ML	Machine learning
CNN	Convolutional Neural Network
FSI	Forest Survey of India
FAO	Food and Agriculture Organization
IoT	Internet of Things
UAVs	Unmanned Aerial Vehicles
GIS	Geographic Information System
SCM	Supply Chain Management
FSOS	Forest Simulation Optimization System
UNFCCC	United Nations Framework Convention on Climate Change
REDD+	Reducing Emissions from Deforestation and Forest Degradation
CARPE	Central Africa Regional Program for the Environment
NDCs	Nationally Determined Contributions
DRC	Democratic Republic of Congo
LiDAR	Light Detection and Ranging
OCR	Optical Character Recognition
NLP	Natural Language Processing

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