Babylonian Journal of Internet of Things
Vol.2025, **pp.** 1–65
DOI: https://doi.org/10.58496/BJIoT/2025/001; ISSN: 3006-1083
https://mesopotamian.press/journals/index.php/BJIoT

Review Article

Leveraging the Internet of Things, Remote Sensing, and Artificial Intelligence for Sustainable Forest Management

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ARTICLE INFO

Article History

Received 15 Oct 2024
Accepted 20 Dec 2024
Published 17 Jan 2025

Keywords

Internet of Things

Remote Sensing

Artificial Intelligence

Sustainable Forest Management

Forest Monitoring

ABSTRACT

Sustainable forest management is vital for addressing climate change, biodiversity loss, and deforestation. Human-induced stresses on forest ecosystems demand innovative approaches to ensure long-term health and productivity. This study explores how cutting-edge technologies, including the Internet of Things (IoT), remote sensing, and artificial intelligence (AI), enhance sustainable forest management practices. Researchers reviewed 196 studies published between 2021 and 2024 from IEEE Xplore Digital Library, MDPI, Taylor & Francis, ScienceDirect, Frontiers, Springer, SAGE, Hindawi, Nature, Wiley Online Library, and Google Scholar. The findings highlight IoT devices like drones, enabling real-time data collection on temperature, humidity, soil moisture, and tree growth, facilitating continuous forest monitoring. Remote sensing technologies, utilizing satellite imagery and aerial surveys, deliver high-resolution data for large-scale forest assessments, including forest cover changes, biomass estimation, and early detection of illegal logging. When integrated with AI, these tools enhance predictive modeling, data analysis, and decision-making, leading to more effective forest management strategies. The study also identifies challenges such as data security concerns, bandwidth limitations, interoperability issues, and high costs. Despite these barriers, IoT, remote sensing, and AI present transformative potential for improving forest resilience, carbon sequestration, and biodiversity conservation. These technologies are crucial in preserving forest ecosystems and mitigating climate change impacts by advancing real-time monitoring, optimizing resource allocation, and enabling data-driven decisions.

1. INTRODUCTION

Forests are invaluable natural resources deeply intertwined with human living environments. They significantly contribute to our planet’s and society’s well-being through carbon sequestration, biodiversity conservation, water cycle regulation, and overall environmental balance [1][2]. According to the Food and Agriculture Organization (FAO), a forest is any area exceeding 0.5 hectares with over 10% tree canopy cover, primarily not utilized for agricultural or other non-forest purposes [2]. Similarly, Masha et al. [3] describe forests as habitats with dense tree cover that support diverse animal species. Forest composition and structure vary depending on climate, soil type, and topography, resulting in different kinds of forests, such as temperate forests, tropical rainforests, and boreal forests. Factors like tree species composition, deadwood volume, and microhabitat diversity significantly influence biodiversity within forest ecosystems [4].

Forests cover over 4 billion hectares, accounting for approximately 31% of the Earth’s land area. In 2021, global forest coverage stood at 4.05 billion hectares, a decline from 4.24 billion hectares in 1990 [5]. Public entities own the majority of forests, accounting for 84.4%, while private owners manage 13.3%, and the remaining 2.3% fall under other ownership categories [6]. Tropical forests comprise 45% of the world’s forested areas, followed by boreal (27%), temperate (16%), and subtropical forests (11%). Europe holds the largest share of forested land at 25%, followed by South America (21%), North and Central America (19%), Africa (16%), Asia (15%), and Oceania (5%). Countries with significant forest areas include Russia, Brazil, Canada, the US, and China [7].

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Throughout history, forests have played a central role in human social, economic, and cultural activities. These ecosystems host 75% of bird species, 80% of amphibians, and 68% of mammals. Forests mitigate climate change, regulate the water cycle, conserve soil, provide water and medicinal resources, supply timber, and support renewable energy. They play a critical role in self-regulating the environment by reducing carbon emissions, preventing droughts, controlling floods, and maintaining agricultural and livestock productivity. Forests also support recreation, mitigate natural disasters, and generate employment for over 86 million people worldwide [1][2][8-14].

Despite their significance, forests face severe threats due to rapid population growth, urban expansion, and increased demand for agricultural land. Deforestation, illegal logging, forest degradation, and natural disasters like fires, pests, and extreme weather continue to devastate forest ecosystems [1][3][15][16]. Climate change intensifies these challenges, leading to the annual loss of 47,000 km² of forest habitat. Between 2000 and 2021, Côte d'Ivoire experienced the highest percentage of forest loss globally, while 28.3 million hectares of tree cover were lost worldwide in 2023, marking a 23.8% increase from the previous year [3][5][17-19].

Sustainable forest management has emerged as a crucial strategy to address these challenges, balancing ecological, economic, and social priorities. However, traditional management methods relying on manual data collection and field surveys are often time-consuming, labor-intensive, and limited scope [17]. Emerging technologies like the IoT, remote sensing, and AI offer innovative solutions for sustainable forest management. IoT devices enable real-time data collection from forests, while remote sensing provides high-resolution imagery of vast forest landscapes. Artificial intelligence algorithms analyze these data streams to detect abnormalities, predict forest growth, and offer actionable insights. Together, these technologies create an integrated framework for monitoring, assessment, and decision-making in forest management. These advancements bring numerous benefits, including precise forest management, threat detection, optimized resource use, enhanced conservation efforts, and climate change mitigation. They also promote efficient regulation enforcement, economic management, and community engagement, ensuring sustainable livelihoods and environmental preservation [1][19]. However, adopting these technologies poses challenges such as AI model biases, connectivity issues, deployment costs, data availability, and quality, data security and governance concerns, ethical and legal matters, problems of interoperability and standardization, and scalability and adaptability issues [1].

Recent research has highlighted the potential of emerging technologies in forest conservation and management. Zakari et al. [1] conducted a comprehensive review of Internet of Forestry Things (IoFT) technologies, emphasizing their applications in forest management. Giannakidou et al. [20] examined how IoT and AI technologies can actively prevent forest fires, detect them early, and aid in restoring affected areas. Singha et al. [21] utilized geospatial tools, remote sensing, and machine learning to actively map areas susceptible to climate-induced forest fires in India's Similipal Tiger Reserve. Similarly, Khan et al. [22] investigated using AI-powered IoT devices to combat illegal logging and enhance forest monitoring. Krishnamoorthy et al. [23] also designed and developed an intelligent forest alert monitoring system utilizing IoT technology. Nonetheless, no studies have focused on combining IoT, remote sensing, and AI to achieve sustainable forest management. This study addresses this gap by providing an overview of how these technologies can work together to improve forest management practices.

This study makes several significant contributions.

- It describes the state-of-the-art, i.e., the ongoing digital transformation within forestry.
- It explores emerging technologies that support sustainable forest management, shedding light on their potential applications and benefits.
- It provides a comprehensive system architecture overview that integrates the IoT, remote sensing, and AI to enhance sustainable forest management practices.
- It delves deeply into these technologies, discussing how they can improve efficiency, decision-making, and sustainability in forestry operations.
- It highlights real-world examples and case studies demonstrating how IoT, remote sensing, and AI are actively used to advance sustainable forest management.
- It identifies the challenges and limitations of using IoT, remote sensing, and AI in sustainable forest management.
- It proposes future research directions and offers recommendations to address these challenges, aiming to guide further advancements in the field.

The article is structured as follows: Section 2 presents the materials and methods, while Section 3 reviews the current state of the art. Section 4 introduces emerging technologies for sustainable forest management, and Section 5 outlines the system architecture. Section 6 discusses the applications of IoT, remote sensing, and AI in sustainable forest management, followed by Section 7 highlights real-world implementations and case studies of these technologies. Section 8 examines challenges and limitations, while Section 9 suggests future research directions and recommendations. Finally, Section 10 concludes the study.

2. MATERIALS AND METHODS

Researchers conducted a comprehensive review to collect, analyze, and synthesize studies on applying IoT, remote sensing, and AI in sustainable forest management. This approach enabled them to thoroughly understand this multidisciplinary field's current advancements, limitations, and future trends. By focusing on material published between January 2020 and November 2024, they ensured the inclusion of the most recent developments in smart forestry. The review examined diverse sources, including journal articles, conference proceedings, book chapters, and websites.

To gather relevant literature, the researchers employed specific keywords. They searched academic databases such as IEEE Xplore Digital Library, MDPI, Taylor & Francis, ScienceDirect, Frontiers, Springer, SAGE, Hindawi, Nature, Wiley Online Library, and Google Scholar. Keywords like "Sustainable forest management," "IoT in forest management," "remote sensing in forestry," "AI for sustainable forestry," "smart forestry," and "forest monitoring technologies."

The team applied specific inclusion and exclusion criteria to focus their analysis on papers related to sustainable forest management. These criteria helped filter the vast amount of data and retain only the most pertinent studies, guaranteeing the review's quality and relevance. Table 1 outlines the inclusion and exclusion criteria for choosing relevant research papers for the study.

TABLE I. OUTLINES THE INCLUSION AND EXCLUSION CRITERIA FOR CHOOSING RELEVANT RESEARCH PAPERS.

S/No	Inclusion Criteria	Exclusion Criteria
1	The researchers selected research papers written in English.	The researchers excluded papers written in languages other than English.
2	They prioritized peer-reviewed journal articles, conference proceedings, book chapters, and other relevant papers.	They omitted non-peer-reviewed works, such as opinion articles, editorials, and unreviewed conference abstracts.
3	The review focused on studies exploring the applications of IoT, remote sensing, and AI in forest management.	Researchers excluded studies unrelated to forest management or lacking practical insights into sustainability.
4	Researchers included research papers that presented experimental evidence or case studies demonstrating the sustainability of forestry practices.	Researchers excluded the studies focusing solely on unrelated IoT, remote sensing, or AI applications.
5	The researchers prioritized research papers with clearly defined methodologies and outcome measures.	The researchers disregarded works with unclear methodologies or ambiguous outcomes.
6	The researchers considered publications released between 1 January 2020 and 30 November 2024.	Researchers excluded the publications released before 1 January 2020.

Eight authors independently collected relevant research papers from selected databases, focusing on predetermined key information. They recorded the title, authors, publication year, and each study's objectives and research questions. Additionally, they documented the study design, analysis methods, results, and conclusions. Specific areas of interest included sustainable forest management, the IoT in forestry, remote sensing for forest monitoring, AI in forest ecosystem management, precision forestry, and smart forest management. The authors also analyzed key findings, identified challenges and limitations, and reviewed future research directions and recommendations proposed by the original authors. The researchers organized the collected data systematically to maintain consistency and accuracy.

To ensure reliability, the authors adopted a test-retest technique. This method involved randomly selecting retrieved publications from the original research pool and verifying their correctness multiple times to eliminate biases in the exclusion criteria. The researchers reviewed 196 relevant research papers in total from various digital libraries, including forty-six from *IEEE Xplore Digital Library*, seventy-five from *MDPI*, three from *Taylor & Francis*, sixteen from *ScienceDirect*, one from *Frontiers*, seven from *Springer*, one from *SAGE*, one from *Hindawi*, three from *Nature*, four from *Wiley Online Library*, and thirty-nine from *Google Scholar*.

The researchers evaluated, appraised, and classified the research papers based on their relevance to IoT, remote sensing, and AI applications in sustainable forest management. Fig. 1 illustrates the distribution of selected research publications across the digital libraries.

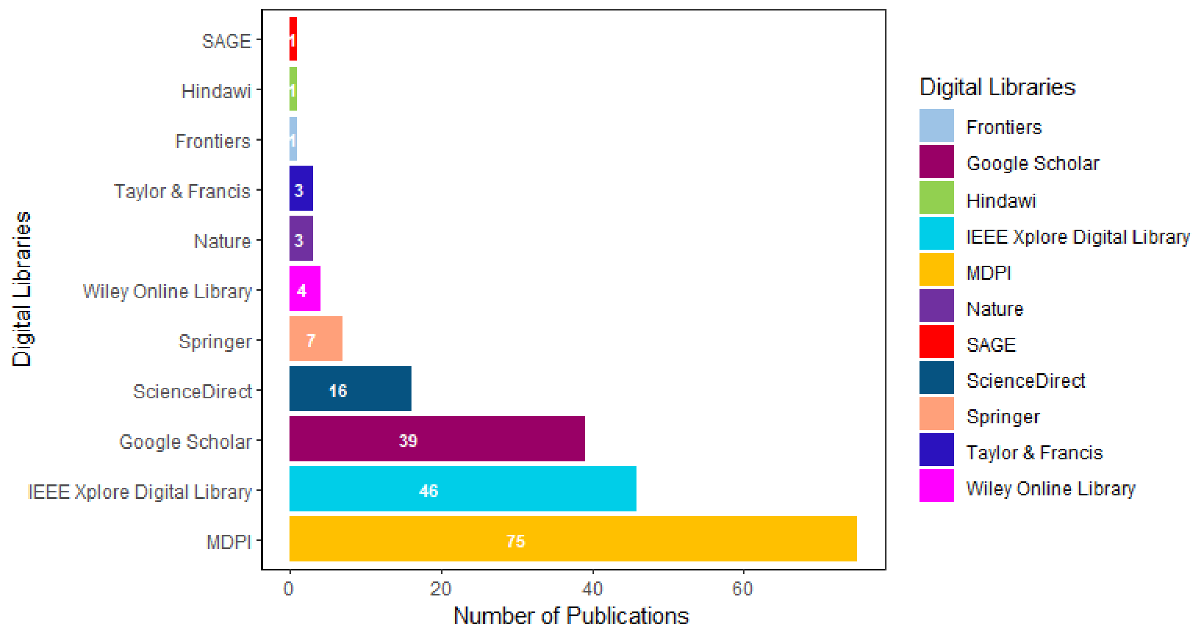

Fig. 1. Illustrates the distribution of selected research publications across digital libraries.

Fig. 2 illustrates the distribution of the selected papers across various digital libraries, categorized by their types.

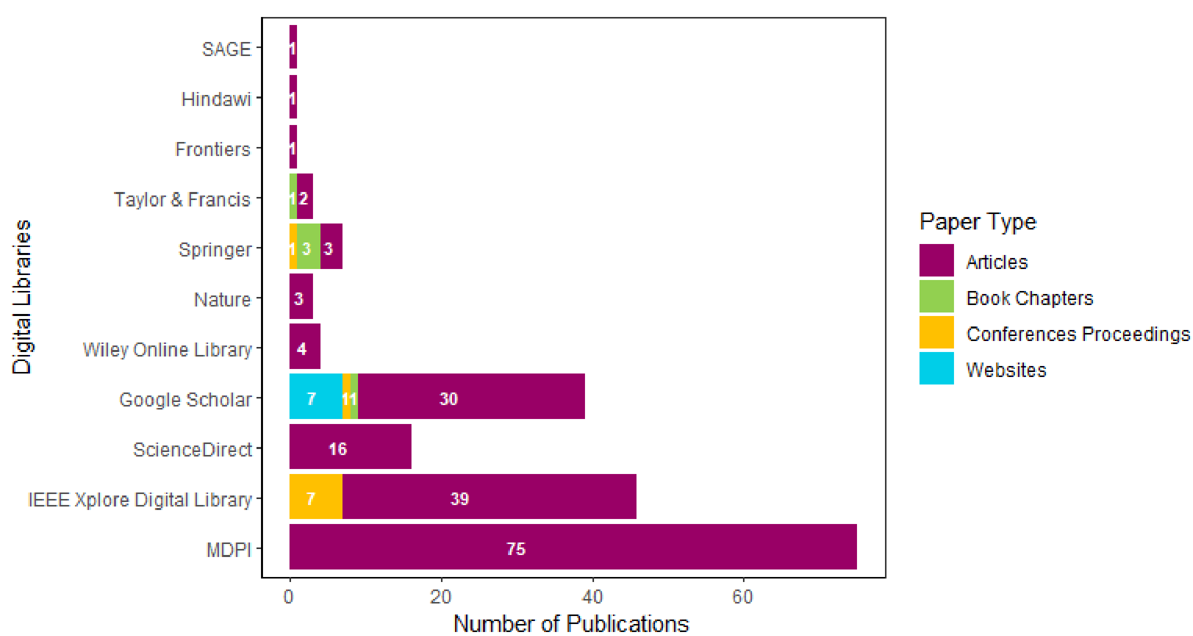

Fig. 2. Displays the distribution of the selected papers across various digital libraries, categorized by their types.

Fig. 3 shows how the selected papers are distributed across digital libraries, categorized by publication year.

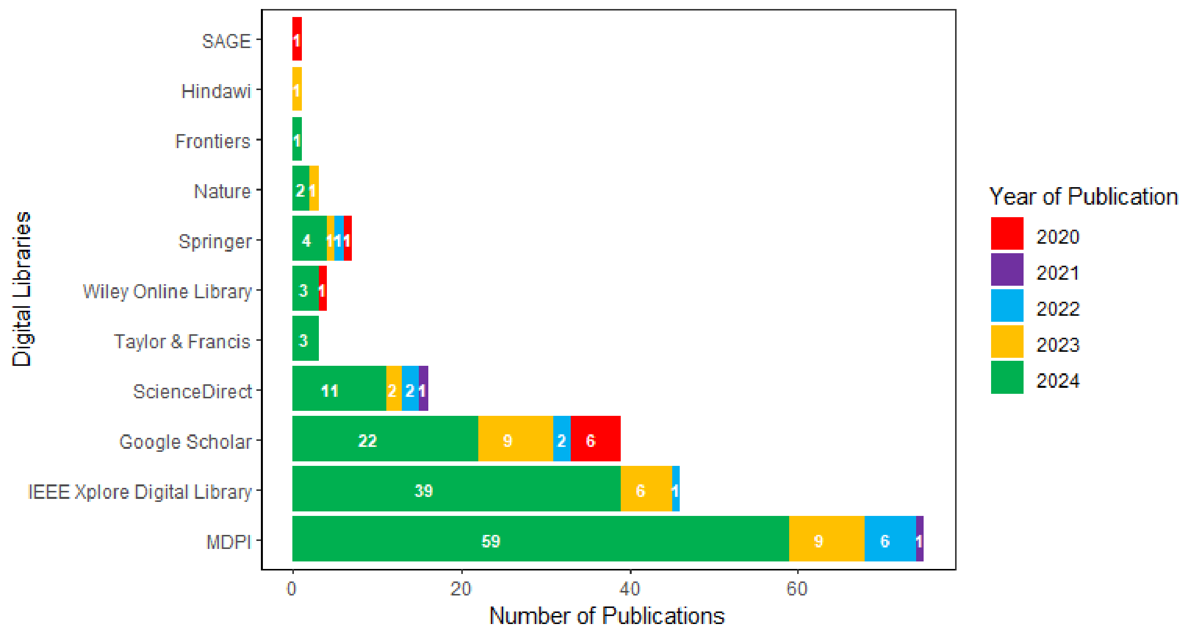

Fig. 3. Shows the distribution of selected papers by digital libraries based on the year of publications.

The researchers categorized the studies based on various technological approaches, including IoT, remote sensing, AI, and their combinations. They also classified the studies according to sustainability metrics, focusing on the specific sustainability outcomes each addressed. Additionally, they organized the studies based on geographic and ecosystem focus, which helped identify regional trends and gaps in the research. The researchers also identified typical IoT, remote sensing, and AI challenges. They analyzed emerging trends, such as integrating different technologies, hybrid IoT-AI frameworks, and novel remote sensing approaches. This classification ensured a uniform and accurate analysis.

After categorizing the studies, the researchers synthesized and analyzed the data using qualitative synthesis and theme analysis methods. They validated their findings by consulting subject matter experts, cross-referencing results with previous literature, and critically examining the robustness of their conclusions. The evaluation of each study focused on assessing the strength of its methodology, the reliability and validity of its findings, and its contribution to smart forest management. Researchers used a scoring methodology to ensure the inclusion of only high-quality research in the final analysis. Since the study relied on existing literature, the researchers did not collect primary data. As a result, ethical approval was not necessary. However, the researchers maintained ethical standards throughout the study by properly crediting all sources.

The researchers conducted a quality evaluation based on research topic relevance, methodological rigor, and scientific integrity to ensure the quality of the selected research papers. The researchers documented the results of this assessment to provide insights into the overall dependability and validity of the reviewed studies, which is essential for proposing actionable findings and future research directions.

This review acknowledges several limitations. First, relying on English-language studies may have excluded relevant literature published in other languages. Second, variations in keyword indexing across databases may have led to the omission of particular studies. Third, there is a limited availability of studies focusing on integrating IoT, remote sensing, and AI in forestry, particularly those that address specific sustainability outcomes. Additionally, the review may have overlooked relevant studies not indexed in the selected databases, and the results could have been influenced by publication bias. Finally, the lack of quantitative analysis or empirical data may undermine the findings, as qualitative assessments alone might not provide sufficient evidence for the conclusions drawn.

3. STATE-OF-THE-ART

3.1. Digital Transformation in Forestry

Forest management is rapidly becoming the primary approach for conserving and restoring forest biodiversity and ecosystem services. According to Li et al. [24], forest management involves planning and executing strategies for forest care and utilization to meet specific environmental, cultural, social, and economic objectives. It combines the art and science of decision-making to organize, protect, and use forest resources. This practice focuses on preserving and improving forest resources through human intervention, aligning traditional and modern approaches to create sustainable ecosystems. Conventional methods, such as selective logging, clear-cutting, controlled burning, and replanting, have traditionally focused on maintaining wood productivity. However, these methods often lack real-time data integration and fail to address challenges like illegal logging, climate change, and biodiversity loss.

Modern forest management increasingly relies on forest inventories, which provide statistical insights into forest quality and quantity. These inventories inform decisions and help address pressing environmental issues, including deforestation and habitat degradation. By integrating traditional and contemporary techniques, forest management enhances biodiversity, prevents degradation, increases biomass, and mitigates the impacts of natural disturbances. Proper forest management balances ecological, economic, and sociocultural considerations, yielding global benefits such as biodiversity conservation, ecosystem protection, poverty reduction, and climate change mitigation [16][25]. Effective strategies also focus on optimizing resource usage, managing forest residues, reducing costs, and increasing the value of forest products. Zhu and Miao [6] emphasize that proper management safeguards environmental and social values while maximizing economic gains.

Despite its importance, forest management faces challenges such as limited real-time data, inefficiencies in monitoring large areas, difficulty addressing environmental degradation, insufficient integration with modern technology, inadequate stakeholder engagement, funding limitations, conflicting land-use priorities, and climate change adaptation [26]. Holistic and integrative management approaches have emerged to overcome these issues. These methods aim to deliver diverse forest ecosystem services within the same geographical context, employing ecosystem-based management, multifunctional forestry, and sustainable forest management [27].

Integrating digital technologies revolutionizes forestry by enabling more effective monitoring, management, and protection. Digitalization involves incorporating advanced technologies to enhance data collection, analysis, and forest environment monitoring [7]. Forest managers can boost productivity, reduce costs, and achieve sustainability goals by employing data-driven solutions. Accurate and up-to-date information is critical, as forest management decisions often have irreversible consequences. Traditional forest inventories, which collect qualitative and quantitative data on forest resources, remain valuable but benefit significantly from technological advancements [26].

Emerging technologies, such as remote sensing, geospatial information systems, IoT, Blockchain, Unmanned Aerial Vehicles (UAVs), and AI, have proven effective in achieving sustainable forest management [1]. These technologies enhance forest monitoring, provide real-time data, prevent illegal logging, and contribute to climate change mitigation. Smart forestry, which combines IoT, remote sensing, and AI, represents a transformative approach to forest management. This digital transformation enables real-time data gathering, proactive decision-making, and precision-based interventions, improving environmental protection and economic sustainability [28].

Automation and digital intelligence have streamlined processes from forest inventory to conservation. Technologies such as multispectral and hyperspectral imaging provide insights into vegetation health, while thermal imaging detects forest fires and monitors wildlife. Soil moisture sensors inform irrigation and drought management, and drones offer rapid and detailed forest assessments. Acoustic sensors contribute to wildlife monitoring and biodiversity studies. By integrating these tools, smart forestry promotes sustainable practices and fosters a proactive, efficient approach to managing forest ecosystems. Artificial intelligence is pivotal in analyzing large datasets to predict forest conditions, such as tree growth, pest infestations, and wildfire risks. High-quality data, collected through sensors and integrated from various sources like satellite imagery and IoT devices, enhances the accuracy of AI predictions. This data-driven approach ensures informed decision-making, aligning forestry operations with sustainability goals.

Digital transformation in forestry advances sustainable practices, enhances biodiversity conservation, and strengthens efforts to mitigate climate change. Smart forestry optimizes resource use, minimizes environmental impacts, and facilitates rapid responses to threats like illegal logging and forest fires. This shift from reactive to proactive management underscores the critical role of technology in preserving forests and ensuring their long-term viability [28].

4. EMERGING TECHNOLOGIES FOR SUSTAINABLE FOREST MANAGEMENT

Cutting-edge technologies like the IoT, remote sensing, and AI are transforming forest management practices by providing advanced tools for monitoring, data collection, and decision-making. These innovations empower managers to adopt more efficient and sustainable approaches to forest management.

4.1.Internet of Things

The IoT is a network of interconnected physical objects with sensors, software, and connectivity features that facilitate data exchange, analysis, and decision-making without human intervention [29-36]. It comprises billions of intelligent gadgets that interact, collect data, and offer accurate results to assist people in making informed decisions [37]. IoT devices use sensors to gather environmental data and actuators to respond to specific conditions, creating a feedback loop that ensures continuous optimization [38]. It has transformed industries by improving efficiency and enabling automation by leveraging technologies such as Radio Frequency Identification (RFID), wireless communications, and AI [30]. The global IoT market has grown exponentially, driven by technological advancements like 5G, Long Range Wide Area Network (LoRaWAN), and ZigBee [39]. Experts predict that by 2030, the number of IoT devices will surge to 29 billion, with the market value expected to skyrocket from US$925.2 billion in 2023 to an impressive US$6 trillion by 2025 [40-42]. The Asia Pacific region leads in IoT adoption, followed by North America and Europe [43].

IoT systems operate on three layers: perception, network, and application. The perception layer captures data using sensors, the network layer transmits and processes this data, and the application layer delivers specialized services to users. These interconnected layers provide IoT systems with intelligence, enabling them to adapt dynamically to user and environmental needs [44]. Intelligent frameworks analyze the vast amounts of data generated by IoT devices, enabling improved decision-making and optimizing processes across industries. IoT applications span various fields, including agriculture, healthcare, and forestry, offering unprecedented control and resource management efficiency [29].

In forestry, the Internet of Forest Things (IoFT) applies IoT principles to monitor and manage ecosystems sustainably. IoFT integrates sensors, drones, and satellite imagery to collect data on forest conditions, such as temperature, soil moisture, and tree health [1][2]. This data, processed using advanced analytics and machine learning, helps predict risks like forest fires or disease outbreaks and supports informed decision-making. IoFT also facilitates remote monitoring, reducing manual inspection needs and enhancing forest conservation efforts. Integration with geographic information systems (GIS) and AI further enhances the ability to map and analyze forest resources, enabling stakeholder collaborative efforts [1][7]. By leveraging IoFT, foresters can protect habitats, optimize wood production, prevent soil degradation, and monitor snowpack changes for water management. These technologies promote sustainable practices and enhance forest resilience, ensuring better conservation outcomes and resource management [1][45][46].

4.2.Remote Sensing

Zakari et al. [1], Haq et al. [19], and Almohsen [47] define remote sensing as the art and science of gathering information about the Earth's surface using satellites, drones, or aircraft-mounted sensors that operate without direct physical contact to observe and analyze features from a distance. Commercial satellites like Sentinel-2, Modis, and Landsat offer superior spatial, spectral, and temporal resolution, with open-access data for various applications. For instance, Sentinel-2 excels in forest studies, change detection, and feature analysis, enabling precise identification of forest types, health, and maturity levels [9]. These innovations have revolutionized data collection, facilitating significant progress in remote sensing. High-resolution satellite imagery has driven the creation of advanced datasets to tackle complex remote sensing challenges. These sensors measure reflected and emitted electromagnetic radiation, which is processed into detailed images and valuable information [48]. Remote sensing efficiently gathers large-scale, high-quality earth observation data, accelerating advancements in the field [49]. Satellite and high-altitude aircraft images provide accessible options for capturing extensive data.

The global remote sensing market, valued at US$17.1 billion in 2023, is projected to exceed US$37 billion by 2030, with India's market expected to grow from US$338 million in 2022 to over US$400 million by 2025 [50]. These trends reflect the increasing reliance on remote sensing for environmental monitoring and resource management.

Modern technologies, including RGB cameras, multispectral and hyperspectral cameras, Light Detection and Ranging (LiDAR), and chlorophyll fluorescence sensors, are used to collect forest data [51]. These tools support classification, change detection, and image fusion, improving forest landscape monitoring. Forest managers use optical imaging, LiDAR, and radar to produce high-resolution photos and 3D models of forest structures. Effective remote sensing data processing has enhanced forest management and resource assessment, offering comprehensive insights into forest cover, vegetation health, and land-use changes. Remote sensing photos, distinguished by their spatial and spectral resolution, enable applications like change detection, object identification, and forest ecosystem mapping [52][53]. Researchers can precisely map and monitor urban forests by integrating remote sensing with AI and machine learning. AI Algorithms analyze imagery, LiDAR data, and ground measurements to create accurate 3D maps, assess vegetation health, track growth, and detect stressors and pathogens. This approach enhances urban forest management, supports sustainability, and addresses environmental challenges effectively [1]. Remote sensing offers a broad perspective, facilitating informed decision-making for fire control, disaster planning, and resource allocation. Combining adaptability, precision, and efficiency delivers high-quality data critical for diverse applications, including mangrove species classification, deforestation tracking, and forest health monitoring [19][54]. Remote sensing also supports environmental monitoring, urban planning, disaster management, and resource evaluation

[55]. It enables early detection of land-use changes, forest fires, and vegetation health while assessing topography and height. Radar sensors penetrate forest canopies to monitor soil moisture, essential for studying drought tolerance in species like the Argane tree. Global positioning system (GPS) technology aids in mapping precise locations of forest populations, evaluating habitat changes, and understanding human impacts [55]. These capabilities help forest managers monitor forest cover, identify deforestation hotspots, and measure long-term health changes. With its adaptability and cost-effectiveness, remote sensing remains a cornerstone of environmental science and resource management.

4.3. Artificial Intelligence

Recent advancements in data science, alongside a revolution in digital and satellite technologies, have significantly expanded the potential for AI applications in forestry. Artificial intelligence is a branch of computer science that focuses on creating intelligent machines, robots, or sensors capable of solving cognitive problems associated with human intelligence, such as learning, logical thinking, problem-solving, image recognition, perception, natural language understanding, and pattern recognition. These intelligent systems can interact with their environment, process information, and make autonomous or semi-autonomous decisions to benefit society [39][56-60]. AI relies on various cognitive processes and behaviors derived from computational models, algorithms, mathematical formulas, or rules that mimic the functioning of the human brain. These systems can learn directly from large datasets, enabling them to conclude independently. The AI process involves recognizing patterns, predicting future states, and detecting anomalies. The objective is to allow computers to replicate human cognitive abilities by learning from data, adapting to new information, and making predictions or decisions without explicit programming for specific tasks [61][62]. AI's computational capabilities, technology, and research advancements have enabled its integration into forest and biodiversity management. These developments enhance the ability to monitor, manage, and protect forest resources and biodiversity more effectively [37][63].

The global AI industry is valued at $184 billion in 2024 and is projected to grow at a CAGR of 28.46%, reaching $826.7 billion by 2030. The United States leads the market with the largest share, estimated at $50.16 billion in 2024.

AI techniques like machine learning, deep learning, natural language processing, computer vision, robotics, expert systems, and fuzzy logic systems actively analyze vast amounts of forest data collected through IoT and remote sensing systems. These technologies derive valuable insights and make informed decisions [64][65]. These methods, which mimic human intelligence in machines, excel at analyzing large datasets, making predictions, and improving decision-making. AI can automate repetitive tasks and data processing, saving time and resources while producing reliable results and enhancing the work environment [66]. Fig. 4 shows how AI, machine learning, deep learning, natural language processing, computer vision, robotics, and expert systems are related.

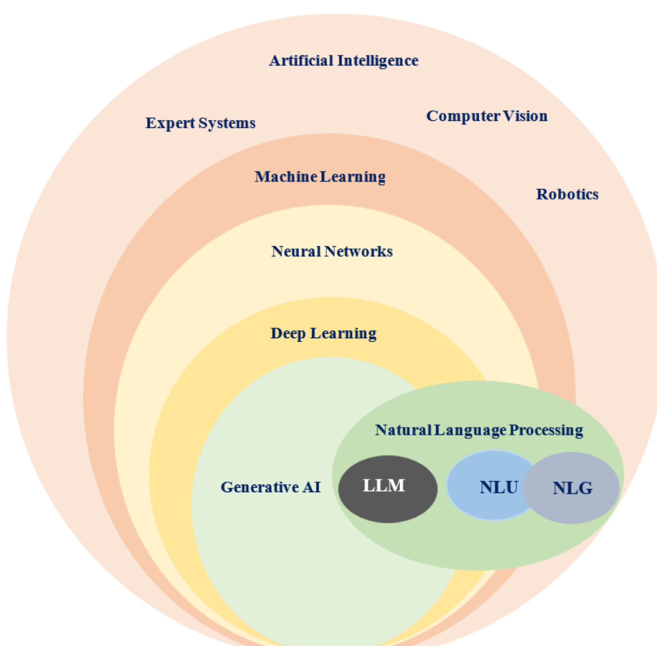

Fig. 4. Illustrates the relationships between artificial intelligence, machine learning, deep learning, natural language processing, computer vision, robotics, and expert systems.

4.3.1. Machine Learning

Machine learning has revolutionized the forestry sector, bringing about a transformative shift in forest management and conservation practices. It develops algorithms and statistical models that enable machines to autonomously learn from data, uncover hidden patterns, and make predictions without explicit programming. The goal is for machines to recognize patterns, perform tasks, and improve over time through mathematical optimization, computational statistics, and data mining. Machine learning systems analyze data and identify patterns to build models that predict new outcomes and continuously improve performance [51][62][67-70].

Machine learning enables machines to learn from input data and build predictive models. It employs statistical techniques and data mining to recognize and forecast patterns without being pre-programmed with specific rules. Through training, a model learns by analyzing instances from a training set consisting of experts' or analysts' observations. This iterative process allows the model to refine its performance over time, improving its accuracy until it can effectively evaluate new, unseen data. The more data the machine processes, the better it becomes at making accurate predictions and automating tasks previously done by humans [58][65-72].

The machine learning market is projected to grow significantly, reaching US$79.29 billion by 2024 and soaring to US$503.40 billion by 2030, with a CAGR of 36.08% from 2024 to 2030. The United States is poised to lead this expansion, with an estimated market size of US$21.14 billion in 2024. Machine learning drives advancements across diverse applications, including image and audio recognition, natural language processing, recommendation systems, self-driving cars, and forestry [61].

Supervised, unsupervised, semi-supervised, and reinforcement learning are the categories of machine learning algorithms offering distinct approaches to solving complex problems in various domains [67][72-74]. Fig. 5 depicts the categorization of machine learning algorithms.

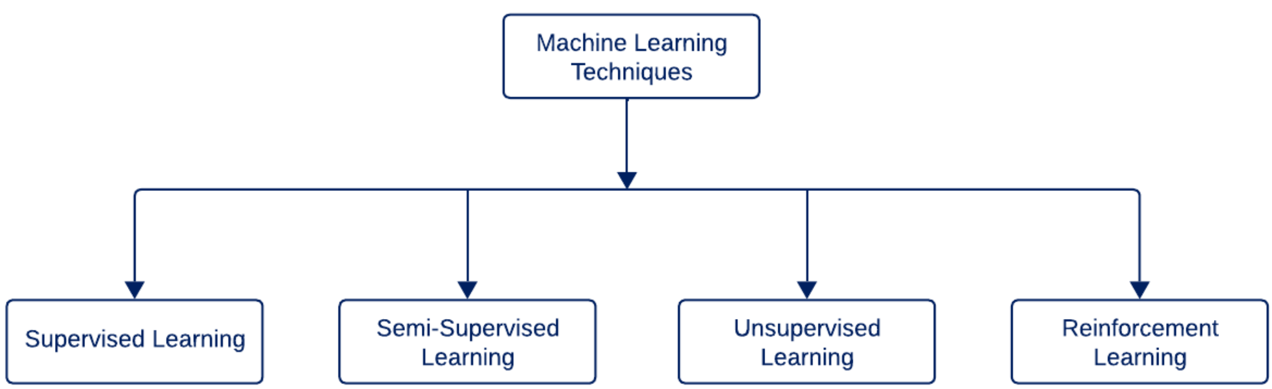

Fig. 5. Shows the classifications of machine learning algorithms.

- ***Supervised learning***

Supervised learning uses well-labeled training data to enable machines to predict outputs. In this approach, data is labeled with both input attributes and their corresponding outputs. The goal is to train a model to accurately predict results for previously unseen data [56][67]. The labeled data serves as a guide for the model, teaching it to make reliable predictions. Initially, the type of training dataset is determined, and the labeled data is collected. The dataset is divided into training, testing, and validation subsets. During training, the model improves its predictions by comparing its outputs with the correct ones [75]. Afterward, its accuracy is evaluated on unseen data to assess its ability to make accurate predictions [72][74]. Classification and regression are the categories of supervised learning. Classification involves predicting a discrete label for an input, such as assigning it to a specific class [72][74]. The model is trained on labeled samples and then applied to predict labels for new, unseen data [76]. In regression, the output is continuous, and the goal is to predict real-valued data based on one or more predictor variables [74][76]. Linear Regression, Logistic Regression, Decision Trees, Random Forest, Support Vector Machines (SVM), K-Nearest Neighbors (KNN), Naive Bayes, Artificial Neural Networks (ANN), Gradient Boosting Machines (GBM), Adaptive Boosting (AdaBoost) are the examples of supervised learning algorithms [65][77].

- ***Unsupervised learning***

Unsupervised learning techniques train models on unlabeled data to uncover patterns, features, and hidden structures without explicit supervision or guidance. These methods are beneficial when training data lacks annotations or classifications [67][75]. The main goal is to analyze the data and derive insights such as clustering, feature extraction, and dimensionality reduction [74]. Unsupervised learning enables the identification of underlying structures in data without predefined labels, making it valuable when labeling is not feasible or too costly [65]. There are three primary subcategories of unsupervised learning: clustering, dimensionality reduction, and association rules. Clustering algorithms group similar data points based on their features, identifying natural clusters in the dataset [65][74][77]. Association rules uncover meaningful relationships or correlations between variables, helping to reveal dependencies within large datasets [65][74][77]. Dimensionality reduction techniques, such as principal component analysis, reduce the number of features in the data, improving the efficiency and performance of subsequent machine learning algorithms [76]. Popular unsupervised learning algorithms include K-means clustering, hierarchical clustering, autoencoders, self-organizing maps (SOMs), Gaussian mixture models (GMM), latent Dirichlet allocation (LDA), and generative adversarial networks (GANs). These techniques are essential for discovering hidden patterns in data that may not be visible through traditional methods [65].

- ***Semi-supervised learning***

Semi-supervised learning is a machine learning approach combining a small amount of labeled data with many unlabeled data for training models. This technique is beneficial when labeled data is limited but unlabeled data is abundant [65][74]. The goal is to use labeled data to guide the learning process while leveraging unlabeled data to enhance the model's generalizability. The model initially trains on the labeled data to develop a basic understanding of the task and then uses its knowledge to predict the unlabeled data. As the model refines these predictions, it continuously updates and improves its knowledge of labeled and unlabeled data [67][72][75]. This approach bridges the gap between supervised and unsupervised learning by using unlabeled data to boost learning accuracy and efficiency. By taking advantage of the available unlabeled data, semi-supervised learning reduces the need for fully labeled datasets, which can be expensive and time-consuming. It offers a practical solution for real-world challenges where labeled data is scarce but unlabeled data is abundant [65]. Generative models, graph-based models, Gaussian Mixture Models (GMM), Hidden Markov Models (HMM), Label Propagation, Graph Convolutional Networks (GCNs), k-means clustering, and hierarchical clustering are the various algorithms employed in semi-supervised learning [65].

- ***Reinforcement learning***

Reinforcement learning is a machine learning approach where a model learns through interactions with its environment, receiving feedback as rewards or penalties [65][72][76]. The goal is determining the best strategy or policy to maximize long-term benefits. In this approach, a reinforcement learning agent receives performance feedback based on its actions over time, which helps it adapt its behavior. The algorithm designer typically defines the reward structure based on the agent's observations. Still, these rewards do not directly instruct the agent on adjusting its behavior, making reinforcement learning a type of trial-and-error learning [58] [67]. This technique is instrumental in decision-making, control, and optimization scenarios where data is acquired sequentially. Model-based, value-based, and policy-based methods are the categories of reinforcement learning. The model-based approach involves creating a virtual model of the world for the agent to explore, while the value-based method focuses on determining the optimal value function. The policy-based method requires the agent to follow a policy to maximize future rewards. Q-learning, Deep Q-Networks (DQN), State-Action-Reward-State-Action (SARSA), Dyna-Q, and Monte Carlo Methods are the most used reinforcement learning algorithms [65].

Machine learning plays a significant role in decision-making, prediction, and optimization in various fields, including forest management. It helps improve forest monitoring, model forest dynamics, conserve biodiversity, estimate forest carbon stocks, and manage resources efficiently. By automating tasks such as forest restoration and evaluating ecosystem services, machine learning enhances the quality of outputs in complex environments with intricate decision boundaries. Additionally, it optimizes resource allocation response and strategies and aids in wildfire detection and prediction [58][69].

4.3.2. Deep Learning

Deep learning has revolutionized AI by demonstrating its effectiveness in forest resource assessment. As a subset of machine learning, deep learning uses artificial neural networks with multiple processing layers to automatically learn key features from vast amounts of raw data. These networks model complex relationships, solve intricate problems, and improve performance without explicit programming [65][69][78][79]. Neural networks, inspired by the human brain, consist of layers of connected nodes that process and analyze data such as text, images, and sound. The structure includes input, output, and hidden layers. In deep learning systems, data enters through an input layer, passes through hidden layers where it is processed and emerges at the output layer, which presents the results. This layered architecture enables the system to identify complex patterns, especially in high-dimensional data such as images, text, and audio [65][68][70][80].

The primary goal of deep learning is to extract complex features from raw data and represent them in a higher-dimensional, semantically abstracted form [81]. Deep learning eliminates human intervention in feature engineering by automatically learning hierarchical features, making it ideal for complex tasks like image identification, natural language processing, and speech synthesis [78], which has driven the rapid growth of deep learning applications in data analysis, prediction, and decision-making [67]. It proves especially valuable in processing large amounts of unstructured data and in tasks like classification and automatic feature extraction, which are vital for overcoming challenges in detecting partial or inaccessible features [65]. The different types of deep learning models include Convolutional Neural Networks (CNNs), Recursive neural network (RvNN), Generative Adversarial Networks (GANs), Federated Learning (FL), Transfer Learning (TL), Recurrent Neural Networks (RNNs), Long Short-Term Memory (LSTM), Autoencoder, variational autoencoder (VAE), Transformer Models, Gated Recurrent Unit (GRU), deep autoencoders (AEs), Graph Neural Networks, Multilayer Perceptron (MLP), Deep Belief Network (DBN), Self-Taught Learning (STL), Restricted Boltzmann Machines (RBMs), Reinforcement Learning (RL), and Deep Neural Networks (DNNs) [65][77][78-85].

In forest management and conservation, deep learning improves forest monitoring, species detection, biodiversity monitoring, and predictive analytics for forest health [51][80]. It also optimizes resource management, enhances fire detection and management, and supports ecosystem mapping [69]. These applications contribute to more efficient decision-making and policy support, offering cost and time efficiency. The high accuracy and scalability of deep learning models, coupled with their ability to process complex data, have led to the development of innovative tools and strategies in forest conservation. By leveraging these capabilities, deep learning transforms how to protect and manage forests in response to growing environmental challenges.

4.3.3. Natural Language Processing

Natural language processing (NLP) is a rapidly advancing field within AI driven by the increasing amount of online text that needs to be understood and its ability to analyze human language through techniques like sentiment analysis. NLP allows machines to interpret, manipulate, and comprehend written and spoken human language. It uses algorithms to process language, enabling translation, sentiment analysis, and interpreting vast data sets. Organizations use supervised and unsupervised NLP techniques to automatically interpret, analyze, and respond to data from various communication channels, such as emails, social media, and audio-visual content [66][86][87].

The NLP industry is rapidly growing, expected to reach US$36.42 billion by 2024, with a CAGR of 27.55%, ultimately reaching US$156.80 billion by 2030. NLP relies on two primary components: natural language understanding (NLU), which enables machines to understand human language, and natural language generation (NLG), which allows machines to produce language. NLP technologies power many tools, including voice assistants like Siri, speech-to-text applications, machine translation, and text generation. These methods fall into two main categories: rule-based approaches, which depend on manually crafted rules, and machine learning-based approaches, which use large datasets to identify language patterns [88][89].

NLP is essential in numerous applications, including machine translation, sentiment analysis, speech recognition, and text summarization. One of the key roles of NLP is extracting useful information from unstructured text, improving data retrieval and processing. Sentiment analysis, which identifies emotions or opinions in text, is a common NLP application, classifying sentiments as positive, negative, or neutral. NLP algorithms like tokenization, word embeddings, and named entity recognition (NER) are pivotal in these tasks. In forest management and conservation sectors, NLP enhances efficiency by automating data collection, monitoring illegal activities, improving communication, and supporting policy development. By incorporating NLP, these fields can become more data-driven and responsive to real-time information, ultimately leading to better ecological outcomes [65][90].

4.3.4. Computer Vision

Computer vision has become a transformative field, significantly impacting how computers interpret digital images and videos. Analyzing data from cameras and closed-circuit television systems in forest environments enhances surveillance, improves decision-making, and supports forest management and conservation. Computer vision focuses on developing algorithms that enable machines to process, understand, and interpret visual information from their surroundings, mimicking the human visual system [66][91-93]. With the rise in data availability and computational power, computer vision is becoming increasingly important for providing accurate object recognition and generating actionable insights across various sectors, including forestry. A computer vision system operates through a series of interconnected stages to interpret visual data effectively. These stages include image acquisition, preprocessing, feature extraction, object recognition, tracking, and interpretation. The process begins with capturing images or videos through cameras, followed by preprocessing to enhance or filter the data. The system then extracts essential features, such as edges or corners, before recognizing objects by comparing these features to a database of known items. Once objects are detected, the system may track their movement over time and analyze the results to generate meaningful outputs based on the task [25][92][94-97].

The computer vision market is projected to reach US$25.80 billion by 2024, with an anticipated CAGR of 10.50% from 2024 to 2030. The United States is expected to lead the market, capturing the most significant share with an estimated US$6.88 billion in 2024. Classification, object detection, image segmentation, and facial recognition are the key computer vision techniques that play vital roles in forestry. These techniques enable the efficient analysis and interpretation of visual data, automating tasks such as detection, tracking, and monitoring, which are crucial for forest management and conservation efforts. Computer vision utilizes various techniques to enable machines to analyze and understand visual input from the world. These algorithms cover multiple tasks, including image classification (using Convolutional Neural Networks, Transfer Learning, and Support Vector Machines), object detection (with methods like You Only Look Once [YOLO], Region-based Convolutional Neural Networks, and Single Shot Multibox Detector), and image segmentation (such as Fully Convolutional Networks, U-Net, and Mask Region-based Convolutional Neural Networks).

Additionally, it handles feature detection and description (using techniques like Scale-Invariant Feature Transform, Speeded Robust Features, and Oriented FAST), image alignment and registration (with Random Sample Consensus, Affine Transformation, and Homography), and optical flow and motion estimation (via methods like Lucas-Kanade, Farneback, and Horn-Schunck). Computer vision also involves 3D vision and reconstruction (including Structure from Motion and Stereo Vision), face identification and recognition (using algorithms like Viola-Jones, Fisherfaces, and FaceNet), and image synthesis (through Generative Adversarial Networks and Variational Autoencoders). Other applications include pose estimation (with tools like OpenPose and MediaPipe), super-resolution (using Bicubic Interpolation and Super-Resolution Convolutional Neural Networks), anomaly detection (with Autoencoders and One-Class Support Vector Machines), tracking algorithms (like Kalman Filter, Mean-Shift, and CamShift), augmented reality (through Simultaneous Localization and Mapping and Marker-based AR), and image denoising and enhancement (using methods like Non-Local Means, Total Variation Denoising, and Gaussian and Bilateral Filters) [98].

In forestry, computer vision has numerous applications, including object detection, motion tracking, and action recognition. Integrating deep learning and neural networks enables large-scale, automated processing and interpretation of visual data. This technology can significantly improve forest management by automating monitoring and surveillance, enhancing forest inventory accuracy, detecting early signs of forest health issues, and aiding in fire prevention. Additionally, computer vision supports reforestation efforts, biodiversity conservation, and sustainable forest resource management by providing real-time data, scalable solutions, and data-driven decision-making capabilities.

4.3.5. Expert Systems

The rapid advancement of forest automation and intelligence has led to more sophisticated decision-making challenges for organizations. Forest management and conservation are becoming increasingly complex, requiring strong decision-making skills. Expert systems play a crucial role by integrating complex resources and data to enhance forest conservation. These computer-based systems use AI techniques to simulate human expert decision-making in specific domains, such as data analysis, problem-solving, and decision-making. By combining a knowledge base with an inference system, expert systems replicate expert problem-solving abilities and allow computers to provide intelligent solutions [49][99][100].

An expert system adapts human knowledge to computers, helping to solve problems by utilizing information, facts, and expert thinking. These systems not only aid users who lack specialized knowledge but also emulate the decision-making processes of human experts. They rely on deep knowledge and practical experience contained in their knowledge base to provide accurate solutions. Expert systems are invaluable tools for simulating expert thinking and decision-making, learning from experts, and assisting users in areas that require specialized expertise [101-103].

The key components of an expert system are the knowledge base, inference engine, user interface, interpreter, knowledge acquisition system, and database. The knowledge base contains domain-specific rules and information essential for decision-making. The inference engine applies reasoning to these rules and facts to generate conclusions. The user interface enables users to interact with the system while the interpreter translates user inputs for the inference engine and conveys its findings. The knowledge acquisition system gathers insights from experts to update the knowledge base, and the database manages the data required for the system to function efficiently. Together, these components ensure that expert systems can handle complex decision-making tasks in various domains [100][103][104].

Expert systems are highly effective in forest management and conservation, offering applications in forest fire management, health monitoring, sustainable timber harvesting, forest restoration, and wildlife habitat management. These systems improve decision-making, efficiency, and sustainability, enabling proactive environmental protection and better long-term management. By providing data-driven insights, expert systems help address ecological and economic challenges in forest conservation, reducing costs and enhancing collaboration. They are essential tools for achieving sustainable forest management and ensuring the health of forests for future generations [100].

4.3.6. Fuzzy Logic

Fuzzy logic has become a promising technique for managing uncertainties and ambiguity in data, especially in mobile robot navigation. This mathematical and computational method mimics human decision-making by handling uncertainty and ambiguity [105][106]. Unlike conventional binary logic, which relies on true or false values, fuzzy logic accommodates variable degrees of truth and membership. This flexibility enables a more adaptable and human-like approach to solving complex problems, particularly in real-world situations where data may be incomplete or unclear. Fuzzy set theory offers powerful tools for developing conceptual frameworks that better address complexity. These frameworks have proven more effective than traditional methods in pattern recognition, information processing, and classification [101][106-108].

Fuzzy expert systems have proven effective in addressing complex problems under uncertainty. These systems can replicate the logical processes of human experts by managing uncertainty due to imprecise information or limited data. This ability has contributed to the widespread adoption of fuzzy logic across various domains, including image processing and AI [109]. While technologies like convolutional neural networks and decision-making frameworks are gaining prominence for risk assessment, fuzzy logic remains crucial in predicting and managing risk concerns, offering a flexible approach to reasoning based on partial or approximate knowledge [110][111]. A typical fuzzy logic system has three main components: fuzzification, rule-based inference, and defuzzification. Fuzzification translates precise numerical values into linguistic terms such as “high,” “low,” or “medium.” Rule-based inference combines these fuzzy sets according to predefined “if-then” rules, producing fuzzy output sets. Finally, defuzzification converts the fuzzy output back into crisp values. Fuzzy logic provides a flexible and interpretable method for modeling complex systems using fuzzy sets and language rules [108][112][113]. In forest management and conservation, fuzzy logic is applied in decision support systems, risk assessment, biodiversity conservation, climate change adaptation, and ecosystem monitoring, offering advantages such as handling uncertainty, improving risk assessment, and promoting sustainable resource use. These qualities make fuzzy logic ideal for managing complex forest ecosystems and ensuring long-term health [113-117].

4.4. Integration of IoT, Remote Sensing, and AI for Sustainable Forest Management

Integrating IoT, remote sensing, and AI is crucial for transforming sustainable forest management. IoT sensors collect real-time, continuous data from within forests, while remote sensing provides broader geographical insights through periodic data. This synergy allows for more accurate and timely monitoring, addressing critical challenges such as deforestation, forest degradation, climate change, and biodiversity loss. Combining these technologies makes forest management systems more responsive and data-driven, ensuring better resource allocation and management decisions. The integration of real-time IoT data, satellite imagery, and AI enables the creation of early warning systems for forest-related threats like fires, deforestation, and biodiversity decline. AI-driven analytics process data from various sources to predict potential risks and recommend optimal actions. This combination supports proactive forest management by identifying emerging problems before they escalate, allowing stakeholders to take timely preventive measures. AI enhances decision-making in forest management by analyzing data from IoT sensors and remote sensing imagery. These AI models assist in making informed decisions regarding reforestation, conservation, and logging activities, ensuring a balance between economic needs and ecological sustainability. By continuously monitoring forest ecosystems, AI models can identify threats and suggest necessary interventions, empowering forest managers to adopt sustainable practices that protect forest health and biodiversity for future generations.

5. SYSTEM ARCHITECTURE

A well-designed system architecture is vital in integrating IoT, remote sensing, and AI for sustainable forest management. This architecture consists of nine interconnected layers: sensor and data acquisition, communication, edge, data storage, data processing and analysis, visualization and decision support, application, integration and interface, and security and privacy, each fulfilling a specific function. Together, these layers support sustainable forest conservation by enabling efficient data collection, secure communication, real-time processing, robust storage, insightful analysis, intuitive visualization, seamless application integration, and stringent privacy measures. Fig. 6 illustrates the layers in the system architecture.

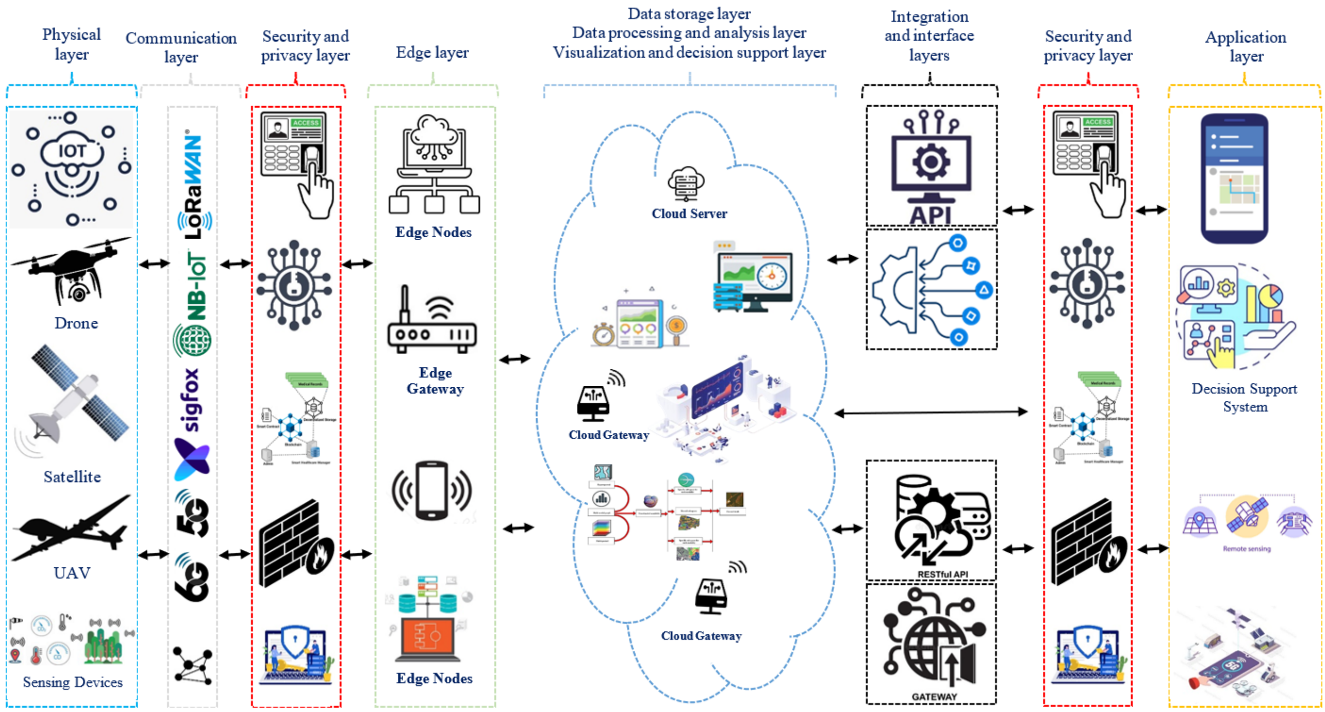

Fig. 6. Depicts the layers in the system architecture.

5.1. The physical layer (sensor and data collection layer)

The physical layer collects and transmits data from forest ecosystems to higher computing and processing levels for analysis, decision-making, and automated actions. It includes IoT sensors and devices, remote sensing devices (e.g., satellites and drones/UAVs), and wildlife and resource monitoring tools. This layer also performs initial data preprocessing, aggregation, and filtering to reduce the burden of data transmission [118].

5.2. Communication layer (Network connectivity layer)

The communication layer actively facilitates data transfer from forest devices to processing and storage systems, ensuring reliable connectivity between IoT sensors, drones, and central servers or the cloud. It incorporates various components, including communication protocols like Low Power Wide Area Networks (LPWAN) such as LoRaWAN, NB-IoT, and Sigfox; Wireless Sensor Networks (WSN) such as Zigbee and Bluetooth Low Energy (BLE); cellular networks (5G) for high-speed connections to transmit extensive data, including drone images and videos; satellite communication for remote areas lacking terrestrial infrastructure; Wi-Fi and Bluetooth for short-range communication among IoT devices and edge gateways; and mesh networks for creating self-healing networks in challenging terrains. Additionally, it employs network infrastructure like gateways that aggregate sensor data and connect to cloud services and repeaters that extend the range in dense forest environments. Encryption protocols like transport layer security (TLS)/secure sockets layer (SSL) ensure secure data transfer, while virtual private networks protect remote access and safeguard information by actively securing communication channels. The communication layer leverages satellite and mesh networks to maintain continuous connectivity in remote or demanding locations.

5.3. Edge layer

The edge layer enables real-time data processing, analysis, and decision-making closer to the data source. It connects networks with applications and end devices, bridging IoT sensors and the cloud or central processing units. This setup reduces latency, improves bandwidth efficiency, enhances security, and supports sustainable forest management by performing key functions such as data collection, preprocessing, filtering, aggregation, edge analytics, local decision support, networking, and communication. Equipped with security features, data filters, decision-making capabilities, and gateways, the edge layer preprocesses and analyzes data, optimizes transmission performance, reduces computational load, and relays data to higher layers for further processing. The edge layer simplifies processing challenges in forests with limited network access by leveraging edge devices, processing units, communication modules, and sensors. By enabling real-time data processing and local decision-making, the edge layer improves operational efficiency and ensures effective resource optimization, contributing significantly to sustainability goals in forestry operations.

5.4. Data storage layer

The data storage layer manages massive volumes of data collected from IoT devices, such as sensors, drones, and cameras, as well as remote sensing technologies like satellite imaging and LIDAR, alongside data processed by AI algorithms. This layer ensures efficient storage, maintenance, and data accessibility for analysis, decision-making, and visualization. Leveraging technologies such as cloud-based storage, on-premises storage, and hybrid cloud solutions, the system effectively handles large-scale and diverse datasets. Building an efficient data storage layer enables secure, scalable, real-time access to analytics and AI-driven insights, supporting sustainable forest management.

5.5. The data processing and analysis layer

The data processing and analysis layer actively converts raw sensor and remote sensing data into actionable information, enabling real-time, data-driven decisions. This layer encompasses data cleansing, aggregation, integration, transformation, and advanced analysis powered by AI and machine learning. It begins with cleaning and preprocessing raw data from IoT sensors, drones, satellites, and other sources, ensuring the data is suitable for analysis. Next, it aggregates and integrates data from multiple sources, such as IoT devices, weather stations, and remote sensing technologies, into a unified framework. The system then transforms the data, extracting key features like forest density, biomass, and temperature trends to make it analysis-ready. Real-time data streaming from IoT devices, particularly for metrics like temperature, humidity, and carbon levels, undergoes immediate processing to facilitate quick decision-making. Advanced analytical techniques are applied to generate actionable insights, while remote sensing data from satellites and drones is analyzed using sophisticated image processing algorithms to monitor extensive forest areas. Predictive analytics models forecast future forest conditions based on historical trends, weather patterns, and human activities, and decision support systems integrate these insights to guide sustainable forest management. AI and machine learning advancements enable predictive analytics, real-time monitoring, and data-driven decision-making to protect and sustainably manage forest ecosystems [118].

5.6. Visualization and decision support layer

The visualization and decision support layer analyzes data and enables informed decisions for sustainable forest management. This layer transforms complex data into precise, actionable visual representations and integrates tools for real-time analysis, modeling, and prediction. It enhances data comprehension, decision-making, and communication through key components such as data visualization tools (e.g., geospatial and time-series visualizations, heatmaps, contour maps, and interactive dashboards), decision support systems (e.g., AI-powered recommendations, scenario analysis, multi-criteria decision analysis, and anomaly detection), reporting tools (e.g., automated reports and stakeholder customization), and platforms (e.g., Tableau, Power BI, GIS, and web-based visualization tools). Additionally, it employs decision support system tools like AI/machine learning libraries, simulation software, and optimization software. This layer ensures that the system architecture delivers valuable outcomes for sustainable forest management by effectively converting data into insights and actionable plans.

5.7. Application layer

The application layer serves as the user's gateway to the technical stack, enabling interaction with the system's data and services through software applications, user interfaces, APIs, and tools for visualization, decision-making, and operational control. It incorporates essential components such as user interfaces, decision support systems, remote sensing applications, IoT apps, and data integration APIs. It provides capabilities like data visualization, analytics and reporting, user management with role-based access, and collaboration tools. The application layer supports sustainable forest management practices by converting raw IoT and remote sensing data into actionable insights. With a focus on user needs, interoperability, security, and scalability, this layer enhances the efficiency of forest management strategies and promotes sustainable practices.

5.8. Security and privacy layer

The security and privacy layer is vital in securing sensitive data and maintaining system integrity in projects leveraging IoT, remote sensing, and AI for sustainable forest management. This layer protects against various risks, ensuring that data gathered and processed remains secure and compliant with privacy standards. Key components include access control, user authentication and role-based permissions, and data encryption using protocols like TLS to secure data during transmission between IoT devices, remote sensing units, and cloud services. Encrypting stored data, implementing network security measures like firewalls and intrusion detection systems, and ensuring data integrity through checksums, hashing, and audit trails further fortify the system. Data anonymization and obtaining user consent enhance user trust. By addressing these critical components, the security and privacy layer fosters stakeholder confidence and supports the successful adoption of these technologies. Continuous monitoring and adaptation of security policies are essential to mitigate evolving threats in the fast-changing technological landscape.

5.9. Integration and interface layers

The integration and interface layer is essential for linking various subsystems, data sources, and components within the system architecture to support sustainable forest management. This layer facilitates seamless data flow and communication among functional elements such as sensors, data storage systems, processing units, analytical tools, and decision-support systems. It standardizes data formats, communication protocols, and interfaces, ensuring compatibility and enabling disparate tools and technologies to interact efficiently. This layer connects critical subsystems, including the sensor and data collection layer, data storage, processing, and display layers, ensuring uninterrupted data exchange. Key components include APIs, gateways, data integration tools, message brokers (e.g., Message Queuing Telemetry Transport, Advanced Message Queuing Protocol), and protocol translators. It employs IoT communication protocols (e.g., Message Queuing Telemetry Transport, Constrained Application Protocol), RESTful APIs, GraphQL, WebSockets, and data-sharing protocols like the Open Geospatial Consortium standards. These integration methods ensure the system operates cohesively, supporting real-time data flow, processing, and decision-making to enhance sustainable forest management.

A system designed for sustainable forest conservation uses IoT, remote sensing, and AI to monitor, evaluate, and manage forest ecosystems. Environmental sensors, GPS trackers, and camera traps are actively deployed throughout the forest to monitor and collect data. These sensors, placed near or on trees, continuously measure temperature, humidity, soil moisture, air quality, carbon dioxide levels, carbon sequestration, tree health, and animal movement. Drones and satellites, equipped with LiDAR sensors and multispectral and hyperspectral cameras, capture high-resolution images, enabling large-scale monitoring of the forest's tree canopy, biodiversity, forest cover, and potential threats like illegal logging or wildfires. Additionally, animal-mounted sensors track movement, migratory patterns, and habitat conditions, helping monitor biodiversity and the interactions between species and their environments.

IoT devices transmit data to a centralized system using wireless communication protocols like LoRaWAN, Zigbee, or NB-IoT, enabling real-time data transfer from remote forest areas to central monitoring hubs. Satellite networks provide additional remote sensing data to ground stations. Drones and satellites supply high-resolution imagery for comprehensive forest monitoring. The data gathered by IoT devices, drones, and satellites is stored in cloud storage systems, allowing easy access and scalable storage for large volumes of information. Edge computing filters, aggregates, and preprocess data, reducing latency and bandwidth requirements before sending it to the cloud. Data is stored in structured and unstructured formats in SQL and NoSQL databases, enabling efficient organization and retrieval for analysis. The raw data undergoes cleaning to remove noise, outliers, and errors, with preprocessing techniques used to handle missing values and prepare the data for artificial intelligence applications.

Artificial intelligence models are employed to detect deforestation, predict and identify fires, monitor biodiversity, and assess tree health based on IoT and remote sensing technologies data. Geographic information systems help interpret spatial data, producing visual maps and models that track forest cover, biodiversity hotspots, and areas at risk of wildfires or landslides. Analytics tools analyze massive datasets to identify patterns, trends, and anomalies in forest conditions, while historical data analysis provides insights into long-term environmental trends. Real-time dashboards display visualizations, such as heat maps of deforestation, fire risks, tree health, carbon sequestration models, and wildlife migration patterns. Customized reports on forest conservation measures, like replanting rates, illegal logging activities, and biodiversity trends, help stakeholders make informed decisions.

Artificial intelligence-powered decision support tools generate actionable insights for conservation managers, suggesting interventions such as deploying drones for closer monitoring, prioritizing reforestation in degraded areas, or increasing patrols to combat illegal logging and poaching. Geographic information system platforms allow forest managers to visualize spatial data on interactive maps, offering a real-time view of forest conditions, risk zones, and changes in vegetation. Dashboards provide visual updates on key parameters like deforestation rates, wildlife population trends, and fire threats. Custom reports are created for stakeholders, including government agencies, Non-governmental organizations (NGOs), and local communities, ensuring they can access the latest data for collaborative decision-making. Artificial intelligence models also simulate various conservation scenarios, forecasting the potential impact of actions like reforestation or creating wildlife corridors on forest health and biodiversity over time.

Application programming interfaces facilitate seamless communication between subsystems in forest management architecture by integrating data from IoT devices, remote sensing tools, and AI platforms into centralized monitoring systems, enhancing interoperability. Mobile applications allow forest rangers, researchers, and conservationists to receive real-time alerts and access forest data while in the field. These apps also enable users to submit observations and take action based on system findings. Platforms designed for communication and collaboration ensure that government agencies, NGOs, and local communities can access up-to-date data and make informed, joint decisions.

The system generates automatic notifications for imminent risks like wildfires, deforestation, or illegal activities by analyzing data with AI. Forest rangers, local authorities, and conservation organizations receive these alerts through mobile apps. When anomalies, such as illegal logging, are detected, AI-powered drones autonomously deploy to monitor the area and collect additional data. Some systems also include drones or ground robots for reforestation tasks, such as seed dispersal in deforested areas, guided by AI models that determine the best locations. In regions vulnerable to illegal logging or poaching, automated security measures, like cameras and alarms, can be triggered to deter criminal activity or notify authorities for prompt action.

Continuous data collection from IoT devices and remote sensing tools ensures real-time monitoring of forest conditions. This ongoing data flow enables continuous analysis, with AI models updating predictions and recommendations based on new information. The feedback loop helps adapt conservation strategies to emerging challenges, such as shifting weather patterns or changes in human activity. Conservation efforts adapt using AI-driven insights, such as rerouting wildlife corridors to prevent human-animal conflicts, adjusting fire prevention strategies based on weather and forest dryness, and implementing targeted interventions to protect endangered species. Decision-makers can modify policies and actions dynamically using AI insights, such as redirecting patrols to areas with high fire risk or increasing monitoring in sensitive biodiversity zones.

Fig. 7 illustrates the operation of this comprehensive system for sustainable forest conservation using IoT, remote sensing, and AI technologies.

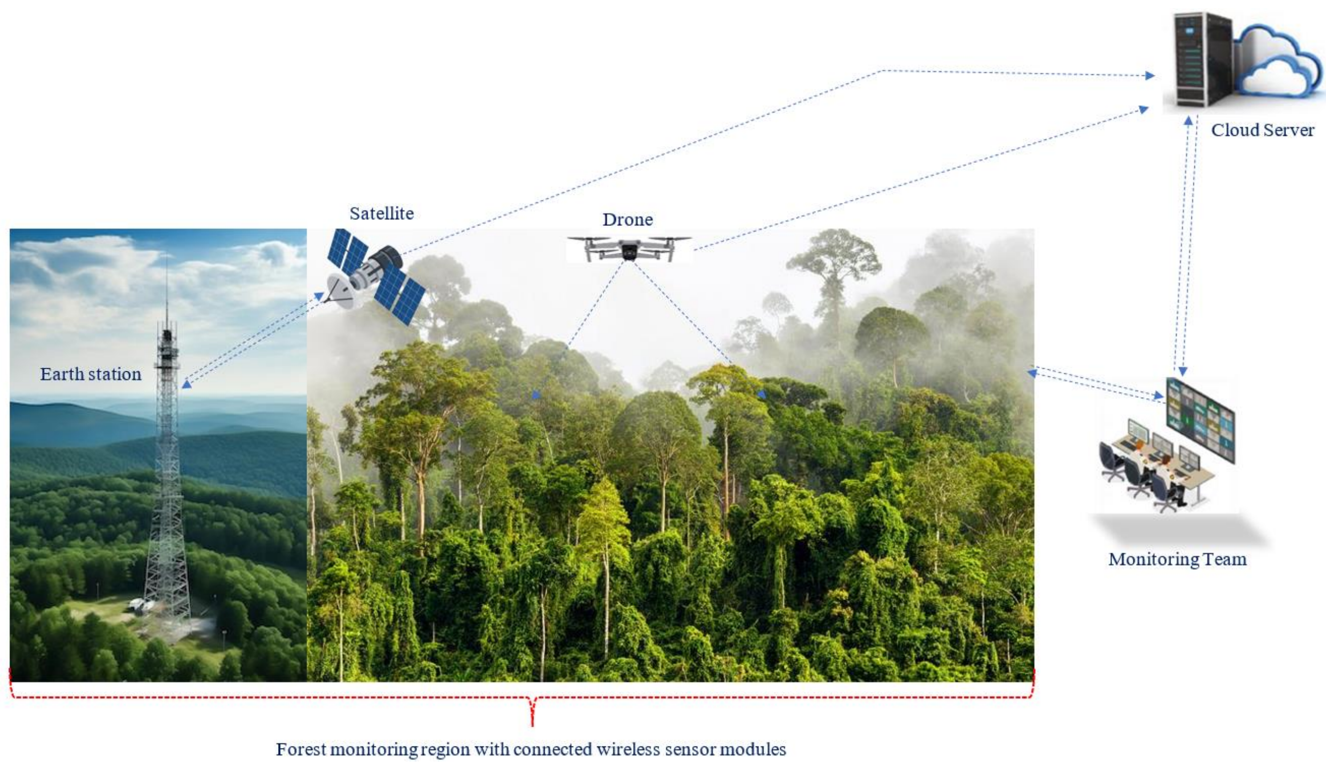

Fig. 7. Displays the functioning of a system that uses IoT, remote sensing, and artificial intelligence to conserve forests sustainably.

6. APPLICATIONS OF THE IoT, REMOTE SENSING, AND AI IN SUSTAINABLE FOREST MANAGEMENT

Sustainable forest management is essential for preserving the long-term health of forest ecosystems while balancing economic, environmental, and social demands. However, challenges like climate change, deforestation, illicit logging, forest fires, and resource overexploitation make this task more difficult. Cutting-edge technologies like IoT, remote sensing, and AI offer innovative solutions to these issues.

6.1. Applications of the IoT in Sustainable Forest Management

The IoT transforms forestry by offering advanced tools for monitoring, managing, and sustaining forest ecosystems. Some of the applications of IoT in sustainable forest management include:

6.1.1. Real-time monitoring of forest conditions

IoT sensors deployed throughout forests provide real-time monitoring of environmental factors like temperature, humidity, soil moisture, and air quality, enabling forest managers to track forest health and detect changes in ecosystem dynamics. This data allows for developing early warning systems that alert authorities to potential issues, such as disease spread or insect infestations, enabling timely intervention to minimize damage. For instance, sensors in remote forests can detect early signs of tree diseases like sudden oak mortality by monitoring moisture and temperature fluctuations. By facilitating prompt action, IoT technology helps protect forest resources, preserve biodiversity, enhance ecosystem health, reduce deforestation, safeguard nearby communities, and support sustainable forestry practices [1].

6.1.2. Wildfire detection and prevention

Forest fires are becoming increasingly common, posing severe threats to ecosystems and human habitats, primarily due to the greenhouse effect and rapid climate change. Dry climates, barren landscapes, intensive grazing, human encroachment on forest areas, and highly flammable vegetation often cause these fires, even though they are sometimes natural [119]. The impact of these fires includes global warming, biodiversity loss, and habitat destruction [20]. IoT-based sensor networks offer wildfire monitoring, prediction, and behavior analysis solutions. These systems detect early fire signs by monitoring temperature, smoke, and air quality changes, providing real-time data on fire spread, speed, and direction [120][121]. Alerts generated by these sensors are sent to forest authorities, enabling quick responses to mitigate widespread damage. Additionally, intelligent fire-detection systems integrate drones and satellite imagery, reducing response times and improving firefighting efforts. Through IoT, authorities can efficiently manage forest fire response, organize evacuation routes, and deploy firefighting resources based on data-driven predictions [120]. Several recent studies highlight the application of IoT in wildfire detection and prevention. Acharya et al. [122] developed a sustainable solution using IoT and LoRa connectivity for cost-effective intrusion and fire detection powered by solar energy. This system showed 97.14% accuracy in detecting intrusions and 100% accuracy in fire detection at Eturnagaram Wildlife Sanctuary, India. Prakash et al. [123] proposed an alarm system integrating vibration and flame sensors with GPS and machine learning methods for real-time fire and theft alerts. Alkhatib and Jaber [120] created a system that uses wireless sensors to monitor fire spread, speed, and direction, delivering real-time alerts to emergency personnel. Avazov et al. [124] demonstrated a strategy using AI and IoT to identify fires and prevent their spread, offering real-time fire location information to authorities. These advancements illustrate the potential of IoT to transform forest fire detection and management.

6.1.3. Wildlife Monitoring

Conservationists use IoT devices like GPS collars, RFID tags, and motion sensors to track wildlife movement and activity, which provides continuous data on animal populations with minimal human involvement [1]. This technology helps monitor endangered species, analyze migratory patterns, and prevent poaching, enabling more effective wildlife population management and a deeper understanding of animal dynamics. With this data, conservationists can design strategies to protect ecosystems, manage human-wildlife conflict, and monitor changes in biodiversity. IoT-based wildlife tracking improves biodiversity preservation, supports evidence-based conservation policies, and promotes peaceful coexistence between humans and wildlife. It also aids in safeguarding habitats, encouraging ecotourism, and ensuring species' long-term survival, such as tracking elephants to prevent poaching by alerting authorities when they approach human populations or protected areas [1].

6.1.4. Forest inventory and resource management

IoT technology, including drones and ground sensors, automates forest inventory operations by counting trees, assessing growth rates, and monitoring biomass. This data is essential for sustainable harvesting strategies that preserve the forest's regenerative capacity. IoT enables forest managers to make informed decisions on timber harvesting using connected devices and sensors to measure tree dimensions, identify species, and estimate biomass. This technology helps ensure sustainable practices and prevents overexploitation of forest resources. As a result, IoT enhances wood harvesting planning, improves operational efficiency, and reduces environmental impact, promoting responsible resource management. This technology supports the long-term sustainability of forest ecosystems, protects biodiversity, and facilitates the fair and efficient use of forest resources for societal benefit [1].

6.1.5. Deforestation monitoring

The IoT has become essential for deforestation monitoring, where satellite-linked sensors and cameras powered by IoT technologies can actively monitor remote areas to detect illegal forestry activities. These systems provide real-time alerts to authorities, helping reduce unlawful deforestation and protect forest ecosystems. IoT improves forest monitoring systems by integrating sensor networks, data analytics, and cloud computing, providing real-time insights into deforestation. This technology enables continuous data collection and analysis, immediately detecting and responding to environmental changes. Recent studies highlight the effectiveness of IoT in this field. For instance, Khan et al. [22] developed a model for real-time monitoring of illegal logging behaviors using smart sensors with AI algorithms. The model achieved 96.2% accuracy in identifying logging activities through machine learning techniques, including CNNs trained on Mel-filter bank energy characteristics. LoRa communication technology enabled real-time data transmission to a centralized server, ensuring quick access. Another study by Simiyu et al. [125] proposed an IoT-based architecture to detect chainsaw sounds using a machine-learning approach. With strategically placed sound sensors and a temporal frequency convolutional neural network (TFCNN), this system instantly categorized logging sounds, leveraging attention mechanisms and feature representation modules for improved sound identification. These studies demonstrate how AI-powered IoT devices can contribute to the fight against illegal logging.

6.1.6. Remote sensing for forest coverage and health assessment

Forest managers can continuously monitor forest cover and assess forest health by combining IoT and remote sensing technology, such as drones or satellites. IoT devices, like drones with LiDAR and multispectral cameras, gather data on forest structure, tree density, and canopy coverage, providing vital insights for forest inventories and estimating forest biomass and carbon sequestration potential. IoFT enables early detection of forest health risks, including insect infestations, disease outbreaks, and environmental stresses, allowing forest managers to take timely actions and prevent widespread damage. This integration supports the development of comprehensive forest management strategies that enhance sustainability, track long-term changes, and promote evidence-based decision-making. Ultimately, IoFT-enabled monitoring helps protect biodiversity, ecosystem services, and the essential role of forests in mitigating climate change [1].

6.1.7. Forest operations optimization

IoT technology can revolutionize forest operations by enhancing efficiency and decision-making in forest management. It provides real-time data on logging activities, machinery use, and worker safety, improving overall performance. Fleet management systems leverage IoT to track vehicle and machine movements, optimize transportation routes, and reduce fuel consumption, thus lowering environmental impact and cutting costs [1]. IoT also enhances remote sensing, monitoring, data analysis, wildfire control, sustainable harvesting, and forest health monitoring. IoT benefits society by optimizing forest operations through increased efficiency, cost savings, and promoting sustainable forest management practices [1].

6.1.8. Forest ecosystem conservation

Ecosystem conservation focuses on preserving and managing natural ecosystems, biodiversity, and ecological processes sustainably to maintain their integrity, function, and resilience. Innovations in the IoT enhance forest ecosystem protection by providing real-time data on forest health, biodiversity, and human impact. These tools enable better-informed decision-making, allowing forest managers and conservationists to respond quickly to threats, optimize resource use, and implement sustainable practices. IoT promotes a proactive, data-driven approach to forest ecosystem management, ensuring the preservation of vital natural resources for future generations. Forest ecosystem conservation works to protect species and habitats, support vital ecological services like clean air and water, regulate climate patterns, and provide cultural and recreational benefits, ultimately ensuring the survival of diverse species, environmental balance, and the well-being of present and future generations [1].

6.1.9. Sustainable forest certification

IoT integration into sustainable forest certification can transform forest management by providing real-time information, enhancing transparency, and improving compliance with certification criteria [1]. Sustainable forest certification ensures that forest management practices meet environmental, social, and economic standards, aiming to promote sustainability, protect biodiversity, and reduce deforestation. IoT technology enhances this process by enabling real-time data collection, monitoring forest health, managing resources efficiently, tracking carbon emissions, and supporting data-driven decision-making. It also aids in wildlife monitoring and remote sensing for audits and boosts transparency in forest management. As IoT continues to evolve, it supports sustainable practices, improves governance, and increases market demand for certified products. Ultimately, IoT fosters forest preservation, biodiversity conservation, and responsible forest management, benefiting society and the environment [1].

6.1.10. Forest species sensing

IoT technology enhances biodiversity monitoring, particularly in tracking forest species. Forests provide a home for countless plants and wildlife, many of which face endangerment due to climate change, deforestation, and habitat loss. Effective conservation requires real-time, accurate data on species populations, behavior, and habitat conditions. IoT-based systems, such as sensors, camera traps, drones, and acoustic recorders, enable real-time species monitoring and preservation, providing crucial data for biodiversity conservation. Applications like acoustic monitoring for animal detection, image recognition via camera traps, environmental sensing for habitat monitoring, RFID and GPS tracking for individual species, drone-based detection, insect sensing, and community-based citizen science initiatives all contribute to advancing conservation efforts. IoT technology actively monitors species and habitats, providing continuous data that improves our understanding of forest ecosystems and helps shape more effective conservation strategies. As IoT devices, machine learning, and data analytics continue to evolve, the future of species sensing will offer greater precision, scalability, and impact in preserving biodiversity across global forests [126].

6.1.11. Forest soil and water management

IoT integration in forest soil and water management ensures real-time monitoring, efficient resource use, and improved decision-making. Soil and water promote plant growth, biodiversity, and ecological balance in forests. Effective management of these resources ensures forest sustainability, reduces soil erosion, mitigates drought, and protects water quality [126]. IoT solutions, utilizing sensors, connected devices, and real-time data analytics, enhance monitoring capabilities and optimize resource use. These systems support sustainable forest management by monitoring soil moisture, nutrient levels, and water quality in streams and rivers and automating irrigation [126]. They also help track erosion, water flow, climate data, and resource planning, providing accurate information that aids forest managers in making informed decisions. As IoT technology advances, it will increasingly support forest sustainability, contributing to healthier ecosystems and more resilient forests.

6.1.12. Intelligent monitoring of forest roads

Forest roads are essential in the management and accessibility of forest regions, supporting activities like logging, animal monitoring, fire control, and tourism. However, these roads face challenges like erosion, landslides, vehicle damage, and other environmental hazards. IoT-enabled technologies, including sensors, drones, GPS tracking, and data analytics, offer real-time monitoring of road conditions, enhancing safety, optimizing maintenance, and preventing environmental harm. These technologies enable applications like road condition monitoring, erosion and landslide detection, weather-based predictive maintenance, traffic management, aerial surveillance with drones, wildlife monitoring, and remote maintenance planning. Using IoT, forest managers can make informed decisions based on real-time data, ensuring road functionality while minimizing ecological impact. As IoT technology evolves, it will be increasingly vital for maintaining sustainable and resilient forest road networks [127].

6.1.13. Tree health sensing

Tree health is a critical indicator of the overall condition of forest ecosystems, as healthy trees are essential for carbon sequestration, biodiversity, and ecological balance. Early detection of diseases, insect infestations, water stress, and nutrient deficiencies is vital for minimizing forest damage. IoT technology is key in monitoring tree health using sensors, data analytics, and real-time reporting systems, enabling forest managers and conservationists to track individual trees or forest areas remotely, which allows for timely interventions that help maintain forest health. IoT applications in tree health include monitoring environmental conditions, soil moisture, tree canopy health, pest and disease detection, physiological stress, tree growth, air quality, and drought or wildfire risks. By providing real-time data, IoT systems facilitate informed decision-making, helping to prevent pest outbreaks, optimize resource use, and support forest sustainability and resilience. As IoT technology evolves, it will become even more crucial in ensuring the long-term health of forests worldwide [126].

6.1.14. Vegetation height sensing

IoT-based vegetation height sensing provides practical tools for monitoring and managing forests and natural ecosystems. By integrating ground-based sensors, drones, and data analytics, IoT systems offer real-time, accurate assessments of vegetation height, enabling better decision-making in forestry and conservation. Vegetation height is crucial in assessing ecosystem health, biomass, habitat quality, and carbon sequestration. Unlike traditional methods, such as human surveys and satellite remote sensing, which can be time-consuming and costly, IoT solutions deliver continuous, precise observations [126]. Applications of IoT in vegetation height sensing include using LIDAR-equipped drones, ultrasonic and infrared sensors, multispectral and hyperspectral imaging, and forest canopy height mapping. These technologies help monitor vegetation growth, track carbon sequestration, assess biodiversity, and detect early signs of stress or growth issues. Integrating height data with other environmental factors improves sustainability, productivity, and biodiversity.

6.1.15. Forest machine-induced stress sensing

Machine-induced stress in forest ecosystems, resulting from logging, road building, and heavy equipment maintenance, leads to soil compaction, root damage, tree stress, habitat disruption, and altered microclimate conditions. IoT technology offers sophisticated methods for monitoring and managing these effects. Using IoT sensors, forest managers can gather real-time data on soil conditions, tree health, and ecosystem integrity, enabling more sustainable forest management and reducing the negative impacts of mechanized operations. Applications such as soil compaction monitoring, root stress detection, vibration sensing, and real-time fleet tracking help improve machinery operations and mitigate environmental damage. As IoT technology evolves, it will play an increasingly vital role in protecting forest health, promoting biodiversity, and supporting sustainable forest management practices [126].

6.1.16. Invasive forest species and fungi sensing

Invasive species and fungi pose significant threats to forest ecosystems by outcompeting native species, spreading diseases, and disrupting natural habitats, which can reduce biodiversity, tree health, soil quality, and forest production. Traditionally, researchers have monitored and managed these threats using human surveys and limited remote sensing technology. However, the IoT has introduced advanced technologies that enable real-time, automated detection and monitoring of invasive species and fungi. By integrating IoT-enabled sensors with data analytics, forest managers can detect and address invasive problems more effectively. IoT applications include environmental monitoring, automated camera traps, soil and air quality sensors, drones, sound-based sensors, trap networks, tree health monitoring, and predictive analytics. These technologies provide comprehensive insights into invasive species' spread, helping preserve forest health, biodiversity, and ecosystem services. As IoT technology evolves, it will play a crucial role in sustainable forest management and combating invasive species and fungi [126].

6.1.17. Carbon sequestration monitoring

Carbon sequestration helps combat climate change by absorbing and storing atmospheric carbon dioxide. Natural habitats, such as forests, wetlands, and soils, play a key role in this process, actively counteracting greenhouse gas emissions. Monitoring these processes is essential for assessing their efficiency, understanding the impact of climate policies, and ensuring ecosystem sustainability. The IoT has become a powerful tool for real-time, scalable, and accurate monitoring of carbon sequestration, enabling applications such as soil and forest carbon stock monitoring, agricultural carbon sequestration, and carbon sequestration in wetlands and oceans. By integrating remote sensing, predictive analytics, and AI, IoT provides a comprehensive system for collecting environmental data across large areas, enhancing the effectiveness and sustainability of climate change mitigation efforts.

6.1.18. Forest pest and disease management

Forest pest and disease control is crucial for maintaining healthy and sustainable forests. With technological advancements, IoT has become a valuable tool for monitoring and managing forest ecosystems. By providing real-time data, IoT enables early detection of pest infestations and disease outbreaks, allowing forest managers to take timely action, minimize losses, and ensure effective long-term management. The growing development of sensor technology, data analytics, and decision support systems will further enhance IoT's ability to monitor and protect the health of forest ecosystems.

6.1.19. Ecotourism and Recreational Forest Management

By integrating IoT technologies, forests become more intelligent, safer, and engaging, promoting environmental and economic sustainability. IoT sensors throughout the forest monitor factors like temperature, humidity, air quality, and soil moisture, helping to track ecosystem health and detect changes from climate change or human activity. GPS collars and video traps monitor animal behavior, supporting conservationists in protecting endangered species and maintaining biodiversity. Tourists benefit from IoT-powered apps and devices that guide them through trails, provide real-time navigation, and offer detailed information about the forest. These systems also enhance safety by tracking visitor locations and sending alerts about weather changes, wildlife presence, and fire hazards. IoT can help manage visitor flow to prevent overcrowding in popular areas. IoT enables real-time monitoring of ecological conditions and facilitates habitat restoration efforts, such as tracking plant growth and optimizing irrigation systems. Intelligent energy management systems ensure that tourist facilities operate sustainably, while IoT-powered smart bins keep recreation areas clean by notifying authorities when they need emptying. Drones and camera traps help detect illegal activities, like poaching, and alert authorities. Predictive analytics uses IoT data to forecast forest conditions and potential hazards like wildfires or floods, improving preparedness and response efforts. Moreover, IoT supports the development of intelligent transportation systems, like electric shuttle services, which reduce the environmental impact of tourism. Open data platforms foster stakeholder collaboration, allowing for more informed, sustainable forest management that balances conservation efforts with the growing demand for ecotourism.

6.1.20. Precision forestry

IoT is revolutionizing precision forestry by integrating advanced sensors, drones, and remote sensing technologies to collect real-time data on forest conditions. This data-driven approach enables forest managers to make informed decisions on tree planting, thinning, and harvesting, optimizing resource use while reducing environmental impacts. With the help of IoT, forest managers can track forest inventory and growth, monitor soil and water quality, and manage forest health and pests effectively. These technologies support sustainable practices by providing insights for optimizing fertilizer and water distribution, ensuring long-term forest development, and minimizing waste. By leveraging IoT, precision forestry contributes to carbon sequestration, climate change mitigation, and wildfire prevention. Forest managers can detect potential threats early, monitor biodiversity, and enhance ecosystem sustainability. IoT-based solutions improve timber harvest optimization, support forest certification, and enable more intelligent forest infrastructure. Ultimately, IoT in precision forestry empowers managers to balance ecological, economic, and social benefits, enhancing the efficiency and sustainability of forestry practices for the future.

6.1.21. Automated reforestation initiatives

IoT technology is revolutionizing forest restoration by accelerating and enhancing reforestation efforts. As deforestation threatens ecosystems and contributes to climate change, replanting has become a vital priority for environmental sustainability. IoT-driven solutions, such as automated planting and soil monitoring, speed up forest regeneration, boost planting success rates, and conserve resources compared to traditional methods. Soil sensors collect data on moisture, pH, temperature, and nutrients, guiding reforestation teams in selecting optimal planting locations and ensuring ideal conditions for tree growth. IoT devices, including weather stations, help monitor environmental factors like rainfall, humidity, and temperature, enabling adaptive strategies for different microclimates. Drones and robots actively contribute to IoT-powered reforestation by enabling large-scale planting and maintenance in difficult-to-access areas. Drones drop seed pods over vast regions, ensuring quick and efficient coverage, while seed pods protect seeds and provide essential nutrients for successful germination. IoT-enabled robots can autonomously plant seeds, using GPS and machine vision to navigate terrain, dig holes, and ensure optimal planting depth. Sensors attached to trees track growth metrics, such as trunk diameter and height, providing real-time data on tree health and helping managers address any issues with growth. IoT technologies also integrate with machine learning to predict the success of different reforestation strategies based on environmental data. IoT systems offer comprehensive monitoring and management of forest health, boosting the sustainability of reforestation efforts. Automated pest management tools with IoT sensors detect invasive species or pests and apply targeted, eco-friendly treatments to protect young trees. Advanced irrigation systems ensure precise water distribution based on soil moisture, reducing waste and maximizing water efficiency. IoT data supports carbon sequestration monitoring, essential for carbon credit programs, and enables transparent, verifiable reporting on environmental impact. By integrating GIS and LiDAR, IoT helps map optimal reforestation areas, ensuring better planning and monitoring. With IoT-driven solutions, reforestation initiatives become more efficient, scalable, and capable of contributing to global climate change mitigation and biodiversity preservation.

6.1.22. Sustainable logging techniques

IoT technology is crucial in balancing economic and environmental sustainability in sustainable logging. It enables real-time monitoring, precise management, and efficient resource usage, reducing the environmental impact of logging while ensuring long-term forest health. IoT applications in forestry include real-time forest monitoring, precision logging, timber tracking, automated resource management, and wildfire prevention. By tracking key data points, such as logging locations, tree-cutting, transportation, and milling processes, IoT helps forest managers ensure compliance with sustainability standards and prevent illegal logging in protected areas. IoT helps reduce waste, improve operational efficiency, and deliver valuable insights for better decision-making by collecting real-time data. It also enables automated monitoring of logging equipment, forest health, and pest control while optimizing water and soil conservation. Sustainable transport and logistics, along with improved community and stakeholder engagement, further strengthen the environmental benefits of IoT in forestry. By integrating these technologies, forestry operations can meet global timber demand while maintaining the integrity of ecosystems, protecting biodiversity, and ensuring the long-term resilience of forests.

6.1.23. Climate change monitoring and adaptation

Forests are vulnerable to climate change, and IoT devices are key in monitoring weather conditions in these regions. IoT systems collect real-time data on temperature, humidity, and precipitation patterns, allowing forest managers to adjust their strategies and effectively mitigate the impacts of climate change on forest ecosystems. These devices also help forecast environmental changes, allowing for proactive, sustainable forest management. IoT-based climate models support climate change monitoring and adaptation by gathering data on temperature, air quality, sea levels, and more, helping policymakers develop data-driven strategies for resilience. IoT technology enhances environmental monitoring, wildlife and ecosystem tracking, agricultural adaptation, water resource management, disaster risk reduction, carbon footprint monitoring, renewable energy management, and emission reductions, driving climate change mitigation efforts. As climate change challenges intensify, IoT will be essential in fostering resilience, promoting sustainability, and enabling proactive, data-driven environmental management across various sectors.

6.1.24. Data-driven decision-making

IoT enables data-driven decision-making by gathering real-time data from devices and sensors, which is then analyzed using advanced analytics and machine learning to generate actionable insights. This process allows industries to make more informed, efficient, and strategic decisions based on reliable data. By integrating IoT with AI and decision support systems, businesses and governments can improve operational efficiency, optimize resource use, reduce risks, and drive innovation. The ability to automate decision-making, enhance customer personalization, and promote sustainability further enhances decision accuracy. IoT revolutionizes forest conservation by providing extensive monitoring capabilities for ecosystems, biodiversity, and climate conditions. Through advanced sensors, remote sensing, and real-time data analytics, IoT offers valuable insights that help decision-makers respond quickly to environmental threats such as illegal logging, wildfires, and deforestation. The technology also supports precision forestry, improving reforestation efforts and enabling data-driven management of forest resources. Its continuous data collection, transmission, and analysis from remote areas allow for precise tracking of forest health, leading to more effective conservation policies. Moreover, IoT promotes sustainable logging practices by monitoring tree harvesting activities, ensuring compliance with conservation regulations, and minimizing environmental damage. In addressing climate change, IoT provides crucial data on carbon sequestration, air quality, and temperature variations, which helps model climate impacts and develop adaptive solutions.

Integrating IoT into conservation strategies enables conservationists to manage forest ecosystems more effectively, mitigate the impacts of global warming, and protect biodiversity. IoT's role in forest conservation will grow as technology progresses, enabling stakeholders to make informed, data-driven decisions that protect forests for future generations.

6.2. Remote Sensing

Remote sensing gathers data about the Earth's surface from a distance and plays a crucial role in sustainable forest management by enabling forest monitoring, evaluation, and conservation. Remote sensing has several vital uses in sustainable forest management, including:

6.2.1. Forest cover mapping and change detection

Remote sensing is vital in forest cover mapping and change detection, offering powerful tools to monitor and analyze forests over time. Through satellite imaging, aerial photography, and advanced sensors, remote sensing actively supplies essential data for analyzing forest dynamics, tracking deforestation, monitoring replanting efforts, and detecting degradation, all while supporting sustainable forest management practices. Optical sensors detect visible and near-infrared wavelengths, enabling plant species to differentiate and assess forest health. Synthetic Aperture Radar (SAR) penetrates cloud cover, capturing information on forest structure, biomass, and height, making it particularly useful in tropical regions with persistent clouds, such as Sentinel-1 and ALOS PALSAR. LiDAR sensors, often mounted on airplanes or drones, generate high-resolution 3D data on canopy height, density, and structure, excelling at mapping biomass and carbon stocks. Hyperspectral sensors, which capture data across hundreds of spectral bands, provide detailed insights into plant types, species composition, and forest health. Platforms like Landsat, Sentinel, and MODIS collect multispectral images of the Earth's surface, enabling land cover classification and forest-type identification. Remote sensing techniques use spectral fingerprints to distinguish forests from other land covers and incorporate digital elevation models to refine maps in challenging terrains. Tools like Global Forest Watch employ these technologies to provide near-real-time monitoring and insights into global forest cover. Recent research highlights the evolving capabilities of remote sensing in forest cover mapping and change detection. Miletić et al. [128] applied advanced remote sensing and machine learning techniques, achieving high accuracy in forest cover assessment using ANN and Random Forest classification methods with Sentinel-2 data. Their temporal layer-stacked approach yielded over 98% training accuracy and 97.75% testing accuracy, while the Random Forest method delivered exceptional results with 99.79% training accuracy and 96.98% validation accuracy. Similarly, Khanwilkar et al. [129] demonstrated the benefits of Very-high-resolution (VHR) satellite data, which enhances the ability to detect fine-scale forest changes and interpret land cover. Wang et al. [130] proposed a cost-effective framework combining multi-source remote sensing data from Sentinel-1 and Sentinel-2 with ensemble learning algorithms. Their approach outperformed basic classifiers, achieving 95.49% accuracy for level 1 forest cover maps and 78.05% for level 2 maps. These studies underscore the potential of advanced remote sensing technologies and methodologies to improve forest monitoring and management.

6.2.2. Tree species mapping

Tree species information is vital for monitoring forest resources, assessing biodiversity, and estimating forest biomass and carbon storage. Rapid and reliable methods to gather this information and analyze geographic distributions are crucial, especially since traditional fieldwork methods are labor-intensive, costly, and time-consuming [131][132]. Remote sensing technologies have become indispensable in identifying forest tree species, leveraging sensor and computer technology advances, machine learning, and deep learning methodologies [133]. These innovations have enhanced the automation and accuracy of data collection for individual trees, which is critical for smart forestry. Accurate tree-species categorization aids forest management and provides essential parameters for modeling ecological processes, contributing to sustainable resource management and conservation [134]. Remote sensing has revolutionized environmental monitoring by offering unparalleled insights into vegetation dynamics, biodiversity, and ecosystem health. It allows precise mapping and categorizing of tree species across landscapes, helping to understand forest composition and structure. High-resolution satellite and airborne remote sensing technologies provide rich spatial, color, and texture data, enabling refined tree species mapping [135]. Tools like drones, satellites, and airplanes with advanced sensors collect accurate spatial and spectral data for forestry, biodiversity protection, and ecological studies. These techniques enhance conservation efforts by identifying critical ecosystems and biodiversity hotspots. Remote sensing supports sustainable forest management by providing detailed information on species composition, forest health, and biomass while enabling timely interventions against invasive species and monitoring climate change impacts on forests.

Recent advancements in remote sensing have greatly improved the ability to map tree species, enabling researchers and practitioners to identify and monitor forest composition more accurately and efficiently. For example, Ji et al. [136] leveraged the BlendMask model with high-resolution satellite images to efficiently segment tree crowns and identify species in

Beijing's Jingyue ecoforestry. By combining deep learning and remote sensing, the model achieved high accuracy in identifying tree crowns and calculating canopy metrics. Similarly, Zhong et al. [133] introduced an improved YOLOv8 model that used multi-source UAV data, including RGB and LiDAR, to identify eight tree species in mixed forests in Northeast China. Their Attention Multi-level Fusion (AMF) Gather-and-Distribute (GD) YOLOv8 model outperformed standard methods, achieving an mAP of 81.0%. Grabska-Szwagrzyk et al. [137] used Sentinel-2 spectral-temporal metrics to map 16 tree species in Poland with over 80% accuracy through random forest classification. Wang et al. [138] focused on optimizing UAV-borne multispectral systems and achieved up to 98.48% classification accuracy using feature band selection and machine learning techniques. Rust and Stoinski [132] employed structural bark traits from terrestrial laser scanner data to classify species with up to 96% accuracy. Lin et al. [135] demonstrated that integrating aerial multispectral and LiDAR data with machine learning provided high-altitude-specific species classifications with accuracies exceeding 87%. These studies underline the efficiency, cost-effectiveness, and ecological significance of remote sensing for large-scale, accurate tree species mapping.

6.2.3. Biodiversity and habitat monitoring

As global biodiversity declines due to climate change, habitat degradation, and invasive species, remote sensing has become a crucial tool for conservation. Monitoring biodiversity and habitats is vital for understanding ecosystem dynamics, species distributions, and environmental change. Remote sensing enables researchers to collect extensive spatial and temporal data through satellite images, aerial photography, and modern sensors, surpassing the capabilities of traditional field approaches. By analyzing vegetation structure, forest types, and land cover, scientists can identify and map habitats, assess habitat suitability, and evaluate connectivity. This technology supports the identification of critical habitat corridors for species mobility and survival, advancing landscape-scale biodiversity conservation. Spectral data from remote sensing highlights biodiversity hotspots and tracks ecosystem composition and diversity changes caused by human or natural processes. When combined with ground surveys, remote sensing can monitor endangered species' habitats and inform forest management practices to minimize harm. Remote sensing offers diverse applications in conservation and biodiversity management. Researchers use satellite imaging and aerial photography to map and classify ecosystems, analyzing habitat distribution, fragmentation, and connectivity. They can model and forecast species distributions by combining species occurrence data with environmental characteristics to identify potential conservation sites. Remote sensing also tracks land use changes, such as deforestation and urbanization, which impact biodiversity. Indicators like the Normalized Difference Vegetation Index (NDVI) help assess vegetation health, a critical factor for species sustenance. This technology monitors water quality and quantity, supports aquatic biodiversity, and evaluates climate change effects on species and ecosystems by observing temperature, precipitation, and extreme weather events. Additionally, drones and satellites track animal movements, aiding species management and invasive species monitoring.

Several studies showcase remote sensing's effectiveness in biodiversity and habitat monitoring. Iglseder et al. [139] demonstrated the advantages of integrating aerial (laser scanning and image-based point clouds) and satellite (Sentinel-1 and Sentinel-2) data for habitat classification in Vienna, Austria. By training a random forest model with these data sources, researchers achieved habitat mapping accuracies between 63% and 76.5%, outperforming models using only aerial or satellite data. Similarly, Ivanova et al. [140] explored drone usage for monitoring large animals during forest fires. Their findings emphasized drones' accuracy and efficiency in dynamic wildlife monitoring under extreme conditions, surpassing traditional methods. These studies highlight the transformative potential of remote sensing in advancing conservation strategies and protecting biodiversity in changing environments.

6.2.4. Early forest wildfire detection, prediction, monitoring, management, and post-fire assessment

Wildfires severely threaten forests, ecosystems, human lives, and property, especially with rising temperatures and increased human activity. Managing these unpredictable and complex events requires specialized techniques, with remote sensing emerging as a critical tool. Remote sensing uses sensors on satellites, drones, airplanes, and ground-based platforms to collect large-scale, real-time data, which is crucial for making informed decisions throughout the entire wildfire lifecycle. Early detection systems, such as the National Aeronautics and Space Administration (NASA)'s Moderate Resolution Imaging Spectroradiometer (MODIS) and Visible Infrared Imaging Radiometer Suite (VIIRS) satellites, detect thermal anomalies signaling fire outbreaks [141]. At the same time, drones and aircraft equipped with infrared sensors monitor isolated and hard-to-reach areas. Ground-based cameras and infrared sensors continuously surveil high-risk zones, helping identify potential fire threats before they escalate.

Remote sensing supports wildfire management by evaluating environmental factors such as vegetation moisture, wind patterns, and temperature influencing fire risks. Satellites and drones provide high-resolution data to monitor active fires, map their extent, and track their spread using thermal and multispectral imaging [142]. This data feeds machine learning models that predict fire behavior, enabling better hazard assessment. SAR allows consistent fire tracking, even through smoke and adverse weather, while tools like NDVI and Normalized Burn Ratio (NBR) indices measure fire severity and vegetation loss. Real-time data assists in resource allocation, evacuation planning, and suppression strategies, offering critical insights into fire intensity and propagation [143].

Remote sensing is crucial in wildfire management, from detection and prediction to post-fire recovery. Several studies have demonstrated its effectiveness in various stages of wildfire control. Singha et al. [21] employed a synergistic approach combining remote sensing, GIS, and machine learning to analyze forest fire-prone regions in the Similipal Tiger Reserve, identifying key factors such as topography, climate, vegetation, and anthropogenic interference. They used models like Neural Net and Particle Swarm Optimization to map forest fire susceptibility and predict future fire zones. Perikleous et al. [144] developed PULSAR, a versatile UAV system for forest mapping and wildfire management, showcasing the potential of robotic technology for precise data collection and control. Hichou et al. [145] used remote sensing data from NASA Fire Information for Resource Management System (FIRMS) and Sentinel-2 satellites to track fire spread, assess burnt areas, and analyze plant cover changes, helping shape effective post-fire strategies. These studies highlight how remote sensing provides real-time data, supports predictive modeling, and enhances resource allocation, making it essential for mitigating the devastating effects of wildfires on forests.

6.2.5. Forest biomass estimation and monitoring

Forests are essential in the global carbon cycle because they actively absorb and store significant amounts of carbon dioxide, which makes them necessary carbon sinks. Their monitoring is crucial to understanding and combating climate change. Estimating and tracking forest biomass, which refers to the total mass of live trees and vegetation, is a key aspect of forest management, biodiversity conservation, and climate research. Forest biomass is closely linked to carbon sinks and sources, providing vital nutrients for the entire ecosystem. Traditional methods of assessing forest biomass, such as field inventories, are time-consuming, labor-intensive, and limited in their geographic reach. Remote sensing technologies, however, have revolutionized forest biomass monitoring by offering large-scale, accurate, and cost-effective alternatives [146][147]. These technologies use satellite imaging, airborne sensors, or drones to collect comprehensive data on forest structure, biomass density, and changes over time, facilitating the evaluation of these critical ecosystem properties. Remote sensing methods, such as optical, radar, and LiDAR, have proven effective in capturing forest attributes. These technologies allow for detailed mapping of carbon stocks and provide insights into deforestation and forest degradation trends. Scientists can now produce more accurate biomass assessments by combining remote sensing techniques with machine learning and data fusion. Satellites like Landsat, MODIS, and Sentinel provide multispectral data that enable the estimation of forest cover and its changes over time. Radar sensors like Sentinel-1, ALOS PALSAR, and RADARSAT offer valuable data on above-ground biomass, especially in tropical regions where cloud cover limits optical observations. LiDAR missions, such as NASA's Global Ecosystem Dynamics Investigation (GEDI), provide high-precision 3D data on forest structure, tree height, and canopy volume, which are essential for biomass calculations. Airborne platforms with LiDAR or high-resolution radar systems allow detailed biomass estimates in localized areas. UAVs with LiDAR or cameras also offer cost-effective and flexible solutions for smaller-scale monitoring, making it easier to capture fine-scale structural data in difficult-to-reach areas.

Several research studies have highlighted the power of remote sensing for forest biomass assessment. For example, Wu et al. [148] developed an above-ground biomass estimation method for lowland tropical forests in Xishuangbanna, combining remote sensing data from Landsat 8 and Sentinel-2 with forest management inventory data. Their findings showed that combining multiple data sources and applying stratified models improved biomass estimation accuracy. Similarly, Zhang et al. [147] proposed a scalable method for mapping biomass in semiarid forests using LiDAR and multi-temporal Sentinel-1 and -2 data. Their study demonstrated that incorporating LiDAR data with optical and SAR information enhanced biomass prediction accuracy, with machine learning models such as XGBoost achieving the best performance. These advancements in remote sensing continue to provide decision-makers with reliable and timely data, improving forest management and climate change mitigation efforts by offering insights into forest health, structure, and biomass trends.

6.2.6. Forest health monitoring

Forests are crucial in maintaining environmental stability, supporting biodiversity, and regulating the global carbon cycle. Deforestation, climate change, insect infestations, diseases, and human activities significantly threaten them. These factors actively impact their survival, causing disruption to ecosystems and endangering species. Effective forest health monitoring is essential for sustainability, and remote sensing has become vital [149]. Remote sensing uses satellite, airborne, and drone-based technologies to gather data on forest ecosystems without requiring direct physical observation. It allows for large-scale, continuous monitoring, offering high-resolution insights into forest characteristics such as vegetation cover, tree health, biomass, and biodiversity. Advances in sensor technology and data analytics have transformed the way we assess and manage forest health. These innovations enable more accurate monitoring, early detection of issues, and data-driven decision-making, improving forest management practices and ensuring better preservation of forest ecosystems. Remote sensing operates by detecting electromagnetic radiation reflected from plants, using multiple spectral bands to assess various forest conditions. The NDVI actively compares the absorption of visible and near-infrared light to determine plant health, vigor, and density [149]. Hyperspectral imaging can identify chlorophyll variations, signaling plant health, while thermal and short-wave infrared sensors detect water stress. Remote sensing also aids in tracking deforestation, forest degradation, and land-use changes, with satellites like Landsat and Sentinel-2 enabling global monitoring [149]. LiDAR technology provides three-dimensional data on forest structure, which helps assess biomass and detect damaged or dying trees. Remote sensing is also essential for detecting forest fires, assessing their intensity, monitoring post-fire recovery, identifying tree species, and measuring biodiversity.

Numerous research efforts showcase the effectiveness of remote sensing in forest health monitoring. Sumiya et al. [150] conducted a comprehensive review of remote sensing applications in Bangladesh's forest health assessment, highlighting the use of Landsat data and machine learning techniques. Dixit et al. [149] demonstrated the potential of lightweight drones for mapping forest features in Jaipur, showcasing their role in early pest detection and forest management. Sunkur et al. [13] used remote sensing and GIS to monitor mangrove cover changes in Mauritius, revealing the power of geospatial tools in tracking environmental shifts. These studies emphasize how remote sensing technologies, including multispectral, hyperspectral, and LiDAR sensors, provide accurate, non-invasive, and scalable data, enabling forest managers to make informed decisions, detect issues early, and implement protective measures for forest ecosystems.

6.2.7. Estimation of forest carbon stock

Accurately calculating forest carbon stock is essential for understanding how forests contribute to climate change mitigation. Forests are important in carbon sinks because they actively absorb and store large amounts of carbon dioxide from the atmosphere. Forest carbon stock represents the carbon stored within these ecosystems, mainly in trees, plants, and soil. This carbon storage is crucial to the global carbon cycle, accounting for 80% of above-ground carbon and 40% of subsurface carbon [151]. Monitoring carbon stock is vital for guiding sustainable forest management, mitigating climate change, and ensuring compliance with international frameworks like the United Nations Framework Convention on Climate Change and Reducing Emissions from Deforestation and Forest Degradation (REDD+). Remote sensing estimates forest carbon stock, offering vast, fast, and reliable data over large and often inaccessible forest areas. Researchers can gather critical forest data, including canopy structure, biomass, and land-use changes, using remote sensing tools like satellite images, LiDAR, SAR, and multispectral or hyperspectral sensors. When combined with field measurements, these tools allow for more accurate assessments of forest carbon stock with fewer resources than traditional ground-based methods.

Remote sensing helps monitor carbon stock over time, assisting researchers in tracking changes due to natural disturbances, deforestation, or afforestation efforts. This technology benefits initiatives like REDD+, which require reliable carbon stock estimates to measure the progress of conservation and afforestation activities. Remote sensing enables forest managers to identify carbon-rich regions, facilitating targeted conservation actions. For example, Cheng et al. [151] used the Google Earth Engine (GEE) platform, national forest resource inventory data, and Landsat 8 multispectral imagery to estimate forest carbon stock in Yunnan Province. The study categorized the province into different forest types and land uses by applying four machine learning algorithms—Random Forest, Classification and Regression Trees, Gradient Boosting Trees, and Support Vector Machine. After a thorough comparison, they found that the Random Forest method was the most accurate and reliable for predicting above-ground carbon storage using remote sensing data. As the demand for precise carbon stock assessments and forest management increases, remote sensing provides scalable, reliable, and comprehensive data essential for global forest carbon evaluations.

6.2.8. Deforestation and forest degradation monitoring

Deforestation and forest degradation are major global environmental issues that threaten biodiversity, contribute to climate change, and disrupt ecosystem services (Megawati et al., 2024). Monitoring these processes is essential for developing sustainable forest management strategies and implementing conservation efforts. Remote sensing effectively tracks changes in forest cover over time, enabling large-scale, cost-efficient forest dynamics monitoring. It provides crucial data to identify, analyze, and address deforestation and degradation, helping to mitigate their impacts. As these environmental threats increase due to logging, agriculture, infrastructure development, and climate change, remote sensing technologies detect and assess forest changes, offering continuous, high-resolution imagery to monitor trends and pinpoint areas of concern. Remote sensing technologies, such as satellite sensors like Landsat, MODIS, and Sentinel, allow for the study of both historical and real-time changes in forest cover. These sensors capture various electromagnetic wavelengths, including visible, infrared, and microwave bands, which provide valuable insights into forest structure, biomass, and canopy health. Tools like optical imaging, radar, and LiDAR enhance the detection of subtle changes in forests that are otherwise hard to detect using traditional methods. For instance, Global Forest Watch uses satellite imagery to provide real-time data on global forest loss, while platforms like Landsat offer historical data to analyze long-term deforestation trends. These technologies also aid in identifying areas affected by forest degradation, such as fires, insect infestations, and selective logging, which often result in significant ecosystem impacts.

Additionally, advanced data processing methods, including machine learning and AI, have enhanced the efficiency and accuracy of remote sensing for forest monitoring. These techniques enable automated identification of deforestation and degradation patterns, reducing the need for manual analysis and speeding up the generation of actionable insights. Remote sensing also supports forest restoration efforts by helping identify priority areas for preservation or replanting. Governments and conservation organizations can use this data to monitor carbon emissions, track the success of initiatives like REDD+, and ensure compliance with environmental regulations. Studies like those by Megawati et al. [152] and Castelo et al. [153] demonstrate the practical application of remote sensing in forest monitoring, providing valuable insights for forest management and conservation. As remote sensing technologies evolve, they will be increasingly vital in promoting sustainable forest management and protecting global forest ecosystems.

6.2.9. Estimating forest inventory information and planning

The increased need for sustainable forest management demands efficient and precise methods for assessing forest inventory data. Forest inventory is crucial in gathering essential data and guiding forestry decisions [154]. Accurate information on forest conditions—such as tree and stand volume, tree number, height, crown, diameter, above-ground biomass, and basal area—is vital for planners, forest managers, and landowners [154]. These factors impact a forest's potential revenue, habitat, and management objectives. Keeping forest inventory updated is also essential for tracking spatial and temporal changes in ecosystems over time, supporting planning, and ensuring the sustainability of natural resources. Traditional ground-based inventory methods are time-consuming, labor-intensive, and often limited in geographic coverage. Remote sensing has emerged as a powerful solution, offering large-scale and high-resolution data to enhance forest management decisions. This technology allows for accurate assessments of forest properties like tree height, biomass, species composition, and overall health—critical for inventory and planning [155]. Remote sensing technologies, including LiDAR and multi-spectral imaging, provide comprehensive insights into forest structure and dynamics. LiDAR, for instance, enables precise tree height measurements and biomass estimations, while hyperspectral imaging distinguishes tree species based on their spectral signatures. Satellite imaging and historical data further support monitoring forest health, deforestation, reforestation, and land-use changes, all contributing to sustainable land management.

Remote sensing also aids in creating effective management strategies that balance environmental, social, and economic factors. It provides crucial data for decision-making processes related to conservation, resource exploitation, and forest resilience. Integrating remote sensing data with GIS allows for comprehensive land-use planning, including habitat conservation, zoning, and urban growth management. It also supports monitoring compliance and assessing the success of conservation efforts. Research studies, such as those by Lee et al. [155] and Zhou et al. [154], demonstrate how remote sensing techniques, including airborne laser scanning and UAV-based imaging, accurately measure and monitor forest conditions. These technological advancements promise to improve forest management practices further, fostering the long-term health and resilience of forest ecosystems.

6.2.10. Illegal logging detection and law enforcement

Illegal logging is a widespread issue that harms the environment, biodiversity, and the livelihoods of communities reliant on forests. It leads to deforestation, destruction of wildlife habitats, and depletion of essential natural resources. Beyond the environmental damage, illegal logging undermines legitimate forestry efforts, causes economic losses, and hinders climate change mitigation efforts. Early detection and enforcement effectively tackle this challenge. Traditional monitoring methods, like ground patrols, are slow, resource-intensive, and limited in coverage, particularly in large, remote areas. As a result, remote sensing technology has emerged as a powerful tool to detect illegal logging and enhance law enforcement efforts. It allows for continuous monitoring of forest cover, enabling real-time identification of illegal deforestation or logging activities. High-resolution satellite images from sources like Landsat, Sentinel, or commercial satellites offer detailed views of forests, even in inaccessible regions. Techniques like NDVI and time-series analysis can detect changes in vegetation, revealing areas of forest degradation or illegal logging. Remote sensing data enables law enforcement to spot deforestation hotspots and respond quickly to unauthorized activities, helping to prevent further damage. With near-real-time satellite data and drone technology, authorities can efficiently gather evidence, track logging routes, and document unlawful activities, supporting legal action against violators.

By integrating remote sensing data with GIS and AI, authorities can automate the detection of suspicious activities, allowing quicker intervention. These technologies enhance monitoring accuracy and efficiency, enabling better decision-making and more effective law enforcement. Remote sensing provides a cost-effective, scalable solution for monitoring forests, detecting illegal logging, and assisting law enforcement in safeguarding forest ecosystems. Sensor technology and data analytics advancements make remote sensing a crucial tool for detecting illegal logging, supporting sustainable forest management, and enhancing global environmental protection efforts.

6.2.11. Forest productivity monitoring

Forests are essential in carbon sequestration, biodiversity protection, and resource provision, making it necessary to monitor their productivity for sustainable management and climate change mitigation. Traditional methods of measuring forest productivity, such as field measurements, are costly, labor-intensive, and limited in their geographical and temporal scope. Remote sensing technologies offer a cost-effective, scalable, and consistent method for observing forest dynamics over large areas and long periods. These technologies provide valuable data on forest health, growth patterns, biomass, and environmental changes, enabling precise evaluations of forest productivity on local, regional, and global scales. With advancements in remote sensing technologies, researchers can now use tools like optical imaging, LiDAR, and radar to assess forest structure, biomass, and productivity. Vegetation indices such as NDVI, alongside modern techniques like SAR and LiDAR, allow for in-depth analysis of tree canopy structure, leaf area, and forest biomass. These techniques enable continuous monitoring of forests, offering long-term, high-resolution data on factors such as photosynthesis, canopy structure, and growth trends. Active remote sensing methods, like radar, can also monitor forest biomass in regions with dense vegetation or cloud cover, such as tropical forests, further enhancing productivity estimates and forest health assessments.

Remote sensing technologies also help identify disturbances like deforestation, forest fires, pests, and diseases, which affect forest productivity. Early detection of these disturbances enables timely interventions to preserve or restore forest health. Moreover, remote sensing provides crucial data for estimating carbon sequestration in forests and assessing their role in climate change mitigation. Integrating remote sensing with technologies like IoT sensors and AI can enhance forest monitoring, improve data analysis, and make more informed decisions for sustainable forest management. These combined technologies offer a robust and effective way to monitor forest productivity, supporting global efforts to mitigate climate change and protect vital forest ecosystems.

6.2.12. Precision forestry

In precision forestry, remote sensing is crucial in improving forest management and sustainability by providing high-resolution, multi-temporal data over large areas. This technology enables more efficient decision-making, resource management, and proactive conservation efforts. Remote sensing offers valuable insights into forest health, structure, and dynamics. With sensors capturing a broad range of electromagnetic wavelengths, remote sensing allows foresters to monitor large-scale forest conditions, assess tree species composition, and track changes caused by climate change, deforestation, or human activity. Remote sensing also enables precise forest maps that provide detailed information about forest cover, tree density, species distribution, and terrain features. Satellites and drones provide high-resolution images that help assess forest inventory by identifying tree species, age, and overall structure. This data is crucial for effective forest management, biodiversity evaluation, and resource allocation. It can also detect early signs of stress in forests, such as insect infestations, diseases, droughts, and nutrient deficiencies, allowing for timely interventions. Additionally, remote sensing helps assess forest biomass and carbon stocks, which are key to climate change mitigation efforts as forests play a critical role in carbon sequestration.

Beyond monitoring forest health and biomass, remote sensing supports conservation efforts by detecting deforestation, forest degradation, and land-use changes. Real-time monitoring of forest fires using satellite and drone technology provides essential information for early detection, spread prediction, and damage assessment. By integrating remote sensing data with GIS and other precision forestry technologies, foresters can make site-specific management decisions that enhance growth, reduce waste, and minimize environmental impact. This technology also contributes to biodiversity conservation by identifying vital habitats and monitoring ecological changes, helping to balance economic development with environmental sustainability. Advancing remote sensing technologies will increasingly drive sustainable forest management, actively addressing global challenges like climate change and resource conservation.

6.2.13. Forest canopy height retrieval and analysis

Forest canopy height is vital for understanding forest structure, biodiversity, and health and evaluating carbon storage, habitat quality, and overall productivity [156]. Accurately measuring canopy height on a large scale is essential for quantifying forest resources and monitoring environmental changes. Traditional ground-based surveys are labor-intensive and limited geographic coverage, making remote sensing a more efficient alternative. Technologies like LiDAR, satellite imagery, and aerial surveys allow for rapid, large-scale assessments of canopy height across diverse forest ecosystems. LiDAR, in particular, is a powerful remote sensing technology for measuring forest canopy height. By sending laser pulses into the forest and timing their return after bouncing off the canopy and ground, LiDAR provides precise data on the canopy structure. This technique generates three-dimensional models of forest canopies, offering valuable insights into forest health and dynamics. In addition to LiDAR, satellite sensors like ALOS PALSAR, Sentinel-1, and TanDEM-X, which utilize radar, can penetrate the canopy and offer information on forest vertical structure. Optical satellite data from sources like Landsat, MODIS, and Sentinel-2, while less accurate, can be combined with other data to improve canopy height estimates.

Recent advancements have integrated various remote sensing data sources, enhancing the accuracy of canopy height assessments. Random Forest and Deep Learning algorithms refine these measurements by incorporating multi-spectral, topographic, and structural data. Zhu et al. [156] introduced a method combining GEDI and ICESat-2 LiDAR data with Landsat 9 imagery and Shuttle Radar Topography Mission (SRTM) terrain data. Using a random forest regression approach, their model produced highly accurate canopy height estimates, with validation from aerial laser scanning (ALS) data. This multi-source integration of LiDAR, radar, optical imaging, and machine learning offers a more comprehensive and accurate approach to understanding forest ecosystems. It informs sustainable forest management and conservation strategies.

6.2.14. Early detection of bark beetle-infested spruce trees

Spruce bark beetles pose a major threat to spruce forests worldwide, causing significant ecological and economic damage. Early detection of infestations is crucial for preventing large outbreaks and minimizing tree mortality. Traditionally, forest managers relied on visual inspections, a labor-intensive method often ineffective in spotting early signs of infestations [157]. However, remote sensing technologies have become essential for early detection and monitoring of bark beetle activity. By collecting large amounts of data from satellites, aircraft, and drones, remote sensing provides a non-invasive and efficient method for monitoring forest health, enabling the identification of subtle changes in trees before visible damage occurs [157]. Remote sensing methods, such as multi-spectral, hyperspectral, and thermal imaging, help detect early physiological stress in spruce trees caused by bark beetle infestations. Vegetation indices like NDVI and Red Edge Position (REP) are particularly useful for monitoring changes in chlorophyll content, a key indicator of beetle activity. As the infestation advances, the tree's chlorophyll content, reflected in these indices, reduces. Thermal sensors can detect subtle changes in canopy temperature, indicating reduced transpiration in infested trees. At the same time, hyperspectral imaging captures detailed spectral data to identify decreases in chlorophyll and other pigments involved in the tree’s defense mechanisms. LiDAR technology is valuable for detecting structural changes in trees, such as canopy loss, which can signify an ongoing infestation [157].

Combining different remote sensing data sources—such as multi-spectral, hyperspectral, thermal, and LiDAR imagery—enhances early detection of bark beetle infestations. By integrating these datasets with machine learning algorithms, forest managers can more accurately identify patterns indicative of early infestation. This integration allows for better forecasting of future outbreaks, enabling proactive measures. Remote sensing technology, coupled with AI-driven systems, enables real-time analysis of vast amounts of data, providing actionable insights to guide forest management decisions. As these technologies advance, remote sensing is poised to transform forest health management and improve the response to bark beetle threats [157].

6.2.15. Assessing the impact of spongy moth infestation

The spongy moth (Lymantria dispar) is a highly invasive forest insect that poses significant risks to forest ecosystems. Its larvae feed heavily on the leaves of hardwood trees, such as oak, birch, and aspen, causing severe defoliation. This feeding behavior disrupts the ecological balance, reduces biodiversity, and negatively impacts lumber production. Effective monitoring and management of spongy moth infestations have become essential in forest management. Remote sensing has become crucial for assessing forest health and tracking pest infestations. By utilizing satellite imagery, aerial photos, and sensor data, remote sensing allows for the early detection of defoliation, changes in vegetation cover, and overall forest condition, providing a comprehensive approach to forest pest management. Remote sensing technology can efficiently monitor vast areas and offer timely, regular updates, making it invaluable in controlling spongy moth infestations. High-resolution multi-spectral and hyperspectral sensors detect subtle differences in leaf color and reflectance, which are early indicators of spongy moth activity. By measuring vegetation indices such as the NDVI, remote sensing identifies stressed or damaged areas before noticeable defoliation occurs. Additionally, remote sensing provides valuable data on changes in canopy structure, tree health, and leaf area, all of which help monitor the progression of infestations, which allows forest managers to track infestation patterns and determine the extent of damage, even before visible signs of defoliation appear.

LiDAR technology enhances remote sensing by providing detailed 3D models of forest canopies. LiDAR data reveals differences in canopy height, density, and biomass, helping to assess the long-term impacts of spongy moth infestations on forest structure and regeneration. Remote sensing enables large-scale, multitemporal data collection, which is critical for long-term monitoring. By comparing data over time, forest managers can evaluate the success of pest management strategies and the recovery of affected forests; in addition to identifying and monitoring infestations, remote sensing aids in planning recovery efforts, such as reforestation and biodiversity protection. Remote sensing provides a scalable and cost-effective alternative to traditional ground-based monitoring, which is crucial in reducing the ecological and economic damage caused by spongy moth outbreaks.

6.2.16. Improved forest stock volume estimation

Remote sensing has revolutionized the estimation of forest stock volume by offering a more efficient, accurate, and scalable alternative to traditional ground-based methods. Forest stock volume is crucial for sustainable forest management, ecological protection, and the economic assessment of forest resources [14]. Accurately assessing this volume helps measure forest productivity, track biomass changes, and ensure appropriate harvesting. Ground-based surveys, which were labor-intensive, expensive, and geographically limited, have been largely replaced by remote sensing techniques. Satellite imagery, aerial photography, LiDAR, and UAVs now provide comprehensive, large-scale, and non-invasive data on forest structure and composition, enabling precise volume estimates over extensive regions. LiDAR enhances these estimations by generating high-resolution 3D models of forest canopies. These models allow for accurate tree height measurements directly correlating with forest volume. LiDAR’s ability to capture fine-scale features significantly improves stock volume predictions. Multi-spectral and hyperspectral photography help differentiate tree species and assess forest health, directly influencing biomass calculations. These sensors gather data across multiple wavelengths, enabling the monitoring of tree species composition and canopy vitality, both essential for precise stock volume estimations. Remote sensing also offers a cost-effective and scalable approach to forest stock estimation. By reducing the need for extensive fieldwork, remote sensing delivers large-scale, high-resolution data at a fraction of the time and cost. Geographic information system technology can further enhance this data, allowing forest managers to generate detailed maps and models of forest stock distribution, plan harvesting activities, and implement conservation measures. Remote sensing allows continuous monitoring of forests, detecting changes over time and supporting sustainable forest management practices. It provides essential information on forest biomass, carbon storage, and overall health, contributing to climate change mitigation and biodiversity conservation.

6.2.17. Identification of damaged trees

The growing demand for effective forest management and environmental protection has driven the use of modern technology, particularly remote sensing, to monitor forest ecosystems. Various factors contribute to tree damage, including insect infestations, diseases, extreme weather, and human activities like logging. Remote sensing addresses the limitations of traditional methods, which are often labor-intensive and time-consuming, by enabling large-scale, real-time data collection across vast forested areas. Remote sensing uses sensors on satellites, drones, and airplanes to capture data across various spectral bands to identify subtle changes in forest and plant structures. For instance, optical sensors detect variations in the near-infrared light reflected by vegetation, enabling the identification of stressed or damaged trees through vegetation indices like NDVI. Remote sensing technology also offers a variety of specialized sensors to monitor forest health. Thermal sensors detect changes in surface temperature that indicate tree stress. Hyperspectral sensors collect detailed data about tree types and health, identifying specific damage like pest infestations or nutrient deficiencies. LiDAR creates 3D models of tree structures and canopy density, helping identify physical damage such as broken branches or crown dieback. Furthermore, SAR systems, which use microwave signals, can monitor forests under challenging conditions like fog or darkness, detecting structural changes caused by storms or human activities. Remote sensing detects early signs of stress in forest ecosystems, enabling timely intervention to prevent the spread of pests, diseases, and other threats [158].

Combining remote sensing with machine learning and AI enhances the precision of tree damage diagnosis and classification. This integration supports more effective decision-making in forest management and conservation efforts. Remote sensing assesses the impact of natural disasters like wildfires and floods by rapidly evaluating tree damage and helping to shape recovery plans. Additionally, it helps detect illegal activities like logging, land-use changes, and deforestation. As climate change threats continue to grow, remote sensing will play an increasingly vital role in maintaining forest health. It will provide actionable insights and enhance the efficiency of conservation and management strategies.

6.2.18. Forest drought observations

Forest ecosystems face significant threats from climate change, particularly drought, which can lead to tree mortality, increased vulnerability to pests and diseases, and disruptions to biodiversity [159]. Drought limits water availability for trees, impairing their physiological processes and weakening their resistance, contributing to long-term ecosystem damage. Monitoring drought's effects on forests is essential for sustainable forest management and conservation. Remote sensing has emerged as a critical tool for addressing this challenge, offering a non-invasive, cost-effective, and large-scale method to assess forest health over time. By utilizing sensors on satellites, drones, and airplanes, remote sensing collects data across various spectral ranges, providing essential insights into forest canopy health, soil moisture, and vegetation stress. These technologies enable early detection of drought stress, support long-term monitoring, and inform strategies to mitigate drought's adverse effects on forests. Different remote sensing techniques, including optical, thermal, and microwave sensing, reveal key drought indicators in forests. Optical sensors detect changes in vegetation indices like the NDVI, which reflect variations in chlorophyll concentration and photosynthetic activity. Thermal sensors identify surface temperature changes linked to water stress, while microwave sensors measure soil moisture, shedding light on water availability for trees. Satellites like MODIS, Landsat, and Sentinel-1 provide crucial data for monitoring these variables. Remote sensing also facilitates early drought detection by identifying stress signals such as reduced photosynthesis, canopy thinning, and increased surface temperatures before visible damage occurs [160]. These capabilities help forest managers take timely action to alleviate drought effects, strengthen ecosystem resilience, and prioritize conservation efforts.

By integrating remote sensing data with machine learning models, researchers can predict drought risks, assess forest susceptibility, and develop targeted management strategies. Combining optical, thermal, and microwave sensor datasets with environmental variables like precipitation, temperature, and terrain enhances drought modeling accuracy. This holistic approach enables forest managers to map drought-affected areas, estimate biomass loss, and track the long-term impacts of drought on forest ecosystems. Time-series remote sensing data analysis highlights forest health and recovery trends, offering insights into how forests adapt to recurring droughts in a changing climate. As advances in remote sensing and artificial intelligence improve monitoring precision, these technologies become indispensable for promoting forest ecosystem resilience and ensuring effective responses to climate change challenges.

6.2.19. Monitoring and managing forest roads

Forest roads are crucial in accessing forest resources, supporting logging activities, and providing essential services such as fire control, recreation, and biodiversity conservation. However, their construction and maintenance can significantly impact the environment, leading to habitat fragmentation, soil erosion, and disruptions to wildlife [161]. Sustainable forest management increasingly uses remote sensing technology to monitor and manage forest roads effectively. By employing satellite imaging, aerial photography, and advanced geospatial analysis, forest managers actively evaluate road conditions, track changes over time, and assess the ecological impacts of road networks [161]. This technology offers several advantages, including covering large areas rapidly, collecting real-time data, and delivering high-resolution imagery to support informed decision-making. Remote sensing techniques precisely map forest road networks, helping managers create comprehensive inventories of road locations, dimensions, and structural characteristics. Historical remote sensing data allows forest managers to track changes in road networks over time, analyzing the impacts of construction, maintenance, and environmental factors such as erosion or vegetation encroachment. It also helps identify unauthorized or illegal road development, facilitating swift interventions to mitigate ecological harm [161]. Additionally, remote sensing supports the evaluation of environmental impacts, such as habitat fragmentation and alterations in water runoff or soil stability. Advanced methods, such as LiDAR and multi-spectral imaging, enable detailed assessments of road conditions, including surface quality and potential hazards like landslides or washouts, ensuring better prioritization of maintenance efforts.

Integrating remote sensing, GIS, and machine learning enhances forest road management by enabling predictive modeling of environmental impacts and optimizing road design and routing to minimize ecological disruption. Forest managers can identify sensitive areas to avoid during construction and maintenance by overlaying remote sensing data with biological and hydrological maps. This technology also promotes transparency by providing visual data that can be shared with stakeholders and local communities, fostering better communication about sustainable practices. Remote sensing improves compliance with environmental regulations, supports responsible forestry operations, and contributes to developing informed policies. As remote sensing technology advances, its applications in forest road management will expand, creating new opportunities to enhance forest road networks' sustainability, efficiency, and resilience.

6.2.20. Estimation of tree plantation stand age

Accurately estimating tree plantation stand age is crucial for effective forest management, ecological research, and sustainable resource use. While reliable, traditional methods like dendrochronology and direct sampling often prove intrusive, time-consuming, and limited in scope. Remote sensing has transformed research by enabling scientists to assess tree plantation stand age efficiently and non-invasively. By analyzing spectral reflectance patterns, biomass distribution, and canopy structure, remote sensing provides valuable insights across vast areas that ground surveys cannot match. This method aligns with precision forestry and sustainable land management goals, offering a scalable solution for understanding forest dynamics in response to climate change and human activities. Remote sensing integrates advanced technologies such as satellite imaging, aerial photography, and LiDAR to extract detailed forest data. Researchers leverage these tools to distinguish spectral signatures unique to tree species and age classes. For instance, indicators like the NDVI measure canopy density and vigor, correlating with stand age. Combining remote sensing data with machine learning models enhances predictive accuracy by training algorithms using datasets with known ages. Techniques like Random Forest and Support Vector Machines have demonstrated remarkable success, with studies achieving classification accuracies exceeding 93% in distinguishing plantation stand ages. This approach enables efficient forest growth and health monitoring while minimizing ecosystem disruption [162].

The application of remote sensing fosters sustainable forest management by optimizing resource use and conservation strategies. Large-scale data collection from diverse geographic locations enables informed decision-making for harvesting, regeneration, and conservation efforts. Remote sensing also reduces costs compared to traditional methods, requiring fewer resources and personnel for field surveys. This technology supports ecological and economic objectives by providing precise tree plantation stand age estimates, ensuring forestry practices align with environmental sustainability. As forests face increasing pressures from ecological changes, remote sensing offers an indispensable tool for safeguarding these vital ecosystems.

6.2.21. Surface soil moisture mapping

Soil moisture is vital in environmental processes, influencing plant growth, water cycles, and ecosystem health. In forest ecosystems, surface soil moisture dynamics are pivotal for regulating plant production, nutrient cycling, and overall biome functionality [163]. Mapping soil moisture accurately and promptly is essential for sustainable forest management, conservation policies, and climate change assessments. Traditional ground-based techniques, though reliable, are labor-intensive, time-consuming, and limited in spatial coverage [163]. Remote sensing technology offers a powerful alternative, enabling efficient soil moisture monitoring across large regions and diverse time scales [163]. Researchers can produce high-resolution soil moisture maps by analyzing data from sensors like SAR, Optical, and Thermal Infrared, and these maps enhance understanding of soil moisture variability and inform effective forest management strategies. Remote sensing provides unparalleled coverage, enabling researchers to monitor soil moisture over extensive and often inaccessible forest regions. This capability supports regional evaluations and landscape-scale hydrological studies [163]. Satellites equipped with advanced sensors collect data at regular intervals, facilitating the assessment of temporal fluctuations and long-term trends in soil moisture. These data capture seasonal changes, drought impacts, and the influence of climatic events, offering critical information for ecosystem management. Advances in satellite technology now allow the production of high-resolution images, which are instrumental in analyzing microclimates and soil moisture variations within diverse plant covers. Additionally, integrating data from multiple sensors, such as SAR and optical systems, enhances measurement accuracy, even in challenging environments like dense forest canopies. Combining remote sensing data with ground-based observations further improves soil moisture estimation models and supports real-time updates using machine learning techniques.

Remote sensing enhances understanding of soil moisture dynamics by linking moisture content to precipitation, temperature, and vegetation. Analyzing temporal variations in soil moisture enables researchers to identify trends associated with climate change, land-use shifts, and ecosystem health. These insights are invaluable for forest managers, farmers, and conservationists in making informed decisions regarding water resource management, drought mitigation, and sustainable land-use practices. Moreover, soil moisture data from remote sensing contributes to evaluating forest ecosystem resilience and productivity, offering a deeper understanding of biodiversity and plant development in response to environmental changes. As remote sensing technology evolves, its ability to map soil moisture dynamics will continue to improve, supporting sustainable forest management and addressing challenges related to climate change and environmental conservation.

6.2.22. Detecting and monitoring plant water stress in forests

Water stress in forests significantly affects ecosystem health, productivity, and biodiversity, as it arises from insufficient water supply, excessive evapotranspiration, or both. These conditions trigger adverse physiological and biochemical responses in plants, making early diagnosis and monitoring crucial for effective forest management, conservation, and land-use planning. While valuable, traditional ground-based methods for detecting water stress are often labor-intensive and limited in scope [164]. Remote sensing technologies offer a transformative solution by enabling large-scale forest health monitoring and water conditions. Satellites, drones, and ground-based sensors actively monitor plant physiological states, soil moisture levels, and atmospheric conditions, delivering crucial insights into these key factors. Advanced techniques such as multi-spectral and hyperspectral imaging, thermal infrared sensing, and LiDAR capture subtle changes in vegetation responses to water availability, improving the ability to identify stressed areas and guide management decisions [164]. Researchers use remote sensing to efficiently measure plant water stress indicators, such as leaf water potential, stomatal conductance, and canopy temperature, allowing them to identify stressed regions quickly [164]. By integrating remote sensing data with ecological models, scientists can unravel the complex relationships between water availability, climatic variability, and forest health. Multi-spectral and hyperspectral imaging methods measure light reflectance to calculate indices like NDVI and Water Stress Index (WSI), which indicate water stress levels. Thermal infrared sensors detect canopy temperature, a key marker of evapotranspiration and water availability, while microwave remote sensing accurately assesses soil moisture by penetrating vegetation and clouds. These tools actively detect stress early, monitor it over the long term, and help develop adaptive strategies to strengthen forest resilience against climate change.

Remote sensing is critical in prioritizing conservation efforts and resource allocation [164]. Generating visualizations and maps of water stress patterns informs forest managers and policymakers about areas needing immediate attention. These tools support early warning systems that detect signs of water stress, allowing for timely interventions like irrigation or selective thinning. The long-term insights gained from monitoring changing climatic conditions highlight the effects of shifting precipitation and temperature patterns on forest ecosystems. Through its broad applications, remote sensing fosters informed decision-making, promotes sustainable forest management practices, and enhances public awareness of forest ecosystems' challenges.

6.2.23. Mapping successional forest stages

Forests are critical in maintaining global ecological health by supporting biodiversity, regulating the climate, and impacting human life. Understanding forest succession, the series of changes forests undergo over time, is vital for effective forest management and conservation. Factors such as disturbances, climate change, and species interactions influence these successional stages, which mark forest regeneration and biodiversity potential [165]. Remote sensing technology has become invaluable in tracking and mapping these stages, allowing researchers and land managers to monitor forest dynamics across vast and often remote areas. With the ability to collect large amounts of spatial data, remote sensing provides insights into forest cover, structure, and biomass, revealing ecological changes that are difficult to detect through traditional ground surveys. Advances in remote sensing technologies, such as high-resolution imaging, LiDAR, and multi-spectral analysis, have significantly improved the precision of mapping forest stages. These methods help distinguish between forest types and age groups, which is crucial for identifying successional trajectories and guiding conservation efforts. Remote sensing enables large-scale monitoring of successional changes, particularly in areas that are hard to access. High-resolution satellite and aerial imaging allow for in-depth study of forest composition and structure, capturing variations in canopy cover, species diversity, and biomass density. By acquiring temporal data through periodic imaging, remote sensing also helps track the effects of natural disturbances like fires and storms and human-induced changes such as logging or land-use alterations.

Integrating remote sensing data with ecological models provides valuable insights into future forest dynamics under various environmental conditions, offering support for sustainable forest management. Remote sensing generates key indicators such as NDVI, Leaf Area Index (LAI), and biomass estimates, which help identify distinct successional phases and assess forest health. When combined with GIS, this data enables the analysis of forest succession about topography, soil type, and climate, deepening our understanding of ecological processes. By facilitating accurate change detection and supporting biodiversity assessments, remote sensing aids in identifying critical habitats and informs conservation priorities. Neto et al. [165] demonstrated the effectiveness of remote sensing in classifying forest succession stages, using multi-spectral satellite data and LiDAR to analyze three successional stages in a subtropical forest in Brazil. Their study showed that combining spectral data with LiDAR information and machine learning algorithms significantly improved classification accuracy, highlighting remote sensing's potential for mapping forest dynamics.

6.2.24. Mapping of forest vegetation

Mapping forest vegetation is essential for effective forest management, conservation, and sustainable land use planning. As the world faces the growing challenges of climate change, habitat loss, and biodiversity decline, having accurate and up-to-date information about forest ecosystems is more critical than ever. Researchers and practitioners use remote sensing technology to monitor and analyze forest vegetation on a large scale with greater precision. Satellites, aerial vehicles, and drones with various sensors actively collect electromagnetic radiation reflected or emitted from the Earth's surface through remote sensing. This data provides valuable insights into forest vegetation's geographical distribution, structure, and health. Remote sensing allows for the collection of high-resolution images that map the distribution of forest vegetation, even in areas that are difficult to access on the ground. It facilitates long-term forest dynamics monitoring, such as seasonal changes, growth patterns, and disturbance responses. Remote sensing uses multi-spectral and hyperspectral imaging to identify various plant species by analyzing their distinct spectral signatures. This capability aids in creating detailed vegetation maps, assessing biodiversity, and guiding conservation efforts. Additionally, remote sensing can estimate forest biomass and carbon stocks, which are crucial for understanding forest health and their role in climate regulation. Techniques like LiDAR and radar provide precise measurements of forest structure, such as tree height and canopy density, which are vital for calculating biomass and carbon sequestration potential.

Remote sensing monitors forest health by detecting stressors such as pests, diseases, and droughts. Indicators like the NDVI allow for early identification of plant health issues, enabling timely interventions to protect forest ecosystems. By integrating remote sensing data with GIS, researchers can analyze spatial relationships within forest ecosystems, considering factors like topography, soil type, and climate. This integrated approach supports sustainable forest management decisions and effective communication with stakeholders, including governments, local communities, and conservation groups. Ultimately, remote sensing improves our understanding of forest dynamics, enhances resource management strategies, and contributes to global efforts to conserve and protect forests.

Gafurov et al. [166] explored using unsupervised classification methods to map forest vegetation and align it with the Braun-Blanquet classification system through remote sensing. To reduce researcher bias, they combined Landsat 8 and 9 satellite images with advanced clustering methods, specifically Weka X-Means, using a two-step clustering process to categorize forest communities accurately. They employed comprehensive vegetation indices to distinguish various forest ecosystem types. They validated their model by comparing it with over 17,000 relevés from the "Flora" database, ensuring accurate alignment with field data. Their approach successfully identified 44 forest community types, grouped into seven main classes using the Braun-Blanquet method. These results demonstrate the effectiveness of unsupervised classification in generating reliable vegetation maps, contributing to remote sensing applications in ecological research, and supporting forest management and conservation strategies to maintain forest ecosystems worldwide.

6.2.25. Estimating forest stand density

Accurately assessing forest stand density, or the number of trees per unit area, is vital for effective forest management, conservation, and sustainable development. While traditional ground-based methods are accurate, they are labor-intensive, time-consuming, and limited geographical coverage [167]. Remote sensing technologies offer a more efficient and scalable solution, enabling large-scale forest structure and density evaluations [167]. Technologies such as LiDAR, multi-spectral, and hyperspectral photography have enhanced the ability to gather precise data on key forest parameters, such as tree height, crown size, and canopy cover, which are essential for estimating stand density. Additionally, remote sensing facilitates continuous forest dynamics monitoring, allowing for quick identification of changes due to disturbances, climate change, or human activities [167]. Remote sensing assesses vast forest areas that would be difficult to cover with traditional ground-based methods. Equipped with sensors, satellites and aircraft can collect data across thousands of hectares, enabling comprehensive evaluations of forest density in diverse terrains. High-resolution satellite images and LiDAR technology provide valuable spatial data, capturing variations in tree height, canopy structure, and spacing for more accurate density estimates. Furthermore, the temporal precision of remote sensing enables the tracking of forest density changes over time, aiding in understanding growth dynamics, disturbances, and management impacts. Remote sensing techniques can also measure crucial parameters affecting stand density, such as tree height, canopy cover, and vegetation indices like NDVI, indirectly providing insights into forest health and density.

While remote sensing technologies may involve higher initial costs, they often prove more cost-effective than traditional ground surveys, especially in extensive forests. Remote sensing reduces personnel and time expenses associated with data collection and processing, making it an appealing choice for forest management. It also integrates seamlessly with GIS systems, allowing for comprehensive spatial analyses and modeling of forest stand density. This integration supports better forest management and conservation decision-making by providing geographic context.

6.2.26. Mapping wetland forests

Wetland forests play a vital role in biodiversity, carbon sequestration, and water purification, yet they face increasing threats from climate change, urbanization, and agricultural expansion. Effective management and conservation rely on accurately mapping and monitoring these ecosystems to ensure their protection and sustainability. Remote sensing technology offers powerful tools for assessing wetland forests by providing geographical and temporal data over large regions [168]. These tools, including satellite data and aerial imagery, enable researchers to detect subtle changes in forest cover, hydrology, and vegetation health that may not be visible through ground surveys, resulting in a more comprehensive understanding of wetland dynamics. Remote sensing, combined with GIS, enhances the ability to monitor vast wetland areas, making it possible to track changes in land use, forest cover, and ecological health over time. Using advanced sensors like multi-spectral, hyperspectral, and LiDAR technology, researchers can gather detailed information about plant species, biomass, and vegetation stress [168]. These technologies also provide valuable insights into the hydrological aspects of wetland ecosystems, including water bodies, soil moisture, and hydrological trends. By analyzing remote sensing data, scientists can create precise land cover maps, detect wetland forests, and identify their boundaries, aiding land management and conservation planning [168]. Integrating remote sensing data with ecological models allows researchers to track biodiversity, habitat quality, and the impact of environmental stressors on wildlife populations in wetland forests. Remote sensing also helps monitor climate change's effects by tracking temperature, precipitation, and seasonal variations. These insights are crucial for developing adaptive management strategies. Remote sensing provides detailed, long-term data supporting informed decision-making, policy formation, and effective conservation strategies to protect wetland forests and their vital ecological services [168].

6.2.27. Assessing forest fragmentation

Forest fragmentation occurs when large forested areas break into smaller, isolated patches, threatening biodiversity, ecosystem services, and forest health. This disruption diminishes habitats for wildlife, limits species movement, and affects the overall functioning of ecosystems. Urbanization, agricultural expansion, and infrastructure development are major drivers of land use and land cover changes, particularly in environmentally sensitive regions [169]. This fragmentation reduces the ecological integrity of landscapes, negatively impacting wildlife habitats, plant diversity, and ecosystem functions. Remote sensing technologies have proven to be powerful tools for measuring and monitoring forest fragmentation. By collecting high-resolution data through satellite images, aerial photography, and advanced sensors, researchers can track changes in forest cover and fragmentation patterns over time, providing a comprehensive view of forest dynamics and aiding conservation efforts [169]. Remote sensing enables researchers to capture fine details about forest environments, making it possible to identify small patches of forest, land use changes, and variations in forest density—key indicators of fragmentation. The technology allows for long-term monitoring, revealing how fragmentation evolves due to human activities, natural disturbances, or climate change. By analyzing historical data, researchers can pinpoint critical periods of fragmentation and identify trends in forest cover loss and regeneration. Remote sensing also offers valuable metrics for assessing fragmentation, such as patch size (influencing species survival), edge density (impacting species movement and biodiversity), and connectivity (affecting wildlife movement and gene flow). Change detection analysis can highlight how urbanization, agriculture, and road development contribute to forest fragmentation [169].

In addition to monitoring forest fragmentation, remote sensing helps evaluate forest health by assessing vegetation indicators like the NDVI, which reflect plant vitality, biomass, and ecosystem well-being. Fragmented ecosystems often support fewer species, and remote sensing helps identify regions where biodiversity may be at risk. By combining remote sensing data with GIS, researchers can conduct spatial analysis and model fragmentation patterns, enhancing our understanding of landscape connectivity and ecological consequences. The data gathered through remote sensing aids policymakers and conservationists in designing effective strategies to mitigate fragmentation, restore degraded ecosystems, and promote sustainable land management. As remote sensing technologies evolve, they provide an increasingly cost-effective way to monitor large-scale forest changes, improving our ability to manage and protect forest ecosystems.

6.2.28. Support for REDD+ programs

Reducing Emissions from Deforestation and Forest Degradation (REDD+) is a global initiative to combat climate change through forest protection and sustainable management. It recognizes trees' vital role in sequestering carbon dioxide, essential for climate stability and local community well-being. Achieving REDD+ goals requires accurate and timely data on forest cover, health, and changes over time. Remote sensing delivers this essential information, enabling effective forest monitoring and management. By utilizing satellite imaging and aerial surveys, remote sensing allows stakeholders to monitor and analyze forest resources at local, national, and global levels, offering insights into forest size, biomass, and carbon stock. This information helps inform better forest management and conservation decisions while enhancing enforcement efforts' effectiveness to curb deforestation and degradation. Remote sensing is crucial in building national forest monitoring systems (NFMS) for REDD+ preparedness. These systems use satellite data, ground observations, and modeling to deliver transparent and comprehensive evaluations of forest resources, fostering accountability and trust among stakeholders like governments, NGOs, and local communities. Machine learning and AI advances enhance the accuracy and efficiency of remote sensing analysis, enabling more effective tracking of changes in forest cover, biomass, and carbon stocks. This ability to detect and measure forest dynamics supports identifying areas at risk of deforestation and degradation, enabling more targeted conservation and management efforts. Moreover, accurate data on carbon reserves is critical for setting baselines and monitoring progress toward emissions reduction targets.

Remote sensing technologies also support spatial planning and land-use management by identifying areas suitable for conservation, replanting, or sustainable forestry practices. This data helps policymakers balance development needs with environmental preservation. Additionally, remote sensing tools empower local communities by providing accessible and transparent information about their forest resources. Engaging these communities in monitoring activities fosters a sense of ownership and involvement in REDD+ projects, enhancing conservation efforts. Remote sensing also contributes to understanding the potential impacts of climate change on forest ecosystems, helping to develop adaptive management strategies that strengthen forest resilience. By combining remote sensing with GIS and other monitoring technologies, REDD+ initiatives can leverage comprehensive data platforms that improve decision-making and increase the success of forest conservation efforts.

6.3. Artificial Intelligence

Artificial intelligence transforms sustainable forest management by enhancing decision-making, optimizing resources, and supporting sustainability efforts. It processes large datasets, automates tasks, and extracts treasured insights, making it a powerful tool for tackling challenges like deforestation, illegal logging, wildfires, and climate change. Some of the most important applications of artificial intelligence in sustainable forest management include:

6.3.1. Pre-, active-, and post-forest wildfire detection and management

Artificial intelligence is transforming the management of forest wildfires by enhancing the pre-, active-, and post-fire detection processes. Wildfires, worsened by climate change, pose significant threats to ecosystems, human life, and property [19]. Traditional forest fire prediction and monitoring methods, which rely heavily on statistical models and expert opinions, are time-consuming. However, AI technologies like machine learning, deep learning, and computer vision offer promising improvements in wildfire detection and management. These systems deliver real-time data and predictive insights for early detection, prevention, and quick response [170]. Decision Trees, Random Forests, and Convolutional Neural Networks have been proven effective in predicting fire occurrences [171][172]. AI models, including fuzzy logic, simulate uncertainty in environmental factors and fuel supply, providing more accurate wildfire behavior predictions [20]. Deep learning algorithms, particularly Deep Neural Networks, have dealt with complex challenges in wildfire control activities. Deep learning systems can handle massive volumes of data, allowing for faster, more efficient, and accurate real-time wildfire detection. Wildfire classification systems use deep learning algorithms to recognize and categorize wildfires based on flame color, smoke density, and temperature trends [69]. AI-driven solutions also offer significant advancements in capturing and analyzing large data streams, facilitating faster decision-making and resource allocation for emergency responders [69].

In the pre-fire phase, AI uses predictive models and machine learning to assess wildfire risk by analyzing historical data, weather patterns, and environmental factors, identifying high-risk areas early, and facilitating proactive interventions like controlled burning and resource deployment [171]. AI technologies, including satellite imagery and drones, support active wildfire control by providing real-time monitoring and mapping of fire spread. AI systems help optimize evacuation plans, resource distribution, and containment strategies. AI algorithms also assist in predicting fire behavior based on environmental conditions, ensuring timely action to prevent further damage. Real-time meteorological data and AI-driven algorithms improve the accuracy of early warning systems, enabling faster response times. During active fire events, AI technologies enable situational awareness and decision support, ensuring more effective resource deployment and coordination among emergency responders. Autonomous drones and robots powered by AI enhance firefighting efforts by collecting data and monitoring hard-to-reach areas.

In the post-fire phase, AI is crucial in damage assessment, ecosystem recovery, and post-fire replanting efforts. AI-driven image analysis uses satellite and drone data to assess forest damage, including the loss of vegetation and soil degradation. It also tracks ecological recovery, monitors soil moisture and vegetation regeneration, and aids in planning reforestation efforts. AI models predict secondary risks such as soil erosion and future fires, assisting in developing mitigation strategies. Additionally, AI evaluates the impact of wildfires on wildlife habitats and supports habitat restoration by combining various environmental data sources. AI-driven air and water quality analysis helps identify post-fire contaminants, guiding public health responses and community safety. Using AI to assess economic damages and facilitate insurance claims speeds up recovery efforts. By streamlining the post-fire analysis and response, AI enhances the ability of forest managers and communities to recover more effectively, reduce risks, and build resilience against future wildfires.

Several recent studies have explored the application of AI in forest wildfire detection and management. Kesarkar et al. [173] developed a proactive strategy integrating advanced technologies like YOLOv8 image classification and predictive modeling. By leveraging UAVs for real-time monitoring of high-risk forest areas, their system effectively detects fires early, allowing timely interventions. Their YOLOv8n model accurately classified fire images, while a logistic regression model predicted fire vulnerability based on environmental factors. Mamadaliev et al. [174] introduced the Edge-Segmentation-Feature Detection (ESFD)-YOLOv8n model, incorporating Wise-IoU v3 for enhanced accuracy, simplified architecture with residual blocks, and generalized efficient layer aggregation network (GELAN) blocks for optimized learning. Their model outperformed YOLOv8n, achieving a mean average precision (mAP@0.5) of 79.4%, with 80.1% accuracy and 72.7% recall. Secilmis et al. [175] actively reviewed machine learning-based methods for fire detection, utilizing a range of datasets to evaluate and compare the performance of different classification models. Their results showed that the Multi-Layer Perceptron (MLP) model achieved the highest accuracy (0.997) and outperformed others in ROC curve performance. Seddouki et al. [176] employed GIS-based machine learning algorithms, including XGBoost, Random Forest, and Support Vector Machines, to create forest fire susceptibility maps in northern Morocco. XGBoost delivered the best performance (AUC = 0.856), enabling better Mediterranean resource management and ecological planning.

6.3.2. Monitoring, tracking, and combating deforestation and illegal wood logging

Deforestation and illicit logging pose significant global challenges with long-term environmental, social, and economic consequences. Unsustainable practices like illegal logging and clear-cutting for agriculture have led to severe forest loss, driving climate change and biodiversity collapse. Effective, scalable, and affordable solutions are necessary to address these issues, focusing on adaptability to emerging threats [63]. Artificial intelligence offers groundbreaking potential in combating deforestation by enhancing monitoring, tracking, and intervention efforts across diverse ecosystems. AI-driven technologies leverage satellite imagery, machine learning, and remote sensing to monitor forests globally, detecting illegal activities and assessing deforestation trends with high precision. Image recognition algorithms can quickly process vast amounts of satellite and drone footage to identify changes in forest cover, with convolutional neural networks excelling at early detection of illicit logging. Predictive AI models, informed by historical deforestation data, socioeconomic factors, and land-use patterns, forecast high-risk areas for illegal activity. These models help allocate resources more efficiently, prioritizing regions for intervention. IoT sensors, such as acoustic and vibration sensors, further enhance monitoring by detecting the sounds of chainsaws or the movement of heavy machinery, alerting authorities to potential illegal logging [63][177]. AI also supports policymakers in creating effective forest conservation strategies by analyzing environmental, economic, and social data. Natural language processing algorithms assist in identifying legal gaps that allow illegal logging to persist, while AI-driven analytics enable informed decision-making for preemptive actions. AI empowers local communities by providing real-time data visualizations and insights into deforestation, fostering accountability and grassroots efforts to protect forests.

Notable research studies, such as those by the World Resources Institute, collaborating with the Central Africa Regional Program for the Environment (CARPE), utilized AI and spatial modeling to pinpoint key causes of deforestation in the Democratic Republic of Congo. They identified factors such as shifting agriculture, highways, and climatic elements like precipitation as major contributors. Their research emphasized the vulnerability of forests near agricultural areas [63]. Similarly, Estonian start-up Timbeter uses AI and the largest database of photometric observations for Roundwood to track timber shipments and piles, enabling real-time monitoring and improving supply chain transparency. German start-up Xylene integrates AI with space technology, Blockchain, IoT devices, and Earth observation to instantly track the wood supply chain, ensuring timber sources' integrity and combating illegal logging and trafficking [178]. AI is transforming how we monitor forests and address unlawful logging, offering solutions for both predictive and preventative measures. By automating and improving monitoring processes, AI enables timely interventions and more effective policy creation. These innovations are helping to safeguard forests, promote sustainable forest management, and create a more sustainable future through cutting-edge, actionable solutions.

6.3.3. Forest tree species classification

Artificial intelligence is crucial in environmental science, particularly forest tree species classification. Machine learning and deep learning provide efficient and automated systems that surpass traditional methods in accuracy and speed. While traditional tree species classification often requires labor-intensive fieldwork, AI-driven approaches utilize large datasets and remote sensing technologies like satellite imagery, LiDAR, and hyperspectral imaging to analyze forest composition on a larger scale. These advancements enable accurate species identification, even in complex and diverse forest ecosystems, improving biodiversity management and conservation efforts [133]. AI-based methods excel in analyzing visual and spectral data, such as images from satellites, drones, and ground-based cameras, to detect distinct features like leaf shape, bark texture, and canopy structure that distinguish tree species. Machine learning algorithms, particularly convolutional neural networks, process this data quickly and highly, eliminating the need for extensive fieldwork. AI also enhances the analysis of multispectral and hyperspectral data, allowing for identifying species that appear similar but have unique spectral signatures. By combining data from various sources, AI provides comprehensive insights that aid species identification, especially in dense and ecologically complex areas. AI's ability to process large-scale data also helps with long-term monitoring, tracking changes in forest composition over time. This capability is crucial for understanding the impacts of climate change, forest disturbances, and other environmental stresses. AI can offer real-time detection in field settings using mobile devices and drones, enabling faster forest management and conservation decision-making. AI supports policy development, sustainable forest management, and targeted conservation efforts by offering reliable biodiversity and forest health data. Studies such as those by Zhong et al. [179] demonstrate the significant potential of AI in revolutionizing tree species classification and forest ecosystem management.

6.3.4. Forest type classification

Artificial intelligence has revolutionized forest-type classification by offering a faster, more accurate, and scalable approach compared to traditional methods. Forest categorization is essential for understanding ecosystems' structure, composition, and function, providing valuable insights for conservation, resource management, and climate action [170]. Traditionally, forest classification relied on time-consuming field surveys and manual interpretation of satellite or aerial imagery, which were costly and prone to observer bias. AI, especially machine learning and deep learning algorithms has made it possible to classify forest types more efficiently by analyzing complex datasets from remote sensing, LiDAR, hyperspectral data, and environmental factors. These AI models can identify subtle ecological differences and detect changes over time, supporting biodiversity conservation and climate resilience efforts. AI excels in processing vast amounts of remote sensing data, identifying intricate patterns that distinguish forest types based on canopy density, leaf types, and structural characteristics. AI can detect slight changes between deciduous, evergreen, and mixed forests through multispectral and hyperspectral data, which capture distinct spectral signatures for various forest types. Combining LiDAR data, which provides detailed topographical and structural features like canopy height and density, AI models can accurately classify forests, particularly in ecologically complex regions where traditional methods struggle. Additionally, AI can analyze temporal data to track changes in forest composition over time, allowing researchers to detect shifts caused by factors like deforestation, reforestation, and climate change, thus aiding long-term forest management.

AI-driven forest-type classification has numerous practical applications, from real-time assessments using drone-mounted systems to supporting policy decisions regarding conservation and resource allocation. AI-powered mobile apps and drone systems enable on-the-ground data collection and quick analysis, making it easier for forest managers and researchers to respond rapidly to issues like wildfires or habitat restoration. By integrating data from various sources, such as climate conditions and soil types, AI enhances the accuracy of forest categorization and contributes to comprehensive ecosystem studies. This integrated approach helps guide sustainable management practices, biodiversity conservation, and policy planning, ensuring more informed decisions about protected areas, deforestation mitigation, and ecosystem service monitoring. AI's role in forest classification strengthens efforts to combat climate change and promotes more effective forest management.

Some notable research works that applied AI in forest-type classification include Zhang et al. [181], who developed a deep learning-based classification system to distinguish between coniferous and broadleaf forests on the Loess Plateau, achieving high efficiency and accuracy. Combining a deep residual neural network (ResNet) architecture with transfer learning and multispectral data from UAVs and Landsat improved classification performance using well-designed experiments. The study identified optimal spectral band combinations through a random forest approach and fine-tuned the pre-trained models based on picture size, sample number, and model depth, boosting classification accuracy from 85% to 93% in Zhengning, 89% to 96% in Yongshou, and 86% to 94% in Baishui. Similarly, Pei et al. [180] used high-resolution aerial images to compare a multiscale global graph convolutional neural network with random forest, U-Net, and U-Net++ models for classifying natural mixed forest, broadleaved forest, and conifer plantation. Their study found that natural mixed forests were more challenging to classify accurately than the other types. These advancements highlight how artificial intelligence enhances forest-type categorization, offering more accurate, efficient, and scalable solutions than traditional methods, ultimately aiding biodiversity conservation, ecosystem monitoring, and sustainable forest management amidst climate change challenges.

6.3.5. Forest tree disease detection

Artificial intelligence is revolutionizing forest tree disease detection by providing an efficient and scalable approach to diagnosing and managing plant diseases. Climate change, invasive species, and human activity increasingly threaten forests, making them more vulnerable to diseases. Traditional methods of disease identification, such as visual inspection and laboratory testing, can be time-consuming, costly, and labor-intensive. AI technologies, including machine learning, computer vision, and deep learning, automate the detection process, enabling faster and more accurate identification of tree diseases across large forest areas. By analyzing extensive datasets from remote sensing tools like satellite images, drone footage, and ground-based sensors, AI offers a robust early diagnosis and treatment solution, helping limit disease spread and improve forest health. AI-driven algorithms, particularly computer vision-based ones, can diagnose tree diseases by analyzing images and multispectral data. These algorithms learn to identify disease-specific symptoms from large annotated datasets, such as leaf discoloration, defoliation, and irregular growth patterns. This reduces the need for manual inspections while enhancing diagnostic speed and precision. Remote sensing technologies like drones, satellite imagery, and LiDAR enable AI to monitor vast, hard-to-reach forest regions continuously. By analyzing the data’s spectral signatures and spatial patterns, AI detects early signs of tree stress and disease, enabling real-time monitoring even in remote areas. Machine learning models can also forecast disease progression and transmission by analyzing various risk factors, including climate conditions, tree species vulnerability, and disease history.

AI insights assist forest managers in developing precision forestry strategies that target areas needing immediate attention. For example, AI can guide selective logging, quarantine measures, and targeted treatment applications, optimizing resources and minimizing environmental impact. Real-time monitoring systems powered by AI can detect deteriorating tree health by collecting data from IoT sensors placed on trees or throughout the ecosystem. These systems can trigger alerts when abnormalities are detected, allowing for swift action and reducing disease transmission risks. By combining data from diverse sources, AI helps forest managers make informed decisions, such as selecting disease-resistant tree species and optimizing forest planting patterns. Zhu et al. [182] conducted significant research on identifying forest tree diseases using artificial intelligence. They used high-resolution helicopter footage and the deep learning model YOLO v7 to detect diseased forest trees. By incorporating attention mechanism technologies, they enhanced the model’s accuracy. In a comparative analysis, the YOLO v7-SE model outperformed others, achieving an accuracy rate of 0.9281, a recall rate of 0.8958, and an F1 score of 0.9117. This work demonstrates the effectiveness of automatic tree disease detection in forest environments, providing reliable support for prevention and control efforts while highlighting the importance of attention mechanisms in improving detection performance.

6.3.6. Estimating forest growth and yield

In recent years, AI has become a transformative tool in forestry, enhancing the precision and efficiency of forest growth and production projections. Traditionally, estimating forest growth and productivity has relied heavily on extensive field data collection, modeling, and statistical analysis. However, the complexity of forest ecosystems—shaped by species composition, climate change, soil conditions, and human impacts—has made accurate assessments difficult using conventional methods. AI enables the integration of massive datasets and advanced algorithms, offering new possibilities for capturing subtle trends and interactions that were previously difficult to quantify. Machine learning and deep learning techniques analyze vast volumes of environmental data, allowing AI models to generate more accurate forecasts of forest dynamics under varying scenarios. AI-based models can combine diverse data sources, such as remote sensing imagery, climate data, soil types, and species distribution, to create a robust foundation for estimating forest growth and yield. Machine learning algorithms identify patterns and correlations between environmental factors and growth rates, enabling more accurate future forest growth and dynamics predictions. Unlike traditional models, which often struggle with the nonlinear relationships typical of ecological systems, AI captures these complexities with greater precision. Using data from satellite images, drones, and sensor networks, AI supports real-time forest monitoring, identifying subtle changes in tree growth, canopy density, and pest or disease infestations. This continuous data stream empowers forest managers to take timely, proactive actions to ensure forest health and productivity.

AI-driven simulations model various scenarios, such as the impacts of climate change, deforestation, and restoration efforts, to predict how forests will respond to different management approaches. By simulating these situations, AI allows forest managers to test the potential outcomes of decisions before implementation, leading to better-informed choices. AI optimization algorithms further support resource allocation by recommending thinning or harvesting schedules and identifying areas requiring conservation efforts. This strategic approach ensures sustainable forest management, balancing ecological health with economic objectives. AI not only refines forest growth and yield predictions but also supports decision-making processes, helping to develop policies that mitigate environmental impact while enhancing forest productivity.

6.3.7. Monitoring ecology and biodiversity

Artificial intelligence revolutionizes ecological monitoring by providing innovative solutions to address some of the most urgent environmental challenges. Traditional ecological monitoring requires extensive fieldwork, making it difficult to gather data at the scale and frequency needed to analyze complex ecosystems properly. AI enables tracking species populations, assessing ecosystem health, and monitoring biodiversity on larger spatial and temporal scales through machine learning, deep learning, and computer vision. AI tools process data from various sources, such as satellite images, remote sensors, camera traps, and bioacoustic recordings, allowing researchers to detect minute environmental changes, identify species, and track trends with unprecedented precision and efficiency [63][178]. AI-driven monitoring is crucial in addressing biodiversity challenges, including habitat loss, climate change, and resource overexploitation. By providing comprehensive insights into ecological patterns, AI helps scientists identify at-risk species and locations, predict potential changes, and implement targeted conservation efforts. For example, AI algorithms can quickly analyze photos and videos from camera traps, drones, and satellites to automate species identification, track individuals, and measure population densities. Machine learning models assess data from various sensors, such as temperature, humidity, and sound, to provide valuable information on ecosystem health, resilience, and the effects of environmental stressors like deforestation and climate change. AI can also simulate ecosystem dynamics, allowing for better predictions of biodiversity shifts over time.

AI's ability to detect invasive species and environmental threats enhances early detection and rapid response. By identifying unusual patterns in data, AI models can pinpoint the spread of non-native species, disease outbreaks, pollution, and habitat degradation at early stages, minimizing potential harm. Shi et al. [146] developed a deep convolutional neural network to identify individual Amur tigers by analyzing photos, achieving accuracy rates of 90.48% for the left and 93.5% for the right sides. Using experimental data from 40 tigers at Tieling Guaipo Tiger Park in China, the team collected 8,277 images, each photographed approximately 200 times. Their method performed comparably to advanced networks such as LeNet, ResNet34, and ZF_Net while significantly reducing runtime. This innovative approach enhances automatic individual identification, contributing to biodiversity monitoring, conservation efforts, and resolving human-wildlife conflicts.

AI is also revolutionizing biodiversity monitoring in dense habitats using bioacoustics, where machine learning identifies animal vocalizations and provides insights into species presence, population, and behavior. AI supports predictive modeling, which forecasts the impact of land-use changes, climate shifts, and human activity on biodiversity. In addition to these capabilities, AI aids citizen science initiatives by processing crowdsourced data, filling data gaps in remote areas, and enhancing biodiversity mapping. With these advancements, AI empowers conservationists to safeguard ecosystems and adapt to a rapidly changing world.

6.3.8. Biodiversity conservation

Human activities are rapidly causing biodiversity loss, driving species to extinction and degrading habitats at an alarming rate. Addressing these challenges requires urgent and innovative approaches to complement traditional conservation strategies. Artificial intelligence offers groundbreaking tools that transform biodiversity conservation efforts by enhancing data collection, analysis, and decision-making processes. Machine learning, computer vision, and NLP enable rapid detection of environmental changes, hazard identification, and species monitoring on a large scale. AI-powered models also deliver predictive insights, helping conservationists anticipate future trends and evaluate the potential impact of conservation measures under varying scenarios. For instance, AI systems can instantly process satellite images and sensor data to detect illegal logging activities, enabling timely interventions to protect forest ecosystems. Integrating AI into conservation efforts accelerates our ability to monitor biodiversity, manage ecosystems, and develop effective policies. AI-enabled video traps and acoustic sensors continuously gather data on wildlife behavior, population dynamics, and habitat use [183]. Advanced models assess geographical information, such as land cover and species ranges, to identify critical habitats and predict how species might respond to environmental changes. Predictive AI applications also analyze data to foresee challenges like climate change impacts, the spread of invasive species, and poaching risks. These technologies empower conservationists to implement proactive strategies, such as designing protected zones, restoring damaged ecosystems, and facilitating species adaptation to shifting habitats [183]. AI-driven conservation also fosters public engagement and interdisciplinary collaboration while emphasizing ethical considerations. Citizen science initiatives use AI to process data submitted by volunteers, increasing awareness and community involvement. AI tools enhance resource allocation by identifying priority areas and crafting cost-effective strategies to maximize conservation benefits. Non-invasive techniques like environmental DNA analysis use AI to detect species presence from genetic material in soil, water, or air samples, broadening biodiversity studies without disturbing ecosystems. AI is increasingly active in biodiversity conservation, offering innovative solutions to safeguard ecosystems and foster sustainable coexistence between human development and nature.

6.3.9. Forest carbon sequestration and carbon stock monitoring

Forests actively combat climate change by absorbing carbon dioxide from the atmosphere, significantly reducing global greenhouse gas emissions. Deforestation and forest degradation, however, contribute approximately 11% of global carbon emissions—surpassing the emissions from the global transportation sector and ranking second only to the energy sector. Through photosynthesis and carbon storage in biomass, forests serve as one of Earth's principal carbon sinks, capable of offsetting substantial emissions if managed and protected effectively. Despite their importance, accurately monitoring carbon stocks and calculating forests' carbon sequestration capacity remains challenging. Traditional methods, like field sampling and manual measurements, provide accuracy but are labor-intensive, time-consuming, and limited in scale. Advances in AI are transforming forest carbon monitoring, offering new tools to analyze carbon dynamics and support climate change mitigation efforts [63]. With remote sensing technologies like satellite imagery and LiDAR data, machine learning techniques enable large-scale and accurate assessments of forest carbon stocks and trends [63]. AI-driven systems process vast datasets in real-time, empowering researchers, forest managers, and policymakers to monitor carbon fluctuations, evaluate forest health, and predict carbon sequestration outcomes. Using remote sensing data, AI generates detailed maps of forest cover, canopy height, and biomass, creating reliable databases to track carbon changes. Organizations like IBM and Pachama have developed AI tools that precisely map individual trees and global biomass, enhancing carbon accounting accuracy and informing conservation strategies [177]. These technologies align with global goals like Sustainable Development Goal 13 by improving carbon sequestration monitoring and reporting and advancing climate adaptation and mitigation efforts.

AI algorithms streamline forest monitoring by analyzing imagery to classify vegetation, assess forest health, and estimate carbon storage [183]. These models integrate diverse datasets—including tree measurements, soil carbon, and meteorological data—to construct comprehensive views of forest ecosystems. Machine learning refines traditional allometric models and adapts them to different species and regions, enhancing carbon stock predictions. AI also detects deforestation and forest degradation in near-real time, enabling swift action against threats to carbon stocks. Additionally, AI-powered simulation models forecast forest growth, carbon capture, and the effects of various climate or land-use scenarios, helping policymakers optimize forest management practices. By improving carbon accounting and supporting sustainable forestry policies, AI ensures forests remain critical allies in the fight against climate change.

6.3.10. Forest hydrology

Forest hydrology, the study of water flow, distribution, and quality in forested habitats, is critical in maintaining ecological balance and ensuring a sustainable freshwater supply. Forests regulate streamflow, groundwater recharge, and water quality, making them vital contributors to the global water cycle. However, climate change, deforestation, and land-use pressures challenge traditional hydrological models, often failing to capture forested watersheds' complex, nonlinear dynamics. Artificial intelligence enables advanced data analysis, prediction, and modeling. Techniques like machine learning and deep learning empower researchers to analyze vast datasets, identify intricate patterns, and predict hydrological behaviors with improved accuracy, even under diverse and changing environmental conditions [178]. By leveraging AI, scientists can enhance streamflow forecasts, optimize soil moisture monitoring, and assess the effects of climate variability on water resources with unprecedented precision [63][178]. AI enhances forest hydrology research by integrating datasets from remote sensing, meteorological stations, and environmental sensors, providing a unified framework for studying hydrological processes. Machine learning models excel at forecasting complex phenomena such as streamflow, rainfall-runoff interactions, groundwater levels, and soil moisture, often outperforming traditional statistical methods. Deep learning models further explore relationships between forest characteristics—like canopy density and tree species—and hydrological processes, revealing insights into interception, infiltration, evapotranspiration, and ecosystem water balance. AI-driven image processing techniques also monitor soil erosion and sediment transport, helping forest managers identify high-risk areas and mitigate sedimentation impacts. Researchers leverage these capabilities to actively predict how floods, droughts, and heat waves impact water availability, quality, and distribution in forested regions over time [63][178].

AI integrates predictive models and risk assessments, supporting sustainable forest and watershed management decision-making. AI models optimize forest management strategies, including selective logging, restoration efforts, and water conservation, ensuring adaptability to changing hydrological and environmental conditions. AI-powered monitoring systems actively track critical hydrological parameters in real-time, delivering early warnings for extreme weather events. These systems enhance community preparedness and strengthen ecological resilience. As AI technologies continue to evolve, their applications in forest hydrology will deepen our understanding of water dynamics, supporting the protection of forests and the vital water resources they provide.

6.3.11. Improving forest above-ground biomass estimation

Accurately assessing above-ground biomass in forest ecosystems is vital for carbon estimation, biodiversity conservation, and sustainable forest management. Traditional methods rely on field observations, which are often labor-intensive and limited by geographical and logistical constraints [184]. However, advancements in remote sensing and AI are transforming this process, offering more precise and efficient approaches. AI enables researchers to process and analyze datasets from LiDAR, multispectral, and hyperspectral imaging sources. Machine learning algorithms, like neural networks and support vector machines, effectively identify complex patterns in high-dimensional data, enhancing biomass estimation across various forest types and regions [184]. AI improves the integration of multiple data sources, such as remote sensing imagery, climate data, and soil properties, to provide a comprehensive understanding of forest conditions. By combining these datasets, AI-driven models achieve greater accuracy in estimating above-ground biomass. Advanced algorithms efficiently process large-scale data, extracting key parameters like canopy height, density, and spectral signatures for biomass calculation. Researchers have demonstrated the effectiveness of ensemble learning approaches, which combine predictions from multiple machine learning models to enhance estimation accuracy and stability [184]. Luo et al. [184] evaluated various machine learning models, including CatBoost, LightGBM, random forest (RF), and XGBoost, and demonstrated that their hybrid model consistently outperformed the individual models. This highlights the effectiveness of ensemble techniques in enhancing the accuracy of biomass forecasting.

AI's ability to monitor forests over time supports adaptive management by detecting changes in biomass caused by natural or human-induced disturbances. It also improves scalability, automating the processing of extensive datasets to deliver reliable biomass estimates across large regions. By quantifying uncertainties in data and predictions, AI offers forest managers more precise insights into the confidence levels of biomass assessments. Integrating AI insights with local ecological knowledge allows for creating models tailored explicitly to ecosystems' unique characteristics and the needs of their communities. These advancements enable stakeholders to make informed decisions on forest conservation, carbon trading, and land-use planning, helping them align with broader sustainability goals. Integrating AI into biomass assessment marks a significant leap forward in forest management and ecological research.

6.3.12. Estimating forest degradation

Forest degradation is a major driver of biodiversity loss and climate change, significantly impacting ecosystems, local communities, and the global carbon cycle. However, precisely quantifying this degradation remains challenging due to its complex and often subtle nature. Traditional monitoring methods, including field surveys and remote sensing, provide valuable insights but face limitations such as geographic constraints, high costs, and the necessity of human involvement. Recent advancements in AI offer new opportunities for more accurate and scalable assessments of forest degradation. By integrating machine learning, deep learning, and computer vision techniques, AI algorithms can analyze large-scale satellite images, LiDAR data, and other remote sensing sources, detecting subtle signs of deterioration such as selective logging, canopy gaps, and edge disturbances that traditional methods often miss. AI efficiently processes vast amounts of remote sensing data, such as satellite imagery, LiDAR, and UAV (drone) data. These algorithms can detect degradation trends like deforestation, canopy thinning, and selective logging that human observers often overlook.

AI also improves the detection of subtle signs of degradation, such as small-scale logging, understory thinning, and changes in tree species composition. Convolutional neural networks excel in identifying minor variations in canopy structure, enhancing sensitivity in degradation assessments. Furthermore, AI models can predict future degradation trends by analyzing current data, historical patterns, and environmental factors, helping conservationists prioritize high-risk areas. AI offers a comprehensive view of forest health by integrating various data sources like climate, socioeconomic indicators, and field observations. This data-driven approach supports informed decision-making for sustainable forest management, guiding conservation, land use, and restoration policies. As AI technology advances, its role in forest conservation and monitoring will continue to expand, offering powerful tools to tackle forest degradation in the face of climate change and biodiversity loss.

6.3.13. Afforestation and reforestation automation

Deforestation drives climate change and biodiversity loss, making implementing scalable and effective forest restoration strategies crucial. Traditional methods of afforestation and reforestation often require extensive labor, significant financial resources, and lengthy timeframes, limiting large-scale adoption. Artificial intelligence offers a disruptive approach, enabling precise planning, monitoring, and managing forest restoration efforts. In recent years, AI technologies such as machine learning, computer vision, and robotics have optimized various stages of the afforestation and reforestation processes, from site and species selection to real-time monitoring. By integrating data from satellites, drones, and sensors, AI-powered solutions reduce costs and improve the efficiency and success of reforestation projects [63][178]. AI systems identify optimal areas for afforestation and reforestation by analyzing vast datasets, including satellite images, topographical maps, and soil composition. Machine learning models assess environmental factors like climate, biodiversity, and land use patterns to pinpoint ideal planting locations. Based on environmental conditions and historical data, AI helps predict the most suitable tree species for specific areas. These systems also aid in selecting species resilient to climate change and local pests, fostering biodiversity and ecosystem stability. AI-powered drones and robots transform the planting process by autonomously planting seeds or seedlings in remote or difficult-to-reach locations. These devices use computer vision algorithms to identify optimal planting spots, ensuring ideal spacing and placement for maximum growth potential. Companies like Dendra and Land Life leverage AI-driven automation and digital intelligence to enhance their reforestation efforts, from seed dispersal to large-scale planting analysis [63][178].

Monitoring afforested and reforested areas is vital for assessing tree health and growth. Emerging technologies such as satellite imaging and sensor-equipped drones provide real-time data on various environmental factors, including tree health and climate conditions. Machine learning algorithms analyze data to identify patterns, detect abnormalities, and recommend treatments for pests or diseases. Predictive analytics further enhance decision-making by forecasting environmental changes and their potential impacts on forest ecosystems. AI also aids in optimizing resource management and ensuring efficient use of water, fertilizers, and other inputs. By analyzing factors such as soil moisture and nutrient availability, AI helps maximize resource efficiency, leading to healthier, more resilient forests. AI platforms actively engage local communities by offering accessible information on forest restoration initiatives, encouraging participation in monitoring efforts, and raising awareness about the roles of trees in combating climate change and preserving biodiversity by absorbing carbon dioxide, improving air quality, and providing habitats for countless species.

6.3.14. Mapping forest surface soil moisture

Soil moisture is crucial in maintaining forest health, productivity, and resilience against environmental stressors. Accurate mapping of surface soil moisture is essential for effective agricultural planning, water resource management, and mitigating the impacts of climate change. Traditional methods of monitoring soil moisture, which relies on limited sampling and sensor technologies, are often time-consuming and provide a narrow view of large forest areas. As climate change intensifies and land use pressures grow, the need for scalable, innovative solutions becomes even more urgent. Machine learning algorithms and remote sensing technologies are increasingly mapping soil moisture in forest ecosystems through the application of AI. These tools process large datasets from satellite imagery, aerial surveys, and ground-based measurements, enabling more efficient and accurate soil moisture mapping. AI-driven techniques, such as neural networks, random forests, support vector machines, and decision trees, are being used to estimate forest surface soil moisture levels with increasing effectiveness. Combining these technologies with remote sensing and ground-truth data allows AI to provide precise and reliable moisture maps across extensive forested regions. Machine learning algorithms excel at filtering and preprocessing data from various sources, focusing on the most relevant information to enhance accuracy and efficiency. Advanced image processing techniques, including computer vision and deep learning, can analyze spectral images to detect moisture patterns, offering detailed predictions about soil moisture based on temperature, precipitation, and vegetation cover. These AI models can forecast current and future moisture conditions, enabling proactive forest management and conservation efforts.

AI systems also facilitate real-time soil moisture monitoring, providing frequent updates and enabling forest managers to make timely, data-driven decisions. Using AI for spatial analysis and combining it with GIS can create high-resolution maps of soil moisture fluctuations, aiding in forest management and conservation planning. Moreover, AI can automatically detect anomalies in moisture data, flagging areas at risk of drought, pest infestations, or other stressors. These technologies actively prioritize areas for intervention by enabling targeted irrigation or conservation measures and seamlessly integrating into decision support systems to enhance resource allocation effectiveness. AI's ability to analyze long-term climate trends and their effects on soil moisture further enhances its role in sustainable forest management.

Win et al. [163] demonstrated that combining multi-source remote sensing data with two machine learning models, random forest and support vector machine, enables accurate surface soil moisture mapping in the temperate woods of Central Japan. They found that the random forest model offered higher accuracy and reliability when applied to five different combinations of remote sensing data than the support vector machine model. Among these combinations, the synergy of Sentinel-2 data and terrain factors—such as elevation, slope, aspect, slope steepness, and valley depth—proved to be the most effective in capturing the spatial distribution of surface soil moisture across various forest types based on classification accuracy and evaluation metrics. This discovery enhances our understanding of soil moisture dynamics in temperate forests and provides valuable insights for managing land and water resources in forest management.

6.3.15. Establishing data-driven tree allometry

Tree allometry is crucial in understanding forest dynamics, ecological services, and carbon cycling. Accurate allometric equations are essential for estimating biomass and productivity in forest ecosystems, which are vital for climate change mitigation efforts [185]. Traditionally, these equations have been derived from empirical observations of a limited number of species and habitats, leading to significant errors and constraints in their applicability across different forest types [185]. The introduction of AI offers promising potential for improving data-driven tree allometry. Using advanced machine learning techniques, AI can analyze large, complex datasets from diverse sources, such as remote sensing, LiDAR, and field measurements. These algorithms can identify subtle patterns and relationships between tree characteristics, resulting in more accurate and generalized allometric models that account for variability across species and environments. AI-powered methods facilitate the integration of diverse datasets, enabling the development of species-specific yet widely applicable allometric equations. Machine learning approaches excel at detecting intricate patterns in multidimensional datasets, such as tree height, diameter, crown area, and volume. By considering environmental variables, growth patterns, and genetic variation, AI can enhance biomass estimations and provide a deeper understanding of forest dynamics. AI can also build predictive models that estimate tree biomass and growth, incorporating ecological factors and species-specific features. These models can be applied to various species and forest types, contributing to more precise equations for forest management and biodiversity conservation. Furthermore, AI techniques, particularly ensemble methods like random forests and gradient boosting, can capture nonlinear relationships in allometric data, increasing the flexibility and accuracy of the models.

AI enhances the reliability and generalization of allometric models by implementing robust cross-validation processes and actively evaluating these models on independent datasets. Additionally, AI can quantify uncertainty in biomass estimations through probabilistic modeling and Bayesian techniques, helping forest managers make informed decisions. Temporal data can also be integrated into AI models, allowing for dynamic tree growth and allometry modeling over time, which enables forecasting of future tree characteristics and supports proactive forest management strategies. Real-time monitoring through AI-powered systems, using sensor and remote sensing data, provides adaptive management capabilities by updating models with new data. Lastly, AI can enhance stakeholder communication by presenting allometry data in accessible formats, fostering collaboration in forest conservation and sustainable practices. Gomez-Fell et al. [185] introduced a machine-learning approach that leverages airborne LiDAR and power-law relationships to create local allometric models for a 20-year-old planted forest in New Zealand. This method successfully generates precise allometric correlations, demonstrating the potential of AI in large-scale forest inventories and ecosystem management.

6.3.16. Conservation of water resources, aquatic and marine biodiversity

Aquatic and marine ecosystems are vital to our planet, supporting food production, regulating climate, and holding cultural significance. These ecosystems face numerous threats, including overfishing, habitat destruction, pollution, and climate change, leading to biodiversity loss and degraded water resources. Comprehensive conservation policies are urgently needed to protect these crucial environments and ensure sustainability. Artificial intelligence addresses the complex challenges of aquatic and marine biodiversity conservation and water resource management. With its ability to process vast amounts of ecological data, AI, through machine learning, big data analytics, and remote sensing, enables researchers to make informed decisions and develop targeted conservation strategies [63][178]. AI is critical in enhancing our understanding of aquatic and marine ecosystems by recognizing patterns, predicting changes, and simulating interactions. AI applications include image recognition for species identification, habitat mapping using satellite and drone imagery, and predictive modeling of ecosystems' responses to environmental stressors. These technologies enhance the accuracy of biodiversity assessments, offering valuable insights that help develop more effective conservation practices [63][178]. Additionally, AI facilitates real-time water quality monitoring, allowing informed decisions regarding sustainable resource management. For example, AI-powered image recognition systems, such as deep learning algorithms, can identify and categorize aquatic species from images and videos, enabling timely and precise monitoring of species populations, especially in hard-to-reach areas.

Furthermore, AI helps create accurate maps of marine environments by using satellite imagery and remote sensing data. These AI systems can identify coral reefs, seagrass beds, and wetlands, essential for conservation planning. AI also supports predictive models that assess ecosystem responses to environmental threats like climate change and pollution, assisting conservationists in implementing proactive management measures. AI analyzes real-time sensor data to detect harmful algal blooms or pollution and identify potential hazards. AI integrates diverse datasets, including ecological, environmental, and social data, to deepen our understanding of aquatic ecosystems and drive more effective conservation efforts. Additionally, AI enables citizen science, empowering communities to monitor biodiversity and contribute to broader conservation initiatives.

6.3.17. Forest risk assessment and forecast

Forests maintain ecological balance, support biodiversity, and provide essential resources for human survival. However, they face increasing threats from climate change, deforestation, wildfires, and insect infestations [63][178]. As forest risks continue to grow, conducting effective risk assessments and forecasting has become crucial for ensuring sustainable management and conservation. Traditional methods, which rely on manual data collection and analysis, are often time-consuming and limited in scope. Recent advances in AI offer new opportunities to enhance the accuracy and efficiency of forest risk evaluations by enabling the analysis of large volumes of data from multiple sources. AI systems use machine learning and remote sensing to process vast amounts of data from satellite imagery, aerial photography, ground-based sensors, and historical records. These technologies uncover patterns and trends that are difficult to detect using traditional approaches, allowing for better identification of risk factors [63][178]. AI-driven predictive models simulate various scenarios, such as climate change impacts, land use changes, and fire risks, helping stakeholders foresee potential hazards and evaluate management strategies. By analyzing remote sensing data through deep learning, AI can monitor forest health, detect early signs of threats like insect infestations or disease outbreaks, and produce risk maps to guide conservation efforts and resource allocation [63][178].

AI also enables real-time monitoring and decision-making, offering forest managers insights and recommendations based on processed data. These AI-powered tools help design proactive management plans, optimize resource use, and enhance adaptive strategies for emerging challenges. Additionally, AI supports community involvement by providing accessible platforms for local stakeholders to track forest changes and identify risks, fostering collaborative conservation. By integrating socioeconomic data, AI provides a holistic approach to understanding the human impact on forests and developing inclusive, sustainable management strategies. AI is transforming forest risk assessment, offering new possibilities for improved decision-making, risk reduction, and sustainable forest management.

6.3.18. Solving supply and demand problems in the forestry sector

The forestry industry provides essential resources like lumber, paper, and non-timber forest products while supporting livelihoods and maintaining biodiversity. However, the sector faces challenges in balancing supply and demand due to fluctuating market prices, changing consumer preferences, and evolving environmental regulations, often leading to inefficiencies such as overexploitation or underutilization of forest resources [63][178]. As a result, sustainable forest management is becoming increasingly important to preserve the long-term health of ecosystems. Artificial intelligence offers an innovative solution to address these challenges using data analytics and algorithms to optimize resource allocation and improve decision-making. Companies like aiTree Ltd. in Canada use AI to manage supply and demand better, offering valuable insights into market trends and providing more accurate forecasting to help forestry stakeholders balance market needs with environmental sustainability [63][178].

AI enables forest managers to make informed decisions by analyzing massive data from historical market trends, consumer behavior, and environmental factors. Using machine learning, AI predicts market shifts, enhances supply chain management, and reduces waste by adjusting supply methods to align with demand. AI-driven technologies such as IoT sensors and Blockchain can track the entire supply chain in real-time, promoting transparency and responsible sourcing, which enhances operational efficiency and builds consumer trust in sustainably sourced products. Furthermore, AI-powered systems can optimize inventory management, improve logistical operations, and identify the best allocation of resources such as labor and machinery, ensuring that forestry operations run efficiently and minimize waste.

AI also helps forestry companies and governments make strategic decisions by continually monitoring market trends, customer preferences, and competitor activities. By analyzing consumer data, AI can provide insights into specific demands for forestry products, allowing businesses to adapt their offerings and marketing strategies. Additionally, AI helps assess the sustainability of supply and demand methods by evaluating environmental impact, supporting conservation efforts, and enabling better collaboration among stakeholders. AI enables forestry professionals to anticipate risks, identify disruptions, and create contingency plans, which allows them to manage forest resources effectively while meeting consumer demands and promoting sustainability.

6.3.19. Forest management

Forests are vital in maintaining ecological balance by providing carbon sequestration, preserving biodiversity, and supporting human livelihoods. However, climate change, deforestation, and unsustainable land use practices threaten forest health and stability [186]. Effective forest management is crucial to address these challenges, ensuring that forests continue to serve their environmental, economic, and social functions. AI improves forest management by offering advanced methods for monitoring and analyzing forest ecosystems. Through machine learning, data analytics, and modern algorithms, AI helps stakeholders make informed decisions, enabling them to respond proactively to emerging threats and optimize resource use. AI-driven solutions allow forest managers to process massive data from satellite imagery, remote sensing technology, and ground-based measurements. By interpreting this data, AI provides real-time insights into forest conditions, allowing for early detection of threats like insect infestations, disease outbreaks, and vegetation stress. This approach enhances the efficiency of forest management practices, ensuring timely interventions that can prevent further damage. For example, AI can identify unauthorized activities such as illegal logging and poaching by analyzing images captured by mobile devices with AI-powered object recognition, as demonstrated by the YOLO-Neural Architecture Search (NAS) forest monitoring system [186]. Additionally, AI-based prediction models simulate various scenarios, such as climate change’s or land-use changes’ impact, enabling better planning and more sustainable management practices.

AI also improves forest planning and decision-making by integrating diverse data sources, including environmental factors, weather conditions, and historical trends. These insights support sustainable harvesting practices, better biodiversity conservation, and more effective fire management by predicting fire hazards and recommending preventive measures. AI systems help land-use planning by considering socioeconomic and environmental data, which fosters the development of strategies that balance ecological health with community needs. Furthermore, AI enhances operational efficiency through decision support systems that provide best practices and optimal resource allocation. By enabling real-time analysis, AI encourages community participation, increases awareness, and improves collaboration in forest conservation efforts, ultimately supporting forest ecosystems’ long-term health and sustainability.

6.3.20. Public forest education

Forests offer essential ecosystem services, fostering biodiversity and providing recreational opportunities. However, urbanization, climate change, and unsustainable land-use practices threaten these resources, highlighting the need for effective public education on forest ecosystems and their importance. Individuals and communities must know the importance of forest conservation and sustainable management to address this issue. Empowering the public with this knowledge encourages responsible interaction with forests and fosters stewardship. Artificial intelligence is transforming public education on forests by enabling the development of interactive, tailored learning programs. AI can analyze extensive volumes of data to generate insights into forest ecosystems, such as species diversity, health, and ecological relationships.

Educators and forest management organizations can use AI to create engaging educational experiences through platforms that provide real-time feedback, monitor user participation, and adjust learning experiences based on individual preferences. AI-powered virtual and augmented reality tools further enhance this by immersing learners in interactive forest environments, helping them better understand complex ecological concepts [183].

AI plays a crucial role in outreach and community engagement by analyzing demographic data and social media trends to create targeted educational initiatives that resonate with specific groups. It helps design programs that cater to diverse audiences' unique needs and preferences, enhancing the effectiveness of community engagement efforts. AI applications, like chatbots, offer instant access to information about forest ecosystems, making educational resources more accessible. By tracking participation rates and learning outcomes, AI helps improve the effectiveness of forest education programs, ensuring that they resonate with the public and promote a greater understanding of the importance of forest conservation. Artificial intelligence offers significant opportunities to enhance public engagement, accessibility, and knowledge of forest ecosystems in educational settings. Educators and organizations can leverage AI to raise awareness, promote stewardship, and advocate for sustainable practices that benefit forests and communities.

IoT, remote sensing, and AI offer a powerful combination that enhances forest management techniques. These technologies allow for real-time monitoring, enable predictive analysis, and support precise interventions, making them vital tools for advancing sustainable forestry practices.

7. REAL-WORLD IMPLEMENTATIONS AND CASE STUDIES

Real-world deployments and case studies demonstrate how IoT, remote sensing, and AI actively contribute to sustainable forest management. Some of the notable examples include the following:

7.1. SMART Forests: A global initiative

The SMART Forests project, led by a multinational partnership of experts, focuses on monitoring forest ecosystems. This effort uses innovative techniques like IoT, remote sensing, and AI to improve forest monitoring, protection, and conservation. IoT-enabled sensors installed on trees in the tropical forests of Brazil and Africa actively monitor moisture levels, temperature, carbon absorption, and other essential characteristics. Artificial intelligence systems analyze data from these sensors and satellite pictures to assess forest health, detect deforestation hazards, and anticipate fires. This program has enabled academics to map deforestation, monitor illegal logging activities, and deliver real-time data to policymakers. IoT and remote sensing data identify key forest areas needing conservation and replanting activities [187].

7.2. TreeTalker: Monitoring Forest Vitality

Monitoring Forest Vitality is a novel approach for assessing and maintaining the health of forest ecosystems using modern monitoring technology. TreeTalker uses IoT devices, remote sensing technologies, and data analytics to track numerous indices of forest health, including tree health, soil conditions, biodiversity, and environmental stressors. The TreeTalker project employs IoT-based sensor networks linked to trees to track their physiological activities instantly. These sensors collect information on tree growth, water content, sap flow, leaf health, and environmental variables. Machine learning models examine the data to forecast how trees react to environmental pressures such as climate change and droughts. The TreeTalker system has been implemented in European forests to gather information on forest dynamics. This comprehensive method offers insights into forest ecosystems, allowing for timely interventions and sustainable management approaches. TreeTalker marks a big step forward in forest monitoring technology, offering a comprehensive approach to understanding and controlling forest life. TreeTalker uses IoT, remote sensing, and data analytics to ensure the sustainability of forest ecosystems for future generations. Forest health has been continuously monitored, allowing foresters to take preventative steps against tree diseases, apply sustainable logging techniques, and encourage biodiversity conservation [188].

7.3. Amazon rainforest monitoring via remote sensing and artificial intelligence

AI and machine learning models are employed with satellite remote sensing data to track deforestation and unlawful land use changes in real-time in the Amazon. Researchers employ AI systems to automatically identify land cover, detect unlawful clearings, and monitor forest regeneration. This method has significantly shortened the time required to identify deforestation activity. The Brazilian government and foreign agencies such as NASA utilize this information to enforce anti-deforestation regulations. Artificial intelligence-powered early detection systems have decreased illicit logging and assisted reforestation efforts [189].

7.4. Wildfire prediction and monitoring in California

In California, IoT-enabled sensors track temperature, humidity, and wind patterns, essential indications of wildfire danger—using AI systems to forecast wildfire outbreaks, remote sensing data from the NASA and National Oceanic and Atmospheric Administration (NOAA) satellites is evaluated. Artificial intelligence programs also assess the fuel load in wooded regions, which is critical for determining how rapidly a fire might spread. These predictive tools have substantially enhanced California's capacity to identify and prevent wildfires, sending real-time notifications to firefighters and forest managers. The method has saved forests and human lives by allowing for improved forest management techniques and more precise risk assessments [190].

7.5. SmartForest Finland: Intelligent Forest Management

Finland's SmartForest program uses IoT devices, 5G networks, and AI to manage its vast forest resources. IoT sensors analyze soil moisture, forest microclimates, and tree growth rates. The data is relayed over 5G networks, allowing AI systems to analyze forest conditions instantly. These insights assist in optimizing logging schedules, promoting forest health, and ensuring long-term forest management. This method maximizes forest resource consumption while protecting biodiversity and forest health. Integrating modern IoT and AI systems contributes to Finland's long-term goals of sustaining carbon-neutral forestry operations, reducing deforestation, and increasing timber production [191].

7.6. Tropical forest conservation in Peru – Global Forest Watch (GFW)

Global Forest Watch (GFW), in conjunction with the World Resources Institute (WRI), employs satellite remote sensing to monitor forest cover changes in Peru's tropical rainforests. It uses data from NASA's Landsat satellites and Sentinel-2. Satellite imagery is processed using AI-based analysis to detect deforestation tendencies or illegal land usage in near-real time. GFW also uses deep learning to detect unlawful activity, such as slash-and-burn tactics. The system takes data from several satellite sources and uses AI algorithms to identify deforestation, wildfires, and other changes in forest ecosystems. IoT devices like drones and on-the-ground sensors provide information like temperature, humidity, and soil conditions. Local governments and non-governmental organizations employ GFW findings to safeguard biodiversity, prevent illicit deforestation, and engage in forest restoration efforts. The technology has enabled more effective monitoring and enforcement measures, considerably reducing illegal logging in Peru's Amazon. It has discovered trends of deforestation and illicit logging in tropical forests. It helped governments, NGOs, and corporations better judge forest protection. It enabled local communities and authorities to take prompt action against illicit activity. GFW data has assisted nations like Brazil, Peru, and Indonesia reduce illicit deforestation by allowing for more effective law enforcement [192].

7.7. IoT for forest inventory and management

The US Forest Service uses IoT technologies for forest inventory and monitoring. The Forest Inventory and Analysis (FIA) program's principal goals are to assess forest health, track changes in forest resources over time, provide data for land management choices, and promote research on forests and their ecosystems. The FIA program combines remote sensing, aerial imaging, and ground-based field studies. Field teams employ IoT technology, such as GPS devices and mobile data gathering tools, to correctly find and capture data on tree species, size, carbon sequestration, vegetation, soils, and other forest features. Forest inventory data is helpful for various management applications, including wood harvesting planning, forest health evaluations, wildlife habitat analysis, biodiversity protection, land-use planning, and wildfire control. The knowledge guides sustainable forest management methods and informs decision-making at all levels [1].

7.8. Forest inventory and management, British Columbia, Canada

Using IoT technology, LiDAR-equipped drones enhance forest inventory and management by enabling data-driven decision-making. These drones act as sensors, emitting laser pulses and measuring the time it takes for the light to reflect, creating a detailed three-dimensional point cloud of the forest structure. This data provides valuable insights for evaluating forest health, estimating tree volume, monitoring vegetation changes, and optimizing forestry activities [1].

7.9. Soil moisture monitoring in the Amazon Rainforest, Brazil

Soil moisture sensors are strategically implanted at varying depths across the Amazon Rainforest to monitor soil moisture levels and support sustainable land use and forest ecosystem management. These sensors measure soil moisture content and transmit the data to a central database or cloud platform via wireless networks or satellite connections. The system records readings regularly and provides researchers, scientists, and forest managers remote access to essential information for analysis and decision-making. Soil moisture patterns reveal water availability across different areas, helping identify regions at risk of drought or excessive moisture. This data enables informed decisions about irrigation, planting, forest health management, and land-use planning [1].

7.10. IoT sensors in Alice Holt Forest

Cutting-edge sensors have been strategically attached to the towering trees of Hampshire's Alice Holt Forest, leveraging Vodafone's renowned NB-IoT network to relay valuable data to the UK's Defra and Forest Research. This intelligent system continuously collects and transmits temperature, humidity, and soil moisture data, enabling advanced analytics to uncover how these factors influence tree growth and function. By precisely measuring tree growth, scientists gain crucial insights into how trees actively mitigate climate change by absorbing and storing carbon. Equipped with these findings, the Department for Environment, Food & Rural Affairs (DEFRA) and Forest Research actively inform policymakers and the public about the environmental changes affecting trees and highlight trees' significant benefits as natural carbon regulators [1].

7.11. The EYE in the SKY Project (Indonesia)

The "EYE in the SKY" project is an Indonesian effort to monitor deforestation and illicit logging operations using satellite technology, drones, and real-time monitoring systems. This initiative is part of Indonesia's more extensive efforts to battle deforestation, manage forests sustainably, and conserve biodiversity while tackling environmental issues such as climate change. Authorities may follow unlawful forest operations, determine trends of forest cover change, and take necessary action to safeguard wooded regions using satellite imaging and aircraft surveillance. The primary purpose is to give reliable, real-time data on forest cover changes and illegal deforestation operations, allowing authorities to spot problems early and intervene more quickly. The initiative uses satellite photography, drone monitoring, and artificial intelligence-powered data analytics to discover and anticipate regions in danger of illicit logging or other deforestation operations. International organizations and NGOs involved in environmental preservation, climate change mitigation, and forestry management frequently support the project. The project's data informs forest management and conservation policy choices. It is also a tool for enforcing rules against illicit logging, which aids Indonesia's national efforts to minimize deforestation rates. By reducing deforestation, the "EYE in the SKY" initiative helps mitigate climate change, preserve ecosystems, and protect indigenous groups that rely on trees [193].

7.12. The Amazon Rainforest – Rainforest Connection (RFCx)

Rainforest Connection (RFCx) uses recycled cell phones, called "Guardians," and places them high in trees around the rainforest. These gadgets function as IoT sensors, continually capturing audio. These sensors collect data transferred over mobile networks and evaluate it in the cloud using AI algorithms. The AI algorithms examine acoustic data to detect chainsaws, gunshots, or vehicles that might suggest illicit logging or poaching. When such noises are detected, local authorities receive real-time notifications requesting assistance. RFCx has effectively decreased illicit logging by facilitating quick responses and enhancing conservation initiatives. The technique also spreads to other forests worldwide, including those in Africa and Southeast Asia.

7.13. The Forest Inventory System in Sweden

Sweden's forestry industry actively leverages IoT sensors and drones with remote sensing technology, such as LIDAR, to streamline forest inventory management. Forest sensors continuously monitor soil health, tree growth rates, and forest density while drones map and measure forest areas. Machine learning algorithms analyze collected data to estimate wood volume and predict growth patterns, improving the accuracy of forest management decisions. This data-driven approach supports sustainable logging practices, ensures effective forest regeneration, reduces costs, and promotes the responsible use of forest resources, effectively replacing traditional methods.

7.14. Forest Smart Mining: Gabon

Gabon, which has considerable mineral deposits in wooded regions, has pioneered "Forest Smart Mining" programs that employ remote sensing and IoT to monitor and mitigate the environmental effects of mining activities. Artificial intelligence algorithms use satellite data to analyze mining's impact on biodiversity and forest loss. At the same time, IoT sensors are put near mine sites to monitor water quality, soil erosion, and tree health. This method has helped Gabon balance economic expansion and environmental objectives. It enables real-time forest degradation monitoring and supports data-driven strategies to mitigate mining's harmful impact on forest ecosystems. This demonstrates how innovative solutions can actively merge sustainable development with environmental preservation.

7.15. Artificial intelligence-driven forest disease detection in Canada

In British Columbia, drones outfitted with high-resolution cameras and remote sensing devices are used to monitor forests for early indicators of illnesses such as bark beetle infestations. Artificial intelligence systems analyze drone and satellite photos to identify places where trees are exhibiting early indications of stress due to insect infestations. Early identification of insect outbreaks has enabled forestry managers to take quick action, such as isolating problematic areas and administering disease-prevention measures. This approach has been vital in ensuring the health and sustainability of Canadian forests, which are essential to the country's economy and ecosystem.

7.16. The ForestWatchers project

ForestWatchers employs IoT devices and satellite remote sensing to monitor and protect the Amazon rainforest. The technology also employs crowdsourcing, which allows volunteers to categorize satellite photos and identify areas of unlawful deforestation. Artificial intelligence algorithms evaluate visual patterns, forecast forest cover loss, and identify high-risk locations for deforestation. The project discovered illegal logging activities in distant places. It enabled faster reaction to environmental issues by sharing real-time data with authorities. It used crowdsourcing to involve the public in biodiversity conservation efforts. The project assisted the Brazilian government in reducing illicit forestry activities while raising worldwide awareness of Amazon dangers.

7.17. NASA's forest carbon monitoring with artificial intelligence and remote sensing

NASA uses AI algorithms and remote sensing technologies, including LiDAR and satellite imagery, to estimate the amount of carbon stored in forests. The system collects data on forest biomass, structure, and composition and then uses AI to assess carbon flow and forecast future trends under various climatic scenarios. The approach allowed for more precise forest carbon storage and sequestration capacity estimations, aiding climate change mitigation efforts. It helped governments set carbon reduction and forest protection objectives and provided data to help improve the design of carbon trading and offset schemes. NASA's carbon monitoring equipment has helped to promote global agreements like the Paris Agreement by providing accurate data on forest carbon stocks.

7.18. Sustainable forest management in the Congo basin

In the Congo Basin, IoT sensors monitor forests to detect illicit harvesting and track timber supply networks. Remote sensing technologies like drones and satellite photography identify deforestation hotspots, while AI analyzes the data to predict deforestation trends. Blockchain technology ensures the timber supply chain transparency, verifying that wood comes from sustainably managed forests. This approach has curbed illegal logging by providing real-time surveillance, secured the sustainability of the timber trade by tracking the legality of harvested wood, and supported conservation by pinpointing critical ecosystems and biodiversity hotspots. As a result, illegal logging has decreased in some of the world's most biodiverse forest areas, benefiting the environment and the local economy.

7.19. ForestSense – artificial intelligence for invasive species management in the US

ForestSense is an AI-powered technology used in American woodlands to detect and manage invasive species. IoT sensors and drones equipped with cameras collect data on forest health, while AI algorithms identify invasive species using image recognition and environmental information. ForestSense intends to use AI to detect, anticipate, and manage invasive species that endanger forests across the United States. The project aims to improve forest management decision-making by combining remote sensing, machine learning, and real-time data processing techniques. ForestSense helps forest managers respond quickly to invasive species, conserve native flora, and maintain the biological balance of forest ecosystems. ForestSense significantly improves using AI for environmental management, aiming to protect US forests' ecological integrity from dangers posed by exotic species. The initiative supports sustainable forestry practices and conservation activities, safeguarding the health of forest ecosystems for future generations.

7.20. Remote sensing for forest health monitoring in Brazil

The Brazilian Space Agency (INPE) uses remote sensing satellites to monitor deforestation across the Amazon Basin. By combining high-resolution satellite data with AI, INPE detects illegal logging and environmental damage in real-time. Machine learning analyzes changes in forest cover to estimate biomass loss and carbon emissions. INPE sends alerts on illicit logging to Brazilian law enforcement, enabling quicker responses to protect the forest. This technology has been crucial in shaping policies and supporting real-time enforcement, helping Brazil significantly reduce deforestation rates during key years of operation.

7.21. Drones and artificial intelligence for tree health assessment in Canada

The University of British Columbia and forestry companies use drones equipped with multispectral sensors to monitor tree health across vast forested areas. The drones capture high-resolution data on tree canopies, which AI algorithms then analyze to detect early signs of disease and pest infestations, such as changes in chlorophyll levels. This technology allows for quicker identification of stress indicators, reducing the need for manual surveys and enabling faster treatment to safeguard forest health and biodiversity.

7.22. Artificial intelligence and satellite data for forest biomass estimation in the Congo Basin

The World Resources Institute (WRI) leads a project that employs AI and remote sensing data to assess forest biomass and tree cover loss across the Congo Basin. This region is crucial for carbon sequestration, and the initiative helps to preserve sustainable practices. WRI can provide accurate biomass and deforestation estimates by training AI on satellite images and LiDAR data, which helps with conservation planning and aids local governments in combating illicit logging. This method helps to get carbon credits under REDD+, which promotes long-term economic growth while protecting biodiversity.

7.23. Carbon stock monitoring with IoT and artificial intelligence in Kenya

Researchers in Kenya employ IoT sensors and AI to quantify and monitor carbon stocks in the Kakamega Forest. The project uses ground-based sensors and satellite data to monitor biomass and estimate carbon sequestration levels. IoT sensors assess soil moisture, temperature, and carbon dioxide levels, fed into AI models to compute biomass changes. With these measurements, forest managers may track the forest's carbon sequestration rate over time, allowing them to quantify the forest's contribution to carbon offsetting and assist replanting efforts. This initiative supports Kenya's national climate targets by certifying carbon credits and influencing policy decisions.

8. CHALLENGES AND LIMITATIONS

Leveraging IoT, remote sensing, and AI for sustainable forest management has incredible prospects but presents substantial challenges and limitations. The following is a complete overview of these challenges and limitations.

8.1. Data security and privacy concerns

IoT and remote sensing technologies collect vast amounts of environmental and, in some cases, personal data. Securely storing and managing this data is crucial to prevent any misuse. Unauthorized access can expose critical ecological and community information, risking misappropriation and compromising forests' integrity and surrounding environments. IoT systems are often targeted by cyber-attacks, such as replay attacks, man-in-the-middle attacks, and denial-of-service attacks, which can disrupt conservation efforts. Compromised devices may provide false data, influencing forest management decisions. Artificial intelligence, which detects illegal activities like logging, often relies on surveillance technologies that raise privacy concerns. Drones and satellites, coupled with AI analysis, can infringe on the privacy of people living in forest areas, and as AI systems depend more on large databases, safeguarding individuals' privacy becomes increasingly important [194].

8.2. Data storage and transmission

Storing and managing large amounts of data from IoT and remote sensing devices requires high-capacity storage systems and efficient data transfer networks. Transferring data to central storage and processing centers becomes difficult in isolated forest locations, where Internet access may be limited or unavailable. Forest conservation efforts often occur in remote, rural, or inaccessible areas with poor or no Internet and cellular connectivity, making it challenging to rely on IoT devices that need continuous data transmission. The absence of reliable network infrastructure hampers real-time data transfer and communication between devices and cloud servers.

8.3. High latency and bandwidth limitations

In an IoT-enabled forest management system, sensors collect real-time data on forest variables like humidity, temperature, soil moisture, and tree health. However, high latency can hinder fast data processing, affecting critical decisions such as responding to forest fires or detecting illegal logging. Artificial intelligence models rely on real-time input to produce timely results, and latency can create delays, reducing their effectiveness [195]. Bandwidth restrictions in rural or wooded areas, where network infrastructure may be inadequate, exacerbate the problem. Remote sensing technologies like drones, satellites, and airborne LiDAR generate large volumes of data that need high bandwidth for efficient transmission. In low-bandwidth environments, data transmission slows down, requiring compression or prioritization, which may lead to data loss or delays. These limitations reduce the frequency and quality of data updates, impairing AI models' ability to make accurate assessments and slowing down responses in forest health monitoring, fire detection, and biodiversity evaluation, ultimately threatening conservation efforts [195].

8.4. Energy and battery limitations

IoT devices like sensors, cameras, and monitoring equipment are often deployed in remote and inaccessible forests, where replacing or recharging batteries is logistically challenging and costly, especially across vast areas. The limited battery life of these devices disrupts data collection continuity and requires frequent maintenance, which is difficult in sensitive environments where human presence can impact wildlife or ecosystems [195]. Artificial intelligence algorithms require substantial processing power and energy, particularly for complex tasks like image recognition or environmental modeling. Running these models on-site, such as on-edge devices for real-time processing, rapidly depletes battery life. Energy-intensive models must be adapted for low-power contexts or offloaded to more energy-efficient cloud facilities. Similarly, remote sensing technologies like drones and satellites face energy limitations, with drone battery life restricting flight times and area coverage, leading to higher logistical costs. While satellites are not reliant on terrestrial batteries, their limited communication windows delay real-time data transmission to ground-based AI models. Although energy-harvesting solutions like solar panels or kinetic systems can extend IoT device lifespans, these are less effective in forests with dense canopies that block sunlight and wind. Researchers are exploring novel technologies, such as microbial fuel cells, to generate electricity from soil microbes as potential solutions for powering low-energy sensors in forest environments.

8.5. Sensor limitations

IoT sensors used in forests monitor various environmental factors like temperature, humidity, soil moisture, and air quality. Still, their accuracy can fluctuate due to ambient conditions such as temperature and humidity. While low-cost sensors are expandable, they tend to have poorer accuracy and shorter lifespans than high-end models, leading to data discrepancies that reduce the reliability of AI models. Additionally, most sensors have limited detection ranges, requiring multiple units to cover large, isolated forest areas, which can create data gaps and skew AI results. Harsh environmental conditions like temperature shifts, high humidity, and animal interactions can damage sensors over time, while vegetation growth may obstruct them, further compromising data collection. Low-power sensors in forest management systems extend battery life but offer lower-resolution data, affecting the responsiveness of AI models. Network connectivity in remote areas can also be unreliable, causing data delays or loss. Specialized sensors for factors like carbon sequestration or biodiversity are not always available, and their proxy measurements can add uncertainty. Technologies like LiDAR or hyperspectral imaging provide high-resolution data but are expensive and resource-intensive. Many sensors require frequent calibration to maintain accuracy. However, sensor drift can lead to faulty readings if not adequately maintained, and autonomous calibration solutions are still in development, requiring occasional human intervention to prevent inaccuracies.

8.6. Data limitations and quality

IoT and remote sensing technologies generate vast amounts of data. However, ensuring high-quality, consistent data across diverse forest zones is challenging due to variations in forest type, seasonal fluctuations, and environmental conditions, which introduce noise and inconsistencies. Satellite images, crucial for tree enumeration, are particularly affected by seasonal changes, cloud cover, and resolution issues, which can decrease model accuracy [196]. Different data sources, such as IoT sensors, remote sensing platforms, and manual observations, have varying accuracy and resolution, complicating data fusion for AI models. Environmental factors like rainfall and animal interactions further impact sensor performance, causing errors that AI algorithms may mistake as significant trends. Forest habitats' dynamic nature introduces additional noise, and malfunctioning sensors or interference create outliers that can bias AI predictions. The lack of continuous data gathering, especially for rapid events like forest fires or insect outbreaks, limits AI's ability to detect quick changes. Managing large volumes of data is costly, and remote areas with limited Internet access or energy resources face additional challenges in storing and processing data. AI models also struggle due to incomplete historical datasets and inconsistent data collection methods, which can lead to biases and reduce their accuracy, especially in less-studied ecosystems. The scarcity of labeled, high-quality datasets for training AI models in forest management limits their ability to generalize across different forest types and conditions, leading to potential biases and inaccuracies in predictions and jeopardizing conservation efforts [177].

8.7. Data accuracy and reliability

IoT sensors in the field can produce incorrect data due to faulty calibration, sensor degradation, or environmental influences, which affects data reliability and can lead to misguided conservation efforts. Gaps in data collection caused by environmental conditions or technical issues reduce the effectiveness of real-time monitoring [195]. High-resolution satellite imagery is often too costly and inaccessible for large-scale conservation programs, especially in developing nations. At the same time, low-resolution images may miss critical details like small-scale deforestation or ecological changes. Remote sensing systems may lack sufficient data to detect rapid environmental changes such as illegal logging or forest fires in real-time, with cloud cover and weather conditions further limiting image availability. Low spectral resolution in sensors may cause misclassification of tree species, leading to inaccurate forest composition assessments. IoT sensors often struggle to transmit real-time data in forested areas with inconsistent network connectivity, resulting in packet loss, delays, and irregular updates that impact AI models. Edge computing can mitigate this by processing data locally before transmission, ensuring consistent input even in low-connectivity environments. Moreover, integrating diverse data sources, such as IoT and remote sensing, proves challenging due to differences in format, quality, and size, potentially creating contradictions in AI models. Standardizing data formats and applying normalization techniques can improve consistency across datasets and enhance model accuracy. Finally, natural variations in forest habitats, such as rapid temperature changes or unexpected wildlife movements, can produce outliers that AI algorithms may misinterpret without validation. Implementing anomaly detection techniques helps filter these outliers, ensuring that only reliable data informs decision-making.

8.8. Data processing and interpretation complexity

Processing raw remote sensing data into usable information requires advanced methods like classification and regression models, machine learning approaches, and statistical analysis. These algorithms are computationally demanding and require expertise to produce reliable results. Inaccuracies in data collection, atmospheric adjustments, or sensor calibration can propagate throughout the data processing pipeline, leading to errors in forest analysis, such as overestimating or underestimating deforestation rates [177]. Integrating data from multiple sources, like optical, LiDAR, and SAR, is often necessary to get a complete view of forest ecosystems. However, combining and harmonizing this information requires complex methods that can be challenging. Misinterpreting AI outcomes by practitioners and decision-makers may lead to poor decisions and overconfidence in AI-driven conclusions, negatively impacting forest monitoring and biodiversity efforts. Furthermore, uncertainty in AI models is often not addressed or communicated, resulting in overconfidence and potential future errors in decision-making [177].

8.9. Interoperability and standardization issues

Integrating IoT, remote sensing, and AI into forest management faces significant challenges because of the absence of established protocols and standards. Devices and platforms from different suppliers are often incompatible, complicating data integration, transmission, and analysis, which leads to higher costs and delays in technology adoption. IoT systems typically involve multiple manufacturers' devices with varying protocols and software standards, causing compatibility issues and reducing system efficiency. Forest conservation projects involving various stakeholders like governments, NGOs, and academic institutions are hindered by the absence of defined data formats, making it difficult to exchange, aggregate, and utilize data from multiple IoT sources. Many AI models, particularly neural networks and other machine learning models, are often called "black-box" systems because they provide accurate predictions without offering clear insight into the decision-making process behind those predictions. This opacity is a significant challenge in forest conservation, where decision-makers must understand the reasoning behind predictions, particularly when these initiatives impact local populations. Moreover, the complexity of deep learning models used for tasks like tree counting raises concerns about comprehending their decision-making processes, which is essential for building confidence and ensuring practical implementation [196].

8.10. Environmental and physical constraints

IoT devices in forests face severe conditions such as humidity, extreme temperatures, rainfall, wildfires, and animal interference, which can damage or shorten their lifespan, leading to premature sensor and equipment failure. Developing durable electronics for extended forest use is costly and technically challenging [63][178]. Dense canopies, mountainous terrains, and thick vegetation often impair wireless signal propagation, leading to signal deterioration over long distances and causing incomplete or inaccurate data [63][178]. Cloud cover in tropical and temperate forests, especially during the rainy season, can obstruct optical remote sensing, hindering data collection and compromising time-sensitive conservation efforts. Additionally, atmospheric conditions like haze, fog, or wildfire smoke can significantly degrade image quality, leading to the loss of vital information.

8.11. High costs of deployment and maintenance

Implementing IoT, remote sensing, and AI systems requires significant investment in equipment, installation, and worker training, which poses a challenge for many forest management organizations, particularly in underdeveloped countries. Setting up an IoT system for forest protection is expensive, as it involves purchasing sensors, cameras, drones, and network infrastructure, which can be unaffordable for governments, NGOs, or conservation organizations with limited budgets. IoT systems also require regular maintenance, including software updates, hardware repairs, and device replacements, which can be costly and difficult in remote areas [195]. While free satellite imagery is available from platforms like Landsat and Sentinel, high-resolution data from commercial satellites can be prohibitively expensive for conservation projects, especially in developing countries with limited resources. Even free remote sensing data often require extensive computer infrastructure and expertise, which small conservation initiatives may lack. The high cost of UAVs, sensors, and hardware further complicates the production and maintenance of scientific datasets [170]. Artificial intelligence solutions, especially those based on large datasets or complex models like deep learning, demand sophisticated computing resources, which may be too costly for regions with inadequate technological infrastructure. Many forest management groups also lack AI expertise, making it challenging to incorporate AI into conservation efforts, and the need for skilled personnel to develop, manage, and analyze AI models adds to the financial burden.

8.12. Scalability concerns

Scaling up the deployment of IoT and remote sensing devices from small forest areas to large regions with diverse topographies presents significant challenges in complexity and cost. Managing large-scale deployments while maintaining consistent performance and coverage remains a barrier. As the network of devices expands, controlling and sustaining them across vast, distributed ecosystems becomes increasingly complex, requiring effective coordination, calibration, and synchronization through powerful platforms. With the growth of sensors and devices, the volume of data collected increases substantially, making it difficult to manage and analyze in real-time, especially when storage, processing, and bandwidth resources are limited. The absence of standardized protocols for large-scale IoT implementation in forest environments further complicates integration. Artificial intelligence algorithms, often trained on specific datasets, may not generalize well across different ecosystems or geographic locations, hindering the development of scalable AI systems for forest conservation. The inherent complexity of forest ecosystems, with numerous interacting species and environmental factors, adds to the difficulty of accurately modeling these systems, particularly when projecting long-term conservation impacts.

8.13. Bias in artificial intelligence models

In forests, IoT devices and remote sensing technologies rely on specialized sensors, geographical locations, or image-capturing equipment, which leads to biased data collection if devices are unevenly distributed or limited to specific sensor types. This uneven distribution may result in disproportionate data from accessible or high-priority conservation areas, neglecting vital but less accessible zones. Such biases can affect AI models, especially when trained on data from wellsampled areas, causing inaccurate forecasting and misrepresentation of forest health in underrepresented regions. AI models may also reinforce biases if trained on data with inherent prejudices, like focusing on limited indicators, such as vegetation indices, while overlooking other signs of environmental stress [194]. Models based on outdated IoT or remote sensing data may fail to account for recent environmental changes, like climatic shifts or disease outbreaks. Decision-makers may misinterpret AI-generated forecasts, particularly without technical expertise, leading to biased decisions that favor certain regions or conservation strategies. Moreover, subjective choices in defining model features or labels, like focusing on tree canopy density or soil moisture, can result in skewed projections, disregarding broader ecological complexities.

8.14. Policy and regulatory hurdles

The regulatory framework for data collection in natural environments, particularly across different jurisdictions, can complicate the deployment of IoT technologies in forest conservation. Cross-border data exchanges often raise legal issues related to data sovereignty, as each country has different laws regarding data collection and privacy, making international collaboration challenging. Strict regulations in some regions may limit the use of specific IoT devices, such as drones or sensors, which could disturb wildlife. Furthermore, outdated or underdeveloped environmental laws may hinder the integration of AI in conservation efforts, especially concerning land ownership, biodiversity protection, and enforcement. Since forests often span multiple countries, implementing AI-based conservation systems requires adherence to international standards, but differing regulations and data-sharing policies create barriers. These regulatory issues and outdated forest management policies limit the effectiveness of emerging technologies like IoT, remote sensing, and AI in forest conservation. Data privacy regulations may also restrict access to critical geospatial and environmental data, further hindering forest management efforts.

8.15. Ethical and legal concerns

IoT devices like drones and ground sensors can disrupt natural ecosystems and wildlife behavior, raising ethical concerns about their environmental impact. When technologies intersect with Indigenous populations, they often provoke privacy concerns and threaten traditional ways of life, particularly in forested areas where tribes have not consented to monitoring. These situations raise pressing legal and ethical questions, especially about using remote sensing technologies for conservation purposes. Governments may limit access to forest data, viewing satellite monitoring as an invasion of sovereignty. AI-driven conservation efforts may ignore Indigenous customs and land rights by imposing policies that restrict activities like hunting and harvesting without involving local communities. The reliance on AI in forest management also poses legal challenges, as it can reduce local employment opportunities and introduce biases that prioritize certain species or locations, potentially undermining effective ecosystem conservation.

8.16. Challenges in integrating with existing systems

Forest management systems often face challenges when integrating IoT and remote sensing data due to differences in data formats, structures, and resolutions. The lack of interoperability standards can cause data discrepancies and gaps. IoT devices scattered across vast, isolated areas require reliable power sources and network connectivity for real-time data transmission, which is difficult in regions with poor cellular or satellite coverage. Ongoing concerns include protecting infrastructure from environmental exposure and ensuring resilience to harsh weather. Expanding IoT and remote sensing installations demands significant resources and planning while processing large datasets from these systems, which requires scalable computing capacity, which traditional systems may lack. Legacy systems, relying on manual or semi-automated processes, struggle to handle large volumes of data and require modernization, which can be costly and challenging due to compatibility issues with new technologies. Furthermore, the shift to AI-based solutions faces cultural and organizational resistance, as ecologists and conservationists may be wary of fully automated decision-making.

8.17. Complexity in artificial intelligence interpretability

Artificial intelligence-powered forest management models, such as those predicting fire risks or disease outbreaks, often lack transparency, making it difficult for forest managers and stakeholders to trust the results. Many AI models, like deep learning and ensemble methods, operate as “black boxes,” offering high accuracy but limited insight into decision-making. For example, convolutional neural networks in remote sensing may identify features in forest data without explaining which factors influenced specific predictions. This opacity undermines confidence, primarily when critical decisions, like deforestation or conservation strategies, rely on AI-driven insights. While models like linear regression and decision trees are interpretable, they may not offer the necessary prediction accuracy for complex forest management tasks. The trade-off between model accuracy and interpretability complicates selecting the right approach for sustainable forest management. Biases inherent in AI models, such as overestimating the impact of environmental factors based on location-specific data, can lead to misleading conclusions. Without a standard framework for AI interpretability in forest management, various models and methods can produce inconsistent or unclear results, affecting decision-making.

8.18. Computational resources and costs

IoT devices and remote sensing systems generate vast amounts of real-time data, such as environmental factors and spatial data on forest health, which require substantial storage and processing power. Cloud storage can handle these data volumes, but the costs rise with the amount of data, creating financial strain on forest management budgets. High-resolution data increases these costs and often demands real-time processing, particularly for critical tasks like wildfire monitoring. Edge computing, which processes data locally to reduce latency, is essential but expensive, especially in remote forest areas with limited connectivity and power. Training AI models like deep learning requires high-performance computing resources and large datasets. These models need extensive training, fine-tuning, and significant computational and energy investments, making long-term cloud-based computing expensive for ongoing projects. Energy consumption is a concern, especially in rural forests lacking energy infrastructure, prompting the need for sustainable solutions like solar-powered systems, although they come with high upfront costs. The environmental impact of these energy needs can conflict with sustainability goals. After training, developers must deploy AI models and integrate them into forest management systems, often requiring extra computational power to support real-time applications. Regular updates and retraining of these models add further financial and computational costs.

8.19. Temporal changes and forest dynamics

Remote sensing offers valuable insights for forest management, but satellite and airborne data's spatial and temporal resolution often falls short for precise applications. High-resolution imaging reduces the frequency, making monitoring fast, dynamic forest changes, such as illegal logging or rapid deforestation, in real-time challenging. Forest ecosystems are highly dynamic, influenced by natural events like storms, insect outbreaks, and human activities such as logging and agricultural development. Remote sensing platforms struggle to keep pace with these changes, especially when imagery is collected infrequently, leading to delayed detection of illegal activities. Forests evolve due to natural growth cycles, seasonal changes, human interventions, and disturbances like fires, pests, and climate change. Accurately capturing these complex cycles requires long-term continuous monitoring, but detecting changes across varying timescales—such as the decades-long regrowth of a forest versus the rapid destruction caused by a pest outbreak—poses a challenge for AI models. Low temporal resolution, resulting from satellite pass frequencies or sensor limitations, leads to data gaps that hinder observing rapid changes like fires. Although high-frequency data can help, it raises logistical and cost concerns due to increased storage and processing needs. Climate change alters seasonal cycles, such as leaf-fall timing and blooming, complicating the adaptation of AI models trained on historical data. These models need constant updates to remain accurate, requiring substantial computing and data resources. Moreover, integrating spatial and temporal data proves difficult due to regional variations in forest conditions and different data resolutions and frequencies, which demand sophisticated data fusion techniques. AI algorithms must also distinguish between natural changes and human-induced impacts, such as deforestation or pollution, which can overlap, posing further challenges in forest health assessments.

8.20. Algorithmic complexity in artificial intelligence models

Forest ecosystems are complex and dynamic, making creating precise AI models for analyzing and forecasting changes challenging. To manage forests sustainably, AI models must process diverse data from IoT sensors, satellite images, and drone footage, each with distinct geographic, temporal, and spectral dimensions, leading to high-dimensional inputs. Specialized algorithms are needed to handle these inputs, but methods like principal component analysis add complexity. Advanced AI models, including convolutional neural networks, recurrent neural networks, and transformers, are commonly used but require significant computational resources. Due to high computational demands, these models face challenges in real-time monitoring for tasks like wildfire detection and illicit logging. Scaling AI systems to handle vast geographic areas, thousands of IoT devices, and large-scale remote sensing data adds complexity, requiring distributed processing and parallelization. While techniques like federated learning help, they introduce data privacy and synchronization challenges. AI models also increase energy consumption, and reducing model complexity without compromising accuracy is difficult. Strategies like model pruning and quantization can help but may affect interpretability and resilience. Forests constantly change, so updating AI models with new data is essential. Incremental learning helps prevent model drift by enabling the model to adapt continuously to changing forest conditions. However, it complicates data management and consistency, as the model must accommodate and process new data over time.

8.21. Inadequate awareness

Inadequate awareness of IoT, remote sensing, and AI technologies is a significant barrier to their practical use in sustainable forest management. Without sufficient understanding, stakeholders, including local communities, government agencies, and conservation groups, may fail to recognize how these technologies can aid in forest conservation, such as monitoring illegal logging, detecting forest fires, and mapping biodiversity. This lack of awareness can lead to mistrust, reluctance to invest, and underutilization of these systems [63][178]. Furthermore, forest management teams in areas with limited technical expertise may struggle with hardware configuration, data processing, and model training, resulting in inaccurate analyses and reduced system effectiveness. Privacy and ethical concerns over data collection also hinder support, as local communities may fear misuse or illegal disclosure of information. Misconceptions about AI's capabilities, such as overestimating its ability to predict complex ecological events, can cause disappointment and distrust. Short-term profit motives may discourage investment in long-term environmental sustainability. At the same time, a lack of integration between modern technology and traditional knowledge may create friction in local forest management practices. Uninformed of the benefits, Policymakers may also be reluctant to support or fund these technologies. Furthermore, the public's limited awareness of AI and IoT in environmental management can generate skepticism and concerns about energy consumption, wildlife impacts, and data privacy. Without specialized training in data analytics and ecological predictions, decision-makers often struggle to interpret and make informed decisions based on the data these technologies generate.

Despite the potential of IoT, remote sensing, and AI to transform forest management, the challenges highlighted emphasize the need for ongoing research, development, and collaboration among technologists, ecologists, policymakers, and local communities. Overcoming these limitations will be crucial for harnessing these technologies to create sustainable and resilient forest ecosystems.

9. FUTURE RESEARCH DIRECTIONS AND RECOMMENDATIONS

As global worries about climate change and ecosystem degradation grow, new technologies such as the IoT, remote sensing, and AI offer unprecedented prospects for sustainable forest management. While these technologies have demonstrated promise in improving the precision and scalability of forest monitoring, significant gaps and obstacles remain. Future studies in this multidisciplinary field should concentrate on the following:

- Improving data integration and interoperability: Standardized protocols and platforms are required to guarantee smooth integration of IoT devices with current systems, such as GIS, remote sensing, and big data analytics, which can improve real-time decision-making processes. Interoperability between IoT, remote sensing, and AI technologies is critical for their seamless incorporation into forest management systems. Researchers should actively work on creating open-source frameworks and protocols that support interoperability, data sharing, and collaboration among forest management stakeholders [1].
- Edge computing and real-time analytics: Edge computing accelerates data processing by IoT devices, enabling sensors in remote forest regions to analyze information directly at the source. Reducing data transmission to central servers can improve real-time decision-making regarding a forest fire or unlawful logging, increasing responsiveness.
- Energy-efficient IoT devices for distant forest monitoring: Developing low-power or self-sustaining IoT devices that run on solar energy or other renewable sources and function in isolated forest regions without connection to the electrical grid. Battery longevity, energy harvesting, and maintenance-free equipment will improve long-term forest monitoring, minimizing the need for human intervention.
- Blockchain and IoT for forest certification and supply chain transparency: Integrating IoT and Blockchain technologies to trace the source and sustainability of forest products along the supply chain, ensuring that forest conservation initiatives are maintained. Verifiable, tamper-proof IoT-based solutions will provide transparency and authenticity, encouraging sustainable forestry practices and raising consumer awareness.
- Policy frameworks and infrastructure development: Establish national and international policy frameworks to encourage IoT usage in forest conservation, including developing digital infrastructure in remote regions. Collaborative strategies among governments, NGOs, and corporate players will be critical for financing and promoting IoT technology in forest conservation activities.
- Addressing privacy, security, and ethical concerns: Because IoT, remote sensing, and AI technologies acquire and transmit sensitive data, adequate data privacy and security safeguards are required. Additional research and development should focus on integrating advanced encryption techniques, secure data transfer protocols, and authentication systems to ensure the security and integrity of forest data. Building privacy-preserving algorithms that enable data analysis while safeguarding individual privacy should be prioritized [1]. Implement robust data security procedures to protect critical environmental and geolocation information. Ethical criteria must guide the proper use of IoT in conservation, particularly when it involves indigenous and protected territories. Innovations in secure data transmission and decentralized IoT networks may alleviate privacy concerns while protecting conservation initiatives from hostile meddling.
- Improved data gathering and resolution: Advances in satellite and drone imaging technology, which give high-resolution, 3D, and hyperspectral photos, will enable more extensive investigation of forest ecosystems and biodiversity. Cloud computing can improve the ability to store, exchange, and analyze remote sensing data from numerous sources, making data access easier for academics and conservationists [178].

- Policy support and global cooperation: Establishing international standards for sharing remote sensing data would make it easier for people worldwide to work together to conserve forests. Collaborations between governments, NGOs, technology companies, and academic institutes can guarantee that the most advanced remote sensing technologies are available and used in conservation efforts. Building the technical ability of local people, forest managers, and conservationists to employ remote sensing methods is critical for efficient forest management.
- Enhanced predictive modeling for forest health: Machine learning models might be improved to forecast forest health outcomes by detecting early warning indicators of pests, diseases, and climate-related pressures. Artificial intelligence-powered systems might predict tree death, habitat deterioration, and biodiversity loss, enabling proactive management.
- Capacity building and training: Invest in educating conservation practitioners and forest managers about AI technologies and applications. Empowering local teams with AI understanding will assist in closing the gap between technology and actual forest management. Implementing IoT, remote sensing, and AI technology in forest management necessitates stakeholder involvement and capacity-building activities. Research should focus on providing training programs, seminars, and instructional materials to help forest managers, policymakers, and local populations better comprehend and use IoT, remote sensing, and AI technologies. Stakeholder engagement during the design, implementation, and assessment phases of IoT, remote sensing, and AI initiatives is critical to their success and sustainability [1].
- Encourage multidisciplinary research and collaboration among AI scientists, ecologists, and forest conservationists. This partnership will spur innovation in AI algorithms, making them more applicable and successful in real-world forest conservation concerns. Collaboration among academics, practitioners, and policymakers is critical to advancing IoT, remote sensing, and AI technologies in forest management. Research institutions, government agencies, and industry stakeholders should promote collaborative networks and platforms for exchanging information, data, and best practices. This cooperative strategy can speed up the development and application of IoT, remote sensing, and AI technologies, ensuring widespread acceptance and influence on forest management [1][63][178].
- Ethical AI practices include designing and implementing models that respect indigenous rights and biodiversity. Ethical guidelines should govern AI use, ensuring that it benefits all stakeholders, including local populations that rely on forests.
- Designing computationally efficient algorithms for rapid analysis of large-scale data: These advancements can potentially enable revolutionary changes in the approach to forest management, biodiversity preservation, and appropriate conservation strategies [63][178].
- Advances in IoT for precision forestry: Researchers are looking into developing low-cost, energy-efficient, and more robust IoT sensors that can resist harsh forest environments. There is a need to research the use of 5/6G technology and edge computing for real-time data processing and transmission in distant forest locations. Researchers are investigating options for long-term IoT deployments in forest ecosystems, focusing on addressing power requirements, minimizing maintenance, and maximizing sensor lifespan.

These future research directions and recommendations aim to strengthen the link between IoT, remote sensing, and AI for forest conservation and sustainable management, ensuring that these ecosystems can continue providing critical environmental and societal services.

10. CONCLUSION

Sustainable forest management is essential for addressing climate change, preserving biodiversity, and maintaining ecological balance. Integrating IoT, remote sensing, and AI transforms how we address forest ecosystems' complex and dynamic challenges, offering innovative and effective solutions. These technologies redefine traditional forest management by enabling precise monitoring, real-time data collection, and informed decision-making. Together, they provide unparalleled tools to monitor, evaluate, and manage forests more effectively and adaptively, paving the way for sustainable practices.

IoT devices continuously collect data on various forest parameters, including temperature, soil moisture, and humidity, providing valuable insights into environmental changes at micro and macro scales. Remote sensing complements this by delivering comprehensive large-scale observations, which facilitate forest health assessment, deforestation detection, and tracking biodiversity changes. AI enhances the potential of these tools by processing vast datasets, identifying patterns, and generating actionable insights. By applying machine learning techniques, AI can predict threats like wildfires, pest outbreaks, and illegal logging, enabling proactive forest management and conservation efforts.

Combining IoT, remote sensing, and AI empowers adaptive management strategies through real-time data analysis and decision-making. These technologies support early intervention, which is crucial for addressing environmental threats and achieving conservation goals. AI strengthens IoT and remote sensing applications through predictive modeling, anomaly detection, and climate impact analysis. This integration promotes sustainable harvesting, ecosystem restoration, and alignment with long-term conservation objectives, ensuring forests are managed effectively in response to dynamic ecological conditions.

Despite their promise, adopting these technologies presents challenges, including ensuring data privacy, addressing high implementation costs, and overcoming technical barriers to interoperability and standardization. Ethical considerations also need attention, including the ecological impact of deploying IoT devices and ensuring equitable access in resource-limited regions. However, advancements in technology and decreasing costs make these tools increasingly accessible. Collaborative efforts among technologists, ecologists, policymakers, and local communities are vital for scaling these solutions responsibly. Supportive policies, funding mechanisms, and innovations such as low-cost IoT sensors and tailored AI algorithms will further democratize these technologies and enhance their applicability.

In conclusion, the strategic integration of IoT, remote sensing, and AI offers a transformative approach to sustainable forest management. These technologies enhance global conservation efforts by enabling precise, efficient, and adaptive strategies and contribute significantly to climate mitigation. Policymakers and stakeholders must work together to ensure these tools' responsible and inclusive deployment, fostering a resilient and sustainable future for forest ecosystems.

Conflicts of Interest

The authors declare no conflict of interest.

Funding

This research received no external funding.

Acknowledgment

The authors thank the anonymous reviewers for their insightful suggestions and constructive comments.

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