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REVIEW ARTICLE

Advancements in remote sensing tools for forestry analysis

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ABSTRACT

Remote sensing technologies have revolutionized forestry analysis by providing valuable information about forest ecosystems on a large scale. This review article explores the latest advancements in remote sensing tools that leverage optical, thermal, RADAR, and LiDAR data, along with state-of-the-art methods of data processing and analysis. We investigate how these tools, combined with artificial intelligence (AI) techniques and cloud-computing facilities, enhance the analytical outreach and offer new insights in the fields of remote sensing and forestry disciplines. The article aims to provide a comprehensive overview of these advancements, discuss their potential applications, and highlight the challenges and future directions. Through this examination, we demonstrate the immense potential of integrating remote sensing and AI to revolutionize forest management and conservation practices.

Keywords: remote sensing; forestry analysis; optical; thermal; RADAR; LiDAR; artificial intelligence (AI); cloud computing

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1. Introduction

Forestry analysis plays a crucial role in understanding and managing forest ecosystems, and remote sensing technologies have significantly advanced this field. Remote sensing involves the acquisition of information about an object or area without direct physical contact. In the context of forestry analysis, remote sensing techniques provide valuable data on forest cover, health, and dynamics over large spatial extents[1].

Over the years, remote sensing tools have evolved to include various data acquisition systems, such as optical sensors, thermal sensors, RADAR systems, and LiDAR scanners. Optical sensors capture images of forests using the visible and near-infrared spectrum, allowing for detailed analysis of vegetation indices, such as NDVI (normalized difference vegetation index), which can indicate forest health and productivity. Thermal sensors measure the emitted heat radiation from the forest, providing insights into temperature variations and identifying potential stress conditions. RADAR systems use electromagnetic waves to penetrate forest canopies, allowing for the estimation of forest biomass and the detection of forest structural properties. LiDAR scanners emit laser pulses and measure their return time, enabling highly detailed 3D representations of forest structure and topography[2].

Advancements in data processing and analysis have also significantly enhanced the capabilities of remote sensing tools for forestry analysis. Machine learning and artificial intelligence (AI) techniques are now being integrated to automate the classification and mapping of forest cover types, detect changes in forest structure and composition, and predict forest disturbances such as wildfires and insect infestations. These AI-driven approaches enable more efficient and accurate analysis of remote sensing data, saving time and resources while providing valuable insights[3].

Furthermore, the integration of remote sensing tools with cloud computing infrastructure has facilitated the storage, processing, and sharing of large volumes of remote sensing data. Cloud-based platforms allow researchers and practitioners to access and analyze remote sensing data remotely, eliminating the need for expensive computing resources and reducing the time required for data processing. This accessibility and scalability have opened up new avenues for collaboration, enabling multidisciplinary approaches and fostering innovation in forest analysis and management[4].

1.1 Importance of remote sensing in forestry analysis

Remote sensing plays a crucial role in forestry analysis by providing valuable information about forest ecosystems at various spatial and temporal scales. **Figure 1** shows the diagram for functions of remote sensing in forestry analysis. Here are some key points highlighting the importance of remote sensing in forestry analysis:

a) Large-scale coverage: Remote sensing allows for the assessment of forest resources over large areas that are often difficult or time-consuming to access on the ground. This enables comprehensive monitoring and analysis of forests at regional, national, and global scales.

b) Forest inventory and mapping: Remote sensing data, such as optical imagery and LiDAR, can be used to estimate forest inventory parameters like tree species, tree height, canopy cover, biomass, and carbon stocks. These measurements are crucial for assessing forest health, productivity, and carbon sequestration potential.

c) Forest change detection: Remote sensing data enables the detection and monitoring of forest changes over time, such as deforestation, forest degradation, regrowth, and natural disturbances like wildfires and insect outbreaks. Timely and accurate information about these changes is vital for implementing effective forest management strategies and conservation measures.

d) Biodiversity monitoring: Remote sensing can contribute to biodiversity assessments by identifying and mapping habitat types, ecological corridors, and key biodiversity areas. It can help monitor changes in habitat conditions and track the distribution of threatened or endangered species.

e) Forest health monitoring: Remote sensing tools, including thermal and hyperspectral sensors, can provide insights into forest health conditions, including stress detection, disease identification, and pest infestations. Early detection of these issues facilitates prompt interventions to mitigate their impacts on forest ecosystems.

f) Sustainable forest management: Remote sensing data can support sustainable forest management practices by providing information on forest growth rates, timber volume estimation, and optimal harvest planning. It enables the identification of suitable areas for afforestation and reforestation, as well as monitoring the success of these initiatives.

g) Risk assessment and planning: Remote sensing helps in assessing risks related to forest hazards, such as wildfires, landslides, and disease outbreaks. By identifying vulnerable areas, stakeholders can develop effective risk management strategies and prioritize resources for prevention and mitigation efforts[5].

h) Policy support and decision-making: Remote sensing data provides objective and spatially explicit information to support evidence-based decision-making in forestry-related policies, conservation planning, and resource allocation. It helps policymakers and stakeholders understand the state of forests, evaluate the effectiveness of interventions, and monitor compliance with environmental regulations.

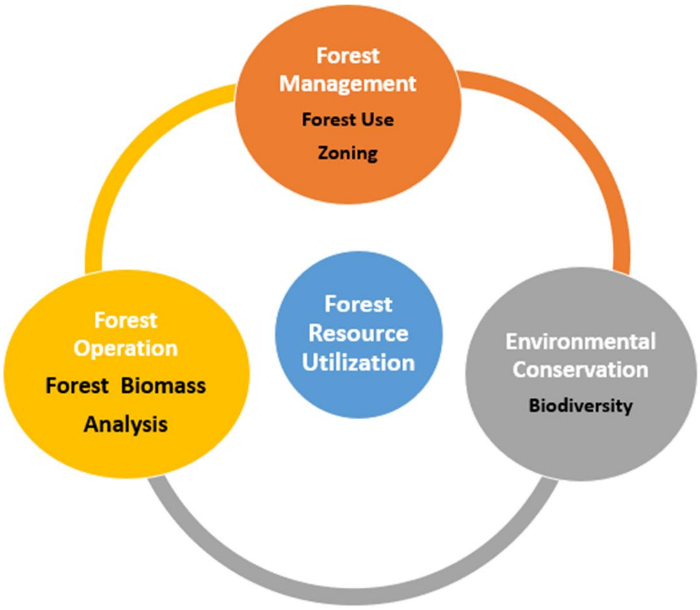

Figure 1. Functions of remote sensing in forestry analysis.

1.2 Overview of optical, thermal, RADAR, and LiDAR remote sensing data

Each type of remote sensing data has its strengths and limitations. Optical data offers high spatial resolution and detailed spectral information but can be affected by cloud cover and limited to daylight imaging[6]. Thermal data captures thermal signatures but may have lower spatial resolution. RADAR data provides all-weather imaging but typically has lower spatial resolution compared to optical data[7]. LiDAR data offers accurate 3D information but can be expensive and limited in spatial coverage. **Figure 2** shows overview of optical, thermal, RADAR, remote sensing data.

a) Optical remote sensing data: Optical remote sensing utilizes sensors that capture the visible and near-infrared portions of the electromagnetic spectrum. It includes data captured by satellites, aerial platforms, and drones. Optical sensors provide detailed information about the spectral characteristics of objects and can be used for various applications such as land cover classification, vegetation health assessment, and mapping.

b) Thermal remote sensing data: Thermal remote sensing data captures the thermal radiation emitted by objects. It measures the surface temperature of objects and can provide valuable information about energy exchange processes, including evapotranspiration and heat stress. Thermal imagery is particularly useful for detecting and monitoring forest fires, assessing vegetation water stress, and analyzing land surface temperature patterns.

c) RADAR remote sensing data: RADAR (radio detection and ranging) remote sensing uses active sensors that emit microwave signals and measure the backscattered signals reflected from the Earth's surface and objects. RADAR data can penetrate clouds and vegetation, making it suitable for all-weather and day-night imaging. It provides information on surface roughness, terrain elevation, and vegetation structure. RADAR data is commonly used for forest mapping, monitoring forest biomass, and detecting forest disturbances such as deforestation and forest degradation.

d) LiDAR remote sensing data: LiDAR (light detection and ranging) remote sensing employs laser sensors that emit pulses of light and measure the time it takes for the light to return after hitting a target. LiDAR data provides highly accurate and detailed three-dimensional (3D) information about the Earth's surface and objects, including vegetation. It is used for generating digital elevation models (DEMs), creating high-resolution canopy height models, identifying individual trees, estimating biomass, and mapping forest structure.

By combining and integrating data from these different remote sensing sources, researchers and analysts can gain a comprehensive understanding of forest ecosystems, including their structure, health, composition, and changes over time. The synergistic use of optical, thermal, RADAR, and LiDAR data enables more robust and accurate analysis, providing valuable insights for forestry applications and environmental management.

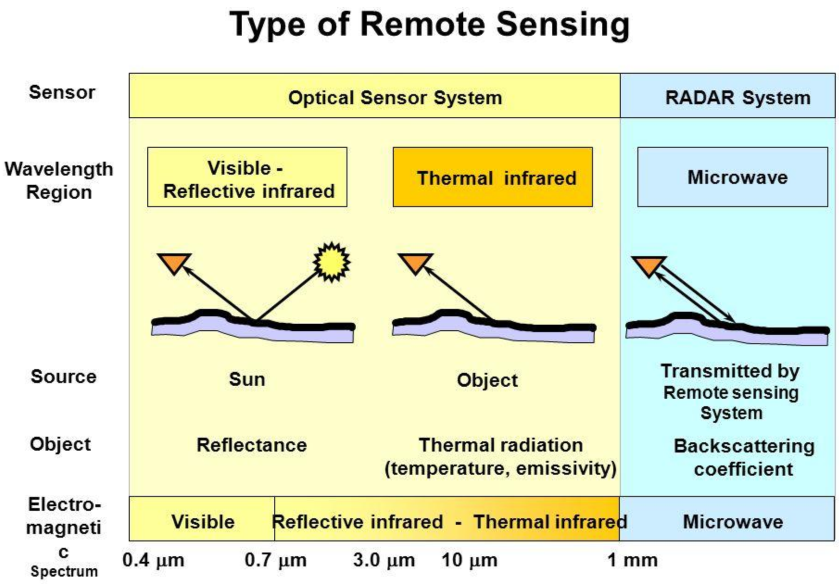

Figure 2. Overview of optical, thermal, RADAR, remote sensing data.

1.3 Advantages of AI and cloud computing in remote sensing applications

AI (artificial intelligence) and cloud computing offer numerous advantages when applied to remote sensing applications. Here are some key benefits:

a) Enhanced data processing: AI techniques, such as machine learning and deep learning, can efficiently process large volumes of remote sensing data. They can automate tasks like feature extraction, classification, and object detection, reducing the time and effort required for manual analysis.

b) Improved accuracy and precision: AI algorithms can improve the accuracy and precision of remote sensing analysis. They can learn complex patterns and relationships from training data, leading to more reliable and consistent results in tasks such as land cover classification, change detection, and species identification.

c) Scalability and efficiency: Cloud computing provides on-demand access to vast computational resources. It allows remote sensing analysts to process and analyze large datasets quickly and efficiently. Cloud-based platforms can scale up or down based on the workload, ensuring timely and cost-effective data processing.

d) Accessibility and collaboration: Cloud-based remote sensing platforms enable easy access to data and tools from anywhere with an internet connection. This accessibility promotes collaboration among researchers, allowing them to share data, algorithms, and models. It facilitates interdisciplinary research and knowledge sharing across different geographic locations.

e) Real-time monitoring and alerts: AI algorithms can be deployed on cloud-based systems to provide real-time monitoring and alerts for specific events or changes detected in remote sensing data. For example, forest fire detection systems can analyze satellite imagery in real-time and issue alerts to authorities, enabling rapid response and mitigation measures.

f) Fusion of multi-source data: AI techniques combined with cloud computing enable the integration and fusion of multi-source remote sensing data. This integration enhances the analysis by combining complementary information from different sensors, such as optical, thermal, RADAR, and LiDAR data. It leads to a more comprehensive understanding of forest ecosystems and enables more accurate and holistic assessments.

g) Adaptability and Learning: AI algorithms can adapt and improve over time by learning from new data. They can be trained on updated datasets to refine and update models, enhancing the accuracy and relevance of remote sensing analysis. Cloud computing provides the infrastructure to support continuous learning and updates of AI models.

h) Cost Savings: Cloud computing eliminates the need for extensive local infrastructure and computational resources. Organizations can leverage the pay-as-you-go model of cloud services, reducing costs associated with hardware, software, maintenance, and upgrades. It makes remote sensing analysis more accessible and cost-effective, particularly for smaller organizations or research projects with limited budgets[8].

By harnessing the power of AI and cloud computing, remote sensing applications can achieve higher efficiency, accuracy, scalability, and accessibility. These technologies are transforming the field by enabling advanced analysis, real-time monitoring, and collaborative research, ultimately leading to improved understanding and management of forest ecosystems. **Figure 3** process of AI Application in forest mapping and monitoring.

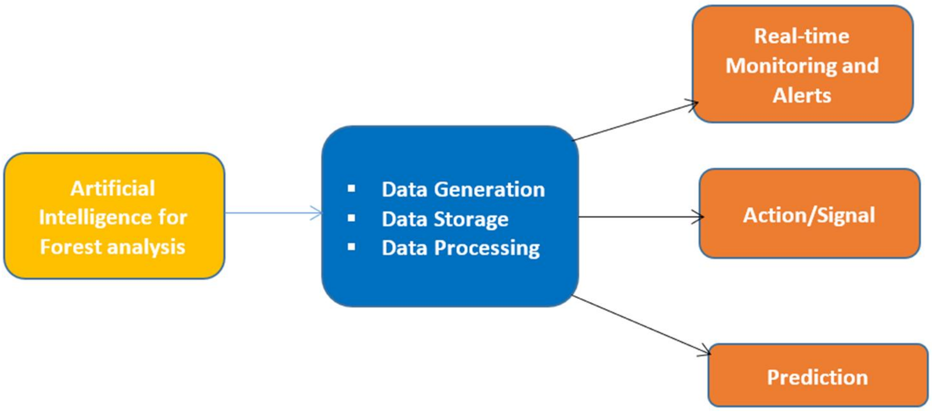

Figure 3. Process of AI application in forest mapping and monitoring.

2. Optical remote sensing tools

2.1 Utilizing high-resolution multispectral and hyperspectral imagery for vegetation mapping and species classification

Utilizing high-resolution multispectral and hyperspectral imagery for vegetation mapping and species classification has become a valuable application in remote sensing[9]. Here are some key aspects and benefits of using these types of imagery for these purposes.

2.1.1 Multispectral imagery

Multispectral imagery captures data in a few distinct spectral bands, typically including the visible and near-infrared regions of the electromagnetic spectrum. It provides valuable information about the reflectance properties of vegetation and other land cover types. Some advantages of using high-resolution multispectral imagery for vegetation mapping and species classification are:

a) Spectral differentiation: Different vegetation species and types exhibit unique spectral signatures due to variations in their chlorophyll content, leaf structure, and physiological properties. Multispectral imagery allows for the differentiation of vegetation classes based on their spectral response patterns.

b) Land cover mapping: Multispectral imagery can be used to classify and map various land cover types, including forests, grasslands, croplands, wetlands, and urban areas. By analyzing the spectral characteristics of different land cover classes, accurate maps can be created to monitor land use changes and assess vegetation dynamics.

c) Vegetation indices: Multispectral imagery enables the calculation of vegetation indices such as the normalized difference vegetation index (NDVI) and Enhanced Vegetation Index (EVI). These indices provide quantitative measures of vegetation health, biomass, and vigor, facilitating vegetation mapping and monitoring of ecosystem conditions.

d) Classification algorithms: high-resolution multispectral imagery can be utilized in conjunction with classification algorithms, such as decision trees, random forests, or support vector machines, to accurately classify vegetation species or land cover types. The combination of spectral information and machine learning techniques improves the accuracy of classification results.

2.1.2 Hyperspectral imagery

Hyperspectral imagery captures data in numerous narrow contiguous spectral bands, providing a more detailed spectral resolution compared to multispectral imagery[10]. It offers several advantages for vegetation mapping and species classification:

a) Spectral signature analysis: Hyperspectral imagery allows for the detection of subtle differences in vegetation spectral signatures, enabling finer discrimination among species and vegetation classes. It can capture unique spectral characteristics related to biochemical and physiological properties of vegetation, leading to more accurate species identification.

b) Species discrimination: Hyperspectral imagery provides a wealth of spectral information that can be used to develop species-specific spectral libraries or signatures. These spectral libraries, combined with advanced classification algorithms, facilitate the identification and discrimination of plant species, including invasive or rare species.

c) Vegetation trait analysis: Hyperspectral data can be used to extract additional vegetation traits beyond spectral classification. It enables the estimation of parameters such as leaf area index (LAI), chlorophyll content, water content, and biochemical composition. These parameters contribute to a more comprehensive understanding of vegetation characteristics and ecosystem processes.

d) Sub-pixel analysis: Hyperspectral imagery allows for sub-pixel analysis, enabling the identification and mapping of mixed pixels where multiple vegetation species or land cover types coexist within a single pixel. This capability enhances the accuracy of vegetation mapping and species classification in complex landscapes.

e) Ecological research and conservation: Hyperspectral imagery provides valuable data for ecological research, habitat mapping, biodiversity assessment, and conservation planning. It aids in the identification of sensitive or threatened ecosystems, monitoring the spread of invasive species, and assessing habitat quality.

Both high-resolution multispectral and hyperspectral imagery offer valuable insights for vegetation mapping and species classification. The choice between the two depends on the specific research objectives, spatial resolution requirements, and spectral resolution needs of the study. Advances in sensor technology and data processing techniques continue to enhance the accuracy and capabilities of these remote sensing tools for vegetation analysis and ecological studies.

2.2 Extraction of forest structural parameters using vegetation indices and machine learning algorithms

The extraction of forest structural parameters using vegetation indices and machine learning algorithms is a powerful approach in remote sensing. By combining spectral information from vegetation indices and the analytical capabilities of machine learning algorithms, accurate and efficient estimation of forest structural parameters can be achieved. **Figure 4** shows methodology flow chart extraction of forest structural parameters. Here are the key aspects and benefits of this approach:

a) Vegetation indices: Vegetation indices are derived from remote sensing data, typically using specific combinations of spectral bands, and provide quantitative measures of vegetation properties. Some commonly used vegetation indices include the normalized difference vegetation index (NDVI), enhanced vegetation index (EVI), and leaf area index (LAI). These indices capture important characteristics related to vegetation health, vigor, and leaf area.

b) Forest structural parameters: Forest structural parameters refer to the physical characteristics of the forest, such as canopy height, crown diameter, tree density, biomass, and volume. Accurately estimating these parameters is crucial for forest management, carbon accounting, biodiversity assessment, and ecosystem modeling[11].

c) Machine learning algorithms: Machine learning algorithms, such as decision trees, random forests, support vector machines, or neural networks, can be trained using labeled or reference data to establish relationships between vegetation indices and forest structural parameters. Once trained, these algorithms can make predictions or classifications on new or unseen data.

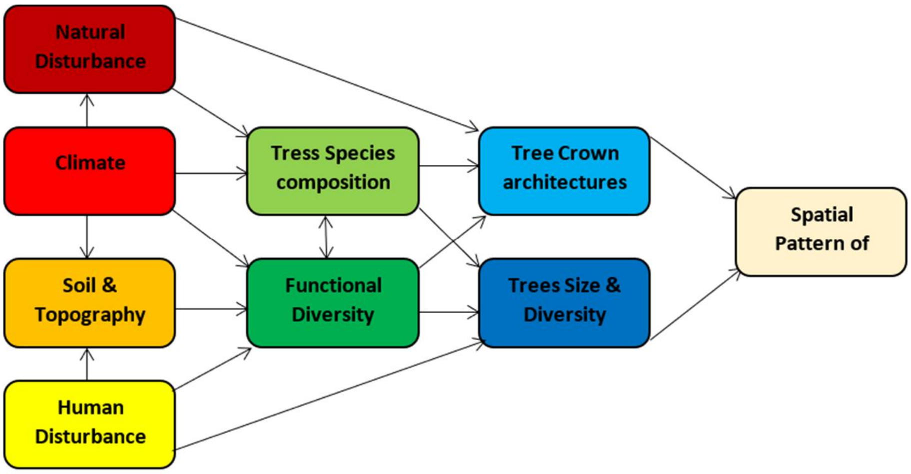

Figure 4. Methodology flow chart extraction of forest structural parameters.

2.3 Integration of AI methods for automated land cover change detection and forest disturbance monitoring

The integration of AI methods for automated land cover change detection and forest disturbance monitoring has revolutionized the field of remote sensing and environmental monitoring. AI techniques, such as machine learning and deep learning, have the capability to analyze large volumes of remote sensing data and automatically detect and classify land cover changes and forest disturbances[12]. Here are the key aspects and benefits of this integration:

a) Efficient change detection: AI methods enable automated change detection by comparing multi-temporal remote sensing data. By training machine learning models on labeled change/no-change data, these algorithms can learn to identify patterns and spectral changes associated with land cover changes and forest disturbances. This eliminates the need for manual visual interpretation of imagery, making the process more efficient and scalable.

b) Multi-sensor data fusion: AI methods facilitate the integration of multi-sensor data, such as optical, thermal, RADAR, and LiDAR, for change detection and forest disturbance monitoring. By combining information from different sensors, the algorithms can leverage the complementary strengths of each data source, resulting in more accurate and comprehensive analysis.

c) High accuracy and reliability: AI algorithms can achieve high accuracy and reliability in detecting land cover changes and forest disturbances. By leveraging the power of deep learning neural networks, these algorithms can learn intricate patterns and spectral characteristics that are not easily discernible to human observers. This leads to improved detection rates and reduced false positives/negatives.

d) Rapid detection and monitoring: AI methods enable real-time or near-real-time land cover change detection and forest disturbance monitoring. With automated processing and analysis, the algorithms can continuously monitor large areas and provide timely information on forest disturbances, such as deforestation, forest fires, insect outbreaks, and disease outbreaks. This allows for proactive and rapid response to mitigate the impacts of disturbances.

e) Scalability and cost-effectiveness: The integration of AI methods with cloud computing provides scalability and cost-effectiveness in processing and analyzing large volumes of remote sensing data. Cloud-based platforms allow for parallel processing and utilization of high-performance computing resources, reducing computational time and costs associated with data storage and processing.

f) Long-term monitoring and trend analysis: By automating land cover change detection and forest disturbance monitoring, AI methods facilitate long-term monitoring and trend analysis. Historical satellite imagery can be processed to identify persistent changes and assess the trajectory of forest disturbances over time. This information is valuable for understanding long-term environmental changes, ecosystem dynamics, and informing land management and conservation strategies.

g) Early warning systems: AI-based change detection algorithms can be integrated into early warning systems for forest disturbances. By continuously monitoring and analyzing remote sensing data, these systems can provide timely alerts and notifications to stakeholders and decision-makers, enabling them to take proactive measures to mitigate and respond to forest disturbances.

The integration of AI methods for automated land cover change detection and forest disturbance monitoring has significantly improved the efficiency, accuracy, and timeliness of environmental monitoring. It empowers researchers, land managers, and policymakers with actionable information for effective land management, conservation planning, and the preservation of forest ecosystems.

3. Thermal remote sensing tools

3.1 Mapping forest health and stress using thermal infrared imagery

Thermal remote sensing tools, particularly thermal infrared imagery, offer valuable insights into mapping forest health and stress. By capturing and analyzing the thermal radiation emitted by objects, including vegetation, thermal remote sensing provides information about the temperature variations within forest ecosystems[13]. Here are key aspects related to mapping forest health and stress using thermal infrared imagery:

a) Temperature as an indicator of forest health: Temperature is a vital parameter for assessing the health and stress levels of forest vegetation. Healthy plants typically exhibit a well-regulated temperature range, while stressed or unhealthy vegetation may show deviations from the normal temperature patterns. Thermal infrared imagery can detect these temperature variations and provide information on the physiological condition of the forest.

b) Water stress and drought monitoring: Water stress is a significant factor affecting forest health, particularly in arid and semi-arid regions. Thermal remote sensing can help identify areas of water stress by detecting higher leaf temperatures in plants experiencing water shortages. By monitoring the thermal patterns of forests over time, it is possible to assess the severity and spatial extent of drought conditions and their impact on forest ecosystems.

c) Detection of pest and disease infestations: Thermal infrared imagery can aid in the detection of pest and disease infestations in forested areas. Infected or infested trees often exhibit abnormal temperature patterns due to physiological changes induced by pests or diseases. By comparing the thermal signatures of healthy and infected vegetation, it is possible to identify areas of potential pest or disease outbreaks and target appropriate management actions.

d) Fire detection and monitoring: Thermal remote sensing is widely used for fire detection and monitoring. Active fires emit significant amounts of thermal radiation, which can be detected by thermal infrared sensors onboard satellites or aerial platforms. By analyzing the thermal anomalies and patterns, such as hotspots and fire fronts, thermal remote sensing contributes to early fire detection, fire behavior modeling, and post-fire monitoring.

e) Vegetation stress and disturbance mapping: Thermal infrared imagery can provide insights into vegetation stress and disturbances caused by factors such as deforestation, land use changes, or human activities. Areas undergoing disturbances often exhibit changes in surface temperature due to alterations in vegetation cover, water availability, or soil properties. By comparing pre- and post-disturbance thermal imagery, it is possible to map and monitor areas of vegetation stress and disturbance.

f) Mapping forest microclimates: Thermal remote sensing enables the mapping of forest microclimates by assessing temperature variations within a forested area. Different forest types, topography, and vegetation structure can create distinct thermal environments. Understanding these microclimates is crucial for characterizing ecological niches, species distribution, and habitat suitability assessments.

g) Integration with other remote sensing data: To enhance the accuracy and reliability of forest health and stress mapping, thermal remote sensing data can be integrated with other remote sensing datasets. Combining thermal infrared imagery with multispectral or hyperspectral data allows for a more comprehensive analysis of vegetation dynamics, land cover change, and ecosystem functioning.

Mapping forest health and stress using thermal infrared imagery has proven to be a valuable application of thermal remote sensing. By leveraging the temperature variations within forest ecosystems, it provides essential information for understanding the impacts of water stress, pest and disease outbreaks, fire occurrences, disturbances, and microclimate variability. These insights contribute to effective forest management, conservation planning, and the preservation of ecosystem resilience.

3.2 Estimation of evapotranspiration and water stress in forests

The estimation of evapotranspiration (ET) and water stress in forests is crucial for understanding water dynamics, assessing ecosystem health, and informing water resource management strategies[14]. Remote sensing techniques, combined with modeling approaches, offer valuable tools to estimate ET and evaluate water stress in forested environments. Here are key aspects related to the estimation of evapotranspiration and water stress in forests:

a) Evapotranspiration estimation: Evapotranspiration represents the combined processes of water evaporation from the soil surface and transpiration from plant leaves. Estimating ET in forests helps quantify the water loss and understand the water requirements of vegetation. Remote sensing plays a vital role in ET estimation by providing spatially and temporally explicit information on vegetation properties, land surface temperature, and energy fluxes.

b) Energy balance models: Energy balance models, such as the surface energy balance algorithm for land (SEBAL) or the simplified surface energy balance (SSEB) approach, utilize remote sensing data to estimate ET. These models rely on measurements of surface temperature (derived from thermal infrared imagery), meteorological data, and vegetation indices to calculate energy fluxes and water vapor exchange between the land surface and the atmosphere.

c) Vegetation indices: Vegetation indices, particularly those derived from multispectral or hyperspectral imagery, provide valuable information for estimating ET and assessing water stress in forests. Indices such as the normalized difference vegetation index (NDVI) or the enhanced vegetation index (EVI) reflect vegetation vigor and biomass, which are correlated with transpiration rates and water availability.

d) Water stress indicators: Water stress in forests can be evaluated by monitoring indicators related to vegetation water content and physiological responses. Remote sensing-based indicators, such as the normalized difference water index (NDWI) or the water stress index (WSI), leverage spectral information from optical or thermal sensors to assess the level of water stress in vegetation. These indicators detect changes in leaf water content or alterations in thermal patterns associated with water limitations.

e) Canopy water content mapping: Remote sensing data, including microwave and L-band radar imagery, can be used to estimate canopy water content in forests. Microwaves penetrate vegetation and are sensitive to changes in water content, allowing the mapping of water storage in the canopy layer. This information contributes to understanding the water balance and water availability in forested areas.

f) Integration of data sources: Integration of remote sensing data with meteorological information, ground-based measurements, and hydrological models enhances the accuracy of ET estimation and water stress assessment. Combining remote sensing observations with ancillary data enables the calibration and validation of models, accounting for local climatic conditions, vegetation types, and soil properties.

g) Monitoring and management applications: Accurate estimation of ET and evaluation of water stress in forests have practical applications in various domains. These include assessing drought impacts on forest ecosystems, optimizing water allocation for irrigation or ecological purposes, guiding forest management practices to maintain healthy vegetation, and supporting water resource planning and decision-making.

The estimation of evapotranspiration and water stress in forests using remote sensing provides valuable insights into the water dynamics and ecosystem functioning. By leveraging the capabilities of remote sensing techniques and modeling approaches, it contributes to improved water resource management, sustainable forest practices, and the conservation of water-dependent ecosystems.

3.3 Combining thermal data with other remote sensing sources for improved forest fire detection and monitoring

Combining thermal data with other remote sensing sources offers significant advantages for improved forest fire detection and monitoring. By integrating multiple data types, such as optical, thermal, and radar imagery[15], a more comprehensive and accurate assessment of forest fires can be achieved. Here are the key benefits of combining thermal data with other remote sensing sources for forest fire detection and monitoring:

a) Enhanced fire detection: Thermal data, particularly from thermal infrared sensors, provide valuable information on the radiant heat emitted by active fires. By integrating thermal imagery with optical data, such as multispectral or hyperspectral imagery, it is possible to improve fire detection capabilities. Optical sensors capture the visual and spectral signatures of smoke, flames, and burned areas, complementing the thermal data and increasing the overall detection accuracy.

b) Improved fire mapping and boundary estimation: Combining thermal data with high-resolution optical imagery allows for more precise mapping and boundary estimation of forest fires. The thermal data provide information about the fire's thermal intensity and extent, while optical data provide detailed spatial information, helping to delineate the fire perimeter and distinguish between burned and unburned areas. This integration enables more accurate fire size estimation and assessment of fire behavior.

c) Smoke plume analysis: Integrating thermal and radar data can provide valuable insights into the analysis of smoke plumes generated by forest fires. Radar sensors are capable of penetrating smoke and capturing the backscatter signals from smoke particles. By combining thermal data for fire location and intensity with radar data for smoke detection and characterization, it is possible to better understand smoke dynamics, dispersion patterns, and potential impacts on air quality.

d) Fire severity assessment: Combining thermal data with post-fire optical and radar data facilitates fire severity assessment. Post-fire optical imagery, such as high-resolution satellite imagery, can capture the extent and severity of burned areas, while radar data can help identify changes in forest structure and biomass. By comparing pre- and post-fire data, it is possible to quantify the severity of the fire's impact on the forest ecosystem and assess vegetation recovery potential.

e) Real-time fire monitoring: Integrating thermal data with near-real-time monitoring systems, such as geostationary satellites or unmanned aerial vehicles (UAVs), enables real-time fire monitoring and early warning systems. Thermal sensors onboard satellites or UAVs can provide continuous updates on fire activity, while other sensors capture complementary information on smoke, flames, and burned areas. This integration allows for timely response and decision-making to mitigate the impacts of forest fires.

f) Fire behavior modeling: Combining thermal data with other remote sensing sources contributes to more accurate fire behavior modeling. By assimilating thermal data into fire behavior models, it is possible to improve the prediction of fire spread, intensity, and direction. This information is valuable for fire management and resource allocation, aiding in the deployment of firefighting resources and the development of effective fire containment strategies.

g) Integration with ancillary data: Integrating thermal data with ancillary data, such as weather data, topographic information, and fuel characteristics, further enhances the understanding and analysis of forest fires. Incorporating these additional data sources into fire detection and monitoring systems enables more robust modeling, considering factors that influence fire behavior and spread, such as wind patterns, slope, and vegetation type.

Combining thermal data with other remote sensing sources significantly improves forest fire detection and monitoring capabilities. By leveraging the strengths of different sensors and data types, it allows for more accurate fire detection, mapping, severity assessment, and real-time monitoring[16]. This integration enhances the effectiveness of fire management efforts and supports proactive measures to mitigate the impacts of forest fires on ecosystems and human populations.

4. RADAR remote sensing tools

4.1 Assessing forest biomass and structure using synthetic aperture radar (SAR) data

Assessing forest biomass and structure using synthetic aperture radar (SAR) data has proven to be a valuable approach in remote sensing. SAR data, with its unique capabilities for penetrating forest canopies and capturing backscatter signals, provides valuable information for estimating forest biomass, characterizing forest structure, and monitoring changes over time[17]. Here are key aspects related to the assessment of forest biomass and structure using SAR data:

a) Backscatter response and biomass estimation: SAR backscatter signals are sensitive to the structural properties and moisture content of forest vegetation. Forest biomass estimation using SAR data is based on the assumption that higher biomass is associated with increased backscatter intensity. By calibrating SAR backscatter measurements with ground-based biomass data, it is possible to establish empirical relationships and develop biomass estimation models.

b) Forest height and canopy structure: SAR data can be used to estimate forest height and characterize canopy structure. The interaction of SAR signals with forest canopies provides information about the vertical structure and density of vegetation. Forest height estimation is typically achieved by correlating SAR backscatter with field measurements of tree height, while canopy structure parameters, such as vegetation density or canopy closure, can be derived from the shape and intensity of the backscatter response.

c) Forest change detection: SAR data allows for the monitoring of forest changes over time, including deforestation, forest degradation, or regrowth. By comparing SAR images acquired at different time points, changes in backscatter patterns can be identified, indicating alterations in forest biomass and structure. Change detection using SAR data contributes to understanding forest dynamics, assessing the impacts of human activities, and supporting forest management and conservation efforts.

d) Polarimetric SAR: Polarimetric SAR data, which provides additional information about the polarization properties of radar signals, enhances the assessment of forest biomass and structure. By analyzing the polarimetric backscatter responses, it is possible to extract more detailed information about the scattering mechanisms within forest canopies. Polarimetric SAR data enables the discrimination of different vegetation types, estimation of biomass components (such as above-ground and below-ground biomass), and identification of structural characteristics, such as tree density and canopy orientation.

e) Interferometric SAR (InSAR): InSAR techniques, using pairs or stacks of SAR images acquired from slightly different positions, allow for the estimation of forest height and monitoring of forest structure changes. By measuring the phase differences between SAR images, it is possible to generate digital elevation models (DEMs) and derive forest height information. InSAR also enables the detection of subtle ground deformations, such as those caused by tree growth or subsidence, providing insights into forest structural dynamics.

f) Data fusion and integration: Integrating SAR data with other remote sensing sources, such as optical imagery or LiDAR data, enhances the assessment of forest biomass and structure. Data fusion techniques enable the integration of SAR information (e.g., backscatter intensity) with optical data (e.g., vegetation indices) or LiDAR-derived metrics (e.g., canopy height). This integration allows for a more comprehensive analysis of forest characteristics, overcoming the limitations and complementing the strengths of each individual data source.

g) Calibration and validation: Accurate estimation of forest biomass and structure using SAR data requires calibration and validation against ground-based measurements. Field data collection, including forest inventory plots, biomass sampling, or LiDAR acquisitions, is essential for establishing empirical relationships and validating the accuracy of SAR-based estimations. Ground truth data play a crucial role in calibrating SAR backscatter models and improving the reliability of biomass and structure assessments.

Assessing forest biomass and structure using SAR data offers valuable insights into forest ecosystems, supporting forest inventory, carbon accounting, and management practices. The unique capabilities of SAR in penetrating forest canopies and providing all-weather.

4.2 Detection and mapping of forest disturbances, such as deforestation and forest degradation, using SAR interferometry

SAR interferometry, commonly known as InSAR (interferometric synthetic aperture radar), is a powerful technique for detecting and mapping forest disturbances, including deforestation and forest degradation[18]. By analyzing the phase differences between pairs of SAR images acquired at different times, InSAR can identify subtle ground deformations associated with changes in forest cover. Here are key aspects related to the detection and mapping of forest disturbances using SAR interferometry:

a) Forest height change detection: One of the main applications of InSAR in forest disturbance mapping is the detection of changes in forest height. When deforestation or forest degradation occurs, the removal or alteration of vegetation results in changes in the surface elevation, which can be detected by InSAR. By comparing two or more SAR images, InSAR can quantify the vertical displacement and provide insights into the extent and magnitude of forest disturbances.

b) Differential interferometric SAR (DInSAR): Differential interferometric SAR (DInSAR) is a variant of InSAR that focuses on measuring small-scale surface deformations. By comparing the phase differences between two or more SAR images acquired at different times, DInSAR can detect and quantify subtle ground movements associated with forest disturbances. It enables the identification of localized areas of deforestation, selective logging, or other forms of forest degradation.

c) Forest cover change detection: In addition to measuring height changes, InSAR can also be used to detect changes in forest cover. By analyzing the coherence, which represents the similarity of radar waves between two images, areas of significant vegetation loss or disturbance can be identified. A decrease in coherence indicates changes in the radar backscatter, indicating forest disturbances such as deforestation, clear-cutting, or fire.

d) Mapping forest degradation: SAR interferometry can be used to map different types of forest degradation, such as selective logging, canopy gaps, or gradual loss of biomass. By quantifying the vertical displacement and coherence changes in SAR images, InSAR provides information about the spatial distribution and severity of forest degradation. These maps can assist in assessing the impact of human activities on forest ecosystems and guiding conservation efforts.

e) Identification of illegal logging: illegal logging is a significant threat to forests worldwide. InSAR can contribute to the identification and monitoring of illegal logging activities by detecting changes in forest cover and height. The ability to detect small-scale ground deformations allows for the identification of localized areas where unauthorized logging activities are taking place, supporting law enforcement and forest management efforts.

f) Forest recovery monitoring: Following disturbances such as deforestation or selective logging, monitoring forest recovery is crucial for assessing the effectiveness of restoration efforts. InSAR can contribute to monitoring the regrowth of forests by detecting changes in surface elevation and canopy height over time. It enables the quantification of forest recovery rates and the evaluation of restoration success.

g) Integration with other data sources: To enhance the accuracy and reliability of forest disturbance mapping, InSAR data can be integrated with other remote sensing sources, such as optical imagery or LiDAR data. Combining InSAR with optical data allows for the identification of changes in forest cover, while LiDAR data can provide additional information on canopy structure and biomass. Data fusion and integration enable a more comprehensive understanding of forest disturbances and their impact on ecosystem dynamics.

Detection and mapping of forest disturbances, such as deforestation and forest degradation, using SAR interferometry, provide valuable insights into the dynamics of forest ecosystems. By leveraging the capabilities of InSAR, it is possible to assess the extent, magnitude, and spatial patterns of forest disturbances, supporting forest management, conservation efforts, and policy-making for sustainable land use.

4.3 Fusion of optical and RADAR data for improved forest characterization and monitoring

The fusion of optical and radar data offers significant advantages for improved forest characterization and monitoring. By integrating the complementary information from these two data sources, a more comprehensive understanding of forest structure, biomass, and dynamics can be achieved[19]. Here are the key benefits of fusing optical and radar data for forest characterization and monitoring:

a) Improved forest structure estimation: Optical data, such as multispectral or hyperspectral imagery, provide high-resolution spatial information about vegetation characteristics, including leaf area index (LAI), canopy height, and vegetation indices. On the other hand, radar data, such as synthetic aperture radar (SAR), can penetrate forest canopies and provide information on forest structure, such as canopy density and vertical structure. By fusing optical and radar data, it is possible to enhance the estimation of forest structure parameters, resulting in more accurate assessments of biomass, canopy height, and forest density.

b) Enhanced biomass estimation: Optical data are sensitive to the photosynthetic activity and green biomass of forests, while radar data can penetrate vegetation canopies and provide information on the overall biomass content, including above-ground and below-ground biomass. By fusing optical and radar data, it is possible to combine the strengths of both sensors for more accurate biomass estimation. The optical data can contribute to estimating the green biomass, while the radar data can provide additional information on the total biomass content, including woody biomass, which is particularly valuable for large-scale biomass assessments.

c) Improved forest disturbance detection: The fusion of optical and radar data enables improved detection and monitoring of forest disturbances, such as deforestation, forest degradation, and illegal logging. Optical data can capture changes in land cover and provide high-resolution spatial information on forest disturbances, while radar data can penetrate clouds and capture surface changes even under adverse weather conditions. By fusing these data sources, it is possible to detect and characterize forest disturbances more effectively, enabling timely response and intervention.

d) Enhanced forest mapping: Integrating optical and radar data facilitates more accurate forest mapping, including forest type classification and land cover mapping. Optical data provide spectral information that is valuable for discriminating different vegetation types and land cover classes, while radar data contribute to distinguishing between forested and non-forested areas and provide information on forest structure and biomass. By combining these data sources, it is possible to generate more detailed and accurate forest maps, supporting various applications, such as forest inventory, land management, and conservation planning.

e) Improved monitoring of forest dynamics: The fusion of optical and radar data allows for better monitoring of forest dynamics, including changes in forest cover, regrowth, and vegetation phenology. Optical data capture the seasonal variations in vegetation greenness and phenological patterns, while radar data can penetrate clouds and capture changes in forest structure and biomass. By fusing these data sources, it is possible to monitor forest dynamics at different spatial and temporal scales, providing insights into forest health, growth, and response to environmental changes.

f) Integration with ancillary data: Fusing optical and radar data can be combined with ancillary data sources, such as topographic information, climate data, and soil properties, to improve forest characterization and monitoring. By integrating these additional data sources, it is possible to account for factors that influence forest dynamics, such as terrain characteristics, water availability, and nutrient content. This integration enhances the understanding of forest ecosystems and supports more comprehensive analyses and modelling.

The fusion of optical and radar data provides a powerful tool for improved forest characterization and monitoring. By combining the strengths of both sensors, it allows for more accurate estimation of forest structure, biomass, and disturbance detection[20]. This integrated approach supports effective forest management, conservation planning, and the assessment of ecosystem services provided by forests.

5. LiDAR remote sensing tools

5.1 3D forest structure modelling and canopy height estimation using LiDAR data

LiDAR (light detection and ranging) remote sensing is a powerful tool for 3D forest structure modelling and canopy height estimation. LiDAR data, acquired from airborne or terrestrial platforms, provides detailed information about the vertical structure of forests, allowing for accurate characterization of forest canopies[20]. Here are key aspects related to 3D forest structure modelling and canopy height estimation using LiDAR data:

a) Point cloud generation: LiDAR data consists of millions or even billions of individual

3D point measurements, commonly referred to as a point cloud. The LiDAR sensor emits laser pulses and records the time it takes for the laser to return after reflecting off the objects in the environment, including tree canopies. By processing these point measurements, a high-resolution point cloud representing the forest canopy is generated.

b) Canopy Height Model (CHM) generation: One of the primary applications of LiDAR data in forestry is the generation of canopy height models (CHMs). CHMs represent the vertical structure of the forest by calculating the difference between the ground elevation and the height of the highest points within the canopy. By subtracting the digital terrain model (DTM) derived from LiDAR data from the digital surface model (DSM), a CHM is generated, providing information on canopy height variations across the study area.

c) Individual tree segmentation: LiDAR data can be used to segment individual trees within a forested area. Using various algorithms, such as watershed segmentation or region growing, LiDAR point clouds can be processed to identify and delineate individual tree crowns. This allows for the extraction of tree-level information, such as tree height, crown diameter, and crown volume, contributing to accurate forest inventory and monitoring.

d) Forest canopy structure analysis: LiDAR data enables detailed analysis of forest canopy structure and its spatial distribution. Metrics such as canopy cover, leaf area index (LAI), crown density, and canopy gap fraction can be derived from LiDAR point clouds. These metrics provide insights into forest structure, species composition, and ecological processes. Canopy structure analysis using LiDAR data supports various applications, including forest ecology research, biodiversity assessments, and habitat modeling.

e) Forest biomass estimation: Canopy height derived from LiDAR data is a crucial parameter for estimating forest biomass. The height information, combined with allometric equations and ground-based measurements, enables the estimation of above-ground biomass and carbon stocks at various scales. LiDAR-based biomass estimation provides accurate and spatially explicit information, supporting forest carbon accounting, climate change modeling, and sustainable forest management practices.

f) Forest change detection: LiDAR data, when acquired at different time points, facilitates the detection and monitoring of forest changes over time. By comparing LiDAR-derived metrics, such as canopy height or canopy cover, changes in forest structure, deforestation, or forest regrowth can be identified. LiDAR-based change detection allows for the assessment of forest dynamics, tracking disturbances, and evaluating the effectiveness of forest management and restoration activities.

g) Integration with other data sources: LiDAR data can be integrated with other remote sensing sources, such as optical imagery or radar data, to enhance forest characterization and monitoring. The fusion of LiDAR data with optical data allows for the extraction of additional information, such as spectral properties and vegetation indices, complementing the 3D structural information provided by LiDAR. Integration with radar data, such as SAR, enables the assessment of forest structure and biomass in areas where LiDAR data may be unavailable or limited due to cloud cover or dense vegetation. 3D forest structure modelling and canopy height estimation using LiDAR data revolutionize our understanding of forest ecosystems. The detailed information provided by LiDAR enables accurate assessments (**Figure 5**).

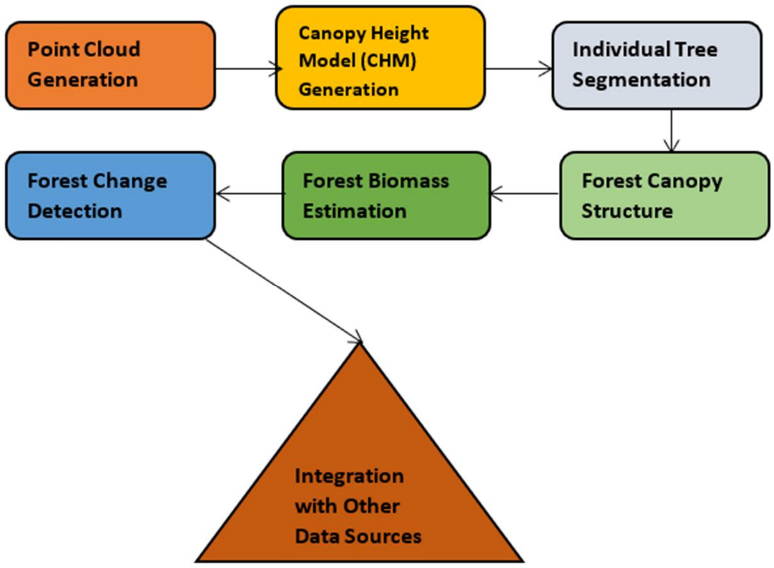

Figure 5. Flow chart showing 3D forest structure modelling and canopy height estimation using LiDAR data.

5.2 Identification and mapping of individual trees and their attributes

LiDAR (light detection and ranging) remote sensing technology is well-suited for the identification and mapping of individual trees and their attributes[21]. By processing the point cloud data acquired from LiDAR sensors, it is possible to extract detailed information about individual trees, including their location, size, species, and other attributes. Here are the key aspects related to the identification and mapping of individual trees using LiDAR:

a) Point cloud segmentation: LiDAR point cloud data can be segmented to separate individual trees from the surrounding vegetation and terrain. Various algorithms and techniques, such as region growing, watershed segmentation, or graph-based methods, can be applied to group the LiDAR points that belong to the same tree crown. This segmentation process enables the isolation of individual tree objects from the LiDAR data.

b) Tree location and position: Once the trees are segmented from the LiDAR point cloud, their precise locations and positions can be determined. The 3D coordinates of the points representing the tree canopy are used to calculate the centroid or representative point of each tree. This provides the spatial information needed to map the distribution of individual trees within a forested area.

c) Tree height and canopy diameter: LiDAR data allows for accurate estimation of tree height and canopy diameter. By analyzing the vertical structure of the LiDAR point cloud within each segmented tree crown, the maximum height and the vertical extent of the canopy can be determined. These measurements provide valuable information about the vertical growth of individual trees and their overall size.

d) Tree species classification: LiDAR data, particularly when integrated with other data sources such as multispectral imagery or hyperspectral data, can support tree species classification. The structural characteristics derived from LiDAR, such as the shape and texture of tree crowns, can be used to differentiate between different tree species. Machine learning algorithms and classification techniques can be employed to automatically assign tree species based on the LiDAR-derived features.

e) Tree diameter at breast height (DBH) estimation: DBH is a critical parameter for characterizing individual trees. LiDAR data can be utilized to estimate DBH accurately. By measuring the width or circumference of the tree trunk within the LiDAR point cloud, the DBH can be estimated. This information is essential for various forest management applications, including growth modeling, carbon sequestration estimation, and timber volume calculations.

f) Crown volume and canopy structure: LiDAR data provides detailed information about the 3D structure of tree canopies. By analyzing the density and distribution of LiDAR points within each segmented tree crown, the crown volume and shape can be derived. This information helps in understanding the spatial arrangement of branches and foliage, providing insights into forest structure, biomass distribution, and ecological processes.

g) Tree health assessment: Changes in the structure and reflectance properties of tree canopies captured by LiDAR data can indicate tree health conditions. LiDAR-derived metrics, such as canopy density, foliage cover, or canopy gaps, can be used to assess tree health and detect signs of stress, disease, or damage. By monitoring these metrics over time, forest managers can identify areas of concern and prioritize interventions for maintaining forest health.

The identification and mapping of individual trees and their attributes using LiDAR data enable detailed forest inventory and monitoring. This information supports forest management practices, ecological research, and conservation efforts. LiDAR-based tree mapping provides essential data for assessing forest structure, carbon sequestration, biodiversity, and ecosystem services.

5.3 Combining LiDAR with other remote sensing data for forest inventory and carbon stock estimation

Combining LiDAR data with other remote sensing data sources can significantly improve forest inventory and carbon stock estimation. By integrating LiDAR with complementary data, such as optical imagery or radar data, a more comprehensive understanding of forest structure and biomass can be achieved[22]. Here are some ways in which LiDAR can be combined with other remote sensing data for forest inventory and carbon stock estimation:

a) Fusion of LiDAR and optical data: Integrating LiDAR with optical imagery, such as multispectral or hyperspectral data, allows for the extraction of additional spectral information about the forest. The fusion of LiDAR and optical data enables more accurate species classification, as the spectral properties of the trees captured by optical sensors can complement the 3D structural information provided by LiDAR. This fusion improves the characterization of forest composition and helps estimate species-specific biomass and carbon stocks.

b) Integration of LiDAR and SAR data: Combining LiDAR with synthetic aperture radar (SAR) data offers advantages in areas where optical imagery may be hindered by cloud cover or dense vegetation. SAR sensors can penetrate through clouds and vegetation to capture information about forest structure and biomass. By integrating LiDAR's detailed 3D information with SAR's ability to detect changes and biomass variations, it is possible to improve forest inventory and carbon stock estimation in challenging environmental conditions.

c) LiDAR and forest inventory plot data: Ground-based forest inventory plot data, such as measurements of tree diameters and heights, can be used in conjunction with LiDAR data to calibrate and validate the remote sensing-based estimates. By comparing the field measurements with the corresponding LiDAR-derived metrics, regression models can be developed to establish relationships between ground-based measurements and remote sensing data. This approach allows for more accurate and scalable estimation of forest inventory attributes and carbon stocks over larger areas.

d) LiDAR and forest growth models: Combining LiDAR data with forest growth models enhances the estimation of carbon stocks over time. LiDAR provides accurate measurements of tree height, canopy volume, and structural attributes, which can be integrated into growth models to simulate the growth and development of forests. By coupling LiDAR-derived parameters with growth models, it is possible to monitor changes in forest structure and estimate carbon stock dynamics, supporting long-term forest management and carbon accounting efforts.

e) LiDAR and LiDAR repeat passes: Repeating LiDAR acquisitions over the same area at different time points enables the assessment of forest dynamics and changes in carbon stocks. By comparing multiple LiDAR datasets acquired at different times, forest growth, biomass accumulation, and carbon stock changes can be quantified. The fusion of LiDAR repeat passes with other remote sensing data sources, such as optical or SAR imagery, further enhances the understanding of forest dynamics and carbon sequestration rates.

f) Integration with environmental and topographic data: LiDAR data can be integrated with environmental and topographic data, such as climate variables, soil properties, and terrain characteristics. By incorporating these additional data sources into the analysis, it is possible to account for factors influencing forest growth and carbon dynamics. This integration enhances the accuracy of carbon stock estimation by considering the environmental context and site-specific conditions that affect forest productivity.

The combination of LiDAR with other remote sensing data sources offers a comprehensive approach to forest inventory and carbon stock estimation. By leveraging the strengths of different sensors and data types, it is possible to improve the accuracy, scalability, and spatial coverage of forest assessments, contributing to better forest management, carbon accounting, and climate change mitigation efforts. Integration of RADAR-derived indices, deep learning models, object segmentation techniques, and GEDI (global ecosystem dynamics investigation) lidar data can provide a comprehensive and multi-layered analysis of forests. Let's consider a hypothetical study that aims to assess forest structure, species classification, and biomass estimation in a mixed-species forest region.

a) RADAR-derived indices: The study could begin with the use of RADAR remote sensing data to obtain a robust understanding of the forest structure and detect changes over time. A RADAR-derived index, such as the radar forest degradation index (RFDI), can be utilized to highlight areas of the forest that have undergone significant changes due to logging or natural disturbances. The RFDI, calculated from the backscatter coefficients obtained from the RADAR imagery, could indicate areas with lower values, signifying potential logging activity or forest degradation.

b) Deep learning models: To identify and classify tree species within the study area, deep learning models can be applied to high-resolution multispectral imagery. Convolutional neural networks (CNNs), a type of deep learning model, can be trained to recognize the unique spectral signatures of different tree species. By feeding the CNN with training data that pairs multispectral imagery with known species classifications, the model can learn to identify different tree species across the entire study area with a high degree of accuracy.

c) Object segmentation: Object-based image analysis (OBIA), which involves segmenting an image into meaningful objects and classifying those objects, can also be used in this study. For example, individual tree crowns could be segmented using algorithms such as Watershed or Mean-shift. The segmented tree crowns, each representing an individual tree, can then be classified into different species using the trained CNN model.

d) GEDI lidar data: To assess the vertical structure of the forest and estimate biomass, GEDI lidar data can be used. GEDI, a lidar instrument on the International Space Station, provides high-quality laser-ranging observations of the Earth's forests and topography. The GEDI data allows for the precise measurement of forest height, canopy structure, and terrain. These measurements can be used to estimate forest biomass and carbon stocks, key indicators of the forest's health and its role in the global carbon cycle.

By integrating RADAR-derived indices, deep learning models, object segmentation techniques, and GEDI lidar data, this hypothetical study would provide a comprehensive assessment of forest structure, species composition, and biomass in the study area. The methodologies and technologies used in the study could serve as a blueprint for future forest monitoring efforts, informing sustainable forest management strategies, conservation planning, and climate change mitigation initiatives.

6. Integration of artificial intelligence and cloud computing

The integration of artificial intelligence (AI) and cloud computing has revolutionized remote sensing applications, including those in the field of forestry[23]. Here are some key aspects of how AI and cloud computing contribute to remote sensing analysis and provide new insights in the forestry discipline:

a) Data processing and analysis: AI algorithms, such as machine learning and deep learning, can process and analyze large volumes of remote sensing data with unprecedented speed and accuracy. Cloud computing provides the necessary computational power and storage capabilities to train AI models and perform complex data processing tasks. AI techniques can be applied to remotely sensed data, including optical, thermal, radar, and LiDAR, to extract meaningful information about forest attributes, such as tree species, biomass, and health. By utilizing cloud resources, these AI-based analyses can be conducted efficiently and at scale.

b) Automated feature extraction: AI algorithms can automatically extract features and patterns from remote sensing data, enabling efficient and objective analysis. In the context of forestry, AI can be used to identify and classify vegetation types, detect tree boundaries, estimate forest parameters, and map land cover changes. By leveraging cloud computing, these AI-based feature extraction processes can be applied to large areas, allowing for comprehensive forest assessments and monitoring on a regional or global scale.

c) Species classification and mapping: AI methods, coupled with remote sensing data, can improve species classification and mapping in forests. Machine learning algorithms can be trained using labeled training data to recognize spectral or structural patterns specific to different tree species. These AI models can then be applied to remotely sensed data, such as hyperspectral or LiDAR, to classify tree species and create detailed species distribution maps. The scalability and computational power of cloud computing enable the training and deployment of these AI models across large spatial extents.

d) Forest change detection: AI algorithms combined with cloud computing capabilities facilitate automated forest change detection and monitoring. By comparing multi-temporal remote sensing data, AI models can identify and quantify forest disturbances, such as deforestation, forest degradation, and regrowth[24,25]. These AI-based change detection methods enable timely and accurate assessment of forest dynamics, aiding in the identification of areas at risk and supporting sustainable forest management practices.

e) Data fusion and integration: Cloud computing platforms provide the infrastructure for integrating and fusing diverse remote sensing datasets. AI algorithms can leverage this capability to combine optical, thermal, radar, and LiDAR data for comprehensive forest characterization[26–28]. The fusion of different data sources enables the extraction of complementary information and provides a more holistic understanding of forest structure, biomass, and ecosystem functioning. Cloud-based AI tools facilitate the seamless integration of multi-sensor data and enable advanced analytics for improved forest monitoring and management.

f) Scalability and accessibility: Cloud computing offers scalability, enabling the processing and analysis of large-scale remote sensing datasets. With cloud-based AI platforms, researchers, scientists, and forest managers can access powerful computing resources on-demand, avoiding the need for costly infrastructure investments[29,30]. This accessibility lowers the entry barrier for utilizing advanced remote sensing and AI techniques, allowing a broader community to benefit from the insights and analysis that these technologies provide.

The integration of AI and cloud computing in remote sensing applications has opened up new possibilities for forest analysis and monitoring. By harnessing the capabilities of AI algorithms and the scalability of cloud computing, forest researchers and managers can leverage large-scale remote sensing datasets to gain valuable insights into forest structure, species composition, biomass estimation, and change detection[31,32]. This integration has the potential to enhance sustainable forest management practices, support conservation efforts, and contribute to global climate change mitigation strategies.

7. Challenges and future directions

While remote sensing technologies have made significant advancements in recent years, there are still several challenges and opportunities for future research and development. Here are some key challenges and potential future directions in the field of remote sensing for forestry:

a) Data availability and accessibility: Access to high-quality, up-to-date remote sensing data, including optical, thermal, radar, and LiDAR, can be a challenge. Improvements in data acquisition, processing, and distribution methods are needed to ensure timely and open access to data for researchers, forest managers, and decision-makers. Additionally, efforts to make remote sensing data more easily accessible and interoperable with other data sources will enhance the integration and analysis of multi-sensor datasets.

b) Data fusion and integration: While there have been advancements in data fusion techniques, integrating multiple remote sensing datasets to obtain a comprehensive understanding of forests remains a challenge. Future research should focus on developing robust and scalable methods for effectively combining and integrating different data sources, such as optical, thermal, radar, and LiDAR, to generate more accurate and detailed forest information.

c) Standardization and validation: The development of standardized methodologies and protocols for processing, analyzing, and validating remote sensing data in the context of forest monitoring is essential. Establishing consistent and transparent approaches will facilitate data comparison, ensure data quality, and improve the reliability of forest assessments. Collaborative efforts between the remote sensing community, forest researchers, and stakeholders are necessary to develop and adopt standardized procedures.

d) Algorithm development and machine learning: Advancements in machine learning algorithms, such as deep learning, hold great potential for extracting valuable information from remote sensing data. However, the development of robust and interpretable AI models specifically tailored for forest applications is an ongoing research area. Improvements in algorithm performance, transferability across different forest ecosystems, and the ability to handle large-scale datasets are important future directions.

e) Integration of ancillary data: The integration of ancillary data, such as climate, topography, and soil information, with remote sensing data can enhance the understanding of forest dynamics and ecosystem processes. Future research should focus on developing methods for effectively integrating these diverse datasets and leveraging their synergistic effects to improve forest monitoring, modeling, and decision-making processes.

f) Improved forest parameter estimation: Accurate estimation of forest parameters, such as biomass, carbon stocks, and structural attributes, is crucial for understanding ecosystem health and dynamics. Further research is needed to refine existing algorithms and develop new approaches for more precise and scalable estimation of these parameters using remote sensing data. Incorporating ground-based measurements, field campaigns, and novel sensor technologies into the modeling process can improve accuracy and reduce uncertainties.

g) Near real-time monitoring and early warning systems: Advancements in cloud computing and AI methods provide opportunities for developing near real-time forest monitoring and early warning systems for rapid detection and response to forest disturbances, such as wildfires, insect infestations, and illegal logging. Integrating real-time data streams, including satellite imagery, aerial surveys, and ground-based observations, with AI-based algorithms can enable timely alerts and support proactive forest management strategies.

h) Integration with decision support systems: The integration of remote sensing data and analysis outputs with decision support systems can enhance the usability and applicability of remote sensing information in forestry decision-making processes. Future research should focus on developing user-friendly interfaces, visualization tools, and decision support frameworks that facilitate the integration of remote sensing data into forest management practices and policies.

Addressing these challenges and exploring future research directions will contribute to advancing the capabilities of remote sensing in forestry. By improving data accessibility, refining algorithms, integrating multi-sensor data, and enhancing the integration of remote sensing with other data sources and decision support systems, remote sensing technologies can better support sustainable forest management, biodiversity conservation, and climate change mitigation efforts.

8. Opportunities for collaboration between researchers, industry, and policymakers

Collaboration between researchers, industry, and policymakers is essential for advancing remote sensing applications in forestry and maximizing their impact. Here are some opportunities for collaboration among these stakeholders:

a) Data sharing and access: Researchers, industry, and policymakers can collaborate to improve data sharing and access. Industry partners and satellite data providers can work together to ensure timely and open access to remote sensing data. Researchers can collaborate with industry to access proprietary data sources or contribute to data collection efforts. Policymakers can play a role in facilitating data sharing agreements and establishing data infrastructure that supports collaboration.

b) Algorithm development and validation: Collaboration between researchers, industry, and policymakers can accelerate the development and validation of algorithms for forest analysis. Researchers can work closely with industry partners to develop and test algorithms using industry-specific datasets or ground truth data. Policymakers can support initiatives that promote algorithm validation and ensure the reliability and accuracy of remote sensing-based information used in decision-making processes.

c) Field data collection and calibration: Industry partners, researchers, and policymakers can collaborate on field data collection campaigns to validate and calibrate remote sensing data. Industry partners can provide access to forest sites and contribute ground-based measurements. Researchers can design and conduct field campaigns to collect data for algorithm development and validation. Policymakers can support and fund collaborative field campaigns that bridge the gap between remote sensing data and on-the-ground forest observations.

d) Application development and deployment: Collaboration between researchers, industry, and policymakers can drive the development and deployment of remote sensing applications for forestry. Researchers can develop innovative applications that address industry and policymaker needs, leveraging their expertise in algorithm development and analysis. Industry partners can contribute their domain knowledge and resources to translate research findings into practical solutions. Policymakers can provide support and create favorable policy environments to encourage the adoption and implementation of remote sensing technologies in forestry.

e) Capacity building and knowledge transfer: Collaboration can promote capacity building and knowledge transfer among researchers, industry, and policymakers. Industry partners can provide training and resources to researchers and policymakers on data acquisition, processing, and analysis techniques. Researchers can share their expertise and findings through workshops, seminars, and training programs. Policymakers can support capacity-building initiatives and create platforms for knowledge exchange between stakeholders.

f) Policy development and implementation: Collaboration between researchers, industry, and policymakers is crucial in developing and implementing policies that promote the effective use of remote sensing in forestry. Researchers can provide scientific evidence and insights to inform policy decisions. Industry partners can contribute their practical knowledge and experiences to shape policies that align with industry needs. Policymakers can engage with researchers and industry stakeholders to understand the potential of remote sensing technologies and develop policies that support their adoption and use in forest management.

By leveraging the strengths and expertise of researchers, industry, and policymakers, collaborative efforts can drive innovation, improve data access and quality, validate algorithms, facilitate knowledge transfer, and ensure that remote sensing technologies are effectively utilized in forestry applications. These collaborations have the potential to enhance forest management practices, support evidence-based policymaking, and contribute to sustainable forest ecosystems.

9. Conclusion

Remote sensing has emerged as a powerful tool for analyzing and monitoring forests, providing valuable insights into their structure, health, and dynamics. Optical, thermal, RADAR, and LiDAR remote sensing data, combined with state-of-the-art methods of data processing and analysis, have contributed to the advancement of forestry disciplines. In this review article, we explored the various remote sensing tools and techniques utilized in forestry analysis. We discussed the advantages of AI and cloud computing in remote sensing applications, including improved data processing, automated feature extraction, and enhanced scalability. We also highlighted the utilization of high-resolution multispectral and hyperspectral imagery for vegetation mapping and species classification, as well as the extraction of forest structural parameters using vegetation indices and machine learning algorithms. Moreover, we examined the integration of AI methods for automated land cover change detection and forest disturbance monitoring, the mapping of forest health and stress using thermal infrared imagery, and the estimation of evapotranspiration and water stress in forests. We also discussed the combination of thermal data with other remote sensing sources for forest fire detection and monitoring. Furthermore, we explored the estimation of forest biomass and structure using synthetic aperture radar (SAR) data, the detection and mapping of forest disturbances using SAR interferometry, and the fusion of optical and RADAR data for improved forest characterization and monitoring. We delved into the applications of LiDAR remote sensing, including 3D forest structure modeling and canopy height estimation, identification and mapping of individual trees and their attributes, as well as the fusion of LiDAR with other remote sensing data for forest inventory and carbon stock estimation. Finally, we highlighted the integration of AI methods and cloud computing, emphasizing their role in advancing remote sensing applications in forestry. We discussed the challenges and future directions in the field, including data availability and accessibility, data fusion and integration, algorithm development and validation, and the integration of remote sensing with decision support systems. We also emphasized the opportunities for collaboration among researchers, industry, and policymakers in driving innovation, data sharing, algorithm development, and policy implementation. In conclusion, remote sensing, coupled with AI and cloud computing, has revolutionized forestry analysis by providing accurate, timely, and scalable information about forests. These advancements have the potential to support sustainable forest management, biodiversity conservation, and climate change mitigation. Continued research, collaboration, and technological advancements will further enhance the capabilities of remote sensing in forestry, facilitating informed decision-making and contributing to the long-term health and resilience of our forests.

Conflict of interest

The author declares no conflict of interest.

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