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Original Article

Relevance of Remote Sensing and its Applications in Forestry. A Critical Review

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ABSTRACT

For several nations who are developing, forests play a crucial role in rural life. Due to the incredible challenges associated with staff, logistics, and chronological consistency of field-based surveys for forest management, a variety of sources of data obtained by airborne, space-borne, and terrestrial remote sensing sensors are now essential sources of knowledge for studies on the spatiotemporal patterns of forests. Most recently, understanding of forests and their conservation has been derived primarily from satellite imagery. The process of organizing and carrying out procedures for the management and use of forests can be done with the assistance of remote sensing in order to achieve economic, social, cultural, and environmental goals. Satellite remote sensing has been providing ever-more-advanced knowledge about woodland structure, management, monitoring, and oversight whenever the first civilian earth-observing program was launched. This article reviewed the application of remote sensing on forestry. Data were gathered from published research papers, books, internet resources, and expert observation. Remote sensing's synoptic view, availability in a rage of spatial-temporal scales, high degree of homogeneity, inexpensiveness as well as the increasing trend in availability make it special in forest science. As observed from the review, remote sensing technology is critical in forest management. It helps to provide up to date information on forest cover change, forest fire, forest disturbance, forest wildlife management, forest biomass and others. Remote sensing is vital in providing scientific information in forest resources monitoring and management.

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INTRODUCTION

Forest is defined as "land with tree crown cover (or equivalent stocking level) of more than 10% and an area of more than 0.5 ha" (FAO, 2015). Based on the definition, trees should reach a height of 5 m to the minimum at maturity in situ, and the area does not embrace land that is chiefly under agricultural or urban land use. Ethiopia's forest definition is different from that of the FAO. Forest in the Ethiopian case is defined as "land spanning at least 0.5 ha covered by trees and bamboo, attaining a height of at least 2 m and a canopy cover of at least 20% or trees with the potential to reach these thresholds in situ in due course" (MEFCC, 2015). Forests and trees are essential to the livelihoods of farmers worldwide, but especially in nations that are developing (FAO, 2015; Zhao and Lu, 2018). According to FAO (2015), there were roughly over 4.06 billion ha of forest cover worldwide (0.52 ha per person on average). This represents 31% of the total land area. The significance of forests for both the climate and human well-being is widely recognized (FAO, 2015). Forests are subjected to profound alterations despite their high global significance, mainly because of human-induced sources in addition to the natural cause.

Field-based surveys for forest management are known to present significant challenges due to labor shortages, logistics, and temporal repeatability. However, a variety of data sources, including airborne, space-borne, and terrestrial remote sensing sensors, have made data on the spatiotemporal dynamics of forests increasingly important. At the moment, information regarding forests and their sustainable management is mostly obtained from satellite data. Forest management, which is the process of organizing and carrying out methods for the oversight and utilization of forests to satisfy the goals of forests in the areas of the environment, economy, society, and culture, can benefit from the use of remote sensing (Barbierato et al., 2020; Grinde et al., 2020; Zhao and Lu, 2018). Remote sensing is essential to forest management in order to maximize the benefits of forests, including their capacity to supply raw materials, regulate the water cycle, absorb CO2 from the atmosphere, support a wide variety of species, and offer recreational opportunities (Zhao & Lu, 2018). For extensive forest areas, remote sensing has been used for huge data collection that enables accurate vegetation and forest mapping. Remote sensing technologies have been used to know forest cover changes, quantify the changes, identify various forest types, and even estimate the number of trees in a specified area. Thus, this review paper aims to explore the relevance and broader applications of remote sensing technologies in forestry. The definition of remote sensing with respect to forestry, the relevance of remote sensing in forestry, and remote sensing platforms and sensors were covered in the first section. Then, the role of remote sensing in forestry, mainly forest cover change mapping, forest change detection, detecting forest fires, biomass estimation, crown height measurement, disease and insect outbreak inspection, forest-wildlife management, and disturbance detection, were elaborated and discussed.

METHODOLOGY

This review paper examines the relevance and role of remote sensing technology in forestry. Sources of data included published papers, books, online databases, and expert observations. Reports for accessible literature were mainly discovered using Google Scholar, the Web of Science, and SCOPUS.

Published journal articles, books, online resources, and expert observation were used as sources of data. The search for available literature was mostly done through Google Scholar, Web of Science, and SCOPUS. To download published articles, books, and online resources, Hvar.is, e-journals, SCI Hub, and Library Genesis were

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used. Additional references were identified using the bibliographies cited in the retrieved literature. The body of literature was summarized through the use of textual narrations, tables, and figures.

REMOTE SENSING (RS)

According to Jensen (2007), RS refers to "the noncontact recording of data from the visible, infrared, microwave, and ultraviolet portions of the electromagnetic spectrum". When it comes to forests, remote sensing is a method of gathering and analyzing data without having the instruments used to collect the data in close proximity to the woods (Cochran et al., 2020). According to Franklin (2010), "remote sensing is both methodology and technology. Franklin (2010) highlighted that "remote sensing is both technology (sensors, platforms, transmission and storage devices, and so on) and methodology (radiometry, geometry, image analysis, data fusion, and so on).

Initially, remote sensing was mostly conducted from relatively low altitude platforms like hot air balloons, kites, and homing pigeons, all of which were characterized by uncertainty and instability (Colwell, 1964). From that point forward, hundreds of Satellites (earth observing satellite) are in orbit and offering a variety of remotely sensed data. The ranges from optical to radar, multispectral to panchromatic imaging, and local to global scale. Remote sensing has long been identified as an effective and efficient tool in forestry studies such as forest cover mapping, forest change detection, fire detection, forest inventory, forest health, forest sustainability, forest growth, and forest ecology etc. (Kohl et al., 2006).

Platforms and Sensors for Remote Sensing

As demonstrated in Figure 1, systems for remote sensing come in a variety of platforms and sensor types. They have been split into two groups according to distinct technical approaches. These are the sensors that are both passive and active. On the other hand, unmanned airliners (UAVs), such as drones with fixed wings and rotaries, are among the platforms used for imagery collection, along with Earth-observing satellites that are aircraft, and helicopters.

Among the most popular detectors used in remote sensing applications are optical imaging devices. A typical digital photograph and an optical imaging system are comparable in terms of design and use, with the exception that the latter may collect data in the electromagnetic spectrum wavelengths other than visible light, such as infrared and thermal wavelengths. Land coverings, notably forest and canopy coverage, can be identified by variations in wavelength at which various elements on Earth absorb and reflect light. The total number of bands and the widths of those bands by which picture data is obtained vary amongst optical sensors.

Hyperspectral sensors include thousands of considerably tighter bands, while multispectral detectors have a fixed number of bands (*Figure 2*). Systems that rely on sunlight that is reflected or thermal energy released are known as passive sensors. These systems comprise optical and thermal devices. Smoke and clouds are impervious to passive sensors. Their night-time usability is hindered by cloud-induced haze. Active sensors are devices that generate a pulse and measure the backscatter that reflects back to the sensor, such as Synthetic Aperture Radar (SAR) and Light Detection and Ranging (LiDAR) systems. In addition to operating at night, active sensors can pass through smoke and clouds. SAR sensors are able to distinguish between distinct land cover elements according to factors including water content, surface roughness, and the 3D structure of objects. On the other hand, LiDAR systems use laser pulses to measure the reflected light and the distance to an object. The target can then be represented digitally in three dimensions by utilizing variations in laser return timings and wavelengths.

Depending to how long it requires for the sensor to return to the exact same place, space-borne sensors continuously monitor various parameters at scheduled times. For instance, Landsat sensors return to the same spot-on Earth each 16 days. The ability to fly in reaction to particular events, like

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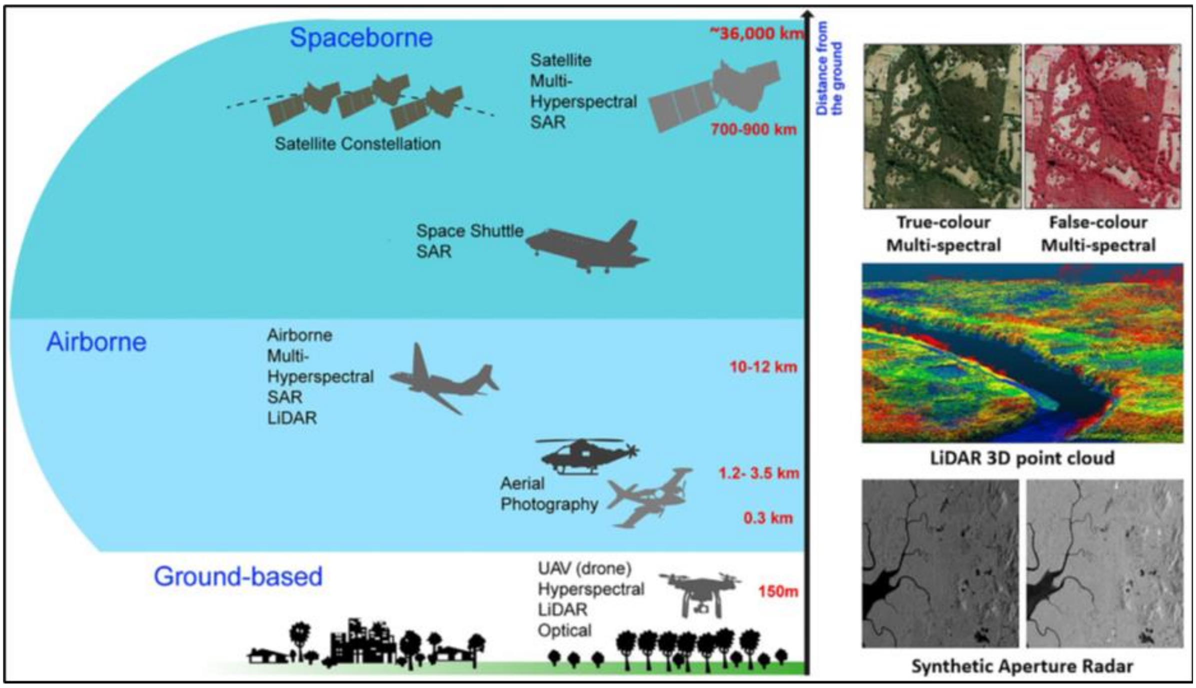
fires, and the ability to fly under clouds, especially with Unmanned Aerial Vehicles (UAVs), address an important drawback of Earth observation satellites. Sentinel and other more recent satellites are usually created as part of a constellation of multiple satellites to improve revisit time

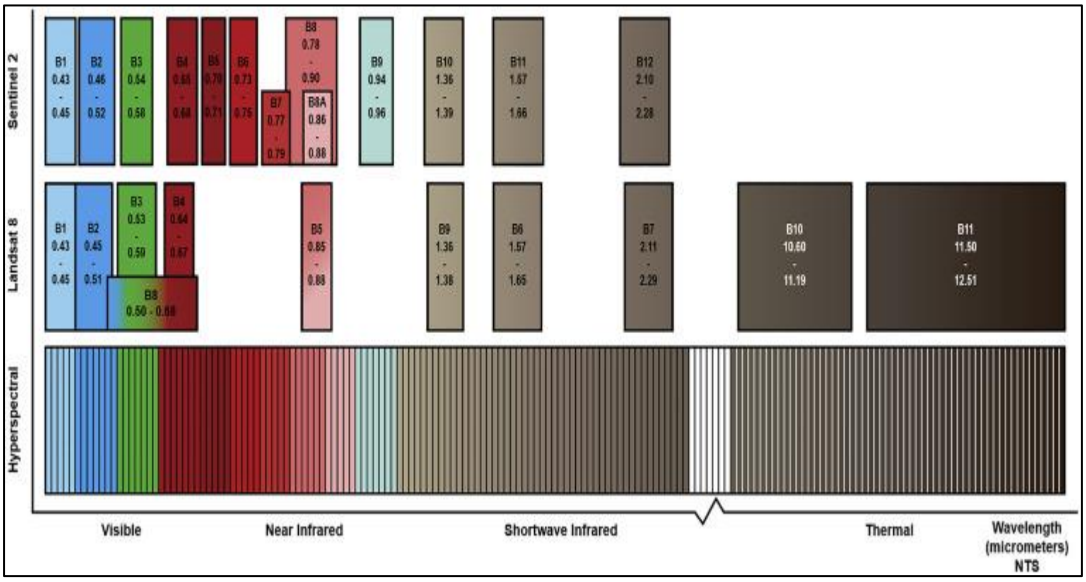
Figure 1: Typical platforms for remote sensing and sensor combinations



Note: For each platform, the most often used sensors are shown on the left. (on the right) SAR data for the two polarizations via Sentinel 1 (bottom), LiDAR point cloud images of vegetation next to a river (middle), and true-color digital aerial photography and fake color with NIR sensing (top).

Source Lechner et al. (2020)

Figure 2: Comparing Hyperspectral and Multispectral Bands (Sentinel 2 and Landsat 8)



Source Lechner et al. (2020)

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Table 1: Relevance of remote seining Applications of RS in Forestry

	Relevance of remote sensing	Descriptions	Sources
1	Synoptic View of the imagery	• The images offer a synoptic perspective. • The imaging fully depicts the surroundings within its field of vision. • Imaging produces a map-like format that provides a thorough survey of the imaged area rather than field data. • Facilitates comprehensive mapping and tracking of important ecological variables, like changes in land cover.	Lechner et al., (2020).
2	Accessibility at different Spatio-Temporal Scales	• No matter where you are, you can access remotely sensed data at anytime and anywhere, which allows for a variety of uses. • It is possible to investigate the origins of contemporary environmental issues by going back in time and using historical remote-sensing data.	Lechner et al., (2020).
3	Homogeneity	• Has a high degree of homogeneity • No human-caused issues, such as variations in measurement techniques between nations.	Lechner et al., (2020).
4	Easy to convert	• straightforward to transform into digital photos and merge with other spatial datasets in a GIS.	Lechner et al., (2020).
5	Not expensive	• It is a cost-effective method of data collection per unit area • However, the financial expenditures associated with building, launching, and operating satellite remote-sensing systems are significant. • Nevertheless, important datasets for environmental science research are frequently made publicly and freely accessible. • For instance: Landsat series and the European Space Agency (ESA) satellites are freely available	Lechner et al., (2020).
6	Growing accessibility and development in data provision	• In addition to being more readily available, there is an increasing tendency in the provision of data products alongside the image data • Minimizes the communication gap between specialists and environmental scientists and the requirement for expert knowledge for image analysis.	Lechner et al., (2020).

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Remote Sensing and Its Relevance in Forestry

The six main reasons for remote sensing is valuable for gathering information is summarised in *Table 1*.

Forest Cover Change Detection

To determine the amount of forest cover loss and gain over time, it is essential to detect changes in forest cover. While knowledge of forest change is vital everywhere, it is particularly crucial in the tropics, where land-use change is changing quickly. According to FAO (2004), almost a third of the surface of the planet is now utilized for crop-growing or pasture for cattle, and the majority of this land for farming has been developed on top of natural forests, grasslands, and wetlands that offer vital habitats for species and services to humanity. The present state of affairs showed that farming methods have been a significant factor in changing the landscape within the globe. This situation entails the need to conserve biological diversity (Kondratyev, 1998) and design meaningful conservation strategies. Research conducted in the field can record changes in the forest cover at the local level, but remote sensing-based methods are needed to record these alterations at both the global and regional levels (Kumar et al., 2010).

Remote sensing-based change detection is a popular application that investigates multi-temporal datasets. It involves using datasets to distinguish between areas of land cover change between dates of imaging (Dalmiya et al., 2019). Many investigations using satellite-based detection techniques have been conducted in various nations to determine the extent of the land use and land cover change (LULCC) (e.g., Deng et al., 2013; Geng et al., 2015; Lark et al., 2017; Gibson et al., 2018; Ru-Mucova et al., 2018; Lei and Zhu, 2018; Negassa et al., 2020; Musei et al., 2021). There is a great deal of susceptible ground being identified, and this threat is caused by anthropogenic-driven deforestation (Fokeng et al., 2019).

For example, Negassa et al. (2020) conducted research at Komto Forest, Gog district of Gambella, Ethiopia, and identified the forest cover change in the years 1991 to 2019 (*Figure 3*) using the land surface times series images of TM 1991, ETM$^+$ of 2002, and OLI-TIRS of 2019 and produced a forest cover map. He found 4.18% dense forest loss and 0.7% open forest loss annually (*Table 2*). Using remote sensing change detection techniques, Othow et al. (2017) investigated the rate of LULCC impact on the forest in Gambella, Ethiopia, between 1990 and 2017. Three images—a 1990 Landsat TM image, a 2002 ETM+ image, and a 2017 OLI-TIRS image—were used to construct the land cover map. The outcome showed that annual forest coverage was declining by 0.33%.

Musei et al. (2021) used LandSat satellite imagery and a cloud-based computer system to calculate the variation in the amount of forest in Somalia from 2000 to 2019. They discovered that there was an almost 23% decrease in the amount of forest cover, from 87,294 hectares in 2000 to 67,199 hectares in 2019. The LANDSAT/TM satellite images from 1986 to 1990 show a decrease in Ethiopian forest by 3.93%, or 45,055 km^2. Similarly, a finding by Mideksa (2009) at Adaba-Dodola Forest, Ethiopia, indicated an annual forest loss of 0.54%. The author used a time series of LandSat images from 1986 to 2005 and supervised and multi-criteria evaluation algorism to show the changes. The summary of studies on forest change detection in east Ethiopia is given in *Table 3*.

Mapping of Forest Types

At a variety of geographical, temporal, and conceptual scales, forests can be observed, identified, classified, and monitored thanks to remote sensing and digital image processing (Rogan & Chen, 2004). Forest type mapping is vital for example; for forest management, habitat and biodiversity assessment, monitoring of forest disturbances, and carbon cycle and energy budget estimation (Ballanti et al., 2016; Fassnacht et al., 2016; Sheeren et al., 2016). By placing the identified pixels in the proper geographic context, the necessary map is created. Generally, there are two types of classification techniques to classify

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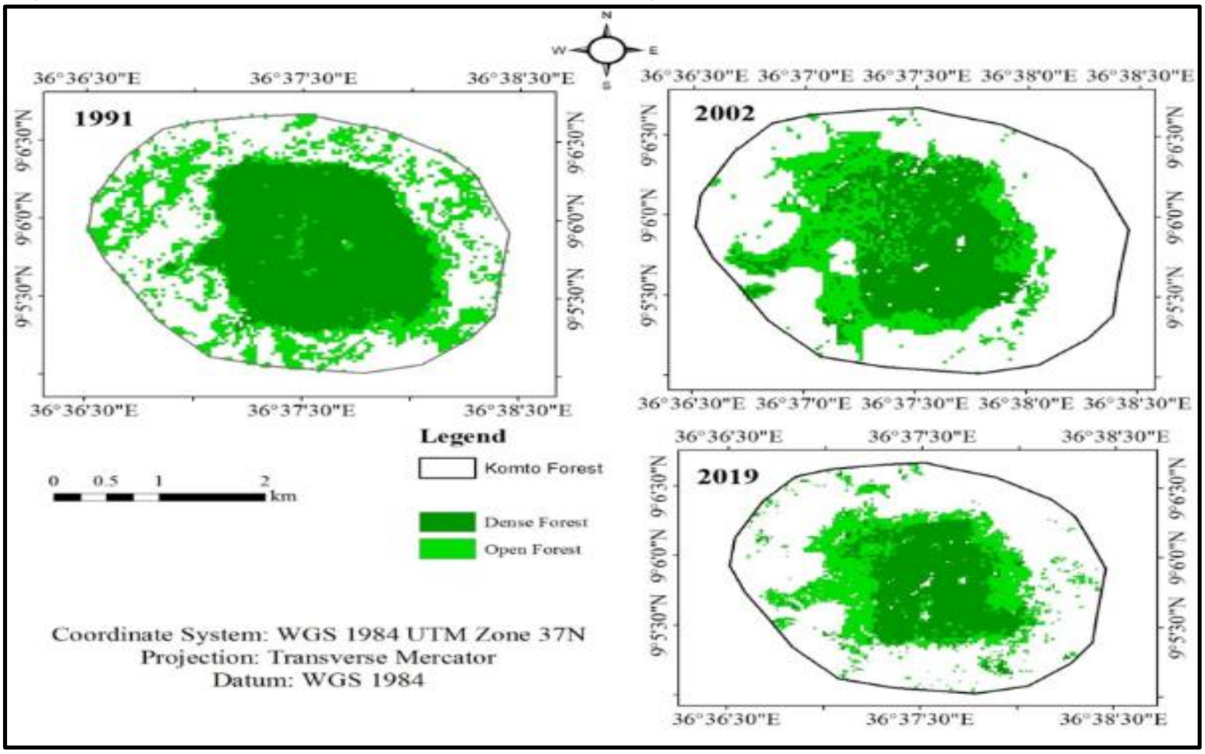
the forest types from a satellite image (Nagamani & Mariappan, 2013). These are the supervised and unsupervised classifications. When it comes to unsupervised categorization, computer algorithms analyze the scene's whole spectrum of data and group pixels that share comparable spectrum characteristics into classes based on the particular clustered algorithm that was applied. In contrast, the operator in supervised classification uses the ground-based data to allocate individual pixels (training sites) to different land cover categories. The leftover pixels are then assigned to land cover classes based on the statistical resemblance of the spectral characteristics after computer algorithms have analyzed the spectral characteristics of various collections of pixels.

During the past 35 years, the total number of investigations devoted to the classification of different kinds of trees has grown steadily (Figure 4). On the other hand, the nearly exponential rise that occurred between the years 2005–2010 and 2010–2015 can also be attributed to the growing quantity of airborne hyperspectral and LiDAR data, as demonstrated by the sensor-specific frequencies (rushed lines in *Figure 4*).

Table 2: Rate of change in East Africa's forest cover

Land cover	Area (ha)			Area lost in ha		
year	1991	2002	2019	1991-2002	2002-2019	1991-2019
Dense forest cover	312.94	250.06	195.95	-5.72	-3.18	-4.18
Open forest cover	173.86	166.7	154.30	-0.65	-0.73	-0.7

Figure 3: Forest covers map of Komto Forest during 1991, 2002 and 2019



Source: Negassa et al., 2020.

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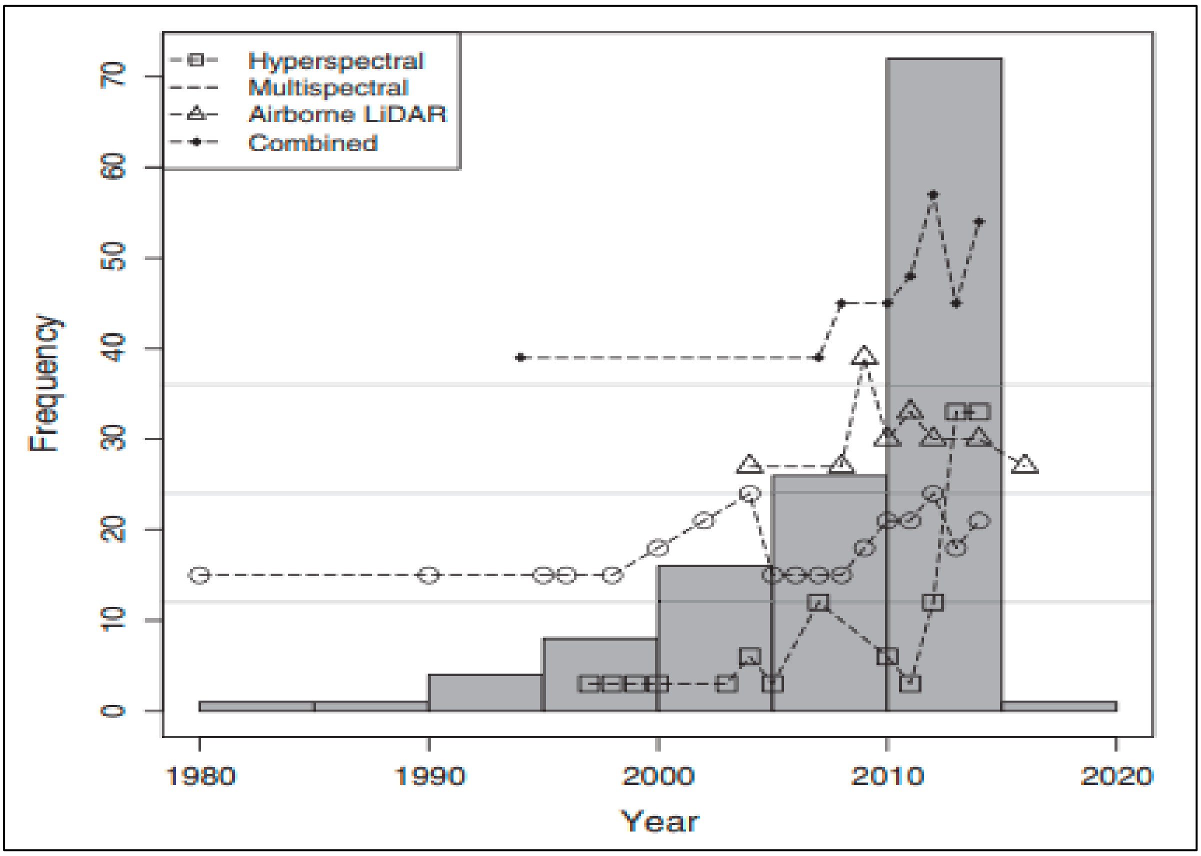
Table 3. Brief summary of for forest cover change detection at different areas in Ethiopia.

Study area	Year covered	Classification and algorism	Data types	Annual gain or loss (%)	Sources
Somalia	2000 to 2019	Supervised	Landsat-based forest	23% forest cover loss	Musei et al. (2021)
Komto Forest, Gog district of Gambella, Ethiopia	1991 to 2019	Supervised	Landsat TM image of 1991, ETM + of 2002 and OLI-TIRS of 2019	4.18% loss	Negassa et al. (2020)
Adaba-Dodola Forest, Ethiopia	1986 to 2005	Supervised and Multi Criteria Evaluation technique	Landsat images of the year 1986, 2000 2005	0.57% loss	Mideksa (2009)
Komto Forest, Gog district of Gambella, Ethiopia	1990 to 2017	Maximum likelihood technique of the supervised classification	Landsat TM image from 1990, ETM$^+$ in 2002, and OLI TIRS in 2017.	0.33% loss	Othow et al. (2017

Figure 4: Study frequency across a five-year span



Source: Fassnacht et al. (2019)

Note: The histogram is topped with sensor-specific frequencies per year; the plotted values are scaled on the y-axis by a factor of three to emphasize the trends; offsets were added to improve the figure's readability; light horizontal lines map to the y-axes (at y = 0) for every kind of sensor.

Several studies (Dorren et al., 2003; Zhang et al., 2010; Zhu and Liu, 2014; Liu et al., 2018; Isuhuaylas et al., 2018; Pasquarella et al., 2018;

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Persson et al., 2018; Grabska et al., 2019; Cheng & Wang, 2019; and Cheng et al., 2021) applied remote sensing technologies for forest type classification and mapping in different parts of the country (*Table 4*). For example, Liu et al. (2018) used spectral and spatial information obtained from multi-source remote sensing data along with a machine learning method to achieve forest type categorization for Wuhan, China. Pasquarella et al. (2018) extracted information on forest type for the western part of Massachusetts by combining temporal and spectral features obtained from Landsat time series images. Zhang and colleagues (2010) employed near-infrared and near-spectral bands to identify shrub forests in higher-altitude regions of Dingri County, Tibet Autonomous Region, China, as well as to estimate temporal and spectral features. In 2019, Grabska et al. utilized Sentinel-2 time series remote sensing images to extract information on different forest types through the calculation of temporal and spectral features, while Cheng and Wang (2019) recognized the temporal patterns of several forest types and joint them with spectral indexes and bands to identify forest types in Hunan, China.

In Chinese geographical regions, such as medium and high latitudes, intricate mountainous areas, foggy and rainy places, Cheng et al. (2021) extracted SST (spectral, spatial, and temporal) forest-type categorization characteristics. Employing a time series of Landsat-8 data and DEM, Isuhuaylas et al. (2018) evaluated the effectiveness of several machine-learning techniques: SVM, RF, and k-Nearest Neighbour (kNN) for categorization of the Andes Mountain forest. Investigators reached an agreement that while the kNN proved more reactive to noise-filled training data, the SVM and RF approaches provided comparable accuracy in differentiating mountain forest from scrublands.

Hościło and Lewandowska (2019) employed topographical information along with multi-temporal Sentinel-2 data to provide an overview of their analysis of the broad mountain range of southern Poland. In this research, a map of forests and non-forests as well as the two types of forests (broadleaf and coniferous) were obtained using a random forest classifier algorism. The outcome demonstrated the importance of using topographic details (DEM data) in conjunction with sentinel 2 data for the designation of forest types. The total accuracy of the result was 94.8% for the categorization of the forest's type and 98.3% for the wood/non-forest cover.

The advantages of combining Landsat time-series data alongside topographic information for the categorization of forest types were also confirmed by Zhu and Liu's (2014) investigation. Investigators classified the broadleaf forest using the hierarchy-based approach, obtaining a higher overall accuracy (92.6%), before dividing it into oak and mixed mesophytic forests. Furthermore, employing all bands from the multi-temporal Sentinel-2 images, Persson et al. (2018)'s latest analysis verified the highest overall accuracy (88.2%) in the discrimination of tree species.

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Table 4: A summary of Remote sensing application in forest type classification across the world

	Algorisms used	Features used/information explored	Data types	Function	Overall accuracy	References
Wuhan, China	Random Forest	spectral and spatial features, textural feature derived from Sentinel-2	multi-temporal Landsat-8, Sentinel-2 and SRTM digital elevation model (DEM)	classification of four tree species and for mixed forest types	82.8%	Liu et al. (2018)
Dingri, China	Object-oriented multi-scale image segmentation techniques	spectral features	ASTER data (NIR and infrared bands)	identified shrub vegetation types	-	Zhang et al. (2010)
western portion of Massachusetts	Landsat time series algorithms	spectral and temporal features	Landsat time series images	extract forest type information	-	Pasquarella et al. (2018)
Polish Carpathian Mountains	Random Forest classification	temporal and spectral features	Time series of Sentinel-2 images	mapping mixed woodlands' tree species	-	Grabska et al. (2019
Hunan, China	Time-weighted dynamic	Combined temporal patterns and spectral indexes	Landsat-8 and Sentinel-2 time-series	identify forest types	93.81%	Cheng and Wang (2019)
Chinese (middle and high latitudes, complex mountainous)	Gini criterion in the random forest algorithm	Spectral feature Temporal features	Sentinel-2 and Landsat	identifying forest types	> 85%	Cheng et al. (2021)
Andes Mountain	machine-learning approaches: (SVM, RF and k-Nearest Neighbor (kNN))	Temporal features	Landsat-8 data and DEM	classification of Andes mountain forest	-	Isuhuaylas et al. (2018)
Steep mountain terrain areas of Austria	Object-based classification method	Spectral bands	Landsat TM band 4 and 5 and DEM	classification of forest stand type mapping	accuracy of classification improved	Dorren et al. (2003)
Southern Poland	Random Forest classifier	Temporal features	Multi-temporal Sentinel-2 data	Eight species of trees are identified, the vegetation type (broadleaf and coniferous) is classified, and the amount of tree cover is divided into two categories.	98.3% and 94.8% accuracy for forest and forest type classification	Hościło and Lewandowska (2019)

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Biomass Estimation

Biomass estimation is very important for the changing climate that affects the daily lives of many of the societies in the world. It provides important information for natural resource management and monitoring. Assuring longevity through managing forests procedures includes estimating biomass as a critical component (Duncanson et al., 2015). Forest biomass estimation provides ample information for sustainable forest and environmental management. A change in above-ground biomass (AGB) stock helps to monitor forest dynamics in a certain specific area. However, in many of the tropical countries where a significant percentage of forests exist, biomass estimations are not precise (Duncanson et al., 2015; Taddese et al., 2020). It is due to the reality that field-based sample surveys are the mainstay of the existing tradition in tropical nations for assessing, tracking, and estimating changes in forest resources. Because of the substantial expenses, logistical difficulties, and restricted field availability, this approach has a tiny sample size (Lu, 2006; Duncanson et al., 2015; Taddese et al., 2020). Furthermore, the intricate structural characteristics of the natural environment lead to discrepancies in the calculation of biomass (Lu, 2006). For example, it is challenging to accurately estimate the height of trees in tropical forests due to their highly dense canopy cover.

But over the last thirty years, a great deal of investigation has been conducted on the calculation of biomass using remote sensing data (Hall et al., 2006; Labrecque et al., 2006; Lu, 2007; Ji et al., 2012; Dube and Mutanga, 2015; Gizachew et al., 2016; Timothy et al., 2016). Most of the studies have utilized optical remote sensing data, as it is operational at local to global scales with sensors including the Landsat Thematic Mapper (TM), Advanced Very High Radiometric Resolution (AVHRR), and Moderate Resolution Imaging Spectroradiometer (MODIS) providing globally consistent spatial data. Assessment above-ground biomass are also possible using synthetic aperture radar (SAR) and airborne laser scanning data (LiDAR) (Asner et al., 2012; Anderson et al., 2014; Mitchell et al., 2017). Timothy et al. (2016) summarized the optical remote sensing (RS) data that are used in biomass estimation (*Table 5*).

The existing scientific works explored the significant contribution of some types of RS data, such as Spectral Index's (SIs) and Spectral Bands (SBs), in AGB estimation (*Tables 6* and *7*). Notably and widely utilized data source for aboveground biomass in forests has been images collected by Landsat (*Table 5*). For example, Günlü et al. (2014) conducted a study on AGB estimate in Northwestern Turkey using Landsat data, and found that SIs performed better in estimating AGBs. AGB estimate was also found to be enhanced by combining SB and textural characteristics in a 2007 study by Lul on AGB estimation using Landsat TM data in the Brazilian Amazon. Given that primary forests contain intricate canopy systems, the outcome demonstrated the significance of texture information. T*ables 5 and 6* show the SBs and SIs used for biomass estimation in different areas, respectively.

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Table 5: A summary table for the use of optical remote sensing data in estimating biomass.

Sensor used	Area of investigation	Approach applied	Main results	Reference
LiDAR & SPOT-5 HRG imagery	Western China, Gansu province	Multiple Stepwise regression	When combined with SPOT-5 data, LiDAR data can improve biomass estimation accuracy (R^2 = 0.736).	Qisheng (2012)
Landsat PALSAR	East Kalimantan, Indonesia	Discrete wavelet transforms (DWT) & Brovery transforms were used.	Biomass estimates ranged between 0.70-0.75 R^2 values.	Basuki et al. (2013)
Landsat	Georgia forest land	Vegetation indices & multiple regression analyses were used to develop AGB estimation models.	Hardwoods biomass was estimated with R^2 of 0.52, 0.30 for softwoods & 0.66 for mixed forests.	Min et al. (2009b)
Landsat (ETM+)	Kampong Thom Province in central Cambodia	Object-based approach was used.	ABG estimates ranges between 0.67 and 0.76 R^2.	Kajisa et al. (2009)
SPOT-5 HRG imagery	Sun Yat-sen, Nanjing, China	Gray Level Co-occurrence Matrix was applied.	The results showed that ABG was poorly correlated with most textures.	Li et al. (2008)
Landsat TM imagery	Western Newfoundland, Canada	Biomass from Cluster Labeling based on Structure and Type (BioCLUST), was used.	BioCLUST offered plausible results.	Luther et al. (2006)

Table 6: Summarized spectral bands used for biomass estimation in different countries.

Satellite	Spectral Bands (SB)	References
Landsat 8	B, G, R, NIR, SWIR1	Hall et al. (2006) Labrecque et al. (2006), Lu (2007), Ji et al. (2012), Dube and Mutanga (2015), Gizachew et al. (2016), Risdiyanto and Fakhrul (2017), Li et al. (2019), Qiu et al. (2019), Taddese et al. (2022),
Sentine 2	B, G, R, RE, NIR, SWIR1	Lu (2007), Gizachew et al. (2016), López-Serrano et al. (2016), Risdiyanto and Fakhrul (2017), Li et al. (2019), Qiu et al. (2019), Taddese et al. (2022)
Planet Scope	B, G, R, NIR	Adam and Mutanga (2012), Sousa et al. (2015), Taddese et al. (2022)
High resolution (QuickBird)	Four bands (B1, B2, B3, and Infrared)	Sousa et al. (2015), Sousa et al. (2017)

Where; MSAVI: Modified Soil Adjusted Vegetation Index, NDVI: Vegetation Index, SR: Simple Ration, NDMI: Normalized Difference Moisture Index, RENDV: Red Edge Normalized Difference Index, VI: Vegetation Index, DVI: Difference Vegetation Index, ExGI: Excess Green Index, GLI: Green Leaf Index, EVI: Enhanced Vegetation Index, SAVI: Soil Adjusted Vegetation Index, NDGI: Normalized Difference Green Index, ARVI: Atmospheric Resistance Vegetation Index and SRRE: Red Edge Sample Ratio.

Study findings by Otukei et al. (2015), Gizachew et al. (2016), Næsset et al. (2016), and Taddese et al. (2020) assessed the use of RS for biomass estimation in the region of east Africa. The contribution of remotely sensed (RS) data to increasing the accuracy of AGB estimation in the Afromontane forests of south-central Ethiopia was evaluated by Taddese et al. (2020). They observed that employing RS data for AGB estimate increased the accuracy of AGB estimation. They used several SBs, SIs (*Table 3*), and texture elements for AGB estimation. The models Landsat-8, Sentinel 2, and Planet Scope, which used shortwave infrared, green band , and shortwave infrared band reflectance as their predictor variable, respectively, had estimation

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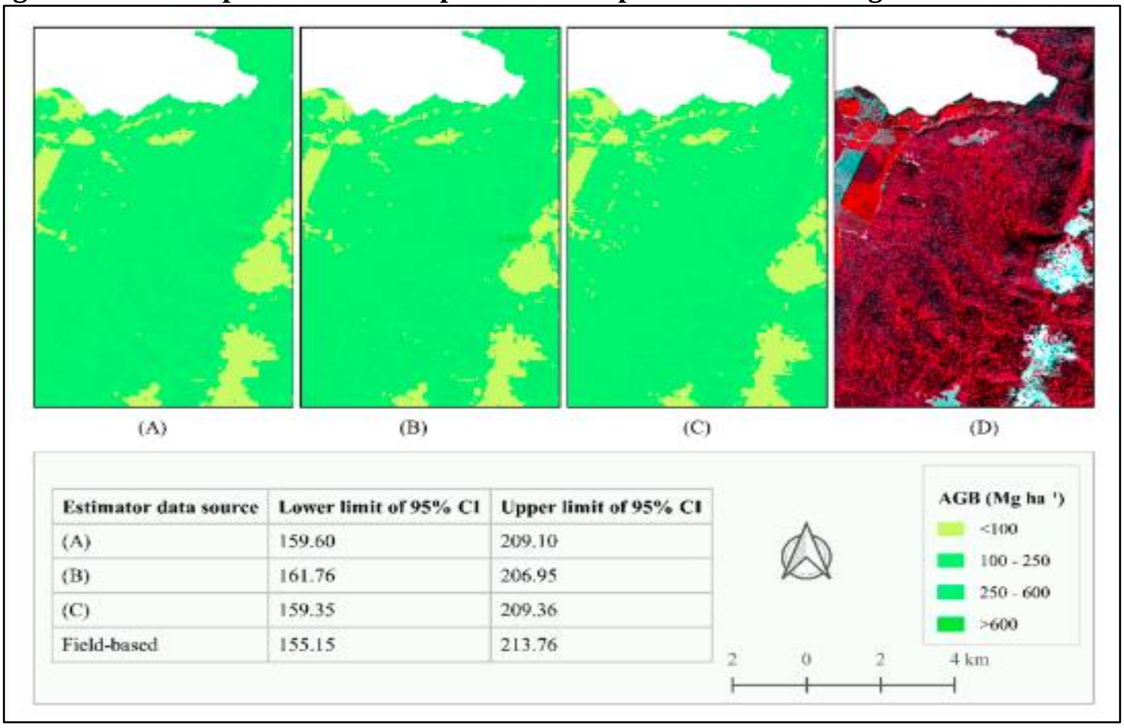
efficiencies of 1.40, 1.37, and 1.68 (Figure 5). This indicated the potential of the different satellite images for estimating and improving forest above-ground biomass.

Table 7: Summarized spectral index's for biomass estimation

SI	Expression/formulas	References
SR	NIR/R	Jordan (1969), Günlü et al. (2014), Macedo et al. (2018), Das and Singh (2022),
NDVI	(NIR−R)/(NIR+R)	Rouse et al. (1974), Huete et al (1999), Gizachew et al. (2016), Das and Singh (2022),
VI	G/R	Adamsen et al. (1999), Günlü et al. (2014), Taddese et al. (2022)
DVI	NIR−R	Richardson and Wiegand (1977), Das and Singh (2022)
ExGI	2×G−(B+R)	Sonnentag et al. (2012), Taddese et al. (2022)
GLI	(G− R)+(G−B)/2×G+ R+B	Louhaichi et al. (2001), Taddese et al. (2022)
EVI	2.5×(NIR−R)/(NIR+6×R−7.5×B+ 1)	Liu and Huete (1995), Gizachew et al. (2016)
SAVI	(NIR−R)/(NIR+R+0.5)×(1.5)	Huete (1988), Das and Singh (2022),
MSA VI	$2\times NIR+1-(\sqrt{(2(NIR)+1)2-8(NIR-R)}/2$	Qi et al. (1994), Das and Singh (2022)
NDMI	(NIR−SWIR1)/(NIR+SWIR1)	Gao (1996), Gizachew et al. (2016), Taddese et al. (2022)
NDGI	(G− R)/(G +R)	Motohka et al. (2010), Taddese et al. (2022)
ARVI	(NIR −(2×R−B))/(NIR+(2×R−B))	Kaufman and Tanre (1992), Qiu et al. (2019), Taddese et al. (2022)
SRRE	NIR/RE	Torino et al. (2014), Rajah et al. (2019), Baloloy et al. (2018)
REND VI	(NIR−RE)/(NIR+RE)	Gitelson and Merzlyak (1994), Imran et al. (2020)

Figure 5: Visual representation of a portion of the predicted AGB using the selected models.



Note: Selected models: L8, S2, PS and false-color composite, respectively from A to D.

Source, Taddess et al. (2020)

Disease and Insect Outbreak Detection

Many years ago, it was thought that remote sensing could be used to identify damage to forests caused by insects and diseases (Woodcock et al., 2008). However, it has received considerable attention only recently, in the late

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1990s, for managing emerging outbreaks. The two primary causes are as follows: 1) internationalization, which has led to the global spread of pests and pathogens, has caused an enormous rise in the incidence and severity of forest diseases during the past 20 years; and 2) the impact of climate change (Boyd et al., 2013). This emphasizes two things: (1) the obtained spectrum data have expanded considerably within the same period, primarily due to the abatement of data collecting costs and (2) the need to understand illness development in order to apply effective mitigation techniques. For instance, it is now easy to methodically evaluate the consequences of individual illnesses or insects in particular areas of interest thanks to the release of more than 40 years of the Landsat archive (Woodcock et al., 2008). A number of additional investigations were conducted in Australia, China, and South Africa, but the majority of the research hotspot were located in North America, which included the United States, Canada, and Europe (Germany, Norway, Spain, Sweden, and the United Kingdom) (Chen & Meentemeyer, 2017). *Table 8* shows remote sensing-based detection of forest diseases in different countries.

Table 8: A summary of remote sensing-based forest disease detection.

Disease (pathogen) name	Species that host the pathogen	Study area	Sensor and Wavelengths used	Approach adopted	References
Sphaeropsis blight (*Sphaeropsis sapinea*, F)	*Pinus radiata*	NSW, Australia	MS-I (12 bands, 450−850 nm)	SS + Imaging	Coops et al. (2004)
	Pinus radiata	NSW, Australia	HS (350−1100 nm)	VSI, SS, LIBERTY	Coops and Stone (2005)
	Pinus radiata	NSW, Australia	MS-I (4 bands, 680−850 nm)	Imaging	Goodwin et al. (2005)
	Pinus radiata	NSW, Australia	MS-I (4 bands, 680−850 nm)	VSI + Imaging	Coops et al. (2006)
	Pinus radiata	NSW, Australia	MS-I (4 bands, 680−850 nm)	VI + Imaging	Sims et al. (2007)
Pine wilt disease (*Bursaphelenchus xylophilus*, N)	*Pinus massoniana*	China	HS (350–1100 nm)	VSI, SS	Ju et al. (2014)
	Pinus thunbergii	South Korea	HS (350–2500 nm)	VSI, SS	Kim et al. (2018)
	Pinus pinaster	Portugal	MS-I (5 bands, 475−840 nm), HS-I (380−1100 nm)	VSI + Imaging	Iordache et al. (2020)
	Pinus spp.	–	–	–	Wu et al. (2020)
	Pinus massoniana	China	HS (350−1100 nm)	SS, PLSR	Zhang et al. (2020b)
Red band needle blight (*Dothistroma septosporum*, F)	*Pinus radiata*	NSW, Australia	MS-I (10 bands, 450−850 nm)	VSI + Imaging	Coops et al. (2003)
	Pinus radiata	NSW, Australia	HS (350−2500 nm)	VSI, SS	Stone et al. (2003)
	Pinus contorta, *Pinus sylvestris*	Scotland, UK	HS-I (450−980 nm), HS (350−2500 nm)	VSI, SS + *Imaging*	Smigaj et al. (2019)
Blister rust (*Cronartium ribicola*, F)	*Pinus albicaulis*	MT, WY, USA	HS-I (450−2500 nm)	SS + Imaging	Hatala et al. (2010)
Pine pitch canker (*Fusarium circinatum*, F)	*Pinus radiata*	South Africa	MS-I (4 bands, 447−874 nm)	VSI + Imaging	Poona and Ismail (2013)
Laminated root rot (*Phellinus weirii*, F)	*Pseudotsuga menziesii*	Canada	MS-I (8 bands, 438−861 nm)	VSI + Imaging	Leckie et al. (2004)

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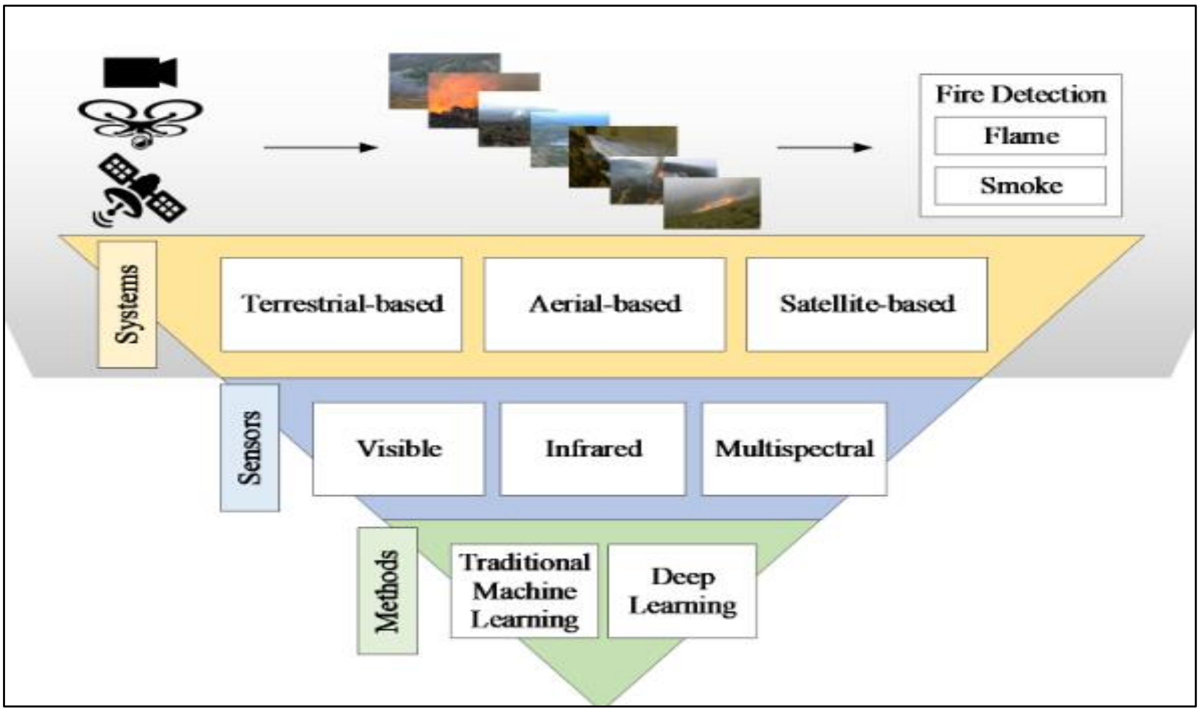
Forest Fires Detection

Over the past few years, the environment has been significantly impacted by both human-caused forces and climate change. Among these events are heat waves, droughts, dust storms, hurricanes, floods, and wildfires. Tanase et al. (2018) claim that wildfires cause major harm to infrastructure, injuries, and fatalities in addition to having a detrimental effect on local and global ecosystems. For these reasons, it is critical to detect fires and accurately monitor the type, size, and impact of disturbances over wide areas. Strong attempts have been undertaken through early fire detection or fire risk mapping to reduce or prevent such repercussions (Pradhan et al., 2007). Traditionally, forest fires were found by eye from fire lookout towers and with only crude instruments like the Osborne fire finder (Kresek, 2007). Nevertheless, this method is ineffective since it is disposed to to weariness and human error.

New methods for identifying and keeping an eye on forest fires have been made possible by recent advancements. Theses includes in computer vision, machine learning, and remote sensing technologies (Barmpoutis et al., 2020). Three commonly used systems can detect or monitor active fire or smoke occurrences, depending on the acquisition level. Barmpoutis et al. (2020) have investigated and compared these three systems as terrestrial, aerial, and satellite (*Figure 6*). When it comes to precision and reaction times to wildfire emergencies systems such as terrestrial systems are typically more effective. Terrain systems are usually more successful in terms of precision and response times to wildfire crises. Furthermore, these systems offers high spatial resolution contingent on viewing angle and distance, as well as camera resolution; nevertheless, their coverage is comparatively narrower than that of the other two due to fixed camera placements and possible other constraints (Barmpoutis et al., 2020). The recent rapid development of UAV technology has drawn a lot of attention to aerial-based systems. Even in areas that are unreachable or deemed too hazardous for firefighting teams, these technologies offer a wider and more accurate view of the fire. Because of their extensive coverage, the third category Earth observation satellite systems has proven effective in detecting wildfires.

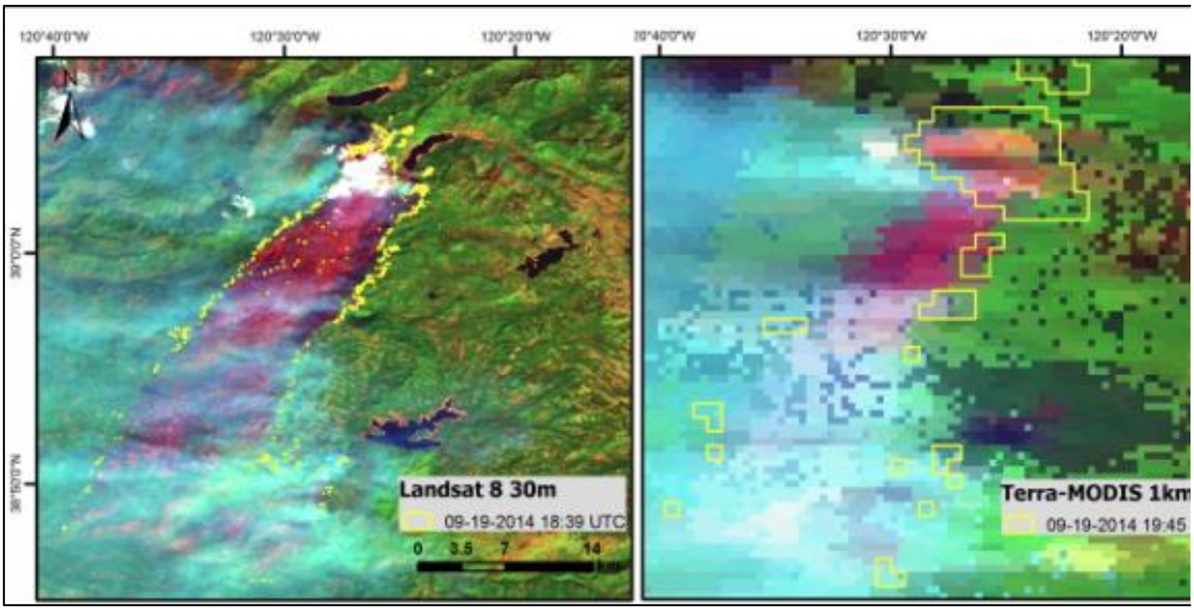
Figure 6: Multispectral imaging systems with a broad use for early fire detection



Source Barmpoutis et al. (2020)

The daylight fire observations from the 2014 King fire in California, as reported by Schroedera et al. (2016), were verified by same-day fire detections from 1-km Terra MODIS and Landsat 8–30 m (*Figure 7*). Both the position and size of the fire fronts were well matched among the various goods. The visualization of the burning front, however, was substantially more comprehensive thanks to Landsat-8 fire pixels, which showed discrete islands of heat inside the blaze's boundary as well as areas of ongoing activity on both the east and west sides.

Figure 7: Multi-sensor imaging of the King fire in California/U.S. on 19 September 2014



Source: Schroedera et al. (2016)

Detecting Forest Disturbance

Ecosystems in forests are frequently disturbed. Many forest ecosystems experience disturbance on a regular basis due to factors including wind, ice storms, disease, insect infestation, pollution, or climate change (Torbick & Ducey, 2010). Therefore, in order for landowners to react efficiently and effectively, fast and precise assessment of incidents of disturbance is essential. Assessing the degree of perturbation (number of lost or damaged trees) throughout the environment is crucial for economic, policy, and large-scale management decisions. Since many of these disturbances only cause minor harm to forest structures, it can be difficult to identify and measure them with traditional optical remote sensing methods.

Nevertheless, when paired with optical images, modern satellite remote sensing technologies such as SAR and LiDAR offer the ability to better recognize perturbations and measure their impact on the environment than when used individually. In order to create and assess a prototype functional image evaluation system, investigators from the Northeastern States Research Cooperative (NSRC), Torbick and Ducey (2010), integrated remotely sensed imagery (MODIS) with field-collected forest measurements from sites in New Hampshire and Maine. The outcome showed that it is both practical and economical to monitor forest disturbances while integrating remote sensing with MODIS.

Canopy Height Change detection using RS

The responsiveness of data obtained from penetrative detectors, for example SAR and LiDAR, to forest structural features, including volume, tree height, and AGB, as well as canopy height recognition, is great. LiDAR is widely employed in the forestry industry for commercial purposes in order to assess forest resources and minimize fieldwork required for field surveysAccording to Castillo et al. (2012), the canopy height calculated by LiDAR has a 1.34 m root mean square error, indicating high accuracy.

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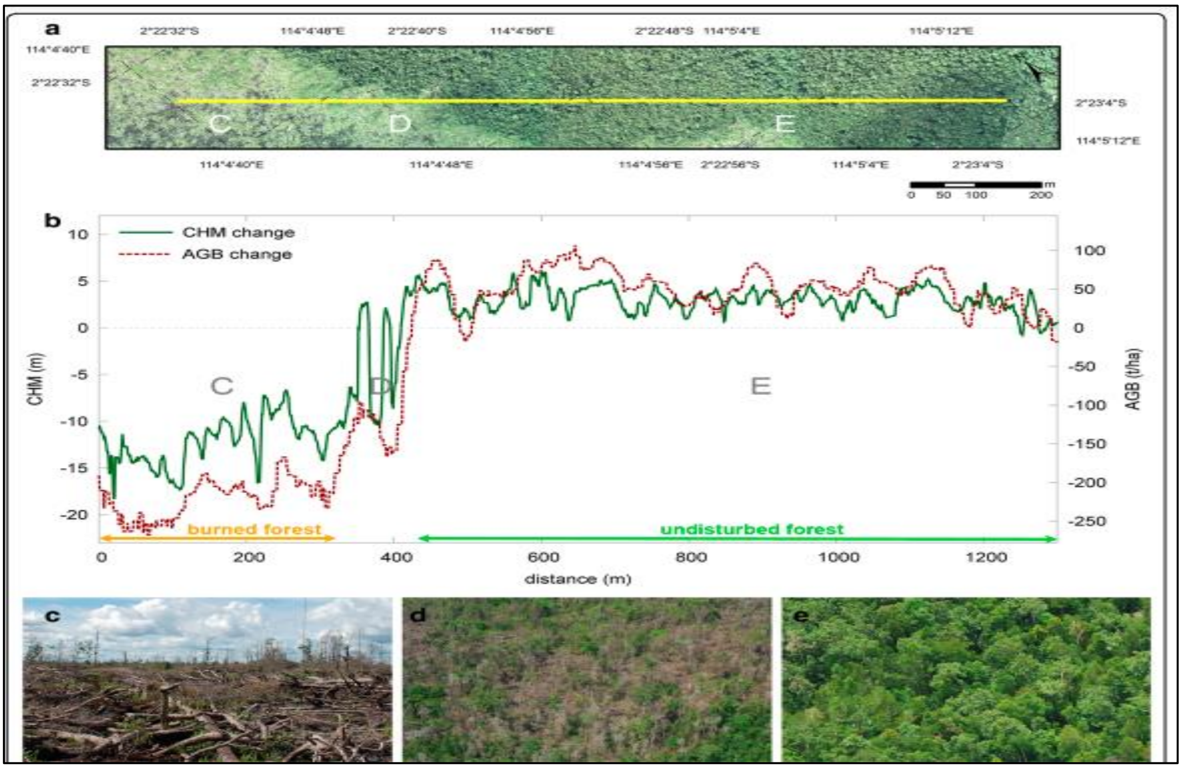
In their study, Anderson et al. (2014) employed repeat LiDAR to assess structural alterations in forests that had been selectively cleared in the Western Brazilian Amazon. They discovered that during the approximately 1.5-year period of picture acquisition, 4.1% of the tall canopy (>30m) had been lost.

In a similar vein, Englhart et al. (2013) measured canopy height and AGB patterns in undamaged, deliberately logged, and burnt forests using multi-temporal LiDAR collected over tropical wetland forest in Kalimantan. The results demonstrate how the forest settings vary in terms of AGB and canopy height (*Figure 8*). In the deliberately logged forest, overall and mean canopy height rose by 0.5 and 1 m, correspondingly, although the typical loss was 55 Mg ha^{-1} within 30 m and 42 Mg ha^{-1} within 50 m of identified cutting roads. In an untouched forest, gains of 20 Mg ha^{-1} AGB and 2.3 m of canopy height were seen each year during the same period (4 years). This indicates how LiDAR is very important in getting forest science. However, the challenge is Airborne LiDAR is currently not freely available and reasonable for governments to obtain a continuous data (Mitchell et al., 2017).

Figure 8: AGB fluctuations and the height of canopy in tropical wetland forests are measured using multi-temporal LiDAR.



Englhart et al., 2013.

Remote Sensing Technologies for Forest Inventories Enhancement

Achieving an acceptable compromise between managing the forest environment sustainably and meeting the needs of a growing human population is seen as sustainable forest management (MacDicken et al., 2015). The demands for managing forests and assessment are changing quickly within the framework of an intricate mix of socioeconomic, environmental, and social policy goals. Technology for remote sensing have the capacity to offer data to help meet these growing information needs and to facilitate further growth. For example, ALS (active remote sensing technology) is useful for characterizing hierarchical tree structure since it analyzes the three-dimensional arrangement of plants within the canopy of the forest (Wehr & Lohr, 1999). The way LiDAR devices capture the energy coming back to the sensor determines their classification.

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Instantaneous return technologies collect one or more distinct responses for every pulse of laser that is generated; as sensor technology has advanced, the maximum quantity of instantaneous returns that may be collected for every generated pulse has grown (Lim et al., 2003). On the other hand, a full-waveform system will capture the energy that is returning as a single, continuous waveform (Lefsky et al., 2002). LiDAR measures the three-dimensional positions of targets, including trees, using a near-infrared light source and sensor (Lim et al., 2003). Goodwin et al. (2006) state that ALS data are typically gathered at altitudes between 500 and 3000 meters for forest surveys. Such information are widely used in the estimation of forestry enumeration characteristics and the development of unimproved digital terrain models (DTM) (Hyyppa et al., 2008).

Growing stock is determined using species-specific biomass and volume formulae as given the same age and location factors, various kinds of trees are going to have various sizes. In order to determine the volume of each particular tree, models that use height and DBH are frequently made to be species-specific (e.g., c; Joanne et al., 2016). As per Joanne et al. (2016), there exists a possibility to classify tree species using ALS data; however, the existing studies indicate that these methods require significantly more expertise than those that utilize an area-based approach (ABA) for estimating basal area or stand volume.

Forest-Wildlife Management

Mapping and tracking ecological diversity also benefit from the use of data from satellites. A model to direct the use of RS data in the mapping and tracking of biodiversity was developed in a research by Stoms and Estes (1993). Subsequently, this area of study has been the subject of numerous investigations (Tuomisto et al., 1995; Nagendra, 2001; Kerr and Ostrovsky, 2003; Wang et al., 2009; Wang et al., 2010). In order to analyze grizzly bear habitat, Franklin et al. (2010) utilized a combined decision- trees method to depict land cover using remotely sensed data.

CONCLUSION

The importance of forests to the climate and human life has been recognized on a global scale. Even so, there are significant alterations that occur in forests. Aside from natural causes, human-induced sources are thought to be the most significant factor in forest modification. Numerous data sources that are accessible via distinct remote sensing technologies—such as air-borne, space-borne, and terrestrial remote sensing sensors—have emerged as vital assets of information for studies regarding the spatiotemporal patterns of forests, owing to the enormous challenges related to the labor, transportation, and chronological consistency of field-based surveys for forest management and study.

The application of imagery from satellites to help comprehend forest characteristics is a long-standing and quickly developing phenomena. With the initial commercial earth-observing satellite launched in 1972, remote sensing by satellite has been able to offer ever-more-advanced data on the framework, control, management, and evaluation of forests. Monitoring and comprehending the world's forests is crucial given the present state of worldwide threat of climate change, loss of biodiversity, deterioration of the environment, and rising demand for wood products. Technology related to remote sensing has been crucial in this instance. The purpose of the present review was to examine the application and role of remote sensing in forestry. Information were gathered from publications, written papers, internet resources, and professional experience. As seen from the review, the use of remote sensing essential because it provides the synoptic, timely information that is only possible with satellite imagery alongside the additional facts required to assist local, national, and international decision-makers in critical decisions. The assessment highlights the crucial role that remote sensing technologies plays in managing forests. Current knowledge on disturbance, fire, shifting forest cover, and managing forest wildlife is helpful.

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