INTEGRATE A HETEROGENEOUS SET OF DATA TOWARD DEVELOPING A FOREST HEALTH INDEX: A REVIEW

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ABSTRACT

Forest health monitoring has become a global issue after increased fire events, droughts, and tree diseases. Researchers developed techniques and approaches for determining a forest health index (FHI). FHI is a tool that uses one or more indicators to measure and assess the different aspects of a forest ecosystem, and it can vary depending on the goal of the assessment. Indicators in forest health refer to ecological, meteorological, and other indicators, such as biological ones. Ecological indicators include productivity, vitality, and biodiversity, while meteorological indicators include temperature, humidity, and precipitation. Different techniques and methodologies have been developed for measuring one or a group of these indicators. Remote sensing, field observation, and ground-based sensor approaches create a forest health monitoring system by monitoring indicators and generating indexes. Remote sensing, such as satellites, manned aircraft, and drones, is excellent for monitoring the forest's health status. However, relying on remote sensing alone to build a forest health monitoring system is still unreliable. This review aims to define forest health and the FHI while identifying various indicators and their relationship to creating an FHI. The paper describes several measurement approaches for developing a forest health monitoring system and defines several applications. The paper also examines the potential multi-data sources in developing a forest health monitoring system. The result suggests that integrating different techniques could enhance forest health monitoring.

Keywords Forest Health Index, Forest Health Monitoring, Remote Sensing, Ground-based Sensor, Field Observation, Multi-data Sources, UAV

1 INTRODUCTION

1.1 Motivation and Contributions

Forest health is a term used without a generally accepted definition. Indeed, forest health cannot be defined unambiguously as it reflects values from social, economic, and ecological aspects. Lausch et al. [1] covered several definitions of forest health. Trumbore et al. [2] quoted one of these definitions: a *"mosaic of successional patches representing all stages of the natural range of disturbance and recovery."* According to the United Nations (UN), *"more than 80% of all land mammals, birds, insects, and plants inhabit forests. About one-third of humanity is estimated to depend on forests and their products directly."*

The United States of America (USA) initiated a forest health monitoring program in 1990 to provide information about forest conditions in the USA. The program investigated four interrelated activities: detection monitoring, evaluation monitoring, research on monitoring techniques, and intensive site monitoring. The program's primary goal is to be aware of the changes in forests, to support decision-makers with accurate information, and to provide an annual review of the health status of forests [3].

The United States Department of Agriculture (USDA) created a program called Forest Inventory and Analysis (FIA) to monitor the status of the forest in the United States. The program depends on forest health indicators covering human needs within the acceptance budget. FIA defines several indicators such as crown condition, tree mortality and standing dead trees, tree damage, vegetation profile, and soil quality that can provide insights into forest health to forest managers [4].

To study and understand the status of the forest, forest managers usually need to harvest a large area to define the area's health status by exploring various ecological indicators depending on the goal of this process. This harvesting needs tools and experts to visit the field, requiring time and money. Developing a model to measure ecological indicators will reduce the costs of this issue. For example, Näsi et al. [5] compared the ability of UAVs to detect beetle damage against aircraft and found that UAVs can detect beetle damage better than aircraft in urban forests. Huo et al. [6] created a new index to detect the bark battle attack on European spruce forests to measure and detect tree damage.

Human activities, natural stressors, and disturbances can affect all levels of biological organization in forest ecosystems and their resilience. The relationships between factors, stressors, disruptions, and impacts are complex, often nonlinear, and multidimensional at the temporal and spatial levels [7]. Both species- and region-specific adaptive processes for forest species make it more challenging to understand causal stress responses and their effects on ecosystem resilience [8]. To understand forest health, scientists must investigate the different factors of stressors and disturbances to support forest managers and decision-makers in building their decisions upon a holistic approach. A holistic approach includes several elements, such as data recording, analysis, monitoring, and assessment of forest health [2].

The paper highlights different measurement approaches and their cooperative role in assessing forest health. Field observation, ground-based sensors, and remote sensing are key approaches used to measure various indicators that provide insights into the current health status of forests. Each of these tools has its own set of features and drawbacks. Field observations offer high accuracy and are considered one of the most reliable techniques for determining forest health status. However, they can be time-consuming and costly. For instance, Park et al. [9] identified the difficulty of accurately assessing tree attributes in tall, dense, multilayered forests.

Ground-based sensors provide valuable information regarding weather conditions and other indicators relevant to forest health. However, they are subject to limitations such as power shortages or network issues, affecting their continuous operation. Considering these limitations when relying on ground-based sensors for monitoring is essential.

Remote sensing enables measuring a wide range of forest health indicators at an acceptable cost. However, remote sensing also has its limitations, including the need for permissions, resolution limitations, and data quality variations. For instance, the resolution ability of satellite remote sensing in monitoring forest ecosystems sometimes needs improvement within the limits of feasibility [10].

Our review focuses on providing and identifying several aspects and techniques to study forest health. Our main contributions are the following:

- This review contributes by offering insights into forest health, forest index data, and innovative techniques for creating forest systems.
- We reviewed and identified several forest indexes and indicators by illustrating each part in a separate section and supporting it with examples. In addition, we presented the key considerations of a forest, the scales of the forest, and external factors that affect the forest.

- We explored various methodologies and techniques to address the challenges of forest health monitoring. The authors provided multiple methods for forest health monitoring, including field observation, ground-based sensors, and remote sensing. The authors identified several applications that have been used in forests. In addition, we illustrated the multiple data sources and provided published papers that used data fusion to enhance forest monitoring
- Lastly, we outlined the existing challenges and the future research direction of forest health.

1.2 Existing Surveys

Forest health has become an important topic to investigate regarding the impact of the forest on the ecosystem. In recent years, techniques and approaches have been developed to measure the sustainability of forests and provide information for forest management plans. However, they mainly focus on the measurement approaches to study forest health. This paper explores the forest health indicators and FHI affecting forests and defines several measurement approaches.

Prior survey articles have reviewed many of the techniques and approaches that we examined in this article. One review paper discussed implementing UAV-based on forest health, and the aim was to produce a review paper covering the requirements for developing forest health monitoring [11]. The authors reviewed 99 papers related to UAV-based forest health in the last 10 years. They identified the features and drawbacks of implementing UAVs in forests. As a result, the authors clarified the value that drones provide in enhancing the techniques of forest health monitoring. However, it is still hard to rely on UAVs alone to build a monitoring system for agriculture or forest.

Another review paper covered the criteria for developing forest health monitoring and discussed the methods of dealing with various data sources and presenting these data to create a decision-support system [7]. The article has covered several essential topics in developing a forest health monitoring system. In addition, it covered the technique of dealing with different data and identifying the difficulties or needs of ground-truth data for validation purposes to develop a monitoring system.

Further, Torres et al. [12] illustrated forest health issues using remote sensing techniques. The authors reviewed articles from 2015 to 2020 to show forest health issues using remote sensing techniques. They found several key features, such as the number of papers on this concern increased in recent years, the satellite method is one of the leading methods in this part, and most of the papers focused on two aspects: evaluating the impact of a specific stress or disturbance factor. By contrast, a few articles discussed the early warning technique. In addition, Camarretta et al. [13] studied the ability of remote sensing to study forest restoration, identify several remote sensing platforms, and investigate each forest structure attribute.

Another survey paper examined the importance of adding biodiversity as an indicator of forest management plans [14]. The authors of that paper selected 94 papers from the 1990s to 2020 that fulfilled these criteria: aspects of biodiversity (structure–composition–function) and four forest management categories (unmanaged, managed, plantation, and silvopastoral). In addition, they used three criteria to evaluate the papers: cost, time, and ease of operation on forest stand and landscape level. Lastly, Pause et al. [15] published a review paper that contained the value that satellite remote sensing provides in monitoring forest health and the role of field observation in enhancing the remote sensing technique for monitoring.

Most of the aforementioned papers explored the importance and ability of remote sensing in studying forests. However, this paper aims to analyze remote sensing techniques with other measurement approaches' techniques, such as field observation and ground-based sensors, intending to provide knowledge regarding the ability of these techniques to measure several indicators and the ability to use or develop an index. In addition, we highlight various parameters, including forest health and FHI, identify ecological and meteorological indicators for forest health, and discuss key considerations and factors that affect forest health. We distinguish our paper by providing an overview of forest health, index, and measurement approaches. Our primary objective is to give readers insights into the forest index and the development of forest monitoring systems. Table 1 compares the approaches of different review papers. In this table, we present a comparison of various review papers, shedding light on their respective approaches to understanding the concept of forest health.

Moreover, the table presents the number of papers considered and analyzed to provide valuable insights. Further, we highlight if a paper covered the definition of forest health or if the authors clarified their paper's analysis or evaluation techniques. Lastly, the researchers described the multi-data sources approach in their article "Integration."

1.3 Structure of the Paper

The obtained papers were categorized based on their relationship with the FHI and the data-gathering techniques. Section 2, covers the methodology of collecting documents. Section 3, provides fundamentals of forest health by

Table 1: Previous survey comparison. Our uniqueness is to study the three measurement approaches intending to generate a forest index

Author	Approach			Year	Studies		Forest Health			
	RS	SO	GB		Considered	Analyzed	Definition	Methods	Evaluation	Integration
[15]	✓	✓		2016				✓	✓	✓
[7]	✓			2018				✓	✓	
[13]	✓			2020					✓	✓
[14]				2020	188	94		✓	✓	
[12]	✓			2021	3722	107		✓	✓	
[11]	✓			2022	1073	99		✓	✓	
This paper	✓	✓	✓	2023	210	90	✓	✓	✓	✓

RS: Remote Sensing. **SO:** Site Observation. **GB:** Ground-Based Sensor.

defining several elements that affect forests, including key considerations of forest, indicators, indexes, scales, and external factors. Section 4 covers the measurement approaches of forest health, such as field observation, ground-based sensors, and remote sensing. Section 5, covers multi-data sources. Section 6 covers the findings in this paper. Section 7 contains research challenges and directions—and finally, the conclusion section.

2 METHODOLOGY

This section discusses the survey method used in this work. To generate this review, the authors focused on the papers related to studying forest health index. This paper focuses on more than just the measurement approach or tool. Still, it discusses several indicators, indexes, and measurement approaches to provide a better vision of forest health monitoring and forest index, which could lead to understanding forest health.

2.1 Research Questions

This review aims to provide insights into forest health, forest index, and measurement approaches that help enhance the ability to monitor the forest health status. Accordingly, the study focuses on answering the following questions.
RQ 1. What is a forest health index? : Indexes offer valuable information regarding specific aspects of a forest, for example, the normalized difference vegetation index (NDVI) and leaf area index (LAI). The NDVI quantifies the presence of green vegetation in a defined area. Consequently, no definitive directive regarding creating or utilizing an existence index exists. Instead, researchers typically select or create an index based on the objectives of their study, such as an FHI.
RQ 2. What indicators are there for studying forest health? : Exploring various indicators becomes paramount in the pursuit of understanding and safeguarding the health of our forests and ecosystems. These indicators span different dimensions, encompassing biological, meteorological, and ecological factors. For instance, delving into meteorological indicators like temperature patterns can revolutionize forest health monitoring. We can detect potential fire outbreaks in their early stages by establishing a robust forest health warning system based on temperature fluctuations. Moreover, using multiple indicators promises a more comprehensive and accurate understanding of a forest's well-being. This research explores the probability of combining these diverse indicators to enhance our forest monitoring capabilities, ultimately contributing to the preservation and sustainability of these vital ecosystems.
RQ 3. What are the techniques for studying forest health? : In forest ecology, the choice of measurement techniques is pivotal, with options ranging from remote sensing to ground-based sensors and traditional field observations. Our research determines several techniques used to measure forest health. For example, the advent of drone and satellite technology has substantially widened our horizons, enabling us to monitor expansive forested regions with unprecedented precision. Our study delves into these questions, aiming to provide valuable insights regarding measurement techniques for forest indicators, ultimately advancing our understanding and conservation of these vital ecosystems.
RQ 4. How do multi-data sources help in monitoring forest health? : The multi-data sources approach in forest health monitoring considers using different types of sensors to gather data regarding forest objects and the ecosystem. Multi-sensor advantages include enhanced data accuracy, improved spatial coverage, and the ability to capture diverse aspects of forest health.
Section 3 will answer the first two questions, Section 4 elaborates to answer question 3, and Section 5 covers question 4.

2.2 Research Methods

To conduct this review, the authors searched several digital libraries, including Google Scholar, Web of Science, IEEE Explore, ACM Computing Survey, and SpringerLink, using the following keywords and phrases: "Forest Health Index," "Physical Environmental Indicators," "Forest Health Monitoring," "Remote Sensing," "UAV," "Tree Health," "Field Observation," "Site Observation," "Ground-Based," "Temperature," "Precipitation," "Stream Flow," "Snowpack," "Ozone," "Soil Moisture," "Multi-Sensor Data Fusion," and "Site Measurement." This review used the Boolean operators "AND" or "OR" to enhance the results. The study's article search and selection method was divided into different stages. The first stage was the search for forest health monitoring, indexes, and indicators. The second stage was the search for remote sensing techniques and approaches for forest health monitoring. During this phase, we examined UAVs more regarding several features that drones provide. The third stage was the investigation of the field observation tools and techniques. The fourth stage was the exploration of the different ground-based sensors—finally, the multi-model (multi-data sources) measurement approaches, especially data fusion.

A total of 210 research papers regarding forest health monitoring, FHI, and forest health measurement approaches were reviewed. These papers were filtered by removing duplicate papers or focusing more on a wildfire or wildlife, reading their title, abstract, and conclusion, and then filtered by full-text reading. This filtration resulted in 90 articles Figure 1.

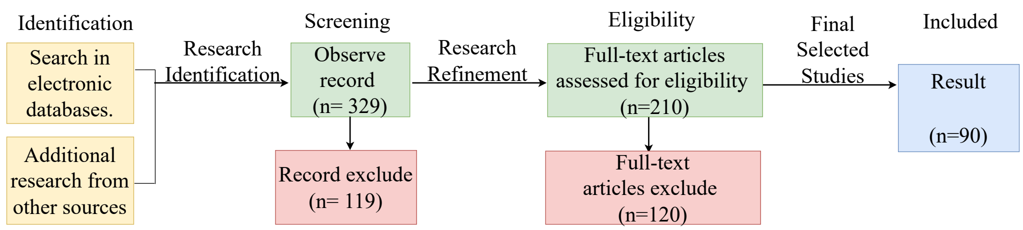

Figure 1: Survey methodology overview: Review Process Illustration.

3 FOREST HEALTH

This section presents an overview of forest health, including the critical considerations of studying forest health (in section 3.1); the authors illustrate the three key considerations of studying forest health (Evaluate the current state, Study the area's history to generate a future prediction system and Generate a warning system). Indicators (in section 3.2), we discussed the three indicators (Ecological, Meteorological, and Biological) as each feeds the idea of forest health from different perspectives. Indexes (in section 3.3): In that particular section, we explore the two most popular indexes (NDVI, LAI) and supply them with determining the published papers focusing on forest health and containing the FHI in the paper's title. Scale (section 3.4) describes the importance of scaling in studying forest health and identifies the three scales (Single Tree, Stand scale, and Landscape-scale). External factors (in section 3.5) define the other factors impacting forest health, such as natural phenomena.

3.1 Forest Key Considerations

There are various considerations for studying forest health. One crucial consideration of forest research involves evaluating the current state of the forest, a practice often referred to as evaluation monitoring. This approach allows researchers to assess various factors influencing forest ecosystems. For instance, in a study conducted by Frey et al. [16], the impact of microclimate and vegetation levels on bird distribution in mountain landscapes in Oregon, USA, was thoroughly investigated as the distribution of birds will help the bioscientist directly or undirect to have a sign about the situation level on that area.

Evaluation monitoring plays a pivotal role in gaining insights into the health and dynamics of forests, helping researchers and conservationists make informed decisions for preserving and managing these areas. It involves an examination of ecological, climatic, and biological variables, contributing to a deeper understanding of the intricate relationships within forest environments.

Another valuable consideration of forest research involves delving into forested regions' historical trends and changes. This exploration can encompass various parameters, including shifts in vegetation levels and alterations in water availability. Understanding the historical context is instrumental in predicting future conditions in these areas, a task often facilitated by applying machine learning models such as random forest.

For example, Roshani et al. [17] employed the random forest technique to assess temporal changes in India's environmental conditions. By analyzing data from the Indian Meteorological Department from 1981 to 2020, their study not only shed light on past transformations but also offered insights crucial for anticipating future developments. Investigating the historical record of forests is a fundamental building block to ensure their continued health and resilience.

The last consideration of forest research encompasses exploring warning systems, a focal component in forest management and conservation. These systems can be categorized into two fundamental types: first, the ability to trigger an alarm when an unusual event occurs; second, the capacity to issue advance warnings based on predictive models. The prediction of advanced warnings is greatly facilitated by applying statistical analysis techniques and machine learning methodologies. For example, Chen et al. [18] harnessed the power of machine learning in the pursuit of precise wildfire prediction. They leveraged a comprehensive dataset containing RGB and thermal fire images, demonstrating how cutting-edge technology can significantly enhance our ability to forecast and mitigate forest-related disasters. Understanding and refining warning systems in forest ecosystems not only aids in safeguarding these invaluable natural resources but also holds the potential to reduce the impact of catastrophic events, thereby contributing to the sustainable management of our forests for generations to come.

3.2 Forest Indicators

Ecological, meteorological, and biological indicators are elements that aid in studying forests and provide insights to determine the health status of the woods. Figure 2 outlines the envisioned system structure of this review paper, depicting the various factors that influence forest health and identifying the appropriate measurement approaches for forestry. In this part, we will describe the indicators in detail; later, in section 4, we will explain the measurement approaches. The first indicator is **ecological indicators** in the context of forests, which are measurable characteristics or variables that provide insights into an ecosystem's overall health, functioning, and dynamics. These indicators assess forest ecosystems' ecological condition, diversity, and sustainability. They help researchers, ecologists, and land managers monitor and understand how ecosystems respond to environmental changes, disturbances, management practices, and human impacts. Several indicators can be used to evaluate the environmental condition of a forest, including vitality, productivity, and biodiversity. Vitality refers to the overall health and vigor of the forest. The quality of tree attributes such as good growth rates, crown condition, and tree damage mainly represent it. Productivity is the ability to produce resources such as timber, tree diameter, and tree height, which are crucial in measuring productivity [19]. Biodiversity refers to the variety and abundance of species within a forest ecosystem [20]. For example, Arwanda & Safe'i claimed that vitality, productivity, site quality, and biodiversity would help determine a forest's health status in Indonesia. The results showed that cluster plots 1, 2, and 4 were in good condition, and 3 were in bad condition. Furthermore, Yang et al. [21] studied the national monitoring program in China to evaluate the ecological function and compared it with other international programs.

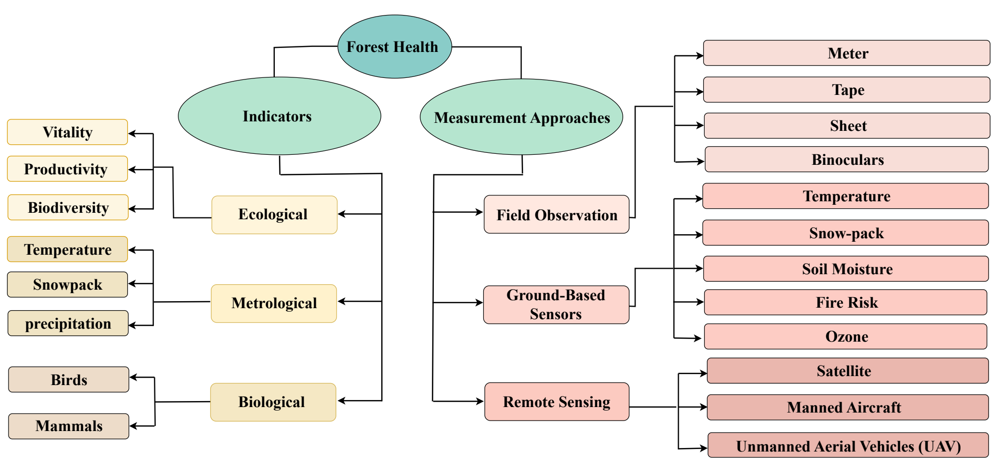

Figure 2: Forest health measurements approaches and indicators. The figure represents different factors that affect the forest status and the techniques to measure these factors.

Second **meteorological indicators**, such as temperature, precipitation, and snowpack also affect the monitoring system. Meteorological indicators in this context refer to specific weather-related variables and measurements that play a crucial role in understanding the environmental conditions within forest ecosystems. Using these indicators, researchers, ecologists, and forest managers may evaluate the effects of meteorological conditions on the health, development, and dynamics of forests. Meteorological indicators are essential for studying various ecological processes and making informed decisions regarding forest management, conservation, and climate change adaptation. For instance, temperature significantly affects the development of trees, which are crucial indicators for describing the health status of the forest. Song et al. [22] explored the impacts of air temperature, tree species, and leaf size on the tree surface temperature in tropical forests. They found that various tree species have different leaf and air temperature differences. In addition, a tree's temperature changes due to climate change depend on the size of its leaves and the amount of air that it releases through tiny pores (stomata) on its surface. Trees with small leaves and high air release are less affected by climate change. Furthermore, Marsh et al. [23] generated a model that studies the correlation between forest structure and air temperature. The result showed that nearly all structural variables significantly differed between vegetation plots, and they recorded a wide range of variation as they found variation by 15.2 °C between data loggers. Moreover, there was a variation of 14.8 °C between data loggers simultaneously at different heights in the same tree. Other meteorological indicators are precipitation and snowpack, which are essential for assessing water availability in a given area [24].

The third **biological indicator** is living organisms or biological parameters used to assess the health of the forest. Several researchers studied the impact of air temperature on the birds' distribution and breeding phenology. For instance, Shutt et al. [25] investigated the effect of microclimate air temperature on three different types of birds in a UK forest. They found a connection between the microclimate air temperature and breeding phenology. In addition, the paper investigated the spatial variance and measured several factors to understand the breeding phenology for all three birds. Han et al. [26] studied the breeding habitats for black-necked cranes in Central Asia using ML. The result showed the ability to predict the birds' breeding distribution using the species distribution model. Furthermore, they presented the rank of each factor that affects the bird. Iijima et al. [27] examined the dynamic seasonal change in bird assemblages. Biological indicators offer essential information regarding the general condition of an ecosystem and the effects of environmental changes or disturbances in the context of environmental monitoring or ecological evaluations. In Table 2, the authors summarized several papers using the three indicator types. Also, the table illustrates the different objectives for each and identifies various notes in each article.

Some other indicators or factors can be highlighted in this paper as they provide different points of view in studying forests. These factors are elevation and distance from the road. Elevation often affects air temperature, as a higher elevation will generally experience a cooler temperature. This factor can help in understanding the habitat preferences of different species. For example, Wu et al. [28] studied the impact of elevation and the relation of temperature and humidity on the growth of leaf phenology in three plant types in a subtropical forest in China. Huerta et al. [29] studied snow depth at different elevations and locations within the forest. The distance from the road is another factor that highlights the impact of humans on forests. At the same time, Han et al. [26] considered the distance from the road as a factor when studying the breeding habitats for the black-necked crane. Mi et al. [30] used the distance from the road to generate the best possible prediction habitat for great bustards. All of these factors can be classified into various categories, such as physical characteristics or human impact.

Table 2: Summary of indicators

Paper	Indicators			Objective
	E	M	B	
[19]	○			The paper aims to assess the health status of Panca Indah Lestari Community Plantation Forest, a plantation forest.
[20]	○			The paper aims to study the health status of a Conservation forest in Indonesia.
[22]	●	○		The paper aims to study the impact of meteorological events, especially air temperature, on plants.
[23]	●	○		The authors are studying climate change in Indonesia's degraded tropical forest.
[24]	●	○		The paper aims to assess the bulk snow isotopic in forested (pine and birch) and open areas.
[25]		●	○	The paper aims to investigate the impact of microclimate air temperature on three different types of birds in a specific UK forest.
[26]		●	○	The paper aims to study the breeding habitats for Black-necked Cranes in Central Asia by using ML.
[27]	●	●	○	The paper aims to study the dynamic seasonal change in bird assemblages in a specific mountain in Japan.

E: Ecological. **M**: Meteorological. **B**: Biological. ○ : Refers to the main focus of the paper. ● : Use as a support factors.

3.3 Forest Indexes

Scientists consider several indicators to study forest health by utilizing or creating indexes. Spectral indexes, such as the NDVI and LAI, are commonly used to assess forest health. These indexes provide valuable information regarding vegetation cover, health, and productivity, which are essential for forest ecosystems. The NDVI refers to the ability to measure the amount of green vegetation in a given area, and it is calculated based on the reflectance of near-infrared (NIR) and red light wavelengths captured by remote sensing. In remote sensing, bands refer to specific wavelength ranges or channels in the electromagnetic spectrum captured by sensors or cameras. These bands recorded data and captured information regarding the Earth's surface or the observed objects. Landsat measured NDVI differences to assess the forest's change to determine the forest's health status in Italy [31]. Bolten et al. [32] used the NDVI with other factors, such as soil texture, to monitor crop growth stage and condition and, subsequently, globally forecast agricultural yields. However, we focused on identifying all forest indexes, not just spectral ones.

The LAI is another popular index in studying forestry, agriculture, climate change, and biodiversity. The LAI is defined as the ground area covered by the plants [33]. The LAI is an essential factor in studying forest health. Although in situ measurement is one possible technique to measure the LAI, it is time-consuming. Conversely, a remote sensing technique can provide a solution to measuring the LAI with an acceptable accuracy rate. Pope & Treitz [34] showed the importance of LiDAR in measuring the LAI. By contrast, both the NDVI and LAI are unsuitable for directly measuring individual trees' physical attributes.

We investigated several articles containing the "forest health index" between 2000 and 2022. We found a few papers that have directly used the word FHI in their title. For example, Olthof & King [35] created an FHI (image-based health index) regarding the most significant image spectral, textural, and radiometric fraction measures. Huo et al. [6] developed a new index, Normalized Projected Red & SWIR (NRPS), to detect the bark beetle attack on European spruce forests. The NRPS index used a red band and a shortwave infrared (SWIF) band to detect the bark battle on a tree. Winarso et al. [36] proposed a new index aimed at developing a satellite-based Mangrove Index as an alternative to NDVI. Unlike NDVI, which relies solely on one parameter, this novel index offers a more comprehensive approach to monitoring mangrove forest health.

Most of the aforementioned papers used remote sensing to develop indexes, and they measured different scale sizes. Table 3 summarizes selected papers focusing on the FHI.

Table 3: Summary FHI

Paper	Index	Aspect	Time-Frame	Sensor & Dataset Information
[35]	Image-based health index	Tree growth	Mid of Augests 1997	Multispectral
[36]	Satellite-based mangrove index	Tree growth	April 10, 2018	Landsat 8
[37]		Tree	July 27, 2009,	Hyperspectral
[38]	Floristic quality assessment index (FQAI)	Species diversity	2018-2021	Existence dataset- survey collection
[6]	Normalized projected red and SWIR (NPRS)	Bark beetle (insect-disease)	04/07, 07/26 and 10/07 of 2019	Sentinel-2 satellite

Table 4 shows several indexes that can be used for several aspects. This table identifies several indexes and shows that the primary index used is the NDVI, and the second is the LAI. The table exposes several elements. Indexes can help study several aspects, for example, using the NDVI as a supporter factor to investigate the tree species or the probability of fire predictions. At the same time, the Aspen Center for Environmental Studies has launched a website dedicated to exploring and monitoring Colorado State's forests. Recognizing these forests' critical role in the local ecosystem, the center's mission is to aid in future planning and to safeguard this vital ecosystem component. To achieve this, they have developed the FHI, a tool that annually measures 12 key indicators on a large scale. These indicators are temperature, extreme temperature, precipitation, frost-free days, stream flow, bear mortality, snowpack, soil moisture, critical fire risk, resource use, ozone levels, and insect and disease prevalence. This website is a valuable resource for understanding and preserving the health of Colorado's forests and the broader ecosystem they support [39].

In conclusion, forest health assessment involves a complex interplay of various factors such as the forest type, geographical location, elevation relative to sea level, distance to roads, and prevailing climatic conditions. The diverse nature of these elements within each forest presents a challenge when establishing a specific index for assessing or monitoring a particular area's health. Developing such an FHI demands effort and careful consideration. In addition to the factors mentioned earlier, it is essential to emphasize the selection of appropriate indicators and tools.

3.4 Scales

Scaling is essential in studying environmental systems and a forest's ecosystem. Understanding forest health requires considering various scales, such as stand, landscape, and individual tree levels. Each scale offers unique insights into ecological processes, impacts, and management strategies. Scales refer to different analyses and perspective levels of forest health. For instance, a single tree refers to individual trees, a stand scale refers to a defined area, and a landscape scale refers to a broader area than a stand scale. In addition, other words can be used to describe the size or the scale, such as the fine scale, which mainly covers the same area as the stand scale. Several researchers identified directly or indirectly the scale's effect in developing the monitoring system model. For example, Ćosović et al. [14] identified the remote sensing technique for data collection as more cost-effective and faster than the field at both stand and landscape scales. Moreover, studying a tree as a validation indicator in different forest areas (production forest, protection forest, and conservation forest) at the landscape level plays a role in understanding the forest's status [57].

Table 4: Summary of the indexes.

Paper	Index														Aspect	Sensor Type
	NDVI	LAI	VI	NDWI	SMI	SDI	TVDI	FWI	GNDVI	NDSI	RSI	DSI	R.A.	CVI		
[40]	✓		✓	✓										✓	Crop Management- Agriculture	Satellite
[32]	✓														Agriculture	Satellite
[41]	✓						✓								Soil Moisture	Satellite
[42]	✓														Soil Moisture	Satellite
[43]	✓														Forestry	UAV
[44]	✓														Fire Detection	UAV
[45]	✓														Canopy Fuels	UAV
[46]	✓														Above Ground Biomass	UAV
[47]	✓														Forest Tree Phenotype	UAV
[48]	✓								✓						Herbicides	UAV
[49]	✓								✓	✓	✓	✓	✓		Tree Defoliation	UAV
[50]	✓	✓													Tree Height	UAV
[51]	✓	✓													Generate Forest Maps	Satellite
[52]		✓				✓									Tree Damage	Satellite
[53]		✓													Forest Health	Satellite
[54]		✓													Tree Volume	UAV
[55]		✓													Leaf	UAV
[56]					✓										Crop Management- Agriculture	Satellite
[57]						✓									Tree Status	Satellite
[58]								✓							Fire Detection	

UAV: Unmanned aerial vehicle.**NDVI**: Normalized difference vegetation index. **LAI**: Leaf area index. **VI**: Vegetation index. **NDWI**: Normalized difference water index. **SMI**: Soil moisture index. **SDI**: Stand damage index. **TVDI**: Temperature vegetation dryness index. **FWI**: Fire weather index. **GNDVI**: Green normalized difference vegetation index. **NDSI**: Normalization of the different spectral indices. **RSI**: Spectral ratio index. **DSI**: Differential spectral index. **R.A.**: Reflectance absorption index. It summarizes the indexes in the remote sensing approach section 4.3. **CVI**: Cumulative vegetation index.

3.5 External Factors

Other factors must be highlighted in studying forest health, including natural disasters such as wildfires or floods, which are hard to prevent. Still, scientists can provide solutions to minimize the loss due to these events. Researchers have developed techniques to reduce the impact of natural disasters, or even prevent them when possible, by utilizing various indicators. These techniques include building prediction models to forecast fires and developing systems to detect fires in their early stages. For instance, one approach involves utilizing a drone equipped with a thermal camera to detect wildfires [18], thereby minimizing forest damage. In addition, studies have been conducted to assess the capabilities of UAVs in measuring canopy fuels and forest structures in the United States to mitigate wildfires in the region [45].

Flood is another natural phenomenon that can affect a city and a forest. Floods can significantly affect forests, disrupting the delicate balance of these ecosystems. Accordingly, Kim et al. [59] generated a multi-sensor system to explore the ability to examine the elements behind flood severity in Cambodia. The authors investigated the relationship between deforestation and flooding in Cambodia, the ninth most vulnerable country to natural disasters in the world, in 2011.

4 MEASUREMENT APPROACHES

Forest health status monitoring has gained significant attention in recent years in public discourse. Scientists and researchers have been actively exploring various methodologies and techniques to address the challenges of forest health monitoring after defining forest health and the elements and attributes used to measure forest health in Section 3; this section will cover three different approaches and tools to measure forest health. The first is field observations in section 4.1, then ground-based sensors in section 4.2, and the last is remote sensing in section 4.3.

4.1 Field Observations

Field or site observation is a method to investigate specific phenomena in a particular location to measure a certain aspect. It requires a physical presence on the site to gather data. Field observation plays a crucial role in forest health monitoring as it provides the ability to assess the ecosystem of forests, allows accurate data collection, and aids in developing a support decision system. The field observation or site observation in this review refers to researchers, scientists, ecologists, or naturalists investigating the forest health status from certain aspects to provide information or measure specific elements.

Data gathering for field or site observation usually requires specific tools and a certain amount of knowledge. This technique involves being physically present in the field to study various aspects of the environment, including ecological or biological indicators. Tools such as meters, cameras, tapes, binoculars, and sheets are examples of what a researcher can carry during the investigation. For instance, binoculars are one of the tools that researchers usually carry during their field observation to investigate different elements, such as the existence of birds, birds' diversity, tree species, and the tree level of damage. Binoculars are used to explore bird diversity in Sabah, Malaysia, to determine the health condition of the forest [60]. Furthermore, Doria et al. [61] claimed that studying primates' existence indicates identifying this area's health status. During observing time, researchers may perform techniques such as visual observations, data collection through sampling methods, recording measurements, taking photographs, or making sketches.

Human observations and laboratory work will help investigate the impact of pests and diseases on plantation forest health in Vietnam [62]. Tree crown condition and diversity can be measured using a 50-m magic card, camera, note-taking pad, stationery, and tally sheet [63]. Other tools can be used during field observations, such as a digital laser tape measure to measure tree height or a camera to document the existence of birds or investigate tree diversity.

Figure 3 illustrates several tools that researchers can use, one or all, during the site observation. Also, we identified several attributes that can be measured using these tools. The format refers to the techniques of cleaning the data to make it more beneficial. Then, the authors define two analysis techniques as an example to process the data and provide an idea about the health status of the specific area.

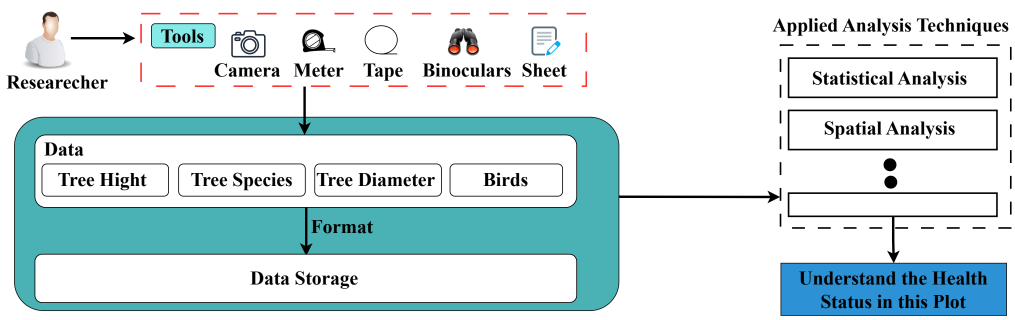

Figure 3: Overview of field observation system structure.

Field observation involves collecting and analyzing data to gain insights into ecological processes to validate existing theories or hypotheses, species interactions, and environmental changes. There are several techniques to study field observation data, such as descriptive statistics, spatial analysis, data mining, and machine learning. These techniques can help generate a system to measure a particular area in a forest. For example, Pranolo & Widyastuti [64] developed an intelligent agent for urban forest health monitoring using the simple additive weighting (SAW) method. The authors used the iLIS software to represent the collected data to the users and used SAW to analyze the data. As a result, the authors help the end users document their work and understand the health status of a particular area from a certain point. In addition, the machine learning approach played a role in developing a model (boosted regression tree models) to study the variables that influence the vegetation plots and the air temperature [23].

Field observation can provide accurate information regarding a specific phenomenon or situation and is used as ground-truth data to validate the results from other approaches. In addition, it can measure different ecological or biological indicators essential to forest health management. By contrast, the drawbacks of this method are high cost and limited accessibility, which make scientists investigate other techniques to evaluate, predict, and monitor the health condition of a forest. One of these techniques is remote sensing, which can streamline data collection, allowing more information to be assessed more accurately and efficiently [14]. However, further research must ensure that these tools are accurate enough to be reliably used in various ecologies across different geographical scales. Until then, researchers can rely on data collected from physical surveys of forest stands (looking at factors such as tree size and density) to help inform management plans and decision-makers and to prepare forests for an uncertain future.

4.2 Ground-Based Sensors

Ground-based sensors refer to sensors installed in a forest to gather data regarding the environment of this plot. Ground-based sensors play an essential role in determining a forest's health condition. These sensors measure temperature, soil, humidity, snowpack, and vibration. Soil moisture is identified by FIA as one of the indicators for forest health monitoring in the United States. In addition, temperature dramatically affects tree growth, vegetation level, and tree crown condition. Regarding ground-based sensors, we overview the system structure in Figure 4. A network of diverse sensors is strategically positioned in the field to continuously monitor real-time data, encompassing variables like temperature, humidity, and soil moisture. The gathered data seamlessly transfers to the nearest computing or edge node through wireless communication protocols such as WiFi, LoRaWAN, and NB-IoT. Subsequently, the edge node undertakes the crucial task of pre-processing the data before promptly transmitting it to the designated server in the cloud via the Internet gateway. Within the cloud infrastructure, one or more servers serve as a database and data processing hub, efficiently handling all collected data from the field. Concurrently, this setup facilitates the visualization of post-processed data on a user-friendly dashboard.

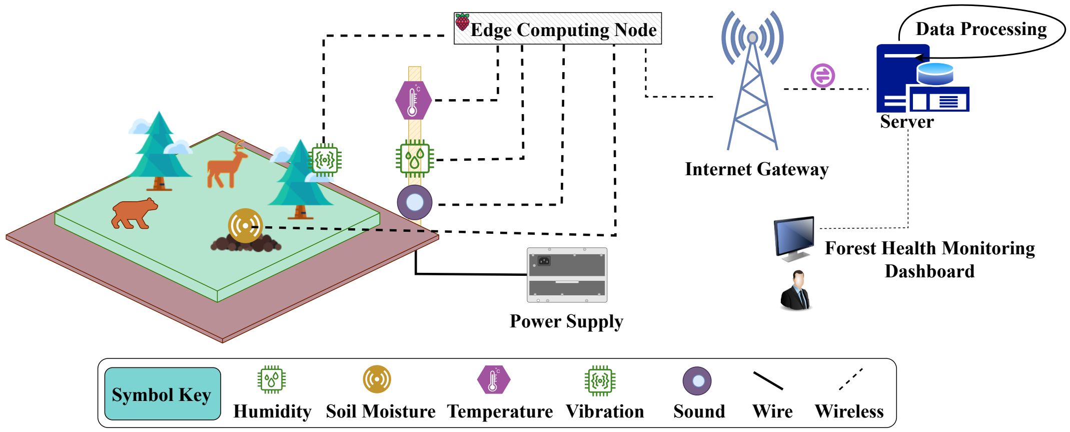

Figure 4: Overview of ground-based sensors system structure.

This section investigates and targets different indicators that are related to ground-based sensors. Those indicators, like temperature, snowpack, stream flow, precipitation, ozone, soil moisture, and fire risk, are identified by the Aspen Centre for Environmental Studies. The center studies the FHI in Colorado. The center identified 12 indicators that provide information regarding the health status of the forest to the forest management department on their website [39]. In addition, it influences other countries and societies to develop a forest health monitoring system, especially in places that are affected by wildfires. This section targets different meteorological indicators and other indicators that are related to ground-based sensors. Temperature is an essential parameter in meteorology and is commonly measured using various types of temperature sensors. Choosing the type and style of the sensors relates to the project's objective, the techniques for collecting data, and the budgetary cost of the project; all of these factors play a role in determining the type of sensors. By collecting temperature data, we can have insights into the health condition in that area by applying different types of analysis. The authors generated a Sankey diagram for ground-based sensors with different indicators. The summary is shown in Figure 5. The first level is the approaches, followed by the second level for sensor types, the third level for the applied model, the fourth for the domain, the fifth for the research subject, and the forest health.

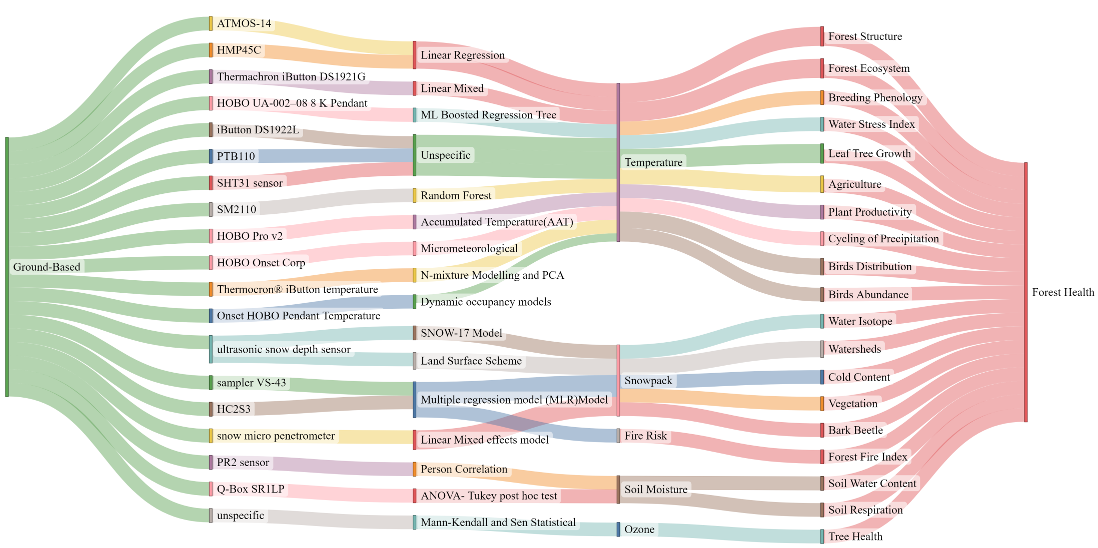

Figure 5: Sankey diagram for ground-based sensors with different indicators summary.

- **Temperature** plays a role in tree leaf phonology, as Wu et al. [28] studied the impact of elevation and the relation of temperature and humidity on the growth of leaf phonology in three plant types in a subtropical forest Chain. Xu et al. [65] used air temperature as a factor to generate a model to predict leaf growth. Studying temperature leads to understanding ecosystems; different forests react differently to weather. Wiesner et al. [66] investigated the ecosystem's response to extreme heat and cold events in three long leaves in the savanna to explore the impact of climate on forest health. Also, temperature plays a role in birds' breeding phonology as it is affected by the temperature as Shutt et al. [25] provided a research paper regarding territory-level temperature influences on breeding phonology and reproductive output in three forest pas-serine birds. In addition, several researchers have approved the impact of temperature on bird distribution [16] and [67] bird abundance.

  As we discussed above, the impact of temperature sensors in understanding the forest, here we illustrate several types of sensors: ATMOS-14, Ther-machron iButton DS1921G, HOBO UA-002–08 8 K Pendant Temperature, SM2110, and SHT31 sensors. In Table 5, we will summarize several papers covering different sensors in the ground-based. Moreover, they illustrate several indicators and define the models, aspects, and study areas.

Table 5: Summary of several indicators for ground-based sensors

Paper	Indicators					Model	Aspect	Location
	T	P	S	SM	FR			
[28]	✓					LR	Tree leaf growth	Chain
[65]	✓					AAT	Tree leaf growth	China
[68]	✓					MG	Tree leaf growth	USA
[25]	✓					LM	Breeding phonology	U.K.
[16]	✓					DO	Birds distribution	USA
[67]	✓					N-mixture - PCA	Bird abundance	USA
[23]	✓					ML- BRT	Forest structure	Indonesia
[69]	✓						Forest ecosystem	China
[70]	✓					RF	Water stress index	China
[66]	✓						Agriculture	USA
[22]	✓					LR	Plant productivity	China
[71]	✓	✓					Cycling of precipitation	Switzerland
[24]			✓			MLR	Water isotope	Siberian
[72]			✓			Semivariogram	Scaling	Canada
[73]			✓			SNOW-17	Watersheds	USA
[74]			✓				Hydrological, meteorological	Canada
[75]			✓			CLS	Cold content	Canada
[29]			✓			MLR - LPL	Interaction between vegetation and snow processes	Chile
[76]			✓			LM	Bark beetle	
[77]				✓		PC	Volumetric soil water content	Malaysia
[78]				✓		TPHT	Soil respiration	India
[79]				✓		RMSD- CC	Soil moisture	Mexico
[80]				✓		LM	Depth to water	Canada
[81]					✓	MLR	Fire risk	Brazil
[82]					✓	ML	Fire risk	Brazil
[83]					✓	ML	Fire risk	Thailand
[84]					✓	ML	Fire risk	Algeria
[85]					✓	ML	Fire risk	Lebanon

T: Temperature. **P**: precipitation. **S**: Snowpack. **SM**: Soil Moisture. **FR**: Fire Risk. "**LR**": Linear regression. "**LM**": Linear mixed. "**ML**" : Machine learning. "**BRT**": Boosted regression trees. "**RF**": Random forest. "**AAT**": Accumulated temperature. "**PCA**": Principal component analysis. "**MLR**": Multiple regression. "**RMSD**": Root Mean Square Deviation. "**Micrometeorological**": MG. "**DO**": Dynamic Occupancy. "**CLS**": Canadian land surface scheme. "**LPL**":local polynomial. "**PC**": Pearson correlation. "**TPHT**": ANOVA-Tukey post hoc test. "**CC**": Correlation coefficient

- **Snowpack** refers to the amount of snow on a mountain during winter. This meteorology indicator provides an angle for understanding the expected amount of water in a specific place. This indicator can be detected using different approaches, but we focus here on ground-based sensors. Studying the snow's water isotopes will help trace hydrological and ecological processes. Exploring the impact of the forest canopy in snow bulk can help understand hydrological and environmental processes in forested (pine and birch) and open areas [24]. Moreover, scaling and location affect snowpack melting. Beaton et al. [72] investigated scaling issues by measuring the snowpack in a northern Great Lakes-St Lawrence forest. Another aspect that influences the snowpack is the type of snowpack, as they are a factor in investigating the amount of net water input to the soil [73]. Various ground-based sensors are there to measure the snowpack, such as a 60 cm snow coring sampler VS-43, SR50, and an ultrasonic snow depth sensor.

- **Soil moisture's** stability is an essential indicator of forest health and is considered a fundamental data source for agriculture. In addition, soil moisture is critical in the study of climate change [86]. Soil moisture refers to the amount of water being held in the ground. Remote sensing and ground-based sensors are the most common techniques for measuring soil moisture. There are several published articles regarding remote sensing techniques measuring soil moisture from different perspectives, for example, [87], [88], and [32]. Another technique is a ground-based sensor where [77] used PR2 sensors to investigate the spatial distribution of volumetric soil water content (VSWC) in tropical rainforests. Further, many soil moisture sensors are available to measure soil moisture, including PR2, ADR, and Q-Box SR1LP.
- **Fire risk** is another indicator for forest health monitoring. (The European Forest Fire Information System) saw an average of 1 million acres burned annually between 2010 and 2019, including countries from the Middle East and Northern Africa (CDP, 2022). As a result of the wildfire, Delgado et al. [81] created a new forest fire index in Brazil to reduce forest damage. In addition, Dubey et al. [89] explored the ability to detect fire in an early stage to reduce the amount of damage. Moreover, Kelleher et al. [90] developed a low-cost system to evaluate PM2.5 to study the forest fire risk. In line with Lertsinsrubtavee et al. [83], the researchers employed a cost-effective wireless sensor network to identify forest fire incidents in Thailand, focusing on the PM2.5 and CO parameters. They utilized the J48 classification algorithm and introduced a decision tree model to predict the risk of forest fires. Additionally, other studies [84] [82] also adopted the J48 classification model, incorporating meteorological variables such as temperature, relative humidity, and wind speed to detect forest fires in Algeria and Brazil, respectively. In a distinct approach, Karouni et al. [85] utilized the ID3 algorithm for forest fire detection in Lebanon, relying solely on temperature and relative humidity.
- **Ozone** refers to a chemical (O3) compound found on the upper level of the atmosphere. Ozone affects different attributes of a forest as it directly affects tree growth. Investigating the effect of temperature and ozone on tree health can give insights into the impact of ozone on forest health [91].

4.3 Remote Sensing

Over the past decade, remote sensing has revolutionized the ability to monitor forests with an acceptable accuracy rate. With different accuracy capabilities, remote sensing can measure several forest attributes, such as the vege Remote level and tree crown. Remote sensing has different definitions: for example, Mcroberts et al., 2010 [51] defined it as observing and sensing the Earth's surface from a distance. In addition, Nicholas M. Short [92] described it as detecting and measuring radiation, particles, and fields from things beyond the location of the sensor device. Another definition of remote sensing is science, art, tool, or technique [93]. Satellites, manned aircraft, or near-surface (drone) sensors are tools utilized in remote sensing. Figure 6 illustrates the three measurement approaches, the relation between operations, the spatial resolutions, and the different scales.

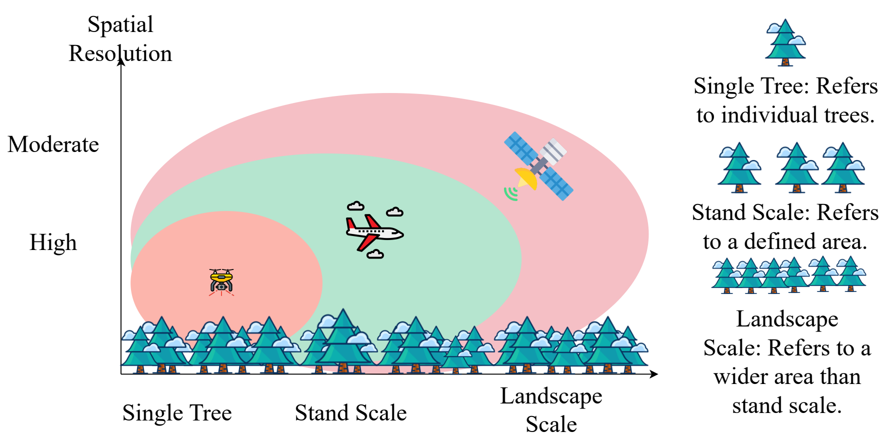

Figure 6: Different approaches of remote sensing.

4.3.1 A satellite

is an object intentionally placed into orbit for several purposes, including communication, weather monitoring, and scientific research. A satellite in this review relates to collecting information regarding forests from different perspectives, such as vegetation level, environmental change, or other goals. Satellite usage dramatically affects studying various forest parts, including forest health monitoring, generating a warning system, and developing a prediction model. We illustrate several published papers demonstrating the use of several satellite applications that have contributed to various forest aspects. For example, for crop management and agriculture, Becker-Reshef et al. [40] discussed the GLAM monitoring system's operational components and new developments and the future role of Earth observations in global agricultural monitoring, especially in studying timely food supply information.

Mohamed et al. [56] studied the relationship between the amount of soil moisture in the ground and crops in Egypt, specifically the Nile Delta, based on remote sensing data and synthetic aperture radar (SAR) Sentinel. In addition, Chen et al. [41] and Ahmad et al. [42] investigated soil moisture using satellite remote sensing. Chen et al. studied if the temperature vegetation dryness index is suitable for estimating soil moisture and if soil moisture is significantly affected by tree species in the Laoshan forest. Ahmad et al. studied the ability to evaluate soil moisture content using remote sensing data for the selected Lower Colorado River Basin sites.

Lu et al. [53] focused on five forest farms in Beijing, identified the influencing factors of forest health, and examined how they contribute to revitalizing rural areas. The research paper explored the pattern of health conditions for different types of forests, based on their age and category, such as young, middle-aged, near-mature, mature, and over-mature forests. In addition, it looks at the conditions in the "shelter forests" and "special-purpose forests" categories. Anwar et al. [57] aimed to understand the characteristics of three types of forests by identifying landscape characteristics regarding the levels of damage to particular kinds of trees in three different forest functions. Tian et al. [94] explored how different sensors, such as satellite and aerial stereo camera systems, can monitor and detect changes in forest areas. Moreover, satellites can detect and monitor insect attacks and catch fire. For example, Sahin [52] observed the larch forest insect in the early stage, and Wang et al. [58] proposed the used of classified animal tracking data and thermal data for forest fire detection, using animals as mobile biological sensors(MBS). Stojanova et al. [95] leveraged datasets representing various regions of Slovenia, namely Kras, Primorska, and Continental Slovenia. Their approach encompassed the utilization of several variables for the purpose of forest fire detection, incorporating a comprehensive array of data sources such as geographic information systems (GIS), MODIS imagery, and meteorological data.

There are several features and drawbacks to satellite monitoring a forest. One feature that satellites provide is the ability to monitor a wide range of areas. However, one of the drawbacks of a satellite presented by Ecke et al. [11] is that satellite imagery, used successfully in temperate and boreal regions to record phenological patterns and their changes in response to climate, is more difficult to interpret in tropical forests. In addition, weather conditions and cloud cover make it hard to collect continuous time series data for multispectral imagery.

4.3.2 Manned aircraft

or human-crewed aircraft is a remote sensing technique requiring a pilot. It is a tool used to gather information regarding one or more objects from a distance. The drawbacks of this technique make it unfavorable to use, such as cost, permission in most cases, and the quality of the image "resolution" negotiable. Guimarães et al. [96] claimed that satellite data's spatial and temporal resolutions are often unsuitable for achieving regional or local forest objectives with traditional aerial and space-based SAR platforms. By contrast, even if their products have a more suitable spatial scale, manned aircraft are expensive when they are frequent. Time series monitoring is desirable. In addition, Xiang et al. [97] described the data from manned aircraft and satellite platforms as susceptible to cloudy sky conditions, which attenuate electromagnetic waves and lead to loss of information and data degradation.

4.3.3 UAVs

Ecke et al. [98] defined it as a drone or unmanned aircraft. A drone is a type of aircraft that operates with a remote control, or that is auto-programmed, and it has been used in various forest applications. It is important to note that the Department of National Defense and Canadian Armed Forces (DND/CAF) has exchanged the term "unmanned air vehicle" for "uncrewed air vehicle" to ensure gender-neutral terminology [11]. Accordingly, Seifert et al. [99] identified that drones use two types of sensors in a forest: the first is laser scanning or airborne LiDAR (ALS). Unmanned airborne vehicles are low-altitude remote sensing platforms, less affected by atmospheric factors during data acquisition. They offer the advantages of affordability, simple operations, fast imaging speed, and high spatial and temporal resolutions [49]. The second is image-based sensors UAV, which provide unprecedented spatial and temporal resolution imagery [100]. In Figure 7, the authors identified the satellite and UAV remote sensing techniques and represented several models and aspects connecting remote sensing with forest health. In Table 6, the authors compare the three remote sensing approaches from different perspectives: cost, permission, distance, weather conditions, temporal resolution, and spatial resolution. This table presents fundamental trends, but their manifestation may vary depending on the project's objectives, tools, and methodologies.

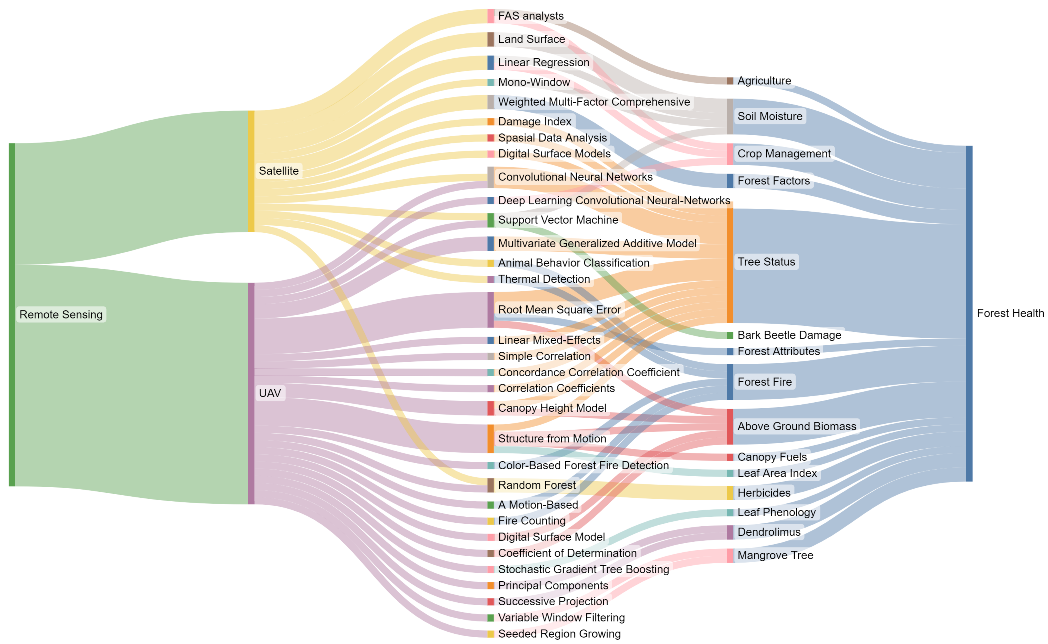

Figure 7: Sankey diagram for remote sensing.

Table 6: Compares different techniques of remote sensing

	Satellite	Manned Aircraft	Near-Surface Remote Sensing (UAV)
Cost	High	High	Low to Moderate
Permission	May required	Need permission	No need in most cases
Distance	Large area	Medium area for fuel reasons	Small area for batteries reasons
Weather Conditions	Low sensitive	Sensitive	Sensitive
Temporal Resolution	Moderate to High	Moderate to High	High
Spatial Resolution	Moderate to High	High	High

UAV Applications UAV applications have become an increasingly popular forest monitoring and management tool, with applications ranging from wildfire prevention to tree damage detection. UAVs are valuable tools in studying forests and ecosystems—UAVs performed in several applications, such as UAVs for wildfires or UAVs for trees. First, the use of UAVs for wildfires has become a growing concern due to their severe impact on ecosystem degradation. Researchers have developed various techniques to address this issue, including using satellites, crewed aircraft, and UAVs to monitor and detect wildfires. Recently, UAVs have been a technique that researchers focus on to detect wildfires with the ability to cover a wider area and within an acceptable cost. A multi-model UAV-collected dataset of dual-feed side-by-side videos, including RGB and thermal images, has achieved higher accuracy than single-channel video feeds using a deep learning-based methodology [18].

Moreover, researchers emphasize the importance of studying forest fires and their impact on ecological degradation. Researchers suggest that the current observation of forest fires requires constant monitoring of all potential locations, particularly those with high fire risk [44]. UAVs have proven invaluable in monitoring and enhancing the quality of wildfire detection. In this regard, researchers proposed a color code identification, smoke motion recognition, and fire classification algorithm to improve the accuracy of detecting forest fires. Given the possibility of false alarms, the authors investigated methods to increase the accuracy of detecting forest fires [44].

Second, UAVs for trees from an ecological perspective can monitor weed vegetation, measure tree height, and estimate deforestation rates. Nowadays, many scientists use UAVs to investigate the status of the forest through tree characteristics, to evaluate soil moisture, or to enhance the quality of the citizen's property or public forest by developing irrigation techniques. Above-ground biomass (AGB) is a critical parameter for many environmental studies in reducing forest degradation. UAVs can measure the AGB in tropical mountain forests using Structure from Motion (SfM) with RGB sensors to estimate the tree height and the breast height (DBH) diameter, which are the inputs in calculating the AGB [46]. In addition, Brede et al. [54] studied the capability of estimating AGB using UAV-laser scanning. They found that measuring the AGB for a single tree using traditional forest inventory methods that use allometric equations has low accuracy, is hard to implement, and is expensive. As a result, the author is investigating the ability to estimate AGB using UAV-LS.

The attributes of trees, including their height, canopy cover, and degree of defoliation, are important indicators of forest health, as they provide information on the ecological and environmental conditions of the ecosystem. Measuring the tree height for intensive forest monitoring using UAV-photogrammetric showed the ability to measure the tree height with the same accuracy level as field measurement [101]. In addition, UAVs can measure the physical attributes of Pinus halepensis trees [47]. Zhang et al. [49] tested the ability of UAV-Hyperspectral to measure the defoliation of trees during the Dendrolimus tabulaeformis Tsai et Liudisaster.

Other areas that UAVs have discovered in the forest ecosystem, such as Näsi et al. [5], identify bark beetle damage at the individual tree level of an urban forest. In addition, Camarretta et al. [13] studied the capability of active and passive sensors to measure the structure of the forest and the ability to restore it. Furthermore, Lu et al. [53] determined the effects of forests on revitalizing rural areas in five forest farms in Beijing, and Shin et al. [45] studied the capability of UAVs to measure the canopy fuels and forest structure in the United States. Lastly, the UAVs showed the ability to measure the physical attributes of a tree.

UAV Approaches UAVs are becoming more commonly used in forestry because of their advantages, such as spatial resolution, cost-effectiveness, adaptability, and more frequent visitations to relatively small areas. Ecke et al. [11] identified different approaches to UAVs: first, an image-based approach (passive approaches), which includes RGB, multispectral, hyperspectral, and thermal. Second is Laser scanning, or airborne LiDAR (active sensors). Figure 8 shows four different sensor types for the image-based approach.

Figure 8: UAV sensors type.

- **Image-based approach (Passive approaches)**
  - RGB: a camera that can be connected to a drone flying to a high altitude and can capture various aspects by considering several steps, such as applying a filter to get a better result. In addition, the visible portion of the electromagnetic spectrum spans frequencies between 400 and 700 nm. The RGB, considering the preprocessing steps, will help researchers calculate plant vegetation.
  - Thermal: Camera sensors for thermal imaging can detect infrared light with a wavelength between 7,500 and 13,500 nm. A thermal sensor can translate the observed energy into a temperature measurement. Modern cameras can detect numerous infrared energy bands, a capacity known as multispectral or hyperspectral. However, it frequently comes at the expense of reduced spatial resolution.
  - Multispectral: In the 400–1000 nm range, multispectral sensors frequently measure certain "bands" of light, such as blue, green, red, red edge, and near-infrared. These bands will measure various vegetative traits, including stress and health. As a result, multispectral can assess the condition of a forest.
  - Hyperspectral: Sensors can evaluate the vegetation level better than multispectral sensors, which can measure large amounts of data. The number of data that the hyperspectral can process increases the accuracy rate.

  Table 7 summarizes the differences between the wavelengths of each image-based approach type. Wavelengths refer to the electromagnetic radiation (light) bands used for data collection and analysis. Wavelengths are important in drone-based remote sensing because they enable researchers to collect information regarding the Earth's surface and features.
- **Laser scanning, or airborne LiDAR (active sensors)**
  Airborne laser scanning (ALS) can be used in forest inventory. Many countries around the world use ALS in forest inventories. Nevertheless, acquiring ALS data requires a degree of planning and investment, making these data sources cost-effective only on a large scale.

Table 7: Sensor types and corresponding wavelengths

Sensor Type	Wavelengths
RGB	400–700 nanometers (nm) band
Multispectral	400–1000 (nm) band
Hyperspectral	Similar spectra as multispectral sensors but significantly differ in band numbers and widths.
Thermal	7500 and 13,500 (nm) band

UAV Parameters UAVs have significantly helped improve the techniques for measuring and monitoring forests. Accordingly, we illustrate several factors that affect the use of UAVs in monitoring or evaluating a forest. The UAV factors are summarized in these factors: altitude, overlap, speed, resolution, and weather conditions. Therefore, the success of UAVs in forest monitoring relies heavily on their flight parameters, including altitude, overlap, speed, resolution, and weather conditions. These factors play a crucial role in the accurate reconstruction and extraction of data. Recent studies have searched for the impact of these parameters on UAV image extractions, such as the research conducted by Seifert et al.[99]. Similarly, Tmušić et al. [102] identified a range of parameters that affect UAV flight time, such as weather conditions, payload, battery power or engine fuel, and UAV type. These findings highlight the importance of carefully considering UAV flight parameters when developing a forest health monitoring system. Table 8 summarizes several UAV parameters.

Table 8: UAV characteristics

Paper	Overlap	Altitude	Flight Speed	Sensor Type	UAV Type
[47]	80%	100 m		RGB-Multispectra-Thermal	Mikrokopter OktoXL
[46]	90%	300 m	9 m/s	RGB-Multispectral	DJI Inspire I
[45]	85-90%	120 m	40–90 km/h	Multispectral	SenseFly eBee fixed-wing UAV
[48]	85%	90 m		Multispectral	A co-axial quad-copter UAV
[50]	75%	75 m	4 m/s	Multispectral	JI Matrice 600
[49]	70-60%	100 m		Hyperspectral	DJI Spreading Wings S1000+multi-rotor octocopter
[5]	75%	500 m		Hyperspectral	
[103]	90%	55 m	8 m/s	LiDAR-Hyperspectral	DJI M600 ProUAV
[104]	100%	50 m	2.0–4.0 m/s	Laser sensor	Riegl RiCOPTER with VUX-1UAV
[105]		40 /150 m	3.6 m/s	Laser sensor	Eight-rotor UAV
[54]		90 m		Laser sensor	VUX-1UA
[106]	90%	109 m		UAV with in-built true colour camera	JI Phantom 3 Professional quadcopter
[101]	80%	75 m			Octo XL 6 12 Octocopter mounted with a fixed lens
[55]	90-60%	300 m			DJI spreading wings S900

UAV Data Data acquisition approaches in UAVs consider different parts, such as the specific task to which the drone flies to achieve, determining the area of this task, weather conditions, and other parameters such as altitude (flight height), speed, and overlap (which help in improving image quality) [69]. The DJI UAV used Inspire 1 to collect data for 24 hours. The software was designed for precision flight to enhance flight characteristics. Data processing occurs after gathering the data and translating them into valuable data. Most of the review studies in this paper relied on commercial SfM software to create data products. Data analysis is a specific technique to measure and illustrate data to achieve a particular result, and different algorithms are considered in UAVs, such as the automatic tree detection and crown segmentation algorithm. Furthermore, machine learning has an impact on image recognition and tree classification. Figure 9 illustrates the process of monitoring a forest.

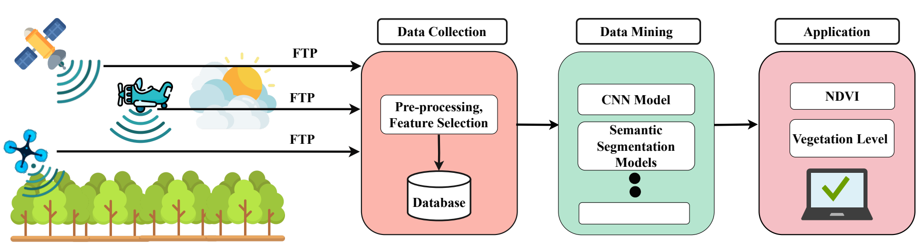

Figure 9: Overview of remote sensing system structure.

In summary, remote sensing has demonstrated the ability to monitor forests under different circumstances. However, relying on remote sensing to monitor forest health remains challenging. Dainelli et al. [107] clarified that in their reviewed papers, 60% of the studies in the entire dataset collected ground data. This type of data is gathered by carrying out field campaigns and measuring properties such as the size of trees, the species of trees present, and their health status. It is often also collected using GPS to help with the accuracy of imagery products. Collecting ground data takes up many resources, such as time and money, and can be challenging over large areas and long periods. Further, Ecke et al. [11] define in their paper that drone surveys can help to simplify and sometimes even substitute for specific tasks in the field. However, drones' general replacement of ground surveys for FHM still needs more investigation to replace the field measurement. In Table 9, the authors illustrate several published papers regarding RS approaches by considering each paper's data acquisition techniques, tools, and aspects.

Table 9: Summarizes remote sensing measurement approaches

Paper	Application	Approach	Aspect	Sensor Type	Data Acquisition	Time-Frame
[40]	Tree	Image-based	Agriculture	Satellite	NASA	
[32]	Tree	Image-based	Agriculture	Satellite	NASA	5 Years
[56]	Tree	Image-based	Agriculture	Satellite	Synthetic Aperture Radar	1 Day
[57]	Tree		Tree Damage	Satellite	Global Navigation Satellite	4 months
[53]	Tree	Image-based	Forest Structure	Near-Surface	Multispectral	2004, 2009, 2014
[106]	Tree	Image-based	Vegetation	Drone	UAV data	1 Month
[9]	Tree	Image-based	Tree	Drone	UAV data	3 Days
[46]	Tree	Image-based	Tree	Drone	UAV data	
[55]	Tree	Image-based	Leaf Index	Drone	UAV data	20 Days
[49]	Tree	Image-based	Tree Damage	Drone	UAV data	1 Month
[44]	Wildfire	Image-based	FireRisk	Drone	UAV data	

UAV Features, Drawbacks, and Challenges Advances in UAV technology are rapidly being adopted and implemented for forests. As with any technology, UAVs offer benefits and limitations for forest monitoring and management. Flexibility, relatively low costs, and the possibility of flying below the cloud cover. Furthermore, it provides a unique spatial resolution and angle of view data and can offer lower ground sample distances (GSDs) [11]. In addition, compared to traditional inventory surveys, UAVs cause less disturbance to the sample area's flora and animals [106].

UAV observations also provided a unique insight and a historical record with the capacity for near real-time reporting and validation of change events and processes in a forest. Despite the many advantages of UAVs, some shortcomings are found. Ecke et al. [11] identified these drawbacks; the long-term monitoring of forests needs to be better presented. The data pipeline from acquisition to final analysis often relies on commercial software at the expense of open-source tools. In addition, other drawbacks related to the hardware include flights such as battery duration, payload weight, and sensitivity to terrible weather conditions. Further, several challenges have been addressed in the UAV approach, such as the lack of accuracy in detecting tree height, measuring AGB, and determining the flight time of the UAV. Other challenges include the limitation of accessing underground attributes and battery duration. Despite all of the critical challenges listed above, the advantages of using UAVs instead of other remote sensing platforms far outweigh the drawbacks if used appropriately.

5 MULTI DATA SOURCES

The multi-data sources approach in forest health monitoring uses different types of sensors to gather data about certain objectives. This technique gives researchers and forest managers better knowledge of a forest as it can cover various aspects. Some common types of sensors are used in forest health monitoring (remote sensing sensors and ground–based sensors). Remote sensing sensors, such as satellites, aircraft, or drones, can capture images and data regarding forests from above. Conversely, Ground-based sensors are installed in a forest to capture environmental data. Combining different types of these techniques or combining the same tools with varying types of sensors can lead to a better version of forest monitoring.

Multi-data sources depend on integrating different tools, sensor types, or data collection methods. There are several general techniques commonly used in the multi-data sources approach. One of these techniques is in-site, which collects data regarding different local environments. Another approach is remote sensing, which detects an object from above. The third approach is data fusion, which combines data from multiple sensors and sources to monitor a specific aspect of a forest. Ultimately, machine learning can analyze, classify, and predict particular events from multi-data source systems.

Data fusion is the third approach, and this technique has provided a wide range of vision in forest health monitoring in recent years. Data fusion combines data from multiple sources to achieve a goal in a specific aspect. Data fusion has been defined by Hall & Llinas [108] as *"data fusion techniques that combine data from multiple sensors, and related information from associated databases, to achieve improved accuracies and more specific inferences than could be achieved by using a single sensor alone."* In addition, they defined the levels of fusing the data. The first level is a row of sensor data when the sensor data are commensurate. However, when they are not commensurate, we move to the other two levels, which work with the same feature/state vector level or decision level. To illustrate the idea, we provide an example of row sensor data when gathering information for the same object, such as two visual images. Another example of a feature level is when you extract a feature from this object, such as tree crown detection. An example of decision-level fusion methods example is weighted decision methods (voting techniques).

Data fusion and multi-sensor techniques showed the ability to monitor or create a decision support system. For example, Yang et al. [109] generated a multi-system data fusion model that can analyze drought-induced mortality in a temperate forest by estimating daily 30-m resolution evapotranspiration (ET) and the associated Evaporative Stress Index (ESI). The paper studied the techniques in two different scales and used different satellite and measurement techniques to detect and predict forest mortality due to drought. Further, multi-sensors can investigate the relationships between flood severity, precipitation, and deforestation, which can increase the ability to understand the reason behind floods and can reduce the damages [59]. The authors applied regression analysis techniques to measure the impact of precipitation and deforestation on floods. The authors found that there is a significant relationship between precipitation and flood. At the same time, flood and deforestation have no tangible relation.

Besides mortality and flood, tree diversity and species are other signs of forest health. UAVs and satellites have played a role in enhancing the capability of detecting tree species. For example, Hartling et al. [110] used data fusion and machine learning methods to investigate UAV-based multi-sensory ability to classify tree species in an urban environment. The authors have explained the techniques for gathering data from UAVs with different types of sensors, such as hyperspectral and multispectral. They also explained the role of machine learning random forest and Support vector machine in this process. In addition, the authors provided the overall accuracy of this process in specifying the classification of the trees and identifying the limitations and future work in this area. Moreover, Host et al. [111] investigated the presence and abundance of ash trees in Minnesota forests. The authors used different satellite techniques and combined a Landsat image with LiDAR to determine the existence of an ash tree. As a result, the authors found that the overall accuracy of detecting an ash tree is 64% for all ash species and 72% for black ash, and accuracy increased with the length of the time series. Table 10 identifies several methods and aspects for using data fusion in forest health monitoring.

Table 10: Summarizes published papers regarding data fusion

Paper	Sensor Type	Aspect	Location
[110]	UAV- Different approaches	Tree Species	USA
[112]	Field - Satellite - UAS (Drone)	Forest Disturbances (Diseases)	USA
[113]	Field - Satellite - UAV (Drone)	Crop Management	USA
[114]	Different Satellite	Tree Species	USA
[109]	Different Satellite	Tree Mortality	USA
[59]	Different Satellite	Flood Severity	Cambodia
[115]	Different Satellite	Crop Management	Vietnam - Lebanon

Crop management is another field in which data fusion has increased the potential to work. Exploring the ability of UAVs and satellites to measure soybean LAI, AGB, and leaf nitrogen concentration (N) [113]. The authors gathered information regarding the canopy spectral information with canopy structure features using satellites and UAVs. The authors applied different techniques (partial least squares regression, random forest regression, support vector regression, and extreme learning regression with a newly proposed activation function) separately to UAV and satellite and then integrated them to measure the accuracy of monitoring crops. As a result, the authors found that the overall accuracy increased when they combined the UAV with satellite techniques rather than using them alone.

6 DISCUSSION

In this section, we synthesize the findings from this paper on the application of forest health. We identify common themes and key insights for each section.

- **Forest Health:** The research has yielded valuable insights into the complexity of developing a forest index or monitoring system, underscoring the significance of considering various factors. These factors encompass the type of forest, geographical location, elevation, distance from roads, and local climatic conditions. Equally critical is the objective of the index, project timelines, and the tools employed for its creation. When establishing a forest index, thoughtful consideration of these elements positively influences ecosystem health, reduces the risk of forest fires, and enhances habitat quality for diverse organisms. This, in turn, facilitates informed future planning based on historical data. For instance, Winarso et al.[36] suggested that a satellite-based mangrove index is an alternative to the widely utilized NDVI. It is important to note a finding: no comprehensive framework or guideline exists for generating an index that characterizes a forest's condition. However, as mentioned before, some researchers investigate techniques to generate an index.
- **Measurement Approaches:** The authors have presented a review of the usage of each measurement and provide several examples of using these technologies in studying forests. Figure 10 shows that remote sensing

has garnered the highest number of reference articles, highlighting the significance of this technology in modern research. Extensive references demonstrate the widespread use and recognition of remote sensing as a powerful tool for studying various aspects of the environment. Remote sensing has shown its remarkable ability to investigate diverse areas, including but not limited to tree damage assessment and wildfire monitoring. These findings emphasize remote sensing's invaluable role in enabling researchers to gather crucial data from vast and inaccessible regions, offering unparalleled insights into ecological changes and natural disasters.

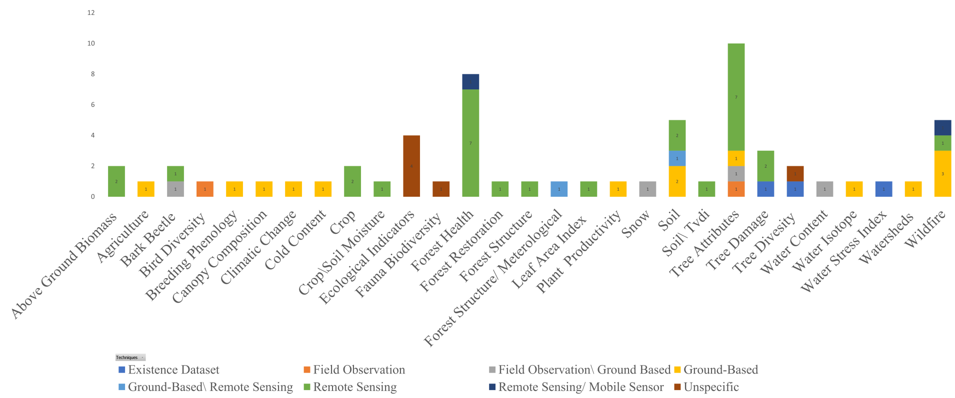

Figure 10: Techniques and aspects.

First, field observation is one of the techniques that researchers and scientists rely on during forest investigation. We found that field observation has been used in most of the reviewed papers for collecting data or validation. Field observations have proven their role in generating accurate forest health by showing the ability to measure various indicators, including biological or ecological. For example, Ranau et al. [60] used the bird as a biological indicator to understand the quality of specific areas. However, finding a recent research paper describing field observation takes time and effort.

Second, ground-based sensors are another technique used in studying forest health. This technique facilitates informed decision-making by enabling stakeholders to implement protective measures and enhance their comprehension of forest ecosystems. We used various published studies covering the importance of ground-based sensors in studying forest health to highlight the knowledge of the impact of this approach in studying forests. For example, Marsh et al. [23] showed that the relationship between canopy cover, forest structure, and microclimate leads to understanding the degradation of forests and expecting climate change. This technique has indisputable value in expanding our comprehension of forest health evaluation. Third, the remote sensing technique stands among the forefront methodologies driving research in forest health assessment. This technique provides the ability to investigate several factors and attributes of forests. Sudhakar et al. [44] studied the ability of UAVs to enhance the warning system for fire risk. In summary, remote sensing has demonstrated undeniable utility in advancing our understanding of forest health assessment, and researchers suggest collaborating remote sensing with field observations can enhance the technique of studying forest health from several perspectives.

Furthermore, as the exact figure, ground-based sensors and field observations are vital components in forest health monitoring. These methods offer distinct advantages, allowing researchers to measure forest health accurately. Ground-based approaches provide valuable on-the-ground data that complement and validate remote sensing findings, contributing to a more comprehensive and reliable assessment of forest ecosystems.

Figure 11 complements the findings by visually representing the geographical distribution of the article references. Each country's proportionate presence on the graph reflects scientific interest and involvement in studying various environmental aspects. The varying sizes of the bars corresponding to different countries signify the relative emphasis and contribution of each nation's research efforts in advancing the field of environmental monitoring and management. As we observe in that figure, the distribution percentages show that this review's findings have wide-reaching implications for global conservation strategies and sustainable practices in diverse forest ecosystems worldwide.

- **Multi Data Sources:** Utilizing multiple sensors provides researchers and forest managers with a comprehensive understanding of forest dynamics, enabling the assessment of various critical aspects. For instance, Yang et al. [109] introduced a data fusion model capable of analyzing drought-induced mortality in temperate forests. This model estimates daily 30 m resolution evapotranspiration (ET) and the associated ESI. In addition, multi-sensor technology proves valuable in studying natural phenomena such as floods, as demonstrated by

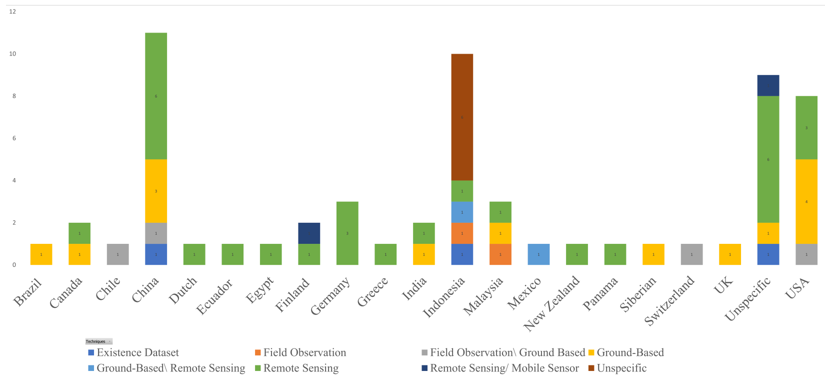

Figure 11: Geographical locations.

Kim et al. [59]. Collectively, these studies underscore the immense potential of multi-data source systems in developing forest indexes and their applications.

7 Research Challenges and Directions

The increasing trend of forest health demands a prediction, evaluation, and monitoring strategy. Considering the various factors that affect forest health, modeling forest health with more than one contributing factor will help develop an assessment, prediction, or warning system. Several approaches and techniques exist for creating an index that can observe and quantify various indicators, ranging from avifauna diversity to overall ecosystem vitality. In addition, deciding which tools, techniques, and indicators to use is challenging. Thus, in this section, the authors will clarify some discussed gaps in existing research and will identify challenges. In Section 7.1, the authors will describe the difficulties in determining the indicators. In Section 7.2, we will cover the challenges of the measurement approaches. Lastly, in Section 7.3, we will highlight the impact of the time frame in an outdoor environment.

7.1 Standardization

From our knowledge perspective, we found difficulties in exploring the indicators that are used to study forest health. Because of the presence of many factors that affect the health of forests, the authors found it a great challenge to know these indicators and determine the appropriate indicators to study forest health in a particular area. Accordingly, there are no well-accepted methodologies used to measure forest health. Some frameworks, such as (foresthealthindex.org) or the USDA reporter, highlight it [4]. Many of these factors encompass ecological, meteorological, and biological indicators, offering unique insights into forest health. Combining two or more indicators can yield an index that provides a view of forest quality. For example, Marsh et al. [23] generated a model that studies the correlation between forest structure and air temperature. However, the challenges do not end with the identification of the indicators. Selecting the most suitable experimental plots is an equally formidable challenge, given the many of factors that must be carefully considered beforehand, including securing the necessary permissions.

Therefore, several approaches can be considered to get over these challenges. Expert insights can help in navigating the intricate landscape of forest health assessment. Additionally, researchers can draw inspiration from various websites and organizations dedicated to forest health research, leveraging the knowledge and methodologies already developed and tested in the field. By organizing our discussion in this manner, we aim to provide a structured exploration of the challenges faced in forest health assessment, starting with identifying indicators and concluding with the practical considerations of selecting suitable experimental plots.

7.2 Measurement Approaches

Another challenge in studying forest health assessment is determining the tools or approaches. Several approaches exist to check forest health, including field observations, ground-based sensors, remote sensing, and multi-sensor methods integrating more than one sensor. Each tool has features, drawbacks, and challenges. This part will discuss these approaches.

Despite the importance of field observation, several challenges can be detected in this technique, including accessibility, time, human mistakes, and cost constraints. Accessibility, time-consuming, and a high chance of a human mistake;

we all know that there is a chance that human eyes or ears could record something that is not right—finally, the cost constraints for preparing and sending a research group to a forest. As a result, Park et al. [9] identified that measuring tree crowns for individual tree leaves is doable but labor-intensive. In addition, it is hard to accurately assess the tree attributes in tall, dense, multi-layered forests. Further, Ampatzidis & Partel, [50] claimed that evaluating the field's phenotype from these perspectives is labor-intensive and time-consuming, mainly when covering large areas. In contrast, the ability to use remote sensing approaches such as a satellite or drone could help to overcome some of these challenges as it showed the ability to measure tree crowns with different accuracy rates.

Since ground-based sensor is a crucial technique, it is essential to acknowledge and address their challenges, such as sensor placement, maintenance, power supply, and cost constraints. All of these challenges are impacting the decision to use this technique. The first challenge involves the difficulty of building a station or installing and maintaining the sensors in an outdoor environment. Other risks include the attacks of bugs and animals and harsh weather conditions. It could also require special permission to install the sensors. The second challenge is to consider the impact of ground-based sensors on the growth of trees or plants. The third challenge is the cost of creating and maintaining a station to monitor the forest's health. Finally, network coverage plays a crucial role in the ground-based approach. For example, regarding budgetary restrictions, Marsh et al. [23] reduced the number of air temperature data loggers during the experiment. However, these challenges can be solved one way or another depending on the importance and value this approach adds to the project. For example, generating a wireless sensor network can solve the problem [116]. As a future direction, several potential works could be done in this field, such as investigating the ability to generate a wireless sensor network in rural areas. Developing a ground-based sensor to monitor illegal logging using the sound of chainsaws.

Over the past decade, remote sensing has revolutionized the ability to monitor forests with an acceptable accuracy rate on a large spatial scale. But it also comes with several challenges, such as cost, accessibility, and other technical challenges regarding spatial and temporal resolution or the battery duration and payload weight with a drone. Ecke et al. [11] identified several challenges and future work regarding remote sensing. One of these future works is looking at the flight parameters, which requires more attention from the author's perspective during influence data quality. Highlighting that the resolution ability of the satellite remote sensing for monitoring forest ecosystems sometimes needs to be improved during the limits of feasibility [10]. Moreover, Lausch et al. [1] explored that linking terrestrial and remote sensing-based approaches is an issue that needs to be addressed, which could provide a better vision of monitoring a forest.

Multi-data source is a technique researchers have provided as a future direction of forest health monitoring, with the capability to cover several issues, such as enhancing the accuracy or reducing the cost. Still, various challenges are addressed, such as data integration, temporal synchronization, data fusion, and model selection. Data integration requires understanding the data format from different sensors and dealing with temporal synchronization, which refers to gathering the data at the exact time. Data fusion and model selection refer to the difficulty of choosing the methods and techniques for a multi-sensor system. So, regarding the aforementioned, Hartling et al. [110] addressed the issues of applying multiple UAV sensors for tree species to create a robust training model that can be used in multiple locations. Also, there are several challenges in accurately engaging data fusion methods between UAV and other sensors; for example, collecting imagery from both data sources on the same date [112].

7.3 Data Collection

In the context of outdoor environments, especially within forest ecosystems, the timing of a research project emerges as a crucial factor warranting closer scrutiny. The temporal dimensions of data collection substantially influence various facets of the research process, encompassing project budgeting and experimental planning. Take, for instance, the investigation by Han et al. [26], which delved into breeding areas within forest ecosystems. Their experiment, conducted in late March, illustrates the critical role of timing, particularly when studying breeding activities. The timing directly affects the availability and behavior of the species under investigation. If a research team must synchronize their data collection with the breeding season, any deviation from the optimal timing might necessitate postponing experiments for nearly a year. Such delays can significantly impact project timelines and resource allocation.

Another illustration of data collection constraints arises when researchers study the effects of seasonal variations in vegetation levels. Such investigations requiring a long period of time necessitate meticulous planning to capture the subtle yet critical changes that unfold over time. This type of project needs to be considered, especially for researchers who have a specific period of time to finish the project. In addition, adhering to the appropriate timing can have profound implications for project timelines and resource allocation.

Researchers can explore various strategies to mitigate these temporal challenges, including leveraging existing datasets. As demonstrated by Han et al. [26] in their previous work, tapping into data from previously published studies to support their collected data makes it more valuable. This approach offers a pragmatic solution and contributes to the accumulation of knowledge within the research community. Lastly, researchers need to expect bias and damage that can happen during data collection.

8 CONCLUSIONS

Forests, as the habitats for most land mammals, birds, insects, and plants, play a crucial role in supporting life on our planet. In addition, the well-being of a substantial portion of the global population is intricately tied to forests and their resources [117]. In light of the increasing challenges posed by wildfires and deforestation, scientists and decision-makers have intensified their efforts toward developing effective forest health monitoring systems. However, creating such monitoring systems in outdoor environments has complexities, demanding both time and financial resources. Consequently, there is a growing need to explore innovative methodologies that enhance the accuracy of forest health monitoring while minimizing time and cost implications.

This review examined the FHI concept, highlighting the various factors influencing its development. Furthermore, it delved into multiple indicators that offer insights into forest structure and condition. In addition to this, it explored diverse techniques and approaches for establishing forest health monitoring systems. Among these, field observations are a valuable tool, although they are hindered by limitations such as restricted access to certain areas at specific times. Another approach involves the deployment of ground-based sensors within the forest environment. Lastly, remote sensing methods, including satellite imagery, crewed aircraft, and drones, have demonstrated significant potential in assessing forest health, particularly concerning ecological indicators such as tree damage, height, and vegetation cover. However, it is still hard to rely on remote sensing techniques to determine the health status of an area.

The findings of this review have identified several areas for improvement in current research. One notable gap concerns the temporal scope of experiments, with many studies focusing on a single year's data [118]. Researchers are also actively exploring incorporating classification filters and textural features to automate the identification process, aiming for improvements [49]. In addition, enhancing the accuracy of canopy height models presents a promising avenue for future research [105]. To address limitations in dense canopy areas, researchers are considering strategies such as increasing point cloud density through repeated flights and optimizing flight paths to maximize trunk visibility [54]. Lastly, harmonizing multimode data fusion with practical operational feasibility remains a critical research challenge [112]. In light of these research gaps, an intriguing avenue for future exploration involves the feasibility of integrating various techniques to construct a robust FHI utilizing multiple sensors. This approach can overcome some of the challenges outlined in this review. I want to emphasize that open questions persist in forest health monitoring and forest health indexing. Furthermore, it is worth noting that although many studies describe the capabilities of monitoring tools for specific aspects of forest health, only a few integrate these findings directly into the broader context of forest monitoring or forest index. In conclusion, the research reviewed here underscores the critical importance of preserving the health of our forests, given their profound ecological and societal significance. The road ahead involves pursuing innovative approaches that leverage the strengths of various monitoring techniques to create a comprehensive and cost-effective forest health assessment system. As we navigate these challenges, it is clear that exploring these open questions will continue to shape the future of forest health index research.

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