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Internet of Things for Sustainable Forestry

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Chapter 5
Internet of Things for Sustainable Forestry

Abstract Forests and grasslands play an important role in water and air purification, prevention of the soil erosion, and in provision of habitat to wildlife. Internet of Things has a tremendous potential to play a vital role in the forest ecosystem management and stability. The conservation of species and habitats, timber production, prevention of forest soil degradation, forest fire prediction, mitigation, and control can be attained through forest management using Internet of Things. The use and adoption of IoT in forest ecosystem management is challenging due to many factors. Vast geographical areas and limited resources in terms of budget and equipment are some of the limiting factors. In digital forestry, IoT deployment offers effective operations, control, and forecasts for soil erosion, fires, and undesirable depositions. In this chapter, IoT sensing and communication applications are presented for digital forestry systems. Different IoT systems for digital forest monitoring applications are also discussed.

5.1 Introduction

In the field of agriculture, there has been a lot of development in soil moisture capability improvements and system design. However, soil moisture sensing in forests is lacking [53]. There are big gaps in data collection in forests and rangeland systems, particularly in 640 million public lands in the USA that also includes grazing lands and reserves. 33% of the water comes from these lands which is supplied to the community in the Western US. Loss of forests through droughts and fires will significantly impact the water supply [43]. This fact underscores the importance of sustainable forests for survival of human life [47].

In twenty-first century the climate is changing dramatically [66, 73, 98]. The average temperature has increased by 1.8 F from 1901 to 2018. This average increase in temperature with same amount of precipitation has resulted in increase in evaporation rate [2]. This increase in temperature is highly correlated with the forest fires [58, 99]. In 2018 and 2019, the State of California in the USA witnessed a very significant fire season [80]. Out of this 1.8 F averaged increase, 1.2 F increased in the last three decades from 1989 to 2019. This rapid increase has caused many disturbances in the forest ecosystem which is leading to extreme cases of shortage of water or abundance of water that system is unable to handle [33, 62, 67, 98].

The IoT hold strong promise for digital forestry [105] applications. An efficient management system can be developed for effective resource management and decision making in forest inventory, in situ and remote soil sensing, and forest fire prediction and control. Forest fires are another threat to sustainable forest management. In the USA, 8000 kilo hectares were burned in 2015 due to forest fires [80]. The IoT technology in forest environment can be used to sense, communicate, analyze, and to make informed decisions for sustainable forest management. Currently, technology is being used in digital forest management. However, the applications of the technology in the forest management lack well-integrated systems for real-time sensing and decision making. IoT has the potential to fill this gap through its well-connected and integrated sensing and communication components.

Moreover, the presence of droughts in the entire forest landscapes [18] (short-term in agriculture, and prolonged droughts [101] in the entire ecological system [29, 31]) present a major challenge. These two drought systems are connected because of the flow of water from the forested mountains to the agricultural lands in the plains [90, 94]. In the ecological drought scenario, the drought progression over time leads to accumulation of droughts on the landscape in the time span of multiple years. Forests have the ability to survive only up to 2 years of drought that extends to 3 years for very healthy forests. After this forests lose their ability to resist insects and diseases which contribute to rapid forest loss. Although it can be argued that because of the water-limited forests systems, this huge amount of biomass cannot be sustained. However, development of early warning IoT systems in forests and rangeland with ability to sense soil moisture, detect and predict water patterns can play a vital role in sustainable forests. Such systems with adaptive capability can inform important decisions such as how to plant and when to reseed. These functions of IoT for sustainable forest management are discussed in the next section (Fig. 5.1).

Furthermore, when a forest is burned it has to be replanted in a very short time span of 2–3 years in order to prevent proliferation of the invasive grass. Therefore, in the forest restoration, the knowledge of seeding conditions and weather pattern becomes utmost important [44]. Due to expensive native seeds, the seeding carried out in poor conditions causes the wastage of valuable resources and times imaging the forest restoration process. Seeding without considering the soil moisture data and short-term weather projection have the success probability of less than 50%. The IoT system in forests can provide this data in real time, hence increasing the success rate of the restoration process.

Additionally, roads in the forest systems are also vulnerable to flooding, landslides, and mudslides after the fire event [17]. The potential risks of these events include burial roads in mudslides and destruction of bridges. An accurate prediction of these events though IoT sensing and communications makes the IoT monitoring a useful tool for sustainability and restoration. Particularly, the upper and lower watershed monitoring is not fully developed. There is need of IoT solutions containing connected weather and soil moisture stations integrated to the cloud for real-time decision making in forests. These can inform hold and absorb decisions

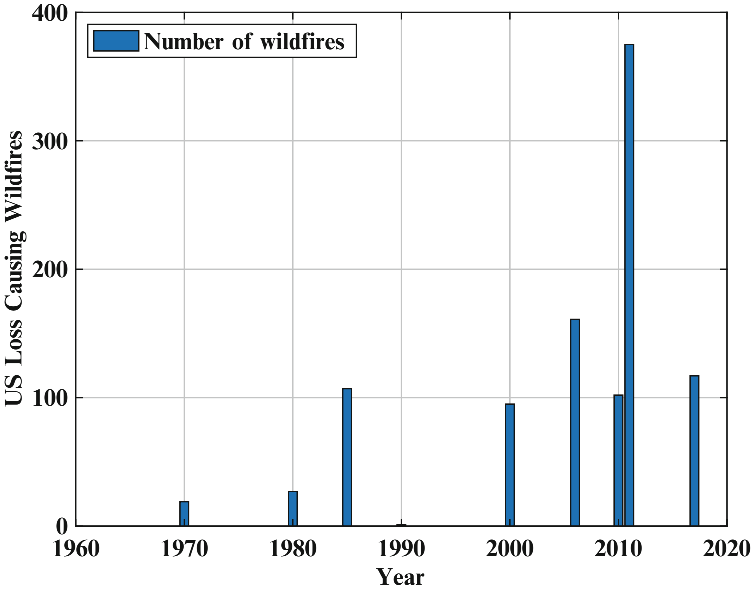

Fig. 5.1 The yearly data of the US wildfires

in the case of big rain events in the upper and lower watersheds. Such IoT systems for digital forestry can bring significant improvements in the areas of climatology, hydrology, and vegetation.

5.1.1 Sustainable Digital Forestry

The UN's sustainable development goal number 15 is related to the forest management and entails terrestrial ecosystem's protection and restoration [7, 93]. The environmental benefits of the forests for the sustainability future span multiple SDGs (see Fig. 5.2) and support natural development of the ecosystem. Forests are the biggest absorbents of fossil fuel caused carbon dioxide (CO_2) emissions [86]. To avoid the reduction of the CO_2 better forest management practices are required. Currently, the biggest challenges faced by the forest ecosystems include droughts, diseases, insect infestations, and high fire-caused tree mortality [101]. The bioenergy technique to meet energy needs by producing biofuels from organic sources such as biomass also underscores the need of restoration of forests. Other important digital forest management factors include land use and ownership, the global scope of forest markets, forestry markets, advancements in biopower technology, forest policies and regulations. These challenges are discussed in detail in the following section.

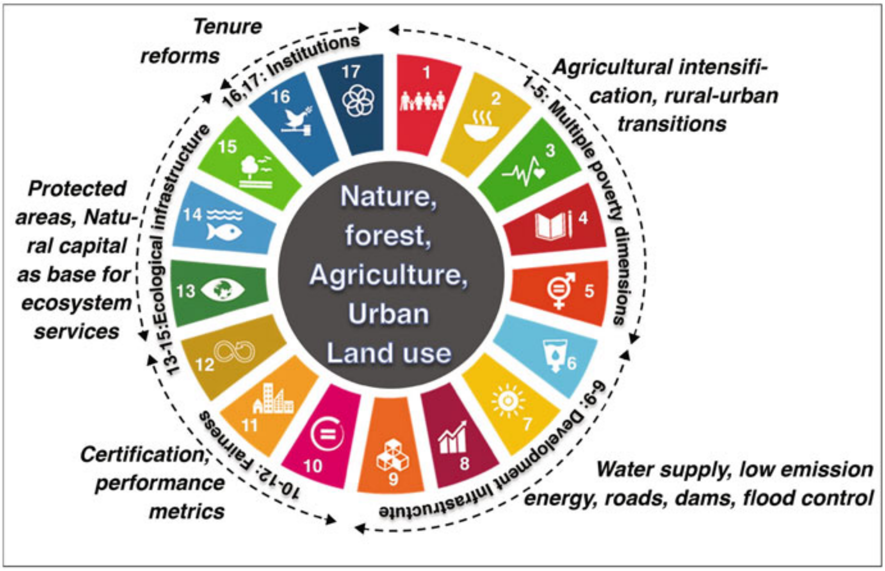

Fig. 5.2 The SDGs and forestry [93]

5.1.2 Challenges in Sustainable Digital Forestry

The digital forestry is defined as:

> Digital Forestry is a framework that links all facets of forestry information at local, national, and global levels through an organized digital network [105].

There are many challenges in the area of digital forestry including changing climate, human caused disturbances to the forests [52], wildfires [57], and invasive species [13, 24, 107]. These are explained in the following:

- The increasing number of fires, insects, and fragmentation are a major challenge to achieve sustainability, and these also leads to decrease in biodiversity. The diseases and insects are causing huge losses to the biomass. The water quality, quantity, and storage capacity are arising. The wildland–urban interface (WUI) [98] is a zone in which forest and homes intermix. This intermixing is a major source of wildfires, disease spread, habitat loss, biotech invasion, subsidized wildlife, and fragmentation [22, 65, 79]. The wildland–urban interface also poses a threat to forests in terms of the forest predators due to availability of abundant sustenance in WUI. To control and reduce the number WUI-caused predators, there is a need of monitoring and elimination of their nesting and perching

sites, invasive trees and unused poles, and other structures by placing a ban on establishment of water facilities, dumps, and garbage in WUI. These predators include species such as crows, ravens, coyotes, magpies, foxes, raccoons, skunks, and other species [10].
- The adaption of sensing and communication technologies in digital forest management practices is lacking. Adoption of these technologies has huge potential to improve sustainable management of forests through development of decision support systems at large spatial scales in a timely manner [23].
- A related consequence of lacking of technology adoption is unavailability of accurate inventory forests [56]. Without the information of forest sources, it is hard to design and implement sustainability initiatives. The non-native insects and other diseases and pests which feed on trees are causing significant tree mortality. The lack of technology implementation is hindering assessment of the impact of these species on the ecosystem.

To overcome, these challenges in digital forest management, multi-pronged efforts are needed at different levels including forest managers, policy makers, scientists, and researchers. The technology can fill the gaps in forest data management and resource inventory by providing reliable data which can be used to create maps, and other reports of resource assessment [85]. Accordingly, the real-time support systems can be developed for data analysis, sustainability, and actuation. Major data needs for sustainable forest management includes:

- Forest health and diseases [92]
- Biomass and forest fuel loads for renewable energy [75]
- Forest carbon stock and sequestration [49, 83, 89]
- Forest species including invasive [13, 24, 107]
- Fires and water data [63]
- Forest inventory [14]

Moreover, coupled with the data needs are modeling and analysis techniques developed based on the data and inventory. The development of such decision making systems will also inform land-use decisions, their impacts and benefits to forests and grazing lands [48]. These analysis techniques can then accordingly be used for pattern prediction and quantification, measurements, valuation, monitoring and assessment of emerging threats and challenges. The IoT for sustainable forest management can overcome these challenges through real-time sensing of the forest ecosystem. It is presented in the next section.

5.2 IoT in Digital Forest Management

The sustainable forestry IoT through its communications, sensing, and systems technologies has the great potential to improve the resilience of forests. It can also reduce the impact of climate change on the forestry ecosystem [11]. Accordingly, it can provide bioenergy sources from biomass which will bring energy and economic prosperity to community while reducing stress on the fossil fuels. The nanotechnology applications will bring improvements in woods [46]. Moreover, detailed watershed insights can be gained (e.g., water resources, pollution, water shortage, water quality, and futuristic water and rain and patterns). Digital forestry IoT has the potential to meet the real-time needs of forest, grazing land, range managers. These include:

- IoT early warning systems for drought stress to initiate and prioritize actions
- Forest soil moisture sensing is used for informed restoration decisions
- The snowpack change detection to plan annual water management and to accordingly adopt effective management practices
- Grazing land productivity changes and projections to guide herd and range allotment
- Real-time sensing and detection in forest covers for informed changes in forest management policies and practices

5.2.1 Elements of the Forest IoT

IoT can be used to connect the upper watershed and user community in a systems approach. Soil moisture sensing and communication systems can be integrated with soil moisture collection system in forested areas. Moreover, the forest drought monitor interconnected with IoT and cloud can provide real-time forest observations for real-time decision making by government agencies. Overall, IoT has the potential to fill the gap in forest soil moisture and impact information with advanced sensing and communications technology.

The IoT in digital forestry envisaged to have the following elements:

- Ability of real-time state-of-the-art data collection and wireless transmission of physical, chemical, environmental, and biological factor at the forest sites scattered across geographical, vegetational, and climatically forest zones.
- Systems to motoring of soil, climate patterns.
- Storage of data in the cloud and real-time access to the decision making through the visual interfaces.

5.2.2 Forest Things

The things of the forests IoT are outlined below:

- Invasive Species. The current needs are related to minimization, reduction, and elimination of invasive species from being introduced, established, and spreading [13, 24, 107].

- Inventory, Monitoring and Analysis. The requirements are availability of resource data, analytic, decision tools for efficient and reliable identification of the status of forest resources, insects, diseases, and fires, and forecasts, and trends for sustainable management [8].
- Land use and Recreation. Forests are major sources of community recreational activities, such as hiking, camping, fishing, canoeing, and skiing, and play an important role in sustainable community health. The land use and management decisions impact these activities [97].
- Wildland fire, Wildland–urban interface (WUI) [98]. For these, the emphasis is on minimizing the determinant impact of fires and enhancing the beneficial effects of fire. Moreover, the WUI posed challenges to forest (e.g., fires and predators). Therefore, any forest decisions and their trade-off related to these needs to be well thought to minimize any negative effects.
- Water, Air, and Soil. Forests and grasslands play an important role in water and air purification, prevention of the soil erosion, and in provision of habitat to wildlife [78].
- Wildlife. The current focus in this area is on getting insights on complex interaction between species, ecosystem processes, emerging threats, land use, and management [45].
- Other things include agroforestry, forest products, landscape management, and operation [95].

5.2.3 The Montréal Process Criteria and Indicators (MP C&I)

In this section, the Montréal Process Working Group [41], its criteria and indicators for sustainable forest management are discussed.

5.2.3.1 Montréal Process

The Montréal Process Working Group consists of multiple representatives from different countries to address the issue of sustainable forest management. The working group was established in 1994. It has developed stipulatory criteria and indicators for forest sustainability and conservation of both boreal and temperate types of forests. Its members are different socio-economic and ecological conditions. They are collaborating on forest monitoring, sustainability, and assessment issues. These members are from the regions that have significant presence of temperate and boreal forests. These countries are:

- The USA
- Argentina
- Australia
- Canada

- Chile
- China
- New Zealand
- Russian Federation
- Japan
- Korea
- Mexico
- Uruguay

5.2.3.2 Criteria and Indicators (MP C&I)

The Montréal Process criteria and indicators (Montréal C&I) [42] are used to collect sustainability and conservation data of temperate and boreal forests for the purpose of assessment, monitoring, and reporting. These criteria and indicators (7 criteria, and 54 indicators) together present a comprehensive sustainability framework reflecting the vital components of forestry such as conditions, biological diversity, ecosystem health, soil and water resources of forests. As this criterion treats forests as ecosystem, hence, it enables robust range of socio-economic, environmental services and benefits. Accordingly, the MP C&I facilitate the regulations and policy development to achieve sustainability in forests. The seven criteria are shown in Fig. 5.3.

5.3 Sensing in Digital Forestry IoT

In this section, different methods of sensing which are applicable to the forest environment are discussed.

5.3.1 Remote Sensing

Applications of the remote sensing approaches in digital forestry offer many benefits as compared to the in-situation sensing. With a sensing unit of 10 m to 40 km, the remote sensing can be used cover area of up to 1000 km [5]. Therefore, a large geographical forest zone can be managed with this technique. Moreover, accurate maps can be produced for efficient decision making. Currently, NASA is running missions for soil moisture measurements. The aim of these missions is to obtain high resolution maps of soil moisture with multiple revisits of the target sites. In digital forestry, this can be used to investigate processes of terrestrial carbon, energy, and water cycles. It can sense energy and water flux in the forests. Moreover, enhanced drought predictions can be made using these missions. It can also be used to quantify the forest landscape carbon flux (Table 5.1).

Fig. 5.3 The Montréal process criteria and indicators

Table 5.1 Satellite systems for remote sensing of soil

System	Frequency	Resolution
The Advanced Microwave Scanning Radiometer—Earth Observing System (AMSR-E)	C, X-band passive	25 km
The Advanced microwave scanning radiometer 2 (AMSR2)	C, X-band passive	25 km
WindSat—US Naval Research Laboratory	C, X-band passive	25 km
The Advanced Scatterometer (ASCAT)	C-band active	12.5 km
Soil Moisture and Ocean Salinity (SMOS)	L-band passive	25 km
Soil Moisture Active Passive (SMAP)	L-band passive	3–36 km
Cyclone Global Navigation Satellite System (CYGNSS)	L-band reflectivity	1–3 km
SAtélite Argentino de Observación COn Microondas (SAOCOM)	L-band active	1 km
NASA-ISRO Synthetic Aperture Radar (NISAR)	Ka-band	200 m

Remote sensing in digital forestry is insufficient due to vegetation thickness. The sensing depth by limited to few centimeters. It further decreases with increase in measurement frequency. Moreover, the vegetation loss also increases with increase in the measurement operation frequency.

The radar and LiDAR based active sensing approaches [61] can also provide useful information. Radar operates at 1.26 GHz frequency with VV, HH, and HV polarization and has resolution of 3 km. The radiometer functions in 1.41 GHz with polarization of H and V, and has resolution of 40 km. Although radar in comparison to radiometer has high spatial resolution (1–3 km) but it is more sensitive to surface roughness and vegetation. There it has limited accuracy in thick forests. However, radiometer has high accuracy because it is less impacted by the surface roughness and vegetation but coarser spatial resolution of 40 km makes it less useful for small geographically separated forests. An alternative of combined radar and radiometer solution gives enhanced results of improved resolution and higher accuracy to meet IoT sensing requirements in digital forestry.

Overall, remote sensing can be used to obtain important data from the forest soils and vegetation. This includes spatial coverage of the vegetation, classification of forests, and soil moisture [61].

5.3.2 *Per-Tree Based Forest Analysis*

High spatial resolution combined with aerial photography approaches can be used to analyze the forests on per tree basis. For this approach to work, less than 0.5 m pixel size is required. Machine learning based image processing techniques are useful for remote sensing based tree detection and delineation approaches. Popular tree delineation methods include local maxima [96], boundary following [54], template matching [69], region based segmentation [102], and model based methods. Extension of these approaches is also used for species genesis.

5.3.3 Phenology Sensing

In phenology monitoring, the impact of environment instigated events (e.g., the temperature and length of the day) on the plants and animals life spans is studied [39, 76]. The study consists of the flowers blooming in the autumn season to color change patterns and subsequently falling of leaves in the fall season for the plants (Fig. 5.4). For the animals, this includes analysis of bird migration patterns and insects hatching activities. Previously the phenology monitoring activities such as forest canopy monitoring were conducted manually on leafs by recording their temperature and color change manually during different seasons [106]. For automated monitoring purpose IoT systems offer a strong monitoring potential. An IoT based automated leaf monitoring system has been developed that is based on cameras and offers image capturing and automated analysis in the real-time. The sensors used in the system can capture multiple colors by using different channels with abscission, coloration, and automated senescence tracking. These systems hold a promise for automated phenology monitoring in the forest environments.

5.3.4 Forest Species Sensing

An analysis of the species habitats in the forest environments is important to assess the impact of forest loss due to fires, droughts, and climate change. Ecological monitoring in the forest environments is a laborious job for human researchers. Often time such efforts require sitting in the field for hours to record birds species in forests. This increases when multiple species are under study requiring multiple experts to record multitude of sounds. The forest IoT system holds promise in this area of automated species monitoring. A monitoring system has been developed to monitor birds with the capability of listening to multiple birds at a time [16]. This system offers a detailed real-time activity of the birds such as bird arrival and departures from their nest, information about location and nesting pattern changes. The system is based on the multi-label and instances and can also be used to identify drops from the rain fall events and human tree cutting and tree falling from the natural events. Currently, it has been tested to work with different species such as frog, grasshopper, crickets, and marine mammals. Major changes include interference from the natural and human noises in the forest environments. Moreover, the bat wings are also being used for monitoring bat populations.

5.3.5 Species Migration Monitoring

A knowledge of the bird's migration patterns can provide useful information to save endangered species and can help in conservation efforts. One such IoT system

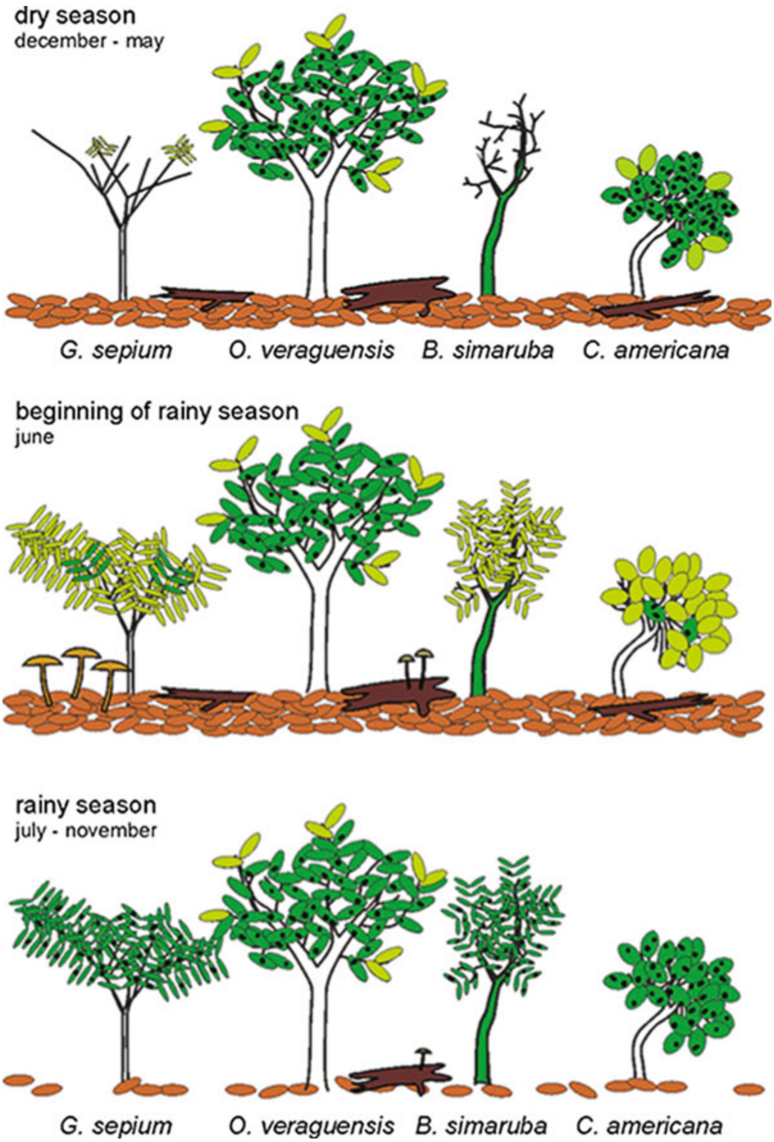

Fig. 5.4 A schematic representation of vegetative characteristics of Gliricidia sepium and Bursera simaruba (both deciduous), Ocotea veraguensis (evergreen), and Curatella americana (brevi-deciduous) at different times of the year [76]

has been developed to monitor Grus Americana (the whooping crane), a Native American bird species in danger of extinction with current count of fewer than 550 birds [3]. This system provides detailed environment and behavior of these birds to

Table 5.2 Number of in situ soil moisture sensing stations in US

Soil moisture measurement systems	Stations	In forests	Percentage
Snow Telemetry (SNOTEL)	445	289	64.9%
U.S. Climate Reference Network (USCRN)	147	18	12.2%
Soil Climate Analysis Network (SCAN)	219	26	11.9%
The Automated Weather Data Network (AWDN)	59	1	1.7%
The U.S. Regional Climate Reference Network (USRCRN)	16	4	25.0%
Delaware Environmental Observing System	42	8	19.0%
Environment and Climate Observing Network (ECONet)	42	6	14.3%
Kentucky Mesonet	23	4	17.4%
NOAA's Hydrometeorolgy Testbed (HMT)	178	35	19.7%
New York Mesonet	126	13	10.3%
Oklahoma Mesonet	141	2	1.4%
Soil moisture Sensing Controller and Optimal Estimator	155	39	25.2%
Georgia Mesonet	86	5	5.8%
Other networks	223	0	0.0%
Summary	1902	450	23.7%

inform migration patterns by using sensing and communication devices attached to the birds. Through these IoT devices real-time information is obtained about every move of the birds (Table 5.2).

5.3.6 Tree Health Sensing

The tree health sensing is done by detecting changes in vital metabolites and cellular functions for early identification of stress [30]. Moreover, it can also be assessed by analyzing the relationship of nitrogen in plants and soils. The high levels of ammonium nitrate and ammonium sulfate (that contains sulfur and nitrogen) are applied. Accordingly, the relationship between nitrogen assimilation and photosynthesis is analyzed. Moreover, the stress exposures also lead to production of anthocyanin production.

The metabolic stress can also be used as an indicator in different trees [30]. By using this approach the low and high risk areas can be identified which can be used to decide treatment options. The tree metabolism and genomics are two approaches for stress sensing. They are related to the genes of the organism understudy. This is also useful to establish long-term indicators for climate related events. Similarly, in polyamine metabolism, the physio-chemical stress related genes are separated and characterized at single plant level, which is then expanded to multiple trees. Accordingly, the impact of disruptive variations in single metabolite and their interconnections can be identified, which can be used to engineer resilient biosynthetic genes to grow healthy plants.

The forest health also depends on photosynthesis, microbial diversity, and soil quality [23]. These factors are impacted by the nitrogen, calcium, and aluminum. Therefore, sensing of these parameters is also important to assess tree health and lack of these can be used to inform customized improvement techniques. These health sensing approaches are useful in scenarios where visual analysis either does not work or yield unreliable results. Accordingly, appropriate treatment actions can be taken before it becomes too late. Moreover, the satellite spectral trajectories can be used to map forest health related variations caused by fire, insects, land use, disease, wind, and harvesting. Furthermore, the tree mortality can also be done using aerial data collection and surveys to assess the area and intensity. This data is utilized to eliminate hazardous tree and fuel reduction before the fire season.

5.3.7 Sensing of Increased Soil and Air Temperature and Elevated Carbon Dioxide

The soil and air temperatures are good indicators of the climate induced variations and wetlands. For this purpose, a testbed has been designed to house different types of soils at field conditions. These soils are exposed to various controlled temperatures and different levels of carbon dioxide to assess the changes in the organisms [21]. The experiment outcomes are discussed in the following:

- This provides useful information about the physiology of plants under high carbon dioxide levels [9, 72].
- The insights about the relation between the underground warming due to temperature increase and corresponding increase in greenhouse gases can be provided [1, 12, 38, 64].
- Accordingly, the suitable soil and air functions for different environmental organisms can be established.
- Moreover, through these empirical analysis, climate related threat and stress and threats to biogeochemical and hydrological services of the ecosystem can be answered.
- Furthermore, the better models can be established for enhanced forecasting, mitigation, and adoption response to environmental changes.

5.3.8 Illegal Logging Sensing

The illegal logging is a major cause of degradation in forest ecosystems and leads to biodiversity losses and deforestation [36]. The sensing of the illegal logging can be done using microphone sensors which can sense logging related sounds such as saws, axes, and transportation. Accordingly, by using the wireless communication links this information can be communicated in real time to forest control centers for proper enforcement actions.

5.3.9 *Fire Sensing*

The fire sensing is discussed in detail in this section. First the impact of the fire on soil is presented [40].

5.3.9.1 Impact of Fire on Soil

The forest fires have many negative impacts on the forest ecosystem.

- Due to prolonged presence of the long chunks of timber, the underneath soil is exposed to acute heat which impacts the soil physical, biological, and chemical properties.
- The soil microbes are also eliminated depending on the burn-extent because of the severe heat. The decreased amount of nutrients is detrimental to the vegetation growth and leads to staggering recovery.
- The structure of soil and texture is also impacted.

Due to these long-term impacts of the intense soil heat, the understanding of these soil dynamics bio-geo-chemical processes is important for proper forest management practices. In this regard, the advanced DNA sequencing approaches are being considered for soil recovery after soil burning.

5.3.9.2 Fire and Environmental Pollution

When the height of the smoke coming from the fire exceeds the near-surface boundary layer, the pollution concentration starts. The fires in boreal forest have intense energy as compared to temperate forests. Therefore, these smokes tend to go well beyond the boundary layer. At those elevations the negative impacts of those smokes include prolonged stay in atmosphere, wider horizontal and downward vertical transport, health related impacts such as asthma and eye burns. The HRRR-Smoke model is fire smoke forecasting model for height and travel direction prediction of near-surface boundary layer smoke.

5.3.9.3 Impact of Fire on Fresh Water and Stream Flow

The wildfires not only impact the soil, but the water supply is also impacted by the fires. The preservation of the fresh water resources is important to achieve sustainability. These wildfires impacts and risks include:

- Watersheds damages and hydrological disturbances
- Soil erosion after extreme rain events
- Sedimentation
- Ecosystem degradation

The models for hydrological disturbances framework are shown below [32]:

- Change point model (CPM)
- Double-mass analysis of precipitation and streamflow (DMC)
- Precipitation duration curves (PDC)
- Flow duration curves (FDC)
- Watershed climate elasticity model (CEM)
- Water Supply Stress Index model (WaSSI)

5.3.9.4 Fire Sensing and Danger Estimation Tools

The fire danger can be estimated based on different measurements which include:

- Using the light detection and ranging systems (LiDAR) for forest structure, carbon loss, smoke emissions, and dangerous fuel loads [104].
- Moreover the real-time measurements of moisture can be taken using a system of networked towers deployed for this purpose. These towers are also used to take other vital measurements of carbon dioxide, the eddy fluxes of energy.
- A sonic detection and ranging system (SODAR) to measure wind speed and direction at different heights can also provide useful information about the fire spreading danger and potential directions [19].
- The aircraft teams and satellites are also employed to get useful remote sensing data for fire management decisions and teams on the ground make the best decisions possible. This airborne and satellite observation [51] is very useful to understand the intensity, perimeter, frequency, spread for burning forest fires. With the advancement in technology and heat signature detection algorithms, the advanced radiometers with very high resolutions are able to detect tiniest fires from the space. The impact of the fire on the spatial structure of forest in Yosemite National Park using airborne LiDAR and satellite data is shown in Fig. 5.5.
- The Moderate Resolution Imaging Spectroradiometer (MODIS), Visible Infrared Imaging Radiometer Suite (VIIRS), NOAA's GOES-16, GOES-17 geostationary satellites, Joint Polar Satellite System's NOAA/NASA Suomi-NPP and NOAA-20 satellites are the satellites and tools used for remote sensing of the fire. These works on the principle of detection, radiation, and reflection of the signal, and can operate both in daylight and night times by sensing the low intensity visible light of fires. Moreover, by using the special equipment with multiple cameras can be used to detect fire flame plume composition.

  The IR based heat sensors can overcome some of the limitations of the satellite based fire detection with such low accuracy of perimeter and location, lack of capability to distinguish between fires and smokes, inability for fire intensity interpretation due to dense smoke layers which act as a curtain [59]. The National Infrared Operations Program (NIROPS) airborne sensing system utilizes infrared based heat sensors. This system has the capability to sense 6 miles under it with 6 in. resolution at 1.89 miles flight altitude. It can map 468.75 square miles in an hour. By using the compressive sensing approaches, the data is transferred in

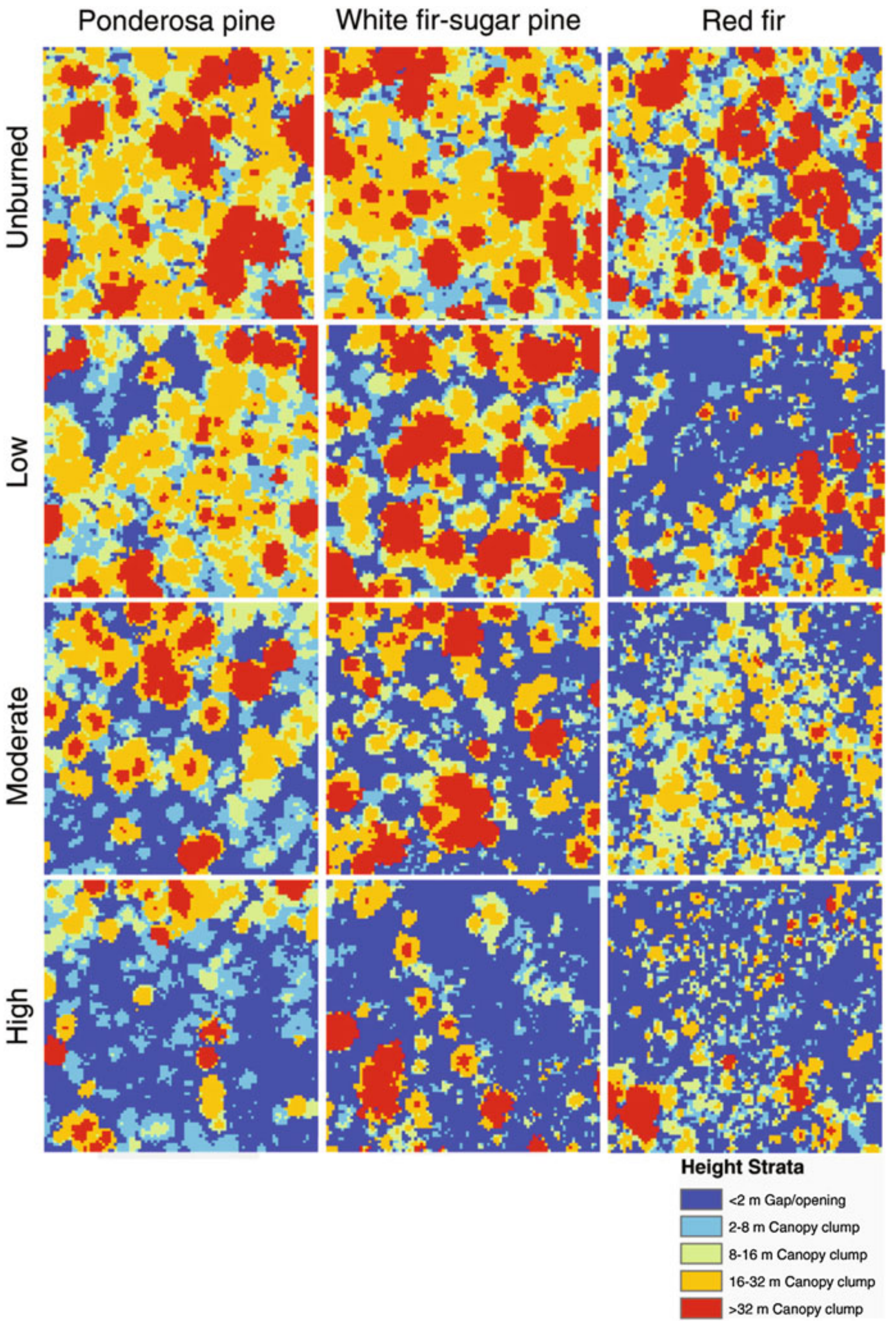

Fig. 5.5 The impact of the fire on the spatial structure of forest in Yosemite National Park using airborne LiDAR and satellite data [51]

real time to the base stations [6]. These sensors work much better at night time as compared to daytime due to the absence of sun glint interference. Currently, there is a need of wider area infrared sensing technologies to reduce the flight times.

These measurements combined with past climate data, current indices (e.g., Hot-Dry-Windy Index—HDW), and moisture data and models can produce highly reliable estimates of the fire danger. Accordingly, the maps can be developed for mitigation approaches to assist firefighters and fire mangers. Accordingly important decisions such as evacuation orders and smoker jumper's dispatch can be made. This systems uses both climate and vegetation data for assessment of fire risks, transitioning to the canopy, where they are much more difficult and expensive to suppress. Moreover, the prescribed fires can also be used to reduce the danger of overhead fuel.

5.3.9.5 Remote Sensing of Amazon Rain Forest Fires

The forest fires sensing can be done using the satellites, where the IR sensors are used to detect the infrared radiation emitted by wildfires. The remote sensing of the 2019 Amazon rain forest fires has shown that these fires started from forest lands that were cleared for the purpose of agriculture and planting. The satellite image of the Amazon fires is shown in Fig. 5.6, where the fires are shown in red color, the forest in shown in green color, and the deforestation is depicted in yellow. The land use and rapid deforestation of Amazon are major environmental issues. Because these are not caused by the natural phenomena rather human activities is a major causation of these fires.

The remote sensing of wildfires has many benefits:

- The real time and enhanced fire monitoring can be done at large geographical areas. Accordingly, this information can be used by fire managers in real-time
- The fire weather data and relevant fire danger alert systems can be developed by using predictive modeling approaches
- The aerial fire control fuel loading management policies can be developed for fire mitigation
- The smoke thickness and movement can be predicted to prevent health related consequences due to smoke inhaling

5.3.10 Invasive Species and Fungi Sensing

The invasive non-native exotic species are a major challenge in forest managements. These species present major ecological challenges and advanced sensing and

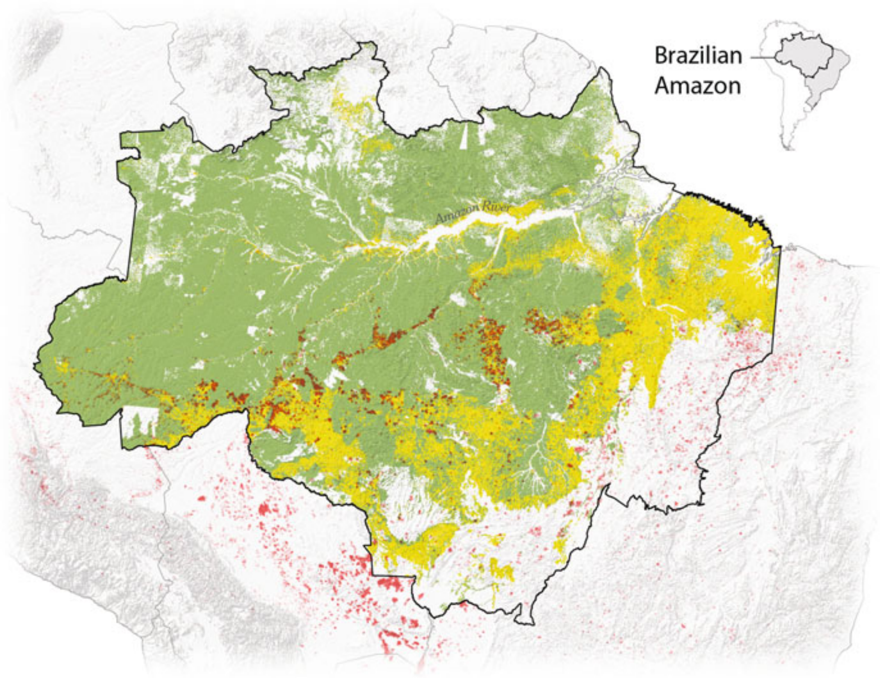

Fig. 5.6 The satellite image of the 2019 Amazon fires shown in red, the forest is shown in green, and the deforestation is depicted in yellow based on NASA data

monitoring approaches are needed to reduce, eliminate, and minimize the impact and spread of invasive species. Their mobility medium is generally the lumber, firewood, and forest vehicles. These mitigation and sensing approaches span across multiple areas [37] such as:

- Sensing of alien pests in forest
- The treatment of hardwood logs for removal of pathogens and insects
- Short for silviculture of allegheny hardwoods
- Pest management with Bacillus thuringiensis
- Biological control, and genetics management
- Technology to reduce impact

Moreover various types of fungi related with the tree also present a conducive environment for invasive species, which outnumbers native species. Moreover, these also lead to wood decomposition. Therefore, fungi sensing becomes important for invasive species management and also for sustainable forest management and restoration [47]. The white rot fungi is also related to carbon cycle of forests and causes detoxification, transport, intense cell walls degradation (e.g., recalcitrant polymer and lignin). These also have the protection for biofuel conversion for bioenergy [28, 35, 88]. The various types of approaches can be used to identify the fungi such as molecular and microscopic. The genetic sequencing is also used to inhibit soil related fungi. The GenBank is an example of sequencing database. The Scanning Electron Microscopy (SEM) [4] approach is utilized for wood decay. The computer tomography (CT) and ground-penetrating radar (GPR) are also utilized for fungal decay and moisture detection providing information into the wood structure. The DNA analysis is also conducted for pathogen identification. The wood metabolite profiles can also be determined by using the time-of-travel approach (direct analysis in real-time (time-of-flight) mass spectrometry DART-TOFMS). These sensing approaches will provide deeper insight into the fungi wood relationship in sustainable forest IoT.

5.3.11 Vegetation Height Sensing

The airborne LiDAR provides an accurate estimate of vegetation height. This approach operates by transmitting the laser beam in the vegetation to the ground. The reflected energy from the vegetation is detected to assess the vegetation height, density, and structure. This sensing approach is used to identify the area for birds habitat related decision making. Moreover, the vegetation change tracker (VCT) [71] can also produce reliable forest estimates using satellite images.

The tracker uses an autonomous program for mapping using the Landsat data. The resulting maps can be used to distinguish forested and non-forested regions. Currently, in ground based mapping systems, the false indicators of forest disturbances are a major challenge in forest management particularly in wetland and agricultural landscapes. This trackers also helps to identify those false positive through improved mapping.

The TimeSync is another systems which uses over 30 years of satellite data to analyze the variations in vegetation status over temporal scale by using the time-series modeling approach [100]. The high correlation with the drought periods and decrease in fresh canopy has been identified. It has been shown that the decay depends on the length and intensity of the short-term summer droughts and other factors such as:

- Geographic variation
- Structure and composition
- Soil and topography
- Insect and disease outbreaks

5.3.12 Machine-Induced Stress Sensing

The forest machinery and equipment affect the soil in forest and change physical properties of the soil, such as compaction, pore size, bulk density, and resistance.

The mechanical stress is sensed using a pressure transducer which provides electrical signal for data logging [81]. The sensor can be used to assess soil conditions for replantation.

5.3.13 *In Situ Soil Moisture Sensing Approaches*

Because large amount of sensors deployment is not feasible in large forests, sensor-free approaches can be employed in forests. The resonant frequency based approaches and Di-Sense are two good candidates for this.

5.3.14 *Radio Waves as Sensor: Propagation Based Sensing in Forests*

In situ measurements and inversion approach can be used to measure the soil properties at higher depths with greater accuracy. In this paper, we have developed Di-Sense, an in situ, real-time soil moisture and permittivity estimation approach based on the wireless underground communications (WUC) in IOUT. For a transmitting antenna in the soil, the generated electromagnetic (EM) waves propagate through the soil, and are not only affected by the depth, distance, frequency, and soil moisture [84], but also depend on the properties of the soil [25]. Path loss of these attenuated waves received at the UG receiver can be used to deduce the proprieties of soil, and can also be used to estimate the soil moisture. Our approach to derive the soil moisture and relative permittivity is based on the path loss of the UG communications channel in IOUT. Path loss of transmitter-receiver (T-R) pair in WUC depends on distance, depth, and soil moisture. In Di-Sense, a transmitter antenna buried at a certain depth in soil transmits a wideband signal in frequency range of 100–500 MHz, which propagates through the UG channel. The received signal is measured at the receiver to determine the path loss. Di-Sense enables an IOUT system to communicate simultaneously besides real-time permittivity estimation and soil moisture sensing. A model has been developed to estimate the soil moisture and permittivity based on path loss using Di-Sense. The model has been validated through experiments in a software-defined radio (SDR) testbed and in an indoor testbed in different soils at different depths under different soil moisture levels. Relative permittivity results show a very good agreement with less than 8 % estimation error from ground truth measurements, semi-empirical Peplinski dielectric mixing model [74], and Topp model [91] (Fig. 5.7).

When EM wave communication is carried through the soil in IOUT, the propagation loss, due to the water molecules held in the soil medium, is a function of the real effective permittivity (dialectic constant) of soil. Therefore, propagation path loss of the soil direct path (between the transmitter-receiver (T-R) pair) can be used to

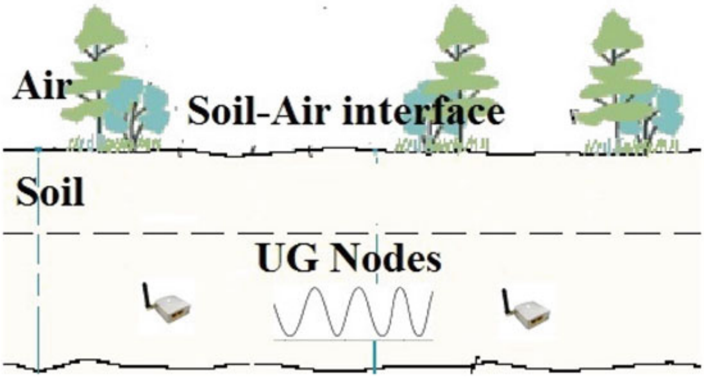

Fig. 5.7 Estimation of soil properties in forests using WUC

estimate the relative permittivity and soil moisture within 100 MHz-500 MHz range. To model soil permittivity, lowest path loss (LPL) across the whole frequency range is found by transmitting a known signal. The propagation path loss is determined by measuring the received signal. The transmitter transmits one signal using the narrow bandwidth at a time and frequency is increased sequentially in predefined step, Δf. Path loss is the ratio (expressed in decibel (dB)) of the transmitted power P_t to the power received P_r at the receiver. Path loss is determined as

$$PL = P_t - P_r = 10 \cdot \log 10(P_t/P_r) \ , \tag{5.1}$$

where PL is the system path loss, and includes the effects of transmitting and receiving antenna gains G_t, and G_r, respectively. Once the path loss is measured, the frequency of the lowest path loss is determined by

$$f_{min} = F(\min(PL(f))) \ , \tag{5.2}$$

where f_{min} is the frequency of the minimum pathloss. The f_{min} is not affected by distance between transmitter and receiver antennas because of the antennas gains. Therefore, system path loss PL is inclusive of the antenna gains. Since PL measurements are done in narrowband, noise effects is minimal. Next the soil factor, ϕ, is calculated as:

$$\phi_s = f_{min}/f_0 \ , \tag{5.3}$$

where f_0 is the resonant frequency of the antenna in the free space. Once the soil factor, ϕ_s, has been determined, the wavelength at the f_0 frequency is found

$$\lambda_0 = c/f_0 \ , \tag{5.4}$$

where c is the speed of light. Accordingly, relative permittivity of the soil is determined as:

$$\epsilon_r = \frac{1}{(\phi_s \times \lambda_0)^2} . \tag{5.5}$$

Permittivity Estimation Through Velocity of Wave Propagation in Soil Due to the inhomogeneity of the soil medium, permittivity of the soil varies along the communication link from point to point. This leads to variations in wavelength and phase velocity, as the wave propagates in soil. Therefore, permittivity of the soil can be measured from the velocity of wave propagation in soil. Power delay profile (PDP) are measured to get velocity of the wave propagation, that is determined from the known geometry layout of the testbed, by calculating the time that wave takes to reach at the receiver from transmitter. Once the velocity of the wave in soil, C_s, is determined relative permittivity in soil is calculated from the difference of transmission and arrival time of the direct component in the soil. Path of the direct component is completely through the soil. Accordingly, ϵ_r is determined as:

$$\epsilon_r = \left[C_s \times \frac{(\tau_{dr} - \tau_{dt})}{l} \right] , \tag{5.6}$$

where l is the distance between transmitter and receiver antennas, $\tau_{dr} - \tau_{dt}$ is travel time of the direct component in the soil, and C_s is the wave propagation velocity in soil. Due to different propagation velocities of the air and soil, direct wave is separate from the lateral wave which travels through the air along the soil–air interface, and has less attenuation as compared to the lateral wave [84]. In [86], an example power delay profile in the silt loam soil in the indoor testbed and attenuation in soil as a function of operation frequency are given.

5.3.15 *From Permittivity to Soil Moisture*

The relationship of the soil moisture and permittivity is independent of the soil texture, bulk density, and frequency [91]. Since, soil permittivity depends on the soil moisture only, soil water content can be determined from soil permittivity [50, 91].[1] Since dry soil has relative permittivity of 3, relative permittivity of the water is 80. Soil permittivity is calculated using (5.5) and (5.6), and accordingly, soil moisture is determined as [50, 91] (Fig. 5.8):

$$\text{VWC}\,(\%) = \frac{\epsilon_r - 3}{0.77} + 14.97. \tag{5.7}$$

[1] Although there is some error in soil moisture-permittivity relationship, and its dependence is also weak for mineral soils, it has been shown to work well in fine, and coarse textured soils [55].

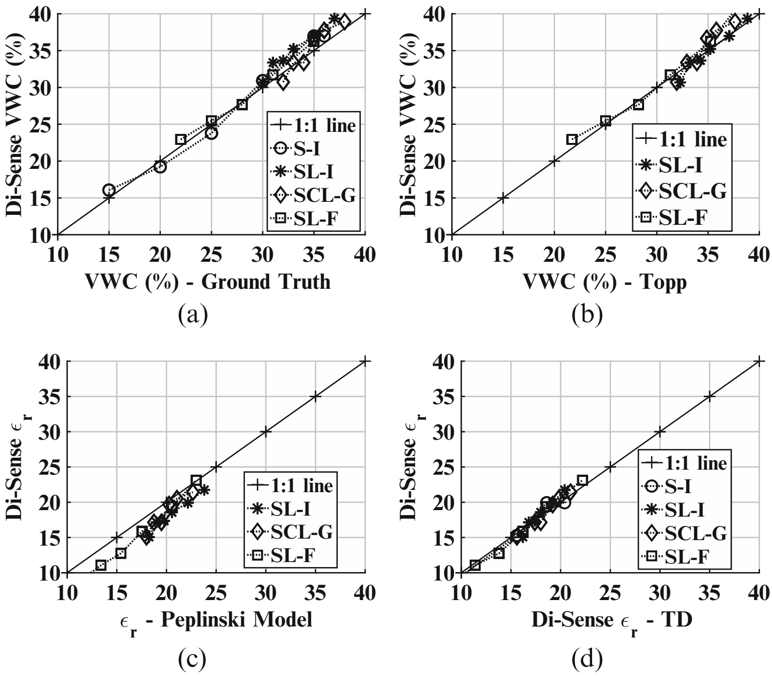

Fig. 5.8 (**a**) Di-Sense VWC compared with ground truth VWC measurements. (**b**) Di-Sense VWC compared with Topp model. (**c**) Di-Sense permittivity compared with Peplinski model. (**d**) Di-Sense permittivity by time-domain velocity of propagation comparison with Di-Sense path loss propagation permittivity method

5.3.16 Transfer Functions

It is worth noting that the results presented here are intended for soil moisture and permittivity estimation, but these can also be used for IOUT communication system design. Moreover, effects of changes in soil permittivity with change in depth are likely to be reduced at higher depths due to the fact that intensity of the reflected wave from soil–air interface is reduced at the deeper depths. For estimation purpose, following procedure would be used:

- Determine the lowest path loss frequency.
- Estimate soil permittivity using (5.5) and (5.6).
- Estimate soil moisture using (5.7).

Di-Sense transfer functions of the soil permittivity and soil moisture are shown in Fig. 5.9. Soil moisture and permittivity of soil medium can be determined using these graphs from measured values of IOUT propagation path loss. Di-Sense measurement technique is simple and easy to use, and no knowledge of type of radios, communication parameters, and antennas, being used in IOUT deployment, is

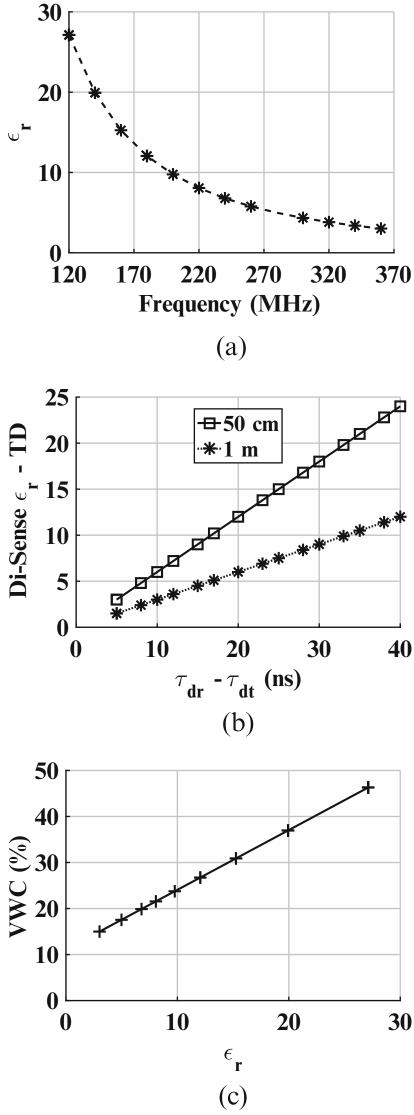

Fig. 5.9 Di-Sense transfer functions: (**a**) soil permittivity, (**b**) soil permittivity time-domain, (**c**) soil moisture

required, as long as propagation path loss can be measured accurately. Moreover, Di-Sense can also be used for different operation frequencies, f_0, because (5.3), (5.4), scale accordingly with respect to the operation frequency. Like other measurement based techniques, there are some limitations for which the Di-Sense method is applicable. The major limitation is that propagation path loss of the soil under test should be measured accurately. For the application of Di-Sense to the application scenarios, where higher accuracy is required, an empirical factor can be used to account for the specific soil properties and soil-water retention capability.

5.4 Modeling in Digital Forestry

The models in sustainable forest management also help to improve the forecasting, coupled with data obtained through sensing, satellite, and ground surveys. The data of spatial and temporal data combined with soil, organism, climate, and topography can be used to produce statistical models for futuristic ecosystems forecast at multiple scales. These different models are discussed in this section.

5.4.1 Habitat Modeling

The statistical habitat modeling provides useful insights about the impacts of future climate change on birds and trees habitats [70]. It has been developed based on the present habitat conditions and climate features. It has five different components:

- Climate Change Tree Atlas
- Climate Change Bird Atlas
- DISTRIB-BIRD: Modeling Potential Bird Habitats
- SHIFT: Modeling Potential Species Colonization
- DISTRIB: Modeling Potential Tree Habitats

5.4.2 Multi-Scale Machine-Learning Predictive Modeling

The deforestation is a major cause of biodiversity loss. A multi-scale machine-learning predictive modeling has been developed to model deforestation [26]. It provides the reliable estimates about the risk of future deforestation. The deforestation model predictions can be used to inform the sustainability and conservation practices in forest management.

5.4.3 Smoke Prediction Models

The operational smoke prediction systems (OSPS) is used to model fire-smoke related hazards. Accordingly, public health alerts can be issued using the sustainability forest IoT systems in WUI zones to avoid the hazardous impacts [82]. Many improvements are needed in smoke prediction modeling such as plume structure, fire dynamics, and weather. The advanced model can also incorporate sensing of fire, meteorology, and atmosphere to enhance the prediction capabilities.

5.4.4 Modeling Invasive Insects

The invasive insects pose a major problem to the forest health. A model has been developed to predict future invasions of various insects by considering their invasion routes and tracks [34]. It provides useful estimates about rates and number of invasions. Currently, this model is being employed to predict the invasion from Europe to the USA. It can be used to forecast and prioritize potential invasions and accordingly detection and identification mechanisms can be put in place in advance for efficient management and alerts. The Invasive Species Specialist Group (ISSG) network deals with invasive species [60]. Two other models are:

- Insect Flight Model. It is used to characterize cell based flight attributes [87].
- Insect Ride Model. A stochastic model to predict the insects ride by using external mediums [77].

5.4.5 Forest Disturbances Modeling

The forest disturbances affect the ability of forest to render important ecosystem services such as carbon sequestration [49, 83, 89]. In the carbon sequestration process the carbon dioxide is captured and stored by forests [68]. A model has been developed by using a satellite data of forest spanning over 25 year to model predict the various types of forest disturbances. This model has two different components:

- The first step uses random forest (RM) models to predict various types of disturbances such as fires, winds, stress, harvest, and conversion [103]. The non-parametric shape-restricted spline fitting algorithm and other spectral change metrics are employed as predictors along with other topographic and biophysical parameters.
- In the second stage, rule based spectral shape parameters are applied to first step output to identify temporal parameters of disturbances such as year.

This model gives highly accurate predictions of disturbances using the spectral metrics and other parameters. The applications of this model are in the area of disturbances mapping in different geographic zones around the globe.

5.4.6 Fire Behavior Modeling

The wildland fire behavior can be modeled using the fuel analysis, other parameters such as inherent vegetative fuels, weather, vegetation, atmosphere, and ignition patterns (e.g., BEHAVE-Plus). These models are divided into physical and empirical models. Currently, many model exists in literature for modeling of different types of fuels. However, the models and fuel modeling science is lagging in terms of the accuracy and fuel complexity issues. The different fuels models are listed in the following [15]:

- Grass Fuel (GR) Type Model
- Grass-Shrub (GS) Fuel Type Model
- Shrub Fuel (SH) Type Models
- Timber-Understory (TU) Fuel Type Models
- Timber Litter (TL) Fuel Type Models
- Slash-Blowdown (SB) Fuel Type Models

The fire spread models are used to estimate spread of fire based on the type of fuel arrays. The test model (TSTMDL) is used for this purpose.

5.4.7 Wildlife Habitat Suitability Modeling

Wildlife habitat models are used to model the survival and reproduction of species in different environments. This model is used to assess the suitability of wild life habitat over long periods of times with variations in forest, tree structures, biomass, timber, and wood debris, and also considers harvesting regeneration processes. It can generate forecasts for large regions for periods of more than 100 years. It is useful to address wildlife conservation issues and challenges [20, 27].

5.4.8 LANDIS

The LANDIS is used to model forests (e.g., landscape, seed dispersal, succession, and disturbances). The grid cells are used to present various landscapes for per specie based representation. It has the ability to simulate different complex ecological scenarios and successions such as age-only, biomass, forest carbon, BFOLDS, PnET, and Net Ecosystem CN for different types of disturbances such as fire, wind, biological disturbance of insects and disease, harvest, and drought.

5.5 Forest Databases Integration with Forestry IoT

The important forest databases for integration into sustainable forest IoT are discussed in this section.

- Urban Tree Canopy Assessment. It is used to assess tree cover in urban environments and gives current and future canopy assessment. It can be used for planning purposes such a tree plantations. These decision can contribute to reduction and reduction in summer heat and air quality improvements.

- iTree. It is sustainability tool to assess the health of tress. It has global reach and provides robust information about the tree health. It can be used both for urban and rural settings for tree value education. It has three components: a database, a web-based mapping tool and model, and a mobile phone application.
- i-Tree PRESTO (PRoduct EStimation Tool Online). It is the enhanced version of iTree carbon storage estimation over large time periods.
- The Forest Inventory and Analysis (FIA) is a US forest databases. It contains enormous information about locations, trends, and status of the US forests. The various tools of FIA include DATIM, EVALIDator, Data Mart, fact sheets, and other reporting tools. It also provides detailed data about the endangered plant and animal species. Overall, FIA integration with forest IoT is useful to achieve sustainable forest management goals.
- Global Invasive Species Database (GISD). A database for effective prevention, mitigation, and management of invasive species.
- IUCN Red List of Threatened Species provides valuable information about facing the dangers of extinction.
- Spatial Hazard Events and Losses Database for the United States (SHELDUS) is used to assess forest losses caused by different hazardous events.
- NASA Disasters Mapping Portal. It has SRI ArcGIS-based web interface for to visualize disaster database in real-time. Other tools for this purpose are Hazards U.S. Multi-Hazard (HAZUS-MH) and Advanced Hydrologic Prediction Service (AHPS).
- The GuidosToolbox provides information about forest landscape and fragmentation at different scales scale.

5.6 International Organizations for Forests Sustainability

A list of organizations active in the area of forests sustainability is given below [42]:

- International Tropical Timber Organization (ITTO)
- Amazon Cooperation Treaty Organization (ACTO)
- Food and Agriculture Organization (FAO) Indicators Site
- FAO/ITTO Expert Consultation on Criteria and Indicators for Sustainable Forest Management
- International Union of Forest Research Organizations (IUFRO)
- Centre for International Forestry Research (CIFOR)
- European Forest Institute (EFI)
- United Nations Environment Programme/World Conservation Monitoring Centre (UNEP-WCMC)
- Forest Europe (formerly the Ministerial Conference on the Protection of Forests in Europe)
- Lepaterique Process of Central America on Criteria and Indicators for Sustainable Forest Management

- The Dry-Zone Africa Process on Criteria and Indicators for Sustainable Forest Management
- Regional Initiative for the Development and Implementation of National Level Criteria and Indicators for the Sustainable Management of Dry Forests in Asia
- The Near East Process on Criteria and Indicators for Sustainable Forest Management
- African Timber Organization
- The Tarapoto Proposal of Criteria and Indicators for Sustainability of the Amazon Forest
- International Conference on the Contribution of Criteria and Indicators for Sustainable Forest Management: The Way Forward (2003)
- Collaborative Partnership on Forests
- Community Indicators Consortium

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