remote sensing

MDPI

*Review*

# *In Situ*/Remote Sensing Integration to Assess Forest Health—A Review

**Marion Pause [1,*], Christian Schweitzer [2], Michael Rosenthal [3], Vanessa Keuck [4], Jan Bumberger [1], Peter Dietrich [1], Marco Heurich [5], András Jung [6] and Angela Lausch [7]**

1 Department Monitoring & Exploration Technologies, Helmholtz Center for Environmental Research—UFZ, Permoserstr. 15, D-04318 Leipzig, Germany; jan.bumberger@ufz.de (J.B.); peter.dietrich@ufz.de (P.D.)
2 German Environment Agency, Wörlitzer Platz 1, D-06844 Dessau-Roßlau, Germany; christian.schweitzer@uba.de
3 Chair of Forest Utilization, Technische Universität Dresden, Pienner Str. 19, D-01737 Tharandt, Germany; rosenthal@forst.tu-dresden.de
4 German Aerospace Center, Space Administration, Koenigswinterer Str. 522-524, D-53227 Bonn, Germany; vanessa.keuck@dlr.de
5 Bavarian Forest National Park, Department of Conservation and Research, Freyunger Straße 2, 94481 Grafenau, Germany; marco.heurich@npv-bw.bayern.de
6 MTA-SZIE Plant Ecological Research Group, Szent István University (SZIU), 2100, Gödöllő, Páter Károly u. 1. and SZIU Technical Department, 1118 Budapest, Villányi út 29-43, Hungary; Jung.Andras@kertk.szie.hu
7 Department Computational Landscape Ecology, Helmholtz Center for Environmental Research—UFZ, Permoser Street 15, 04318 Leipzig, Germany; angela.lausch@ufz.de
* Correspondence: marion.pause@ufz.de; Tel.: +49-341-235-1281

Academic Editors: Lars T. Waser and Prasad S. Thenkabail
Received: 4 March 2016; Accepted: 30 May 2016; Published: 3 June 2016

**Abstract:** For mapping, quantifying and monitoring regional and global forest health, satellite remote sensing provides fundamental data for the observation of spatial and temporal forest patterns and processes. While new remote-sensing technologies are able to detect forest data in high quality and large quantity, operational applications are still limited by deficits of *in situ* verification. *In situ* sampling data as input is required in order to add value to physical imaging remote sensing observations and possibilities to interlink the forest health assessment with biotic and abiotic factors. Numerous methods on how to link remote sensing and *in situ* data have been presented in the scientific literature using e.g. empirical and physical-based models. *In situ* data differs in type, quality and quantity between case studies. The irregular subsets of *in situ* data availability limit the exploitation of available satellite remote sensing data. To achieve a broad implementation of satellite remote sensing data in forest monitoring and management, a standardization of *in situ* data, workflows and products is essential and necessary for user acceptance. The key focus of the review is a discussion of concept and is designed to bridge gaps of understanding between forestry and remote sensing science community. Methodological approaches for *in situ*/remote-sensing implementation are organized and evaluated with respect to qualifying for forest monitoring. Research gaps and recommendations for standardization of remote-sensing based products are discussed. Concluding the importance of outstanding organizational work to provide a legally accepted framework for new information products in forestry are highlighted.

**Keywords:** remote sensing; *in situ* sampling; sensor networks; monitoring; standardization; forest health; sentinel satellites; Copernicus

## 1. Forest Health and Identification Using Remote Sensing

Forest health is of major interest for national and international sustainable forest management, decision makers and policy. Forests have short-term effects on local ecosystems and landscapes, balances global carbon stock and influence global climate [1]. In Europe, two aspects are of major concern for influencing forest health: (i) forest damage from air pollution (*i.e.*, atmospheric ozone and nitrogen input); and (ii) the impact of climate change. In addition to naturally-occurring impacts on forest health (*i.e.*, from natural disturbances), the international timber trade and regional renewable energy production are key drivers for changes to European forest ecosystems at all geographic levels. As the disturbance types are very different, a wide range of indicators of forest health require consideration. An overview of quantitative forest health indicators is presented in Table 1 and are recently published by the 7th FOREST EUROPE Ministerial Conference in October 2015 and applied as a basis for the report "The State of Europe's Forests" by the United Nations.

**Table 1.** Quantitative indicators used by the 7th FOREST EUROPE Ministerial Conference, in October 2015. Source and modified after the United Nations Report "State of Europe's Forests 2015". FOREST EUROPE, 2015: State of Europe's Forests 2015.

| Criterion | Indicators |
|---|---|
| Maintenance and Appropriate Enhancement of Forest Resources and their Contribution to Global Carbon Cycles | - forest area<br>- growing stock<br>- age structure and/or diameter distribution of forest<br>- carbon stock |
| Maintenance of forest ecosystem health and vitality | - Deposition and air pollutants<br>- Soil condition<br>- Defoliation<br>- Forest damage |
| Maintenance and encouragement of productive functions of forests | - Increment and fellings<br>- Roundwood value<br>- Non-timber products<br>- Services<br>- Forest under management plans |
| Maintenance, conservation and appropriate enhancement of biological diversity in forest ecosystems | - Tree species composition<br>- Regeneration<br>- Naturalness<br>- Introduced tree species<br>- Deadwood<br>- Genetic resources<br>- Landscape pattern<br>- Threatened forest species<br>- Protected forests |
| Maintenance and appropriate enhancement of protective functions in forest management (notably soil and water) | - Protective forests—soil, water and other ecosystem functions<br>- Protective forests—infrastructure and managed natural resources |
| Maintenance of other socio-economic functions and conditions | - Forest holdings<br>- Contribution of forest sector to GDP resources<br>- Net revenue<br>- Expenditures for services<br>- Forest sector work force<br>- Occupational safety and health<br>- Timber consumption<br>- Timber trade<br>- Energy from timber resources<br>- Accessibility for recreation<br>- Cultural and spiritual values |

The development of sustainable strategies for national and international forest management has increased the demand for spatially explicit information at various geographic and management levels. Annual area-based estimations of carbon sequestration in forest biomass, dead organic matter and soil organic carbon are still quite uncertain for European forests, because they are largely based on change rate estimations [2]. Here satellite imaging remote sensing technologies from national, European and global Earth observation programs can provide data for the large-scale monitoring of forest ecosystems to study the causal relationships of disturbance factors across spatial scales and understand relevant feedback processes *i.e.*, between soil, vegetation and the atmosphere [3–5]. Our review focuses on biotic and abiotic disturbances (*i.e.*, drought stress, pest infestation and environmental pollutants) in European forest inventory that are of special interest for the implementation of an area-based forest monitoring on a regular basis supported by satellite remote sensing observations. The review is designed to bridge gaps of understanding between forestry and remote sensing science community by presenting state-of-the-art information on methods to the two user groups relevant for *in situ*/remote-sensing integration and necessary to enhance the application value of remote sensing data for the assessment of forest health.

The forest area in Europe accounts for 33% of total land area, which amounts to 215 million ha. The number of European countries with a formal National Forest Program (NFP) has almost tripled since 2007 (FOREST EUROPE 2015). For European countries, accurate measurements of forest parameters are widely available at the local scale. However, many countries are still not able to provide reliable quantitative information about forest health because they do not systematically monitor relevant forest and tree parameters for multiple reasons. Very good examples to learn from are Finland and Sweden. Here National Forest Inventories measure more than 10.000 field plots with approximately 200 variables per plot and combine *in situ* data operationally with satellite data for nationwide forest map production [6,7].

New satellite remote-sensing technologies, particularly hyperspectral imaging spectroscopy and full polarimetric SAR data promise to extend the database of forest observations with new potential for forest ecosystem assessment (see Section 3) [8]. Over the last four decades, fundamental research on the applicability of satellite remote sensing observations for forest parameter estimation have been conducted within the framework of numerous case studies [9,10]. Based on extensive calibration/validation experiments and technological innovation, new satellite missions (*i.e.*, Sentinels, EnMAP, FLEX, TanDEM-L/or see Section 3) have been proposed, are under development, scheduled for launch or already operating [11,12]. While the data from past missions was mainly available and usable for the research community, latest and coming missions (*i.e.*, Sentinels, RapidEye) focus on ease of use and aim to achieve an early collaboration with end-users.

Satellite remote sensing is widely applied in forest research and forest vegetation mapping for forest inventories—mainly using multispectral data and airborne laser scanning [13]. However, the role of coming satellite data (*i.e.*, hyperspectral, multi-sensor concepts) has not been critically evaluated in terms of frequent forest health process-pattern monitoring and operational requirements.

While satellite remote-sensing signals provide no direct measures of forest state variables, its great benefit lies in the indirect retrieval of forest health indicators for large areas and the monitoring of forest ecosystem boundary conditions [4,14]. However, various measures applied in numerous case studies limit the inter-comparability of study results and hinder a comprehensive evaluation of the suitability of remote sensing for forestry [15].

Standardized and transferable workflows for satellite remote-sensing data analysis are required to enhance the operational implementation and provide comparable information quality. Key conflicts in the standardization process arise from deficits in ancillary *in situ* data related to: (i) the fluctuating quality of *in situ* data (*i.e.*, sampling method or spatial availability); (ii) the fluctuating quantity of *in situ* data (*i.e.*, spatial and temporal availability); and (iii) political and commercial restrictions on data availability. Furthermore, the integration of satellite remote sensing observations and land cover data into innovative forest monitoring strategies would require modifications to modeling concepts *i.e.*, with respect to model parameterization and data assimilation [16]. To take the next step from science to operational implementation, policy aspects need to be addressed more thoroughly [17].

For a broader implementation of satellite remote sensing in forest information systems, information about up-to-date forest data sampling practices is essential for remote sensing scientists (presented in Section 2). Up-to-date earth observation satellites and future missions with specific relevance for forest information retrieval from the local to the continental scale are discussed in Section 3. The combination of *in situ* and remote sensing observations for a frequent monitoring of forests is discussed, focusing on data sampling concepts and integrated data processing (Section 4). In addition, we list operational requirements for comparable and sustainable forest monitoring using satellite remote sensing including standardization (Section 4). a conclusion that incorporates remote sensing, *in situ* data sampling, methods and standardization is provided in Section 5.

## 2. *In Situ* Data Sampling in Forestry

In general, *in situ* data is used for different purposes in the context of remote sensing in forest monitoring [6,18]. From the remote sensing perspective, information that has been collected *in situ* is largely used to validate satellite data or products, calibrate methods or applied as input for nearest neighbor methodologies [19]. When combined, *in situ* and satellite remote sensing data may be used in a complementary sense, generating additional information where a single source dataset would be too imprecise [9,20]. Conversely, remote sensing could be helpful to validate maps produced by interpolating information that was sampled *in situ*. In the latter context, pattern-wise validation is often used due to the lack of remote sensing used to derive forest parameters directly. Another field of application is when both *in situ* and satellite remote sensing data are used as input data into forest models.

Here, our intention is to provide a comprehensive overview of *in situ* data sampling in german and european forestry for the remote sensing community. The progression of information from local forest measurement levels to forest health indicators at larger scales and as spatially integrated/extrapolated information (*i.e.*, using remote sensing) requires knowledge from available *in situ* measurements and monitoring methods in forestry. When identifying forest health on different geographic scales and at various management levels, measurements collected directly at the local level provide valuable ground truth linkages for satellite remote sensing based mapping of forest parameters, especially in the case of upscaling [21].

First of all, *in situ* data sampling in european forests varies in space, time and consequently in statistical representativeness at european and national management levels. Three main monitoring activities can be distinguished in germany and are representative for many european countries:

(i) Forest inventories at the forest enterprise level are mostly conducted in state-owned forests at time intervals of 10 to 15 years. The main objective is the assessment of a sustainable timber yield to optimize forest management. The data is collected on permanent and non-permanent inventory plots. Usually the data is retained by the commercial forest management and not easily accessible.

(ii) The decennial national forest condition inventory was initiated by the German government as a long-term national forest monitoring project and was conducted in 1986, 2002 and 2012. Its main objective is to obtain information about forest structure, composition and round wood quantities. Data sampling is conducted on a 4 km $\times$ 4 km raster base. For each corner the Trakt method is applied, including data sampling at the corners of a 150 m $\times$ 150 m square [22].

(iii) European forest damage monitoring for the protection of forests with annual reports to the ICP Forests (International Co-operative Programme on Assessment and Monitoring of Air Pollution Effects on Forests) was initiated by the convention on long-range Transboundary Air Pollution of the UN/ECE as a pan-European monitoring programme and a basis for the coordination of relevant national activities for sustainable forestry. The environmental monitoring of forests is divided into two levels. Level 1: In Europe, around 6000 sampling locations with a plot size of 16 km $\times$ 16 km were recently considered for long-term monitoring and annual data collection. The assessment of health is carried out visually *i.e.*, by observing (using field glasses), tree crown condition, density and leaf color separated by tree species. Level 2 includes process-orientated studies on selected experimental locations that are equipped with various *in situ* sampling probes (*i.e.*, in the region of saxony in germany there are 6 long-term intensive monitoring sites). furthermore, the evolution and decomposition of soil nutrients and water availability, soil and vegetation cover is observed and air pollution levels may be determined for area wide mapping [23].

The above mentioned monitoring activities are characterized by *in situ* data sampling in small areas ranging from single trees or soil sensor locations (point scale) to tree-stand level (plot scale). In Table 2 a comprehensive list of the most widely-used forest parameters including best-practice *in situ* sampling methods is presented. It should be taken into consideration that only a subset of the measurements are performed on a regular basis at the national or european level. For the assessment of the state of the forests at regional or even european scale, *in situ* point and plot data is transferred into a set of indicators, which should be considered when deriving management information (see Table 1). Therefore, *in situ* data is generally provided with geographic coordinates determined from measurements using global positioning systems (gps) receivers. Here, forest canopy has strong influence on the accuracy of gps measurements [24] and easily introduce uncertainties of several meters to the sampling point location, which should be considered especially in high spatial resolution mapping.

**Table 2.** Summary of key forest and stand tree parameters observed in different forest inventories. (* generally sampled for forest inventory).

| | Parameter | Traditional Methods and Measurement Standard in Forestry |
|---|---|---|
| vegetation data | tree species and number of trees * | manual counting in defined plots |
| | tree height | geometric principle (*i.e.*, Kramer's Dendrometer) trigonometric principle (*i.e.*, Blume-Leiss altimeter) |
| | tree crown diameter | average crown spread, spoke method, azimuth method, polygonal method, laser method |
| | tree crown density | physical direct measurement taken by tree climbers, and modeling of limb and branch volume |
| | tree diameter at breast height * | measured at breast height at 130 cm above the average soil level using a tree caliper or a diameter tape |
| | basal area per hectare | Bitterlich sampling |
| | phenological state * | visual assessment by expert |
| | leaf and needle color and state * | visual assessment by expert |
| | social role and stand structure * | visual assessment by expert considering tree neighborhood to assess light, nutrient and water concurrence |
| | Deadwood * | visual assessment by expert: upright/lying, quantity, decomposition |
| | ground vegetation and shrubs layer * | visual assessment by expert, vertical vegetation species type and distribution and vegetation density covering soil |
| soil and ground data | litter (L) and humus (O) layer * | visual assessment of litter and humus layer thickness, composition, decomposition |
| | humus form (*i.e.*, raw humus, model, mull) * | visual assessment of the upper soil layers (L, O, A) identification of indicator species of ground vegetation |
| | soil horizon: A (surface soil), B (subsoil), C, E,G, *etc.* | visual assessment by destructive soil sampling, *i.e.*, using spade and soil auger |
| | soil type * | *i.e.*, sand, silt, clay, loam visual assessment by expert (finger test) |
| | soil classification | *i.e.*, brown soil, podzol classification of soils on the basis of characteristic combinations of soil horizons and soil types |
| | soil moisture | visual assessment of soil consistence and water discharge |
| | plant available water content | derivation from soil type (grain size), stratification, humus content |
| | groundwater and backwater | measurement of water level below surface estimation of variation amplitude, drying out period, evaporation potential due to relief structure |
| | local relief | estimation of slope inclination, slope aspect, curvature |
| | soil chemistry | estimation of carbonate content by means of the intensity of $CO_2$ emissions after reacting with HCl<br>pH: pH test strips<br>C/N ratio for A horizon<br>nutritional element for plants: laboratory analysis |

**Table 2.** *Cont.*

| | Parameter | Traditional Methods and Measurement Standard in Forestry |
|---|---|---|
| other data, no regular sampling, experimental and scientific purpose | geology and geomorphology | campaign specific sampling |
| | foliar chemistry | campaign specific sampling |
| | age class distribution | dendrochronology by core sampling from living tree using a borer |
| | epiphytic lichens | campaign specific sampling |
| | atmospheric deposition | campaign specific sampling |
| | ambient air quality | campaign specific sampling |
| | meteorology | *i.e.*, measurement of precipitation, air temperature, wind speed, wind direction, global radiation, flux measurements, humidity; sampled by experimental/scientific test site monitoring, flux net tower station, German weather forecast monitoring |
| | soil moisture | vertical soil hydraulic properties observed with long-term lysimeter experiments |

Recently, critical tree stress has often been recognized at an advanced phase by visually observed tree crown conditions (*i.e.*, leaf and needle color and state). However, these conditions alone are no reliable source for detecting stress caused by nutrition and water supply. Biochemical leaf and needle nutrient state provides ancillary information for identifying the level of stress, but is mostly measured in scientifically motivated experiments (see Table 2, other data). The differentiation between critical and non-critical stress symptoms requires ancillary meteorological (time-series) and soil information (spatially distributed), *i.e.*, can an early wilting of leaves also be a natural protective reaction to droughts.

Existing *in situ* data sampling in forests provide core information for pattern interpretation in remote-sensing imagery (methods and references are summarized in Section 4.1). In the following section we will provide information about up-to-date earth observation satellites and future missions with specific relevance to forest health assessment from the local to the continental scale.

## 3. Satellite Remote Sensing of Forest Health Boundary Conditions

A state-of-the-art review and comparison of available and future earth observation data from space is often essential for the forest user community ranging from small local district offices to federal forest management. National and international remote sensing satellite missions for environmental monitoring on land are about to enter a new era due to technological innovations and scientific experimental achievements that have taken place over the last 10 years. New satellite-based analyses of soil and vegetation will be possible by increasing temporal coverage and sensor innovations (*i.e.*, FLEX, TanDEM-L). Quantitative assessments of forest health will benefit from observation synergies and complementarities, *i.e.*, by combining data to reduce ambiguities of disturbance factors. Early information and collaboration of remote sensing experts with the forest user community will be imperative to benefit from novel satellite missions from the very onset. Table 3 provides information on recent satellite remote sensing missions that are in operation, in the development phase or under study with specific relevance to retrieving information and indicators on forest stands. A very comprehensive satellite sensor overview for issues in biodiversity monitoring that also includes past missions is provided in the scientific literature *i.e.*, by Kuenzer *et al.* 2014 [14].

Optical remote sensing imagery using areal and satellite images is the backbone of vegetation ecosystem studies (*i.e.*, forests, greenland, agriculture, urban vegetation) as it allows a reliable determination of pattern texture variables (size, shape, *etc.*) *i.e.*, in forest stands, information of spatial and temporal species distributions and de- and afforestation. Changes to forest environmental boundary conditions including temperature, precipitation and air pollution affect foliar nutrient concentration, which in turn affect the spectral signatures in VNIR and SWIR. Frequently, optical remote sensing applications (*i.e.*, for growing stock, tree species change maps, leaf and needle color) are greatly limited by atmospheric dust and clouds and require atmospheric correction for the spectral signals [25,26]. Here, ground based sun photometers to measure the aerosol depth of the atmosphere provide *in situ* data and improve quantitative parameter retrieval [27,28]. Additionally, observations from other remote sensing technologies provide advantages in combined sensor data (*i.e.*, active and passive microwave data and optical reflectance or thermal emissions) approaches [29–31].

As airborne LIDAR (Light Detection and Ranging) data provide highly accurate geometric information on the vertical and horizontal vegetation distribution in forests (*i.e.*, tree height and crown shape, vertical vegetation layer) [32] its observation is not frequently available from satellites due to technological limitations (*i.e.*, beam footprint size and signal loss). For frequent satellite-based monitoring of biomass, SAR data is a promising alternative to airborne LIDAR biomass estimations [33,34]. Radar scattering components are weather and daytime independent observations that vary during the annual growing cycle mainly due to biomass changes in terms of geometrical properties and changes in vegetation water content. Combining frequently available SAR observations with temporal non-regular (due to cloud cover) optical remote-sensing data may provide a sound information source even at the inner forest level.

Kuenzer *et al.* 2014 [14] point out the value of long-term thermal infrared observations of land surface temperature (LST) and its contribution to any biodiversity-related analyses. LST and particular multi-band thermal emissions observed at different parts of the electromagnetic spectrum are directly connected to processes of water and energy fluxes in soils and vegetation and are key input in physical-based environmental models [35,36].

It is worth noting the design of recently launched and missions scheduled for the future in terms of their possibilities for integration concepts using different sensor types by exploiting their synergies and complementarities to reduce uncertainties. For example combining L-band SAR and the L-band radiometer data concept of SMAP (Soil Moisture Active Passive) for soil moisture mapping or reducing atmospheric noise on future FLEX vegetation vigor products using Sentinel-3 data. As SAR failed aboard the U.S. space agency's SMAP satellite in July 2015, NASA is auditioning the implementation of Sentinel-1A (later also 1B) to use in tandem with SMAP L-band radiometer to produce a finer resolution (approximately 9 km) soil moisture map. Furthermore, core products of new and upcoming earth observation satellite missions directly focus on the supply of data products (*i.e.*, soil moisture maps, chlorophyll *a* maps, biomass carbon stock) as user services.

The mapping of forest parameters using imaging satellite remote sensing is performed by completely different measurement technology (*i.e.*, physical signals integrated over varying time and space, see Table 3) and completely different spatial representativeness (*i.e.*, spatial and spectral signal integration) compared to traditional *in situ* measurements presented in Section 2. A direct comparison of satellite remote sensing "measurement" and *in situ* "measurement" is not provided from a physical point of view. Spatially integrated remote sensing observations provide no direct measurement of the key variable. The benefit of novel satellite remote sensing observations is the spatial and process integrated perspective covering large areas under dynamic and complex environmental boundary conditions (*i.e.*, climate, vegetation, soil and water matter fluxes). Therefore, satellite remote sensing signals provide additional proxy information that can be interlinked with forest health indicators and disturbance factors (see Figure 1). Approaches for linking satellite remote-sensing observations with key forest state variables are presented in Section 4.

**Table 3.** Summary of recent satellite remote-sensing missions. * missions under development; ** missions under study or proposal phase; *** relevant to the assessment of forest health.

| Mission Name/Organization | Launch Date/Revisit Time for Europe | Type of Sensor/Number of Observations/Pixel Size | Relevance to forests | Selected Scientific References Relevant to Forestry |
|---|---|---|---|---|
| RapidEye */PlanetLabs | 2008/1 day | Multi-spectral push broom imager/5 spectral bands/5 m × 5 m | - qualitative and quantitative vegetation information, *i.e.*, species distribution, phenology, stand height, forest biomass, - indirect soil information, - spatial and temporal dynamics through high revisit time | [37–39] |
| WorldView-2,3 */Ball Aerospace & Technologies Corporation, fully commercial | 2009 and 2014/1 day | Multi-spectral push broom imager/9 spectral bands/0.5 m–1.8 m | | [40,41] |
| Sentinel-1A */B * two-satellite configuration/ESA | 2014 and 2015/2 days | C-band SAR/5 m × 20 m | - qualitative and quantitative vegetation structure *i.e.*, biomass, stem volume, deforestation, soil moisture, land deformation | [42–45] |
| Sentinel-2A */B ** two-satellite configuration/ESA | 2015 and 2016 5 days | Multi-spectral imaging spectrometer/ 12 spectral bands/10 m (visible and VNIR), 20 m (VNIR, SWIR), 60 m (SWIR) | - qualitative and quantitative vegetation information (*i.e.*, species distribution, phenology, LAI, vegetation water content) - soil color and moisture information - spatial and temporal dynamics | [46–48] |
| Sentinel-3A*/B** two-satellite configuration/ESA | 2016/2017 4 days | - Land Surface Temperature Radiometer (SLSTR)/9 bands/500 m–1 km, - Ocean and Land Color Instrument (OLCI)/ 21 bands/300 m–1.3 km, - dual-frequency (Ku and C band) advanced Synthetic Aperture Radar Altimeter (SRAL)/60 m | - active fire monitoring and burn severity, - land temperature, - evapotranspiration, - vegetation state, vegetation monitoring, - species classification, soil moisture | [49–51] |
| Landsat 8 */NASA & USGS | 2013/16 days | - OLI- Imaging multiband spectrometer & TIR multi band thermal infrared radiometer/15 m (PAN), 30 m (VNIR), 100 m (TIR) | Qualitative and quantitative vegetation (*i.e.*, species distribution, phenology) and soil and information | [52,53] |
| SMAP * soil moisture active passive/NASA | 2015/1–2 days | - L-band SAR SMAP SAR is not operating! - L-band radiometer 30 km | land surface soil moisture | [54,55] |
| SMOS * soil moisture and ocean salinity/ESA | 2009/1–2 days | L-band radiometer 40 km | land surface at continental and global scale | [56] |
| Terra MODIS */NASA | 1999/16 days | MODIS: Moderate imaging spectrometer/ 250 m, 500 m | biological and physical processes, land surface temperatures, forest fires and detection of burnt areas | [57,58] |
| TerraSAR-X */DLR and Airbus Space and Defence | 2007/2–3 days | X-band SAR/1 m/3 m/16 m | Biomass Geometric and volumetric information and dynamics | [59] |
| TanDEM-X */DLR and Airbus Space and Defence | 2010/3 years for global elevation model | X-band SAR/12 m (HRTI-3 DEM) | - Digital elevation measurements, biomass - flying in close formation with TerraSAR-X to achieve cross-track interferograms | [34,60] |

**Table 3.** *Cont.*

| Mission Name/Organization | Launch Date/Revisit Time for Europe | Type of Sensor/Number of Observations/Pixel Size | Relevance to forests | Selected Scientific References Relevant to Forestry |
|---|---|---|---|---|
| OCO-2 */NASA | 2014/16 days | Spectrometer/spatial resolution not specified | column-averaged carbon dioxide dry air mole fraction (XCO2) on regional scales, detection and monitoring of sinks and sources | [61] |
| EnMAP ** (Environmental Mapping and Analysis Program)/BMBF & BMWi Germany | 2019/4 days | Imaging hyperspectral spectrometer 420 nm–2450 nm, and >200 spectral bands, 30 m | - soil information *i.e.*, soil color, minerals, moisture) - qualitative and quantitative forest information *i.e.*, species distribution, phenology, foliar chemistry | [48,62] |
| FLEX ** (Fluorescence Explorer) in tandem with Sentinel-3/ESA | 2022/N.N. | Imaging ultraspectral spectrometer—*"Fluorescence Imaging Spectrometer" FLORIS* 300 m | vegetation chlorophyll fluorescence Photosynthetic activity Plant vitality and plant-atmospheric carbon exchange | [63–65] |
| BIOMASS ** ESA | scheduled launch 2020/N.N. | P-band SAR 200 m | Forest biomass monitoring, forest carbon stock | [66] and see ESA Earth Explorer 7: reports for mission selection SP-1324 |
| TANDEM-L *** DLR | N.N./N.N. | two twin L-band SAR | vertical forest structure information, forest height, forest biomass, soil moisture | [12,67] |
| CarbonSAT *** ESA | N.N./N.N. | | Carbon dioxide, methane | [68] |
| ECOSTRESS *** NASA | N.N./N.N. | Multi band thermal infrared radiometer | Evapotranspiration, plant-water dynamics | visit: http://science.nasa.gov/missions/ecostress/ |
| GEDI *** (Global Ecosystem Dynamics Investigation Lidar)/NASA | N.N./N.N. | LIDAR | Forest canopy structure and its spatial and temporal dynamics, focus on tropical and temperate forests (coverage between 50° N and 50° S) | visit: http://science.nasa.gov/missions/gedi/ |
| Sentinel 2C/D ** | >2020/N.N. | Multi-spectral imaging spectrometer | see Sentinel 2A/B | |

Abbreviation: L-band, frequency/wavelength: 390 MHz–1.55 GHz/76.9 cm–19.35 cm; C-band, frequency/wavelength: 4.20 GHz–5.75 GHz/7.14 cm–5.22 cm; X-band, frequency/wavelength: 5.75 GHz–10.9 GHz/5.22 cm–2.75 cm; BMWi Germany—Federal Ministry of Economics and Technology, Germany; BMBF Germany—Federal Ministry of Education and Research, Germany; DLR—German Aerospace Center; ESA—European Space Agency; ISRO—Indian Space Research Organization NASA & USGS; NASA—National Aeronautics and Space Administration.

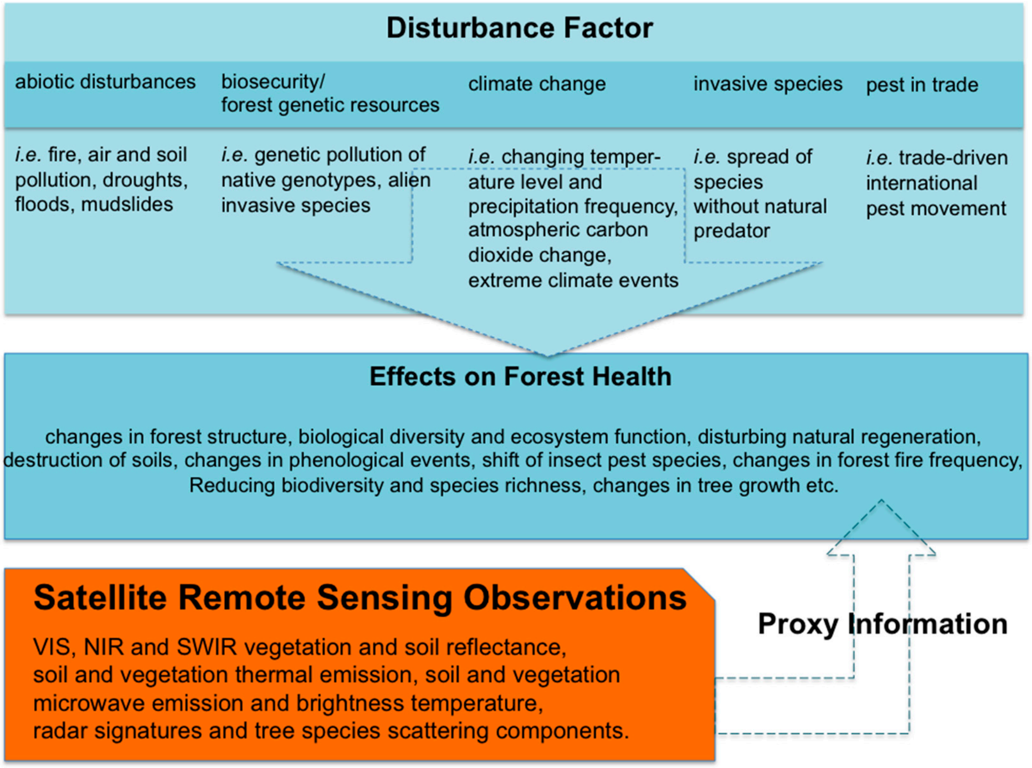


**Figure 1.** General impacts on forests, their origins and their effects on forest health together with remote sensing observations for identifying proxy information for factors relevant to forest health. The disturbance groups and factors are modified after FAO (Food and Agriculture Organization of the United Nations).

## 4. Integration Aspects of *In Situ*/Remote Sensing Data

*In situ* observations usually deliver very accurate measurements (*i.e.*, biomass, tree height, climate variables, foliar chemistry). However, the measurements vary in level of detail, scale and applied approach and are only available infrequently for a few distributed locations causing gaps of years and decades between measurements [13]. Due to the high costs, the sampling point locations are often not collected for larger areas and due to regional differences the information is not suitable for the use of spatial upscaling. A combination of *in situ* and remote sensing observations can reduce uncertainty in area-wide mapping of forest parameters (see summary of methods provided in Table 2). To exploit the potential of new satellite missions (*i.e.*, enmap, flex, sentinels) with its focus on identifying environmental processes (*i.e.*, senescence, photosynthesis activity, evapotranspiration) frequent *in situ* data is required to validate boundary conditions (*i.e.*, temperature, leaf color, soil moisture). In the following, we list temporal, thematic and spatial aspects for an operational implementation of satellite remote-sensing data in forestry.

Temporal aspects are:

- data continuity (*i.e.*, providing min/max availability of data information products) for the implementation of standardized workflows and products,
- multi-temporal analyses on a weekly, monthly, seasonal and annual basis for the frequent updating of thematic maps,
- inter-comparability of remote-sensing data from different sensors to close gaps in time series, *i.e.*, by translation to a standard unit (spectrally and spatially),
- intermediated information products for event-based irregular needs (*i.e.*, higher observation frequency during drought periods, assessment of large-scale wind blow events).

Thematic aspects in forestry are:

- Clear communication of limitations (*i.e.*, remote sensing cannot measure vegetation vitality or measure soil moisture in the vadose zone), but rather focuses on satellite remote sensing observation strengths (*i.e.*, retrieval of spatio-temporal trends) for an operational use (*i.e.*, sustainable wood production and environmental boundary conditions).
- In terms of the spatially and temporally integrated remotely sensed "measurement", remote sensing sensors observe physical signal patterns that are linked to natural processes (*i.e.*, evapotranspiration, vadose zone water fluxes) and data assimilation concepts to run quantitative physically-based models, which are very important because of the available multidisciplinary data [69].
- Physical remote sensing observations are difficult to translate into actual forest measurements because it is difficult to get a precise inversion into the forest parameter of choice. Therefore, the remote sensing measurement can be used i) as an indicator for the forest parameter or ii) as input into a process model used by an operator to simulate or estimate the forest parameter of choice [70].

Aspects regarding the mismatch of spatial observation scales are:

- The mismatch between *in situ* point or small-scale plot measurements and remotely-sensed large-scale signals plays an important role for the final application and choice of retrieval method.
- parameter sensitivity (*i.e.*, leaf angle distribution, foliar pigments) changes with the spatial observation scale and can be modeled using radiative transfer models for better understanding the remotely-sensed data and modifying retrieval algorithms for specific sensor data.
- the effect of up-and downscaling of spectro-radiometer data varies with the heterogeneity of the vegetation cover and transfer functions should take into consideration vegetation boundary conditions *i.e.*, soil moisture properties [71].
- as sub-pixel heterogeneity of soil and vegetation parameters has control over processes (*i.e.*, evapotranspiration, thermal emissions) *in situ* sampling design needs to take into consideration the spatial footprint of relevant remotely-sensed data (*i.e.*, 5 m × 5 m multi-spectral data from rapideye or 30 m × 30 m hyperspectral data from enmap or 60 m × 60 m swir data from sentinel-2).
- the choice of *in situ* sampling locations and measurement density in time and space can be supported by analyzing the available time series of remote sensing image data, topographic information and meteorological time series. the quantified spatio-temporal stationarity of the different observations deliver information for the design of *in situ* sampling to reduce the mismatch between observation scales.

### *4.1. Methods and Implementation Criteria*

Remote sensing and *in situ* data can generally be linked by empirical or physically based methods for the retrieval of quantitative information (*i.e.*, soil moisture in vol. %, chlorophyll $a + b$ content in g/cm$^2$). Table 4 provides a list of methods, applications and references for quantitative forest parameter mapping. Qualitative mapping methods classify the spatially explicit remote sensing observations by using multiple methods. Classification methods, such as k-means, ISO data or support vector machines, but also visual interpretation or linkage of the resulting discrete classes using lookup tables. Another method uses empirical functions in order to derive forest conditions (*i.e.*, groups of senescence levels using classified NDVI maps), or species groups or biomass. Hence, the transfer of satellite remote sensing data into value-added maps frequently requires soil, vegetation and atmospheric *in situ* data to initialize, calibrate and validate qualitative and quantitative methods.

**Table 4.** Summary of the key advantages and disadvantages of methods for retrieving quantitative forest variables from remote sensing observations.

| | **Physically-Based Models/Radiative Transfer Descriptors** | **Empirical Approaches** |
|---|---|---|
| Advantages | - more generic and transferable,<br>- allows physically-based process feedback studies,<br>- provide physically-based interfaces to environmental models (*i.e.*, hydrological models through soil moisture and soil texture) | - simple set up,<br>- regression coefficient estimation is straightforward and spatial and spectral resolution effects are considered indirectly through observation-specific calibration,<br>- high site-specific performance may be achieved,<br>- if large data sets available robust results may be achieved,<br>- no programming skills required, various GUI-based statistical tools are available |
| Disadvantages | - limited by accurately representing parameterization as *in situ* data cannot be seen in reality in most cases (*i.e.*, soil moisture and temperature profile data, leaf angle distribution and biochemical quantities),<br>- accuracy of output variable varies with applied inversion procedure,<br>- process level description, no spatial integrated effects are considered (*i.e.*, spectral effect of leaf angle distribution under varying spatial observation scale)<br>- difficult implementation as programming skills and model process knowledge is required | - transferability is limited by site-specific regression coefficient estimation,<br>- lack of generalization and reproducibility as it describes a site-specific observation predictor concept on the basis of defined dependencies and independencies |
| Model examples and References | *For reflectance data of VNIR & SWIR:*<br>- PROSPECT (leaf optical properties model) [73–75]<br>- PROSAIL [77,78] (canopy bidirectional reflectance)<br>*For passive microwave data:*<br>- LPRM (land parameter retrieval model): [29,81]<br>- CMEM (community microwave emission model): [83,84]<br>*For SAR data:*<br>- polarimetric decomposition [85]<br>- TomoSAR [66]<br>*For TIR data:*<br>- CUPID [86]<br>- Thermal inertia modeling [87] | - multi-SAR band forest biomass retrieval: [72]<br>- NDVI measurements for tracking canopy structure and phenology: [76]<br>- Spectral vegetation index based biomass retrieval using different regression approaches and random forest regression trees: [79,80]<br>- Forest carbon estimation: [82] |
| Aspects for Application | The physically-based analysis of feedback processes allows an identification and description of process changes. Relevant observables can be identified and optimized for the application of empirical and data mining approaches. | Adjacent stand-alone empirical modeling, empirical functions are components of physically-based approaches and are somehow the individual proof of the concept. |
| Data mining/Machine Learning [88]: Random Forest [41,52], SupportVector Machine [89], Decision trees [39], Artificial Neural Networks [90] | | |

| Application and Technologies | **Advantages** | **Disadvantages** |
|---|---|---|
| -To preferably automate the input data for physically-based or empirical models [91].<br>- To optimize the inversion of physical-based models [92].<br>- As data mining may include data selection, pre-processing and transformation to other data formats it is very applicable to multi-source datasets related to forest health without assumptions [88]. | - fusion of data from different sources without assumptions on feedback processes,<br>- process identification and output by self learning,<br>- allows the detection of new processes, feedbacks and spatial and temporal dependencies | - transferability and generalization is limited by different *in situ* data sources,<br>- lack of physical process reproducibility |

Recently the application of available methods (see Table 4) for remote sensing based mapping is limited by *in situ* data availability, data quality or political and commercial restrictions. Methods successfully tested are not easily applicable due to missing *in situ* data or the fact that they are not transferable to other scales [71]. furthermore, remotely sensed image data is mostly at much lower resolution than reference data (*i.e.*, landsat pixel 900 $m^2$/modis pixel 25 ha *vs.* single tree or tree stand sample data) and contains overlaying signal information from different species and soil conditions (problem of spectral mixing).

*To increase the implementation value of satellite remote sensing in forestry, the following aspects are promising:*

- Technological innovations on wireless terrestrial and underground sensor networks can play an important role in managing forest resources by collecting continuous data of soil, vegetation and atmospheric conditions. existing and new forest sampling locations can be equipped (*i.e.*, with temperature and soil moisture sensors) and the temporal and spatial statistical representativeness of the *in situ* information will increase. The first step is to parameterize plot-specific statistical functions to estimate *i.e.*, evapotranspiration or soil moisture in the vadose zone [93] and to link these to remote sensing based vegetation data for "water state" mapping.
- Phenological ground networks will provide frequent information on leaf and needle conditions for monitoring changes in tree growth, phenology (start, middle and end of the growing season) and provide valuable data for the analyses of tree species conditions under changing climatological and hydrological conditions [76].
- Terrestrial and UAV (Unmanned Airborne Vehicle) based sensor innovations can provide information on the structural dynamics of forest ecosystems and deliver input data for process models [94].
- Multi-dimensional spatial data sets available from new satellite missions can be used to complement each other and compensate for limited local *in situ* data.
- This rapidly increasing observation database provided by satellite and *in situ* observations can be used to identify recently unknown spatio-temporal process patterns, feedbacks and physically-based process simulations may be modified to provide scenarios for sustainable forest management under changing environmental conditions.
- The implementation of digital forest information systems, the growing demand of geospatial information and the increasing application of remote-sensing data by forest professionals is a big step forward to bridge the gap between science and practical application [95].

Research on the design of vegetation, soil and underground (wireless) sensor networks in ongoing and best-practice approaches can be found in the scientific literature [96–99]. A promising technological setup to close the gap between local soil moisture measurements (*i.e.*, by wireless sensor networks) and satellite observations for soil and vegetation water assessment are cosmic-ray probes [96,100]. As the soil moisture observation sensitivity and the footprint of the cosmic-ray is affected by aboveground biomass [101], it may be calibrated in operational workflows using biomass data from *i.e.*, optical remote sensing and local soil moisture sensors. In the proceeding step the biomass corrected intermediate soil moisture product can in turn be linked to *i.e.*, SAR (*i.e.*, Sentinel-1, Tandem-L) or L-band radiometer (*i.e.*, SMAP) satellite observations.

The installation of standardized vegetation, soil and underground networks with defined extent, spacing and data support rates is a promising terrestrial component to enhance the remote-sensing monitoring of forest health under various climate, hydrological and geological conditions.

### *4.2. Standards for Remote-Sensing Based Products*

As of recently, no standards for the application of remote-sensing data in forestry exist. The processing of the physical remote-sensing signals differs between sites and dates. The lack of standardizations *i.e.*, on reflectance quantities in optical remote sensing is a considerable source of error [26]. The numerous remote-sensing data pre- and post-processing methods that are available (compare Table 5) require (i) documentation and metadata standards; and (ii) the development of product standards. Standards of the workflows for remote-sensing analyses (including all observation types) for forest health indication assessment are particularly essential:

- to increase comparability, the exchange and consistence of data from different forest regions and dates,
- to provide standard data formats for sustainable information management within digital forest information systems,
- to make information reproducible,
- to develop legal commercial products that stand up to testing from decision makers and policy.

A meaningful definition *i.e.*, for the classification of tree species, stand height and growing stock is required from an application perspective, whereas from a technological perspective, the following standardization aspects are required:

- spatial resolution/ground pixel size,
- spectral signal characteristics (*i.e.*, for optical remote sensing data) such as the central wavelength and band width or SAR backscatter and polarization and processing level,
- processing level and physical units,
- time and frequency of observation for multi-temporal processing,
- statistical representativeness of applied *in situ* data,
- Thematic representativeness of applied *in situ* data.

A major contribution towards standardization efforts for remote-sensing products could come from the implementation of terrestrial and underground sensor networks. Existing standards on such data may bridge the gap to achieve sustainable and comparable information products. Today a strong commitment from the community exists to implement satellite remote sensing data in new information products. innovative methodologies (*i.e.*, the design thinking approach, the requirement engineering method) to efficiently create new products are available in industrial practice and promise high value for remote-sensing based product development, by bringing the "collectors" who have countless data, together with "analysts" who have the tools and methods to gain the necessary insight into the data and the end user.

## 5. Conclusions and Outlook

Standardized *in situ*/remote-sensing integration in forest monitoring is challenged both practically and conceptually. The review intends to provide a comprehensive overview about state-of-the-art methods in *in situ* data sampling of forest parameters and novel remote-sensing technologies with specific importance for forest health monitoring. we argue that for an operational implementation of innovative remote-sensing approaches in forest health monitoring, terrestrial sensor networks may play a key role when implementing standardization, which is required independently of the *in situ* data approach.

The comprehensive reliability for an assessment of forest and tree conditions is directly linked to the quality and quantity of the *in situ* data. An implementation of standardized remote-sensing products in monitoring workflows might be a basis for an efficient and early detection of changes to forest ecosystems. The temporal continuous analysis is helpful in understanding the internal forest feedback processes (between the environment, animal/vegetation species and soils) and is a source of evidence for decision makers in forest management and policy.

The growing number of data sources (sensors and web-based data portals) and data formats (one-to-n-dimensional) requires the rapid development of a new generation of analytical methods so that the data for monitoring forest conditions can be exploited efficiently. Here, data mining approaches, semantic and linked-open data concepts promise to play a major role in remote-sensing based information technology and industry 4.0 concepts (*i.e.*, combining innovations of information technology with forest management production issues) for handling multi-source and multi-criteria data in application.

To achieve a successful implementation of satellite remote-sensing observations in sustainable and standardized forest monitoring, the following organizational duties will pave the way:

- information- and knowledge transfer (benefits and limitations) about today's and future remote sensing technologies for potential end users, students and trainees,
- professional and frequent analyses on the demands, needs and current information deficits in forests on different levels of forest management and decision making in Europe,
- an analysis of the criteria on standardizing product requirements in remote sensing (*i.e.*, requirements on physically-based reproducibility) and the forest user community (*i.e.*, needs on uncertainty levels of information products),
- the provision of remote-sensing data free of charge or at certain special rates if used for the operational management of ecosystems which provide a wide range of ecosystem services.

The organizational implementation is accompanied by technical aspects in the framework of information retrieval from remotely sensed physical signals including:

- further development of best practice workflows and products that integrate remote-sensing data to complement existing data and services,
- the development of methods to retrieve information from multi-source remote sensing data to make use of synergies and complementarities and handle gaps in time series and areas,
- the further development of the data assimilation concept to utilize multi-source remote-sensing data for the prediction of forest health indicators using environmental models (*i.e.*, growth models),
- research to provide evidence of the concept on the integration of terrestrial sensor network data (*in situ*) and satellite remote-sensing data in forestry as a basis for standardized information products based on remote-sensing data.

The significantly increasing availability of satellite remote sensing data will enlarge the database for spatial and temporal forest data in Europe. On the basis of this data, knowledge of feedbacks between forest vegetation, water availability and the atmosphere can be obtained and estimations of carbon sequestration in forest biomass, dead organic matter and soil organic carbon can be provided at the national and European level together with new modeling concepts (*i.e.*, the assimilation of satellite data). To achieve this goal the important statement of the review is the need to implement terrestrial sensor networks to achieve standardization, which in turn is required as evidence in forest management, policy and the court as well as to increase acceptance.

A serious limitation in terms of the wide collection and provision of *in situ* data of forest (health) parameters is a structural problem, as large parts of European forests are managed for commercial purposes. Because of the possibility of being able to derive monetary values (income but also losses from negative impacts) from the data, forest owners are not interested in sharing such information. Hence, the organizational tasks stated above are the basis for a successful and timely implementation of the technology (new satellite data) for monitoring the state of national and European forests.

**Acknowledgments:** We are very grateful to many principle investigators and co-workers of the Helmholtz Centre for Environmental Research—UFZ and TERENO funded by the Helmholtz Association and the Federal Ministry of Education and Research. The authors also wish to thank all the reviewers for their valuable comments and suggestions.

**Author Contributions:** Marion Pause was responsible for the main part of the review analysis and writing the article. Marco Heurich and Michael Rosenthal contributed important aspects from the forest management community and end-user views. Vanessa Keuck, Christian Schweitzer and Andras Jung contributed information on satellite missions with a focus on environmental monitoring and product development. Jan Bumberger and Peter Dietrich contributed knowledge about terrestrial sensor networks. Angela Lausch provided impulses on modeling approaches and new concepts for the implementation of satellite remote sensing data in ecosystem monitoring. Marion Pause and Angela Lausch initiated and managed the review. All authors checked and contributed to the final text.

**Conflicts of Interest:** The authors declare no conflicts of interest.

## References


1. Milad, M.; Schaich, H.; Bürgi, M.; Konold, W. Climate change and nature conservation in Central European forests: A review of consequences, concepts and challenges. *For. Ecol. Manag.* **2011**, *261*, 829–843. [CrossRef]
2. Lindner, M.; Fitzgerald, J.B.; Zimmermann, N.E.; Reyer, C.; Delzon, S.; van der Maaten, E.; Schelhaas, M.J.; Lasch, P.; Eggers, J.; van der Maaten-Theunissen, M.; *et al.* Climate change and European forests: What do we know, what are the uncertainties, and what are the implications for forest management? *J. Environ. Manag.* **2014**, *146*, 69–83. [CrossRef] [PubMed]
3. Seidl, R.; Müller, J.; Hothorn, T.; Bässler, C.; Heurich, M.; Kautz, M. Small beetle, large-scale drivers: How regional and landscape factors affect outbreaks of the European spruce bark beetle. *J. Appl. Ecol.* **2015**. [CrossRef] [PubMed]
4. Masek, J.G.; Hayes, D.J.; Joseph Hughes, M.; Healey, S.P.; Turner, D.P. The role of remote sensing in process-scaling studies of managed forest ecosystems. *For. Ecol. Manag.* **2015**, *355*, 109–123. [CrossRef]
5. McDowell, N.G.; Coops, N.C.; Beck, P.S.A.; Chambers, J.Q.; Gangodagamage, C.; Hicke, J.A.; Huang, C.; Kennedy, R.; Krofcheck, D.J.; Litvak, M.; *et al.* Global satellite monitoring of climate-induced vegetation disturbances. *Trends Plant Sci.* **2015**, *20*, 114–123. [CrossRef] [PubMed]
6. Tomppo, E.; Olsson, H.; Ståhl, G.; Nilsson, M.; Hagner, O.; Katila, M. Combining national forest inventory field plots and remote sensing data for forest databases. *Remote Sens. Environ.* **2008**, *112*, 1982–1999. [CrossRef]
7. Halme, M.; Tomppo, E. Improving the accuracy of multisource forest inventory estimates to reducing plot location error—A multicriteria approach. *Remote Sens. Environ.* **2001**, *78*, 321–327. [CrossRef]
8. Wang, J.; Sammis, T.W.; Gutschick, V.P.; Gebremichael, M.; Dennis, S.O.; Harrison, R.E. Review of Satellite Remote Sensing Use in Forest Health Studies. *Open Geogr. J.* **2010**, *3*, 28–42. [CrossRef]
9. Mäkelä, H.; Hirvelä, H.; Nuutinen, T.; Kärkkäinen, L. Estimating forest data for analyses of forest production and utilization possibilities at local level by means of multi-source National Forest Inventory. *For. Ecol. Manag.* **2011**, *262*, 1345–1359. [CrossRef]
10. McRoberts, R.E.; Tomppo, E.O. Remote sensing support for national forest inventories. *Remote Sens. Environ.* **2007**, *110*, 412–419. [CrossRef]
11. Goetz, A.F.H. Three decades of hyperspectral remote sensing of the Earth: A personal view. *Remote Sens. Environ.* **2009**, *113*, S5–S16. [CrossRef]
12. Moreira, A.; Krieger, G.; Hajnsek, I.; Papathanassiou, K.; Younis, M.; Lopez-Dekker, P.; Huber, S.; Villano, M.; Pardini, M.; Eineder, M.; *et al.* Tandem-L: A Highly Innovative Bistatic SAR Mission for Global Observation of Dynamic Processes on the Earth's Surface. *IEEE Geosci. Remote Sens. Mag.* **2015**, *3*, 8–23. [CrossRef]
13. Barrett, F.; McRoberts, R.E.; Tomppo, E.; Cienciala, E.; Waser, L.T. A questionnaire-based review of the operational use of remotely sensed data by national forest inventories. *Remote Sens. Environ.* **2016**, *174*, 279–289. [CrossRef]
14. Kuenzer, C.; Ottinger, M.; Wegmann, M.; Guo, H.; Wang, C.; Zhang, J.; Dech, S.; Wikelski, M. Earth observation satellite sensors for biodiversity monitoring: Potentials and bottlenecks. *Int. J. Remote Sens.* **2014**, *35*, 6599–6647. [CrossRef]
15. Petrou, Z.I.; Manakos, I.; Stathaki, T. Remote sensing for biodiversity monitoring: A review of methods for biodiversity indicator extraction and assessment of progress towards international targets. *Biodivers. Conserv.* **2015**, *24*, 2333–2363. [CrossRef]
16. Nyström, M.; Lindgren, N.; Wallerman, J.; Grafström, A.; Muszta, A.; Nyström, K.; Bohlin, J.; Willen, E.; Fransson, J.E.S.; Ehlers, S.; *et al.* Data assimilation in forest inventory: First empirical results. *Forests* **2015**, *6*, 4540–4557. [CrossRef]

17. Nabuurs, G.; Delacote, P.; Ellison, D.; Hanewinkel, M.; Lindner, M.; Nesbit, M.; Ollikainen, M.; Savaresi, A. *A New Role for Forests and the Forest Sector in the EU Post-2020 Climate Targets*; European Forest Institute: Joensuu, Finland, 2015.
18. Fassnacht, F.E.; Hartig, F.; Latifi, H.; Berger, C.; Hernández, J.; Corvalán, P.; Koch, B. Importance of sample size, data type and prediction method for remote sensing-based estimations of aboveground forest biomass. *Remote Sens. Environ.* **2014**, *154*, 102–114. [CrossRef]
19. McRoberts, R.E.; Tomppo, E.O.; Finley, A.O.; Heikkinen, J. Estimating areal means and variances of forest attributes using the k-Nearest Neighbors technique and satellite imagery. *Remote Sens. Environ.* **2007**, *111*, 466–480. [CrossRef]
20. Katila, M.; Tomppo, E. Selecting estimation parameters for the Finnish multisource National Forest Inventory. *Remote Sens. Environ.* **2001**, *76*, 16–32. [CrossRef]
21. Fassnacht, F.E.; Latifi, H.; Ghosh, A.; Joshi, P.K.; Koch, B. Assessing the potential of hyperspectral imagery to map bark beetle-induced tree mortality. *Remote Sens. Environ.* **2014**, *140*, 533–548. [CrossRef]
22. Kandler, G. The design of the second German national forest inventory. In Proceedings of the Eighth Annual Forest Inventory and Analysis Symposium, Monterey, CA, USA, 16–19 October 2006; CA. Gen. Tech. Report WO-79; McRoberts, R.E., Reams, G.A., van Deusen, P.C., McWilliams, W.H., Eds.; U.S. Department of Agriculture, Forest Service: Washington, DC, USA, 2009; pp. 19–24.
23. Matyssek, R.; Wieser, G.; Calfapietra, C.; de Vries, W.; Dizengremel, P.; Ernst, D.; Jolivet, Y.; Mikkelsen, T.N.; Mohren, G.M.J.; le Thiec, D.; *et al.* Forests under climate change and air pollution: Gaps in understanding and future directions for research. *Environ. Pollut.* **2012**, *160*, 57–65. [CrossRef] [PubMed]
24. Ordóñez Galán, C.; Rodríguez-Pérez, J.R.; Martínez Torres, J.; García Nieto, P.J. Analysis of the influence of forest environments on the accuracy of GPS measurements by using genetic algorithms. *Math. Comput. Model.* **2011**, *54*, 1829–1834. [CrossRef]
25. Mannschatz, T.; Pflug, B.; Borg, E.; Feger, K.-H.; Dietrich, P. Uncertainties of LAI estimation from satellite imaging due to atmospheric correction. *Remote Sens. Environ.* **2014**, *153*, 24–39. [CrossRef]
26. Schaepman-Strub, G.; Schaepman, M.E.; Painter, T.H.; Dangel, S.; Martonchik, J.V. Reflectance quantities in optical remote sensing—Definitions and case studies. *Remote Sens. Environ.* **2006**, *103*, 27–42. [CrossRef]
27. Tang, J.; Xue, Y.; Yu, T.; Guan, Y. Aerosol optical thickness determination by exploiting the synergy of TERRA and AQUA MODIS. *Remote Sens. Environ.* **2005**, *94*, 327–334. [CrossRef]
28. Sinyuk, A.; Dubovik, O.; Holben, B.; Eck, T.F.; Breon, F.-M.; Martonchik, J.; Kahn, R.; Diner, D.J.; Vermote, E.F.; Roger, J.-C.; *et al.* Simultaneous retrieval of aerosol and surface properties from a combination of AERONET and satellite data. *Remote Sens. Environ.* **2007**, *107*, 90–108. [CrossRef]
29. Pause, M.; Lausch, A.; Bernhardt, M.; Hacker, J.; Schulz, K. Improving Soil Moisture Retrieval from Airborne L-band Radiometer Data by Considering Spatially Varying Roughness. *Can. J. Remote Sens.* **2014**, *40*, 15–25. [CrossRef]
30. Pause, M.; Schulz, K.; Zacharias, S.; Lausch, A. Near-surface soil moisture estimation by combining airborne L-band brightness temperature observations and imaging hyperspectral data at the field scale. *J. Appl. Remote Sens.* **2012**, *6*, 1–13.
31. Doxani, G.; Mitraka, Z.; Gascon, F.; Goryl, P.; Bojkov, B.R. A Spectral Unmixing Model for the Integration of Multi-Sensor Imagery: A Tool to Generate Consistent Time Series Data. *Remote Sens.* **2015**, *7*, 14000–14018. [CrossRef]
32. Latifi, H.; Fassnacht, F.E.; Müller, J.; Tharani, A.; Dech, S.; Heurich, M. Forest inventories by LiDAR data: A comparison of single tree segmentation and metric-based methods for inventories of a heterogeneous temperate forest. *Int. J. Appl. Earth Obs. Geoinf.* **2015**, *42*, 162–174. [CrossRef]
33. Tanase, M.A.; Panciera, R.; Lowell, K.; Aponte, C.; Hacker, J.M.; Walker, J.P. Forest Biomass Estimation at High Spatial Resolution: Radar Versus Lidar Sensors. *IEEE Geosci. Remote Sens. Lett.* **2014**, *11*, 711–715. [CrossRef]
34. Karila, K.; Vastaranta, M.; Karjalainen, M.; Kaasalainen, S. Tandem-X interferometry in the prediction of forest inventory attributes in managed boreal forests. *Remote Sens. Environ.* **2015**, *159*, 259–268. [CrossRef]
35. Anderson, M.C.; Norman, J.M.; Kustas, W.P.; Houborg, R.; Starks, P.J.; Agam, N. A thermal-based remote sensing technique for routine mapping of land-surface carbon, water and energy fluxes from field to regional scales. *Remote Sens. Environ.* **2008**, *112*, 4227–4241. [CrossRef]

36. Moran, M.S. Thermal infrared measurement as an indicator of plant ecosystem health. *Therm. Remote Sens. Land Surf. Process.* **2003**, 257–282. [CrossRef]
37. Elatawneh, A.; Wallner, A.; Manakos, I.; Schneider, T.; Knoke, T. Forest Cover Database Updates Using Multi-Seasonal RapidEye Data—Storm Event Assessment in the Bavarian Forest National Park. *Forests* **2014**, *5*, 1284–1303. [CrossRef]
38. Wallner, A.; Elatawneh, A.; Schneider, T.; Knoke, T. Estimation of forest structural information using RapidEye satellite data. *Forestry* **2014**. [CrossRef]
39. Ortiz, S.; Breidenbach, J.; Kändler, G. Early Detection of Bark Beetle Green Attack Using TerraSAR-X and RapidEye Data. *Remote Sens.* **2013**, *5*, 1912–1931. [CrossRef]
40. Pu, R.; Cheng, J. Mapping forest leaf area index using reflectance and textural information derived from WorldView-2 imagery in a mixed natural forest area in Florida, US. *Int. J. Appl. Earth Obs. Geoinf.* **2015**, *42*, 11–23. [CrossRef]
41. Immitzer, M.; Stepper, C.; Böck, S.; Straub, C.; Atzberger, C. Use of WorldView-2 stereo imagery and National Forest Inventory data for wall-to-wall mapping of growing stock. *For. Ecol. Manag.* **2016**, *359*, 232–246. [CrossRef]
42. Torres, R.; Snoeij, P.; Geudtner, D.; Bibby, D.; Davidson, M.; Attema, E.; Potin, P.; Rommen, B.; Floury, N.; Brown, M.; *et al.* GMES Sentinel-1 mission. *Remote Sens. Environ.* **2012**, *120*, 9–24. [CrossRef]
43. Balzter, H.; Cole, B.; Thiel, C.; Schmullius, C. Mapping CORINE Land Cover from Sentinel-1A SAR and SRTM Digital Elevation Model Data using Random Forests. *Remote Sens.* **2015**, *7*, 14876–14898. [CrossRef]
44. Carvalhais, N.; Forkel, M.; Khomik, M.; Bellarby, J.; Jung, M.; Migliavacca, M.; Mingquan, M.; Saatchi, S.; Santoro, M.; Thurner, M.; *et al.* Climate in Terrestrial Ecosystems. *Nature* **2014**, *514*, 213–217. [PubMed]
45. Santoro, M.; Askne, J.; Smith, G.; Fransson, J.E.S. Stem volume retrieval in boreal forests from ERS-1/2 interferometry. *Remote Sens. Environ.* **2002**, *81*, 19–35. [CrossRef]
46. Dotzler, S.; Hill, J.; Buddenbaum, H.; Stoffels, J. The Potential of EnMAP and Sentinel-2 Data for Detecting Drought Stress Phenomena in Deciduous Forest Communities. *Remote Sens.* **2015**, *7*, 14227–14258. [CrossRef]
47. Drusch, M.; del Bello, U.; Carlier, S.; Colin, O.; Fernandez, V.; Gascon, F.; Hoersch, B.; Isola, C.; Laberinti, P.; Martimort, P.; *et al.* Sentinel-2: ESA's Optical High-Resolution Mission for GMES Operational Services. *Remote Sens. Environ.* **2012**, *120*, 25–36. [CrossRef]
48. Clasen, A.; Somers, B.; Pipkins, K.; Tits, L.; Segl, K.; Brell, M.; Kleinschmit, B.; Spengler, D.; Lausch, A.; Förster, M. Spectral Unmixing of Forest Crown Components at Close Range, Airborne and Simulated Sentinel-2 and EnMAP Spectral Imaging Scale. *Remote Sens.* **2015**, *7*, 15361–15387. [CrossRef]
49. Donlon, C.; Berruti, B.; Buongiorno, A.; Ferreira, M.H.; Féménias, P.; Frerick, J.; Goryl, P.; Klein, U.; Laur, H.; Mavrocordatos, C.; *et al.* The Global Monitoring for Environment and Security (GMES) Sentinel-3 mission. *Remote Sens. Environ.* **2012**, *120*, 37–57. [CrossRef]
50. Vuolo, F.; Dash, J.; Curran, P.J.; Lajas, D.; Kwiatkowska, E. Methodologies and uncertainties in the use of the terrestrial chlorophyll index for the sentinel-3 mission. *Remote Sens.* **2012**, *4*, 1112–1133. [CrossRef]
51. Sun, L.; Schulz, K. The Improvement of Land Cover Classification by Thermal Remote Sensing. *Remote Sens.* **2015**, *7*, 8368–8390. [CrossRef]
52. Karlson, M.; Ostwald, M.; Reese, H.; Sanou, J.; Tankoano, B.; Mattsson, E. Mapping Tree Canopy Cover and Aboveground Biomass in Sudano-Sahelian Woodlands Using Landsat 8 and Random Forest. *Remote Sens.* **2015**, *7*, 10017–10041. [CrossRef]
53. Yuan, H.; Ma, R.; Atzberger, C.; Li, F.; Loiselle, S.; Luo, J. Estimating Forest fAPAR from Multispectral Landsat-8 Data Using the Invertible Forest Reflectance Model INFORM. *Remote Sens.* **2015**, *7*, 7425–7446. [CrossRef]
54. Entekhabi, D.; Njoku, E.G.; O'Neill, P.E.; Kellogg, K.H.; Crow, W.T.; Edelstein, W.N.; Entin, J.K.; Goodman, S.D.; Jackson, T.J.; Johnson, J.; *et al.* The soil moisture active passive (SMAP) mission. *Proc. IEEE* **2010**, *98*, 704–716. [CrossRef]
55. Bruscantini, C.A.; Konings, A.G.; Narvekar, P.; McColl, K.A.; Entekhabi, D. L-band radar soil moisture retrieval without ancillary information. *IEEE Trans. Geosci. Remote Sens.* **2015**, *8*, 5526–5540. [CrossRef]
56. Kerr, Y.H.; Waldteufel, P.; Wigneron, J.-P.; Martinuzzi, J.; Font, J.; Berger, M. Soil moisture retrieval from space: The Soil Moisture and Ocean Salinity (SMOS) mission. *IEEE Trans. Geosci. Remote Sens.* **2001**, *39*, 1729–1735. [CrossRef]

57. Major, G.R. Impact of NASA EOS Instrument Data on the Scientific Literature: 10 Years of Published Research Results from Terra, Aqua, and Aura. *Issues Sci. Technol. Librariansh.* **2011**, *4*. [CrossRef]
58. Soudani, K.; le Maire, G.; Dufrêne, E.; François, C.; Delpierre, N.; Ulrich, E.; Cecchini, S. Evaluation of the onset of green-up in temperate deciduous broadleaf forests derived from Moderate Resolution Imaging Spectroradiometer (MODIS) data. *Remote Sens. Environ.* **2008**, *112*, 2643–2655. [CrossRef]
59. Solberg, S.; Riegler, G.; Nonin, P. Estimating Forest Biomass From TerraSAR-X Stripmap Radargrammetrye. *IEEE Trans. Geosci. Remote Sens.* **2015**, *53*, 154–161. [CrossRef]
60. Krieger, G.; Zink, M.; Bachmann, M.; Bräutigam, B.; Schulze, D.; Martone, M.; Rizzoli, P.; Steinbrecher, U.; Walter Antony, J.; de Zan, F.; *et al.* TanDEM-X: A radar interferometer with two formation-flying satellites. *Acta Astronaut.* **2013**, *89*, 83–98. [CrossRef]
61. Boesch, H.; Baker, D.; Connor, B.; Crisp, D.; Miller, C. Global characterization of $CO_2$ column retrievals from shortwave-infrared satellite observations of the Orbiting Carbon Observatory-2 mission. *Remote Sens.* **2011**, *3*, 270–304. [CrossRef]
62. Guanter, L.; Kaufmann, H.; Segl, K.; Foerster, S.; Rogass, C.; Chabrillat, S.; Kuester, T.; Hollstein, A.; Rossner, G.; Chlebek, C.; *et al.* The EnMAP Spaceborne Imaging Spectroscopy Mission for Earth Observation. *Remote Sens.* **2015**, *7*, 8830–8857. [CrossRef]
63. Kraft, S.; del Bello, U.; Bouvet, M.; Drusch, M. FLEX: ESA'S Earth Explorer 8 Candidate Mission. In Proceedings of the 2012 IEEE International Geoscience and Remote Sensing Symposium, Munich, Germany, 22–27 July 2012; pp. 7125–7128.
64. Joiner, J.; Yoshida, Y.; Vasilkov, A.P.; Schaefer, K.; Jung, M.; Guanter, L.; Zhang, Y.; Garrity, S.; Middleton, E.M.; Huemmrich, K.F.; *et al.* The seasonal cycle of satellite chlorophyll fluorescence observations and its relationship to vegetation phenology and ecosystem atmosphere carbon exchange. *Remote Sens. Environ.* **2014**, *152*, 375–391. [CrossRef]
65. Meroni, M.; Rossini, M.; Guanter, L.; Alonso, L.; Rascher, U.; Colombo, R.; Moreno, J. Remote sensing of solar-induced chlorophyll fluorescence: Review of methods and applications. *Remote Sens. Environ.* **2009**, *113*, 2037–2051. [CrossRef]
66. Ho Tong Minh, D.; le Toan, T.; Rocca, F.; Tebaldini, S.; Villard, L.; Rejou-Mechain, M.; Phillips, O.L.; Feldpausch, T.R.; Dubois-Fernandez, P.; Scipal, K.; *et al.* SAR tomography for the retrieval of forest biomass and height: Cross-validation at two tropical forest sites in French Guiana. *Remote Sens. Environ.* **2016**, *175*, 138–147. [CrossRef]
67. Tanase, M.A.; Panciera, R.; Lowell, K.; Tian, S.Y.; Garcia-Martin, A.; Walker, J.P. Sensitivity of L-Band Radar Backscatter to Forest Biomass in Semiarid Environments: A Comparative Analysis of Parametric and Nonparametric Models. *IEEE Trans. Geosci. Remote Sens.* **2014**, *52*, 4671–4685. [CrossRef]
68. Boesch, H.; Vogel, L.; Bovensmann, H.; Buchwitz, M.; Reuter, M. Characterization of $CO_2$ and $CH_4$ Sunglint Retrievals from CarbonSat. *Geophys. Res. Abstr.* **2014**, *16*, 3024.
69. Schaepman, M.E. Spectrodirectional remote sensing: From pixels to processes. *Int. J. Appl. Earth Obs. Geoinf.* **2007**, *9*, 204–223. [CrossRef]
70. Laurent, V.C.E.; Verhoef, W.; Clevers, J.G.P.W.; Schaepman, M.E. Inversion of a coupled canopy-atmosphere model using multi-angular top-of-atmosphere radiance data: A forest case study. *Remote Sens. Environ.* **2011**, *115*, 2603–2612. [CrossRef]
71. Lausch, A.; Pause, M.; Doktor, D.; Preidl, S.; Schulz, K. Monitoring and assessing of landscape heterogeneity at different scales. *Environ. Monit. Assess.* **2013**, *185*, 9419–9434. [CrossRef] [PubMed]
72. Sandberg, G.; Ulander, L.M.H.; Fransson, J.E.S.; Holmgren, J.; le Toan, T. L- and P-band backscatter intensity for biomass retrieval in hemiboreal forest. *Remote Sens. Environ.* **2011**, *115*, 2874–2886. [CrossRef]
73. Ali, A.M.; Darvishzadeh, R.; Skidmore, A.K.; van Duren, I.; Heiden, U.; Heurich, M. Estimating leaf functional traits by inversion of PROSPECT: Assessing leaf dry matter content and specific leaf area in mixed mountainous forest. *Int. J. Appl. Earth Obs. Geoinf.* **2016**, *45*, 66–76. [CrossRef]
74. Wang, Z.; Skidmore, A.K.; Darvishzadeh, R.; Heiden, U.; Heurich, M.; Wang, T. Leaf Nitrogen Content Indirectly Estimated by Leaf Traits Derived From the PROSPECT Model. *IEEE J. Sel. Top. Appl. Earth Obs. Remote Sens.* **2015**, *8*, 1–11. [CrossRef]
75. Jacquemoud, S.; Baret, F. PROSPECT: A model of leaf optical properties spectra. *Remote Sens. Environ.* **1990**, *34*, 75–91. [CrossRef]

76. Soudani, K.; Hmimina, G.; Delpierre, N.; Pontailler, J.Y.; Aubinet, M.; Bonal, D.; Caquet, B.; de Grandcourt, A.; Burban, B.; Flechard, C.; *et al.* Ground-based Network of NDVI measurements for tracking temporal dynamics of canopy structure and vegetation phenology in different biomes. *Remote Sens. Environ.* **2012**, *123*, 234–245. [CrossRef]
77. Jacquemoud, S.; Verhoef, W.; Baret, F.; Bacour, C.; Zarco-Tejada, P.J.; Asner, G.P.; François, C.; Ustin, S.L. PROSPECT+SAIL models: A review of use for vegetation characterization. *Remote Sens. Environ.* **2009**, *113*, S56–S66. [CrossRef]
78. Verhoef, W. Light scattering by leaf layers with application to canopy reflectance modeling: The SAIL model. *Remote Sens. Environ.* **1984**, *16*, 125–141. [CrossRef]
79. Powell, S.L.; Cohen, W.B.; Healey, S.P.; Kennedy, R.E.; Moisen, G.G.; Pierce, K.B.; Ohmann, J.L. Quantification of live aboveground forest biomass dynamics with Landsat time-series and field inventory data: A comparison of empirical modeling approaches. *Remote Sens. Environ.* **2010**, *114*, 1053–1068. [CrossRef]
80. Hall, R.J.; Skakun, R.S.; Arsenault, E.J.; Case, B.S. Modeling forest stand structure attributes using Landsat ETM+ data: Application to mapping of aboveground biomass and stand volume. *For. Ecol. Manag.* **2006**, *225*, 378–390. [CrossRef]
81. Owe, M.; de Jeu, R.; Walker, J. A methodology for surface soil moisture and vegetation optical depth retrieval using the microwave polarization difference index. *IEEE Trans. Geosci. Remote Sens.* **2001**, *39*, 1643–1654. [CrossRef]
82. Rahman, M.M.; Csaplovics, E.; Koch, B. Satellite estimation of forest carbon using regression models. *Int. J. Remote Sens.* **2008**, *29*, 6917–6936. [CrossRef]
83. De Rosnay, P.; Drusch, M.; Wigneron, J.-P.; Holmes, T.; Balsamo, G.; Boone, A.; Rudiger, C.; Calvet, J.-C.; Kerr, Y. Soil Moisture Remote Sensing for Numerical Weather Prediction: L-Band and C-Band Emission Modeling Over Land Surfaces, the Community Microwave Emission Model (CMEM). In Proceedings of the IGARRS IEEE International Geoscience & Remote Sensing Symposium, Boston, FL, USA, 6–11 July 2008.
84. De Rosnay, P.; Drusch, M.; Boone, A.; Balsamo, G.; Decharme, B.; Harris, P.; Kerr, Y.; Pellarin, T.; Polcher, J.; Wigneron, J.-P. AMMA Land Surface Model Intercomparison Experiment coupled to the Community Microwave Emission Model: ALMIP-MEM. *J. Geophys. Res.* **2009**, *114*, D05108. [CrossRef]
85. Jagdhuber, T.; Hajnsek, I.; Papathanassiou, K.P.; Bronstert, A. Soil moisture estimation using a multi-angular modified three component polarimetric decomposition. *IEEE Int.* **2009**, *5*, 5–8.
86. Jia, L.; Li, Z.; Menenti, M.; Pasteur, U.L.; Brant, B.S. Modeling of TIR radiative transfer in the soil—Vegetation—Atmosphere system: Sensitivity to soil water content and LAI and simulation of complex scenes. In Proceedings of the IEEE International Geoscience and Remote Sensing Symposium, Toronto, ON, Canada, 24–28 June 2002; pp. 39–41.
87. Minacapilli, M.; Ciraolo, G.; Iovino, M. Thermal Inertia Modeling for Soil Surface Water Content Estimation: A Laboratory Experiment. *Soil Sci. Soc. Am. J.* **2012**, *76*, 92–100. [CrossRef]
88. Lausch, A.; Schmidt, A.; Tischendorf, L. Data mining and linked open data—New perspectives for data analysis in environmental research. *Ecol. Model.* **2015**, *295*, 5–17. [CrossRef]
89. Lausch, A.; Heurich, M.; Gordalla, D.; Dobner, H.J.; Gwillym-Margianto, S.; Salbach, C. Forecasting potential bark beetle outbreaks based on spruce forest vitality using hyperspectral remote-sensing techniques at different scales. *For. Ecol. Manag.* **2013**, *308*, 76–89. [CrossRef]
90. Trombetti, M.; Riano, D.; Rubio, M.; Cheng, Y.; Ustin, S. Multi-temporal vegetation canopy water content retrieval and interpretation using artificial neural networks for the continental USA☆. *Remote Sens. Environ.* **2008**, *112*, 203–215. [CrossRef]
91. Doktor, D.; Lausch, A.; Spengler, D.; Thurner, M. Extraction of Plant Physiological Status from Hyperspectral Signatures Using Machine Learning Methods. *Remote Sens.* **2014**, *6*, 12247–12274. [CrossRef]
92. Kimes, D.S.; Ranson, K.J.; Sun, G. Inversion of a forest backscatter model using neural networks. *Int. J. Remote Sens.* **1997**, *18*, 2181–2199. [CrossRef]
93. Vereecken, H.; Huisman, J.A.; Bogena, H.; Vanderborght, J.; Vrugt, J.A.; Hopmans, J.W. On the value of soil moisture measurements in vadose zone hydrology: A review. *Water Resour. Res.* **2008**, *44*. [CrossRef]
94. Eitel, J.U.H.; Vierling, L.A.; Magney, T.S. A lightweight, low cost autonomously operating terrestrial laser scanner for quantifying and monitoring ecosystem structural dynamics. *Agric. For. Meteorol.* **2013**, *180*, 86–96. [CrossRef]

95. Felbermeier, B.; Hahn, A.; Schneider, T.; München, T.U.; Management, F. *Study on User Requirements for Remote Sensing Applications in Forestry*; Copernicus Publications: Göttingen, Germany, 2010; Volume 38, pp. 210–212.
96. Coopersmith, E.J.; Cosh, M.H.; Daughtry, C.S. T. Field-scale moisture estimates using COSMOS sensors: A validation study with temporary networks and Leaf-Area-Indices. *J. Hydrol.* **2014**, *519*, 637–643. [CrossRef]
97. Ojha, T.; Misra, S.; Raghuwanshi, N.S. Wireless sensor networks for agriculture: The state-of-the-art in practice and future challenges. *Comput. Electron. Agric.* **2015**, *118*, 66–84. [CrossRef]
98. Akyildiz, I.F.; Stuntebeck, E.P. Wireless underground sensor networks: Research challenges. *Ad Hoc Netw.* **2006**, *4*, 669–686. [CrossRef]
99. Döner, Ç.; Şimşek, G.; Yıldırım, K.S.; Kantarcı, A. Forest Fire Detection with Wireless Sensor Networks. Available online: http://artemis-new.cslab.ece.ntua.gr:8080/jspui/handle/123456789/6788 (accessed on 1 June 2016).
100. Zreda, M.; Desilets, D.; Ferré, T.P.A.; Scott, R.L. Measuring soil moisture content non-invasively at intermediate spatial scale using cosmic-ray neutrons. *Geophys. Res. Lett.* **2008**, *35*, L21402. [CrossRef]
101. Baatz, R.; Bogena, H.R.; Hendricks Franssen, H.-J.; Huisman, J.A.; Montzka, C.; Vereecken, H. An empirical vegetation correction for soil water content quantification using cosmic ray probes. *Water Resour. Res.* **2015**, *51*, 2030–2046. [CrossRef]