

Review

# Understanding Forest Health with Remote Sensing -Part I—A Review of Spectral Traits, Processes and Remote-Sensing Characteristics

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Academic Editors: Lars T. Waser, Clement Atzberger and Prasad S. Thenkabail

Received: 6 September 2016; Accepted: 5 December 2016; Published: 18 December 2016

**Abstract:** Anthropogenic stress and disturbance of forest ecosystems (FES) has been increasing at all scales from local to global. In rapidly changing environments, in-situ terrestrial FES monitoring approaches have made tremendous progress but they are intensive and often integrate subjective indicators for forest health (FH). Remote sensing (RS) bridges the gaps of these limitations, by monitoring indicators of FH on different spatio-temporal scales, and in a cost-effective, rapid, repetitive and objective manner. In this paper, we provide an overview of the definitions of FH, discussing the drivers, processes, stress and adaptation mechanisms of forest plants, and how we can observe FH with RS. We introduce the concept of spectral traits (ST) and spectral trait variations (STV) in the context of FH monitoring and discuss the prospects, limitations and constraints. Stress, disturbances and resource limitations can cause changes in FES taxonomic, structural and functional diversity; we provide examples how the ST/STV approach can be used for monitoring these FES characteristics. We show that RS based assessments of FH indicators using the ST/STV approach is a competent, affordable, repetitive and objective technique for monitoring. Even though the possibilities for observing the taxonomic diversity of animal species is limited with RS, the taxonomy of forest tree species can be recorded with RS, even though its accuracy is subject to certain constraints. RS has proved successful for monitoring the impacts from stress on structural and functional diversity. In particular, it has proven to be very suitable for recording the short-term dynamics of stress on FH, which cannot be cost-effectively recorded using in-situ methods. This paper gives an overview of the ST/STV approach, whereas the second paper of this series concentrates on discussing in-situ terrestrial monitoring, in-situ RS approaches and RS sensors and techniques for measuring ST/STV for FH.

**Keywords:** forest health; forest ecosystem; earth observation; remote sensing; traits; spectral traits (ST); spectral trait variations (STV); non-spectral traits (N-ST)

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## 1. Introduction

About one third of the Earth's land surface is covered by forests [1]. They provide important ecosystem services, such as carbon sequestration, habitat for species that contribute to maintaining

biodiversity, mitigating climate change and the ability to filter and maintain water resources [2,3]. However, forests are facing numerous threats and stress factors such as deforestation [4], drought [5] climate change [6], invasive species [7] susceptibility to pests and pathogens [8,9], air pollution [10], disturbance-induced mortality from fire, water or windthrow [8] land-use changes [11] or unsustainable management [12].

The conservation and improvement of key forest functions is therefore imperative, as healthy forests are more stable and resilient to various stress types, disturbance and resource limitations. Given the global importance of forests and the expected increase in threats, the implementation of sustainable forest management is vital to our future. It therefore follows that forest ecosystem health has gained popular attention over recent years with growing concerns about air pollution, acid rain, global climate change, population growth, and long-term resource management. In response to these environmental concerns and to current legislative and policy directions, federal and state agencies worldwide have been working together to develop programs for monitoring and reporting on the status and trends of forest ecosystem health. The United States national Forest Health Monitoring (FHM) program, for example, was established to accomplish this objective [13,14]. The FOREST EUROPE program of the European Union, the International Co-operative Programme on Assessment and Monitoring of Air Pollution Effects on Forests (EU/ICP Forests) [15], and the Chinese national program on ecological functions [16] are large programs for monitoring and assessing forest health.

Numerous definitions of forest health exist, ranging from the recording of economic-related indicators [17] to ecological-function indicators that preserve resilience and stability [3,18]. Kolb et al., [18] name four qualitative indicators of FH: (i) “The physical environment, biotic resources, and trophic networks to support productive forest during at least some seral stages; (ii) The resistance to catastrophic change and/or the ability to recover from catastrophic change at the landscape level; (iii) A functional equilibrium between the supply and demand of essential resources; and (iv) a diversity of seral stages and stand structures that provide habitat for many native species and all essential ecosystem processes”. Trumbore et al., [2], on the other hand, characterised FH as a “mosaic of successional patches representing all stages of the natural range of disturbance and recovery”. On the tree scale, health is often defined as the absence of disease or damage, but if this concept is applied to forest stands or landscapes, the indicators of FH are more difficult to assess [2]. In forestry, widely used health indicators on the stand level are yield measures or metrics representing the health status of tree crowns. Examples include the visible assessment of infestation levels, leaf defoliation, leaf chlorosis and other discolouration, dead branches, trunk damage, or the quantitative assessment of canopy damage or deterioration using metrics such as leaf area index, crown closure, numbers and volume of standing, dead and fallen trees. However, for a comprehensive description of FH, such an indicator set should also include utilitarian as well as ecosystem indicators, which have to be implemented across different spatial scales. The above definition (absence of disease or damage) is essentially binary, but in practice it is desired to assess FH on an interval or ratio scale, and the definition of such scales often includes subjective elements.

Altered structures, functions or taxonomy are present on all spatial levels of forest diversity—from the molecular level to the landscape level and biomes. Therefore, a holistic approach as well as a global strategy are imperative when it comes to monitoring FH and defining the indicators that need to be observed [9]. To assess FH and to understand the influence of different stress factors, a monitoring system which combines in-situ terrestrial observations and remote-sensing technologies is crucial [2,9,19]. While in-situ terrestrial forest monitoring is generally applied on a plot level, RS approaches provide wall-to-wall information on multiple temporal and spatial scales [3,20,21].

There are a wide range of RS applications to measure FH indicators [22], while at the same time the number and availability of high quality RS data is constantly growing [23–27]. Furthermore, there are numerous methodology approaches that use RS technologies for long-term monitoring of FH [28–31]. In recent years, the development of RS technologies and applications has gained advantage from the opening of large RS-data archives to the public (e.g., Landsat) [32,33]), including entire space missions

developed for the public domain (e.g., the Sentinel Missions of the European Space Agency (ESA) [34]) as well as the development of open source tools for processing RS data [35]. As a consequence of such developments it can be expected that they will lead to a tremendous impetus in the use of RS techniques for understanding FH [33].

Generally, the spatial, spectral and thematic resolution that can be reliably assessed by RS decreases as the required spatial extent increases. Local to regional FH assessments can use sensors with small area coverage and high spatial resolution, while global assessments are conducted at coarse scales. Recently developed sensors such as Worldview-3 provide more than 10 spectral bands over the visible-near infrared-short wave infrared regions of the spectrum with very high spatial resolution (0.3–2.5 m pixel size). However, their limited coverage per image (10–20 km swath) makes this type of imagery only suitable for local and regional mapping. Lower spatial resolution satellite-based hyperspectral, polarimetric, RADAR and LiDAR sensors have been developed and launched and more are under development for the near future. These have the potential to significantly improve the information content relevant to FH assessment over broader spatial scales.

In monitoring FH, in-situ forest condition surveys and RS based approaches are fundamentally different. As a physically-based system, RS follows regulations, mechanisms and constraints that have to be in the context of FH. The goal of this paper is to demonstrate how RS can be used to monitor and understand FH. To illustrate this, we consider the following research questions: (i) How can forest health be defined? What are its mechanisms, drivers and processes? On which spatial and temporal scales should indicators of forest health be measured? (ii) Why and under which conditions are remote-sensing approaches suitable for observing indicators of forest health? (iii) What is the concept of spectral traits (ST) and spectral trait variations (STV) for quantifying, monitoring and assessing forest health using remote sensing? Through addressing these questions, we discuss the usability of the ST/STV approach to measure stress and disturbances in taxonomic, structural and functional diversity of FES.

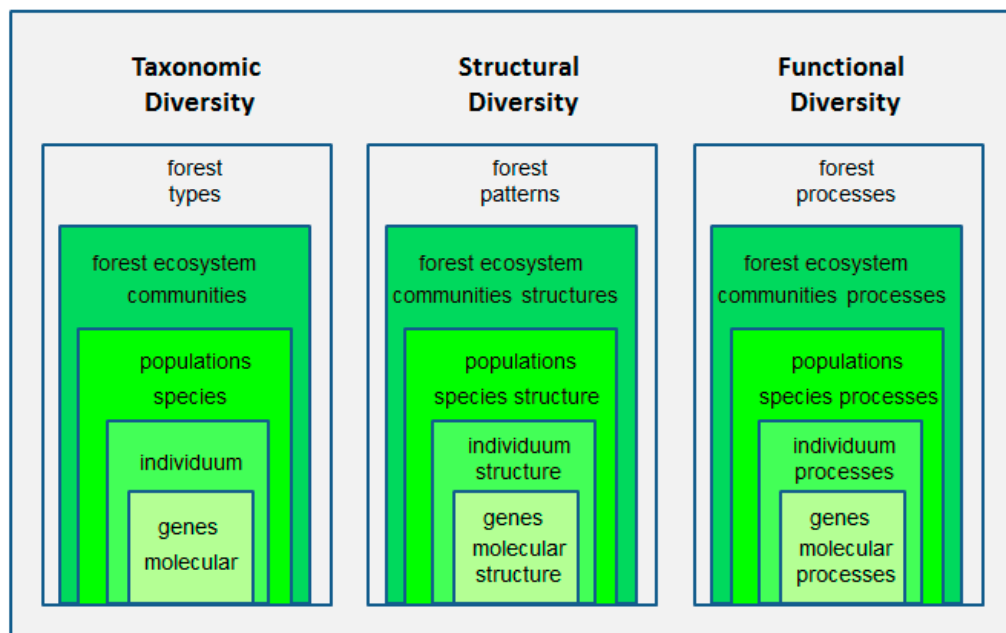
## 2. Understanding Forest Health

In order to quantify and assess FH, a clear and unambiguous definition is needed. One approach is to understand FH as a component of FES. A stable ecosystem can be characterized by its high resistance and resilience to disturbance. The greater its resilience, the quicker the system can return to its initial state following an external disturbance and any resulting changes to its systemic nature. The greater its resistance, the greater the system's capability of withstanding the negative impacts from external influences [36]. Those ecosystems that are more complex and more diverse (more species, communities and food chains) are usually more stable (given a few exceptions). Positive feedbacks of biodiversity on the functionality of ecosystems have been analysed in different biodiversity-ecosystem functioning (BEF) experiments [37–39]. The BEF experiments are primarily concerned with fast-growing primary producer systems [40,41] whereas interactions or disturbances to slow-growing FES on ecosystem services such as climate regulation, carbon storage, water filtration or erosion control without RS methods are still insufficiently understood [42–44]. A proper understanding of FH, as well as its stability or instability requires knowledge of the following factors: (i) the characteristics of forest ecosystem diversity—taxonomy, structure and functional diversity as well as their meaning for FH; (ii) the influence of phylogenetic information from forest species, which defines their potential for adaptation and reaction to multiple stress factors; (iii) drivers, processes and their characteristics, which affect FH; and (iv) the time frame of the monitoring conducted.

### 2.1. Characteristics of Forest Ecosystem Diversity

To assess FH, the characteristics of FES diversity, the taxonomic, structural and functional diversity provide us with important indications of adaptation mechanisms, stress or irreversible changes. FES are characterized by their different organizational levels such as the molecular, genetic, individual, species, population, community, ecosystem, landscape and biome levels, which consist of three

essential characteristics (Figure 1). Taxonomic diversity of FES refers to the diversity of biotic entities of forest ecosystems, structural diversity explains the arrangement and distribution (composition and configuration) of the structure of biotic entities in FES, and functional diversity describes the realized ecological functions and processes in FES. These characteristics help us to understand the importance of taxonomy, structure, functions and processes for maintaining entire forest systems and the shifts, disturbances and crucial changes that can lead to disturbances or irreversible impairment of FES [45,46].



**Figure 1.** The essential characteristics of diversity in forest ecosystems—Taxonomic Diversity, Structural Diversity and Functional Diversity on different levels of organization in terms of the biotic features of the forest—molecular, genetic, individual, species, populations, communities, biomes, ecosystems and landscapes (modified after Noss [45] and Lausch [46]).

## 2.2. Drivers and Process Effects on Forest Health

While the taxonomic and phylogenetic structures of the forest determine its resistance and resilience, it is the characteristics of the drivers and processes that determine the impact of the disturbances. In FES, there are multiple levels of interacting biological entities, which underlie abiotic and anthropogenic processes and pressures like deforestation, N and S depositions, land-use, or climate change, which causes extreme events such as heavy precipitation, high temperatures or high ozone concentrations. All of these can affect FH in a different way at different spatial and temporal scales (Figure 1). It is not just the process or driver itself that is crucial for understanding the effect on FH, but also its characteristics that determine the levels (e.g., genetic, molecular or community), direction and reversibility of the effects. Important process characteristics for FH include the range, scope, duration, intensity, continuity, dominance, or overlap [47], which can alter the taxonomic, structural or functional diversity of FES on different spatio-temporal scales.

Land-use changes, deforestation or fire can alter forest traits in their overall complexity [11,48–51]. Furthermore, anthropogenic management can lead to a change in the spectrum of species and, thus, also in plant and plant community traits over space and time. When using RS for monitoring, we assume that these alterations are reflected in changes of the spectral response of RS signals. Garnier et al., [50] showed a direct relationship between plant characteristics (e.g., plant height and flowering phenology) as a response to land-use changes and disturbance regimes. The short and long-term dynamics resulting from disturbance in soil and vegetation can also lead to adaptations

and often systematic, complex and sometimes even irreversible shifts in species compositions, configurations or distributions [52]. Moreover, deforestation, clearing, harvesting and disturbances often cause a complete and/or irreversible loss of entire forest communities and ecosystems, producing complex changes in the characteristics of the species or communities [50].

### 2.3. Stress and Adaptation in FES

From an evolutionary perspective, FES constitute the final stage of succession and thus the longest lived and largest plant species on land [39]. In fast-growing primary producer systems, interactions could be found between biodiversity and the functions, stability, vitality or health of ecosystems [39] whereas these are difficult to measure and understand in long lived FES. In their phylogenetic evolution, forests have developed adaptation strategies and reaction mechanisms to multiple-stress factors. Due to the long life of trees, there is still little knowledge about the length of time and the extent to which trees have to be impaired by stress factors in order to be able to observe visible changes in the branching geometry, necrobiotic processes, leaf production and tree functional processes [53]. Forest ecosystems can therefore appear to be stable over very long periods of time, when in reality they are irreversibly impaired. Lindenmayer and Likens [54] showed that species are not equally sensitive to environmental stress factors and changes. In addition to the species [55], a number of other factors can be crucial, including age [56] or the occupation of different ecological niches. Research work conducted after the nuclear reactor disaster from Chernobyl has provided important insights into the stress behaviour of different species. It was proven that intensive levels of exposure to radioactivity led to changes in trees, but the intensity and direction of the reaction depended on the tree species [57]. Furthermore, the ability of different tree species to adapt to expected climate change is still very much unclear [55].

At the same time, the effects of multiple stress factors on FH must be understood. It could be proven that a change in complex stress factors can have an influence in changing the respective system functions. Thus, when faced with changes from multiple stress factors, species and populations are able to adapt their respective functions or to take on complementary functions in the ecosystem [58]. To really understand FH in all of its complexity, the implementation of RS technologies as a global strategy for monitoring FH is imperative, which firstly entails understanding the basic principles, limitations and constraints of RS for monitoring FH.

## 3. Quantifying Forest Health Using RS

There is a wide range of remote sensing sensors, models and applications that deal with measuring, explaining and predicting FH [7,29,31,59–63]. Table 1 summarizes the RS applications, which can only be partially described in this paper. In addition to the sensors and platforms used, FH indicators are also categorized as indicators of taxonomic, functional or structural diversity of FES.

The ability to monitor FH indicators with RS data is dependent on the following factors: (i) the characteristics of forest traits and the shape, density and distribution of forest traits in space and time; (ii) the spatial, spectral, radiometric, angular and temporal resolutions of RS sensors or multi-sensor systems; (iii) the choice of the modelling technique (classification or biophysical/chemical variable estimation) and entity representation (pixel-based or (geographic) object-based); and (iv) how well the RS algorithm and its assumptions fit the RS data and the plant traits and trait variations in FES.

**Table 1.** Spectral plant traits of forest health quantified by RS technologies.

Spectral Traits (ST) of Forest Ecosystems	Aspects of Diversity in FES: Taxonomic Diversity—TD Structural Diversity—ST Functional Diversity—FD	Reference
<b>Biochemical-Biophysical ST</b>		
Pigment content (chlorophyll a,b, $\alpha,\beta$ Carotene, Xanthophyll)	ST, FD	[64–74]
Nitrogen	ST, FD	[27,70,72,75–83]
Phosphorus content	ST, FD	[27,72,82,84–86]
Lignin	ST, FD	[68,72,82,87–90]
Cellulose	ST, FD	[72,82,90]
Phenole	ST, FD	[82,91]
Plant water content	ST, FD	[72,92–97]
Wax, Starch, Sugar	ST, FD	[72,98–103]
Carbon content	ST, FD	[104–107]
<b>Phenotypical ST</b>		
Tree height	ST, FD	[108–115]
Tree crown size	ST, FD	[110,114,116–120]
<b>Physiognomic-Morphological ST</b>		
Leaf size, form, type, leaf anatomy, leaf optical properties, leaf wettability traits	ST, FD	[121–124]
Leaf dray matter content (LDMC)	ST, FD	[63,87,125–130]
Specific leaf area (SLA)	ST, FD	[64,76,121,123,126,131]
Leaf mass per area (LMA)	ST, FD	[27,72,82,132–135]
Leaf carbon content (LCC)	ST, FD	[104–107]
Leaf nitrogen content (LNC)	ST, FD	[27,72,78–83,87,136]
Leaf phosphorus content (LPC)	ST, FD	[27,72,82,84–86]
Leaf pigment content	ST, FD	[64–72,137,138]
Leaf water content	ST, FD	[72,92–97,138]
Wood, stem density, timber volume	ST, FD	[115,139–145]
<b>Physiological and Functional ST</b>		
Photosynthesis, photosynthesis pathway, chlorophyll fluorescence	FD	[146–157]
Carbon sequestration	FD	[106,158–169]
Evapotranspiration	FD	[170–176]
Leaf respiration	FD	[177–182]
<b>Phenology and senescence ST</b>		
Leaf phenology type, leaf age, leaf development	FD	[183–189]
Plant and canopy phenology	FD	[96,190–199]
Flower mapping (Pollination types)	TD, ST, FD	[130,200–205]
<b>Stress-Adaptation and Disturbance ST</b>		
Ecological strategy types, plant functional types (PFT), Ellenberg indicator values	TD, ST, FD	[206–211]
Naturalness, intact forest landscape, Monitoring of protected areas, conservation and landscapes, habitat quality, forest health index	ST, FD	[212–216]
Damage, disturbances (fire, water, storm, fallen tree, dead wood), deforestation, degradation, resource limitations	ST, FD	[114,131,217–229]
Damage, disturbances by species, defoliating and tree mortality insects, parasites, forest insect outbreaks and pest damage (e.g., bark beetles; pine beetles)	ST, FD	[53,60,230–240]
Forest recovery	ST, FD	[241–250]
<b>Chorology, Distribution and Dispersalt ST</b>		
Gradient traits (climate, soil, water, altitude, biotic, biochemical)	ST, FD	[101,103,124,251–254]
<b>Structural ST</b>		
Spatial distribution, configuration patterns, structure, heterogeneity, homogeneity, diversity (alpha, beta, gamma diversity), abundance, Connectivity, neighbourhood relationship, area, density, size, shape, extent of forest areas; Spatial distribution of biochemical ST, phylogenetic ST, individual, forest tree species, communities, forest ecosystem, forest types	ST, FD	[27,84,89,115,142,143,187,255–266]
Fragmentation	ST, FD	[267–272]
2.5 D/3 D architecture & layering, Canopy volume	ST, FD	[74,110,113,257,273–283]
Leaf Area Index (LAI)	ST, FD	[131,284–292]

Table 1. Cont.

Spectral Traits (ST) of Forest Ecosystems	Aspects of Diversity in FES: Taxonomic Diversity—TD Structural Diversity—ST Functional Diversity—FD	Reference
<b>Aggregated ST</b>		
Net Primary Production (NPP)	FD	[6,293–302]
Fraction of Photosynthetically Active Radiation (fPAR)	FD	[287,292,303–309]
Biomass	ST, FD	[143,167,255,298,310–316]
Scaling traits	TD, ST, FD	[317,318]
Phylogenetic information of traits	TD, ST, FD	[89,319]
<b>Additional Indicators of Forest Health</b>		
<b>Animals</b>		
Animal species—direct detection, GPS tracking (e.g., birds, wildebeest, deer storks, cranes, gulls, geese, lynx, bear, deer)	TD	[46,320–332]
Modelling of animal and forest plant species behaviour (e.g., birds, chimpanzee, bison, cattle, grizzly bear, wild dogs, deer, lions, forest tree cover)	TD, ST, FD	[46,320–322,333–340]
<b>Forest Vegetation (Individual, Plant, Population, Community)</b>		
Tree species discrimination, tropical forest types, dominant species, and mapping of functional guilds	TD	[64,134,210,274,341–353]
Invasive species	TD	[76,335,354–361]
<b>Shifts of Traits, Plants, Populations, Communities of FES</b>		
Shifting biochemical traits (photosynthesis respiration, plant productivity, phenology, growing season length, variation in carbon dioxide exchange and carbon balance, greening response)	ST, FD	[77,82,84,162,191,194,197,362,363]
Shifts in plants, populations, communities	ST, FD	[364,365]
Forest inventory indicators	ST, FD	[366–372]
Tree age, forest age structure, forest stand age	ST, FD	[283,373–375]
Deadwood	ST, FD	[131,224,376–378]
Defoliation	ST, FD	[379–385]
Drought and heat induced tree mortality, drought-stress	ST, FD	[92,173,386–390]
Forest monitoring, forest change Land-use and land cover changes (LULC)	ST, FD	[62,131,314,391–408]

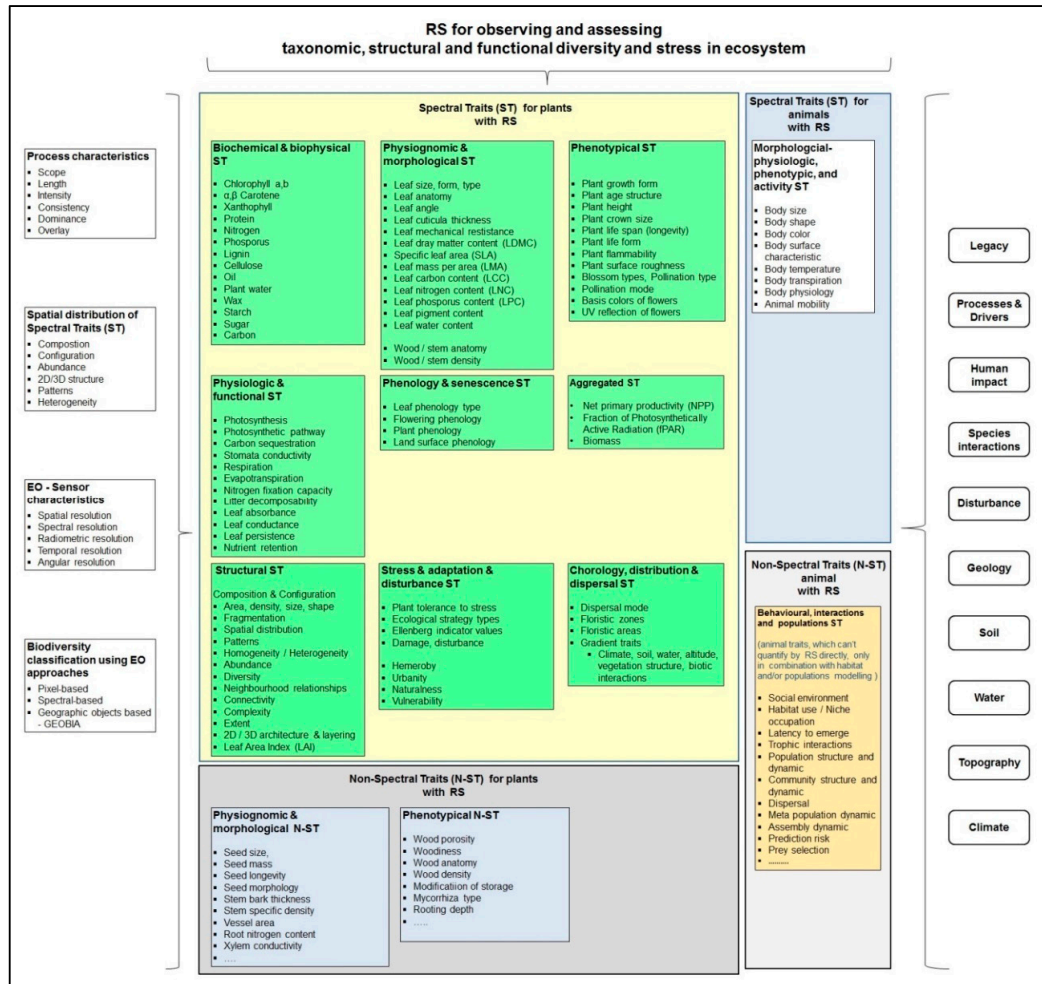
### 3.1. Spectral Traits & Spectral Trait Variation Paradigms for Quantifying Forest Health Using RS

RS technology can only record entities of FH based on physical characteristics. This means that the reflectance and scattering properties in individuals, plants, communities, habitats and biomes are “based on principles of spectroscopy across the electromagnetic spectrum from visible to microwave bands” [137]. The use of RS technology with optical, thermal, active and passive RS to record indicators of FH follows a specific characteristic and is subject to specific parameters that significantly influence quality as well as reproducibility (Figures 2–4).

**Step 1:** Remote sensors record the amount of electromagnetic radiance at the sensor in different wavebands and this radiance represents the traits of abiotic and biotic surfaces from which the radiance emanated. Biotic traits are biochemical, physiological, morphological, structural, phenological or functional characteristics of plants, populations or communities [46,409–411]. With the help of biotic traits, we are able to describe, explain and predict (1) why forest plants and communities “live where they do” [412]; and (2) how forest plants respond to different natural and anthropogenic processes, drivers, stress factors and resource limitations. Furthermore, traits form the only link between in-situ terrestrial forest monitoring approaches and RS approaches to quantify and understand indicators of FH.

Not all of the biotic traits which are basically used in in-situ species trait approaches [410,413] can be detected by RS [137,414]. Therefore, traits that can be recorded using RS are in contrast to the in-situ species trait approaches, referred to as “Spectral Traits” (ST) and “Spectral Trait Variations” (STV) [46]. Traits that cannot be recorded using RS are referred to as “Non-Spectral Traits” (N-ST, Figures 2 and 3). N-ST are for example: (i) when the traits are underground or when they cannot be detected by a given

sensor, such as forest undergrowth or roots (i.e., the type of mycorrhiza and rooting depth (Figure 3), seed size, seed longevity); or (ii) when current RS characteristics (the spatial, spectral, radiometric, angular or temporal resolution of the sensor or multi-sensor RS techniques) are not able to record the traits either directly or indirectly or have not been detected yet.



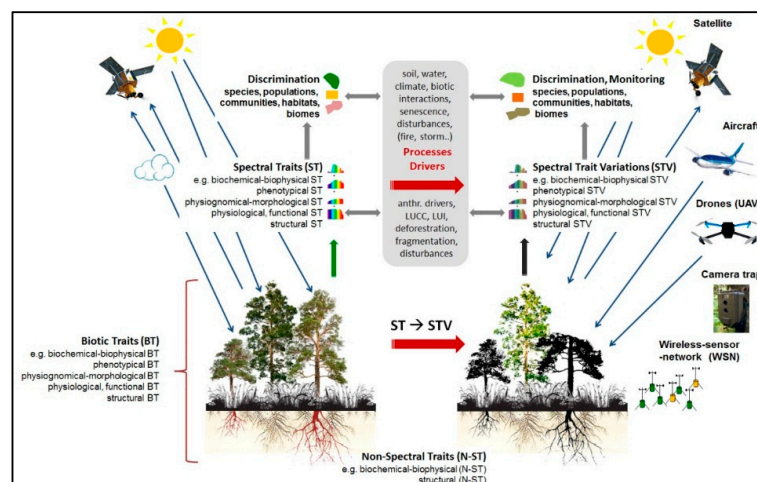
**Figure 2.** Spectral traits (ST) and Non-Spectral Traits observing and assessing taxonomic, structural and functional diversity and stress in ecosystems (modified after Lausch et al., [46]).

The definitions of Spectral Traits (ST), Non-Spectral Traits (N-ST) and Spectral Trait Variations (STV) for plants, populations and communities are as follows:

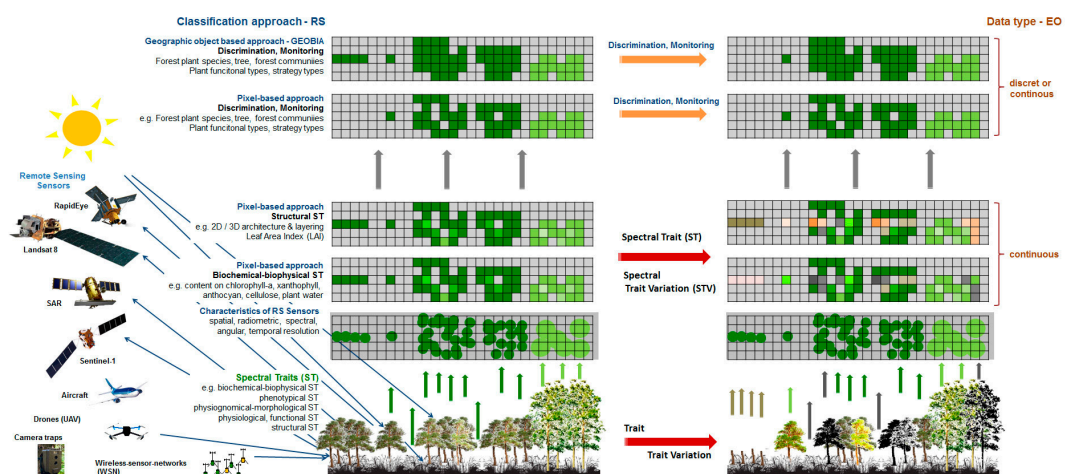
- ST are anatomical, morphological, biochemical, biophysical, physiological, structural, phenological or functional, etc. characteristics of plants, populations and communities that are influenced by phylogenetic, taxonomic, populations and communities characteristics, which can be directly or indirectly recorded using remote-sensing techniques in space.
- N-ST are anatomical, morphological, biochemical, biophysical, physiological, structural, phenological or functional, etc. characteristics of plants, populations and communities that are influenced by phylogenetic, taxonomic, populations and communities characteristics, which cannot be directly or indirectly recorded using remote-sensing techniques in space.
- STV are changes to Spectral Traits (ST) in terms of physiology, senescence and phenology, but also caused by stress, disturbances and the resource limitations of plants, populations and communities, which can be directly or indirectly recorded by remote-sensing techniques in space and over time.



**Step 2:** In addition to recording and quantifying spectral traits using RS, taxonomically different species, populations, communities, habitats or biomes of FES (Figure 2) can be distinguished and monitored with RS if the biochemical, biophysical, morphometric, geometric, morphological or functional spectral traits among forest species or communities differ. If it is not possible to distinguish the spectral traits of the species or communities, then processes in seasonal changes of the species like senescence, phenology, physiological changes (gas exchange, photosynthetic activity or evapotranspiration, changes in 3D geometry), changes in biomass or seasonal changes in geometry can help with this distinction. Other supporting information may also aid this process, including the ability to identify traits against the soil background, the filling of specific ecological niches, resource constraints, specific adaptation mechanisms or ecological strategy types. The spatial composition and configuration such as the distribution, size, shape, aggregation and extent of forest spectral traits also play a crucial role when it comes to distinguishing among forest species.



**Figure 3.** Quantifying spectral traits (ST) and spectral traits variations (STV) and their interactions with drivers and processes to record and monitor FH with RS (modified after Lausch et al., [46]).



**Figure 4.** Remote sensing—a physically-based system, which records indicators of FH in two consecutive steps: Step 1 records spectral traits (ST) and spectral trait variations (STV); Step 2 distinguishes species, populations, communities and biomes of FES depending on the spatial, spectral, radiometric, angular and temporal resolution of the RS techniques, the distribution of ST/STV in space and their temporal changes, the choice of the modelling method (classification; biophysical/chemical parameter estimation) and the geographic data representation (pixel-based or (geographic) object-based) and the appropriateness of the RS algorithm and its assumptions for the given spectral traits.

### 3.2. Importance of Spatio-Temporal Patterns of ST/STV in FES

In addition to the characteristics of forest traits, the spatial distribution, size, aggregation, shape and the extent over which given spectral traits are manifested play a crucial role in detecting ST/STV. A high density, small size or unfavorable shape of similar biochemical, morphological and structural forest traits makes it all the more difficult or even prevents the recording of forest traits using RS [46,78]. In contrast, high density forest vegetation with very diverse plant traits generates greater remotely-sensed spectral responses and favors the recording of indicators of FH. At the same time, by deriving a spatio-temporal variability of traits with RS using the available knowledge of species diversity at a given location, conclusions can be drawn about the impact of external ecosystem processes. A high degree of species diversity does not always lead to an equally high diversity of traits. Moreover, a high diversity of traits—given low species diversity—can provide insight into adaptations or even disturbances in an ecosystem. The spatial distribution of individual plant and community ST/STV may only be evaluated in connection with specific sensor characteristics—the spatial, spectral, radiometric, temporal and directional resolution.

### 3.3. Characteristics of RS Data for Quantifying FH

RS data to record indicators of FH vary in their spatial, spectral, radiometric, temporal and directional resolution (Figures 2 and 4) and therefore in their ability to record forest ST/STV. Depending on the sensor platform, the spatial resolution may be millimeters (e.g., drone-based cameras), 0.5–2 m (airborne, hyperspectral sensors—AISA, HySPEX, APEX), 2–10 m (satellite sensors such as WorldView-2, RapidEye, Sentinel-2), 10–30 m (Spot, Landsat), and up to 250–1000 m or greater (MODIS and NOAA AVHRR). The spatial resolution, the characteristics and the density of forest ST/STV will determine the characteristics that are contained in one pixel. In this way, every pixel can contain a combined reflectivity of multiple characteristics of ST/STV [46].

Spectral resolution is also crucial for making qualitative distinctions among forest traits and taxonomic distinctions among forest species and communities. Narrowband hyperspectral RS sensors with a spectral range of 0.4–2.5  $\mu\text{m}$  like the “Cubert UHD 185-Firefly” [415], the airborne hyperspectral system sensors HySpex, HyMAP, AISA or satellite-based hyperspectral sensor EnMAP (Environmental Mapping and Analysis Program, to be launched in 2018, Guanter et al., [416] are able to quantify many different biochemical and biophysical ST and STV in forest ecosystems [7,64,65,77,84,152] (see also Figure 2). Furthermore, these sensors are able to taxonomically recognize more than 20–30 different tree species [343] compared to sensors with broad spectral bands such as Landsat, Spot, Aster, Sentinel-2 and RapidEye. The development of sensors with high spectral resolution (0.3–3.0  $\mu\text{m}$ , Fluorescence Explorer Satellite, FLEX, ESA, 2018, [152] allows for the detection of important eco-physiological process traits such as photosynthesis and solar-induced chlorophyll fluorescence for a better understanding of global photosynthetic activity, CO<sub>2</sub> fluxes and budgets [21,152].

The temporal resolution of RS sensors is another decisive factor for improving the discrimination of species, populations, communities or forest types (see Chapter 4) as well as the quantification of ST/STV. Senescence, phenology, stress, disturbances and resource limitations are all factors that lead to changes in traits at very different time intervals. Therefore, it is essential to have sensors that can also record processes and STV at different temporal frequencies. Lausch et al., [21] extensively discuss the implementation of in-situ RS methods such as plant phenomics facilities and the Ecotron (controlled environment facility), spectral measurements from towers or terrestrial wireless sensor networks (WSN), where a monitoring of ST/STV of FH is carried out at high temporal frequencies. Moreover, spaceborne RS are developed or can be used with a high temporal resolution and revisit time such as TerraSAR-X (DLR and Airbus Space and Defence, 1–2 days), WorldView-2,3 (Ball Aerospace & forest biomass, Technologies Corporation, fully commercial, 2009 and 2014, 1 day), EnMAP (Environmental Mapping and Analysis Program)/BMBF & BMWi Germany, 2019, 4 days), RapidEye (PlanetLabs 2008, 1 day), Sentinel-1A /B two-satellite configuration/ESA (2014 and 2015, 2 days),

Sentinel-2A /B two-satellite configuration/ESA (2015 and 2016, 5 days), Sentinel-3A/B two-satellite configuration/ESA (2016 and 2017, 4 days) [22].

Until today, only limited research has been conducted into the spatial, spectral or temporal resolution of such sensors for the assessment of ST/STV. Lausch et al., [417,418] showed that for a given stable experimental design (the same sensor, time, recording frames and region) the spatial resolution is more important than the spectral resolution in discriminating the spatial heterogeneity in vegetation. Sensors with a low spatial resolution often have a higher temporal resolution (e.g., AVHRR, MODIS with 1–2 revisits/day). Sensors with high spatial and spectral resolution are generally limited in temporal resolution. However, these constraints are gradually being improved upon with the development of new sensor technologies (e.g., Sentinel 2—10 m, 20 m, and 60 m spatial resolution in the VNIR to SWIR spectral range, 5-day revisit time). In addition, more approaches are being developed that enable data merging from sensors with different spatial, spectral and temporal resolutions for the purpose of extracting information relevant to different indicators of FH [21].

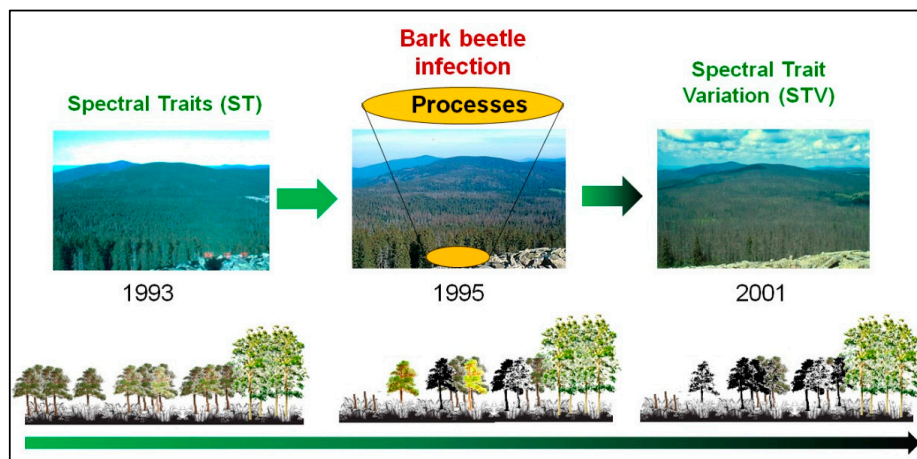
Detecting indicators of forest health is not only based on spatial, spectral and temporal resolutions. Due to different growth forms, geometry, tree height and structural diversity as well as the heterogeneity of the tree stands such as tree density, crown shape and leaf orientation, diversity of tree height, the angular (or directional) resolution plays a major role [419–421]. According to Koukal [419], “the directional domain of reflectance is mostly ignored, although the variation of reflectance properties with the sun and view angle (anisotropy) of forest canopies is substantial”. If the anisotropy of reflectance is not taken into account in forest health models, it will lead to noise in the spectral signatures and thus to errors in the quantification and monitoring of ST/STV with RS [419].

#### 4. How Can Remote Sensing Contribute to the Quantification of Stress in FES?

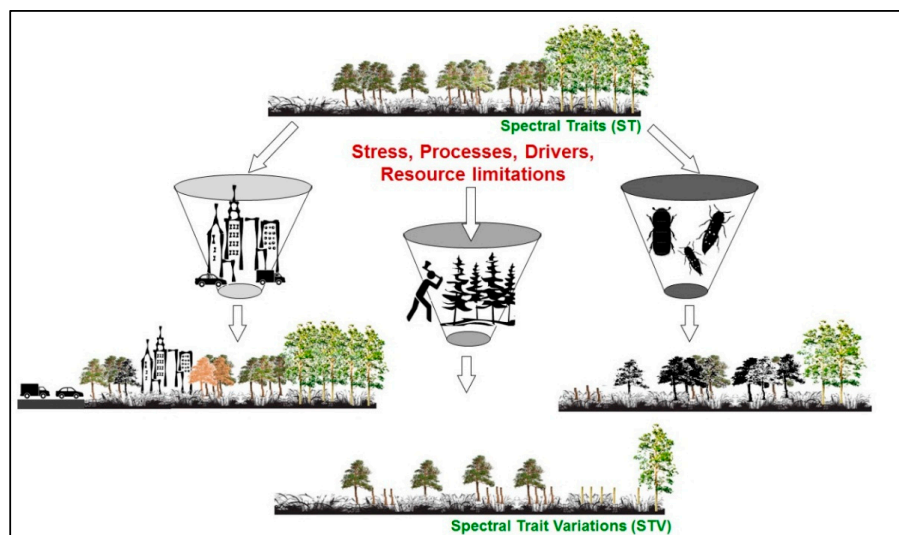
The crucial question that we need to ask is why are RS techniques suitable for detecting and monitoring stress, distribution or resource limitations for assessing FH? The following points help us to answer this question:

1. Taxonomic and phylogenetic characteristics of forest plant species as well as natural and anthropogenic processes and drivers affect biotic traits or lead to trait variations in plants, populations, communities, habitats or biomes of FES in space and time [50].
2. Plant traits and plant trait variations are therefore proxies of the state, abiotic and biotic limitations, ecological interactions, processes and pressures which affect forest plant species and communities [46,206,208].
3. Drivers, processes and stress can manifest in the molecular, genetic, epigenetic, biochemical, biophysical or morphological–structural changes of traits [422–424] which can lead to irreversible changes in taxonomic, structural and functional diversity in FES. These changes can be measured by spectral traits and spectral trait variations (Figure 3).
4. RS is a physically-based system that can only directly or indirectly record the spectral traits and spectral trait variations in plants, communities or biomes [137,414] (Figure 4).
5. Spectral signatures, patterns and heterogeneity recorded by remote-sensing techniques are therefore proxies of spectral traits and spectral trait variations and thus the results of their state and changes through biotic and abiotic source limitations and interactions and lastly the results of drivers, processes and pressures on FH [46].

Therefore, the plant trait approach allows a new way of understanding some fundamental questions about forest diversity. Traits and trait variations help us to understand, “why organisms live where they do and how they will respond to environmental change” [412] and interact with different stressors, disturbances, resource limitations and drivers. Traits and trait variations can therefore be described as filters for status, changes, stress, disturbances or resource limitations to taxonomic, structural and functional diversity of FES and FH [423,425] (Figures 5 and 6).



**Figure 5.** Changes to forest traits caused by different processes, drivers and stressors which can be observed using remote-sensing technologies. Photos by Marco Heurich.



**Figure 6.** Different stress factors, processes, drivers or resource limitations result in changes of spectral traits (ST) to spectral trait variations (STV) in forest ecosystems.

Not every change of FH, however, can be specifically assigned to a particular trait variation. For example, bark beetle infections of *Picea abies* lead to a reduction of chlorophyll and subsequently to a reduction of photosynthetic activity. These symptoms can also be caused by soil limitations or acid rain. Furthermore, reduction of chlorophyll concentration is also a process of senescence in forest plant species such as deciduous trees. Only with the integration of information on process characteristics such as process duration or intensity is it possible to differentiate the processes and drivers based on ST/STV.

ST/STV of FH that can be observed using different RS technologies can be:

- Alterations to biochemical spectral traits such as cellulose, nitrogen and lignin [128,426], or changes in the composition and configuration of photosynthetically-active pigments in leaves—chlorophyll, xanthophyll,  $\alpha,\beta$  carotene, xanthophyll [7,64,76,99,427]. Changes to the intra- and extra-cellular water content or the percentage water in plants [428–430].
- Variations in the physiological and functional spectral traits such as photosynthesis activity and efficiency photosynthetic pathways, carbon sequestration, plant respiration or nutrient retention [153,431,432].

- Changes and shifts in bio-functional processes (evapotranspiration, energy balance in plants and mechanisms such as the phenotypical plasticity and phenotypic shifts of plants [82,84,162,170,194].
- Changes in 2D or 3D structural spectral traits such as leaf arrangement and geometry, tree height or area, density, size, the shape of forest patches as well as fragmentation, complexity, homogeneity or the diversity of species or communities. Furthermore, forest canopy height, forest extent as well as the vertical and horizontal vegetation structure of forests [258,433].
- Alterations in the stress levels and adaptation or the disturbance of spectral traits such as the protective mechanisms of leaf hair and cuticles.
- Plant functional types (PFTs) or plant strategy types [206,208,209] or the Ellenberg indicator plant species [207,211].
- Turnover in species composition like spatial heterogeneity and dissimilarity [258,349,434] or spatial structure and distribution of species composition, tree community turnover [435–437].
- Spectral traits of productivity and diversity and disturbances [241,437].

For more examples, see Table 1 and [21,46].

## 5. Monitoring Stress in Taxonomic, Structural and Functional FES Diversity to Assess FH

Stress effects and changes to taxonomic, structural and functional diversity are good indicators of the stability, resilience or stress and instability of FES. The real question, however, is the extent to which RS is able to detect and monitor taxonomic, structural and functional diversity as well as its changes.

There are many different approaches for quantifying, predicting and modeling species distributions using RS sensors on different spatial scales: (i) the direct identification or detection of forest species; (ii) the detection and quantification of habitats or forest ecosystem types; and (iii) the use of proxy variables for predictive species distribution models (SDMs) [46].

### 5.1. Direct Monitoring of Stress on Animal Species in FES with RS

Animals are constantly subjected to pressure from predators, environmental changes, stress and disturbances [324]. Stress leads to changes in species distributions, species losses, changes in habitat patterns and fragmentation as well as the different morphological adaptation mechanisms of animal species. It has long been recognised, for example, that birds are extremely sensitive to the intensive use of pesticides such as DDT in the landscape [438]. Similarly, it was discovered that the dramatic decline in bee populations as a reaction to pesticides and land use changes has led to a loss of pollination, one of the most important ecosystem functions. There exist many studies examining the effect of forest fragmentation and forest patch size on the physiological stress response in forest animals and animal communities [439–441]. Therefore, animals are crucial bio-indicators of disturbances, stress and environmental changes.

Recording animal species with RS is only possible under certain circumstances. Comprehensive reviews on detecting animals using RS techniques can be found in [46,320,321]. Factors that are important if animal species are to be directly recorded using RS are: (i) their characteristic traits such as body size, shape, colour, surface characteristics, movement, sounds or body temperature; (ii) the characteristics of the RS sensors; and (iii) the RS platforms that are used (in-situ RS platforms such as camera traps, UAV, airborne, spaceborne RS platforms, see Figure 2).

The GPS lifetime tracking of animal species in FES has proven to be successful (e.g., for lynx, wild boar, red deer, storks, cranes, gulls, geese, brown bears, chimpanzee) in recording movement and behaviour and helps to gain a better understanding of population effects from environmental changes in FES [323,325,442–444]. The most state-of-the-art lifetime tracking technology will soon enable smaller animals such as bees or beetles to carry transmitters. In addition to GPS information, multi-sensors will also be increasingly implemented to record images and videos, and to monitor numerous physiological parameters such as body temperature, physiological stress indicators, but also

activity patterns, habitat characteristics, and mating and feeding behaviour. All transmitter information will be recorded in the future over the “satellite-based ICARUS system, which is to be installed by German and Russian space agencies in 2017” [324]. Data will be stored centrally in the movement database [323,445].

Recently, the implementation of camera traps has increased in FES to estimate population sizes, to understand behavioural and activity patterns and under some circumstances to record the habitat of animals [326,334]. Low cost camera traps with high battery lifetimes and memory capacity integrate thermal and movement sensors as well as RGB-photo and video technology and can record animals in FES [326,327,334,446]. Thermal cameras and multi-sensor combinations with optical sensors and LiDAR on UAV- and airborne platforms have been used to record wild animal species such as the white-tailed deer [331,447,448]. In this instance, the body temperature of the animals is used, as it differs considerably from the surrounding environment (especially at night, at dusk or dawn). Direct classification of FES animals have been conducted using satellite RS techniques such as RapidEye or Worldview-2 for a number of animal species such as deer, wildebeest or birds [320,449], and UAV technology is becoming more commonly applied in recording wild animal species [448]. However, the success of UAV and satellite technologies for recording wild animals within forest has been found to be very limited.

### *5.2. Modelling Stress and Disturbances in Species Distributions and Animal Behaviour in FES*

The quantification of species–environment relationships based on species distribution models (SDMs) is an important methodical approach [450,451] to monitor and understand the stress or resource limitations on forest species. RS data on different platforms, i.e., camera traps, drones, air- and spaceborne data, are able to map and quantify biotic and abiotic land surface traits. In terms of SDM modelling, RS can also be used to record a number of abiotic environmental variables such as topographic- [452] soil- [453,454] and climate conditions [455,456], their status, alterations and, therefore, also their impacts on animal species in FES. SDM based on RS approaches will “shape the next generation” of SDMs [335]. With RS it is not just the status quo or the long-term monitoring and changes in FES that can be examined, but also significant short-term changes to the taxonomic, structural and functional traits of FES from the regional to the global scale, which is not possible with in-situ recording of animal behaviour.

The SDM approach is very different from the detection and quantification of the forest habitat quantification approach. The objective of SDM is “to predict the probabilities of species occurrence as the single target variable” [457]. The opening of Landsat RS portals as well as an increasingly more common data policy of freely available RS data and data products such as the Copernicus missions (Sentinel 1–5) or the hyperspectral (EnMAP) satellite missions makes extensive spatio-temporal data available to SDM. Determining the growth period [194] deriving global NDVI trends [458], recording shifts in biochemical traits [82,84,162,194], recording changes in land-use [459], land-use intensity [460] or long-term deforestation dynamics as well as quantifying structural forest characteristics like fragmentation, spatial distribution, structure, heterogeneity or homogeneity configuration of forest patterns are all factors that provide us with crucial information [143,257,259,271]. Deblauwe et al., [461] used remotely-sensed temperatures and precipitation data derived from RS-data to improve species distribution modelling in tropical forest areas. Franklin et al., [462] analysed global change and terrestrial plant community dynamics using remote-sensing based monitoring of vegetation changes. Furthermore, Boiffin et al., [463] used SDM to determine the migration rate and the species occurrence of Douglas-fir and climate predictors in North America. Furthermore, Coops et al., [337] used RS land cover and RS data to estimate tree species migration. The modelling of animal behaviour is a widespread method for modelling animal distributions (e.g., birds, deer, lynx, bears, foxes, wolves, moose or bison), [320,330,338,464,465]. High-resolution RS data were also used, for example, in an unmanned aerial vehicle (UAV) and RS data for monitoring and discrimination of forest and tree species in the context of assessing the suitability of chimpanzee habitats in Tanzania as a basis for

making critical decisions about species conservation [336,466]. An extensive overview of recording terrestrial animals using remote sensing is provided by [46,320–322].

A crucial application of RS is to record changing biochemical forest traits such as chlorophyll and water content or a reduction in the photosynthetic activity in trees. High resolution temporal as well as spectral RS data such as Sentinel-2, WorldView-2 Data or hyperspectral RS sensors such as APEX, AVIRIS, HySpex, AISA and the upcoming spaceborne hyperspectral sensor EnMAP are used to record disturbances in the vitality of forests resulting from climate change, resource limitations and disturbances or damaging insects such as bark beetles or pine beetles, [53,237,240,467,468] as well as fungal infestations (such as the recent infestation of ash trees). In this context, the investigations on early detection of Bark Beetle infestations of spruce trees are particularly noteworthy. In this case, non-infested trees are separated from infested ones that are still not suffering from “green-attack” from already highly infested or dead trees due to their spectral reflectance using RS data. Immitzer & Atzberger [240], for example, used WorldView-2 data for the early detection of Bark Beetle infestation in Norway Spruce (*Picea abies*, L.). The classes that were investigated, namely: “healthy”, “infested, but no visible change in colour” and “dead” were separated with a total accuracy of around 75%. Lausch et al., [53] on the other hand used hyperspectral HyMAP remote-sensing data with a spatial resolution of 4 m. In spite of the high spectral resolution of the RS data with a spatial resolution of 4 m, only a total accuracy of 64% was obtained. This example shows that the high spatial resolution (1.8 m) of the multispectral WorldView-2 data can lead to better results than the high resolution hyperspectral RS data, if the multi-spectral RS data contain spectral channel information that are decisive for classification. Similar conclusions are drawn by Lausch et al., [425] when comparing spatial vs. spectral resolution from RS data.

### 5.3. Monitoring Stress on Vegetation in FES with RS

**Tree species richness and diversity** are key parameters for describing the status, stability and the resilience of FES [341]. Numerous studies have mentioned the potential of RS technologies to record tree species taxonomy, richness and diversity [341–345]. As already described in detail in Chapter 3.1, the discrimination and monitoring of different taxa in forest plant species with RS is only possible when tree species can be differentiated from one another by their ST/STV (biochemical & biophysical ST, physiognomic & morphological ST or phenotypical ST, see Figure 2). Broadband RS sensors record less ST/STV than narrowband hyperspectral. Therefore, the forest tree species discrimination for broadband RS sensors such as Landsat, Spot, RapidEye, Worldview-2 and QuickBird is possible, but not as successful [344–348,352] as narrowband hyperspectral RS data [64,341–343,349]. Immitzer et al., [344] used very high spatial resolution 8-band WorldView-2 Satellite Data for classifying 10 tree species with an overall accuracy of around 82% (eight bands, object-based). Magnard et al., [353] used SAR interferometry data as an alternative to airborne laser scanning (ALS) or photogrammetry-based RS for discriminating various tree species. By implementing multi-sensor approaches (optical, thermal, RADAR, LiDAR) as well as multi-temporal approaches, the number and type of ST/STV is increased, whereby a greater number of tree species can be differentiated. In this way, Elatawneh [350] were able to improve the discrimination for forest tree species by including multi-temporal phenological stages. Hill et al., [351] also used time-series multi-spectral data for the discrimination of tree species in temperate deciduous forest, whereas Neyret et al., [134] integrated ST indicators such as the variation of leaf mass per area to investigate dominant species across two contrasting tropical gradients in the context of community assemblages. Pierce et al., [210] used the leaf economics and size traits of CSR plant functional types to classify woody and herbaceous vascular plants. Various authors have also used multi-sensor approaches whereby the fusion of optical, RADAR, thermal and LiDAR data [31,469] extends the spectrum of recordable ST/STV, which ultimately leads to an improved discrimination of different tree species [21].

**Invasive species:** Various studies have shown that invasive plant species in FES can be mapped using RS techniques [355–358]. Asner and Martin [76] found that the biochemistry of invasive species

is very different compared to that of native species. The ST/STV are therefore crucial indicators of the spectral discrimination of invasive species [335]. Asner and Martin [76] used the biochemical and biophysical ST of leaves, while Schneider and Fernando [359] used plant pigments and leaf coloration for successful mapping. Blumenthal et al., [360] integrated structural ST in addition to purely biochemical ST or indicators of structural homogeneity, like those that emerge from the specific arrangement of monocultures [470]. Somers and Asner [356], on the other hand, used multi-temporal Hyperion spaceborne imaging spectroscopy for invasive species mapping in Hawaiian rainforests. Apart from spectral biochemical, morphological and texture traits, other plant traits have also been used for species distinctions such as seasonality and phenology [357,361]. In addition to recording tree species taxonomy and distribution, the monitoring of forest populations and forest community structures [471] or forest types is also possible using RS, although it is also subject to the same constraints as for the discrimination of tree species. Ioki et al., [472] assessed the similarity between tree community compositions in a tropical rainforest using airborne LiDAR RS data, whereas Laurin et al., [436] recorded tropical forest types, dominant species, and functional guilds in FES by using hyperspectral and simulated multispectral Sentinel-2 data.

**Plant functional types and plant strategy types:** Environmental stress is a major factor, influencing plant traits and trait combinations [473,474]. Recurring combinations of structural, physiological or phenological traits are used to group plant species into Plant Functional Types (PFTs) [48,206,475]. PFTs are therefore important indicators of resource limitations or various stressors on FES, which can be measured using RS technologies [137]. The most important examples of PFTs are the CSR (Competitive, Ruderal, Stress tolerant) strategy types by [476], where plant traits change depending on their stressors and disturbance regimes. According to this system, community composition in FES is established from ruderal plants, competitive plants, and stress-tolerant plants. Plant traits such as the dry matter content, the canopy height, the onset of flowering, the flowering period, lateral spread, specific leaf area and leaf dry weight are all crucial factors for the position and mapping of plant species in the CSR trait space [206,208,209,477].

**Land Use Land Cover (LULC)** in forests can cause changes in the taxonomic, structural and functional diversity. Changes in LULC influence forest plant and community traits, leading to trait variations in forest ecosystems in their entire complexity [11,48,50,51]. For example, different forest management strategies are characterised by specific ST/STV. Pristine forests display a heterogeneous ST/STV in space and over time due to different forest tree species, different traits in growth forms, age, geometry or phenology and senescence compared to the relatively homogenous ST/STV in single species forest stands. Garnier et al., [50] were able to prove a direct relationship between plant traits (regeneration traits such as reproductive plant height and flowering phenology) as a response to land-use changes and disturbance regimes. Crucial changes to forest traits can be measured by spatial-temporal analyses of forest heterogeneity patterns [258], 3D distribution of forest canopy species patches [257], forest fragmentation [267–271], mapping of forest structures [259], or estimating forest area and forest biomass with TanDEM-X and RapidEye RS Data [143]. For more examples, see Table 1.

Monitoring forest cover changes or forest area dynamic on the local to the global scale has for some time now been extensively and successfully conducted using RS [62,314,402–407] helped along by open access and forward-thinking data policies with free use and storage in databases and archives from different RS data and data products [32,33,478]. Furthermore, global environmental programs such as REDD+ (Reducing Emissions from forest Degradation and Deforestation) have been developed and require intensive forest cover monitoring. In addition to multi-sensor RS approaches with various RS sensors [401], multi-temporal RS have frequently been employed for LULC monitoring (for an extensive discussion see [22,46]).

There are numerous remote-sensing data products and methods for the different types of RS data, which help us to use data for monitoring forest stress, disturbance and FH in a pre-processed and standardized way. These include the LandSat change detection products (CCDC), which integrate data from a 40-year monitoring period [399,400]. Furthermore, LandTrend (Landsat Detection of Trends in



Disturbance and Recovery, [479]) is a trajectory-based land cover change detection method [480] which analyses time-series of Landsat RS data at once. The LandTrend algorithms can be used to analyse, monitor and describe sequences of disturbances and regrowth in FES. Comprehensive analyses of FH have been conducted based on LandTrend and LandSat Time Series (LTS) [392–396]. Comprehensive information and reviews of remote-sensing change detection and ecological monitoring can be found in [397,398].

**Functional and structural stress:** RS approaches are crucial for assessing the structure and functioning of FES [20,137]. This is based on functional traits sharing similar functions and showing similar effects and responses to environmental stressors, disturbances or resource limitations [48,413]. Here, the ST/STV paradigm helps to understand the effects of stress on functional diversity such as interactions between the absorbed radiation (APAR) and plant productivity (net primary production, NPP), [481], the relationship between biodiversity and carbon stocks [482] or interactions between canopy structure, canopy nitrogen and canopy near-infrared (near-IR) reflectance detected by RS [483]. Moreover, FES are crucial carbon pools and, therefore, important ecosystems in the global carbon cycle. Changes of carbon stocks are observed and monitored extensively using RS technologies [105,482,484–486]. Similarly, canopy foliar N distribution in FES [83], the global variability in leaf respiration in relation to plant functional types, leaf traits and the climate [487], the assessment of forest biomass [488], or the loss of canopy water in FES [389] or the shifting distributions of chemical traits in forest [82] are all monitored using RS. Furthermore, the biochemical, structural and functional characteristics of ST/STV such as photosynthetic pathways, pigment and nitrogen content, 2/3 D plant/canopy vegetation height, or leaf phenology are crucial for assessing ecosystem functions and ecosystem services such as photosynthetic activities, primary production, gas exchange and climate regulation [414].

In addition to monitoring stress on functional diversity, it is also possible to monitor changes to structural diversity in FES using RS. This ranges from analysing the composition, configuration and distribution of phylogenetic structures [89] to molecular biochemical structures and patterns in plants [21,489,490] to 2/3 D individual geometry and structure [491–493], populations and community structures [349,435,436] and the recording of patterns and fragmentation in FES [494]. Further examples of monitoring stress and changes to the functional and structural diversity can also be recorded very well using RS. For an extensive list of other examples, see [19–21,46,137,219].

In the field of investigations on vegetation stress, rapid advances are currently taking place in the development of new RS technologies. For example, plant photosynthesis conditions and their changes are crucial for modelling carbon fluxes and water exchanges in soil-landscape-atmosphere modelling. However, the spatio-temporal variation of photosynthesis activity of the canopy vegetation shows great variations in seasonal, diurnal and spatial patterns but cannot be predicted sufficiently with conventional RS techniques [153,495]. At the same time, forecasts on stress and shifts in the photosynthesis system are currently only indirectly possible through plant traits of greenness and the amount of chlorophyll. The development of sensors with a high spectral resolution (0.3–3.0  $\mu\text{m}$ , Fluorescence Explorer Satellite, FLEX, ESA, 2018, [152] means that it is now possible for the first time to directly measure functional plant traits such as the solar-induced chlorophyll fluorescence signal as an indicator of photosynthesis conditions and efficiency in order to make better estimates of global photosynthetic activity, CO<sub>2</sub> fluxes and budgets [152–155,496].

Furthermore, the new airborne instrument HyPlant was developed to monitor vegetation over a spectral range of 380–2500 nm (spectral resolution of 3–10 nm) and an additional segment, to monitor the chlorophyll fluorescence over the spectral region from 670 to 780 nm (with a high spectral resolution of 0.25 nm) as an indicator of photosynthesis conditions as well as to effectively detect stress and shifts in photosynthesis for vegetation [153]. Research at plant phenomics facilities [497] and the controlled environmental facility Ecotron [498,499] have made tremendous contributions towards the development of FLEX and HyPlant sensors [21].

In the future, RS sensors will be enhanced with high spectral, spatial and temporal resolution, on the one hand, such as HyPlant, FLEX, EnMAP as well as the future hyperspectral/thermals combination HypSIRI (to be launched in 2020, [500]) or the multispectral/hyperspectral RS combination HISIRI (Hyperspectral Imager Suite) and used in combination with other RS techniques (multi-sensor) such as RADAR or thermal radiometer (ECOSystem Spaceborne Thermal Radiometer Experiment on Space Station (ECOSTRESS, scheduled for 2017, [501]), in order to increase the number of spectral traits and spectral trait variations of forest vegetation that can be recorded and to obtain better predictions about the resilience, stability or stress and instability of FES [502,503].

## 6. Conclusions

FH is characterized by a high degree of stability, elasticity and resistance to stress, disturbances and resource limitations, when a scale- and FES-dependent taxonomic, phylogenetic, structural as well as functional diversity is maintained or at least restored after the impacts of stress. To monitor and understand the entire complexity of FH, its driving forces and mechanisms, it is imperative to establish a cost-effective, extensive, repeatable and standardised FH monitoring program. Remote sensing is a key technology in these programs.

RS as a physically-based system records spectral traits as well as spectral trait variations in FES. Since ST and STV are proxies for stress, disturbances and resource limitations can be found on all spatio-temporal scales. The ST/STV approach with RS techniques is suitable for monitoring the status and changes of the taxonomic, structural and functional diversity in FES. Structural as well as functional disturbances to FH can be effectively recorded with RS techniques using the ST/STV approach, whereas the ability to monitor stress in the taxonomic and phylogenetic diversity of forest animal and plant species is limited with RS techniques.

Extensive investigations have established the constraints under which the taxonomic, structural and functional monitoring of forest species, populations and communities is possible with RS. In this way, the characteristics ST and STV, the shape, density and distribution of ST/STV, different sensor characteristics, the choice of the classification method and the use of different RS algorithms all influence accuracy in the monitoring of indicators of FH.

RS is suitable for recording disturbance processes to FH (from short-term to long-term processes), which is not (or only insufficiently) possible with terrestrial FH surveys. In contrast to RS, however, terrestrial FH surveys can record precise taxonomic and phylogenetic information about forest species, making crucial information on phylogeny, tolerances, resilience and threshold values available, which are important input variables for calibrating RS data as well as understanding stress and spectral response processes.

It should therefore be the goal of future research on FH to link terrestrial and RS-based approaches [20,46]. In doing so the ST/STV paradigm might be used as an interface between both information sources. Future research on RS technologies should focus on making previously non-recordable yet relevant non-spectral traits (N-ST) recordable in the future through new technologies and multi-sensor approaches.

Since numerous constraints influence the ability to ascertain FH indicators using RS, the standardised recording of FH indicators using terrestrial and RS-based approaches will be one of the greatest challenges in the future if we are to gain a better understanding of FH and forest ecosystems. Furthermore, compared to the Essential Biodiversity Variables (EBV) for FH, the “Essential Forest Health Variables” (EFHV) also need to be clearly defined, so that comparable indicators of FH can be monitored on all spatio-temporal scales.

**Acknowledgments:** We particularly thank the researchers for the Hyperspectral Equipment 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 thank the reviewers for their very valuable comments and recommendations.

**Author Contributions:** A.L. was responsible for the main part of this review analysis, writing and production of the figures. M.H. and P.M. provided extensive contributions on recording terrestrial forest health as well as substantial input about methods used for implementing sensors in the context of forest health. D.J.K. and S.E. added their knowledge about extensive methodology aspects for using optical, RADAR and LiDAR as well as modelling forest health with remote-sensing techniques. All authors checked and contributed to the final text.

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

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