

# Chapter 13

## A Range of Earth Observation Techniques for Assessing Plant Diversity



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### 13.1 Understanding Plant Diversity with Remote Sensing

Stress, disturbance, and resource limitations such as anthropogenic changes to ecosystems all lead to changes in biodiversity and vegetation diversity (Cardinale et al. 2012) on different scales of biological organization as well as disturbances in the interactions between trophic levels and ecosystem functions, impairing ecosystem services such as pollination or soil fertility (Cord et al. 2017). Vegetation diversity is multidimensional, multifactorial, and tremendously complex in time and space (Lausch et al. 2018a). This level of complexity can only be fully understood when

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monitoring approaches are applied to record different characteristics of vegetation (i.e., phylo-diversity; taxonomic, structural, functional, and trait diversity on different levels of biotic organization—molecular, genetic, individual, species, population, community, biome, ecosystem, and landscape). Different processes and drivers influence the resilience of vegetation diversity (Fig. 13.1).

To record the status, stress, disturbances, and resource limitations in vegetation diversity, we have to differentiate between two monitoring approaches: (i) in-situ approaches, whereby the most important monitoring concepts are the phylogenetic species concept (PSC, Eldredge and Cracraft 1980), the biological species concept (BSC, Mayr 1942) and the morphological species concept (MSC, Mayr 1969) and (ii) physically based approaches of remote sensing (RS) (Lausch et al. 2018b). Unlike in-situ approaches, RS records the biochemical, biophysical, physiognomic, morphological, structural, phenological, and functional characteristics of vegetation diversity at all scales, from the molecular and individual plant levels to communities and the entire ecosystem, based on the principles of image spectroscopy across the electromagnetic spectrum from the visible to the microwave (Ustin and Gamon 2010). When compared with the traits approach of the MSC used by taxonomists, RS approaches are not able to record the same number and characteristics of traits or trait variations as the in-situ approaches (Homolová et al. 2013; Lausch et al. 2016a).

Traits and trait variations that can be recorded using RS techniques are hereafter referred to as *spectral traits* (ST), and the changes to their spectral characteristics are referred to as *spectral trait variations* (STV). The overall approach is referred to as the *remote sensing-spectral trait/spectral trait variations* (RS-ST/STV) concept for monitoring biodiversity (Lausch et al. 2016b) as well as geodiversity (Lausch et al. 2019) (Fig. 13.7).

Traits bridge the gap between in-situ and RS monitoring approaches. Species traits have allowed us to take a completely new direction and to gain a better understanding of fundamental questions of status, stress, disturbances, resource limitations, and resilience in biodiversity—i.e., “why organisms live where they do and how they will respond to environmental change” (Green et al. 2008). Therefore, ecologists are increasingly focusing on traits rather than species to better understand

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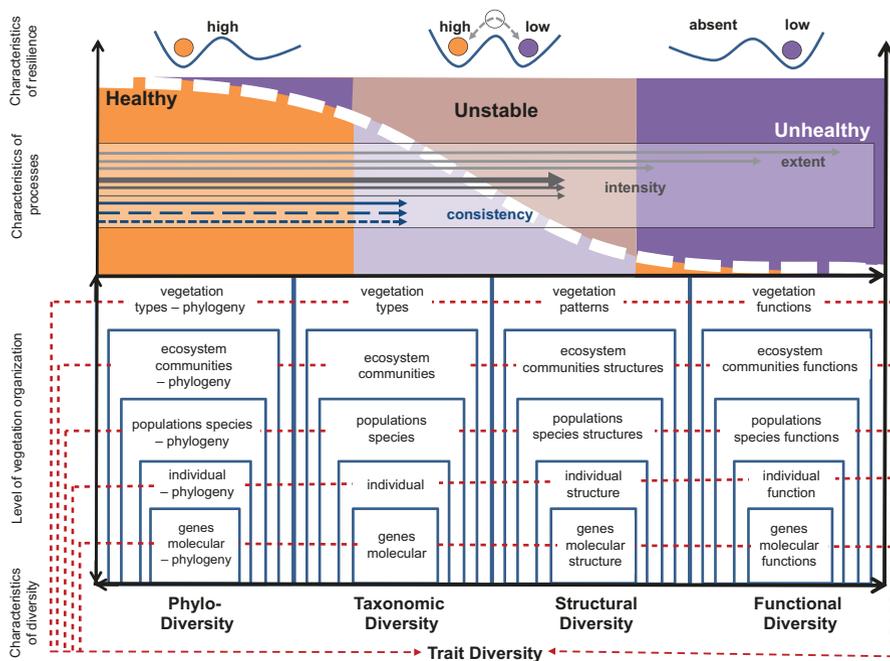
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**Fig. 13.1** Schematic diagram of the different levels of vegetation organization from genes up to vegetation types showing characteristics of phylo-diversity, taxonomic diversity, structural diversity, functional diversity, and trait diversity. This also shows how the different characteristics of the processes (the extent, process intensity, process consistency, resilience, and their characteristics) all influence the resilience and health of vegetation. (From Lausch et al. 2018a)

the status, changes, health, and resilience of ecosystems (Cernansky 2017) and the internal patterns and heterogeneity of communities and landscapes (Lausch et al. 2015a). To understand the complexity of ecosystems, no one monitoring approach, no single model, scale, or RS platform on its own is sufficient to discern the effects of processes and different drivers of vegetation diversity (Lausch et al. 2018a, b).

This chapter introduces the different ranges of EO techniques for assessing vegetation diversity. The focus here is to give an overview of existing close-range RS platforms as well as air- and spaceborne RS platforms for assessing plant diversity.

### 13.2 Range of EO Platforms to Assess Plant Diversity

RS sensors are mounted on different platforms such as camera traps or handheld, or they may have fixed supports (e.g., a tripod) or towers for field-based spectral measurements. Drones, aircraft (airborne RS), or satellites (spaceborne RS) are also

used in field-based studies, depending on the spatial scale of the study (Gamon et al., Chap. 16). In laboratories, cameras and sensors may be mounted in plant phenomics facilities or ecotrons (Fig. 13.2; Lausch et al. 2017). The characteristics of all RS approaches are the same, irrespective of the platform. Vegetation stress, disturbance, and diversity result in variations in spectral radiance or reflectance that are recorded using RS in a nondestructive manner. The RS sensor on the platform records the spectral radiance at a distance of just a few millimeters up to thousands of kilometers to the object of interest.



**Fig. 13.2** Overview of different close-range, air-, and spaceborne RS platforms for assessing plant and vegetation diversity and vegetation health. (a) Laboratory spectrometer; (b) ash trees monitored in a close-range RS spectral laboratory (manual) with imaging hyperspectral sensors AISA-EAGLE/HAWK (Modified after Brosinsky et al. 2013); (c) automated plant phenomics facilities; (d) ecotrons (Modified after Türke et al. 2017); (e) Global Change Experimental Facility (GCEF)/Helmholtz-Zentrum für Umweltforschung (UFZ), Germany as platforms with different RS sensors (photo: A. Künzelmann/UFZ); (f) manual measuring with field spectrometer; (g) WSNs; (h) one sensor node of the WSN (Graphic, photo g, h by J. Bumberger and H. Mollenhauer/UFZ); (i) flux tower with different RS instruments, test area grassland/UFZ; (j) flux tower with different RS instruments, test area Hohe Holz/UFZ (Photo i, j by C. Rebmann/UFZ); (k) mobile crane with RS sensors; (l) unmanned aerial systems (UAS)—drone with different RS sensors; (m) microlight of the UFZ with different RS sensors like the AISA-EAGLE (hyperspectral 400–970 nm); (n) gyrocopter of the Institute for Geoinformation and Surveying, Dessau, Germany, with different RS sensors (Photo by L. Bannehr); (o) Cessna; (p) Spaceborne RS platforms. (Modified after Lausch et al. 2017)

## 13.2.1 Close-Range EO Approaches

### 13.2.1.1 Spectral Laboratory

The reactions of plants to stress phenomena depend on the plant species (Müller 2009; Teodoro et al. 2016). Teodoro et al. (2016) analyzed the different strategies of Brazilian tree species like *Campomanesia pubescens* (Myrtaceae), *Eremanthus seidellii*, and *Lessingianthus warmingianus* (Asteraceae) to cope with drought stress. The results showed different reactions and trade-offs to maintain plant functioning under drought stress conditions. Moreover, the ability of different tree species to adapt to climate change is still not well understood (Beck and Müller 2007). Reactions of woody plants to stress factors such as drought can often only be observed years later in the form of biochemical, physiological, or geometric changes to woody plant traits (Buddenbaum et al. 2015b). Therefore, specific in-situ investigations need to be conducted on the stress reactions of different taxonomic plants to determine the spectral responses to different drivers.

With the help of close-range laboratory spectroscopy (see Fig. 13.2a, b), extensive long-term stress monitoring can be carried out that takes into account entire vegetation periods as well as investigations over several years. Scenarios specifically targeted at investigating different stress factors such as stress from drought, ozone levels, fungal infestations, pesticide deposits, or temperature increases or decreases are conducted under comparable settings and environmental conditions, enabling good inputs for models and eliminating confounding factors. In addition to imaging and nonimaging spectrometer measurements, a broad range of parameters for vegetation traits, soil, and climate can be measured with in-situ approaches. Brosinsky et al. (2013) investigated the spectral response from the impacts of flooding on the physiological stress reactions of ash trees *Fraxinus excelsior L.* over a 3-month period, whereas Buddenbaum et al. (2015b) modeled the photosynthesis rate of young European beech trees under drought stress using hyperspectral visible infrared and hyperspectral thermal sensors. They created high spatial resolution (cm) maps of photosynthetic activity using the photochemical reflectance index (PRI), fluorescence, and temperature. Other approaches have derived the different phenology indicators of barley with imaging hyperspectral RS over its entire development period (Lausch et al. 2015b).

### 13.2.1.2 Plant Phenomics Facilities

One of the most important challenges in plant biology and vegetation stress physiology is the qualitative, quantitative, and spectroscopic recording of plant species phenotypes to gain a better understanding of interactions between the genotype and the phenotype. The genotype of a plant species comprises its genetic information, while the phenotype represents the physiological, morphological, anatomical, and development characteristics as well as interactions with the environment, resource

limitations, and stress factors (see Cavender-Bares et al., Chap. 2). The interaction of the genotype with its environment give rise to the functional and structural traits of plants and their specific phenotype (Großkinsky et al. 2015a, b; Pieruschka and Lawson 2015). Insights into the role of genotype and phenotype in plant stress physiology can be gained not only from recording individual plant spectral trait-stress factor interactions but also by including the entire genotype-epigenetic-phenotype-environment matrix (Mittler and Blumwald 2010). This can be achieved by recording phenotypical plant traits in plant phenomics facilities (Furbank 2009; Großkinsky et al. 2015a, b) (see Fig. 13.2c). Due to the high number of plant species, plant phenomics facilities have been established all over the world that collaborate as part of the International Plant Phenotyping Network (IPPN, <http://www.plant-phenotyping.org/>), where in an automated and often robotic manner, noninvasive measurement methods such as RS techniques are implemented, enabling a holistic and quantitative recording of the phenotype of a plant over its entire development period at a reasonable cost (Ehrhardt and Frommer 2012; Fiorani and Schurr 2013).

Plant phenomics facilities thus include comparable analyses of genotype-phenotype interactions under experimental as well as natural growth conditions. The goal of plant phenomics facilities is to implement and develop innovative non-invasive measurement methods and RS techniques such as stereo hyperspectral, RGB, thermal, and fluorescence cameras, laser scanning instruments, or x-ray tomographs (Fiorani and Schurr 2013). Data from such facilities are then saved in databases (Krajewski et al. 2015) to make such information available for future research with airborne and spaceborne RS applications.

With plant phenomics facilities, crucial investigations have been carried out on the effects of different plant stresses on photosynthetic performance (Jansen et al. 2009; Konishi et al. 2009; Rascher 2007). This research on chlorophyll fluorescence and its acquisition using spectroscopic techniques forms the basis for developing the Fluorescence Explorer (FLEX) sensors (Kraft et al. 2012; Rascher 2007; Rascher et al. 2015). On the basis of its very high spectral resolution of 0.3–3.0  $\mu\text{m}$ , FLEX will be the first satellite that is able to directly measure the solar-induced chlorophyll fluorescence and thus the stress levels in plants and other types of vegetation using RS.

### 13.2.1.3 Ecotrons

Ecotrons are controlled environmental facilities (see Fig. 13.2d) for the investigation of plant and animal populations and ecosystem processes under near-natural conditions using noninvasive methods (Lawton et al. 1993; Türke et al. 2017). They differ from greenhouse experiments because not only plant populations, but interactions between plant and animal populations, can be investigated. Furthermore, ecotrons enable investigations of aboveground and belowground interactions, which drive the relationship between plant diversity and ecosystem function (Eisenhauer 2018).

Ecological processes and material flows can be measured by ecotrons with non-invasive methods, while at the same time, the environmental conditions are controlled and regulated. Ecosystems that are investigated by ecotrons are thus closed systems. There is no undesired input or outflow of water, nutrients, resources, organisms, or gases, or input from undesired disturbance variables or stress factors. All changes taking place in such ecosystem processes are documented and can be compared with one another and with different scenarios in a standardized manner. In ecotrons, biodiversity is manipulated at different trophic levels at the same time. In this manner, the responses of different species and genotypes and species to stress, disturbances, or resource limitations and their effects on ecosystem functions can be examined. This approach enables a much better recording and understanding of aboveground and belowground interactions between different plant and animal species, microorganisms, and abiotic factors, as well as material and energy flows. The integration of close-range RS sensors in ecotrons is still very new and in need of further development if we are to understand the complete system of soil-vegetation-climate-biotic interactions with spectral response.

#### 13.2.1.4 WSNs, Sensorboxes

WSNs can be used to record complex vegetation processes both extensively and continually in a noninvasive, cost-effective, and automated manner (Hart and Martinez 2006).

The implementation of wireless mobile and stationary sensor networks in terrestrial environmental systems (Fig. 13.2g, h) enables high-frequency in-situ information to be recorded using various sensor types (e.g., thermal, multispectral, hyperspectral, soil moisture, air condition). Another advantage of mobile wireless ad hoc sensor networks is their self-organizing infrastructure, leading to significant reduction of cost and time consumption for installation, maintenance, and operation.

WSNs are being implemented more frequently in environmental and vegetation monitoring (Hwang et al. 2010; Mollenhauer et al. 2016) in agriculture and the food industry (Mafuta et al. 2013; Ruiz-Garcia et al. 2009), for monitoring terrestrial and underground conditions such as soils, and for aquatic applications (Yick et al. 2008). They have also been used for experimental platforms such as greenhouses or the GCEF (Mollenhauer et al. 2016). In the context of vegetation health, WSNs are implemented to detect and verify forest fires in real time (Liyang Yu et al. 2005; Lloret et al. 2009) or to demonstrate the effects of the 2015 El Niño extreme drought on the sap flow of trees in eastern Amazonia (Mauro et al. 2016).

WSNs have also been used to record how important processes of soil-plant-atmosphere interactions; vegetation processes such as transpiration, carbon uptake and storage, and water stripping from clouds are affected by climatic variation and the temporal and spatial structure of the vegetation interior in whole ecosystems (Oliveira et al. 2016). Teodoro et al. (2016) used WSN to demonstrate the interplay between hydraulic traits, growth performance, and stomata regulation capacity in three shrub species in a tropical montane scrubland of Brazil under contrasting

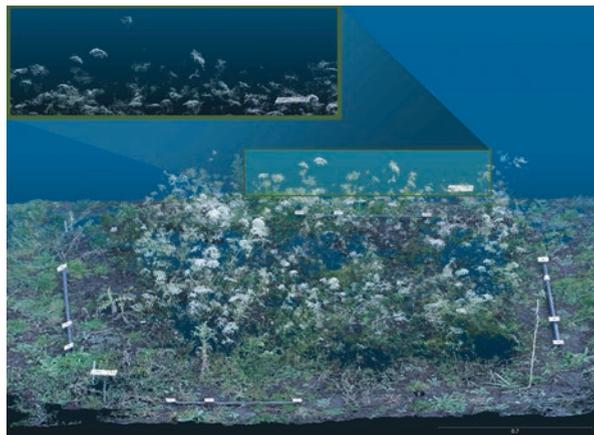
water availability. The results showed that these plant species employ different strategies in the regulation of hydraulic and stomatal conductivity during drought stress and thus substantiate the need for setting up WSN for different plant species and communities (Teodoro et al. 2016).

Grassland ecology experiments in remote locations requiring quantitative analysis of biomass, which is a key ecosystem variable, are becoming increasingly widespread but are still limited by manual sampling methodologies. To provide a cost-effective automated solution for biomass determination, several photogrammetric techniques have been examined to generate 3-D point cloud representations of plots, which are used to estimate aboveground biomass. Methods investigated include structure from motion (SfM) techniques (Kröhnert et al. 2018; see Fig. 13.3).

### 13.2.1.5 Towers

Flux towers involve an integrated sampling approach (see Fig. 13.2i, j, k) that supports the acquisition of different ecosystem parameters such as carbon dioxide, water vapor, and energy fluxes as they cycle through the atmosphere, as well as vegetation and soil parameters. FLUX towers are often coupled with sensor technologies such as airborne RS or soil sensors. Towers acquire individual point and local area information and are of particular importance in terms of long-term in-situ measurement for the calibration and validation of air- and spaceborne RS data. By linking flux towers to an international network (FLUXNET, Baldocchi et al. 2001), greater understanding of ecological processes and changes to vegetation health has been achieved using RS (Chen 2016; Yang et al. 2016). Towers and mobile in-situ stations are often combined as global sensor networks. Furthermore, the physiological reactions of plant species and communities depend on the taxonomy and phylogeny of plant species characteristics and numerous abiotic ecosystem variables as well as the intensity of land use (Garnier et al. 2007). Simple drones are also avail-

**Fig. 13.3** Generated 3-D representations of *Onobrychis viciifolia* and *Daucus carota* using structure from motion (SfM) techniques as well as the use of a time-of-flight (TOF) 3-D camera, a laser light sheet triangulation system, and a coded light projection system. (From Kröhnert et al. 2018)



able, enabling a mapping of the distribution of plant species in mixed grassland communities using close-range imaging spectroscopy (Lopatin et al. 2017). The special value of both fixed and mobile towers or simple close-range RS platforms is that vegetation diversity can be monitored more frequently and with a higher spatial resolution. Table 13.1 lists the advantages and disadvantages of close-range EO approaches to monitor and assess vegetation diversity.

## 13.2.2 Air- and Spaceborne RS Platforms and Sensors

### 13.2.2.1 Unmanned Aerial Systems (UAS)

In recent years, UAS has become an important RS technology in spatial ecology. Nowadays a plethora of platforms, including fixed-wing and rotor-based systems, can carry multispectral, hyperspectral, thermal, LiDAR, and radar sensors and can navigate autonomously on predefined routes using [global navigation satellite system](#) (GNSS). With the increased availability and simplicity, such platforms are being used more and more in ecological research and monitoring (Anderson and Gaston 2013). In this context two essential characteristics of UAS are relevant:

- (i) *High flexibility and low cost of operation:* UASs offer high flexibility in terms of payloads, flight time, and flight specifications such as altitude, time of day, and weather condition. When compared with manned aircraft or satellites, it is much easier to plan and conduct an image acquisition campaign once a UAS and a trained pilot are available. Due to low fixed costs, UAS can be cheaper than manned planes and helicopters.
- (ii) *High spatial and temporal resolutions:* Within the technical and legal limitations, flight heights of UAS can be freely set and typically range from a couple of meters to hundreds of meters. Depending on the sensor system, images with very high spatial resolution (<5 cm) can be acquired when flown at low altitudes. The high flexibility of operation and the low image acquisition costs enable users to efficiently create multitemporal image series.

In the context of biodiversity monitoring, UASs are used in vegetated ecosystems to obtain optical images with high spatial and spectral resolution and 3-D point clouds of the Earth's surface and vegetation structures.

In grassland ecosystems, high-resolution UAS images are used to map habitat types (Cruzan et al. 2016) or single target species such as weeds (Hardin and Jackson 2005). In recent studies, proximal RS using scaffolds has been used to link species and functional diversity to spectral traits (Schweiger et al. 2018). Here the high spatial resolution is of utmost importance because grassland plants are typically small and highly mixed (Lu et al. 2016). Very high spatial resolution imagery offers the potential for both community- and plant-based analysis (Lopatin et al. 2017). However, even with spatial resolutions <1 cm, species identification of individuals is challenging and might only work under favorable conditions such as low structural

**Table 13.1** Close-range Remote Sensing (RS) approaches and their advantages and disadvantages for monitoring and assessing plant diversity

Close-range RS approaches	Advantages	Disadvantages
<p><i>Spectral analyses of plant species</i> (Asner et al. 2015; Asner and Martin 2009)</p>	<ol style="list-style-type: none"> <li>I. Basis for conducting research on the spectral characteristics of specific biochemical, biophysical, and morphological traits in various organs of plants, including leaves and flowers</li> <li>II. Storage in spectral databases for validation and calibration</li> <li>III. Basis for the spectral fingerprints (SFP) of the vegetation</li> <li>IV. Basis for conducting research on taxonomic, phylogenetic, genetic, epigenetic, or morphological-functional features</li> </ol>	<p>Analysis on molecular level Geometric, structural, distribution, population, and community effects are not measurable</p>
<p><i>Spectral laboratory</i> (manual operation) (Brosinsky et al. 2013; Buddenbaum et al. 2015a, b; Buddenbaum and Hill 2015; Doktor et al. 2014; Lausch et al. 2013)</p> <p><i>Plant phenomics facilities and ecotrons</i> (fully automatic operation) (Ehrhardt and Frommer 2012; Fiorani and Schurr 2013; Furbank 2009; Großkinsky et al. 2015a, b; Li et al. 2014; Pieruschka and Lawson 2015; Virlet et al. 2015)</p>	<ol style="list-style-type: none"> <li>1. Long-term monitoring is possible (entire vegetation period, over several years, specific investigations of impact phases of stressors on plant plants)</li> <li>2. Experimental stress analyses are possible (drought stress, heavy metals, tropospheric ozone, flooding, flood stress, nitrogen loads, etc.)</li> <li>3. Extensive measurement program is possible for biotic, abiotic, and climate conditions within the spectral laboratory</li> <li>4. Storage in spectral databases for validation and calibration</li> <li>5. Comparative analyses can be conducted under natural or artificial conditions to investigate the influence of artificial light, geometry effects, or additional effects on the spectral signal</li> <li>6. Multisensor recording at specific plant development stages a possible</li> </ol>	<p>Development of the measuring boxes for the sensors (automated) Age and development stages of trees are a limiting factor (often only trees up to age 5 can be recorded)</p>

(continued)

**Table 13.1** (continued)

Close-range RS approaches	Advantages	Disadvantages
<i>Tower (flux tower) with different noninvasive measuring technologies as well as RS technology (mobile, permanently installed)</i> <a href="http://www.fluxnet.ornl.gov/">http://www.fluxnet.ornl.gov/</a> <i>Phenocams</i> (Brown et al. 2016)	Advantages II, IV, 1, 3, 4, 6 above also apply (a) Links with international networks are possible (b) Important ground-truth RS information for plant health under natural growth conditions, with certain variables	Local results for a particular site, which do not enable results for extensive areas, but are limited to the forest stand under investigation Primarily nonimaging sensor technology can be implemented
<i>WSNs (WSN)</i> (Hwang et al. 2010; Liyang Yu et al. 2005; Lloret et al. 2009; Mafuta et al. 2013; Mauro et al. 2016; Mollenhauer et al. 2015, 2016; Oliveira et al. 2016; Ruiz-Garcia et al. 2009; Teodoro et al. 2016)	Advantages II, IV, 1, 3, 4, 6, a, b above also apply Long-term monitoring with high time frequencies WSN enables results over more extensive areas from the network distribution Terrestrial sensor networks as well as aquatic WSNs are possible	The number of wireless sensor nodes determines the accuracy of information over extensive areas Primarily nonimaging sensor technology can be implemented
<i>Field measurements (manual operation)</i> Long-term vegetation monitoring experiments (Bruehlheide et al. 2014; Hantsch et al. 2013; Hector et al. 2011; Scherer-Lorenzen et al. 2007)	Spectral measurements directly on trees Investigation of geometric effects (different heights, recording angle) Measuring various biochemical, biophysical, and structural variables in organs (roots, leaf, stem) of a tree Recording microclimate information about soil, water, climate of a tree	Not applicable: IV, 1, 2, 3, 4, 5, 6

complexity, low spatial overlap, and low number of species (Lopatin et al. 2017). Schweiger et al. (2018) showed a strong relationship between functional diversity of grassland species and spectral traits collected using a hyperspectral sensor mounted on a scaffolding. Following this new approach, detection of individuals is no longer needed to monitor functional aspects of biodiversity. If models are to be developed that link the spectral signals to properties of plant diversity, it is important that both the field data collection and the image campaign are synchronized, particular in highly dynamic ecosystems such as grasslands with high land-use intensities. The high flexibility of UAS is a major advantage in such situations.

In vegetated ecosystems, vegetation structure is a key characteristic that is strongly related to the diversity of many taxa. UAS high-resolution images are used to characterize different aspects of vegetation structure: Getzin et al. (2014) used high-resolution RGB images to create canopy gap maps. They showed strong relations between spatial gap metrics and herbal plant species diversity in temperate forests. 3-D point clouds derived from UAS images can be used to characterize the

3-D vegetation structure, for example, by deriving canopy height models to characterize the structural complexity (Saarinen et al. 2017) or by describing vegetation structures directly based on the vertical profiles of the 3-D point clouds (Wallace et al. 2016).

Currently, the efficient use of UASs is limited to areas of less than a couple of square kilometers. Therefore, their main application in the context of biodiversity assessments is for sample-based observations (e.g., plots, transects) where relationships between spectral and structural traits and components of vegetation diversity can be established. Given the option to create dense time series at user-defined frequencies with low effort, UASs offer scientists new opportunities for scale-appropriate measurement of ecological phenomena (Anderson and Gaston 2013) such as phenological and other seasonal effects on canopy reflectance. Thus, they can be used to bridge the gap between scale of observation and the scale of the ecological phenomena that long existed in the temporal and spatial domain when using air- or spaceborne platforms. Therefore, UAS technology needs to be considered as an important intermediate-scale technology for biodiversity monitoring systems and upscaling from field-based measurements and models to larger area estimation.

### 13.2.2.2 Optical RS

The relationship between optical spectral variability over space or time and species diversity can be used to optimize the inventory of species diversity, so priority may be given to sites that are spectrally more different and hence more diverse in species composition (Rocchini et al. 2005). Such analyses can be conducted at different spatial extents and resolutions, from a few meters [e.g., using high-resolution (~1–3 m multispectral) satellite data such as Worldview or GeoEye] to 10–30 m (e.g., Sentinel, Landsat) up to large spatial grain and extent [e.g., Moderate Resolution Imaging Spectroradiometer (MODIS) data from 250 m to 1000 m].

#### Alpha Diversity

Alpha diversity is the number of species living within a given local area and is a measure of within-ecosystem species richness. Most research dealing with RS-based estimates of alpha diversity has focused on mapping localized biodiversity hot spots, based on the spectral variation hypothesis (SVH, (Palmer et al. 2002)). The SVH states that the spatial variability in the remotely sensed signal, i.e., the spectral heterogeneity, is expected to be positively related to environmental heterogeneity and could therefore be used as a powerful proxy of species diversity. In other terms, the greater the habitat heterogeneity, the greater the local species diversity within it, regardless of the taxonomic group under consideration. Besides random variation in species distribution, higher heterogeneity habitats will host a higher number of species each occupying a particular niche (niche difference model, Nekola and White 1999).

Different modeling techniques have been used to model the local species diversity-spectral heterogeneity relationship, ranging from simple univariate models (Gould 2000), to multivariate statistics (Feilhauer and Schmidlein 2009), to neural networks (Foody and Cutler 2003) and generalized additive models (GAMs, Parviainen et al. 2009). A number of different measures of spectral heterogeneity have been proposed and used to assess ecological heterogeneity and thus species diversity (Cavender-Bares et al., Chap. 2). Many of these are related to the variability in a spectral space of different pixel values, such as the variance or texture in a neighborhood of the spectral response (Gillespie 2005) or the distance from the spectral centroid, which may be represented as the mean of spectral values in a multidimensional system whose axes are represented by each image band or by principal components where noise related to band collinearity has been removed (Rocchini 2007). Moreover, in addition to the use of common vegetation indices such as the Normalized Difference Vegetation Index (NDVI), some studies have demonstrated an increase in the strength of the relationship when using additional spectral information (e.g., Landsat bands 5 and 7 in the shortwave infrared (SWIR) (Rocchini 2007) and (Nagendra et al. 2010)).

### Beta Diversity

While alpha diversity is related to local variability, species turnover (beta diversity) is a crucial parameter when trying to identify high-biodiversity areas (Baselga 2013). In fact, for a given level of local species richness, high beta diversity leads to high global diversity of the area. This is one of the basic rules underpinning the concept of irreplaceability of protected areas (e.g., Wegmann et al. 2014).

In some cases spatial distance/dispersal ability might not be the only driver of species turnover, which seems to be more strictly related to environmental conditions. Hence, models have been built to relate species and spectral turnover to explain their potential relationship and its causes (Rocchini et al. 2018b). In some cases, spatial distance accounted only for a small fraction of variance in species similarity, while environmental variation is expected to account for a much larger one. When using spatial distances, distance decay does not necessarily account for environmental heterogeneity (Palmer and Michael 2005), especially in heavily fragmented landscapes. Thus, the use of spectral distances for summarizing beta diversity patterns may be more reliable because this method explicitly takes environmental heterogeneity into account instead of mere spatial distances among sites. Therefore, it is expected that the higher the spectral distance among sites, the higher their difference in terms of environmental niches, potentially leading to higher beta diversity.

A straightforward method for measuring beta diversity is to calculate the differences between pairs of plots in terms of their species composition using one of the many (dis)similarity coefficients proposed in the ecological literature (e.g., Legendre and Legendre 1998) and assess the spectral turnover variability derived remotely from the variation in species composition among sites. This has been mainly related to spectral distance decay models in which species similarity decays once spectral

distance increases, using all pairwise distances among  $N$  plots, based on an a priori defined statistical sampling design.

Another powerful method to estimate beta diversity is related to the so-called spectral species concept (Féret and Asner 2014). This approach is based on the preliminary unsupervised clustering of spectral data, assigning each pixel to a “spectral species.” After spectral clustering, the image is divided into homogeneous elementary surface units, and a dissimilarity metric is then used to compute pairwise dissimilarity between each pair of surface units. Finally, the resulting dissimilarity matrix is processed using nonmetric multidimensional scaling to project elementary units in a 3-D Euclidean space, allowing the creation of a map in the standard red-green-blue (RGB) color system. Such a map expresses changes in species composition with changes in color or color intensity.

While the previously described methods are powerful in describing and estimating diversity from space, they are mainly related to spectral heterogeneity measurement, with no direct relationship with drivers of diversity, such as climate drivers, which might be better estimated by thermal RS.

A very important milestone in biodiversity research was the development of plant functional types (PFTs) such as the Ellenberg indicator values (Schmidtlein 2005) or the CSR-strategy types (C, competitive species; S, stress-tolerant species; R, ruderal species), which altered their functional traits as a consequence of the adaptation to changes in abiotic conditions and/or human pressures such as land-use intensity or management practices. Schmidtlein et al. (2012) developed the foundations for linking RS with this biodiversity concept. Rocchini et al. (2018a) used this research as a basis for calculating a global biodiversity index, namely, “Rao’s Q.” The Rao’s Q is calculated on a set of CSR score maps (derived from Schmidtlein et al. 2012) to estimate the diversity of functional-type probability in space (Rocchini et al. 2018a, see Fig. 13.4).



**Fig. 13.4** Rao’s quadratic diversity metric applied to a MODIS-derived 250 m pixel NDVI map of the world NDVI (date 2016-06-06, <http://land.copernicus.eu/global/products/ndvi>), resampled at 2 km resolution with a moving window of 5 pixels. (Copyright: License number: 4466960473531. From Rocchini et al. (2018a)). Courtesy: Matteo Marcantonio

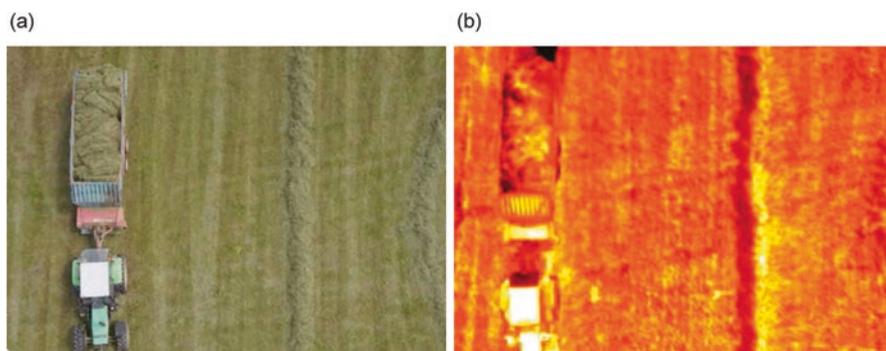
### 13.2.2.3 Thermal RS

Thermal RS detects the energy emitted from Earth's surface as electromagnetic radiation in the thermal infrared spectral range (TIR, 3–15  $\mu\text{m}$ ). This energy can be radiated by all bodies with a temperature above absolute zero and is dependent on the surface temperature and the thermal properties (emissivity) of the observed target (Kuenzer et al. 2013; Künzer and Dech 2013).

Land surface temperature (LST) is one of the most important state variables representing the coupled interaction of the surface energy and water balance from local to global scale (e.g., Kustas et al. 2003). LST is highly influenced by the radiative, thermal, and hydraulic properties of the soil-plant-atmosphere system and has therefore been recognized as one of the high-priority parameters of the International Geosphere and Biosphere Program (IGBP, Townshend et al. 1994).

Various RS platforms and sensors currently provide TIR data at different spatial, spectral, and temporal resolutions. The most common include the Advanced Very High Resolution Radiometer (AVHRR) onboard the Polar Orbiting Environmental Satellites (POES); Landsat 5, 7, and 8; the MODIS sensor on board the NASA Terra and Aqua satellite, the Advanced Spaceborne Thermal Emission and Reflection Radiometer (ASTER) on the Terra Earth observing satellite platform; and Sea and Land Surface Temperature Radiometer (SLSTR) onboard the Sentinel-3 mission.

Although LST is rarely used by ecologists (Wang et al. 2010), a number of applications are closely linked to understanding landscape and biodiversity characteristics. Most often, LST is taken as source to estimate evapotranspiration (see Krajewski et al. 2006 for a review). LST is highly controlled by atmospheric conditions, but also by stomata conductance and plant-available soil moisture (Bonan 2008). In this sense, monitoring of LST with sufficiently high spatial and temporal resolution is able to provide valuable information about the water and energy exchange between the soil-plant-atmosphere continuum and related photosynthetic activities of the vegetation (see Fig. 13.5). Differences in the spatiotemporal behavior of LST can therefore be related to different plant/species distributions and/or to differences



**Fig. 13.5** Optical (a) and TIR (b) image of a ScaleX field campaign test site in July 2016 at the TERENO pre-alpine grassland site, Fendt, Germany. Elevated land surface temperatures (yellow) are detected, especially for the rows of hay mounds facing the sun

related to local energy, water, or nutrient conditions. Examples will be briefly described of methods to disentangle the effects of water, energy, and nutrients on plants in the context of vegetation.

Müller et al. (2014, 2016) applied principal component analysis (PCA) to extract dominant LST patterns from time series (28 scenes covering 12 years) of ASTER TIR images of the mesoscale Attert catchment in midwestern Luxembourg. The PCA-component values for each pixel were related to land use/vegetation data and to geological and soil texture data, indicating a strong information signal in the temporal dynamics of LST data with regard to plant diversity.

Environmental disturbances have been investigated (e.g., by Duro et al. 2007) making use of the negative relationship between vegetation density and LST. Mildrexler et al. (2007) proposed a disturbance detection index based on this principle that uses the 16-day MODIS Enhanced Vegetation Index (EVI) and 8-day LST. They were able to successfully detect disturbance events such as wildfire, irrigated vegetation, precipitation variability, and the recovery of disturbed landscapes at the continental scale.

Sun and Schulz (2015) could demonstrate that an integration of TIR data from Landsat 5 and 8 was able to significantly enhance the classification results for different aggregation levels of land-use and land cover categories for a mesoscale catchment in Luxembourg. This indicates the high potential of TIR data to support more specific and selective plant species monitoring as relevant for biodiversity research.

Environmental stress induced by long-term heat waves and/or a limited availability of water is likely to reduce stomata conductance, limit transpiration, and thereby increase leaf surface temperature (Stoll and Jones 2007). The difference between air temperature and leaf temperature combined with information on vegetation density can serve as an indicator of plant stress. Hoffmann et al. (2016) used a spectral vegetation index and LST data from cameras mounted on UAVs to develop a water deficit index (WDI). The WDI was highly correlated to eddy covariance measurements of latent heat fluxes over a growing season, and that was used to map spatially distributed water demands of various crops.

Environmental stress may also cause changes in leaves and the structure of plants, dependent on their biophysiological characteristics. Buitrago et al. (2016) found that two plant species [European beech, (*Fagus sylvatica*) and rhododendron (*Rhododendron catawbiense*)], when exposed to either water or temperature stress, experience significant changes in TIR radiance. The changes in TIR in response to stress were similar within a species, regardless of the stress. However, changes in TIR spectra differed between species, and these differences could be explained by changes in the microstructure and biochemistry of leaves (e.g., cuticula).

Overall, the potential for exploiting LST information data in plant biodiversity research is manifold. While LST is easily measured by thermometers at the point scale, satellite RS TIR data are needed in order to derive LST routinely at high temporal and spatial resolutions over large spatial extents. However, the derivation of LST from TIR data is a difficult task because such radiance measurements depend

not only on LST but also on surface emissivity and atmospheric conditions (Li and Becker 1993). Therefore, besides cloud detection and radiometric calibration, corrections for emissivity and atmospheric effects have to be carried out. A large number of studies have addressed these issues in the past. It is beyond the scope of this section to summarize these studies, but an excellent review is provided by Dash et al. (2002).

#### 13.2.2.4 Light Detection and Ranging (LiDAR)

LiDAR is an active RS technique in which short pulses of laser light emitted from a scanning device are distributed across a wide area and their reflections from objects are subsequently recorded by a sensor. The distance to the objects can be calculated from the elapsed time and the speed of light. The absolute position of the reflection can be reconstructed using the position recorded by the Global Positioning System (GPS) and the orientation of the sensor determined by the inertial navigation system (INS). The result is a set of 3-D points that represents the scanned surface from which the pulses were reflected. More detailed descriptions of LiDAR technology can be found in Popescu (2011) and Wehr and Lohr (1999).

The primary characteristic that makes LiDAR well suited for monitoring plant biodiversity, vegetation structure, and landscape diversity is the penetration of light beams below the forest canopy. When a LiDAR beam hits the top of the canopy, the beam is reflected by leaves, needles, and branches, and the reflection is recorded by the receiver. If the energy of the beam is still high when it hits the first reflective surface, the beam will split and can penetrate farther through openings in the canopy until it hits additional vegetation, which can again cause reflections. This process continues until a massive reflector, such as a tree trunk or the ground, reflects the beam or until the signal becomes too weak. These properties of LiDAR beams allow a detailed reconstruction of 3-D vegetation structures below the forest canopy, which cannot be provided by passive RS techniques (Koch et al. 2014). Hence, LiDAR RS is a valuable technique for monitoring plant diversity and vegetation structure, and it adds a further dimension to the properties of optical RS.

LiDAR systems can be classified as discrete-return systems or full-waveform systems, based on the capabilities of data recording. At the onset of LiDAR development, sensors were only able to record either the first or the last reflection of the LiDAR beam, which is generally the top of trees and the terrain, respectively. As LiDAR evolved, discrete-return systems were developed, which were able to record a fixed number of range measurements per LiDAR beam, usually up to four to five. The returns were based on thresholds, which were integrated into the proprietary detection method (Thiel and Wehr 2004).

With the more recently developed full-waveform systems, the entire pathway of the LiDAR beam through the canopy can be detected and recorded (Wagner and Ullrich 2004). The post-processing of this data can be applied to theoretically extract an unlimited number of echoes. Moreover, with Gaussian decomposition—

the standard procedure for waveform decomposition—additional echo attributes, such as amplitude and intensity of the return signal, can be provided, which can support the classification process. As a result, full-waveform data provide a much more detailed characterization of the vertical vegetation structure. In this way, important indicators for vegetation structure and biodiversity, e.g., vegetation height and cover of the different vegetation layers, can be estimated with a lower bias and higher consistency (Reitberger et al. 2008).

Nowadays, laser-based instruments are mounted on all kinds of RS platforms, including stationary or mobile scanners and terrestrial-, drone-, and aircraft-based platforms (e.g., the well-established airborne LiDAR scanning). To record a variety of structural parameters, it is possible to combine information from LiDAR sensors with optical, thermal, or radar RS sensors (Joshi et al. 2015, 2016). Li et al. (2014) provide an overview of 3-D imaging techniques for describing plant phenotyping of vegetation. Rosell and Sanz (2012) review methods and applications of 3-D imaging techniques for the geometric characterization of tree crops in agricultural systems. Wulder et al. (2012) provide a review of LiDAR sampling for characterizing landscapes.

The LiDAR systems used for ecological applications generally have a beam footprint of less than 1 m diameter on the ground. These so-called small-footprint systems are preferred because they provide a good link between the LiDAR beam and the structural vegetation attributes that could subtly change as a consequence of stress or damage, sometimes within individual trees. By comparison, large-footprint systems have beam diameters of up to scores of meters on the ground; e.g., the Geoscience Laser Altimeter System (GLAS) instrument mounted on the Ice, Cloud, and land Elevation Satellite (ICESat) platform has a footprint of 38 m (Schutz et al. 2005). Such systems can be used to model and map broad vegetation structural attributes and are well suited for detecting structural vegetation characteristics across large areas.

The most important environmental application of LiDAR is the precise mapping of terrain and surface elevations. Such digital terrain models (DTMs) or digital surface models (DSMs) can be useful in determining topographic information important for plant growth and monitoring of vegetation structure and biodiversity, e.g., changes in vegetation height or density resulting from succession or natural disturbance (Heurich 2008). Many filtering methods have been developed to extract terrain elevation from point clouds, which produces DTMs with high spatial resolution and root mean square errors (RMSEs) of 0.15–0.35 m (Andersen et al. 2005; Heurich 2008; Sithole and Vosselman 2004). No other RS technique has the ability to deliver DTMs of similar quality within dense vegetation. Recent studies show that it is even possible for LiDAR to detect objects located on the ground surface. Coarse woody debris, as an example, is an important indicator of past disturbances that might influence biodiversity because it provides habitat to a multitude of plant and animal species and plays an important role in the forest carbon cycle.

Because of its characteristics, LiDAR is well suited for measuring biophysical parameters of vegetation, such as tree dimensions and canopy properties. Two main approaches have been developed over recent years. The area-based approach is a

straightforward methodology in which the height distribution of the LiDAR beam reflections is analyzed for a given area. In the first step, plenty of different “LiDAR metrics,” e.g., maximum height or fractional cover, are calculated for each area. The second step is model calibration, where these metrics are compared to on-the-ground survey data such as plant species richness, aboveground biomass (AGB), or vertical and horizontal vegetation structure. In the final step, the models are used to estimate the selected biodiversity indicators for large areas using square grid cells. Such an analysis is generally conducted using a priori stratification of structural vegetation types and plant species. In the years that followed, this methodology was proven to be able to determine key biophysical vegetation variables on a larger scale. To date, this method has been shown to deliver a precision of 4–8% for height, 6–12% for mean diameter, 9–12% for basal area, 17–22% for stem number, and 11–14% for volume estimations of boreal forests (Maltamo et al. 2006; Næsset 2002, 2007). Because of the highly accurate estimation of important vegetation structural parameters, the area-based approach was further developed and adapted to operational forest inventories in boreal forests of Scandinavia. Similar accuracies have also been achieved for the temperate zone, although the more complex vegetation structures in this zone, especially the higher number of tree and plant species and higher amount of biomass, led to less accurate estimations and more effort in stratification and ground measurement to obtain species-specific results (Heurich and Thoma 2008; Latifi et al. 2010, 2015).

The second methodology is the individual-tree approach, which has the objective of extracting data on single trees and modeling the tree properties. The procedure consists of four steps. In the first step, individual trees are delineated by dividing each crown into segments with techniques originally used for raster analysis, such as watershed analysis and local maxima detection (Heurich 2008; Persson et al. 2002). However, these techniques do not take advantage of the full information of the 3-D point cloud, and therefore, trees beneath the crown surface cannot be detected. For this reason, new methods based on 3-D point clouds have been developed over recent years (Tang et al. 2013; Yao et al. 2012). When these novel techniques are employed, more than 80% of the trees of the upper canopy level can be detected. Moreover, tree detection in the lower canopy is much improved compared to 2-D techniques. In the second step, parameters of each tree (e.g., height, species, and crown parameters) are derived. Tree height can be determined by measuring the distance of the highest reflection of a LiDAR beam within the tree segment and the DTM, with an accuracy of less than 2 m and a slight underestimation (Heurich 2008). The third step is the model calibration of the biophysical parameters of the tree, namely, diameter at breast height (DBH), volume, and biomass, using trees measured on the ground as a reference. The tree crown can be modeled using convex hulls and alpha shapes. The fourth step involves the application of these models to predict DBH, volume, and biomass of all trees delineated by LiDAR. Based on these crown representations, basic attributes reflecting tree health can be derived, e.g., total volume, crown length, crown area, and crown base height (Yao et al. 2012). The extracted parameters of individual trees also form the basis for identifying the tree species by calculating point cloud and waveform features within the 2-D

or 3-D representation of the tree and with the help of classification techniques (Reitberger et al. 2008). While differentiation between deciduous and coniferous trees is highly accurate (>80%, up to ca. 97%), differentiation within these classes is more difficult and leads to a higher classification error. Moreover, it is possible to distinguish between living trees, standing dead trees, and snags (Yao et al. 2012) and to map dead trees at the plot or stand level. However, 3-D LiDAR has its limitations in differentiating between trees species and dead trees when not combined with multispectral optical data. One drawback of the individual-tree approach is that the LiDAR beam loses some transmission on its way through the canopy and is therefore not always suitable for smaller understory trees, which results in their underestimation. To overcome this problem, methods have been developed to predict diameter distributions of forest stands based on detectable trees in the upper canopy and LiDAR-derived information on the vertical forest structure and density (Lefsky et al. 2002).

In addition to the traditional parameters related to forestry, a multitude of traits that describe the ecological conditions of the forest can be estimated with LiDAR sensors. One key element for assessing plant diversity and vegetation structure is canopy cover, which is defined as the projection of the tree crowns onto the ground divided by ground surface area. This parameter can be easily obtained from LiDAR data by dividing the number of returns measured above a certain height threshold by the total number of returns. Many studies have proven the strong ( $R^2 > 0.7$ ) relationship between this LiDAR metric and ground measurements. By using hemispherical images or other ground-based instruments for calibration, leaf area index (LAI) and solar radiation can also be derived from LiDAR data with a high precision over large areas (Moeser et al. 2014). Because canopy metrics are affected by sensor and flight characteristics, it is recommended that each campaign be calibrated to obtain high-quality results. However, it has been shown that even without calibration, fairly reliable results can be obtained.

Vertical vegetation structure is highly relevant for the description of forest and vegetation heterogeneity and highly important for biodiversity studies. A widely used LiDAR metric for representing vertical canopy complexity is the coefficient of variation. High coefficient values correspond to more diverse multilayer stands, whereas low values represent single-layer stands. The coefficient of variation can be applied at point clouds, the digital crown model, or individual trees. Zimble et al. (2003) applied this principle and classified vegetation types according to stand structure with an overall accuracy of 97%.

Another approach is the partitioning of the vertical structure into different height layers in relation to ecological importance. Latifi et al. (2015) divided the canopy into height layers according to phytosociological mapping standards and found a strong relationship to various LiDAR metrics in regression models. Similar approaches were used by Ewald et al. (2014) to represent understory offering protection for birds and deer and to detect forest regeneration. A more recent study applied a 3-D segmentation algorithm to estimate regeneration cover with an accuracy of 70%. LiDAR-derived information about the vertical structure is also used

for the assessment of forest fuels and their vertical distribution, which are important input variables in forest fire models used in fire management.

In summary, LiDAR RS is a powerful tool for monitoring vegetation structure and plant diversity. It delivers detailed and accurate information about forest properties down to the scale of the individual tree and is therefore regarded as the gold standard for determining vegetation structure. Nowadays, LiDAR is widely applied in RS research as a reference to test the accuracy of other methods and is used in practical forest management in the boreal zone of Scandinavia (Næsset 2007). The development of new sensors will lead to multi- or hyperspectral LiDAR technology, which will combine the advantages of today's LiDAR and optical sensors. These systems will be able to collect accurate 3-D information and calibrated spectral information without facing the problems of varying illumination in the tree crowns. Furthermore, the resolution of the data will increase, thereby enabling parameter extraction at the branch level.

### 13.2.2.5 Radar

Several reviews have been conducted on radar alone or radar and optical sensors for vegetation applications relevant to habitat and biodiversity. They typically include classification of vegetation or land cover types, biophysical modeling of parameters such as biomass or tree height, and ecosystem disturbance detection and mapping (e.g., Baltzer 2001; Treuhaft et al. 2004; Lu 2006, which includes summaries of four previous reviews; Lutz et al. 2008; Bergen et al. 2009; Lowry et al. 2009; Koch 2010; Nagendra et al. 2013; Tiner et al. 2014; White et al. 2015; Timothy et al. 2016; Baltzer 2017).

#### Systems and Techniques

Active radar is the focus of this section because the resolution of passive sensors is generally too coarse for all but large extent studies. In active radar, transmitted pulses interact with scattering elements of the surface in terms of their dielectric properties, size, and arrangement. In vegetation, moisture (increasing dielectric constant) and more complex stem-branch-leaf arrangements result in increased backscatter intensity. Much research has been conducted using physically based models to characterize and understand backscatter effects in vegetated canopies (e.g., Sun and Ranson 1995; Ningthoujam et al. 2016). Spatial and temporal variations in these properties associated with different vegetation types, age distribution, health, and management provide information or indicators of potential habitat and biodiversity. Radar data are available at different frequencies/wavelengths; X-, C-, and L-bands (2.5–3.75 cm, 3.75–7.5 cm, and 15–30 cm wavelengths, respectively) are the most common on satellite platforms. S-band (7.5–15 cm) has been deployed on a couple of satellites, and new S- and P-band (30–100 cm) satellite sensors are planned for the near future (e.g., NISAR L- and S-bands; NovaSAR S-band;

BIOMASS P-band). Backscatter of shorter wavelengths is generally from the upper canopy, while longer wavelengths penetrate farther into vegetation. Combining shorter and longer wavelength data can be advantageous to detect contributions of multiple scattering from different vertical portions of the canopy as well as ground surface scattering and double bounce ground-stem scattering. Transmitted and received radar signal polarizations [commonly horizontal (H) and vertical (V)] can provide information on vegetation composition and structure. Co-polarized signals (e.g., HH) respond more to trunk-ground configurations (double bounce scattering), particularly at longer wavelengths, while cross-polarizations (e.g., HV) respond more to canopy woody biomass (Ningthoujam et al. 2017). Combinations such as ratios (e.g., HH/HV) can therefore enhance spatial differences in scattering types and magnitude due to varying vegetation density (Mitchard et al. 2011). Similarly, steeper incidence angles generally penetrate farther into the canopy, particularly in leaf-on conditions, but multiple angles may enhance differences in vertical structure (Henderson and Lewis 1998). All of the above characteristics related to the degree of canopy penetration provide opportunity for analysis of vertical structural complexity and composition diversity by using multiple bands, polarizations, and incidence angles. Radar image texture information has also been found to be useful in classification (Simard et al. 2000) and biophysical modeling (Kuplich et al. 2005).

Polarimetric data, where phase information is preserved (Ulaby et al. 1987), allows additional analysis of polarization parameters and, through decomposition analysis, the relative contributions from the various scattering mechanisms (e.g., surface, volume, double bounce) that are associated with canopy structural characteristics. Commonly applied decomposition techniques include (van Zyl 1989; Cloude et al. 1996; Freeman and Durden 1998; Yamaguchi et al. 2005; Touzi 2007). Several others were designed to build on or correct issues with previous techniques (Hong and Wdowinski 2014). The Interferometric SAR (InSAR, e.g., Balzter (2001)), provides a plain language description) incorporates transmission from two different angles either simultaneously or in repeat passes (less preferable given potential decorrelation of the response signals between passes). The phase differences between the radar response signals can be used to estimate the scattering phase height center, which is associated with canopy density and arrangement. They can also be used to generate digital elevation models (DEMs), with longer wavelengths that penetrate the canopy being more suitable. Using multiple parallel base-lines, SAR tomography has been used to construct a 3-D representation of a given volume such as a forest (e.g., Reigber and Moreira 2000).

### Classification and Biophysical Modeling Applications

As with other RS technologies, landscape or vegetation diversity as an indicator of biodiversity can be mapped through thematic classification. This can be accomplished across a broad gradient from nonvegetated to dense vegetation classes, to map landscape cover types (e.g., Devaney et al. 2015) that may be associated with

the spatial distribution of biodiversity. For example, within the context of developing understanding of the spatial distribution of sensitive arctic shore habitat and biodiversity areas in the event of oil spills, Banks et al. (2014a) used decomposition parameters in a comparison of three unsupervised polarimetric classifiers for their potential in mapping multiple classes of substrate (nonvegetated), tundra vegetation, and wetland type. Similarly, Varghese et al. (2016) classified water, settlements, agriculture, shrub/scrub, and three forest density classes in a comparison of parameters derived from six decomposition techniques. In an analogous manner, specific classes within an ecotype can be mapped. For example, mapping the diversity of given classes within a wetland complex (e.g., Touzi and Deschamps 2007; Gosselin et al. 2013; Dingle Robertson et al. 2015; Hong et al. 2015; Dubeau et al. 2017) can aid identification of the variety of habitat conditions available and potential biodiversity. In general, radar data have not been found to provide consistently better overall classification accuracy than optical data. However, since radar data are typically complementary and not highly correlated with optical data, they can provide additional information for certain vegetation classes that can be distinguished by structure in cases where optically derived spectral reflectance and vegetation indices are similar. Thus, combining radar and optical imagery has often been shown to improve the accuracy of such classes over either data type alone (e.g., Bergen et al. 2007; Wang et al. 2009; Bwangoy et al. 2010; Banks et al. 2014b).

An alternative approach to thematic classification is estimation of vegetation structure parameters that can serve as indicators of potential habitat diversity or biodiversity, for example, the average or spatial heterogeneity of AGB, LAI, vegetation height, and stem and branch parameters. Luckman et al. (1997), Lucas et al. (2006), and Le Toan et al. (2004), among others, have reported that the backscatter-AGB relationship typically saturates in the range of 100–150 t/ha. However, AGB spatial variability can be mapped in environments with lower vegetation density (e.g., Häme et al. 2013), and efforts to produce suitable models with a higher saturation threshold by improving data information content are common. For example, use of the following has proven beneficial: cross-polarized (HV) data rather than co-polarized; longer wavelengths that penetrate deeper into the canopy (Santos et al. 2003); ratios such as VV/HH (Manninen et al. 2009 for LAI); shorter-to-longer wavelength ratios such as C-/L-bands (Foody et al. 1997); averaging of multitemporal data sets to reduce moisture/rain effects (Englhart et al. 2011); and integrating optical and radar data (Vaglio et al. 2017). Imhoff et al. (1997) modeled canopy parameters using steep incidence angle C-, L-, and P-band airborne radar and found strong correlations for C-HV and LAI, L-VV and branch surface area or volume, and P-VV with bole surface area or volume; these relationships were then used to map broad avian habitat classes. Bergen et al. (2009) combined biomass estimates from C- and L-band backscatter with Landsat vegetation classification, thereby improving habitat mapping for three bird species over use of vegetation type alone.

InSAR has been used to estimate canopy height and height variance, which can be an indicator of vegetation type, structural complexity, and age diversity. Canopy height is most commonly estimated from the difference between scattering phase

height center estimates derived from short wavelength (X- or C-band) InSAR and a ground DEM derived from longer wavelength InSAR (L- or P-bands, Neeff et al. 2005; Balzter et al. 2007a) or from another source such as LiDAR (e.g., Kellndorfer et al. 2004; Andersen et al. 2008; Tighe 2012). Tighe et al. (2009) applied this approach with the addition of correction factors for various forest ecotypes in US and Canadian environments from semiarid to boreal. Integrating polarimetric response with InSAR (i.e., PolInSAR; Cloude and Papathanassiou 1998) can improve InSAR estimates of tree height (e.g., Balzter et al. 2007b). Tomography has also shown promise in modeling the vertical distribution of canopy biomass, but multiple acquisitions must be conducted within a short time to minimize temporal decorrelation. The DEMs produced from InSAR can also be used to generate topographic indices for analysis of topographic complexity or roughness related to habitat diversity and biodiversity (Turner et al. 2003; Kuenzer et al. 2014). Fusion of optical imagery and/or LiDAR with InSAR (e.g., as reviewed in Treuhaft et al. 2004) can also improve vertical canopy and topographic information.

Mapping of disturbance or environmental change can serve as an indicator of potential impacts on habitat diversity and biodiversity. Many studies have been conducted in diverse applications that cannot be fully reviewed here. Most early applications were in mapping of deforestation, particularly in tropical regions where deforestation had become a major issue (e.g., Rignot et al. 1997; van der Sanden and Hoekman 1999). Temporal data have become widely used in land cover change analysis using classification approaches (e.g., Thapa et al. 2013), analysis of backscatter change (e.g., Whittle et al. 2012; Mermoz and Le Toan 2016), and biophysical modeling for biomass loss (e.g., Mitchard et al. 2011). Other major radar applications of environmental change with implications for biodiversity impacts are burn and inundation detection and mapping. Early fire impact studies focused on backscatter variations related to burn intensity classes (e.g., Kasischke et al. 1992). More recent work has included temporal backscatter data in pre-/postburn analysis (e.g., Tanase et al. 2015) and polarimetric analysis and decomposition in modeling biomass changes due to fire (Martins et al. 2016). Radar is particularly useful in detecting inundation under vegetated canopies due to specular reflection off the water surface; in the case of inundated forests, penetration of the canopy by longer wavelengths occurs with double bounce scattering off the water surface and tree trunks (e.g., Kim et al. 2009) and phase differences between different polarizations (e.g., Rignot et al. 1997).

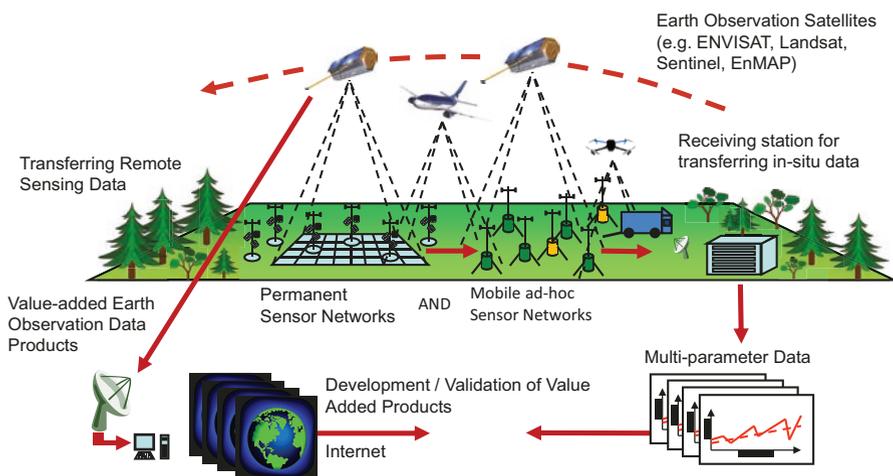
Overall, use of radar for biodiversity and landscape diversity analysis, modeling, mapping, and monitoring follows similar approaches to optical RS. Diversity of land cover types or specific classes within a given ecotype may be directly mapped using classification or modeling, while estimation of biophysical variables can serve as indicators of spatial heterogeneity and potential habitat diversity or biodiversity. The main contributions of radar are in its unique response to vegetation structure that complements spectral reflectance characteristics of vegetation in the optical regions. With the multitude of wavelengths, incidence angles, and polarizations available, as well as the capability to acquire and process InSAR and polarimetric data, much promise has been shown for mapping and monitoring land cover diversity- and biodiversity-related vegetation metrics. New satellite systems are being

developed, and particularly the 2021 BIOMASS P-band InSAR mission (Le Toan et al. 2011) will provide consistent means for global biomass mapping and monitoring.

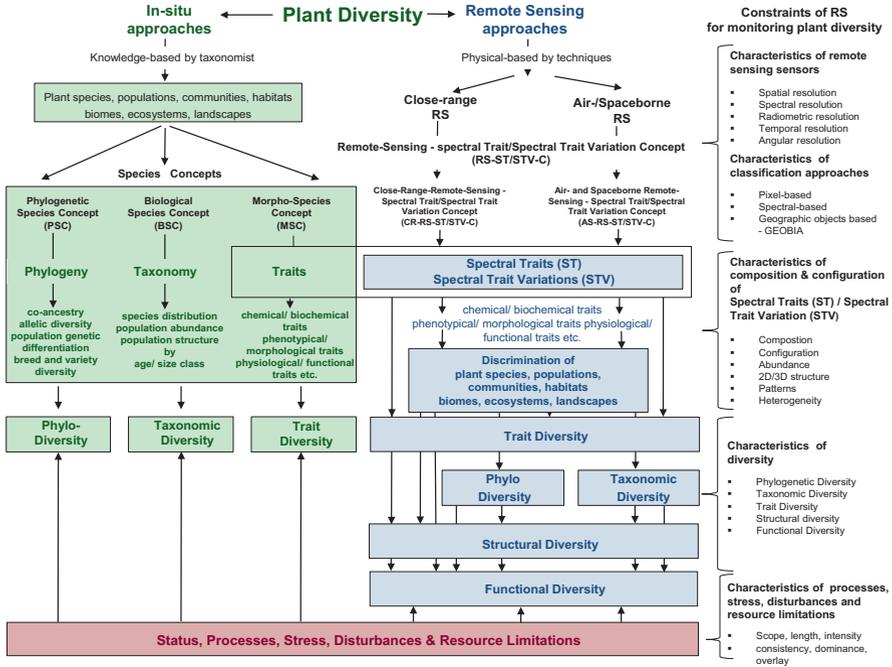
### 13.3 Conclusion and Further Work

Traits, drivers, and effects on biodiversity exist on all spatiotemporal scales. Air- and spaceborne RS data capture processes and patterns in ecosystems, but often without the knowledge of the cause of the phenomenon and real high-frequency ground information. Therefore, close-range RS platforms that record RS information at high frequency must be coupled with air- and spaceborne RS platforms (see Fig. 13.6).

No monitoring approach alone is sufficient, comprehensive, cost-effective, and flexible enough to perform vegetation health monitoring from local to global scales and for short- to long-term processes as well as to monitor changes in phylo-, taxonomic, functional, and trait diversity and to assess the resilience of ecosystems. Therefore, the development and application of a multisource vegetation diversity and health monitoring network (MUSO-VDH-MN) is important where multisource data (close-range, air-, and spaceborne RS data) as well as different in-situ monitoring approaches can be linked in an effort to compensate for the shortcomings of one approach with the advantages of another and to achieve additional benefits for VH monitoring. A future MUSO-VDH-MN should therefore contain the following elements (see Fig. 13.7):



**Fig. 13.6** Linking different approaches (high-frequency WSNs up to spaceborne satellites) with relative frequency monitoring, sensors, and different platforms of RS to better describe, explain, predict, and understand vegetation diversity with RS techniques as well as improve the calibration and validation of RS data. (From Lausch et al. 2018a)



**Fig. 13.7** Overview of in-situ approaches—the phylogenetic species concept (PSC), the biological species concept (BSC), the morphological species concept (MSC), and the RS-spectral trait/spectral trait variation (RS-ST/STV) concept, which integrates the close-range RS approaches and the air-/spaceborne RS approach. The different in-situ and RS approaches are crucial for determining phylo-, taxonomic, structural, trait diversity as well as functional diversity, in order to be able to monitor and assess status, stress, shifts, disturbances, or resource limitations at different levels of vegetation organization. Components that need to be included for a future multisource vegetation diversity and health monitoring network (MUSO-VDH-MN): (I) linking of existing monitoring approaches; (II) integration of existing data, networks, and platforms; and (III) the use of data science as a bridge for handling and coupling big vegetation diversity and health data. (Modified after Lausch et al. 2018a)

- (i) *Coupling of the different monitoring approaches (in-situ and RS) for plant diversity.*
- (ii) *The integration and linking of multisource data and RS platforms. MUSO-VDH-MN should integrate the following data and site survey platforms:*

Species/habitats: Data from site surveys for species, species lists, metabarcoding, microgenomics (Bush et al. 2017), and phenotyping (Deans et al. 2015) and data from museums, lysimeters, plant phenomic facilities (Furbank 2009), controlled environmental facilities (ecotrons, Lawton et al. 1993), long-term ecological research (Mueller et al. 2010), spectral laboratory experiments, and biodiversity ecosystem functioning experiments (Bruehlheide et al. 2014)

RS: optical (multispectral, hyperspectral), thermal, radar, LiDAR data, laboratory, tower, camera traps, WSNs, drones, and close-range, air- and space-borne RS platforms. Additionally, it should link monitoring databases, networks, citizen science information, abiotic (soil, water, air) information, and social and economic information.

- (iii) *Data science, linked open data, and semantic web as a bridge for understanding and monitoring vegetation diversity.* For further information see also Lausch et al. (2015c, 2018a, b) (Fig. 13.7).

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