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Review

Linking Earth Observation and taxonomic, structural and functional biodiversity: Local to ecosystem perspectives

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ABSTRACT

Impacts of human civilization on ecosystems threaten global biodiversity. In a changing environment, traditional in situ approaches to biodiversity monitoring have made significant steps forward to quantify and evaluate BD at many scales but still, these methods are limited to comparatively small areas. Earth observation (EO) techniques may provide a solution to overcome this shortcoming by measuring entities of interest at different spatial and temporal scales.

This paper provides a comprehensive overview of the role of EO to detect, describe, explain, predict and assess biodiversity. Here, we focus on three main aspects related to biodiversity – taxonomic diversity, functional diversity and structural diversity, which integrate different levels of organization – molecular, genetic, individual, species, populations, communities, biomes, ecosystems and landscapes. In particular, we discuss the recording of taxonomic elements of biodiversity through the identification of animal and plant species. We highlight the importance of the spectral traits (ST) and spectral trait variations (STV) concept for EO-based biodiversity research. Furthermore we provide examples of spectral traits/spectral

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trait variations used in EO applications for quantifying taxonomic diversity, functional diversity and structural diversity. We discuss the use of EO to monitor biodiversity and habitat quality using different remote-sensing techniques. Finally, we suggest specifically important steps for a better integration of EO in biodiversity research.

EO methods represent an affordable, repeatable and comparable method for measuring, describing, explaining and modelling taxonomic, functional and structural diversity. Upcoming sensor developments will provide opportunities to quantify spectral traits, currently not detectable with EO, and will surely help to describe biodiversity in more detail. Therefore, new concepts are needed to tightly integrate EO sensor networks with the identification of biodiversity. This will mean taking completely new directions in the future to link complex, large data, different approaches and models.

Contents

1. Introduction

The importance of biodiversity (BD) for ecosystem functioning and the provision of ecosystem services and its relevance for mankind has been investigated by numerous recent studies (Duffy, 2009; Cardinale et al., 2012) and is widely accepted in the Millennium Ecosystem Assessment (MA, 2003). However, it is not only necessary to emphasize its significance but much more important to provide precise statements about qualitative and quantitative changes and threats to BD as well as estimates of the monetary value of ecosystem functions for entire ecosystems (Pasher et al., 2014). It goes without saying that Earth Observation (EO) has tremendous potential for providing large-scale, long-term, standardized, spatially complete, continuous as well as economically feasible information that is urgently needed for the detecting, quantifying, assessment and forecasting of global BD (Belward and Skøien, 2014; Kuenzer et al., 2015; Pettorelli et al., 2016). Consequently, there has been an increasing focus on measuring, quantifying and modelling BD, based on air- and spaceborne EO techniques (Turner et al., 2003; Nagendra, 2001; Gould, 2000; Gillespie et al., 2008; Asner and Martin, 2008). Also, the monitoring of Essential Biodiversity Variables (Pereira et al., 2013a,b) in general and those using remote sensing in particular was recently emphasized by Skidmore et al. (2015) and Pettorelli et al. (2016).

Implementing remote-sensing techniques for the detection, describing, explaining, predicting and assessing of BD using forthcoming EO sensors is expected to spark off some very new methods of monitoring BD (Jetz et al., 2016). However, it remains to be seen as to whether the current implementation of EO systems is sufficient to make use of the purely physical potential in terms of resolution and spectral bandwidth that these novel EO sensors will provide. According to the sensor characteristics of the hyperspectral satellite EnMAP (Environmental Mapping and Analysis Program, Guanter et al., 2015), significant progress for assessing BD is expected by 2018. In the spectral range of 0.4-2.5 μm, with more than a hundred narrowband spectral channels, a highly differentiated spectrometric signal of optical characteristics of morphological and/or physiological traits and their changes in plants, plant communities and BD will be possible across global scales (Asner and Martin, 2008). The emergence of airborne imaging spectroscopy has really paved the way forward to a comprehensive assessment of BD (Green et al., 1998; Asner and Martin, 2008; Baldeck et al., 2015; Schaepman et al., 2015). Furthermore a number of satellite-based imaging spectrometers such as PRISMA (ASI/Italy), HISUI (METI/Japan), HYPXIM-P (CNES, France) or HyspIRI (NASA/USA) are planned in the future (Kuenzer et al., 2015; Houborg et al., 2015). For the first time, the combination of 0.4-2.4 μm (VNIR – Visible and Near-Infrared, SWIR-Shortwave Infra-Red) and thermal hyperspectral wavelengths on a satellite platform will be available in 2020 from the Hyperspectral Infrared Imager HyspIRI (Roberts et al., 2012). Also, the development of very high spectral resolution sensors (0.3-3.0 μm) will facilitate the quantification of eco-physiological plant processes such as solar-induced chlorophyll fluorescence and photosynthesis in terrestrial vegetation (Jansen et al., 2009; Rascher, 2007; Rascher et al., 2015; Meroni et al., 2009; Rossini et al., 2015). The FLEX Satellite (Fluorescence Explorer, FLEX, ESA, 2018; Kraft et al., 2012), will allow the physiological traits in plants to be measured, enabling analyses on global photosynthetic activity, CO_2 fluxes and budgets (Rascher, 2007; Kraft et al., 2012; Rascher et al., 2015). A number of new EO technologies are planned, including laser-based instruments (Global Ecosystem Dynamics Investigation, GEDI – 3D-LiDAR, NASA, launch in 2019, Fig. 7a), which will enable the 3D quantification of vegetation such as volume, stand structure, biomass with a 1 m resolution (Stysley et al., 2015). A combination of FLEX and GEDI LiDAR will fill the gaps in the missing functional and structural information, enabling a more accurate modelling and understanding of climate change and its effects on ecosystems. At the same time, the increasing openness of the data archives of Landsat, Spot, the Copernicus Mission (Sentinel 1–5) or EnMAP will make information relevant to BD research more readily available in the future in a timely, continuous, comparable and transferable manner (Wulder and Coops, 2014).

In addition to optical sensors, there is a wide range of radar sensors (Radio Detection and Ranging) that play and will increasingly play a tremendous role in deriving BD indicators. Unlike optical sensors, as cloud cover and unfavourable weather conditions do not limit them, these active sensors can record images both day and night and will thus continuously deliver EO data. The latest and upcoming radar satellites already provide and will increasingly provide in the future high spatial resolution data. The radar mission TerraSAR-X, launched in 2007, for example represent a new generation of radar satellites that has been extensively improved. The HRWS mission (High Resolution Wide Swath) aims to address user needs by adding the capability to provide data with very high spatial resolution (up to 0.25 m). The HRWS mission will initiate the next steps in the German X-Band SAR data and will make radar data available to users in approximately 2030 (Fischer et al., 2012; Kuenzer et al., 2015). Radar data can be used as single source of information in BD research (DeFries et al., 1999; Amarsaikhan et al., 2007; Urbazaev et al., 2015) or alternatively in combination with different optical EO data (e.g., Landsat TM, RapidEye, Quickbird) by applying data merging techniques (Erasmi and Twele, 2009; Malenovský et al., 2012; Joshi et al., 2016). In particular, the processes of quantifying Land Use Cover Change (LUCC), land management systems, analysing Land-Use intensity (LUI) or monitoring forest structure heterogeneity and complexity require time series with high temporal resolution (Estes et al., 2010; Pereira et al., 2013a,b; Stefanski et al., 2014; Joshi et al., 2015; Hostert et al., 2015; Verburg et al., 2015). This necessitates robust, comparable and repetitive radar data and sensor combinations from radar, optical and thermal data. Sentinel-1, the latest EO radar satellite from the Copernicus mission provides robust and systematic information on terrestrial surface structures with a spatial resolution of typically 10 m (Torres et al., 2012). These data enable deriving various abiotic variables that are imperative for understanding processes relevant to BD monitoring such as the detection of interferometric processes in surfaces like earth-moving (Yague-Martinez et al., 2016), soil moisture retrieval (Pause et al., 2012, 2014), flood mapping (Twele et al., 2016) or the detection of earthquake processes (Grandin et al., 2016). Moreover, all Sentinel-EO data are freely available and will be saved in a consistent data archive for long time series (Torres et al., 2012).

In light of these recent technical achievements, the requirements to meet the Aichi targets of the Convention on Biological Diversity (CBD) for 2020 and the reporting needs for Natura 2000 (http://ec.europa.eu/environment/nature/natura2000/index_en.htm) or the United Nations Framework Convention on Climate Change (UNFCC) the pressure and expectations to succeed in using EO to monitor and assess BD are very high. Numerous reviews document the technical issues and methodical applications in using EO for quantifying and monitoring BD and ecosystem variables (Kerr and Ostrovsky, 2003; Duro et al., 2007; Petrou et al., 2015).

Building on previous literature, our goal here is to provide a comprehensive and up-to-date overview on this topic including forthcoming EO missions. By considering taxonomic, functional as well as structural BD (section 2), we set a broader scope than previous papers. We also specifically discuss how BD 'entities' need to de defined from an EO perspective and explain the necessary contraints for recording entities of biodiversity using EO (section 3). Based on this conceptual background, we outline the state of the art and identify recent trends in detecting and quantifying taxonomic, functional and structural diversity using EO (section 4). We finally discuss the advantages, knowledge gaps and remaining limitations of linking BD and EO (section 5).

2. Characteristics of biodiversity – taxonomic, structural and functional diversity

Biological diversity or biodiversity means "the variability among living organisms from all sources including, inter alia, terrestrial, marine and other aquatic ecosystems and the ecological complexes of which they are part; this includes diversity within species, between species and of ecosystems" (CBD, Article 2, www.cbd.int.). It therefore encompasses the diversity of living entities on different levels of organization – from molecular, genetic, individual and species to populations, communities, biomes, ecosystems and landscapes. As our focus here is on EO-applications, we slightly modified the definition of BD after Noss (1990) who proposed three essential characteristics of BD: the composition, structure and function that integrate different levels of organization of biotic entities (Fig. 1). The characteristics of BD that we focus on are: (I) Taxonomic BD – the diversity of taxonomically different biotic entities (molecular, genes, individuals, populations, communities, ecosystems, landscapes); (II) Functional BD – the diversity of functions and processes (genetic, demographic, intra-species, and landscape processes) and (III) Structural BD – the arrangement and distribution (composition and configuration) of biotic entities (molecular structures, genetic structures, population structures, physiognomy, habitat structures and landscape patterns). These characteristics of BD help us to categorise and understand how EO-derived information is linked to BD. Furthermore, they help us to answer how well and in which way different EO sensors and platforms together with EO-based model approaches can describe, explain, predict and assess the taxonomic, structural and functional diversity (Fig. 1).

3. Entities of biodiversity from an EO perspective

When biodiversity is measured using EO technology, the following key questions can be asked:

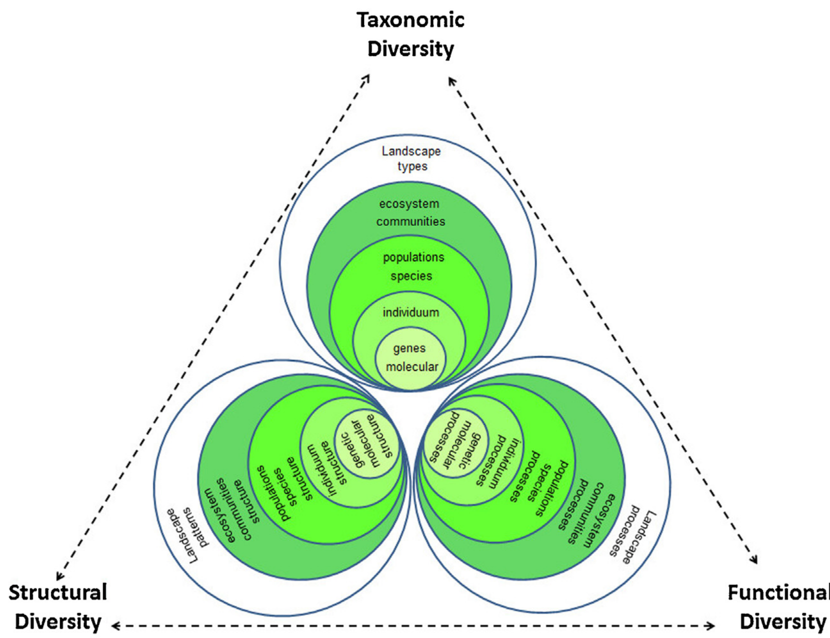

Fig. 1. Three essential characteristics of biodiversity – taxonomic diversity, structural diversity and functional diversity on different levels of organization – molecular, genetic, individual, species, populations, communities, biomes, ecosystems and landscapes (modified after Noss, 1990).

1 Which entities of BD can be measured using EO technology?
2 Why are EO techniques suitable for detecting and recording entities of BD?
3 Which framework conditions define the measurement of entities of BD using EO?
4 What are the constraints for recording of entities of biodiversity using EO?

3.1. Which entities of biodiversity can be measured using EO technology?

All EO techniques (optical, thermal and radar sensors) record the characteristics or traits of the abiotic and biotic earth surfaces (vegetation as well as animal species) based on the "principles of spectroscopy across the electromagnetic spectrum from visible to microwave bands" (Ustin and Gamon, 2010).

Traits of species have been defined for animal species (Deans et al., 2012; Pettorelli et al., 2015) as well as for plants, populations, communities and beyond (Homolová et al., 2013; Pérez-Harguindeguy et al., 2013). Likewise, animal species are characterised by various anatomical, morphological, or functional traits (Pawar et al., 2015) that can be partly recorded using EO techniques (e.g. the temperature of endotherms can be measured using thermal sensors attached to drones or cameras, see chapter 4.1.1).

Traits of plants, plant populations or communities are anatomical, morphological, biochemical, physiological, structural or phenological characteristics of entities of BD. There are an wide range of traits, the characteristics of which have been stored for vegetation in the Global Databases of Traits – TRY (Kattge et al., 2011). EO as a physical system based mostly on measuring spectral reflectance can directly or indirectly record the "Spectral traits" (ST) of plants (Fig. 2). An assessment of non-spectral traits is, however, possible through a high degree of trait inter-correlation (Feilhauer et al., 2016). Usting and Gamon, (2010) defined spectral traits as "optical traits" thereby excluding non-optical EO technologies such as radar from the definition of 'optical traits'. We therefore introduce the term "spectral traits", which includes the detection capability of all spectral recorded EO data like optical, thermal or radar EO technologies. Fig. 2 provides an overview of the spectral traits of plants and animals that can be recorded using EO (Ustin and Gamon, 2010; Homolová et al., 2013; Schimel et al., 2013).

Because the recording of animals by means of remote sensing, however, is extremely limited (see chapter 4.1.1), the following paragraphs mainly refer to plants, populations, communities and beyond.

3.2. Why are EO suitable for detecting and recording entities of BD?

We have to think about the question, why are EO suitable for recording entities of BD? EO can quantify entities of BD because there exist basically the following relationship between the BD and EO:

- Taxonomic, phylogenetic characteristics of species, as well as the processes and drivers affect traits or lead to trait variations in plants, populations, communities, habitats and biomes in space and time (Garnier et al., 2007; Violle et al., 2014).
- Plant traits and trait variations are proxies of state, abiotic and biotic limitations, processes and pressures acting on plant species, populations or communities. These traits and trait variations can manifest themselves as a result of molecular, genetic, biochemical, biophysical, functional and morphological or structural changes (De Vries et al., 2012; Garnier et al., 2016).
- EO is a physical-based system that can only record spectral traits and spectral trait variations in plants, communities or biomes in space and over time (Fig. 2 and Fig. 3).
- Spectral signatures, patterns and heterogeneity obtained from EO data are hence proxies of the diversity of plant species traits and the results of their state, abiotic source limitations and processes and pressures.

The assessment of spectral traits using EO can be measured and quantified on all levels of the vegetation and BD hierarchy – from the molecular and biochemical level (Asner et al., 2008), to leaves (Thenkabail et al., 2012) individual plants (Violle et al., 2007); populations and plant communities (Ustin and Gamon, 2010; Baldeck et al., 2015), biomes and ecosystems (Asner, 2015; Homolová et al.,

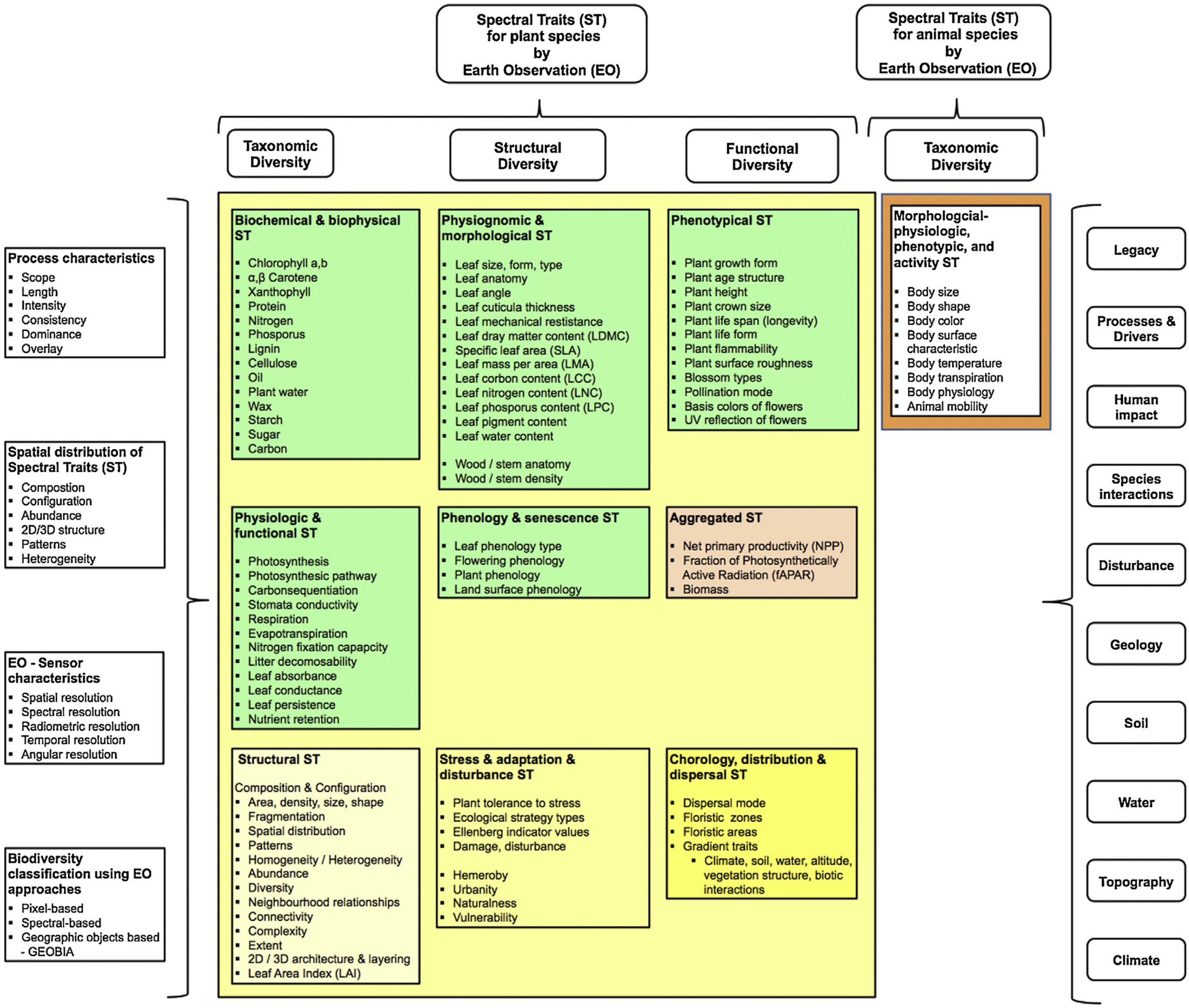

Fig. 2. Spectral traits (ST) for quantifying biodiversity by earth observation techniques and the relevant intrinsic and extrinsic factors.

2013). Furthermore, the assessment of spectral traits using EO is of paramount importance for the discrimination and monitoring of taxonomically different plant species, communities or biomes. Spectral traits therefore form a crucial basis for the definition of the entities of BD.

3.3. What are the constraints for recording of entities of biodiversity using EO?

The acquisition of spectral plant traits und trait variations using EO techniques is subject to several constraints, which have a considerable influence on the demarcation, the detection and the discrimination of entities of biodiversity. These include the characteristics and composition of spectral traits, the intensity and orientation of spectral trait variations, the spatio-temporal configuration and composition of spectral traits and their variations. A low density, shape, small size or similar biochemical spectral traits (e.g. content of chlorophyll, cellulose or plant water), morphological-geometrical or physiological traits (e.g. photosynthetic activity, evapotranspiration) can hinder or even prevent the discrimination and monitoring of different entities of biodiversity (Wang et al., 2016; Lawley et al., 2016).

Besides this, the ability to detect entities of biodiversity is limited by the spatial, spectral, radiometric and temporal resolution of the EO sensors used. In addition to the characteristics of the sensor, the selection of the sensor platform (handheld RS sensors, goniometer, cherry picker, drone, airborne, spaceborne) is also of paramount importance, particularly for the geometric resolution. These can range from just a few millimetres (spectral video camera “Cubert”, multispectral camera by drones) to 0.5–2 m (hyperspectral sensors on airborne platforms like HySPEX, APEX, AISA); to 3–10 m (WorldView, RapidEye, Sentinel 2); to 30 m medium spatial resolution (IRS-1C, Spot, Landsat) right up to 250–1000 m or more (MODIS and NOAA-AVHRR). The spectral and temporal resolutions likewise determine the detection and discrimination of spectral traits and spectral trait variations in species, communities or even biomes. Hyperspectral EO sensors with a spectral range of 0.4-2.5 μm such as the airborne hyperspectral sensors HyMap, HySpex, HyMAP, AISA or EnMAP (Ansner 1998, 2015; Guanter et al., 2015) are very well suited to record different biochemical-biophysical spectral traits (i.e. chlorophyll, xanthophyll, carotene or

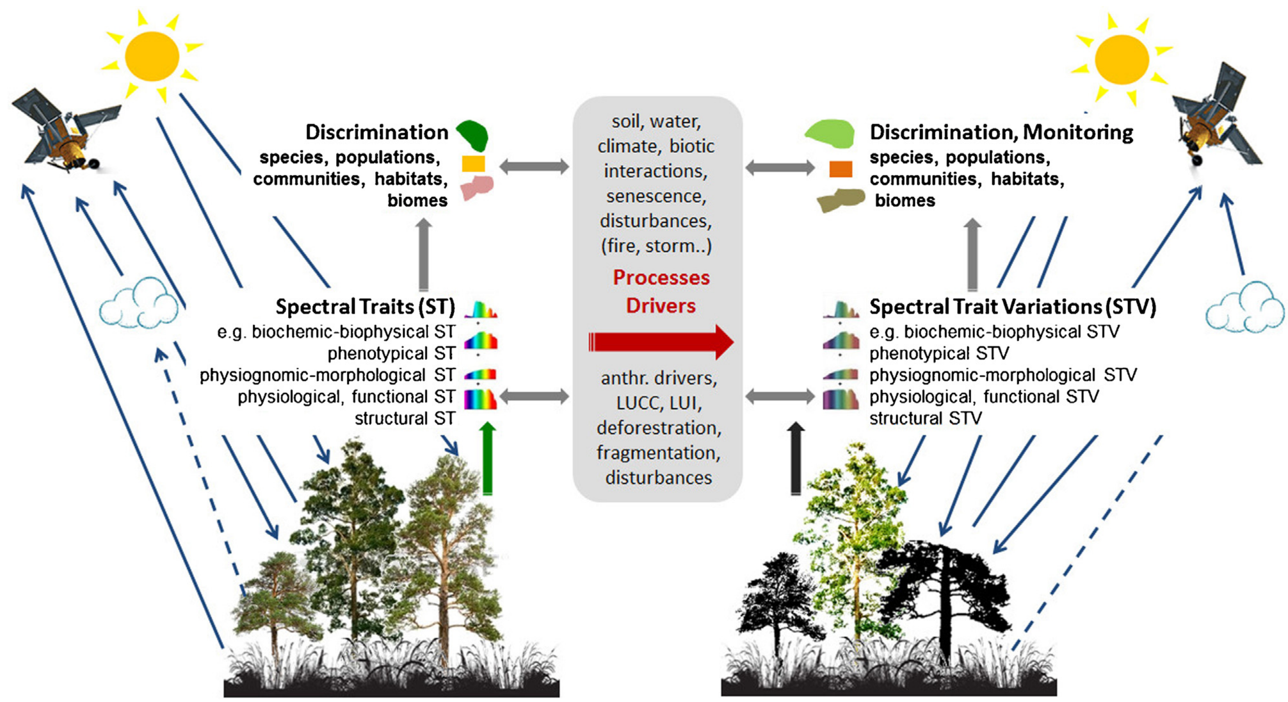

Fig. 3. Quantification of spectral traits and their interactions with drivers and processes to discriminate and monitor plant species, populations, habitats, communities and biomes using EO.

plant water content) as well as functional spectral traits and even structural spectral traits such as growth forms or 3D tree geometry. In contrast, broad spectral bandage EO such as RapidEye, Spot, Aster, Sentinel-2, Landsat or MODIS with a low number of spectral bands are much less suitable for recording spectral traits and trait variations. Through the analysis of multi-temporal EO data sets (Landsat, MODIS, NOAA-AVHRR) that allows recording spectral trait variations over time, the goodness of fit regarding the discrimination of plant traits and the identification of different land cover or crop types is substantially improved. The same effect can be obtained from merging different EO sensors such as radar data (e.g. Sentinel-1) and optical data (e.g. Landsat, RapidEye) (Joshi et al., 2015). Radar data and optical data record different spectral traits and trait variations in plant species, plant communities or biomes that are imperative for the discrimination and identification entities of biodiversity.

3.4. What are the entities of biodiversity from an EO technology perspective?

In order to answer the question as to what the entities of BD from an EO technology perspective are, one has to look very closely at the two well known EO approaches for the discrimination or classification of entities of interest in BD, namely (a) the per-pixel approach (Hoffer, 1975) and (b) the spectral-spatial filtering and region growing approaches (Kauth et al., 1977; Skidmore, 1989), or later the (geographic) object based approach – GEOBIA (Blaschke, 2010; Blaschke et al., 2014; Fig. 4).

The digital discrimination of entities of biodiversity using EO first began with classification techniques based on the per-pixel approach (Hoffer, 1975; Strahler et al., 1986). The characteristics and content, the proportion, density, shape, spatial distribution, texture of spectral biotic and abiotic traits and trait variations, shadows or context as well as the spatial, spectral, radiometric and temporal characteristics of EO sensors determine the spectral information that is contained within the pixel of a sensor. Every pixel can contain a combined reflectivity of various characteristics of abiotic and biotic traits and trait variations as well as the afore-mentioned factors (Strahler et al., 1986). If the size of the measured entitiy of biodiversity (e.g. a tree) is larger than the grain of the EO data (Hay et al., 2001; Blaschke et al., 2014), the characteristics and content of the spectral traits of the tree will primarily influence the reflectivity of this pixel. On the contrary, if the spatial resolution of the EO data is coarser than the entities of biodiversity (e.g. the same tree), the obtained spectral signal made up of different pixels ("mixed-pixel problem"). In the per-pixel approach, however, information on density, shape or spatial distribution, texture and patterns of the spectral traits is not used in the classification algorithm. For this reason, the pixel-based approach has often been subject to criticism (Fisher, 1997; Blaschke and Strobl, 2001; Blaschke, 2010). Blaschke and Strobl (2001) and Blaschke (2010) have substantially discussed the topic: "what is wrong with pixels". In (geographic) object-based approaches, in addition to the spectral trait characteristic, one also uses the shape, density or distribution of the spectral traits to identify entities (Inglada and Christophe, 2009; Blaschke, 2010; Blaschke et al., 2014; Kralisch et al., 2012; Fig. 4). A last factor for detection of entities of BD is how well the EO algorithm and its assumptions fit the RS data and the spectral traits of the species.

Therefore we summarized, that the characteristics of spectral traits (ST) and spectral trait variations (STV) of plants, populations or communties, the shape, density and distribution of ST/STV, the spatial, spectral, radiometric, angular and temporal characteristics of EO sensors, the choice of the classification method (pixel-based or (geographic) object-based approach), as well as how well the EO algorithm and its assumptions fit the RS data and the spectral traits of the species will determine the measurability, discrimination and thus the derivation and assessing of the entities of BD using EO (Fig. 4).

4. State of the art in quantifying biodiversity using EO

There is a wide range of remote-sensing applications and sensors (Table 1) that deal with many topics and research questions related to BD (Turner et al., 2003; Gillespie et al., 2008; Pettorelli

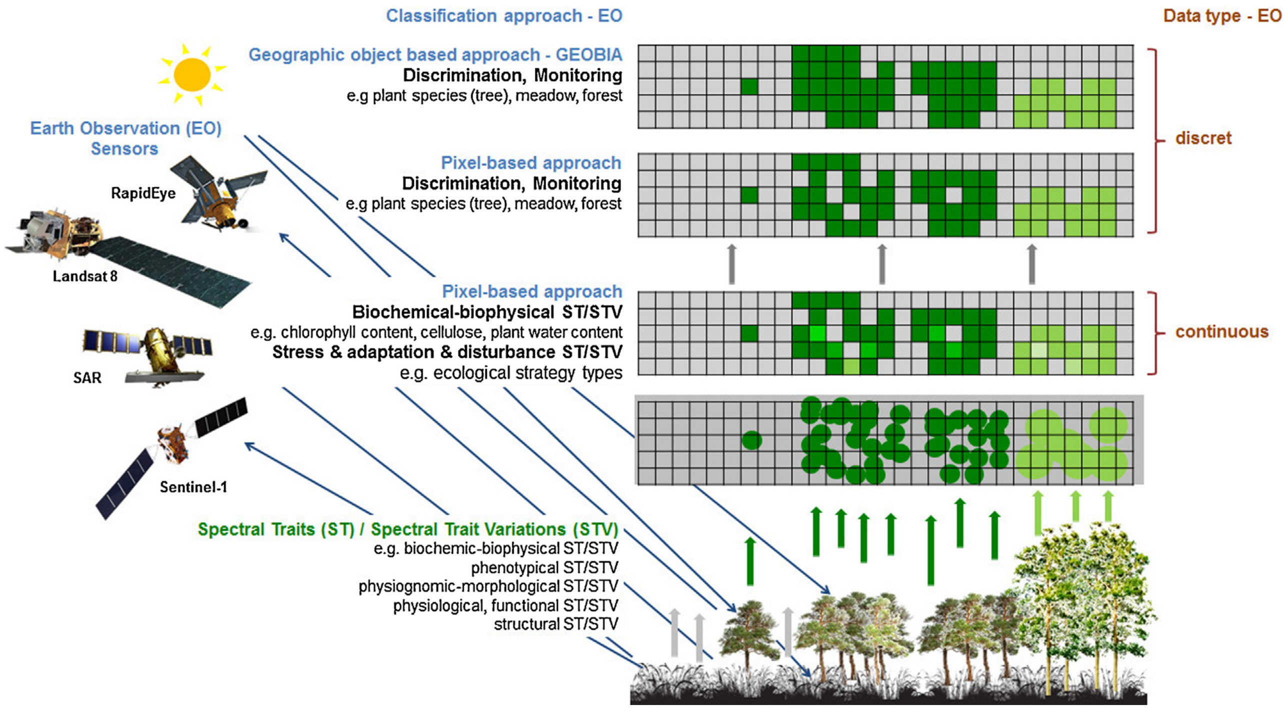

Fig. 4. The characteristics of spectral traits (ST) and spectral trait variations (STV) of plants, populations or communties, the shape, density and distribution of ST/STV, the characteristics of earth observation sensors, the classification method (pixel-based or (geographic) object-based approach) are factors which will determine the measurability, discrimination and thus the derivation and definition of the entities of biodiversity with earth observation techniques.

et al., 2016; Kuenzer et al., 2015). Table 1 summarizes the broad field of applications of EO, which can only be covered briefly in this paper. Based on their research focus, only some of these studies can be assigned either to the fields of taxonomic, functional or structural diversity research. In most cases, however, there is substantial overlap regarding the aspects of BD covered, also due to the use of a plethora of indirect indicators or other surrogate variables.

4.1. Trends in taxonomic diversity and modelling species distributions by EO

Despite the multiplicity of efforts, our knowledge of the spatial patterns of species distributions and diversity at global, regional, and even local scales is insufficient, a problem referred to as the Wallacean shortfall (Whittaker et al., 2005). Three general approaches have been distinguished that aim at predicting species distributions using EO data across different spatial scales (Kerr and Ostrovsky, 2003; Strand et al., 2007): (1) the direct detection or identification of individuals and populations, (2) the detection and quantification of habitats or ecosystem types and (3) the analysis of proxy variables for the use in predictive species distribution models (SDMs).

4.1.1. Detecting animal species using EO

The most common method is to observe animals individuals or flocks with the naked eye. The range of detectability can be increased by distance-based techniques such as binoculars, where the researcher is also the recorder, airborne cameras controlled either directly by the researcher out of the aircraft window or mounted to the aircraft, sound recording with single microphones or arrays (2D, 3D in air and water), and sonar (hydro-acoustic RS, Rattray et al., 2009), thermal imaging (Franke et al., 2012; Dell et al., 2014, Fig. 5a–c), radar and high-resolution X-ray microtomography (Johnson et al., 2007). The use of these techniques depends very much on the species groups in focus, the scale of the study area and the medium of the habitat.

With the rise of microelectronics in the eighties, it became possible to mark larger animals with small devices that can either actively send a radio signal on a specific frequency or even send a signal with an individual marker. This was a great advantage compared to individual marks such as colour rings or wing marks, which can only be recognized on rather short distances and only under very good conditions of light and visibility. Meanwhile, these kinds of transmitters are available in miniature (ca. the size of a child's finger nail), weighing around only 0.4 g. The most limiting part in terms of size and weight is actually the battery. The detector for these radio signals are either hand-held devices used for positioning and homing (direct tracking) or by means of triangulation (the angles between the transmitter and the receiver to estimate an animal's position at any given time). For smaller animals or a simple detection of the flight direction, it is possible to construct automatic tracking fields where two, three or four fixed antennae stations with attached receivers are used to calculate the position inside the field based on the differences in the strength of the received radio signals from the stations. A similar principle is used if the GPRS frequencies from mobile phone networks are used.

A very promising and less time and personnel consuming approach is the use of GPS signals for positioning. This can either be carried out actively (a receiver is combined with a radio transmitter sending the coordinates to a satellite) or passively (a receiver is combined with a data logger). The passive mode requires the animal to be caught again after a certain period of time in order to read the positions through USB etc. GPS tracking is particularly used for tracking over a longer period of time with a rather coarse resolution because of the sampling of positions.

Another approach using imaging techniques but in a very different way compared to EO is the use of digital optical cameras with an infrared sensor and an automatic trigger as "traps", e.g. for estimating lion density in the Serengeti National Park, Tanzania (Cusack et al., 2015). In this case, the animal is not caught physically, but only in a picture. If the animal is marked individually (e.g. with number tags, combinations of coloured marks/rings) or can be

Table 1
Earth observation applications to understand biodiversity.

Topic or research question	Characteristics of biodiversity Taxonomic Diversity – TD Functional Diversity – FD Structural Diversity – SD	References
Animals		
Animal species – discrete classification, (e.g. birds, penguins, flamingos; wildebeest, deer, whales)	TD	Leyequien et al. (2007); Sasamal et al. (2008); Curtis et al. (2009); Groom et al. (2011); Fretwell et al. (2014); Zhang et al. (2014)
Movement of animals – GPS tracking (e.g. storks, cranes, gulls, geese)	TD	Wikelski et al. (2007); Witt et al. (2010); Kranstauber et al. (2011); Safi et al. (2013)
Modelling of animal behaviour (e.g. elephants, bison, cattle, birds)	TD, FD	Leyequien et al. (2007); Pasher et al. (2007); Kuemmerle et al. (2010); Murwira et al. (2010), Barker and King (2012); Swatantran et al. (2012) Raizman et al. (2013); Vermeulen et al. (2013); Kivinen and Kumpula (2014), Duro et al. (2014), Luft et al. (2016)
Behaviour of animals – Epidemiology (distribution of mosquitos)	TD, FD	Herbreteau et al. (2007); Benali et al. (2014a,b)
Defoliating insects (e.g. bark beetles; pine beetles)	FD,	Wulder et al. (2006); Leyequien et al. (2007); Lausch et al. (2013); Fassnacht et al. (2014)
Vegetation (entity, individual, plant, population, community)		
Vegetation distribution on the species level – discrete species classification	SD	Saatchi et al. (2008); Pu and Landry, (2012); Engler et al. (2013), Baldeck et al. (2015), Asner (2015)
Modelling plant species distribution on the species level	SD, FD	Saatchi et al. (2008); Walsh et al. (2008), Rocchini et al. (2015a,b)
Biochemical biodiversity of vegetation (photosynthetic active pigments,	FD, SD	Asner (1998); Asner et al. (2008), Asner and Martin (2009); Asner et al. (2012a,b); Ustin (2013)
Mapping spatial variation of species-level traits and assemblage-level trait distribution (phenology, floristic compositions, vegetation height, vitality, age, density, productivity, LAI, pollination strategies)	FD, SD	Chen et al. (2002); McElhinny et al. (2005); Bergen et al. (2009), Ustin and Gamon (2010); Pasher and King, (2011), Feilhauer and Schmidtlein (2011); Nagendra et al. (2012); Thenkabail et al. (2012); Homolová et al. (2013); Lausch et al. (2013a, 2015a); Asner et al. (2014); He et al. (2015); Stysley et al. (2015), Feilhauer et al. (2016)
Taxonomic and phylogenetic plant species patterns, heterogeneity (alpha, beta, gamma diversity)	TD, FD	Nagendra, (2001); Kerr et al. (2001); Asner and Martin, (2009); Rocchini et al. (2010, 2015a,b), Feilhauer and Schmidtlein (2011); Fricker et al. (2015).
Phyto-geographical and ecological patterns, vegetation and species patterns in environmental gradients	FD	Dillabaugh and King, (2008); Bodegom et al. (2015); Mannion et al. (2014), Dingle Robertson et al. (2015a,b)
Functional niches (spaces) of species, populations to biomes	FD	Schmidtlein et al. (2007, 2012); Feilhauer and Schmidtlein (2009); Schimel et al. (2013)
Diversity within Plant Functional Types (PFT)	FD, SD	Ustin and Gamon, (2010); Schmidtlein et al. (2012)
Mapping of functional vegetation diversity (FD), (e.g. net primary productivity (NPP), biomass, global photosynthetic activity, CO_2 fluxes and budget	FD, SD	Nagendra (2001); Hostert et al. (2003); Kerr et al. (2001); Dillabaugh and King., (2008); Saatchi et al. (2008); Ustin and Gamon, (2010); Kraft et al. (2012); Turner (2014); Ač et al. (2015), Clasen et al. (2015); Tanase et al. (2014)
Biotic interactions, species interactions	FD, SD	Kerr and Ostrovsky, (2003); Schmidtlein et al. (2007, 2012); Conrad et al. (2016)
Vegetation trait-environmental relationships	FD, SD	Schmidtlein et al. (2007, 2012); Mücher et al. (2009); Pause et al. (2012, 2014); Lausch et al. (2013c);, Feilhauer et al. (2016)
Plant species adaptation and distribution	FD	Schmidtlein et al. (2007, 2012)
Mapping invasive plant species	TD, FD	Asner and Vitousek (2005), Asner et al. (2008); Andrew and Ustin (2008); Walsh et al. (2008); He et al. (2011); Müllerová et al. (2013); Bradley (2014), Olsson and Morisette (2014); Robinson et al. (2016)
Vegetation community assemblages and structure	TD, FD, SD	Lavorel and Garnier, (2002); Schmidtlein et al. (2012); Baldeck et al. (2015); Möckel et al. (2014)
Landscape and vegetation fragmentation, connectivity	TD, FD, SD	Briant et al. (2010); Duro et al. (2014); Fahrig et al. (2015); Zhai et al. (2015)
Stress and disturbances on vegetation, status or habitat degradation; deadwood as habitat and enhancement of biodiversity	FD, SD	Olthof and King. (2003); Hernando et al. (2010); Ač et al. (2015); McDowell et al. (2015); Griffiths et al. (2014); Pause et al. (2016)
Monitoring of vegetation, habitats, protected areas, conservation and landscapes, land cover changes, habitat quality, habitat fragmentation	TD, FD, SD	Chiarucci et al. (2001); Oldeland et al. (2010); Nagendra et al. (2012); Hecheltjen et al. (2014); Corbane et al. (2015); Buck et al. (2015); Fahrig et al. (2015); Neumann et al. (2015); Zhai et al. (2015)
Assessment of ecosystem services	TD, FD, SD	Ayanu et al. (2012), Martínez-Harms and Balvanera (2012); Andrew et al. (2014); de Araujo Barbosa et al. (2015)
Land-use and land cover changes), land-use (LUCC), Land use intensity (LUI)	FD, SD	Friedl et al. (2002); Engdahl and Hyyppa (2003); Hansen and DeFries (2004); Erasmi and Twele, (2009); Wulder et al. (2012); Malenovský et al. (2012), Erb et al. (2013), Kuemmerle et al. (2013), Hansen et al. (2013), Dusseux et al. (2014); Hong and Wdowinski (2014); Balzter et al. (2015), Kuenzer et al. (2015), Estel et al. (2015), Hostert et al. (2015), Joshi et al. (2015); Tanase et al. (2015); Verburg et al. (2015)

identified individually by it's unique skin/fur colour pattern, scars or other similar natural marks, then these data can be used not only for occupancy modelling, but also for coarse-grained movement tracking and population density estimation. A special case of this is the use of thermal cameras, which simply use another frequency range of the electromagnetic spectrum, but the same principle.

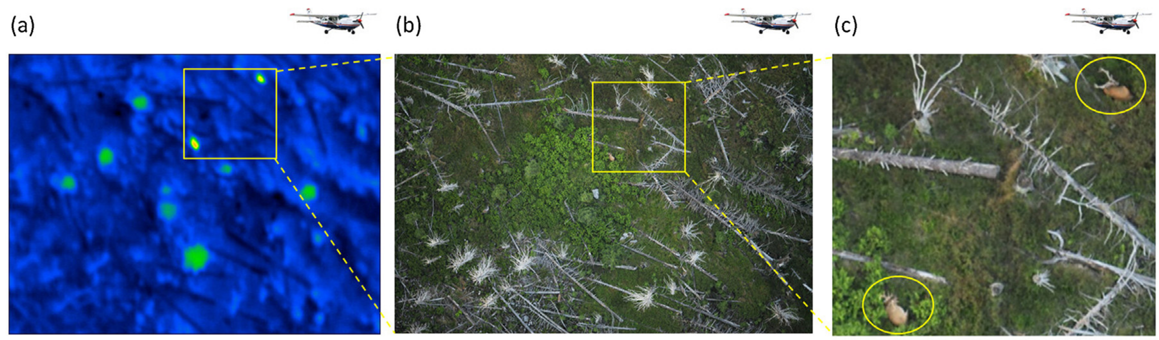

Fig. 5. Detection of animals red deer using infrared camera (a) in combination with high-resolution natural colour images, showing red deer (b,c) in Bavarian Forest National Park, Germany.

The most frequent reason, why we cannot use EO techniques to detect animals in the same way that we can plants is the difference in the size or more often the extent of the entity that we are focusing on relative to the pixel size. Generally speaking, the limits for quantifying BD with EO are the scale of the analysis and the relationship between sensor resolution and the spatial extent of the structure we want to analyse on earth. We seldom focus on the detection of individuals of animals but rather on aggregations of individuals of the same species or on aggregations of individuals of two or more species with either similar ecological requirements or even interspecific dependencies forming a community. The resulting spectral signal is spatially more or less homogeneous over a larger extent, so that usually the area covered by the plant species or community is much larger than a single pixel of the sensor.

For most animal species, this is not the case. The entity that we want to detect are often much smaller than the area (spatial resolution of EO sensor) sampled by the sensor. However, in spite of the problems mentioned above, successful examples of identifying animals, as well as evidence of animal activity such as tunnelling or guano, from higher resolution imagery such as RapidEye have been developed for birds, penguins, flamingos; whales (Leyequien et al., 2007; Sasamal et al., 2008; Groom et al., 2011; Fretwell et al., 2014) and wildebeest in African savannahs (Zhang et al., 2014).

Unfortunately, there are still some other problems that hinder the use of EO for surveying animals. Animals often live inside or below structures that are formed by plants. Therefore, even if we could use a high-resolution sensor and had found methods for either individual or at least species recognition, it would still be very difficult to sample the animals because they are covered by a dense layer of plants. What we can measure however are indirect effects, e.g. if the collapse of an insect species changed the spectral signal of a host plant. If this signal was very specific and only caused by one insect species, then we could use EO and the vegetation as a surrogate variable to derive information about the distribution of this insect species – in an indirect way.

In addition to the spatial resolution, the temporal resolution is also very important. Because plants do not move, sampling can be repeated after days or even weeks and this is still frequently enough. By comparison, the detection of animal movements requires more or less continuous sampling, which is either not possible because the satellites orbits only cross the same position again after several days or due to the fact that it would be very expensive in general because the satellite has to focus on the same point and be moved actively (Ropert-Coudert and Wilson, 2005). To record movements, habitats and the behaviour of small animals, high-resolution X-ray micro-tomography (Johnson et al., 2007), near infrared video or thermal imaging under laboratory conditions are used (Dell et al., 2014). An increase in the degree of habitat complexity requires more image-based techniques such as the use of stereo and light-field cameras, newly-developed giga-pixel camera technologies as well as the latest technology for slow-motion cameras to record animal tracking in 3D and 4D modes (Dell et al., 2014).

Recently, thermal cameras were also successfully used to count different animal species such as narwhales (Heide-JØrgensen, 2004), big horn sheep (Bernatas and Nelson, 2004), and deer (Curtis et al., 2009). This technique makes use of the higher body temperature of animals compared to their surroundings for detection, although it has trouble distinguishing between different animal species of similar size and shape. This limitation was recently overcome by Matzner et al. (2015) who combined thermal videography to detect differences in temperature and digital photography for identifying species such as birds. However, thermal videography has many limitations. Thermal videography does not work for poikilothermic species. Furthermore, animal species that are shielded by tree or vegetation cover cannot be recorded. Thermal videography can only be used when there are thermal differences between animal species and their environment, which is primarily the case in the late evening or early morning, in the spring, autumn and winter in temperate zones. The winter is thus generally the best time to apply thermal videography to record animal species in temperate zones.

High-resolution satellite imagery offers new possibilities for estimating animal population sizes (e.g. based on guano; LaRue et al., 2014). Even though these estimates are often not as accurate as aerial photography due to limited spatial resolution, this technology is much more cost-effective and logistically less intense. In inaccessible areas, it often provides the only means for obtaining population data (Fretwell et al., 2014). Further, UAVs (Unmanned Aircraft Vehicles) are a new technology, which has been increasingly applied for the direct EO of animals that can provide information about abundance, age structure and reproduction, depending on the species surveyed and the attached sensors. A major drawback for the operation of these systems, however, is their limited battery lifetime, resulting in a limited flight time (Linchant et al., 2015).

Several natural limitations to EO-based population assessments still remain, such as limited visibility in dense vegetation stands, the variability of meteorological conditions and the behavior of animals such as nocturnal activity rhythms, the usage of caves or diving habits. Therefore, comprehensive information about animal behavior and the visibility of the target species is required to account for these natural sources of variation under different environmental conditions (Bernatas and Nelson, 2004; Oishi and Matsunaga, 2014). Although human observers on aircraft have largely been replaced by imaging devices over recent decades, human interaction is still required for image interpretation. Hence, there is a strong need to develop methods for the (semi-) automatic processing and analysis of EO data (Groom et al., 2011; Oishi and Matsunaga, 2014). Semi and automatic processing and analysis in EO is imperative, since a high image frequency is required for airborne campaigns when recording moving animals, which in turn generates a large quantity of images. In order to be able to process and analyse all of this data, numerous image-merging algorithms (Hirschmuller, 2008) enable semi- and automatic image processing. For the automatic detection of moving wild animals, a computer-aided detection of moving wild animals (DWA) algorithm (Oishi and Matsunaga, 2014) is applied that compares two EO images. Indeed, the automation of image processing supports this process, but it cannot overcome the limitations of EO in detecting animals.

In addition to being able to quantify animals directly, the presence of animal species can be deduced indirectly using RS. Spectroscopic RS can detect the change in vegetation characteristics, which were caused by biotic stressors such as plant and animal parasites. The broad range of spectroscopic resolution detects changes in biochemical, biophysical, structural and functional characteristics of plants in a process (i.e. changes in chlorophyll, xanthophyll, and water content, among others), caused by parasites on the plants and in the canopy. The predictions on the spread of the bark beetle as a result of direct and indirect detection of tree damage (Lausch et al., 2013; Fassnacht et al., 2014) as well as pest-protected plants (Nutter et al., 2010) are only possible using spatial and spectral high resolution RS data. There are also many applications in epidemiology that use EO for an indirect quantification of the distribution of mosquitos (Herbreteau et al., 2007).

Most animal species are too small to be detected with image-based tracking systems. Therefore, to detect animals location, behaviour, habitats and physiology, bio-logging technologies were developed early on such as global positioning systems, video cameras, accelerometers and telemetry (Dell et al., 2014). Methods such as telemetry with transponders (Riley et al., 1996), passive radar (Gauthreaux and Belser, 2003) and radio and satellite transmitters (Berthold et al., 2002; Cochran et al., 2004) have proven to be more successful compared to the bio-logging of animals. The initial tracking of penguins and their detection using telemetry followed in 1965.

The world's first space-borne bio-logging of animal movements was attempted using the NIMBUS-3 satellite on a Wapiti (Cervus canadensis, Gillespie, 2001). In 1981, the ARGOS satellite system was used to monitor the mobility of seals (Gillespie, 2001). However, as the ARGOS satellite was designed as a weather satellite, these measurements turned out to be too imprecise for further mobility monitoring. Setbacks in the recording of animal movements using space-borne RS increasingly necessitated the use of terrestrial measurements using more conventional tracking methods that also have their own issues, limitations and problems. Transponders are relatively small but have to be activated externally by radar or microwaves, which reduces their range considerably (Riley et al., 1996). Passive radar technologies record large areas but require portable instruments or permanent stations (Gauthreaux and Belser, 2003). Radio transmitters (Cochran et al., 2004) and satellite transmitters (Berthold et al., 2002) reach a high degree of accuracy in bio-logging, but they are very expensive and so far are only suitable for large animals (~300 g).

Even with these limitations, all of these bio-logging techniques make local animal research possible. However, so far it has only really been possible to make regional or even global statements on the migration patterns and social behaviour of just a few animal species. The latest bio-logging developments are bound to change all of this. A prime example of a new technology and methodology is the ICARUS Project (International Cooperation for Animal Research Using Space, Wikelski et al., 2007), a high-tech, global, animal tracking system, which, with the help of permanent GPS transmitters in the high-frequency range, records extremely precise information about the animals. The transmitters, whose prototypes currently weigh between 5 g and 40 g, will weigh around just 1 g in the future, making it possible to track even very small species such as bees, butterflies and bugs. The transmitters are currently equipped with solar cells and transmit information over the course of their service life, to the exact metre and at high temporal resolution (every minute). The sensors record a wide range of parameters in terms of the movement and speed of the animals. In the future, sensors will also be able to quantify other parameters such as blood sugar, muscle tension, brain activity, heart rate, calorie consumption, stress level intensities as well as body temperature. Also planned, for instance, are cameras that are installed on the beaks of birds and on the shells of turtles, which by way of image-logging will allow their feeding or mating behaviour to be investigated.

At this stage, data is sent by the mobile phone network or read locally. Starting from 2016, all global sensor information of tracked animals will be recorded by the Space Station ISS and archived in the world's largest data base for animal migration "Movebank" (https://www.movebank.org). In addition to the Move data, a number of other ecosystem parameters such as temperature, air pressure, wind direction, vegetation density, oxygen content and weather data, to name just a few, will be stored in the environmental data products accessed by the Env-DATA System (Dodge et al., 2013). Information on Move data is available to everyone free of charge for research purposes. In addition to the Move data, specifically developed apps such as Animal App "Animal Tracker' will support the input of more observations. The ICARUS project will revolutionize research into the behaviour and social life, habitat and population research of animal species (Wikelski et al., 2007) and extend the scope of investigations tremendously. Wikelski et al. (2007) assume that there will be an explosive increase of information in the future. "Then the area of Big Data will also start in behavioural research,̈(Wikelski et al., 2007) which will necessitate new concepts for data storage and data linkage.

4.1.2. Detecting and quantifying plant species and canopy using EO

Because the direct detecting and quantifying of individual plants is dependent on their unique spectral signature and limited by the size of the study organism, early approaches mainly used high-resolution aerial photography to identify individual plants to the species level or vegetation classes such as forest type (Gillespie et al., 2008). Today, mainly high-resolution optical data, e.g. IKONOS (Laba et al., 2010) or Quickbird (Everitt et al., 2006), WorldView-2 (Robinson et al., 2016), GeoEye (van Coillie et al., 2016) as well as LiDAR (Light Detection and Ranging) data (Cho et al., 2012) are utilized. LiDAR data has also been combined with hyperspectral airborne systems to further improve quantifying accuracy (Asner et al., 2012a,b; Asner, 2015). Some invasive plant species show spectral profiles that are distinct from the native vegetation; they can directly be mapped using hyperspectral imagery (Asner et al., 2008; Bradley, 2014). The 'ideal' spatial resolution (pixel size) used for detecting species minimizes within-entity (shade and sunlit leaves, bark, understory plants) variance and maximizes between-entity (different individuals or species) variance. Due to limitations in the resolution (spatial, spectral, and temporal) of the EO data, the direct quantifying approach is only applicable over smaller areas (typically several ha to several hundred km^2). However, simulations have shown substantial potential to model species-specific diversity using 3D modelling approaches (Schneider et al., 2014).

At landscape to regional scales, quantifying of habitats is one of the typical applications of EO. In the habitat quantifying approach, previously identified univariate relationships between species occurrences and vegetation (e.g. in field studies or from prior knowledge) are then transferred to indirectly infer species presence or absence. Vegetation is mostly mapped based on medium-resolution Terra-ASTER, Landsat-TM/ETM+ or the new satellite generation Sentinel-2 data (Corbane et al., 2015; Kuenzer et al., 2015). Classification of vegetation types with coarser resolution data typically requires the use of higher resolution data to generate training data (Hüttich et al., 2009).

4.1.3. Species distribution models (SDM)

The quantification of species-environment relationships using species distribution models (SDMs), however, is the most effective way to analyze information gathered from species point data collections such as Map of Life (www.mol.org) or GBIF (Global Biodiversity Information Facility, www.gbif.org). EO data may directly contribute to SDMs by adding measured land surface characteristics beyond topographic and climatic conditions (Saatchi et al., 2008) and are expected to contribute significantly to a "next generation" of SDMs (He et al., 2015). Species distribution modelling with EO data is different from detecting species distributions – since it is not the spectral signature of the species itself but rather its environment (i.e. vegetation community) is identified from the remotely sensed signal. Furthermore, it also differs from habitat quantifying approaches, as certain algorithms that were initially developed for predicting climatic niches into geographical space are applied. The aim of these algorithms is not to classify the landscape into certain categories as in the habitat quantifying approach, but to predict the probabilities of species occurrence as the single target variable (Elith and Leathwick, 2009).

Because mainly large (continental to global) spatial areas are of interest in the SDM approach, mainly coarse-resolution EO data such as Terra-MODIS (Saatchi et al., 2008) or NOAA-AVHRR (Foody, 2005) are utilized. Global scale NDVI trend analysis (de Jong et al., 2013) and growing season length assessment (Garonna et al., 2015) have also been made possible through the NASA GIMMS data set. Moreover, active radar measurements that quantify structural vegetation characteristics provide complementary information (Bradley and Fleishman, 2008). Despite their constraints in geographical coverage, upcoming multispectral (especially Sentinel-2 and Sentinel-3) or hyperspectral (EnMAP) satellite missions will most definitely enlarge this array of suitable EO data. In addition, even though the causal relationship between land cover and species distributions is indirect (Thuiller et al., 2004), several studies have also made use of existing land cover or land use classifications that had previously been derived from EO data (Pearson et al., 2004; Pompe et al., 2008). In contrast to Thuiller et al. (2004), Pompe et al. (2008) were even able to show that climate variation can only explain ca. 50% of the variation, whereas geology and land cover share the other half almost equally. However, the suitability of each land cover product for a focal species may be influenced by the detail and the validity of its class definitions as well as its spatial resolution (Cord et al., 2013, 2014). From an applied perspective, the inclusion of EO in SDMs has great potential for supporting early warning systems for invasive species distributions (Morisette et al., 2005), for guiding new field surveys based on the identification of areas with suitable conditions (similar to those known to be already occupied) and for a more realistic estimation of ecological distances between patches in order to improve the estimation of dispersal success.

4.2. Functional diversity using the spectral trait paradigm

The traits of plant species and communities have been characterised (i) by the emergence and disappearance of characteristics during plant phylogeny, (ii) by environmental and anthropogenic stressors as well as (iii) by the stress and adaptation of plants and communities to today's environmental factors (Klotz et al., 2002). Cadotte et al. (2010) explain that the phylogeny and legacy of plant traits affect the heterogeneity, patterns and diversity of plants, populations and communities. Furthermore, the functional and adapted roles of vegetation are directly linked to biochemical, morphological and physiological traits and trait combinations that are driven by resources and stresses (Schmidtlein et al., 2012). These often lead to functional and adapted convergences in plants, populations and communities (Kumar et al., 2001; Ustin and Gamon, 2010). Traits and their changes are therefore a proxy of the specific status and changes in plant and community ecology (Kraft et al., 2015), as well as of impacts from and responses to environmental and anthropogenic pressures (Carboni et al., 2014), plant invasions (Asner et al., 2008) plant interactions and coexistence (Kraft et al., 2015). Likewise, traits can also alter due to plant interactions with soil characteristics and soil moisture properties (De Vries et al., 2012; Lausch et al., 2013c) or are the spectral result of infestations with parasites and pathogens (Herbreteau et al., 2007; Benali et al., 2014a,b)

Due to their functional as well as structural characteristics, such as photosynthetic pathways, nitrogen content, plant/canopy height, or leaf phenology, traits can be successfully implemented for the satellite-based quantification and assessment of ecosystem services and ecosystem functions such as primary production, photosynthetic activities, gas exchange or climate regulation (Lavorel, 2013). The detecting and quantifying of functional traits is therefore a crucial technique for detecting and monitoring the status of vegetation, as well as changes and shifts in biomes and ecosystems (Schmidtlein et al., 2012). On the one hand, traits are important variables to describe structures, functions, processes, drivers and changes in BD and ecosystems and on the other they are the only entities in plants, populations and communities that can be spectroscopically measured using remote-sensing techniques (Ustin and Gamon, 2010).

4.2.1. Detecting and quantifying biochemical patterns using EO

Ecologists realised a long time ago that the biochemical composition of plants, populations, communities and beyond are crucial for the functioning of most ecosystem processes such as the nitrogen and carbon cycle, because photosynthetic pathways that generate the energy and carbon molecules are important for the reproduction and growth of vegetation (Reich, 2012; Ustin, 2013). Findings on the biochemical make-up and their changes and diversity can provide crucial insights into disruptions in the functional circulation of ecosystems. Biochemical traits in the canopy can therefore be proxies for the status, changes and pressures of humans on vegetation (Garnier et al., 2007, 2016; Schmidtlein et al., 2012).

There have been comprehensive investigations on the biochemical content, configuration, diversity and their changes of photosynthetic active pigments using the EO sensors AVHRR, MODIS or Landsat TM/ETM (Estel et al., 2015). Recently, there has been tremendous progress in research on biochemical diversity through the opening of the EO sensor portals of Landsat (Wulder and Coops, 2014) and SPOT. The comprehensive studies by Asner (1998), Asner et al. (2008, 2012a,b), and Asner and Martin (2009) in the area of measuring biochemical diversity by means of airborne hyperspectral EO show that the quantifying of different biochemical characteristics directly depends on the spectral EO characteristics. Based on novel hyperspectral EO data, Asner et al. (2012a,b, 2014, 2009) were able to show that the biochemical-structural properties of plants create a "fingerprint for each species and community", which is also referred to as the "spectrometric approach". These studies on biochemical diversity make reference to the enormous potential of the new generation of EO Sensors such as HyMAP or InSPIRI in quantifying biochemical diversity. Advanced retrieval methods, such as coupled models (Laurent et al., 2011b), multiangular observations (Laurent et al., 2011a), object-based (Laurent et al., 2013) and Bayesian inversion schemes

(Laurent et al., 2014) have substantially improved retrieval accuracy of important spectral traits.

4.2.2. Detecting and quantifying plant functional types using EO

Plant functional types (PFTs) are functional convergences based on environmental resources and stress constraints (Lavorel and Garnier 2002; Ustin and Gamon, 2010). The "PFT concept allows us to explore the possibility of regionally and globally distinct functional categories" (Ustin and Gamon, 2010), which are based on various spectrums of plant traits affected by the dominant species. Dominant species have the most crucial influence on ecosystem properties like biogeochemical cycling, carbon and water budgets or productivity. Therefore, PFTs play an important role in understanding and deriving plant functions and in the assessment of ecosystem services (de Araujo Barbosa et al., 2015) from a local to a global scale. For instance, dominant species at the ecosystem level have a consistent relationship between the absorbed photosynthetic active radiation (APAR) measured by EO for much of the world's vegetation (Ustin and Gamon, 2010). Furthermore, Ustin and Gamon (2010) point out that the structural and functional characteristics of plant and vegetation traits recording, quantification and modelling by EO helps to understand many ecosystem functions such as photosynthetic activities, primary production as well as gas exchange and climate regulation (Homolová et al., 2013).

4.2.3. Detecting and quantifying plant biomass using EO

Assessing above-ground biomass (AGB) is an essential prerequisite in the monitoring of global carbon fluxes. Most of the studies on AGB estimation were conducted in forest ecosystems. Landsat-TM and other optical sensors in general are the most widely used EO systems for biomass estimation (Main-Knorn et al., 2013; Latifi et al., 2015). Landsat, a medium spatial-resolution sensor, is a good compromise regarding data-availability, data-processing efforts and a sufficient level of detail. Due to the long time-series of Landsat imagery, this data allows the reconstruction of forest disturbance and recovery over long time periods (Main-Knorn et al., 2013; Czerwinski et al., 2014). The application of coarser scale spatial-resolution optical imagery such as MODIS, AVHRR and SPOT VEGETATION is limited by the occurrence of mixed pixels. However, those sensors have the advantage of large spatial and temporal datasets. Fine spatial-resolution sensors are only feasible for small sites. For example, Dillabaugh and King (2008) used spectral and spatial metrics derived from IKONOS data to estimate emergent and aquatic wetland plant biomass. Recently, radar and LiDAR sensors that detect the canopy volume and describe the vertical canopy profile, respectively, have gained in importance (Fig. 6a–c). The performance of radar systems varies with wavelength and polarization properties, whereby longer wavelengths showed better results. LiDAR data can successfully supplement field-based inventories as a systematic sampling tool (Ene et al., 2013). K-nearest-neighbour clustering, linear and multiple regression and machine learning algorithms such as regression trees and neural networks are used to establish relationships between the spectral reflectance and structural vegetation parameters. The latter again have empirical allometric relationships to AGB. Vegetation Indices such as the Normalized Difference Vegetation Index (NDVI) reduce distracting effects of environmental conditions. More research, however, is needed for the generalization and spatial transferability of predictive relationships and to deal with saturation problems in regions with high vegetation density (Cutler et al., 2007). Solar induced fluorescence (SIF) is an emerging topic, allowing NPP and/or GPP to be retrieved from narrow-band measurements (Damm et al., 2014, 2015). The combination of multi-sensor or multi-resolution data might be an approach to further improve AGB estimation. ESA's "Biomass-Mission" will be launched in 2020 (Le Toan et al., 2011). This satellite will provide information on the state and change of forest ecosystems by quantifying forest biomass at 200 m resolution with a P-Band SAR.

4.3. Structural diversity using EO

4.3.1. Vertical vegetation structure and structural complexity

Vertical vegetation structure is defined as the configuration of above-ground vegetation from the ground to the top of the canopy (Brokaw and Lent, 1999) and can be measured with different platforms such as airborne platforms, drones or under laboratory conditions (Fig. 7a–d). It has a strong effect on BD, based on the assumption that higher structural complexity creates more habitat niches, which, in turn, leads to greater species diversity for other taxa (MacArthur and MacArthur, 1961). There are a number of methods and statistics available to measure and describe vegetation structure from the ground, but these methods are time consuming and cannot easily be applied to large areas (McElhinny et al., 2005). Passive optical sensors, which record the radiation of the sun reflected and emitted by the Earth, are not able to directly measure vertical vegetation structure but canopy radiance does respond to horizontal and vertical structure. Estimation and quantifying of individual structural metrics such as LAI at broad scales has become commonplace (Chen et al., 2002), and more local scale multivariate approaches to represent of canopy, understory and ground vegetation structure in structural complexity indices have also shown promise (Pasher and King, 2011). Torontow and King (2012) combined field measured structural and compositional metrics in multivariate complexity index derived from redundancy analysis against image spectral and spatial metrics as well as topography. This approach of deriving a structural complexity index based on multivariate relationships between image/terrain data and field measured vegetation data was compared to the deterministic approach described in Estes et al. (2010) where a pre-defined structural complexity index as presented in McElhinny et al. (2005) was modelled against image data.

The unique thing about radar sensors is the fact that the microwaves react to the dielectric (water content) and geometrical properties of the entities of interest, producing a volume scattering response, making them an ideal tool for detecting and quantifying volumetric structural indicators. Moreover, radar systems are able to penetrate cloud cover, are independent of solar illumination and can cover large areas (Lewis, 1998). Over recent decades, there has been a steady improvement in the sensors from SAR (Synthetic Aperture Radar) backscatter systems. In the past, they were only able to measure the backscatter of the sensors interferometric SAR (InSAR) systems that gather 3D information of the surface, such as the DTM of the Shuttle SRTM mission and multi-baseline polarimetric InSAR (Pol-InSAR) systems, which are now able to gather information about structural vegetation metrics such as forest canopy cover, forest canopy volume and forest height (Treuhaft and Siqueira, 2000; Mathieu et al., 2013). The first study using SAR to evaluate habitat relationships and BD patterns was conducted back in 1997 (Imhoff et al., 1997).

As an alternative, active sensors such as LiDAR, have been successfully applied to quantify the vertical dimension of vegetation structure (Heurich and Thoma, 2008; Bergen et al., 2009). LiDAR systems measure the distance between the sensor and the spot on the ground were the LiDAR beam is reflected, by using the time interval between the emission of the beam and the recording of its reflection, taking into consideration the speed of light. Beams of LiDAR sensors working in the near infrared spectrum are reflected by vegetation and soil, making them suitable for recording both vegetation and ground signals.

Over the last decade, LiDAR has also been applied to address ecological and conservation issues (Vierling et al., 2008). In particular, its capability of determining vertical structural metrics from

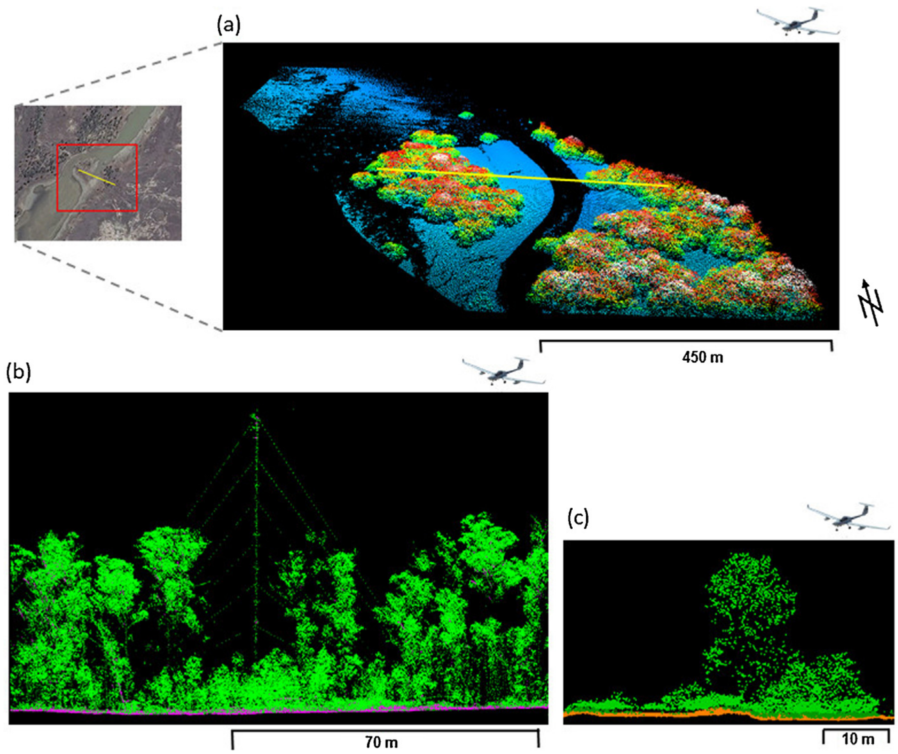

Fig. 6. Biomass and vegetation structure: Quantification of vertical vegetation structure with airborne laser scanning data (ALS) – Riegl Q560/240, (airborne, aircraft Dimona), (a) Mangroves in "Woods Lake", Aboriginal Heritage Area near Burketown, different colors indicate different tree hights, Queensland, Australia, Recording date 2012-09-25; (b,c) Bago State Forest with FluxTower (70m) near Tumbarumba, New South Wales, Australia, Recording date: 2012-12-18.

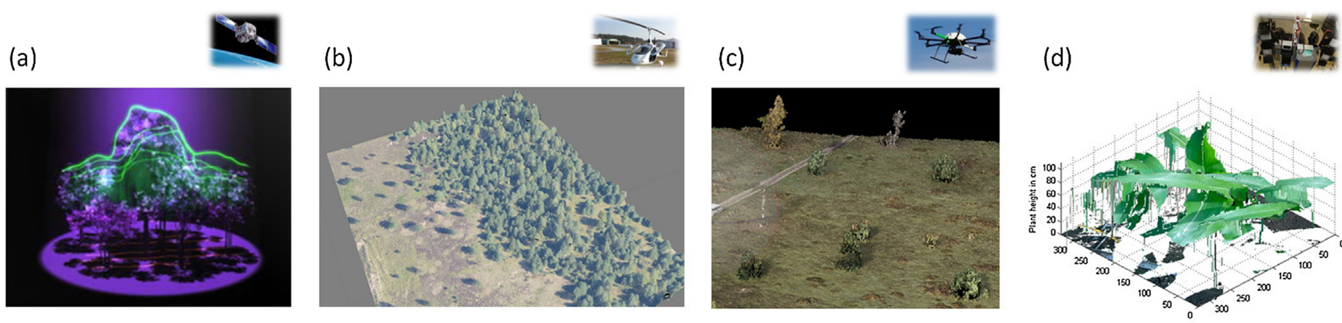

Fig. 7. Vertical vegetation structure of vegetation objects on different spatial scales (a) laser-based instruments (Global Ecosystem Dynamics Investigation), GEDI – 3D-LiDAR, NASA, (spaceborne launch in 2019), (b) biosphere reserve "Oranienbaumer Heide", recording date: 2014-8-28 (airborne – gyrocopter), (c) biosphere reserve "Oranienbaumer Heide", (drone- octocopter), (d) 3D model of maize by Light-Field Camera on laboratory scale.

LiDAR point clouds and the automatic detection of single trees including their properties (height, volume, crown length, diameter at breast height, species allows an in-depth and large-scale exploration of species-habitat relationships and the prediction of species assemblages for BD and conservation assessments). There are several studies across different taxa such as birds (Lesak et al., 2011), bats (Jung et al., 2012), squirrels (Nelson et al., 2005), beetles (Müller and Brandl, 2009) and spiders which have all underlined the importance of LiDAR in assessing vertical vegetation structure and in identifying BD hotspots across landscapes. LiDAR has also been successfully applied to explain plant species diversity (Simonson et al., 2012) and at the same time vertical and horizontal canopy layering (Leiterer et al., 2015, 2015a), making it a well-established tool for BD research and conservation. In addition, data fusion methods using both LiDAR and optical sensors will allow the functional diversity of canopies to be characterized by using structural and biochemical attributes (Torabzadeh et al., 2014). The next step for BD research could be to make use of bathymetric LiDAR and SONAR (SOund Navigation And Ranging), which has the potential to quantify the abundance and behavioural patterns of fish, marine mammals, as well as the characteristics of their underwater habitat. In addition, the combination of radar and LiDAR measurements is promising for ecosystem studies, because LiDAR provides better information about height and the vertical profile, while radar is more sensitive to wood volume and density (Hall et al., 2011; Antonarakis et al., 2011). The next generation of EO should be able to measure and combine different levels of BD into ones like the forest biogeochemistry, structural change, and individual-based models "which can predict the fates of vast numbers of simulated trees, all growing and competing according to their ecological attributes in altered environments across large areas" (Shugart et al., 2015). A future step forward could be to merge radar and LiDAR measurements for ecosystem studies, because LiDAR provides better information about the height and the vertical profile while radar is more sensitive to forest volume and density (Antonarakis et al., 2011; Hall et al., 2011). Sensor combinations

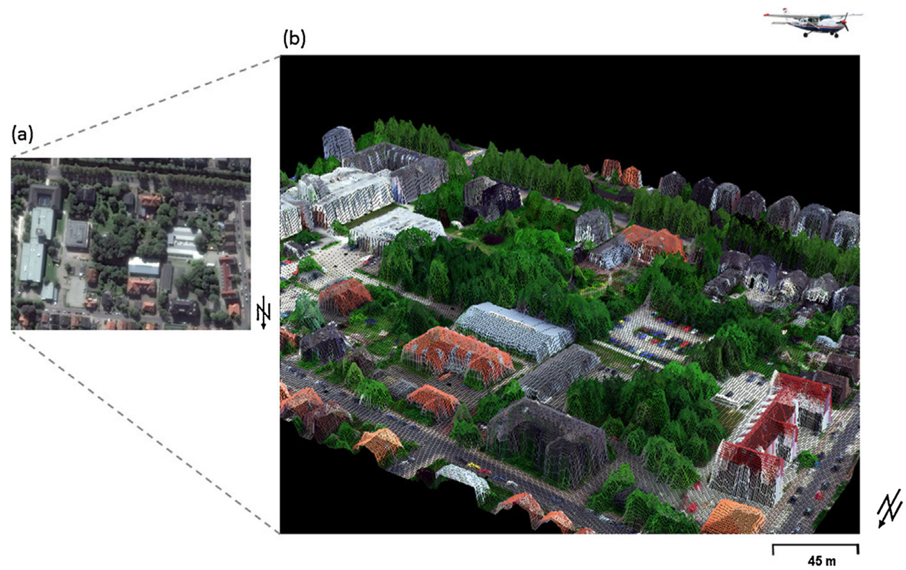

Fig. 8. Vertical vegetation and building structures for modelling species distribution, also in the context of microclimate and heat islands and human influences in cities: (a) Part of the city of Oldenburg for the flight campaign – Google earth (b) Vegetation and buildings in the city of Oldenburg, true colour image from Hyperspectral Data – AISA-DUAL mapped onto the digital surface model (DSM) generated from the airborne laser scanning data (ALS), Recording date: 2010-6-15.

such as hyperspectral and LiDAR sensors are also meaningful for quantify variables of BD and are likely to gain importance in the near future (Fig. 8).

4.3.2. Spatial spectral heterogeneity for monitoring community diversity using EO

According to Diamond (1988) and Palmer et al. (2002), a higher heterogeneity in habitat characteristics results in higher species richness. The addition of new habitats in a sample therefore leads to an increase in the recorded pooled species richness (Fairbanks and McGwire, 2004) – a key aspect related to the use of spectral heterogeneity for predicting species diversity. Therefore, the relationship between spectral heterogeneity and species richness (spectral variation hypothesis) can be used to locate the sites with the highest species richness (α-diversity). Spectral heterogeneity has been demonstrated to have a high predictive power with respect to species richness within a given site, at different spatial scales (Kerr et al., 2001; Oindo and Skidmore, 2002). Further, spatial image properties (e.g. spatial autocorrelation and image texture) have been found to be significantly related to BD (Duro et al., 2014). Further, Rocchini et al. (2010, 2015a) demonstrated that species complementarity among sites (β-diversity) can also be maximized by a spectrally-based ordering. Furthermore, spectral heterogeneity can be regarded as a proxy of natural processes such as soil characteristics but also human pressure on vegetation (Lausch et al., 2013b,c, 2015). This approach allows the detection of important spatial gradients of species diversity, and thus maximizes the inventories made of plant species in an area with reduced sampling effort.

Making plant species inventories in relatively large areas has always been an important task for plant ecologists, in spite of a lack of common standards for measuring the completeness of the resulting species lists and for quantifying the sampling effort (Palmer et al., 2002). This type of data has been utilized for describing and testing phyto-geographical and ecological patterns (Bodegom et al., 2015), but also for nature reserve evaluation and planning. However, as stated by Palmer et al. (2002), making accurate species inventories over a large region is complicated by the fact that botanists cannot inspect every individual plant in the region and that species compositions change over time. On the other hand, lists of flora for relatively large areas cannot yet be obtained with objective sampling combined with statistical estimators of species richness (Chiarucci et al., 2003). Thus, the development of methods for perfecting species lists is potentially useful for developing lists of species compositions over large areas (Palmer et al., 2002).

Different methods have been proposed to locate those environmental gradients offering the maximum change in species richness (Mannion et al., 2014), and the availability of satellite data could render the proposed method straightforward to apply, especially in regions where basic environmental data are scarce or inaccurate. To date, few researchers have tried to assess species diversity on a detailed scale by using these high-resolution multispectral data (Rocchini et al., 2015a,b). Satellites with a coarser spatial resolution (e.g., Landsat, 30 m; see Fig. 9a,b) are widely used (Fairbanks and McGwire, 2004) due to their lower cost and easier availability, but they can hide fine grained patterns, such as margins between vegetation types, hedges and small forest gaps, and thus result in the loss of many species within the obtained lists. Even if Landsat imagery has a higher spectral resolution than QuickBird or IKONOS sensors, the addition of redundant data can increase noise without adding valuable information, by including spectral information not related to habitat heterogeneity as noise in statistical models (Bajwa et al., 2004).

4.3.3. Monitoring of habitats, their changes and ecosystem quality using EO

Detecting, quantifying and monitoring vegetation patterns has been a key application of EO early on (Spurr, 1948). Accordingly, detailed and accurate spatio-temporal information on the distribution of vegetation types is available from local (Lewis, 1998; Oldeland et al., 2010) to continental scales even though limitations due to the spatio-temporal variable appearance of vegetation stands and the spectral similarity of plant species in general are well known (Feilhauer et al., 2011). In spite of these uncertainties, EO offers great potential for vegetation assessing that has been used in a similar way to map the distribution of habitat types for conservation programs (Feilhauer et al., 2014) and has the advantage of being able to map on different scales and RS sensor platforms e.g. spaceborne, airborne, drones and on the laboratory level (Fig. 10a–h). The related applications are manifold, successfully local scale quantifying the distribution of grassland (Buck et al., 2015), heathland (Delalieux et al., 2012), wetland

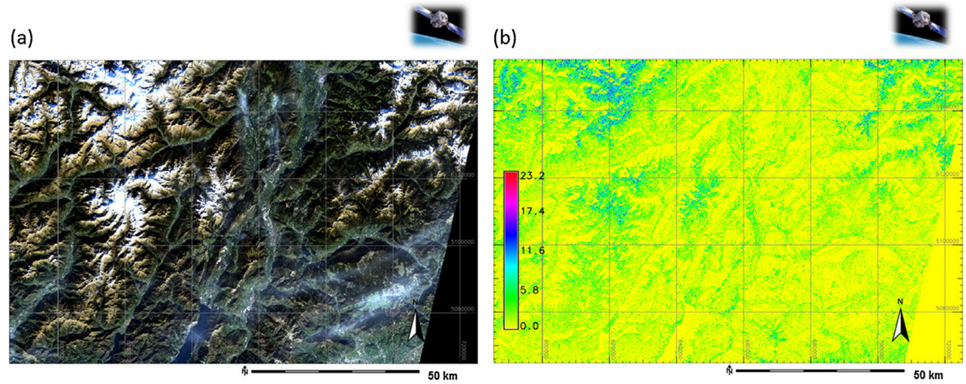

Fig. 9. (a) A Landsat ETM+ image of the Trentino region (Italy, Northern alps, path 192 row 028, acquisition date: 21-8-2014), processed by a moving window estimator of local heterogeneity, based on the contrast method (Haralick, 1973) available in the r.texture module in GRASS GIS. (b) 2D spatial view, local heterogeneity has been proven to be strictly related to species diversity based on the spectral variation hypothesis (Palmer et al., 2002). Refer to the main text for additional information.

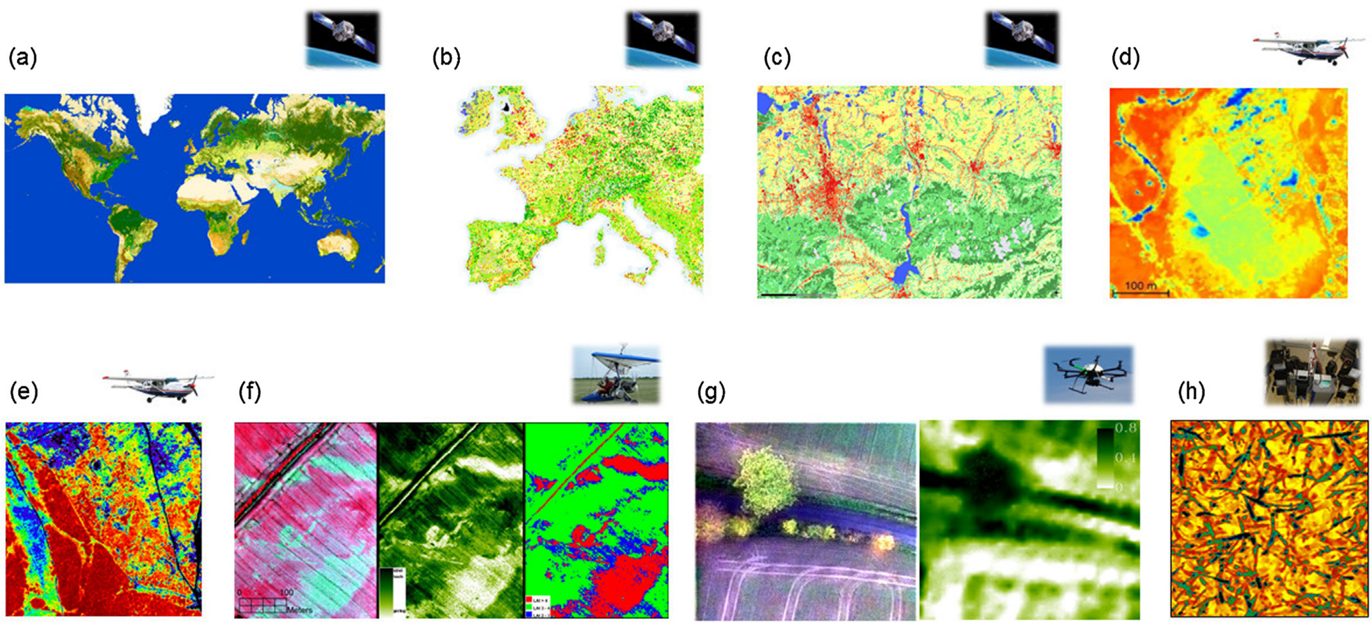

Fig. 10. Vegetation monitoring on different scales and platforms: (a) GlobCover ESA 2009 (Global Land Cover); (b) Mapping of CORINE- Corine Land Cover Europe (2006) based on Landsat TM Data (c) Land Cover Classification – Region: Sola Polska (satellite: Landsat TM), (d) Hyperspectral data – AISA-DUAL, Region: catchment of the river Ammer, south of Munich, Germany; (airborne, Piper), (e) NDVI – hyperspectral data – AISA-DUAL, Region: near Cottbus; (airborne, Piper), (f) Color-Infrared image, NDVI, modelled LAI – hyperspectral data – AISA-Eagle, Region Großbardau, near Leipzig; (airborne, microlight), (g) image raw data courtesy of Cubert GmbH, NDVI image of this image of Cubert GmbH; NDVI on the field scale – (drone-octocopter) (h) NDVI – vegetation/plant heterogeneity of spring barley– (laboratory – hyperspectral AISA-DUAL).

(Alexandridis et al., 2009; Dingle Robertson et al., 2015a,b) and forest habitats (Bässler et al., 2011), including habitat attributes of individual species (Pasher et al., 2007; Barker and King, 2012 for threatened forest bird and wetland turtle species, respectively). The approaches used for this purpose cover a broad range of data types such as colour orthophotos (Barker and King, 2012), multispectral (Pasher et al., 2007; Buck et al., 2015; Dingle Robertson et al., 2015a,b), hyperspectral (Delalieux et al., 2012), LiDAR (Bässler et al., 2011) and SAR imagery (Alexandridis et al., 2009; Dingle Robertson et al., 2015a,b). Nagendra et al. (2012) provide an overview of the potential of different EO data for habitat assessing. To map habitat types over large areas or even at continental scales, the consideration of additional environmental parameters such as the distribution of ecoregions, soil types, and elevation data may be required (Mücher et al., 2009).

Various studies show that a remote assessment of the conservation status or habitat degradation is similarly possible (Hernando et al., 2010; Czerwinski et al., 2014; Dingle Robertson et al., 2015a; Neumann et al., 2015). It is, however, important to note that these EO applications still require field data for calibration and validation and therefore they can be of assistance in conservation management by identifying target areas for field-based assessments and potential land management actions. Further, while most studies result in a map of the status quo of the habitat under consideration, only a few studies have so far attempted to implement at least short-term monitoring based on EO data. No long-term monitoring based on airborne EO data (e.g. airborne hyperspectral EO Data, AISA, HySPEX) has been implemented so far. This is most likely to be a result of both data availability and funding policies that rarely support airborne-based long-term studies as well as the technical challenges of change detection (Hecheltjen et al., 2014). Frequently, the habitats under assessment are scattered and widely dispersed across large areas. In such cases, one class classifiers that only require calibration data of the target habitats and not the co-occurring land-cover classes are powerful tools that enable efficient quantifying (Sanchez-Hernandez et al., 2007; Stenzel et al., 2014) compared to conventional approaches.

Detailed information on habitat conditions and ecosystem quality has likewise been derived from EO data (Corbane et al., 2015). Indicators may include the cover fractions of trees, shrubs and grasses to assess their encroachment (Marignani et al., 2008; Hellesen and Matikainen, 2013), cover fractions of water, vegetation and soil to assess wetland disturbance and long term trends of change (Dingle Robertson et al., 2015a,b), succession stages of heathlands (Delalieux et al., 2012) and the compositional structure of habitats (Mücher et al., 2013). Information on properties such as grassland structure (Zlinszky et al., 2014), the quantification of mowing events (Schuster et al., 2015) or the detection of hedgerows (Betbeder et al., 2014) can be added through the analysis of data acquired by active sensors.

4.3.4. Monitoring of LUCC and LUI in landscapes using EO

Land use and land cover changes (LUCC) are influenced by a number of natural as well as anthropogenic drivers (Turner et al., 2007; Brand et al., 2015; Lewis et al., 2015). In order to understand the processes, the dynamics, the direction as well as the intensity of LUCC in landscapes, and to develop potential management and global strategies such as REDD (Reducing Emissions from forest Degradation and Deforestration), there has been a successful use of extensive optical EO data (Townshend et al., 1991; Friedl et al., 2002; Hansen et al., 2013; Wulder and Coops, 2014), thermal EO data (Kuenzer et al., 2015) and radar EO data (Engdahl and Hyyppa, 2003; Hansen and DeFries 2004; Erasmi and Twele, 2009; Malenovský et al., 2012, Hong and Wdowinski, 2014). Multisensor approaches from optical, thermal and radar data are also extensively used for LUCC mapping (Pereira et al., 2013a,b; Stefanski et al., 2014; Joshi et al., 2016) as well as multi-temporal approaches with different EO sensor types (Chust et al., 2004; Lu and Weng, 2007).

To record LUCC, long-term EO time series of optical and radar data are required (Wulder et al., 2012; Joshi et al., 2016) whereby changes to the physical properties of land surfaces of different vegetation types such as forest, woody vegetation or grassland are quantified. Furthermore, EO data can be used to record different surface structures and abiotic variables such as soil, rock, water bodies (Joshi et al., 2016) or LUCC types like plant biomass, leaf area, or canopy cover or even specific vegetation characteristics and their changes (Hansen et al., 2013; Joshi et al., 2015). EO techniques also enable the quantification of changes to LUI such as fertilizer application rates, mechanization levels, harvesting frequency and production (Erb et al., 2013; Kuemmerle et al., 2013; Estel et al., 2015) or cropland and pastureland dynamics (Graesser et al., 2015). In order to be able to use global information about LUCC, global land cover characteristics like the IGBP DISCover from 1 km AVHRR data as well as various optical data like Landsat TM, Sentinel-data are saved in databases and archives (Loveland et al., 2000; Wulder et al., 2012).

5. Advantages, knowledge gaps and limitations to EO for quantifying biodiversity

In EO, a change is planned and can already be observed in the latest sensors towards the needs-based sensor technology of the European Space Agency-ESA, (Johann Dietrich Wörner, in "Forschung aktuell", 19.12.2014). For BD research, this means that the development of hyperspectral sensors (HyMAP – launch planned for 2018) as well as the implementation of multisensors (hyperspectral and LiDAR, APEX, (Schaepman et al., 2015) hyperspectral and thermal, e.g. the Hyperspectral Infrared Imager – HySpIRI (Roberts et al., 2012) and the Copernicus-Missions (Sentinel 1–5) are being actively promoted to improve the quantification, description, explanation and prediction of taxonomic, functional and structural BD. In the context of BD, the following general statements can be made about taxonomic, functional and structural BD from EO:

5.1. EO techniques for quantifying taxonomic diversity

5.1.1. Animals

EO techniques can only detect the presence of animal species under very specific circumstances, depending on their body size and the resolution and the characteristic of the sensor. However, remotely sensed data has been successfully used to estimate animal species distributions by indirectly modelling ecological niches. Generalist species with a ubiquitous distribution or with less specific ecological niches are very difficult to predict using habitat modelling based on EO. The distributions of those animal species whose habitat quality cannot be measured with remote-sensing techniques are difficult to model. In this respect, remote-sensing techniques only provide incomplete information and no conclusions about true animal distribution patterns, species diversity and patterns of change can be drawn. The use of thermal sensors, motion sensors, slow-motion cameras as well as radio-collaring using telemetry (recordings from the ISS space station) make it increasingly possible to derive information about the mobility, the habitat use and distributions of animal species. There is tremendous potential for the future use of EO, in particular when radio-collaring is put in place sooner rather than later and the sensors are optimised in terms of their cost-effectiveness and weight. Furthermore, the development and increased implementation of low cost Smart Citizen Kit sensors in smartphones and their applications can be expected to greatly facilitate the extensive mapping of habitat characteristics as well as the distribution and mobility of animal species.

5.1.2. Plants, populations, communities and beyond

This review showed that plant species, populations and community diversity can indeed be measured using EO, but that the goodness of fit and the level of discrimination of vegetation differ considerably, depending on the EO sensor used and the characteristics of the species considered. In fact, the only direct link between the remotely-sensed signal and plant species, plant populations and communities can be established from the spectral traits (Ustin and Gamon, 2010) of plants, populations, communities and beyond that measured spectroscopically (Thenkabail et al., 2012; Homolová et al., 2013; Jetz et al., 2016; Schaepman et al., 2015).

5.2. EO techniques for quantifying functional diversity

The functional roles of vegetation such as solar-induced chlorophyll fluorescence, photosynthesis or CO_2 sequestration are directly linked with remotely detectable signals through biochemical, morphological and physiological traits and trait combinations (Ustin and Gamon, 2010). Hence, the greatest challenge for EO research in the future will be in evaluating and assessing the importance of plant traits for assessing taxonomic, functional and structural BD. Furthermore, the development of sensors must be directed to optimise, simplify and standardise the measurement of plant traits, and to enable the detection of traits that could previously not be measured spectroscopically e.g. in the UV range or EO sensors with x-ray imaging (Schaepman et al., 2015). Since EO can measure a variety of optical plant traits (Homolová et al., 2013), EO processes provide rapid, standardized and optimised methods to measure functional diversity in terrestrial vegetation. New EO sensor technology may allow to measure parameters of functional diversity.

5.3. EO techniques for quantifying structural diversity and heterogeneity

Processes and their characteristics in landscapes affect the patterns in the traits of plants and vegetation. For this reason, plant traits can be regarded as proxies of state, processes and pressures on vegetation. EO can record the traits of plants and vegetation and their changes in space and time. Hence, spectral RS patterns and heterogeneity are a proxy for plant species traits diversity and heterogeneity, and the results of processes and pressures of plant traits in space and time, which can be measured by EO techniques.

6. Concluding remarks and future research

EO methods represent an affordable, repeatable and comparable method for measuring, describing, explaining and modelling taxonomic, functional and structural diversity. Based on their research focus, only some studies can be assigned either to the fields of taxonomic, functional or structural diversity research. In most cases, however, there is substantial overlap regarding the aspects of biodiversity covered, also due to the use of a plethora of indirect indicators or other surrogate variables. In particular, taxonomic biodiversity poses a challenge to remote sensing techniques. As EO is a physically-based system, it is not able to record biodiversity according to taxonomical classifications of species. The assessment and evaluation thereof, despite further sensor development, will hence always be only successful in those cases where spectral diversity matches taxonomic diversity observed in situ.

When using EO sensors there are numerous factors that can have an effect on measurability, discrimination and thus the derivation and assessing of the entities of BD using, in the future when BD is recorded using EO, one should refer to a "Spectral Biodiversity" (SBD).

The approach of deriving biodiversity by means of 'Spectral Traits' (ST) and "Spectral Trait Variations" (STV) detectable with EO is promising. Spectral traits represent a suitable interface between EO-based and in-situ-species approaches and the potential linking of both of them (Jetz et al., 2016) to achieve a better understanding of BD. They are relevant at all levels of organisation of biotic entities – from the molecular, genetic, individual and species levels to populations, communities, biomes, ecosystems and landscapes. Hence, the density, shape and distribution of plant traits (as well as their combinations and variations), the spatial, spectral, radiometric and temporal characteristics of EO sensors as well as the selected classification method (pixel-based or object-based), as well as how well the EO algorithm and its assumptions fit the RS data and the spectral traits of the species, all contribute to how well the discrimination and characterization and thus definition of the entities of BD can be determined using EO.

New sensor development to describe other previously insufficiently quantifiable spectral traits and spectral trait variations such as sensors in the UV range, chlorophyll fluorescence, or to describe photosynthesis activities at different times of the day (observation of daily rhythms) must be accelerated in order to be able to comprehensively describe biodiversity in its complexity in the future. In this respect, priority should be given to the evaluation of the meaning and discovery of causes for changes in spectral traits and trait variations. In addition to biotic spectral traits, assessments of abiotic spectral traits that can be comprehensively recorded using EO (Wulf et al., 2016; Kuenzer et al., 2015) to evaluate changes in biotic spectral traits and effect on biodiversity must be brought to the fore.

Wide areas of biodiversity will, however, still only be able to be recorded in the future by means of in situ techniques. The advantages and disadvantages of each method in-situ species and EO have yet to be worked out on a comparative basis, in order to link up existing approaches. To overcome the complexity of the data from different biodiversity approaches and to make them suitable for analysis, methods of semantics and Linked Open Data – LOD (Lausch et al., 2015b) are required. Comprehensive efforts regarding semantics of plant and animal traits, semantics of crop science as well as semantics of EO data do in fact already exist.

Furthermore, new concepts and frameworks for data calibration in EO and the linking of terrestrial, airborne and space-borne sensor networks (Turner, 2014), as well as methods for citizens science are required for an improved quantification, recording, explanation and prediction of biotic entities of biodiversity when using remote-sensing techniques in the future. A close link between in-situ and EO-based approaches is absolutely imperative for a better understanding of biodiversity. This will mean taking completely new directions in the future to link complex, large data, approaches and models.

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References

Ač, Malenovský, Z., Olejníčková, J., Gallé, A., Rascher, U., Mohammed, G., 2015. Meta-analysis assessing potential of steady-state chlorophyll fluorescence for remote sensing detection of plant water, temperature and nitrogen stress. Remote Sens. Environ. 168, 420–436.

Alexandridis, T.K., Lazaridou, E., Tsirika, A., Zalidis, G., 2009. Using Earth Observation to update a Natura 2000 habitat mpa for a wetland in Greece. J. Environ. Manage. 90, 2243–2251.

Amarsaikhan, D., Ganzorig, M., Ache, P., Blotevogel, H., 2007. The integrated use of optical and InSAR data for urban land-cover mapping. Int. J. Remote Sens. 28, 1161–1171.

Andrew, M., Ustin, S.L., 2008. The role of environmental context in mapping invasive plants with hyperspectral image data. Remote Sens. Environ. 112, 4301–4317.

Andrew, M.E., Wulder, M.A., Nelson, T.A., 2014. Potential contributions of remote sensing to ecosystem service assessments. Prog. Phys. Geog. 38, 328–353, http://dx.doi.org/10.1177/0309133314528942.

Antonarakis, A.S., Saatchi, S.S., Chazdon, R.L., Moorcroft, P.R., 2011. Using Lidar and Radar measurements to constrain predictions of forest ecosystem structure and function. Ecol. Appl. 21, 1120–1137.

Asner, G.P., Martin, R.E., 2008. Spectral and chemical analysis of tropical forest: scaling from leaf to canopy levels. Remote Sens. Environ. 63, 155–165.

Asner, G.P., Martin, R.E., 2009. Airborne spectranomics: mapping canopy chemical and taxonomic diversity in tropical forests. Front. Ecol. Environ. 7, 269–276.

Asner, G.P., Vitousek, P.M., 2005. Remote analysis of biological invasion and biogeochemical change. Proc. Natl. Acad. Sci. U. S. A. 102, 4383–4386.

Asner, G.P., Jones, M.O., Martin, R.E., Knapp, D.E., Hughes, R.F., 2008. Remote Sensing of native and invasive species in Hawaiian forests. Remote Sens. Environ. 112, 1942–1955.

Asner, G.P., Martin, R.E., Suhaili, A.Bin., 2012a. Sources of canopy chemical and spectral diversity in lowland bornean forest. Ecosystems 15, 504–517, http://dx.doi.org/10.1007/s10021-012-9526-.

Asner, G.P., Mascaro, J., Muller-Landau, H.C., Vieilledent, G., Vaudry, R., Rasamoelina, M., Hall, J., van Breugel, M., 2012b. A universal airborne LiDAR approach for tropical forest carbon mapping. Oecologia 168, 1147–1160.

Asner, G.P., 1998. Biophysical and biochemical sources of variability in canopy reflectance. Remote Sens. Environ. 64, 234–253.

Asner, G.P., 2015. Organismic remote sensing for tropical forest ecology and conservation. Ann. Missouri Bot. Garden 100, 127–140.

Ayanu, Y.Z., Conrad, C., Nauss, T., Wegmann, M., Loellner, T., 2012. Quantifying and mapping ecosystem services supplies and demands: a review of remote sensing applications. Environ. Sci. Technol. 46, 8529–8541.

Bässler, C., Stadler, J., Müller, J., Förster, B., Göttlein, A., Brandl, R., 2011. LiDAR as a rapid tool to predict forest habitat types in Natura 200 networks. Biodivers. Conserv. 20, 465–481.

Bajwa, S.G., Bajcsy, P.B., Groves, P., Tian, L.F., 2004. Hyperspectral image data mining for band selection in agricultural application. Trans. ASAE 47, 895–907.

Baldeck, C.A., Asner, G.P., Martin, R.E., Anderson, C.B., Knapp, D.E., Kellner, J.R., Wright, J., 2015. Operational tree species mapping in a diverse tropical forest with airborne imaging spectroscopy. PLoS One 10 (7), e0118403, http://dx.doi.org/10.1371/journal.pone.0118403.

Balzter, H., Cole, B., Thiel, C., Schmullius, C., 2015. Mapping CORINE land cover from sentinel-1A SAR and SRTM digital elevation model data using random forests. Remote Sens. 7, 14876–14898.

Barker, R., King, D.J., 2012. Blanding's Turtle (Emydoidea blandingii) potential habitat mapping using aerial orthophotographic imagery and object based classification. Remote Sens. 4, 194–219.

Belward, A.S., Skøien, J.O., 2014. Who launched what, when and why; trends in a global land-cover observation capacity from civilian earth observation satellites. ISPRS J. Photogramm. Remote Sens. 103, 115–128, http://dx.doi.org/10.1016/j.isprsjprs.2014.03.009.

Benali, A., Nunes, J.P., Freitas, F.B., Sousa, C.A., Novo, M.T., Lourenço, P.M., Lima, J.C., Seixas, J.A., Almeida, P.G., 2014a. Satellite-Derived estimation of environmental suitability for malaria vector development in Portugal. Remote Sens. Environ. 145, 116–130, http://dx.doi.org/10.1016/j.rse.2014.01.014.

Benali, A., Nunes, J.P., Freitas, F.B., Sousa, C.A., Novo, M.T., Lourenço, P.M., Lima, J.C., Seixas, J., Almeida, A.P.G., 2014b. Satellite-derived estimation of environmental suitability for malaria vector development in Portugal. Remote Sens. Environ. 145, 116–130, http://dx.doi.org/10.1016/j.rse.2014.01.014.

Bergen, K.M., Goetz, S.J., Dubayah, R.O., Henebry, G.M., Hunsaker, C.T., Imhoff, M.L., Nelson, R.F., Parker, G.G., Radeloff, V.C., 2009. Remote sensing of vegetation 3-D structure for biodiversity and habitat: review and implications for LiDAR and radar spaceborne missions. J. Geophys. Res. 430, http://dx.doi.org/10.1029/2008JG000883.

Bernatas, S., Nelson, L., 2004. Sightability model for California bighorn sheep in canyonlands using forward?looking infrared (FLIR). Wildl. Soc. Bull. 32, 638–647.

Berthold, P., Bosch, W.V.D., Zakubiec, Z., Kaatz, C., Kaatz, M., Querner, U., 2002. Long-term satellite tracking sheds light upon variable migration strategies of White Storks (Ciconia ciconia). J. Ornithol. 143, 498–493.

Betbeder, J., Nabucet, J., Pottier, E., Baudry, J., Corgne, S., Hubert-Moy, L., 2014. Detection and characterization of hedgerows using TerraSAR-X imagery. Remote Sens. 6, 3725–3769.

Blaschke, T., Strobl, J., 2001. What's wrong with pixels? Some recent developments interfacing remote sensing and GIS. GIS–Zeitschrift für Geoinformationssysteme 14 (6), 12–17.

Blaschke, T., Hay, G.J., Kelly, M., Lang, S., Hofmann, P., Addink, E., Tiede, D., 2014. Geographic object-based image analysis-towards a new paradigm. ISPRS-J. Photogramm. Remote Sens 87, 180–191.

Blaschke, T., 2010. Object based image analysis for remote sensing. ISPRS J. Photogramm. Remote Sens. 65, 2–16.

Bodegom, P.M., Douma, J.C., Verheijen, L.M., 2015. A fully triat-based approach to modeling global vegetation distribution. PNAS 111, 13733–13738.

Bradley, B.A., Fleishman, E., 2008. Can remote sensing of land cover improve species distribution modelling? J. Biogeogr. 35, 1158–1159.

Bradley, B.A., 2014. Remote detection of invasive plants: a review of spectral, textural and phenological approaches. Biol. Invasions 16, 1411–1425.

Briant, G., Gond, V., Laurance, S.W.G., 2010. Habitat fragmentation and the desiccation of forest canopies: a case study from Eastern Amazonia. Biol. Conserv. 143, 2763–2769, http://dx.doi.org/10.1016/j.biocon.2010.07.024.

Brokaw, N., Lent, R., 1999. In: Hunter, M. (Ed.), Vertical Structure. – Maintaining Biodiversity Forest Ecosystems. Cambridge Univ. Press, Cambridge U.K, pp. 373–399.

Buck, O., Garcia Millan, V.E., Klink, A., Pakzad, K., 2015. Using information layers for mapping grassland habitat distribution at local to regional scales. Int. J. Appl. Earth Obs. Geoinf. 37, 83–89.

Cadotte, M.W., Jonathan Davies, T., Regetz, J., Kembel, S.W., Cleland, E., Oakley, T.H., 2010. Phylogenetic diversity metrics for ecological communities: integrating species richness, abundance and evolutionary history. Ecol. Lett. 13, 96–105, http://dx.doi.org/10.1111/j.1461-0248.2009.01405.x.

Carboni, M., de Bello, F., Janeček, S., Doležal, J., Horník, J., Lepš, J., Reitalu, T., Klimešová, J., 2014. Changes in trait divergence and convergence along a productivity gradient in wet meadows. Agr. Ecosyst. Environ. 182, 96–105.

Cardinale, B.J., Duffy, J.E., Gonzalez, A., Hooper, D.U., Perrings, C., Venail, P., Narwani, A., Mace, G.M., Tilman, D., Wardle, A., Kinzig, A.P., Daily, G.C., Loreau, M., Grace, J.B., Larigauderie, A., Srivastava, D.S., Naeem, S., 2012. Biodiversity loss and its impact on humanity. Nature 486 (7401), 59–67, http://dx.doi.org/10.1038/nature11148.

Chen, J.M., Pavlic, G., Brown, L., Cihlar, J., Leblanc, S.G., White, P., Hall, R.J., Peddle, D., King, D.J., Trofymow, J.A., Swift, E., Van der Sanden, J., Pellikka, P., 2002. Validation of Canada-wide leaf area index maps using ground measurements and high and moderate resolution satellite imagery. Remote Sens. Environ. 80, 165–184.

Chiarucci, A., Maccherini, S., De Dominicis, V., 2001. Evaluation and monitoring of the flora in a nature reserve by estimation methods. Biol. Conserv. 101, 305–314.

Chiarucci, A., Enright, N.J., Perry, G.L., Miller, B.P., Lamont, B.B., 2003. Performance of nonparametric species richness estimators in a high diversity plant community. Divers. Distrib. 9, 283–295.

Cho, M.Z., Mathieu, R., Asner, G.P., Naidoo, L., van Aardt, J., Ramoelo, A., Debba, P., Wessels, K., Main, R., Smit, I.P.J., Erasmus, B., 2012. Mapping tree species composition in South African savannas using an integrated airborne spectral and LiDAR system. Remote Sens. 125, 214–226.

Chust, G., Ducrot, D., Pretus, J.L., 2004. Land cover discrimination potential of radar multitemporal series and optical multispectral images in a Mediterranean cultural landscape. Int. J. Remote Sens. 25, 3513–3528.

Clasen, A., Somers, B., Pipkins, K., Tits, L., Segl, K., Brell, M., Kleinschmit, B., Spengler, D., Lausch, A., Förster, M., 2015. Spectral unmixing of forest crown components at close range, airborne and simulated EnMAP imaging scale. Remote Sens. 7, 15361–15387;, http://dx.doi.org/10.3390/rs71115361.

Cochran, W.W., Mouritsen, H., Wikelski, M., 2004. Migrating songbirds recalibrate their magnetic compass daily from twilight cues. Science 304, 405–408.

Conrad, J.L., Bibian, A.J., Weinersmith, K.J., Carion, D.D., Young, M.J., Crain, P., Hestir, E.L., Santos, M.J., Sih, A., 2016. Novel species interactions in a highly modified estuary: association of largemouth bass with Brazilian Waterweed Egeria densa. T Am. Fish. Soc. 145, 249–263, http://dx.doi.org/10.1080/00028487.2015.1114521.

Corbane, C., Lang, S., Pipkins, K., Alleaume, S., Deshayes, M., Millán, V.E.G., Strasser, T., Borre, J.V., Toon, S., Förster, M., 2015. Remote sensing for mapping natural habitats and their conservation status – New opportunities and challenges. Int. J. Appl. Earth Obs. Geoinf. 37, 7–16.

Cord, A.F., Meentemeyer, R.K., Leitão, P.J., Vaclavik, T., 2013. Modelling species distributions with remote sensing data: bridging disciplinary perspectives. J. Biogeogr. 40, 2226–2227.

Cord, A.F., Klein, D., Mora, F., Dech, S., 2014. Comparing the suitability of classified land cover data and remote sensing variables for modeling disribtuion patterns of plants. Ecol. Model. 272, 129–140.

Curtis, P.D., Boldgiv, B., Mattison, P.M., Boulanger, J.R., 2009. Estimating deer abundance in suburban areas with infrared?triggered cameras. Hum.Wildl. Conflicts 3, 116–128.

Cusack, J.J., Swanson, A., Coulson, T., Packer, C., Carbone, C., Dicman, A.J., Kosmala, M., Lintott, C., Rowcliffe, J.M., 2015. Applying a randaom encounter model to estimate lion density from camera traps in serengeti national park. Tanzania. The Journal of Willife Management 79, 1014–1021, http://dx.doi.org/10.1002/jwmg.902.

Cutler, D.R., Edwards, T.C., Beard, K.H., Cutler, A., Hess, K.T., Gibson, J., Lawler, J.J., 2007. Random forests for classification in ecology. Ecology 88, 2783–2792.

Czerwinski, C.J., King, D.J., Mitchell, S.W., 2014. Mapping forest growth and decline in a temperate mixed forest using temporal trend analysis of Landsat imagery, 1987–2010. Remote Sens. Environ. 141, 188–200, http://dx.doi.org/10.1016/j.rse.2013.11.006.

Damm, A., Guanter, L., Laurent, V.C.E., Schaepman, M.E., Schickling, A., Rascher, U., 2014. FLD-based retrieval of sun-induced chlorophyll fluorescence from medium spectral resolution airborne spectroscopy data. Remote Sens. Environ. 147, 256–266.

Damm, A., Guanter, L., Paul-Limoges, E., van der Tol, C., Hueni, A., Buchmann, N., Eugster, W., Ammann, C., Schaepman, M.E., 2015. Far-red sun-induced chlorophyll fluorescence shows ecosystem-specific relationships to gross primary production: an assessment based on observational and modeling approaches. Remote Sens. Environ. 166, 91–105.

de Arauja Barbosa, C.C., Atkinson, P.M., Dearing, J.A., 2015. Remote Sensing of ecosystem services: a systematic review. Ecol. Indic. 52, 430–443.

de Jong, R., Schaepman, M.E., Furrer, R., de Bruin, S., Verburg, P.H., 2013. Spatial relationship between climatologies and changes in global vegetation activity. Glob Chang Biol 19, 1953–1964.

De Vries, F.T., Manning, P., Tallowin, J.R.B., Mortimer, S.R., Pilgrim, E.S., Harroson, K.A., Hobbs, P.J., Quirk, H., Shipley, B., Cornelissen, J.H.C., Kattge, J., Bardgett, R.D., 2012. Abiotic drivers and plant traits explain landscape-scale patterns in soil microbial communities. Ecol. Lett. 15, 1230–1239.

DeFries, R.S., Townshend, J.R.G., Hansen, M.C., 1999. Continuous fields of vegetation characteristics at the global scale at 1-km resolution. J. Geophys. Res. Atmos. 104, 16911–16923.

Deans, A.R., Yoder, M.J., Balhoff, J.P., 2012. Time to change how we describe biodiversity. Trends Ecol. Evol. 27, http://dx.doi.org/10.1016/j.tree.2011.11.007.

Delalieux, S., Somers, B., Haest, B., Spanhove, T., Vanden Borre, J., Mücher, C.A., 2012. Heathland conservation status mapping through integration of hyperspectral mixture analysis and decision tree classifiers. Remote Sens. Environ. 126, 222–231.

Dell, A., Bender, J.A., Brandson, K., Couzin, I.D., de Papavieja, G.G., Noldus, L.P.J.J., Perez-Escudero, A., Perona, P., Straw, A.D., Wikelski, M., Brose, U., 2014. Automated image-bades tracking and its application in ecology. Trends Ecol. Evol. 29, 417–428.

Diamond, J., 1988. Factors controlling species diversity: over-view and synthesis. Ann. Missouri Bot. Garden 75, 117–129.

Dillabaugh, K.A., King, D.J., 2008. Riparian marshland composition and biomass mapping using Ikonos imagery. Can. J. Remote Sens. 34, 143–158.

Dingle Robertson, L., King, D.J., Davies, C., 2015a. Object-based image analysis of optical and radar variables for wetland evaluation. Int. J. Remote sens. 36, 5811–5841.

Dingle Robertson, L., King, D.J., Davies, C., 2015b. Assessing land cover change and anthropogenic disturbance in wetlands using vegetation fractions derived from Landsat TM5 imagery (1984–2010). Wetlands 35, 1077–1091.

Dodge, S., Bohrer, G., Weinzierl, R., Davidson, S.C., Kays, R., Douglas, D., Cruz, S., Han, J., Brandes, D., Wilkelski, M., 2013. The environmental-Data automated track annotation (Env-DATA) system: linking animal tracks with environmental data. Mov. Ecol. 1, http://dx.doi.org/10.1186/2051-3933-1-3.

Duffy, J.E., 2009. Why biodiversity is important to the functioning of real-world ecosystems. Front. Ecol. Environ. 7, 437–444.

Duro, D., Coops, N.C., Wulder, M.A., Han, T., 2007. Development of a large area biodiversity monitoring system driven by remote sensing. Prog. Phys. Geogr. 31, 235–260.

Duro, D.C., Girard, J., King, D.J., Fahrig, L., Mitchell, S., Lindsay, K., Tischendorf, L., 2014. Predicting species diversity in agricultural environments using Landsat TM imagery. Remote Sens. Environ. 144, 214–225.

Dusseux, P., Corpetti, T., Hubert-Moy, L., Corgne, S., 2014. Combined use of multi-temporal optical and radar satellite images for grassland monitoring. Remote Sens. 6, 6163–6182.

Elith, J., Leathwick, J.R., 2009. Species distribution models: ecological explanation and prediction across space and time. Annu. Rev. Ecol. Syst. 40, 677–697, http://dx.doi.org/10.1146/annurev.ecolsys.110308.120159.

Ene, L., Næsset, E., Gobakken, T., Gregoire, T.G., Ståhl, G., Holm, S., 2013. A simulation approach for accuracy assessment of two-phase post-stratified estimation in large-area LiDAR biomass surveys. Remote Sens. Environ. 133, 210–224.

Engdahl, M., Hyyppa, J., 2003. Land-cover classification using multitemporal ERS-1/2 InSAR data. IEEE Trans. Geosci. Remote Sens. 41, 1620–1628.

Engler, R., Waser, L.T., Zimmermann, N.E., Schaub, M., Berdos, S., Ginzler, C., Psomas, A., 2013. Combining ensemble modeling and remote sensing for mapping individual tree species at high spatial resolution. For. Ecol. Manage. 310, 64–73, http://dx.doi.org/10.1016/j.foreco.2013.07.059.

Erasmi, S., Twele, A., 2009. Regional land cover mapping in the humid tropics using combined optical and SAR satellite dataa case study from Central Sulawesi, Indonesia.I nt. J. Remote Sens. 30, 2465–2478.

Erb, K.H., Haberl, H., Jepsen, M.R., Kuemmerle, T., Lindner, M., MÃijller, D., Verburg, P.H., Reenberg, A., 2013. A conceptual framework for analysing and measuring land-use intensity. Curr. Opin. Environ. Sustain. 5, 464–470.

Estel, S., Kümmerle, T., Levers, C., Baumann, M., Hostert, P., 2015. Mapping cropland-use intensity across Europe using MODIS NDVI time series. Environ. Res. Lett. 11, 024015.

Estes, L.D., Reillo, P.R., Mwangi, A.G., Okin, G.S., Shugart, H.H., 2010. Remote sensing of structural complexity indices for habitat and species distribution modelling. Remote Sens. Environ. 114, 792–804.

Everitt, J.H., Yang, C., Deloach, C.J., 2006. Remote sensing of giant reed with QuickBird satellite imagery. J. Aquat. Plant Manage. 43, 81–85.

Fahrig, L., Girard, J., Duro, D., Pasher, J., Smith, A., Javorek, S., King, D., Lindsay, F.K., Mitchell, S., Tischendorf, L., 2015. Farmlands with smaller crop fields have higher within-field biodiversity. Agric. Ecosyst. Environ. 200, 219–234.

Fairbanks, D.H.K., McGwire, K.C., 2004. Patterns of floristic richness in vegetation communities of California: regional scale analysis with multi-temporal NDVI. Glob. Ecol. Biogeogr. 13, 221–235.

Fassnacht, F.E., Latifi, H., Ghosh, A., Joshi, P., Koch, B., 2014. Assessing the potential of hyperspectral imagery to map bark beetle-induced tree mortality. Remote Sens. Environ. 140, 533–548.

Feilhauer, H., Schmidtlein, S., 2009. Mapping continuous fields of alpha and beta diversity. Appl. Veg. Sci. 12, 429–439.

Feilhauer, H., Schmidtlein, S., 2011. On variable relations between vegetation patterns and canopy reflectance. Ecol. Inform. 6, 83–92.

Feilhauer, H., Faude, U., Schmidtlein, S., 2011. Combining Isomap ordination and imaging spectroscopy to map continuous floristic gradients in a heterogeneous landscape. Remote Sens. Environ. 115, 2513–2524.

Feilhauer, H., Doktor, D., Lausch, A., Schmidtlein, S., Schulz, G., Stenzel, S., 2014. Mapping Natura 2000 habitats and their local variability with remote sensing. Appl. Veg. Sci. 17, 765–779, http://dx.doi.org/10.1111/avsc.12115.

Feilhauer, H., Doktor, D., Schmidtlein, S., Skidmore, A.K., 2016. Mapping pollination types with remote sensing. J. Veg. Sci., http://dx.doi.org/10.1111/jvs.12421.

Fischer, C., Heer, C., Werninghaus, R., 2012. X-band HRWS demonstrator digital beamforming test results. In: Proc 9th Eur. Conf. Synthetic Aperture Radar, Nuremberg, Germany, pp. 1–4.

Fisher, P., 1997. The pixel: a snare and a delusion. Int. J. Remote Sens. 18, 679–685.

Foody, G.M., 2005. Mapping the richness and composition of British breeding birds from coarse spatial resolution satellite sensor imagery. Int. J Appl. Earth. Obs. 26, 3943–3956.

Franke, U., Goll, B., Hohmann, U., Heurich, M., 2012. Aerial ungulate surveys with a combination of infrared and high-resolution natural colour images. Anim, Biodivers. Conserv 35.2, 285–293.

Fretwell, P.T., Staniland, I.J., Forcada, J., 2014. Whales from space: counting southern right whales by satellite. PLoS One 9, 1–9, http://dx.doi.org/10.1371/journal.pone.0088655.

Fricker, G.A., Wolf, J.A., Saatchi, S.S., Gillespie, T.W., 2015. Predicting spatial variations of tree species richness in tropical forests from high-resolution remote sensing. Ecol. Appl. 25, 1776–1789.

Friedl, M., McIver, D., Hodges, J., Zhang, X., Muchoney, D., Strahler, A., Woodcock, C., Gopal, S., Schneider, A., Cooper, A., Baccini, A., Gao, F., Schaaf, C., 2002. Global land cover mapping from MODIS: Algorithms and early results. Remote Sens. Environ. 83, 287–302.

Garnier, E., Lavorel, S., Ansquer, P., Castro, H., Cruz, P., Doležal, J., Eriksson, O., Fortunel, C., Freitas, H., Golodets, C., Grigulis, et al., 2007. Assessing the effects of land-use change on plant traits, communities and ecosystem functioning in grasslands: a standardized methodology and lessons from an application to 11 European sites. Ann. Bot. London 99, 967–985.

Garnier, E., Lavas, M.-L., Grigults, K., 2016. Plant Functional Diversity. Oxford University Press, London.

Garonna, I., De Jong, R., Schaepman, M.E., 2015. Variability and evolution of global land surface phenology over the past three decades (1982–2012). Glob. Change Biol., http://dx.doi.org/10.1111/gcb.13168.

Gauthreaux, S.A., Belser, C.G., 2003. Radar ornithology and biological conservation. Auk 120, 266–277.

Gillespie, T.W., Foody, G.M., Rocchini, D., Giorgi, A.P., Saatchi, S., 2008. Measuring and modelling biodiversity from space. Prog. Phys. Geogr. 32, 203–221.

Gillespie, T.W., 2001. Remote sensing of animals. Prog. Phys. Geogr. 25, 355–362.

Gould, W., 2000. Remote sensing of vegetation plant species richness, and regional biodiversity hotspots. Ecol. Appl. 10, 1861–1870.

Graesser, J., Aide, T.M., Grau, H.R., Ramankutty, N., 2015. Cropland/pastureland dynamics and the slowdown of deforestation in Latin America. Environ. Res. Lett. 10, 034017.

Grandin, R., Klein, E., Mětois, M., Vigny, C., 2016. Three-dimensional displacement field of the 2015 Mw8.3 Illapel earthquake (Chile) from across- and along-track Sentinel-1 TOPS interferometry. Geophys. Res. Lett. 43, 2552–2561, http://dx.doi.org/10.1002/2016GL067954.

Green, R.O., Eastwood, M.L., Sarture, C.M., Chrien, T.G., Aronsson, M., Chippendale, B.J., Faust, J.A., Pavri, B.E., Chovit, C.J., Solis, M., Olah, M.R., Williams, O., 1998. Imaging spectroscopy and the airborne Visible/Infrared imaging spectrometer (AVIRIS). Remote Sens. Environ. 65, 227–248.

Griffiths, P., Kuemmerle, T., Baumann, M., Radeloff, V.C., Abrudan, I.V., Lieskovsky, J., Munteanu, C., Ostapowicz, K., Hostert, P., 2014. Forest disturbances, forest recovery, and changes in forest types across the Carpathian ecoregion from 1985 to 2010 based on Landsat image composites. Remote Sens. Environ. 151, 72–88.

Groom, G., Petersen, I.K., Anderson, M.D., Fox, A.D., 2011. Using object-based analysis of image data to count birds: mapping of lesser flamingos at Kamfers Dam, Northern Cape, South Africa. Int J. Remote Sens. 32, 4611–4639.

Guanter, L., ·Kaufmann, H., Segl, K., Foerster, S., Rogass, C., Chabrillat, S., Kuester, T., Hollstein, A., Rossner, Chlebek, C., Rabe, A., Doerffer, A., Krasemann, H., Xi, H., Mauser, W., Hank, T., Locherer, M., Rast, M., Staenz, K., Sang, B., 2015. The EnMAP spaceborne imaging spectroscopy mission for earth observation. Remote Sens. 7, 8830–8857, http://dx.doi.org/10.3390/rs70708830.

Hüttich, C., Gessner, U., Herold, M., Strohbach, B.J., Schmidt, M., Keil, M., Dech, S., 2009. On the suitability of MODIS time series metrics to map vegetation types in dry savanna ecosystems: a case study in the Kalahari of NE Namibia. Remote Sens. 1, 620–643.

Hall, F.G., Bergen, K., Blair, J.B., Dubayah, R., Houghton, R., Hurtt, G., Kellndorfer, J., Lefsky, M., Ranson, J., Saatchi, S., Shugart, H.H., Wickland, D., 2011. Characterizing 3D vegetation structure from space: mission requirements. Remote Sens. Environ. 115, 2753–2775.

Hansen, M.C., DeFries, R.S., 2004. Detecting long-term global forest change using continuous fields of tree-Cover maps from 8-km advanced very high resolution radiometer (AVHRR) data for the years 1982-99. Ecosystems 7, 695–716.

Hansen, M.C., Potapov, P.V., Moore, R., Hancher, M., Turubanova, S.A., Tyukavina, A., Thau, D., Stehman, S.V., Goetz, S.J., Loveland, T.R., Kommareddy, A., Egorow, A., Chini, L., Justice, C.O., Townshend, J.R.C., 2013. High-Resolution global maps of 21st-century forest cover change. Science 342, 850–853.

Hay, G.J., Marceau, D., Dube, P., Bouchard, A., 2001. A multiscale framework for landscape analysis: object-specific analysis and upscaling. Landscape Ecol. 16, 471–490.

He, K.S., Rocchini, D., Neteler, M., Nagendra, H., 2011. Benefits of hyperspectral remote sensing for tracking plant invasions. Divers. Distrib. 17, 381–392.

He, K.S., Bradley, B.A., Cord, A.F., Rocchini, D., Tuanmu, M.-N., Schmidtlein, S., Turner, W., Wegmann, M., Pettorelli, N., 2015. Will remote sensing shape the next generation of species distribution models? Remote Sens. Ecol.Conserv. 1, 4–18.

Hecheltjen, A., Thonfeld, F., Menz, G., 2014. Recent advances in remote sensing change detection – a review. In: Manakos, I., Braun, M. (Eds.), Land Use and Land Cover Mapping in Europe – Practices & Trends. Springer, Dordrecht, pp. 145–178.

Heide-JØrgensen, M.P., 2004. Aerial digital photographic surveys of narwhals Monodon monoceros, in northwest Greenland. Mar. Mamm. Sci. 20, 246–261.

Hellesen, T., Matikainen, L., 2013. An object-based approach for mapping shrub and tree cover on grassland habitats by use of LiDAR and CIR orthoimages. Remote Sens. 5, 558–583.

Herbreteau, V., Salem, G., Souris, M., Hugot, J.-P., Gonzalez, J.-P., 2007. Thirty years of use and improvement of remote sensing, applied to epidemiology: from early promises to lasting frustration. Health Place 13, 400–403, http://dx.doi.org/10.1016/j.healthplace.2006.03.003.

Hernando, A., Tejera, R., Velazquez, J., Nunez, M.V., 2010. Quantitatively defining the conservation status of Natura 2000 forest habitats and improving management options for enhancing biodiversity. Biodivers. Conserv. 19, 2221–2233.

Heurich, M., Thoma, F., 2008. Estimation of forestry stand parameters using laser scanning data in temperate, structurally rich natural beech (Fagus sylvatica) and spruce (Picea abies) forests. Forestry 81, 645–661.
Hirschmuller, H., 2008. Stereo processing by semiglobal match-ing and mutual information. IEEE Trans. Pattern Anal. Mach. Intell. (PAMI) 30 (2), 328–341.
Hoffer, R.M., 1975. Natural Resource Mapping in Mountainous Terrain by Computer Analysis of ERTS-1 Satellite Data. Purdue Univ, Indiana.
Homolová, L., Malenovský, Z., Clevers, J.G.P.W., García-Santos, G., Schaepman, M.E., 2013. Review of optical-based remote sensing for plant traits mapping. Ecol. Complex. 15, 1–16.
Hong, S.H., Wdowinski, S., 2014. Multitemporal multitrack monitoring of wetland water levels in the Florida Everglades using ALOS PALSAR data with interferometric processing. IEEE Geosci. Remote Sens. Lett. 11, 1355–1359.
Hostert, P., Röder, A., Hill, J., 2003. Coupling spectral unmixing and trend analysis for monitoring of long-term vegetation dynamics in Mediterranean rangelands. Remote Sens. Environ. 87, 183–197.
Hostert, P., Griffiths, P., van der Linden, S., Pflugmacher, D., 2015. Time series analyses in a New Era of optical satellite data. Remote Sens. Time Ser. 22, 25–41.
Houborg, R., Fisher, J.B., Skidmore, A.K., 2015. Advances in remote sensing of vegetation functions and traits. Int. J. Appl. Earth Obs. Geoinf 43, 1–6.
Imhoff, M.L., Lawrence, W.T., Stutzer, D.C., Elwidge, C.D., 1997. A technique for using composite DMSP/OLS "City Lights" satellite data to map urban area. Remote Sens, Environ. 61, 361–370.
Inglada, J., Christophe, E., 2009. The orfeo toolbox remote sensing image processing software. IEEE Geosci. Remote Sens. (978-1-42443395-7/09).
Jansen, M., Gilmer, F., Biskup, B., Nagel, K.A., Rascher, U., et al., 2009. Simultaneous phenotyping of leaf growth and chlorophyll fluorescence via GROWSCREEN FLUORO allows detection of stress tolerance in Arabidopsis thaliana and other rosette plants. Funct. Plant Biol. 36, 902–914, http://dx.doi.org/10.1071/FP09095.
Jetz, W., Cavender-Bares, J., Pavlick, J., Schimel, D., Davis, F.W., Asner, G.P., Guralnick, R., Kattge, J., Latimer, A.M., Moorcroft, P., Schaepman, M.E., Schildhauer, M.P., Schneider, F.D., Schrodt, F., Stahl, U., Ustin, S.L., 2016. Monitoring plant functional diversity from space. Nat. Plants 16024, http://dx.doi.org/10.1038/NPPLANTS.2016.24.
Johnson, S.N., Crawford, J.W., Gregory, P.J., Grinory, P.J., Grinev, D.V., Mankin, R.R., Masters, G.J., Murray, P.J., Wall, D.H., Zhang, X., 2007. Non-invasive techniques for investigating and modelling root-feeding insects in managed and natural systems. Agric. Forest Entomol. 9, 39–46.
Joshi, N., Mitchard, E.T., Woo, N., Torres, J., Moll-Rocek, J., Ehammer, A., Collins, M., Jepsen, M.R., Fensholt, R., 2015. Mapping dynamics of deforestation and forest degradation in tropical forests using radar satellite data. Environ. Res. Lett. 10, 034014.
Joshi, N., Baumann, M., Ehammer, A., Fensholt, R., Grogan, K., Hostert, P., Jepsen, M.R., Kuemmerle, T., Meyfroidt, P., Mitchard, E.T.A., Reiche, J., Ryan, C.M., Waske, B., 2016. A review of the application of optical and radar remote sensing data fusion to land use mapping and monitoring. Remote Sens. 8, http://dx.doi.org/10.3390/rs8010070.
Jung, K., Kaiser, S., Böhm, S., Nieschulze, J., Kalko, E.K.V., 2012. Moving in three dimensions: effects 495 of structural complexity on occurrence and activity of insectivorous bats in managed forest 496 stands. J. Appl. Ecol. 49, 523–531.
Kattge, J., Diaz, S., Lavorel, S., Prentice, I.C., Leadley, P., Bönisch, G., Garnier, E., Westoby, M., Reich, P.B., Wright, I.J., et al., 2011. TRY — a global database of plant traits. Global Change Biol. 17, 2905–2935.
Kauth, R.J., Pentland, A.P., Thomas, G.S., 1977. BLOB: an unsupervised clustering approach to spatial processing of MSS imagery proceedings. 11th International Symposium on Remote Sensing of Environment 2, 1309–1317.
Kerr, J., Ostrovsky, M., 2003. From space to species: ecological applications for remote sensing. Trends Ecol. Evol. 18, 299–305.
Kerr, J.T., Southwood, T.R.E., Cihlar, J., 2001. Remotely sensed habitat diversity predicts butterfly species richness and community similarity in Canada. Proc. Natl. Acad. Sci. U. S. A 98, 11365–11370.
Kivinen, S., Kumpula, T., 2014. Detecting land cover disturbances in the lappi reindeer herding district using multi-Source remote sensing and GIS data. Int. J. Appl. Earth Obs. Geoinf. 27, 13–19, http://dx.doi.org/10.1016/j.jag.2013.05.009.
Klotz, S., Kühn, I., Durka, W., 2002. BIOLFLOR – eine datenbank zu biologisch-ökologischen merkmalen zur flora von deutschland. Schriftenreihe für Vegetationskunde 38, 1–333, Bundesamt für Naturschutz, Bonn.
Kraft, S., Del Bello, U., Bouvet, M., Drusch, M., Moreno, J., 2012. FLEX: ESA's earth explorer 8 candidate mission. In: Geoscience and Remote Sensing Symposium (IGARSS), IEEE International, Munch, 22–27 July 2012, pp. 7125–7128.
Kraft, N.J.B., Dooy, O., Levine, J.M., 2015. Plant functional traits and the multidimensional nature of species coexistence. PNAS 112, 797–802.
Kralisch, S., Böhm, B., Böhm, C., Busch, C., Fink, M., Fischer, C., Schartze, C., Selsam, P., Zander, P., Flügel, W.-A., 2012. ILMS ? a software platform for integrated environmental management. In: Proceedings of the International Environmental Modelling and Software Society (iEMSs), Managing Resources of a Limited Planet, Sisth Biennial Meeting, Leipzig, Germany http://www.iemss.org/society/index.php/iemss-2012-proceedings.
Kranstauber, B., Cameron, A., Weinzerl, R., Fountain, T., Tilak, S., Wikelski, M., Kays, R., 2011. The movebank data model for animal tracking. Environ. Modell. Softw. 26, 834–835, http://dx.doi.org/10.1016/j.envsoft.2010.12.005.
Kuemmerle, T., Perzanowski, K., Chaskovskyy, O., Ostapowicz, K., Halada, L., Bashta, A.-T., Kruhlov, I., Hostert, P., Waller, D.M., Radeloff, V.C., 2010. European bison habitat in the carpathian mountains. Biol. Conserv. 143, 908–916, http://dx.doi.org/10.1016/j.biocon.2009.12.038.
Kuemmerle, T., Erb, K., Meyfroidt, P., Müller, D., Verburg, P.H., Estel, S., Haberl, H., Hostert, P., Jepsen, M.R., Kastner, T., et al., 2013. Challenges and opportunities in mapping land use intensity globally. Curr. Opin. Environ. Sustain 5, 484–493.
Kuenzer, C., Ottinger, M., Wegmann, M., Guo, H., Wang, C., Zhang, J., Dech, S., Wikelski, M., 2015. Earth observation stellite sensors for biodiversity monitoring: potentials and bottlenecks. Int. J. Remote Sens. 35, 6599–6647.
Kumar, L., Schmidt, K.S., Dury, S., Skidmore, A.K., 2001. Imaging Spectroscopy and Vegetation Science. In: Meer, F.D.v.d., Jong, S.M. (Eds.), Imaging spectrometry: basic principles and prospective applications. Kluwer Academic, Dordrecht,NL, pp. 111–155.
LaRue, M.A., Lynch, H.J., Lyver, P.O.B., Barton, K., Ainley, D.G., Pollard, A., Fraser, W.R., Ballard, G., 2014. A method for estimating colony sizes of Adélie penguins using remote sensing imagery. Polar Biol. 37, 507–517.
Laba, M., Blair, B., Downs, R., Monger, B., Philpot, W., Smith, S., Sullivan, P., Baveye, P.C., 2010. Use of textural measurements to map invasive wetland plants in the Hudson River National Estuarine Research Reserve with IKONOS satellite imagery. Remote Sensing of Environ 114, 876–886.
Latifi, H., Fassnacht, F.E., Hartig, F., Berger, C., Hernández, J., Corvalán, P., Koch, B., 2015. Stratified aboveground forest biomass estimation by remote sensing data. Int. J. Appl. Earth Obs. Geoinf. 38, 229–241.
Laurent, V.C.E., Verhoef, W., Clevers, J.G.P.W., Schaepman, M.E., 2011a. Estimating forest variables from top-of-atmosphere radiance satellite measurements using coupled radiative transfer models. Remote Sens. Environ. 115, 1043–1052.
Laurent, V.C.E., Verhoef, W., Clevers, J.G.P.W., Schaepman, M.E., 2011b. Inversion of a coupled canopy-atmosphere model using multi-angular top-of-atmosphere radiance data: a forest case study. Remote Sens. Environ. 115, 2603–2612.
Laurent, V.C.E., Verhoef, W., Damm, A., Schaepman, M.E., Clevers, J.G.P.W., 2013. A Bayesian object-based approach for estimating vegetation biophysical and biochemical variables from APEX at-sensor radiance data. Remote Sens. Environ. 139, 6–17.
Laurent, V.C.E., Schaepman, M.E., Verhoef, W., Weyermann, J., Chavez, R.O., 2014. Bayesian object-based estimation of LAI and chlorophyll from a simulated Sentinel-2 top-of-atmosphere radiance image. Remote Sens. Environ. 140, 318–329.
Lausch, A., Heurich, M., Gordalla, D., Dobner, H.-J., Gwillym-Margianto, S., Salbach, C., 2013. Forecasting potential bark beetle outbreaks based on spruce forest vitality using hyperspectral remote-sensing techniques at different scales. For. Ecol. Manage. 308, 76–89, http://dx.doi.org/10.1016/j.foreco.2013.07.043.
Lausch, A., Pause, M., Schmidt, A., Salbach, C., Gwillym-Margianto, S., Merbach, I., 2013a. Temporal hyperspectral monitoring of chlorophyll LAI and water content of barley during a growing season. Can. J. Remote Sens. 39 (3), 191–207.
Lausch, A., Pause, M., Doktor, D., Preidl, S., Schulz, K., 2013b. Monitoring and assessing of landscape heterogeniety at different scales. Environ. Monit. Assess. 185 (11), 9419–9434, http://dx.doi.org/10.1007/s10661-013-3262-8.
Lausch, A., Zacharias, S., Dierke, C., Pause, M., Kühn, I., Doktor, D., Dietrich, P., Werban, U., 2013c. Analysis of vegetation and soil pattern using hyperspectral remote sensing EMI and Gamma ray measurements. Vadose Zone J. 12, http://dx.doi.org/10.2136/vzj2012.0217.
Lausch, A., Blaschke, T., Haase, D., Herzog, F., Syrbe, R.-U., Tischendorf, L., Walz, U., 2015. Understanding and quantifying landscape structure – A review on relevant process characteristics, data models and landscape metrics. Ecol. Model. 295, 31–41.
Lausch, A., Salbach, C., Doktor, D., Schmidt, A., Merbach, I., Pause, M., 2015a. Deriving phenology of barley with imaging hyperspectral remote sensing. Ecol. Model. 295, 123–135, http://dx.doi.org/10.1016/j.ecolmodel.2014.10.001.
Lausch, A., Schmidt, A., Tischendorf, L., 2015b. Data mining and linked open data – A new perspective for data analysis in environmental research. Ecol. Model. 295, 5–17, http://dx.doi.org/10.1016/j.ecolmodel.2014.09.018.
Lavorel, S., Garnier, E., 2002. Predicting changes in community composition and ecosystem functioning from plant traits: revisiting the Holy Grai. Funct. Ecol. 16, 545–556.
Lavorel, S., 2013. Plant functional effects on ecosystem services. J. Ecol. 101, 4–8.
Lawley, V., Lewis, M., Clarke, K., Ostendorf, B., 2016. Site-based and remote sensing methods for monitoring indicators of vegetation condition: an Australien review. Ecol. Indic. 60, 1273–1283.
Le Toan, L., Quegan, S., Davidson, M.W.J., Balzter, H., Paillou, P., Plummer, S., Papathanassiou, K., Rocca, F., Saatchi, S., Shugart, H., Ulander, L., 2011. The BIOMASS mission: mapping global forest biomass to better understand the terrestrial carbon cycle. Remote Sens. Environ. 115, 2850–2860.
Leiterer, R., Furrer, R., Schaepman, M.E., Morsdorf, F., 2015. Forest canopy-structure characterization: a data-driven approach. For. Ecol. Manage. 358, 48–61.
Leiterer, R., Torabzadeh, H., Furrer, R., Schaepman, M., Morsdorf, F., 2015a. Towards automated characterization of canopy layering in mixed temperate forests using airborne laser scanning. Forests 6, 4146.
Lesak, A.A., Radeloff, V.C., Hawbaker, T.J., Pidgeon, A.M., Gobakken, T., Contrucci, K., 2011. Modeling forest song bird species richness using LiDAR-derived measures of forest structure. Remote Sens. Environ. 115, 2823–2835.
Lewis, S.L., Edwards, D.P., Galbraith, D., 2015. Increasing human dominance of tropical forests. Science 349, 827–832.
Lewis, M.M., 1998. Numeric classification as an aid to spectral mapping of vegetation communities. Plant Ecol. 136, 133–149.

Leyequien, E., Verrelst, J., Slot, M., Schaepman-Strub, G., Heitkönig, I.M.A., Skidmore, A., 2007. Capturing the fugitive: applying remote sensing to terrestrial animal distribution and diversity. Int. J. Appl. Earth Obs. Geoinf. 9, 1–20, http://dx.doi.org/10.1016/j.jag.2006.08.002.
Linchant, J., Lisein, J., Semeki, J., Lejeune, P., Vermeulen, C., 2015. Are unmanned aircraft systems (UASs) the future of wildlife monitoring? a review of accomplishments and challenges. Mammal Rev. 45, 239–252.
Loveland, T.R., Reed, B.C., Brown, J.F., Ohlen, D.O., Zhu, Z., Yang, L., Merchant, J.W., 2000. Development of a global land cover characteristics database and IGBP DISCover from 1 km AVHRR data. Int. J. Remote Sens. 21, 1303–1330.
Lu, D., Weng, Q., 2007. A survey of image classification methods and techniques for improving classification performance. Int. J. Remote Sens. 28, 823–870.
Luft, L., Neumann, C., Itzerott, S., Lausch, A., Doktor, D., Freude, M., Blaum, N., Jeltsch, F., 2016. Digital and real-habitat modeling of Hipparchia statilinus based on hyper spetral remote sensing data. Int. J. Environ. Sci. Technol. 13 (1), 187–200, http://dx.doi.org/10.1007/s13762-015-0859-1.
Möckel, T., Dalmayne, J., Prentice, H.C., Eklundh, L., Purschke, O., Schmidtlein, S., Hall, K., 2014. Classification of grassland successional stages using airborne hyperspectral imagery. Remote Sens. 6, 7732–7761.
Mücher, C.A., Hennekens, S.M., Bunce, R.G.H., Schaminee, J.H.J., Schaepman, M.E., 2009. Modelling the spatial distribution of Natura 2000 habitats across Europe. Landsc. Urban Plan. 92, 148–159.
Mücher, C.A., Kooistra, L., Vermeulen, M., Vanden Borre, J., Haest, B., Haveman, R., 2013. Quantifying structure of Natura 2000 heathland habitats using spectral mixture analysis and segmentation techniques on hyperspectral imagery. Ecol. Indic. 33, 71–81.
Müller, J., Brandl, R., 2009. Assessing biodiversity by remote sensing and ground survey in mountainous terrain: the potential of LiDAR to predict forest beetle assemblages. J. Appl. Ecol. 533 (46), 897–905.
Müllerová, J., Pergl, J., Pyšek, P., 2013. Remote sensing as a tool for monitoring plant invasions: testing the effects of data resolution and image classification approach on the detection of a model plant species Heracleum mantegazzianum (giant hogweed). Int. J. Appl. Earth Obs. Geoinf. 25, 55–65.
MacArthur, R.H., MacArthur, J., 1961. On bird species diversity. Ecology 42, 594–598.
Main-Knorn, M., Cohen, W.B., Kennedy, R.E., Grodzki, W., Pflugmacher, D., Griffiths, P., Hostert, P., 2013. Monitoring coniferous forest biomass change using a Landsat trajectory-based approach. Remote Sens. Environ. 139, 277–290.
Malenovský, Z., Rott, H., Cihlar, J., Schaepman, M.E., García-Santos, G., Fernandes, R., Berger, M., 2012. Sentinels for science: potential of Sentinel-1 –2, and –3 missions for scientific observations of ocean, cryosphere, and land. Remote Sens. Environ. 120, 91–101.
Mannion, P.D., Upchurch, P., Benson, Roger B.J., Goswami, A., 2014. The latitudinal biodiversity gradient throuh deep time. Trends Ecol. Evol. 29, 42–50.
Marignani, M., Maccherini, S., Rocchini, D., Chiarucci, A., Torri, D., 2008. Planning restoration in a cultural landscape in Italy using object-based approach and historical analysis. Landsc. Urban Plan. 84, 28–37.
Martínez-Harms, M.J., Balvanera, P., 2012. Methods for mapping ecosystem service supply: a review. International Journal of Biodiversity Science. Ecosyst. Serv. Manage. 8, 17–25.
Mathieu, R., Naidoo, L., Cho, M.A., Leblon, B., Main, R., Wessels, K., et al., 2013. Toward structural assessment of semi-arid African savannahs and woodlands: the potential of multitemporal polarimetric RADARSAT-2 fine beam images. Remote Sens. Environ. 138, 215–231.
Matzner, S., Cullinan, V.I., Duberstein, C.A., 2015. Two-dimensional thermal video analysis of offshore bird and bat flight. Ecol. Inform. 30, 20–28.
McDowell, N.G., Coops, N., Beck, P.S.A., Chambers, J.Q., Gangodagamage, C., Hicke, J., Huang, C.-y., Kennedy, R., Krofcheck, D.J., Litvak, M., Meddens, A.J.H., Muss, J., Negrón-Juarez, R., Peng, C., Schwantes, A.M., Swenson, J.J., Vernon, L.J., Williams, A.P., Xu, C., Zhao, M., Running, S.W., Allen, C.D., 2015. Global satellite monitoring of climate-induced vegetation disturbances. Trends Plant Sci. 20, 114–123.
McElhinny, C., Gibbons, P., Brack, C., Bauhus, J., 2005. Forest and woodland stand structural complexity: its definition and measurement. For. Ecol. Manage. 218, 1–24.
Meroni, M., Rossini, M., Guanter, L., Alonso, L., Rascher, U., Colombo, R., Moreno, J., 2009. Remote sensing of solar-induced chlorophyll fluorescence: review of methods and applications. Remote Sens. Environ. 113, 2037–2051, http://dx.doi.org/10.1016/j.rse.2009.05.003.
Morisette, J.T., Jarnevich, C.S., Ullah, A., Cai, W., Pedelty, J.A., Gentle, J.E., Stohlgren, T.J., Schnase, J.L., 2005. A tamarisk habitat suitability map for the continental United States. Front. Ecol. Environ. 4 (1), 11–17.
Murwira, A., Skidmore, A.K., Huizing, H.J.G., Prins, H.H.T., 2010. Remote sensing of the link between arable field and elephant (Loxodonta africana) distribution change along a tsetse eradication gradient in the zambezi valley Zimbabwe. Int. J. Appl. Earth Obs. Geoinf. 12, 123–130, http://dx.doi.org/10.1016/j.jag.2009.09.007.
Nagendra, H., Lucas, R., Honrado, J.P., Jongman, R.H.G., Tarantino, C., Adamo, M., Mairota, P., 2012. Remote sensing for conservation monitoring: assessing protected areas, habitat extent, habitat condition species diversity, and threats. Ecol. Indic. 33, 45–59, http://dx.doi.org/10.1016/j.ecolind.2012.09.014.
Nagendra, H., 2001. Using remote sensing to assess biodiversity. Int. J. Remote Sens. 22, 2377–2400, http://dx.doi.org/10.1080/01431160117096.
Nelson, R., Keller, C., Ratnaswamy, M., 2005. Locating and estimating the extent of Delmarva fox squirrel habitat using an airborne LiDAR profiler. Remote Sens. Environ. 96, 292–301.
Neumann, C., Weiss, G., Schmidtlein, S., Itzerott, S., Lausch, A., Doktor, D., Brell, M., 2015. Ecological gradient-based habitat quality assessment for spectral ecosystem monitoring. Remote Sens. 7, 2871–2898;, http://dx.doi.org/10.3390/rs70302871.
Noss, R.F., 1990. Indicators for monitoring biodiversity: a hierarchical approach. Conserv. Biol., 355–364.
Nutter Jr, W.F., Rij, N.v., Eggenberger, S.K., Holah, N., 2010. Spatial and temporal dynamics of plant pathogens. In: Oerke, E.-C., Gerhards, R., Menz, G., Sikora, R.A. (Eds.), Precision Crop Protection–the Challenge and Use of Heterogeneity. , pp. 27–50, 101.1007/978–90-481–9277-9_3.
Oindo, B.O., Skidmore, A.K., 2002. Interannual variability of NDVI and species richness in Kenya. Int. J. Remote Sens. 23, 285–298.
Oishi, Y., Matsunaga, T., 2014. Support system for survieying moving wild animals in the snow using aerial remote-sensing images. Int. J. Remote Sens. 35, 1374–1394, http://dx.doi.org/10.1080/01431161.2013.876516.
Oldeland, J., Dorigo, W., Lieckfeld, L., Lucieer, A., Jürgens, N., 2010. Combining vegetation indices, constrained ordination and fuzzy classification for mapping semi-natural vegetation units from hyperspectral data. Remote Sens. Environ. 114, 1155–1166.
Olsson, A.D., Morisette, J.T., 2014. Comparison of simulated HyspIRI with two multispectral sensors for invasive species mapping. Photogramm. Eng. Remote Sens. 3, 217–227.
Pérez-Harguindeguy, Díaz, N.S., Garnier, E., Lavorel, S., Poorter, H., Jaureguiberry, P., Bret-Harte, M.S., et al., 2013. New handbook for standardized measurement of plant functional traits worldwide. Aust. J. Bot. 61, 167–234.
Palmer, M.W., Earls, P., Hoagland, B.W., White, P.S., Wohlge-muth, T., 2002. Quantitative tools for perfecting species lists. Environmetrics 13, 121–137.
Pasher, J., King, D.J., 2011. Development of a forest structural complexity index based on multispectral airborne remote sensing and topographic data. Can. J. For. Res. 41, 44–58.
Pasher, J., King, D.J., Lindsay, K., 2007. Modelling and mapping potential hooded warbler (Wilsonia citrina) habitat using remotely sensed imagery. Remote Sens. Environ. 107, 471–483.
Pasher, J., Smith, P.A., Forbes, M.R., Duffe, J., 2014. Terrestrial ecosystem monitoring in Canada and the greater role for integrated earth observation. Environ. Rev. 22, 179–187, http://dx.doi.org/10.1139/er-2013-0017.
Pause, M., Schulz, K., Zacharias, St., Lausch, A., 2012. Near-surface soil moisture estimation by combining airborne L-band brightness temperature observations and imaging hyperspectral data at the field scale. J. Appl. Remote Sens., http://dx.doi.org/10.1117/1.JRS.6.063516.
Pause, M., Lausch, A., Bernhardt, M., Hacker, J., Schulz, K., 2014. Improving soil moisture retrieval from airborne L-band radiometer data by considering spatially varying roughness. Can. J. Remote Sens. 40 (1), 15–25, http://dx.doi.org/10.1080/07038992.2014.907522.
Pause, M., Schweitzer, C., Rosenthal, M., Keuck, V., Bumberger, J., Dietrich, P., Heurich, M., Jung, A., Lausch, A., 2016. In situ/remote sensing integration to assess forest health - a review. Remote Sens. 8, 471, http://dx.doi.org/10.3390/rs8060471.
Pawar, S., Woodward, G., Dell, A.I., 2015. Advances in Ecological Research – Trait Based Ecology from Structure to Functions. Elsevier Press, USA.
Pearson, R.G., Dawson, T.P., Liu, C., 2004. Modelling species distributions in Britain: a hierarchical integration of climate and land-cover data. Ecography 27, 285–298.
Pereira, H.M., Ferrier, S., Walters, M., Geller, G.N., Jongman, R.H.G., Scholes, M.W., Bruford, N., Brummit, N., Buchard, S.H.M., Caroso, A.C., Coops, N.C., Dulloo, E., Feith, D.P., Freyhof, J., Gregory, R.D., Heip, C., Höft, R., Hurtt, G., Jetz, W., Karp, D.S., McGeoch, M.A., Bura, D., Onoda, Y., Pettorelli, N., Reyers, B., Sayre, R., Scharlemann, J.P.W., Stuart, S.N., Turak, E., Walpole, M., Wegmann, M., 2013a. Essential biodiversity variables. Science 339, 277–278.
Pereira, L.D.O., Freitas, C.D.C., St Anna, S.J.S., Lu, D., Moran, E.F., 2013b. Optical and radar data integration for land use and land cover mapping in the Brazilian Amazon. GISci. Remote Sens. 50, 301–321.
Petrou, Z.I., Manakos, I., Stathaki, T., 2015. Remote Sensing for biodiversity monitoring: a review of methods for biodiversity indicators extraction and assessment of progress towards international targets. Biodivers Conserv., http://dx.doi.org/10.1007/s10531-015-0947–z.
Pettorelli, N., Hilborn, A., Cuncan, C., Durant, S.M., 2015. Individual variability: the missing component to our understanding of predator-Prey interactions. In: Pawar, S., Woodward, G., Dell, A. (Eds.), Advantages in Ecological Research – Trait Based Ecology from Structure to Function, vol 52. Elsevier, pp. 19–44.
Pettorelli, N., Wegmann, M., Skidmore, A., Mücher, S., Dawson, T.P., Fernandez, M., Lucas, R., Schaepman, M.E., Wang, T., O'Connor, B., Jongman, R.H.G., Kempeneers, P., Sonnenschein, R., Leidner, A.K., Böhm, M., He, K.S., Nagendra, H., Dubois, G., Fatoyinbo, T., Hansen, M.C., Paganini, M., de Klerk, H.M., Asner, G., Kerr, J., Estes, A.B., Schmeller, D.S., Heiden, U., Rocchini, D., Pereira, H.M., Turak, E., Fernandez, N., Lausch, A., Cho, M.A., Alcaraz-Segura, D., McGeoch, M.A., Turner, W., Mueller, A., St-Louis, V., Penner, J., Geller, G.N., 2016. Framing the concept of satellite remote sensing essential biodiversity variables: challenges and future directions. Remote Sens. Ecol. Conserv. 1–10, http://dx.doi.org/10.1002/rse2.15.
Pompe, S., Janspch, J., Badeck, F., Klotz, S., Thuiller, W., Kühn, I., 2008. Climate and land use changes impacts on plant distributions in Germany. Biol. Lett. 4, 564–567.
Pu, R., Landry, S., 2012. A comparative analysis of high spatial resolution IKONOS and worldview-2 imagery for mapping urban tree species. Remote Sens. Environ. 124, 516–533, http://dx.doi.org/10.1016/j.rse.2012.06.011.

Raizman, E.A., Rasmussen, H.B., King, L.E., Ihwagi, F.W., Douglas-Hamilton, I., 2013. Feasibility study on the spatial and temporal movement of samburu's cattle and wildlife in Kenya using GPS radio-Tracking. Remote Sens. GIS Prev. Vet. Med. 111 (1–2), 76–80, http://dx.doi.org/10.1016/j.prevetmed.2013.04.007.

Rascher, U., Alonso, L., Burkart, A., Cilia, C., Cogliati, S., Colombo, R., Damm, A., Drusch, M., Guanter, L., Hanus, J., Hyvärinen, T., Julitta, T., Jussila, J., Kataja, K., Kokkalis, P., Kraft, S., Kraska, T., Matveeva, M., Moreno, J., Muller, O., Panigada, C., Pikl, M., Pinto, F., Prey, L., Pude, R., Rossini, M., Schickling, A., Schurr, U., Schüttemeyer, D., Verrelst, J., Zemek, F., 2015. Sun-induced fluorescence – a new probe of photosynthesis: first maps from the imaging spectrometer HyPlant. Global Change Biol. 21, 4673–4684.

Rascher, U., 2007. FLEX – fluorescence explorer: a remote sensing approach to quatify spatio-temporal variations of photosynthetic efficiency from space. Photosynth. Res. 91, 293–294.

Rattray, A., Lerodiaconou, D., Laurenson, L., Burq, S., Reston, M., 2009. Hydro-acoustic remote sensing of benthic biological communities on the shallow South East Australian continental shelf, Estuarine Coastal and Shelf. Science 84, 237–245.

Reich, P.B., 2012. Key canopy traits drive forest productivity. Proc. Biol. Sci. 279, 2128–2134.

Riley, J.R., Smith, A.D., Reynolds, D.R., Edwards, A.S., Osborne, J.L., Williams, I.H., Carreck, N.L., Poppy, G.M., 1996. Tracking bees with harmonic radar. Nature 379, 27–30.

Roberts, D.A., Quattrochi, D.A., Hulley, G.C., Hook, S.J., Green, R.O., 2012. Synergies between VSWIR and TIR data for the urban environment: an evaluation of the potential for the hyperspectral infrared imager (HyspIRI) decadal survey mission. Remote Sens. Environ. 117, 83–101.

Robinson, T.P., Wardell-Johnson, G.W., Pracilio, G., Brown, C., Corner, R., van Klinken, R.D., 2016. Testing the discrimination and detection limits of WorldView-2 imagery on a challenging invasive plant target. Int. J. Appl. Earth Obs. 44, 23–30, http://dx.doi.org/10.1016/j.jag.2015.07.004.

Rocchini, D., Balkenhol, N., Carter, G.A., Foody, G.M., Gillespie, R.W., He, K.S., Kark, S., Levin, N., Lucas, K., Luoto, M., Nagendra, H., Oldeland, J., Ricotta, C., Southworth, J., Neteler, M., 2010. Remotely sensed spectral heterogeneity as a proxy of species diversity: recent advances and open challenges. Ecol. Inform. 5, 318–329.

Rocchini, D., Boyd, D., Feret, J.-B., Foody, Giles M., He, K.S., Lausch, A., Nagendra, H., Neteler, M., Wegmann, M., Pettorelli, N., 2015a. Remotely sensed spatial heterogeneity as a proxy of species community diversity: potential and pitfalls. Remote Sens. Ecol. Conserv., http://dx.doi.org/10.1002/rse2.9.

Rocchini, D., Hernández Stefanoni, J.L., He, K.S., 2015b. Advancing species diversity estimate by remotely sensed proxies: a conceptual review. Ecol. Inform. 25, 22–28.

Ropert-Coudert, Y., Wilson, R.P., 2005. Trends and perspectives in animal-attached remote sensing. Front. Ecol. Environ. 3, 437–444.

Rossini, M., Nedbal, L., Guanter, L., Ač, A., Alonso, L., Burkart, A., Cogliati, S., Colombo, R., Damm, A., Drusch, M., Hanus, J., Janoutova, R., Julitta, T., Kokkalis, P., Moreno, J., Novotny, J., Panigada, C., Pinto, F., Schickling, A., Schüttemeyer, D., Zemek, F., Rascher, U., 2015. Red and far red Sun-induced chlorophyll fluorescence as a measure of plant photosynthesis. Geophys. Res. Lett. 42, 1632–1639.

Saatchi, S., Buermann, W., Steege, H., Mori, S., Smith, T.B., 2008. Modeling distribution of Amazonian tree species and diversity using remote sensing measurements. Remote Sens. Environ. 112, 2000–2017.

Safi, K., Armour-Marshall, K., Baillie, J.E.M., Isaac, N.J.B., Davies, Z.G., 2013. Global patterns of evolutionary distinct and globally endangered amphibians and mammals. PLoS One 8 (5), http://dx.doi.org/10.1371/journal.pone.0063582.

Sanchez-Hernandez, C., Boyd, D.S., Foody, G.M., 2007. Mapping specific habitats from remotely sensed imagery: support vector machine and support vector data description based classification of coastal salt marsh habitats. Ecol. Inform. 2, 83–88.

Sasamal, S.K., Chaudhury, S.B., Samal, R.N., Pattanaik, A.K., 2008. Quickbird spots flamingos off nalabana island, Chilika Lake India. Int. J. Remote Sens. 29, 4865–4870, http://dx.doi.org/10.1080/01431160701814336.

Schaepman, M.E., Jehle, M., Hueni, A., D'Odorico, P., Damm, A., Weyermann, J., Schneider, F.D., Laurent, V., Popp, C., Seidel, F.C., Lenhard, K., Gege, P., Küchler, C., Brazile, J., Kohler, P., De Vos, L., Meuleman, K., Meynart, R., Schläpfer, D., Kneubühler, M., Itten, K.I., 2015. Advanced radiometry measurements and Earth science applications with the Airborne Prism Experiment (APEX). Remote Sens. Environ. 158, 207–219.

Schimel, D.S., Asner, G.P., Moorcroft, P., 2013. Observing changing ecological diversity in the Anthropocene. Front. Ecol. Environ. 11, 129–137, http://dx.doi.org/10.1890/120111.

Schmidtlein, S., Zimmermann, P., Schüpferling, R., Weiß, C., 2007. Mapping the floristic continuum: ordination space position estimated from imaging spectroscopy. J. Veg. Sci. 18, 131–140.

Schmidtlein, S., Feilhauer, H., Bruehlheide, H., 2012. Mapping plant strategy types using remote sensing. J. Veg. Sci. 23, 395–405.

Schneider, F.D., Leiterer, R., Morsdorf, F., Gastellu-Etchegorry, J.P., Lauret, N., Pfeifer, N., Schaepman, M.E., 2014. Simulating imaging spectrometer data: 3D forest modeling based on LiDAR and in situ data. Remote Sens. Environ. 152, 235–250.

Schuster, C., Schmidt, T., Conrad, C., Kleinschmidt, B., Förster, M., 2015. Graslands habitat mapping by intra-annual time series analysis – Comparison of RapidEye and Terra-SAR-X satellite-Data. Int. Jo. Appl. Earth Observ. Geoinformatioin 34, 25–34.

Shugart, H.H., Asner, G.P., Fischer, R., Huth, A., Knapp, N., Toan, T.L., Shuman, J.K., 2015. Computer and remote-semsing infrastructure to enhance large-scale testing of individual-basde forst models. Front. Ecol. Environ. 13, 503–511, http://dx.doi.org/10.1890/140327.

Simonson, W.D., Allen, H.D., Coomes, D.A., 2012. Use of an airborne LiDAR system to model plant species composition and diversity of Mediterranean oak forests. Conserv. Biol. 26, 840–850.

Skidmore, A.K., Pettorelli, N., Coops, N.C., Gary, N., Geller, N., Hansen, M., Lucas, R., Mücher, C.A., O'Connor, B., Paganini, M., Pereira, H.M., Schaepman, M.E., Turner, W., Wang, T., Wegmann, M., 2015. Agree on biodiversity metrics ot track from space. Nature, 523.

Skidmore, A.K., 1989. Unsupervised training area selection in forests using a nonparametric distance measure and spatial information. Int. J. Remote Sens. 10, 133–146.

Spurr, S.H., 1948. Aerial Photographs in Forestry. Ronald Press Company, New York.

Stefanski, J., Kuemmerle, T., Chaskovskyy, O., Griffiths, P., Havryluk, V., Knorn, J., Korol, N., Sieber, A., Waske, B., 2014. Mapping land management regimes in western Ukraine using optical and SAR data. Remote Sens. 6, 5279–5305.

Stenzel, S., Feilhauer, H., Mack, B., Metz, A., Schmidtlein, S., 2014. Remote sensing of scattered Natura 2000 habitats using a one-class classifier. Int. J. Appl. Earth Obs. Geoinf. 33, 211–217.

Strahler, A.H., Woodcock, C.E., Smith, J.A., 1986. On the nature of models in remote sensing. Remote Sens. Environ. 20, 121–139.

Strand, H., Höft, R., Strittholt, J., Miles, L., Horning, N., Fosnight, E., Turner, W., 2007. Sourcebook on Remote Sensing and Biodiversity Indicators, CBD Technical Series No. 32. Secretariat of the Convention on Biological Diversity, Montreal, Canada.

Stysley, P.R., Cyle, D.B., Kay, R.B., Frederickson, R., Poulios, D., Cory, K., Clarke, G., 2015. Long term performance of the high output maximum efficiency resonator (HOMER) laser for NASA's global ecosystem dynamics investigation (GEDI) lidar. Optics & Laser Technology 68, 67–72.

Swatantran, A., Dubayah, R., Goetz, S., Hofton, M., Betts, M.G., Sun, M., Simard, M., Holmes, R., 2012. Mapping migratory bird prevalence using remote sensing data fusion. PLoS One, 7.

Tanase, M.A., Panciera, R., Lowell, K., Tian, S., Hacker, J., Walker, J.P., 2014. Airborne multi-temporal L-band polarimetric SAR data for biomass estimation in semi-arid forests. Remote Sens. Environ. 145, 93–104, http://dx.doi.org/10.1016/j.rse.2014.01.024.

Tanase, M.A., Ismail, I., Lowell, K., Karyanto, O., Santoro, M., 2015. Detecting and quantifying forest change: the potential of existing C-and X-Band radar datasets. PLoS One 10 (6), e0131079.

Thenkabail, P.S., Lyon, J.G., Huete, A., 2012. Hyperspectral Remote Sensing of Vegetation. CRC Press Taylor & Francis Group.

Thuiller, W., Brotons, L., Araújo, M.B., Lavorel, S., 2004. Effects of restricting environmental range of data to project current and future species distributions. Ecography 27, 165–172.

Torabzadeh, H., Morsdorf, F., Schaepman, M.E., 2014. Fusion of imaging spectrometry and airborne laser scanning for characterization of forest ecosystems–a review. ISPRS-J. Photogramm. Remote Sens. 97, 25–35.

Torontow, V.A., King, D.J., 2012. Forest complexity modelling and mapping with remote sensing and topographic data: comparison of three methods. Can. J. Remote Sens. 37, 387–402.

Torres, R., Snoej, P., Geudtner, D., Bibby, Da., Davidson, M., Attema, E., Potin, P., Rommen, B., Floury, N., Brown, M., Traver, I.N., Deghaye, P., Duesmann, B., Rosich, B., Miranda, N., Bruno, C., L'Abbate, M., Croci, R., Pietrapaolo, A., Huchler, M., Rostan, F., 2012. GMES sentinel-1 mission. Remote Sens. Environ. 120, 9–24.

Townshend, J., Justice, C., Li, W., Gurney, C., McManus, J., 1991. Global land cover classification by remote sensing: present capabilities and future possibilities. Remote Sens. Environ. 35, 243–255.

Treuhaft, R.N., Siqueira, P.R., 2000. Vertical structure of vegetated land surfaces from interferometric and polarimetric radar. Radio Sci. 35 (1), 141–177.

Turner, W., Spector, S., Gardiner, N., Fladeland, M., Sterling, E., Steininger, M., 2003. remote sensing for biodiversity science and conservation. Trends Ecol. Evol. 18, 306–314.

Turner, B.L., Lambin, E.F., Reenberg, A., 2007. The emergence of land change science for global environmental change and sustainability. Proc. Natl. Acad. Sci. U. S. A. 2007 (104), 20666–20671.

Turner, W., 2014. Sensing biodiversity. Science 346 (6207), 301–302.

Twele, A., Cao, W., Plank, S., Martinis, S., 2016. Sentinel-1 based flood mapping: a fully automated processing chain. Int. J. Remote Sens., 0143–1161 (Taylor & Francis. ISSN).

Urbazaev, M., Thiel, C., Mathieu, R., Naidoo, L., Levick, S.R., Smit, I.P.J., Asner, G.P., Schmullius, C., 2015. Assessment of the mapping of fractional woody cover in southern African savannas using multi-temporal and polarimetric ALOS PALSAR L-band images. Remote Sens. Environ. 166, 138–153.

Ustin, S.L., Gamon, J.A., 2010. Remote sensing of plant functional types. New Phytol. 186, 795–816.

Ustin, S.L., 2013. Remote Sensing for canopy biochemistry. PNAS 110, 805.

van Coillie, F., Delaplace, K., Gabriels, D., de Smet, K., Ouessar, M., Belgacem, A.O., Taamallah, H., de Wulf, R., 2016. Monotemporal assessment of the population structure of Acacia tortilis (Forssk.) Hayne ssp. raddiana (Savi) Brenan in Bou Hedma National Park, Tunisia : A terrestrial and remote sensing approach. J Arid. Environ. 129, 80–92.

Verburg, P.H., Crossman, N., Ellis, E.C., Heinimann, A., Hostert, P., Mertz, O., Nagendra, H., Sikor, T., Erb, K.H., Golubiewski, N., Grau, R., Grove, M., Konaté, S.,

Meyfroidt, P., Parker, D.C., Chowdhury, R.R., Shibata, H., Thomson, A., Zhen, L., 2015. Land system science and sustainable development of earth system: a global land project perspective. Anthropocene 12, 29–41.
Vermeulen, C., Lejeune, P., Lisein, J., Sawadogo, P., Bouche, P., 2013. Unmanned aerial survey of elephants. PLoS One 8, e54700.
Vierling, K.T., Vierling, L.A., Gould, W.A., Martinuzzi, S.R., Clawges, M., 2008. LiDAR: Shedding new light on habitat characterization and modeling. Front. Ecol. Environ. 6, 90–98.
Violle, C., Navas, M.-L., Vile, D., Kazakou, E., Fortunel, C., Hummel, I., Garnier, E., 2007. Let the concept of trait be functional! Oikos 116, 882–892.
Violle, C., Reich, P., Pacala, S.W., Enquist, B.J., Kattge, J., 2014. The emergence and promise of functional biography. PNAS 11, 13690–13696.
Walsh, S.J., McCleary, A.L., Mena, C.F., Shao, Y., Tuttle, J.P., González, A., Atkinson, R., 2008. Augusto gonzález, rachel atkinson quickbird and hyperion data analysis of an invasive plant species in the galapagos islands of Ecuador: implications for control and land use management. Remote Sens. Environ. 112, 1927–1941, http://dx.doi.org/10.1016/j.rse.2007.06.028.
Wang, C., Wang, L., Fu, H., Xie, Q., Zhu, J., 2016. The impact of forest density on forest height inversion modeling from polarimetric InSAR data. Remote Sens. 8, 291, http://dx.doi.org/10.3390/rs8040291.
Whittaker, R.J., Araújo, M.B., Jepson, P., Ladle, R.J., Watson, J.E.M., Willis, K.J., 2005. Conservation biogeography: assessment and prospect. Divers. Distrib. 11, 3–23.
Wikelski, M., Kays, R., Kasdin, N.J., Thorup, K., Smith, J.A., Swenson, G.W., 2007. Going wild: what a global small-animal tracking system could do for experimental biologists. J. Exp. Biol. 210, 181–186, http://dx.doi.org/10.1242/jeb.02629.
Witt, M.J., Åkesson, S., Broderick, A.C., Coyne, M.S., Ellick, J., Formia, A., Hays, G.C., Luschi, P., Stroud, S., Godley, B.J., 2010. Assessing accuracy and utility of satellite-Tracking data using argos-Linked fastloc-GPS. Anim. Behav. 80, 571–581, http://dx.doi.org/10.1016/j.anbehav.2010.05.022.
Wulder, M.A., Coops, N.C., 2014. Satellites: make earth observations open access. Nature 513 (7516), 30–331.
Wulder, M.A., Dymond, C.C., White, J.C., Leckie, D.G., Carroll, A.L., 2006. Surveying mountain pine beetle damage of forests: a review of remote sensing opportunities. For. Ecol. Manage. 221, 27–41.
Wulder, M.E., Masek, J.G., Cohen, W.B., Loveland, T.R., Woodcock, C.E., 2012. Opening the archive: how free data has enabled in science and monitoring promise of Landsat. Remote Sens. Environ. 122, 2–12.
Wulf, H., Mulder, T., Schaepman, M.E., Keller, A., Jörg, P., 2016. Remote Sensing of Soils, Tech. Rep. Remote Sensing Laboratories, University of Zrich, http://dx.doi.org/10.13140/2.1.1098.0649.
Yague-Martinez, N., Prats-Iraola, P., Rodriguez Gonzalez, F., Brcic, R., Shau, R., Geudtner, D., Eineder, M., Bamler, R., 2016. Interferometric processing of sentinel-1 TOPS data. IEEE Trans. Geosci. Remote Sens. 54, 2220–2234, http://dx.doi.org/10.1109/TGRS.2015.2497902, IEEE Xplore ISSN 0196–2892.
Zhai, D.L., Cannon, C.H., Dei, Z.-C., Zhang, C.-P., Xu, J.-C., 2015. Deforstation and fragmentation of natural forests in the upper Changhua watershed, Hainan, China: implication for biodiversity conservation. Environ. Monit. Asses. 187, 4137.
Zhang, Q., Hou, X., Li, F.Y., Niu, J., Zhou, Y., Ding, Y., Zhao, L., Li, X., Ma, W., Kang, S., 2014. Alpha. beta and gamma diversity differ in response to precipitation in the inner Mongolia grassland. PLoS One 9 (3), e93518, http://dx.doi.org/10.1371/journal.pone.0093518.
Zlinszky, A., Schroiff, A., Kania, A., Deak, B., Mücke, W., Vari, A., Szekely, B., Pfeifer, N., 2014. Categorizing grassland vegetation with full-waveform airborne laser scanning: a feasibility study for detecting Natura 2000 habitat types. Remote Sens. 6, 8056–8087.