ECOSYSTEMS

Check for updates

25TH ANNIVERSARY PAPER

Seeing the System from Above: The Use and Potential of Remote Sensing for Studying Ecosystem Dynamics

Cornelius Senf*

Technical University of Munich, School of Life Sciences, Ecosystem Dynamics and Forest Management Group, Hans-Carl-von-Carlowitz-Platz 2, 85354 Freising, Germany

ABSTRACT

Remote sensing techniques are increasingly used for studying ecosystem dynamics, delivering spatially explicit information on the properties of Earth over large spatial and multi-decadal temporal extents. Yet, there is still a gap between the more technology-driven development of novel remote sensing techniques and their applications for studying ecosystem dynamics. Here, I review the existing literature to explore how addressing these gaps might enable recent methods to overcome longstanding challenges in ecological research. First, I trace the emergence of remote sensing as a major tool for understanding ecosystem dynamics.

Second, I examine recent developments in the field of remote sensing that are of particular importance for studying ecosystem dynamics. Third, I consider opportunities and challenges for emerging open data and software policies and suggest that remote sensing is at its most powerful when it is theoretically motivated and rigorously ground-truthed. I close with an outlook on four exciting new research frontiers that will define remote sensing ecology in the upcoming decade.

Key words: remote sensing; satellite; geospatial; imagery; airborne; drone.

INTRODUCTION

Ecosystem dynamics emerge from interactions between biotic agents and their spatially and temporally heterogenous abiotic environments (Turner 2005). Understanding ecosystem dynamics is crucial for the sustainable management of ecosystems, especially in the face of global land use and climate change (Turner 2010; Trumbore and others 2015; Lindenmayer and others 2016). In this regard, it is of particular importance to consider ecosystem dynamics at multiple spatial and temporal scales, as

well as across scales (Levin 1992; Peters and others 2007; Raffa and others 2008). Selecting the appropriate scale of analysis, however, is often challenging, especially when considering processes acting over large spatial and long temporal extents (Druckenbrod and others 2019). Remote sensing fills an important niche in this regard by offering spatially explicit information on ecological processes over large spatial (meters to thousands of kilometers) and long temporal (days to decades) extents (Asner 2013; Figure 1).

Even though many ecologists have grown confident integrating remote sensing data into their research, technological development—historically driven by physicists and computer scientists—continues to push the frontier forward, often with

Corresponding author; e-mail: cornelius.senf@tum.de

minimal input from ecologists themselves. There hence is still a significant lag between the development of novel remote sensing techniques and their applications in ecological research. Closing this gap has the potential to significantly improve ecological analysis across spatial and temporal scales, yet requires further disciplinary coordination, including encouraging ecologists to pursue specialized training in remote sensing and vice versa (Bernd and others 2017; Wegmann 2017).

Here, I review the use of remote sensing for studying ecosystem dynamics for non-remote sensing scientists. After a conceptual background, I briefly summarize the emergence of remote sensing as a major tool for understanding ecosystem dynamics, review novel applications of remote sensing for studying ecosystem dynamics, discuss opportunities and challenges for emerging open data and software policies, and call for acknowledging the importance of uncertainty analysis and ground-truthing.

CONCEPTUAL BACKGROUND

For our purposes, *remote sensing* refers to any technique that uses a sensor installed on a vehicle like a satellite, plane, or car, to acquire information at a distance by detecting radiation that has been reflected or emitted from a surface. Analyzing the characteristics of this radiation can reveal information about the surface, such as its color and albedo, whether it is cold or warm, dry or wet, vegetated or bare, and so on. Depending on the sensor system, the spatial resolution can range from very high (< 1 m) to high (1–10 m), moderate (10–100 m), or coarse (> 100 m). For satellite-based systems, however, there is typically a trade-off between spatial and temporal resolution (the time between two observations of the same location on Earth; see also Figure 1). Although satellite-based sensors with coarse spatial resolution offer daily imagery from the same location, temporal observation frequency decreases rapidly when using moderate or high spatial resolution sensors. Unmanned systems offer a possible exception to this rule, since flights can be repeated frequently in theory (see Figure 1), even though this might be challenging in practice. Remote sensing thus offers data at variable spatial and temporal resolutions, which makes it an interesting method for investigating ecological processes across spatial and temporal scales. Yet it also requires researchers to pick the correct resolution for their scale of interest—a choice that can substantially influence results, and which thus needs to be taken with caution.

Besides the variable spatial and temporal resolutions of remote sensing systems, there are also differences in what remote sensing sensors measure. Passive sensors (for example, classical aerial imagery or optical satellites such as Landsat or Sentinel-2) use the incoming solar irradiance as source of energy. The incoming solar irradiance is either reflected by the Earth's surface and atmosphere, or absorbed and re-emitted. Passive sensors measure the reflected or emitted solar irradiance. Active sensors, in turn, have their own source of radiation and thus are independent of sunlight (active sensors include, for example, radar or Light Detection and Ranging [LiDAR]). Most passive sensors are sensitive to the optical part of the electromagnetic spectrum (optical remote sensing), that is the part visible to the human eye (approx. 400–700 nm in wavelength; Figure 1, upper right panel) and the infrared region (approx. 700–2500 nm in wavelength; Figure 1, upper right panel). Optical sensors thereby integrate over wavelength bands, and the number of spectral bands determines the spectral resolution of a sensor. Spectral resolutions can range from red–green–blue (RGB), to multispectral (RGB plus several bands in the near infrared) and hyperspectral sensors (> 100 narrow wavelength bands over the full optical range). Besides passive optical sensors, there are also passive thermal sensors that measure the emitted, longer-wave radiation of objects (approx. 10,000–13,000 nm in wavelength, see Figure 1). Active sensors often use the non-optical, microwave part of the electromagnetic spectrum (radar remote sensing; see Figure 1), or coherent optical light sources (laser remote sensing, see Figure 1). Depending on the system (passive or active) and the spectral region a sensor is sensitive to, it can detect different ecological processes (for example, photosynthesis, water content, vegetation structures). Similar to the spatial and temporal resolution, researchers also need to decide between active and passive remote sensing systems and choose an appropriate spectral resolution for their process of interest.

A Brief History of Remote Sensing for Studying Ecosystem Dynamics

Remote sensing has a long history in the study of ecosystems. The first studies using remote sensing were based on airborne (infrared) imagery that allowed for a birds-eye view of ecosystems (Estes 1966; Bowden and Brooner 1970), as well as for
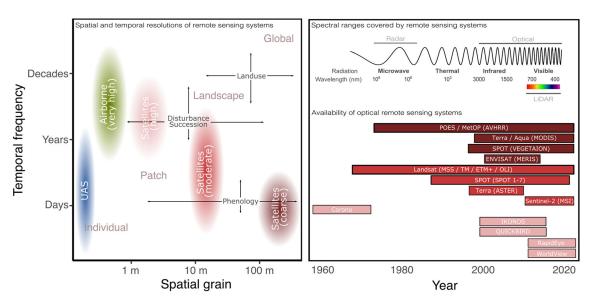
Figure 1. Spatial grain and temporal frequency of different remote sensing systems and their relation to examples of ecosystem dynamics (left panel). Spectral ranges covered by common remote sensing systems (right upper panel). Examples of optical satellite missions with sensors given in brackets grouped into high, moderate and coarse resolution systems and their spatial extent (right lower panel).

the stereographic analysis of vegetation properties (Spencer 1979). Repeating aerial image analysis over time revealed novel insights into how ecosystems change (Mast and others 1997), insights that were impossible to generate with field data alone. Yet, aerial imagery was limited in spatial extent as it was costly to acquire. On 23 July 1972, the launch of the first multispectral scanner system (MSS) on board Landsat 1 (formerly Earth Resources Technology Satellite) ushered a new era for scientists' study of Earth. With its four spectral bands covering the optical part of the electromagnetic spectrum (green, red and two bands in the near-infrared for vegetation analysis), a spatial resolution of approximately 80 m, a theoretical temporal sampling of 18 days and a large spatial extent (approximately 185×185 km^2), Landsat 1 allowed scientists—for the first time—to study the Earth's geo- and bio-physical properties across the globe on a regular basis without the need for acquiring costly aerial imagery (Pecora 1967). The use of satellite-based remote sensing has allowed scientists to reference their typically field-based research in the context of the surrounding landscape, giving novel insights into how spatial patterns determine ecological processes—and vice versa.

Possibilities for using satellite-based remote sensing to explore ecosystem dynamics have continued to expand at an impressive pace: Landsat 1 was followed by eight satellites in the Landsat family, with Landsat 9 launched in 2021. These systems have improved spatial resolution to 30 m and added additional spectral bands in the short wave infrared, which are especially sensitive to leaf water content (Ceccato and others 2001) and thus helped to even better characterize vegetation status and change (Cohen and Goward 2004; Schroeder and others 2011). Landsat is now the longest-running civilian satellite mission, with an astonishing 50 years of data available, which is longer than the majority of international Long Term Ecological Research (LTER) sites. Other space agencies have followed and launched similar operational programs (see Belward and Skøien 2015 for a review on who launched what when), such as the Copernicus program of the European Space Agency (ESA) with its six Sentinel satellites. Two of the Sentinels, namely Sentinel-2a and Sentinel-2b (launched in 2015 and 2017, respectively), carry optical sensors for the analysis of ecosystem dynamics. Today, there is also a large variety of commercial satellite programs offering manifold data, especially in the high spatial resolution domain. Combining different satellite-based remote sensing data into so-called virtual constellations can further increase data densities beyond the capacity of a single satellite (Wulder and others 2015), rendering modern satellite missions some of the most important sources of environmental data globally.

One of the first uses of satellite-based remote sensing in ecosystem ecology was for mapping of land cover and land cover change. For instance, satellite data were already used to estimate forest area, map forest types, and identify clear-cut harvests in the 1980s (Fleming and Hoffer 1979; Malila 1980; Nelson and others 1987; Jarvis 1994). Mapping land cover and land cover changes continued to be the primary application of satellite-based remote sensing in the early twenty-first century (Cohen and others 2002; Hansen and DeFries 2004; Yuan and others 2005; Knorn and others 2009). The creation of categorial maps from remote sensing data allowed scientists to characterize the spatial patterns of land cover and land cover changes, such as the proportion of specific land cover classes in the surrounding of a plot (Radeloff and others 2000), as well as how these patterns change over time—for instance, in response to disturbance (De Cola 1989; Kuemmerle and others 2007; Coops and others 2010). Using satellite data thus allowed the consideration of the spatial domain in ecological analyses (Riera and others 1998; Roberts and others 2004), with strong connections to the fields of landscape and ecosystem ecology (Lopez and Frohn 2017). In fact, many developments in landscape ecology (for example, spatial pattern analysis) would have been impossible without the categorial maps created from remote sensing systems. Besides the creation of categorial maps, remote sensing was also increasingly used for estimating vegetation properties from the spectral reflectance signal (Knipling 1970; Tucker 1980), mainly through the use of vegetation indices based on infrared spectral reflectance properties. Well-known and widely used indices include the Normalized Difference Vegetation Index (NDVI; Tucker 1979) and the Tasseled Cap transformation (Crist and Cicone 1984). The use of vegetation indices became even more important with the rise of global ecosystem models that required spatially explicit and dynamic information on biophysical properties such as leaf area or photosynthesis, which were approximated using satellite-based vegetation indices (Running and others 1986, 1989; Running and Nemani 1988).

Although remote sensing offered insights into ecosystems at spatial scales yet hardly studied by ecologists, analyses were often restricted to one or two points in time, presenting an obvious mismatch between the temporal scale of many ecological processes and the frequency of measurements (Kennedy and others 2014). The major reason for this was cost: each individual Landsat image, for instance, had to be purchased at approximately \$600 (Wulder and others 2012). In 2008, however, a new data policy introduced by the United States Geological Survey (USGS) changed the way remote sensing was used in ecological research forever: all archives maintained by the USGS were made free to access, which allowed scientists to rely not only on individual images, but to analyze hundreds of thousands of images simultaneously (Zhu and others 2019). Other space agencies such as Europe's ESA followed this example, and by 2022, most of the national satellite achieves are free to access (at least for scientific purposes). In response to the opening of the archives, novel techniques making use of the rapidly growing availability of satellite data have been developed (Wulder and others 2012). Those new developments allowed for characterizing both intra- (that is, seasonal) and inter-annual dynamics of ecosystems, such as spatiotemporal phenological dynamics (Fisher and Mustard 2007), land use dynamics in response to political changes (Griffiths and others 2012, 2013a) and conflict (Baumann and others 2015; Yin and others 2019), trends in forest biomass (Powell and others 2014), and disturbance dynamics in response to drought (Senf and others 2020a).

Besides the increasing temporal dimension offered by satellite-based remote sensing data, analyses were also no longer restricted in the spatial domain. Prior to the opening of the archives, many study sites were delineated by the footprint of a single Landsat image. After 2008, however, image compositing techniques allowed for delineating study sites based on ecological (and socio-ecological) processes instead (Roy and others 2010; Griffiths and others 2013b; White and others 2014). The seemingly endless availability of remote sensing data has thus greatly improved our understanding of ecosystem dynamics over broad spatial and temporal extents, and resulted in a series of large-scale data products capturing the dynamics of diverse terrestrial ecosystems at national, continental, or even global scales. Such data products include, for example, large-scale assessments of forest disturbance dynamics (Hansen and others 2013; White and others 2017; Senf and Seidl 2021a), phenology (Bolton and others 2020; Kowalski and others 2020), surface water changes (Pekel and others 2016; Pickens and others 2020), grasslands dynamics (Griffiths and others 2020; Schwieder and others 2022), or urban development (Liu and others 2020), all of which are now captured at fine spatial grain (30 m or finer) and high temporal resolution (annual or even intra-annual). Given this rich history of using remote

Figure 2. Examples of a LiDAR point cloud for a 500 m^2 forest research plot (left plot) with individual trees segmented to derive tree based structural metrics (for example, height; middle plot). The data were collected from a helicopter in 2021 and processed using the open-source lidR package (Roussel and others 2020). The right plot shows a canopy height model derived from the point cloud at a spatial grain of 1 m^2.

sensing in ecosystem ecology, is there anything new to discover?

Recent Developments in Remote Sensing for Studying Ecosystem Dynamics

Remote sensing has become an invaluable tool for studying ecosystem dynamics and the borders between the pure technical development of remote sensing approaches and ecosystem sciences have blurred. With increasing literacy in programming and geospatial methods, as well as increasing computer resources, many ecologists have themselves turned into remote sensing specialists. There is thus an emerging suite of methods developed by—and for—ecologists. In the following, I highlight seven recent developments in remote sensing that can greatly enhance ecological research and the understanding of global ecosystem dynamics in the upcoming decade (see also Figure 2).

Spatially and Temporally Seamless Data and Data Products

In the past, users of remote sensing data needed to have in-depth knowledge of radiation physics and image processing to make remote sensing data useful for ecological analysis. Nowadays, data are distributed as mostly analysis-ready data (ARD; Dwyer and others 2018; see also Table 1 for examples). ARD processing includes geometric corrections (that is, matching ground locations to pixels), radiometric corrections (that is, eliminating atmospheric influence) and masking (that is, identifying clouds and other artefacts), which is mostly done through data providers. In other words, these data can be downloaded and analyzed by users right away. This reduces the need for

heavy and often complex data processing by the user, which has certainly accelerated the adoption of remote sensing techniques in ecology. In response to the availability of standardized data products, the analysis of remote sensing data has moved away from thinking in images toward thinking in terms of pixels. Methods such as image compositing, for instance, take all available pixels and create seamless, cloud-free artificial images composed of millions of pixels coming from different base images (Roy and others 2010; Griffiths and others 2013b; White and others 2014; Frantz 2019; Potapov and others 2020). That way, analysis over large areas becomes possible, even though individual images might be useless due to cloud cover. Likewise, temporal consistency has improved by standardized adjustment and correction of images, allowing users the ability to track changes in the Earth's surface properties over time (Banskota and others 2014). The ever-increasing number of observations facilitated analysis over longer periods, as well as increasing temporal resolution: from decadal to annual to sub-annual analyses, for instance, creating consistent seasonal or monthly composite images (Flood 2013; Griffiths and others 2020). Finally, many remote sensing agencies recently added a series of higher-level data products that are directly applicable to ecological analysis and modeling. This movement has started with the moderate-resolution imaging spectroradiometer (MODIS) program, which offers standardized products featuring biogeophysical variables like leaf area, land surface temperature or gross and net primary productivity (Savtchenko and others 2004). Other satellite programs, such as Landsat by the USA and Copernicus by the ESA, have followed this example and now provide standardized prod-

Table 1. Examples of Analysis-Ready-Data Products and Frameworks

Name	Satellites (sensors)	Spatial resolution	Temporal resolution	Temporal coverage	Geographic coverage	Geographic tiling	Notes	Resources
Landsat Level-2	Landsat 4–5 (TM), Landsat 7 (ETM+), Landsat 8 (OLI)	30 * 30 m	Irregular, min. 8 days, often longer	1982–present	Global	Landsat footprint (185 * 185 km², overlapping)		https://www.usgs.gov/landsat-missions
Landsat U.S. ARD	Landsat 4–5 (TM), Landsat 7 (ETM+), Landsat 8 (OLI)	30 * 30 m	Irregular, min. 8 days, often longer	1982- present	USA (incl. Alaska and Hawaii)	150 * 150² km (non-overlapping)		https://www.usgs.gov/landsat-missions/landsat-us-analysis-ready-data
Sentinel-2 Level 2A	Sentinel 2 a/b (MSI)	Depending on spectral band: 10 * 10 m², 20 * 20 m² or 30 * 30 m²	Irregular, min. 5 days, often longer	2013-present	Global	100 * 100 km² (non-overlapping)		https://sentinel.esa.int/web/sentinel/missions/sentinel-2
FORCE	Landsat 4–5 (TM), Landsat 7 (ETM+), Landsat 8 (OLI), Sentinel 2 a/b (MSI)	User-definable	Irregular and regular, min. 5 days, often longer	1982-recent (Landsat) and 2013-recent (Sentinel-2)	Global (depending on processing capacities)	User-definable	Own processing capabilities needed	Frantz (2019)
GLAD Landsat ARD Tools	Landsat 4–5 (TM), Landsat 7 (ETM+), Landsat 8 (OLI)	30 * 30 m	Regular, 16 days	1997-present	Global (between 75° N and 56° S)	1° * 1° (non-overlapping)		Potapov and others (2020)
Open Data Cube	Landsat 4–5 (TM), Landsat 7 (ETM+), Landsat 8 (OLI), Sentinel 2 a/b (MSI), Aqua/terra (MODIS)	User-definable	Irregular and regular, min. 5 days, often longer	Variable	Australia (Digital Earth Australia), Central Africa (Africa Regional Data Cube), Switzerland	User-definable	Expandable to own region of interest	Australia (Dhu and others 2017); Central Africa (Killough 2019); Switzerland (Giuliani and others 2017); https://www.opendatacube.org

ucts for monitoring ecosystem dynamics. For example, based on Landsat ARD, the USGS offers standardized products for the analysis of surface water extent, burned area and snow cover fractions (Landsat Sciences Products). Likewise, Copernicus by the European Space Agency offers a series of high-resolution layers, including annual maps of land cover (that is, impervious, forest, grasslands, water, and small woody features), as well as annual maps of key biophysical variables (that is, vegetation phenology and snow/ice cover). Such data products offer a clear advantage: users can analyze the spatial and temporal dynamics of ecosystems (for example, changes in area burnt or snow cover over time) without performing intensive remote sensing analyses—although accuracy and spatial and temporal consistency might be lower compared to tailor-made data solutions (Congedo and others 2016; Palomino and Kelly 2019).

Upscaling of Ecological Processes

Ecological research has classically focused on measuring ecological processes at relatively small scales, like single plots. The role of spatial variation in these processes was studied by experimental design, for example, over elevation gradients. A recent development in the intersection of remote sensing and field ecology is using remote sensing to upscale ecological processes measured at the plot-scale to the landscape-scale. For example, the distribution of biomass within a forest can be modeled from satellite data to understand the landscape-level variability of biomass and how it is related to climate and topography (Zald and others 2016). Phenological indicators derived from cameras can be linked to satellite time series to better understand how phenological dynamics vary at the landscape scale (Fisher and Mustard 2007; Melaas and others 2016). Likewise, camera trap data can be combined with remote sensing data to better understand global biodiversity patterns (Steenweg and others 2017). Although the general idea of upscaling local processes to the landscape scale by means of geospatial technologies is not novel by itself (Masek and others 2015), the fine spatial grain and high temporal frequency of newer satellite data offers novel applications. For example, although classical approaches to mapping habitat suitability made use of static predictors—such as topography, land cover and climate—more recent approaches use dynamic predictors derived from remote sensing (for example, phenology, snow cover) that are much closer to the actual ecological process one wants to model (Coops and Wulder

2019; Oeser and others 2020). This makes it possible to directly model the dynamics of the process, for example, changes in species occurrence in response to disturbance (Rickbeil and others 2016; Oeser and others 2021). Remote sensing thus will improve our understanding of scaling and drivers of change in ecological systems, a central point of interest in the study of ecosystem dynamics.

LiDAR

Optical remote sensing is largely limited to the study of the vegetation overstory since sunlight does not penetrate deeply into vegetation. Most passive data thus cannot be used for characterizing vegetation structures. In recent decades, however, a new type of active sensor has emerged as valuable tool for taking a close look at vegetation structures: light detection and ranging (LiDAR). LiDAR has a long-standing tradition in resource management and forestry (Lefsky and others 2002), but its use has only recently intensified in ecosystem and landscape ecology (Valbuena and others 2020; Lepczyk and others 2021). LiDAR sensors use laser beams to measure the time it takes for an emitted beam to travel to the ground and back, from which the elevation above ground can be derived if exact aerial flight coordinates are known (see Lim and others 2003 for a detailed description on the technology behind LiDAR data). From the laser beams returned, a three-dimensional 'point cloud' can be created that shows the distribution of laser returns (see Figure 2). Because of the coherent light source of lasers systems, laser beams can penetrate into vegetation canopies, but will be reflected eventually by both stems and leaves. The distribution of laser returns thus correlates with the horizontal and vertical distribution of vegetation and individual trees or objects can be segmented and analysed (for example, the height and dimension of individual trees, see Figure 2). From the point cloud, the highest returns can be identified and converted into a regular grid of grid-cells indicating the elevation of the vegetation canopy (the so-called surface model). Some of the laser beams will also reach the ground, from which gridded fine-scaled terrain models can be derived. By subtracting the terrain model from the surface model one can calculate the vegetation height above ground at fine spatial resolution, called canopy height model (see Figure 2). The ability to describe the vertical and horizontal distribution of vegetation certainly drives the high interest in LiDAR data among ecologists, especially as software for processing Li-

DAR data is nowadays freely available (Roussel and others 2020).

LiDAR has been used recently to better understand forest structures and their impacts on other ecological processes. For example, recent studies used airborne LiDAR data to quantify gap size distributions in forests (Silva and others 2019), disturbance impacts on forest structures (Senf and others 2020b), surface and canopy fuels (Braziunas and others 2022), and to map habitat and biodiversity, which both are closely related to structural variability (Davies and Asner 2014). Also, field-based LiDAR tools (that is, terrestrial laser scanning) have gained ample attention recently, as they allow for developing highly detailed three-dimensional models of vegetation structure (Calders and others 2020). LiDAR data thus allow to move from a dominating two-dimensional toward a three-dimensional view on landscapes and ecosystem processes (Lepczyk and others 2021). Multiple LiDAR acquisitions (both aerial and terrestrial) further allow for a detailed assessment of changing vegetation structures. For example, by analyzing repeated LiDAR datasets, Leitold and others (2021) quantified forest canopy changes and recovery following a hurricane at the individual tree level, and Zhao and others (2018) estimated tree growth, biomass dynamics and carbon fluxes of individual trees. Despite the power of aerial LiDAR for understanding the spatial (and spatiotemporal) dynamics of ecosystems, however, it remains a costly tool because of the high operation cost of platforms such as aircraft or helicopters, especially across large spatial extents. Analysis is thus often restricted to areas of existing data (for ex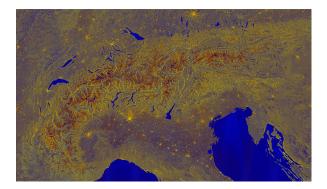ample, using airborne LiDAR data from national surveying programs or the National Ecological Observatory Network [NEON]; Ordway and others 2021) or to small areas and single acquisitions. This gap might be filled by novel spaceborne LiDAR data from the Global Ecosystem Dynamics Investigation (GEDI) system (Dubayah and others 2020), which provides 25-m-diameter 'LiDAR-plots' on a regular grid of 60×600 m and thus allows for quantifying ecosystem structure over large spatial extents (Schneider and others 2020). By fusion of GEDI with optical satellite data, global maps of key vegetation features can be created in the future, for example, global tree height (Potapov and others 2021).

Radar

Radar is another type of active data collection, making use of system-emitted microwaves to determine the range, angle and physical properties of objects on the Earth's surface (see Figure 3 for an example). In contrast to LiDAR, radar systems used for remote sensing are classically space-borne, allowing for easy global data acquisition. Moreover, as an active sensor, radar is independent of sunlight as an irradiation source and thus can be operated also at night and in cloudy conditions. Although radar techniques are not novel per se and have been applied historically for land-surveying (that is, creation of digital elevation models) as well as for land cover (change) mapping (that is, early work
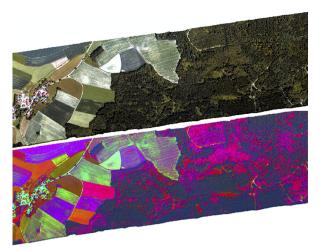

Figure 3. Example of a seamless radar data set derived over the European Alps from Sentinel-1. Red/green/blue colors show different polarizations of the radar signal averaged over the summer of 2021. The data were derived using: https://kristofvantricht.users.earthengine. app/view/sarworld.

Figure 4. Example of an airborne hyperspectral data set acquired using the HySpex sensor with 416 narrow spectral bands in the range from ∼ 400 to ∼ 2500 nm. The upper image shows the reflectance in red/green/ blue, whereas the lower image shows the first three principal components derived from all 416 bands, providing detailed insights into the variable land cover types.

on detection of deforestation in the Amazon; Saatchi and others 1997), radar data have begun to play an increasingly prominent role in ecosystem dynamics research due to the recent emergence of open-access space-borne radar systems like the ESA's Sentinel-1 satellite, the high spatial resolution of modern radar systems (< 10 m), and radar's ability to penetrate cloud cover. Recent studies have tested the ability of radar to monitor vegetation phenology (Vreugdenhil and others 2018), forest disturbances caused by bark beetles and fires (Tanase and others 2018; Belenguer-Plomer and others 2019), and forest clearing in the tropics, where the ability to see through clouds has greatly enhanced monitoring capabilities (Reiche and others 2016). Even more than LiDAR, radar can penetrate the canopy and thus estimate vegetation structure (Saatchi and others 2011). Early studies using radar data indicate it may be as useful as LiDAR for mapping structure-dependent ecosystem features, including biodiversity (Bae and others 2019). Although more research is needed, radar holds great promise for analyzing vegetation structures through space and time—and independent of cloud cover. Radar has also been applied for studying wetlands (Henderson and Lewis 2008; see also Figure 4) and urban areas (Frantz and others 2021; see also Figure 4), and its usefulness thus extends beyond the more classical applications in forest ecosystems. Finally, radar is well suited to measure biomass (Yu and Saatchi 2016), which makes it a useful tool for monitoring biomass dynamics over time. Upcoming radar systems are thus specifically designed for monitoring biomass dynamics globally (Le Toan and others 2011).

Hyperspectral Data

Hyperspectral remote sensing, also known as image spectroscopy, differs from classical optical multispectral approaches in the number and width of spectral bands recorded by the sensor. Although multispectral sensors measure the optical part of the electromagnetic spectrum in a few (< 10) relatively wide bands (approx. 40–100 nm in width), hyperspectral sensors measure the optical part of the electromagnetic spectrum in many (> 50 but often many more), regularly spaced narrow bands of approximately 5 to 10 nm in width. Hyperspectral data hence allows for sampling the full spectral reflectance properties in high detail, which can be used to quantify various biological, geological and chemical properties of the Earth's surface (Goetz 2009; see also Figure 4). For example, certain wavelength regions are strongly linked to physio-

logical traits, for example, leaf pigments such as chlorophyll (Blackburn 2007), and hyperspectral data can hence ben used to estimate their spatial and temporal variability (Carlson and others 2007; Townsend and others 2008; Asner and others 2012; Schneider and others 2017). Likewise, canopy water content can be well characterized using hyperspectral data, thus allowing for advanced monitoring of vegetation response to drought (Asner and others 2016). Although hyperspectral data enable a high level of analytical detail, handling this high-dimensional data often requires advanced processing tools (Bioucas-Dias and others 2013).

Hyperspectral sensors have been used mostly onboard aircrafts, because it is technically challenging to measure radiation in narrow bands over long distances (that is, a typical satellite orbit being around 800 km above the Earth's surface). That said, with increasing technological development there are several spaceborne hyperspectral sensors available nowadays (for example, Hyperion on board EO-1 or the Compact High-Resolution Imaging Spectrometer on board PROBA-1), with the newest addition being Italy's PRISM mission (launched in 2019; Loizzo and others 2018) and Germany's EnMAP mission (launched in 2022, Guanter and others 2015). Those space-borne hyperspectral sensors will help better our understanding of the global spatial and temporal variability in biogeochemical properties of ecosystems, but their full potential has yet to be explored. It is interesting to note that classical multispectral sensor systems are also increasingly using narrow spectral bands to measure specific vegetation properties. The multispectral instruments on board Sentinel-2a and Sentinel-2b, for instance, have three narrow bands in the red-edge region as well as a narrow near infrared band, allowing for a more detailed characterization of vegetation properties (Delegido and others 2011). It is thus likely that future satellite sensor systems will bridge classical multispectral and hyperspectral remote sensing.

Unmanned Aircraft Systems

With falling prices and an increasing range of vendors, unmanned aircraft systems (UASs) have become reality in research (Marris 2013). UAS consist of an unmanned aerial vehicle carrying a sensor to survey small areas from a relatively low altitude compared to manned aerial vehicles or satellites. Typically, UAS are used to survey areas on the order of several hectares, but might be able to cover several thousand. Sensors on UAS range from simple RGB-cameras or multispectral sensors

to LiDAR, hyperspectral, and thermal sensors. The advantages of UAS are, on the one hand, the ability to record remote sensing data wherever and whenever needed and, on the other, to get high-quality data that is often much finer in spatial grain than data collected from aircraft or satellites. This fine-grained data enable, for instance, the reconstruction of detailed 3D surfaces using structure-from-motion techniques (Pell and others 2022), offering a new scale in remote sensing analysis (< 10 cm) that can be used to study fine-scale processes such as changes in the dimensions of individual shrubs (Cunliffe and others 2016). This makes UAS a valuable tool for creating spatially explicit data on the individual plant or animal level that can be scaled across landscapes. For example, Zhang and others (2016) analyzed UAS-based canopy height models to explain fine-scale spatial variation in biodiversity and gap-dynamics in a 20-ha research plot. Stovall and others (2019) used UAS to survey an area of 40,000 ha to get at individual tree positions and heights, which allowed them to identify a consistent relationship between tree height and drought tolerance—insights that would have been challenging or even impossible to test using field data alone. Likewise, Schenone and others 2022 used UAS data to characterize ecosystem functions in an intertidal system at scales relevant to management and conservation without the need for intensive field-data collection. Using UAS can also substantially increase temporal observation frequencies by flying the same area regularly throughout the year (Assmann and others 2020). UAS can thus complement field-based surveys by increasing temporal frequency, or even allowing observations in terrain that is challenging to traverse or restricted to access (Paneque-Gálvez and others 2014; Duffy and others 2018). That being said, there are still many restrictions for flying UAS (e.g., near airports) and acceptance of UAS can be low due to environmental burden (e.g., noise), privacy or misuse concerns, or conceptual associations with military UAS (Clothier and others 2015).

Artificial Intelligence

The increasing availability of remote sensing data puts a burden on traditional analysis methods, which often are designed to only handle one or two of the available dimensions (that is, spatial, temporal, spectral). However, novel insights might be revealed by analyzing all dimensions simultaneously, for example, by tracking spatial and spectral patterns over time. This might become even more important with the increasing availability of high- and very high-resolution imagery, which allows researchers to take a deeper look at the spatial patterns of individual plants or animals. In this context, the field of remote sensing has recently seen increased use of artificial intelligence methods, and more specifically from deep learning (Kattenborn and others 2021). An advantage of these approaches is their ability to independently learn how to transform the data into useful predictors—a step that traditionally has required a lot of experience and system knowledge (or good luck). Moreover, deep learning allows for not only classification on a per-pixel basis, but also identifying spatial objects in an image (Brodrick and others 2019). Identifying spatial objects that are composed of several pixels, instead of doing analysis per pixel and ignoring spatial pattern, is an important task in remote sensing (object-based remote sensing; see Blaschke 2010 for a review on the topic).

Recognizing spatial objects from remote sensing data can be of particular interest in the study of ecosystem dynamics, which is fundamentally concerned with quantifying spatial patterns like disturbance patches or tropical forest canopy gaps. In this regard, deep neural networks have recently been used to identify all trees outside forests in the West African Sahara and Sahel (Brandt and others 2020) or fir trees affected by bark beetles (Safonova and others 2019). Applying such techniques over time will allow researchers to better estimate spatiotemporal processes, such as bark beetle outbreak progression (Rammer and Seidl 2019) or land use dynamics (de Bem and others 2020). Artificial intelligence can also help in analyzing imagery taken from neither satellites nor airplanes, but from close-range remote sensing systems such as camera traps (Norouzzadeh and others 2018). The field of artificial intelligence is obviously very dynamic, and its ultimate contribution to the remote sensing of ecosystem dynamics remains to be seen. Yet, it is already clear that artificial intelligence will likely help to unravel the multi-scale processes driving ecosystem dynamics in all their dimensions.

Opening Remote Sensing Data to the World

The recent years have seen a strong move of the remote sensing community toward free data, open-source software and cloud-bases services, which has amplified the use of remote sensing beyond the remote sensing community. In the past, using remote sensing data has been restricted to remote

sensing specialists, mostly due to the historical cost of data acquisitions, expensive proprietary software and the often-high computational costs involved in processing remote sensing data. All this, however, has changed profoundly in the past decade (Kwok 2018). Many remote sensing data sources are now free to access (Zhu and others 2019) and one might argue that there are more data available than can be analyzed. Many remote sensing scientists have moved from using proprietary to open-source software (Kwok 2018), such as R (Goslee 2011; Tuck and others 2014; Ranghetti and others 2020; Atkins and others 2022), Python (Canty 2014), QGIS (Grizonnet and others 2017), the EnMAP-Box (Van der Linden and others 2015), or the Sentinel Toolboxes (https://sentinel.esa.int/web/sentinel/toolboxes). Those open-source tools should also be the preferred choice when teaching remote sensing to ecology students, as it allows them to replicate analyses on their own computers without buying expensive software licenses. Also, practices like code-sharing and publishing algorithms alongside scientific papers are becoming increasingly commonplace, and further uptake can be encouraged by, for example, journals requiring full access to all code needed for reproducing remote sensing analyses (Balz and Rocca 2020) or by badging systems that transparently mark code as open-access (Frery and others 2020).

With respect to impact beyond the remote sensing community, the biggest change of the past decade is certainly centered on computational costs. Although it was common in the past for remote sensing labs to host a large server infrastructure and massive storage space for dealing with remote sensing data, most analyses have now moved to cloud-based services (De Luca and others 2017; Gorelick and others 2017). Instead of downloading the data and processing them in-house, it is more common today to upload the code to the data, theoretically removing all computational limitations. This transition toward cloud-based processing of remote sensing data has triggered a new age of large-scale analyses, with several global data products being published recently (Hansen and others 2013; Pekel and others 2016; Liu and others 2020). Also, more and more research-grade software has now been professionally translated into cloud-based environments (for example, Kennedy and others 2018; Hamunyela and others 2020), allowing for the application of state-of-the-art algorithms by scientists who are not specialized in remote sensing. Local authorities or non-governmental organizations can now rapidly assess land use changes by running analyses in the cloud, needing—in theory—nothing more than a laptop and an internet connection (Lee and others 2016).

Despite the increasing access to remote sensing data, software and computation power, many global inequalities remain. In the early years of the Landsat mission, for instance, some regions were prioritized over others due to limited download capacities, resulting in far less data over, for example, the African continent compared to North America or Europe (Wulder and others 2016). Inequalities are further amplified by high costs of proprietary remote sensing systems (that is, commercial satellite data, airborne campaigns) and unfair data sharing agreements (that is, data acquired within a country are not shared with researchers from this country). There hence is room for improving access to remote sensing data and analyses globally, for example, through making image archives open access (such as a recent program by the Norwegian International Climate and Forest Initiative granting free access to high-resolution satellite data for approximately 45 million km^2 of tropical forests), or by developing targeted educational programs. Investing into an open-source culture will help making remote sensing even more important for studying ecosystem dynamics globally.

The Need for Better Quantification of Uncertainty in Remote Sensing Analyses

Despite their power, remote sensing data and associated products are always subject to uncertainty, bias, and error (Foody and Atkinson 2003). Remote sensing is thus not an exact science, and its data and outputs must be taken with a grain of salt. Uncertainties, for example, might arise from geometric inaccuracies or poor atmospheric correction due to missing atmospheric data or complex topography. Biases can stem from inconsistent data coverage across space and time, variable cloud cover, or sensor degradation. Errors might result from image artefacts, undetected clouds, or simply from the fact that no remote sensing algorithm will ever yield 100 percent accuracy. It is vital that researchers using remote sensing data understand these limitations; failure to do so can lead to demonstrably false scientific conclusions (Palahí and others 2021). Embracing potential uncertainties, biases, and errors is particularly important when using off-the-shelf remote sensing products, where researchers might not be aware of all limitations and drawbacks. For instance, categorical

Table 2. Thinking About Your System Before Diving into Remote Sensing Analysis

---

Deciding for the correct remote sensing data and tools can be overwhelming, especially given the sharp rise in free and easy-to-access data and tools. Every scientist interested in remote sensing should answer the following questions before diving into their analysis:

1. What is the spatial and temporal extent of my study system, for example, stand, landscape, or global; a week, year, or decade?
2. What data source will best quantify the process I am interested in, for example, optical multispectral or hyperspectral data, LiDAR data, radar data?
3. What spatial grain and temporal frequency do I need to identify the process I am interested in, for example, < 1 m, 1–10 m, 10–100 m, or > 100 m; seasonal, inter-annual, decadal?
4. What method do I need to identify the process I am interested in, for example, pixel- vs. object-based, complex methods to deal with high-dimensional data, statistical methods to estimate a trend?
5. What sources of uncertainties do I need to consider and how can I quantify those, for example, classification uncertainties, changes in sensor systems over time, different data densities between regions?

Answering those five questions will help scientists choosing the correct data for analyzing their system and process of interest, as well as force them to think about potential sources of uncertainties.

---

maps created from remote sensing data will always have errors that will propagate into subsequent analyses (Langford and others 2006). Those errors can be—and should be—quantified using standard protocols (Olofsson and others 2013, 2014). Estimates derived from such maps (for example, forest area) should thus also always be accompanied by measures of uncertainty. The same applies for continuous variables derived from remote sensing, such as biomass maps (Ploton and others 2020). This becomes especially important when tracking estimates over time: is a change in remotely sensed forest area really caused by a decline in forests or is it just due to statistical artefact (Olofsson and others 2013, 2014; Ives and others 2021)?

The topic of uncertainties quantification becomes even more important with the increasing availability of remote sensing data and the ability to perform large-scale remote sensing analysis in just a few clicks. The easy access to remote sensing data and analyses tools might allure scientists into ignoring the many sources of uncertainties discussed above. There is hence a need to place greater emphasis on remote sensing basics in ecology curricula, and especially sources of uncertainty in remotely sensed data and analyses. Moreover, each researcher should critically assess their choice of remote sensing data and tools and always check which analyses of uncertainty need to be done (see Table 2). If this is not done, the availability of open-source, easy-to-access remote sensing data and tools might otherwise undermine scientific progress.

Seeing the System from Above and Below: The Importance of Ground Referencing and System Knowledge

Ground referencing describes the process of comparing a remote sensing-based measurement to the actual conditions on ground. It is an important step in calibrating and validating remote sensing-based models. At the same time, the power of remote sensing lies with its ability to cover large spatial and long temporal extents. Covering the same extents with field data for ground referencing is often not feasible or even possible: when doing historical analyses, for instance, the only option for ground referencing is to use secondary data. However, many secondary data (for example, field data, forest inventories) were collected without planning for later applications in remote sensing studies. This makes the integration of field and remote sensing data challenging. For example, combining remote sensing and field data requires exact geolocations of field plots—ideally recorded with a high-precision GPS device—and exact definitions of plot areas (McRoberts 2010; Frazer and others 2011). Many field data, however, lack those basic requirements for matching plots to pixels. Similarly, field plots are often smaller than the pixel size of moderate-resolution sensors, leading to a noisy relationship between field-based measurements and the spectral signal recorded at the pixel level (Gonzalez and others 2010; Zald and others 2014). Facilitating the integration of remote sensing data and field-based measurements thus requires improved understanding of remote sensing techniques from field ecologists, who must design their campaigns to facilitate seamless integration with remote sensing

data. This might be achieved by using UAS or other high-spatial resolution data, allowing field crews to obtain an instant view from above and thus the possibility to adapt plot designs to better suit subsequent remote sensing analyses (Marris 2013). An example of using UAS for aiding field work might involve labeling each tree based on whether it is visible from above (and thus potentially detectible from space) or not. Establishing the interoperability of ground-based measurements with remote sensing data as requirements in field protocols might thus enable long-term insights into ecosystem dynamics far beyond the individual datasets.

Although remote sensing allows scientist to see their system from above, it is important to also appreciate the view from below. Through the lens of a remote sensing scientist, landscapes are composed of pixels, sometimes hiding the complexity of the real world, especially at scales smaller than the spatial grain of the data. It is thus important for scientists working mainly with remote sensing data to also go to the field and to appreciate the complexity of ecological systems. A thorough understanding of the study system will help scientists to make more informed decision on what remote sensing data and analyses to choose, as well as it will help in better understanding the limitations of remote sensing approaches. The choice of remote sensing data and analyses should thus always be theoretically motivated (what data/analysis do I need to answer a question; see Table 2), and not by technological availability (what question can I answer with this data/analyses). Following this principal will help in designing new remote sensing approaches that truly help with studying ecosystem dynamics.

What is Next?

Recent advances in remote sensing have opened doors to exciting new research in ecosystem ecology. I see four especially promising avenues for progress in the coming decade: (1) Bridging between local and global scales, (2) better quantification and understanding of ecosystem heterogeneity and resilience, (3) a more nuanced understanding of how humans shape ecosystems and vice versa, and (4) new opportunities for calibrating and validating spatially explicit models of ecosystem dynamics.

Using remote sensing to bridge between local and global scales will allow researchers to test and develop ecological theories beyond local scales and hence beyond individual study systems. For example, by conducting consistent, standardized analyses of remotely sensed data from different parts of the world, researchers can determine whether similar processes have similar effects in different forest landscapes (Sommerfeld and others 2018; Seidl and others 2020) or lake systems (Rose and others 2017; Ho and others 2019). Remote sensing can thus contribute to developing more robust and generalizable ecological theories, which is especially important for studying global change impacts on ecosystems (Heffernan and others 2014). Doing so requires increasing collaboration between—and understanding among—ecosystem ecologists and remote sensing scientists. An example of this cross-pollination is the substantial contribution remote sensing has brought to the explicit mapping of microclimates in recent years (Zellweger and others 2019), which substantially improved subsequent predictive models (Lembrechts and others 2019).

Remote sensing will allow for a better quantification of ecosystem heterogeneity (that is, spatial and temporal variation in ecological processes) and thus for a substantially improved understanding of ecosystem resilience. For example, tracking vegetation indices consistently through space and time allows for the detection of early-warning signals, such as increasing temporal autocorrelation, that might indicate an abrupt change of ecosystem states (Verbesselt and others 2016). In this regard, the ability of remote sensing to track spatial patterns through time (for example, forest fragmentation (Taubert and others 2018) or disturbance patch composition and configuration (Senf and Seidl 2021b)) opens up new directions in quantifying ecosystem resilience beyond traditional measures (Scheffer and others 2015; Allen and others 2016; Cumming and others 2017). Remote sensing can also help with quantifying ecosystem resilience directly, for example, through mapping the rate and speed of recovery after disturbances (Cole and others 2014; White and others 2017; Senf and others 2019; Leitold and others 2022; Senf and Seidl 2022). With the ever-increasing length of remote sensing time series (now more than four decades), remote sensing will thus help to also identifying critical changes in ecosystem resilience directly through monitoring recovery rates over time (Ingrisch and Bahn 2018).

Finally, ecosystem ecology has seen a rise in process-based landscape models in recent years. Calibration and validation of those models needs spatially explicit data and a better understanding of landscape scale ecological processes. Remote sensing can help in this respect, calling for a stronger collaboration between remote sensing scientists

and ecosystem modelers. With those exciting research directions ahead and a better education of ecologists in remote sensing data and analyses, one might even think about *remote sensing ecology* becoming an essential subfield of ecosystem ecology.

REFERENCES

Allen CR, Angeler DG, Cumming GS, Folke C, Twidwell D, Uden DR. 2016. Quantifying spatial resilience. Journal of Applied Ecology 53:625–635.

Asner GP. 2013. Geography of forest disturbance. Proceedings of the National Academy of Sciences of the United States of America 110:3711–3712.

Asner GP, Martin RE, Suhaili AB. 2012. Sources of canopy chemical and spectral diversity in lowland Bornean forest. Ecosystems 15:504–517.

Asner Gregory P, Brodrick Philip G, Anderson Christopher B, Nicholas Vaughn, Knapp David E, Martin Roberta E. 2016. Progressive forest canopy water loss during the 2012–2015 California drought. Proceedings of the National Academy of Sciences 113:E249–E255.

Assmann JJ, Myers-Smith IH, Kerby JT, Cunliffe AM, Daskalova GN. 2020. Drone data reveal heterogeneity in tundra greenness and phenology not captured by satellites. Environmental Research Letters 15:125002.

Atkins JW, Stovall AEL, Alberto Silva C. 2022. Open-source tools in R for forestry and forest ecology. Forest Ecology and Management 503:119813.

Bae S, Levick SR, Heidrich L, Magdon P, Leutner BF, Wöllauer S, Serebryanyk A, Nauss T, Krzystek P, Gossner MM, Schall P, Heibl C, Bässler C, Doerfler I, Schulze E-D, Krah F-S, Culmsee H, Jung K, Heurich M, Fischer M, Seibold S, Thorn S, Gerlach T, Hothorn T, Weisser WW, Müller J. 2019. Radar vision in the mapping of forest biodiversity from space. Nature Communications 10:4757.

Balz T, Rocca F. 2020. Reproducibility and replicability in SAR remote sensing. IEEE Journal of Selected Topics in Applied Earth Observations and Remote Sensing 13:3834–3843.

Banskota A, Kayastha N, Falkowski MJ, Wulder MA, Froese RE, White JC. 2014. Forest monitoring using Landsat time series data: a review. Canadian Journal of Remote Sensing 40:362–384.

Baumann M, Radeloff VC, Avedian V, Kuemmerle T. 2015. Land-use change in the Caucasus during and after the Nagorno-Karabakh conflict. Regional Environmental Change 15:1703–1716.

Belenguer-Plomer MA, Tanase MA, Fernandez-Carrillo A, Chuvieco E. 2019. Burned area detection and mapping using Sentinel-1 backscatter coefficient and thermal anomalies. Remote Sensing of Environment 233:111345.

Belward AS, Skøien JO. 2015. Who launched what, when and why; trends in global land-cover observation capacity from civilian earth observation satellites. ISPRS Journal of Photogrammetry and Remote Sensing 103:115–128.

Bernd A, Braun D, Ortmann A, Ulloa-Torrealba YZ, Wohlfart C, Bell A. 2017. More than counting pixels–perspectives on the importance of remote sensing training in ecology and conservation. Remote Sensing in Ecology and Conservation 3:38–47.

Bioucas-Dias JM, Plaza A, Camps-Valls G, Scheunders P, Nasrabadi N, Chanussot J. 2013. Hyperspectral remote sensing data analysis and future challenges. IEEE Geoscience and Remote Sensing Magazine 1:6–36.

Blackburn GA. 2007. Hyperspectral remote sensing of plant pigments. Journal of Experimental Botany 58:855–867.

Blaschke T. 2010. Object based image analysis for remote sensing. ISPRS Journal of Photogrammetry and Remote Sensing 65:2–16.

Bolton DK, Gray JM, Melaas EK, Moon M, Eklundh L, Friedl MA. 2020. Continental-scale land surface phenology from harmonized Landsat 8 and Sentinel-2 imagery. Remote Sensing of Environment 240:111685.

Bowden LW, Brooner WG. 1970. Aerial photography: a diversified tool. Geoforum 1:19–32.

Brandt M, Tucker CJ, Kariryaa A, Rasmussen K, Abel C, Small J, Chave J, Rasmussen LV, Hiernaux P, Diouf AA, Kergoat L, Mertz O, Igel C, Gieseke F, Schöning J, Li S, Melocik K, Meyer J, Sinno S, Romero E, Glennie E, Montagu A, Dendoncker M, Fensholt R. 2020. An unexpectedly large count of trees in the West African Sahara and Sahel. Nature 587:78–82.

Braziunas KH, Abendroth DC, Turner MG. 2022. Young forests and fire: Using lidar–imagery fusion to explore fuels and burn severity in a subalpine forest reburn. Ecosphere 13:e4096.

Brodrick PG, Davies AB, Asner GP. 2019. Uncovering ecological patterns with convolutional neural networks. Trends in Ecology & Evolution 34:734–745.

Calders K, Adams J, Armston J, Bartholomeus H, Bauwens S, Bentley LP, Chave J, Danson FM, Demol M, Disney M, Gaulton R, Krishna Moorthy SM, Levick SR, Saarinen N, Schaaf C, Stovall A, Terryn L, Wilkes P, Verbeeck H. 2020. Terrestrial laser scanning in forest ecology: Expanding the horizon. Remote Sensing of Environment 251:112102.

Canty MJ. 2014. Image analysis, classification and change detection in remote sensing: with algorithms for ENVI/IDL and Python. London: CRC Press.

Carlson KM, Asner GP, Hughes RF, Ostertag R, Martin RE. 2007. Hyperspectral remote sensing of canopy biodiversity in Hawaiian Lowland Rainforests. Ecosystems 10:536–549.

Ceccato P, Flasse S, Tarantola S, Jacquemoud S, Grégoire J-M. 2001. Detecting vegetation leaf water content using reflectance in the optical domain. Remote Sensing of Environment 77:22–33.

Clothier RA, Greer DA, Greer DG, Mehta AM. 2015. Risk perception and the public acceptance of drones. Risk Analysis 35:1167–1183.

Cohen WB, Goward SN. 2004. Landsat's role in ecological applications of remote sensing. BioScience 54:535–545.

Cohen WB, Spies TA, Alig RJ, Oetter DR, Maiersperger TK, Fiorella M. 2002. Characterizing 23 Years (1972–95) of stand replacement disturbance in Western Oregon forests with Landsat imagery. Ecosystems 5:122–137.

Cole LES, Bhagwat SA, Willis KJ. 2014. Recovery and resilience of tropical forests after disturbance. Nature Communications 5:3906.

Congedo L, Sallustio L, Munafò M, Ottaviano M, Tonti D, Marchetti M. 2016. Copernicus high-resolution layers for land cover classification in Italy. Journal of Maps 12:1195–1205.

Coops NC, Gillanders SN, Wulder MA, Gergel SE, Nelson T, Goodwin NR. 2010. Assessing changes in forest fragmentation following infestation using time series Landsat imagery. Forest Ecology and Management 259:2355–2365.

Coops NC, Wulder MA. 2019. Breaking the Habit(at). Trends in Ecology & Evolution 34:585–587.

Crist EP, Cicone RC. 1984. A physically-based transformation of Thematic Mapper data—the TM Tasseled Cap. IEEE Transactions on Geoscience and Remote Sensing GE-22:256–263.

Cumming GS, Morrison TH, Hughes TP. 2017. New directions for understanding the spatial resilience of social-ecological systems. Ecosystems 20:649–664.

Cunliffe AM, Brazier RE, Anderson K. 2016. Ultra-fine grain landscape-scale quantification of dryland vegetation structure with drone-acquired structure-from-motion photogrammetry. Remote Sensing of Environment 183:129–143.

Davies AB, Asner GP. 2014. Advances in animal ecology from 3D-LiDAR ecosystem mapping. Trends in Ecology & Evolution 29:681–691.

de Bem PP, de Carvalho Junior OA, Fontes Guimarães R, Trancoso Gomes RA. 2020. Change detection of deforestation in the Brazilian Amazon using Landsat data and convolutional neural networks. Remote Sensing 12:901.

De Cola L. 1989. Fractal analysis of a classified Landsat scene. Photogrammetric Engineering and Remote Sensing 55:601–610.

De Luca C, Zinno I, Manunta M, Lanari R, Casu F. 2017. Large areas surface deformation analysis through a cloud computing P-SBAS approach for massive processing of DInSAR time series. Remote Sensing of Environment 202:3–17.

Delegido J, Verrelst J, Alonso L, Moreno J. 2011. Evaluation of Sentinel-2 red-edge bands for empirical estimation of green LAI and chlorophyll content. Sensors 11:7063–7081.

Dhu T, Dunn B, Lewis B, Lymburner L, Mueller N, Telfer E, Lewis A, McIntyre A, Minchin S, Phillips C. 2017. Digital earth Australia—unlocking new value from earth observation data. Big Earth Data 1:64–74.

Druckenbrod DL, Martin-Benito D, Orwig DA, Pederson N, Poulter B, Renwick KM, Shugart HH, Mayfield M. 2019. Redefining temperate forest responses to climate and disturbance in the eastern United States: new insights at the mesoscale. Global Ecology and Biogeography 28:557–575.

Dubayah R, Blair JB, Goetz S, Fatoyinbo L, Hansen M, Healey S, Hofton M, Hurtt G, Kellner J, Luthcke S, Armston J, Tang H, Duncanson L, Hancock S, Jantz P, Marselis S, Patterson P, Qi W, Silva C. 2020. The global ecosystem dynamics investigation: high-resolution laser ranging of the Earth's forests and topography. Science of Remote Sensing 1:100002.

Duffy JP, Cunliffe AM, DeBell L, Sandbrook C, Wich SA, Shutler JD, Myers-Smith IH, Varela MR, Anderson K. 2018. Location, location, location: considerations when using lightweight drones in challenging environments. Remote Sensing in Ecology and Conservation 4:7–19.

Dwyer JL, Roy DP, Sauer B, Jenkerson CB, Zhang HK, Lymburner L. 2018. Analysis ready data: enabling analysis of the Landsat archive. Remote Sensing 10:1363.

Estes JE. 1966. Some applications of aerial infrared imagery. Annals of the Association of American Geographers 56:673–682.

Fisher JI, Mustard JF. 2007. Cross-scalar satellite phenology from ground, Landsat, and MODIS data. Remote Sensing of Environment 109:261–273.

Fleming MD, Hoffer RM. 1979. Machine processing of Landsat MSS data and DMA topographic data for forest cover type mapping. In: LARS symposia. p 302.

Flood N. 2013. Seasonal composite Landsat TM/ETM+ images using the Medoid (a multi-dimensional median). Remote Sensing 5:6481–6500.

Foody GM, Atkinson PM. 2003. Uncertainty in remote sensing and GIS. Wiley.

Frantz D. 2019. FORCE—Landsat + Sentinel-2 analysis ready data and beyond. Remote Sensing 11:1124.

Frantz D, Schug F, Okujeni A, Navacchi C, Wagner W, van der Linden S, Hostert P. 2021. National-scale mapping of building height using Sentinel-1 and Sentinel-2 time series. Remote Sensing of Environment 252:112128.

Frazer GW, Magnussen S, Wulder MA, Niemann KO. 2011. Simulated impact of sample plot size and co-registration error on the accuracy and uncertainty of LiDAR-derived estimates of forest stand biomass. Remote Sensing of Environment 115:636–649.

Frery AC, Gomez L, Medeiros AC. 2020. A badging system for reproducibility and replicability in remote sensing research. IEEE Journal of Selected Topics in Applied Earth Observations and Remote Sensing 13:4988–4995.

Giuliani G, Chatenoux B, De Bono A, Rodila D, Richard J-P, Allenbach K, Dao H, Peduzzi P. 2017. Building an Earth Observations Data Cube: lessons learned from the Swiss Data Cube (SDC) on generating Analysis Ready Data (ARD). Big Earth Data 1:100–117.

Goetz AFH. 2009. Three decades of hyperspectral remote sensing of the Earth: a personal view. Remote Sensing of Environment 113:S5-16.

Gonzalez P, Asner GP, Battles JJ, Lefsky MA, Waring KM, Palace M. 2010. Forest carbon densities and uncertainties from Lidar, QuickBird, and field measurements in California. Remote Sensing of Environment 114:1561–1575.

Gorelick N, Hancher M, Dixon M, Ilyushchenko S, Thau D, Moore R. 2017. Google Earth Engine: planetary-scale geospatial analysis for everyone. Remote Sensing of Environment 202:18–27.

Goslee SC. 2011. Analyzing remote sensing data in R: the Landsat package. Journal of Statistical Software 43:1–25.

Griffiths P, Kuemmerle T, Kennedy RE, Abrudan IV, Knorn J, Hostert P. 2012. Using annual time-series of Landsat images to assess the effects of forest restitution in post-socialist Romania. Remote Sensing of Environment 118:199–214.

Griffiths P, Müller D, Kuemmerle T, Hostert P. 2013a. Agricultural land change in the Carpathian ecoregion after the breakdown of socialism and expansion of the European Union. Environmental Research Letters 8:045024.

Griffiths P, Nendel C, Pickert J, Hostert P. 2020. Towards national-scale characterization of grassland use intensity from integrated Sentinel-2 and Landsat time series. Remote Sensing of Environment 238:111124.

Griffiths P, Van der Linden S, Kuemmerle T, Hostert P. 2013b. A pixel-based Landsat compositing algorithm for large area land cover mapping. IEEE Journal of Selected Topics in Applied Earth Observations and Remote Sensing 6:2088–2101.

Grizonnet M, Michel J, Poughon V, Inglada J, Savinaud M, Cresson R. 2017. Orfeo ToolBox: open source processing of remote sensing images. Open Geospatial Data, Software and Standards 2:15.

Guanter L, Kaufmann H, Segl K, Foerster S, Rogass C, Chabrillat S, Kuester T, Hollstein A, Rossner G, Chlebek C, and others 2015. The EnMAP spaceborne imaging spectroscopy mission for earth observation. Remote Sensing 7:8830–8857.

Hamunyela E, Rosca S, Mirt A, Engle E, Herold M, Gieseke F, Verbesselt J. 2020. Implementation of BFASTmonitor algorithm on Google Earth Engine to support large-area and sub-annual change monitoring using Earth Observation Data. Remote Sensing 12:2953.

Hansen MC, DeFries RS. 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 MC, Potapov PV, Moore R, Hancher M, Turubanova SA, Tyukavina A, Thau D, Stehman SV, Goetz SJ, Loveland TR, Kommareddy A, Egorov A, Chini L, Justice CO, Townshend JR. 2013. High-resolution global maps of 21st-century forest cover change. Science 342:850–853.

Henderson FM, Lewis AJ. 2008. Radar detection of wetland ecosystems: a review. International Journal of Remote Sensing 29:5809–5835.

Ho JC, Michalak AM, Pahlevan N. 2019. Widespread global increase in intense lake phytoplankton blooms since the 1980s. Nature 574:667–670.

Ingrisch J, Bahn M. 2018. Towards a comparable quantification of resilience. Trends in Ecology & Evolution 33:251–259.

Ives AR, Zhu L, Wang F, Zhu J, Morrow CJ, Radeloff VC. 2021. Statistical inference for trends in spatiotemporal data. Remote Sensing of Environment 266:112678.

Jarvis C. 1994. Modelling forest ecosystem dynamics using multitemporal multispectral scanner (MSS) data. Advances in Space Research 14:277–281.

Kattenborn T, Leitloff J, Schiefer F, Hinz S. 2021. Review on convolutional neural networks (CNN) in vegetation remote sensing. ISPRS Journal of Photogrammetry and Remote Sensing 173:24–49.

Kennedy R, Yang Z, Gorelick N, Braaten J, Cavalcante L, Cohen W, Healey S. 2018. Implementation of the LandTrendr algorithm on Google Earth Engine. Remote Sensing 10:691.

Kennedy RE, Andréfouët S, Cohen WB, Gómez C, Griffiths P, Hais M, Healey SP, Helmer EH, Hostert P, Lyons MB, Meigs GW, Pflugmacher D, Phinn SR, Powell SL, Scarth P, Sen S, Schroeder TA, Schneider A, Sonnenschein R, Vogelmann JE, Wulder MA, Zhu Z. 2014. Bringing an ecological view of change to Landsat-based remote sensing. Frontiers in Ecology and the Environment 12:339–346.

Killough B. 2019. The impact of analysis ready data in the Africa Regional Data Cube. In: IGARSS 2019—2019 IEEE international geoscience and remote sensing symposium. pp 5646–9.

Knipling EB. 1970. Physical and physiological basis for the reflectance of visible and near-infrared radiation from vegetation. Remote Sensing of Environment 1:155–159.

Knorn J, Rabe A, Radeloff VC, Kuemmerle T, Kozak J, Hostert P. 2009. Land cover mapping of large areas using chain classification of neighboring Landsat satellite images. Remote Sensing of Environment 113:957–964.

Kowalski K, Senf C, Hostert P, Pflugmacher D. 2020. Characterizing spring phenology of temperate broadleaf forests using Landsat and Sentinel-2 time series. International Journal of Applied Earth Observation and Geoinformation 92:102172.

Kuemmerle T, Hostert P, Radeloff VC, Perzanowski K, Kruhlov I. 2007. Post-socialist forest disturbance in the Carpathian Border Region of Poland, Slovakia, and Ukraine. Ecological Applications 17:1279–1295.

Kwok R. 2018. Ecology's remote-sensing revolution. Nature 556:137–138.

Langford WT, Gergel SE, Dietterich TG, Cohen W. 2006. Map misclassification can cause large errors in landscape pattern indices: examples from habitat fragmentation. Ecosystems 9:474–488.

Le Toan T, Quegan S, Davidson M, Balzter H, Paillou P, Papathanassiou K, Plummer S, Rocca F, Saatchi S, Shugart H, et al. 2011. THE BIOMASS mission: Mapping global forest biomass to better understand the terrestrial carbon cycle. Remote Sensing of Environment 115:2850–2860.

Lee JSH, Wich S, Widayati A, Koh LP. 2016. Detecting industrial oil palm plantations on Landsat images with Google Earth Engine. Remote Sensing Applications: Society and Environment 4:219–224.

Lefsky MA, Cohen WB, Parker GG, Harding DJ. 2002. Lidar remote sensing for ecosystem studies: Lidar, an emerging remote sensing technology that directly measures the three-dimensional distribution of plant canopies, can accurately estimate vegetation structural attributes and should be of particular interest to forest, landscape, and global ecologists. BioScience 52:19–30.

Leitold V, Morton DC, Martinuzzi S, Paynter I, Uriarte M, Keller M, Ferraz A, Cook BD, Corp LA, González G. 2022. Tracking the rates and mechanisms of canopy damage and recovery following Hurricane Maria using multitemporal Lidar data. Ecosystems 25:892–910.

Lembrechts JJ, Nijs I, Lenoir J. 2019. Incorporating microclimate into species distribution models. Ecography 42:1267–1279.

Lepczyk CA, Wedding LM, Asner GP, Pittman SJ, Goulden T, Linderman MA, Gang J, Wright R. 2021. Advancing landscape and seascape ecology from a 2D to a 3D science. BioScience 71:596–608.

Levin SA. 1992. The problem of pattern and scale in ecology: the Robert H. MacArthur Award Lecture. Ecology 73:1943–1967.

Lim K, Treitz P, Wulder M, St-Onge B, Flood M. 2003. LiDAR remote sensing of forest structure. Progress in Physical Geography: Earth and Environment 27:88–106.

Lindenmayer D, Messier C, Sato C. 2016. Avoiding ecosystem collapse in managed forest ecosystems. Frontiers in Ecology and the Environment 14:561–568.

Liu X, Huang Y, Xu X, Li X, Li X, Ciais P, Lin P, Gong K, Ziegler AD, Chen A, Gong P, Chen J, Hu G, Chen Y, Wang S, Wu Q, Huang K, Estes L, Zeng Z. 2020. High-spatiotemporal-resolution mapping of global urban change from 1985 to 2015. Nature Sustainability 3:564–570.

Loizzo R, Guarini R, Longo F, Scopa T, Formaro R, Facchinetti C, Varacalli G. 2018. Prisma: The Italian Hyperspectral Mission. In: IGARSS 2018—2018 IEEE international geoscience and remote sensing symposium. pp 175–8.

Lopez RD, Frohn RC. 2017. Remote sensing for landscape ecology: monitoring, modeling, and assessment of ecosystems, 2nd edn. London: CRC Press.

Malila WA. 1980. Change vector analysis: an approach for detecting forest changes with Landsat. In: LARS symposia. p 385.

Marris E. 2013. Drones in science: Fly, and bring me data. Nature 498:156–158.

Masek JG, Hayes DJ, Joseph Hughes M, Healey SP, Turner DP. 2015. The role of remote sensing in process-scaling studies of managed forest ecosystems. Forest Ecology and Management 355:109–123.

Mast JN, Veblen TT, Hodgson ME. 1997. Tree invasion within a pine/grassland ecotone: an approach with historic aerial photography and GIS modeling. Forest Ecology and Management 93:181–194.

McRoberts RE. 2010. The effects of rectification and Global Positioning System errors on satellite image-based estimates of forest area. Remote Sensing of Environment 114:1710–1717.

Melaas EK, Friedl MA, Richardson AD. 2016. Multiscale modeling of spring phenology across Deciduous Forests in the Eastern United States. Global Change Biology 22:792–805.

Nelson R, Case D, Horning N, Anderson V, Pillai S. 1987. Continental land cover assessment using landsat MSS data. Remote Sensing of Environment 21:61–81.

Norouzzadeh MS, Nguyen A, Kosmala M, Swanson A, Palmer MS, Packer C, Clune J. 2018. Automatically identifying, counting, and describing wild animals in camera-trap images with deep learning. Proceedings of the National Academy of Sciences 115:E5716–E5725.

Oeser J, Heurich M, Senf C, Pflugmacher D, Belotti E, Kuemmerle T. 2020. Habitat metrics based on multi-temporal Landsat imagery for mapping large mammal habitat. Remote Sensing in Ecology and Conservation 6:52–69.

Oeser J, Heurich M, Senf C, Pflugmacher D, Kuemmerle T. 2021. Satellite-based habitat monitoring reveals long-term dynamics of deer habitat in response to forest disturbances. Ecological Applications 31:e2269.

Olofsson P, Foody GM, Herold M, Stehman SV, Woodcock CE, Wulder MA. 2014. Good practices for estimating area and assessing accuracy of land change. Remote Sensing of Environment 148:42–57.

Olofsson P, Foody GM, Stehman SV, Woodcock CE. 2013. Making better use of accuracy data in land change studies: estimating accuracy and area and quantifying uncertainty using stratified estimation. Remote Sensing of Environment 129:122–131.

Ordway EM, Elmore AJ, Kolstoe S, Quinn JE, Swanwick R, Cattau M, Taillie D, Guinn SM, Chadwick KD, Atkins JW, et al. 2021. Leveraging the NEON Airborne Observation Platform for socio-environmental systems research. Ecosphere 12:e03640.

Palahí M, Valbuena R, Senf C, Acil N, Pugh TAM, Sadler J, Seidl R, Potapov P, Gardiner B, Hetemäki L, Chirici G, Francini S, Hlásny T, Lerink BJW, Olsson H, González Olabarria JR, Ascoli D, Asikainen A, Bauhus J, Berndes G, Donis J, Fridman J, Hanewinkel M, Jactel H, Lindner M, Marchetti M, Marušák R, Sheil D, Tomé M, Trasobares A, Verkerk PJ, Korhonen M, Nabuurs G-J. 2021. Concerns about reported harvests in European forests. Nature 592:E15–E17.

Palomino J, Kelly M. 2019. Differing sensitivities to fire disturbance result in large differences among remotely sensed products of vegetation disturbance. Ecosystems 22:1767–1786.

Paneque-Gálvez J, McCall MK, Napoletano BM, Wich SA, Koh LP. 2014. Small drones for community-based forest monitoring: an assessment of their feasibility and potential in tropical areas. Forests 5:1481–1507.

Pecora WT. 1967. Surveying the earth's resources from space. Surveying and Mapping 27:639–643.

Pekel J-F, Cottam A, Gorelick N, Belward AS. 2016. High-resolution mapping of global surface water and its long-term changes. Nature 540:418–422.

Pell T, Li JYQ, Joyce KE. 2022. Demystifying the differences between structure-from-MotionSoftware packages for pre-processing drone data. Drones 6:1–24.

Peters DPC, Bestelmeyer BT, Turner MG. 2007. Cross-scale interactions and changing pattern-process relationships: consequences for system dynamics. Ecosystems 10:790–796.

Pickens AH, Hansen MC, Hancher M, Stehman SV, Tyukavina A, Potapov P, Marroquin B, Sherani Z. 2020. Mapping and sampling to characterize global inland water dynamics from 1999 to 2018 with full Landsat time-series. Remote Sensing of Environment 243:111792.

Ploton P, Mortier F, Réjou-Méchain M, Barbier N, Picard N, Rossi V, Dormann C, Cornu G, Viennois G, Bayol N, Lyapustin A, Gourlet-Fleury S, Pélissier R. 2020. Spatial validation reveals poor predictive performance of large-scale ecological mapping models. Nature Communications 11:4540.

Potapov P, Hansen MC, Kommareddy I, Kommareddy A, Turubanova S, Pickens A, Adusei B, Tyukavina A, Ying Q. 2020. Landsat analysis ready data for global land cover and land cover change mapping. Remote Sensing 12:426.

Potapov P, Li X, Hernandez-Serna A, Tyukavina A, Hansen MC, Kommareddy A, Pickens A, Turubanova S, Tang H, Silva CE, Armston J, Dubayah R, Blair JB, Hofton M. 2021. Mapping global forest canopy height through integration of GEDI and Landsat data. Remote Sensing of Environment 253:112165.

Powell SL, Cohen WB, Kennedy RE, Healey SP, Huang C. 2014. Observation of trends in biomass loss as a result of disturbance

in the conterminous U.S.: 1986–2004. Ecosystems 17:142–157.

Radeloff VC, Mladenoff DJ, Boyce MS. 2000. The changing relation of landscape patterns and jack pine budworm populations during an outbreak. Oikos 90:417–430.

Raffa KF, Aukema BH, Bentz BJ, Carroll AL, Hicke JA, Turner MG, Romme WH. 2008. Cross-scale drivers of natural disturbances prone to anthropogenic amplification: the dynamics of bark beetle eruptions. BioScience 58:501–517.

Rammer W, Seidl R. 2019. Harnessing deep learning in ecology: an example predicting bark beetle outbreaks. Frontiers in Plant Science 10:1327.

Ranghetti L, Boschetti M, Nutini F, Busetto L. 2020. ''sen2r'': an R toolbox for automatically downloading and preprocessing Sentinel-2 satellite data. Computers & Geosciences 139:104473.

Reiche J, Lucas R, Mitchell AL, Verbesselt J, Hoekman DH, Haarpaintner J, Kellndorfer JM, Rosenqvist A, Lehmann EA, Woodcock CE, Seifert FM, Herold M. 2016. Combining satellite data for better tropical forest monitoring. Nature Climate Change 6:120–122.

Rickbeil GJ, Hermosilla T, Coops NC, White JC, Wulder MA. 2016. Barren-ground caribou (Rangifer tarandus groenlandicus) behaviour after recent fire events; integrating caribou telemetry data with Landsat fire detection techniques. Global Change Biology 23:1036–1047.

Riera JL, Magnuson JJ, Vande Castle JR, MacKenzie MD. 1998. Analysis of large-scale spatial heterogeneity in vegetation indices among North American landscapes. Ecosystems 1:268–282.

Roberts DA, Ustin SL, Ogunjemiyo S, Greenberg J, Dobrowski SZ, Chen J, Hinckley TM. 2004. Spectral and structural measures of northwest forest vegetation at leaf to landscape scales. Ecosystems 7:545–562.

Rose KC, Greb SR, Diebel M, Turner MG. 2017. Annual precipitation regulates spatial and temporal drivers of lake water clarity. Ecological Applications 27:632–643.

Roussel J-R, Auty D, Coops NC, Tompalski P, Goodbody TRH, Meador AS, Bourdon J-F, de Boissieu F, Achim A. 2020. lidR: an R package for analysis of Airborne Laser Scanning (ALS) data. Remote Sensing of Environment 251:112061.

Roy DP, Ju J, Kline K, Scaramuzza PL, Kovalskyy V, Hansen M, Loveland TR, Vermote E, Zhang C. 2010. Web-enabled Landsat Data (WELD): Landsat ETM+ composited mosaics of the conterminous United States. Remote Sensing of Environment 114:35–49.

Running SW, Nemani RR. 1988. Relating seasonal patterns of the AVHRR vegetation index to simulated photosynthesis and transpiration of forests in different climates. Remote Sens Environ. https://doi.org/10.1016/0034-4257(88)90034-X.

Running SW, Nemani RR, Peterson DL, Band LE, Potts DF, Pierce LL, Spanner MA. 1989. Mapping regional forest evapotranspiration and photosynthesis by coupling satellite data with ecosystem simulation. Ecology 70:1090–1101.

Running SW, Peterson DL, Spanner MA, Teuber KB. 1986. Remote sensing of coniferous forest leaf area. Ecology 67:273–276.

Saatchi S, Marlier M, Chazdon RL, Clark DB, Russell AE. 2011. Impact of spatial variability of tropical forest structure on radar estimation of aboveground biomass. Remote Sensing of Environment 115:2836–2849.

Saatchi SS, Soares JV, Alves DS. 1997. Mapping deforestation and land use in amazon rainforest by using SIR-C imagery. Remote Sensing of Environment 59:191–202.

Safonova A, Tabik S, Alcaraz-Segura D, Rubtsov A, Maglinets Y, Herrera F. 2019. Detection of fir trees (Abies sibirica) damaged by the bark beetle in unmanned aerial vehicle images with deep learning. Remote Sensing 11:643.

Savtchenko A, Ouzounov D, Ahmad S, Acker J, Leptoukh G, Koziana J, Nickless D. 2004. Terra and Aqua MODIS products available from NASA GES DAAC. Advances in Space Research 34:710–714.

Scheffer M, Carpenter SR, Dakos V, van Nes EH. 2015. Generic indicators of ecological resilience: inferring the chance of a critical transition. Annual Review of Ecology, Evolution, and Systematics 46:145–167.

Schenone S, Azhar M, Ramírez CAV, Strozzi AG, Delmas P, Thrush SF. 2022. Mapping the delivery of ecological functions combining field collected data and unmanned aerial vehicles (UAVs). Ecosystems 25:948–959.

Schneider FD, Ferraz A, Hancock S, Duncanson LI, Dubayah RO, Pavlick RP, Schimel DS. 2020. Towards mapping the diversity of canopy structure from space with GEDI. Environmental Research Letters 15:115006.

Schneider FD, Morsdorf F, Schmid B, Petchey OL, Hueni A, Schimel DS, Schaepman ME. 2017. Mapping functional diversity from remotely sensed morphological and physiological forest traits. Nature Communications 8:1441.

Schroeder TA, Wulder MA, Healey SP, Moisen GG. 2011. Mapping wildfire and clearcut harvest disturbances in boreal forests with Landsat time series data. Remote Sensing of Environment 115:1421–1433.

Schwieder M, Wesemeyer M, Frantz D, Pfoch K, Erasmi S, Pickert J, Nendel C, Hostert P. 2022. Mapping grassland mowing events across Germany based on combined Sentinel-2 and Landsat 8 time series. Remote Sensing of Environment 269:112795.

Seidl R, Honkaniemi J, Aakala T, Aleinikov A, Angelstam P, Bouchard M, Boulanger Y, Burton PJ, De Grandpré L, Gauthier S, Hansen WD, Jepsen JU, Jõgiste K, Kneeshaw DD, Kuuluvainen T, Lisitsyna O, Makoto K, Mori AS, Pureswaran DS, Shorohova E, Shubnitsina E, Taylor AR, Vladimirova N, Vodde F, Senf C. 2020. Globally consistent climate sensitivity of natural disturbances across boreal and temperate forest ecosystems. Ecography 43:967–978.

Senf C, Buras A, Zang CS, Rammig A, Seidl R. 2020a. Excess forest mortality is consistently linked to drought across Europe. Nature Communications 11:6200.

Senf C, Mori AS, Müller J, Seidl R. 2020b. The response of canopy height diversity to natural disturbances in two temperate forest landscapes. Landscape Ecology 35:2101–2112.

Senf C, Müller Seidl R. 2019. Post-disturbance recovery of forest cover and tree height differ with management in Central Europe. Landscape Ecology 34:2837–2850.

Senf C, Seidl R. 2021a. Mapping the forest disturbance regimes of Europe. Nature Sustainability 4:63–70.

Senf C, Seidl R. 2021b. Persistent impacts of the 2018 drought on forest disturbance regimes in Europe. Biogeosciences 2021:5223–5230.

Senf C, Seidl R. 2022. Post-disturbance canopy recovery and the resilience of Europe's forests. Global Ecology and Biogeography 31:25–36.

Silva CA, Valbuena R, Pinagé ER, Mohan M, de Almeida DRA, North Broadbent E, Jaafar WSWM, de Almeida Papa D, Cardil A, Klauberg C. 2019. ForestGapR: an r package for forest gap

analysis from canopy height models. Methods in Ecology and Evolution 10:1347–1356.

Sommerfeld A, Senf C, Buma B, D'Amato AW, Després T, Díaz-Hormazábal I, Fraver S, Freilich LE, Gutiérrez ÁG, Hart SJ, Harvey BJ, He HS, Hlásny T, Holz A, Kitzberger T, Kulakowski D, Lindenmayer DB, Mori AS, Müller J, Paritsis J, Perry GLW, Stephens SL, Svoboda M, Turner MG, Veblen TT, Seidl R. 2018. Patterns and drivers of recent disturbances across the temperate forest biome. Nature Communications 9:4355.

Spencer RD. 1979. Fixed-base large-scale photographs for forest sampling. Photogrammetria 35:117–140.

Steenweg R, Hebblewhite M, Kays R, Ahumada J, Fisher JT, Burton C, Townsend SE, Carbone C, Rowcliffe JM, Whittington J, et al. 2017. Scaling-up camera traps: monitoring the planet's biodiversity with networks of remote sensors. Frontiers in Ecology and the Environment 15:26–34.

Stovall AEL, Shugart H, Yang X. 2019. Tree height explains mortality risk during an intense drought. Nature Communications 10:4385.

Tanase MA, Aponte C, Mermoz S, Bouvet A, Toan TL, Heurich M. 2018. Detection of windthrows and insect outbreaks by L-band SAR: A case study in the Bavarian Forest National Park. Remote Sensing of Environment 209:700–711.

Taubert F, Fischer R, Groeneveld J, Lehmann S, Müller MS, Rödig E, Wiegand T, Huth A. 2018. Global patterns of tropical forest fragmentation. Nature 554:519–522.

Townsend AR, Asner GP, Cleveland CC. 2008. The biogeochemical heterogeneity of tropical forests. Trends in Ecology & Evolution 23:424–431.

Trumbore S, Brando P, Hartmann H. 2015. Forest health and global change. Science 349:814–818.

Tuck SL, Phillips HR, Hintzen RE, Scharlemann JP, Purvis A, Hudson LN. 2014. MODISTools–downloading and processing MODIS remotely sensed data in R. Ecology and Evolution 4:4658–4668.

Tucker CJ. 1979. Red and photographic infrared linear combinations for monitoring vegetation. Remote Sensing of Environment 8:127–150.

Tucker CJ. 1980. Remote sensing of leaf water content in the near infrared. Remote Sensing of Environment 10:23–32.

Turner MG. 2005. Landscape ecology: what is the state of the science? Annual Review of Ecology, Evolution, and Systematics 36:319–344.

Turner MG. 2010. Disturbance and landscape dynamics in a changing world. Ecology 91:2833–2849.

Valbuena R, O'Connor B, Zellweger F, Simonson W, Vihervaara P, Maltamo M, Silva CA, Almeida DRA, Danks F, Morsdorf F, Chirici G, Lucas R, Coomes DA, Coops NC. 2020. Standardizing ecosystem morphological traits from 3D information sources. Trends in Ecology & Evolution 35:656–667.

Van der Linden S, Rabe A, Held M, Jakimow B, Leitão PJ, Okujeni A, Schwieder M, Suess S, Hostert P. 2015. The EnMAP-box—a toolbox and application programming interface for EnMAP data processing. Remote Sensing 7:11249.

Verbesselt J, Umlauf N, Hirota M, Holmgren M, Van Nes EH, Herold M, Zeileis A, Scheffer M. 2016. Remotely sensed resilience of tropical forests. Nature Climate Change 6:1028–1031.

Vreugdenhil M, Wagner W, Bauer-Marschallinger B, Pfeil I, Teubner I, Rüdiger C, Strauss P. 2018. Sensitivity of Sentinel-1 backscatter to vegetation dynamics: an Austrian case study. Remote Sensing 10:1396.

Wegmann M. 2017. Remote sensing training in ecology and conservation—challenges and potential. Remote Sensing in Ecology and Conservation 3:5–6.

White JC, Wulder MA, Hermosilla T, Coops NC, Hobart GW. 2017. A nationwide annual characterization of 25 years of forest disturbance and recovery for Canada using Landsat time series. Remote Sensing of Environment 194:303–321.

White JC, Wulder MA, Hobart GW, Luther JE, Hermosilla T, Griffiths P, Coops NC, Hall RJ, Hostert P, Dyk A, Guindon L. 2014. Pixel-based image compositing for large-area dense time series applications and science. Canadian Journal of Remote Sensing 40:192–212.

Wulder MA, Hilker T, White JC, Coops NC, Masek JG, Pflugmacher D, Crevier Y. 2015. Virtual constellations for global terrestrial monitoring. Remote Sensing of Environment 170:62–76.

Wulder MA, Masek JG, Cohen WB, Loveland TR, Woodcock CE. 2012. Opening the archive: How free data has enabled the science and monitoring promise of Landsat. Remote Sensing of Environment 122:2–10.

Wulder MA, White JC, Loveland TR, Woodcock CE, Belward AS, Cohen WB, Fosnight EA, Shaw J, Masek JG, Roy DP. 2016. The global Landsat archive: status, consolidation, and direction. Remote Sensing of Environment 185:271–283.

Yin H, Butsic V, Buchner J, Kuemmerle T, Prishchepov AV, Baumann M, Bragina EV, Sayadyan H, Radeloff VC. 2019. Agricultural abandonment and re-cultivation during and after the Chechen Wars in the northern Caucasus. Global Environmental Change 55:149–159.

Yu Y, Saatchi S. 2016. Sensitivity of L-Band SAR backscatter to aboveground biomass of global forests. Remote Sensing 8:522.

Yuan F, Sawaya KE, Loeffelholz BC, Bauer ME. 2005. Land cover classification and change analysis of the Twin Cities (Minnesota) Metropolitan Area by multitemporal Landsat remote sensing. Remote Sensing of Environment 98:317–328.

Zald HS, Spies TA, Seidl R, Pabst RJ, Olsen KA, Steel EA. 2016. Complex mountain terrain and disturbance history drive variation in forest aboveground live carbon density in the western Oregon Cascades, USA. Forest Ecology and Management 366:193–207.

Zald HSJ, Ohmann JL, Roberts HM, Gregory MJ, Henderson EB, McGaughey RJ, Braaten J. 2014. Influence of lidar, Landsat imagery, disturbance history, plot location accuracy, and plot size on accuracy of imputation maps of forest composition and structure. Remote Sensing of Environment 143:26–38.

Zellweger F, De Frenne P, Lenoir J, Rocchini D, Coomes D. 2019. Advances in microclimate ecology arising from remote sensing. Trends in Ecology & Evolution 34:327–341.

Zhang J, Hu J, Lian J, Fan Z, Ouyang X, Ye W. 2016. Seeing the forest from drones: testing the potential of lightweight drones as a tool for long-term forest monitoring. Biological Conservation 198:60–69.

Zhao K, Suarez JC, Garcia M, Hu T, Wang C, Londo A. 2018. Utility of multitemporal lidar for forest and carbon monitoring: tree growth, biomass dynamics, and carbon flux. Remote Sensing of Environment 204:883–897.

Zhu Z, Wulder MA, Roy DP, Woodcock CE, Hansen MC, Radeloff VC, Healey SP, Schaaf C, Hostert P, Strobl P, Pekel J-F, Lymburner L, Pahlevan N, Scambos TA. 2019. Benefits of the free and open Landsat data policy. Remote Sensing of Environment 224:382–385.