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Monitoring biodiversity in the Anthropocene using remote sensing in species distribution models

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Abstract

In the face of the growing challenges brought about by human activities, effective planning and decision-making in biodiversity and ecosystem conservation, restoration, and sustainable

development are urgently needed. Ecological models can play a key role in supporting this need and helping to safeguard the natural assets that underpin human wellbeing and support life on land and under water (United Nations Sustainable Development Goals; SDG 14 & 15). The urgency and complexity of safeguarding forest (SDG 15.2) and mountain ecosystems (SDG 15.4), for example, and halting decline in biodiversity (SDG 15.5) in the Anthropocene requires a re-envisioning of how ecological models can best support the comprehensive assessments of biodiversity and its change that are required for successful action.

A key opportunity to advance ecological modeling for both predictive and explanatory purposes arises through a collaboration between ecologists and the Earth observation community to achieve a close integration of remote sensing and species distribution models. Remote sensing data products have the capacity to provide continuous spatiotemporal information about key factors driving the distribution of organisms, therefore improving both the use and accuracy of these models for management and planning.

Here we first survey the literature on remote sensing data products available to ecological modelers interested in improving predictions of species range dynamics under global change. We specifically explore the key biophysical processes underlying the distribution of species in the Anthropocene including climate variability, changes in land cover, and disturbance. We then discuss potential synergies between the ecological modeling and remote sensing communities, and highlight opportunities to close the data and conceptual gaps that currently impede a more effective application of remote sensing for the monitoring and modeling of ecological systems. Specific attention is given to how potential collaborations between the two communities could lead to new opportunities to report on progress towards global agendas such as the Agenda 2030 for sustainable development of the United Nations or the Post-2020 Global Biodiversity Framework of the Convention for Biological Diversity, and help guide conservation and management strategies towards sustainability.

1. Introduction

Human society in the Anthropocene has emerged as a global driver rapidly transforming ecosystems (Ellis, 2015, 2011; Waters et al., 2016). Anthropogenic transformation affects the distribution of species and habitats through a range of drivers and processes including land-use and land-cover change, climate change, pollution, (over-)exploitation (Benítez-López et al., 2019), and biological invasions (Chaudhary et al., 2015; Lenzen et al., 2009; Newbold et al., 2016, 2015; Pekin and Pijanowski, 2012; Pereira et al., 2012). Importantly, the existence of global supply chains that interconnect human societies implies that local anthropogenic impact can also be driven by consumptive demands thousands of kilometers away (Chaudhary and Kastner, 2016; Marques et al., 2019; Meyfroidt et al., 2013; Rudel, 2007; Verburg et al., 2015). Furthermore, novel disturbance regimes are emerging, such as altered frequency and intensity of extreme climatic and fire events (IPCC, 2014; Mahecha et al., 2017; Ummenhofer and Meehl, 2017). Such events impact the state, structure, functionality, and evolution of biological systems at different scales, potentially increasing vulnerability to further changes in climate variability (Dirzo et al., 2014; IPCC, 2014).

The challenges posed by anthropogenic impact on the environment are increasingly recognized at national and international levels. This has resulted in large integrated monitoring and reporting frameworks. At the global level, such frameworks include the United Nations' Sustainable Development Goals (2030 Agenda) and the Aichi biodiversity targets of the Convention on Biological Diversity (Strategic Plan for Biodiversity 2011-2020). For example, UN goal 15.5 aims to 'Take urgent and significant action to … halt the loss of biodiversity and, by 2020, protect and prevent the extinction of threatened species', whilst the closely related Aichi target 12 focuses on improving the conservation status of threatened species. These targets are used to monitor progress, inform actions, and evaluate alternative options for governance and decision-making. Meeting the SDGs and Aichi targets requires a suite of monitoring strategies for the acquisition of high quality data and a thorough understanding of current and emerging pressures acting on species and ecosystems (Chen et al., 2011; Lenoir et al., 2019; Lenoir and Svenning, 2015; Mirtl et al., 2018). Monitoring programs should help conservation and management strategies based on explanatory as well as predictive models and support the regular evaluation of the effectiveness of policy interventions (Haase et al., 2018).

The development of monitoring design and management strategies that account for the scale, pace, and complexity of anthropogenic impacts on species and ecosystems (Ceballos et al., 2017; Dirzo et al., 2014; Kim et al., 2018) requires assessments of past and current biodiversity changes as well as robust projections of the potential future distributions of species and ecosystems (i.e., satisfactory accuracy and precision of models transferred to novel conditions. Species Distribution Models (SDMs, *sensu* Guisan and Thuiller, 2005; Guisan and Zimmermann, 2000, Box 1) provide a powerful explanatory and predictive modeling framework in this context. In conservation and decision-making, SDMs can for example be used as explanatory models (*sensu* Shmueli, 2009) to identify critical environmental variables for species or communities (e.g. Droz et al., 2019), or for interpolating and extrapolating potential geographic distributions from available observations of species or communities (McShea, 2014). These predicted ranges can then be used in conservation planning to minimize the impact of development (Guisan et al., 2013) and may be linked to biodiversity monitoring through frameworks such as Essential Biodiversity Variables[1] (EBVs, Fernandez et al., 2019; Pereira et al., 2013). SDMs have further evolved to provide scenarios for past and future species distributions and community composition, based on the use of environmental variables such as climate, land cover and biotic constraints. This allows stakeholders to identify the natural resources they want to sustain and assess the projected effects of environmental policy options on the distribution of threatened, rare, flagship or invasive species (e.g. Cianfrani et al., 2018, 2015; Esselman and Allan, 2011). SDM projections can also

[1] a minimum set of biodiversity state variables required to study, report, and manage multiple facets of biodiversity change (Pereira et al., 2013)

indicate whether current protected areas or networks of protected sites match with likely future species and community distributions (e.g. Araujo et al., 2004; Bolliger et al., 2007; Droz et al., 2019). Collectively, these applications illustrate the high relevance of SDMs for biodiversity conservation and hence for meeting the SDGs and the Aichi targets.

However, there are numerous criticisms of current implementations of SDMs, in particular when applied to assist biodiversity monitoring. Such criticisms originate primarily from the reliance of both correlative and process-based SDMs (see Box 1) on long-term, averaged, and interpolated spatial climate variables, routinely used without accounting for their temporal variability (Zimmermann et al., 2009). Moreover, correlative models are calibrated on statistical relationships that fail to capture the actual biological processes underlying the geographical distributions of species and biodiversity (Dormann et al., 2012). Finally, projections from both correlative and process-based SDMs are often based on calibration datasets with limited spatial and temporal extent, which restricts transferability of model projections (Werkowska et al., 2017; Yates et al., 2018). Although hybrid and process-based distribution models (see Box 1) address flaws such as the causality between the response and the predictors as well as the spatiotemporal transferability, these models are data intensive (and thus limited to few species) and typically rely on climate interpolations.

The development of free, open, easily accessible remote sensing data provide opportunities for resolving some of the limitations of SDMs. For example, a large variety of products derived from various satellite sensors are available to assess key natural systems and environmental conditions as well as extremes affecting the land surface in a contiguous spatial and temporal fashion (Mahecha et al., 2017), thereby capturing the environmental processes underlying species, and thus biodiversity, distribution. For example, these products allow assessment of land use and cover (e.g. Verburg et al., 2011), forest cover (e.g. Hansen et al., 2008; Klein et al., 2015), vegetation structure (e.g. Schneider et al., 2014), vegetation productivity and phenology (e.g. de Jong et al., 2013; Garonna et al., 2018; Jolly et al., 2005), snow (e.g. Hüsler et al., 2014; Xie et al., 2017), temperature (e.g. Ibrahim et al., 2018), and precipitation (e.g. Naumann et al., 2012). Additionally, continuous time series deliver observations over large spatial extents and at ecologically relevant time scales, improving the transferability of model projections and at least partially solving data sparsity with respect to spatial and temporal resolution.

Some remote sensing data products are already used in SDMs (see Franklin, 1995 for an early review), mostly as abiotic and biotic predictor variables and occasionally as response variables (see He et al., 2015 for a comprehensive review). However, remote sensing and species distribution modeling are still quite distinct fields that have not typically overlapped extensively, resulting in a lack of awareness of potential opportunities. Accordingly, we argue that remote sensing-derived data products are not yet used to their full potential and that they can contribute more to the development of SDMs for biodiversity monitoring and policy.

Here, we[2] first discuss how current developments in remote sensing may improve our understanding and projections of species distributions (see section 2: Modeling species distribution using remote sensing data: state-of-the-art). This discussion is based on a selection of processes and a prioritization of relevant literature, which by no means aims to be exhaustive. We then suggest synergistic activities between the ecological modeling and remote sensing communities (see section 3: Modeling species distribution using remote sensing data: closing gaps and moving forward). These activities may serve to fill data and conceptual gaps and develop remote sensing data products that can effectively contribute to the monitoring and modeling of ecological systems and ultimately guide and inform conservation and management strategies towards sustainability. Unlike previous contributions (e.g. He et al., 2015), this paper is organized around some of the key biophysical dimensions and processes (Mackey and Lindenmayer, 2001; Pearson and Dawson, 2003) underlying the distribution of species in the

[2] This publication is the result of a workshop supported by the European Space Agency and Future Earth that brought together participants from the ecological modelling, biodiversity, land systems science, and remote sensing communities

Anthropocene, such as climate variability and land-cover change. As such, it is aimed at species distribution modelers and remote sensing specialists who jointly want to better support monitoring and conservation actions at different spatial and temporal scales.

2. Modeling species distribution using remote sensing data: state-of-the-art

Key processes and biophysical factors that underlie the distribution of species in the Anthropocene and are required for modeling include: climate and its variability from the global to the regional scale (Fig. 1(a), see paragraph 2 “Climate and its variability”), topo- and microclimate from the regional to the local scale (Fig. 1(b), see paragraph 3 “Topography”), physical disturbance processes modulating distribution at various scales (Fig. 1(c), see paragraph “Physical disturbances”), and anthropogenic pressures (Fig. 1(d)), such as changes in land cover and land use. Additional factors that are not explicitly discussed but merely mentioned throughout the text include resource variables (e.g., water, food resources, and nutrient availability, Austin and Van Niel, 2011). Climate and topography are often used as proxies for these types of variables. Ideally, the predictor variables in SDMs meet at least two of three requirements (holy grail, Fig. 1): spatiotemporal contiguity (i.e., full coverage of a process in space and time), intensity (i.e., the full range of variation of a continuous variable is covered, including the extremes likely to impact on an organism’s traits and ultimately on its demography), and 3D-structure.

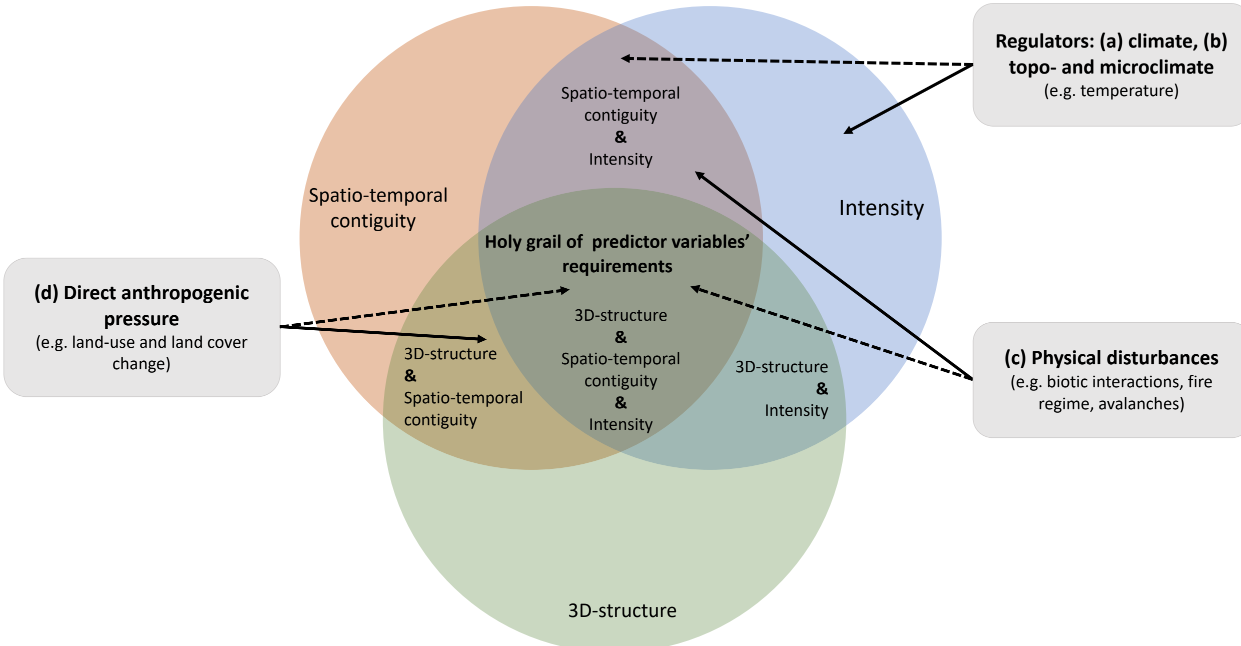

Fig. 1. Main categories of predictor variables in SDMs and requirements they meet. Variables consist of regulators (a, b), physical disturbances (c), and direct anthropogenic pressures (d) (*sensu* Austin and Smith, 1989; Guisan and Zimmermann, 2000; Randin et al., 2009c). Requirements are contiguity, intensity, and 3D structure. Categories of predictor variables point with continuous lines to requirements they can currently meet and with dotted lines to requirements they could meet with the integration of remote sensing data.

Climate and its variability

Climate has been consistently identified as the main determinant of species ranges at the broad scale (Woodward, 1990), whereas non-climate predictors (such as topography and habitat) are more important at finer scales (e.g. Luoto et al., 2007; Normand et al., 2009). It is therefore common to build large-scale and coarse-resolution SDMs to characterize species geographic extents and spatial patterns of occurrence using only climate predictors (see e.g. Mod et al., 2016 for plants; Thuiller et al., 2005). This approach is commonly referred to as bioclimatic envelope modeling and climate predictor variables are defined as direct or regulator predictors (Fig. 1(a): Austin and Smith, 1989; Guisan and Zimmermann, 2000), because the spatial resolution at which models operate may be much greater than the processes experienced by species (Austin, 2002). These variables are also routinely used without accounting for their measurement errors and uncertainty, which can lead to biased estimates and erroneous inferences (Stoklosa et al., 2015). In addition, temperature and precipitation interpolations from weather stations (e.g. Worldclim) capture neither temperature-related processes, such as inversion, air stagnation (Vitasse et al., 2017) or cold air pooling (e.g. Patsiou et al., 2017), nor precipitation-related processes, such as orographic effects (Fernandez et al. 2015; but see CHELSA Karger et al., 2017). However, some of these physical patterns can be captured by remote sensing products such as from the Operational land Imager (OL) on Landsat8 and the Moderate Resolution Imaging Spectroradiometer (MODIS) on TERRA and AQUA for surface temperature or Tropical Rainfall Measuring Mission (TRMM) and Global Precipitation Mission (GPM) for precipitation (e.g. at the scale of the Andes; Bookhagen and Strecker, 2008). These products have been successfully integrated in SDM studies (Cord et al., 2010; Estrada-Peña et al., 2016; Neteler et al., 2013). Alongside the development of improved remote sensing data products, considerable advances have also been achieved in terms of the algorithms needed to process remote sensing data. For instance, algorithms for deriving land surface temperature are now sufficiently advanced that a typical accuracy of 1 Kelvin is possible with data acquired at around 100 m resolution from recent Landsat satellites. Such high spatial resolution surface temperature data can ultimately be used to detect local features such as urban heat islands (Liu et al., 2011), which are key components for the persistence or extinction of plants and animals. However, pros and cons of surface temperature should be carefully listed before its integration into SDMs. On one hand, SDMs mostly relate the occurrence or the abundance of species to data from standardized shaded 2-m air temperature sensors, although interpolated between weather stations that can be sparse and located in specific locations (e.g. low altitudes Hik and Williamson 2019). On the other hand, temperature derived from remote sensing might integrate, depending on the spatial resolution and the post-processing considered, a mix of surfaces such as rock, tree canopy or grassland.

Although land surface temperature derived from remotely sensed datasets can substantially improve projections of SDMs (Deblauwe et al., 2016), precipitation data derived from sensors still rely on the ground projected spatial resolution of the data and the addition of ground observations (e.g. TRMM at a 0.05° native resolution versus CHIRPS at a 0.25° resolution and calibrated with 45’707 weather stations worldwide). In addition, precipitation is measured precisely but locally with water gauges, whereas currently available satellite sensors detect rainfall patterns at resolutions > 1 km. As a consequence, both satellite sensors and interpolations from direct measurements are not able to adequately capture small-scale processes (e.g. orographic processes) that influence species distribution (Deblauwe et al., 2016; Lenoir et al., 2017) (Deblauwe et al., 2016). Additionally, rainfall is usually an indirect predictor, whereas variables reflecting soil water budget or snow cover and depth are more direct predictors.

Climate also enters SDM-based studies in the form of long-term averaged variables used to define range limits. However, such averages overlook information contained in the distribution of climate values, including climate extremes of increasing frequencies, whose influence on range limits remains to be fully understood (Ummenhofer and Meehl, 2017). Accordingly, Kollas and colleagues (2014) called for the use of temperature extremes during key phenological stages of focal species when attempting to explain range limits. Zimmermann and co-authors (2009) showed that the primary effect of including information on climate variability and extremes is to correct local SDMs for over- and underprediction. Such results speak in favor of the incorporation of targeted absolute climate values instead of long-term means that are only proxies of unknown relevance for the physiologically critical facets of climate that control species abundances and distributions. They also have important implications for projections of climate-change impacts on species distributions that are based on correlative approaches only. Relevant data for deriving extremes are spectral time series. With such series approaching 20 years of records and daily time steps, it is now becoming possible, for example, to use land surface temperature from remote sensing to derive extreme climatic events. The Global Climate Observing System (GCOS) was specifically set up under the auspices of United Nations organizations and the International Council for Science to ensure the availability of so-called Essential Climate Variables (ECV, GCOS 2010), which are systematic and long-term observations of climate. An Essential Climate Variable is a physical, chemical, or biological variable or a group of linked variables that contributes to the characterization of the Earth's climate (Bojinski et al., 2014). Specific Essential Climate Variables of interests for the SDM community include land surface temperature, precipitation, snow, glaciers, permafrost, albedo, land cover, fraction of absorbed photosynthetically active radiation (FAPAR), Leaf area index (LAI), above-ground biomass, soil carbon, fire, and soil moisture. For the latter, a global ECV surface soil moisture data set has been generated within the European Space Agency (ESA) Climate Change Initiative. This soil moisture dataset covers a 38-year period from 1978 to 2016 at a daily time step and at a 0.25° spatial resolution. Snow, high-resolution land cover, surface temperature and permaforst are other ECVs currently developed by ESA (http://cci.esa.int/). Similar initiatives have also been developed at smaller scales. The Sentinel Alpine Observatory of Eurac Research (http://sao.eurac.edu/sao/) and satellite-based snow cover climatology (Hüsler et al., 2014) are two examples for the European Alps. Yet, although the temporal resolution might be appealing for the SDM community, typical spatial resolutions of 0.25° (at best 500 m) do not match the requirements for safe calibration and projections of SDMs for many organisms, calling for further data integration (Lembrechts et al., 2019).

Topography

When SDMs are calibrated only with climate data at a low spatial resolution (e.g. Worldclim; ~1-km grid cells), their fit and predictive power are often improved by incorporating additional predictors (Luoto and Heikkinen, 2008; Pradervand et al., 2014), or by enhancing them to consider finer-scale processes (e.g. topoclimate Daly, 2006; Karger et al., 2017). One important predictor is the topography, which locally controls biota, habitat structure, and growing conditions (albeit mostly indirectly, Austin and Van Niel, 2011). It does so primarily by affecting local climate (<1 km^2) through elevation (adiabatic lapse rate), exposure (to solar radiation and wind), and cold air pooling (Böhner and Antonić, 2009), but also through its effect on soil development, causing spatial variability in soil depth and nutrient as well as water availability (Fisk et al., 1998).

Topography-related indirect variables (*sensu* Guisan and Zimmermann, 2000), such as slope or topographic position, or more direct variables such as potential solar radiation are broadly used in SDMs and evolutionary ecology (Kozak et al., 2008; Leempoel et al., 2015). The topographic wetness index is also a commonly used proxy for soil moisture (see e.g. le Roux et al., 2013a). Including these variables improves SDMs, but interpreting the actual drivers of species distributions related to these variables can be difficult. Topographic data are indeed only surrogates for direct environmental controls of occurrence and abundance and the effects of topographic variables on plant distributions are therefore distal (*sensu* Austin, 2002, 2007; Mod et al., 2016; Moeslund et al., 2013). Improvements are also scale-dependent as topographic variables that make sense over a small geographic area can become problematic at broader scales if they are not linearly related to the environmental factors for which they serve as proxies. Regardless of scale, the problem with using indirect (i.e. distal) predictors of topography is that the identified relationships are inherently non-causal, which therefore reduces model transferability in space and time. This limitation also applies for other predictor variables based on climate or land cover, notably when SDMs are calibrated for species situated at high trophic levels.

One solution to this problem is to utilize more direct and causal predictors or resource variables (Austin, 2002; *sensu* Guisan and Zimmermann, 2000). For example, SDMs can be calibrated with nutrient status (Bertrand et al., 2012; Buri et al., 2017; Coudun et al., 2006; Dubuis et al., 2013; Vries et al., 2010), as well as fine resolution climate predictors based on topography and remote sensing-derived estimates of vegetation cover (Ashcroft and Gollan, 2011; Lenoir et al., 2017). Digital elevation models, in turn, can be used to directly estimate cold-air drainage, which can lead to improved predictions of species distributions over indirect estimates of topography (Ashcroft et al., 2014; Patsiou et al., 2017). Remote sensing offers another solution. Relevant accurate high-resolution terrain data (Jaboyedoff et al., 2012; Leempoel et al., 2015) are increasingly obtained using Light Detection and Ranging (LiDAR) technology (e.g. Mathys et al., 2004; Sørensen and Seibert, 2007; Vierling et al., 2008). The benefits of LiDAR are specifically related to its capacity to detect minor terrain features, such as hill tops, ridges, small depressions, and minor hydrological features (Engstrom et al., 2005; Kammer et al., 2013; Kemppinen et al., 2018), which are expected to play an important role in determining species distribution (Graf et al., 2009; Pradervand et al., 2014). Moreover, high point return densities (1–10 points/m) and relative ease of data collection across large areas makes LiDAR a popular option for measuring bare earth elevation and vegetation height (Hancock et al., 2017). However, the accuracy of LiDAR-derived digital elevation models can vary considerably across topographic and land-cover gradients (Leitold et al., 2015). For instance, it is common to achieve high elevation accuracies (<0.15 m root mean square error) in areas with low vegetation cover and relatively flat terrain, (Montané and Torres, 2006; Spaete et al., 2011), but elevation errors in digital elevation models tend to increase in areas covered by dense vegetation. Further work is required to determine how these errors in elevation are propagated to the direct predictors that are desirable in SDMs (cold air drainage, vegetation structure, exposure to winds and radiation, microclimate), and to the SDM itself.

Unlike high-resolution topographic information, the availability of spatial layers of soil conditions is still limited (Fang et al., 2016). Yet spaceborne multispectral and imaging spectroscopy instruments have a high potential for mapping topsoil carbon (Peón et al., 2017) and organic matter content as well as soil physical properties (Rosero-Vlasova et al., 2018). These novel possibilities should be tested in SDMs in the future.

Physical disturbances

Physical disturbances include geomorphological disturbances such as fluvial erosion, nivation, landslides, rock falls and other disturbances such as mechanical abrasion by wind or fire. Geomorphological processes in particular, create a wide range of disturbance regimes across landscapes (Aalto et al., 2017; Gooseff et al., 2003; Niittynen and Luoto, 2018) that may significantly alter local soil stability, moisture conditions, and nutrient availability (Kozłowska and Rączkowska, 2002). Due to ongoing land-use and climate change, these disturbance regimes are predicted to change rapidly as many geomorphical processes have a significant climate response (Knight and Harrison, 2013), with small changes in climate forcing triggering large changes in Earth system processes (Aalto et al., 2017). Accordingly, Earth system processes potentially represent key drivers of local habitat heterogeneity (Cannone et al., 2016), variation in ecosystem functioning (Frost et al., 2013), and species assemblages (le Roux et al., 2013b; Malanson et al., 2012).

Recent studies demonstrate that the incorporation of direct Earth system processes variables – as opposed to the indirect topographic and soil surface properties used as surrogates in plant SDMs (Dirnböck et al., 2003; Mellert et al., 2011) – can improve the explanatory and predictive power of SDMs (le Roux et al., 2013b; le Roux and Luoto, 2014; Niittynen and Luoto, 2018; Randin et al. 2009a). However, the type and necessity of including disturbance variables in models are highly environment-specific. For decades, remote sensing data have been used for the mapping of geomorphological landforms and processes (Walsh et al., 1998). The high spatial resolution of airborne photographs provides a valuable data source in that context, particularly for detecting smaller landforms (e.g. 1-10 m). Yet, the precision (< 10 m) and increasing temporal resolution (revisit time of 1-5 days) of satellite data, such as WorldView 3 (http://worldview3.digitalglobe.com), the Planetscope satellite constellation (https://www.planet.com), or open access ESA Sentinel-2 (https://sentinel.esa.int), can now compete with that of aerial photography. High-resolution satellite imagery is thereby becoming a valuable data source for the modeling of dynamic processes. Attempts to include remote sensing-based geomorphological and other non-anthropogenic physical disturbances into SDMs include Miller and Franklin (2002) with landforms derived from a DEM, and Connell et al. (2017) as well as Madani et al. (2016) for fire.

Direct anthropogenic pressure

The availability of spatially and temporally highly resolved land-cover information is central to many monitoring programs and land-cover mapping is probably one of the oldest application of remote sensing, starting with aerial photographs from hot air balloon in the 1860's and from airplane in the 1910's (Fuller et al., 1994). Assessments of changes in land systems range from local to regional and global (Stürck and Verburg, 2017; van Asselen and Verburg, 2013) and from historical (Bolliger et al., 2017; Kaim et al., 2016; Loran et al., 2017) to predictive, with scenario-based assessments of potential future changes in land use (Martinuzzi et al., 2015; Pazúr and Bolliger, 2017; Price et al., 2015).

Changes in land cover and land use affect biodiversity in different ways. In the case of urbanization, there is usually a complete replacement of (semi-)natural open land with buildings or other impervious infrastructures such as roads, which profoundly changes species distributions (Lembrechts et al., 2017). However, impacts on species distributions or abundances can also be triggered by other forms of land-use and land management such as slash and burn cultivation or deforestation, or by modification of their intensity (e.g., agricultural practice, Randin et al., 2009b). Both the detection of changes in land cover and the differentiation between changes in land cover and land use are difficult. Yet progress has been made over recent years using change patterns in remotely sensed data as indicators of change in management and land-use intensity (Eckert et al., 2017; Franke et al., 2012; Gómez Giménez et al., 2017; Jakimow et al., 2018; Rufin et al., 2015). Examples include the mapping of grassland mowing frequencies through the identification of typical variations in greenness during the growing season (Kolecka et al., 2018), observed agricultural intensification in Kenya through the successful long-term monitoring of rainfed and irrigated agriculture using monthly satellite data composites (Eckert et al., 2017), or the occurrence of plantation forests in in the southeastern United States based on high resolution spatial patterns (Fagan et al., 2018).

Until recently, small or heterogeneous areas important to landscape structure and land-use management were not detected due to low spatial, spectral, and temporal resolution. These limitations are partially addressed with spatially, spectrally, and temporally highly resolved instruments such as on the Sentinel-2 constellation (ESA, 2018). Every five days, these sensors provide global coverage of the land surface at a spatial resolution of 10, 20, and 60 m (depending on spectral band setting and product definition).

However, in spite of the novel developments and achievements of remote sensing, limitations will persist in observing land management practices relevant to biodiversity. Proper characterization of land-cover and land-use change faces the difficulty of the ‘curse of dimensionality’. By improving any of the spatial, spectral or temporal resolutions of an Earth observation instrument, exponential increase of the other two remaining dimensions is needed to properly describe the dimensionality of the signal per se. Currently, data integration, fusion or multi-modality seems to hold most promise. Examples of such approaches are provided by Van Asselen and Verburg (2013), Price et al. (2015), See et al. (2015), and Estel et al. (2018).

Land cover and land use have traditionally relied on two-dimensional (2D) representations of the environment. Yet, 3D vegetation structure not only allows for more continuous landscape representations but is also a crucial determinant of species habitat (Fawcett et al., 2018; Gastón et al., 2017; Huber et al., 2016; Milanesi et al., 2017; Torabzadeh et al., 2014; Zellweger et al., 2016) and functional connectivity (Marrotte et al., 2017; Milanesi et al., 2017). Such evidence stresses the need for more detailed landscape-content information, and for 3D structure information to supplement habitat assessments. These structures are captured using digital aerial photogrammetry (Ginzler and Hobi, 2015) or active remote sensors, e.g., LiDAR (Bergen et al., 2009; Merrick and Koprowski, 2017). 3D structure represented as morphological traits are increasingly combined with physiological traits allowing to model and predict substantial detail on functional diversity (Asner et al., 2017; Schneider et al., 2017) as well as light interaction within the 3D canopy (Schneider et al., 2019).

Moving from simple land-cover representations to more species-relevant representations of land use requires advances in remote sensing and integration with other data (Wulder et al., 2018). Yet, following Franklin et al. (2014) and others (Boulangeat et al., 2014; Martin et al., 2013; Newbold, 2018), adaptations are also needed for SDMs to properly account for such novel landscape representations and address not only climate change (Titeux et al., 2016) but also land-use change. Increasing the detail in landscape characterization not only requires SDMs to be capable of addressing the represented diversity, but it also requires understanding of the temporal dynamics and climate responses of land use at a higher level of detail. To avoid overwhelming and, sometimes unnecessary, complexity, the sensitivity of the SDMs to the refined detail should be continuously tested and simplifications made as part of the modeling process.

Besides land-use composition, land-use configuration can in some cases represent a good proxy for those species requiring corridors and landscape borders to survive (e.g., Neilan et al., 2019; Vinter et al., 2016). Accordingly, the heterogeneity of land use or of satellite reflectance data has been widely assessed in the past, using various algorithms and metrics such as multivariate statistical analysis (Feilhauer and Schmidtlein, 2009), the spectral species concept (Féret and Asner, 2014), self-organizing feature maps (Foody, 1999), multidimensional distance metrics (Rocchini et al., 2016), and Rao's Q diversity (Rocchini et al., 2017). Each of them addresses one or several issues related to heterogeneity measurements. These can then be incorporated as metrics of land-cover heterogeneity and land-cover change into SDMs to drive future predictions, such as in Coops et al. (2016).

3. Modeling species distribution using remote sensing data: closing gaps and moving forward

We are coming to an era of cost-efficient mass processing of high-resolution remote sensing data products over extensive geographical areas and long periods of time (Hansen et al., 2013). This coincides with the increasing demand for reliable, spatially comprehensive and time-sensitive information on the status of and trends in biodiversity (Navarro et al., 2017) and the urgent need to achieve significant progress towards sustainability. Remote sensing data are increasingly recommended for and applied to biodiversity monitoring and conservation (e.g. see Alleaume et al., 2018; Lausch et al., 2016; Rocchini et al., 2016; Schneider et al., 2017; Schulte to Bühne and Pettorelli, 2018; Vihervaara et al., 2017). In this context, such data are used notably in the monitoring of EBVs (e.g., see Alleaume et al., 2018; Fernandez et al., 2019; Pettorelli et al., 2016) and the adoption of systematic observation requirements is steadily improving (Navarro et al., 2017; Pettorelli et al., 2016; Skidmore et al., 2015). However, the use of remote sensing data in the reporting on individual sustainable development goal indicators is not systematic. For instance, whereas the methodologies to assess progress on "forest area as a proportion of total land" (SDG 15.1.1), "sustainable forest management" (SDG 15.2.1), "proportion of land that is degraded over total land area" (SDG 15.3.1), or "mountain green cover index" (SDG 15.4.2) are largely or fully based on remote sensing data, this is not the case for reporting on the "coverage by protected areas of important sites for mountain biodiversity" (SDG 15.4.1). Here we discuss joint ventures between the ecological modeling and remote sensing communities that could ultimately contribute to improving as well as accelerating the modeling and prediction of species' distributions across large spatial scales and the delivery of reliable information for reporting on progress towards specific sustainable developments goals such as SDG 15.4.1. The joint ventures we propose pertain to time series and temporal stacking (see paragraph 2 below, Fig. 2), the direct detection and sampling of species and their traits (see paragraph 3), the improvement of integrated and dynamic range models (see paragraph 4, Fig. 3), and the prediction of belowground processes, disease and biotic interactions (see paragraph 5).

Time series and temporal stacking

Most SDM studies that have included remote sensing data products so far have used static and temporally aggregated remote sensing-derived layers as predictors (e.g. land surface temperature, water availability, topography, land cover and 3D structure, section 2). Fewer attempts have been made to take advantage of the existing time series data and the dynamic information contained in remote sensing data products (Fernández et al., 2016; Pinto-Ledezma and Cavender-Bares, 2020), despite the pivotal role that such temporally explicit data play. For instance, long-term time series of remote sensing data are key to test the temporal transferability of SDMs (Yates et al., 2018), a basic requirement to formally guide and inform monitoring strategies in changing environments and make sure that model projections follow the observed trajectories of species. Likewise, long-term observations of response variables, such as occurrences or abundances of focal organisms, are essential to understand and project the impact of global change with SDMs. Andrew and Ustin (2009), Bradley and Mustard (2006), or Malavasi et al. (2019) provide examples of the integration of occurrence data derived from remote sensing into SDMs. The availability of long time series from satellites or cost-effective tools such as Unmanned Aerial Vehicles (UAVs, e.g. Kellenberger et al., 2018) will undoubtedly lead to a rapid increase in such applications. Finally, long-term time series are also critical for estimating lag times. The Anthropocene is an era of rapid environmental changes. Under such conditions, lag times in cause-effect chains may severely confound the identification of species-environment relations via correlated distribution patterns. Rapid climate change, for example, is expected to cause a severe disequilibrium between climate and species distribution due to both slow colonization of areas that become newly suitable and delayed extinction from those sites that are no longer suitable to the species (i.e., extinction debts; Dullinger et al., 2012; Svenning and Sandel, 2013; Talluto et al., 2017). Land-use changes may have similar effects and many studies have demonstrated that in landscapes undergoing changes in human usage, spatial biodiversity patterns often represent habitat configurations of decades back rather than current ones (Auffret et al., 2018; Krauss et al., 2010). Matching current species distributions and environmental conditions in statistical models will hence result in flawed correlation and, as a corollary, inappropriate prediction of future development. Remote sensing data products offer a way forward here, because time series of many of these products now cover two decades, and several of them up to five (He et al., 2015). These time series have great potential in detecting and quantifying lag times, e.g. in the response of biological populations to land-cover conversions (Wearn et al., 2012). Incorporating these lag times into models of species responses to past, current, and future environmental change has important ramifications for the management of biodiversity because it defines 'windows of opportunity' for mitigating the anticipated consequences (Kuussaari et al., 2009; Wiens et al., 2015).

One reason for the limited transferability of purely correlative models is the generally coarse or inadequate spatial and temporal resolution of the data used to calibrate models (Connor et al., 2018; Manzoor et al., 2018; Potter et al., 2013). This spatial-resolution paradox (Lenoir et al., 2017) is inherent to correlative models and stems from the spatial mismatch between the resolution at which the predictor variables (e.g. biophysical variables, see section 2) are available, the resolution that matches the response variables (e.g., species occurrence, presence-absence, abundance or trait data; Guisan and Thuiller, 2005), and the size of the studied organism (Potter et al., 2013).

Here, we argue that remote sensing could be used to better calibrate SDMs, by integrating spatially and temporally (through multiple years) more proximal environmental data to derive more comprehensive quantifications of species' response curves along environmental gradients (see Austin and Gaywood, 1994). An improved calibration process may in turn increase the spatial and temporal transferability of both correlative and process-based models. This can be illustrated by focusing on environmentally-specific species response curves, such as temperature response curves (sensu Austin, 2002; Fig. 2(a)) and thermal performance curves (*sensu* Schulte et al., 2011; Fig. 2(a)-(b)) are at the foundation of both correlative (Guisan and Zimmermann, 2000) and certain types of process-based (Kearney and Porter, 2009) models, respectively. Temperature response curves generated by SDMs are usually parameterized through the statistical relationship between field observations and spatial layers of temperature. Temperature performance curves used in process-based models on the other hand are best parameterized from experimental data depicting metabolic requirements, usually in the absence of competition (e.g., Chuine and Beaubien, 2001). Because they explicitly rely on a physiological basis, temperature performance curves are expected to better identify species thermal tolerance limits that set range boundaries and to be thus more robust when extrapolating species redistributions under future climate change (Eckert et al., 2017). However, physiologically-based species performance curves represent the fundamental rather than post-interactive realized niches of species (Hutchinson, 1978; Pulliam, 2000). Such performance curves are not as time- and cost-efficient as statistically-based species response curves. For some species, the quantifications of statistically-based performance curves by the integration of remote sensing data (Fig. 2(c)) might better inform on the real microhabitat conditions experienced by living organisms, and thus might help to capture species' response curves that are closer to the fundamental responses (response niche; Maiorano et al., 2013 ; e.g. for dominant late-successional species; Pearman et al., 2008) obtained from experiments. Hence, the integration of remote sensing data into SDMs has the potential to generate more transferable SDMs (Maiorano et al., 2013). Similarly, the combination of experimental and remote sensing data (i.e. the combination of fundamental and realized niches) through e.g. the direct use of land surface temperature to derive thermal performance curves could better capture the geographic variability caused by local adaptations (Fig. 2(d)).

Temporal stacking of remote sensing images (e.g. spectroscopy, thermal or radar images; Fig. 2) allows more observations of both response and predictor variables to be obtained and can be used to reduce the temporal mismatch between these variables (e.g. George et al., 2015). This in turn allows the generation of more comprehensive representations of the realized response curves. Images from imaging spectroscopy in particular can be used to gather a large amount of occurrence, abundance, and trait data (Lausch et al., 2019; e.g. van Ewijk et al., 2014). Conversely, remote sensing data can also be used to develop more accurate estimates of elevation, microclimate and other direct environmental predictors (see section 2, paragraph 3 “Topography”), which will improve estimates based on coarse-scale climate grids or indirect predictors alone.

Similarly, process-based distribution models such as Phenofit that integrate phenology and frost resistance for instance (Chuine and Beaubien, 2001) also strongly rely on experimental response curves (Fig. 2(b)). As a consequence, responses such as the completion of a phenological phase as a function of temperature are usually limited to a restricted set of plant species for which data are available. When remote sensing data cover large geographic extents, the same combination of temporally-stacked remote sensing images could potentially help extend such models to more species and take into account the variability due to local adaptation.

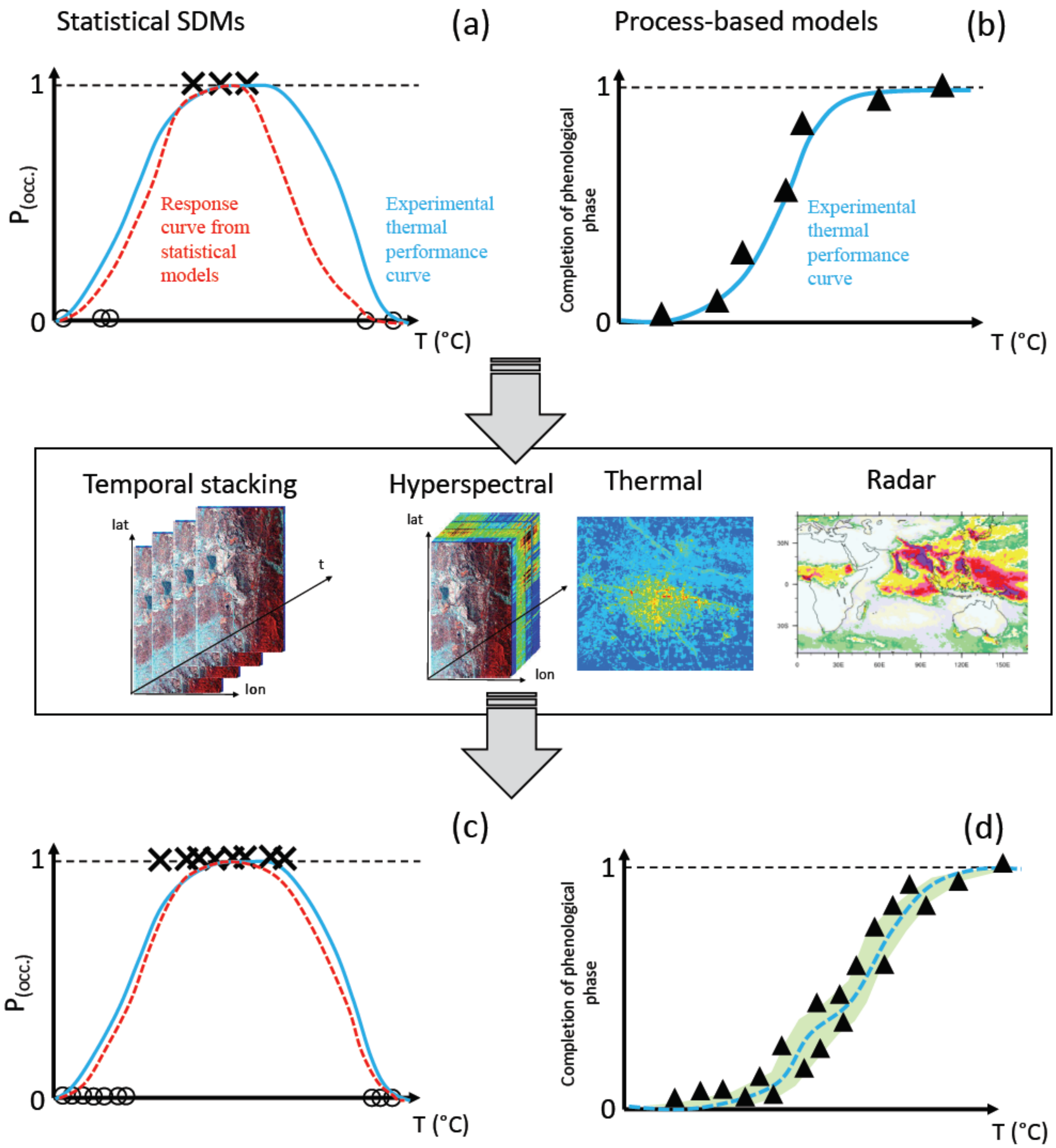

Fig. 2. Temporal stacking of imaging spectroscopy, thermal or radar images for improving response curves of statistical (a and c) and process-based (b and d) models. Thermal response curves derived from statistical models (a) describe the realized thermal niche of species whereas experimental thermal performance curves are closer to the thermal fundamental niche, thus

potentially increasing the transferability of such relationship in space and time. The response curve from statistical models in (a) is calibrated with presence (black crosses) and absence (black circles). Thermal performance curve of a phenological phase in (b) derived from phenological observations (black triangle). Time series of remote sensing images potentially allows to increase the number of observations for both calibrating thermal response curves of statistical SDMs (c) and thermal performance curves used in process-based models (d). In (c), presences and absences are extracted from remote sensing data, thus allowing to derive a high number of observations and to calibrate a response curve closer to the thermal performance curve. Similarly, in (d), phenological observations are derived from remote sensing data, allowing to estimate the spatiotemporal variability of the performance curve caused by e.g. local adaptation (green surface on d). It is also important to note that the spatiotemporal accuracy of species' occurrence, presence-absence or abundance data collected from field observations need to be at least as high as the spatiotemporal resolution of the predictors used to fit the model to ensure robust model transferability (Manzoor et al., 2018). Optimizing environmental and biological monitoring for better data availability is hence key for the usefulness of remote sensing in SDMs (Bush et al., 2017). A promising development is the European research infrastructure for Long-Term Ecological Research (http://www.lter-europe.net/elter-esfri), which is being rolled out during the coming years to provide the combined *in situ* data needed for future SDM improvements (Haase et al., 2018; Mirtl et al., 2018).

Direct detection and sampling of species and their traits

The direct detection of species using full-range (400-2500 nm) spectroscopic data (Féret and Asner, 2014) is becoming increasingly accurate, notably for trees but also for smaller organisms such as bryophytes (Skowronek et al., 2017). However, the spatial resolution of data collection remains critical and successful detection will likely remain limited to certain lifeforms and groups of species in the near future. Beyond the detection of species, new possibilities are also emerging for capturing plant functional types using spectroscopy (Ustin and Gamon, 2010). Accurately mapping of some functional traits such as canopy traits (Asner and Martin, 2009; Singh et al., 2015) and changes in other plant traits (Jetz et al., 2016; Schneider et al., 2017) is now also possible. Direct species detection and the link of spectra to the tree of life (Cavender-Bares et al., 2017) can equally be achieved by using a combination of high spatial and high spectral resolution. Spectra from leaves (Cavender-Bares et al., 2016; Deacon et al., 2017) can be used with high accuracy to differentiate populations within a species and to separate hybrids from parental species. Partial Least Squares Regression methods applied to spectral profiles differentiate species with higher accuracy than genotypes and clades with higher accuracy than species (Cavender-Bares et al., 2016). In some cases, with 1 m^2 spatial resolution remote sensing allows differentiation of different genotypes of poplar clones (Madritch et al., 2014). Tree canopies are likely to be well distinguished if functional information on morphology and physiology at species level are available (Torabzadeh et al., 2019). In recent years, the use of remote sensing has enabled great advances in both functional as well as scaling-based approaches (Gamon et al., 2019; Malenovský et al., 2019). In forests where species groups are well characterized and occur in clumps, species distributions can be fairly readily mapped using satellite derived data (Chastain and Townsend, 2007). Many living resources exist that contain geolocated and botanically identified trees for developing spectral libraries for tree canopies.

UAVs or drones are mainly used to capture data with limited spectral resolution, to acquire thermal data, or to produce very high-resolution digital elevation models by means of stereophotogrammetry (Coops et al., 2019). UAVs can notably serve to overcome the issue of partially missing spectral resolution with high-density time series (Böhler et al., 2019). Multi-View Stereo analysis (Furukawa and Ponce, 2010) and Structure-from-Motion (Westoby et al., 2012) algorithms are increasingly used as they make it possible to estimate three-dimensional structures from partly overlapping image sequences. These approaches are very useful to analyze forest and vegetation structures (Webster et al., 2018) and also to model marine environments including the complex structure of coral reefs (Ferrari et al., 2016), a domain of particular interest in the current period of intense coral bleaching (Walsworth et al., 2019).

Another function is the collection of animal occurrences to calibrate SDMs with presence only or presence/absence data. Van Gemert et al. (2015) evaluated how animal detection and animal counting could be implemented on the basis of a combination of images acquired by drones and state-of-the-art object recognition methods. Most of the time, such images are used to carry out surveys and to count animals in a management or conservation projects (Hodgson et al., 2018; Koh and Wich, 2012). However, as all UAVs are equipped with a GPS device, the exact location of investigated individuals can also be retrieved from precisely georeferenced image data. The main challenge is related to the detection and recognition of the correct species by means of machine learning algorithms (Kellenberger et al., 2018; Ofli et al., 2016; Rey et al., 2017). Beyond this step, the generation of presence/absence of a single taxon is straightforward. This is a component included in the concept of Next Generation Species Distribution Models proposed by He et al. (2015).

Improving integrated and dynamic range models

Demographic processes and demographic data are increasingly integrated into models of the spatiotemporal dynamics of species' ranges. This results from the realization that considering dynamic aspects is important and potentially markedly improves the quantification of ecological niches, the process-based understanding of range dynamics, and the forecasting of species responses to environmental change (Pagel and Schurr, 2012). This is because commonly-used static SDMs ignore spatial population dynamics, which can cause mismatches between species niches and species distributions (Holt, 2009; Pellissier et al., 2013). The data needed to parameterize dynamic range models can be obtained from demographic field measurements and small-scale experiments. However, small-scale environmental responses are not necessarily transferable to the spatial and temporal scales of dynamic range models. In this context, time series of multi-spectral, imaging spectroscopy, and LiDAR data (Fig. 3(a)) can help to quantify changes in the environment of the focal and modeled species such as changes of suitable vegetation (Strecha et al., 2012; Fig. 3(b)) or 3D structures such as buildings or tree canopy height (e.g. Droz et al., 2019; Fig. 3(b)). Knowledge of suitable areas for, and population size of, animals in large wildlife reserves helps park rangers and managers in their efforts to protect endangered species (Guisan et al., 2013). However, correlative SDMs rely on the assumptions that species location data used for modeling are representative of a species' true distribution and that observed species distributions are in equilibrium with environmental factors that limit those distributions. To better support conservation practice, conservation biogeography should thus favor dynamic range models and metapopulation dynamics rather than correlative SDMs. However, the more detailed information needed for dynamic range models (e.g. manual animal censuses) is expensive and sometimes potentially dangerous to collect. Hence, UAVs with consumer level digital cameras are becoming a popular alternative tool to estimate populations of large mammals (Fig. 3(a); Kellenberger et al., 2018). Furthermore, such data allow the modeling of metapopulation dynamics (Fernández et al., 2016) and species migration in order to understand the ability of a species to occupy suitable habitat in new locations. At the same time, movements of species can be linked to landscape disturbance and succession also obtained by remote sensing and models of habitat suitability (Fig. 3(b); Franklin, 2010).

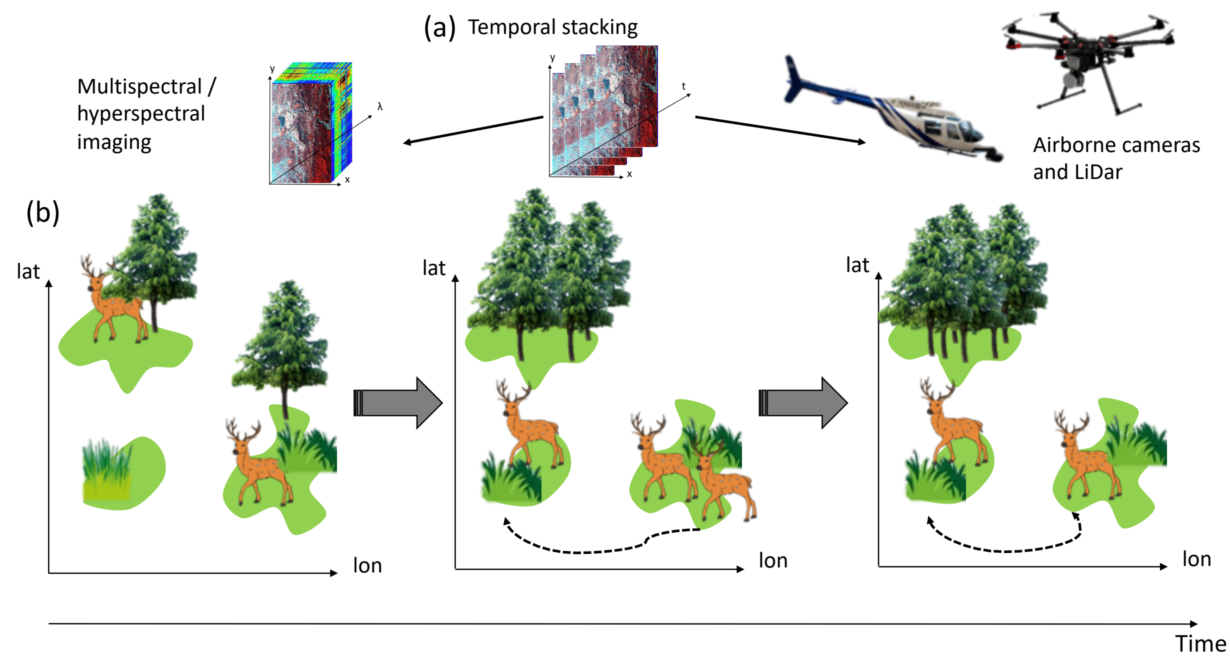

Fig. 3. Acquisition of demographic parameters for dynamic range models with time series of multispectral and / or imaging spectroscopy and airborne laser scanning data (a). The combination of such data allows to track movements of animals in suitable habitats.

Predicting belowground processes, disease and biotic interactions

Valuable information on belowground processes, disease, and biotic interactions can be obtained from imaging spectroscopy data. Carbon-based defense traits can be retrieved from spectral information (Couture et al., 2016), facilitating integration of information on host-specific herbivores and pathogens with leaf chemical composition. Variation in biomass and leaf chemistry, including condensed tannins, lignin, and nitrogen should be linked to the chemistry of below-ground root exudation and to litter chemistry and litter abundance (Cavender-Bares et al., 2017). These inputs from aboveground vegetation to soil influence substrates available as food for soil organisms, the activity of enzymes secreted by soil microorganisms, and thus decomposition and nutrient cycling (Madritch et al., 2014), which are all important for species distribution. An example of the use of imaging spectroscopy in the context of biotic interactions is that of the detection of declines in hemlock (*Tsuga canadensis*) stands in the eastern United States due to invasion of the exotic woolly adelgid (*Adelges tsugae*) (Hanavan et al., 2015). Recent work has also shown that a combination of imaging sepctroscopy and thermal data can be used to diagnose *Xylella fastidiosa* plants that are visually asymptomatic (Zarco-Tejada et al., 2018), and that airborne imaging spectroscopy can be used to track the spread of invasive submerged aquatic vegetation at high spatial resolution (Santos et al., 2016). These examples, and others from the early detection of moss species (Skowronek et al., 2017) and the assessment of ecosystem processes in forests (Ewald et al., 2018) illustrate the high potential of leveraging the rich information content of imaging spectroscopy data, for the description of biotic environments in SDMs.

4. Conclusions

In their review, He et al. (2015) discussed the importance of remote sensing data for the development of new predictor variables and the next generation of SDMs, which will include spatially explicit values of uncertainty. Here we argue that an additional value of remote sensing data lies in their temporal coverage (see section 3, paragraph and Fig. 2), which could overcome the inability of current temporally-aggregated variables to reflect the intensity or the frequency of biophysical processes and contribute to fulfilling all requirements across variables (Fig. 1). Taking advantage of long-term time series of remote sensing data to extract (absolute) extremes as well as frequencies and improve both these variables and the models in which they are used would be an avenue to explore through formal evaluation and model improvement (e.g. Zimmermann et al., 2009).

Temporal stacking of available time series (see section 3, paragraph and Fig. 2) can also be performed to better capture the realized niche of species, their actual rather than potential distributions, and increase the transferability of SDMs. In this context, evidence exists that building the niche as an ensemble through time allows a better understanding and forecasting of species' ranges under changing environmental conditions (Maiorano et al., 2013). To support this, airborne or satellite sensors can deliver a large amount of observations pertaining to the response variable at a very high spatiotemporal resolution for both animal and plant organisms (e.g. drone multispectral images, LiDAR or high-resolution satellite data). Temporal stacking thus further allows tracking population dynamics and dispersal, which are both key variables to build hybrid and process-based models such as dynamic range models. Such observations can then be transformed from occurrences to abundance. Ultimately, gathering a large amount of data to build models should allow correlative SDMs to better estimate the true response curves along environmental gradients.

Over the last decade, several studies have questioned the ability of SDMs to predict the persistence of species when these models are projected into warming conditions. Indeed, some species may be able to escape the negative effects of climate warming by moving into or persisting in microrefugia with unusual and stable climates conditions (Ashcroft and Gollan, 2013), or by adapting to new conditions. In all these cases, remotely sensed data of high spatial resolution could be used in SDMs to better capture microclimatic conditions (e.g., soil humidity, surface and air temperature). However, important challenges remain in determining to which extent microclimate detected by remote sensing can be scaled and coupled to climate change projections from broader scale Earth system models. Indeed, models such as regional climate models provide values and anomalies of e.g. 2 m air temperature, precipitations and cloudiness and it remains to be tested whether relationships between microclimate detected by remote sensing and climate from e.g. regional climate models can be described statistically and later projected into a future climate. However, remote sensing products could be used to bias-correct Regional Climate Modes and Global Climate Models outputs (e.g. as done in Lange, 2019).

Land cover has been identified as one of the thirteen terrestrial ECVs because of its feedbacks on climate through the modification of water and energy exchanges with the atmosphere. Land use and land-use change, assessed from the local to the global scale, are typically more difficult to map and in many cases cannot be remotely sensed. As a consequence, spatially-explicit data

of land use are less available and land-use changes, variability, and intensity are often neglected in SDMs, despite their potentially critical importance for species distributions. Despite recent progress to develop indicators of changes in management and land-use intensity obtained from remote sensing, online access to spatially explicit data of land use can be improved.
This is particularly critical to identify the contribution of land use in SDMs applied as explanatory tools or to improve the accuracy of projections of SDMs integrated in monitoring programs.

In situ monitoring, modeling, and remote sensing

Although developments of remote sensing and SDM techniques have occasionally intersected over the last 30 years, combining these two fields better has great potential for future scientific progress. In line with Franklin and colleagues (Franklin et al., 2016) and others, we advocate a closer integration of remote sensing in the monitoring and modeling of species and ecosystems to better understand and predict current and future impacts of global change drivers on biodiversity (Fernandez et al., 2019). We stress that models should serve the same fundamental role in ecological monitoring as in any other scientific activity; that is, both the *a priori* guiding of monitoring designs, and the *a posteriori* guiding of data analyses. Essential elements of the monitoring design are management actions, replicated spatial climatic gradients, as well as temporal resolution and extents that capture both fast and slow processes. Ecosystem-based monitoring should be dynamic and adaptive in the sense that models and monitoring designs are iteratively improved by new empirical results, new technologies and the evolving needs of stakeholders (Ims and Yoccoz, 2017; Fig. 4). Once conceptual models (Fig. 4(a)) and appropriate monitoring designs (Fig. 4(b)) have been built, field data can be collected (Fig. 4(c)) for tracking the trajectories of individual species or the entire ecosystems. In this context, SDMs can serve as tools to identify the main drivers of changes or to project the fate of species or ecosystems (by e.g. stacked SDMs; Calabrese et al., 2014; Guisan and Rahbek, 2011; Fig. 4(d)). Finally, new field monitoring can later validate projections of SDMs and the robustness of conceptual models

(Fig. 4(e)). Here, remote sensing data can strongly contribute to adaptive monitoring programs by providing simultaneously additional data that complement field monitoring and observations for the validation of SDM projections in-between two field campaigns that are often expensive in terms of time and money.

A better integration of *in situ* and remote sensing observations through SDMs will also contribute to devise monitoring systems capable to provide consistent biodiversity data for addressing conservation targets in multi-scale policy contexts ranging from subnational to national and global. A major area of application is the production of data informing on EBVs for species populations, which typically require interpolation and extrapolation models with the view of obtaining continuous and temporally consistent probabilistic species occurrence data from sparsely-distributed observations. These model-derived data are critical for deriving consistent and scalable biodiversity change indicators that can accommodate the reporting needs of multiple management programs and policy targets (Jetz et al., 2019; Navarro et al., 2017).

The SDGs are one of the key global frameworks for addressing the environmental challenges of the Anthropocene. From a biodiversity perspective, to safeguard life below water (SDG 14) and life on land (SDG 15) it is crucial to characterize and understand current species distributions and how these may change under future land use and climate scenarios. SDMs make an essential contribution to providing this information but have several important limitations that can compromise their accuracy and hence the effectiveness of resulting conservation interventions and environmental policy. We suggest that, together with novel methodological applications such as the temporal image stacking, currently available and upcoming remote sensing data can alleviate or resolve many of the data gaps that constrain SDMs. However, there is the risk that non-specialists may unintentionally misinterpret remote sensing data, and that key data requirements for SDMs are not fully appreciated. We argue that greater collaboration between the two communities by developing jointly data platforms with standardized metadata and documentation will be a key step in achieving the full potential of remote sensing data and products for SDMs, thereby supporting more effective conservation monitoring, management, and policy decisions for a sustainable future.

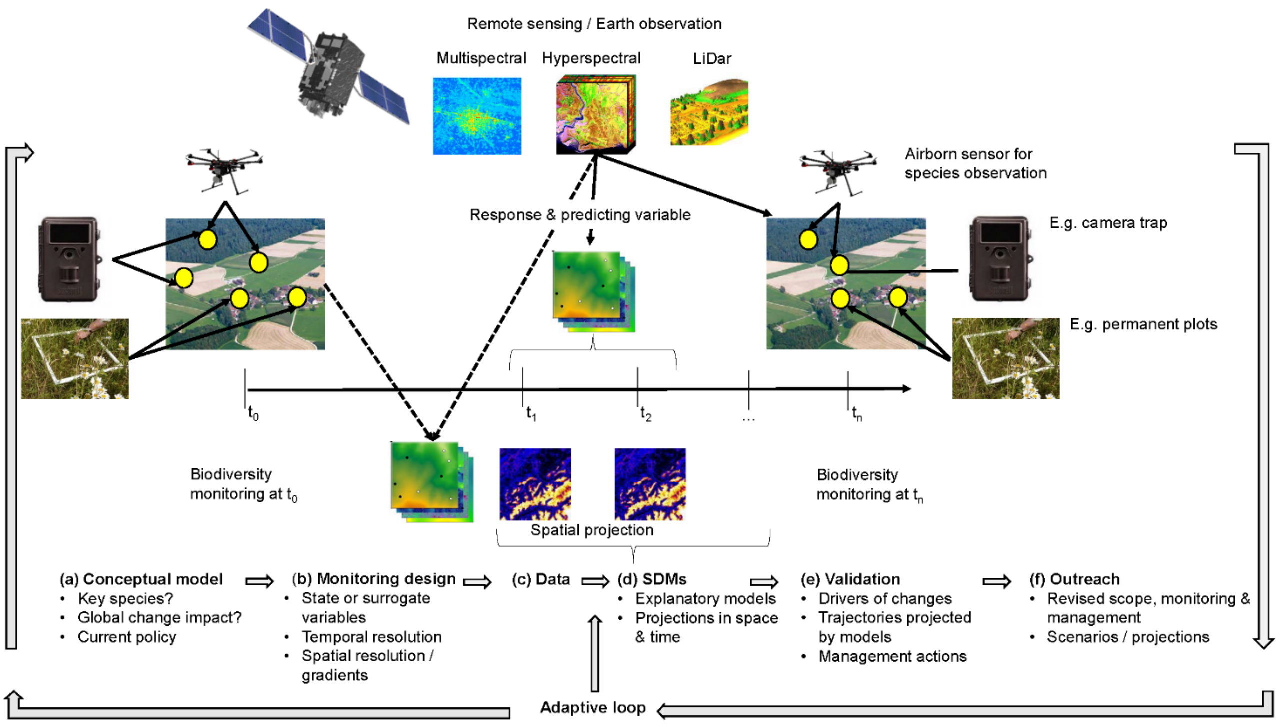

Fig. 4. An ideal loop of adaptive monitoring in which remote sensing data and SDMs are combined (adapted from Ims and Yoccoz, 2017).

5. Acknowledgements

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BOX 1 | Species Distribution Models

Two categories of SDMs can be distinguished: statistical (or statistical learning *sensu* Drake 2014) and process-based models. Statistical SDMs (*sensu* Franklin 2010 also called habitat suitability models *sensu* Guisan et al. 2017) are methods that relate field observations or museum specimens (e.g. occurrences, abundances, or species' traits) to environmental predictor variables. In such models, processes are empirically inferred from a combination of statistically or theoretically derived response curves (Guisan et al. 2017). In contrast, process-based models build upon explicit causal relationships determined experimentally. In these models, processes such as phenology and distribution are explicitly described (see Chuine and Régnière, 2017), which increases the confidence in extrapolating beyond the known spatiotemporal extent (Zurell et al., 2016). The continuum between these two modeling approaches includes hybrid (e.g. Dullinger et al., 2012), dynamic range (e.g. Cotto et al., 2017; Engler et al., 2012; Pagel and Schurr, 2012), and integrated models (Pagel and Schurr, 2012).

References

Aalto, J., Harrison, S., Luoto, M., 2017. Statistical modelling predicts almost complete loss of major periglacial processes in Northern Europe by 2100. Nat. Commun. 8, 515. https://doi.org/10.1038/s41467-017-00669-3

Alleaume, S., Dusseux, P., Thierion, V., Commagnac, L., Laventure, S., Lang, M., Féret, J.-B., Hubert-Moy, L., Luque, S., 2018. A generic remote sensing approach to derive operational essential biodiversity variables (EBVs) for conservation planning. Methods Ecol. Evol. 9, 1822–1836. https://doi.org/10.1111/2041-210X.13033

Araujo, M.B., Cabeza, M., Thuiller, W., Hannah, L., Williams, P.H., 2004. Would climate change drive species out of reserves? An assessment of existing reserve-selection methods. Glob. Chang. Biol. 10, 1618–1626. https://doi.org/10.1111/j.1365-2486.2004.00828.x

Ashcroft, M.B., Cavanagh, M., Eldridge, M.D.B., Gollan, J.R., 2014. Testing the ability of topoclimatic grids of extreme temperatures to explain the distribution of the endangered brush-tailed rock-wallaby (Petrogale penicillata). J. Biogeogr. 41, 1402–1413. https://doi.org/10.1111/jbi.12298

Ashcroft, M.B., Gollan, J.R., 2013. Moisture, thermal inertia, and the spatial distributions of near-surface soil and air temperatures: understanding factors that promote microrefugia. Agric. For. Meteorol. 176, 77–89. https://doi.org/10.1016/J.AGRFORMET.2013.03.008

Ashcroft, M.B., Gollan, J.R., 2011. Fine-resolution (25 m) topoclimatic grids of near-surface (5 cm) extreme temperatures and humidities across various habitats in a large (200 × 300 km) and diverse region. Int. J. Climatol. 32, n/a-n/a. https://doi.org/10.1002/joc.2428

Asner, G.P., Martin, R.E., 2009. Airborne spectranomics: mapping canopy chemical and taxonomic diversity in tropical forests. Front. Ecol. Environ. 7, 269–276. https://doi.org/10.1890/070152

Asner, G.P., Martin, R.E., Knapp, D.E., Tupayachi, R., Anderson, C.B., Sinca, F., Vaughn, N.R., Llactayo, W., 2017. Airborne laser-guided imaging spectroscopy to map forest trait diversity and guide conservation. Science (80-.). 355, 385–389. https://doi.org/10.1126/science.aaj1987

Auffret, A.G., Kimberley, A., Plue, J., Waldén, E., 2018. Super-regional land-use change and effects on the grassland specialist flora. Nat. Commun. 9, 3464. https://doi.org/10.1038/s41467-018-05991-y

Austin, M.., 2002. Spatial prediction of species distribution: an interface between ecological theory and statistical modelling. Ecol. Modell. 157, 101–118. https://doi.org/10.1016/S0304-3800(02)00205-3

Austin, M., 2007. Species distribution models and ecological theory: a critical assessment and some possible new approaches. Ecol. Modell. 200, 1–19. https://doi.org/10.1016/J.ECOLMODEL.2006.07.005

Austin, M.P., Gaywood, M.J., 1994. Current problems of environmental gradients and species response curves in relation to continuum theory. J. Veg. Sci. 5, 473–482. https://doi.org/10.2307/3235973

Austin, M.P., Smith, T.M., 1989. A new model for the continuum concept. Vegetatio 83, 35–47. https://doi.org/10.1007/BF00031679

Austin, M.P., Van Niel, K.P., 2011. Improving species distribution models for climate change studies: variable selection and scale. J. Biogeogr. 38, 1–8. https://doi.org/10.1111/j.1365-2699.2010.02416.x

Benítez-López, A., Santini, L., Schipper, A.M., Busana, M., Huijbregts, M.A.J., 2019. Intact but empty forests? Patterns of hunting-induced mammal defaunation in the tropics. PLOS Biol. 17, e3000247. https://doi.org/10.1371/journal.pbio.3000247

Bergen, K.M., Goetz, S.J., Dubayah, R.O., Henebry, G.M., Hunsaker, C.T., Imhoff, M.L., Nelson, R.F., Parker, G.G., Radeloff, V.C., 2009. Remote sensing of vegetation 3-D structure for biodiversity and habitat: review and implications for lidar and radar spaceborne missions. J. Geophys. Res. Biogeosciences 114, n/a-n/a. https://doi.org/10.1029/2008JG000883

Bertrand, R., Perez, V., Gégout, J.-C., 2012. Disregarding the edaphic dimension in species distribution models leads to the omission of crucial spatial information under climate change: the case of *Quercus pubescens* in France. Glob. Chang. Biol. 18, 2648–2660. https://doi.org/10.1111/j.1365-2486.2012.02679.x

Böhler, J.E., Schaepman, M.E., Kneubühler, M., 2019. Optimal timing assessment for crop separation using multispectral Unmanned Aerial Vehicle (UAV) data and textural features. Remote Sens. 11, 1780. https://doi.org/10.3390/rs11151780

Böhner, J., Antonić, O., 2009. Land-surface parameters specific to topo-climatology. Dev. Soil Sci. 33, 195–226. https://doi.org/10.1016/S0166-2481(08)00008-1

Bojinski, S., Verstraete, M., Peterson, T.C., Richter, C., Simmons, A., Zemp, M., Bojinski, S., Verstraete, M., Peterson, T.C., Richter, C., Simmons, A., Zemp, M., 2014. The concept of

Essential Climate Variables in support of climate research, applications, and policy. Bull. Am. Meteorol. Soc. 95, 1431–1443. https://doi.org/10.1175/BAMS-D-13-00047.1

Bolliger, J., Kienast, F., Soliva, R., Rutherford, G., 2007. Spatial sensitivity of species habitat patterns to scenarios of land use change (Switzerland). Landsc. Ecol. 22, 773–789. https://doi.org/10.1007/s10980-007-9077-7

Bolliger, J., Schmatz, D., Pazúr, R., Ostapowicz, K., Psomas, A., 2017. Reconstructing forest-cover change in the Swiss Alps between 1880 and 2010 using ensemble modelling. Reg. Environ. Chang. 17, 2265–2277. https://doi.org/10.1007/s10113-016-1090-4

Bookhagen, B., Strecker, M.R., 2008. Orographic barriers, high-resolution TRMM rainfall, and relief variations along the eastern Andes. Geophys. Res. Lett. 35, L06403. https://doi.org/10.1029/2007GL032011

Boulangeat, I., Georges, D., Dentant, C., Bonet, R., Es, J. Van, Abdulhak, S., Zimmermann, N.E., Thuiller, W., 2014. Anticipating the spatio-temporal response of plant diversity and vegetation structure to climate and land use change in a protected area 1230–1239. https://doi.org/10.1111/ecog.00694

Buri, A., Cianfrani, C., Pinto-Figueroa, E., Yashiro, E., Spangenberg, J.E., Adatte, T., Verrecchia, E., Guisan, A., Pradervand, J.-N., 2017. Soil factors improve predictions of plant species distribution in a mountain environment. Prog. Phys. Geogr. Earth Environ. 41, 703–722. https://doi.org/10.1177/0309133317738162

Bush, A., Sollmann, R., Wilting, A., Bohmann, K., Cole, B., Balzter, H., Martius, C., Zlinszky, A., Calvignac-Spencer, S., Cobbold, C.A., Dawson, T.P., Emerson, B.C., Ferrier, S., Gilbert, M.T.P., Herold, M., Jones, L., Leendertz, F.H., Matthews, L., Millington, J.D.A., Olson, J.R., Ovaskainen, O., Raffaelli, D., Reeve, R., Rödel, M.-O., Rodgers, T.W., Snape, S., Visseren-Hamakers, I., Vogler, A.P., White, P.C.L., Wooster, M.J., Yu, D.W., 2017. Connecting Earth observation to high-throughput biodiversity data. Nat. Ecol. Evol. 1, 0176. https://doi.org/10.1038/s41559-017-0176

Calabrese, J.M., Certain, G., Kraan, C., Dormann, C.F., 2014. Stacking species distribution models and adjusting bias by linking them to macroecological models. Glob. Ecol. Biogeogr. 23, 99–112. https://doi.org/10.1111/geb.12102

Cannone, N., Guglielmin, M., Convey, P., Worland, M.R., Favero Longo, S.E., 2016. Vascular plant changes in extreme environments: effects of multiple drivers. Clim. Change 134, 651–665. https://doi.org/10.1007/s10584-015-1551-7

Cavender-Bares, J., Gamon, J.A., Hobbie, S.E., Madritch, M.D., Meireles, J.E., Schweiger, A.K., Townsend, P.A., 2017. Harnessing plant spectra to integrate the biodiversity sciences across biological and spatial scales. Am. J. Bot. 104, 966–969. https://doi.org/10.3732/ajb.1700061

Cavender-Bares, J., Meireles, J., Couture, J., Kaproth, M., Kingdon, C., Singh, A., Serbin, S., Center, A., Zuniga, E., Pilz, G., Townsend, P., Cavender-Bares, J., Meireles, J.E., Couture, J.J., Kaproth, M.A., Kingdon, C.C., Singh, A., Serbin, S.P., Center, A., Zuniga, E., Pilz, G., Townsend, P.A., 2016. Associations of leaf spectra with genetic and phylogenetic variation in oaks: prospects for remote detection of biodiversity. Remote Sens. 8, 221. https://doi.org/10.3390/rs8030221

Ceballos, G., Ehrlich, P.R., Dirzo, R., 2017. Biological annihilation via the ongoing sixth mass extinction signaled by vertebrate population losses and declines. Proc. Natl. Acad. Sci. U. S. A. 114, E6089–E6096. https://doi.org/10.1073/pnas.1704949114

Chastain, R. a., Townsend, P. a., 2007. Use of Landsat ETM and topographic data to characterize evergreen understory communities in appalachian deciduous forests. Photogramm. Eng. Remote Sens. 73, 563–575. https://doi.org/10.14358/PERS.73.5.563

Chaudhary, A., Kastner, T., 2016. Land use biodiversity impacts embodied in international food trade. Glob. Environ. Chang. 38, 195–204. https://doi.org/10.1016/j.gloenvcha.2016.03.013

Chaudhary, S., McGregor, A., Houston, D., Chettri, N., 2015. The evolution of ecosystem services: A time series and discourse-centered analysis. Environ. Sci. Policy 54, 25–34. https://doi.org/10.1016/j.envsci.2015.04.025

Chen, I.-C., Hill, J.K., Ohlemüller, R., Roy, D.B., Thomas, C.D., 2011. Rapid range shifts of species associated with high levels of climate warming. Science 333, 1024–6. https://doi.org/10.1126/science.1206432

Chuine, I., Beaubien, E.G., 2001. Phenology is a major determinant of tree species range. Ecol. Lett. 4, 500–510. https://doi.org/10.1046/j.1461-0248.2001.00261.x

Chuine, I., Régnière, J., 2017. Process-based models of phenology for plants and a nimals. Annu. Rev. Ecol. Evol. Syst. 48, 159–182. https://doi.org/10.1146/annurev-ecolsys-110316-022706

Cianfrani, C., Broennimann, O., Loy, A., Guisan, A., 2018. More than range exposure: global otter vulnerability to climate change. Biol. Conserv. 221, 103–113. https://doi.org/10.1016/J.BIOCON.2018.02.031

Cianfrani, C., Satizábal, H.F., Randin, C., 2015. A spatial modelling framework for assessing climate change impacts on freshwater ecosystems: response of brown trout (Salmo trutta L.) biomass to warming water temperature. Ecol. Modell. 313, 1–12. https://doi.org/10.1016/J.ECOLMODEL.2015.06.023

Connell, J., Watson, S.J., Taylor, R.S., Avitabile, S.C., Clarke, R.H., Bennett, A.F., Clarke, M.F., Manorina, M., 2017. Testing the effects of a century of fires : Requirements for fire succession predict the distribution of threatened bird species 1078–1089. https://doi.org/10.1111/ddi.12597

Connor, T., Hull, V., Viña, A., Shortridge, A., Tang, Y., Zhang, J., Wang, F., Liu, J., 2018. Effects of grain size and niche breadth on species distribution modeling. Ecography (Cop.). 41, 1270–1282. https://doi.org/10.1111/ecog.03416

Coops, N.C., Goodbody, T.R.H., Cao, L., 2019. Four steps to extend drone use in research. Nature 572, 433–435. https://doi.org/10.1038/d41586-019-02474-y

Coops, N.C., Waring, R.H., Plowright, A., Lee, J., Dilts, T.E., 2016. Using remotely-sensed land cover and distribution modeling to estimate tree species migration in the Pacific Northwest region of North America. Remote Sens. 8. https://doi.org/10.14288/1.0378973

Cord, A.F., Dech, S., Klein, D., Dech, S., 2010. Remote sensing time series for modeling invasive species distribution: a case study of Tamarix spp. in the US and Mexico. Proc. Int. Congr. Environ. Model. Softw. Model. Environ. Sake 5th Bienni.

Cotto, O., Wessely, J., Georges, D., Klonner, G., Schmid, M., Dullinger, S., Thuiller, W., Guillaume, F., 2017. A dynamic eco-evolutionary model predicts slow response of alpine plants to climate warming. Nat. Commun. 8, 15399. https://doi.org/10.1038/ncomms15399

Coudun, C., Gégout, J.-C., Piedallu, C., Rameau, J.-C., 2006. Soil nutritional factors improve models of plant species distribution: an illustration with Acer campestre (L.) in France. J. Biogeogr. 33, 1750–1763. https://doi.org/10.1111/j.1365-2699.2005.01443.x

Couture, J.J., Singh, A., Rubert-Nason, K.F., Serbin, S.P., Lindroth, R.L., Townsend, P.A., 2016. Spectroscopic determination of ecologically relevant plant secondary metabolites. Methods Ecol. Evol. 7, 1402–1412. https://doi.org/10.1111/2041-210X.12596

Daly, C., 2006. Guidelines for assessing the suitability of spatial climate data sets. Int. J. Climatol. 26, 707–721. https://doi.org/10.1002/joc.1322

de Jong, R., Verbesselt, J., Zeileis, A., Schaepman, M., de Jong, R., Verbesselt, J., Zeileis, A., Schaepman, M.E., 2013. Shifts in global vegetation activity trends. Remote Sens. 5, 1117–1133. https://doi.org/10.3390/rs5031117

Deacon, N.J., Grossman, J.J., Schweiger, A.K., Armour, I., Cavender-Bares, J., 2017. Genetic, morphological, and spectral characterization of relictual Niobrara River hybrid aspens (*Populus* × *smithii*). Am. J. Bot. 104, 1878–1890. https://doi.org/10.3732/ajb.1700268

Deblauwe, V., Droissart, V., Bose, R., Sonké, B., Blach-Overgaard, A., Svenning, J.-C., Wieringa, J.J., Ramesh, B.R., Stévart, T., Couvreur, T.L.P., 2016. Remotely sensed temperature and precipitation data improve species distribution modelling in the tropics. Glob. Ecol. Biogeogr. 25, 443–454. https://doi.org/10.1111/geb.12426

Dirnböck, T., Dullinger, S., Grabherr, G., 2003. A regional impact assessment of climate and land-use change on alpine vegetation. J. Biogeogr. 30, 401–417. https://doi.org/10.1046/j.1365-2699.2003.00839.x

Dirzo, R., Young, H.S., Galetti, M., Ceballos, G., Isaac, N.J.B., Collen, B., 2014. Defaunation in the Anthropocene. Science (80-.). 345, 401–6. https://doi.org/10.1126/science.1251817

Dormann, C.F., Schymanski, S.J., Cabral, J., Chuine, I., Graham, C., Hartig, F., Kearney, M., Morin, X., Römermann, C., Schröder, B., Singer, A., 2012. Correlation and process in species distribution models: bridging a dichotomy. J. Biogeogr. 39, 2119–2131. https://doi.org/10.1111/j.1365-2699.2011.02659.x

Droz, B., Arnoux, R., Bohnenstengel, T., Laesser, J., Spaar, R., Ayé, R., Randin, C.F., 2019. Moderately urbanized areas as a conservation opportunity for an endangered songbird. Landsc. Urban Plan. 181, 1–9. https://doi.org/10.1016/J.LANDURBPLAN.2018.09.011

Dubuis, A., Giovanettina, S., Pellissier, L., Pottier, J., Vittoz, P., Guisan, A., 2013. Improving the prediction of plant species distribution and community composition by adding edaphic to topo-climatic variables. J. Veg. Sci. 24, 593–606. https://doi.org/10.1111/jvs.12002

Dullinger, S., Gattringer, A., Thuiller, W., Moser, D., Zimmermann, N.E., Guisan, A., Willner, W., Plutzar, C., Leitner, M., Mang, T., Caccianiga, M., Dirnböck, T., Ertl, S., Fischer, A., Lenoir, J., Svenning, J.-C., Psomas, A., Schmatz, D.R., Silc, U., Vittoz, P., Hülber, K., 2012. Extinction debt of high-mountain plants under twenty-first-century climate change. Nat. Clim. Chang. 2, 619–622. https://doi.org/10.1038/nclimate1514

Eckert, S., Kiteme, B., Njuguna, E., Zaehringer, J., Eckert, S., Kiteme, B., Njuguna, E., Zaehringer, J.G., 2017. Agriculturaliexpansion and intensification in the foothills of Mount Kenya: a landscape perspective. Remote Sens. 9, 784. https://doi.org/10.3390/rs9080784

Ellis, E.C., 2015. Ecology in an anthropogenic biosphere. Ecol. Monogr. 85, 287–331. https://doi.org/10.1890/14-2274.1

Ellis, E.C., 2011. Anthropogenic transformation of the terrestrial biosphere. Philos. Trans. R. Soc. A Math. Phys. Eng. Sci. 369, 1010–1035. https://doi.org/10.1098/rsta.2010.0331

Engler, R., Hordijk, W., Guisan, A., 2012. The MIGCLIM R package - seamless integration of dispersal constraints into projections of species distribution models. Ecography (Cop.). 35, 872–878. https://doi.org/10.1111/j.1600-0587.2012.07608.x

Engstrom, R., Hope, A., Kwon, H., Stow, D., Zamolodchikov, D., 2005. Spatial distribution of near surface soil moisture and its relationship to microtopography in the Alaskan Arctic coastal plain. Hydrol. Res. 36, 219–234. https://doi.org/10.2166/nh.2005.0016

Esselman, P.C., Allan, J.D., 2011. Application of species distribution models and conservation planning software to the design of a reserve network for the riverine fishes of northeastern Mesoamerica. Freshw. Biol. 56, 71–88. https://doi.org/10.1111/j.1365-2427.2010.02417.x

Estel, S., Mader, S., Levers, C., Verburg, P.H., Baumann, M., Kuemmerle, T., 2018. Combining satellite data and agricultural statistics to map grassland management intensity in Europe. Environ. Res. Lett. 13, 074020. https://doi.org/10.1088/1748-9326/aacc7a

Estrada-Peña, A., Alexander, N., Wint, G.R.W., 2016. Perspectives on modelling the distribution of ticks for large areas: so far so good? Parasit. Vectors 9, 179. https://doi.org/10.1186/s13071-016-1474-9

Ewald, M., Aerts, R., Lenoir, J., Fassnacht, F.E., Nicolas, M., Skowronek, S., Piat, J., Honnay, O., Garzón-López, C.X., Feilhauer, H., Van De Kerchove, R., Somers, B., Hattab, T., Rocchini, D., Schmidtlein, S., 2018. LiDAR derived forest structure data improves predictions of canopy N and P concentrations from imaging spectroscopy. Remote Sens. Environ. 211, 13–25. https://doi.org/10.1016/J.RSE.2018.03.038

Fagan, M.E., Morton, D.C., Cook, B.D., Masek, J., Zhao, F., Nelson, R.F., Huang, C., 2018. Mapping pine plantations in the southeastern U.S. using structural, spectral, and temporal remote sensing data. Remote Sens. Environ. 216, 415–426. https://doi.org/10.1016/J.RSE.2018.07.007

Fang, L., Hain, C.R., Zhan, X., Anderson, M.C., 2016. An inter-comparison of soil moisture data products from satellite remote sensing and a land surface model. Int. J. Appl. Earth Obs. Geoinf. 48, 37–50. https://doi.org/10.1016/J.JAG.2015.10.006

Fawcett, D., Verhoef, W., Schläpfer, D., Schneider, F.D., Schaepman, M.E., Damm, A., 2018. Advancing retrievals of surface reflectance and vegetation indices over forest ecosystems by combining imaging spectroscopy, digital object models, and 3D canopy modelling. Remote Sens. Environ. 204, 583–595. https://doi.org/10.1016/J.RSE.2017.09.040

Feilhauer, H., Schmidtlein, S., 2009. Mapping continuous fields of forest alpha and beta diversity. Appl. Veg. Sci. 12, 429–439. https://doi.org/10.1111/j.1654-109X.2009.01037.x

Féret, J.-B., Asner, G.P., 2014. Mapping tropical forest canopy diversity using high-fidelity imaging spectroscopy. Ecol. Appl. 24, 1289–1296. https://doi.org/10.1890/13-1824.1

Fernandez, N., Ferrier, S., Navarro, L.M., Pereira, H.M., 2019. Essential Biodiversity Variables: integrating in-situ observations and remote sensing through modelling, in: Cavender-Bares, J., Gamon, J.A., Towsend, P.A. (Eds.), Remote Sensing of Vegetation. Springer.

Fernández, N., Román, J., Delibes, M., 2016. Variability in primary productivity determines metapopulation dynamics. Proc. R. Soc. B Biol. Sci. 283, 20152998. https://doi.org/10.1098/rspb.2015.2998

Ferrari, R., McKinnon, D., He, H., Smith, R., Corke, P., González-Rivero, M., Mumby, P., Upcroft, B., 2016. Quantifying multiscale habitat structural complexity: a cost-effective framework for underwater 3D modelling. Remote Sens. 8, 113. https://doi.org/10.3390/rs8020113

Fisk, M.C., Schmidt, S.K., Seastedt, T.R., 1998. Topographic pattersn of above- and belowground production and nitrogen cycling in alpine tundra. Ecology 79, 2253–2266. https://doi.org/10.1890/0012-9658(1998)079[2253:TPOAAB]2.0.CO;2

Foody, G.M., 1999. Applications of the self-organising feature map neural network in community data analysis. Ecol. Modell. 120, 97–107. https://doi.org/10.1016/S0304-3800(99)00094-0

Franke, J., Keuck, V., Siegert, F., 2012. Assessment of grassland use intensity by remote sensing to support conservation schemes. J. Nat. Conserv. 20, 125–134. https://doi.org/10.1016/J.JNC.2012.02.001

Franklin, J., 2010. Moving beyond static species distribution models in support of conservation biogeography. Divers. Distrib. 16, 321–330. https://doi.org/10.1111/j.1472-4642.2010.00641.x

Franklin, J., 1995. Predictive vegetation mapping: Geographic modelling of biospatial patterns in relation to environmental gradients. Prog. Phys. Geogr. 19, 474–499. https://doi.org/10.1177/030913339501900403

Franklin, J., Regan, H.M., Syphard, A.D., 2014. Linking spatially explicit species distribution and population models to plan for the persistence of plant. Environ. Conserv. 41, 97–109. https://doi.org/10.1017/S0376892913000453

Franklin, J., Serra-Diaz, J.M., Syphard, A.D., Regan, H.M., 2016. Global change and terrestrial plant community dynamics. Proc. Natl. Acad. Sci. U. S. A. 113, 3725–3734. https://doi.org/10.1073/pnas.1519911113

Frost, G. V, Epstein, H.E., Walker, D.A., Matyshak, G., Ermokhina, K., 2013. Patterned-ground facilitates shrub expansion in Low Arctic tundra. Environ. Res. Lett. 8, 015035. https://doi.org/10.1088/1748-9326/8/1/015035

Fuller, R.M., Groom, G.B., Jones, A.R., 1994. The Land Cover Map of Great Britain: An Automated Classification of Landsat Thematic Mapper Data. Photogramm. Eng. Remote Sens. 60, 553–562. https://doi.org/10.1016/j.jmarsys.2011.11.027

Furukawa, Y., Ponce, J., 2010. Accurate, dense, and robust multiview stereopsis. IEEE Trans. Pattern Anal. Mach. Intell. 32, 1362–1376. https://doi.org/10.1109/TPAMI.2009.161

Gamon, J.A., Somers, B., Malenovský, Z., Middleton, E.M., Rascher, U., Schaepman, M.E., 2019. Assessing vegetation function with imaging spectroscopy. Surv. Geophys. 40, 489–513. https://doi.org/10.1007/s10712-019-09511-5

Garonna, I., de Jong, R., Stöckli, R., Schmid, B., Schenkel, D., Schimel, D., Schaepman, M.E., 2018. Shifting relative importance of climatic constraints on land surface phenology. Environ. Res. Lett. 13, 024025. https://doi.org/10.1088/1748-9326/aaa17b

Gastón, A., Ciudad, C., Mateo-Sánchez, M.C., García-Viñas, J.I., López-Leiva, C., Fernández-Landa, A., Marchamalo, M., Cuevas, J., de la Fuente, B., Fortin, M.-J., Saura, S., 2017. Species' habitat use inferred from environmental variables at multiple scales: How much we gain from high-resolution vegetation data? Int. J. Appl. Earth Obs. Geoinf. 55, 1–8. https://doi.org/10.1016/J.JAG.2016.10.007

George, A.D., Thompson, F.R., Faaborg, J., 2015. Using LiDAR and remote microclimate loggers to downscale near-surface air temperatures for site-level studies. Remote Sens. Lett. 6, 924–932. https://doi.org/10.1080/2150704X.2015.1088671

Ginzler, C., Hobi, M., 2015. Countrywide stereo-image matching for updating digital surface models in the framework of the Swiss national forest inventory. Remote Sens. 7, 4343–4370. https://doi.org/10.3390/rs70404343

Gómez Giménez, M., de Jong, R., Della Peruta, R., Keller, A., Schaepman, M.E., 2017. Determination of grassland use intensity based on multi-temporal remote sensing data and ecological indicators. Remote Sens. Environ. 198, 126–139. https://doi.org/10.1016/J.RSE.2017.06.003

Gooseff, M.N., Barrett, J.E., Doran, P.T., Fountain, A.G., Lyons, W.B., Parsons, A.N., Porazinska, D.L., Virginia, R.A., Wall, D.H., 2003. Snow-patch influence on soil biogeochemical processes and invertebrate distribution in the McMurdo Dry Valleys, Antarctica. Arctic, Antarct. Alp. Res. 35, 91–99. https://doi.org/10.1657/1523-0430(2003)035[0091:SPIOSB]2.0.CO;2

Graf, R.F., Mathys, L., Bollmann, K., 2009. Habitat assessment for forest dwelling species using LiDAR remote sensing: Capercaillie in the Alps. For. Ecol. Manage. 257, 160–167. https://doi.org/10.1016/J.FORECO.2008.08.021

Guisan, A., Rahbek, C., 2011. SESAM - a new framework integrating macroecological and species distribution models for predicting spatio-temporal patterns of species assemblages. J. Biogeogr. 38, 1433–1444. https://doi.org/10.1111/j.1365-2699.2011.02550.x

Guisan, A., Thuiller, W., 2005. Predicting species distribution: offering more than simple habitat models. Ecol. Lett. 8, 993–1009. https://doi.org/10.1111/j.1461-0248.2005.00792.x

Guisan, A., Tingley, R., Baumgartner, J.B., Naujokaitis-Lewis, I., Sutcliffe, P.R., Tulloch, A.I.T., Regan, T.J., Brotons, L., McDonald-Madden, E., Mantyka-Pringle, C., Martin, T.G., Rhodes, J.R., Maggini, R., Setterfield, S.A., Elith, J., Schwartz, M.W., Wintle, B.A., Broennimann, O., Austin, M., Ferrier, S., Kearney, M.R., Possingham, H.P., Buckley, Y.M., 2013. Predicting species distributions for conservation decisions. Ecol. Lett. 16, 1424–1435. https://doi.org/10.1111/ele.12189

Guisan, A., Zimmermann, N.E., 2000. Predictive habitat distribution models in ecology. Ecol. Modell. 135, 147–186. https://doi.org/10.1016/S0304-3800(00)00354-9

Haase, P., Tonkin, J.D., Stoll, S., Burkhard, B., Frenzel, M., Geijzendorffer, I.R., Häuser, C., Klotz, S., Kühn, I., McDowell, W.H., Mirtl, M., Müller, F., Musche, M., Penner, J., Zacharias, S., Schmeller, D.S., 2018. The next generation of site-based long-term ecological monitoring: linking essential biodiversity variables and ecosystem integrity. Sci. Total Environ. 613–614, 1376–1384. https://doi.org/10.1016/J.SCITOTENV.2017.08.111

Hanavan, R.P., Pontius, J., Hallett, R., 2015. A 10-year assessment of Hemlock decline in the Catskill mountain region of New York State using hyperspectral remote sensing techniques. J. Econ. Entomol. 108, 339–349. https://doi.org/10.1093/jee/tou015

Hancock, S., Anderson, K., Disney, M., Gaston, K.J., 2017. Measurement of fine-spatial-resolution 3D vegetation structure with airborne waveform lidar: calibration and validation with voxelised terrestrial lidar. Remote Sens. Environ. 188, 37–50. https://doi.org/10.1016/J.RSE.2016.10.041

Hansen, M.C., Potapov, P. V, Moore, R., Hancher, M., Turubanova, S. a, Tyukavina, A., Thau, D., Stehman, S. V, Goetz, S.J., Loveland, T.R., Kommareddy, A., Egorov, A., Chini, L., Justice, C.O., Townshend, J.R.G., 2013. High-resolution global maps of 21st-century forest cover change. Science (80-.). 850, 2011–2014. https://doi.org/10.1126/science.1244693

Hansen, M.C., Roy, D.P., Lindquist, E., Adusei, B., Justice, C.O., Altstatt, A., 2008. A method for integrating MODIS and Landsat data for systematic monitoring of forest cover and change in the Congo Basin. Remote Sens. Environ. 112, 2495–2513. https://doi.org/10.1016/J.RSE.2007.11.012

He, K.S., Bradley, B.A., Cord, A.F., Rocchini, D., Tuanmu, M., Schmidtlein, S., Turner, W., Wegmann, M., Pettorelli, N., 2015. Will remote sensing shape the next generation of species distribution models ? Remote Sens. Ecol. Conserv. 4–18. https://doi.org/10.1002/rse2.7

Hodgson, J.C., Mott, R., Baylis, S.M., Pham, T.T., Wotherspoon, S., Kilpatrick, A.D., Raja Segaran, R., Reid, I., Terauds, A., Koh, L.P., 2018. Drones count wildlife more accurately and precisely than humans. Methods Ecol. Evol. 9, 1160–1167. https://doi.org/10.1111/2041-210X.12974

Holt, R.D., 2009. Bringing the Hutchinsonian niche into the 21st century: ecological and evolutionary perspectives. Proc. Natl. Acad. Sci. U. S. A. 106 Suppl 2, 19659–65. https://doi.org/10.1073/pnas.0905137106

Huber, N., Kienast, F., Ginzler, C., Pasinelli, G., 2016. Using remote-sensing data to assess habitat selection of a declining passerine at two spatial scales. Landsc. Ecol. 31, 1919–1937. https://doi.org/10.1007/s10980-016-0370-1

Hüsler, F., Jonas, T., Riffler, M., Musial, J.P., Wunderle, S., 2014. A satellite-based snow cover climatology (1985–2011) for the European Alps derived from AVHRR data. Cryosph. 8, 73–90. https://doi.org/10.5194/tc-8-73-2014

Hutchinson, G.E. (George E., 1978. An introduction to population ecology. Yale University Press.

Ibrahim, S., Balzter, H., Tansey, K., Tsutsumida, N., Mathieu, R., 2018. Estimating fractional cover of plant functional types in African savannah from harmonic analysis of MODIS time-series data. Int. J. Remote Sens. 39, 2718–2745. https://doi.org/10.1080/01431161.2018.1430914

Ims, R.A., Yoccoz, N.G., 2017. Ecosystem-based monitoring in the age of rapid climate change and new technologies. Curr. Opin. Environ. Sustain. 29, 170–176. https://doi.org/10.1016/J.COSUST.2018.01.003

IPCC, 2014. Summary for policymakers, in: Field, C.B., Barros, V.R., Dokken, D.J., Mach, K.J., Mastrandrea, M.D., Bilir, T.E., Chatterjee, M., Ebi, K.L., Estrad, a Y.O., Genova, R.C., Girms, B., Kissel, E.S., Levy, A.N., MacCracken, S., Mastrandrea, P.R., White, L.L. (Eds.), Climate Change 2014: Impacts, Adaptation, and Vulnerability. Part A: Global and Sectoral Aspects. Contribution of Working Group II to the Fifth Assessment Report of the Intergovernmental Panel on Climate Change. Cambridge University Press, Cambridge, UK and New York, USA, pp. 1–32.

Jaboyedoff, M., Oppikofer, T., Abellán, A., Derron, M.-H., Loye, A., Metzger, R., Pedrazzini, A., 2012. Use of LIDAR in landslide investigations: a review. Nat. Hazards 61, 5–28. https://doi.org/10.1007/s11069-010-9634-2

Jakimow, B., Griffiths, P., van der Linden, S., Hostert, P., 2018. Mapping pasture management in the Brazilian Amazon from dense Landsat time series. Remote Sens. Environ. 205, 453–468. https://doi.org/10.1016/J.RSE.2017.10.009

Jetz, W., Cavender-Bares, J., Pavlick, R., Schimel, D., Davis, F.W., Asner, G.P., Guralnick, R., Kattge, J., Latimer, A.M., Moorcroft, P., Schaepman, M.E., Schildhauer, M.P., Schneider, F.D., Schrodt, F., Stahl, U., Ustin, S.L., 2016. Monitoring plant functional diversity from space. Nat. Plants 2, 16024. https://doi.org/10.1038/nplants.2016.24

Jetz, W., McGeoch, M.A., Guralnick, R., Ferrier, S., Beck, J., Costello, M.J., Fernandez, M., Geller, G.N., Keil, P., Merow, C., Meyer, C., Muller-Karger, F.E., Pereira, H.M., Regan, E.C., Schmeller, D.S., Turak, E., 2019. Essential biodiversity variables for mapping and monitoring species populations. Nat. Ecol. Evol. 3, 539–551. https://doi.org/10.1038/s41559-019-0826-1

Jolly, W.M., Nemani, R., Running, S.W., 2005. A generalized, bioclimatic index to predict foliar phenology in response to climate. Glob. Chang. Biol. 11, 619–632. https://doi.org/10.1111/j.1365-2486.2005.00930.x

Kaim, D., Kozak, J., Kolecka, N., Ziółkowska, E., Ostafin, K., Ostapowicz, K., Gimmi, U., Munteanu, C., Radeloff, V.C., 2016. Broad scale forest cover reconstruction from historical topographic maps. Appl. Geogr. 67, 39–48. https://doi.org/10.1016/J.APGEOG.2015.12.003

Kammer, P.M., Schöb, C., Eberhard, G., Gallina, R., Meyer, R., Tschanz, C., 2013. The relationship between soil water storage capacity and plant species diversity in high alpine vegetation. Plant Ecol. Divers. 6, 457–466. https://doi.org/10.1080/17550874.2013.783142

Karger, D.N., Conrad, O., Böhner, J., Kawohl, T., Kreft, H., Soria-Auza, R.W., Zimmermann, N.E., Linder, H.P., Kessler, M., 2017. Climatologies at high resolution for the earth's land surface areas. Sci. Data 4, 170122. https://doi.org/10.1038/sdata.2017.122

Kearney, M., Porter, W., 2009. Mechanistic niche modelling: combining physiological and spatial data to predict species' ranges. Ecol. Lett. 12, 334–350. https://doi.org/10.1111/j.1461-0248.2008.01277.x

Kellenberger, B., Marcos, D., Tuia, D., 2018. Detecting mammals in UAV images: Best practices to address a substantially imbalanced dataset with deep learning. Remote Sens. Environ. 216, 139–153. https://doi.org/10.1016/J.RSE.2018.06.028

Kemppinen, J., Niittynen, P., Riihimäki, H., Luoto, M., 2018. Modelling soil moisture in a high-latitude landscape using LiDAR and soil data. Earth Surf. Process. Landforms 43, 1019–1031. https://doi.org/10.1002/esp.4301

Kim, H., Rosa, I.M.D., Alkemade, R., Leadley, P., Hurtt, G., Popp, A., van Vuuren, D.P., Anthoni, P., Arneth, A., Baisero, D., Caton, E., Chaplin-Kramer, R., Chini, L., De Palma, A., Di Fulvio, F., Di Marco, M., Espinoza, F., Ferrier, S., Fujimori, S., Gonzalez, R.E., Gueguen, M., Guerra, C., Harfoot, M., Harwood, T.D., Hasegawa, T., Haverd, V., Havlík, P., Hellweg, S., Hill, S.L.L., Hirata, A., Hoskins, A.J., Janse, J.H., Jetz, W., Johnson, J.A., Krause, A., Leclère, D., Martins, I.S., Matsui, T., Merow, C., Obersteiner, M., Ohashi, H., Poulter, B., Purvis, A., Quesada, B., Rondinini, C., Schipper, A.M., Sharp, R., Takahashi, K., Thuiller, W., Titeux, N., Visconti, P., Ware, C., Wolf, F., Pereira, H.M., 2018. A protocol for an intercomparison of biodiversity and ecosystem services models using harmonized land-use and climate scenarios. Geosci. Model Dev. 11, 4537–4562. https://doi.org/10.5194/gmd-11-4537-2018

Klein, T., Randin, C., Körner, C., 2015. Water availability predicts forest canopy height at the global scale. Ecol. Lett. 18, 1311–1320. https://doi.org/10.1111/ele.12525

Knight, J., Harrison, S., 2013. The impacts of climate change on terrestrial Earth surface systems. Nat. Clim. Chang. 3, 24–29. https://doi.org/10.1038/nclimate1660

Koh, L.P., Wich, S.A., 2012. Dawn of drone ecology: low-cost autonomous aerial vehicles for conservation. Trop. Conserv. Sci. 5, 121–132. https://doi.org/10.1177/194008291200500202

Kolecka, N., Ginzler, C., Pazur, R., Price, B., Verburg, P., Kolecka, N., Ginzler, C., Pazur, R., Price, B., Verburg, P.H., 2018. Regional scale mapping of grassland mowing frequency with Sentinel-2 time series. Remote Sens. 10, 1221. https://doi.org/10.3390/rs10081221

Kollas, C., Körner, C., Randin, C.F., 2014. Spring frost and growing season length co-control the cold range limits of broad-leaved trees. J. Biogeogr. 41, 773–783. https://doi.org/10.1111/jbi.12238

Kozak, K.H., Graham, C.H., Wiens, J.J., 2008. Integrating GIS-based environmental data into evolutionary biology. Trends Ecol. Evol. 23, 141–148. https://doi.org/10.1016/J.TREE.2008.02.001

Kozłowska, A., Rączkowska, Z., 2002. Vegetation as a tool in the characterisation of geomorphological forms and processes: an example from the abisko mountains. Geogr. Ann. Ser. A, Phys. Geogr. 84, 233–244. https://doi.org/10.1111/j.0435-3676.2002.00178.x

Krauss, J., Bommarco, R., Guardiola, M., Heikkinen, R.K., Helm, A., Kuussaari, M., Lindborg, R., Öckinger, E., Pärtel, M., Pino, J., Pöyry, J., Raatikainen, K.M., Sang, A., Stefanescu, C., Teder, T., Zobel, M., Steffan-Dewenter, I., 2010. Habitat fragmentation causes immediate and time-delayed biodiversity loss at different trophic levels. Ecol. Lett. 13, 597–605. https://doi.org/10.1111/j.1461-0248.2010.01457.x

Kuussaari, M., Bommarco, R., Heikkinen, R.K., Helm, A., Krauss, J., Lindborg, R., Ockinger, E., Pärtel, M., Pino, J., Rodà, F., Stefanescu, C., Teder, T., Zobel, M., Steffan-Dewenter, I., 2009. Extinction debt: a challenge for biodiversity conservation. Trends Ecol. Evol. 24, 564–71. https://doi.org/10.1016/j.tree.2009.04.011

Lange, S., 2019. Trend-preserving bias adjustment and statistical downscaling with ISIMIP3BASD (v1.0). Geosci. Model Dev. 12, 3055–3070. https://doi.org/10.5194/gmd-12-3055-2019

Lausch, A., Baade, J., Bannehr, L., Borg, E., Bumberger, J., Chabrilliat, S., Dietrich, P., Gerighausen, H., Glässer, C., Hacker, J.M., Haase, D., Jagdhuber, T., Jany, S., Jung, A., Karnieli, A., Kraemer, R., Makki, M., Mielke, C., Möller, M., Mollenhauer, H., Montzka, C., Pause, M., Rogass, C., Rozenstein, O., Schmullius, C., Schrodt, F., Schrön, M., Schulz, K., Schütze, C., Schweitzer, C., Selsam, P., Skidmore, A.K., Spengler, D., Thiel, C., Truckenbrodt, S.C., Vohland, M., Wagner, R., Weber, U., Werban, U., Wollschläger, U., Zacharias, S., Schaepman, M.E., 2019. Linking remote sensing and geodiversity and their traits relevant to biodiversity—Part I: soil characteristics. Remote Sens. 11, 2356. https://doi.org/10.3390/rs11202356

le Roux, P.C., Aalto, J., Luoto, M., 2013a. Soil moisture's underestimated role in climate change impact modelling in low-energy systems. Glob. Chang. Biol. 19, 2965–2975. https://doi.org/10.1111/gcb.12286

le Roux, P.C., Luoto, M., 2014. Earth surface processes drive the richness, composition and occurrence of plant species in an arctic-alpine environment. J. Veg. Sci. 25, 45–54. https://doi.org/10.1111/jvs.12059

le Roux, P.C., Virtanen, R., Luoto, M., 2013b. Geomorphological disturbance is necessary for predicting fine-scale species distributions. Ecography (Cop.). 36, 800–808. https://doi.org/10.1111/j.1600-0587.2012.07922.x

Leempoel, K., Parisod, C., Geiser, C., Daprà, L., Vittoz, P., Joost, S., 2015. Very high-resolution digital elevation models: are multi-scale derived variables ecologically relevant? Methods Ecol. Evol. 6, 1373–1383. https://doi.org/10.1111/2041-210X.12427

Leitold, V., Keller, M., Morton, D.C., Cook, B.D., Shimabukuro, Y.E., 2015. Airborne lidar-based estimates of tropical forest structure in complex terrain: opportunities and trade-offs for REDD+. Carbon Balance Manag. 10, 3. https://doi.org/10.1186/s13021-015-0013-x

Lembrechts, J.J., Alexander, J.M., Cavieres, L.A., Haider, S., Lenoir, J., Kueffer, C., McDougall, K., Naylor, B.J., Nuñez, M.A., Pauchard, A., Rew, L.J., Nijs, I., Milbau, A., 2017. Mountain roads shift native and non-native plant species' ranges. Ecography (Cop.). 40, 353–364. https://doi.org/10.1111/ecog.02200

Lembrechts, J.J., Lenoir, J., Roth, N., Hattab, T., Milbau, A., Haider, S., Pellissier, L., Pauchard, A., Ratier Backes, A., Dimarco, R.D., Nuñez, M.A., Aalto, J., Nijs, I., 2019. Comparing temperature data sources for use in species distribution models: From in-situ logging to remote sensing. Glob. Ecol. Biogeogr. 28, 1578–1596. https://doi.org/10.1111/geb.12974

Lenoir, J., Bertrand, R., Comte, L., Bourgeaud, L., Hattab, T., Murienne, J., Grenouillet, G., 2019. Species better track the shifting isotherms in the oceans than on lands. bioRxiv 765776. https://doi.org/10.1101/765776

Lenoir, J., Hattab, T., Pierre, G., 2017. Climatic microrefugia under anthropogenic climate change: implications for species redistribution. Ecography (Cop.). 40, 253–266. https://doi.org/10.1111/ecog.02788

Lenoir, J., Svenning, J.-C., 2015. Climate-related range shifts - a global multidimensional synthesis and new research directions. Ecography (Cop.). 38, 15–28. https://doi.org/10.1111/ecog.00967

Lenzen, M., LANE, A., Widmer-Cooper, A., Williams, M., 2009. Effects of land use on threatened species. Conserv. Biol. 23, 294–306. https://doi.org/10.1111/j.1523-1739.2008.01126.x

Liu, L., Zhang, Y., Liu, L., Zhang, Y., 2011. Urban heat island analysis using the Landsat TM data and ASTER data: a case study in Hong Kong. Remote Sens. 3, 1535–1552. https://doi.org/10.3390/rs3071535

Loran, C., Munteanu, C., Verburg, P.H., Schmatz, D.R., Bürgi, M., Zimmermann, N.E., 2017. Long-term change in drivers of forest cover expansion: an analysis for Switzerland (1850-2000). Reg. Environ. Chang. 17, 2223–2235. https://doi.org/10.1007/s10113-017-1148-y

Luoto, M., Heikkinen, R.K., 2008. Disregarding topographical heterogeneity biases species turnover assessments based on bioclimatic models. Glob. Chang. Biol. 14, 483–494. https://doi.org/10.1111/j.1365-2486.2007.01527.x

Luoto, M., Virkkala, R., Heikkinen, R.K., 2007. The role of land cover in bioclimatic models depends on spatial resolution. Glob. Ecol. Biogeogr. 16, 34–42. https://doi.org/10.1111/j.1466-8238.2006.00262.x

Mackey, B.G., Lindenmayer, D.B., 2001. Towards a hierarchical framework for modelling the spatial distribution of animals. J. Biogeogr. 28, 1147–1166. https://doi.org/10.1046/j.1365-2699.2001.00626.x

Madani, N., Kimball, J.S., Nazeri, M., Kumar, L., Affleck, D.L.R., 2016. Remote sensing derived fire frequency, soil moisture and ecosystem productivity rxplain regional movements in emu over Australia. PLoS One 11, e0147285. https://doi.org/10.1371/journal.pone.0147285

Madritch, M.D., Kingdon, C.C., Singh, A., Mock, K.E., Lindroth, R.L., Townsend, P.A., 2014. Imaging spectroscopy links aspen genotype with below-ground processes at landscape scales. Philos. Trans. R. Soc. Lond. B. Biol. Sci. 369, 20130194. https://doi.org/10.1098/rstb.2013.0194

Mahecha, M.D., Gans, F., Sippel, S., Donges, J.F., Kaminski, T., Metzger, S., Migliavacca, M., Papale, D., Rammig, A., Zscheischler, J., 2017. Detecting impacts of extreme events with ecological in situ monitoring networks. Biogeosciences 1–33. https://doi.org/10.5194/bg-2017-130

Maiorano, L., Cheddadi, R., Zimmermann, N.E., Pellissier, L., Petitpierre, B., Pottier, J., Laborde, H., Hurdu, B.I., Pearman, P.B., Psomas, A., Singarayer, J.S., Broennimann, O., Vittoz, P., Dubuis, A., Edwards, M.E., Binney, H.A., Guisan, A., 2013. Building the niche through time: using 13,000 years of data to predict the effects of climate change on three tree species in Europe. Glob. Ecol. Biogeogr. 22, 302–317. https://doi.org/10.1111/j.1466-8238.2012.00767.x

Malanson, G.P., Bengtson, L.E., Fagre, D.B., 2012. Geomorphic determinants of species composition of alpine tundra, Glacier National Park, U.S.A. Arctic, Antarct. Alp. Res. 44, 197–209. https://doi.org/10.1657/1938-4246-44.2.197

Malavasi, M., Barták, V., Jucker, T., Acosta, A.T.R., Carranza, M.L., Bazzichetto, M., 2019. Strength in Numbers: Combining Multi-Source Remotely Sensed Data to Model Plant Invasions in Coastal Dune Ecosystems. Remote Sens. 11, 275. https://doi.org/10.3390/rs11030275

Malenovský, Z., Homolová, L., Lukeš, P., Buddenbaum, H., Verrelst, J., Alonso, L., Schaepman, M.E., Lauret, N., Gastellu-Etchegorry, J.-P., 2019. Variability and uncertainty challenges in scaling imaging spectroscopy retrievals and validations from leaves up to vegetation canopies. Surv. Geophys. 40, 631–656. https://doi.org/10.1007/s10712-019-09534-y

Manzoor, S.A., Griffiths, G., Lukac, M., 2018. Species distribution model transferability and model grain size – finer may not always be better. Sci. Rep. 8, 7168. https://doi.org/10.1038/s41598-018-25437-1

Marques, A., Martins, I.S., Kastner, T., Plutzar, C., Theurl, M.C., Eisenmenger, N., Huijbregts, M.A.J., Wood, R., Stadler, K., Bruckner, M., Canelas, J., Hilbers, J.P., Tukker, A., Erb, K., Pereira, H.M., 2019. Increasing impacts of land use on biodiversity and carbon sequestration driven by population and economic growth. Nat. Ecol. Evol. 3, 628–637. https://doi.org/10.1038/s41559-019-0824-3

Marrotte, R.R., Bowman, J., Brown, M.G.C., Cordes, C., Morris, K.Y., Prentice, M.B., Wilson, P.J., 2017. Multi-species genetic connectivity in a terrestrial habitat network. Mov. Ecol. 5, 21. https://doi.org/10.1186/s40462-017-0112-2

Martin, Y., Dyck, H. Van, Dendoncker, N., Titeux, N., 2013. Testing instead of assuming the importance of land use change scenarios to model species distributions under climate change. Glob. Ecol. Biogeogr. 22, 1204–1216. https://doi.org/10.1111/geb.12087

Martinuzzi, S., Radeloff, V.C., Joppa, L.N., Hamilton, C.M., Helmers, D.P., Plantinga, A.J., Lewis, D.J., 2015. Scenarios of future land use change around United States' protected areas. Biol. Conserv. 184, 446–455. https://doi.org/10.1016/J.BIOCON.2015.02.015

Mathys, L., Zimmermann, N.E., Guisan, A., 2004. Spatial pattern of forest resources in a multifunctional landscape . Int. Arch. Photogramm. Remote Sens. Spat. Inf. Sci. 36, 340–342.

McShea, W.J., 2014. What are the roles of species distribution models in conservation planning? Environ. Conserv. 41, 93–96. https://doi.org/10.1017/S0376892913000581

Mellert, K.H., Fensterer, V., Küchenhoff, H., Reger, B., Kölling, C., Klemmt, H.J., Ewald, J.,

2011. Hypothesis-driven species distribution models for tree species in the Bavarian Alps. J. Veg. Sci. 22, 635–646. https://doi.org/10.1111/j.1654-1103.2011.01274.x

Merrick, M.J., Koprowski, J.L., 2017. Circuit theory to estimate natal dispersal routes and functional landscape connectivity for an endangered small mammal. Landsc. Ecol. 32, 1163–1179. https://doi.org/10.1007/s10980-017-0521-z

Meyfroidt, P., Lambin, E.F., Hertel, T.W., 2013. Globalization of land use: distant drivers of land change and geographic displacement of land use. Curr. Opin. Environ. Sustain. 5, 438–444. https://doi.org/10.1016/J.COSUST.2013.04.003

Milanesi, P., Holderegger, R., Bollmann, K., Gugerli, F., Zellweger, F., 2017. Three-dimensional habitat structure and landscape genetics: a step forward in estimating functional connectivity. Ecology 98, 393–402. https://doi.org/10.1002/ecy.1645

Miller, J., Franklin, J., 2002. Modeling the distribution of four v egetation alliances using generalized linear models and classification trees with spatial dependence 157.

Mirtl, M., T. Borer, E., Djukic, I., Forsius, M., Haubold, H., Hugo, W., Jourdan, J., Lindenmayer, D., McDowell, W.H., Muraoka, H., Orenstein, D.E., Pauw, J.C., Peterseil, J., Shibata, H., Wohner, C., Yu, X., Haase, P., 2018. Genesis, goals and achievements of Long-Term Ecological Research at the global scale: a critical review of ILTER and future directions. Sci. Total Environ. 626, 1439–1462. https://doi.org/10.1016/J.SCITOTENV.2017.12.001

Mod, H.K., Scherrer, D., Luoto, M., Guisan, A., 2016. What we use is not what we know: environmental predictors in plant distribution models. J. Veg. Sci. 27, 1308–1322. https://doi.org/10.1111/jvs.12444

Moeslund, J.E., Arge, L., Bøcher, P.K., Dalgaard, T., Odgaard, M. V, Nygaard, B., Svenning, J.-C., 2013. Topographically controlled soil moisture is the primary driver of local vegetation patterns across a lowland region. Ecosphere 4, art91. https://doi.org/10.1890/ES13-00134.1

Montané, J.M., Torres, R., 2006. Accuracy assessment of Lidar saltmarsh topographic data using RTK GPS. Photogramm. Eng. Remote Sensing 72, 961–967.

Naumann, G., Barbosa, P., Carrao, H., Singleton, A., Vogt, J., Naumann, G., Barbosa, P., Carrao, H., Singleton, A., Vogt, J., 2012. Monitoring drought conditions and their uncertainties in Africa using TRMM data. J. Appl. Meteorol. Climatol. 51, 1867–1874. https://doi.org/10.1175/JAMC-D-12-0113.1

Navarro, L.M., Fernández, N., Guerra, C., Guralnick, R., Kissling, W.D., Londoño, M.C., Muller-

Karger, F., Turak, E., Balvanera, P., Costello, M.J., Delavaud, A., El Serafy, G., Ferrier, S., Geijzendorffer, I., Geller, G.N., Jetz, W., Kim, E.-S., Kim, H., Martin, C.S., McGeoch, M.A., Mwampamba, T.H., Nel, J.L., Nicholson, E., Pettorelli, N., Schaepman, M.E., Skidmore, A., Sousa Pinto, I., Vergara, S., Vihervaara, P., Xu, H., Yahara, T., Gill, M., Pereira, H.M., 2017. Monitoring biodiversity change through effective global coordination. Curr. Opin. Environ. Sustain. 29, 158–169. https://doi.org/10.1016/J.COSUST.2018.02.005

Neilan, W.L., Barton, P.S., McAlpine, C.A., Wood, J.T., Lindenmayer, D.B., 2019. Contrasting effects of mosaic structure on alpha and beta diversity of bird assemblages in a human-modified landscape. Ecography (Cop.). 42, 173–186. https://doi.org/10.1111/ecog.02981

Neteler, M., Metz, M., Rocchini, D., Rizzoli, A., Flacio, E., Engeler, L., Guidi, V., Lüthy, P., Tonolla, M., 2013. Is Switzerland suitable for the invasion of Aedes albopictus? PLoS One 8, e82090. https://doi.org/10.1371/journal.pone.0082090

Newbold, T., 2018. Future effects of climate and land-use change on terrestrial vertebrate community diversity under different scenarios. Proc. R. Soc. B Biol. Sci. 285, 20180792. https://doi.org/10.1098/rspb.2018.0792

Newbold, T., Hudson, L., Hill, S., Contu, S., Lysenko, I., Senior, R., Boerger, L., Bennett, D.J., Choimes, A., Collen, B., Day, J., De Palma, A., Dıaz, S., Echeverria-Londono, S., Edgar, M.J., Feldman, A., Garon, M., Harrison, M.L.K., Alhusseini, T., Ingram, D.J., Itescu, Y., Kattge, J., Kemp, V., Kirkpatrick, L., Kleyer, M., Pinto Correia, D., Martin, C.D., Meiri, S., Novosolov, M., Pan, Y., Phillips, H.R.P., Purves, D.W., Robinson, A., Simpson, J., Tuck, S.L., Weiher, E., White, H.J., Ewers, R.M., Mace, G.M., Scharlemann, J.P.W., Purvis, A., 2015. Global effects of land use on local terrestrial biodiversity. Nature 520, 45–50. https://doi.org/10.1038/nature14324

Newbold, T., Hudson, L.N., Hill, S.L.L., Contu, S., Gray, C.L., Scharlemann, J.P.W., Börger, L., Phillips, H.R.P., Sheil, D., Lysenko, I., Purvis, A., 2016. Global patterns of terrestrial assemblage turnover within and among land uses. Ecography (Cop.). 39, 1151–1163. https://doi.org/10.1111/ecog.01932

Niittynen, P., Luoto, M., 2018. The importance of snow in species distribution models of arctic vegetation. Ecography (Cop.). 41, 1024–1037. https://doi.org/10.1111/ecog.03348

Normand, S., Treier, U.A., Randin, C., Vittoz, P., Guisan, A., Svenning, J.-C., 2009. Importance of abiotic stress as a range-limit determinant for European plants: insights from species responses to climatic gradients. Glob. Ecol. Biogeogr. 18, 437–449. https://doi.org/10.1111/j.1466-8238.2009.00451.x

Ofli, F., Meier, P., Imran, M., Castillo, C., Tuia, D., Rey, N., Briant, J., Millet, P., Reinhard, F., Parkan, M., Joost, S., 2016. Combining human computing and machine learning to make sense of big (aerial) data for disaster response. Big Data 4, 47–59. https://doi.org/10.1089/big.2014.0064

Pagel, J., Schurr, F.M., 2012. Forecasting species ranges by statistical estimation of ecological niches and spatial population dynamics. Glob. Ecol. Biogeogr. 21, 293–304. https://doi.org/10.1111/j.1466-8238.2011.00663.x

Patsiou, T.S., Conti, E., Theodoridis, S., Randin, C.F., 2017. The contribution of cold air pooling to the distribution of a rare and endemic plant of the Alps. Plant Ecol. Divers. 10, 29–42. https://doi.org/10.1080/17550874.2017.1302997

Pazúr, R., Bolliger, J., 2017. Land changes in Slovakia: Past processes and future directions. Appl. Geogr. 85, 163–175. https://doi.org/10.1016/J.APGEOG.2017.05.009

Pearman, P.B., Randin, C.F., Broennimann, O., Vittoz, P., Knaap, W.O. van der, Engler, R., Lay, G. Le, Zimmermann, N.E., Guisan, A., 2008. Prediction of plant species distributions across six millennia. Ecol. Lett. 11, 357–369. https://doi.org/10.1111/j.1461-0248.2007.01150.x

Pearson, R.G., Dawson, T.P., 2003. Predicting the impacts of climate change on the distribution of species: are bioclimate envelope models useful? Glob. Ecol. Biogeogr. 12, 361–371. https://doi.org/10.1046/j.1466-822X.2003.00042.x

Pekin, B.K., Pijanowski, B.C., 2012. Global land use intensity and the endangerment status of mammal species. Divers. Distrib. 18, 909–918. https://doi.org/10.1111/j.1472-4642.2012.00928.x

Pellissier, L., Meltofte, H., Hansen, J., Schmidt, N.M., Tamstorf, M.P., Maiorano, L., Aastrup, P., Olsen, J., Guisan, A., Wisz, M.S., 2013. Suitability, success and sinks: how do predictions of nesting distributions relate to fitness parameters in high arctic waders? Divers. Distrib. 19, 1496–1505. https://doi.org/10.1111/ddi.12109

Peón, J., Recondo, C., Fernández, S., F. Calleja, J., De Miguel, E., Carretero, L., Peón, J., Recondo, C., Fernández, S., F. Calleja, J., De Miguel, E., Carretero, L., 2017. Prediction of topsoil organic carbon using airborne and satellite hyperspectral imagery. Remote Sens. 9, 1211. https://doi.org/10.3390/rs9121211

Pereira, H.M., Ferrier, S., Walters, M., Geller, G.N., Jongman, R.H.G., Scholes, R.J., Bruford, M.W., Brummitt, N., Butchart, S.H.M., Cardoso, A.C., Coops, N.C., Dulloo, E., Faith, D.P., Freyhof, J., Gregory, R.D., Heip, C., Hoft, R., Hurtt, G., Jetz, W., Karp, D.S., McGeoch, M.A., Obura, D., Onoda, Y., Pettorelli, N., Reyers, B., Sayre, R., Scharlemann, J.P.W., Stuart, S.N., Turak, E., Walpole, M., Wegmann, M., 2013. Essential Biodiversity Variables. Science (80-.). 339, 277–278. https://doi.org/10.1126/science.1229931

Pereira, H.M., Navarro, L.M., Martins, I.S., 2012. Global Biodiversity Change: The Bad, the Good, and the Unknown. Annu. Rev. Environ. Resour. 37, 25–50. https://doi.org/10.1146/annurev-environ-042911-093511

Pettorelli, N., Wegmann, M., Skidmore, A., Mücher, S., Dawson, T.P., Fernandez, M., Lucas, R., Schaepman, M.E., Wang, T., O'Connor, B., Jongman, R.H.G., Kempeneers, P., Sonnenschein, R., Leidner, A.K., Böhm, M., He, K.S., Nagendra, H., Dubois, G., Fatoyinbo, T., Hansen, M.C., Paganini, M., de Klerk, H.M., Asner, G.P., Kerr, J.T., Estes, A.B., Schmeller, D.S., Heiden, U., Rocchini, D., Pereira, H.M., Turak, E., Fernandez, N., Lausch, A., Cho, M.A., Alcaraz-Segura, D., McGeoch, M.A., Turner, W., Mueller, A., St-Louis, V., Penner, J., Vihervaara, P., Belward, A., Reyers, B., Geller, G.N., 2016. Framing the concept of satellite remote sensing essential biodiversity variables: challenges and future directions. Remote Sens. Ecol. Conserv. 2, 122–131. https://doi.org/10.1002/rse2.15

Pinto-Ledezma, J., Cavender-Bares, Jeannine, 2020. Using remote sensing for modeling and monitoring species distributions, in: Cavender-Bares, J, Gamon, J., Townsend, P. (Eds.), Remote Sensing of Plant Biodiverist. Springer.

Potter, K.A., Arthur Woods, H., Pincebourde, S., 2013. Microclimatic challenges in global change biology. Glob. Chang. Biol. 19, 2932–2939. https://doi.org/10.1111/gcb.12257

Pradervand, J.-N., Dubuis, A., Pellissier, L., Guisan, A., Randin, C., 2014. Very high resolution environmental predictors in species distribution models. Prog. Phys. Geogr. 38, 79–96. https://doi.org/10.1177/0309133313512667

Price, B., Kienast, F., Seidl, I., Ginzler, C., Verburg, P.H., Bolliger, J., 2015. Future landscapes of Switzerland: risk areas for urbanisation and land abandonment. Appl. Geogr. 57, 32–41. https://doi.org/10.1016/J.APGEOG.2014.12.009

Pulliam, H.R., 2000. On the relationship between niche and distribution. Ecol. Lett. 3, 349–361. https://doi.org/10.1046/j.1461-0248.2000.00143.x

Randin, C.F., Engler, R., Normand, S., Zappa, M., Zimmermann, N.E., Pearman, P.B., Vittoz, P., Thuiller, W., Guisan, A., 2009a. Climate change and plant distribution: local models predict high-elevation persistence. Glob. Chang. Biol. 15, 1557–1569. https://doi.org/10.1111/j.1365-2486.2008.01766.x

Randin, C.F., Jaccard, H., Vittoz, P., Yoccoz, N.G., Guisan, A., 2009b. Land use improves spatial predictions of mountain plant abundance but not presence-absence. J. Veg. Sci. 20, 996–1008. https://doi.org/10.1111/j.1654-1103.2009.01098.x

Randin, C.F., Vuissoz, G., Liston, G.E., Vittoz, P., Guisan, A., 2009c. Introduction of snow and geomorphic disturbance variables into predictive models of alpine plant distribution in the Western Swiss Alps. Arctic, Antarct. Alp. Res. 41, 347–361. https://doi.org/10.1657/1938-4246-41.3.347

Rey, N., Volpi, M., Joost, S., Tuia, D., 2017. Detecting animals in African Savanna with UAVs and the crowds. https://doi.org/10.1016/j.rse.2017.08.026

Rocchini, D., Boyd, D.S., Féret, J.-B., Foody, G.M., He, K.S., Lausch, A., Nagendra, H., Wegmann, M., Pettorelli, N., 2016. Satellite remote sensing to monitor species diversity: potential and pitfalls. Remote Sens. Ecol. Conserv. 2, 25–36. https://doi.org/10.1002/rse2.9

Rocchini, D., Marcantonio, M., Ricotta, C., 2017. Measuring Rao’s Q diversity index from remote sensing: a n open source solution. Ecol. Indic. 72, 234–238. https://doi.org/10.1016/J.ECOLIND.2016.07.039

Rosero-Vlasova, O.A., Vlassova, L., Pérez-Cabello, F., Montorio, R., Nadal-Romero, E., 2018. Modeling soil organic matter and texture from satellite data in areas affected by wildfires and cropland abandonment in Aragón, Northern Spain. J. Appl. Remote Sens. 12, 1. https://doi.org/10.1117/1.JRS.12.042803

Rudel, T.K., 2007. Changing agents of deforestation: from state-initiated to enterprise driven processes, 1970–2000. Land use policy 24, 35–41. https://doi.org/10.1016/J.LANDUSEPOL.2005.11.004

Rufin, P., Müller, H., Pflugmacher, D., Hostert, P., 2015. Land use intensity trajectories on Amazonian pastures derived from Landsat time series. Int. J. Appl. Earth Obs. Geoinf. 41, 1–10. https://doi.org/10.1016/J.JAG.2015.04.010

Santos, M.J., Khanna, S., Hestir, E.L., Greenberg, J.A., Ustin, S.L., 2016. Measuring landscape-scale spread and persistence of an invaded submerged plant community from airborne remote sensing. Ecol. Appl. 26, 1733–1744. https://doi.org/10.1890/15-0615

Schneider, F.D., Kükenbrink, D., Schaepman, M.E., Schimel, D.S., Morsdorf, F., 2019. Quantifying 3D structure and occlusion in dense tropical and temperate forests using close-range LiDAR. Agric. For. Meteorol. 268, 249–257. https://doi.org/10.1016/J.AGRFORMET.2019.01.033

Schneider, F.D., Leiterer, R., Morsdorf, F., Gastellu-Etchegorry, J.-P., Lauret, N., Pfeifer, N., Schaepman, M.E., 2014. Simulating imaging spectrometer data: 3D forest modeling based on LiDAR and in situ data. Remote Sens. Environ. 152, 235–250. https://doi.org/10.1016/j.rse.2014.06.015

Schneider, F.D., Morsdorf, F., Schmid, B., Petchey, O.L., Hueni, A., Schimel, D.S., Schaepman, M.E., 2017. Mapping functional diversity from remotely sensed morphological and physiological forest traits. Nat. Commun. 8, 1441. https://doi.org/10.1038/s41467-017-01530-3

Schulte, P.M., Healy, T.M., Fangue, N.A., 2011. Thermal performance curves, phenotypic plasticity, and the time scales of temperature exposure. Integr. Comp. Biol. 51, 691–702. https://doi.org/10.1093/icb/icr097

See, L., Schepaschenko, D., Lesiv, M., McCallum, I., Fritz, S., Comber, A., Perger, C., Schill, C., Zhao, Y., Maus, V., Siraj, M.A., Albrecht, F., Cipriani, A., Vakolyuk, M., Garcia, A., Rabia, A.H., Singha, K., Marcarini, A.A., Kattenborn, T., Hazarika, R., Schepaschenko, M., van der Velde, M., Kraxner, F., Obersteiner, M., 2015. Building a hybrid land cover map with crowdsourcing and geographically weighted regression. ISPRS J. Photogramm. Remote Sens. 103, 48–56. https://doi.org/10.1016/J.ISPRSJPRS.2014.06.016

Shmueli, G., 2009. To explain or to predict? Stat. Sci. 25, 289–310. https://doi.org/10.2139/ssrn.1351252

Singh, A., Serbin, S.P., McNeil, B.E., Kingdon, C.C., Townsend, P.A., 2015. Imaging spectroscopy algorithms for mapping canopy foliar chemical and morphological traits and their uncertainties. Ecol. Appl. 25, 2180–2197. https://doi.org/10.1890/14-2098.1

Skidmore, A., Pettorelli, N., Coops, N.C., Geller, G.N., Hansen, M., Lucas, R., Muecher, C., O'Connor, B., Paganini, M., Pereira, H.M., Schaepman, M.E., Turner, W., Wang, T., Wegmann, M., 2015. Agree on biodiversity metrics to track from space. Nature 523, 5–7.

Skowronek, S., Ewald, M., Isermann, M., Kerchove, R. Van De, Lenoir, J., Aerts, R., Warrie, J., Hattab, T., Honnay, O., Schmidtlein, S., Rocchini, D., Somers, B., Feilhauer, H., 2017. Mapping an invasive bryophyte species using hyperspectral remote sensing data. Biol. Invasions 19, 239–254. https://doi.org/10.1007/S10530-016-1276-1

Sørensen, R., Seibert, J., 2007. Effects of DEM resolution on the calculation of topographical indices: TWI and its components. J. Hydrol. 347, 79–89. https://doi.org/10.1016/J.JHYDROL.2007.09.001

Spaete, L.P., Glenn, N.F., Derryberry, D.R., Sankey, T.T., Mitchell, J.J., Hardegree, S.P., 2011. Vegetation and slope effects on accuracy of a LiDAR-derived DEM in the sagebrush steppe. Remote Sens. Lett. 2, 317–326. https://doi.org/10.1080/01431161.2010.515267

Stoklosa, J., Daly, C., Foster, S.D., Ashcroft, M.B., Warton, D.I., 2015. A climate of uncertainty: accounting for error in climate variables for species distribution models. Methods Ecol. Evol. 6, 412–423. https://doi.org/10.1111/2041-210X.12217

Strecha, C., Fletcher, A., Lechner, A., Erskine, P., Fua, P., 2012. Developing species specific vegetation maps using multi-spectral hyperspatial imagery from unmanned aerial vehicles. ISPRS Ann. Photogramm. Remote Sens. Spat. Inf. Sci. 1, 311–316. https://doi.org/10.5194/isprsannals-I-3-311-2012

Stürck, J., Verburg, P.H., 2017. Multifunctionality at what scale? A landscape multifunctionality assessment for the European Union under conditions of land use change. Landsc. Ecol. 32, 481–500. https://doi.org/10.1007/s10980-016-0459-6

Svenning, J.-C., Sandel, B., 2013. Disequilibrium vegetation dynamics under future climate change. Am. J. Bot. 100, 1266–1286. https://doi.org/10.3732/ajb.1200469

Talluto, M. V., Boulangeat, I., Vissault, S., Thuiller, W., Gravel, D., 2017. Extinction debt and colonization credit delay range shifts of eastern North American trees. Nat. Ecol. Evol. 1, 0182. https://doi.org/10.1038/s41559-017-0182

Thuiller, W., Lavorel, S., Araújo, M.B., Sykes, M.T., Prentice, I.C., 2005. Climate change threats to plant diversity in Europe. Proc. Natl. Acad. Sci. U. S. A. 102, 8245–50. https://doi.org/10.1073/pnas.0409902102

Titeux, N., Henle, K., Mihoub, J.-B., Regos, A., Geijzendorffer, I.R., Cramer, W., Verburg, P.H., Brotons, L., 2016. Biodiversity scenarios neglect future land-use changes. Glob. Chang. Biol. 22, 2505–2515. https://doi.org/10.1111/gcb.13272

Torabzadeh, H., Leiterer, R., Hueni, A., Schaepman, M.E., Morsdorf, F., 2019. Tree species classification in a temperate mixed forest using a combination of imaging spectroscopy and airborne laser scanning. Agric. For. Meteorol. 279, 107744. https://doi.org/10.1016/J.AGRFORMET.2019.107744

Torabzadeh, H., Morsdorf, F., Schaepman, M.E., 2014. Fusion of imaging spectroscopy and airborne laser scanning data for characterization of forest ecosystems – A review. ISPRS J. Photogramm. Remote Sens. 97, 25–35. https://doi.org/10.1016/J.ISPRSJPRS.2014.08.001

Ummenhofer, C.C., Meehl, G.A., 2017. Extreme weather and climate events with ecological relevance : a review. Philos. Trans. R. Soc. B. https://doi.org/10.1098/rstb.2016.0135

Ustin, S.L., Gamon, J.A., 2010. Remote sensing of plant functional types. New Phytol. 186, 795–816. https://doi.org/10.1111/j.1469-8137.2010.03284.x

van Asselen, S., Verburg, P.H., 2013. Land cover change or land-use intensification: simulating land system change with a global-scale land change model. Glob. Chang. Biol. 19, 3648–3667. https://doi.org/10.1111/gcb.12331

van Ewijk, K.Y., Randin, C.F., Treitz, P.M., Scott, N.A., 2014. Predicting fine-scale tree species abundance patterns using biotic variables derived from LiDAR and high spatial resolution imagery. Remote Sens. Environ. 150, 120–131. https://doi.org/10.1016/J.RSE.2014.04.026

van Gemert, J.C., Verschoor, C.R., Mettes, P., Epema, K., Koh, L.P., Wich, S., 2015. Nature conservation drones for automatic localization and counting of animals, in: European Conference on Computer Vision. Springer, Cham, pp. 255–270. https://doi.org/10.1007/978-3-319-16178-5_17

Verburg, P.H., Crossman, N., Ellis, E.C., Heinimann, A., Hostert, P., Mertz, O., Nagendra, H., Sikor, T., Erb, K.-H., Golubiewski, N., Grau, R., Grove, M., Konaté, S., Meyfroidt, P., Parker, D.C., Chowdhury, R.R., Shibata, H., Thomson, A., Zhen, L., 2015. Land system science and sustainable development of the earth system: a global land project perspective. Anthropocene 12, 29–41. https://doi.org/10.1016/J.ANCENE.2015.09.004

Verburg, P.H., Neumann, K., Nol, L., 2011. Challenges in using land use and land cover data for global change studies. Glob. Chang. Biol. 17, 974–989. https://doi.org/10.1111/j.1365-2486.2010.02307.x

Vierling, K.T., Vierling, L.A., Gould, W.A., Martinuzzi, S., Clawges, R.M., 2008. Lidar: shedding new light on habitat characterization and modeling. Front. Ecol. Environ. 6, 90–98. https://doi.org/10.1890/070001

Vinter, T., Dinnétz, P., Danzer, U., Lehtilä, K., 2016. The relationship between landscape configuration and plant species richness in forests is dependent on habitat preferences of species. Eur. J. For. Res. 135, 1071–1082. https://doi.org/10.1007/s10342-016-0994-3

Vitasse, Y., Klein, G., Kirchner, J.W., Rebetez, M., 2017. Intensity, frequency and spatial configuration of winter temperature inversions in the closed La Brevine valley, Switzerland. Theor. Appl. Climatol. 130, 1073–1083. https://doi.org/10.1007/s00704-016-1944-1

Vries, W. De, Wamelink, G.W.W., Dobben, H. van, Kros, J., Reinds, G.J., Mol-Dijkstra, J.P., Smart, S.M., Evans, C.D., Rowe, E.C., Belyazid, S., Sverdrup, H.U., Hinsberg, A. van, Posch, M., Hettelingh, J.-P., Spranger, T., Bobbink, R., 2010. Use of dynamic soil–vegetation models to assess impacts of nitrogen deposition on plant species composition:

an overview. Ecol. Appl. 20, 60–79. https://doi.org/10.1890/08-1019.1

Walsh, S.J., Butler, D.R., Malanson, G.P., 1998. An overview of scale, pattern, process relationships in geomorphology: a remote sensing and GIS perspective. Geomorphology 21, 183–205. https://doi.org/10.1016/S0169-555X(97)00057-3

Walsworth, T.E., Schindler, D.E., Colton, M.A., Webster, M.S., Palumbi, S.R., Mumby, P.J., Essington, T.E., Pinsky, M.L., 2019. Management for network diversity speeds evolutionary adaptation to climate change. Nat. Clim. Chang. 9, 632–636. https://doi.org/10.1038/s41558-019-0518-5

Waters, C.N., Zalasiewicz, J., Summerhayes, C., Barnosky, A.D., Poirier, C., Gałuszka, A., Cearreta, A., Edgeworth, M., Ellis, E.C., Ellis, M., Jeandel, C., Leinfelder, R., McNeill, J.R., Richter, D. deB, Steffen, W., Syvitski, J., Vidas, D., Wagreich, M., Williams, M., Zhisheng, A., Grinevald, J., Odada, E., Oreskes, N., Wolfe, A.P., 2016. The Anthropocene is functionally and stratigraphically distinct from the Holocene. Science 351, aad2622. https://doi.org/10.1126/science.aad2622

Wearn, O.R., Reuman, D.C., Ewers, R.M., 2012. Extinction debt and windows of conservation opportunity in the Brazilian Amazon. Science 337, 228–32. https://doi.org/10.1126/science.1219013

Webster, C., Westoby, M., Rutter, N., Jonas, T., 2018. Three-dimensional thermal characterization of forest canopies using UAV photogrammetry. Remote Sens. Environ. 209, 835–847. https://doi.org/10.1016/J.RSE.2017.09.033

Werkowska, W., Márquez, A.L., Real, R., Acevedo, P., 2017. A practical overview of transferability in species distribution modeling. Environ. Rev. 25, 127–133. https://doi.org/10.1139/er-2016-0045

Westoby, M.J., Brasington, J., Glasser, N.F., Hambrey, M.J., Reynolds, J.M., 2012. 'Structure-from-Motion' photogrammetry: A low-cost, effective tool for geoscience applications. Geomorphology 179, 300–314. https://doi.org/10.1016/J.GEOMORPH.2012.08.021

Wiens, J.J., Lapoint, R.T., Whiteman, N.K., 2015. Herbivory increases diversification across insect clades. Nat. Commun. 6, 8370. https://doi.org/10.1038/ncomms9370

Woodward, F.I., 1990. The impact of low temperatures in controlling the geographical distribution of plants. Philos. Trans. R. Soc. B Biol. Sci. 326, 585–593. https://doi.org/10.1098/rstb.1990.0033

Wulder, M.A., Coops, N.C., Roy, D.P., White, J.C., Hermosilla, T., 2018. Land cover 2.0. Int. J.

Remote Sens. 39, 4254–4284. https://doi.org/10.1080/01431161.2018.1452075

Xie, J., Kneubühler, M., Garonna, I., Notarnicola, C., De Gregorio, L., De Jong, R., Chimani, B., Schaepman, M.E., 2017. Altitude-dependent influence of snow cover on alpine land surface phenology. J. Geophys. Res. Biogeosciences 122, 1107–1122. https://doi.org/10.1002/2016JG003728

Yates, K.L., Bouchet, P.J., Caley, M.J., Mengersen, K., Randin, C.F., Parnell, S., Fielding, A.H., Bamford, A.J., Ban, S., Barbosa, A.M., Dormann, C.F., Elith, J., Embling, C.B., Ervin, G.N., Fisher, R., Gould, S., Graf, R.F., Gregr, E.J., Halpin, P.N., Heikkinen, R.K., Heinänen, S., Jones, A.R., Krishnakumar, P.K., Lauria, V., Lozano-Montes, H., Mannocci, L., Mellin, C., Mesgaran, M.B., Moreno-Amat, E., Mormede, S., Novaczek, E., Oppel, S., Ortuño Crespo, G., Peterson, A.T., Rapacciuolo, G., Roberts, J.J., Ross, R.E., Scales, K.L., Schoeman, D., Snelgrove, P., Sundblad, G., Thuiller, W., Torres, L.G., Verbruggen, H., Wang, L., Wenger, S., Whittingham, M.J., Zharikov, Y., Zurell, D., Sequeira, A.M.M., 2018. Outstanding challenges in the transferability of ecological models. Trends Ecol. Evol. 33, 790–802. https://doi.org/10.1016/j.tree.2018.08.001

Zarco-Tejada, P.J., Camino, C., Beck, P.S.A., Calderon, R., Hornero, A., Hernández-Clemente, R., Kattenborn, T., Montes-Borrego, M., Susca, L., Morelli, M., Gonzalez-Dugo, V., North, P.R.J., Landa, B.B., Boscia, D., Saponari, M., Navas-Cortes, J.A., 2018. Previsual symptoms of Xylella fastidiosa infection revealed in spectral plant-trait alterations. Nat. Plants 4, 432–439. https://doi.org/10.1038/s41477-018-0189-7

Zellweger, F., Baltensweiler, A., Ginzler, C., Roth, T., Braunisch, V., Bugmann, H., Bollmann, K., 2016. Environmental predictors of species richness in forest landscapes: abiotic factors versus vegetation structure. J. Biogeogr. 43, 1080–1090. https://doi.org/10.1111/jbi.12696

Zimmermann, N.E., Yoccoz, N.G., Edwards, T.C., Meier, E.S., Thuiller, W., Guisan, A., Schmatz, D.R., Pearman, P.B., 2009. Climatic extremes improve predictions of spatial patterns of tree species. Proc. Natl. Acad. Sci. U. S. A. 106 Suppl, 19723–8. https://doi.org/10.1073/pnas.0901643106

Zurell, D., Thuiller, W., Pagel, J., Cabral, J.S., Münkemüller, T., Gravel, D., Dullinger, S., Normand, S., Schiffers, K.H., Moore, K.A., Zimmermann, N.E., 2016. Benchmarking novel approaches for modelling species range dynamics. Glob. Chang. Biol. 22, 2651–2664. https://doi.org/10.1111/gcb.13251