

# Observing changing ecological diversity in the Anthropocene

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As the world enters the Anthropocene (a new geologic period, defined by humanity's massive impact on the planet), the Earth's rapidly changing environment is putting critical ecosystem services at risk. To understand and forecast how ecosystems will change over the coming decades, scientists will require an understanding of the sensitivity of species to environmental change. The current distribution of species and functional groups provides valuable information about the performance of various species in different environments. However, when the rate of environmental change is high, information inherent in the ranges of many species will disappear, since that information exists only under more or less steady-state conditions. The amount of information about species' relationships to temperature declines as their distributions move farther from steady state. New remote-sensing technologies can map the chemical and structural traits of plant canopies and will allow for the inference of traits and, in many cases, species' ranges. Current satellite remote-sensing data can only produce relatively simple classifications, but new techniques will produce data with dramatically higher biological information content.

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Information derived from a species' range is central to the science of ecology. Current patterns of species and physiological trait distributions contain important information about plant functional relationships to climate and other environmental controls (Cody and Mooney 1978; Davis 1986; Bonan and Sirois 1992; Kearney and Porter 2009; Rödder *et al.* 2011). In a foundational paper, Ter Braak and Prentice (1988) wrote, "All species occur in a characteristic, limited range of habitats, and within their range, they tend to be most abundant around their particular environmental optimum". While this appraisal of the range–niche relationship is too simplistic, ignoring the

effects of species interactions (competition, mutualisms, predation, parasitism, and herbivory), distributional information is nonetheless crucial for constructing models that will help us to understand future ecological responses to global climate change. Some modeling paradigms extract information directly from species' ranges to estimate model parameters, while others rely on distributions to validate models based on mechanistic simulation of reproduction, mobility, and competition.

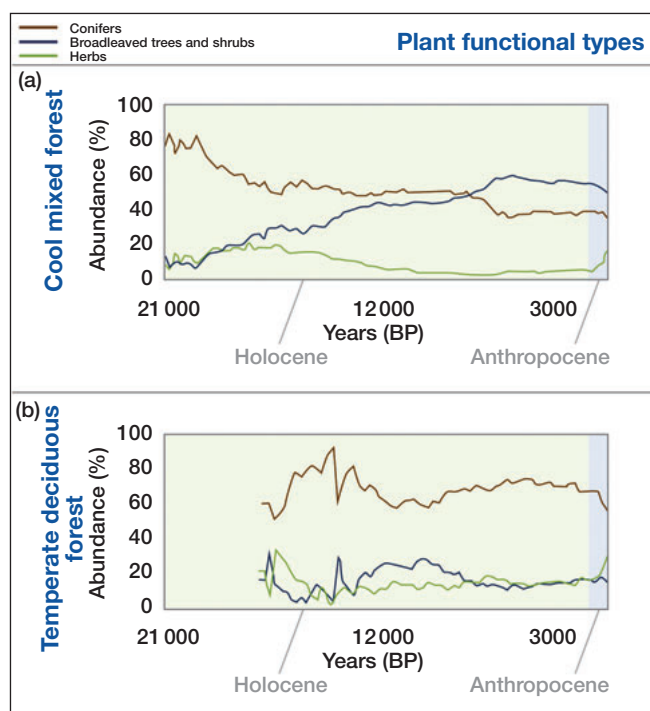
Current rates of climate change equal or exceed the highest rates observed in the recent paleorecord (Loarie *et al.* 2009), while the impacts of land-use changes and invasive species are unprecedented. Given current rates of environmental change, the information inherent in species' range information will soon reflect transient rather than steady-state conditions (Figure 1). While vagile, fast-reproducing plant and animal species may track shifts in climate and its impacts on key resources (Tingley *et al.* 2009), the abundance and spatial distribution of many species will diverge more and more from their historical climate limits. High rates of environmental change imply that distributional data will contain less and less information about species' niches. The farther the planet moves away from the pre-Anthropocene biome configuration, the more important it will become to model community reassembly into new configurations.

Observations are urgently needed to provide a baseline global inventory of the biosphere. This information will be critical for developing robust relationships between environmental characteristics and biotic properties. It will also serve as a useful initial condition for describing the current state of the terrestrial biosphere that can be used to form the baseline for global ecological forecasts. Given our current state of knowledge, we cannot know at

## In a nutshell:

- The Earth's environments are changing faster than species' ranges can re-equilibrate to new environmental conditions, leading to growing inconsistencies between environmental conditions and ranges
- As species' distributions move away from steady state, information about their environmental niches from range–environment correlations is lost
- New remote-sensing technologies deployed on airplanes and spacecraft can provide vast quantities of distributional data about vegetation and can be deployed quickly enough to observe species' range–environment correlations before they are lost
- Next-generation remote sensing will allow us to identify species from observed canopy traits, opening up the possibility of global maps of plant species and traits at high resolution

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**Figure 1.** Rates of biotic change in the Holocene and Anthropocene (adapted from Williams *et al.* 2004). Rates of ecosystem compositional change over 21 000 years in two North American ecosystems: (a) cool mixed forests and (b) temperate deciduous forests. After the deglaciation of North America, relatively rapid changes are seen during the early Holocene. This was followed by a period of relative stability during the mid- (12 000–6000 years before present [BP]) and later Holocene (6000–3000 BP). Rates of change then accelerate in the Anthropocene. The Anthropocene changes seen here primarily reflect the impacts of land use following the European settlement of North America, but may include some early effects of climate change.

what point the distributions of a particular species will move out of its Holocene quasi-equilibrium; however, given current rates of climate and environmental change, the sooner the baseline is measured the better. Traditional methods of field identification and mapping and lab-based assays of variability are too slow and limited to provide increased amounts of new information quickly. Technological innovations are required and the sooner those innovations are implemented, the greater the amount of information will be obtained about the present-day distribution of diversity.

### ■ Species' ranges as legacy information

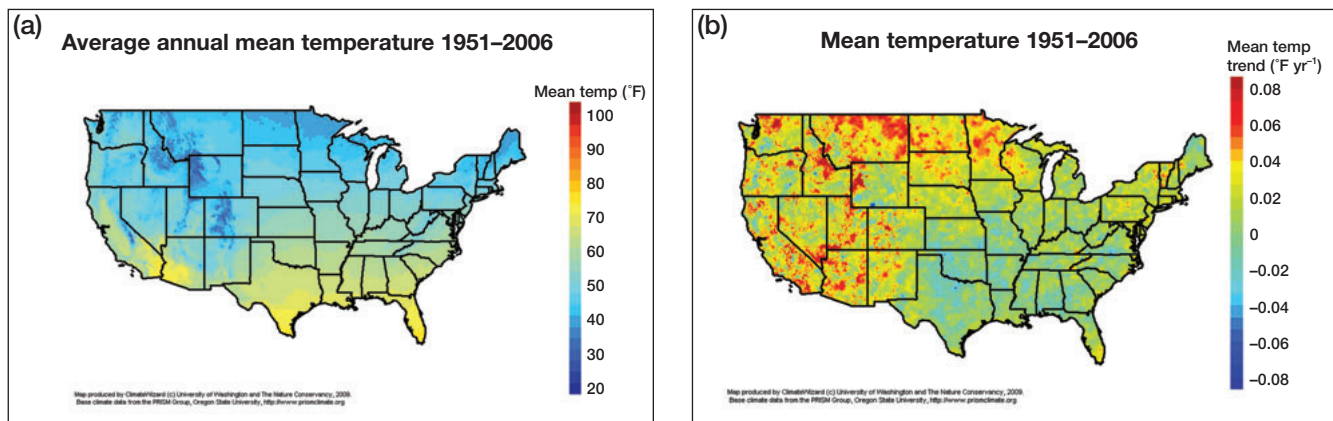
What is the current status of climate–vegetation relationships? The modern-day configuration of biomes began late in the Holocene, a 12 000-year-long period of relatively stable climate conditions, during the latter part of which global mean temperatures varied by only about 1°F (Figure 1). Species' ranges contain information because of the conditions that prevailed during the Holocene, and while the details remain unclear, Holocene condi-

tions allowed many taxa to establish range equilibria. Stable species' ranges do not imply stable local populations; instead, ranges are a statistical estimate and always include absences at some sites, as a result of local population and metapopulation dynamics, even though these sites might be suitable for the species. Such sites may also include refugia, even though these may not be suitable for long-term occupancy.

Later in the Holocene, evidence from measurements of atmospheric carbon dioxide and its isotopes support the idea that, despite emerging human activity (Stocker *et al.* 2011), the global land biosphere and its large-scale carbon balance have been relatively stable; although again, there were continuous, fine-grained variations (Elsig *et al.* 2009). The late Holocene left a legacy of biological information in the form of species–climate correlations. Ecologists have found links between the distribution of species and their traits, often supported mechanistically by experimental studies (Mooney 1977; Kearney and Porter 2009). Evidence that climatic factors exert a strong physical control over species distributions can be seen at the microhabitat level, where subtle meter-scale topography influences vegetation composition (Ackerly *et al.* 2002), from the classic regional orographic mountain range scales of Whittaker and Niering (1965) to the global level (Emanuel *et al.* 1985). While the preponderance of evidence links climate and plant species traits closely, there is sufficient evidence of dynamic processes (Davis and Botkin 1985; Davis 1986; Cohen and Pastor 1991) to suggest that stable species–climate relationships are being disrupted by changing climates, leading to complex dynamics.

Such variability can be viewed hierarchically in the paleorecord. At any given site, species' composition over time is typically very dynamic, reflecting local disturbance regimes, interspecific competition, and changes in climate. When large datasets are assembled, more stable species' range patterns emerge, even though some sites suitable for occupancy are vacant only randomly and some unsuitable sites may still be occupied. As a result, geographic range data provide different information from single site-based field studies. Range data provide information on climate dependence in the context of trophic relationships; some apparent species–range correlations may in fact be correlations with the climate sensitivities of prey or forage species (Tingley *et al.* 2009).

Conditions in the mid- to late Holocene (Figure 1) allowed many species to develop spatial distributions reflective of their underlying realized niches (Holt 2009), and those distributions are an important resource for modeling. Given sufficient time, fine-grained patterns of variation do not prevent large-scale correlations with coarser-grained climate patterns from emerging. The correlations may not be the same in novel future climates. Under climate conditions with no modern analog, some important North American species had different environmental ranges relative to climate than those same species do today, while other species appear more stable (Veloz *et al.*



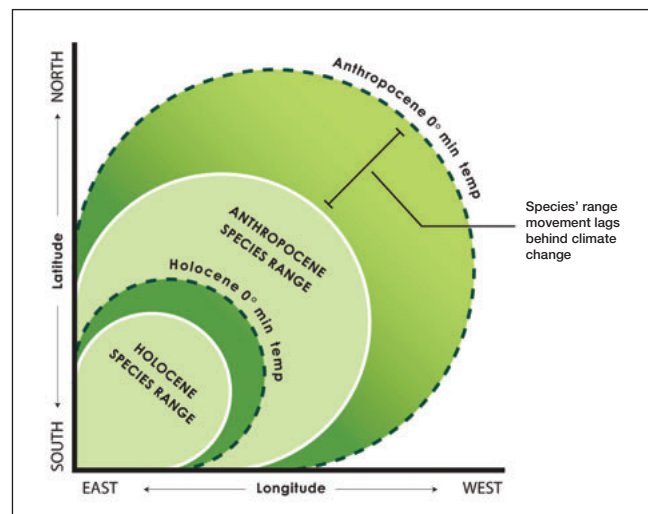
**Figure 2.** Rates and spatial variability of temperature change across the US. Although patterns of mean climate are complex, spatial variation in rates of change adds even more complexity. (a) Average temperatures for the US and (b) rates of temperature change, both for the period 1951–2006. The data are based on assembled station data, interpolated by means of a terrain-sensitive algorithm. Data are derived from Climate Wizard ([www.climatewizard.org](http://www.climatewizard.org)), developed by the University of Washington, the University of Southern Mississippi, and The Nature Conservancy.

2012). This suggests that current-day realized niches may provide limited information regarding the future. The generality of this problem is unknown. By contrast, another recent study (Petitpierre *et al.* 2012) demonstrated that most invasive plant species expand into a climatic niche similar to the one they inhabited in their home range, suggesting that present-day climate relationships are stable; this conclusion was also reached by Tingley *et al.* (2009) with regard to birds. The proportion of species for which present-day ranges are, or are not, robust predictors of future behavior remains unresolved.

The global climate is changing but rates of change vary widely between regions (Solomon *et al.* 2007). Interpolated average annual air temperatures for the conterminous US from 1951 to 2006, and the changes observed over the same period, are depicted in Figure 2a and b, respectively. In parts of the US, mean temperatures have changed by between 1–2.5 °F over this period, more than enough to disrupt the calibration of temperature–species range analyses; precipitation rates have also changed. Case studies show some species apparently responding directly to temperature (Erb *et al.* 2011), while others are responding because their forage, prey, or predators are doing so (Tingley *et al.* 2009). Other observational evidence that bioclimate is changing abounds; a graphic example is evident in the shifts in the Plant Hardiness Zones, the regions suitable for different horticultural and crop plants as defined by the US Department of Agriculture ([www.arborday.org/media/mapchanges.cfm](http://www.arborday.org/media/mapchanges.cfm)).

Loarie *et al.* (2009) calculated the velocity of climate change, defined as the rate of movement required for a species to maintain the center of its range at the same temperature as now, based on climate model projections of rates of change. This calculation suggests a global mean of 0.5 kilometers per year ( $\text{km yr}^{-1}$ ), with many areas as high as 1–10  $\text{km yr}^{-1}$ . This high rate of movement implies that, especially in fragmented or managed landscapes, many species will have difficulty in keeping pace

(Figure 3). Species' ranges have already begun to change (Root and Weckstein 1994; Parmesan 2006; Wake *et al.* 2009) and data on species distributions collected in the future will be less likely to be reflective of adjustment to climate and more likely to exhibit transient responses



**Figure 3.** Conceptual model of transient niche responses to climate change (inspired by LaDeau *et al.* 2011), illustrating a hypothetical species with a range that ends at the 0° minimum temperature isotherm. The axes are latitude and longitude, with a conceptual temperature range mapped into that space. Initially, in the Holocene, the species is near equilibrium with temperature across its range. A climate envelope estimated here would allow the temperature dimension of the species' niche to be inferred. The Anthropocene contour shows the species' distribution at a sample point in time, before it reaches equilibrium with new temperatures. As temperatures change, the species' range will lag behind its climate constraints and at any given moment in time will still be moving toward steady state. At any point within or along the species' temperature limit, non-climatic factors (eg disturbance, competitive interactions between species) can cause population changes, so the species need not occupy the entire range at any specific time.

(Wikle 2003). Species' responses to climate change can be more or less linear, as has been seen in some migratory species (Root and Weckstein 1994), but other transient, non-linear responses to climate increase initially but then decline over the long term (Schimel *et al.* 1990).

Techniques exist that can be used for ecological forecasting in complex systems (Scheffer *et al.* 2001). In some situations the actual future trajectory of a system may be predicted, while in others only the likelihood of a dramatic change may be quantifiable (Scheffer *et al.* 2009). In terrestrial ecosystems, one of the best understood examples of complex variability occurs in the dynamic tension between grass and woody vegetation in savanna ecosystems. Changes to climate, fire, and grazing regimes can drive shifts from a grassy state with sparse trees to woodlands with minimal grass cover (Scholes and Archer 1997; Scheffer *et al.* 2001). The savanna is one of the simpler multi-state systems and contains relatively few interacting species, yet can produce very complex dynamics.

While abstract and idealized simulations of ecosystems can be carried out with very simple models, quantitative forecasting requires not only an appropriate model but also detailed observations of the current state of the system (Hibbard *et al.* 2001, 2003). The paleorecord suggests that many ecosystems that have no analog in either present-day or paleocommunities will emerge as a result of climate change, non-native species invasions, and land-use change impacts. Community re-assembly will occur at the species level, thereby reducing the utility of simpler modeling techniques. The likelihood of complex changes occurring further highlights the need for comprehensive range observations at the species and trait level as early as possible in the Anthropocene.

### ■ The range “scale gap” and the potential for new remote-sensing tools

The length of time needed to collect comprehensive ground-based measurements of species' distributions is such that critical information about species ranges and niches could be lost; Jetz *et al.* (2011) described a *gap* in resolution or scale, the “scale gap”, between species' data and other environmental datasets: “Global knowledge about the spatial distribution of species is orders of magnitude coarser in resolution than other geographically structured environmental datasets, such as topography or land cover”. Land cover, topography, and climate are all now observed from space through the use of remote-sensing techniques that provide global coverage. There is a substantial gap between the fine scales of these abiotic data and the coarse resolution of most species' distribution datasets. Global coverage allows analyses and models based on complete coverage, rather than on sparse statistical samples (Buermann *et al.* 2008).

Remote-sensing observations are uniquely valuable because they can provide complete spatial sampling even when the measurements reveal only part of a complex

reality, as is the case with land-cover data. Recent technological advances are poised to move terrestrial remote sensing beyond the monitoring of land-cover change to mapping of functional diversity and habitat. Such regional and global remote-sensing data on vegetation diversity have the potential to bridge Jetz *et al.*'s (2009) scale gap between species distribution and other environmental data.

A global baseline dataset obtained while biogeographic distributions are in the early stages of change will provide correlations between species' distributions and climate and between species' traits and climate. This baseline will provide a data-based constraint on the sensitivity of many plant species to climate. The baseline will also provide a global-scale measurement of the initial state of the terrestrial biotic system, in terms of the distribution of different species, traits, or functional types that can serve as a starting point for simulations of vegetation change.

While current multispectral remote-sensing techniques can detect variations in biological information only at gross scales (typically classifying into tens of land-cover classes rather than identifying many hundreds of thousands of species), new techniques provide spectral information content (Figure 4) and signal-to-noise ratios (SNRs) at much higher resolutions. Spectral resolution controls how many distinct plant constituents can be detected (Figures 4 and 5). The SNR defines how great a physical difference can be detected in any spectral region. For typical vegetation, current and near-term sensors (eg MODIS, LANDSAT, LDCM) have SNRs of 60–300, while modern spectrometers have SNRs of >600, thereby increasing their ability to resolve biological variation beyond the additional degrees of freedom evident in Figure 4.

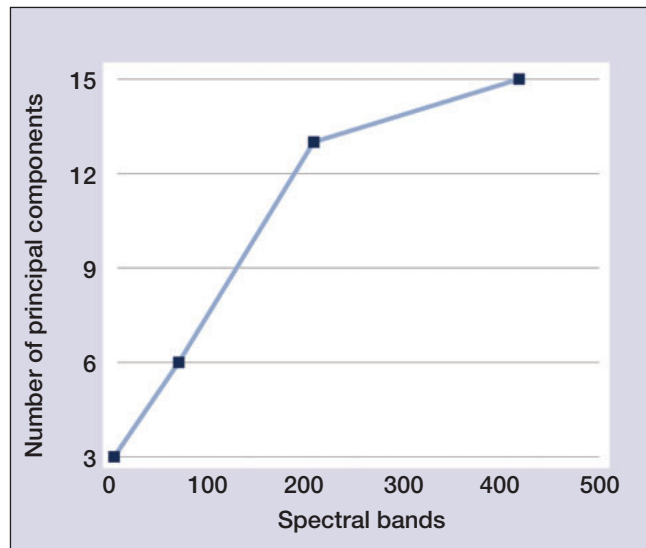
Several opportunities exist for remote-sensing technology to provide a dramatic increase in the amount of information about vegetation characteristics per unit area, using airborne and spaceborne systems. These two approaches are complementary. Airborne data coverage gained from systems such as the National Aeronautics and Space Administration's (NASA's) AVIRIS series as well as Carnegie and National Science Foundation (NSF)-supported systems is limited in terms of both time and space (Asner and Martin 2009; Kampe *et al.* 2010) but is at the scale of individual trees (~1 m<sup>2</sup>), while spaceborne data (at 30–70 m<sup>2</sup>) can provide global and seasonal coverage, albeit at coarser resolutions. With regard to spaceborne measurements, NASA's proposed HypSPIRI (Hyperspectral and InfraRed Imager; [www.hyspiri.jpl.nasa.gov/](http://www.hyspiri.jpl.nasa.gov/)) satellite mission, scheduled for the 2020s, would provide a global dataset of vegetation functional diversity. Successful studies of diversity have already been carried out using sensors with a wide range of spatial resolutions, but there is still a critical need for research on the effects of resolution in retrieving species' identity and diversity to guide future trade-offs between spaceborne sensor coverage, frequency of data collection, and resolution.

Quantitative remote-sensing techniques produce data

on the distributions of species and their traits (Table 1) by directly measuring the chemical composition of plant canopies (Figure 5; Asner and Martin 2009) and by quantifying plant traits linked to water, light, and nutrient use (Ustin and Gamon 2010; Ollinger 2011). Multiple studies have successfully used this approach, which takes advantage of airborne and (the limited existing) spaceborne data. Table 1 lists recent studies that have retrieved diversity-related information through a wide range of airborne and spaceborne sensors. These studies show that hyperspectral data can aid in plant species identification and diversity estimations in temperate and tropical forests, grasslands, and shrublands, as well as a range of wetland ecosystems (Luoto *et al.* 2010). Some of these studies were able to clearly identify individual plants to the species level, while others were able to classify vegetation into multiple functional types, based on canopy signatures, in a way that could be more or less directly used in models of ecosystem function.

Imaging spectroscopy is reaching performance levels that allow quantification of canopy chemistry at large spatial scales. Many of the leaf traits that control photosynthesis rates can be measured by spectroscopic remote sensing, including stoichiometric ratios (Kokaly *et al.* 2009), leaf mass per unit area (Asner *et al.* 2011), and photosynthetic pigments (Ustin *et al.* 2009). In addition to mapping process controls, preliminary studies show that photosynthesis rates, and consequently key traits such as resource-use efficiencies, may be directly estimated spectroscopically by measuring chlorophyll fluorescence (Frankenberg *et al.* 2011). Spectroscopic measurements can also estimate key controls on decomposition and subsequent soil nutrient cycling, such as nitrogen, lignin, and cellulose content (Kokaly *et al.* 2009). By affecting decomposition rates, species' changes can influence productivity and plant successional dynamics (Hobbie *et al.* 1993). While taxonomic and evolutionary relationships may be deduced from spectral data (Asner and Martin 2011), the actual measurements often focus on traits related to growth, longevity, and defense, and can be directly used in mechanistic models. As Davis *et al.* (2005) demonstrated, these traits and their diversity within populations are important drivers of plant community responses to climate change.

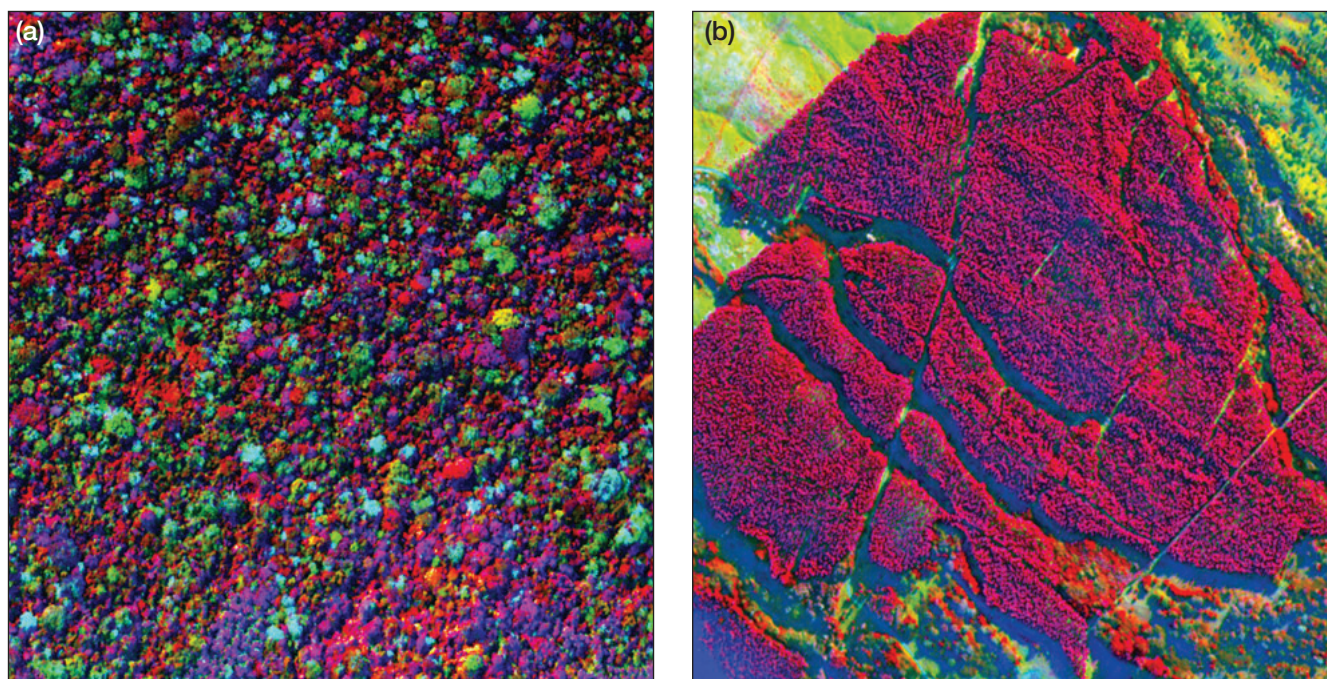
Complementary measurements of vegetation structure, and by extension, key habitat variables, may be measured through light detection and ranging (LiDAR) techniques and also possibly by active microwave techniques (Hyde *et al.* 2005). LiDAR works by detecting the time delay of laser light pulses; by measuring multiple returns, which correspond to leaves and wood at different heights in the canopy, the vertical distribution of foliage may also be inferred. The architectural information obtained from LiDAR can be used in process studies to aid in identifying plant traits and in mapping their distributions (Dalponte *et al.* 2008). Active LiDAR and new microwave techniques are proving to be accurate and informative and



**Figure 4.** The information content of spectral data, showing the impact of spectral resolution on the information content of remote-sensing data, by computing the principal components of the image. The number of independent components is less than the number of spectral channels because the underlying spectral features are often broader than a single channel. Also, many plant constituents have spectral features in multiple parts of the spectrum, reducing the amount of independent information. We used a 420-band hyperspectral image (380–2510-nm range; 5-nm increments) of closed-canopy forest taken by the Carnegie Airborne Observatory. These data were degraded to simulate the spectral resolution of other sensors while holding the spatial resolution (2 m) and signal-to-noise ratio constant. The simulated sensors included NASA's AVIRIS classic (210 bands; 400–2500-nm; 10-nm increments), the commercially available instrument, CASI (72 bands; 400–1050-nm; 10-nm increments), and Landsat ETM+ (6 bands; 400–2200-nm; 20-nm increments). The dimensionality of information in any given scene will vary with diversity, plant chemistry, and canopy structure, but follows this relative scaling of information content.

can provide data that are highly complementary to canopy chemistry information. LiDAR can also quantify the structure of canopy layers, weighting of leaves between the top and bottom of canopies, and the presence of understory plants.

Here, we have focused on the potential for remote-sensing measurements to inform our understanding of plant distributions in relation to climate, but trends in the distribution and abundance of higher trophic levels – herbivores, carnivores, and pests and pathogens – are also critical. While these taxa cannot be observed from space, detailed global coverage of habitat data from remote sensors will provide information critical to modeling the distributions and dynamics of higher trophic levels (Vierling *et al.* 2010). Chemical and structural measurements can provide information on food resources and quality for herbivores and heterotrophs, and three-dimensional vegetation structure provides habitat information for many taxa. Today's relatively crude biological remote-sensing



**Figure 5.** Airborne remote-sensing images of ecosystems with high and low plant diversity, obtained by retrieving combinations of growth, longevity, and defense compounds, including nitrogen, ligno-cellulose and polyphenols. (a) High diversity canopy in the lowland Peruvian Amazon; (b) a monospecific eucalyptus plantation on the Island of Hawaii. High species and chemical diversity is expressed as a kaleidoscope of colors in Peru, while low diversity is shown as near constant color in the Hawaiian plantation ecosystem. These detailed maps of functional diversity were obtained by airborne imaging spectroscopy from the Carnegie Airborne Observatory.

data have been used successfully in modeling animal and microbial distribution and activity, but the qualitatively more advanced sensors that will soon be available will greatly enhance this type of modeling (Hyde *et al.* 2005; Goetz *et al.* 2007; Gilbert *et al.* 2012).

If present-day realized niches are not stable, or if they only represent one of a family of possible niches accessible to a species, then current distributional information may limit our ability to make forecasts (Veloz *et al.* 2012).

Novel species' interactions and the effects of within-species variability in traits may limit the predictability of niche-based processes (Beckage *et al.* 2011). The amplitude of trait variability within species may influence their future distributional and evolutionary responses to climate change (Davis *et al.* 2005).

Spectroscopy and allied techniques can map traits from which species' identity may be inferred, thereby assisting in direct taxonomic identification. Spectroscopy can, in prin-

**Table 1. Examples of identifying species or functional diversity through the use of imaging spectroscopy**

Ecosystem type	Sensor	Spatial resolution (m)	Source
Subtropical broadleaf forest (S)	CAO	0.5	Féret and Asner (2011)
Subtropical broadleaf forest (F)	AVIRIS	3.0	Carlson <i>et al.</i> (2007)
Temperate broadleaf forest (F)	EO-1 Hyperion	30.0	Goodenough <i>et al.</i> (2003)
Temperate grasslands (S)	AVIRIS	19.0	Carter <i>et al.</i> (2005)
Temperate mixed forest (S)	AVIRIS	20.0	Martin <i>et al.</i> (1998)
Temperate needleleaf forest (S)	DAIS	1.0	Gong <i>et al.</i> (1997)
Temperate shrubland-grassland (F)	DAIS	1.0	Yu <i>et al.</i> (2006)
Temperate wetlands (F)	CASI, other	1.0–3.0	Belluco <i>et al.</i> (2006)
Temperate wetlands (S)	HyMap	3.0	Lucas and Carter (2008)
Tropical broadleaf forest (S)	HYDICE	1.6	Clark <i>et al.</i> (2005)
Tropical broadleaf forest (F)	EO-1 Hyperion	30.0	Papeş <i>et al.</i> (2010)
Tropical lowland-to-montane rainforest (S, I)	AVIRIS	3.0	Asner <i>et al.</i> (2008)
Tropical mangroves (S)	CASI	2.5	Held <i>et al.</i> (2003)

**Notes:** S = studies that classified to taxonomic species; F = studies that primarily identified functional types; I = identification of invasive species. CAO = Carnegie Airborne Observatory; AVIRIS = Airborne Visible and Infrared Imaging Spectrometer; EO-1 Hyperion = Earth Observing-1 (spaceborne); DAIS = Digital Airborne Imaging System; CASI = Compact Airborne Spectrographic Imager; HyMap = Hyperspectral Mapper (airborne); HYDICE = Hyperspectral Digital Imagery Collection Experiment (airborne). See WebReferences for the citations in this table.

principle, provide insights in addition to those derived from maps of species' distributions by quantifying spatial variability in key traits within taxa. This is not possible with methods that map taxonomic identity, unless these are supplemented by labor-intensive genomic or physiological measurements. Remote sensing also intrinsically maps biological variation in the context of land use and land-use change, and so allows scientists to integrate human impacts on landscape structure with other drivers of biotic change. Only the most intensive ground-based species-range mapping can provide both the detail necessary to integrate land-cover information and the global coverage required to assess climate effects (Jetz *et al.* 2011).

If climate and other environmental changes lead to complex evolving niches (Beckage *et al.* 2011), sustained imaging of dynamic species' ranges over time will be crucial. The level of effort required to track changing species' ranges or trait variability within species by traditional field methods is such that only relative few taxa could ever be covered. Satellite observations can be sustained over decades, as has been shown by the LANDSAT, AVHRR, and MODIS time series, and are therefore an appropriate means of observing dynamic changes in geographic patterns. NASA's current plan for the launch of HypsIRI, based on the National Research Council's Decadal Study (Schimel *et al.* 2006), is not scheduled for another decade or more; given current rates of climate change, much of the data inherent in species' ranges will by then already have been lost.

## ■ Conclusions

Forecasting the future of ecosystems will increasingly require species- and trait-level data. Today, data with the spatial and temporal coverage and resolution needed to define species' ranges and niches in detail do not exist (Jetz *et al.* 2011). High-resolution data are needed, as are models that will help us to understand and forecast the dynamics of newly assembling communities and ecosystems. The biogeographic patterns that provide information on niche dimensions needed to construct this theory and associated models are being disrupted and the information inherent in these patterns is being lost – at a time when forecasting will become an ever-more-critical tool, and also increasingly challenging, as complex and non-linear ecological responses to climate accelerate.

As a result of human development, the world is now committed to an era of rapid biological change. With accelerating rates of environmental change, species' ranges are shifting. The information content of distributional data obtained now is greater than it would be if obtained in the future, lending urgency to the need for investment in new remote-sensing technology and platforms now. At the same time, continuous observations of these changes from space will provide critical constraints on models of movement and range dynamics. Hyperspectral and active laser and microwave technolo-

gies for remote sensing can map chemical and canopy structural traits for plants and, by extension, provide information on food resources and habitat structure for other taxa.

Typically, life-form classifications are used to assign plant physiological and structural properties in models. Mapping species and life forms from canopy traits reverses this, and identifies taxonomic entities from their physiological and structural characteristics, thereby creating the possibility of inferring species, trait, and habitat distributions globally. When traits are assigned based on mapped species of functional types, only very limited information exists about variation within taxonomic entities. Mapping traits directly, and inferring identity from those traits, allows for a much fuller estimation of within-taxon or type variability, which may be critical information for predictive ecological models. Space-based observations will qualitatively increase the amount and resolution of data relevant to both species and trait distributions that we can obtain, and will transform the science in the same way that global observations have affected climate, topographic, and land-cover science.

A consistently collected global dataset will provide a wealth of information that can be mined for niche information over the coming decades, and will provide information on both current conditions as well as observations of change. Such baseline data can only be obtained by combining traditional field approaches with innovative new remote observation techniques, and the development of techniques for combining such information across scales. Ecologists have not typically attempted to use technology to increase the pace of species-level data collection; however, it is now imperative that we obtain global synoptic coverage of the abundance and spatial distribution of biological diversity. The NSF has supported the construction of three airborne remote-sensing systems as part of the National Ecological Observatory Network (NEON; Kampe *et al.* 2011); the Carnegie Institution for Science operates a similar system, and NASA supports two further systems. Spectroscopic data will soon be commonly available, and from a more diverse range of ecosystems, than ever before. However, the most important opportunity for collecting vegetation data arises from the planned NASA HypsIRI satellite mission, which would provide global spectroscopic data over a period of years. The timing of this mission is extremely important and, unlike missions connected with many other areas of the Earth sciences, the information content depends on when the measurements are made. The longer it takes for the global mission to be deployed, the less information will still exist about realized niches. The timing of launch of all missions affects the pace of scientific discovery, but in the case of HypsIRI, timing actually affects the science that may be done. To obtain the greatest value from planned satellite missions such as HypsIRI, substantial research is still required. Extracting the information about biodiversity inherent in new spec-

troscopy techniques requires the development of algorithms to extract diversity-related data as well as appropriate ground truthing for calibration and validation. Not only are species being lost to extinction, but the information about species is being lost as a result of the high rates of environmental change. The sooner that global observational data can be collected, the more scientific value they will provide.

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