Chapter 10
Remote Sensing of Geodiversity as a Link to Biodiversity

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10.1 Conserving Nature's Stage

Biodiversity is essential for ecosystem functioning and ecosystem services (Chapin et al. 1997; Yachi and Loreau 1999). Yet rapid global change is altering biodiversity and endangering its vital functions, with human-caused habitat deterioration being the number one cause of biodiversity loss (Sala et al. 2000). In addition, climate change is directly affecting individual species abundances and distributions and indirectly affecting species via biotic interactions (Walther et al. 2002). When combined, these effects lead to novel ecological communities for which there are no modern analogs (Williams and Jackson 2007). Although species have continually experienced shifts in climate, the recent rate of temperature change is more rapid than in any other timeframe in the past 10,000 years (Marcott et al. 2013), and temperatures are expected to rise even faster in the near future (Smith et al. 2015). In light of these rapid global changes, a major challenge for biodiversity scientists is to generate robust statistical models that describe and predict biodiversity in space and

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time, from which changes in hot spots (highs) and cold spots (lows) of biodiversity may indicate shifts in ecosystem functions and services.

Contemporary strategies for addressing and managing biodiversity loss align with a metaphor developed by G. Evelyn Hutchinson in his book *The Ecological Theater and the Evolutionary Play* from Shakespeare's *As You Like It* (Hutchinson 1965). In Act II, Scene VII, of *As You Like It*, Shakespeare wrote, "All the world's a stage, and all the men and women merely players. They have their exits and their entrances." In Hutchinson's metaphor, the world's biota comprises the players, and the script is an evolutionary play. More recently, the metaphor has been extended to consider the Earth's abiotic setting as the stage (Beier et al. 2015).

Conservation efforts often emphasize management plans for the actors [e.g., Essential Biodiversity Variables (EBVs)] (Fernandez and Pereira, Chap. 18).

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For instance, the US Endangered Species Act and International Union for Conservation of Nature (IUCN) Red List focus on individual species (ESA 1973; IUCN 2001). However, an inherent challenge to managing species is that, during the course of a play, the actors move across the stage. Geo-referenced fossils from the paleoecological record provide evidence of how species' geographic ranges shifted in the past as Earth's climate fluctuated (Williams and Jackson 2007; Veloz et al. 2012). For instance, in terms of estimating EBVs (Fernandez and Pereira, Chap. 18), species distribution models (SDMs) are one of the most common tools for understanding how species ranges might shift over time and space (Elith and Leathwick 2009; Record and Charney 2016), but they are fraught with statistical (Record et al. 2013) and biological shortcomings (Belmaker et al. 2015; Charney et al. 2016; Evans et al. 2016) that hamper their ability to reliably inform management. Given the challenges of managing species whose ranges might be shifting in response to climate change (Veloz et al. 2012), there is interest in focusing conservation efforts on areas that are likely to support biodiversity and on the processes that generate it (Pressey et al. 2007; Anderson and Ferree 2010; Beier and Brost 2010). Indeed, The Nature Conservancy, one of the world's leading nonprofit conservation organizations, has adopted the rallying cry of "conserving nature's stage" (Beier et al. 2015). Conserving nature's stage entails identifying parcels of Earth that are valuable for their geodiversity and for their capacity to support diverse life forms today and into the future.

Geodiversity has been defined in several ways (see Table 1.2 in Gray 2013). Some definitions of geodiversity refer to variability in soil, geological, and geomorphological features and the processes that give rise to them (Gray 2013 and references therein). Other definitions tend to have a wider scope and also include topography, hydrology, and climate (Benito-Calvo et al. 2009; Parks and Mulligan 2010). These more inclusive definitions of geodiversity capture variability in the entire geosphere (Hjort et al. 2012) that link to important drivers of biodiversity (e.g., energy, water, and nutrients (Richerson and Lum 1980; Kerr and Packer 1997)). The geosphere includes the lithosphere, atmosphere, hydrosphere, and cryosphere (Williams 2012) and processes within and among them and encompasses the abiotic components of Earth's "Critical Zone," or the portion of Earth where biotic and abiotic processes support life on Earth's surface (NRC 2001). Just as the Critical Zone arises from interactions among abiotic and biotic processes, geodiversity is not separated from biotic influences and biodiversity. A key step in the prioritization of conservation areas using this approach is to understand the relationships between biodiversity and geodiversity. Remotely sensed biodiversity and geodiversity data have the potential to answer questions of scale to better inform conservation decisions because they can provide coverage at nearly continuous large spatial extents (i.e., regional to global) and at fine spatial and temporal resolutions (Fig. 10.1 for a spatial example). Here, we provide an overview of remotely sensed data sources that can be used to measure geodiversity and biodiversity to better understand biodiversity-geodiversity relationships, which is a key step in conserving nature's stage.
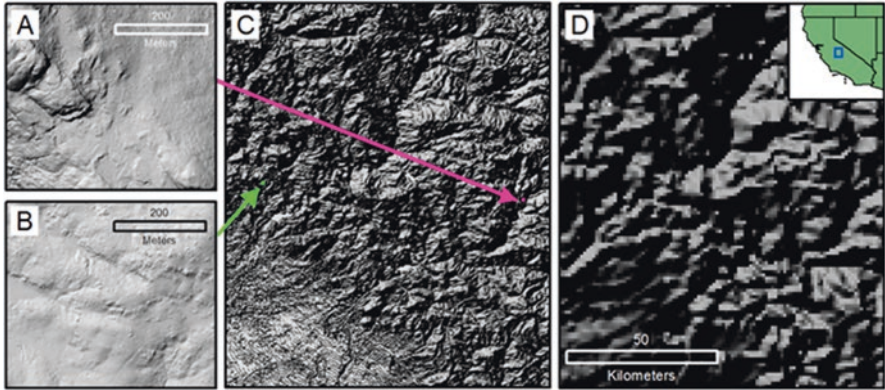
Fig. 10.1 Topography at different spatial grains. Hillshade maps calculated from digital elevation models (DEMs) at 1 m resolution (**a**) and (**b**), 90 m resolution (**c**), and 1 km resolution (**d**). The inset map in (**d**) shows the locations of panels (**c**) and (**d**) in California, which have the same extent. Data for panels (**a**) and (**b**) are from the National Ecological Observatory Network's (NEON) Airborne Observation Platform Light Detection and Ranging (LiDAR) system (Kampe et al. 2010). Data for panels (**c**) and (**d**) are from the Shuttle Radar Topography Mission (SRTM) via earthenv.org (Robinson et al. 2014)

10.2   Geodiversity Indices

Geodiversity represents an opportunity for habitat differentiation (Radford 1981) and available niche space (Dufour et al. 2006) that is thought to support biodiversity (Gray 2008). The continuous nature of remote sensing (RS) data enables exploration of novel measures of geodiversity. In this section we focus our discussion on metrics of variability, although absolute values (e.g., minimum and maximum thresholds) of some geographical features are also informative for understanding species' limits and ultimately species diversity. Studies have used two aspects of variability: the absolute range of conditions and the spatial configuration of these conditions (Spehn and Körner 2005; Dufour et al. 2006; Jackova and Romportl 2008; Serrano et al. 2009; Hjort and Luoto 2010; Hjort and Luoto 2012). The range in conditions is an estimate of the different elements in the area of interest. Given sampling units larger than the minimum pixel resolution, the proportional area covered by distinct geographical features could be used to calculate an evenness index of geodiversity. Categorical features have also treated geodiversity variables similarly to species with measured presences or abundances in various geodiversity metrics (Serrano et al. 2009; Tuanmu and Jetz 2015).

Alternatively, geodiversity could be quantified as variability in continuous observations such as elevation or climate. A focus on variability allows for different geological contexts (past and present) to be taken into account. One of the most common measures of environmental heterogeneity is elevational range (Stein et al. 2014), simply the absolute difference between elevation at two sites or sample units (i.e., among or within sites, respectively). Using elevation as an example, the average

difference, squared, between the elevation in a focal cell and all other cells in a sample unit could be used as a measure of topographic heterogeneity. The coefficient of variation is a similar measure of heterogeneity, though it is standardized to the mean elevation of the sample unit. Pairwise site differences in multiple geographical features can be used as predictors in matrix regression such as generalized dissimilarity models (Ferrier et al. 2007) or more generally a Mantel test (Tuomisto et al. 2003; Legendre et al. 2005), though mechanistic interpretation is limited when geographical features are combined in this way.

Additional approaches include a geodiversity atlas that classifies areas as having very high, high, moderate, low, and very low geodiversity (Kozlowski 1999), quantifying geodiversity in terms of total component resource potential (i.e., energy, water, space, and nutrients; Parks and Mulligan 2010), and the geodiversity index (Gd) that relates the variety of physical elements (i.e., geomorphological, hydrological, soils) with the roughness and surface of the previously established geomorphological units according to the formula:

$$Gd = \frac{EgR}{lnS} \tag{10.1}$$

where Eg is the number of different physical elements, R is the coefficient of roughness of the unit, and S is the surface of the unit (km^2). The Gd is a semiquantitative scale that permits the establishment of five values of geodiversity, from very low to very high for each homogeneous unit. It is argued that use of Gd would allow easier comparison of units and aid suitable management of protected areas (Serrano et al. 2009; Hjort and Luoto 2010; Tukiainen et al. 2017).

With continuously measured remotely sensed geographical features, the sample unit (i.e., grain size) can be modified to examine within site and total site (and thus between sites) geodiversity. Additionally, RS data can uniquely address how relationships between geodiversity and biodiversity change across scales. Various combinations of changing grain and extent (change grain maintain extent, change extent maintain grain, change grain and extent) could be examined to explore scaling relationships (Barton et al. 2013).

10.3   Remote Sensing of Geodiversity

In the following sections, we describe the different components of geodiversity (Table 10.1), some of the ways they can be quantified, and the current state of technologies available to measure them remotely via airborne or satellite observations (Table 10.2). To match current interests in global biodiversity databases (e.g., the Global Biodiversity Information Facility, gbif.org), and because of the importance of scaling from local to much larger extents, we focus here on globally available data; however, we also mention some local scale RS applications. In particular, given that more and more remotely sensed data have been made publically available, we highlight open access remotely sensed geodiversity data.

Table 10.1 Elements of geodiversity

Lithosphere	Geology	Minerals	
		Rocks	
		Unconsolidated solids	
		Fossils	
	Geomorphology	Tectonics	
	Soils	Soil chemical properties	
		Soil physical properties	
	Topography	Elevation	
		Landforms (e.g., ridges, spurs)	
		Slope	
		Aspect	
		Energy	
		Roughness	
Atmosphere	Climate and weather	Temperature	Extreme events
		Precipitation	
		Wind	
Hydrosphere	Surface water		
	Groundwater		
Cryosphere	Ice		
	Snow		

Adapted from Serrano et al. (2009)

Table 10.2 Examples of remotely sensed geodiversity elements

| Geosphere	Geodiversity element	RS data set
Lithosphere	Geology	Ground-penetrating radar (GPR)
	Topography	Advanced Spaceborne Thermal Emission and Reflection Radiometer (ASTER)
		Shuttle Radar Topography Mission (SRTM)
		Sentinel-2
Atmosphere	Surface temperature	MODIS (Moderate Resolution Imaging Spectroradiometer) surface temperature
		AVHRR (Advanced Very High Resolution Radiometer) surface temperature
		Sentinel-3
	Rainfall	Tropical Rainfall Measurement Mission (TRMM)
		Global Precipitation Measurement (GPM) mission
	Wind direction and speed	Quick Scatterometer (QuickSCAT)
		Rapid Scatterometer (RapidScat)
Hydrosphere	Soil moisture	ESA's Soil Moisture and Ocean Salinity (SMOS)
		NASA's Soil Moisture Active Passive (SMAP) observatory
	Gravity anomalies	Gravity Recovery and Climate Experiment (GRACE)
Cryosphere	Ice sheet mass balance	Geoscience Laser Altimeter System (GLAS) sensor onboard the Ice, Cloud, and land Elevation Satellite (ICESat)

10.3.1 Lithosphere

10.3.1.1 Lithosphere: Topography

Topographic barriers can influence geographic patterns of biodiversity by physically isolating populations of plants and animals (Janzen 1967). Topography also can be used as an indirect measure of microclimate, as topographic position can influence temperature and precipitation (e.g., Ollinger et al. 1995). Topography of the lithosphere crust is often represented by elevation (the height above sea level of a given point on the ground) or bathymetry (the depth to the bottom of a water body). In February 2000 the SRTM radar system flew on the US Space Shuttle Endeavour for 11 days collecting radar-derived elevation data from 60°N to 56°S. These data were originally released at 90 m resolution; however, in 2015, 30 m data (1 arc second) were released for the entire SRTM extent. There are many other sources of elevation data including NASA Advanced Spaceborne Thermal Emission and Reflection Radiometer ASTER (Fig. 10.2), *active* radar satellites designed for ice measurement (see the Cryosphere section), and more. NASA is currently working to develop a best available digital elevation model (DEM) for the planet, NASADEM. For this the entire SRTM data set will be reprocessed, Geoscience Laser Altimeter System (GLAS) data will be incorporated to remove artifacts, and the Advanced Spaceborne Thermal Emission and Reflection Radiometer Global Digital Elevation Model version 2 (ASTER) and Global Digital Elevation Map (GDEM) V2 DEMs will be used for refinement.

Elevation is only one of many products under the umbrella of topography. Slope (the angle between two elevation points) and aspect (the direction a slope is facing) are two of the many indices that can be derived from elevation data. Importantly, most of these indices are kernel-dependent, meaning they rely on data not just from an individual point but from surrounding points as well. For example, ArcGIS 10.3 (ESRI; Redlands, California) calculates the slope of a given pixel (elevation value) as the maximum slope between that center pixel and the eight surrounding pixels. The "terrain" function in the raster package in R statistical software (Hijmans and van Etten 2019) permits several different methods for calculating slope based on either a 4- or an 8-cell kernel, and these calculations differ slightly from those in the Geospatial Data Abstraction Library (GDAL; gdal.org). Environment for Visualizing Images (ENVI) software (Harris Geospatial Solutions, Broomfield, Colorado) allows the user to select any kernel size then fits a quadratic surface to the entire kernel, calculating slope and other parameters based on that surface (Wood 1996). These different methods could lead to somewhat different results; in particular, the selection of a small versus a large kernel could change the slope estimated. Imagine, for example, with fine-grained data, the inside of a tip-up pit on the side of a north-facing slope. The local aspect could be south facing, while a larger kernel could reveal that the landscape is north facing.

Beyond slope and aspect, there are many other kernel-dependent topographic measures. For instance, Topographic Position Index (TPI) is defined as the difference between a central pixel and the mean of its surrounding pixels. Terrain
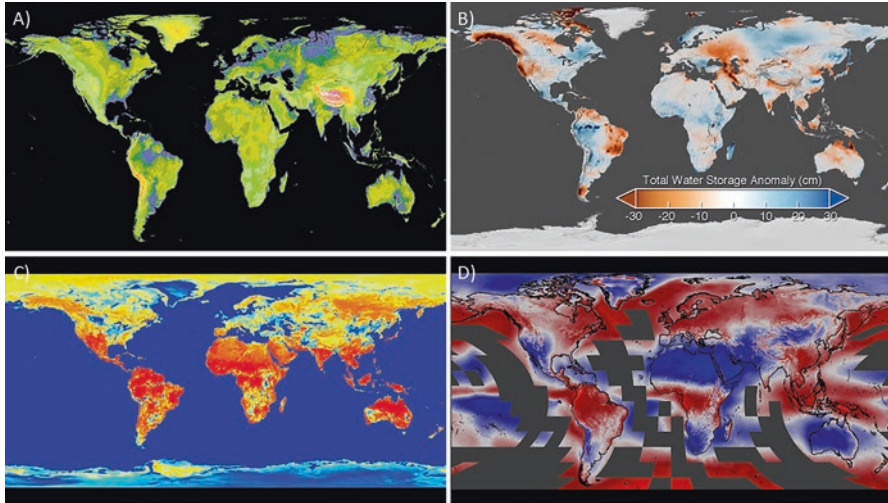
Fig. 10.2 Four examples of geodiversity variables derived from National Aeronautics and Space Administration (NASA) data products. (**a**) Earth's elevation, from which topographic diversity can be calculated, from 2009 imagery from the Advanced Spaceborne Thermal Emission and Reflection Radiometer (ASTER) instrument aboard NASA's Terra satellite (30 m spatial resolution). Image courtesy of NASA/JPL/METI/ASTER Team, NASA's Goddard Space Flight Center. https://svs.gsfc.nasa.gov/11734. Elevation in meters shown with yellows being lower in elevation than greens or reds. (**b**) Gravity Recovery and Climate Experiment's (GRACE) Terrestrial Water Storage Anomaly as of April 2015 relative to a 2002–2015 mean. Image courtesy of NASA's Scientific Visualization Studio (1° spatial resolution). (**c**) Soil Moisture Active Passive (SMAP) global radiometer map. Image courtesy of NASA (9 km spatial resolution). H-polarized brightness temperatures are shown in degrees Kelvin with warmer colors (reds and oranges) showing warmer temperatures and cooler colors (blues and yellows) showing cooler temperatures. (**d**) Mean annual cloud frequency (%; reds indicate higher cloud frequency than blues) over 2000–2014 derived from NASA's Moderate Resolution Imaging Spectroradiometer (MODIS) satellites (Wilson and Jetz 2016; 1 km spatial resolution)

Ruggedness Index (TRI), in contrast, is the mean of the difference between the central pixel and its surrounding pixels (Riley et al. 1999). Wood (1996) describes a number of convexity and curvature metrics based on the first and second derivatives of the quadratic surface described above. DEMs can also be classified into topographic features or landforms like peaks, ridges, channels, and pits, though these definitions depend on specific threshold values that may either be prescribed by software or defined by the user. Incident solar radiation can also be calculated for a given day or aggregated for a year based on a given point's elevation and latitude and the elevations of surrounding pixels. Although this section mainly describes DEM-derived morphometric landforms, it is also important to acknowledge that the genesis of landforms interacts with the ecology of a system. For instance, two hills with similar shapes may have very different associated vegetation if one is sandy (e.g., a dune) and the other is made of tills (e.g., end moraine).

While SRTM-derived products are typically used to produce "best available" topographic information, a challenge with SRTM is that the mission occurred

only once. In geologically and tectonically active areas and areas where humans are influencing geology, satellite-derived data can be used to detect even very small changes over time. For example, Ge et al. (2014) used synthetic aperture radar (SAR) interferometry to detect subsidence in the Bandung Basin (Indonesia) likely due to groundwater extraction. Yun et al. (2015) used SAR data to map areas of change and potential damage after the 2015 Gorkha earthquake in central Nepal. Using SAR instruments in concert with LiDAR instruments on airborne flights has allowed for greater than 30 cm vertical accuracy (Corbley 2010). The launch of the Global Ecosystem Dynamics Investigation (GEDI) mission onboard the International Space Station has the potential to allow for improved global topographic data (Stavros et al. 2017).

10.3.1.2 Lithosphere: Geology and Soils

Geology consists of several subdisciplines, including lithology, tectonics, volcanology, and seismology. A modern geologic "map" in a geographic information system (GIS) framework may include polygons outlining the different substrate types and their ages, lines showing faults, and points identifying small outcrops or places where cores were collected. These static (unchanging through time) representations are developed through the painstaking work of geologists who gather in-situ records of rock type and estimates of geologic feature extents. Geologic maps vary in quality and access due largely to the density and biases of field technicians. When considering long-term evolutionary histories that generate deeper phylogenetic patterns, geological processes of uplift and erosion can become important (Cowling et al. 2009). Nevertheless, for more historically proximate species, community assembly, the available minerals, substrate structure, and topography are likely to play a more important role, especially in plants. For example, although all locations across the Mauna Loa environmental matrix in Hawai'i share a common parent material, differences in age, texture, and nutrient availability (due to variation in climate and weathering) lead to dramatically different vegetation patterns (Vitousek et al. 1992).

Similar to geologic maps, soil maps are typically developed through fieldwork and image interpretation for a single time period. Nevertheless, soils have higher spatial variability than bedrock and may change rapidly in response to natural or man-made disturbance. Recently there have been calls to improve the quality and dynamism of soil maps (Grunwald et al. 2011). The SoilGrids1km data product (Hengl et al. 2014) is one such example. It is a modeled product that relies on indirect remotely sensed variables, such as Moderate Resolution Imaging Spectroradiometer (MODIS), leaf area index (LAI), land surface temperature (LST), and topography from the SRTM to produce estimates at six depths of soil organic carbon, soil pH, sand, silt, and clay fractions, bulk density, cation-exchange capacity, coarse fragments, and depth to bedrock.

Imaging spectroscopy has been broadly applied for geologic mapping (Goetz et al. 1985; Gupta 2013). Multispectral imagery, like NASA's ASTER instrument and the European Space Agency's (ESA's) Sentinel-2 satellite, that is part of the

Copernicus program has long been used for mapping lithography in exposed surface environments (Rowan and Mars 2003; Hewson et al. 2005; Massironi et al. 2008; van der Werff and van der Meer 2016). Hyperspectral imagery has been used successfully to map minerals in many low-vegetation landscapes. For example, the Hyperion sensor, aboard the now decommissioned EO-1 satellite, was used to map mineralogy in Australia (Cudahy et al. 2001). The Airborne Visible/Infrared Imaging Spectrometer (AVIRIS) and new AVIRIS-Next Generation missions continue to push the boundary of imaging spectroscopy used in mineral mapping (Krause et al. 1993; Crowley 1993; Green et al. 1998). These instruments can also provide information on soil nutrient availability in areas dominated by vegetation cover via the influence of soils on foliar chemistry (e.g., Ollinger et al. 2002).

Ground-based RS has also provided insights for subsurface geologic mapping. For instance, ground-penetrating radar (GPR) uses radar pulses to map the relative densities of materials belowground and effectively maps soil and bedrock in layers (Davis and Annan 1989). Airborne GPR can greatly enhance the temporal and spatial resolution of geologic maps (Catapano et al. 2014; Campbell et al. 2018).

10.3.2   Atmosphere: Climate and Weather

Climate is an important control on mineral weathering, soil formation, and landforms (Jenny 1941). Surface temperature and cloud cover are readily observed with RS. The Advanced Very High Resolution Radiometers [AVHRR; National Oceanographic and Atmospheric Administration (NOAA)] have been collecting surface radiation data in the visible, infrared, and thermal spectra with twice-daily global coverage since 1981 that currently gathers data at ~1 km spatial resolution. AVHRR data can be used to map cloud cover and land and water surface temperatures; however, changes in satellite technology and the lack of onboard calibration in the AVHRR sensors have made the use of these data challenging due to a need for standardization of data across satellite technologies (Cao et al. 2008). The launch of the MODIS sensors on NASA's Terra (launched in 1999) and Aqua (launched in 2002) satellites and ESA's Sentinel-3 satellite as part of the Copernicus program (3-A launched in 2016 and 3-B launched in 2018) significantly improved global mapping capabilities. The two MODIS sensors map most of the planet twice a day with 36 bands ranging from the visible to the thermal infrared. The MODIS bands were selected to capture properties of the land surface but also ocean properties, atmospheric water vapor, surface temperature, and clouds (Fig. 10.2). Products from MODIS, such as surface temperature and cloud presence, have been used either to directly map climate variables for use in ecological research (e.g., Cord and Rödder 2011; Wilson and Jetz 2016) or to inform modeled climate products like Worldclim-2 (Fick and Hijmans 2017). Furthermore, surface temperature can better characterize plant ecological differences (Still et al. 2014) because it more accurately captures canopy temperature, which is not the same as air temperature, and because many air temperature products (such as Worldclim-2) are interpolated (see Pinto-Ledézma and Cavender-Bares, Chap. 9).

Satellite-derived rainfall products are estimated through a combination of measurements, including surface reflectance of clouds (i.e., cloud coverage, type, and top temperature), passive microwave (i.e., column precipitation content, cloud water and ice, rain intensity and type), and lightning sensors. The Tropical Rainfall Measurement Mission (TRMM) operated from 1997 to 2015, providing information on rainfall amount and intensity and lightning activity globally every 3 hours at 5 km resolution from 38°N to 38°S. As a follow-up to TRMM, the Global Precipitation Measurement (GPM) mission relies on a constellation of satellites, including a core GPM observatory, to produce 0.1° resolution data every 30 minutes from 60°N to 60°S. Initiated in 2014, GPM allows new explorations of extreme weather events. Like MODIS temperature measurements, TRMM and GPM precipitation measures have been directly incorporated into ecological research (e.g., Deblauwe et al. 2016) and used to inform modeled climate products like the Climate Hazards Group Infrared Precipitation with Station data product (CHIRPS; Funk et al. 2015).

There is also a broad set of efforts to generate reanalysis products that combine the history of Earth observations to develop temporally and spatially consistent global models of climatic and environmental variables. For instance, the NASA Modern-Era Retrospective Analysis for Research and Applications (MERRA) models close to 800 radiative and physical properties of the Earth's atmosphere at 3- to 6-hour time steps from 1979 to present at ~50 km spatial resolution (Rienecker et al. 2011). While this obviously sacrifices spatial resolution, these efforts open the door for longer-term analysis of climatic influence on biologic phenomena.

One commonly overlooked source of geologic substrate lies in the atmosphere. Airborne dust particles provide an essential source of nutrients in many environments and can originate from sources hundreds to thousands of miles away (Chadwick et al. 1999). Aeolian transport of phosphorus from North Africa to South America is thought to be an important driver of Amazonian productivity (e.g., Okin et al. 2004). Studies have mapped dust sources and rates using MODIS products (Ginoux et al. 2012) and produced 3-D models of dust transportation using LiDAR on the Cloud-Aerosol Lidar and Infrared Pathfinder Satellite Observation (CALIPSO) satellite (Yu et al. 2015). Furthermore, the SeaWinds instrument on the Quick Scatterometer (QuickSCAT) satellite and the subsequent Rapid Scatterometer (RapidSCAT) aboard the International Space Station measures wind speed and direction over the ocean's surface.

10.3.3 Hydrosphere

The hydrosphere consists of the water on, in, and above Earth's surface and is known to have a large influence in structuring riparian and aquatic communities of organisms (reviewed by Atkinson et al. 2017). The hydrosphere interacts with other types of geodiversity in the lithosphere, cryosphere, and atmosphere. Topography alone can be used to indirectly provide a crude estimate of many hydrological

variables, including watershed size, soil water content (Moore et al. 1991), flow paths, and surface water. In addition, two types of satellite data can be used to estimate soil moisture and groundwater, which in some systems are important drivers of plant diversity because drought sensitivity may shape plant distributions (e.g., Engelbrecht et al. 2007). The ESA's Soil Moisture and Ocean Salinity (SMOS; launched 2009) and NASA's Soil Moisture Active Passive observatory (SMAP; launched 2015; Fig. 10.2) both use microwave radiometers to detect surface soil moisture globally in areas with low topographic variation and low-vegetation cover. The Gravity Recovery and Climate Experiment (GRACE; launched in 2002; Fig. 10.2) is a pair of satellites that measure gravity anomalies around the world, allowing researchers to estimate available groundwater reserves and their change over time.

Water quality is a critical driver of aquatic biodiversity across taxa, from plants to animals (Stendera et al. 2012). Watershed disturbance, sediment runoff, and nutrient pollution are major aquatic biodiversity stressors, affecting phytoplankton and aquatic and wetland vegetation abundance and diversity (Lacoul and Freedman 2006; Mouillot et al. 2013) and higher trophic levels (e.g., zooplankton, shrimps, larval fish, and birds (Thackeray et al. 2010). Optical RS can be used to retrieve a limited but important set of water quality variables, including particulate and dissolved organic and inorganic matter, chlorophyll-a, as well as other phytoplankton pigments like the phycocyanins common in potentially harmful cyanobacteria blooms. Surface or "skin" water temperature is measured from instruments with thermal bands (Giardino et al. 2018; Alcântara et al. 2010). The major limitation in RS of water quality is in sensor resolution. Sensors must have a fine enough pixel size to resolve water bodies, with high enough radiometric sensitivity to detect small changes in a dark target (10% or less of the total signal received by the sensor, Muller-Karger et al. 2018; Hestir et al. 2015). While some water quality products are publically distributed with limited spatial coverage [e.g., United Nations Educational, Scientific and Cultural Organization (UNESCO) regions], free data processors distributed by NASA (Sea-viewing Data Analysis System [SeaDAS]) and the ESA (Sentinel Application Platform) enable users to compute their own water quality products.

10.3.4   Cryosphere

Earth's fossil record illustrates how changes in glacial cover over time have governed the distribution of biodiversity (e.g., Veloz et al. 2012), and many aspects of the globe's biodiversity are influenced by snow, ice, and permafrost (reviewed by Vincent et al. 2011). The frozen parts of the Earth system, the cryosphere, can be detected with a number of different RS tools. The cryosphere can be divided into several different components—seasonally snow-covered land, permafrost, glaciers and ice sheets, lake ice, and sea ice. Because cloud cover is a frequent problem at high latitudes, cryosphere RS often relies on longwave techniques that can pass

through clouds. A recent book, *Remote Sensing of the Cryosphere* (Tedesco 2014), describes these tools and methods in great detail; here we review some of the major techniques. In all of the discussion below, the importance of change over time is paramount; inter- and intra-annual variation in snow and ice cover are important drivers of physical and biological processes.

The 3-D extent of snow and ice can easily be mapped using optical techniques; snow reflects strongly in the visible and near-infrared (NIR) range but absorbs in the shortwave infrared (SWIR), making it spectrally distinct from other white objects such as rooftops and clouds. These distinctions may still be challenging with multi-spectral sensors, but hyperspectral sensors permit mapping of snow versus clouds and even some estimation of snow particle size (e.g., Burakowski et al. 2015). Passive microwave sensors can be used to estimate snow depth and snow water equivalent, while active microwave sensors can map liquid water content. Tools and techniques for mapping snow are reviewed by Dietz et al. (2011).

Ice and permafrost features can be mapped with many of the tools and methods described in preceding sections. Snow cover can be mapped using optical sensors and methods; subsidence of the cryosphere can be mapped with SRTM (near global extent, 30–90 m spatial resolution, single snapshot in time) and SAR (airborne, 2 m spatial resolution); and passive microwave radiometers such as SMOS (global extent, 50 km spatial resolution, 3-day temporal resolution) and SMAP (near global extent for low-vegetation areas, 9–36 km spatial resolution, 8-day temporal resolution) can be used to map frozen versus thawed ground surfaces (Entekhabi et al. 2014). Because glaciers and ice sheets are fundamentally a combination of snow, ice, and liquid water, many of the techniques described above, such as optical sensors and passive microwave radiometers, can be used to map their extent and status. In addition, the GLAS sensor onboard the Ice, Cloud, and land Elevation Satellite (ICESat; near global spatial extent, 70 m spatial resolution, 91-day temporal resolution from 2003 to 2009) permitted the mapping of ice sheet mass balance (Zwally et al. 2011). ICESat-2 is scheduled for launch in 2018 (global spatial extent, 14 km spatial resolution, 91-day temporal resolution). SAR has also been used to map ice flow on Antarctica (Rignot et al. 2011).

Sea, lake, and river ice cover can be mapped using optical techniques (Jeffries et al. 2005), while thickness has been measured using ICESat and passive microwave sensors (e.g., Kwok and Rothrock 2009). The difference between first-year sea ice and older sea ice can be identified by changes in salinity using multichannel passive microwave sensors like the Advanced Microwave Scanning Radiometer for Earth Observing System (AMSR-E) onboard NASA's Aqua satellite (global spatial extent, 474 km spatial resolution, 12-hour temporal resolution, operational 2002–2015). River ice mapping is critical for monitoring and predicting river habitat quality and duration for a variety of organisms (e.g., Charney and Record 2016; Pavelsky and Zarnetske 2017). The extent and duration of river icing types have been mapped with different polarizations of passive microwave data from Canada's RADARSAT-1 (1995–2013) and RADARSAT-2 (launched 2007) (Weber et al. 2003; Jeffries et al. 2005; Yoshikawa et al. 2007 for aufeis features) and with MODIS Terra (Pavelsky and Zarnetske 2017).

10.4 Remote Sensing of Biodiversity

Approaches for using RS to track biodiversity are reviewed in several chapters in this book (Fernandez and Pereira, Chap. 18; Serbin and Townsend, Chap. 4; Meireles et al., Chap. 7). Biodiversity has many forms—including taxonomic, functional, genetic, and phylogenetic diversity (Serbin and Townsend, Chap. 4; Meireles et al., Chap. 7). Each form may exhibit different relationships with both geophysical and biological drivers, owing to a variety of mechanisms (Gaston 2000; Lomolino et al. 2010). For example, reorganization of organisms in response to changing environments leads to species assemblages becoming more or less similar through biotic homogenization or differentiation (Baiser et al. 2012). Such biotic homogenization/ differentiation is usually characterized taxonomically (Olden and Rooney 2006). However, functional traits (i.e., traits representing the interface between species and their environment) possessed by species are often more important to ecosystem functions valued by society (Baiser and Lockwood 2011) and may be more appropriate to use in assessing biodiversity-ecosystem function relationships (Flynn et al. 2011). Many functional traits may also exhibit a phylogenetic signal (Srivastava et al. 2012), so it is important to consider multiple measures of diversity (i.e., taxonomic, functional, and phylogenetic) when assessing patterns of biodiversity (Serbin and Townsend, Chap. 4; Meireles et al., Chap. 7; Lausch et al. 2016; Lausch et al. 2018).

One caveat to measures of biodiversity generated from high-resolution RS data is that as the spatial resolution of data increases, the spatial extent typically decreases (Turner 2014; Gamon et al., Chap. 16). This limitation hinders our ability to understand how biodiversity relates to different drivers (e.g., geodiversity) at different spatial scales to better inform conservation decisions. There have been recent calls from scientists for new satellite missions and data integration efforts to address this issue (Schimel et al., Chap. 19). For instance, Jetz et al. (2016) call for a Global Biodiversity Observatory to generate worldwide remotely sensed data on several plant functional traits. Petorelli et al. (2016) and Fernández and Pereira (Chap. 18) identify satellite RS data that, given technological and algorithmic developments in the near future, could be capable of meeting the criteria of EBVs for conservation outlined by the international Group on Earth Observations—Biodiversity Observation Network (GEO BON) at a global spatial extent.

Until finer resolution, remotely sensed biodiversity data exist at large spatial extents, data available from in-situ measurements of organisms can inform the relationships between biodiversity and geodiversity. Publically available biodiversity data with geographic locations include expert range maps of individual species from IUCN (IUCN 2017), occurrence data [e.g., Global Biodiversity Information Facility (GBIF, GBIF 2016); Botanical Information and Ecology Network (BIEN, Enquist et al. 2016)], citizen science networks [e.g., Invasive Plant Atlas of New England, IPANE, Bois et al. 2011], and national [e.g., US Forest Service Forest Inventory and Analysis (FIA), Bechtold and Paterson 2005)] and international inventory networks [e.g., the Amazon Forest Inventory Network (RAINFOR), Peacock et al. 2007].

Each of these data sets comes with its own uncertainties (e.g., observation errors) and user challenges. For instance, citizen science data require detailed metadata on the sampling process to ensure that citizen scientists are able to reduce error and bias as they collect data and to enable those analyzing the data to model potential uncertainty (Bird et al. 2014). Despite these sources of uncertainty and logistical hurdles, these data provide a useful starting point for understanding the relationship between biodiversity and geodiversity.

10.5 A Case Study Linking RS of Geodiversity to Tree Diversity in the Eastern United States

To motivate explorations of the relationship between biodiversity and geodiversity with remotely sensed data, we provide an example using biodiversity data from the FIA program of the US Forest Service (O'Connell et al. 2017) and geodiversity data on elevation from SRTM. We selected elevation as a covariate because patterns of tree diversity often vary with elevation (Körner 2012). While some studies promote the use of many geodiversity components (Serrano et al. 2009; Hjort and Luoto 2010; Bailey et al. 2017; Tukiainen et al. 2017), a great deal of the variation in geodiversity is captured by the standard deviation in elevation (Hjort and Luoto 2012), which is used in this analysis.

The FIA program uses a two-phase protocol to characterize the nation's forest resources. In phase one, all land in the United States is categorized as either "forested" or "not forested" using remotely sensed data. In phase two, in every 2428 ha of land classified as forested, one permanent FIA plot is placed for in-situ sampling. Each FIA plot consists of four 7.2-m-fixed-radius subplots wherein all trees >12.7 cm diameter at breast height are measured. FIA plot measurements began in the 1940s, but a consistent nationwide sampling protocol was not implemented until 2001. In the analysis presented, we used data from the most recent full plot FIA inventory from 2012–2016; the SRTM data were collected in 2009. Although there is not perfect temporal overlap in the geodiversity and biodiversity data used in this example, we do not expect that topography at a spatial resolution of 50 km would have changed much over the time period encompassed by both data sets for this part of the world.

We fixed the spatial extent of the analysis to the contiguous United States east of 100°W longitude (n = 90,250 plots total) and selected a grain size of 50 km for calculating alpha (within site), beta (turnover between sites), and gamma (total across all sites) diversities within a radius centered on each FIA plot. All biodiversity metrics were based on species abundances as quantified by the total basal area of each tree species in each plot. Alpha diversity was calculated as the median abundance-weighted effective species number of all plots falling within a 50 km radius of the focal FIA plot, including the focal plot. Beta diversity was calculated as the mean abundance-weighted pairwise Sørensen dissimilarity of all pairs of plots within a 50 km radius of the focal plot, including the focal plot. Gamma
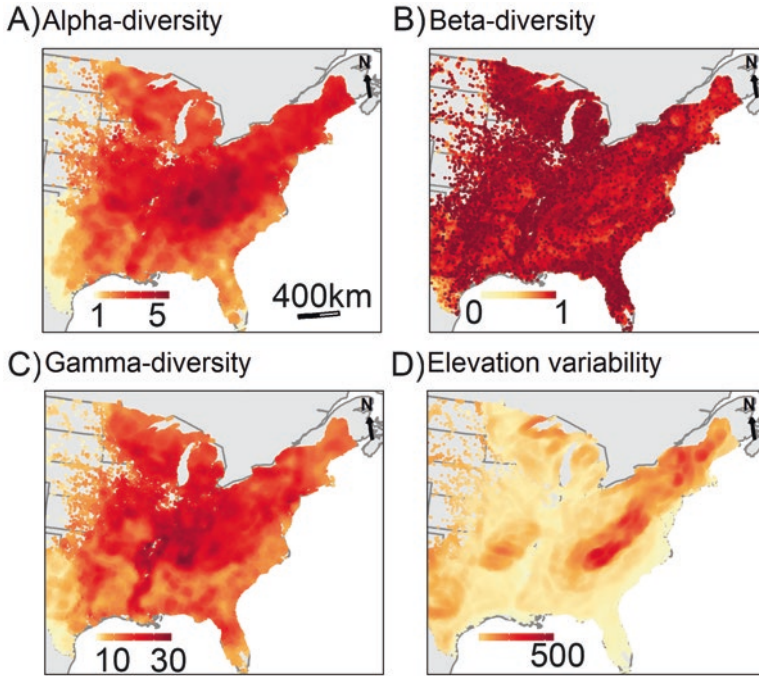
Fig. 10.3 Mapped variation in tree diversity calculated within 50 km radii. Tree data come from the Forest Inventory and Analysis of the US Forest Service (FIA, O'Connell et al. 2017. (**a**) Taxonomic alpha diversity. (**b**) Taxonomic beta diversity. (**c**) Taxonomic gamma diversity. (**d**) The standard deviation of all elevation pixels within the radius from 30 m Shuttle Radar Topography Mission (SRTM) data

diversity was calculated as the aggregated effective species number of all plots within a 50 km radius of the focal plot, including the focal plot. For each 50 km radius centered on a focal plot, we computed the standard deviation of elevation across pixels within the radius from 30 m SRTM data (Fig. 10.3). To avoid edge effects, all plots within 100 km of the political borders of the United States were excluded, retaining 80,411 plots. To avoid pseudo-replication, we generated 999 subsamples of plots separated by at least 100 km, yielding ~370 plots per subsample. Because of the saturating relationship between biodiversity and geodiversity, we fit natural splines with 3 degrees of freedom to relate all focal plots' univariate diversity to elevation standard deviation (SD) (linear regression for alpha and gamma diversity; beta regression for beta diversity), and goodness of fits of the models were assessed with r-squared (Fig. 10.4).

This example shows how the relationships between biodiversity and geodiversity for a subset of different biodiversity metrics vary depending on the metric of biodiversity calculated. Here beta and gamma diversity do not show a strong relationship ($r^2 = 0.03$ and $r^2 = 0.07$, respectively; Figs. 10.3 and 10.4) with geodiversity, but alpha diversity shows a stronger, positive relationship with elevation variability
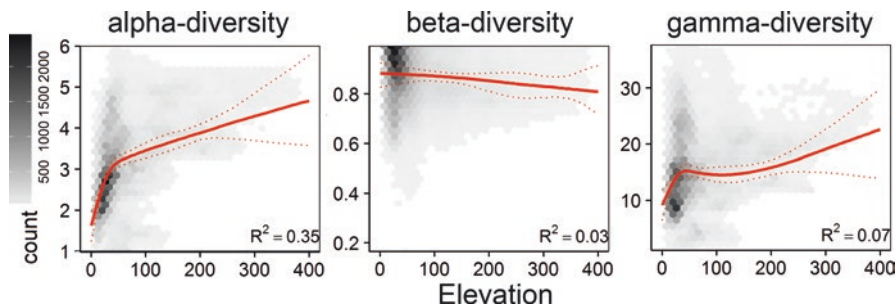
Fig. 10.4 The relationships between three measures of tree taxonomic diversity (alpha, beta, and gamma) and geodiversity (i.e., elevation standard deviation) at a spatial resolution of 50 km. Points indicate the aggregated plots, and the red line indicates the natural spline relationship fitted with a linear regression model for alpha and gamma diversity and a beta regression model for beta diversity. Dotted lines represent the 2.5% and 97.5% quantiles of predicted values across 999 spatially stratified random subsamples of the data, and the given r-squared value is the mean across all the subsamples

($r^2 = 0.35$; Figs. 10.3 and 10.4). Interestingly, in a sister study, Zarnetske et al. (2019) found that FIA tree diversity with a different spatial extent—in California, Washington, and Oregon—showed a different relationship with elevation variability. Furthermore, beta and gamma diversity showed a strong increasing relationship with elevation variability, whereas alpha diversity did not. This comparison between the case study illustrated in this chapter and the results of Zarnetske et al. (2019) highlights the importance of considering how the relationship between geodiversity and biodiversity may change with different spatial scales (Gamon et al., Chap. 16). Bailey et al. (2017) also showed that landforms detected with airborne RS at smaller spatial resolutions explained more of the variation in alpha diversity of alien vascular plants in Great Britain than did climate measured at larger spatial resolutions. While these examples do not provide an exhaustive exploration of the ways in which tree diversity responds to geodiversity, they clearly show how remotely sensed data may help us understand the relationships between geodiversity and biodiversity and how these relationships may be different in different geographic areas.

This example shows how the relationship between taxonomic biodiversity and geodiversity depends on the biodiversity metric chosen. There are various methodologies for calculating biodiversity metrics and various facets of biodiversity (e.g., functional, taxonomic, phylogenetic), and the theoretical pros and cons of each remain controversial (e.g., Jost 2007; Clark 2016), so it may not be obvious which metric is the best. Furthermore, different conclusions may be drawn depending on the types of taxa used in the analysis.

In a similar vein, the choice of an appropriate geodiversity metric may not be obvious. Here we use a single measure of geodiversity, standard deviation of elevation. However, different definitions of the term *geodiversity* include different components of geology, topography, and, in some instances, climate (Parks and Mulligan 2010; Gray 2013). The amalgamation of these different variables to characterize geodiversity as a whole is an area in need of development.

10.5.1 Challenges and Opportunities

10.5.1.1 The Interplay Between Biodiversity and Geodiversity over Time

Although we have focused thus far on the effects of geodiversity on biodiversity, biodiversity can also affect geodiversity. Ecosystem engineers (Jones et al. 1994) and foundation species (Record et al. 2018) can influence biodiversity through habitat formation (Hastings et al. 2007). Geodiversity can be modified by species impacting the structure and function of landscape features. For example, elephants dig, form trails, and trample (Haynes 2012), and vegetation and sediment interact to form streams and coastal dunes (Zarnetske et al. 2012; Atkinson et al. 2017). In turn, these species-modified features can feed back to mediate the strength and direction of biotic interactions among species and ultimately influence patterns of biodiversity (Zarnetske et al. 2017). Even climate can be influenced by biodiversity and biogeographic patterns. Forests directly affect Earth's climate through atmospheric exchange (Bonan 2008). If shrubs expand by 20% and continue to dominate in areas north of 60°N latitude, for example, Arctic annual temperature could increase by 0.66°C– 1.84°C, via decreased albedo and increased evapotranspiration (Bonfills et al. 2012).

Many of these feedbacks between biodiversity and geodiversity are not detectable given a single snapshot in time and require longer time series. RS with repeat samples taken as satellites orbit the Earth provide data with high spatial and deep temporal coverage that can be used to assess changes in the dominance of a species within a community (Pau and Dee 2016). Changes in the dominance structure of communities (or its counterpart, evenness) should be early indicators of global change because these changes occur before the complete loss or replacement of species (Hillebrand et al. 2008). Furthermore, tracking dominant species should be especially important for quantifying biomass or abundance-driven ecosystem functions and services (Pau and Dee 2016). For instance, Cavanaugh et al. (2013) used 28 years of Landsat imagery to map the poleward expansion of mangroves, which are important in preventing coastal erosion, in the eastern United States. Furthermore, the 45-year time series of Landsat data provide an excellent opportunity for detecting changes in habitat due to species, which may have extreme impacts on the abiotic stage.

#### 10.5.1.2 Scale and Expertise Mismatches

The relationships between geodiversity and biodiversity are likely to change across spatial and temporal scales. For instance, a focused spotlight shining down on one part of the stage (e.g., the tip of a mountaintop) might exhibit different covariation between geodiversity and biodiversity than a broad swath of light on another portion of the stage (e.g., an expansive low-lying valley). Spatial patterns of biodiversity and geodiversity are each scale dependent (Rahbek 2005; Bailey et al. 2017; Cavender-Bares et al., Chap. 2; Gamon et al., Chap. 16), and it is well established

that ecological processes influencing the assembly of communities of organisms are scale dependent (Levin 1992; McGill 2010). A spatially explicit framework for conceptualizing community assembly describes external filters (e.g., climate or soils) that sort species from a regional pool at a spatial scale larger than the community and internal filters that sort species into a community from a subset of the species that make it through the external filter (e.g., microenvironmental heterogeneity, biotic interactions; Violle et al. 2012; Fig. 10.5). These "assembly rules" about how communities form remain a controversial paradigm with uncertainty about which processes operate at which scales (McGill 2010; Belmaker et al. 2015). Observing and quantifying relationships between geodiversity and biodiversity and how these relationships change with scale, however, are essential for moving forward regardless of one's position on these controversies. To most effectively use geodiversity to help explain and predict patterns of biodiversity, we need a framework that addresses the scaling relationship between biodiversity and geodiversity.

Furthermore, there are important disconnects in both scale and expertise between biodiversity science and RS (Petorelli et al. 2014) that once addressed will aid in the development of such a framework. Whereas the availability of remotely sensed geodiversity data products has increased, many of the scales are too coarse to reflect the environmental and biological conditions that often drive more fine-scaled spatially heterogeneous biodiversity patterns (Nadeau et al. 2017) and thus may require complex post-processing techniques unfamiliar to most biodiversity scientists before they can be used appropriately in biodiversity models. Also, there are likely many important aspects of geodiversity that at this time can only be derived through in-situ measurements and cannot be remotely sensed. Determining how physical and biological drivers influence biodiversity across spatial and temporal scales is a central focus of ecology. However, most models predicting future patterns of biodiversity assume broad-scale climatic drivers—temperature and precipitation—are sole drivers and leave out important biological drivers (Zarnetske et al. 2012; Record et al. 2013). Biological drivers such as dispersal ability and biotic interactions (e.g., competition) are often mediated by the structure of the landscape, including geophysical feature configuration, topographic complexity, and habitat patch arrangement (Zarnetske et al. 2017). Yet a significant knowledge gap remains about how the relationships between biodiversity and its geophysical and biological drivers change with respect to space and time—perhaps owing to the scale mismatch between fine-scale point-level biodiversity data and many coarse-scale remotely sensed data products.

Many ecological questions are addressed at scales much finer than the grain size of MODIS or GPM, which makes statistical downscaling a necessity for remotely sensed products to be used. Yet the landscape of options for statistical downscaling is vast and complex (Pourmokhtarian et al. 2016). In addition, the increasing availability of airborne topographic data like LiDAR makes the possibility of finer-grain analysis even more viable, yet these data also bring another dimension of complexity and a lack of standardization across platforms and methods.

Open access analytical tools and training will provide ways forward given data downloading and processing challenges. The Application for Extracting and
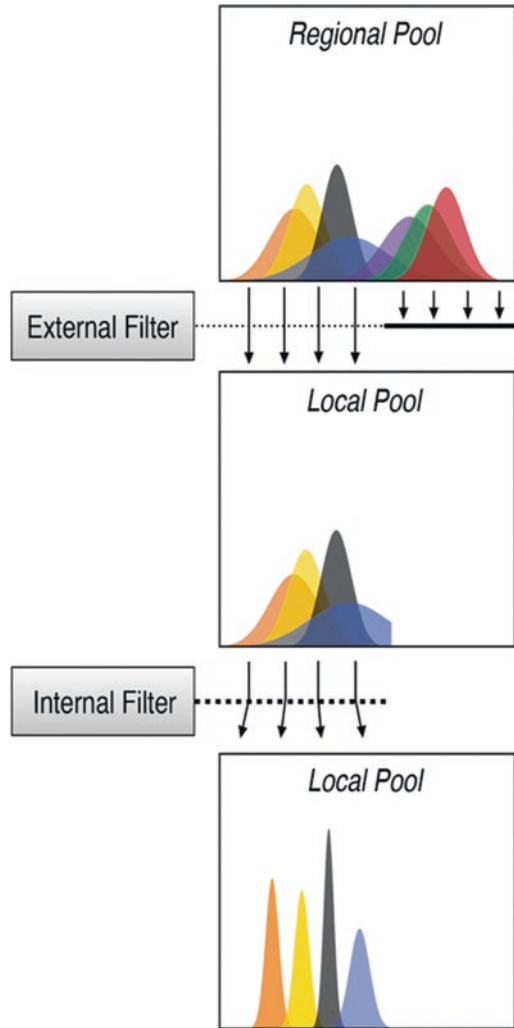
Fig. 10.5 Conceptual diagram adapted from Violle et al. (2012) showing how spatially explicit (i.e., local versus regional) filters influence the assembly of traits in an observed community (bottom schematic). The regional species pool (top schematic) contains all of the species capable of seeding into the local community. However, the observed local community may only contain a subset of the species in the regional pool after species have passed through a series of filters. Both internal and external filters encompass different aspects of the stage, whereas internal filters may also include the actors. Examples of external filters include broad-scale climate or soil types for which some species may not have physiological tolerances. Internal filters include microenvironmental heterogeneity and/or biotic interactions. In this schematic, the traits that passed through the external and internal filters partition in the observed local community, perhaps due to competitive effects between species for resources

Exploring Analysis Ready Samples (AppEEARS) offered by NASA and US Geological Survey (USGS) is a user-friendly tool that enables simple and efficient downloads and transformations of geospatial data from a number of federal data archives from the United States [e.g., the Land Process Distributed Active Archive Center (LP DAAC)]. Additionally, Geomorphons provides a user-friendly interface that automates the calculation of complex geodiversity features from topography data (Jasiewicz and Stepinski 2013). Training the next generation of ecologists and conservation biologists in RS will be integral to overcoming some of these hurdles and bridging the gaps between RS and ecology and conservation.

10.6 Conclusion

Cross-scale studies of relationships between geodiversity and biodiversity using RS and large field-based data sets hold promise for evaluating processes underlying biodiversity and identifying scales and methods for its monitoring and management. Realizing this potential will require more interaction among biodiversity scientists, geoscientists, RS experts, and statisticians to reconcile the challenges associated with differences in scales, available data products, disciplinary barriers, and available methods for connecting geodiversity to biodiversity. These challenges are far from trivial, but overcoming them has the potential to result in key ecological insights that will help us to be better stewards of the entire ecological theater.

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