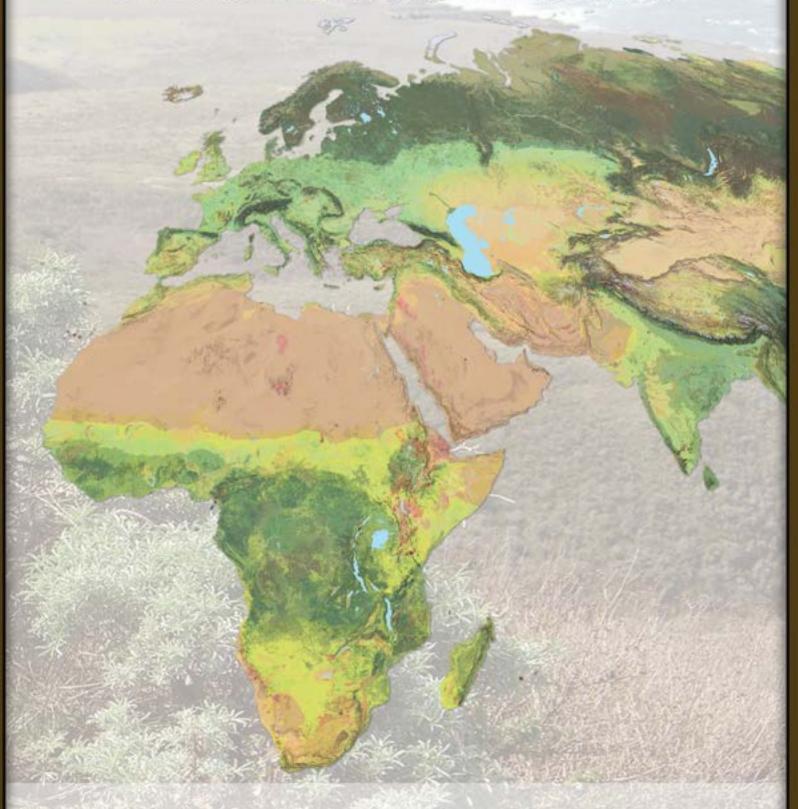
A NEW MAP OF GLOBAL ECOLOGICAL LAND UNITS

AN ECOPHYSIOGRAPHIC STRATIFICATION APPROACH





















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ISBN 978-0-89291-276-6

Cover design: Becky Pendergast (AAG) and Roger Sayre (USGS); cover photo, Jason Hollinger; inside back cover photo, Lori McCallister

Citation: Sayre, R., J. Dangermond, C. Frye, R. Vaughan, P. Aniello, S. Breyer, D. Cribbs, D. Hopkins, R. Nauman, W. Derrenbacher, D. Wright, C. Brown, C. Convis, J. Smith, L. Benson, D. Paco VanSistine, H. Warner, J. Cress, J. Danielson, S. Hamann, T. Cecere, A. Reddy, D. Burton, A. Grosse, D. True, M. Metzger, J. Hartmann, N. Moosdorf, H. Dürr, M. Paganini, P. DeFourny, O. Arino, S. Maynard, M. Anderson, and P. Comer. 2014. A New Map of Global Ecological Land Units — An Ecophysiographic Stratification Approach. Washington, DC: Association of American Geographers. 46 pages.

A New Map of Global Ecological Land Units — An Ecophysiographic Stratification Approach

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Foreword

Mapping the World's Ecosystems

Roger Sayre is an unstoppable force when it comes to mapping global ecosystems. His decades of work at the Nature Conservancy and the U.S.Geological Survey have literally changed how we map and understand ecosystems. This latest and perhaps most important new map on global ecological land units (ELUs), championed by Sayre and implemented by USGS and Esri, represents the third USGS ecosystem mapping effort to be published by the Association of American Geographers (AAG). In 2008, the AAG published the "Terrestrial Ecosystems of South America" as part of a collection of papers from the North America Land Cover Summit. In 2013, the AAG published "A New Map of Standardized Terrestrial Ecosystems of Africa" as a special supplement to the AAG journal, the *African Geographical Review*. With experience gained from those two continental ecosystem mapping efforts, as well as United States terrestrial ecosystems mapping project, the USGS has now collaborated with Esri to map standardized, high resolution terrestrial ecosystems of the Earth.

This map, "A New Map of Global Ecological Land Units," is a groundbreaking 250 meter spatial resolution global map and database of ELUs, derived from a stratification of the earth into unique physical environments and their associated vegetation. The mapping approach first characterizes the climate regime, the landforms, the geology, and the land cover of the Earth, and then models terrestrial ecosystems as a combination of those four land surface characteristics. As such, the work is a classic example of a physical geography approach to understanding ecological diversity.

This ecosystem map and its associated data are a valuable new asset for research and management of our planet, at scales from the community to the global. The data will be downloadable in the public domain and also accessible from the AAG and USGS websites and through Esri's cloud-based ArcGIS Online, with powerful visualization environments, ecosystem tour and browser applications, and sophisticated online analysis tools. "A New Map of Global Ecological Land Units" will be an important tool and resource for climate change impacts assessments, biodiversity conservation planning, and economic and social valuation studies of ecosystem goods and services. Mark Schaefer, former Assistant Secretary of Commerce for Conservation and Management, NOAA, recently emphasized the value of linking these detailed maps of ecosystem units globally at various scales with ecosystem services valuations.

The publication of this map and its data has adhered to a rigorous set of protocols, called the USGS Fundamental Science Practices, for obtaining peer review of scientific papers. That process included peer evaluations from multiple internal scientists not associated with the effort. Endorsed by the international Biodiversity Observation Network of the Group on Earth Observations (GEO), it also draws on data-sharing principles to promote full and open exchange of data. These GEO and other USGS international collaborations will help facilitate interoperability among ecosystem observation systems and databases, generate regularly updated assessments of global biodiversity trends, and design decision-support systems that integrate monitoring with ecological modelling and forecasting.

Jack Dangermond of Esri, which contributed much of the heavy lifting to produce this global map, notes that this new approach and foundation promises to advance the use of geographic science in ecosystem analysis worldwide. Finally, I would like to congratulate and thank Roger Sayre for his lifetime passion and commitment to better understanding the ecosystems that sustain our planet, and for this latest global ecosystems map, a most magnificent achievement.

Douglas Richardson Executive Director Association of American Geographers

Contents

A Special Publication of the Association of American Geographers

Abstract Abstract	7
Introduction	7
Terrestrial Ecosystems	7
Ecosystem Mapping Scales	8
Ecosystems vs. Ecological Land Units.	8
The Need for Global Ecosystem Maps.	9
The Global Earth Observation System of Systems (GEOSS) Global Ecosystem Mapping Task	10
Method	10
General Mapping and Classification Approach	10
Input Datalayers	11
Bioclimates	12
Landforms	13
Lithology	13
Land Cover	14
A Note on Surface Water	14
Accuracy Assessment Approach	14
Ecophysiographic Diversity Index	15
Results	26
Ecological Facets	26
Global, Continental, and Regional ELU Maps	26
ELU Labels.	38
Cartographic Treatment	38
Ecophysiographic Diversity	38
Accuracy Assessment	40
Discussion	40
"Big Data" Considerations	41
Data Dissemination Plans.	41
Limitations of the Approach and Suggestions for Improvements	41
Future Directions	42
Conclusion	43
Acknowledgments	43

A New Map of Global Ecological Land Units — An Ecophysiographic Stratification Approach

List of Figures

Figure 1. The vertical structure of an ecosystem, showing the spatial integration of biological and non-living components. Reproduced with permission from Robert G. Bailey (1996).

Figure 2. The geospatial model and the four input layers used to produce the global ecological facets (EFs) and global ecological land units (ELUs). a) Bioclimate regions (modified from Metzger et al., 2013), b) Landforms (Sayre et al., 2013), c) Lithology (Hartmann and Moosdorf, 2012) and d) Land cover (Arino et al., 2008).

Figure 3. Global bioclimate regions modeled from temperature and precipitation data. Modified from Metzger et al., 2013.

Figure 4. Global landforms modeled from a 250 m digital elevation model.

Figure 5. Global lithology representing rock type at the surface of the Earth. From Hartmann and Moosdorf, 2012.

Figure 6. Global land cover classes from the GlobCover 2009 dataset. Produced by Université Catholique de Louvain and the European Space Agency (Arino et al., 2008).

Figure 7. Map of global ecological land units (ELUs) produced as an aggegation of the ecological facets (EFs) data.

Figure 8. Map of ELUs of North and Central America.

Figure 9. Map of ELUs of Europe.

Figure 10. Map of ELUs of Asia.

Figure 11. Map of ELUs of Australia.

Figure 12. Map of ELUs of South America.

Figure 13. Map of ELUs of Africa.

Figure 14. Map of ELUs of the Ethiopian Highlands, Africa

Figure 15. Map of ELUs of the Eastern Sierra Nevada Mountains region, southwestern United States.

Figure 16. Map of the ecophysiographic diversity index of the Eastern Sierra Nevada Mountains region, southwestern United States, showing the same area depicted in Figure 15. In the center of this image are the Sweetwater Mountains, near Bridgeport, California, discernible as a small magenta and blue area, signifying a very high ecophysiographic diversity. An ecophysiographic diversity index value of 1.0 is the global mean diversity. The higher the index value, the greater the ecophysiographic diversity.

List of Tables

Table 1. Attribute classes for each of the four input layers used to model ecological facets (EFs).

Table 2. Growing Degree Days (GDD) and Aridity Index (AI) values and class names used to model bioclimate regions. GDD is a measure of the temperature regime, and AI is a measure of the moisture regime. The data used to calculate these two bioclimate variables were obtained from global meteorological stations over a 50 year period (1950 – 2000) (Hijmanns et al., 2005).

Table 3. Slope and relative relief values for landform determination.

Table 4. Aggregated attribute classes for the ecological land units (ELUs).

A Special Publication of the Association of American Geographers

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By Roger Sayre, Jack Dangermond, Charlie Frye, Randy Vaughan, Peter Aniello, Sean Breyer, Douglas Cribbs, Dabney Hopkins, Richard Nauman, William Derrenbacher, Dawn Wright, Clint Brown, Charles Convis, Jonathan Smith, Laurence Benson, D. Paco VanSistine, Harumi Warner, Jill Cress, Jeffrey Danielson, Sharon Hamann, Tom Cecere, Ashwan Reddy, Devon Burton, Andrea Grosse, Diane True, Marc Metzger, Jens Hartmann, Nils Moosdorf, Hans Dürr, Marc Paganini, Pierre DeFourny, Olivier Arino, Simone Maynard, Mark Anderson, and Patrick Comer

Abstract

In response to the need and an intergovernmental commission for a high resolution and data-derived global ecosystem map, land surface elements of global ecological pattern were characterized in an ecophysiographic stratification of the planet. The stratification produced 3,923 terrestrial ecological land units (ELUs) at a base resolution of 250 meters. The ELUs were derived from data on land surface features in a three step approach. The first step involved acquiring or developing four global raster datalayers representing the primary components of ecosystem structure: bioclimate, landform, lithology, and land cover. These datasets generally represent the most accurate, current, globally comprehensive, and finest spatial and thematic resolution data available for each of the four inputs. The second step involved a spatial combination of the four inputs into a single, new integrated raster dataset where every cell represents a combination of values from the bioclimate, landforms, lithology, and land cover datalayers. This foundational global raster datalayer, called ecological facets (EFs), contains 47,650 unique combinations of the four inputs. The third step involved an aggregation of the EFs into the 3,923 ELUs. This subdivision of the Earth's surface into relatively fine, ecological land areas is designed to be useful for various types of ecosystem research and management applications, including assessments of climate change impacts to ecosystems, economic and non-economic valuation of ecosystem services, and conservation planning.

Introduction

Terrestrial Ecosystems

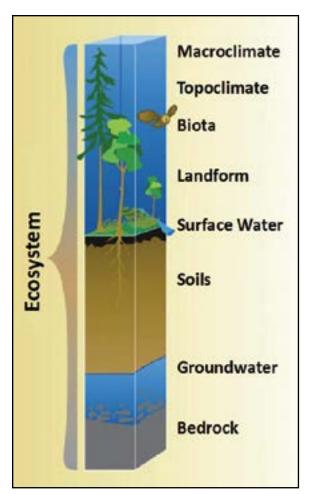
Ecosystems are assemblages of biotic communities interacting with each other and with their physical environment. This concept was first put forward by Tansley (1935), and ecosystems were subsequently recognized in the classic work by Eugene Odum (1953) as fundamental units of research and analysis in the emerging discipline of ecology. By definition, ecosystems have biotic and abiotic components. For terrestrial ecosystems, these components are depicted graphically in Figure 1 as a vertical integration of the climate regime, organisms, landforms, and substrate. Ecosystems occur in terrestrial, freshwater, and marine domains, and the biological communities that are found in these environments exist in response to both the physical potential of the environment (Bailey, 1996) and its evolutionary history (e.g. Hewitt, 1996; Williams, 2009).

In addition to their structural components (Figure 1), ecosystems are also characterized by their many functional properties and processes including nutrient cycling, productivity, energy balance, disturbance regimes, biotic interactions, etc. (Odum, 1953). Specialists in ecosystem function and ecosystem processes are primarily interested in understanding how ecosystems work, while ecosystem geographers study where ecosystems occur, and why.

There are a variety of approaches and a rich terminology for describing Earth's natural and human-constructed environments. Certain terms like ecosystems, habitats, vegetation types, and land cover, are commonly used to describe natural and built environments. These terms are sometimes used interchangeably, which can lead to confusion about what is being described. For example, the terms habitat and ecosystem are commonly confused.

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Figure 1. The vertical structure of an ecosystem, showing the spatial integration of biological and non-living components. Reproduced with permission from Robert G. Bailey (1996).



Habitat is usually used in reference to a particular species (e.g. elephant habitat), and denotes the set of resource requirements (food, space, energy, etc.) needed by that species to survive and reproduce (e.g. Grinnell, 1917; Hall et al., 1997).

Conceptually, an ecosystem is more broadly encompassing than a habitat, and ecosystems in fact include multiple habitats. Land cover and vegetation are also terms describing the vegetative and non-vegetative cover of an area. Land cover classifications and maps tend to emphasize vegetation structure at the general biome level (forests, grasslands, wetlands, deserts), while vegetation type classifications and maps include both structural and compositional (e.g. dominant and co-dominant species) information about vegetation assemblages (Comer et al., 2003).

Ecosystem Mapping Scales

Ecosystems occupy space, and can be conceptualized as occurring at multiple scales as large as biome-level systems like tundra, taiga, deserts, tropical forests, tropical grasslands, etc., or as small as ponds, meadows, forest patches, or even grains of soil. Very large ecosystems, on the order of tens to hundreds of thousands of hectares, are termed macroecosystems. Smaller, site-based ecosystems in the tens of hectares size range are called microscale, or local, ecosystems. In between microscale and macroscale ecosystems are a range of regional scale ecosystems, called mesoscale ecosystems, with size ranges in the hundreds to thousands of hectares. At mesoscales, ecosystem distributions are generally represented in maps as repeating occurrences, or patches, in a mosaic of different ecosystem types.

The scales at which ecosystems are conceptualized and mapped depend on the application for which they are to be used. For example, a resource manager charged with minimizing threats to ecosystems in a small national park typically needs a map of the local, microscale ecosystems in that protected area. A large, international conservation organization, on the other hand, may be focused on protecting representative global tropical forests, and may be working with macroscale ecosystem maps.

Ecosystems vs. Ecological Land Units

The biotic content of ecosystems is typically rich, but complete descriptions of the many biological communities and species found in ecosystems are rare. Vegetation types are often used as a proxy for describing the biotic composition of ecosystems because vegetation is stationary and provides habitat resouces for species. Moreover, vegetation distributions are mappable using satellite imagery or modeling approaches. Vegetation can be mapped in the context of the biophysical environment in which it occurs. In this case, as both the biota and the physical environment giving rise to the biota are included, these maps can correctly be considered ecosystem maps, with the caveat that vegetation type is the sole proxy for all biota. Vegetation mapping requires both structural and compositional information about on-the-ground vegetation distributions. While vegetation structure is often identifiable from satellite image interpretation, information on vegetation composition is normally provided from field surveys, and is therefore often not available. For this reason, satellite image-derived land cover is often used as a proxy for vegetation in ecosystem studies. Ecosystem mapping, then, commonly involves a two-level conceptual proxy; vegetation as a proxy for all biota, and land cover as a proxy for vegetation.

When vegetation is known and mapped in its physical environmental context, the resulting areas can be considered ecosystems (Sayre et al., 2008; Sayre et al., 2009; Sayre et al., 2013). However, when only land cover is mapped with its physical environment context, the resulting areas are better conceptualized as ecological land units rather than ecosystems, as less is known about the vegetation. When the description of an area emphasizes its biophysical features, and also notes associated image-derived land cover, that area is better regarded as an ecological land unit than an ecosystem.

Ecological land classification is an approach to characterizing ecological areas where the emphasis is placed on the land, rather than the biota. Ecological land classification and mapping involves the delineation of ecologically distinct landscapes from a consideration of physical land surface features that influence the distribution of biota (Anderson et al., 1999). Whereas ecosystem maps and classifications may tend to emphasize biotic distributions, ecological land classifications and maps tend to emphasize the physical environment factors which control the biotic distributions (Rowe and Barnes, 1984).

We define an ecological land unit (ELU) herein as an area of distinct bioclimate, landform, lithology, and land cover. These are four basic elements of ecosystem structure, the first three of which (bioclimate, landforms, and lithology) are physical drivers (environmental controls) on the distribution of vegetation, while land cover is the vegetative response to those physical environment drivers. Bioclimate, landform (topography), and lithology are classically regarded as the primary drivers of vegetation (Bailey, 1996 and 2009) distribution because they influence soil, evapotranspiration, precipitation, temperature, wind, cloud, and radiation regimes, which in turn establish physical gradients in substrate chemistry, soil and air water potential, heat balance, and photosynthetically active radiation (Guisan and Zimmerman, 2000). The ecological classification of climates by Walter et al., (1975) was developed to help explain the distribution of world vegetation formations. Climate is perhaps the greatest control on vegetation distributions, and ecological classification of large areas traditionally incorporates a climate dimension (e.g. Holdridge, 1947; Kuchler, 1964; Walter et al., 1975; and Bailey, 1996). Moreover, as climate change results in a redistribution of future bioclimate regions and the appearance of novel bioclimates, vegetation assemblages are likely to redistribute accordingly (Torregrosa et al., 2013).

On the spectrum of ecological classification between taxonomic (emphasizing biological features) and environmental (emphasizing physical features), ELUs are closer to the environmental classifications, and as such, more closely relate to the geo-ecosystems concept than the bio-ecosystems concept (Rowe and Barnes, 1994). The use of abiotic units for representation analysis and reserve selection planning in Australia is well established (Pressey et al., 2000). In the United States, ELUs, defined as "mapping units used in large-scale conservation planning projects that are typically defined by two or more environmental variables such as elevation, geological type, and landform" (Anderson et al., 1999), have been used extensively as both conservation targets and stratification units for conservation priority setting (Groves, 2003).

The ELUs are a characterization of unique biophysical settings and their associated land cover types, and the ELU model explicitly recognizes humans as part of the biosphere. The inclusion of land cover in the ELU model recognizes the role of human beings in shaping the configuration of the land surface, as some of the land cover classes are related to land use by humans (e.g. artificial surfaces and urban areas, croplands, etc.). Moreover, some of the classes (e.g. mosaic vegetation) represent a blending of natural pattern with low intensity human use. In this sense, the ELUs characterize the actual (current) rather than the potential (prior to human disturbance, e.g. Kuchler, 1964) ecological land pattern.

Having conceptually distinguished ELUs from ecosystems based on the relative amount of abiotic vs. biotic information content, it is nevertheless recognized that ELUs have been and will continue to be regarded, generally, as ecosystems. In the absence of rigorous, high biotic content ecosystem maps, the global ELUs are intended to be useful for a variety of global ecosystem assessments, characterized in the following section.

The Need for Global Ecosystem Maps

Maps showing the distribution of ecological areas are used in a variety of applications. Along with genetic and species-level biodiversity, ecosystems are fundamental units of biodiversity (Convention on Biological Diversity, 1992), and ecosystem maps are commonly used in biodiversity conservation planning to ensure ecological representation in protected area networks (Groves, 2003). In the United States, a gap analysis of the representation of terrestrial ecosystems in the protected areas network (Ayerigg et al., 2013) showed that terrestrial ecosystems at three different levels of ecological organization were inadequately represented in protected areas, especially at certain elevations and on certain soil types. This assessment would not have been possible without a spatially explicit, fine resolution map of ecosystem distributions. On a global scale, the Convention on Biological Diversity's Aichi Target (Target Number 11) (http://www.cbd. int/sp/targets/) establishes a 17% goal for ecologically representative land in protected area status. If there is an interest in ensuring that representative ecosystems comprise the 17% land allocation, then ecosystem maps are needed for the protected area planning. Moreover, the distributional extent and change in extent of ecosystems has been proposed for assessment and monitoring as an essential biodiversity variable (EBV) (Pereira et al., 2013).

Understanding climate change impacts (as well as other impacts like fire, invasive species, land use change, etc.) also requires information on the types and distributions of ecosystems that are being impacted (Watson et al., 2013). Moreover, the production of spatially explicit and accurate maps which quantify the production, flow, and consumption of ecosystem goods (food, fiber, fuel, etc.) and services (water purification, soil formation, pollination, etc.) is an increasingly recognized element of assessments of nature's benefits (Bagstad, 2013). Maps of ecosystem distributions underpin these assessments as the ecosystems themselves are the "service provider units" (sources) of the ecosystem goods and services (Maynard et al., 2010).

Several ecoregion maps of the planet exist (e.g. Bailey, 1998; Olson et al., 2001) as macroscale, interpretive characterizations of ecologically meaningful regions, often developed as a compendium of existing maps. Frequently used in assessments of global biodiversity, these maps have considerably advanced conservation priority setting, and have helped guide past and current global conservation agendas of non-governmental conservation groups such as The Nature Conservancy (Groves et al., 2000), and World Wildlife Fund (Olson and Dinerstein, 2002). While quantitative modeling of ecological areas exist for local (Rolf et al., 2012), national (Hargrove and Hoffman, 2005), and regional (Mucher et al., 2010) landscapes, a standardized, data-derived, high resolution map of global ecological areas has been lacking. Such a map could complement existing expert-based, macroscale ecoregion maps by extending the depth of available information and improving the spatial resolution.

The Global Earth Observation System of Systems (GEOSS) Global Ecosystem Mapping Task

Given this need for a global ecosystem map, the Group on Earth Observations (GEO – a consortium of over 80 nations) has commissioned the work as part of an intergovernmental protocol called GEOSS (the Global Earth Observation System of Systems) (https://www.earthobservations.org/index.php).

GEOSS seeks to leverage the use of Earth observations to help solve some of society's greatest challenges (Group on Earth Observations, 2005). One of the many activities in the GEOSS workplan is a task EC-01-C1, (https://www.earthobservations.org/area.php?id=ec&smsid=310&aid=5&did=1450274626) to develop standardized, global, ecosystem classifications and maps at management-appropriate scales for the planet's terrestrial, freshwater, and marine environments (Sayre at al., 2007). The United States is the member nation of GEO responsible for this activity, and the U.S. Geological Survey (USGS) is the designated federal agency implementing the work. To date, working with numerous governmental and non-governmental partners, the terrestrial ecosystems of three continental-scale regions have been mapped: South America (Sayre et al., 2008), the United States (Sayre et al., 2009), and Africa (Sayre et al., 2013). Having developed a working methodology and detailed map and data products at continental scales, and responding to the need for a standardized global ecosystems map, the USGS has undertaken a major collaboration with the Esri Corporation and others in a first attempt to delineate standardized, replicable, mesoscale (tens to thousands of hectares) ecological land units for the Earth at a base resolution of 250 meters.

Method

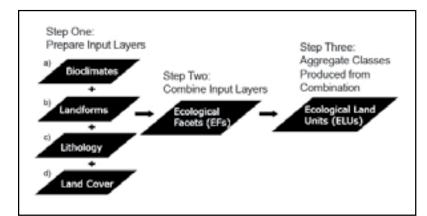
General Mapping and Classification Approach

The fundamental approach undertaken herein was to stratify the Earth into physically distinct areas with their associated land cover. The approach is ecophysiographic in that it emphasizes both ecological (e.g. bioclimates and land cover) and physiographic (e.g. landform and lithology) properties of landscapes. The stratification was executed as a geospatial combination of the four input layers (bioclimate, landform, lithology, and land cover) to produce a single raster datalayer where every cell represented a unique combination of the four inputs. Following the production of the foundational raster datalayer, a data reduction step was undertaken to reduce the large number

of combinations produced from the union of the input datalayers. A graphical description of this geospatial model is presented in Figure 2.

The approach outlined in Figure 2 was undertaken in three steps. Step One involved acquiring or developing the four input raster base layers (bioclimates, landforms, lithology, and land cover), and reconciling them to a standard, 250 meter global raster framework. The choice of 250 m as the base resolution for the project was based on the availability of a global 250 m digital elevation model (Danielson and Gesch, 2011) whose raster framework could be used as the geospatial reference standard, as well as the desire to improve over the typical square kilometer resolution associated with many global data

Figure 2. The geospatial model and the four input layers used to produce the global ecological facets (EFs) and global ecological land units (ELUs). a) Bioclimate regions (modified from Metzger et al., 2013). b) Landforms (Sayre et al., 2013). c) Lithology (Hartmann and Moosdorf, 2012). d) Land cover (Arino et al., 2008).



products (e.g. Gesch et al., 1999; Hijmans et al., 2005). While the native spatial resolution of the landforms and land cover layers were equal or very close to 250 m, it is acknowledged that the other two inputs, bioclimates and lithology had coarser spatial resolutions. These two layers were subsampled at 250 m resolutions to spatially reconcile them with the other inputs. It is acknowledged that this subsampling was conducted to achieve a common raster framework for all layers, and is not intended to introduce increased artificial spatial resolution into the data. The subsampling assumes that the attribute values are homogenous throughout a larger area, in the same manner as all points in a vector polygon feature are assumed to have the same attribute values. In reality, it is recognized that a considerable amount of heterogeneity may exist that is not captured when subsampling.

Step Two involved combining all four raster inputs into a single master 250 m global raster datalayer where each cell was the resulting combination of the values from the four input rasters. This foundational raster dataset was called the ecological facets (EFs) layer. Finally, Step Three involved reducing the many classes of EFs resulting from the spatial combination into a more manageable and cartographically approachable number of ecological land units (ELUs). The aggregation was achieved by generalizing the input layer attribute classes.

This approach to developing global ELUs can be con-

sidered as classification neutral in the sense that no a priori ecosystem classification was used to label the mapped entities. In the three previous GEOSS continental-scale mapping efforts for South America, the United States, and Africa, ecosystem classifications were available (or developed) as an aggregation framework and set of labels for the resultant ecosystems. In those cases, the EFs were allocated by modeling or using expert rule-sets into a predetermined set of ecosystem classes. However, although a global vegetation formation classification is in development (Faber-Langendoen et al., 2012), no standardized, rigorous, mesoscale terrestrial ecosytems classification yet exists for the planet, so no classification was available to guide the aggregation step. The labeling of the ELUs was accomplished as a concatenation of the

descriptors for the input layers. The label for each ELU therefore describes exactly what it is. This approach is advantageous in that it avoids bias in selection and use of an *a priori* classification system which may or may not be considered a consensus, or widely accepted classification.

The ecological facets (EFs) product is a foundational global raster datalayer at a 250 m spatial resolution where each pixel has four attributes: bioclimate region, landform type, surficial lithology, and land cover. As discussed earlier, the first three of these inputs (bioclimate, landforms, and lithology) represent the primary environmental controls on the distribution of biota, while the fourth (land cover) is the vegetative response to the physical environmental potential. Through the aggregation by class reduction approach described above, the EFs data are used to bound and/or refine the delineations of the ELUs. The ELUs represent a quantitative, consistent, and globally comprehensive spatial analytical framework for ecological areas of the planet. The input layers to create the EFs and ELUs are described in detail in the following section.

Input Datalayers

The data for all of the input components are categorical, with the number of classes for each as follows: bioclimates (37), landforms (10), lithology (16), and land cover (23). The classes for each of the input layers are presented in Table 1, as follows:

Table 1. Attribute classes for each of the four input layers used to model ecological facets (EFs).

Bioclimate				
Arctic	Cold Very Wet	Cool Wet	Warm Moist	Hot Dry
Very Cold Very Wet	Cold Wet	Cool Moist	Warm Semi-Dry	Hot Very Dry
Very Cold Wet	Cold Moist	Cool Semi-Dry	Warm Dry	Very Hot Very Wet
Very Cold Moist	Cold Semi-Dry	Cool Dry	Warm Very Dry	Very Hot Wet
Very Cold Semi-Dry	Cold Dry	Cool Very Dry	Hot Very Wet	Very Hot Moist
Very Cold Dry	Cold Very Dry	Warm Very Wet	Hot Wet	Very Hot Semi-Dry
Very Cold Very Dry	Cool Very Wet	Warm Wet	Hot Moist	Very Hot Dry
			Hot Semi-Dry	Very Hot Very Dry

Landform				
Flat Plains	Irregular Plains	Low Hills	Breaks	High Mountains/Deep Canyons
Smooth Plains	Escarpments	Hills	Low Mountains	Surface Water

Lithology				
Siliciclastic Sedimentary Rock	Unconsolidated Sediments	Acidic Plutonics	Acidic Volcanics	Pyroclastics
Carbonate Sedimentary Rock	Evaporites	Intermediate Plutonics	Intermediate Volcanics	Ice and Glaciers
Mixed Sedimentary Rock	Metamorphic Rock	Basic Plutonics	Basic Volcanics	Water
				Undefined

Land Cover		
Bare Areas	Rainfed croplands	Forest, Closed (>40%), Needleleaved Evergreen,>5m
Artificial Surfaces and Urban Areas (>50% pixel	Mosaic Cropland (50-70%) with Mixed Vegetation	Canopy Height
composition)	(Grassland/Shrubland/Forest) (20-50%)	Snow and Ice
Shrubland, Closed to Open (>15%), Broadleaved or	Post-flooding or Irrigated Croplands (or Aquatic)	Sparse (<15%) Vegetation
Needleleaved, Evergreen or Deciduous, <5m Canopy Height	Forest/Woodland, Open (15-40%), Broadleaved	Water bodies
	Deciduous, >5m Canopy Height	Forest, Closed to Open (>15%), Broadleaved, Regularly Flooded (Semi-permanently or Temporarily), Fresh or Brackish Water
Herbaceous Vegetation, Closed to Open (>15%) Grassland, Savannas or Lichens/Mosses	Forest, Closed (>40%), Broadleaved Deciduous, >5m Canopy Height	
Mosaic Forest or Shrubland (50-70%) with Grassland (20-50%)	Forest, Closed to Open (>15%), Broadleaved Evergreen or Semi-deciduous, >5m Canopy Height	Grassland or Woody Vegetation, Closed to Open (>15%), Regularly Flooded or Waterlogged Soil, Fresh,
Mosaic Grassland (50-70%) with Forest or Shrubland	Forest, Closed to Open (>15%) Mixed Broadleaved and	Brackish or Saline Water
(20-50%)	Needleleaved, >5m Canopy Height	Forest or Shrubland, Closed (>40%), Broadleaved,
Mosaic Vegetation (Grassland/Shrubland/Forest) (50-	Forest, Open (15-40%), Needleleaved Deciduous or	Permanently Flooded, Saline or Brackish Water
70%) with Cropland (20-50%)	Evergreen, >5m Canopy Height	No Data (Burnt Areas, Clouds,etc.)

Bioclimates — The bioclimates input layer was a modified version of the Global Environmental Stratification (GEnS) dataset recently produced by Metzger et al. (2013) in another GEOSS-commissioned effort. The modified GEnS bioclimate strata are depicted in Figure 3, on page 16.

The original GEnS was statistically derived using a clustering algorithm that produced 125 bioclimate strata, which were aggregated into 18 bioclimate zones. The strata were produced using the 1 km spatial resolution temperature and precipitation data from WorldClim (Hijmanns et al., 2005). WorldClim data is a set of spatially

interpolated raster data surfaces from point data (global meteorological stations) collected over a 50 year (1950 – 2000) period. Precipitation data from 47,554 meteorological stations were combined with temperature data from 24,542 stations to build the WorldClim dataset. Several commonly-used climate variables were generated from the data and screened for autocorrelation, and the autocorrelates were dropped from further inclusion in the modeling. The remainder of the variables were subsequently included in a Principle Components Analysis (PCA). The following variables emerged as explaining the majority of the variation in the data: Growing Degree Days (GDD; 80.1%), Aridity Index (AI; 19.2%), and

Temperature Seasonality (T Seasonal; 0.4%). GDD is an expression of the temperature regime, and is derived from mean monthly temperature, which, if greater than zero, is multiplied by the number of days in that month. The sum of all degree day months is the GDD. Aridity Index (AI) is a measure of the moisture regime and is derived as the quotient of precipitation divided by evapotranspiration (Zomer et al., 2008). Together, GDD and AI accounted for 99.2 % of the variation in the climate data.

These variables were then used in an equally-weighted clustering process to create 125 bioclimate clusters. Four datasets were included in the bioclimate clustering routine: growing degree days (GDD), aridity index (AI), mean of temperature seasonality (T Seasonal mean), and standard deviation of temperature seasonality (T Seasonal standard variation). The clusters were then aggregated into 18 climate zones (GEnZ), and labeled using temperature and moisture groupings of the GDD and AI data.

For this effort, each 1 km² GEnZ global raster was then subdivided into sixteen 250 m² cells, conforming with the base mapping resolution of the analysis. A preliminary visual inspection of the GEnZ data at this point revealed that additional information on the global humidity regime was desirable as the AI component appeared underemphasized in certain areas. It is plausible that the AI was underemphasized in the GEnZ because it was the only moisture-related variable included in the clustering, while the other three equally-weighted variables were all derived from temperature data. The AI datalayer was therefore obtained and spatially combined with the GEnZ datalayer to reinforce the humidity attribute of the GEnZ pixels. The resulting global bioclimates layer was therefore a characterization of ombrotypic (moisture regime) and thermotypic (temperature regime) combinations, with class values for the GDD and AI parameters presented in Table 2.

Landforms — No DEM-derived global landforms datalayer existed prior to this effort. A 250 m global landforms product was therefore developed (Figure 4, on page 18) from digital elevation data.

The landform model used (True, 2002) was originally developed by the Missouri Resource Assessment Partnership (MoRAP), following in the landform classification tradition of Fenneman (1916) and E. Hammond (1954). This method has been used to model landforms of South America (450 m spatial resolution), the conterminous United States (30 m), and Africa (90 m) as an input to the ecosystem modeling process (Sayre et al., 2008; Sayre et al., 2009; and Sayre et al., 2013, respectively). The source data for the landforms development was the 250 m resolution level of the USGS GMTED2010 digital elevation model (Danielson and

Table 2. Growing Degree Days (GDD) and Aridity Index (AI) values and class names used to model bioclimate regions. GDD is a measure of the temperature regime, and AI is a measure of the moisture regime. The data used to calculate these two bioclimate variables were obtained from global meteorological stations over a 50-year period (1950 – 2000) (Hijmanns et al., 2005)

Growing Degree Days (GDD)		Aridity Index	(AI)
9,000 - 13,500	Very Hot	1.5 - 70	Very Wet
7,000 - 9,000	Hot	1.0 – 1.5	Wet
4,500 - 7,000	Warm	0.6 – 1.0	Moist
2,500 – 4,500	Cool	0.3 – 0.6	Semi-Dry
1,000 – 2,500	Cold	0.1 – 0.3	Dry
300 – 1,000	Very Cold	0.01 – 0.1	Very Dry
0 – 300	Arctic		

Gesch, 2011). The GMTED2010 was developed as a higher resolution, more current, multi-product update to the 1 km resolution GTOPO30 global DEM previously produced by USGS (Gesch et al., 1999).

The landform model incorporates a standard circular 1 km² sliding neighborhood analysis window (NAW) which assigns a parameter value to every pixel based on an analysis of all the pixels in the neighborhood. It then computes the average slope in the neighborhood and assigns the central pixel into one of two classes: gently sloping (<8%) or sloping (>8%). The model then computes the relative relief in the neighborhood as the difference between maximum elevation and minimum elevation. The combination of slope class and relief class determines the ultimate landform class (Table 3), where mild slopes and little relief produce different kinds of plains, and steeply sloping areas with considerable relief are classed as hills and mountains. Post-classification, surface water features from the Global Lakes and Waterbodies Dataset – Level 2 (Lehner and Döll, 2004) were added (burned in) to the landforms layer. One of the original MoRAP landform classes, irregular plains, was subsequently reclassed as low hills, after inspection revealed that these areas were often regarded as hills in local geographic naming convention. The escarpments class was observed in very low frequencies, likely due to the spatial resolution being too coarse to adequately capture these abrupt, steep slopes separating relief formations. The escarpments class, when it occurred, was therefore reclassified as hills.

Lithology — The lithology input layer is the recently produced (Hartmann and Moosdorf, 2012) Global Lithology Map (GLiM) depicted in Figure 5, on page 20.

The GLiM identifies 16 lithological classes at its most general level of classification. The lithological classes describe rock (including unconsolidated sediments) proper-

Table 3. Slope and relative relief values for landform determination.

Slope Class	Relative Relief	Landform
	1 - 15 m	Flat plains
Flat or Gently Sloping (> 50% of	16 - 30 m	Smooth plains
the neighborhood analysis window (NAW) pixels are < 8% slope)	31 - 90 m	Irregular plains
	91 - 400 m	Escarpments
	1 - 15 m	Low Hills
	16 - 30 m	Hills
Sloping (> 50% of the NAW pixels	31 - 90 m	Breaks
are ≥ 8% slope)	91 - 400 m	Low Mountains
	> 400 m	High Mountains/ Deep Canyons

ties at the surface, and essentially reflect areas of different substrate chemistry (Hartmann et al., 2012), an important determinant in the distribution of ecosystems (Bailey, 1996; Kruckeberg, 2002). The GLiM was developed as a compendium approach to acquire and integrate existing surficial lithology maps into a single, comprehensive, global lithology map. The GLiM is an improvement over earlier, coarser spatial and thematic resolution global lithology maps (e.g. Dürr et al., 2005), and was developed from 92 regional lithology maps. It was constructed as a vector GIS datalayer with over a million distinct polygons. The scale of the input maps used to construct the GLiM ranged from 1:500,000 to 1:10,000,000, and the "average" scale of the GLiM was reported as 1:3,750,000. The GLiM documents the terrestrial distribution of igneous, metamorphic, and sedimentary rocks as 13%, 13% and 64%, respectively, with the remaining area in water or ice. While the GLiM contains additional attribution at a second and third level of detail, this information is not comprehensively included throughout the dataset, and was therefore not coded into the makeup of the EFs.

Land Cover — The global land cover dataset used in this effort is the GlobCover 2009 (Figure 6, on page 22) product (Arino et al., 2008) collaboratively produced by the European Space Agency and the Université Catholique de Louvain.

The GlobCover 2009 product represents the global distribution of 23 land cover classes as interpreted from 300 m spatial resolution data from the MERIS satellite. The GlobCover 2009 product was chosen because it was the finest spatial and classification resolution, most current, globally comprehensive land cover data available at the time the work was undertaken, and its spatial resolution (300 m) was consistent with the base resolution of the effort. Although a finer spatial resolution (30 m) global land cover

dataset is now available (Gong et al., 2013), the classification resolution (14 classes) is coarser. A global mangrove assessment has been conducted (Giri et al., 2010) and a 30 m global mangrove distribution map, interpreted from Landsat imagery, is available. This comprehensive information has not been incorporated into our ecophysiographic stratification, and its inclusion in future refinements of the stratification is probably warranted and should be investigated for this unique ecosystem.

A Note on Surface Water — Surface water is a class in three of the four input layers, landforms, lithology, and land cover. The surface water feature as represented in the lithology layer was coarser in spatial resolution, and more dated, than the representation of surface water in the landforms and land cover layers. The lithology water class was therefore reclassed as unconsolidated sediments, with the acknowledgment that this could lead to misclassification if other lithologies (e.g. evaporites) are more appropriate. Then for the remaining two layers that contained a surface water class, we found that they complemented, rather than contradicted, one another, and so left those classes intact. For example, we found that the water class in the landforms layer could be used to extend the representation of rivers on the land cover dataset, but had a poorer representation of larger lakes and inland seas. In combining the two sources we achieved a better overall representation of surface water than from either as an individual source.

Accuracy Assessment Approach

To verify the logical consistency and overall quality of the EFs, and by extension the ELUs, an accuracy assessment is necessary. A global field campaign to collect ground-truthed information for comparison with our modeled ecosystems data would be an enormous undertaking and is beyond the scope of this effort. However, we conducted a preliminary accuracy assessment of African, Australian, Californian and North American EFs using high resolution satellite imagery, best available thematic maps of ecosytems and vegetation, and for some locations, volunteered geographic information from the Degree Confluence project (http://confluence.org/). The Degree Confluence project is a crowd-sourced set of photographs and observations taken at intersections of integer latitude and longitude lines across the planet.

The accuracy assessment was based primarily on confirmation of EFs through visual inspection of high resolution satellite imagery. High resolution imagery generally permits confirmation of topography and vegetation, and sometimes lithology. The imagery source used was Esri's composite World Imagery collection (http://goto.arcgisonline.com/maps/World Imagery). World Imagery provides one meter

or better satellite and aerial imagery in many parts of the world and lower resolution satellite imagery worldwide. The map includes NASA Blue Marble: Next Generation 500m resolution imagery at small scales (above 1:1,000,000), i-cubed 15m eSAT imagery at medium-to-large scales (down to 1:70,000) for the world, and USGS 15m Landsat imagery for Antarctica. The map features 0.3m resolution imagery in the continental United States and 0.6m resolution imagery in parts of Western Europe from Digital Globe. In other parts of the world, 1 meter resolution imagery is available from GeoEye IKONOS, i-cubed Nationwide Prime, Getmapping, AeroGRID, IGN Spain, and IGP Portugal. Additionally, imagery at different resolutions has been contributed to the World Imagery composite resource by the GIS user community.

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A total of 330 points were used in the image-based assessment of the four areas: Africa (150 points), Australia (55 points), California (50 points) and elsewhere in North America (75 points). For Africa and California, a mixture of mostly randomly generated (80%) and select targeted (20%) points were identified. The targeted points were manually selected to reflect known points of interest and unique physical features. For Australia and elsewhere in North America, the selected points were all Degree Confluence locations, and both the photography and the VGI description were used in addition to the high resolution imagery. In all cases, the point locations were queried for EF and then compared with the corresponding World Imagery resouces. Likelihood of general agreement between EFs and the image source was recorded by subjective, visual interpretation as either yes or no. For this and all visual comparison-based assessments described below, the emphasis was on identifying mutually incompatible pairings, such as wet, montane forests systems paired with dry grasslands on plains.

In addition to comparing EFs to imagery, we used two sets of thematic information to assess accuracy. The first set of thematic information was the three continental-scale ecosystem maps for South America, the conterminous United States, and Africa (Sayre et al., 2008; Sayre et al., 2009; Sayre et al., 2013), all of which had been produced using a very similar approach to the global ELU model, but at different spatial resolutions and with different sources of input layers. This approach essentially compares the results from the GEO global-scale ecological land units map with three GEO continental-scale ecosystem maps. We generated 100 random points each for South America and the continental United States, and 200 points for Africa, and identified these locations on the global ELU map. We then compared the ELU label with the ecosystem label from the corresponding locations on the three reference maps. Likelihood of general

agreement between ELUs and the reference map was recorded by subjective, visual interpretation as either yes or no.

The second set of thematic information used in the accuracy assessment included geospatial and photographic reference information on vegetation and land cover. These sources included the UNESCO Vegetation Map of Africa (White, 1983), the USGS GAP Land Cover Map (Ayerigg et al., 2013) and the National Land Cover Database (NLCD: Homer et al., 2007) for the United States, and the Regolith Map (Craig, 2013) and Dynamic Land Cover Map (Lymburner et al., 2011) of Australia. For the vegetation and land cover comparisons, the same set of points used to compare the EFs to the high resolution imagery were used: Africa (150 points), Australia (55 points), California (50 points), and elsewhere in North America (75 points). All points were identified on the EFs map and compared with the vegetation or land cover labels on the corresponding locations on the reference maps. Likelihood of general agreement between EFs and the reference maps was recorded by subjective, visual interpretation as either yes or no. Finally, we used the locations and data from the 55 points in Australia, obtained from the Degree Confluence project, and the 75 Degree Confluence points from North America, to compare EF labels with photographs and text descriptions. Likelihood of general agreement between EFs and the Degree Confluence information was recorded by subjective, visual interpretation as either yes or no.

Ecophysiographic Diversity Index

We developed an ecophysiographic diversity index to assess the spatial distribution of EFs from a diversity, or richness, perspective. The objective of this assessment was to identify EF "hotspots," or areas of relatively high EF diversity. The ecophsyiographic diversity index is a measure of any cell's relative departure from the global mean EF diversity. The number of distinct EFs in a 5 km² neighborhood analysis window (NAW) around each cell is determined and attributed to the cell. This creates a global raster data surface where each cell value represents the number of distinct EFs in the NAW. The global mean EF diversity is then calculated from this datalayer, relativized to the value of 1, and subsequently used as the basis for calculation of relative diversity of every pixel. The index provides a quantitative assessment of the degree to which any cell has more or fewer EFs than the global average. For example, a cell with an ecophysiographic index value of 3 would have three times the number of EFs in the NAW than the global average, and a cell with an index of 0.5 would have half as many EFs as the global average. With this index, an identification of areas with high EF diversity was possible.

Figure 3. Global bioclimate regions modeled from temperature and precipitation data. Modified from Metzger et al., 2013.

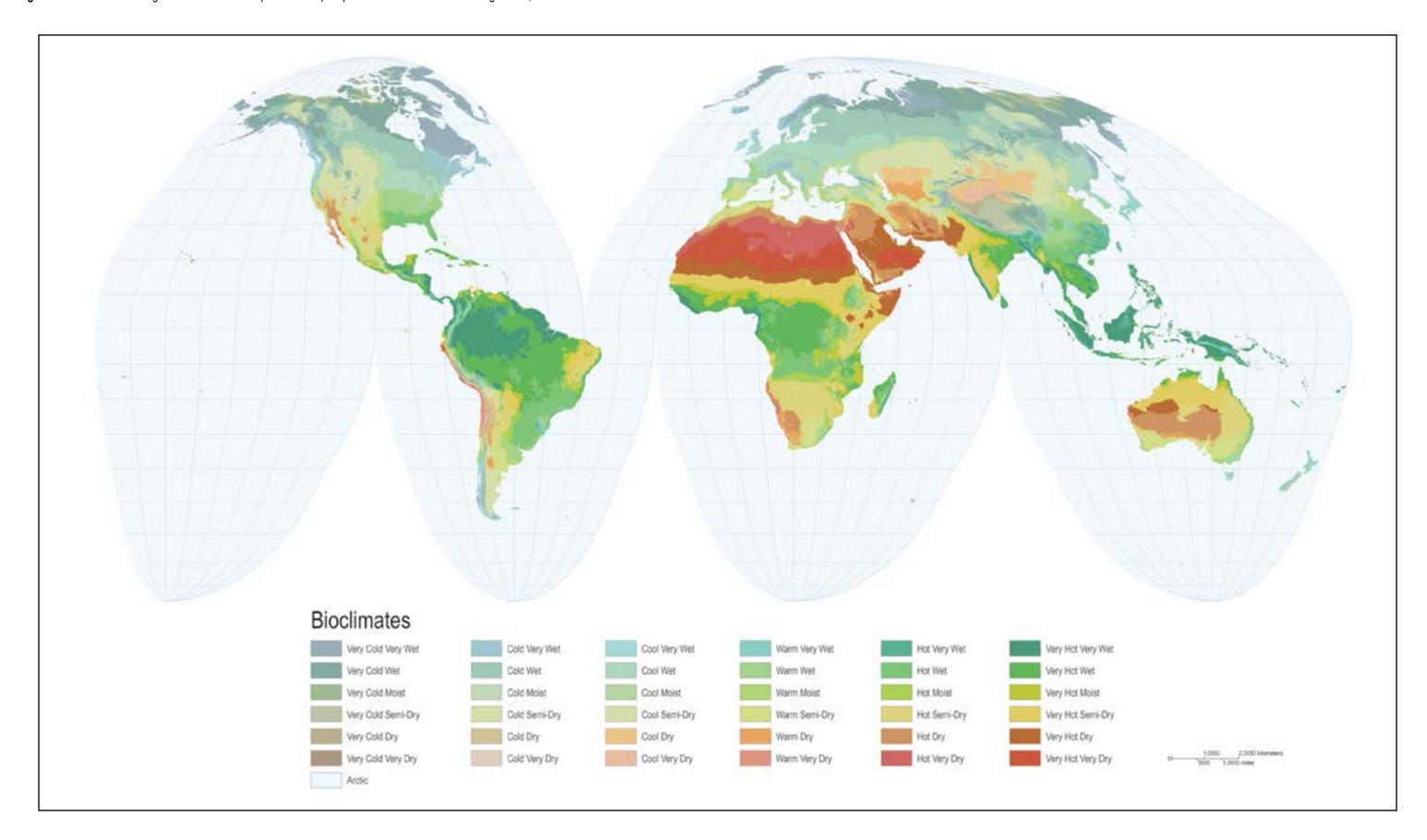


Figure 4. Global landforms modeled from a 250 m digital elevation model.

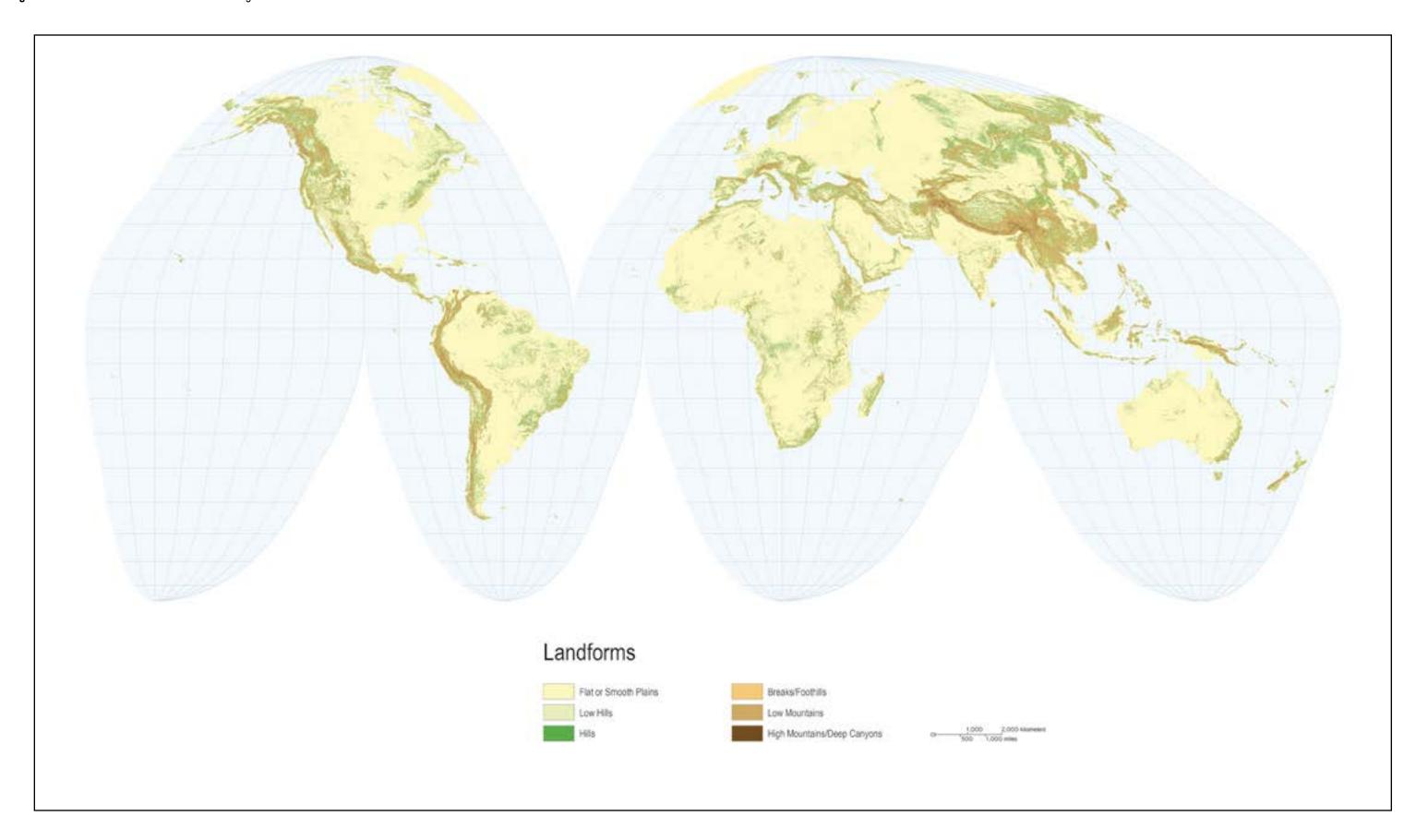


Figure 5. Global lithology representing rock type at the surface of the Earth. From Hartmann and Moosdorf, 2012.

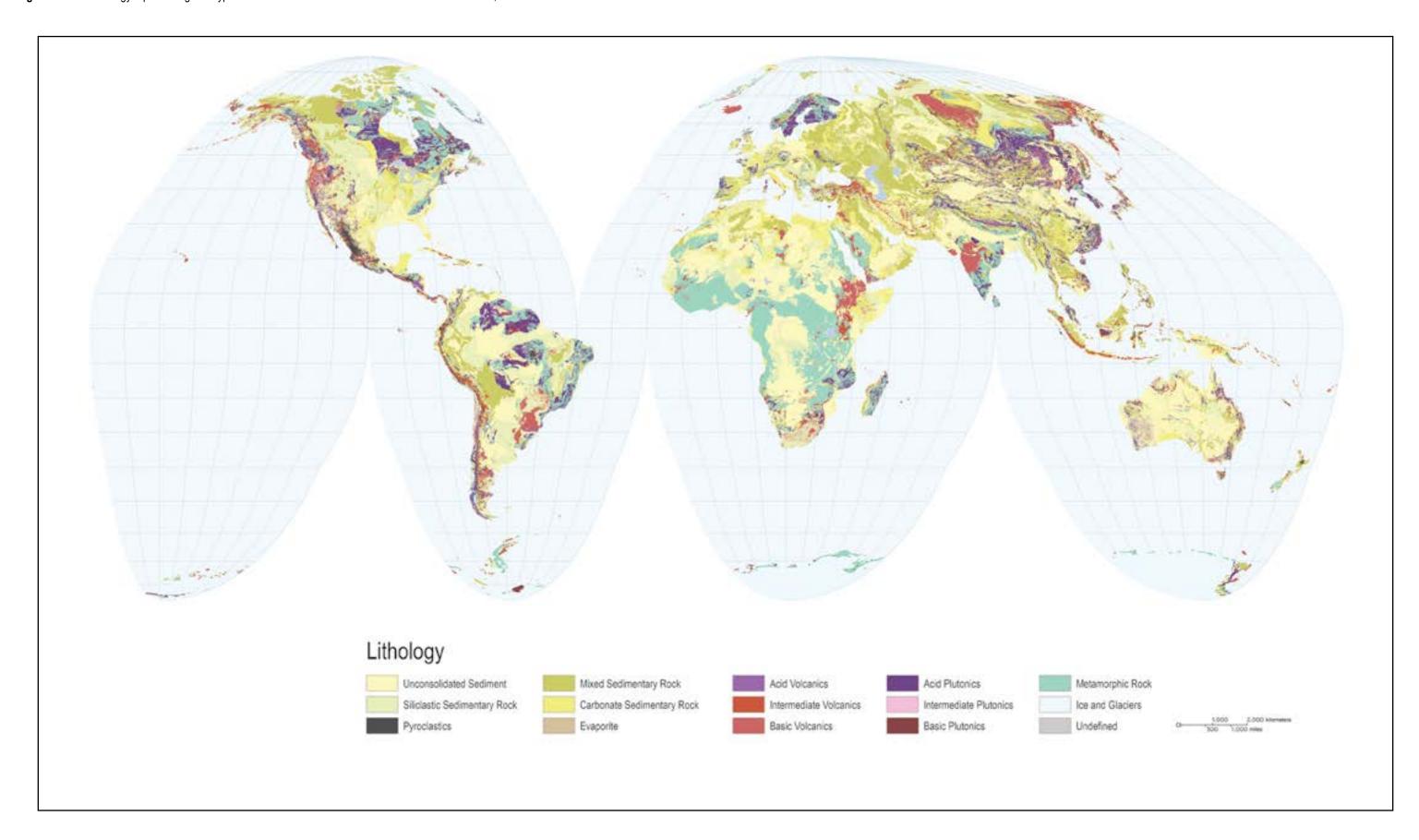
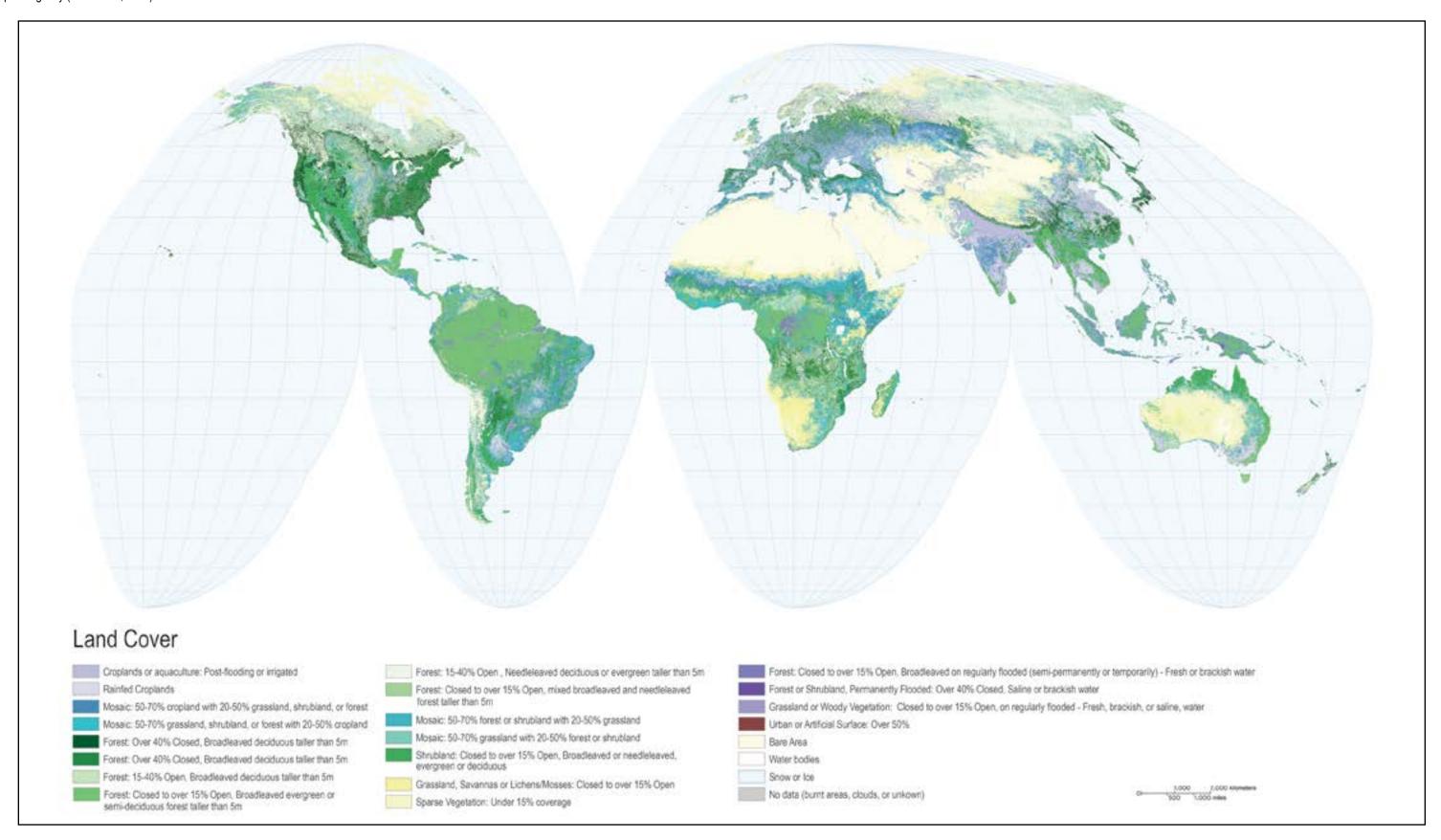
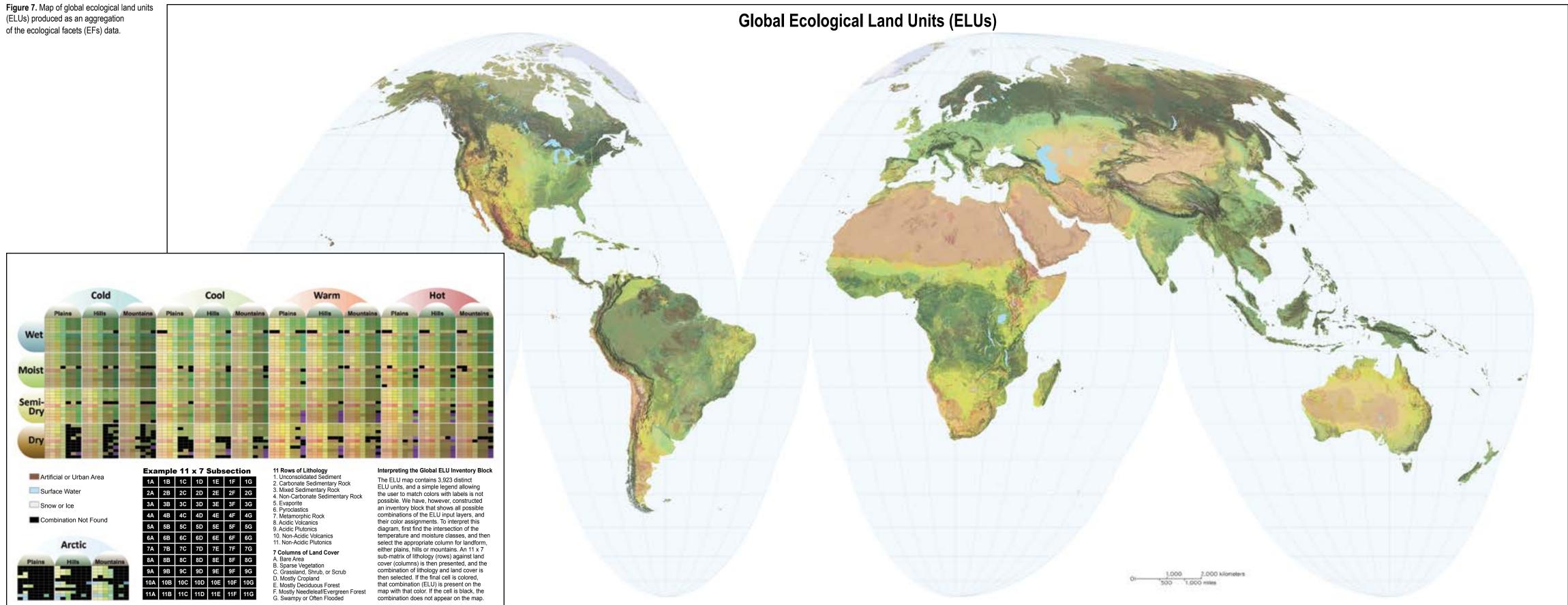


Figure 6. Global land cover classes from the GlobCover 2009 dataset. Produced by the Université Catholique de Louvain and the European Space Agency (Arino et al., 2008).



(ELUs) produced as an aggregation of the ecological facets (EFs) data.



Results

Ecological Facets

The maximum possible number of unique combinations that could have resulted from the integration of the input layers is the product of the number of classes of each input layer, i.e. (37 bioclimates)(10 landforms) (16 rock types)(23 land cover types) = 136,160 combinations. The actual number of classes produced from the integration of the input layers was 48,872 unique combinations of bioclimate, landform, lithology, and land cover. These 48,872 combinations, termed ecological facets (EFs), are too numerous to display cartographically. The EFs represent the finest spatial resolution, globally comprehensive biophysical stratification yet attempted, and are a detailed geospatial delineation of unique physical environments and their associated land cover. While not cartographically feasible at their full spatial and thematic classification resolution, the EFs nevertheless represent a rich data foundation for scientific inquiry and assessment at global, continental, regional, and many local scales.

Every EF is a combination of one value from each of the four inputs. Close visual inspection of the EFs, however, revealed that some of the combinations were suspect, due to unexpected associations of certain attributes in the underlying input layers. For example, an EF with the following values would be unlikely to occur: a Warm or Hot bioclimate with a land cover of Permanent Snow or Ice. These suspect EF combinations were flagged in the dataset, and removed from the totals. Moreover, if a value was "no data" or "unknown" for any of the four inputs in the combination, the EF could not be properly labeled, and was similarly flagged and removed from the totals. A total of 1222 EFs were therefore not included in the final list due either to missing or suspect data, yielding a total of 47,650 unique EFs.

Global, Continental, and Regional ELU Maps

Although rich in detail, the large number of EFs precludes meaningful cartographic display, and is essentially an unmanageable number of ecosystems from a practical and management perspective. We therefore created a generalized product from the foundational raster EF layer with many fewer classes, termed ecological land units (ELUs). There are a number of different approaches that could be undertaken for accomplishing this generalization step, including a statistical clustering procedure such as was executed for the bioclimates input layer (Metzger et al., 2013). An effort to statistically delineate ecologically meaningful regions with similar groupings of EFs is

currently underway, although complicated by the use of categorical rather than continuous data.

Alternatively, we generalized the large number of EFs by aggregating within classes. For example, each of the non-water landform classes were generalized to either plains, hills, or mountains. Data reduction by class aggregation yielded a total of 3,923 global ELUs. Table 4 shows the number and names of the aggregated classes for each of the four inputs. Unlike the 47,650 EFs, this much smaller number of ELUs is cartographically feasible, and a global map of ELUs is presented in Figure 7, on the foldout map (pages 24-25).

The 250 m spatial resolution of the global ELU data permits their visualization at a variety of progressive zoom levels from very coarse (e.g. global) to very fine (a local area). To demonstrate this underlying resolution in the data, a set of continental ELU maps is presented, followed by examples of ELU maps for specific locations at a site-based scale. ELU maps of North and Central America, Europe, Asia, Australia, South America, and Africa are presented in Figures 8, 9, 10, 11, 12, and 13, respectively, followed by regional scale ELU maps for the Ethiopian Highlands in Africa (Figure 14) and the Eastern Sierra Nevada Mountains region in the western United States (Figure 15).

 Table 4. Aggregated attribute classes for the ecological land units

Bioclimate			
Arctic	Cold Dry	Cool Dry	Warm Dry
Cold Wet	Cool Wet	Warm Wet	Hot Wet
Cold Moist	Cool Moist	Warm Moist	Hot Moist
Cold Semi-Dry	Cool Semi-Dry	Warm Semi-Dry	Hot Semi-Dry
			Hot Dry
Landforms			

Mountains

Lithology	
Pyroclastics	Metamorphics
Unconsolidated Sediment or Surface Water	Evaporites
	Acidic Volcanics
Non-Carbonate Sedimentary Rock	Acidic Plutonics
Carbonate Sedimentary Rock	Non-Acidic Volcanics
Mixed Sedimentary Rock	Non-Acidic Plutonics

Global Landcover	
Swampy or Often Flooded Vegetation	Mostly Cropland
Sparse Vegetation	Grassland, Scrub, or Shrub
Mostly Needleleaf/Evergreen Forest	Bare Area
Mostly Deciduous Forest	Artificial Surface or Urban Area
	Surface Water

Figure 8. Map of ELUs of North and Central America

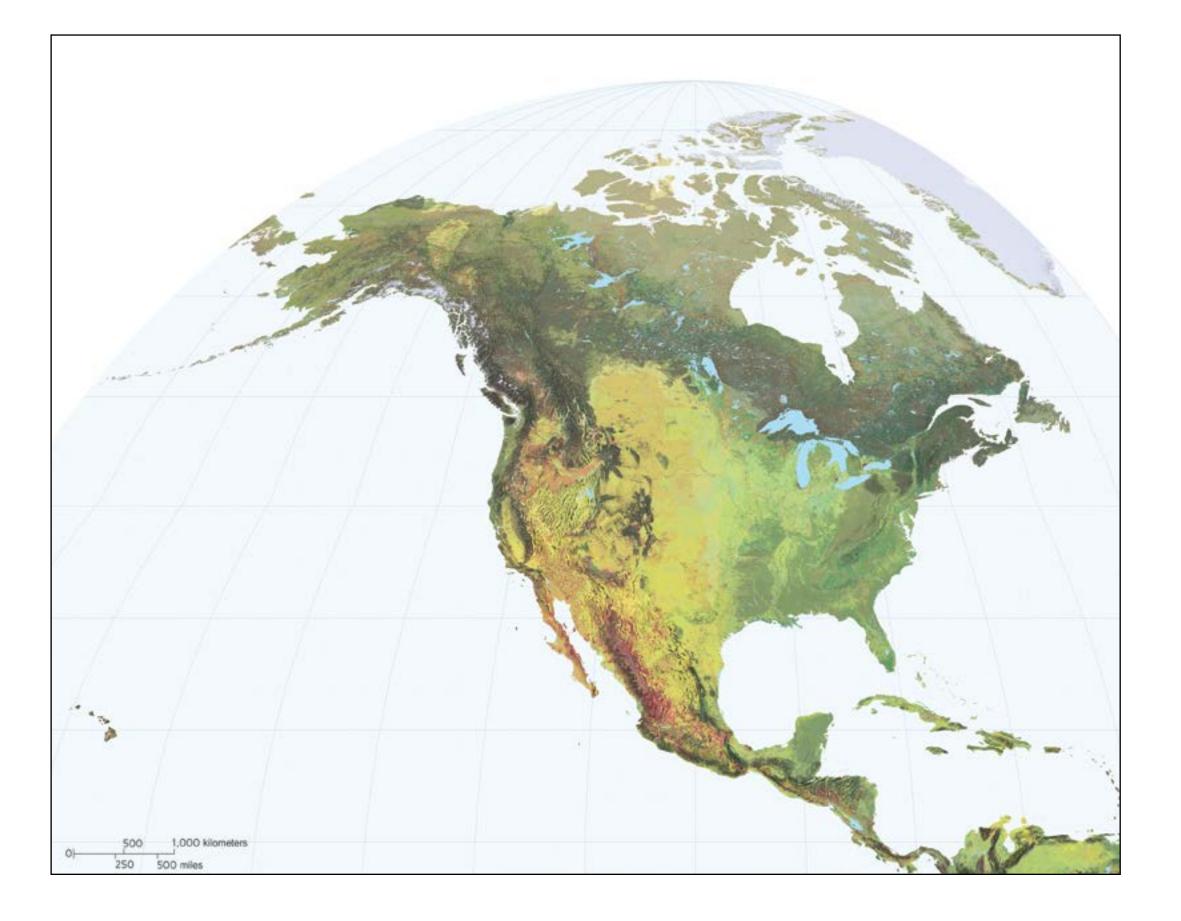
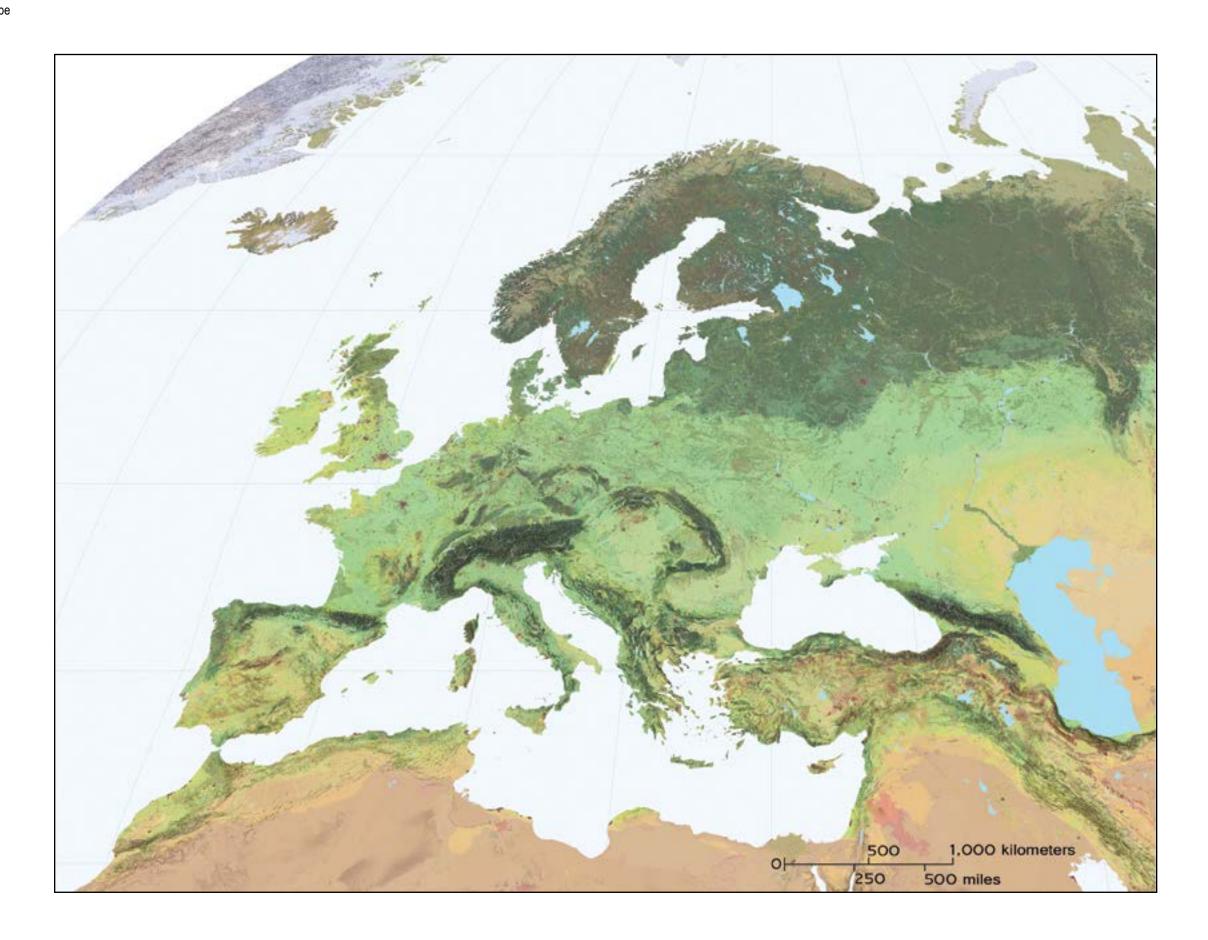
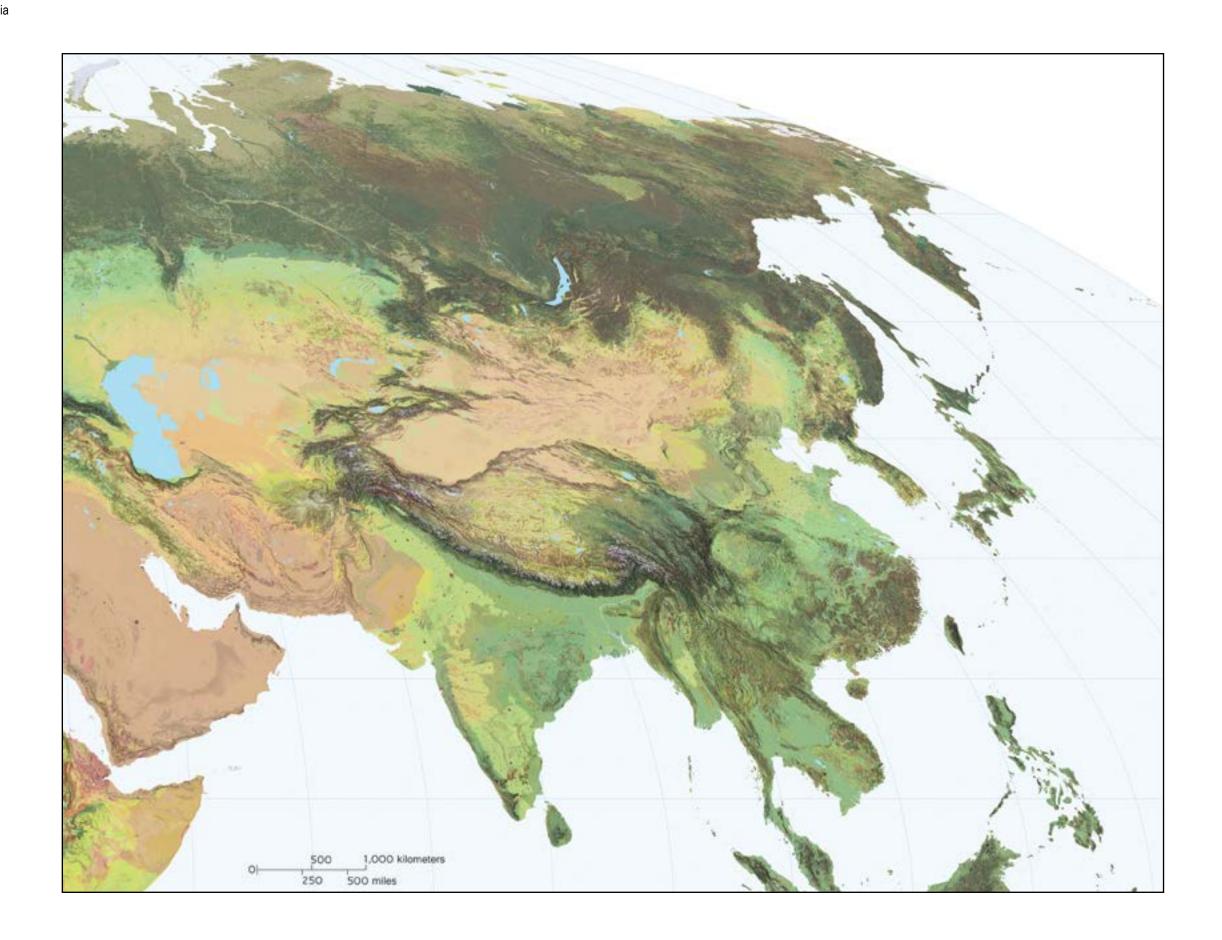


Figure 9. Map of ELUs of Europe



A New Map of Global Ecological Land Units — An Ecophysiographic Stratification Approach

Figure 10. Map of ELUs of Asia



A New Map of Global Ecological Land Units — An Ecophysiographic Stratification Approach

Figure 11. Map of ELUs of Australia

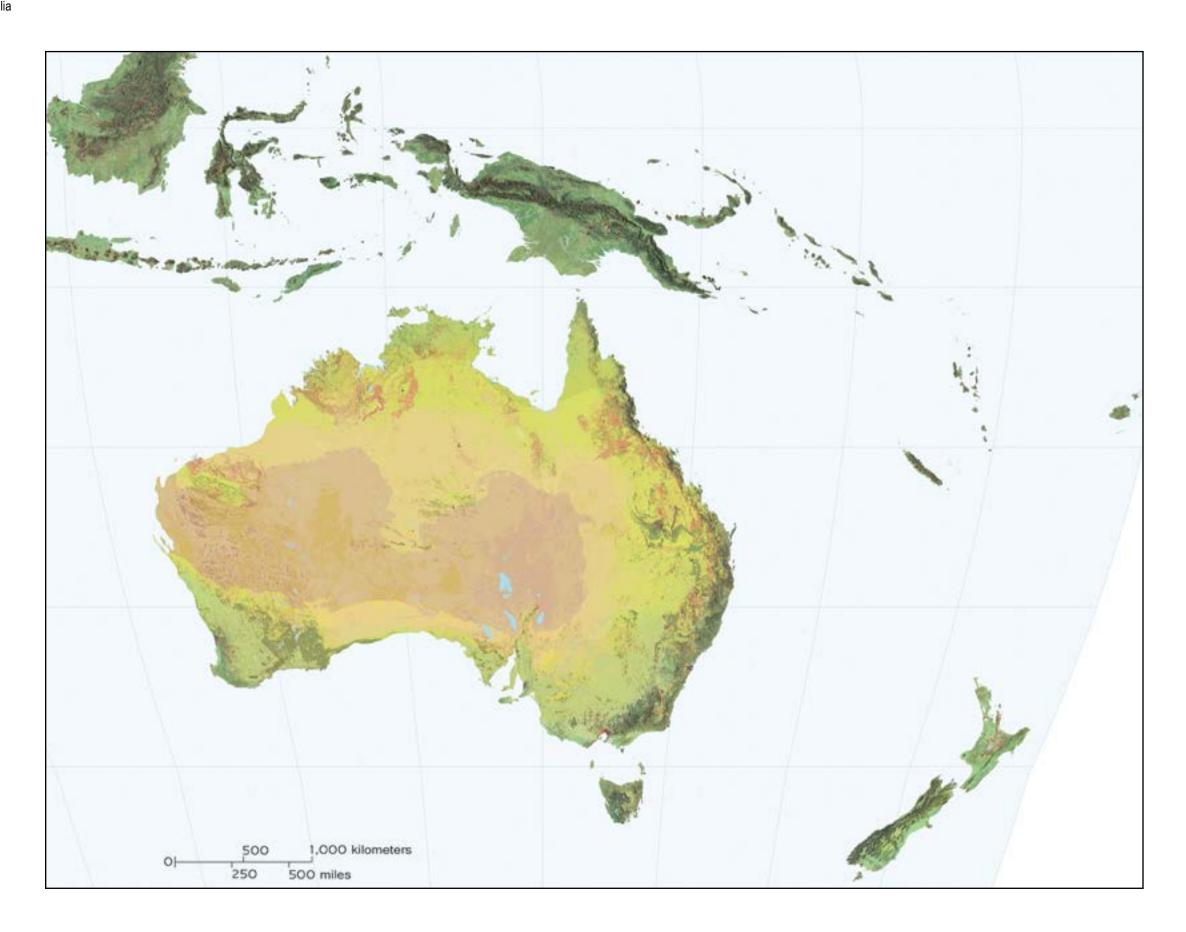


Figure 12. Map of ELUs of South America

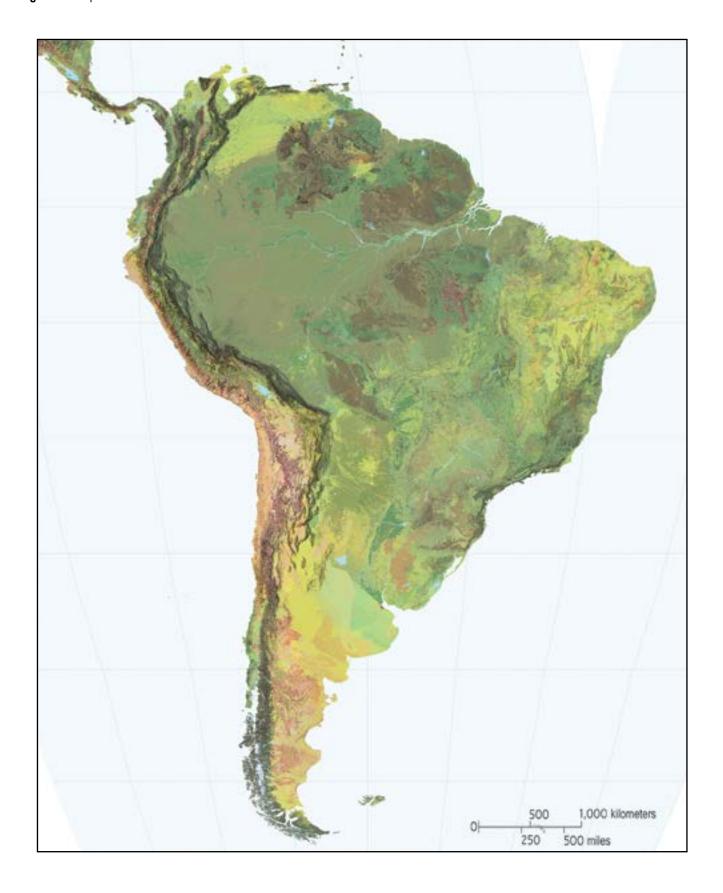


Figure 13. Map of ELUs of Africa

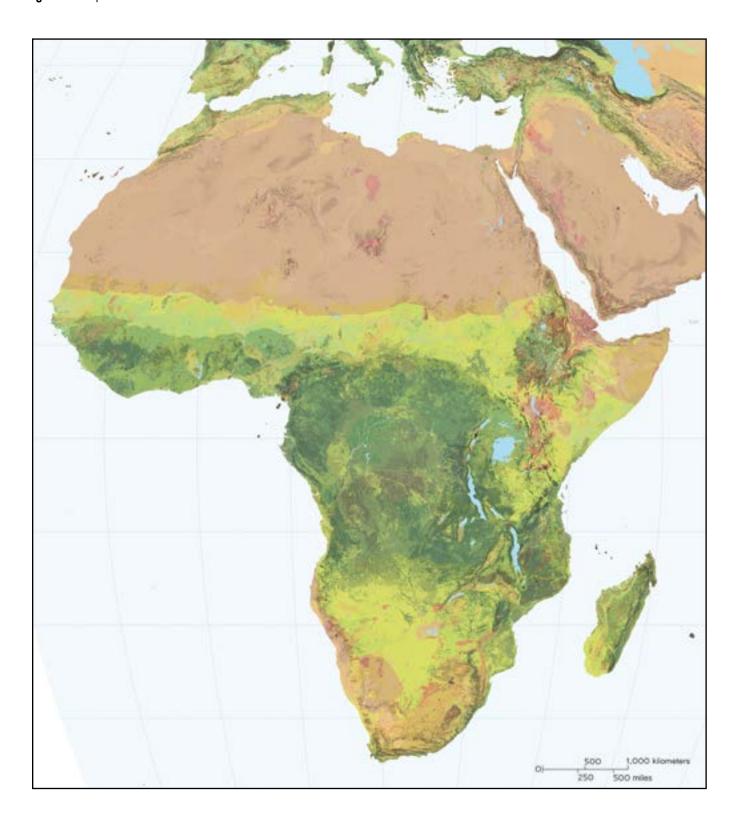


Figure 14. Map of ELUs of the Ethiopian Highlands, Africa

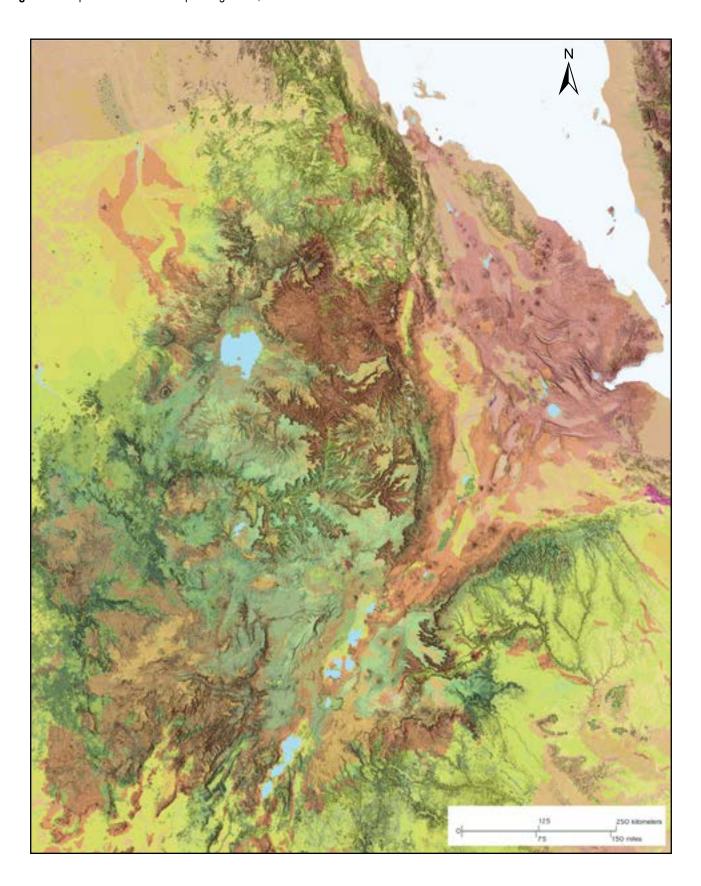
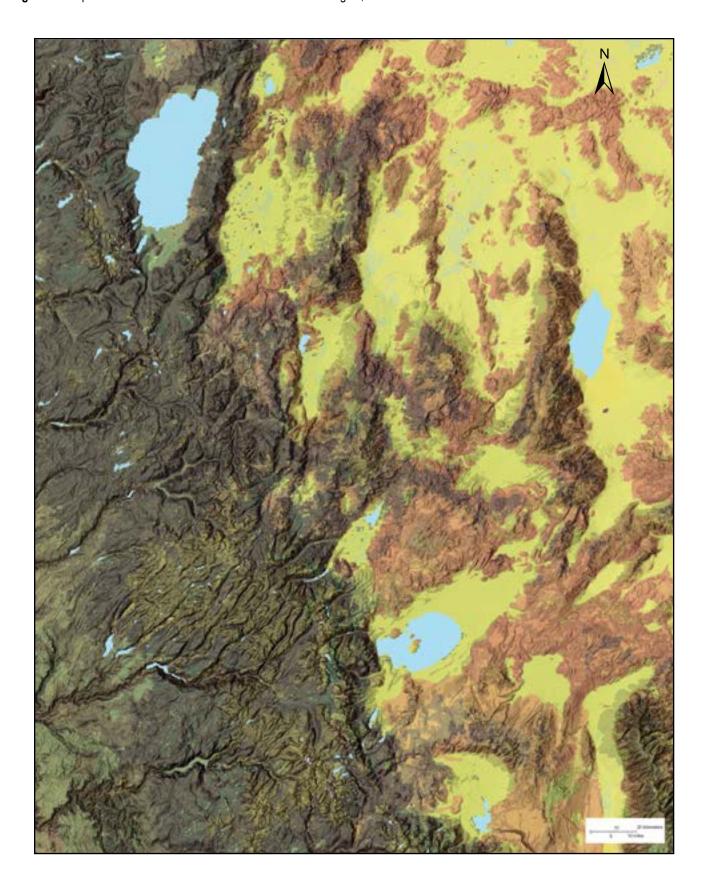


Figure 15. Map of ELUs of the Eastern Sierra Nevada Mountains region, southwestern United States.



ELU Labels

The ELU maps depict the variety of distinct landscape/land cover combinations that comprise the Earth's terrestrial surface. Although the large number of ELUs (3,923) are too numerous and impractical to show in a typical map legend, the datalayer is rich in information content. A GIS query of the attributes of any one of the 250 m pixels returns the entire set of attribute values, including the name (label), of the ELU. As mentioned above, the ELU label is a concatenation of the input layer descriptors presented in the following sequence, which also represents the order of importance of the inputs in determining the ecosystem distributions: bioclimate descriptor, landform descriptor, lithology descriptor, and land cover descriptor. A few examples of ELU labels illustrates the naming convention:

- Very Hot Dry Plains on Evaporites with Sparse Vegetation
- Hot Moist Plains on Unconsolidated Sediments with Grasslands, Shrub or Scrub
- Warm Moist Hills on Carbonate Sedimentary Rock with Mostly Croplands
- Cool Moist Mountains on Metamorphic Rock with Mostly Deciduous Forest
- Cold Wet Mountains on Acidic Volcanics with Mostly Needleleaf/Evergreen Forest

These labels are classification-neutral in that they describe the ELU based on its components, rather than giving it a name from some existing, a priori classification. While this approach avoids the difficulty of seeking consensus on which classification should be used, it can also be disadvantageous in that there may be a commonly used and respected classification system for ecosystems of a particular area that is not incorporated. Moreover, familiar geographic place names (e.g. Sahara, Karoo, Great Basin, Chaco, Himalayan, etc.) are not incorporated in the ELU naming convention. It is anticipated that local users may develop additional or alternative naming conventions for the standardized ELUs that incorporate geographic descriptors and local traditions. Such enrichment of the ELU labels would likely improve their utility for local applications, and would probably also result in in a more focused evaluation of data quality.

Cartographic Treatment

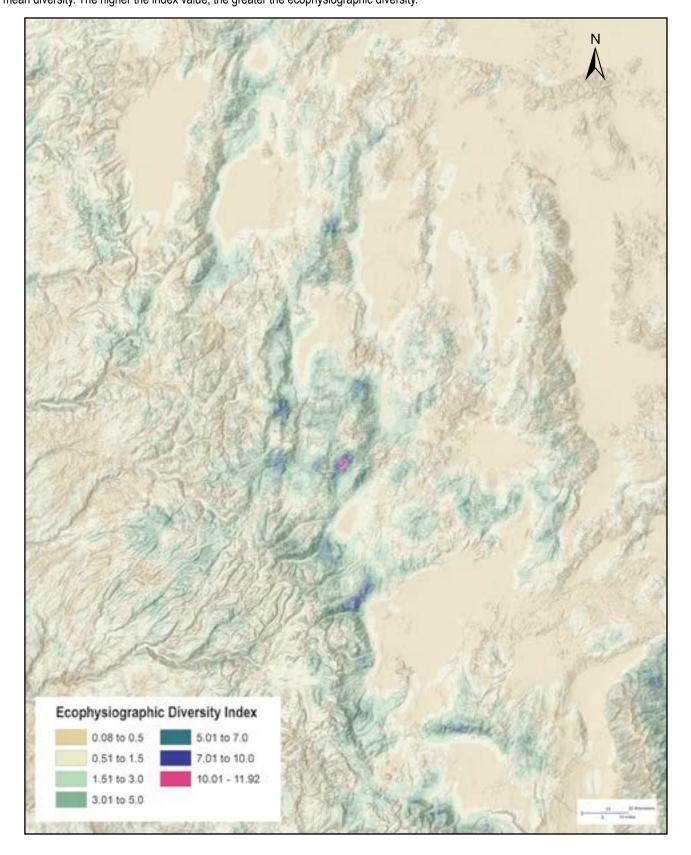
The ELU maps above represent a range of scales from global to local, and a diversity of landscapes ranging from uniform flat deserts to diverse mountain landscapes. The ELU maps are all presented in the Goode Homolosine projection, an equal area projection for world maps (Goode, 1925). At first impression, these graphics may suggest remotely-sensed pictures of the Earth taken from satellites. However, these images have been constructed from thematic data, and are modeled, rather than photomorphic, pictures of the Earth. This effect was achieved using an advanced cartographic approach which matched the weight of the environmental input values to the assignment of colors. Each class within each of the four input layers was assigned a color designed to be intuitive when viewed independently. For the ELU map, the color of each cell was a blend of the four colors from each input layer. The blending incorporated a weighting scheme which emphasized bioclimate and landform over lithology and land cover, in the same manner that bioclimate and landform are the strongest drivers of ecosystem distributions, as discussed above. Determining an ELU's cell color started with bioclimate color, which was modified by blending the hue, saturation, and value of the landform color, then the lithology and finally the land cover. The final color of an ELU cell is therefore a sequential and weighted custom application of hue, saturation, and value characteristics from the colors of each of the input layers.

Ecophysiographic Diversity

Areas with a relatively high diversity of EFs were identified through application of the ecophysiographic diversity index, described above. The Sweetwater Mountains in the southwestern United States, three miles north of Bridgeport, California, and straddling the California/Nevada border, have the highest ecophysiographic index (11.9) in the entire global dataset. The ELUs of this area are depicted in Figure 15 (above). In this image, the Sweetwater Mountains are a north-south range located roughly in the center of a triangular area bounded by the three largest lakes (Mono Lake, in the south; Lake Tahoe, in the northwest; and Walker Lake, in the east). A map of ecophysiographic diversity for this same area is presented in Figure 16 below.

Figure 16. Map of the ecophysiographic diversity index of the Eastern Sierra Nevada Mountains region, southwestern United States, showing the same area depicted in Figure 15. In the center of this image are the Sweetwater Mountains, near Bridgeport, California, discernible as a small magenta and blue area, signifying a very high ecophysiographic diversity. An ecophysiographic diversity index value of 1.0 is the global mean diversity. The higher the index value, the greater the ecophysiographic diversity.

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The Sweetwater Mountains appear in the center of the image as a small magenta-colored area surrounded by blue. This area is very lithologically diverse, with mineral resources that include iron, gold, silver, copper, tungsten, and molybdenum. Geologic formations include silicic granite, basaltic columns, metamorphosed volcanic and marine sediments, and other lithologies (Kennedy and Lambeth, 1984). Surveyors (Kennedy and Lambeth, 1984) characterized the area as "a series of spectacular barren peaks, ranging from East Sister in the north to Mount Jackson in the south, underlain by bleached or brightly colored Mesozoic basement rocks and Tertiary volcanics. Altitudes range from 11,673 ft on Mt. Patterson to 6160 ft near Devils Gate on the East Walker River. Vegetation types vary from semiarid to alpine." The vegetation diversity in the area is high. The Sweetwater Mountains are a transition zone between the Sierra Nevada and the Great Basin biological provinces, with florisitic elements from each co-occurring in the area (Hunter and Johnson, 1983). An unusually high flora of xerophytic and mesophytic species is documented in the area, as well as a number of rare, substrate-dependent species (Hunter and Johnson, 1983).

The high ecophysiographic diversity index for the Sweetwater Mountains, more than ten times the global mean diversity index, identifies the region as a globally unique area with numerous different ecological facets occurring in proximity. In this area, high abiotic diversity is associated with biological uniqueness. As such, the ecophysiographic diversity index may have utility in identifying important biodiversity areas elsewhere which merit conservation attention. Globally, we identified 114 areas where the ecophysiographic diversity index was

at least ten times the global mean. After the Sweetwater Mountains site, the second through fifth highest ecophysiographic indices observed were at: 2) a site near Milas, in the Muğla Province, Turkey; 3) a site in the Scottish Highlands near Barbreck, Argyll and Bute council areas, Scotland; 4) a site near the town of Kydně in the Plzeň region of southwestern Czech Republic; and 5) another site in the Eastern Sierra Nevada Mountains region near near the town of Aspendell, west of Bishop, California, in the southwestern United States.

Accuracy Assessment

The primary accuracy assessment approach was to compare EFs at randomly generated points to their corresponding locations on high resolution imagery. This match of EFs to imagery was generally very high, with the following level of confirmation observed: Africa, 91%; California, 98%; Australia, 98%; and elsewhere in North America, 97%. The secondary accuracy assessment approaches included comparing ELUs to their corresponding ecosystem labels on the three GEO continental-scale ecosystem maps for South America, the conterminous United States, and Africa. The results for those comparisons were 88%, 87%, and 94%, for South America, the conterminous United States, and Africa, respectively. The comparison of EFs to other sources of thematic information yielded the following probable matches: Africa (81%), California (88%), Australia (96%) and elsewhere in North America (93%). Finally, for the Degree Confluence project points, a 100% match between the EFs and the VGI (photos and descriptions) was observed for Australia, and a 98% match was observed for elsewhere in North America.

Discussion

This paper describes a methodology and initial results for characterization of important land-based elements of global ecological pattern at a base spatial resolution of 250 meters. Four essential structural dimensions of ecosystems (bioclimate, landform, lithology, and land cover) were modeled as vertically coherent, 250 m spatial resolution, raster datalayers. These four inputs were then integrated (spatially combined) to produce 47,650 unique combinations of the values of the input datalayers. A subsequent data reduction, label development, and cartographic treatment process resulted in a set of 3,923 ELUs for the planet. The ELUs are intended as a new set of standardized and potentially useful analysis units for a variety of applications (e.g. climate change and other impact assessments, ecosystem services assess-

ments, biodiversity conservation priority setting, etc.). Developed as a biophysical stratification of the planet using four essential ecosystem components, the map extends and adds additional ecological value to existing climate stratifications (Metzger et al., 2013). The new map and database are also intended as a quantitative and data-derived complement to the numerous expert opinion-based, coarser spatial resolution ecoregionalizations of the planet produced to date.

The ELU map represents an ecophysiographic classification of the Earth's surface based on the geographic coincidence of climate, landforms, geology, and land cover. Climate, landforms and geology represent the physical setting that gives rise to ecological process, pattern, and the distribution of living things. Land cover

represents a biotic response to the physical setting and is a key element of the physical and organic cycles that continue to shape the environment. The ecophysiographic stratification identifies ecological patterns at a global scale, which provides a context that is important to the subsequent mapping of ecological and geographic units at finer scales. It supports the synthesis and comparison of disparate ecological studies at local and regional levels, and it provides a geospatial accounting framework for assessments of ecosystem service values.

"Big Data" Considerations

This work is an example of a "big data" processing and analytical effort, as it represents a multi-sourced identification of physically distinct areas and their associated land cover at a fine spatial resolution for the entire planet. Big data are generally regarded as large and complex datasets whose creation and use are enabled by advances in digital and mobile computing technologies, and which can be difficult to work with using standard analysis softwares (Snijders et al., 2012). The 250 m pixel framework for each of the four inputs and two outputs is 67,049 rows and 172,800 columns for a total of 11,586,067,200 cells per layer. For these datalayers, which are in a geographic coordinate system (WGS 1984), the surface of the Earth is made up of over 11 billion cells. The four inputs and the two outputs collectively contain almost 70 billion discrete values. Recent advances in data manipulation and dissemination technologies now permit the use of these data in GIS computing environments (http://www. esri.com/products/technology-topics/big-data). The ELU mapping effort complies with guidance on big data initiatives as characterized in the White House Open Government Initiative (http://www.whitehouse.gov/open), as well as the President's Council of Advisors on Science and Technology (PCAST) report on Sustaining Environmental Capital (http://www.whitehouse.gov/sites/ default/files/microsites/ostp/pcast sustaining environmental capital report.pdf).

Data Dissemination Plans

The data produced from this effort will be available to users through a variety of mechanisms, and is in keeping with emerging principles and best practices for broad-scale data sharing (e.g. Tenopir et al., 2011; Goth, 2012). The spatial datalayers, including the four basic input layers (bioclimates, landforms, lithology, and land cover) as well as the two major outputs (EFs and ELUs) will be available in the public domain for ftp-download as raster GIS datalayers (http://rmgsc.cr.usgs.gov/out-going/ecosystems/Global/). Moreover, the data will be

made available as part of the Landscape Analysis content offered by Esri, and usable in desktop or online ArcGIS configurations. This mechanism will allow for query and analysis of all six datalayers in the context of numerous other data resources (e.g. watersheds, species distribution maps, satellite imagery, etc.) by a broad audience of scientists, GIS professionals, and policy-makers. Ecosystem browser and tour applications are also in development.

Limitations of the Approach and Suggestions for Improvements

The data produced from this effort are very detailed in both thematic (classification) and spatial resolution, and will be broadly available. They are intended to be useful for a variety of applications, and accessible by a number of different audiences. Certain limitations to the approach, however, bear mention. For example, the ecosystems have been modeled from a consideration of basic ecosystem structure, but do not incorporate essential elements of ecosystem function (e.g. primary productivity, nutrient cycling, biotic interactions, etc.). The ELUs should be assessed from the standpoint of ecosystem function as well, to see if the bounding of ecosystems should incorporate an ecosystem function dimension.

The quality of the data used in the global stratification will obviously influence the quality of the derived ecosystem products, and anomalous values were found in each of the input layers. While some of these data quality issues are discussed below, it is important to first note that both the input layers and the output products should be considered as collaborative best efforts and works in progress, rather than definitive, current, and complete representations of their themes. The production of any high resolution, globally comprehensive datalayer that characterizes a particular feature of the environment is an ambitious and sometimes very difficult undertaking. These efforts to develop and disseminate best available datasets are appreciated by the scientific community, and making the information broadly available is the best way to ensure it can be improved over time.

Identification of anomalous values and other data quality issues in underlying data is important for both the understanding of unexpected results, and for the improvement of the input datasets. The bioclimates layer, as mentioned, represents an interpolated data surface from point observations obtained at meteorological stations. Some areas of the planet are not well-covered by weather stations, and the modeled climate regions in those areas (e.g. western Sahara Desert region) were developed from very little data. Moreover, we felt the

original bioclimate regions were underrepresentative of aridity, and we modified the data accordingly. The landforms layer was built from a 250 m global DEM, and 250 m was the base resolution of the effort, given the big data nature of the effort and the difficulty of working at finer spatial resolutions. Nevertheless, 90 m and 30 m global DEMs do exist, and a finer spatial resolution global landforms layer could be developed. The global lithology layer, built as a compendium of a variety of best available regional and national scale lithology datasets, lacks complete attribution at all levels of the hierarchy, and does not attempt to reconcile or harmonize classes across maps from adjacent geographies produced by different organizations. We used the GlobCover 2009 land cover product, and a newer version has just been released (http://www.esa-landcover-cci.org/?q=node/156). The above-mentioned limitations in the data really represent opportunities for collective improvements in the characterization of ecologically important Earth surface features, and we anticipate working with these data providers and others in future collaborations to advance the quality, currency, resolution, and accessibility of Earth science data.

Similarly, while the ecophysiographic hotspots analysis is promising, it is preliminary and warrants additional investigation. It would be straightforward to identify the primary contributors to the overall ecophysiographic diversity by assessing the range of values of each of the four EF input layers (bioclimates, landforms, lithology, and land cover). Moreover, it would be important to ensure that the detail in the underlying data is uniform throughout the global layer, and that identification of ecophysiographic hotspots is not an artifact of relatively rich detail in some areas, and poor detail in others. Finally, it is recognized that an area with a variety of different land uses in proximity (e.g. the site in the Czech Republic discussed above) can have a high ecophysiographic diversity which is really a function of human activity on the land surface. It may be desirable to develop an additional index of ecophysiographic diversity which does not include the land cover input in order to focus on environmentally distinct areas without consideration of human alteration.

The EFs represent spatially fine, land-based ecological pattern over the surface of the Earth. In a data reduction step to simplify the ecological pattern into a smaller number of types, we used a set of simple rules to aggregate and simplify classes. While this approach is useful in providing a number of easily understood and mappable ecosystems, it is nevertheless a subjective activity. The ELUs are a first-approximation simplification of raw ecological pattern based on a human construct. A statistical

classification of the EFs would provide an automated and less-biased characterization of the grouping of ecological features into ecosystem units. More work is necessary to improve the identification of ecological landscapes based on the grouping of repeating ecological patterns. We look forward to future collaborations with experts from the spatial statistics community to advance this work from an identification and inventory of land-based ecological pattern to more of a scientific grouping and analysis of ecological pattern into ecosystem areas. We invite others to join in the research on how to best aggregate and classify the EFs.

The input datalayers used to model the EFs and ELUs were considered a 'minimum set' of the controls on vegetation distribution and the biotic response to those environmental drivers. Other input layers (e.g. solar radiation, soil moisture potential, etc.) might have been included in the model as well. Future assessments of this type might incorporate more environmental inputs to the model, with testing to see if the modeled ELU distributions were changed.

Future Directions

While the preliminary accuracy assessment results are encouraging, we acknowledge that a more robust accuracy assessment based on an error matrix constructed from a cross tabulation of mapped class label against reference (ground-truthed) data is desirable. This type of rigorous assessment might be implemented through a targeted, crowd-sourced, field verification campaign in the future. Moreover, a series of in-region workshops on several continents would be useful for educating potential users of the product on its use and utility, and at the same time collecting valuable information on the veracity of the results.

We anticipate the development of an automated statistical clustering method to group areas of similar ecological pattern into higher-order ecosystems. We also anticipate the development of a multi-tiered, ecophysiographic hierarchy where EFs and ELUs constitute the lowest levels, and regional to continental to global physiographic regions constitue the higher levels. In parallel, we anticipate the development of a related set of mesoscale spatial accounting units based on enduring (relatively unchanging) physical features of the environment (e.g. landforms within hydrophysiographic regions).

We anticipate investment in the curation and updating of the EF and ELU products over time, and contemplate future iterations of the ecosystem maps built in a similar fashion but using updated, and possibly additional (e.g. global soils in addition to global lithology), inputs. We anticipate using "change maps" derived from satellite image series to identify types and extents of ecosystems impacted from land use change, fire, climate change, etc.

An analogous, GEO-commissioned effort to map

global coastal and marine ecosystems by their essential structural elements is currently in the planning stages, and a global freshwater ecosystems mapping concept is in development.

Conclusion

A rich, spatially explicit database and map of global ecological land units has been developed which allows the identification and analysis of any 250 m pixel on the planet with respect to its ecological land unit type, and its bioclimate, landform, lithology, and land cover attributes. This dataset allows for the evaluation of ecosystem representation in protected area networks, and supports climate change impacts studies. The ELUs may also have considerable utility in ecosystem services assessments as they

depict the areas from which ecosystem services are being produced. Ecosystem-based management programs and ecosystem research programs may also benefit from this detailed and globally comprehensive dataset and map of ELUs. As a freely available, easily accessible, fine resolution inventory of land-based ecological features, these data will contribute to increased understanding of terrestrial ecological pattern and terrestrial ecosystem distributions.

Acknowledgments

We acknowledge and appreciate the insights and suggestions from three U.S. Geological Survey scientists who provided peer review comments: Alicia Torregrosa, Chandra Giri, and Shawn Carter (with additional comments from Laura Thompson). Cindy Cunningham of the U.S. Geological Survey provided technology support throughout the effort. A number of geospatial professionals, although they did not work directly on this global analysis, have contributed valuable spatial analytical methods, experience, and best practices from previous continental efforts which have become part of the overall GEOSS ecosystem mapping approach. These mapping experts include Jacque Bow, Jon Hak, Leonardo Sotomayor, Timothy Boucher, and Marcelo Matsumoto. Similarly, we acknowledge the ecological and vegetation classification expertise of Carmen Josse and Don Faber-Langendoen, and the conservation practitioner wisdom of Jerry Touval and Alberto Yanosky. Alberto co-led the effort when it was first initiated, and hosted the kickoff meeting in his country, Paraguay, to begin to frame the approach. The Steering Committee of GEO BON has embraced and supported this work as a priority deliverable, as has the leadership of GEO, and in particular Barbara Ryan. Finally, the Association of American Geographers (AAG) has supported this work from the beginning, and in addition to this publication, also published the South America Ecosystems and Africa Ecosytems documents. Rebecca Pendergast of AAG has contributed beautiful design concepts and layout for both the global ecosystems and the Africa ecosystems publications, and is a consummate professional in her field. Douglas Richardson has provided unfailing support, encouragement, technical and academic guidance, outreach, and added value to the entire effort. He recognized the importance of publishing this work early on, and has committed the support of his organization, AAG, to advancing ecosystems geography through this work. Any use of trade, product, or firm names is for descriptive purposes only and does not imply endorsement by the U.S. Government.

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