Potential contributions of remote sensing to ecosystem service assessments

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Abstract

Ecological and conservation research has provided a strong scientific underpinning to the modeling of ecosystem services (ESs) over space and time, by identifying the ecological processes and components of biodiversity (ecosystem service providers, functional traits) that drive ES supply. Despite this knowledge, efforts to map the distribution of ESs often rely on simple spatial surrogates that provide incomplete and non-mechanistic representations of the biophysical variables they are intended to proxy. However, alternative datasets are available that allow for more direct, spatially nuanced inputs to ES mapping efforts. Many spatially explicit, quantitative estimates of biophysical parameters are currently supported by remote sensing, with great relevance to ES mapping. Additional parameters that are not amenable to direct detection by remote sensing may be indirectly modeled with spatial environmental data layers. We review the capabilities of modern remote sensing for describing biodiversity, plant traits, vegetation condition, ecological processes, soil properties, and hydrological variables and highlight how these products may contribute to ES assessments. Because these products often provide more direct estimates of the ecological properties controlling ESs than the spatial proxies currently in use, they can support greater mechanistic realism in models of ESs. By drawing on the increasing range of remote sensing instruments and measurements, datasets appropriate to the estimation of a given ES can be selected or developed. In so doing, we anticipate rapid progress to the spatial characterization of ecosystem services, in turn supporting ecological conservation, management, and integrated land use planning.

Keywords: Biodiversity, ecosystem function, ecosystem processes, ecosystem services, functional traits, hyperspectral, Landsat, landscape functions, LiDAR, MODIS

I Introduction

Natural and managed ecosystems provide physical, emotional, and economic well-being to human societies via benefits known as ecosystem services (ESs). There are a great many ways by which ecosystems benefit humanity. Conceptually, this diversity of ecosystem services is often grouped into provisioning (natural resources provided by ecological systems such as food, forage, and timber), cultural (spiritual and heritage values derived from natural and managed systems, as well as natural areas tourism and recreation), and regulating and supporting services (life support services such as air or water purification, climate regulation, and ecological processes that maintain functioning ecosystems, contributing to all services) (MEA, 2005).

Historically, ESs have been given little formal attention, especially those services that are not traditionally traded in a market (Costanza et al., 1997), leading to unsustainable land use practices with unintended consequences (Bennett et al., 2009; MEA, 2005). There is growing recognition that conservation and land use planning should strive to maintain the multifunctionality of natural and managed systems through balanced portfolios of ESs. Knowledge about the environmental and anthropogenic controls of ESs and the spatial distribution of ESs are necessary to achieve this goal.

Ecosystem services are produced by organisms (ecosystem service providers, ESPs) and their activities (ecological processes/functions, which are linked to organisms by their functional traits). In turn, these are controlled by a system's abiotic characteristics and the anthropogenic impacts it experiences. Table 1 lists examples of ecological processes, ESPs, and drivers of change that influence ES supply. Several recent reviews summarize the known dependencies of ESs on ESPs (Kremen, 2005; Luck et al., 2009), functional traits (de Bello et al., 2010), and ecological processes (de Groot, 2006; van Oudenhoven et al., 2012). By drawing on this mechanistic understanding of the drivers of ESs, any or all of these ecosystem properties (or indicators of their presence or level) can be used to map and model ES supply.

Although many spatial assessments do build upon a conceptual understanding of the factors controlling ES supply, they often map the distribution of ESs using indirect proxies that have limited mechanistic relevance (Andrew et al., *in review*; Seppelt et al., 2011). These surrogates are based on hypothesized but largely untested relationships between ESs and widely available spatial data products (especially land use/land cover [LULC] maps; de Groot et al., 2010; Haines-Young et al., 2012; Martínez-Harms and Balvanera, 2012). Even assessments that mechanistically model the supply of ESs (such as with production functions) often resort to parameterizing these models with spatial datasets that imperfectly indicate the biophysical variables of interest (Andrew et al., *in review*). In particular, quantitative estimates of vegetation and soil characteristics are often extrapolated across all occurrences of a given LULC class or soil type, respectively (Andrew et al., *in review*), despite available capacity to more directly map those parameters with remote sensing.

One reason that direct spatial estimates of biophysical variables are not often used to map ESs is that spatial assessments of ESs are typically collations of existing spatial datasets (Layke, 2009; Martínez-Harms and Balvanera, 2012; Seppelt et al., 2011). It is not surprising that LULC products are extensively used in ES assessments: LULC products are widely available, and LULC change is a primary driver of altered ES supply (Foley et al., 2005; MEA, 2005). Additionally, awareness of alternative, quantitative spatial products of biophysical variables appears to be limited, in part because there has been relatively little contribution of remote sensing scientists to ES mapping efforts to date. In an earlier review, Feld et al. (2010) concluded that the application of remote sensing to ES assessments is limited to indirect, generic indicators. Tallis et al. (2012) also identified the need to develop the capacity of remote sensing for ES assessments. We believe much of this capacity currently exists, although it has not yet been applied in the context of ES mapping. Thus, drawing on previous work reviewing the spatial information needed to map the distribution of ESs (Andrew et al., *in review*), this manuscript highlights the ways that remote sensing can meet these information needs, but that are currently underutilized in ES assessments. These remotely sensed products are relevant to many ESs and their expanded use can contribute to advances in ES assessments.

II A framework for incorporating remote sensing expertise into ES assessments

Several recent reviews have noted that the majority of ES assessments rely on LULC in some manner (Andrew et al., *in review*; de Groot et al., 2010; Haines-Young et al., 2012; Martínez-Harms and Balvanera, 2012). Indeed, land cover classifications are also a frequent goal of remotely sensed image analyses. A number of such classifications have been developed at local to global scales, for a variety of applications, and are freely available. However, remote sensing offers many more capabilities than land cover classifications (Table 2), some of which provide more direct estimates of ecosystem properties and service provisioning. In order to capitalize on the best available spatial data, we recommend that ES assessments commence by answering the questions posed in Figure 1, with the full participation of social scientists, ecologists, and remote sensing scientists. The contributions of these disciplines in the planning stages will allow the rigorous identification of relevant ESs and human communities that rely on them, the ecosystem properties controlling ES supply, and the spatial data that can best map those properties and model the services. By doing so, ES mapping efforts can rapidly progress towards more quantitative evaluations with improved parameterization of socioecological properties.

In the remainder of this paper, we describe some current capabilities of remote sensing relevant to ESs. Although Figure 1 integrates parallel spatial assessments of ES supply and demand, this review focuses on possible contributions of remote sensing to mapping ES supply. We suggest answers to the following questions posed: *3A. Can the ecosystem processes and components that provide the service be mapped directly, with what spatial products?* and, in situations where direct mapping will not be possible, *5A. What spatial data can indirectly estimate the ecosystem properties that drive ES supply?* (Figure 1). To date there has been greater emphasis on mapping ES supply than demand (Andrew et al., *in review*). Although additional socioeconomic information will be necessary to map ES demand (questions 4B and 5B), the spatial environmental variables identified to map ES supply may also prove relevant to models of demand.

III Remotely sensed information products relevant to ESs

There is an ongoing trend in remote sensing towards the generation of continuous products of environmental variables (DeFries et al., 1999; Ustin and Gamon, 2010). Remote sensing can provide quantitative, spatially explicit, and (in some cases) physically-based estimates of a number of the biophysical parameters that are currently spatialized for ES assessments with LULC maps. Although not all ecosystem properties are amenable to direct detection by remote sensing, many more can be indirectly modeled using (1) empirical models of ESs or ESPs derived from spatial environmental covariates, or (2) inferences or mechanistic models parameterized by maps of the biophysical drivers of ES supply (Table 1).

1 Biophysical data describing organisms

a Species mapping. In some cases, individual species or groups of species are responsible for the provision of a given ES. The functional importance of species is the subject of ecological research (Hooper et al., 2005), but is not often emphasized in ES assessments (Kremen, 2005) unless the link between species and services is well understood. This criterion is most often met when the species is the service itself (such as when it is targeted for food or fiber production).

Earth observation data can be used to directly map some species (e.g., Andrew and Ustin, 2008; Ustin and Gamon, 2010). We know of no examples where remotely sensed species distributions have been used as indicators of ESs. The majority of the species mapping literature is related to (1) detecting and monitoring invasive species (He et al., 2011) or (2) forest management (e.g., Lucas et al., 2008; Ørka et al., 2009; Zhang et al., 2004), both of which have applied relevance to ES assessments. The latter is directly related to timber production services and may be applied in this context once geomatics approaches to forest inventory become operational. Remotely sensed maps of biological invasions may also inform ES assessments as some invasive species alter or disrupt ES supply (Vicente et al., 2013). Moreover, there is no need for the remote sensing of species distributions to be restricted to these applications.

The species mapping literature illustrates that a wide range of plant species inhabiting diverse ecological systems can be detected, suggesting that a variety of ESPs supplying various services might be mapped. However, the direct detection of individual species with remotely sensed data can be difficult. Because all plants possess the same broad characteristics, they all appear fairly similar in image data. Variation in plant reflectance spectra can be introduced by differences in leaf properties, especially pigment composition, water content, and structure (Jacquemoud and Baret, 1990; Feret et al., 2008); and differences in canopy architecture, such as leaf area index (LAI) and leaf angle distribution (Asner, 1998). In general, species mapping is more likely to be successful in simpler ecosystems (Andrew and Ustin, 2008) with fewer species occurring in monospecific patches. More complex environments with species occurring in mixtures present a more demanding problem, with needs for increased training data and higher spatial- and/or spectral resolution imagery. Hyperspectral image data (containing numerous narrow spectral bands) may be sensitive to the subtle chemical and structural differences between species. Examples include the detection of invasive species on the basis of elevated foliar nitrogen and water content (Asner and Vitousek, 2005) or unique pigment composition (Hunt et al., 2004; Parker Williams and Hunt, 2002), and of eucalyptus trees due to spectral features related to characteristic leaf oils and waxes (Lewis et al., 2001).

Differences in the size, shape, and vertical structure of canopies can aid with species differentiation in hyperspatial (pixels 10 cm-1 m on a side) or active remotely sensed data (such as light detection and ranging [LiDAR]). Structural differences may be manifested in the textural information of high spatial resolution image data (i.e., in the spatial heterogeneity of reflectance values; e.g., Laba et al., 2010). Alternatively, object-oriented analyses can be used to group contiguous pixels into patches of vegetation or individual tree crowns (or, given sufficiently high resolution, even individual branches, Brandtberg, 2002), the characteristics of which might indicate particular species (Erikson, 2004). Very high spatial resolution data can also be used to survey certain animal species, such as cattle and deer (Begall et al., 2008), flamingos (Groom et al., 2011), or elephants (Vermeulen et al., 2013).

In contrast to analyses of very high spatial resolution data, which often rely on correlations between the horizontal and vertical structure of vegetation, active sensors directly detect plant vertical structure. These instruments emit a pulse of electromagnetic radiation and record the time it takes to interact with the Earth's surface and return, providing height measurements that may differentiate vegetation with different heights and vertical distributions of branches and foliage (e.g., Hilker et al., 2010). Species identification can also be informed using the intensity values (a measure of the reflectance of the emitted lidar signal) (Ørka et al., 2009). Finally, species may be distinct in their phenological timing, enabling species mapping with multi-season image composites (Bradley and Mustard, 2006; Dymond et al., 2002; Key et al., 2001).

b Biodiversity. Biodiversity has a complicated relationship with ES assessments (Mace et al., 2012) and is variously treated as (1) a driver of ES supply, (2) an ES itself, or (3) a conservation priority to consider alongside ESs. In some cases, there may be a clear relationship between species richness and ESs: for example, more biodiverse sites may have greater ecotourism potential (Ruiz-Frau et al., 2013). Regardless of their specific use, maps of biodiversity are likely to remain valuable to ES assessments. It is impractical to use the species mapping approaches described above to directly detect the biodiversity of an area. Alternative approaches exist to estimate biodiversity from spectral data, often taking advantage of the heterogeneity of reflectance values within a set of pixels (Carlson et al., 2007; Palmer et al., 2002; Rocchini et al., 2004).

c Modeling species distributions and biodiversity. Species mapping efforts are usually limited to a small subset of species that are canopy dominants (but see Asner and Vitousek, 2005) and that are sufficiently distinct to enable remote detection. However, the spatial distributions of biodiversity and ESPs that are not spectrally unique, animals, or components of the understory or soil communities may be indirectly mapped using remotely sensed environmental correlates. For example, even microbial communities, which are impossible to detect in image data, exhibit biogeographic patterns (Bru et al., 2011; Fierer and Jackson, 2006), which might be mapped using distribution models. Andrew and Ustin (2009) and Duro et al. (2007) list contributions of remote sensing to models of species distributions and biodiversity including LULC, topography, vegetation indexes, estimates of the vertical and horizontal structure of vegetation, vegetation functioning, phenology, weather data, image texture, and detection of disturbance events.

d Plant traits. There are a number of challenges related to using ESPs as indicators of ESs. These stem not only from the difficulties of identifying ESPs and of species mapping, but also from the limitations of indicators developed from species, which might be narrowly distributed and poorly scalable (Orians and Policansky, 2009). A more generalizable approach may be to indicate ES supply with species traits, rather than species themselves. Trait-based assessments acknowledge that the connection between ESs and ESPs is mediated by species functional attributes. Remote sensing offers capabilities to map quantitative plant traits (e.g., Berry and Roderick, 2002), especially utilizing the current and rapidly developing generation of hyperspectral and LiDAR instruments (Table 2), supporting trait-based assessments of ESs.

i Chemical traits. As noted in the subsection about species mapping, information about foliar chemistry is present in the detailed reflectance spectra of hyperspectral image data and can be used to map leaf chemical traits. At present, the traits that have received the most active research are pigment composition (Ustin et al., 2009), water content (e.g., Cheng et al., 2008), and nitrogen content (e.g., Martin et al., 2008). These chemical traits have clear relevance to ecological processes and ESs. The absolute and relative amounts of plant pigments can indicate photosynthetic capacity and efficiency – related to productivity, carbon sequestration, and other production-related services, and also vegetation condition. Foliar nitrogen is strongly related to productivity (Ollinger et al., 2008) and to aspects of the nitrogen cycle (McNeil et al. 2012) and may be useful in assessments of soil fertility, water purification (especially the filtration of nutrient pollutants), and other ESs supported by nitrogen cycling. However, with the exception of Lavorel et al. (2011), who used empirically modeled leaf nitrogen in an indicator of forage production, plant chemical traits have not yet been used in spatial assessments of ESs.

Plant chemical traits can be mapped remotely because of characteristic effects of foliar chemistry on reflectance. Chlorophyll and water have strong absorptions that are readily observed in visible-infrared reflectance spectra. Chlorophyll and water content can be estimated from the depth of these absorption features in hyperspectral image data, radiative transfer model inversions (e.g., Cheng et al., 2008; Jacquemoud and Baret, 1990), or simple spectral indexes (Gao, 1996). The latter two approaches can also be applied to multispectral satellite data (e.g., Landsat; MODIS, Trombetti et al., 2008). In contrast, absorption features of auxiliary pigments (such as carotenoids) and nitrogen compounds are weaker and can be difficult to isolate against the strong chlorophyll and water absorptions. However, the wavelengths of carotenoid absorptions are slightly offset from those of chlorophyll. Radiative transfer modeling now supports retrievals of foliar carotenoid concentrations (Feret et al., 2008) and narrow-band indexes have been developed to estimate auxiliary pigment concentrations and pigment ratios (Ustin et al., 2009). Foliar nitrogen is typically estimated with empirical models that take advantage of the complete spectral information present in hyperspectral data (Martin et al., 2008). These models often select bands associated with known nitrogen absorptions in the near infrared, but also include spectral information related to pigment absorptions due to biophysical correlations within the leaf (Martin et al., 2008). Expanding on these techniques, recent research has discovered that leaf nitrogen content is strongly correlated to near infrared albedo, suggesting that foliar nitrogen may be estimated by multispectral data (Ollinger et al., 2008).

ii Structural traits. Many plant structural traits have known associations with ESs. Structural traits that have been used to model ES supply include biomass, to indicate carbon storage (e.g., Milne and Brown, 1997) or combined provisioning services (Koschke et al., 2013); and vegetation height, which can indicate carbon storage (Freudenberger et al., 2013) and forage production (Butterfield and Suding, 2013). LAI, together with foliar nitrogen, drives productivity (Reich, 2012), and could be applied to assessments of carbon and provisioning services. Erosion control and hydrological services have been modeled with the cover of vegetation (e.g., Nelson et al., 2009; Schulp et al., 2012) and nonphotosythnetic vegetation (NPV, or plant litter; Guo et al., 2000), as well as by root depth (Band et al., 2012) and surface roughness (e.g., Mendoza et al., 2011). NPV can also indicate soil accumulation (Egoh et al., 2008) and aesthetic value (Lavorel et al., 2011). Currently, ES assessments primarily rely on LULC products as surrogates for structural traits (Andrew et al., *in review*).

Remotely sensed vegetation cover, LAI, and vegetation indexes may be highly relevant to ES models that depend on the amount of vegetation present and may provide greater spatial realism than extrapolating single values across land cover classes. LAI and measures of vegetation abundance (via vegetation indexes such as the normalized difference vegetation index, NDVI) are traditional remotely sensed products and will not be described in depth here. These fields of research are sufficiently well developed that operational products are available from a variety of sensors (e.g., MODIS: Myneni et al., 2002, MERIS: Poilvé, 2009). Also of note are vegetation continuous fields (VCF) products, which estimate the fractional cover by a given life form in each pixel, as an alternative to categorical land cover classifications (Hansen and deFries, 2004; DiMiceli et al., 2011). With few exceptions (e.g., erosion control modeled by NDVI [Fu et al., 2011], carbon services indicated by VCF tree cover [Freudenberger et al., 2013]), quantitative maps of plant structure have not been widely applied to ES assessments.

Additional structural traits, including height, biomass, LAI, life form, crown morphology, canopy cover, and canopy roughness are accurately estimated by active sensors (LiDAR: Asner et al., 2012; van Leeuwen and Nieuwenhuis, 2010; RADAR: Hyyppä et al., 2000; Kasischke et al., 1997). These parameters can also be empirically modeled from spectral data or image texture metrics (Falkowski et al., 2009; Wulder et al., 2004). For example, taller vegetation casts more shadows, resulting in a more heterogeneous appearance in imagery. Global tree height maps have been developed from point samples of the spaceborne LiDAR GLAS and made spatially continuous with MODIS reflectance data (e.g., Lefsky, 2010), and have been included in a global mapping of carbon services (Freudenberger et al., 2013).

The abundance of NPV is more challenging to estimate remotely than the previously discussed structural traits. NPV shares similar characteristics to the reflectance of bare soil and can be difficult to detect in reflectance data. However, NPV exhibits a strong cellulose absorption feature in the shortwave infrared that readily differentiates NPV from soil in full-range hyperspectral data (Nagler et al., 2000). This feature is not resolved by multispectral instruments, but recent research has developed tools that successfully distinguish NPV from soil (Khanna et al., 2007) or quantify NPV cover (Guerschman et al., 2009; Pacheco and McNairn, 2010) with multispectral MODIS data, suggesting that such quantitative information can be made widely available for ES assessments.

iii Indirect spectral estimates of other plant traits. An advantage of the chemical and structural traits described above is that they influence the variables that remote sensors directly detect (reflectance, vertical structure). Other plant traits that are relevant to ESs (De Bello et al., 2010) are less amenable to direct mapping and are not widely used in ES assessments. But, as with the distribution of species and biodiversity (III.1.c), traits can be indirectly modeled across a planning region from spectral data (Oldeland et al., 2012; Schmidtlein et al., 2012). Such efforts require correlations between the traits of interest and those that influence optical properties, but suites of traits are not uncommon (Wright et al., 2004). For example, Band et al. (2012) took advantage of strong relationships between NDVI and root depth in a process model of erosion control. Alternatively, plant traits can be indirectly modeled using biophysical characteristics of the environment (e.g., Lavorel et al., 2011).

e Measures of vegetation condition. Habitat degradation or plant stress may influence ES supply (e.g., Price et al., 2010). (But note that vegetation condition should be considered mechanistically and degraded systems may provide certain services [Vira and Adams, 2009].) Though ecological integrity is recognized to affect ES supply (Arkema and Samhouri, 2012; Burkhard et al., 2009; Maes et al., 2012), ES assessments rarely incorporate vegetation condition. In those that do, estimates of vegetation condition and its effects are often rule-based and derived from LULC products (e.g., Reyers et al., 2009; Thackway and Lesslie, 2008; Yapp et al., 2010) or applied after the fact (e.g., Kienast et al., 2009). Alternatively, spatial overlays of stressors may be used to assess impacts to ESs (Allan et al., 2013). Yet there is strong potential for developing maps of vegetation condition to inform spatial models of ES supply.

Many of the plant traits described above are sensitive indicators of vegetation condition. Changes in pigments may indicate a variety of stresses, including disease, pollution, or adverse weather conditions (Ustin et al., 2004, 2009). Narrow-band spectral indexes sensitive to pigment ratios or the state of the xanthophyll cycle (a stress response involving pigment transformations) have been developed to indicate plant stress (e.g., Peñuelas et al., 1995). The specific wavelength location of the ‘red edge’, the steep increase in vegetation reflectance from red to near-infrared wavelengths, can also indicate vegetation stress (e.g., Li et al., 2005), as can leaf water content (e.g., Pontius et al., 2005), temperature (related to evapotranspiration, see section III.2.a), and changes in productivity. For example, a discrepancy between observed and potential productivity may suggest degradation or unsustainability (Bindraban et al., 2000; Kienast et al., 2009). Finally, vegetation condition can be empirically modeled by spatial environmental data layers (Zerger et al., 2009).

2 Remote estimates of ecological processes

Many ESs are ecological processes or the direct products of them (Costanza et al., 1997; Kienast et al., 2009; van Oudenhoven et al., 2012). Other ecological processes can have detrimental effects on service supply. Thus, maps of the spatial distribution and the level of ecosystem functionality can provide useful information to the direct mapping or indirect modeling of ESs.

a Biogeochemical processes. Biogeochemical cycles underpin a number of ESs. Nutrient, carbon, and water cycles are supporting services and components of these cycles contribute to many regulating and provisioning services, including climate regulation, air/water purification, and food, fiber, and water provisioning (MEA, 2005). There is great potential to apply remotely sensed indicators of these biogeochemical cycles to spatial assessments of ESs.

Remote sensing has been widely adopted by the ecosystem ecology community to map and monitor biogeochemical cycles. This has resulted in the development of a variety of data products (e.g., Frankenberg et al., 2011; Saatchi et al., 2011), including MODIS standard products (http://modis.gsfc.nasa.gov/data/dataprod/index.php), relevant to the process oriented ESs, especially carbon services. Vegetation production can be estimated using the product of (1) the fraction of photosynthetically available radiation absorbed by plants (fPAR), which is directly related to reflectance and several standard products exist (e.g., MODIS: Myneni et al., 2002; MERIS: Gobron et al., 1999), and (2) photosynthetic efficiency. This latter parameter can be modeled using climate data and known limitations to plant growth (Field et al., 1995). Alternatively, photosynthetic efficiency can be derived from spectral data, for example using the photochemical reflectance index (PRI, Gamon et al., 1992), which is sensitive to the xanthophyll cycle noted above and to chlorophyll:carotenoid ratios, and is consistently related to photosynthetic efficiency (Garbulsky et al., 2011). There are MODIS standard GPP and NPP products available, derived from remotely sensed biophysical products (land cover, fPAR, LAI) and climate data (Zhao et al., 2010).

Evapotranspiration (ET) is a key means by which ecosystems influence water supply. Current ES tools use LULC products to represent variation in ET (e.g., Nelson et al., 2009). However, ET can be quantitatively estimated on a pixel basis (Schmugge et al., 2002; Tang et al., 2009) using either (1) relationships between vegetation indexes and ET (Glenn et al., 2010) or (2) temperature differences caused by the latent heat of evaporation (Anderson et al., 2012). A MODIS ET product exists (Mu et al., 2011) and finer resolution information can be provided by Landsat (Anderson et al., 2012). The water use information generated using remotely sensed data and modeling is perceived as sufficiently accurate to inform and resolve legal disputes (Anderson et al., 2012).

b Phenology. The timing of vegetation activity relative to environmental processes and human demand is likely to affect ESs. Growing season length is a critical control of productivity (Churkina et al., 2005; Reich, 2012) and the ESs it supports. Phenology will also influence hydrological services and ESs dependent on species interactions, via synchronies or mismatches between vegetation activity and precipitation events (Ponette-González et al., 2010) or ESP phenology (e.g., pollination: Kremen et al., 2007). Satellite time series provide an excellent opportunity for mapping spatiotemporal patterns of phenological timing (Cleland et al., 2007; Verbesselt et al., 2010a). Coarse spatial resolution, high temporal resolution sensors such as MODIS are the primary source of remotely sensed phenology information (Zhang et al., 2006), but Landsat has also been used to map finer patterns of phenology over regional extents (Fisher et al., 2006).

c Disturbance. The prevention, amelioration, and recovery from disturbances are important services to be assessed in their own right (e.g., Grêt-Regamey et al., 2008). In addition, maps of disturbance events may highlight areas of changed or disrupted service supply. Anielski and Wilson (2009) acknowledge disturbances as one of the data needs to rigorously estimate ESs and the ARIES toolkit treats disturbances 'sinks' for various ESs (Bagstad et al., 2011). However, the effects of disturbances are otherwise rarely considered in ES assessments.

Disturbances may be mapped indirectly (i.e., the potential for a given disturbance) using spatial soils, vegetation, and climate data (e.g., Lorz et al., 2010) or plant traits (e.g., mapping fire risk from vegetation water content [Yebra et al., 2013] or forest structure [Riaño et al., 2003]), or directly from remotely sensed observations (Frolking et al., 2009). Disturbances may be detectable in single-date image data if they leave distinct legacies (e.g., burn scars, cutblock edges). Multi-date imagery can detect disturbances and subsequent recovery of vegetation through changes in reflectance or in any of the derived products describing the activity and characteristics of vegetation. Discrete disturbances that result in land cover changes are frequently mapped by analyses of before and after image dates (Lu et al., 2004). High temporal resolution sensors such as MODIS and the opening of the vast Landsat archive (Wulder et al., 2012) have supported the remote sensing of disturbance with detailed temporal trajectories and time series analyses (Kennedy et al., 2007), including detection of both abrupt disturbances and subtle changes in vegetation condition (Verbesselt et al., 2010b). For example, Koltunov et al. (2009) demonstrate that forest disturbances affecting as little as 5-10% of a 1km MODIS pixel are detectable. Additionally, high spatial and high temporal resolution information can be fused to capitalize on the advantages of each, producing detailed maps of vegetation change (e.g., Hilker et al., 2009).

d Inferring process from spatial pattern. Due to their inherent temporal nature, processes are notoriously difficult to observe and represent in a geographic information system (GIS). Instead, processes are often simulated with process models, represented with static proxies (e.g., NDVI or fPAR for productivity or carbon sequestration), or inferred from spatial pattern (Cale et al., 1989; McIntire and Fajardo, 2009). As an example of the latter, spatial analysis techniques that rely on the distances between objects can provide information on the population and community dynamics of ESPs (e.g., Atkinson et al., 2007; Nelson and Boots, 2008; Nelson et al., 2004) and may yield improved detection of ES hotspots over the existing thresholding approaches (Nelson and Boots, 2008).

3 Physical data describing the environment

Characteristics of the abiotic environment may be directly involved in the ecological processes that support ESs, or they may indirectly influence service supply, for example by determining suitability for the relevant ESPs. Thus, spatial data of such environmental variables can inform ES assessments. A number of abiotic features can be mapped by remote sensing, including topography (digital elevation models are well established and widely used in ES assessments [Andrew et al., *in review*] and are not discussed further here), quantitative soil characteristics, and aspects of hydrology.

a Soil properties. Soil processes drive a number of ESs and soil characteristics influence many others: many biogeochemical processes occur in soils, soils store pools of carbon and nutrients that support vegetation production and provisioning services, and soils may determine habitat suitability for ESPs (Haygarth and Ritz, 2009; Robinson et al., 2013). Consequently, soils are widely incorporated into ES assessments. However, quantitative soil characteristics are frequently proxied by categorical soil maps (Andrew et al., *in review*).

Although it is difficult to develop spatial estimates of quantitative soil properties, some soil characteristics may be mapped with remote sensing, where soils are not obscured by vegetation (Mulder et al., 2011). Remote sensing can estimate soil carbon and texture, with relevance to carbon and hydrological services, respectively. Both of these attributes affect soil reflectance properties. As soil particle sizes decrease, reflectance increases throughout the spectrum (Okin and Painter, 2004). Soil organic matter may be quantified using particular absorption features, the degree of concavity of the reflectance spectrum in visible wavelengths (Palacios-Orueta and Ustin, 1998; Palacios-Orueta et al., 1999), or empirical models that take advantage of all available spectral information (Stevens et al., 2010). Organic residue on the soil surface can be estimated by mapping NPV cover (III.1.d.ii). Microwave remote sensing (passive and RADAR) has been used to map soil properties (e.g., soil texture: Chang and Islam, 2000) and may offer several advantages. The longer microwave wavelengths can penetrate vegetation and upper soil layers and thus may provide information on a wider range of soil properties, including subsurface properties, and in regions with dense vegetation.

Quantitative soil properties may also be indirectly modeled with spatial datasets of the variables that influence soil formation: climate, topography, and vegetation (Doetterl et al. 2013; Mulder et al., 2011; Sanchez et al., 2009). However, some authors note that these models may have limited generality (Thompson et al., 2006) or that unmeasured variables such as local management practices may be more important (Page et al., 2005).

b Hydrological variables. Hydrological services are currently mapped with an assortment of gridded climate data, streamflow monitoring data, and hydrological models (Andrew et al., *in review*; Vigerstol and Aukema, 2011). Some hydrological variables are amenable to remote sensing, and may be useful in the spatial assessment of ESs. Microwave wavelengths are strongly sensitive to the dielectric constant of materials. Water has an extremely high dielectric constant, which makes active (i.e., RADAR) and passive microwave remote sensing particularly well suited for assessing hydrological services. Microwave data may provide estimates of the volume of water stocks (e.g., snow water equivalents: Derksen et al., 1998) and inputs (e.g., precipitation rates: Huffman et al., 2007), and are not limited by canopy cover (e.g., inundation and soil moisture under vegetation: Kasischke et al., 1997). Alternatively, volume estimates can be provided by remote sensing of Earth's gravity field (Tapley et al., 2004). This technology has been used to map groundwater declines (Tiwari et al., 2009) and changes in ice mass balance and sea level (Cazenave et al., 2009; Jacob et al., 2012), albeit at coarse spatial resolution.

Optical data are also useful for hydrological applications, for example to estimate the areal extent of surface water, snow, and ice (e.g., Robinson et al., 1993). Spatial estimates of foliar water (III.1.d.i) and evapotranspiration (III.2.a) are also supported. Finally, reflectance data may be used to monitor water quality, especially concentrations of chlorophyll and suspended sediment (Ritchie et al., 2003), although a general approach for remote sensing of freshwater quality is yet to be developed (Malthus et al., 2012).

4 Landscape structure

The spatial configuration of habitats may be a crucial control of services that involve lateral flows of material or organisms (Goldstein et al., 2012; e.g., pollination: Lonsdorf et al., 2009; pest control: Winqvist et al., 2011; water supply and filtration: Lautenbach et al., 2011), which is especially relevent when services are modeled at fine scales (Locatelli et al., 2011). Even services that do not require cross-system interactions can be influenced by landscape structure: aesthetic services are linked to landscape diversity (Groot et al., 2007) or configuration (Frank et al., 2013; Gulickx et al., 2013), and the quality and amount of various services can be influenced by landscape and patch characteristics (Goldstein et al., 2012). Laterra et al. (2012) found that landscape structure was more explanatory of the spatial patterning of ESs than was LULC information alone, and the spatial configuration of green space has been shown to have significant effects on cultural services in hedonic pricing studies (Cho et al., 2008; Kong et al., 2007).

Mechanistic models of ESs can explicitly represent flows across landscapes, but many ES indicators are pixel-level measures, uninfluenced by a pixel's context. Quantitative measures of landscape structure, often calculated from remotely sensed products, are a staple of landscape ecology research. Many are derived from LULC classifications and a patch-matrix view of spatial variation, but ecologically relevant estimates of spatial heterogeneity from quantitative remotely sensed products also exist (Gustafson, 1998; Skidmore et al., 2011). Several researchers have urged for the incorporation of landscape metrics into ES assessments (Bastian et al., 2012; Blaschke, 2006; Syrbe and Walz, 2012). To date, such approaches have been implemented in indicators of ecological value (Frank et al., 2012; Labiosa et al., 2009), as informed by the body of landscape ecology research, but not to map true services. If incorporated into ES assessments, landscape metrics should be selected with care. These measures can be sensitive to the spatial and thematic resolution of the input image product (O'Neill et al., 1996; Castilla et al., 2009) and may not exhibit straightforward relationships with the ecosystem properties (Li and Wu, 2004) and services of interest.

5 Management

The explicit connection between ESs and human societies makes land use an important control of services, underscoring the use of LULC products in ES assessments. Unlike land cover, land use conveys information on what activities are being conducted in an area and what services are actually being used (Ericksen et al., 2012). However, while land cover may be directly detected by remote sensing, it is unlikely that remote sensing alone can provide a thorough portrayal of land use and management (Verburg et al., 2009). Nevertheless, some of the biophysical products described above may prove helpful. Species mapping (III.1.a) may identify specific agricultural crops with concomitant differences in farming practices, conservation tillage can be indicated by the detection of NPV (III.1.d.ii), and agricultural intensification, fertilization, and irrigation may be observable in maps of foliar nitrogen, water content, evapotranspiration, and phenology (III.1.d.i, III.2.a, and III.2.b). Remote sensing of temporal trajectories can provide information about a range of land uses. For example, timber harvest is clearly discernable in image data (e.g., White et al., 2011) and even small-scale selective logging can be detected (Koltunov et al., 2009). Finally, some aspects of land use may be inferred from the distribution of anthropogenic infrastructure (including signals of human activity evident in nighttime satellite image data: Elvidge et al., 1997) and landscape structure.

6 Ecosystem classifications

Remotely sensed data can also provide a regional stratification within which ESs are monitored and managed. A regional perspective may be most relevant for ESs, as the relationships between services and drivers, other services, or beneficiaries varies regionally (Anderson et al., 2009; Birch et al., 2010). Ecologically defined regions may accommodate for the context-dependence of simple ES proxies and allow for more reliable parameterization of ES models (Saad et al., 2011). Ecological regions can also assist with the standardization and comparison of ES supply across geographically and environmentally disparate areas (Metzger et al., 2006).

A number of ecological region schemes (ecoregionalizations or ecosystem classifications) are in use. Because each ecosystem property and ES differentially responds to the environment, there is no “one size fits all” ecoregionalization. Rather, the ability of a regionalization to summarize the spatial patterns of an ES will depend on which variables were used to construct the regionalization and whether they are key influences on the ES of interest (e.g., Andrew et al., 2011, 2013). Objective, quantitative ecoregionalizations can be developed using the spatial variables in Table 2 to augment existing ecoregionalization schemes and explicitly tailor them to the drivers of ESs. Regionalizations incorporating measures of human activity (Ellis and Ramankutty, 2008; Kupfer et al., 2012) can capture patterns of ES demand.

7 Challenges to expanded use of remote sensing in ecosystem service assessments

Although remote sensing has the demonstrated potential to provide spatially explicit biophysical information, challenges remain to their implementation in operational ES assessments. Many of these products are developed with empirical models relating the biophysical parameter of interest to the spectral response received by the sensor, requiring *in situ* training and validation data, and may be poorly transportable to different study areas or different sensors. However, some general models are being developed and show promise (e.g., foliar nitrogen: Martin et al., 2008; Ollinger et al., 2008; biomass: Asner et al., 2012). Radiative transfer models provide greater generality for estimating biophysical characteristics, but may require specialized training to apply and are difficult to invert (although inversions can be approximated with artificial neural networks, which are less computationally demanding; Trombetti et al., 2008).

A related challenge is that remote sensing is limited to features that are detectable by sensors. In the case of optical remote sensing, this corresponds to surface characteristics that have a unique, predictable spectral response (either at the individual pixel level, or in pixel neighborhoods or time series of image data) and that are not obscured by overlying features (vegetation canopy, cloud cover, or atmospheric effects). Although we emphasize that the biophysical parameter of interest may instead be indirectly modeled using remotely sensed data layers, this may also introduce errors or limit the portability of the model. The spatial, spectral, temporal, and radiometric characteristics of a given remotely sensed data source all combine to determine which ESs can be captured (i.e., mapped directly) or modeled (i.e., mapped indirectly). The information need and the characteristics of a given ES of interest need to be known and articulated in order to determine what remotely sensed data is appropriate and what methods are to be applied.

Perhaps the biggest impediment to the incorporation of a wider variety of data products into ES assessments is data availability. Many of the sensors needed to create these products do not provide global coverage (especially airborne hyperspectral and LiDAR instruments) and may be costly to acquire (Ayanu et al., 2012). Availability of the processed products is also limited by the technical expertise and specialized software that are often required for advanced remote sensing analyses. For this reason, we believe that the adoption of novel remotely sensed products for ES mapping will most likely be achieved through inclusion of a dedicated remote sensing scientist in a multidisciplinary project team (Figure 1). That being said, there are a number of operational, standard products currently available, which we highlight in the relevant sections, that have received relatively little attention to date in ES frameworks. We encourage their rapid uptake in ES assessments conducted at an appropriate spatial resolution.

IV Conclusions

Attention to ecosystem services can enable a more complete consideration of the values of natural and managed systems, leading to more sustainable land use planning decisions (e.g., Goldstein et al., 2012). Ecosystem services can also diversify the motivations and funding sources available for conservation (Goldman and Tallis, 2009). However, the success of these initiatives will require an improved ability to evaluate and forecast the distribution of ESs across space and time. It is inevitable that remotely sensed information be used in spatial assessments of ESs. Although extensive field surveys directly censusing services are excellent sources of information (Eigenbrod et al., 2010a), they are unrealistic across large areas and may not be perceived as cost-effective by stakeholders (Crossman et al., 2011). Moreover, there is general acceptance of the information content of remotely sensed data and its efficiency in providing synoptic coverage of large areas. However, the remotely sensed products that are currently used to map ESs are a relatively small subset of those available.

Rather than using existing spatial data products that are often only of limited relevance to services and provide little indication of ecological or physical mechanisms, ESs and the organisms and ecological processes that maintain them should be specifically mapped, either directly, when possible, or using empirical or physical ecological models. Remote sensing can make important contributions to the improved parameterization of ES models via quantitative and, in many cases, physically-based estimates of biophysical variables that are relevant to a variety of ESs. In particular, remote sensing can provide spatially nuanced depictions of plant functional traits, including chemical and structural traits; soil properties, including estimates of soil texture and carbon content; and can monitor aspects of critical biogeochemical processes, including cycling of carbon, nitrogen, and water. These parameters are known to influence the supply of many ESs. In fact, a number of these biophysical variables are already included in models of ES supply (such as the InVEST models described in Karieva et al., 2011), suggesting that existing ES toolkits can be readily adapted to direct estimates of the biophysical inputs, rather than by coupling LULC products and lookup tables.

An increased incorporation of the current generation of remotely sensed data products into ES assessments can help drive a shift from reliance on simple spatial proxies of ESs to a more mechanistic focus on the ecological processes, the organisms, and their traits that underlie ES provisioning. Rapid progress can be made in ES mapping and modeling by closing the gap between the data that are currently used and the data opportunities that can be supported by remote sensing. Close collaboration is required between ecologists and social scientists, to identify the key ESs of a given study region and the ecosystem properties that drive them, and remote sensing scientists, to identify and provide spatial information of those properties. Bringing together these burgeoning areas of expertise will stimulate important gains to the study, monitoring, and conservation of ESs.

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Table 1. Factors that drive and influence ecosystem service supply: ecological processes (including supporting ecosystem services), ecosystem service providers, and drivers of change.

Ecological processes	Ecosystem service providers	Drivers of change
Soil formation	Genotypes	Land cover / Land use change
Photosynthesis	Populations	
Primary production	Species	Climate change
Trophic dynamics	Functional groups / guilds	Fragmentation
Water cycling	Communities	Habitat degradation
- water storage	Ecosystems	Biological invasions
- evapotranspiration	Landscapes	Species composition changes
- infiltration	Biodiversity	Pollution
Nutrient cycling	Micro-organisms	Overexploitation
- decomposition / mineralization	Plants	
	Insects	
- nutrient / sediment retention	Birds	
	Mammals	
- nutrient mobilization	Parasites	
Heat exchange	Predators	
Energy dissipation (wind, water)	Soil organisms	
	Aquatic organisms	
Disturbance	Fungi	
Evolution	Functional traits	
Weathering	- canopy architecture	
Species interactions	- leaf structure & chemistry	
Habitat formation	- phenology	
Bioturbation	- size	
Geomorphology	- litter traits	
	- life history	
	- metabolism	
	- behavior	

Compiled from: MEA, 2005; Costanza et al., 1997; de Bello et al., 2010; Kienast et al., 2009; Kremen, 2005; Balmford, 2008

Table 2. Capabilities of remote sensing to provide spatial data relevant to ecosystem services.

ES, ESP, or ecological process	**RS Products**	**Source**
Plant traits	Pigment, dry matter, water, chemistry content, LAI, LAD	Spectral analysis or radiative transfer models
	Roughness, height, vertical structure	LiDAR, RADAR, multiangle RS
	Life form	Land cover classification
	Phenology	Multitemporal RS
Species	Species map	Chemical or structural uniqueness, HSI, LiDAR, image texture
	Habitat suitability map	Varied, e.g., climate, topography, land cover, productivity
Biodiversity	Spectral diversity	Range or variability of biochemistry, NDVI, or reflectance in set of pixels
	Environmental surrogates	Varied, e.g., productivity, topography, land cover, disturbance
Abundance of functional components	Vegetation fraction, litter fraction	Spectral unmixing, MODIS Continuous Fields
Biomass, C storage	Canopy structure	LiDAR, RADAR, multiangle RS
Photosynthesis, C sequestration	Productivity	fPAR, photosynthetic efficiency, fluorescence, MODIS NPP
Disturbance	Change in biomass, plant traits, land cover	Multitemporal RS
	Fire detection	Thermal anomalies
	Drought monitoring	Water content, surface temperature, ETo
	Plant stress	Spectral indexes
Soil characteristics	Land form	DEM
	Soil texture, moisture, chemistry	RADAR, HSI
Evapotranspiration	Evapotranspiration	Thermal remote sensing, VIs, climate data
Hydrology variables	Precipitation	RADAR, passive microwave
	Soil moisture	RADAR
	Water, snow/ice extent	Optical, RADAR, passive microwave
	Water level	RADAR altimetry
	Ground water	Gravity surveys, subsidence, surface water fluxes
Landscape structure	Landscape metrics	Land cover, quantitative heterogeneity patterns
Ecosystem classification	Ecosystem classification	Varied, e.g., productivity, climate, topography, land cover

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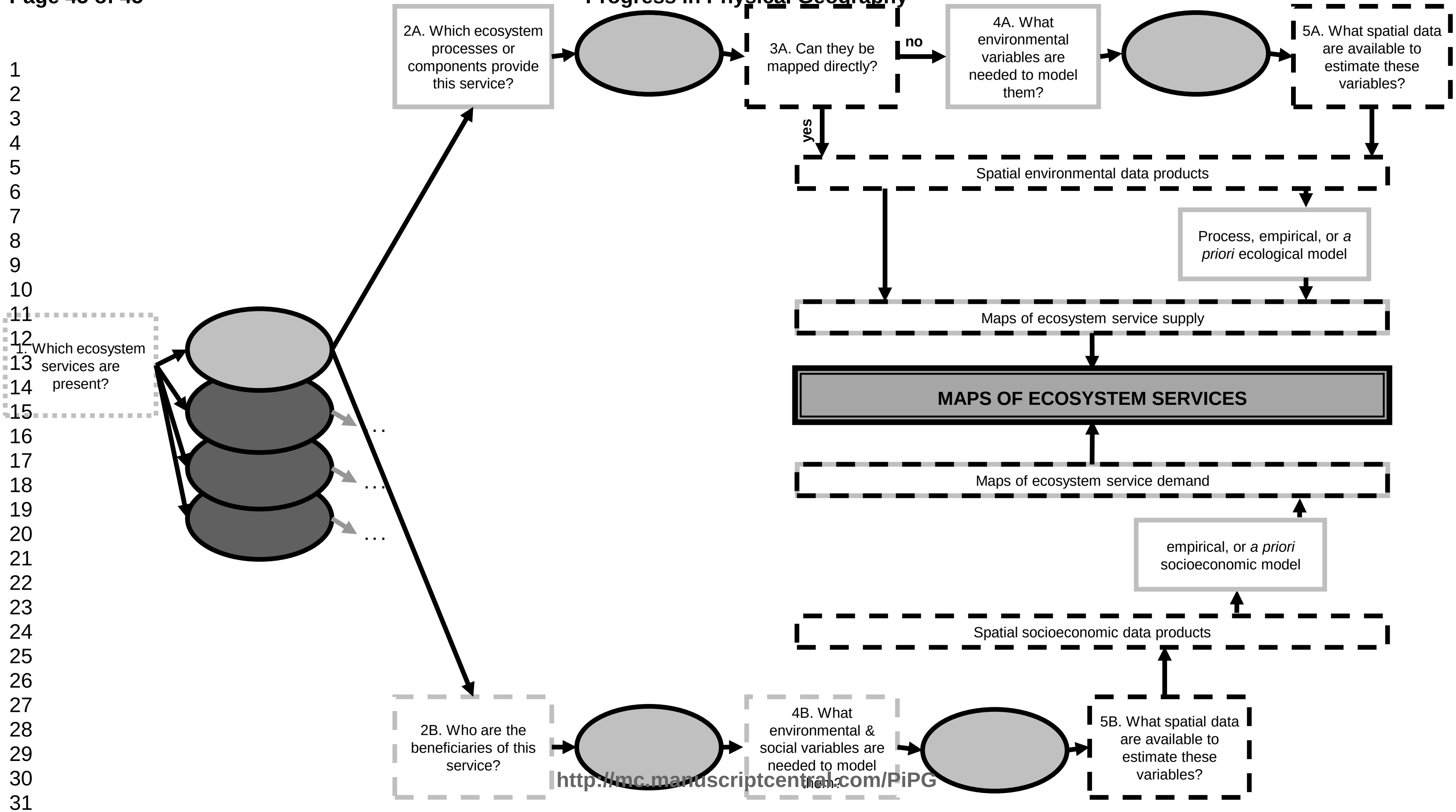
Abbreviations: ES (ecosystem service); ESP (ecosystem service provider); RS (remote sensing); LAI (leaf area index); LAD (leaf angle distribution); LiDAR (light detection and ranging); RADAR (radio detection and ranging); HSI (hyperspectral imagery); NDVI (normalized difference vegetation index); MODIS (moderate resolution imaging spectroradiometer); fPAR (fraction of absorbed photosynthetically active radiation); NPP (net primary productivity), ETo (evapotranspiration); DEM (digital elevation model); VI (vegetation index)

Compiled from: Ustin and Gamon 2010; Frolking et al. 2009; Asner and Martin 2009; Mulder et al. 2011; DeFries et al. 1999; Frankenberg et al. 2011; Saatchi et al. 2011; Simard et al. 2011; Tang et al. 2009; Alsdorf et al. 2008; Schmugge et al. 2002; Andrew and Ustin 2009; Duro et al. 2007; http://modis.gsfc.nasa.gov/data/dataprod/index.php

Figure captions

Figure 1. Flow chart describing the collaborative framework integrating social, ecological, and geographic/remote sensing expertise to map ecosystem services. The questions outlined in dashed grey lines indicate contributions of social scientists, solid grey lines indicate the contributions of ecologists and conservationists, while those in dashed black lines are to be addressed by remote sensing scientists and geographers. Question 1, in short-dashed grey, is most appropriately addressed by the combined expertise of social scientists and ecologists/conservationists, and dashed black and grey lines indicate the inclusion of geographic/remote sensing expertise with these fields. This figure is necessarily vague as the answer to each of these questions may be highly service dependent.


1. Which ecosystem services are present?
2A. Which ecosystem processes or components provide this service?
3A. Can they be mapped directly?
no
yes
4A. What environmental variables are needed to model them?
5A. What spatial data are available to estimate these variables?
Spatial environmental data products
Process, empirical, or *a priori* ecological model
Maps of ecosystem service supply
MAPS OF ECOSYSTEM SERVICES
Maps of ecosystem service demand
empirical, or *a priori* socioeconomic model
Spatial socioeconomic data products
2B. Who are the beneficiaries of this service?
4B. What environmental & social variables are needed to model them?
5B. What spatial data are available to estimate these variables?