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Enhancing ecosystem services maps combining field and environmental data

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ABSTRACT

Ecosystem service maps are increasingly being used to prioritize management and conservation decisions. Most of these maps rely on estimates of ecosystem services estimated for individual land cover classes rather than incorporating field data. We developed combined field models (CFM) using regression analysis to estimate ecosystem services based on the observed relationship between environmental and land cover data and field measurements of ecosystem services. Local ecosystem service supply was estimated from vegetation data measured at fifty sites covering the widest range of environmental conditions across a watershed in Mexico. We compared the accuracy of the CFM approach for forage, timber, firewood and carbon storage over a more commonly "look up table" method relying on a uniform estimate of ecosystem service supply by land cover type. The CFM revealed higher accuracy when compared to the "look up table" approach. The resulting CFM models explained a large fraction of the variance (42–89%) using a combination of land cover, remote sensing data, hydrology and distance from developed areas. In addition, mapping residuals from Geographically Weighted Regressions provided an estimate of uncertainty across the CFM model results. This approach provides better estimates of ecosystem service delivery and uncertainty for land managers and decision-makers.

1. Introduction

The Ecosystem Services (ES) concept has become widely used because it connects ecosystem benefits to human wellbeing (Bürgi et al., 2014). International policy is now embracing and incorporating the conservation and management of ES along with biodiversity. For example the Convention on Biological Diversity (CBD) explicitly included ecosystem services conservation in the Aichi Targets (CBD, 2010) and the creation of the Intergovernmental Science-Policy Platform on Biodiversity and Ecosystem Services (Perrings et al., 2011). Still a major endeavor for the effective integration of ES in decision-making is to develop solid methods for mapping and assessing ES useful for the multiple objectives assessed by these policies (Maes et al., 2013).

Ecosystem Services (ES) maps are increasingly used to highlight key areas of ES supply, to assess spatial trade-offs and synergies among multiple ES and biodiversity and to improve land use planning tools for biodiversity and ES conservation and management (Seppelt et al., 2011; Martinez-Harms and Balvanera, 2012; Sousa et al., 2016). Maps of ES now play a key role in policy and decision-making; in fact, the European Union's Biodiversity Strategy, explicitly requires Member States to map ES (Maes et al., 2013). The value of ES maps depends on their accuracy and adoption rate by decision makers for use in land use planning (Martinez-Harms et al., 2015; Atkinson et al., 2016).

A range of modeling techniques have been used to map ES (Martinez-harms and Balvanera 2012; Crossman et al., 2013; Wolff et al., 2015) and the resulting spatial patterns observed are highly dependent on the methods used (Anderson et al., 2009; Eigenbrod et al., 2010a). The choice of an ES spatial model will depend on the level of accuracy needed for the decision making application and

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this will determine how complex the spatial models need to be (Schröter et al., 2014). It will also depend on data availability and the associated costs on building the desired maps. Many policy applications often involve large spatial scales (e.g. national, regional, provincial) for which gathering primary data would involve significant investment beyond what is generally available, especially in developing countries (Wong et al., 2015).

The most common technique used to address this data gap is to model ES relying on secondary data, information readily available from external sources like land cover, geographical databases, remote sensed data among others (Martinez-Harms and Balvanera, 2012). Land cover data is the most common used due to the widespread availability of this information. Examples include benefit transfer approaches using the economic value of ecosystem services from one location to estimate ecosystem service values at other locations with similar environmental conditions (Wong et al., 2015) and Look Up Tables (LUT) that rely on constant or average values of ecosystem services by land cover type to target important areas for ecosystem services (e.g. Lautenbach et al., 2011; Burkhard et al., 2012; Schröter et al., 2014). However, assigning a single value of ES to each land cover category is susceptible to uniformity errors, resulting in a poor fit of modeled ES values with observed conditions (Plummer, 2009; Eigenbrod et al., 2010b; Brown et al., 2016).

Eigenbrod et al. (2010a) and Lavorel et al. (2011) have shown that maps based purely on broad land cover types have high levels of error compared to maps based on primary data. ES supply varies within and across land cover classes in real landscapes due to biophysical (e.g. topographic, climate fluctuations) and management (e.g. grazing or logging regimes) heterogeneity (Grêt-Regamey et al., 2014), and their addition provides better models. The improvement that may result from modeling ecosystems services based on field data, environmental data and land cover variables as a way of estimating ES levels has not been examined in most regions of the world (Plummer, 2009; Eigenbrod et al., 2010a).

Some policy applications, as is the case of the design and application of financial mechanisms for ES (Wendland et al., 2010; Venter et al., 2013), require higher levels of accuracy (Schröter et al., 2014; Wong et al., 2015), and have led to the use of primary data to model ES across space. To develop more accurate estimates of ES spatially explicit models based on field data collections from the area of interest are in demand. An approach that relies primarily on regression models to assess the relationship between biophysical and management explanatory variables and representative field measures of ES as response variables (Lavorel et al., 2011; Martínez-Harms and Balvanera, 2012) is presented in this study. The application of these models hereafter called Combined Field Models (CFM) explain the variation of modeled ES and can lead to more accurate ES models.

CFM have been used to model carbon sequestration (Bowker et al., 2008) and storage (Krishnaswamy et al., 2009; Timilsina et al., 2013), forage production (Malmstrom et al., 2009; Lavorel et al., 2011), water quality (Uriarte et al., 2011), biological control (Garcia and Martínez, 2012), pollination and soil fertility (Lavorel et al., 2011). Given the diversity of landscapes and ecosystem services being investigated, we need to explore the relationship between readily available independent Geographic Information System (GIS) variables and field measurements for estimating ES values. Equally important, such methods have seldom been applied simultaneously to various ecosystem services (but see Lavorel et al. (2011)). Here we test whether the addition of local field data and a range of GIS variables improves the accuracy of ES maps compared to LUT approaches and explore the spatial heterogeneity in model accuracy.

2. Methods

2.1. Study area

The study was undertaken at the Cuixmala watershed, located along the Mexican Pacific Coast at latitude between 19°21′ and 19°51′ N and 104°59′ and 104°37′W with a total area of 1080 km², with an elevation gradient ranging from 0 to 1730 m (see Fig. 1). The lower part of the watershed hosts a tropical dry forest system well known for its high biodiversity, which is protected under a Federal level Biosphere Reserve status (Chamela-Cuixmala Biosphere Reserve). The structure and functioning of these ecosystems have been studied for the last 20 years and already synthesized from the ES perspective (Maass et al., 2005). The rest of the watershed is largely managed for cattle ranching, wood extraction and biofuel extraction, while the whole area is eligible for payments for ES. Agriculture is only sparsely found in a few areas with deep soils and access to ground water. Local associations of decision makers (including individuals working for the government and those organized into an NGO) have been interested in designing management strategies that would better align with sustainability. Also comparable watersheds maybe found along most of the Pacific Coast of Mexico.

2.2. Field sampling

Field sites were stratified across the existing biophysical gradient resulting from differences in physiography and management history based on elevation, soil, and land cover data. Fifty sites were distributed to proportionally represent the elevation gradients, soil and land cover classes (see Fig. 1). In each site we surveyed the vegetation in 400 m^2 nested plots, in which individuals of smaller sizes were measured in smaller plots of 100 m^2 and 25 m^2; the plots were divided into four quadrats to assess the variability of the vegetation components inside the sites. We used the average value of these quadrats to develop our CFM models.

DBH and height of the individuals were measured as follows: (i) 25 m^2 quadrats were used to measure woody individuals with a DBH greater than 1 cm; (ii) 100 m^2 quadrats for those with DBH $\geq$ 2.5 cm and (iii) 400 m^2 for those with DBH $\geq$ 5 cm. Herbaceous and shrub components were measured in 1 m^2 plot nested within each 25 m^2 quadrats, in two of these 1 m^2 plots the above-ground biomass was harvested and the samples oven dried at 70 °C (48 h) and weighted. We only considered herbaceous and shrub individuals between 20 cm and 1 m height.

2.3. ES definition and local quantification

Forage supply was defined as the total above-ground biomass available for livestock fodder expressed as dry weight (kg) per unit area (ha) (Jaramillo et al., 2003). Forage was calculated as the sum of above-ground biomass of all the 1 m^2 plots considering the understory cover (herbaceous and shrub individuals). Timber delivery was defined as the volume of wood found in individual trees of commercial size (DBH > 30 cm) (Balvanera et al., 2005) expressed in volume (m^3) per unit area (ha). Timber delivery was calculated by multiplying basal area (m^2) of the individuals with a DBH larger than 30 cm by the height of individuals (m) to obtain volume (m^3) per unit area (ha). Firewood was defined as all above-ground woody biomass with DBH < 30 cm expressed in tons per hectare. Firewood supply was calculated with the allometric equation proposed to quantify the biomass of the tropical dry forest found in the lower part of the watershed (Martínez-Yrizar et al., 1992). This equation uses basal area to obtain the logarithm of biomass in tons per hectare (Martínez-Yrizar et al., 1992):