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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):

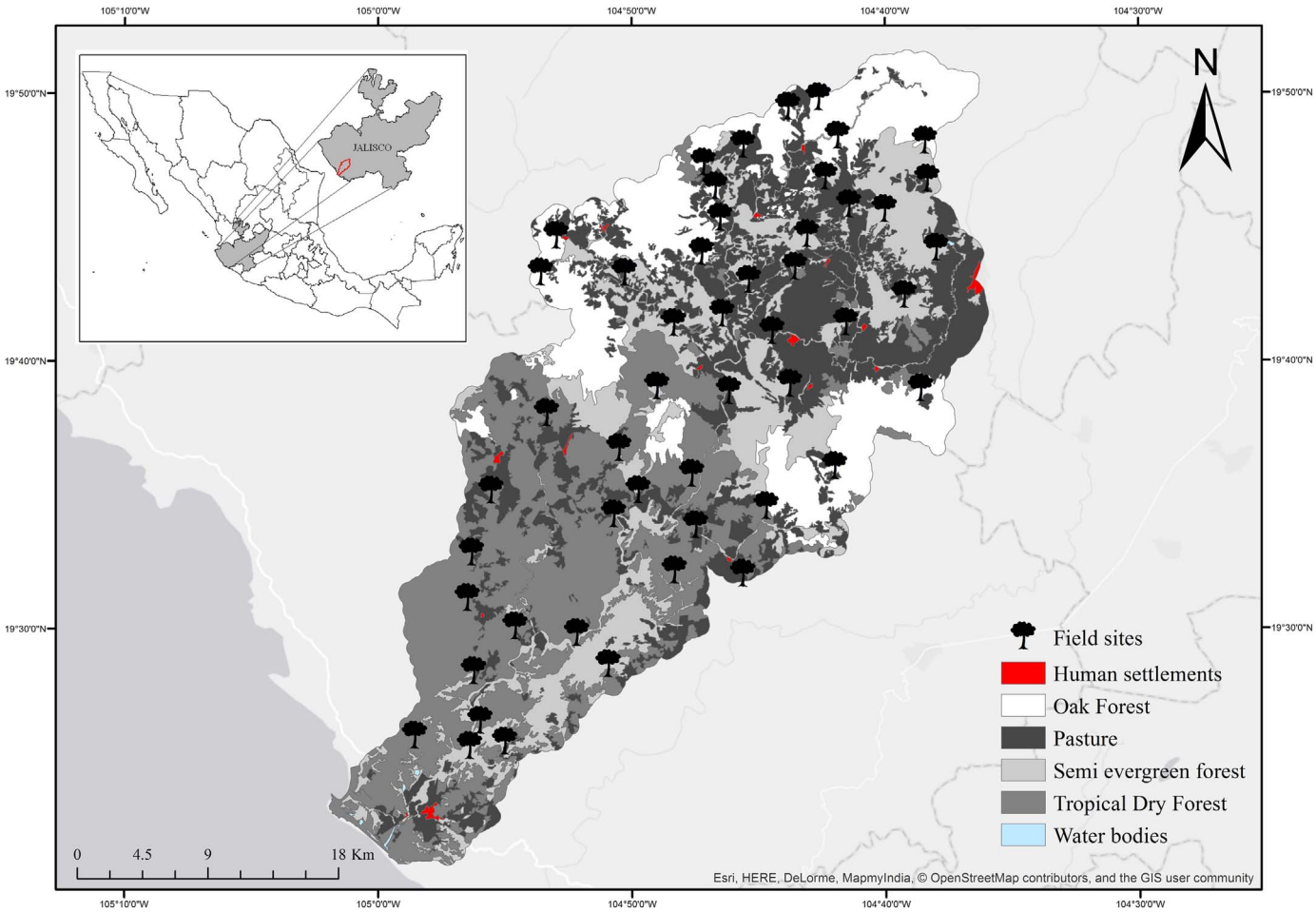

Fig. 1. Land cover map of the Cuixmala Watershed and location of field sites.

$$\mathrm{Log}(Y) = -0.5352 + 0.996(BA)$$

Where:

Y: above-ground biomass (ton).

BA: Basal area.

The use of Martínez-Yrizar allometric model was preferred over habitat specific allometric regressions due to limited availability of equivalent models for other types of land cover types and to maximize comparability among sites throughout the watershed. We did not take into account the differential palatability of the species by cattle, or data on local preference for particular timber of firewood species by local inhabitants which are regional markets, hindered more detailed assessments. Above ground carbon storage was defined as the total content of carbon in above-ground biomass from both herbaceous and woody elements expressed in tons per hectare. Above-ground carbon storage was calculated as the sum of the biomass of the forage, timber and firewood. To convert biomass into carbon content we used the carbon contained in the biomass (50% of carbon in total biomass) reported in the literature (Aalde et al., 2006).

2.4. Explanatory variables

We used GIS and remote sensed variables with largest potential to explain spatial patterns of ES at the watershed scale. Explanatory variables were divided into five different categories: topographical, disturbance, hydrological, remote sensed and land cover variables (Chan et al., 2006; Egoh et al., 2008; Nelson et al., 2009) (see Table 1). Topography influence patterns of rainfall,

Table 1
List of explanatory variables with source of data applied in the ES modeling approach.

Categories	Explanatory variables	Source of data
Topography	Radiation	10 × 10 m, DEM
	Elevation	10 × 10 m, DEM
Disturbance	Distance to roads (Euclidean and path distance)	10 × 10 m, DEM
	Distance to towns (path distance to small and large towns)	10 × 10 m, DEM
Hydrology	Distance to streams (to streams and to main river)	10 × 10 m, DEM
Remote sensed	Normalized vegetation index (NDVI) for rainy season	20 × 20 m, SPOT image (sept. 2007)
	Normalized vegetation index (NDVI) for dry season	10 × 10 m, SPOT image (march 2007)
	Canopy cover 50 m circle	10 × 10 m, SPOT image (march 2007)
Land cover	Oak Forest (OF), Pasture (P), Tropical dry forest (TDF) and Semi-evergreen forest (SEF)	10 × 10 m, land cover map (Larrazábal et al., 2008)

Table 2
Average value (± Standard Error) of the ecosystem services obtained in the field by land cover category that were used in the LUT approach.

Ecosystem services/land cover categories	Oak Forest (average)	Tropical Dry Forest (average)	Semi-evergreen Forest (average)	Pasture (average)
Forage (kg/ha)	0.6 ± 0.2	0.5 ± 0.2	0.7 ± 0.2	4 ± 0.5
Timber (m^3/ha)	308 ± 112	86 ± 100	427 ± 89	0 ± 193
Firewood (Ton/ha)	56 ± 9	59 ± 8	67 ± 7	0.9 ± 16
Above-ground Carbon Storage (Ton/ha)	28 ± 4	30 ± 4	33 ± 4	0.4 ± 8

resulting in biomass production differences, both locally and regionally (Chen et al., 2007; Deng et al., 2007). Disturbance variables assess the management history of ecosystems (Reyers et al., 2013). Hydrological variables predict water availability that is the main limiting factor for biomass production in tropical dry forests (Balvanera et al., 2011). Remote sensed variables including the Normalized Vegetation Index (NDVI) and canopy cover are good indicators of photosynthetically active biomass, the water contained in vegetation and the presence of forest cover respectively (Deng et al., 2007). Land cover information were derived from a recent interpretation of satellite images (Larrazábal et al., 2008), were incorporated as well (Egoh et al., 2008; Tallis et al., 2008; Nelson et al., 2009).

2.5. Modeling ES

The field sites were stratified by elevation and then 20 sites were randomly selected across the elevation strata as a test data set and the remaining 30 sites were used to build the CFM model. A set of independent variables were selected that did not show multicolinearity using a two-step approach. To start we applied a correlation analysis to the 31 explanatory variables. The variables that were highly correlated were excluded before building the model; we used an arbitrary threshold of $|r| > 0.76$ between pairs of explanatory variables and a total of 21 variables were finally included in the analysis (see Table 1). Second, we calculated the Variation Inflation Factor (VIF). A VIF of 5 or 10 and above indicates that high multicollinearity hinders the use of those variables together in multiple regression models according to O'Brien and Robert (2007). We found VIF values lower than 5 for all our explanatory variables, except for the case of land cover variables. To reduce VIF values, we excluded two of the land cover variables to obtain adequate VIF values for all our variables (the maximum VIF value was 3.6). Multiple regressions models were built from all possible combinations of independent variables (a total of 412 models); no interactions or non-linear relationships were included. Model selection followed standard protocols (Burnham and Anderson, 2002; Diniz-Filho et al., 2008).

Model selection consisted of three steps (Burnham and Anderson, 2002; Diniz-Filho et al., 2008). For the first we used the second order Akaike Information Criterion, corrected for small sample size (AICc) for model selection ($n/K < \sim 40$) where n is the sample size and K is the number of parameters included in the model plus two:

$$AICc = -2(\log - likelihood) + 2K + 2K(K+1)/(n-K-1)$$

We chose the 10 models with the lowest AICc. In the second step, we used the AICc of each model i to calculate the Δi value, which is the difference between AICci of each model i and the minimum AICc found for the set of models compared; we selected only those models with $\Delta i < 2$. For the third step we chose a single best model among them, by maximizing both explanatory power and inclusion of the independent variables with the highest contribution to the explanatory power. This was done by using the Akaike weight of each model (wi), which assess the explanatory power,

$$Wi = \mathrm{Exp}(-\Delta i/2)/\Sigma \mathrm{Exp}(-\Delta i/2)$$

The individual contribution of each explanatory variable to the explanatory power of the models was obtained by adding up *wi* values across all models that include the explanatory variable (Burnham and Anderson, 2002).

A LUT was developed for all four vegetation land cover variables mapped in the area following the approach suggested by Eigenbrod et al. (2010b). We assigned a constant value to each of the four land cover categories based on the average value of ES obtained in the field quantification for such condition (Table 2). We did not use estimates for each land cover class from the literature because there aren't available for our study area.

The results of the CFM model were extrapolated across the study area at a 30 × 30 m resolution. This minimum mapping unit was selected to reduce the ratio between the size of the pixel and the field sampling plot (Cayuela et al., 2006). The frequency distributions of the data limit options for controlling spatial autocorrelation in residuals. Because of this and because we lack information regarding spatial processes we present non spatial statistics. To validate our results we compared the test data set with the estimated values from both modeling methods using linear regression to examine the relationship between observed and modeled values (Bowker et al., 2008).

To assess the spatial heterogeneity of the predicted values of ecosystem services we applied Geographically Weighted Regressions (GWR). GWR allow analysis of spatial patterns of change among the variables by generating a series of local regression models that give greater weight to nearer observations and less weight to those that are more distant (Fotheringham et al., 1998; Zhang et al., 2004). Using outputs of the GWR we obtained residual maps showing where the regression fits well (non-significant residuals) and where the model is causing problems, by consistently under or over predicting ecosystem service values (Fotheringham et al., 1998). We applied in ArcGIS (ESRI 2011) standard Ordinary Least Squared Regression using the predicted ecosystem services values and their respective explanatory variables.

3. Results

Combined field models explained a large to moderate amount of variance (Table 3). The amount of variance explained by CFM models was highest for forage (89%), followed by timber (77%) and carbon (71%), and lower for firewood (42%). Explanatory variables for CFM models varied greatly among types of ES. Forage was best explained by presence of pastures, and distance to streams. Timber was best explained by NDVI during the dry season and firewood was best explained by NDVI for the rainy season and the presence of pastures. However, NDVI based on imagery from the rainy season contributed most to explaining above-ground carbon storage.

CFM maps tended to adequately represent the range of values of ES delivery observed in the field (0–5.8 kg/ha for forage; 0–580 m^3/ha for timber; 0–83 t/ha for firewood; 0–74 t/ha for above-ground carbon storage). Instead, LUT maps consistently underestimated the range of ES values, except for above-ground carbon storage (Fig. 2). In general, the spatial patterns of ES delivery obtained from CFM models were similar to those obtained from the

Table 3
Combined field models for four ecosystem services using field data (response variable) and cartographic and remote sensed data (independent variables). AICc: Akaike Information Criterion corrected for small sample size, *Wi:* Akaike Weight.

Ecosystem Service	*AICc*	*Wi*	F-	R^2	P	Variables	Coefficients	*P*	R^2	Wi
Forage	66	0.50	73.2	0.89	< 0.001					
						Intercept	1.18	1		
						Pasture	4.56	****	0.82	1
						Distance to stream	0.0004	****	0.21	1
						Elevation	−0.0021	***	0.00	1
Timber	220	0.13	10.50	0.77	< 0.001					
						Intercept	31.14			
						NDVI dry	474.33	****	0.44	1.00
						Distance to large towns	−0.002	*	0.16	0.60
						NDII rainy	−527.31	*	0.16	0.30
						TRMI	−3.15	*	0.08	0.80
						NDVI rainy	420.61	**	0.01	0.30
Firewood	690	0.37	9.9	0.42	< 0.001					
						Intercept	624.85	1		
						NDVI rainy	128836.38	***	0.25	1
						Pasture	−36918.92	**	0.21	1
Above-ground carbon storage	670	0.43	7.7	0.71	< 0.001					
						Intercept	−3200.30	1		
						Pasture	−37450.67	****	0.25	1
						NDVI rainy	134236.26	****	0.10	1
						NDII dry	57231.33	***	0.04	1
						Town distance (large towns)	−0.94	***	0.01	1
						Town distance	1.33	**	0.01	0.43
						Stream distance	3.83	***	0.00	1
						Road distance	−3.92	**	0.00	1

* Statistical probability values (P) < 0.05. ** Statistical probability values (P) < 0.01. *** Statistical probability values (P) < 0.005. **** Statistical probability values (P) < 0.001.

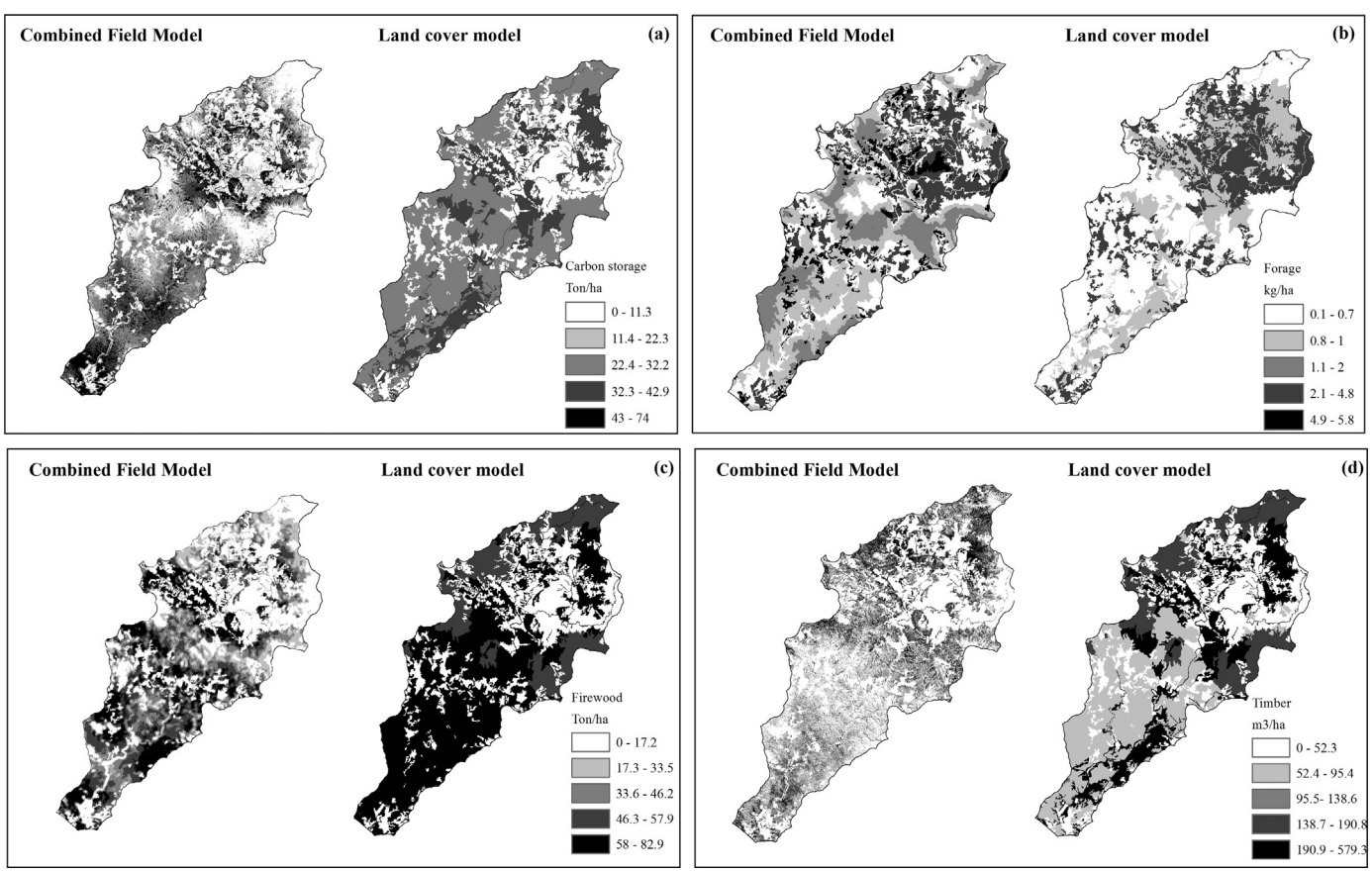

Fig. 2. Maps of ES delivery in a watershed of western Mexico using the CFM and LUT approach. (a) Above-ground carbon storage in tons per hectare, (b) Forage supply in kilograms per hectare (c) Firewood supply in tons per hectare and (d) Timber supply in m³ per hectare.

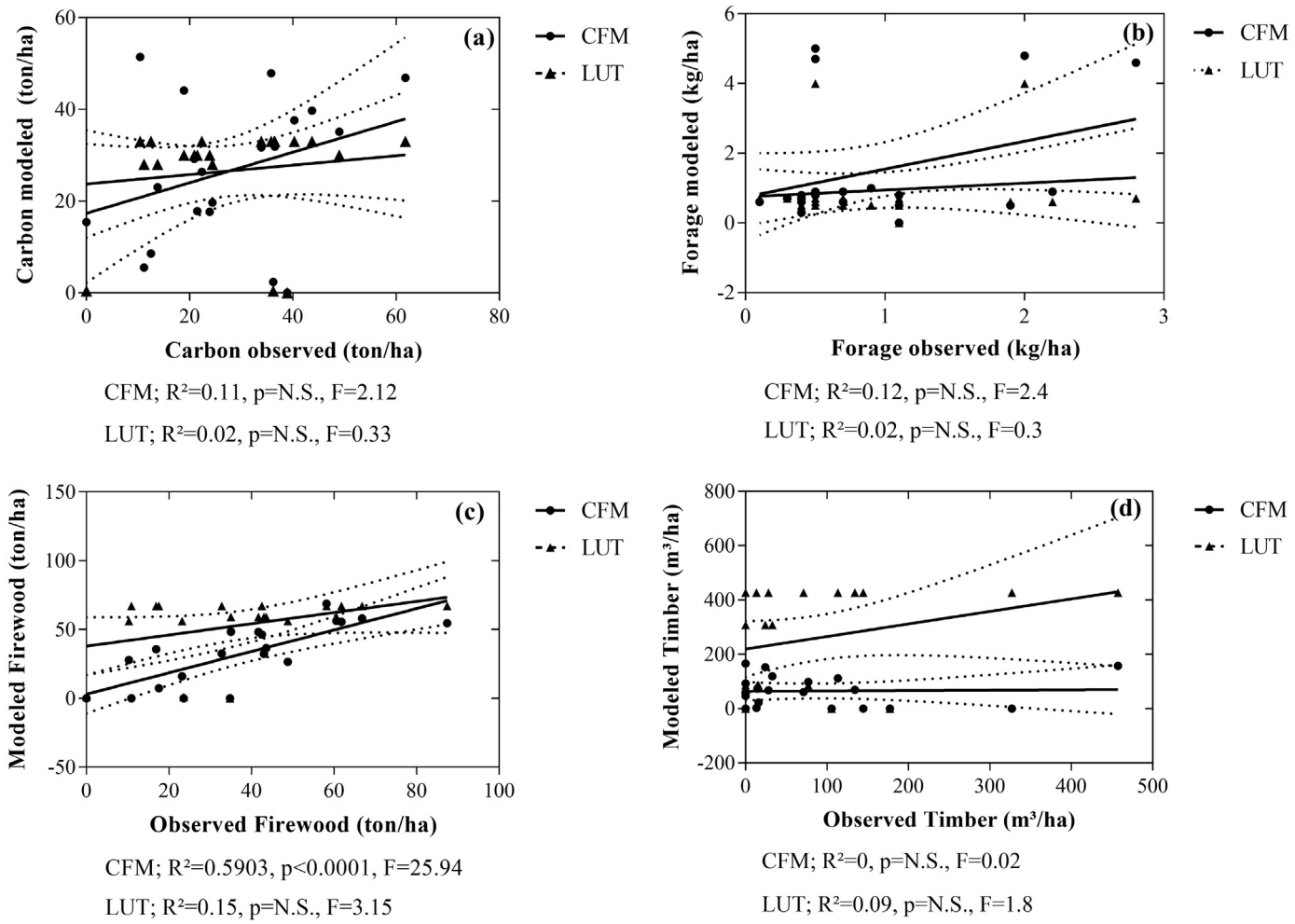

Fig. 3. Results of validation for the Combined Field Models (CFM) and Look Up Table (LUT) approach comparing observed values (test data set) versus modeled values for: (a) above-ground carbon storage (b) forage, (c) firewood and (d) timber.

LUT approach (Fig. 2). Higher forage supply was present in the northern middle section of the watershed, an area dominated by pastures. Timber supply was higher at higher elevations and in the northern part of the watershed where oak forests are found. A higher supply of firewood was present in the southern lower part of the watershed where tropical dry and semi evergreen forests can be found. Above-ground carbon storage was higher in the lower part of the watershed in the area covered by tropical dry forests. All these patterns were consistent with those observed in the field (see Table 2). The maps based on the LUT approach results in a coarser resolution map than that generated from the CFM models.

The firewood services model using the CFM approach explained nearly 60% of the variance in the observed values ($F=25.94$, $P<0.0001$, $R^2=0.59$) (Fig. 3c). Whereas the CFM models for carbon storage and forage only explained 11% and 12% of the observed variance among the test data (Fig. 3a and b).

The GWR residual maps revealed that for firewood, carbon storage, forage and timber the area of the watershed showing an adequate model fit (non-significant residuals between −0.5 and 0.5 Fig. 4) represented 45%, 50%, 75% and 39% respectively. Significant over- and under-predictions were found for firewood, carbon storage, forage and timber only in 22%, 13%, 4% and 16% of the area of the watershed respectively (Fig. 4).

4. Discussion

The CFM approach provided a finer scale understanding of where different services are delivered across the landscape and thus towards understanding the mechanisms behind ES (Schröter et al., 2014). Our findings place an increased importance on local field measurements of ecosystem services to build combined models to map ecosystem services rather than using ecosystem services estimates from other regions with similar biophysical conditions. The field data used here is straightforward to collect compare to other methods based on trait measurements of vegetation (see Lavorel et al. (2011)).

In this study a large amount of variance in ES supply was explained by variables derived from GIS and remote sensing. Remote sense variables explained a large fraction of the variance for timber, firewood and above-ground carbon storage. Seasonal differences in remote sensed data were relevant for our study area, where both evergreen and deciduous forests were found. NDVI during the dry season allowed separating temperate oak and pine forests that keep their foliage as deciduous forests. NDVI during the dry season reflects the total amount of biomass when foliage is present and is a good predictor of above-ground carbon storage. These indices have been widely used as a surrogate of biomass production and the results confirm what has been reported in other ES assessments in forested landscapes (Zheng et al., 2007, Krishnaswamy et al., 2009, Ramachandra, 2010).

This study also highlights the relevance of explanatory

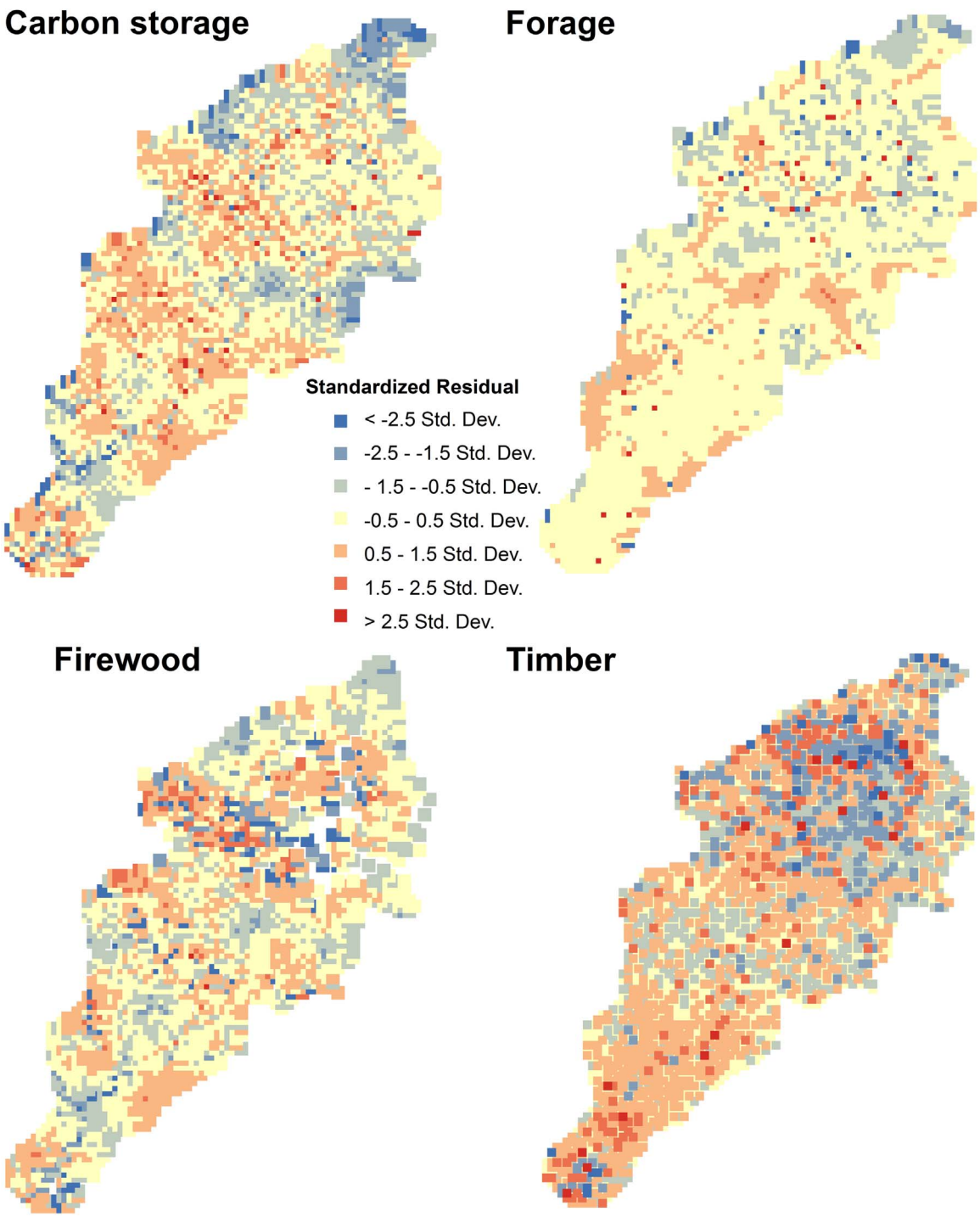

Fig. 4. Residual maps generated by the Geographically Weighted Regression through a series of local ecosystem service regression models.

variables that are not often incorporated into ES models but are easily available. Distance to streams, a predictor of water availability, was found related to forage. This positive relationship where more pastures can be found farther from streams reflects the fact that areas closer to streams are used by local people for intensive agriculture rather than pasture (Burgos and Maass, 2004).

The variable distance to towns explained an important amount of variance for timber supply. A negative relationship between timber and distance to towns is most certainly due to the fact that nearby wood supplies have been depleted and it's more difficult to convert far off temperate forests with more rugged topography. Similarly, a negative relationship between firewood and pasture highlighted management decisions to convert tropical dry forests into pastures.

The ES predictors used in this study are practical as these are widely accessible and are helpful towards developing tools with improved accuracy compared to LUT models even under time, data or budget reduced availability. This data can be obtained from open access databases like global roads data (gROADS, 2009), carbon databases (Gibbs, 2006), the gridded population of the world (GPW, 2010), global river hydrography (Lehner and Grill, 2013) among other data sources. Open access databases offer great promise to the application of combined field models over large

spatial scales.

Ecosystem services maps can be a useful tool for informing decision makers about the spatial distribution of service values but it's also important to note where and to what extent models may be more and less reliable at predicting service delivery. The residual maps that we developed were particularly helpful on highlighting where spatial heterogeneity is occurring showing where the model fits well and where decision makers need to be cautious because there are prediction problems. The carbon storage and firewood present similar residual patterns with problems of under prediction in the upper and middle sections of the watershed where there are no sampling sites. The timber residual map (Fig. 4) reveals the largest prevalence of prediction problems across the watershed and should be tested further prior to extrapolating the results any further.

The CFM models shown here could be improved with finer scale data and incorporation of missing environmental controls (e.g. high resolution climate data, soil depth, and water availability). For example, studies performed at the lower part of the watershed highlight the importance of groundwater table flows at different soil depths for forest productivity (Maass and Burgos, 2011). Variables associated to land use intensity and past land uses that reflect management regimes could also be driving spatial heterogeneity (Maass et al., 2005).

Other limitations of this study is that ES were defined based on their potential biophysical supply (Tallis et al., 2012). We did not distinguish the commercial species used for timber or consider other woody material in addition to basal area and height for firewood and above-ground carbon storage. Another limitation of our approach is that we used the same allometric regression for all land cover types to estimate firewood and carbon storage, despite large differences in plant structure and wood allocations among them. If locally tested regressions developed for each land cover class were available, ES quantification could have improved.

The model estimates from the CFM approach reflect a single best model selected according to the lowest AIC value and highest variance explained by the model. Differences were observed among the unselected models with higher but similar AIC values, leading to uncertainty that Bayesian model averaging can address in part (Raftery et al., 1997). However, forecasting using model averaging is in debate (Hendry and Reade, 2005). The amount of variance explained by the relationship between modeled and observed values tended to be low and was only significant explaining a large amount of variance for firewood under the CFM approach. This probably occurred because of the high level of uncertainty involved in working at plot level and extrapolating these values to a regional watershed scale (Wu et al., 2006). The watershed heterogeneity makes it difficult to predict ES delivery across spatial scales with high levels of confidence or certainty (Peters et al., 2007). Nevertheless, the ranges predicted by our models were quite similar to those observed in the field.

The choice to adopt a spatial model approach within a particular decision-making context will be relative to the accuracy needed for the specific policy purpose (Schröter et al., 2014). We found that a higher level of accuracy can be achieved with CFM models.

The use of CFM models, can provide finer resolution maps and be helpful for monitoring ES (Schröter et al., 2014), setting priorities for the application of ES conservation and management strategies (Kovacs et al., 2013) or could help the design of policy instruments for ES such as payment schemes for ES (Wendland et al., 2010).

5. Conclusion

In this study we compared CFM models with traditional LUT approaches to map and explore ecosystems services supply. The CFM approach used enhanced our ability to predict spatial patterns of ES. The CFM models allowed us to understand the spatial distribution of ecosystem services provision and the spatial heterogeneity of the predicted values (where the model fits well and where there are problems) at the watershed level enhancing utility for land managers and decision-makers.

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