International Journal of Applied Earth Observation and Geoinformation 30 (2014) 179–189

Contents lists available at ScienceDirect

International Journal of Applied Earth Observation and Geoinformation

journal homepage: www.elsevier.com/locate/jag

Modeling the spatial distribution of above-ground carbon in Mexican coniferous forests using remote sensing and a geostatistical approach

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ARTICLE INFO

Article history:
Received 28 August 2013
Accepted 12 February 2014
Available online 13 March 2014

Keywords:
Above-ground biomass
Interferometric coherence
Spatial autocorrelation
Regression-kriging
Coniferous forest
Mexico

ABSTRACT

Forest conservation is considered an option for mitigating the effect of greenhouse gases on global climate, hence monitoring forest carbon pools at global and local levels is important. The present study explores the capability of remote-sensing variables (vegetation indices and textures derived from SPOT-5; backscattering coefficient and interferometric coherence of ALOS PALSAR images) for modeling the spatial distribution of above-ground biomass in the Environmental Conservation Zone of Mexico City. Correlation and spatial autocorrelation coefficients were used to select significant explanatory variables in fir and pine forests. The correlation for interferometric coherence in HV polarization was negative, with correlations coefficients $r = -0.83$ for the fir and $r = -0.75$ for the pine forests. Regression-kriging showed the least root mean square error among the spatial interpolation methods used, with 37.75 tC/ha for fir forests and 29.15 tC/ha for pine forests. The results showed that a hybrid geospatial method, based on interferometric coherence data and a regression-kriging interpolator, has good potential for estimating above-ground biomass carbon.

Introduction

An understanding of atmospheric gas exchange is crucial for identifying biogeochemical cycles and the elements involved, such as carbon dioxide (CO_2) sources and pools (Goetz et al., 2009). The spatiotemporal distribution of above-ground forest carbon pools can be derived through forest inventories, although these require a good deal of time and money, with a frequency limited to 5 years (Goetz et al., 2009). The typical information of forest inventories includes the average of volumes of wood by administrative region.

The synergy between remote sensing and geostatistics has been developing since the late 1980s in different ways as the spatial analysis structure of the objects by variograms, such as pixel neighborhood in textural approach with variograms as variance measure that included spatial association, as technique for optimal image resolution in relation of average local variance method, in the improvement of spectral classifiers, in replace process from clouded pixels and as hybrid method in bivariates interpolations (Van der Meer, 2012). Remote sensing and geostatistical approaches have been used to map above-ground biomass by calibrating statistical models with field information (Goetz et al., 2009). A common approach has been the use of regression analyses of reflectance channels, and spectral and textural indices based on information from sampling sites (Steininger, 2000; De Jong et al., 2003; Castillo-Santiago et al., 2010). Other works have explored active sensors such as synthetic-aperture radar (SAR) and light detection and ranging (LiDAR). In radar data, five main approaches have been studied, which benefit from the relationship between above-ground biomass and SAR backscattering coefficient (Collins et al., 2009; Santoro et al., 2009; Saatchi et al., 2011; Carreiras et al., 2012; Cartus et al., 2012); Interferometric coherence (Santoro et al., 2007; Solberg et al., 2010); Polarimetric backscattering coefficient (Sandberg et al., 2011); Polarimetric interferometric coherence (Le Toan et al., 2011; Garestier et al., 2011) and via simulations of canopy microwave canopy models for estimation of backscattering coefficient through different forest stand conditions (Ranson et al., 1997; Thirion-Leferevre and Colin-Koeniguer, 2007). In LiDAR data, the main approach considers the relationship of above-ground biomass with respect to canopy height, canopy cover and variety of canopy density (Lefsky et al., 2002; García et al., 2009; Gleason and Im, 2012; Zolkos et al., 2013).

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http://dx.doi.org/10.1016/j.jag.2014.02.005
0303-2434/

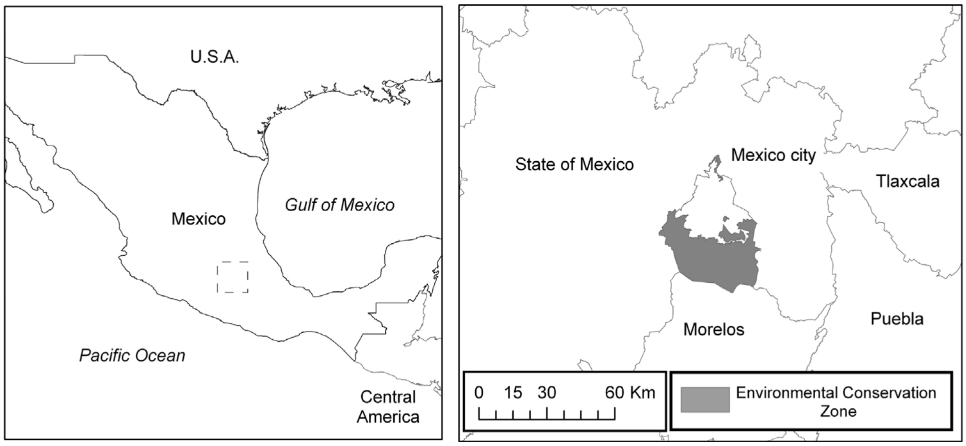

Fig. 1. Geographic location of the study site.

In addition some studies have employed geostatistics to estimate biomass in unsampled sites based on known values of forest inventory data (Maselli and Chiesi, 2006; Sales et al., 2007). More recently, some of them combine spatial models with remotely sensed data to improve geostatistical estimations using remote sensing indices as spatial secondary variables (Propastin, 2012; Viana et al., 2012; Castillo-Santiago et al., 2013). Furthermore, machine learning algorithms such as neural networks and support vector machines have improved forest biomass estimations (Gleason and Im, 2012; Carreiras et al., 2012), as well as the integrating multiple data sources as forest inventory, different satellite data and geographic information systems to assess the spatial structure and variability of natural vegetation and biomass estimation (Wulder et al., 2008; Nijland et al., 2009).

However, studies of spatial autocorrelation of auxiliary satellite data and the quantification of relative improvements of spatial statistics approaches over non-spatial statistical approaches are scarce (Viana et al., 2012; Castillo-Santiago et al., 2013), especially in dynamic sub-tropical settings in less-industrialized countries.

The present study is a comparative analysis between regression-kriging and simple regressions approaches using satellite-derived indices for modeling the above-ground biomass of forests in the Environmental Conservation Zone (ECZ) of Mexico City. The objectives were

1) to identify satellite-derived indices that are better associated with above-ground biomass, either from visible-IR (SPOT) or radar (ALOS PALSAR) imagery,
2) to quantify spatial patterns of the residuals derived from simple regression between satellite indices and carbon values using spatial autocorrelation, and
3) to determine whether spatial statistics methods improve the estimates of above-ground biomass carbon pools over non-spatial conventional regression methods.

In order to reach these objectives, a correlation analysis was performed between, on the one hand, spectral and texture indices (SPOT data), and backscattering coefficient, textures and interferometric coherence (ALOS PALSAR data) and, on the other hand, ground biomass estimates at forest inventory sites (Data Preparation Section). Then, the spatial autocorrelation was calculated for residuals with highest correlation coefficient (Correlation and Autocorrelation Coefficients Section) in order to define the variables to be used in simple regression models and regression-kriging methods (Regression Models Section). Once models were obtained, the root mean square error (RMSE) was computed for each approach (Model Accuracy Section).

Study area

The study area lies within the ECZ of Mexico City (882 km^2; Fig. 1) and is covered by Sacred fir or Oyamel (*Abies religiosa*; Fig. 2) and Mexican mountain pine (*Pinus hartwegii*) forests (Fig. 2). The fir forests include alder (*Alnus firmifolia*), white cedar (*Cupressus lindleyi*) and oak (*Quercus laurina*) (Rzedowski, 1978). The pines are often interspersed with *Festuca* and *Muhlenbergia* grasslands (Rzedowski, 1978). Because the ECZ provides Mexico City with

Fig. 2. Fir and pine forest of the study area.