Mapping aboveground forest biomass from Ikonos high resolution satellite image and multi-source geospatial data using neural networks and Kriging interpolation

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Abstract:

Several projects aiming for a better understanding of the state of Canadian forests and designing techniques for fast and effective interpretations of their situation have been carried out or are being developed by a great number of universities and institutions. Among these projects, we have the "Earth Observation for Sustainable Development (EOSD)" project which aims at developing techniques for monitoring forest ecosystem changes, estimating biomass and automated data processing to create tools for forest inventory. In this research context, our study has as objectives the estimation and the mapping of aboveground forest biomass, using inventory plot biomass data, remote sensing and/or environmental data. Forest biomass is defined as the mass of the aboveground portion of live trees per unit area (Bonner, 1985). Forest biomass contributes to the reduction of greenhouse gases like atmospheric CO_2, by fixing it and thus allowing the creation of carbon stocks. Besides, forest biomass is also related to indicators of forests sustainable development, forest productivity and ecosystem processes. Thus, monitoring the aboveground forest biomass changes can yield a wealth of information relating to the state of our forests. Several methods of biomass mapping have been developed in pilot regions across Canada within the framework of the Earth Observation for Sustainable Development (Fournier *et al.* 2003; Hall *et al.* 2006a; Labrecque *et al.* 2006; Luther *et al.* 2006). Some of these methods map forest biomass from forest structure (Exp.: BioCLUST, Luther *et al.* 2006; BioSTRUCT, Hall *et al.* 2006b). Others directly use inventory plot biomass data using the k-nearest neighbour approach (kNN, Guindon *et al.* 2005). An other approach called BioSF method is based on Shadow Fraction (SF) extracted from high resolution imagery such as QuickBird or Ikonos to derive surrogate plots (Leboeuf *et al.* 2007). The generated surrogate plots are then used as inputs to any of the above-mentioned methods.

The present study develops another method of aboveground forest biomass mapping from Ikonos high resolution satellite imagery and geospatial data. We assessed a geostatistical method (ordinary kriging) to map the biomass estimated with the neural networks approach trained with inventory plot biomass data. The study area, covering approximately 19720 hectares, is located in the North-West of New Brunswick (Canada). Reference biomass values by group of species (spruce, balsam fir, intolerant hardwood, tolerant hardwood and other conifers) were estimated using the equations of Ker (1980, 1984) and inventory data from permanent sample plots (PEP) of 400 m^2. Following an image pre-processing, a fusion of different bands of the Ikonos image (red, green and near infra-red bands with the panchromatic one) by means of the Brovey method at 1 m spatial resolution was carried out. The fusion was followed by a supervised classification based on the maximum likelihood method which yielded a result of 70.4% accuracy. The obtained classified image presented the five species groups inventoried in the field study. Thereafter, various vegetation indices (NDVI: *normalised difference vegetation index*, TSAVI:

transformed soil adjusted vegetation index, ARVI: *atmospherically resistant vegetation index*, OSAVI: *optimized soil-adjusted vegetation index*, etc.) and texture parameters (*entropy*, *homogeneity*, *average*, *second angular momentum*, etc.) were extracted from the Ikonos image. The extracted Ikonos data were then combined with geospatial data (DEM, slope, aspect, soil type, drainage, precipitation, etc.) at the same 1 m spatial resolution. Inventory plots biomass values estimated by group of species were used for the neural networks (*Multilayer Perceptron Network* model) training with the *backpropagation* algorithm. For all species groups, the neural networks estimates showed excellent values of standard deviations ratios for both validation and training plots, ranging between 0.003 and 0.196, and 0.5 and 0.7, respectively. Thereafter, biomass values for sample pixels generated randomly by group of species were predicted with the *Multilayer Perceptron Network* model. Then, sample pixels biomass values of each group were used to derive biomass values of other pixels of the same species group by interpolation with the ordinary kriging method using five different variogram models. In order to take into account discontinuities of the forest environment related to variations in forest types, cut areas, streams, fires and others, the cartography of biomass by kriging was carried out for each species group within corresponding polygons of the same species group derived from the classified image converted into five binary images (one binary image for each species group). For each species group, a biomass map showing only pixels of that group was obtained. A fusion of the five biomass maps representing the five groups of species was finally carried out to generate the biomass of the study zone. Among the various variogram types considered, the Gaussian one was retained; it yielded the best biomass estimates by comparison with reference biomass values, with percentages of residual errors ranging between 2,6 and 9,8% (absolute value) and percentages of RMSE (root mean square error) ranging between 17,2 and 61,1%.

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