Assessing the Role of Environmental and Remote Sensing Variables in Modeling Canada's Forest Biomass

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Abstract

Mapping the spatial distribution of Canada's forest biomass is needed for estimating large-scale forest carbon budgets and to assess the possible responses of Canada's forests to a changing climate. Large areas of forest in Canada, particularly those of lower productivity in more northerly regions, do not have ground-based inventories from which to estimate biomass. Hence, in these regions, methods of estimating biomass from environmental and biophysical data is of considerable interest. This study reports a preliminary statistical modelling approach using such data in combination with SPOT VEGETATION remote sensing data to estimate the large scale distribution of forest biomass for softwoods, hardwoods and mixed-wood species. The RED, NIR, and SWIR bands and NDVI computed from SPOT VEGETATION data were correlated with biomass density and key environmental variables, although their magnitudes varied appreciably among the three species groups. The combination of environmental and remote sensing variables selected from a stepwise process resulted in statistical models with higher adjusted R^2 and lower root mean square error values than either variable set alone. Moreover, the statistically best models were found to predict the overall distribution of observed biomass with a statistical precision comparable to that of the ground-based source data. Highly accurate estimations of biomass density from these predictor variables cannot be expected due to spatial variations associated with forest age-class structure that cannot be detected using data from passive sensors and descriptors of the environment. This suggests the addition of spatial disturbance data to these methods may be a particularly promising approach for biomass estimation at national scales in non-inventoried areas.

Introduction

Simply defined, forest biomass is the dry mass of live plant material (trees and understory species) occurring in a forest ecosystem. When expressed in density terms (kg m^{-2}, tonne ha^{-1}), it can be considered a measure of forest ecosystem condition (Canadian Council of Forest Ministers, 1997). The estimation of forest biomass is becoming increasingly important for sustainable forest management (Natural Resources Canada 1998; Sips 1996), and to support scientific studies of ecosystem productivity, energy and nutrient flows, and for assessing the contribution of forests to the global carbon (C) cycle (Parresol 1999; Penner et al. 1997). Accurate estimation of forest biomass over extensive regions is, however, extremely challenging, and said to be one of the most persistent uncertainties concerning global C budgets (Harrell et al. 1995). For countries such as Canada with large forested landscapes, there is considerable

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policy interest in estimating biomass stocks because changes in these stocks can represent substantial losses or gains of stored carbon, which will affect the national C balance (reference: http://www.cnn.com /SPECIALS/1997/global.warming/stories/treaty/).
The influence of climate on the spatial distribution of forest biomass, particularly in boreal forests, is also of great interest. Better understanding of the ecosystem processes (growth, decomposition, natural disturbances) that affect forest biomass distribution will allow the testing of process models needed to assess the potential impacts of climate change on global forests (Bonan et al. 1990; Kasischke et al. 1995). Estimates of forest biomass are therefore critical to the development and testing of models used for calculating and forecasting carbon budgets (Kurz and Apps 1999; Price et al. 1997, 1999), and to assess impacts of global change (Michael et al. 1999).

In Canada, large areas of forest are considered unproductive and therefore have not been subjected to detailed ground-level sampling. Hence there is considerable interest in estimating biomass in such regions directly from biophysical data using models (Canadian Council of Forest Ministers, 1997). The spatial distribution of forest biomass is to some extent determined by climate and topography, as well as by the frequency of natural disturbances. Additional ecological information for classifying regions characterised by differing biomass densities could be obtained using remote sensing data (Harrell et al. 1995). There are at least three roles that remote sensing may serve in estimating forest biomass at regional and national scales. First, by classifying images into cover types (i.e., species) and structure (i.e., crown closure and height). Biomass estimates could then be obtained by use of look-up tables that assign biomass densities to specific species and structure categories mapped from remote sensing (Fournier et al., 2001). Second, by mapping biomass based on empirical relationships obtained between image radiometric values and known biomass densities. Third, by combining environmental and remote sensing variables as drivers of spatial biomass distribution in statistical models. This last approach was employed in the study reported here, but focused at the national level.

The primary objective was to determine whether it was possible to estimate the distribution of forest biomass density and species types across Canada from environmental and remote sensing variables using traditional forest inventory-based biomass data for calibration and testing. It was recognized at the outset that remote sensing using low resolution passive sensors cannot easily distinguish forest stands containing few large old trees with large crowns from those containing younger and many smaller trees of similar species composition and crown closure. Nevertheless, because biomass has not previously been estimated from environmental or remote sensing data sources at the national scale, we pursued an exploratory study to determine what relationships may exist. The results should provide useful insights into scaling issues that are likely to arise from modeling 30 m to 1 km resolution data over the Canadian land mass.

To achieve the study objective, two questions were posed: *(i)* How do empirical regression models for estimating biomass compare when developed as a function of environmental variables, remote sensing variables, or their combination? and *(ii)* What is the influence of broad forest types determined from coarse resolution remote sensing data on the sampling and modeling of forest biomass? This paper addresses the first question by presenting some initial modeling results based on forest types defined by the compilation of the 1991 Canadian National Forest Inventory as updated in 1994 (CanFI-91) (Lowe et al. 1994, 1996). Future reporting will focus on biomass estimation based on forest types mapped from Advanced Very High Resolution Radiometer (AVHRR) (Beaubien et al., 1997; Cihlar et al., 1997a) and SPOT VEGETATION sensors.

Methods

Biomass data base

A rasterized spatial database of Canada's aboveground forest biomass on timber-productive land was developed from the Canadian forest biomass estimates of Penner et al. (1997), derived from CanFI-91. The CanFI GIS polygons have a nominal 10 km resolution that prevents the forest inventory data from being geo-located with any higher precision. In addition these polygons are irregularly distributed, and follows provincial township boundaries across the country. Some polygons covering remote northern areas are in fact significantly larger than 10 km.

These vector GIS coverages were first converted to a national raster grid with a nominal 1 km cell size (Lambert Conformal Conic projection) to preserve as much as possible, the original spatial information. The Penner et al. (1997) biomass estimates and inventoried area data were then linked to this grid to create a set of biomass and inventoried area grids. These 1 km grid cells were then reaggregated into 10 km cells, so that the spatial precision was comparable to that of the original polygons, but the numerical data, organised as a grid of uniform density, could be used with other gridded data sets for statistical analysis. For the purposes of this study, forest biomass density (tonnes/ha) and inventoried area data were totalled for all species groups and age classes on timber productive land. Biomass density within each 10 km cell was then calculated by dividing the biomass estimates by the total inventoried area data.

A 10 km resolution cover type classification grid was also derived from the CanFI "land-type" variable distributed on the CanFI web site (http://www.pfc.cfs.nrcan.gc.ca/monitoring/inventory /canfi/landtype/ltypdisc_e.html). This land-type gives the area within a CanFI cell covered by combinations of broad forest cover type (softwood, hardwood, mixedwood) and CanFI-91 land class as defined in Gray and Power (1997). The dominant land-type for timber productive land was determined for each 10 km grid cell.

An overlay mask was made by comparing the CanFI inventoried area of timber productive land within each cell to its true ground area, and selecting only cells where at least 90% of the cell area was inventoried. In this way, the statistical relationships between inventoried biomass at 10 km resolution and the environmental or remote sensing variables could be constrained to only those cells for which the spatial correspondence would be very high.

Regression models were then developed treating the CanFI biomass density data as a dependent variable and the remote sensing and biophysical data as predictors variables.

Predictor variables

Data sets that served as drivers or predictor variables for modeling biomass included the GTOPO30 Digital Elevation Model (DEM) (Verdin and Jenson 1996), total annual precipitation (PPT), and total annual growing degree days (GDD) (calculated from monthly mean temperature above 5°C). The latter climate variables were products of the Canadian Forest Service National Geo-Referenced Information for Decision-makers (NatGrid) project (McKenney et al. 1998) that utilizes the ANUSPLIN thin-plate spline interpolation software (Hutchinson 1999; see also Price et al. 2000) to interpolate climatic variables across Canada from weather station data. Soil texture data were represented by sand fractions (SD) of the dominant parent material extracted by the Canada Centre for Remote Sensing (CCRS) from the Canadian Soil Information System (CanSIS) (http://sis.agr.gc.ca/cansis/intro.html).

A national coverage of climatic moisture index (CMI) expressed as total precipitation minus estimated potential evapotranspiration (PET) was also created. This followed Hogg (1994, 1997) who used the Jensen-Haise method for estimating PET, but in our case precipitation, solar radiation, and temperature data were first interpolated to the 10 km grid from the 1961-1990 Meteorological Service of Canada (MSC) climate station normals (McKenney et al 1998).

Remote sensing variables

The SPOT VEGETATION instrument provides daily imagery at a 1.15 km resolution in four reflectance channels (0.45 mm BLUE, 0.66 mm RED, 0.83 mm NIR, and 1.65 mm SWIR). In this analysis we used nominal clear-sky ten-day VGT composites (S10 syntheses) covering the snow-free period June 1 - September 30, 1999. The top-of-atmosphere reflectances were corrected for bi-directional reflectance effects and atmospheric contamination using the CCRS ABC3 algorithms developed for the NOAA/AVHRR sensor (Cihlar et al., 1997b). After the corrections were applied, representative summer reflectance values were computed for the RED, NIR and SWIR channels by averaging the 12 ten-day composites. The BLUE channel was not analyzed due to severe atmospheric contamination. NDVI was computed as the ratio of the difference-over-sum of the RED and NIR channels.

Nine environmental and remote sensing variables were therefore assembled for modeling of forest biomass for softwood, hardwood and mixed-wood species groups (Table 1).

Table 1. Environmental and remote sensing variables used to model biomass.

Variable	Abbreviation
Digital elevation	DEM
Precipitation	PPT
Growing degree days	GDD
Percent Sand fraction	SD
Climate moisture index	CMI
Spot Vegetation: Red	RED
Spot Vegetation: Near infrared	NIR
Spot Vegetation: Shortwave infrared	SWIR
Spot Vegetation: NDVI	NDVI

Sampling and statistical analysis

A 60% systematic sample was drawn as a fitting data set and the remaining 40% was used as a validation data set for statistical analysis and model validation. A two-sample T-test for sample means and an F-test for ratio of variances for all variables (Table 1), were computed at the 5% probability level to test for statistical differences in the fitting data set relative to the full sample.

Descriptive statistics and calculations of correlation coefficients were undertaken to describe the environmental and remote sensing variables and their relationship with softwood, hardwood and mixed-wood biomass distribution. Biomass is most frequently estimated using regression methods (Parresol 1999) and similar methods were applied in this study. Three sets of stepwise linear regressions were undertaken for each species to produce models as a function of environmental variables, remote sensing variables, and the combination of these variable sets. These models were then assessed for statistical differences using a two-sample T-test between predicted biomass and Penner et al. (1997) biomass for the validation data set.

Results and Discussion

The 10 km grid coverage of Canada consists of 480 rows by 570 columns of which 101,089 cells contain the land mass of Canada. When only cells with at least 90% of the area in the CanFI inventory were selected, 1189 cells were softwood-dominated, compared to 98 for hardwood and 363 for mixed wood.

For the biomass variable and the nine environmental and remote sensing variables (Table 1), there were no statistical differences between the 60% sample for model fitting and the 100% sample when means (prob > | t | = 0.41 – 0.97) and variances (prob > F = 0.13 – 0.98) were compared. These results were considered important because the remaining 40% of the cells could then be used as independent data sets to further test the models that were generated

Average biomass density was largest and most variable for softwoods (mean (m) = 120.8, standard deviation (s) = 65.3) compared to hardwoods (m = 97.3, s = 22.1) and mixed woods (m = 90.5, s = 29.6). As expected, the range of biomass density was largest for softwoods (533.2), followed by mixed woods (204.7) and hardwoods (122.8).

Elevations (contained in the DEM) were highest and most variable for softwood-dominated cells (m = 926, s = 365), followed by mixed woods (m = 484, s = 243) and hardwoods (m = 543, s = 229). These values corresponded to their ranges that were 2199, 1187, and 853 m, respectively. Similarly, PPT was largest and most variable for softwoods (m = 708, s = 348), and smallest for hardwoods (m = 570, s = 233) with mixed woods in between (m = 597, s = 295). GDD was least variable for hardwoods, and most variable for softwoods. On average, GDD was largest for hardwoods (m = 1116, s = 91), followed by mixed woods (m = 1110, s = 205) and softwoods (m = 848, s = 209). There were little differences in the SD amongst the three species. The patterns for CMI were most similar to PPT being largest and most variable for softwoods (m = 34.5, s = 38), followed by mixed woods (m = 26.2, s = 26), and smallest for hardwoods (m = 18.7, s = 23). The computed mean and variance values were therefore largest across all environmental variables for softwoods, followed by mixed woods and hardwoods with the exception of GDD. We would expect these variable characteristics to manifest itself in the variation associated with biomass estimation.

Of greater interest was how these environmental variables were correlated with each other (Table 2), and which were most highly correlated with biomass as these relationships would influence which variables would be selected in the stepwise regressions. Observing the largest three statistically significant correlations among the nine environmental and remote sensing variables showed some remarkably high correlations despite the coarse resolution cell size (Table 2). Of the 27 correlation coefficients presented in Table 2 for mixed woods, 15 remote sensing variables were significantly related to environmental and remote sensing variables compared to only 7 and 6 variables for softwoods and hardwoods, respectively. Softwood biomass was most highly correlated to PPT ($r=0.39$, $p< 0.0001$), CMI ($r=0.35$, $p<0.0001$) and NDVI ($r=0.25$, $p<0.0001$). Hardwood biomass was most highly correlated to DEM ($r=0.45$, $p<0.0001$) and GDD ($r=-0.19$, $p=0.05$); and mixed-wood biomass was most highly correlated to RED ($r=-0.39$, $p<0.0001$), NDVI ($r=0.34$, $p<0.0001$) and GDD ($r=0.33$, $p<0.0001$). Based on these observations, coarse resolution remote sensing may offer some particular benefits for biomass estimation and biophysical characterization of sites occupied by mixed woods relative to softwoods and hardwoods.

Stepwise regressions resulted in selections of variables that differed among the three species groups

(Table 3). The use of remote sensing variables alone resulted in the weakest models for biomass estimation, and the strongest models were based on a combination of environmental and remote sensing variables, as characterized by larger adjusted R^2 and smaller root mean square error (RMSE) values (Table 3). The combined variable set resulted in the largest improvement in model performance for mixed woods, which was consistent with observations from the correlation coefficients between biomass density and the predictor variables. The biomass regression RMSE values were largest for softwoods that maybe due, in part, to the relatively larger softwood species predictor variable standard deviations.

Table 2. Largest 3 statistically significant correlation coefficients ($p < 0.05$) for environmental and remote sensing variables.

Predictor variable	3 most significantly correlated variables		
Softwoods			
DEM	GDD(-0.49)	CMI (-0.46)	PPT (-0.39)
PPT	CMI (0.97)	NDVI(0.43)	DEM (-0.39)
GDD	NIR (0.59)	DEM (0.49)	NDVI(0.46)
SD	PPT (0.24)	CMI (0.23)	SWIR(-0.09)
CMI	PPT (0.97)	DEM (-0.46)	NDVI(0.37)
RED	SWIR(0.45)	DEM (0.32)	GDD (0.59)
NIR	GDD (0.59)	NDVI (0.59)	SWIR(0.42)
SWIR	NDVI(0.47)	RED (0.45)	NIR (0.42)
NDVI	NIR (0.59)	SWIR(0.47)	GDD (0.59)
Hardwoods			
DEM	GDD (-0.67)	CMI (-0.29)	PPT (-0.21)
PPT	CMI (0.99)	NDVI(0.49)	NIR (0.66)
GDD	DEM (-0.67)	NDVI(0.49)	PPT (0.48)
SD	PPT (0.63)	CMI (0.61)	NIR (0.66)
CMI	PPT (0.99)	NDVI(0.65)	NIR (0.63)
RED	NDVI(-0.76)	PPT (-0.59)	CMI (-0.59)
NIR	SWIR(0.67)	PPT (0.66)	CMI (0.61)
SWIR	NIR (0.67)	RED (0.58)	- -
NDVI	RED (-0.76)	PPT (0.67)	CMI (0.61)
Mixed woods			
DEM	GDD(-0.32)	SWIR(-0.30)	CMI (-0.26)
PPT	CMI (0.98)	NIR (0.82)	RED (-0.74)
GDD	NIR (0.78)	NDVI(0.73)	PPT (-0.74)
SD	NDVI(-0.31)	SWIR (0.29)	CMI (0.21)
CMI	PPT (0.98)	NIR (0.75)	RED (-0.66)
RED	NDVI(-0.84)	PPT (-0.74)	NIR (-0.72)
NIR	NDVI(0.86)	PPT (-0.74)	GDD (0.78)
SWIR	NDVI(-0.62)	RED (0.58)	DEM (-0.30)
NDVI	NIR (0.86)	RED (-0.84)	PPT (0.66)

Based on Paired T-tests for biomass estimation using the validation sample data set, there were no significant differences between biomass densities estimated using the regression model(s) (Table 3), and the Penner et al. (1997) biomass data for softwood ($p = 0.43 - 0.77$), hardwood ($p = 0.07 - 0.12$) and mixed-wood ($p = 0.80 - 0.99$) species. Notably, the probability level indicating no statistical difference was highest for mixed woods and smallest for hardwoods. The relative small sample size and small frequency of predominant hardwoods reported at the 10 km cell size likely influenced the latter result. Nevertheless, these initial models reflected the biomass values they were designed to predict, and suggest promise for further modeling of forest biomass at coarse resolution scales from a combination of environmental and remote sensing variables.

Table 3. Summary stepwise regression model statistics.

Selected variables	Adjusted R^2	RMSE (tonnes/ha)	Non-significant variables
Softwoods			
Environ.: CMI, DEM, GDD, PPT, SD	0.34	54.8	- -
Remote Sensing: RED, SWIR, VGT	0.15	62.4	- -
Combined: CMI, DEM, GDD, PPT, SD, RED, SWIR	0.36	54.3	Intercept p = 0.19
Hardwoods			
Environ.: CMI, DEM, GDD, PPT	0.41	18.1	- -
Remote Sensing: NIR, RED, SWIR, NDVI	0.27	20.2	- -
Combined: CMI, DEM, GDD, PPT, RED, SWIR	0.48	17.3	- -
Mixed woods			
Environ.: CMI, DEM, GDD	0.35	23.8	- -
Remote Sensing: RED, NIR, SWIR, NDVI	0.24	25.6	Intercept p = 0.45
Combined: CMI, DEM, PPT, NDVI, RED, NIR, SWIR	0.44	22.4	Intercept p = 0.92

The biomass data used in this study, derived from those estimated by Penner et al. (1997), were of low spatial resolution, and likely contain many inaccuracies. Nevertheless these are at present the only national ground-based forest biomass dataset available. This study represents the first iteration for producing the Canadian biomass prediction model. The next iteration will model the variations in biomass densities by adding to the environmental and remote sensing predictors, the disturbance effects on forest age-class structure for better discriminating between regions of high and low biomass. The second iteration will be realised from the ongoing development of a new Canadian national biomass database (Gillis and Ung 2001) as the methods developed in this study can be replicated when the new biomass data set is available.

Conclusions and Future Work

In this study we attempted to estimate the spatial distribution of forest biomass, within broad species groupings, at the national level based on a model developed from environmental and remote sensing variables. The results demonstrate that such models can estimate biomass with a precision statistically comparable to the source data, and that the combination of these variables is better than either used alone, particularly for the mixed-wood cover type. Further stratification at the national level, e.g. by terrestrial ecozones and using narrower species groups, incorporation of disturbance data for fire and forest pests, and the use of a new, national biomass data set now under construction would likely improve upon the models and results obtained in this study.

Future reporting will focus on biomass estimation based on forest types mapped from AVHRR and SPOT VEGETATION sensors, and determining whether the independent variables used to estimate biomass will change as a function of the remote sensing data source. This work at the national level is intended to complement ongoing biomass modeling and mapping research with Landsat TM data, and will facilitate investigation of problems that may arise when scaling from regional to national levels.

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