Session 5a

MAPPING OF CANADIAN NORTHERN BOREAL FOREST BIOMASS USING QUICKBIRD HIGH SPATIAL RESOLUTION IMAGERY

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ABSTRACT

The limited availability of ground sample plots in Canadian northern regions requires a greater dependency of biomass mapping methods on modeling and remote sensing. We have developed and tested a method to map above-ground biomass of black spruce (*Picea mariana)* stands in northeastern boreal regions of Canada using high resolution satellite images. The method relies on QuickBird images transformed into biomass maps through image processing algorithms using the shadow fraction of tree crowns (SF). Three images provided test sites in diversified areas. A bitmap layer comprising the tree shadow was derived from the images. SF was calculated from the fraction of shadow area over the total area of reference square areas of fixed dimension overlaid on 108 ground sample plots (GSP). A linear regression was applied between GSP biomass and SF. The regressions for each of the test sites produced R^2, RMSE and bias in the range of 85 to 88% (except one case at 44%), 14 to 18 t/ha and -3 to 8 t/ha, respectively. As statistical tests showed that there is no evidence that the 3 sites regressions are different, a global regression was calculated with all GSPs and produced R^2, RMSE and bias of 82%, 15.3 t/ha and 4.2 t/ha respectively. Generalization of these results to extended areas of the boreal forest remains to be assessed in more details. However, the method appears to be an efficient mean to map biomass of black spruce stands in Canadian northern boreal forests.

Keywords: remote sensing, mapping, biomass, subarctic forest, black spruce, QuickBird, shadow fraction.

1 INTRODUCTION

The importance of carbon balance accounting related to climate change and increasing pressure for forest exploitation in the northern boreal forests of Canada has led to a demand for better estimates of total above-ground tree biomass at the stand level (hereafter referred to as biomass) and related carbon stocks. Unfortunately, the number of ground sample plots (GSP) in northern Canada is very small. Furthermore, GSP are very expensive to establish in northern regions due to the remoteness and lack of infrastructure. On the other hand, northern forests cover huge areas and are relatively homogenous in terms of species composition and structure. For instance, the boreal and taiga forests of eastern Canada, north of the 49th parallel in Quebec and Labrador, are largely dominated by black spruce (*Picea mariana*) stands. This context requires the development and use of satellite remote sensing methods to map biomass and calculate carbon stocks. Therefore, we investigated the usefulness of QuickBird (QB) high-resolution spatial imagery (HSRI) to provide biomass maps as surrogates to GSP.

Segmentation of HRSI has been used successfully to assess timber volume (Pekkarinen, 2002) and to identify land cover units in ecology (Lobo, 1997). Peddle and Johnson (2000), Peddle *et al.* (2001) and Seed and King (2003) found significant statistical relationships between tree shadow fraction (SF) and biomass or leaf area index of boreal forest stands. This relationship has been explained in large part by a model using spectral mixture analysis (Peddle and Johnson, 2000; Peddle *et al.,* 2001). The results of these studies suggest that SF may be a suitable variable for estimating biomass, provided that a reliable image processing algorithm to measure SF can be developed.

The goal of this study was to develop and test a SF-based method to map biomass of northern black spruce stands which can be applied to HRSI. The method provided biomass maps, which were subsequently used as surrogate GSPs to scale up biomass at the regional scale (Guindon et al., 2005). This study was conducted in the larger context of the Earth Observation for Sustainable Development of Forests

(EOSD) project whose goal is to map the forest biomass of Canada using Landsat imagery (Luther et al. 2002).

2 TEST SITES AND DATA

Three test sites were selected within the eastern taiga shield and boreal shield ecozones (Fig. 1). The sites are near the towns of Chibougamau (CH) and Radisson (RA) in Quebec, and Wabush (WA) in Labrador. Their location and extent provided a good sample for the spatial variability of biomass range and forest stand conditions typical of northeastern boreal forests in Canada. Forest stands in the test sites were largely composed of black spruce (*Picea mariana*) with the presence of a few other species like jack pine (*Pinus banksiana*) (Rowe, 1972). The understory of the black spruce stands was generally covered by lichen, moss and shrub in various proportions. Topography was flat or gently rolling.

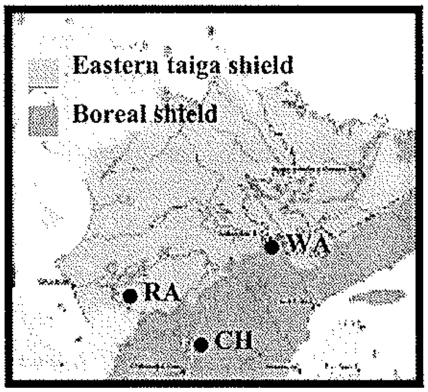

Figure 1: Location of the three test sites in two northern ecozones

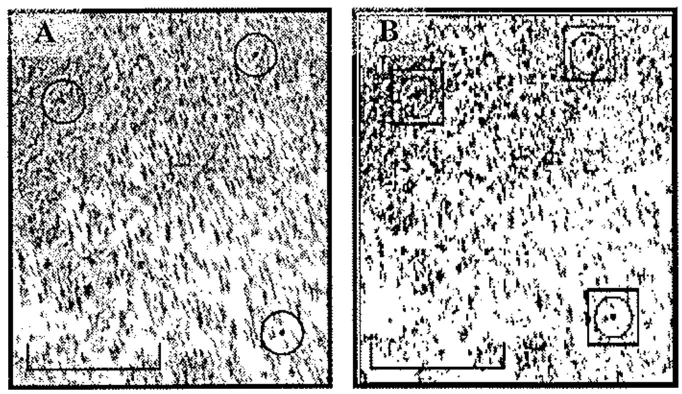

Figure 2: GSP and squares used to estimate SF, overlaid on A) the HRSI and B) the tree shadow bitmap layer

The spatial extent of each test site corresponded to the coverage of a single QB image (Table 1). A total of 108 circular GSP (400m^2) dominated by black spruce (basal area > 75%) were established between 2002 and 2004 across the three test sites (31 in CH, 49 in RA, and 28 in WA) using a stratified semi-random sampling design. The position of each GSP was calculated from differential GPS with a precision better than 5m. Plots measurement followed the methods of the Canadian National Forest Inventory (Gillis, 2001). For a given GSP, the diameter at breast height (DBH) was measured for all trees (DBH > 5cm) and in a 4m sub-plot for seedlings (DBH < 5cm). Above-ground, oven-dry biomass of each tree (kg) including seedlings was estimated from DBH using the allometric equation developed by Ouellet (1983). Plot-level biomass, obtained by summing biomass values of all trees in the GSP, ranged from 4.8 t/ha to 163.0 t/ha with a mean value of 50.0 t/ha. Crown closure and mean height was also measured for each GSP with values ranging from 5 to 85% and 0 to 18m.

Table 1. QB image acquisition parameters for each test site

	CH	RA	WA
Date, local time	07/10/2003, 10:43	08/12/2003, 10:57	08/10/2002, 10:35
Sun elevation / azimuth (°)	58.6 / 143.2	49.0 /152.9	51.1 / 157.7
Sensor elevation / azimuth (°)	78.5 / 96.4	76.7 / 172.3	80.4 / 225.6
Coverage (km²)	147	93	107

QB panchromatic (PAN) and multispectral (MS) images were acquired under clear-sky conditions with similar sun/sensor-viewing geometry for each test site and during the growing season in 2002 or 2003 (Table 1). Each QB image was geometrically corrected using at least 12 ground control points accurate within 5m. A first order polynomial resulted in an average positional RMSE of 10m. Since results achieved with both the PAN and MS-pansharped bands were similar (Leboeuf, 2005), here we report only on the results obtained using the PAN band (400-900nm) (subsection seen in Fig. 2a).

3 METHOD

The development of a method to estimate stand biomass from SF was divided into four separate sets of procedures that were designed to: (1) estimate SF values for GSPs from HRSI, (2) generate regression functions between GSP biomass and SF values for each test site, (3) calculate a global regression function for all sites and (4) map biomass as a grid layer for each site. The first set of procedures involved four steps. First, each HRSI was segmented with eCognition software (Definiens, 2002). Five scale factors were tested: 0, 5, 10, 20, and 40, whereby a scale of 0 implies no segmentation and an increasing scale factor produced objects of higher dimension (i.e. larger clusters of pixels). A tree shadow (TS) bitmap layer was generated from the segmented HSRI using the mean radiance value of pixels or objects and an image-specific threshold. The image threshold was determined by visual comparison of the threshold image with an enhanced image of the HRSI. Reference squares of fixed size were aligned on the 108 GSPs and provided a reference area from which SF (shadow area / reference square area) was calculated (Fig. 2b). Five sizes of squares were tested: 10, 30, 60, and 90m. Finally, SF values were geometrically normalized to a common sun-terrain-sensor viewing geometry to reduce variability associated with various image acquisition parameters.

A linear regression relationship was then established between GSP biomass and normalized SF for each of the three test sites. The regressions were calculated using a 70% random selection of GSP (GSP_{cal}) and adjusted R^2 values were reported. The remaining 30% GSP (GSP_{val}) were used to calculate error statistics: RMSE and bias. For each test site, linear regressions were calculated for each of the 20 potential configurations: five segmentation scale factors, four reference square sizes, and a constant image-specific classification threshold. The optimal configuration was identified as the one which maximised the R^2, minimized RMSE and bias, while meeting practical considerations.

A weighted analysis of covariance was performed to assess if the relationships described by the regression equations for each test site were functionally the same. The residual normality was tested with Shapiro-Wilk test and the homogeneity of its variance was tested with residual graphics. The Fisher test was used to evaluate the coincidence and parallelism hypothesis with a threshold of $\forall=0.05$ (Milton and Arnold, 2003) using GSP_{cal} data set. If no evidence was found that the three regressions were significantly different from each other, a global regression was calculated with a pooled dataset of all GSP_{cal}. Evaluation of these regressions relationship used the pooled dataset of GSP_{val}.

Finally, mapping biomass over the extent of each HRSI involved the derivation of an optimal TS bitmap layer using the optimal segmentation scale parameter and threshold. Post-classification was used to remove false TS such as water bodies having similar low radiance values. Then, for each cell of a grid layer where the cell size was given by the optimal reference square size, we calculated SF, normalized it and estimated biomass using the global regression equation. The resulting map was a grid layer where each cell with its biomass value can be used as a surrogate to traditional GSP. We assessed overall the precision of the three maps using the pooled GSP_{val} dataset.

4 RESULTS

A range of small scale parameters (0 to 10) and reference square sizes (10 to 30m) provided the best statistical results and were similar within these parameter ranges. Therefore, a segmentation scale parameter of 0 and a square size of 30m were selected as the optimal input parameters, considering the following practical considerations: (i) ease of application and short processing time of a pixel-based threshold approach and (ii) estimation done at the resolution of Landsat imagery appropriate for stand-level mapping and further biomass scaling-up at the regional scale using Landsat imagery. The three site-specific linear regressions Bio = a + b*SF with optimal input parameters are shown in Fig. 3a (dotted lines) with related statistics reported in Table 2. High R^2 values were obtained (85-88%) except for WA site (44%). This poorer result was partly explained by the more rugged relief, resulting in higher GSP-HRSI co-registration errors and additional variance of the SF values. Error statistics were similar between the three sites, with RMSE ranging from 14 to 18 t/ha and absolute bias value below 7.5 t/ha. There was no evidence that the three linear regressions were different (F=0.89 (p-value=0.41) for the slope and F=2.14 (p-value=0.12) for the intercept). The global regression using a pooled dataset of all GSP_{cal} (Fig. 3a) resulted in a RMSE value of 15.29 t/ha, providing a relative error of about 20%, and a low bias of 4.18 t/ha. Biomass estimated by the global regression equation corresponded well with biomass measured at GSP for the full range of conditions sampled (Fig. 3b).

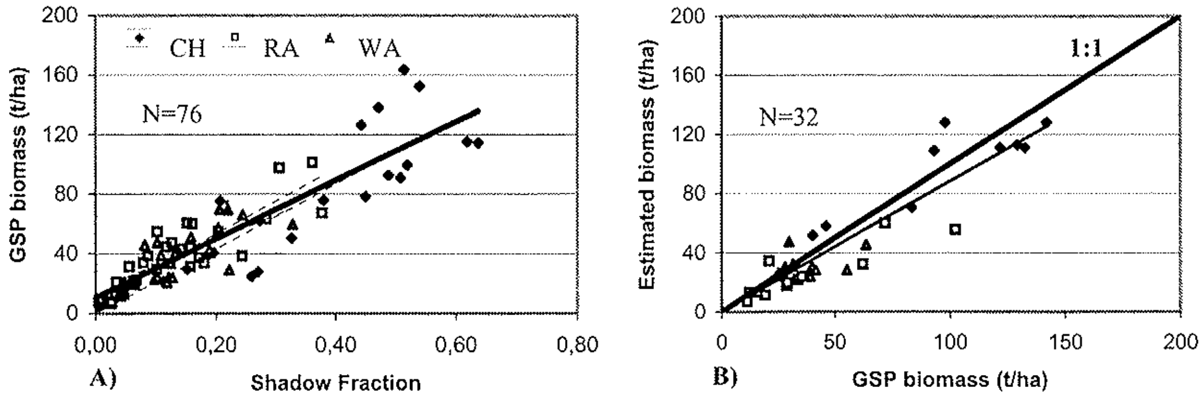

Figure 3. A) Linear regressions calibrated using 76 GSP_{cal} (dotted lines: local regressions; thick line: global regression; B) estimated vs GSP biomass using remaining 32 GSP_{val}.

Table 2. Local and global linear regressions with intersect a and slope b, and statistics from GSP_{cal} and GSP_{val}

GSP set	Nb GSP_{cal}	a	b	Adj. R^2	Nb GSP_{val}	RMSE	BIAS
CH	22	1.94	211.89	88 %	9	17.30	-2.50
RA	35	6.57	238.92	85 %	14	14.46	6.47
WA	19	16.19	177.40	44 %	9	14.39	7.31
Pooled	76	7.36	215.13	82 %	32	15.29	4.18

Assessment of the maps generated for the three test sites using the GSP_{val} pooled dataset provided an overall RMSE of 9.97 t/ha and a bias of 4.66 t/ha (Biomass map for Radisson in Fig. 4). Despite the low number of GSP used to validate the maps, biomass values were spatially consistent considering the strong influence of drainage and topography on forest biomass which is well reflected in the map (high biomass in valleys, low biomass in wetlands and on dry hill tops). In addition, mapped biomass values were consistent and close to zero over non-forested areas (shrublands, bare soils). However, water bodies of all sizes had to be masked out carefully through post-classification to avoid estimating biomass over them.

Figure 4. Biomass map derived from shadow fraction for Radisson test-site with GSP overlaid.

Several factors that may have contributed to the residual sources of variance between SF and biomass estimates and the reliability of the biomass mapping method were explored. For example, our analysis showed that the method can tolerate a large range of threshold values for each HRSI without increasing significantly the variance of SF. Preliminary statistical tests study showed that stratification based on understory type did not reduce significantly the variance of the resulting biomass. However, further investigation of the impact of understory type may be warranted given the highly variable combination of lichen, moss and shrub in black spruce stands. Geometric normalization taking into account the variability in sun-terrain-sensor viewing geometry was shown to be important for generalisation of the method across the three test sites. In particular, normalization for the variable sun elevation angle between HRSI acquisitions reduced significantly the variance of resulting biomass values. However, normalization of terrain effects were not addressed due to low slope and aspect angles for all GSP and for most test sites.

5 CONCLUSIONS AND PERSPECTIVES

We successfully developed and tested a SF-based method to estimate and map stand biomass of black spruce stands dominating the northeastern subarctic forests of Canada. This approach relied on normalized SF estimated from HRSI and used a pixel-based threshold approach. SF was then used as an independent variable in a global regression equation relating biomass to shadow fraction with a R^2 value of 82%. The sole use of the QB PAN band makes the method simple and cost effective relative to other approaches using HRSI. The method proved to be efficient to estimate biomass for: black spruce stands associated with lichen or moss; a range of biomass from 0 to 170 t/ha; and stand density and height up to 85% and 18m, respectively. Future work will assess further the validity domain of the method: (i) over a larger range of stand conditions (species composition, biomass range, understory type) and relief situations; (ii) using different HRSI types and related acquisition parameters; and (iii) for estimating other inventory attributes of interest.

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