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Effects of subpixel water area fraction on mapping leaf area index and modeling net primary productivity in Canada

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Abstract. Retrieving biophysical parameters, such as the leaf area index (LAI) and the net primary productivity (NPP), from remote sensing imagery is very useful for modeling terrestrial ecosystems. Spatial heterogeneity of the land surface often leads to biases in the retrieved parameters when algorithms derived based on high-resolution images are directly used for coarse-resolution images. In the northern environment in Canada, open water bodies are one of the major features of surface heterogeneity, and in remote sensing images a considerable number of land pixels are mixed with open water bodies of different fractions. In an image of Canada at 1 km resolution, there are 47% water-containing land pixels, and their average water area fraction is 14%. In this article, we investigate the effects of subpixel water area fraction on LAI retrieval and NPP estimation for all land areas in Canada. A linear mixture model was developed to use the available subpixel information for this purpose. Previous Canada-wide LAI and NPP maps at 1 km resolution derived without considering the subpixel information were used for comparison. The following conclusions are drawn from this investigation: (*i*) LAI retrieval errors are proportional to water area fraction in a pixel, and on average for all of Canada's land mass the retrieved LAI per unit land area without considering the open water effect is 13% smaller than the correct LAI; (*ii*) the influence of the subpixel water area on LAI retrieval is the largest for the conifer cover type and the smallest for the deciduous cover type among forests; and (*iii*) because of the LAI bias, NPP per unit land area is also negatively biased by 9% when the subpixel water effect is not considered. The annual Canada-wide NPP summed from the land portion calculated using the water-corrected LAI is only 0.69% higher than that summed from the total pixel area calculated using LAI without the water correction. However, the difference in these two NPP values can be either positive or negative among different provinces and territories, depending on the water area fraction and its distribution.

Résumé. L'extraction des paramètres biophysiques, tels que le LAI (indice de surface foliaire) et la production primaire nette (PPN), à partir des images de télédétection est très utile pour la modélisation des écosystèmes terrestres. L'hétérogénéité spatiale de la surface terrestre entraîne souvent des biais dans les paramètres extraits lorsque les algorithmes dérivés des images à haute résolution sont utilisés directement pour des images à basse résolution. Dans l'environnement nordique du Canada, les masses d'eau ouvertes constituent l'une des constituantes majeures de l'hétérogénéité de surface et, dans les images de télédétection, de nombreux pixels de sol sont mélangés avec ceux des masses d'eau ouvertes de fractions différentes. Dans une image du Canada à une résolution de 1 km, 47% des pixels terrestres contiennent de l'eau et la surface moyenne de fraction d'eau est de 14%. Dans cet article, nous examinons les effets des fractions d'eau à l'échelle du sous-pixel sur l'extraction du LAI et l'estimation de PPN pour l'ensemble des surfaces terrestres au Canada. Un modèle linéaire de fraction a été développé faisant usage de l'information disponible à l'échelle du sous-pixel à cette fin. Les cartes existantes de LAI et de PPN à l'échelle du Canada à une résolution de 1 km dérivées sans recours à l'information au niveau du sous-pixel ont été utilisées pour fins de comparaison. Cette recherche a permis de tirer les conclusions suivantes: (*i*) les erreurs d'extraction du LAI sont proportionnelles à la fraction d'eau dans un pixel et, en moyenne, pour l'ensemble de la masse terrestre du Canada, la valeur de LAI extraite par unité de surface terrestre sans considération pour l'effet des masses d'eau ouvertes est de 13% plus petite que la valeur réelle de LAI; (*ii*) l'influence de la surface d'eau à l'échelle du sous-pixel sur l'extraction du LAI est plus considérable dans le cas d'un couvert de conifères et plus faible dans le cas d'un couvert de feuillus au plan des forêts; et (*iii*) à cause du biais dans le LAI, la valeur de PPN par unité de surface terrestre est également biaisé négativement par 9% lorsque l'effet de l'eau à l'échelle du sous-pixel n'est pas pris en considération. La valeur annuelle de PPN à l'échelle du Canada, cumulée à partir des portions terrestres en utilisant la valeur de LAI corrigée pour l'eau, est de seulement 0,69% plus élevée que la valeur cumulée à partir de la surface totale des pixels calculée en utilisant le LAI sans correction pour l'eau. Toutefois, la différence dans ces deux valeurs de PPN peut être positive ou négative selon les différentes provinces, dépendant de la fraction de surface d'eau et de sa répartition.
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Introduction

Forest resources are intensively utilized for many purposes. Forests are a source of wood products and also play a key role in the global climate system. Research has indicated that global warming may have led to significant changes in the carbon cycle and ecological functioning of forests, and their feedbacks can in turn modify the global climate system. Leaves in forest canopies are the primary surfaces for energy and mass exchange between the atmosphere and the land surface (Danson, 2000). Variables, such as the leaf area index (LAI), are often used to quantify the effect of forest structure on light interception and absorption, nutrient cycling, and productivity. In Canada, LAI maps were produced using the advanced very high resolution radiometer (AVHRR), and annual net primary productivity (NPP) and evapotranspiration (ET) were calculated using the boreal ecosystem productivity simulator (BEPS) model (Liu et al., 1997; 2002). In reality, AVHRR pixels at 1 km resolution are often mixed with several cover types (Settle and Campbell, 1998), and the unknown subpixel mixture introduces major errors and biases in retrieved parameters (Chen et al., 2002). For example, a pixel labeled as conifer forest may be composed of conifer and broadleaf deciduous forests, open water bodies, etc. Errors produced in calculating LAI in mixed pixels mainly result from two sources. One is introduced from using nonlinear algorithms, and the other is caused by applying cover-type-dependent algorithms to mixed pixels labeled as one dominant cover type (Chen, 1999).

There are several techniques, such as artificial neural networks, mixture modeling, and supervised fuzzy c-means classification, to resolve the problem of information retrieval for mixed pixels (Atkinson et al., 1997; Aplain and Atkinson, 2001). In this article, we address issues related to retrieving LAI and calculating NPP for pixels mixed with land and open water. Open water bodies are one of the main features causing surface heterogeneity. Water bodies strongly absorb solar radiation at all wavelengths and greatly reduce the average reflectance in land–water mixed pixels. Therefore, the effect of surface heterogeneity caused by open water is expected to be the largest among all types of surface heterogeneity, and it would be the first step in spatial scaling of remotely derived surface parameters. Linear algorithms of LAI such as those based on the simple ratio (SR) incur no errors for pure pixels, and even in a mixed pixel, linear algorithms cause smaller errors than nonlinear algorithms (Chen, 1999). However, the relationship between LAI and SR is often not linear for many cover types (Chen et al., 2002). In this paper, both linear and nonlinear LAI–SR algorithms were used for investigating the effects of subpixel water area fraction on LAI retrieval and NPP estimation. As an example, **Figure 1** demonstrates a simple case of a linear relationship between LAI and SR for pixels of various water area fractions. Also shown is a relationship for pure land pixels of conifer stands. The water area fraction is assumed to vary from 100% at LAI = 0 to 0% at the intercept (SR = 7, LAI = 5) between the two lines representing these two relationships. For a pixel containing 50% water and 50% land with LAI = 5, the mean LAI value for the pixel is 2.5. But if the SR value of 4.2 for this pixel is used to invert LAI assuming it is a pure land pixel, the LAI value will be 1.4, which is negatively biased by 0.9.

In Canada, the total forest area assembled from forest inventory is 416 Mha (Kurz and Apps, 1996), whereas the area estimated using AVHRR imagery at 1 km resolution is about 460 Mha (Cihlar, 2000). The difference is mostly due to the subpixel water area fraction in the coarse-resolution imagery. Although the area statistics can be easily corrected once fine-resolution water area masks are available, the effects of the subpixel water bodies on water and carbon flux estimation cannot yet be readily assessed without a systematic investigation. Whether open water bodies in land pixels cause overestimation or underestimation of the fluxes is a question of interest to scientists who are concerned with the interaction between the land and the atmosphere. The goal of the present study is to provide the first-order estimate of bias errors in retrieving biophysical parameters of the surface and in modeling the carbon flux.

Methods

Linear mixture model and LAI correction

Land cover classes are treated as end members in linear mixture models (LMM) (Settle and Drake, 1993; Asner et al.,

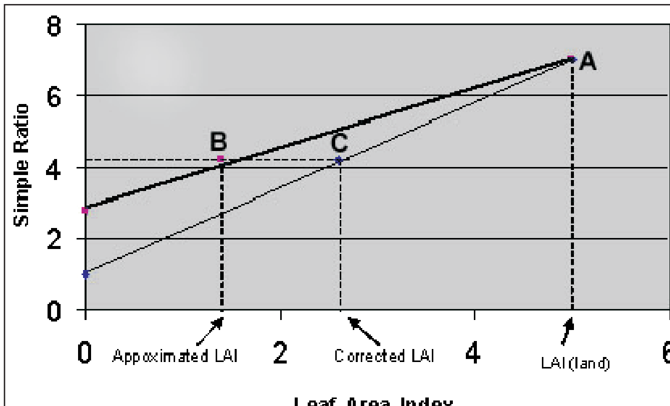

Figure 1. The effect of subpixel open water bodies on LAI estimation using SR. The thick line represents a relationship between SR and LAI (Chen, 1999) for boreal conifer forests. The thin line represents a hypothetical relationship for pixels mixed with open water and land, with a linear variation of the water area fraction from zero at LAI = A to 100% at LAI = 0. The point A is the LAI value over the land portion (L_0). For a pixel with 50% land and 50% open water, point C gives the correct average LAI value (L_c) for the pixel (per unit area of the pixel). Point B is the LAI value (L_b) derived using the relationship for pure land pixel. The difference between C and B is the error caused by the open water bodies in the pixel when the algorithm derived for pure land surface is applied to water–land mixed pixels, a general case when the water area fraction in a pixel is ignored.

1997; Peddle et al., 1999). The LMM used in this study can be expressed as follows:

$$R_i = \sum_{j=1}^{n} (r_{ij}\, x_j) + e_i \tag{1}$$

where $i = 1, \ldots, m$ (number of spectral bands); $j = 1, \ldots, n$ (numbers of end members in a pixel); r_{ij} is the spectral reflectance of the jth end member for the ith spectral band; x_j is the proportion value of the jth component in the pixel; e_i is the error term for the ith spectral band; and R_i is the spectral reflectance for the ith spectral band of a pixel containing one or more components.

In this research, we only consider two end members, land and water, as the first spatial scaling step because the contrast between land and water is the largest among the various cover types. The vegetation index SR is defined as

$$\mathrm{SR} = \rho_n/\rho_r \tag{2}$$

where ρ_n and ρ_r are the reflectances in the near-infrared (NIR) and red channels, respectively. In a mixed vegetation–water pixel, the mean reflectances in the red and NIR channels can be given as (Chen, 1999)

$$\rho_n = w\rho_{nw} + (1 - w)\rho_{nl} \tag{3}$$

and

$$\rho_r = w\rho_{rw} + (1 - w)\rho_{rl} \tag{4}$$

where w is the water area fraction; ρ_{nw} and ρ_{nl} are the NIR reflectances of water and land surface, respectively; and ρ_{rw} and ρ_{rl} are the red reflectances of water and land surface, respectively. The mean SR for the pixel can then be expressed as

$$\mathrm{SR} = [w\rho_{nw} + (1 - w)\rho_{nl}]/[w\rho_{rw} + (1 - w)\rho_{rl}] \tag{5}$$

Based on the LAI algorithms developed by Chen et al. (2002), Canada-wide LAI maps were recomputed in consideration of the effect of the subpixel water area fraction. The relationship between SR and LAI was found to be approximately linear for conifer species, i.e.,

$$\mathrm{SR} = a + bL \tag{6}$$

where a and b are constants found from experimental data, and L is the leaf area index.

The relationship between SR and LAI was found to be nonlinear for deciduous and mixed forests and other cover types (Chen et al., 2002):

$$\mathrm{SR} = a - (a - B)\mathrm{e}^{(-L/c)} \tag{7}$$

where a and c are constants determined from experimental data, and B is the SR value for the background (grass, moss, litter and soil for forests, and soil for grassland and cropland). To avoid the effect of the seasonal change in the background of forest stands, a seasonal background SR is estimated using the following equation (Liu et al., 1999; Chen et al., 2002):

$$B_c = -15.286 + 0.53574D - 6.7709 \times 10^{-3}D^2 + 4.0678 \times 10^{-5}D^3 - 1.1411 \times 10^{-7}D^4 + 1.1975 \times 10^{-10}D^5$$

$$B_d = 2.781$$

$$B_m = (B_c + B_d)/2$$

where B_c, B_d, and B_m are the background SR values for conifer, deciduous, and mixed forests, respectively; and D is the day of year.

Theoretically, we can use Equation (5) to estimate pixel reflectance as the sum of reflectance for land and water parts, weighted by their fractional presence within each pixel. For a forest–water mixed pixel, however, the scaling process is controlled mostly by the NIR reflectance, as the red reflectance is small. From Chen's (1999) observation, the composite SR varies with w almost linearly. Consequently, the approximated SR and land portion SR_0 in a pixel can be expressed as follows:

$$\mathrm{SR} = \mathrm{SR}_0(1 - w) + \mathrm{SR}_w w \tag{8}$$

where SR_0 and SR_w are the SRs of the land and water portions, respectively. After rearranging Equation (8), we have

$$\mathrm{SR}_0 = (\mathrm{SR} - \mathrm{SR}_w w)/(1 - w) \tag{9}$$

The value of SR_w depends on the depth and turbidity of the water and can vary in a wide range from 0 to 1. Through a sensitivity test with SR_w varying from 0 to 1, we only found very small (<0.7%) effects on LAI and NPP. For simplicity and efficiency in image processing, we have chosen to set SR_w = 0.5. Equation (9) converts remotely observed SR values for a land–water mixed pixel to the SR value of the land portion (SR_0) in the pixel based on w. SR_0 is then used to calculate the LAI of the land portion denoted as L_0 (i.e., point A in **Figure 1**) using Equations (6) and (7) for different land covers. The SR value for the mixed pixel was directly used to estimate the LAI (L_b) of the mixed pixel with the same equations without considering the water effect (i.e., point B in **Figure 1**). Because L_0 accounts for the LAI contributed by the land portions, the average LAI of a pixel is expressed as

$$L_c = L_w w + L_0(1 - w) = L_0(1 - w) \tag{10}$$

where L_w is the LAI of water and is equal to zero.

The difference between L_c and L_b, i.e., $L_c - L_b$, is considered as the correction for the water effect on the land portion.

Net primary productivity (NPP) calculation and its correction

Net primary productivity (NPP) provides highly synthesized information useful for natural resources management and is also a foremost indicator of the carbon budget regionally and globally. The BEPS process model (Liu et al., 1997; 2002) is used for estimating NPP. Inputs to the model include remotely sensed LAI maps every 10 days, biomass, available water holding capability of soil, and daily meteorological variables (Liu et al., 2002). Canada-wide NPP maps at 1 km resolution were recalculated using new LAI maps derived after the water area fraction correction. Because the LAI value for the land portion of a mixed pixel, i.e., L_0, always increases after the correction, the value of the NPP (in kg C $m^{-2}\cdot year^{-1}$) per unit land area in the pixel, i.e., NPP_0, is always higher than the NPP per unit pixel area calculated using the uncorrected LAI. For the corrected NPP value per unit pixel area, NPP_c, whether mixed with water or not, it is necessary to discount for the portion of the area occupied by open water, i.e.,

$$NPP_c = (1 - w)NPP_0 \tag{11}$$

In this case, the total amount of NPP (in kg C) in a region depends on the mean water area fraction and the magnitude of NPP increase for the land portion after the correction for LAI. In other words, the regional mean value of NPP can either increase or decrease after the recalculation using the corrected LAI. Because NPP_0 is calculated based on the corrected LAI of the land portion instead of the whole pixel, it is useful for comparing with ground-based measurements of NPP. In the meantime, the NPP change (increase or decrease) based on the total pixel area quantifies the biases in the total NPP caused by ignoring the subpixel water bodies.

Date sets and the water fraction mask

Canada-wide LAI maps every 10 days produced by Chen et al. (2002) and annual NPP maps presented in Liu et al. (2002) are used in this study. Both map series were produced using the AVHRR imagery at 1 km resolution without the subpixel water area correction. In this study, LAI composite images in 1994 are investigated with the water area correction methodology, and annual NPP results before and after the correction are analyzed. Whereas the LAI correction requires only the additional input of the subpixel water area fraction, the NPP recalculation using the corrected LAI requires all other inputs necessary for calculating NPP, including land cover, available water holding capacity, and daily meteorological variables. A description of all these inputs is found in Liu et al. (2002).

Critical to this study is the Canada-wide water area fraction map (**Figure 2**) produced by the Canada Centre for Remote Sensing (available at http://www.ccrs.nrcan.gc.ca/ccrs/data/data_e.html). This map was produced through digitizing topographical maps at a resolution of about 20 m. This fine-resolution water area mask can be resampled to produce subpixel water area fraction maps at desired resolutions. In this study, the mask is resampled to 1 km to be compatible with remote sensing imagery.

Results

Land cover statistics of the Canadian landmass are shown in **Figure 1**. Statistical items shown in **Table 1** include the number of pixels of every land cover, percentage of every land cover to the whole land area, number of water-containing pixels in different land covers, average water area fraction of all pixels, and water-containing pixel percentage for every land cover. Obviously, 50% conifer pixels contain significant open water bodies, and the mean water area fraction of conifer pixels is 14.6%. With their high percentage (30%) as a Canadian land cover type, conifers contribute a large portion of the total NPP in Canada.

Images of LAI and NPP are reproduced for the period of 1994, and the average LAI and NPP values before and after the subpixel water area fraction correction are investigated. The statistical results are shown in **Tables 1–4**, where L_b and NPP_b are LAI and NPP values per unit pixel area before the correction, L_0 and NPP_0 are the LAI and NPP values per unit land area after the correction, and L_c and NPP_c are the LAI and NPP values per unit pixel area after the correction. All these statistics are calculated after regrouping all cover types into six classes: coniferous forest, deciduous forest, mixed forest, agricultural land, grassland, and others (including burned forest, barren land, urban area, and ice), or according to the 12 Canadian provinces and territories.

LAI correction

The three sets of LAI values of different land cover types before and after the water area correction are shown in **Table 2**. Averaged for all cover types, the mean negative bias in LAI per unit land area without considering the effect of subpixel water bodies is 13%, and the mean negative bias in LAI per unit pixel area (L_c) is reduced to 1.85%. However, it should be realized that L_c is meaningless in further modeling of NPP and other variables because it is artificially spread from the land area to the total pixel area. As shown in **Table 1**, coniferous forests occupy about 30% of the Canadian landmass. It is the largest cover type in Canada, and meanwhile the water area fraction in coniferous forests is also highest among all forest covers. For the cloud-free composite images in 1994, the relative negative bias in LAI retrieval for the land portion in each pixel for the conifer type without considering the water area fraction is 15%, which is the largest among all cover types that contribute to the carbon cycle. The results also indicate that LAI retrieval errors resulting from water effects are inversely related to the proportion of the land area in a pixel, and this is consistent with Tian et al. (2002). Considering the large areas of Canadian landmass, the results certainly indicate that bias errors in LAI retrieval caused by open water bodies in the boreal landscape are considerable and cannot be ignored. The correction to the

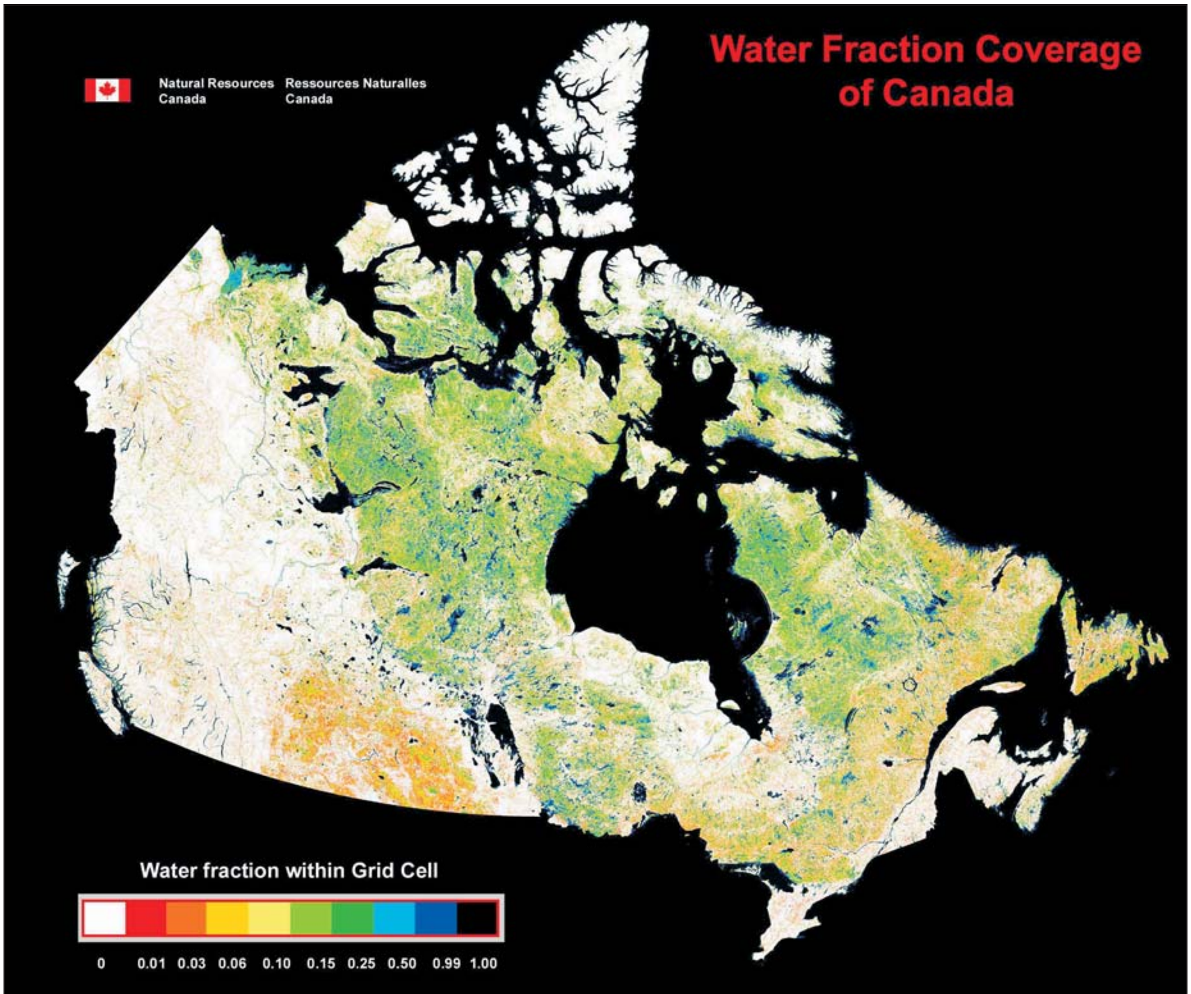

Figure 2. Canada-wide coverage of water area fraction at 1 km resolution. The original water area mask at 20 m resolution digitized from topographical maps is resampled to produce this map.

Table 1. Land cover statistics of Canada.

	Conifer	Deciduous	Mixed	Cropland	Grassland	Other	Total
No. of pixels	2 642 329	40 240	1 121 650	670 234	51 615	4 385 890	8 911 959
Land cover percentage (%)	29.65	0.45	12.59	7.52	0.58	49.21	100.00
No. of water-containing pixels	1 383 280	12 907	436 425	332 466	31 079	1 994 309	4 190 466
Average water fraction (%)	14.57	4.99	8.37	5.92	8.36	16.44	14.05
Water pixel percentage (%)	52.35	32.08	38.91	49.60	60.21	45.47	47.02

Table 2. Relative difference of LAI before and after the water area fraction correction for different cover types in 1994.

	Conifer	Deciduous	Mixed	Cropland	Grassland	Other	Total
L_b	2.22	3.52	3.00	1.09	0.35	0.33	1.30
L_0	2.61	3.70	3.22	1.16	0.41	0.42	1.49
L_c	2.28	3.48	2.99	1.10	0.36	0.34	1.32
Relative difference between L_b and L_0 (%)	14.96	4.65	7.05	6.22	13.24	20.66	13.00
Relative difference between L_b and L_c (%)	2.74	–1.26	–0.11	1.07	1.62	3.31	1.85

Table 3. Relative difference of NPP calculated using L_b and L_0 for different cover types in 1994.

	Conifer	Deciduous	Mixed	Cropland	Grassland	Other	Total
NPP_b (kg C $m^{-2} \cdot year^{-1}$)	0.2396	0.4201	0.3649	0.1566	0.0716	0.0157	0.1388
NPP_0 (kg C $m^{-2} \cdot year^{-1}$)	0.2684	0.4289	0.3837	0.1626	0.0826	0.0188	0.1518
NPP_c (kg C $m^{-2} \cdot year^{-1}$)	0.2418	0.4203	0.3670	0.1556	0.0718	0.0159	0.1397
Relative difference between NPP_0 and NPP_b (%)	10.72	1.90	4.89	3.69	13.41	16.48	8.55
Relative difference between NPP_c and NPP_b (%)	0.92	–0.09	0.57	–0.70	0.40	1.54	0.69

Table 4. Relative difference of NPP calculated using L_b and L_0 for the Canadian provinces and territories in 1994.

	Area (km^2)	Area percentage (%)	Percentage of water-containing pixels (%)	Average water fraction	NPP_b (kg C)	NPP_c (kg C)	Relative error of NPP (%)	Annual C difference ($\times 10^6$ kg C)
Newfoundland	434 207	4.06	86.07	0.17	0.0317	0.0350	9.31	1413.78
New Brunswick	66 240	0.62	45.04	0.22	0.2545	0.2559	0.53	89.42
Prince Edward Island	6 817	0.06	38.72	0.31	0.1194	0.1197	0.26	2.16
Nova Scotia	87 066	0.81	22.57	0.13	0.2424	0.2451	1.09	232.55
Quebec	1 633 565	15.28	68.53	0.18	0.1464	0.1506	2.80	6900.18
Ontario	1 112 580	10.41	48.73	0.17	0.2869	0.2877	0.28	884.50
Manitoba	646 504	6.05	51.29	0.20	0.2197	0.2197	0.01	10.99
Saskatchewan	696 618	6.52	61.84	0.14	0.2118	0.2092	–1.25	–1816.78
Alberta	751 501	7.03	27.99	0.09	0.2524	0.2519	–0.23	–426.10
British Columbia	1 065 436	9.97	16.98	0.15	0.2155	0.2138	–0.77	–1760.10
Yukon Territory	523 273	4.89	17.48	0.09	0.0923	0.0926	0.34	164.83
Northwest Territories	3 667 699	34.30	48.52	0.23	0.0316	0.0327	3.49	4192.18
Total	10 691 506	100.00	47.02	0.19	0.1388	0.1397	0.69	9878.95

LAI of water-containing pixels would also be an essential step for the comparison between ground-based LAI measurements and remote-sensing-based LAI estimates.

NPP correction

After using water-corrected LAI (L_0), the annual total NPP in 1994 is recalculated, and a water-corrected annual image of NPP per unit pixel area (NPP_c) is produced (**Figure 3a**). In 1994, the change in NPP before (NPP_b) and after (NPP_0) the correction per unit land area in a pixel has a spatial pattern similar to that of LAI, and a map showing the spatial distribution of this change is shown in **Figure 3b**. In **Table 3**, the difference in NPP before and after the correction is given. For each land cover type, the average annual NPP (in kg C $m^{-2} \cdot year^{-1}$) and their relative differences are shown. The relative negative bias error in NPP calculation for the conifer type without considering the water area fraction is 10.7%, which is still the largest among all cover types. The mean negative bias error is 8.6% for all cover types including conifer. The corrected NPP_0 per unit land area in a pixel should be the quantity to compare with ground-based estimates, such as those derived from forest inventory data. In comparison, the relative difference between uncorrected NPP_b and corrected NPP_c per unit pixel area is less than 1% (0.69%) when averaged for all of Canada's landmass. However, this does not mean that we can ignore the influence of open water bodies on NPP estimation. **Table 4** shows LAI and NPP statistics by province and territory. These statistics include the land areas of 12 provinces and territories, the percentage of each provincial area to the whole land area, the percentage of water-containing pixels to all pixels for each province, the average water area fraction of water-containing pixels, the average uncorrected NPP_b and corrected NPP_c (in kg C $m^{-2} \cdot year^{-1}$), and the relative differences between NPP_0 and NPP_b and between NPP_c and NPP_b. **Table 4** suggests that there are positive or negative bias errors due to the influence of water bodies, and the relative negative bias errors in NPP per unit pixel area could be very large in some regions. For example, the relative error for Newfoundland is as high as 9.3%. According to **Tables 3** and **4**, the uncorrected and corrected annual net primary production for Canada was 1.48 and 1.49 Gt C $year^{-1}$, respectively. Among all of provinces, Quebec has the largest absolute difference in NPP before and after the correction, up to 6.9 Mt C $year^{-1}$.

Finding these positive and negative bias errors in NPP estimation without considering the subpixel water area fraction suggests the importance of spatial scaling in terrestrial carbon cycle estimation. It also suggests that the NPP statistics as presented in Liu et al. (2002) are biased by the same amount and that the carbon sink values calculated by Chen et al. (2003) may also be underestimated by the same percentage. In the methodology of Chen et al., the magnitude of relative errors in the net biome productivity (NBP) is similar to that of the relative errors in NPP. The Canada-wide NBP annual mean values are therefore affected by less than 1%, relatively, but the spatial pattern would change significantly after this water correction.

To demonstrate the reason for the positive and negative NPP biases, an example of the uncorrected and corrected NPP variations with water area fraction is shown in **Figure 4**. Both NPP_b and NPP_c decrease with increasing water area fraction (w). The two curves intersect at $w = 0.58$. If $w < 0.58$, NPP_b shows a negative bias from NPP_c, and if $w > 0.58$, NPP_b shows a positive bias. The absolute difference between NPP_c and NPP_b indicates a nonlinear variation with water area faction. This further suggests that corrected NPP could be larger or smaller that uncorrected NPP depending on the mean water area fraction. In addition, the variation in the number of all water-containing pixels with water area fraction is shown in **Figure 5**, which indicates that there are many pixels with w smaller than 0.58 in Canada, resulting in the uncorrected NPP being negatively biased.

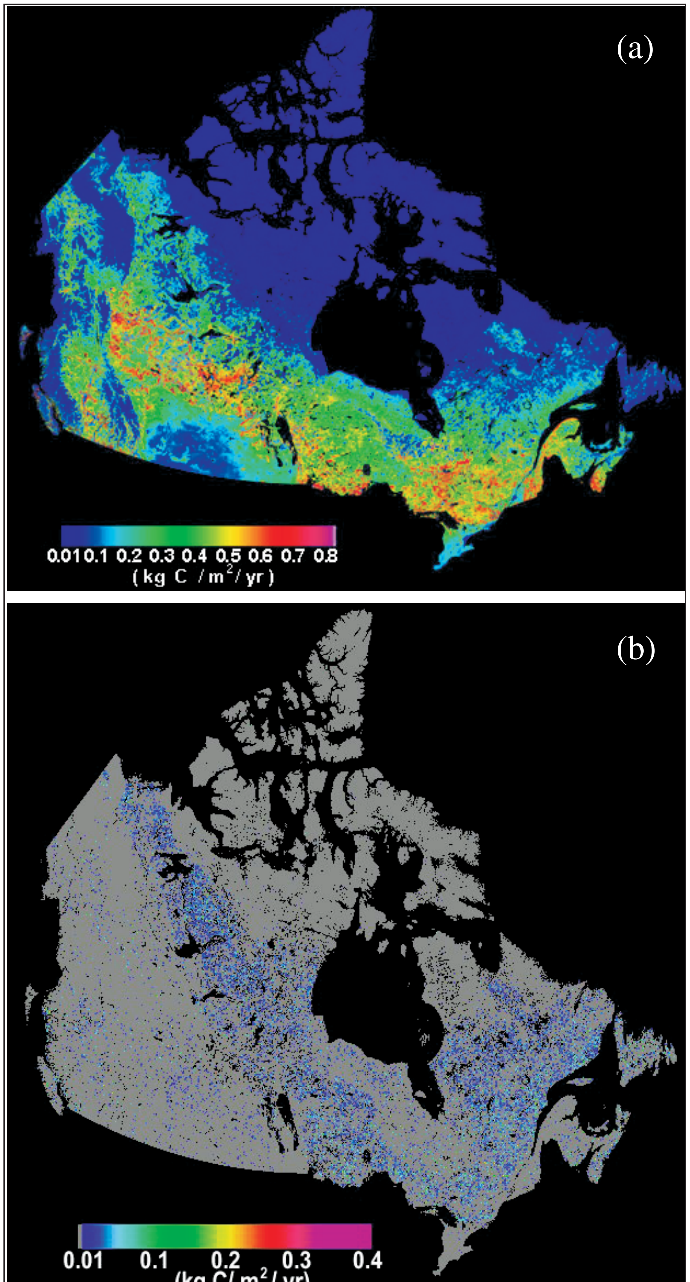

Figure 3. Spatial distribution of NPP and the water area effects on NPP estimation: (a) NPP map of Canada after correction for the effects of subpixel water area fraction; (b) relative change in NPP per unit land area before and after the correction.

Improvements in the future

In this study, we focus on the effect of subpixel water area fraction on LAI retrieval and NPP calculation, while the effect of other types of surface heterogeneity is ignored. However, the same methodology can also be used for pixels mixed with cover types other than just water and land. In particular, pixels mixed with conifer and deciduous forests, with forest and open land, or with forest and cropland–grassland can all cause considerable errors. Estimation of the effects of these pixel mixtures is more complex. However, the effects of these mixtures may be more random than systematic, unlike the case of pixels mixed with open water, which generally causes negative biases in LAI and often the same biases in NPP. A step forward in scaling research may be to use the soft land

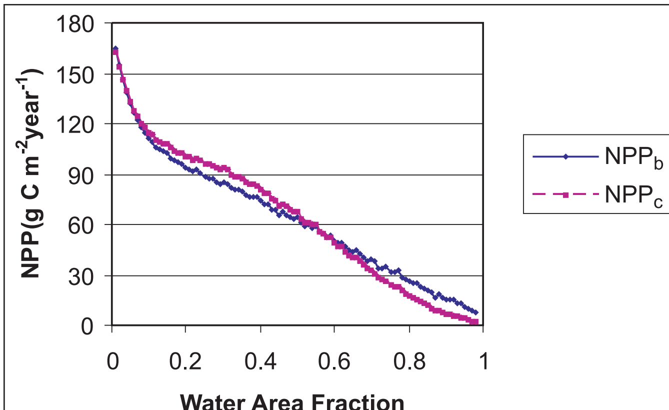

Figure 4. Variations of uncorrected NPP (NPP_b) and corrected NPP (NPP_c) per unit pixel area with water area fraction for typical conifer pixels.

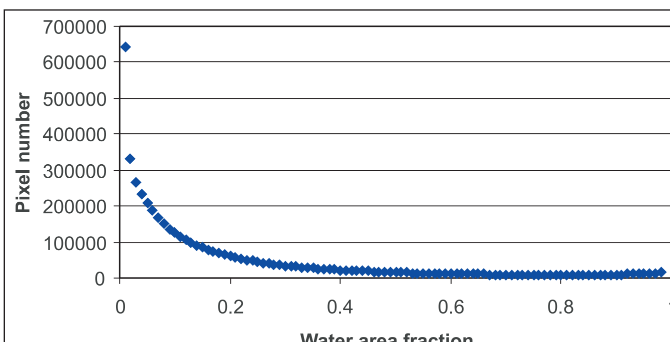

Figure 5. Number of water-containing pixels at various water area fractions in all of Canada's landmass.

classification approach, e.g., the continuous field approach (DeFries et al., 1999), although it is a considerable challenge to control the errors in soft classification (Latifovic and Olthof, 2004). The spectral signals of various cover types in a pixel do not always mix linearly. Therefore, linear mixture analysis techniques have limitations in some circumstances. Some nonlinear mixture modeling methods could be used, such as the artificial neutral network (ANN) (Foody et al., 1997). Deriving subpixel information for spatial scaling purposes would be a useful research topic for regional and global applications.

Conclusions

With the wide application of coarse spatial resolution satellite imagery for regional and global carbon cycle studies, spatial scaling is of particular importance. In Canada, 47% of remote sensing pixels at 1 km resolution contain open water bodies. As open water bodies are the most apparent features of land surface heterogeneity, our first attention in spatial scaling was given to their effects on remote-sensing-based estimates of land surface parameters. Using a Canada-wide water area mask at 20 m resolution, a subpixel water area fraction map at 1 km resolution was produced for this study. A simple methodology was adopted and refined to remove the errors in Canada-wide maps of LAI and NPP. Open water bodies occupying a significant fraction of a remote sensing pixel often cause a negative bias in the LAI estimate for the land portion in the pixel. Their effects are greatest for conifer types (15%). Their effects on NPP estimation per unit land surface area (excluding the water area fraction) are also always negative, but NPP per unit pixel area (including both land and water) can be either positive or negative depending on the water area fraction. Canada-wide total NPP estimates are affected by less than 1% after the water area correction, but the spatial distribution pattern is significantly altered from the results published previously (Liu et al., 2002), with the largest changes of +9.3% in Newfoundland and –1.3% in Saskatchewan.

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