SATellite Imagery for Mapping Carbon Source and Sink Distributions in Canada's Forests and Wetlands

by Jing M. Chen

Optical remote sensing imagery can be used to retrieve the following land surface parameters that are useful for carbon cycle modeling: (1) land cover type, (2) leaf area index, (3) fire scar age, (4) clumping index, (5) biomass, (6) wetland area, and (7) leaf pigment contents. In our regional carbon modeling, the first three parameters have been used, while progresses are being made to mapping the other parameters. In addition to these remotely sensed land surface parameters, soil texture and organic carbon maps, gridded monthly climate data from 1901 to 1998, and forest inventory data are used to produce annual spatial distributions of carbon sources and sinks in the entire Canada's forests and wetlands at 1 km resolution for the period from 1901 to 1998. The focus of this article is to review methodologies for retrieving surface parameters from remote sensing imagery and their use in modeling the carbon source and sink distribution.

INTRODUCTION

Terrestrial ecosystems have undergone changes due to direct and indirect impacts of human activities and are found to be carbon sinks in recent decades, i.e., sequestering carbon from the atmosphere \[1,2\]. The heterogeneous nature of terrestrial ecosystems presents a major challenge in our effort to improve regional and global carbon cycle estimation, and yet the ecosystem carbon budget information not only has significance in understanding the global climate change \[3,4\], but has also become a major knowledge gap in formulating policies related climate change, given the options of including sinks in national greenhouse gas inventory under the Kyoto Protocol (http://unfccc.int/resource/docs/convkp/kpeng.html). Since the first polar orbiting meteorological sensor launched in 1978, i.e., the Advanced Very High Resolution Radiometer (AVHRR), remote sensing from space has afforded us data for quantitative description of global land surface heterogeneities and changes, although high quality data acquired from sensors specifically designed for regional and global land surface applications only has a short history since 1998, when both VEGETATION on board SPOT 4 and the Moderate-resolution Imaging Spectrometer (MODIS) on board Terra became operational (Table 1). Although remote sensing imagery is currently insufficient in terms of the record length relative to carbon cycle time scales as well as its capability in providing key surface parameters, space-borne data nevertheless have given us indispensable information based on which much improved carbon cycle knowledge has been gained. The purpose of this article is to provide a concise review on the status of remote sensing data used for terrestrial ecosystem modeling with a main focus on the work done for Canada's forests and wetlands.

METHODS FOR BIOPHYSICAL PARAMETER RETRIEVAL

There are a number of surface parameters that can be derived from remote sensing and are useful for carbon cycle modeling (Table 2). Some of the parameters, such as land cover and LAI, are widely used in global and regional modeling and are available from many sources. Some parameters, such as clumping index, are relatively new and are only

**TABLE 1**

<table>
<thead>
<tr>
<th>Sensor Name</th>
<th>Abbreviation</th>
<th>Major Characteristics</th>
<th>Information Source</th>
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<tbody>
<tr>
<td>Advanced Alone Track Scanning Radiometer</td>
<td>AATSR</td>
<td>4 optical bands, 3 thermal bands, 2 view angles, 1 km resolution Since 2002</td>
<td><a href="http://envisat.esa.int/m-s/">http://envisat.esa.int/m-s/</a></td>
</tr>
<tr>
<td>Advanced Very High Resolution Radiometer</td>
<td>AVHRR</td>
<td>2 optical bands, 3 thermal bands, 1.1 km resolution Since 1978</td>
<td><a href="http://noaasis.noaa.gov/NOAASIS/ml/avhrr.html">http://noaasis.noaa.gov/NOAASIS/ml/avhrr.html</a></td>
</tr>
<tr>
<td>Global Imager</td>
<td>GLI</td>
<td>29 optical bands, 7 thermal bands, 0.25-1 km resolution 12/02-10/03</td>
<td><a href="http://www.eoc.jaxa.jp/satellite/sendata/gli_c.html">http://www.eoc.jaxa.jp/satellite/sendata/gli_c.html</a></td>
</tr>
<tr>
<td>Medium Resolution Imaging Spectrometer</td>
<td>MERIS</td>
<td>15 optical bands, 100 m resolution Since 2002</td>
<td><a href="http://envisat.esa.int/instruments/meris/">http://envisat.esa.int/instruments/meris/</a></td>
</tr>
<tr>
<td>Moderate-Resolution Imaging Spectrometer</td>
<td>MODIS</td>
<td>20 optical bands, 16 thermal bands, 0.25-1 km resolution Since 1998</td>
<td><a href="http://modis.gsfc.nasa.gov/">http://modis.gsfc.nasa.gov/</a></td>
</tr>
<tr>
<td>Polarization and Directionality of the Earth's Reflectances</td>
<td>POLDER</td>
<td>15 optical bands, 3 polarization bands up to 14 view angles, 7 km resolution 08/86-06/97, 12/02-10/03</td>
<td><a href="http://smsc.cnes.fr/POLDER/">http://smsc.cnes.fr/POLDER/</a></td>
</tr>
<tr>
<td>VEGETATION</td>
<td>VGT</td>
<td>4 optical bands, 1.1 km resolution Since 1998</td>
<td><a href="http://www.spot-vegetation.com/">http://www.spot-vegetation.com/</a></td>
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To address the need to know the carbon source and sink distribution in terrestrial ecosystems for various science and policy purposes, satellite remote sensing can play a critical and indispensable role.

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available for limited regions, while several other parameters, which are retrievable from remote sensing and critically useful for carbon cycle estimation, are not yet available for any large regions. The retrieval methodologies and the current status for each of these parameters are briefly reviewed here.

Land Cover Map

Globally, the most updated land cover map is the GLC2000 (http://www.eogeo.org/GLC2000) produced by individual countries using the SPOT4 VEGETATION data supported by the European Space Agency. The North America part of the map was jointly produced by the Canada Centre for Remote Sensing and the US Geological Survey [5] using the method of classification by progressive generalization initially developed by Cihlar et al. [6]. There are 35 cover types based on the Natural Vegetation Classification Standard adopted by the US Federal Geographic Data Committee. These are matched with 23 cover types in GLC2000. For carbon modeling, these cover types are grouped into several functional types, such as deciduous forest, conifer forest, grassland, cropland, tundra, barren, etc., and carbon related parameter sets are assigned to these grouped cover types [7].

Leaf Area Index

Leaf area index (LAI) is defined as one half the total leaf area (all sided) per unit ground surface area [8]. This definition is suitable for both broadleaf and needleleaf forms and is now accepted by the international community [9]. There are several global LAI products that have been produced using MODIS [10], POLDER [11], MERIS [12], and VEGETATION and AATSR [13] (see Table 1 for information of these sensors). Large discrepancies are found among some of the products over Canada [14], MODIS LAI [10] being consistently 30-50% larger than VEGETATION LAI derived using an algorithm developed in Fernandes et al. [15]. In addition to the differences in band width and response function between the various sensors, LAI retrieval algorithms used to produce these products are also quite different, causing these large discrepancies. There are also inconsistencies in LAI definition and measurement techniques and protocols. In producing and validating Canada-wide LAI products, Chen et al. [16] proposed a set of LAI measurement protocols as well as validation procedures, which are similar to the recent work by Abuelgasim et al. [14]. Through previous studies [15-19], consistent ground-based measurements of LAI were made in many forest and crop canopies over large geographical areas, providing a solid foundation for LAI map validation over Canada. For forests, it is shown that the reduced simple ratio (RSR) [20] is most significantly correlated with LAI, where RSR is defined as

$$ RSR = \frac{\rho_n}{\rho_r} (1 - \frac{\rho_s - \rho_{min}}{\rho_{max} - \rho_{min}}) $$

where $\rho_n$, $\rho_r$, and $\rho_s$ are the reflectances in near infrared (NIR), red, and shortwave infrared (SWIR) bands, respectively, and $\rho_{min}$ and $\rho_{max}$ are the minimum and maximum reflectances in the SWIR band, determined from 1% cutoff points in the histogram of a given image. Figures 1a and 1b show the relationships between LAI and SR (i.e., $\rho_n/\rho_r$) and between LAI and RSR for major cover types, respectively. Compared with SR, RSR has a large sensitivity to LAI changes through suppression of the effects of the back-
ground greenness (moss and grass under forest canopy) and variability. RSR differs less for the various cover types at the same LAI than does SR, giving a clear advantage for applications to pixels of mixed cover types, which are the norm in coarse pixels because at 1 km resolution a pixel is seldom covered by only one vegetation type. This advantage is confirmed by Stenberg et al. [21]. Fernandes et al. [15] proposed an infrared simple ratio (ISR) between NIR and SWIR reflectances, showing similar sensitivities to LAI changes, however, further studies are needed to see if ISR and RSR are too sensitive to the surface water conditions and are seriously affected by rainfall events shortly prior to imaging.

**Clumping Index**

Nilson [22] first proposed the use of a leaf dispersion parameter to estimate the effect of nonrandom leaf spatial distributions on radiation transmission through plant canopies. The leaf distribution can either be more regular than random, or more clumped than random. Natural ecosystems generally have clumped distributions of leaves, such as groupings of leaves in shrubs and tree crowns, and this dispersion parameter is therefore often called the clumping index [17]. This clumping index is a critical input to canopy photosynthesis models with sunlit and shaded leaf stratification [23], and this stratification avoids flaws in big-leaf models, which treats a canopy as a big leaf regardless of differences in photosynthesis between sunlit and shaded leaves [24]. With the same LAI, sunlit leaves reduce and shaded leaves increase when a canopy is clumped. Chen and Cihlar [25] developed an optical instrument named TRAC (Tracing Radiation and Architecture of Canopies) to measure this clumping index based on a gap size distribution theory [26]. Measuring this clumping index has therefore become an integral part of LAI measurements, and a large dataset of clumping index for various ecosystems has been accumulated. However, as the three-dimensional canopy structure varies greatly in space, the clumping index also varies greatly, and it is highly desirable to map this index. It was not possible to do this for a large area until recently when the multi-angle POLDER data become available globally. Chen et al. [27] first demonstrated that the magnitude of reflectance variation from the hotspot, where the illumination and observation directions coincide, to the darkspot, where the reflectance is minimum in forward scattering direction in the principal solar plane, is mostly determined by the degree of foliage organization (clumping). Through geometrical optical simulations using the 4-Scale model [28] with a new multiple scattering scheme [29], they demonstrated that clumped canopies cast strong shadows in the forward scattering directions, reducing the darkspot reflectance. The reduction was found from data and simulations to be the largest for conifer forest, smallest for grassland, and deciduous forests are the intermediate case. They developed an angular index based on the hotspot and darkspot reflectance. These model simulations were later validated using airborne POLDER data [30] and space-borne POLDER data [24]. Through a large number of model simulations [31,32], it is shown that the normalized difference between hotspot and darkspot (NDHD) is most linearly related to the clumping index. NDHD is defined as:

\[
NDHD = \frac{\rho_h - \rho_d}{\rho_h + \rho_d}
\]

where \(\rho_h\) and \(\rho_d\) are the hotspot and darkspot reflectance, respectively. Figure 2 shows the relationships between NDHD and the clumping index for conifer and deciduous forests separately.

![Fig. 2 The relationship between the clumping index and the normalized difference between hotspot and darkspot (NDHD) for (a) conifer forest and (b) deciduous forests, respectively. For a random spatial distribution of leaves, the clumping index equals unity, and when foliage is clumped, it is smaller than one. The greyness indicates the number density of model results using 4-Scale with large ranges of stand structural and optical parameter inputs [33].](image)
These modeled relationships are applied to multiple angle POLDER data for regional and global clumping index mapping [31,32]. For this purpose, POLDER data for the same pixel observed at different angles (up to 14 in one single overpass) are fitted with a simple kernel based model named FLAIR [33] or a simple exponential function [34] to find the most reliable hotspot and darkspot values for a given set of observations. Using these methodologies, Chen et al. [32] for the first time produced a global clumping index map using POLDER data at 7 km resolution (Figure 3). From the multiple angle views of the globe, we see that forests are most clumped (clumping index much smaller than unity) and grassland is least clumped (clumping index close to unity), and also within the same forest type, there are large variations in the index. The multiple angle view can also differentiate between the shrubland and the grassland, which are generally inseparable in a single view image. In mountainous areas, the remaining challenge is to separate the topographical effect on the angular index.

Biomass

Biomass, both above and below ground, is the living carbon stock. However, so far aboveground biomass mapping for large regions has not been achieved, although it has been demonstrated that the synthetic aperture radar (SAR) can be used to retrieve biomass information, especially using not only the backscatter strength but also the coherence information [40,41]. However, regional mapping of biomass using SAR may experience variations in topography, surface dielectric constant, vegetation structure, saturation of signals at high biomass values, etc. [42], and therefore it has not yet been accomplished. Airborne light detection and ranging (LIDAR) systems have been demonstrated to be effective in retrieving forest biomass information [43,44]. Spaceborne LIDAR systems may be available in the near future [45].

Biomass is also needed in carbon cycle models to estimate the plant maintenance respiration [46]. In Canada-wide net primary productivity mapping using the Boreal Ecosystem Productivity Simulator (BEPS) [7], correlations between biomass and leaf area for two forest types (deciduous or conifer) were used. These correlations, however, can not handle variations of biomass with age at approximately the same leaf area. However, as the maintenance respiration is generally proportional to sapwood biomass rather than the total biomass [47], these crude biomass estimates may be adequate as inputs to carbon cycle models, because sapwood biomass is generally uniquely related to leaf area [48].

Fire Scar

Wildfires are one of the major causes of forest disturbance affecting stand dynamics, renewals, biomass and soil carbon pools, which in turn are important in forest carbon cycles [35]. Although the Large Fire Polygon Database of Canada was constructed by the Canadian Forest Service based on provincial reports [36], this database covers the periods from 1959 to 1995 and misses considerable northern fire scarring in remote areas. Remote sensing data were therefore used to fill in gaps in both space and time [37]. After a forest is burned, leaf area is greatly damaged and the standing liquid water in biomass is drastically reduced, causing the reflectance in near-infrared (NIR) to decrease and the reflectance in shortwave-infrared (SWIR) to increase. The ratio of SWIR to NIR reflectance therefore increases dramatically immediately after a fire. Figure 4, shows the variation of this ratio obtained from SPOT VEGETATION images in the summer 1998 with time since fire for a large sample of burned fire scars across Canada. The correlations are higher when separate regressions are made for individual ecoregions in Canada, $r^2=0.57-80$ for 16 of the 18 ecoregions [38]. As the variation in this ratio becomes small in about 25 years after the fire, fire scar dating was restricted to 25 years before the image date in 1998, with an error of ±7 years. When images acquired in multiple years are used, the accuracy in fire scar mapping and dating can be further improved [39].
Wetland

Wetlands have unique biogeochemical cycles involving both aerobic and anaerobic processes under fluctuating water table conditions [49]. As wetland vegetation is different from the surrounding forests and the water regime is different from the surrounding terrain, it is potentially possible to map wetland areas with both SAR (responding to water conditions) [50,51] and optical (responding to vegetation conditions) sensors [52]. However, regional mapping of wetlands suffers from variable size and shape of wetland areas as well as seasonal variation in water table affecting SAR signals. It is an area in which remote sensing techniques are underutilized.

In Canada-wide wetland carbon cycle modeling [53], wetlands are identified from drainage class information in the Soil Landscape of Canada [54]. The use of drainage class information in conjunction with topographical data allows estimation of changes in wetland water table with time, and therefore making it possible to investigate the variations of aerobic and anaerobic processes under changing climate [55].

Leaf Pigments

Leaf pigments, including chlorophyll, carotenoids and xanthophylls, absorb visible radiation and therefore affect optical remote sensing signals. Among these pigments, chlorophyll is of particular interest to carbon cycle modeling as the amount of chlorophyll per unit leaf surface area is the main control on the photosynthesis rate under given radiation and environmental conditions [56]. For natural ecosystems, the leaf chlorophyll content is closely related to the leaf nitrogen level [57,58], which is an important parameter in carbon cycle models that consider nutrient cycles [23,47]. There are leaf-level radiative transfer models that are capable of retrieving leaf pigments from leaf reflectance and/or transmittance [59,60]. Jacquemoud's leaf-level model has been applied to closed canopies for leaf chlorophyll retrieval [61]. Through combining a leaf-level model with a canopy-level model, hyperspectral remote sensing images were successfully used to retrieve leaf chlorophyll content [62]. However, reliable techniques are yet to be developed and tested for deriving leaf-level chlorophyll information for open canopies using hyperspectral remote sensing data. Using MERIS data (Table 1), some initial efforts are being made to map leaf chlorophyll globally [12], and it is expected that this parameter will be used in regional and global carbon cycle modeling in the near future.

SPATIALLY EXPLICIT CARBON CYCLE MODELING: AN EXAMPLE

Extensive research was previously done for Canada’s forest carbon budgets based on forest type and age structure provided in forest inventory data [35]. In this previous study, biomass-age relationships were derived from the inventory compiled over about 100 years regardless of possible changes in growth conditions over the long period, and these relationships were applied to 457 forest types in 48 spatial units over Canada’s landmass. This previous study does not include the effects of non-disturbance factors, such as the climate change, and is limited in spatial resolution (48 spatial units). The use of remote sensing not only greatly improves the spatial resolution (<1 km) but also allows estimation of changes in forest growth conditions when the past climate and current vegetation data are used in process-based modeling [37]. Figure 5 shows the major remote sensing parameters used in Canada-wide forest carbon cycle modeling as well as the major steps. One unique aspect of this modeling approach based on remote sensing is that not only non-disturbance factors (nitrogen and CO2 fertilization effects, climate variables) are considered, as many process models do, but also disturbance factors (fire, insect, harvest) are explicitly considered. Of particular importance in modeling the disturbance effects is the forest age map in 1998 (Figure 6) created by combining forest inventory, large fire polygons, and remote sensing data for dating fire scars (Section 2.4).

The essential information that remote sensing can provide is the quantitative surface conditions in recent years useful for spatially explicit modeling. However, the carbon cycle is a slow process, involving photosynthesis, dead organic matter accumulation and decomposition, biomass accumulation and turnover, disturbance and regrowth, etc., and on average the carbon residence time is about 50 years in boreal forests [63]. In order to estimate the current carbon cycle, the spatially explicit data (including a forest age map) must be combined with historical climate records of length at least twice the residence time in order to model changes in vegetation and soil conditions over time. As the sizes of various soil carbon pools and their decomposition rates are crucial in carbon cycle estimation and are not directly available from measurements for large areas, a model spin-up approach, similar to many other ecosystem models [64], was used to estimate the pool sizes and their decomposition rates at the beginning of the modeling period at 1901 [37]. The Integrated Terrestrial Ecosystem Carbon Cycle model (InTEC) was developed to simulate disturbance and non-disturbance...
InTEC is a combination of (i) Farquhar’s leaf-level photosynthesis model [66] applied to remote sensing pixels through a spatial and temporal scaling scheme, (ii) CENTURY’s soil biogeochemical model [67] modified for forest applications [65] and (iii) an empirical forest regrowth model depending on air temperature [37]. Using InTEC with inputs from remote sensing and other spatial datasets, the carbon budget of Canada’s forests was calculated at 1 km resolution in annual time steps. Figure 7 shows the carbon source and sink distribution in Canada’s forests averaged over the 1984-1998 period. The term, net biome productivity (NBP), is defined as net primary productivity less heterotrophic respiration (organic matter decomposition) and the direct carbon emission at the time of disturbance. When NBP is larger than zero, the surface is a sink, meaning absorbing carbon from the atmosphere, and when NBP is smaller than zero, the surface is a source. Compared with the forest age map (Figure 6), it is obvious that NBP is closely related to forest age. In BC, where most forests are older than 100 years, forests are near carbon neutral conditions because small positive effects of warming (improved nutrient cycles) and CO₂ fertilization might have offset the small decline in growth in aging forests. These results may have underestimated sinks in B.C. if the second growth forest areas are underrepresented in the forest inventory data. In prairie provinces, the overall forests are carbon sources due to frequent disturbances, and the increase in regrowth could not compensate for the dramatic increase in disturbance in 1980’s and 1990’s. Eastern and maritime provinces are generally carbon sinks because of large areas of productive forests gaining benefits from increased nitrogen deposition and improved nutrient conditions under warming conditions as well as a small effect of CO₂ fertilization. There is also a general gradient of decreasing sink strength from south to north because of the differential effects of warming on forests and soils. In InTEC, the decomposition of soil organic matter at higher latitudes is more sensitive to warming, while forest growth benefits less immediately from warming at higher latitudes where vegetation is sparse. Critical to modeling these spatial patterns are remotely sensed forest fire patches and forest density (LAI). Partial validations of the results of soil and vegetation carbon stocks and carbon budgets were initially made against soil carbon data in Soil Landscape of Canada, aboveground biomass data in forest inventory, and four flux tower sites [37]. Validation using more tower sites of the Fluxnet Canada Research Network was made by Ju et al. [55].

InTEC has recently been expanded to include aerobic and anaerobic processes in wetlands [53] and to include hydrological processes responsible for the lateral water redistribution [55] so that the total carbon absorption and release by CO₂ and CH₄ gases are also included. For these purposes, additional spatial data of the digital terrain model and drainage class are used to estimate water table and soil moisture, giving the possibility of modeling coupled water and carbon cycles.

CONCLUSIONS

Through the use of remote sensing data in combination with climate and other spatial datasets, spatially explicit carbon cycle processes in Canada’s forests are simulated for the last century. The results suggest that positive effects of climate warming, nitrogen deposition, and CO₂ fertilization outweighed the negative effects of increased disturbance and
heterotrophic respiration in 1980's and 1990's, making Canada's forests a net carbon sink of about 60 MtC/y in 1980-1998. Remote sensing provided the critical spatial information to achieve this conclusion through process modeling. Active research is being conducted to consider fully the coupled water and carbon cycles and to make use of other remote sensing parameters, such as clumping index, leaf chlorophyll content, and wetland area and types.

REFERENCES
