A new approach for estimating northern peatland gross primary productivity using a satellite-sensor-derived chlorophyll index

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[1] Carbon flux models that are largely driven by remotely sensed data can be used to estimate gross primary productivity (GPP) over large areas, but despite the importance of peatland ecosystems in the global carbon cycle, relatively little attention has been given to determining their success in these ecosystems. This paper is the first to explore the potential of chlorophyll-based vegetation index models for estimating peatland GPP from satellite data. Using several years of carbon flux data from contrasting peatlands, we explored the relationships between the MERIS terrestrial chlorophyll index (MTCI) and GPP, and determined whether the inclusion of environmental variables such as PAR and temperature, thought to be important determinants of peatland carbon flux, improved upon direct relationships. To place our results in context, we compared the newly developed GPP models with the MODIS (Moderate Resolution Imaging Spectrometer) GPP product. Our results show that simple MTCI-based models can be used for estimates of interannual and intra-annual variability in peatland GPP. The MTCI is a good indicator of GPP and compares favorably with more complex products derived from the MODIS sensor on a site-specific basis. The incorporation of MTCI into a light use efficiency type model, by means of partitioning the fraction of photosynthetic material within a plant canopy, shows most promise for peatland GPP estimation, outperforming all other models. Our results demonstrate that satellite data specifically related to vegetation chlorophyll content may ultimately facilitate improved quantification of peatland carbon flux dynamics.

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1. Introduction

[2] Despite their limited coverage of the Earth's surface, peatland ecosystems play an important role in the global carbon cycle through the sequestration of atmospheric carbon as peat and the release of carbon gases (carbon dioxide (CO_2) and methane (CH_4)) through respiration and plant decay. Today most northern peatlands are a significant sink of atmospheric carbon, containing 20%–30% of the global soil carbon pool [*Post et al.*, 1982; *Smith et al.*, 2004]. However, the balance between carbon sequestration and release (as CO_2 and CH_4) is largely dependent on hydrology and temperature [*Bubier et al.*, 2005; *Bubier*, 1995; *Dise et al.*, 1993; *Moore et al.*, 2006]. Changes in climate may affect the rate of CO_2 uptake and the overall carbon dynamics of peatland ecosystems [*Moore*, 1998]; estimates of gross primary productivity (GPP) are thus critical for understanding how these ecosystems respond to climatic changes.

[3] Eddy covariance (EC) methods can measure peatland seasonal and interannual carbon fluxes over long periods of time. While EC techniques have proven to be of great importance in peatland carbon balance modeling efforts [e.g., *Lafleur et al.*, 2003; *Laine et al.*, 2006], these measurements account only for carbon fluxes within the designated flux tower footprint, and the number and geographical distribution of towers across the globe is limited. Consequently, scaling carbon fluxes from flux towers to produce regional and global estimates is challenging. Other attempts to estimate peatland carbon fluxes have concentrated on the development of process-based models, although the difficulties in modeling peatland hydrology mean that there have been relatively few attempts to model carbon exchange in peatlands as compared with other terrestrial ecosystems [e.g., *Frolking et al.*, 2002; *Soegaard et al.*, 2003; *Wang et al.*, 2002; *Yurova et al.*, 2007]. Peatland process-based models, such as the Peatland Carbon Simulator (PCARS) [*Frolking et al.*, 2002; *Lafleur et al.*, 2003], and ecosystem models that have been adapted to northern peatlands, such as the Boreal Ecosystem Productivity Simulator (BEPS) [*Liu et al.*, 1997; *Sonnentag et al.*, 2008] and GUESS-ROMUL [*Yurova et al.*, 2007; *Yurova and Lankreijer*, 2007], have shown promise. However, the applicability of these models at the regional and global scales is particularly challenging because of their

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complexity and requirements for data that are often scarce or unavailable at the appropriate spatial and temporal scales. Carbon flux models that are largely driven by remotely sensed data can be used to estimate gross primary productivity (GPP) over large areas, but despite the importance of peatland ecosystems in the global carbon cycle, relatively little attention has been given to determining their success in these ecosystems.

[4] Many current remote-sensing-based carbon flux models utilize the light use efficiency (LUE) concept of *Monteith* [1972], which suggests that GPP is linearly related to the amount of absorbed photosynthetically active radiation:

$$\mathrm{GPP} = \varepsilon * (f\mathrm{PAR} * \mathrm{PAR}). \tag{1}$$

Where PAR is the incident photosynthetically active radiation, fPAR is the fraction of PAR absorbed by the vegetation canopy and ε is the efficiency with which a plant is able to export or utilize the product of photosynthesis.

[5] The primary advantage of the Monteith model for regional and global carbon flux estimations is that many of the model parameters can be estimated remotely from satellite data. In remote sensing analysis fPAR is estimated either as a function of the normalized difference vegetation index (NDVI) [*Prince and Goward*, 1995; *Ruimy et al.*, 1994] or by utilizing physically based models to describe the propagation of light in plant canopies [*Myneni et al.*, 2003]. However, the estimation of the LUE component is often more difficult, since LUE varies spatially across biomes, species and plant functional types [*Gower et al.*, 1999] and temporally across seasons and in response to environmental variations [*Nouvellon et al.*, 2000; *Schwalm et al.*, 2006; *Sims et al.*, 2006b]. Many remote-sensing-based GPP models utilize "look up" tables based on vegetation type to estimate the maximum LUE of a given biome and then adjust this value according to meteorological indicators of environmental stress [*Running et al.*, 2004]. However, there can be substantial errors in the estimation of LUE due to the coarseness of the metrological inputs commonly used to scale LUE and the quality and resolution of the land cover classification on which biome specific maximum LUE values are initially based. A number of studies have suggested that the use of coarse resolution data and look-up table LUE inputs may result in significant errors in the estimation of carbon fluxes [*Heinsch et al.*, 2006; *Zhao et al.*, 2006]. For heterogeneous environments, such as peatlands, the coarseness of such inputs may be particularly problematic, especially given that the land cover classification schemes on which such algorithms are based, often fail to include a peatland land cover category [*Harris and Bryant*, 2009; *Krankina et al.*, 2008].

[6] To try and overcome some of these limitations, several studies advocate a simpler and more direct approach by devising carbon exchange models that are entirely based on remote sensing data (e.g., vegetation indices (VIs)). Such models have the benefit of a continuous output at the spatial resolution of the sensor and are not always reliant on independent meteorological data sets or estimations of LUE [*Rahman et al.*, 2005]. Although the use of VIs in isolation may not be able to track daily fluctuations in carbon exchange, because rapid changes in environmental variables such as PAR, temperature and soil moisture are unlikely to have an immediate impact upon canopy physiology, studies have shown that VIs are able to characterize carbon fluxes integrated over a period of several days. Spectral indices that are related to vegetation greenness such as the normalized difference vegetation index (NDVI) or the enhanced vegetation index (EVI) have been correlated with GPP with varying degrees of success [e.g., *La Puma et al.*, 2007; *Rahman et al.*, 2005; *Sims et al.*, 2006a; *Sims et al.*, 2006b; *Wylie et al.*, 2003]. *Sims et al.* [2006b] reported correlations between EVI and GPP that were as good as or better than more complex algorithms, such as the MODIS GPP product (MOD17), during active photosynthesis. However, the model functions less well for sites dominated by evergreen species and those susceptible to summer drought, primarily because of the lack of a correlation between LUE and vegetation greenness. Recent developments to the *Sims et al.* [2006a] EVI model, through the incorporation of an additional land surface temperature component, have improved predictions of GPP from EVI [*Sims et al.*, 2008].

[7] Despite the recent proliferation of VI-based carbon models, there have been very few attempts to utilize these approaches to model GPP in peatland ecosystems and, like the vast majority of satellite-based GPP models, those that have, rely heavily upon spectral indices derived from the Moderate Imaging Spectrometer (MODIS) [e.g., *Schubert et al.*, 2010]. The use of common MODIS-derived vegetation indices, such as the NDVI and EVI, may be problematic for satellite-based GPP estimation over peatlands because of the narrow red absorption feature and narrow near-infrared reflectance peak, which is commonly observed in dominant peat forming species such as *Sphagnum* mosses [*Bubier et al.*, 1997]. A more general concern about the reliance solely upon MODIS data for satellite-based GPP model development, is the current uncertainty relating to the continuity of the MODIS program, thus there is clearly a motivation to extend knowledge acquired from modeling efforts with the MODIS data sets to other sensor's data.

[8] In this study, we focus on exploring new ways of estimating peatland GPP from alternative sources of satellite data. Our approach is also based upon the logic of *Monteith* [1972] but focuses specifically on the estimation of vegetation chlorophyll content to inform GPP estimations, as opposed to more integrated measures of greenness and structure (e.g., the NDVI and EVI). Previous studies have shown good relationships between chlorophyll content and vegetation stresses, phenology and photosynthetic capacity [e.g., *Gitelson et al.*, 2006; *Jago et al.*, 1999; *Sun et al.*, 2008]. Because chlorophyll is essential for photosynthesis, estimations of chlorophyll content may constitute as a surrogate for the amount of energy that can be transferred for photosynthesis. A number of studies by *Gitelson et al.* [2008, 2006] have demonstrated that remote sensing techniques, developed for chlorophyll retrieval, can be used to estimate GPP in rainfed and irrigated Maize and Soybean crops. Using VIs derived from field spectroradiometry; the product of chlorophyll and photosynthetically active radiation (PAR) was shown to account for 98% of GPP variation in the crop canopies [*Gitelson et al.*, 2005]. Furthermore the relationship was non-species-specific. More recently *Harris and Dash* [2010] were the first to demonstrate strong correlations between EC estimated GPP and a chlorophyll index derived from the Medium Resolution Imaging Spectrometer (MERIS) on board the ENVISAT satellite. The MERIS terrestrial chlorophyll index (MTCI) product effectively combines information on leaf area index and the chlorophyll

concentration of leaves to produce an image of chlorophyll content [*Dash and Curran*, 2004]. The correlations between the MTCI and EC measures of GPP across a range of North American ecosystems was as good as, if not better than, those observed between EC GPP and the MODIS EVI and the more complex MODIS GPP (MOD17) product [*Harris and Dash*, 2010].

[9] In this study, we focus on exploring the relationships between the MTCI and EC measures of GPP in peatland ecosystems. We also develop and test a series of LUE-type regression models based on the MTCI to determine whether the inclusion of environmental variables such as PAR and temperature, improve the direct relationship between MTCI and GPP. To put the results in context, we compare the MTCI model results to those of obtained from the MODIS GPP product (MOD17), which is a satellite-based LUE model commonly use to estimate GPP [*Heinsch et al.*, 2003].

2. Methods

2.1. Peatland Study Sites

[10] We used carbon flux data from two contrasting Fluxnet Canada Research Network sites: the Mer Bleue peatland (Eastern Peatland) and the Western Peatland. Mer Bleue is a large, open, low-shrub raised bog covering approximately 25 km^2 [*Moore et al.*, 2002], located east of Ottawa, Ontario, Canada (45.40°N, 75.52°W). The region has a cool continental climate, with a mean annual temperature of 6°C and an annual rainfall of 732 mm [*Environment Canada*, 2006]. Due to the acidic nutrient-poor nature of the site, the vegetation mainly consists of evergreen species. Overstorey vegetation is dominated by a shrub canopy 20–30 cm high, and the bog surface is dominated by a hummock-hollow microtopography. Hummocks are occupied by the evergreen shrubs *Ledum groenlandicum*, *Kalmia angustifolium*, *Chamaedaphne calyculata* and the deciduous shrub *Vaccinium myrtilloides*. Hollows are approximately 20 cm lower, compose about 25% of the bog surface and have a sparser coverage of *L. groenlandicum, K. angustifolium*, and *C. calyculata*. The bog ground cover is dominated by *Sphagnum* mosses [*Moore et al.*, 2002]. The growing season is from May to September [*Lafleur et al.*, 2003] with an average temperature during this period of 17°C [*Environment Canada*, 2006]. The Western Peatland is a moderately rich treed fen located in the La Biche River area in Alberta, Canada (54.95°N, 112.46°W). The climate of the region is classified as continental with a mean annual temperature of 2.1°C and an annual rainfall of 382 mm [*Environment Canada*, 2006]. In contrast to Mer Bleue, the vegetation is largely composed of deciduous species. Stunted trees of *Picea maiana* and *Larix laricina* dominate the vegetation, with high abundance of the shrub *Betula pumila*, and a wide range of moss species including *Sphagnum*, brown and feather mosses [*Syed et al.*, 2006]. The growing season at the Western Peatland is from May to October [*Syed et al.*, 2006]. The avaerage tempertaure during this period is 12°C [*Environment Canada*, 2006]. Both sites are representative of peatlands in the boreal region.

2.2. Satellite Data

[11] Table 1 displays the sensor specifications for the MODIS and MERIS instruments. The spatial location of both the MERIS and MODIS data were carefully chosen to maximize the area of peatland covered by each 1 km pixel. At Mer Bleue, the EC tower is located approximately 300 m from the margin of the bog and has an ~1 km footprint. Approximately 80% of the flux emanates from within 200 m of the tower [*Connolly et al.*, 2009], which is largely dominated by hummocks [*Moore et al.*, 2006]. Inspection of the MERIS pixel footprint using Landsat data together with high resolution data obtained from Google Earth™, indicated that approximately 80% of the MERIS pixel was dominated by peatland land cover, deemed representative of the flux tower footprint, with the remainder covering a narrow band of mixed forest and cattail marsh to the south of the pixel (Figure 1). The EC tower footprint at the Western Peatland site ranges from 1.5 to 2 km in all directions except north where the fetch is ~1 km. The flux tower footprint is dominated by relatively homogeneous vegetation [*Syed et al.*, 2006] and is located toward the western edge of both the MERIS and MODIS pixels.

2.2.1. Medium Resolution Imaging Spectrometer (MERIS) Data

[12] The 1 km spatial resolution 8-day composites of MERIS MTCI were downloaded from the UK Natural Environment Research Council Earth Observation Data Centre (NERC NEODC; http://www.neodc.rl.ac.uk). The MTCI is a ratio of the difference in reflectance between band 10 and band 9 and the difference in reflectance between band 9 and band 8 of the MERIS standard band setting using the following equation [*Dash and Curran*, 2004]:

$$\begin{aligned} \mathrm{MTCI} &= \rho_{\mathrm{Band10}} - \rho_{\mathrm{Band9}} / \rho_{\mathrm{Band9}} - \rho_{\mathrm{Band8}} \\ &= \rho_{753.75} - \rho_{708.75} / \rho_{708.75} - \rho_{681.25}, \end{aligned} \tag{2}$$

where $\rho_{753.75}$, $\rho_{708.75}$, $\rho_{681.25}$ are reflectance in the center wavelengths of the MERIS standard band setting. The MTCI data were composited from standard Level 2 reduced resolution (geophysical) products using an arithmetic mean and a flux conversion resampling [*Curran et al.*, 2007].

[13] To determine how representative the 1 km MERIS MTCI data were of the tower footprints at each site, we obtained MTCI data from two years of full resolution (300m) MERIS data. We identified the 300 m pixels that were most representative of the 1 km pixel extents and extracted the standard level 2 MTCI values (Figure 1). For each site, we compared the amplitude and seasonal patterns of the 300 m and 1 km MTCI data.

2.2.2. Moderate Resolution Imaging Spectrometer (MODIS) Data

[14] The 1 km 8-day composites of MODIS Land Surface Temperature (LST; collection 5.0 data sets), fPAR and MOD17 GPP data (collection 5.1 data sets) were acquired from the Oak Ridge National Laboratory's Distributed Active Archive Centre (DAAC) (http://www.modis.ornl.gov/modis/index.cfm). We used the MODIS quality control flags to select data with low cloud cover and listed as "Good Quality." All LST data were derived from the Terra satellite, which has a morning overpass time between 1000 and 1100 h. The MOD17 GPP product is calculated using a LUE type model:

$$GPP = \varepsilon_{\max} * m(T_{\min}) * m(VPD) * fPAR * SWrad * 0.45, \tag{3}$$