Soil respiration mapped by exclusively use of MODIS data for forest landscapes of Saskatchewan, Canada

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A B S T R A C T

Soil respiration ($R_s$) is of great importance to the global carbon balance. Remote sensing of $R_s$ is challenging because of (1) the lack of long-term $R_s$ data for model development and (2) limited knowledge of using satellite-based products to estimate $R_s$. Using 8-years (2002–2009) of continuous $R_s$ measurements with nonsteady-state automated chamber systems at a Canadian boreal black spruce stand (SK-OBS), we found that $R_s$ was strongly correlated with the product of the normalized difference vegetation index (NDVI) and the nighttime land surface temperature (LSTn) derived from Moderate Resolution Imaging Spectroradiometer (MODIS) imagery. The coefficients of the linear regression equation of this correlation between $R_s$ and NDVI × LSTn could be further calibrated using the MODIS leaf area index (LAI) product, resulting in an algorithm that is driven solely by remote sensing observations. Modeled $R_s$ closely tracked the seasonal patterns of measured $R_s$ and explained 74–92% of the variance in $R_s$ with a root mean square error (RMSE) less than 1.0 g C/m²/d. Further validation of the model from SK-OBS site at another two independent sites (SK-OA and SK-OJP, old aspen and old jack pine, respectively) showed that the algorithm can produce good estimates of $R_s$ with an overall $R^2$ of 0.78 ($p < 0.001$) for data of these two sites. Consequently, we mapped $R_s$ of forest landscapes of Saskatchewan using entirely MODIS observations for 2003 and spatial and temporal patterns of $R_s$ were well modeled. These results point to a strong relationship between the soil respiratory process and canopy photosynthesis as indicated from the greenness index (i.e., NDVI), thereby implying the potential of remote sensing data for detecting variations in $R_s$. A combination of both biological and environmental variables estimated from remote sensing in this analysis may be valuable in future investigations of spatial and temporal characteristics of $R_s$.

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1. Introduction

The interannual variability in net ecosystem production (NEP) has been mainly attributed to the direct effects of climate variability on CO₂ assimilation through gross primary photosynthesis (GPP) and CO₂ loss through ecosystem respiration ($R_e$) (Valentini et al., 2000; Wu et al., 2013a). Soil respiration ($R_s$), the flux of microbially- and plant-respired CO₂ from the soil surface to the atmosphere, is the second-largest terrestrial carbon (C) flux (Bond-Lamberty and Thomson, 2010), and therefore is considered as one of the most significant components of the global C balance (Högberg et al., 2001). Recent results of Wu et al. (2013a) even suggest that respiration process might be more important than photosynthesis in determination of interannual variability of C balance in forests.

$R_s$ integrates several biological and physical processes, including the production of CO₂ by roots, mycorrhizal fungi, microorganisms and soil fauna throughout the soil profile, and the subsequent diffusion of CO₂ to the soil surface (Bond-Lamberty and Thomson, 2010; Gaumont-Guay et al., 2014). Seasonal variation in the ratio of $R_e$ to $R_s$ is constrained by the interactions among (a) phenological differences between aboveground and belowground plant tissues, (b) mobilization and use of stored substrates within woody plants, and (c) seasonal variation in photosynthesize and litter substrates (Davidson et al., 2006). The rate of $R_s$ is influenced by many
factors, which generally can be classified into abiotic (e.g., soil water content, SWC) and biotic elements (e.g., canopy photosynthesis). There is considerable evidence that $R_s$ is tied to soil temperature ($T_s$), across multiple spatial and temporal scales (Gaumont-Guay et al., 2006; Jassal et al., 2005; Jassal et al., 2012a). Consequently, $T_s$ plays an important role in many models of soil CO$_2$ production (Reichstein et al., 2003; Jassal et al., 2004; Ngao et al., 2012). SWC is suggested to have a more complicated effect on $R_s$ due to its strong link with soil-vascular processes (Gaumont-Guay et al., 2006; Griffis et al., 2004). Although the effects of $T_s$ and SWC on $R_s$ cannot always be separated easily, the relative importance of the two factors may be different in various climate conditions (Ekblad et al., 2005). As $R_s$ depends on the availability of organic substances respired by roots and microorganisms, photosynthetic activity supplying carbohydrates from leaves to roots and rhizosphere is also recognized as a key driver of $R_s$ (Moyano et al., 2008; Kuzyakov and Gavrichkoa, 2010; Caquet et al., 2012). This conclusion is supported by correlations between $R_s$ and GPP across land cover types (Yuan et al., 2009) as well as between $R_s$ and photosynthesis-related vegetation indices (Huang et al., 2012; Bond-Lamberty et al., 2012; Jassal et al., 2012a). Therefore, these environmental and biological variables may potentially provide useful insights into modeling $R_s$.

Large scale quantification of $R_s$ is a major challenge albeit we have long-term observations at many sites worldwide (Bond-Lamberty and Thomson, 2010) and fine spatial landcover information (Zhu and Toutin, 2013; Mitrakis et al., 2012). While a large dataset can provide a unique insight into $R_s$ patterns and its changes with climate, it is still limited considering both temporal and spatial heterogeneity in physical and biochemical properties. For example, observations of $R_s$ from the dataset of Bond-Lamberty and Thomson (2010) are at annual scale, making it impossible to analyze fine temporal (e.g., daily, monthly and seasonal) variations in $R_s$. Since an increasing number of global carbon cycling models include $R_s$ as a model input (Blongquist et al., 2006; Mahecha et al., 2011), it is important if $R_s$ can be modeled on the basis of remotely sensed data, which is also the most convenient way to investigate its spatiotemporal patterns. Such knowledge is useful in modeling ecosystem C changes over time and space (Trumbore, 2006; Bahn et al., 2010). Currently, there is no report on the operational use of $R_s$ modeling based on remote sensing observations. One important reason is that long-term $R_s$ measurements require a great amount of field work and such long $R_s$ record has not been accumulated sufficiently long to ensure a robust testing of algorithms. Recent analysis of Huang et al. (2012) show that the vegetation index derived from canopy measurements may be a good proxy of $R_s$. However, a limitation of these results is the inappropriate consideration of abiotic factors (e.g., temperature) that have been shown for long to have effects on $R_s$. Therefore, new algorithms are needed with reasonable parameterizations of both biotic and abiotic factors to estimate $R_s$ and such efforts would be helpful for analyzing spatial and temporal patterns of $R_s$ in future.

Using eight years (2002–2009) of soil CO$_2$ efflux measurements obtained with nonsteady-state automated chamber systems in a boreal black spruce stand (Jassal et al., 2012b; Gaumont-Guay et al., 2014), we propose a new approach to model $R_s$ based entirely on remotely sensed imagery from the Moderate Resolution Imaging Spectroradiometer (MODIS). We further applied the model at other two forest sites (an evergreen needleleaf forest and a deciduous broadleaf forest) with independent chamber measurements. Finally, we mapped $R_s$ of forest landscapes of the whole province using MODIS data and these efforts may serve as an important step in the investigation of spatial and temporal variability of $R_s$ in future.

### 2. Materials and methods

#### 2.1. Study sites

Three Boreal Forest Research and Monitoring Sites (BERMS) were used in this study, including (1) a mature aspen stand (SK-OAS, deciduous broadleaf forest), (2) a mature black spruce stand (SK-OBS, evergreen needleleaf forest) and (3) a mature jack pine stand (SK-OJP, evergreen needleleaf forest) (Black et al., 2000; Barr et al., 2004; Dunn et al., 2007; Zhang et al., 2009; Gaumont-Guay et al., 2009). These sites are located in the mid-boreal lowland ecoregion in the boreal plain ecozone near Prince Albert, Saskatchewan, Canada (Fig. 1). The climate of the region is typified by short, warm, dry summers and long, cold winters. These sites provide an opportunity to analyze $R_s$ of contrasting species at different sites. Detailed site characteristics for each site are provided in Table 1.

#### 2.2. MODIS data

Three land surface MODIS products were used and they were downloaded from the Oak Ridge National Laboratory’s Distributed Active Archive Center (DAAC) website (http://www.modis.ornl.gov/modis/index.cfm). The first is the 8-day Terra MODIS surface reflectance product (MOD09A1, 0.5 km) that provides surface reflectance for seven wavelength bands (centered at 448, 588, 470, 555, 1240, 1640, and 2130 nm, respectively). Each pixel contains the best possible observation during an 8-day period as selected on the basis of high observation coverage, low viewing angle, the absence of clouds or cloud shadow, and aerosol loading (Justice et al., 2002). The reflectance for the first two wavelength bands were used to calculate the normalized difference vegetation index (NDVI) as,

$$\text{NDVI} = \frac{(R_{\text{NIR}} - R_{\text{Red}})}{(R_{\text{NIR}} + R_{\text{Red}})}$$

where $R_{\text{NIR}}$ and $R_{\text{Red}}$ represent the reflectance for the near-infrared (MODIS band 2) and red (MODIS band 1) wavelength bands (nm), respectively.

The second MODIS product is the 8-day Land Surface Temperature (LST) (MOD11A2, 1 km) derived by applying the generalized split-window algorithm (Wan, 2008). In the split-window algorithm, emissivities in bands 31 and 32 are estimated from land cover types, and atmospheric column water vapor and lower boundary air surface air temperature are separated into tractable sub-ranges for optimal retrieval (Wan, 2008). Both daytime and nighttime LST (referred as LSTd and LSTn, respectively, hereafter) were used in this study.

The third MODIS product is the 8-day leaf area index (LAI) product (MOD15A2, 1 km). LAI is defined as the one-sided green leaf area per unit ground area in broadleaf canopies and as half the total needle surface area per unit ground area in coniferous canopies (Chen et al., 1997). The MODIS LAI product is derived from the surface reflectance, the land cover type, and ancillary information on surface characteristics such as background (Myhneni et al., 2002).

Based on the geo-location information of the site, NDVI was extracted from the 3 × 3 pixel area with its center point close to the flux tower (Xiao et al., 2004; Wu et al., 2011, 2014). For the LST (both LSTd and LSTn) and LAI products, we also used the values for the 3 × 3 pixels considering the seasonal variations of the flux footprints reported for these sites (>3 km$^2$, Chen et al., 2011) and previous C fluxes modeling approaches (Sims et al., 2008; Wu et al., 2012).
2.3. Soil CO2 efflux measurements

Similar nonsteady-state automated chamber systems were used to continuously measure soil CO2 efflux at these three sites. Other variables such as near-surface soil temperature (\(T_s\), 5-cm depth), volumetric soil water content (SWC, 7.5-cm depth) and radiation, were also measured. All chambers, which had a volume of approximately 60 L, were randomly located within a 25-m radius of temperature-controlled housings (TCHs) containing an infrared gas analyzer, pumping and data logging equipment. Each chamber consisted of a moveable transparent lid attached by hinges to a fixed collar inserted between 3 and 4 cm into the soil. The lids were kept open when the chambers were not in use to allow rain, snow and litter to fall into the collar area.

For SK-OBS site (modeling site), a long-term dataset was obtained during 2002–2009 (Gaumont-Guay et al., 2014). Two identical chamber systems were used during the eight years; the first system was used from 2002 to 2003 and the second system from 2004 to 2009. The total number of chambers used during the periods of 2002–2003, 2004–2006 and 2007–2009 were 5, 7 and 6, respectively. The forest-floor vegetation during the first measurement period contained the feather moss, herbaceous,

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**Table 1**

<table>
<thead>
<tr>
<th>Sites</th>
<th>Old black spruce (SK-OBS)</th>
<th>Old aspen (SK-OA)</th>
<th>Old jack pine (SK-OJP)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Location</td>
<td>53.99 N, -105.12 W</td>
<td>53.63 N, -106.20 W</td>
<td>53.92 N, -104.69 W</td>
</tr>
<tr>
<td>Plant functional type</td>
<td>Evergreen needle-leaf forest</td>
<td>Deciduous broad-leaf forest</td>
<td>Evergreen needle-leaf forest</td>
</tr>
<tr>
<td>Data usability</td>
<td>Modeling</td>
<td>Independent validation</td>
<td>Independent validation</td>
</tr>
<tr>
<td>Stand age (2012)</td>
<td>133</td>
<td>93</td>
<td>83</td>
</tr>
<tr>
<td>Dominant species</td>
<td>Black spruce, jack pine, tamarack</td>
<td>Trembling aspen, hazelnut</td>
<td>Jack pine, alder, lichen</td>
</tr>
<tr>
<td>Drainage*</td>
<td>Imperfect to poor</td>
<td>Well to moderately well</td>
<td>Very well</td>
</tr>
<tr>
<td>Mineral layer</td>
<td>Sandy clay</td>
<td>Loam to clay</td>
<td>Fine sand</td>
</tr>
<tr>
<td>Stand density (trees ha-1)</td>
<td>4330</td>
<td>980</td>
<td>1520</td>
</tr>
<tr>
<td>Tree height (m)</td>
<td>7.2</td>
<td>20.1</td>
<td>12.7</td>
</tr>
<tr>
<td>DBH (cm)</td>
<td>7.1</td>
<td>20.5</td>
<td>12.9</td>
</tr>
</tbody>
</table>

* Data from Gaumont-Guay et al. (2009).
and hollow. Additional forest-floor vegetation, such as sphagnum, lichen, and mineral soil, were included during the second measuring period. For both SK-OA and SK-OJP, four soil chambers were used throughout 2003. For SK-OA, herbaceous plants growing in the collar area were clipped regularly to expose only the bare soil. For SK-OJP, three of the four chambers were used to represent the lichen community and the remaining one represented the mixed feather moss and lichen area. More detailed descriptions of ground measurements and instruments can be found in Gaumont-Guay et al. (2009).

Half-hourly soil CO₂ efflux, \( F_{cs} \) (\( \mu \text{mol CO}_2 \text{ m}^{-2} \text{ s}^{-1} \)), was calculated as:

\[
F_{cs} = \rho_a \frac{V_e \, ds_e}{dt}
\]

where \( \rho_a \) is the molar density of dry air (\( \text{mol m}^{-3} \)), \( V_e \) is the effective volume of the chamber (\( \text{m}^3 \)), \( A \) is the area of ground covered by the chamber (\( \text{m}^2 \)), \( \frac{ds_e}{dt} \) is the time rate of change in the CO₂ molar mixing ratio (\( \mu \text{mol CO}_2 \text{ mol}^{-1} \text{ dry air s}^{-1} \)) following lid closure, and \( t \) is the time (s).

Half-hourly measurements from all chambers were averaged to obtain representative half-hour values and were then summed to acquire daily totals (Griffis et al., 2004; Gaumont-Guay et al., 2009). Considering that the remote sensing data provide observations at ecosystem scale (i.e., 1 km resolution), a scaling-up algorithm was used to scale the component fluxes of chamber measurements to ecosystem level according to the percent coverage of the forest-floor communities as described in Bisbee et al. (2001) and Gaumont-Guay et al. (2014). In particular, previous results of Gaumont-Guay et al. (2014) at SK-OBS site showed that the data-scaling algorithm is independent on the time of data acquisition and did not introduce significant inaccuracies in the model development for \( R_s \) estimation.

2.4. Partitioning soil CO₂ efflux into \( R_s \) and \( P_{ff} \) at SK-OBS and SK-OJP

Considering the lids of chambers for soil CO₂ efflux measurements were transparent, which would allow radiation to reach the forest floor covered by a thick mat of feather and sphagnum mosses, for SK-OBS and SK-OJP, the half-hourly measured soil CO₂ efflux is the net forest-floor CO₂ exchange, which represents the balance between \( R_s \) (autotrophic (roots and mosses) and heterotrophic (microbial) respiration) and moss photosynthesis. For SK-OA, no contribution of forest-floor photosynthesis (\( P_{ff} \)) was observed since the chambers only included bare soil (Gaumont-Guay et al., 2009). Therefore, for the two evergreen needleleaf forest stands (SK-OBS and SK-OJP), procedures were needed to partition \( F_{cs} \) into \( R_s \) and \( P_{ff} \).

To separate \( R_s \) from \( F_{cs} \), we used the method proposed by Gaumont-Guay et al. (2014). Briefly, an exponential equation relating surface soil temperature (\( T_s \), 5-cm depth) and the nighttime (below canopy PAR<sub>1m</sub> < 5 \( \mu \text{mol m}^{-2} \text{ s}^{-1} \), \( P_{ff} \) equals to zero) half-hourly measured soil CO₂ efflux (i.e., nighttime soil respiration) was used to estimate daytime \( R_s \).

\[
F_{cs} = R_{10}Q_{10}^{(T_s-10)/10}
\]

where \( Q_{10} \) and \( R_{10} \) represent the temperature sensitivity coefficient and the base soil respiration at 10 °C (\( \mu \text{mol m}^{-2} \text{ s}^{-1} \)), respectively. These parameters together with daytime \( T_s \) were used to model daytime \( R_s \), and \( P_{ff} \) was then determined as the difference between measured \( F_{cs} \) and the modeled daytime \( R_s \).
Gaps in the $P_{ff}$ record were filled using a rectangular hyperbolic function (Gaumont-Guay et al., 2009),

$$P_{ff} = aP_{ff,max} + P_{below}$$

where $a$, $P_{ff,max}$, and $P_{below}$ represent the apparent quantum use efficiency, the horizontal asymptotic value of $P_{ff}$, and the below canopy radiation, respectively.

2.5. Modeling strategy

The objective of our analysis is to develop a new model that estimates $R_s$ entirely based on MODIS data and to validate the model at independent sites. Since much longer dataset was available at SK-OBS site, we mainly focused on this site to develop the model and measurements from other two sites were then used for independent validation. Therefore, we first explored MODIS-derived NDVI and LST (both LSTd and LSTn) in their strength to explain $R_s$ variations using 8 years of records at SK-OBS site. The evaluation was conducted considering that $R_s$ was controlled by both biotic (e.g., photosynthesis) and abiotic factors (e.g., temperature). We then also calibrated the model, i.e., determining coefficients of regression, using MODIS observations (i.e., statistics of time series of LAI) to ensure that all inputs are from remote sensing data. In addition, we tested the general applicability of the model derived at SK-OBS site at another two sites of both deciduous broadleaf and evergreen needleleaf forests with independent measurements. Finally, we mapped $R_s$ of forest landscapes (forest pixels were identified from the 2005 North American Land Cover at 250 m spatial resolution, http://www.cec.org/naatlas/) of the whole province of Saskatchewan with the algorithm using entirely MODIS data to show the spatial and temporal patterns of $R_s$. Since the MODIS LSTn had the lowest spatial resolution among all inputs of the algorithm (MODIS reflectance, LST and LAI products), the final $R_s$ map was produced at 1 km spatial resolution monthly, which was summed from each 8-day simulation.

3. Results

3.1. Relationship between $R_s$ and MODIS NDVI, LSTd and LSTn

We found that NDVI was an important driver of $R_s$ explaining 82% of the variance in $R_s$ in the black spruce stand, confirming the connection between belowground processes and photosynthetic activity (Fig. 2a). However, this connection seemed time dependent as NDVI was only useful in predicting $R_s$ during the growing season, i.e. for NDVI > 0.4. For NDVI < 0.4, $R_s$ was relatively constant, probably due to low respiratory activity at low temperatures and thus cannot be captured by variations in NDVI. Furthermore, there were also significant relationships between $R_s$ and MODIS-derived LST and LSTn was found to be a stronger predictor of $R_s$ (Fig. 2b and c). Based on these results, we hypothesized that predicting $R_s$ using the product of NDVI and LSTn would be successful. We found that 8-day-averaged $R_s$ was highly correlated with NDVI × LSTn with $R^2 = 0.86$, $p < 0.001$ (Fig. 2d). In particular, a linear relationship between $R_s$ and NDVI × LSTn would be helpful for improving $R_s$ modeling both at its high and low ends as,

$$R_s = a(NDVI × LSTn) + b$$

where $a$ is the slope and $b$ is the intercept.

3.2. Model calibration using site specific indicators

We calibrated this algorithm, i.e., determining the parameters, $a$ and $b$ in Eq. (5), using site specific indicators. For each year, we correlated 8-day average $R_s$ with NDVI × LSTn using annual data and obtained yearly values of $a$ and $b$ for 2002–2009. Results showed that while the annual value of $a$ was linearly correlated ($R^2 = 0.73$, $p = 0.007$) to annual LAImax, the annual value of $b$ was linearly correlated ($R^2 = 0.74$, $p = 0.005$) to annual LAIave (Fig. 3).
Fig. 5. Relationship between the modeled and measured soil respiration ($R_s$) at SK-OBS for the years 2002–2009. The dashed lines show the 95% confidence intervals of mean prediction for the regression line.
Therefore, the new model of Eq. (5) with calibration coefficients can be further written as,

\[ R_t = a(NDVI \times LSTn) + b \]

\[ a = 0.09LAI_{max} - 0.01 \]

\[ b = 1.98LAI_{ave} - 0.43 \]  \hspace{1cm} (6)

3.3. Modeled soil respiration validation

As expected, a comparison of using Eqs. (5) and (6) to calculate \( R_t \) values for each year showed that Eq. (6) described the measurements better for each year (Fig. 4). Accordingly, relationships between measured and modeled values of \( R_t \) for each year using Eq (6) are shown in Fig. 5. The highest correlation between modeled and measured \( R_t \) was observed in 2006 with an \( R^2 \) of 0.92 (p < 0.001) and the lowest correlation was found for 2004 and 2005 both with an \( R^2 \) of 0.74 (p < 0.001). For the remaining years, values of \( R^2 \) were greater than 0.80, indicating a good performance of this model. The root mean square error of the modeled values varied between 0.6 g C m\(^{-2}\) d\(^{-1}\) in 2006 and 1.0 g C m\(^{-2}\) d\(^{-1}\) in 2005.

Model validation using independent measurements at SK-OA and SK-OJP sites was also promising (Fig. 6). We found that for both sites, modeled \( R_t \) was significantly correlated with measurements with \( R^2 \) of 0.82 (p < 0.001) and 0.73 (p < 0.001) for SK-OA and SK-OJP, respectively. RMSE for each site was also reasonable. For the combined data of two sites, a significant correlation was found between model estimates and measurements that the model can explain 78% of \( R_t \) variance using entirely MODIS data with an RMSE of 1.5 g C m\(^{-2}\) d\(^{-1}\).

3.4. Spatial and temporal patterns of mapped \( R_t \)

Based on above evaluations, we mapped monthly \( R_t \) using entirely MODIS data for forest landscapes of the whole province in 2003 (Fig. 7). Temporal patterns of \( R_t \) were well captured that modeled \( R_t \) showed clear seasonal evolutions with relatively low simulations in the dormant season (November–March). \( R_t \) increased quickly after the start of the growing season and maximized in summer months and then underwent an evident decrease since autumn. Spatial patterns of \( R_t \) were also well simulated that broadleaf deciduous forests showed higher \( R_t \) than that of the evergreen needleleaf forests. A general decrease pattern in \( R_t \) was also found from south to north regions, probably because of lower temperature as latitude increases.

4. Discussion

4.1. The role of nighttime LST

The impact of soil temperature on \( R_t \) has been intensively investigated. Here we found that the MODIS LST product could be used in models predicting \( R_t \). Our data suggest that LSTn has a greater potential in explaining variations in \( R_t \) than LSTd. A possible reason from all data at SK-OBS site is that LSTn is much more resistant to various residual noise components (Fig. 8). We calculated standard deviations of both LSTd and LSTn (i.e., sdLSTd and sdLSTn) from 2002 to 2009 and found that sdLSTn was much lower than sdLSTd, implying the former will reduce noise in the calculated temporal course of \( R_t \). These results may also imply that LSTn could be a better estimate of the baseline temperature that regulates plant phenology (Sims et al., 2008).

4.2. Implications of calibration

We found that the slopes and intercepts of the \( R_t \) vs. NDVI \times LSTn relationship (i.e., \( a \) and \( b \)) could be expressed as functions of seasonal LAImax and LAIave, respectively. The slopes should ideally represent the rate at which \( R_t \) increases with per unit NDVI \times LSTn. Since \( R_t \) consists of both microbially and root-respired C, it should be dependent directly on the input of carbon from living plants (Moyano et al., 2008). This likely explains why \( a \) was found to be significantly correlated with LAImax, since it partly determines the amount of carbohydrates that are transferred from leaves to the rhizosphere. This is consistent with the results of Janssens et al. (2001) that productivity (LAI being a proxy for it in this study) is tied to \( R_t \) since the availability of organic matter (leaves, fine roots) for respiration depends on primary productivity. The value of \( b \) may not have specific physiological indications and is simply the value of \( R_t \) at an LSTn of zero. One significant contribution of our analysis is that the calibration approach (i.e., using statistics of LAI to determine regression coefficients) works well for the other two independent sites, suggesting the general suitability of our algorithm to estimate \( R_t \) across plant functional types. This probably could be a great advantage towards the exploration of spatial patterns of \( R_t \) using remote sensing in future.

4.3. Factors influencing model performance

To better explain the interannual behavior of model performance, using long-term data at SK-OBS site, we found that the value of \( R^2 \) between \( R_t \) and NDVI \times LSTn was negatively correlated with the standard deviation of SWC (sdSWC) while being positively correlated with the standard deviation of LAI (sdLAI) (Fig. 9). The relationship between \( R^2 \) and sdSWC suggests that our model is affected by soil water status, which has been recognized as a quite challenging task from optical remote sensing (Albergel et al., 2012). Larger values of sdSWC in SK-OBS appeared to be the result of above-average precipitation during the growing season. For example, a value of sdSWC of 14.3% was observed in 2004, when the growing season precipitation was 30% above the 8-year average. A similar condition was also observed in 2005 (sdSWC of 11.2%). For these two years, NDVI \times LSTn was only able to explain 71% and 72% of the variance in \( R_t \), respectively. For severe drought years, e.g., 2003, NDVI \times LSTn also had a moderate accuracy in estimating \( R_t \). The highest ability of NDVI \times LSTn to explain \( R_t \) \((R^2 = 0.92)\) was found in 2006, a year with slightly high annual precipitation (5% above average). These results imply that the SWC...
may have competing effects on model performance, so that our algorithm still performed moderately well in capturing variations in $R_s$ under these conditions. A complicated relationship between soil water status and ecosystem functioning will make modeling $R_s$ challenging in either extremely wet or droughty conditions (Wu et al., 2013b). Analysis aimed at partitioning $R_s$ into its autotrophic and heterotrophic components may be a potential way to better understand the response of $R_s$ to SWC (Moyano et al., 2013). This agrees with findings reported in Gaumont-Guay et al. (2014) that SWC alone was only able to explain 18% of $R_s$ variations and may also explain that even without considering water status in the algorithm, our approach still has the potential to capture the first order of spatial and temporal variations of $R_s$. Better model performances for years with large variations in LAI may simply be a reflection that the model would give better results under favorable growth conditions because larger $sd_{LAI}$ is associated with higher seasonal LAI$_{max}$.

4.4. Temporal and spatial constrains of the model

Temporal and spatial constrains of the model should be highlighted to address its sensitivity with respect to sampling size and temporal resolution. Our algorithm is proposed at 8-day temporal scale, and this excludes the interface from seasonality. For
example, the good model performance would be definitely influenced by vegetation seasonality at monthly temporal scale. However, if we can demonstrate the model at 8-day period, such concern can be resolved. For the spatial aspect, we only have validation data at flux tower sites and this limits the resolution to 1 km. Currently, it might be impossible to analyze the spatial sensitivity since there is no ground data to support such experiment. Therefore, the confidence of spatial patterns of Rs modeled is based on the results shown in Figs. 5 and 6. Consequently, it is difficult to show the areas with low correlations because of data availability. Overall, our analysis is focused on the development of new models for soil respiration modeling and to link the model with semi-physical explanations. Technical issues related to computational ability and algorithm portability are not concerned at present.

4.5. Potentials and implications for remote sensing of Rs

Remote sensing data provide a real opportunity to robustly test predictions of Rs with respect to changes in controlling factors for large spatial extent and sample size. We found that Rs was correlated with NDVI. However, NDVI alone is not able to explain variations in Rs very well, especially considering the relatively constant values of Rs for NDVI < 0.4 at SK-OBS site (Fig. 2a). This feature potentially suggests that NDVI may only provide useful signals of Rs during the growing season when photosynthesis is active. For dormant seasons when photosynthesis is limited by low temperature, NDVI is no longer an indicator of Rs, which is largely controlled by soil temperature. Thus, results of recently reported relationships between Rs and spectral vegetation index in Huang et al. (2012) should be viewed with caution because only measurements of two crops during the growing season were included. Here we showed high precision in predicting Rs by combining NDVI and LSTn and the model also showed promising validation at independent sites with different plant functional types. By combine both NDVI and LSTn, our model still reasonably reproduced Rs both for the growing season and the dormant season. Though there was overestimation of Rs at its low range (Fig. 5), improvements can be achieved compared with the NDVI-only estimation. By including LSTn, we can partly mitigate the strong dependence on the quality of NDVI. For example, even when NDVI is contaminated by the presence of snow in winter, restriction from low LSTn can still provide reasonable estimates of Rs. One potential way to solve this problem would be the separation of growing and dormant seasons, which might require a new module to determine the time of growing season start and end. This might not be easily determined using empirical approach of temperature because of large interannual variability of growing season length reported at these sites (Wu et al., 2013a). Furthermore, this may also lead to additional variables that make our approach not entirely driven by remote sensing observations.

Our results mainly contribute to our understanding in two aspects. First, it confirms that belowground activities, to some degree, can be linked to aboveground photosynthesis, supporting the claim that Rs is an indicator of plant metabolism (Moyano et al., 2008; Caquet et al., 2012). However, this linkage may be time dependent and is only valid within the growing season. More importantly, since NDVI and LSTn can be acquired by satellite data, this method has the potential to be upscaled regionally or even globally after rigorous calibrations among other plant functional types (e.g., crops and grasslands). Therefore, it will provide a unique way to analyze the response of Rs to climate change spatially and temporally, considering the long term records of NDVI going back to late the 70s of the last century.

5. Conclusions

The availability of automated soil respiration measurements provides sub-hourly information to observe short-term variation in soil respiration and allows for better understanding of the controls of soil respiration across various temporal scales. An eight-
year continuous soil CO₂ efflux was measured at a boreal black spruce stand and a new approach was proposed to predict 8-day average \( R_s \) using solely MODIS observations. Additional validation at other two sites of different plant functional types was also successful, indicating high level of portability of the new model. Spatial and temporal patterns of \( R_s \) for all forested areas in Saskatchewan were well captured using the model we proposed, representing a potential way to upscale \( R_s \) from site level measurements to regional scale. These results suggest the close linkage between the processes of photosynthesis and respiration. In particular, we have shown the potential of satellite data in the estimation of \( R_s \), which would be a valuable tool in the exploration of the spatio-temporal characteristics of \( R_s \) in future climate change scenarios. Further analysis would involve the application of this model at more sites in diverse ecoregions and calibration across various plant functional types (e.g., grasslands, savannas).

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