Estimating landscape net ecosystem exchange at high spatial–temporal resolution based on Landsat data, an improved upscaling model framework, and eddy covariance flux measurements

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A B S T R A C T

More accurate estimation of the carbon dioxide flux depends on the improved scientific understanding of the terrestrial carbon cycle. Remote-sensing-based approaches to continental-scale estimation of net ecosystem exchange (NEE) have been developed but coarse spatial resolution is a source of errors. Here we demonstrate a satellite-based method of estimating NEE using Landsat TM/ETM + data and an upscaling framework. The upscaling framework contains flux-footprint climatology modeling, modified regression tree (MRT) analysis and image fusion. By scaling NEE measured at flux towers to landscape and regional scales, this satellite-based method can improve NEE estimation at high spatial-temporal resolution at the landscape scale relative to methods based on MODIS data with coarser spatial–temporal resolution. This method was applied to sixteen flux sites from the Canadian Carbon Program and AmeriFlux networks located in North America, covering forest, grass, and cropland biomes. Compared to a similar method using MODIS data, our estimation is more effective for diagnosing landscape NEE with the same temporal resolution and higher spatial resolution (30 m versus 1 km) ($r^2 = 0.7548$ vs. 0.5868, RMSE = 1.3979 vs. 1.7497 g C m$^{-2}$ day$^{-1}$, average error = 0.8950 vs. 1.0178 g C m$^{-2}$ day$^{-1}$, relative error = 0.47 vs. 0.54 for fused Landsat and MODIS imagery, respectively). We also compared the regional NEE estimations using Carbon Tracker, our method and eddy-covariance observations. This study demonstrates that the data-driven satellite-based NEE diagnosed model can be used to upscale eddy-flux observations to landscape scales with high spatial–temporal resolutions.

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1. Introduction

A number of different methods have been developed to estimate net ecosystem carbon exchange (NEE), which can be classified as top-down or bottom-up approaches. Under some pieces of constraining information, such as regional prior flux estimates (e.g. Gurney et al., 2003) or an imposed error covariance structure (e.g. Gourjdi, Mueller, Schaefer, & Michalak, 2008; Michalak, Bruhwiler, & Tans, 2004; Mueller, Gourjdi, & Michalak, 2008), the top-down approaches are based on atmospheric CO2 concentration measurements and inverse modeling (Claeys et al., 2010; Deng et al., 2007; Gurney, Baker, Rayner, & Denning, 2002, 2008; Gurney et al., 2002; Hayes et al., 2012; Peters et al., 2010) to estimate the surface emissions given observed fields of atmospheric CO2 concentration, wind speed and wind direction. The bottom-up approaches use...
observations of the surface properties to resolve CO2 emission rates, including using emission models based on observations from eddy-covariance (EC) flux-towers, biomass inventories (Peylin et al., 2005;ustinson et al., 2011), terrestrial biosphere models (Hayes et al., 2012; Keenan, Baker, et al., 2012) and remote sensing data products (Churkina, Schimel, Braswell, & Xiao, 2005; Xiao, Zhuang, et al., 2011; Xiao et al., 2008). Progress in estimating carbon fluxes has been achieved at either the large, continental scale (Gurney et al., 2002, 2008) or the local, ecosystem scale (typically less than 1–3 km² for each site) (Chen et al., 2012). However, the landscape-scale (10¹–10² km²) carbon flux and especially its spatial–temporal variations remain poorly modeled (Chen, Chen, Mo, Black, & Worthy, 2008; Cook et al., 2004; Piao et al., 2009). Accurate quantification of the NEE dynamics at the landscape and regional scales is comparatively weak and achieving greater accuracy and precision of modeling at this level are crucial to improving our understanding of the terrestrial carbon cycle locally and for reducing global carbon budget errors (Keenan, Davidson, Moffat, Munger, & Richardson, 2012; Tang et al., 2012; Xiao, Chen, Davis, & Reichstein, 2012; Xiao, Davis, Urban, Keller, & Saliendra, 2011; Xiao, Zhuang, et al., 2011; Xiao et al., 2008).

Remote-sensing-based methods have the potential to scale the EC measurement of NEE to larger spatial scales. Unlike other bottom-up methods, remote-sensing-based approaches are not limited by the availability of the in situ ground measurements. Veroustraete, Patyn, and Mylnei (1996) combined normalized difference vegetation index (NDVI) and land surface flux data to estimate NEE using an ecosystem model. Maselli, Chiesi, Fibbi, and Moriondo (2008) and Maselli et al. (2010) combined aircraft EC flux data, remote-sensing-based and process-based ecosystem models to estimate NEE at different spatial–temporal scales. Mahadevan et al. (2008) used a satellite-based assimilation scheme to estimate NEE based on vegetation indices derived from Moderate Resolution Imaging Spectroradiometer (MODIS) data, climate data and tower EC flux data. Xiao et al. (2008), Xiao, Zhuang, et al. (2011) estimated NEE at 1-km and 8-day resolutions over the conterminous United States by combining MODIS imagery and tower EC flux data from the AmeriFlux database using the modified regression tree (MRT) method. To our knowledge, there has been no such published study estimating landscape-scale NEE with high spatial (less than 100 m) and high temporal resolutions by making use of available global EC flux data and remote sensing imagery.

In this study, we developed an integrated method to estimate NEE at landscape scales with high spatial resolution (30 m) by synthesizing EC flux measurements with remotely-sensed data to account for the land surface heterogeneity. This approach combines an enhanced spatial and temporal adaptive reflectance fusion model (ESTARFM, Zhu, Chen, Gao, Chen, & Masek, 2010), a Simple Analytical Footprint model on Eulerian coordinates (SAFE-f, Chen, Black, Coops, Hilker, et al., 2009; Chen et al., 2010, 2012) and the MRT method.

This approach employs these assumptions: i) only the target land-cover type observed by the flux tower (of which the flux footprint is typically less than 1–3 km², Chen et al., 2010) is taken as the contribution of observed carbon flux and selected for upscaling using a footprint model, ii) the variation of phenology and the difference between the nearest available Landsat surface reflectance data and the corresponding MODIS
8-day surface reflectance products during a short time interval (i.e., 8 days) are small enough to be ignored, and iii) the land surface temperature (LST) data derived from Landsat (around local noon time) can represent the average temperature status of land surface over 8-day period.

### 2. Data and methods

Fig. 1 presents the flowchart of the landscape NEE estimation algorithm with high spatial–temporal resolution. First, the probability distribution functions of the EC flux footprint for the corresponding Landsat or fused Landsat-like imagery periods (an 8-day interval, 2000–2006) were calculated using the footprint model—SAFE-f (Chen, Black, Coops, Hilker, et al., 2009), and then the Landsat data were weighted by a flux footprint probability density function (PDF) for the area surrounding the tower. The fused Landsat-like imagery was produced by an image fusion model which will be used at the third step. The image fusion model, described in details at Section 2.3.3, was used to produce Landsat-like imagery after blending Landsat TM/ETM+ and MODIS imagery. Second, the regression-based NEE diagnosed model, which combined with several linear regression models and subjected to certain limits (see Section 2.3.1), was produced and then calibrated by MRT. The data used for the diagnosed model were the weighted reflectance, derived vegetation index, LST of Landsat imagery and the corresponding EC flux data. The period for training set and test set of MRT were 2000–2004 and 2005–2006, respectively. Third, the landscape NEE at 8-day intervals was estimated using the regression-based NEE diagnosed model based on the combination of original and fused Landsat surface reflectance data using an image fusion model (ESTARFM), vegetation index derived from original and fused Landsat reflectance, Landsat LST and MODIS LST data. The MODIS LST data were combined with fused

### Table 1

Descriptions of flux sites in this study. Site ID and name: First two letters indicate the province (MB – Manitoba, SK – Saskatchewan, BC – British Columbia) of Canada (CA), US indicates United States.

<table>
<thead>
<tr>
<th>Land cover type</th>
<th>Site ID</th>
<th>Site name</th>
<th>Longitude</th>
<th>Latitude</th>
<th>Flux data range</th>
<th>Path</th>
<th>Row</th>
<th>Reference</th>
</tr>
</thead>
</table>
Landsat reflectance data. Combined with previous three steps, it called Landsat-based diagnosed model compared to MODIS-based diagnosed model which using surface reflectance, vegetation index and LST derived from MODIS data. These are both bottom-up models while Carbon Tracker (CT) (Peters et al., 2007; Zhang, Chen, & Peters, 2013) discussed below is a top-down model. Finally, the diagnosed NEE was evaluated using tower EC flux data and compared to CT.

2.1. Study area and data

2.1.1. Study area

We selected a west–east continental region of North America containing sixteen representative flux towers, where include the most parts of Canada and the contiguous US (Fig. 2). We were able to take advantage of the established flux stations in the AmeriFlux and the Fluxnet-Canada/Canadian Carbon Program networks. This region contains four plant functional types (Table 1): needleleaf forest (4 sites), broadleaf forest (4 sites), grassland (4 sites) and cropland (4 sites), which were reclassified from ten broad classes based on the University of Maryland classification system (Friedl et al., 2002). Specifically, needleleaf forest type includes the evergreen needleleaf forest (ENF) and deciduous needleleaf forest (DNF); the broadleaf forest type includes evergreen broadleaf forest (EBF) and deciduous broadleaf forest (DBF); the grassland type includes closed shrublands (CSH), open shrublands (OSH), wood savannas (WSA), savannas (SAV) and grassland (GRA); the cropland type includes cropland (CRO).

2.1.2. Data

The datasets used in this study include the following four types for the period 2000–2006: i) Landsat TM/ETM+ reflectance and LST data,
ii) MODIS reflectance, LST and land cover type data; iii) NEE data obtained from EC flux towers, and iv) meteorological data measured at the flux towers for the SAFE-f model inputs.

Landsat TM/ETM+-level 1 products around the EC flux towers (6 km × 6 km) were acquired from the United States Geological Survey (USGS) EarthExplorer (http://edc17.cr.usgs.gov/NewEarthExplorer/) for the period 2000–2006. The path and row of Landsat data for the SAFE-f model inputs were processed for Landsat TM/ETM+ using the automated registration and orthorectification package (AROP) (Gao, Masek, & Wolfe, 2009). Subsequently, the digital number (DN) values of Landsat TM/ETM+ were calibrated and atmospherically corrected to surface reflectance using the Landsat Ecosystem Disturbance Adaptive Processing System (LEDAPS) (Masek et al., 2006). For Landsat thermal band, DN values are converted to radiance values using the bias and gain values specific to the individual scene, then convert radiance data to LST applying the inverse of the Planck function (Sobrino, Jiménez-Muñoz, & Masek, 2010) to the individual scene, then convert radiance data to LST apply

<table>
<thead>
<tr>
<th>ID</th>
<th>Condition</th>
<th>NEE simulation (g C m⁻² day⁻¹)</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>Rₜ ≤ 0.047516, LST &gt; 23.799, LST ≤ 26.476, EVI &gt; 0.33611, land cover in (CL)</td>
<td>NEE = -2.3967259 - 385.1 Rₜ + 236.9 Rₜ + 145.9 Rₜ - 44.7 EVI + 39.6 Rₜ + 33.5 Rₜ - 33.9 Rₜ</td>
</tr>
<tr>
<td>2</td>
<td>Rₜ ≤ 0.047516, LST &gt; 26.476, land cover in (CL)</td>
<td>NEE = 43.1281896 - 1.792 LST + 34.6 Rₜ - 26.7 Rₜ + 3.4 Rₜ - 1 EVI - 1.4 Rₜ + 0.9 Rₜ - 0.8 Rₜ</td>
</tr>
<tr>
<td>3</td>
<td>Rₜ &gt; 0.11248, LST &gt; 23.799, EVI &gt; 0.33611, land cover in (CL)</td>
<td>NEE = 15.7906973 - 692.9 Rₜ + 354.8 Rₜ + 262.4 Rₜ - 89.3 LST + 70 Rₜ + 73.8 Rₜ - 59.8 Rₜ - 5.1 NDWI</td>
</tr>
<tr>
<td>4</td>
<td>Rₜ &gt; 0.19474, Rₜ ≤ 0.11248, LST &gt; 23.799, EVI &gt; 0.33611</td>
<td>NEE = -9.8359327 + 147.9 Rₜ - 69 Rₜ + 68.5 Rₜ - 16 EVI + 6.6 Rₜ - 3.7 Rₜ + 0.8 NDWI</td>
</tr>
<tr>
<td>5</td>
<td>Rₜ &gt; 0.052542, EVI &gt; 0.33611, NDWI &gt; 0.30323, NDWI ≤ 0.41188, land cover in (BF, GR, NF)</td>
<td>NEE = 8.7090229 - 85.8 Rₜ - 23.7 NDWI + 42.4 Rₜ</td>
</tr>
<tr>
<td>6</td>
<td>Rₜ &gt; 0.047516, LST &gt; 23.799, EVI &gt; 0.33611, land cover in (CL)</td>
<td>NEE = 23.5193427 - 819.1 Rₜ + 571.9 Rₜ - 86.1 EVI + 166.5 Rₜ + 44.4 Rₜ + 46.8 Rₜ - 37.9 Rₜ</td>
</tr>
<tr>
<td>7</td>
<td>EVI &gt; 0.33611, NDWI &gt; 0.41188, land cover in (BF, GR, NF)</td>
<td>NEE = 1.8582904 - 44.6 Rₜ</td>
</tr>
<tr>
<td>8</td>
<td>Rₜ &gt; 0.19474, LST &gt; 23.799, EVI &gt; 0.33611, land cover in (CL)</td>
<td>NEE = -13.0236512 + 211.3 Rₜ - 16.8 EVI - 29.1 Rₜ + 13.2 Rₜ + 12.5 Rₜ + 3.3 Rₜ + 3.5 Rₜ</td>
</tr>
<tr>
<td>9</td>
<td>EVI &gt; 0.33611, land cover in (GR)</td>
<td>NEE = -2.2579083 + 83.3 Rₜ - 74.5 Rₜ + 12 NDWI + 30.9 Rₜ - 23.3 Rₜ - 8.7 EVI</td>
</tr>
<tr>
<td>10</td>
<td>Rₜ &gt; 0.052542, EVI &gt; 0.33611, NDWI ≤ 0.33023, land cover in (BF, NF)</td>
<td>NEE = -7.3993489 + 50.5 Rₜ + 51.4 Rₜ + 8 NDWI - 19 Rₜ + 13.3 Rₜ - 0.034 LST - 1.9 EVI</td>
</tr>
<tr>
<td>11</td>
<td>LST ≤ 6.7781, EVI ≤ 0.33611, NDWI &gt; 0.0003819, land cover in (GR, NF)</td>
<td>NEE = 0.7230217 + 110.6 Rₜ - 102.8 Rₜ - 18.6 Rₜ - 3.6 Rₜ + 2.4 Rₜ + 0.5 NDWI + 0.5 EVI + 0.4 Rₜ</td>
</tr>
<tr>
<td>12</td>
<td>Rₜ &gt; 0.052542, EVI &gt; 0.33611, NDWI ≤ 0.33023, land cover in (BF, NF)</td>
<td>NEE = -0.4287566 + 27.3 Rₜ - 27.4 Rₜ - 8.6 Rₜ + 10.5 Rₜ - 2.2 NDWI - 3 EVI + 4.5 Rₜ - 1.5 Rₜ</td>
</tr>
<tr>
<td>13</td>
<td>LST ≤ 6.7781, EVI ≤ 0.33611, NDWI &gt; 0.0003819, land cover in (GR, NF)</td>
<td>NEE = -0.2237048 + 0.9 NDWI + 2.7 Rₜ - 2.2 Rₜ + 1.5 Rₜ - 0.8 Rₜ + 0.3 EVI - 0.8 Rₜ</td>
</tr>
<tr>
<td>14</td>
<td>LST &gt; 19.474, EVI &gt; 0.33611, land cover in (GR, NF)</td>
<td>NEE = -3.7808319 + 101.9 Rₜ - 28.7 EVI - 61.3 Rₜ - 40.7 Rₜ + 16.8 Rₜ - 13.4 Rₜ + 0.069 LST</td>
</tr>
<tr>
<td>15</td>
<td>LST &gt; 19.474, NDWI ≤ 0.0003819, land cover in (GR, NF)</td>
<td>NEE = -0.050819 + 6.3 EVI - 13.5 Rₜ + 10.2 Rₜ - 8.6 Rₜ + 6.3 Rₜ + 4.3 Rₜ + 0.015 LST</td>
</tr>
<tr>
<td>16</td>
<td>Rₜ &gt; 0.053207, EVI ≤ 0.24045, land cover in (CL)</td>
<td>NEE = 12.9306716 - 37.6 EVI + 56.9 Rₜ - 51.3 Rₜ - 1 Rₜ + 0.7 Rₜ - 0.6 Rₜ</td>
</tr>
<tr>
<td>17</td>
<td>Rₜ &gt; 0.053207, EVI &gt; 0.24045, EVI &gt; 0.33611, land cover in (CL)</td>
<td>NEE = 0.6354929 - 32.5 Rₜ + 27.5 Rₜ + 8.4 Rₜ - 5.7 Rₜ - 7 Rₜ + 5.2 Rₜ + 0.008 LST</td>
</tr>
<tr>
<td>18</td>
<td>EVI &gt; 0.33611, land cover in (BF)</td>
<td>NEE = -8.2499909 + 223.1 Rₜ + 3.1 Rₜ - 2.1 Rₜ + 1.4 Rₜ - 0.2 EVI + 0.2 NDWI - 0.6 Rₜ</td>
</tr>
</tbody>
</table>

Table 3

The statistical comparison of the diagnosed overall NEE (g C m⁻² day⁻¹) using different data and models with the sixteen EC towers measurements.

<table>
<thead>
<tr>
<th>Data used</th>
<th>rmseab</th>
<th>p-Value</th>
<th>ε₀b</th>
<th>εp</th>
<th>Slope</th>
<th>Interceptb</th>
</tr>
</thead>
<tbody>
<tr>
<td>Landsat</td>
<td>0.0816</td>
<td>0.9877</td>
<td>0.14</td>
<td>0.88</td>
<td>0.56</td>
<td>-0.145</td>
</tr>
<tr>
<td>MODIS</td>
<td>0.1446</td>
<td>0.9616</td>
<td>0.19</td>
<td>0.85</td>
<td>0.56</td>
<td>-0.145</td>
</tr>
<tr>
<td>Fused Landsat*</td>
<td>0.1748</td>
<td>0.9726</td>
<td>0.14</td>
<td>0.88</td>
<td>0.56</td>
<td>-0.145</td>
</tr>
</tbody>
</table>

a Fused Landsat data contain original Landsat data and Landsat-like data produced by the image fusion method.

b Units: g C m⁻² day⁻¹.
(2008). For the CCP NEE data, data gaps were filled following Barr et al. (2004, 2007). The canopy height ($h_c$), EC sensor height ($h_m$), friction velocity ($u^*$), friction velocity threshold for EC flux calculation ($u^{*th}$), horizontal wind speed ($u$), wind direction (WD), standard deviation of horizontal wind speed ($u^*$), sensible heat flux ($H$) and latent heat flux ($LE$) measured half-hourly at EC sensor height required by the SAFE-f footprint model were obtained from the same database as NEE. The value of $u^{*th}$ was obtained by visually examining the plot of nighttime CO$_2$ fluxes versus $u^*$, and locating where the flux begins to level off as $u^*$ increases (Chen et al., 2012; Gu et al., 2005). In this approach, missing half-hourly meteorological data were filled using interpolation from adjacent levels in the measurement profile (e.g. air temperature profile) and the average diurnal method for the days before and after the gap with a 15-day moving window in 5-day increments (Chen, Black, Coops, Krishnan, et al., 2009). The roughness length ($z_0$) was roughly estimated as 10% of $h_c$ (Raupach, 1994).

2.2. Remote-sensing-related parameters and variables

The value of NEE is influenced by many factors including physical, atmospheric, hydrologic, physiological and edaphic variables (Xiao et al., 2008). We assumed these factors could be assessed by the information derived from satellite remote-sensing data: land surface reflectance, enhanced vegetation index (EVI), normalized difference water index (NDWI) and LST. All these variables were derived from Landsat TM/ETM+ imagery. The reflectance of a particular land cover type depends on wave-length coverage, soil moisture, sun-object-sensor geometry, biophysical and biochemical properties (stand age, pigment composition, biomass etc.) (Penuelas, Gamon, Griffin, & Field, 1993; Penuelas, Garbulsky, & Filella, 2011; Penuelas, Garbulsky, Gamon, Inoue, & Filella, 2011; Ranson, Daughtry, Biehl, & Bauer, 1985). The land surface reflectance varies with view zenith, solar zenith and relative azimuth angle which lead to brighter or darker spectral observations as a result of the interaction of solar irradiance with a given surface and sun-sensor geometry (Roujean, Leroy, & Deschamps, 1992). NDVI is a widely used vegetation index which is often applied in production efficiency models because of its close correlation with the fraction of photosynthetically active radiation (fPAR) absorbed by vegetation and the fractional vegetation cover and other vegetation-related variables (Asrar, Fuchs, Kanemasu, & Hatfield, 1984; Choudhury, 1987; Myneni, Hall, Sellers, & Marshak, 1995; Sellers, Berry, Collatz, & Field, 1992; Zhang et al., 2007). However, NDVI has several limitations including its sensitivity to soil background conditions, atmospheric conditions, and saturation in a multilayered, closed canopy (Huete et al., 2002; Xiao et al., 2004, 2008). We also used EVI, an improved vegetation index (Huete, Liu,
Table 4
The statistical parameters in the comparison of the diagnosed NEE (g C m\(^{-2}\) day\(^{-1}\)) using Landsat and MODIS datasets with measurements at each of the fifteen EC towers (2005–2006).

<table>
<thead>
<tr>
<th>Land cover type</th>
<th>Site ID</th>
<th>Slope</th>
<th>Intercept(^a)</th>
<th>(r^2)</th>
<th>RMSE(^a)</th>
<th>(p)-Value</th>
</tr>
</thead>
<tbody>
<tr>
<td>Needleleaf forest</td>
<td>CA-Obs</td>
<td>1.08</td>
<td>−0.03</td>
<td>0.70</td>
<td>0.68</td>
<td>&lt;0.0001</td>
</tr>
<tr>
<td></td>
<td>CA-Opp</td>
<td>0.688</td>
<td>−0.02</td>
<td>0.49</td>
<td>0.57</td>
<td>&lt;0.0001</td>
</tr>
<tr>
<td></td>
<td>CA-Ca1</td>
<td>1.06</td>
<td>0.45</td>
<td>0.17</td>
<td>0.24</td>
<td>&lt;0.0001</td>
</tr>
<tr>
<td></td>
<td>CA-Man</td>
<td>0.96</td>
<td>0.06</td>
<td>0.61</td>
<td>0.56</td>
<td>&lt;0.0001</td>
</tr>
<tr>
<td>Broadleaf forest</td>
<td>CA-Oas</td>
<td>1.28</td>
<td>−0.34</td>
<td>0.87</td>
<td>0.76</td>
<td>&lt;0.0001</td>
</tr>
<tr>
<td></td>
<td>US-MMS</td>
<td>1.02</td>
<td>−0.22</td>
<td>0.89</td>
<td>0.87</td>
<td>&lt;0.0001</td>
</tr>
<tr>
<td></td>
<td>US-UMB</td>
<td>0.92</td>
<td>0.05</td>
<td>0.81</td>
<td>0.80</td>
<td>&lt;0.0001</td>
</tr>
<tr>
<td></td>
<td>US-WCr</td>
<td>1.19</td>
<td>0.10</td>
<td>0.90</td>
<td>0.72</td>
<td>&lt;0.0001</td>
</tr>
<tr>
<td>Cropland</td>
<td>US-Bo1</td>
<td>0.73</td>
<td>−0.31</td>
<td>0.66</td>
<td>0.46</td>
<td>&lt;0.0001</td>
</tr>
<tr>
<td></td>
<td>US-Ne1</td>
<td>0.78</td>
<td>0.88</td>
<td>0.81</td>
<td>0.60</td>
<td>&lt;0.0001</td>
</tr>
<tr>
<td></td>
<td>US-Ne2</td>
<td>0.78</td>
<td>0.51</td>
<td>0.91</td>
<td>0.55</td>
<td>&lt;0.0001</td>
</tr>
<tr>
<td></td>
<td>US-Ne3</td>
<td>0.73</td>
<td>−0.64</td>
<td>0.89</td>
<td>0.84</td>
<td>&lt;0.0001</td>
</tr>
<tr>
<td>Grass</td>
<td>US-FPe</td>
<td>0.43</td>
<td>−0.08</td>
<td>0.06</td>
<td>0.02</td>
<td>&lt;0.0001</td>
</tr>
<tr>
<td></td>
<td>US-Var</td>
<td>1.15</td>
<td>0.49</td>
<td>0.68</td>
<td>0.72</td>
<td>&lt;0.0001</td>
</tr>
<tr>
<td></td>
<td>US-Aud</td>
<td>1.13</td>
<td>−0.57</td>
<td>0.58</td>
<td>0.14</td>
<td>&lt;0.0001</td>
</tr>
</tbody>
</table>

\(^a\) Units: g C m\(^{-2}\) day\(^{-1}\).

As mentioned above, we used a method for scaling EC-derived NEE to landscape scales at high spatial (30 m) and high temporal (8-day intervals) resolutions by combining a regression model, a footprint climatology model, and image-fusion model. This regression-based approach was used to estimate NEE based on trained rules. The trained rules were mathematical conditional expressions for NEE estimation produced by comparing a training data set to observe NEE. The input variables contained in training set and test set for the diagnosed model include the surface visible/NIR/SWIR reflectance (6 bands), LST, EVI and NDVI derived from the Landsat imagery, which were weighted by a footprint PDF estimated using the SAFE-f footprint model. A Landsat-like reflectance dataset was produced using the image-fusion method (see Section 2.3.3) to fill any gaps in Landsat data that were contaminated by clouds or not available.

2.3. Simulation approaches

As mentioned above, we used a method for scaling EC-derived NEE to landscape scales at high spatial (30 m) and high temporal (8-day intervals) resolutions by combining a regression model, a footprint climatology model, and image-fusion model. This regression-based approach was used to estimate NEE based on trained rules. The trained rules were mathematical conditional expressions for NEE estimation produced by comparing a training data set to observe NEE. The input variables contained in training set and test set for the diagnosed model include the surface visible/NIR/SWIR reflectance (6 bands), LST, EVI and NDVI derived from the Landsat imagery, which were weighted by a footprint PDF estimated using the SAFE-f footprint model. A Landsat-like reflectance dataset was produced using the image-fusion method (see Section 2.3.3) to fill any gaps in Landsat data that were contaminated by clouds or not available.

2.3.1. The regression-based diagnosed model

The regression tree is a method which can account for the nonlinear relationship between diagnosed and target variables by producing a regression-based diagnosed model containing more than one rule. A rule is a multivariate linear regression sub-model subject to a set of conditions. Both continuous and discrete variables can be set as the input data for a regression tree (Xiao et al., 2008; Yang, Huang, Homer, Wylie, & Coan, 2003; Yang, Xian, Klaver, & Deal, 2003). The modified regression tree approach used in this study is the commercial software package called Cubist (RuleQuest, 2012), linked to R, an open-source statistical computing software environment. Cubist is one type of regression-based method which was developed by Quinlan (1992). The regression-based diagnosed model for NEE (the target variable) is produced by Cubist based on EC flux and satellite data as inputs.
The inputs were weighted using the EC flux footprint PDF. The input variables were divided into two parts, a training set (the years 2000–2004, 16 flux sites, 1083 data points) and a test set (the years 2005–2006, 15 flux sites, 363 data points).

2.3.2. Footprint weighted NEE

Measured EC tower fluxes (i.e. NEE) representing the integrated flux within the tower footprint area (typically 1–3 km²) cannot simply be compared with the remotely sensed NEE derived from the Landsat (30-m) or MODIS (1-km) data because of mismatching at the spatial scale. We used a footprint weighting method to match the Landsat pixel-scale and the EC measurement-scale and hence to optimize the regression-based NEE diagnosed model. The landscape-scale NEE ($F_{\text{NEE,la}}$) was up-scaled from the spatially distributed 30-m NEE field ($F_{\text{NEE,rs}}$) using

$$F_{\text{NEE,la}} = \int \int F_{\text{NEE,rs}}(x,y) \varphi_{\text{pure}}(x,y) \, dx \, dy$$

$$F_{\text{NEE,la}} = a_1R_1 + a_2R_2 + a_3R_3 + a_4R_4 + a_5R_5 + a_6LST + a_7EVI + a_8NDWI$$

where $\varphi_{\text{pure}}$ is the pure flux footprint (Chen, Black, Coops, Hilker, et al., 2009), $\Omega_{\Pi}$ is the upwind footprint source area for the 95% accumulative footprint, $a_1, \ldots, a_8$ are parameters obtained using the regression-based

![Figure 7](image-url)

Fig. 7. Observed and diagnosed 8-day NEE (g C m⁻² day⁻¹) for each flux site over the period 2005–2006 using Landsat (contained Landsat-like) and MODIS data. The black circle symbols represent the observed values, the black solid line with red symbols (circle and triangle) represents the diagnosed NEE using Landsat data, and the dashed line with blue pentagram symbols represents the diagnosed NEE using MODIS data. Abbreviations for each site can be obtained in Table 1. (a) NF: needleleaf forest, BF: broadleaf forest, (b) GR: grassland, and CL: cropland.
NEE diagnosed model, $R_1, R_2, R_3, R_4, R_5, R_7$ are the reflectance values for each respective Landsat band, $LST$ is the land surface temperature derived from Landsat imagery, and $EVI, NDWI$ are two vegetation indices derived from the Landsat reflectance data. The $F_{\text{NEE,} \phi}$ was estimated from Landsat data using the regression-based NEE diagnosed model with 30-m resolution. The scale of EC-derived NEE can be matched using the footprint-integrated $F_{\text{NEE,} \phi}$. The land cover maps (Fig. 3) for Canadian sites were acquired from the Earth Observation for Sustainable Development (EOSD) land cover product of the Canadian Forest Service and the Canadian Space Agency (Wulder et al., 2003, 2008), and for the US sites data they were obtained from the National Land Cover Dataset (NLCD, 2006) from the USGS EarthExplorer (Fry et al., 2011; Wickham et al., 2013; Xian, Homer, & Fry, 2009).

2.3.3. Satellite image fusion

We produced a Landsat-like reflectance dataset, which involved two models: the Spatial and Temporal Adaptive Reflectance Fusion Model (STARFM) (Gao, Masek, Schwaller, & Hall, 2006) and the Enhanced STARFM (ESTARFM) (Zhu et al., 2010). The STARFM blends Landsat TM/ETM + images and MODIS images to simulate daily surface reflectance at Landsat spatial resolution and MODIS temporal frequency (Gao et al., 2006). Compared to the traditional image fusion methods which produce new multispectral high-resolution images with different spatial and spectral characteristics, such as principle component analysis (PCA) (Metwalli, Nasr, Allah, El-Rabaie, & Abd El-Samie, 2010; Naidu & Rao, 2008), intensity-hue-saturation (IHS) (Choi, 2006; Tu, Su, Shyu, & Huang, 2001), Brovey transform (Zhang, 2004) and wavelet...
transform (Li, Manjunath, & Mitra, 1995; Nunez et al., 1999), STARFM has several advantages: for example, the outputs of traditional image fusion are not calibrated to spectral radiance or reflectance (Gao et al., 2006), and may therefore not capture the vegetation changes due to phenological cycles (Gao et al., 2006; Zhu et al., 2010).

The ESTARFM is an improved version of STARFM, which can obtain better simulated reflectance values in heterogeneous and changing landscapes by using remotely sensed reflectance trends between two dates and spectral unmixing theory (Zhu et al., 2010). We selected ESTARFM as the default model, while STARFM was used when two pairs of input data between two dates were not available for ESTARFM.

2.3.4. Accuracy assessment

The performance of the regression-based diagnosed model for NEE was evaluated using several statistical parameters, the average error ($\varepsilon_a$), measuring the quality of the constructed regression tree; the relative error ($\varepsilon_r$), comparing the quality of several regression trees; the coefficient of determination ($r^2$), measuring the correlation between actual and diagnosed values for the relative variables; and the root-mean-square error (RMSE), measuring the differences between the values produced by the rule set approach and the EC-measured NEE.

The average error, $\varepsilon_a$, was calculated as (Xiao et al., 2008; Yang, Huang, et al., 2003; Yang, Xian, et al., 2003):

$$\varepsilon_a = \frac{1}{N} \sum_{t=1}^{N} |y_t - y'_t|$$

where $N$ is the number of the samples used to construct the diagnosed model, $y_t$ and $y'_t$ are the $t$th actual and diagnosed value of the relative variables respectively. Relative error, $\varepsilon_r$, is expressed by (Xiao et al., 2008; Yang, Huang, et al., 2003; Yang, Xian, et al., 2003):

$$\varepsilon_r = \frac{1}{N} \sum_{t=1}^{N} |y_t - y'_t|$$

where $\bar{y}$ is the diagnosed mean value. It is used to standardize the average error ($\varepsilon_a$). The RMSE was calculated as

$$\text{RMSE} = \sqrt{\frac{1}{N} \sum_{t=1}^{N} (y_t - y'_t)^2}.$$  

A two-sided $t$-test is used to determine the statistical significance of $\alpha_1$, $\cdots$, $\alpha_9$ from Eq. (1). A $p$-value $< 0.05$ is assumed to be significant.
3. Results

3.1. Landscape scale NEE comparisons

The regression-based NEE diagnosed model comprises 19 sub-models (Table 2). The input parameters were weighted by the pure footprint for each EC flux site when using Landsat data. Fig. 3 shows the land cover maps overlaid by the 8-day cumulative footprint contours (50%, 80%, 95% and 99%) for each site. For most sites, the 8-day footprint PDFs are distributed asymmetrically around the tower. The footprint areas and spatial distribution patterns varied among the flux sites. The footprint areas for the forest sites are larger than for grass and cropland sites.

For the modeling method comparison, we used the same flux data and corresponding MODIS data of our method (Landsat-based model) as input parameters for the method of Xiao et al. (2008) (MODIS-based model). The importance of each input parameter, which gives the percentage of times where each parameter was used in the diagnosed model, for our method can be quantified as: 33.5% (R1), 42.0% (R2), 38.8% (R3), 33.0% (R4), 45.5% (R5), 49.5% (R6), 79.5% (EVI), 36.0% (NDWI), 51.0% (LST), and 48.5% (land cover) respectively. Compared with the method using MODIS data, the estimation of NEE using fused Landsat showed better agreement with the EC flux measurements (Table 3).

As shown in Fig. 4, in terms of land cover, the diagnosed NEE of cropland has larger scatter, especially when using Landsat data. Both the Landsat- and MODIS-based models can reasonably diagnose landscape NEE ($r^2 = 0.59$, $p < 0.0001$); however, the MODIS-based model tends to underestimate the magnitude of summed NEE, while the Landsat-based model tends to overestimate it, especially for the cropland (Fig. 5). The overestimation from Landsat-based model is likely attributable to a large overestimation for croplands due to probable ill-parameterizations for this plant function type as which only based on a limited number of available eddy covariance sites. Model accuracy varied widely (Table 4). We also compared the observed and estimated 8-day NEE in a more detailed manner for each EC flux site (Figs. 6–7, Table 4). For most sites, the performance of the model using Landsat was better than using MODIS except for the CA-Ojp site ($r^2 = 0.49$ vs. 0.57 and RMSE = 0.42 vs. 0.39 g C m$^{-2}$ day$^{-1}$ for Landsat vs. MODIS, respectively) and the CA-Cal site ($r^2 = 0.17$ vs. 0.24 and RMSE = 1.50 vs. 1.43 g C m$^{-2}$ day$^{-1}$, Landsat versus MODIS, respectively). For the US-FPe site, both models did not perform well ($r^2 = 0.0016$ vs. 0.06, respectively).
RMSE = 1.13 vs. 1.16 g C m$^{-2}$ day$^{-1}$ for MODIS vs. Landsat, respectively). The MODIS-based model of Xiao et al. (2008) also performed poorly for this site.

A large overestimation in magnitude of NEE by the model was found at the Mead-irrigated continuous maize site (US-Ne1), the Mead-irrigated maize-soybean rotation site (US-Ne2), and the Mead-rain-fed maize-soybean rotation site (US-Ne3) using Landsat data, and the US-Ne1 site using MODIS data; whereas a large underestimation in magnitude of NEE occurred at the Audubon Research Ranch (US-Aud), SK-Old Aspen (CA-Oas) using Landsat data, and US-Aud, US-Ne3 and CA-Oas using MODIS data. For most flux sites, the NEE estimations using Landsat and MODIS both captured most features of observed NEE at seasonal and annual scales from 2005 to 2006. Underestimation and overestimation occurred for some sites, but there were larger over- or under-estimations using MODIS data, such as CA-Oas, US-UMB, US-WG, US-Bo1, and US-Aud, compared to using Landsat data, such as CA-Ca1, US-Bo1, US-Ne1, US-Ne2, and US-Ne3 (Fig. 7). Specifically, the model could not capture exceptionally high or low NEE values (extremes of large carbon release or uptake rates occurred at several sites, such as US-FPe, US-Aud, and CA-Ca1). In general, the model using Landsat data performed better than when using MODIS data. Fig. 8 compares the estimated annual average NEE in 2005 obtained using the model with Landsat and MODIS data with EC tower observed values. The annual NEE of cropland was larger than other land cover types. The estimated annual NEE using Landsat was larger than MODIS for most EC flux tower sites. Two grassland sites (US-FPe, US-Aud) were carbon sources according to model simulation using Landsat and MODIS data while EC measurements indicated they were carbon sinks.

3.2. Regional scale NEE comparisons

The temporal and spatial comparisons of NEE at regional scale were shown in Figs. 9 and 10. As shown in Fig. 9, compared to the annual variation of NEE estimation using a top-down method, such as Carbon Tracker (CT) (Peters et al., 2007; Zhang et al., 2013), the differences between CT-derived NEE estimates and values from the two bottom-up upscaling models were large in this study. The time interval of CT was scaled to eight days from weekly periods using linear interpolation. For the other three methods (EC-Observed, bottom-up based on Landsat and MODIS imagery), the mean NEE was the weighted average of NEE using the percentage of each land cover. The peak magnitude of estimated NEE from CT appeared around June 18 (day of year: 169), while for the other two models (Landsat- and MODIS-based models) and measurements it appeared around July 4 (day of year: 185 for Landsat-based model), and August 5 (day of year: 217, for EC-Observed method and for the MODIS-based model).

The regional NEE estimation can be obtained from the analysis methods that upscale data from selected fifteen flux sites with the assumption that these sites for different land cover types are representative of the study region (Fig. 10). The regional NEE for each land cover was estimated using the mean values of corresponding site data. The regional NEE mapping shows that the strong net carbon uptake in cropland is distributed in the central to the southeast of the study area. The spatially distributed pattern of NEE produced by CT was similar to that of the two bottom-up approaches; the largest carbon sink for example was distributed in cropland land (compare Fig. 10 with Fig. 1).

4. Discussions

There are two advantages to our method. Our model can be applied to estimating seasonal and annual variations at the landscape scale. Several studies have used remote-sensing-based methods to estimate NEE; however, either the spatial resolution is coarse or the other input data not derived from remote sensing are not easy to obtain (Maselli et al., 2010; Xiao et al., 2008). For example, using the Carnegie-Stanford-Ames (CASA) biogeochemical model with Landsat imagery, Advanced Very High Resolution Radiometer (AVHRR) data, forest inventory data, Masek and Collatz (2006) estimated forest carbon fluxes in a disturbed landscape; however, the Landsat data were not always available. Although the revisit cycle of Landsat is 16 days, the available imagery data frequency was reduced due to cloud contamination. We used an image fusion method to reproduce Landsat-like reflectance data to make up for the missing periods. Theoretically, it is feasible to produce daily Landsat-like reflectance; but the Landsat-like reflectance on cloudy days cannot be used, and it is very time consuming to produce daily reflectance data.

The PDFs of the integrated flux within EC tower-flux measurement footprint areas were taken into account in our methods. The size and spatial structure of the footprint obtained using SAFE-f was variable at 8-day, monthly, seasonal and annual intervals, and asymmetrically distributed around the tower (Chen, Black, Coops, Hilker, et al., 2009). Consequently, the remotely sensed NEE using Landsat (30-m) or MODIS (1-km) data cannot simply be compared with the NEE measured from EC tower flux because of their spatial mismatching of their areas. Compared to the simple averaged method using MODIS (Xiao et al., 2008), the estimated NEE using the model with footprint weighted input parameters was more reasonable.

Compared to the annual variation of NEE estimation using CT method, the peak magnitude of estimated NEE from other three methods was different (Fig. 9). There exists an apparent seasonal phase shift between the top-down and the bottom-up methods and the main differences in magnitudes between CT and the other three methods (Landsat-, MODIS-based models and measurements) were found during the peak growing season (July to August). Some mean disagreement between CT and the bottom-up methods can be explained by the differences in small and persistent fluxes in the non-growing seasons (Desai, Helliker, Moorcroft, Andrews, & Berry, 2010). The large overestimation in magnitudes for cropland contributed mainly to the overestimated regional carbon sink by the bottom-up upscaling models especially when using Landsat data.

The spatially distributed pattern of strong net carbon uptake in cropland was similar to the pattern found by Hayes et al. (2012). The diagnosed regional NEE using Landsat had large biases in the summer compared to the EC measurements because of the overestimation of flux from cropland. To sum up, the estimated total annual NEE over the large study region (with an area of 1.56 × 109 ha) using the three models that were being evaluated using the measurements was −3.62 Pg C (Landsat), −2.10 Pg C (MODIS), −0.40 Pg C (CT), −3.56 Pg C (EC-Observed), respectively. The magnitude of the CT estimate was significantly lower than the bottom-up methods and EC flux measurements. The 20th century carbon balance estimation for North America by Hayes et al. (2012) shows the magnitude of CO2 uptake varying from 0.1 to 2.0 Pg yr$^{-1}$ in the 20th century to 1.8 Pg yr$^{-1}$ in the early 21st century. The reason of the large biases for the two bottom-up methods (upscaling using Landsat and MODIS) and EC observed method, perhaps is caused by a too coarse land cover type classification (only 4 groups) and the limited number of flux sites. The dominant land cover type surrounding the EC towers of US-Ne1, US-Ne2 and US-Ne3 is cropland, but the three sites are closely located so that the EC tower representativeness is poor over the large cropland area (about 2.6 × 109 ha) in the region.

There are several limitations and constraints while using the NEE diagnosed model in this study. First, the land cover around the flux tower we used is heterogeneous and our assumption of only one land cover type within the footprint area affects the estimation accuracy. Chen et al. (2012) studied the representativeness of flux tower EC measurements for the main sites of Fluxnet-Canada and found that the percentage of target land cover type area observed by an EC flux tower was higher than 60%. The bias between estimated and observed NEE will be smaller if the heterogeneous land cover around an EC flux tower was considered. When the target and other land cover types observed by EC flux tower are taken into account, the performance of NEE diagnosed model will be better. Second, the phenology may change within
the 8-day period invalidating the assumption of representativeness of Landsat reflectance and LST data for 8 days. For LST data, although Landsat samples a local study area around noon time, there can be a large variation and possible bias (Li et al., 2013). The diagnosed NEE is also affected when the number of available original Landsat images were few. For example, the available original Landsat data for the CA1 site during the period 2005–2006 was limited with only ten available original data points due to cloud contamination. This would affect the quality of Landsat-like reflectance. Subsequently, the performance of diagnosed NEE for this site using Landsat was the worst of all sites (Table 4). For the CA-Oopi site, the original EC observed NEE had many fluctuations in magnitude in 2005 and the performance for this site was also poor. Third, the land-cover type classifications are coarse with only four major groups. The growing conditions and land-cover types can vary greatly over large region; few EC flux sites may contribute the bias of NEE diagnosed model for the spatial distribution and seasonal variations. We selected sixteen EC flux sites, but the performance of the diagnosed model is expected to be better if there were more available representative flux sites to account for land surface heterogeneities.

5. Conclusions

This study introduced a modeling approach for landscape NEE estimation at high spatial–temporal resolutions (30-m and 8-day intervals) based on sixteen EC flux-tower measurements and related remotely sensed data. Compared to the similar model of Xiao et al. (2008) which scaled the EC flux tower’s NEE at 1-km resolution, we found that higher spatial resolution remote sensing data (Landsat vs. MODIS) jointly with flux tower footprint analysis result in better model fit to observed data and thus obtain more robust landscape NEE estimation. The differences in regional NEE estimates between based on bottom-up up-scaling models and based on top-down inversion models (e.g. CT) can be decrease if more flux towers and accurate land cover data are taken into account. This study demonstrated that the data-driven satellite-based NEE simulation model has the potential to upscale EC flux NEE observations to landscape and regional scales with high spatial-temporal resolutions.

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