Modeling spatially explicit fire impact on gross primary production in interior Alaska using satellite images coupled with eddy covariance

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ABSTRACT

In interior Alaska, wildfires change gross primary production (GPP) after the initial disturbance. The impact of fires on GPP is spatially heterogeneous, which is difficult to evaluate by limited point-based comparisons or insufficient to assess by satellite vegetation index. The direct prefire and postfire comparison is widely used, but the recovery identification may become biased due to interannual climate variability. The objective of this study is to propose a method to quantify the spatially explicit GPP change caused by fires and succession. We collected three Landsat images acquired on 13 July 2004, 5 August 2004, and 6 September 2004 to examine the GPP recovery of burned area from 1987 to 2004. A prefire Landsat image acquired in 1986 was used to reconstruct satellite images assuming that the fires of 1987–2004 had not occurred. We used a light-use efficiency model to estimate the GPP. This model was driven by maximum light-use efficiency (Emax) and fraction of photosynthetically active radiation absorbed by vegetation (FPAR). We applied this model to two scenarios (i.e., an actual postfire scenario and an assuming-no-fire scenario), where the changes in Emax and FPAR were taken into account. The changes in Emax were represented by the change in land cover of evergreen needleleaf forest, deciduous broadleaf forest, and shrub/grass mixed, whose Emax was determined from three fire chronosequence flux towers as 1.1556, 1.3336, and 0.5098 gC/MJ PAR. The changes in FPAR were inferred from NDVI change between the actual postfire NDVI and the reconstructed NDVI. After GPP quantification for July, August, and September 2004, we calculated the difference between the two scenarios in absolute and percent GPP changes. Our results showed rapid recovery of GPP post-fire with a 24% recovery immediately after burning and 43% one year later. For the fire scars with an age range of 2–17 years, the recovery rate ranged from 54% to 95%. In addition to the averaging, our approach further revealed the spatial heterogeneity of fire impact on GPP, allowing one to examine the spatially explicit GPP change caused by fires.

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1. Introduction

Gross primary production (GPP) is the amount of carbon fixed by vegetation through photosynthetic assimilation: it is critical in land surface–atmosphere interactions and a key component of ecosystem carbon fluxes and the carbon balance between the biosphere and the atmosphere (Mäkelä et al., 2008). The quantification of carbon fluxes between the terrestrial biosphere and the atmosphere is of scientific importance and relevant to climate policy making (Xiao et al., 2010). In a boreal region, the vegetation production plays an important role in the global cycles of carbon and the climate system (Melillo et al., 1993; Schulze et al., 1999). However, fire is the primary disturbance agent in most of the North American boreal forest; the frequency of large fires has increased dramatically over the past four decades and fire frequency and severity may increase further due to climate warming (Kasischke and Turetsky, 2006; Kasischke et al., 2011; Yi et al., 2010). After a disturbance, carbon dynamics are primarily driven by GPP (Amiro et al., 2010; Goulden et al., 2011). The successional trajectories of boreal forests after fires are various (Beck et al., 2011; Johnstone et al., 2010; Shenoy et al., 2011). More frequent and larger fires in the late twentieth century resulted in deciduous trees and mosses increasing production at the expense of coniferous trees (Bond-Lamberty et al., 2007). Consequently, wildfires strongly influence boreal forest age structure, species composition, and thus vegetation photosynthesis process, affecting the carbon cycle and climate.
which may persist for many decades (Bond-Lamberty et al., 2004; Randerson et al., 2006). This illustrates the need for a comprehensive examination of the magnitude and direction of changes in primary productivity as a result of altered ecosystem processes (Beck and Goetz, 2011).

Eddy covariance flux towers, which directly measure net ecosystem exchange (NEE) separable into GPP and ecosystem respiration (Re) (Baldocchi et al., 2001; Reichstein et al., 2005), and field measurements can be used to study the fire impact on carbon fixation. For example, Bond-Lamberty et al. (2004), Litvak et al. (2003), Goulden et al. (2006), and Welp et al. (2006), and Goulden et al. (2011) all investigated carbon dynamics for chronosequence of postfire boreal forest stands based on field or flux measurements. These site-specific field measurement and flux observation studies have provided excellent information and aided a better understanding of the vegetation production associated with fire. Unfortunately, the high spatial and temporal variability of terrestrial ecosystems across complex landscapes results in a challenging task of regional extrapolation from point-based GPP measurements (Maselli et al., 2009). Significant efforts are still needed to upscale field observations or flux tower measurements from the stand scale to landscape, regional, continental, or global scales to advance toward explicitly incorporating the impacts of disturbance on ecosystem carbon exchange (Xiao et al., 2010, 2012), because the long-term carbon effects of fire disturbance are spatially heterogeneous at scales of 10 m to approximately 1000 m due to the complex interactions and the variation of burn severity, topography, drainage, prefire vegetation condition, and weather (Goetz et al., 2012; Huang et al., 2013).

Due to the weakness of spatial representation of point-based study, consistent and spatially continuous satellite remote sensing has played an increasing role in production estimation (Goetz et al., 1999; Potter et al., 1993). Several studies used satellite vegetation index to examine forest recovery in the boreal region. Kasischke and French (1997) analyzed Normalized Difference Vegetation Index (NDVI) of 14 test sites in the boreal forest of interior Alaska to examine the patterns of recovery. Epting and Verbyla (2005) used Landsat vegetation index to analyze the vegetation recovery. Goetz et al. (2006) compared NDVI anomalies of burned and unburned areas to analyze fire disturbance and forest recovery across Canada. Cueva-González et al. (2009) used satellite vegetation index to analyze forest recovery after wildfire disturbance in boreal Siberia. Veraverbeke et al. (2012) assessed postfire vegetation recovery using red–near infrared vegetation indices. Unitless vegetation index is a good proxy of vegetation production, but it does not represent the impacts of disturbance on ecosystem carbon exchange (Xiao et al., 2013). In this study area, we set up three sites for field survey: one that burned in 1987, one that burned in 1999, and one that burned in approximately 2000. These sites were located on relatively well drained silty loam soil and will be hereinafter referred to as the 1987 burn, 1999 burn, and control sites (Fig. 1). In the 1999 burn site, the Donnelly Flats crown fire consumed much of the aboveground biomass and soil organic matter. In 2002, there were 2691 ± 778 standing dead boles of black spruce per hectare with a mean height of 4 m, and 30% of the ground surface was covered by bunch grasses (Festuca altaica) and deciduous shrubs less than 1 m tall. In the 1987 burn site, the Granite Creek fire killed all of the aboveground vegetation, primarily black spruce. By 2002, some of the dead spruce boles remained standing, but most had fallen over. In 2002, the stand was dominated by an overstory of willow shrubs (Salix spp.) and deciduous aspen trees (Populus tremuloides) with a mean canopy height of 5 m and a density of 3956 ± 370 trees per hectare. The sparse understory vegetation included shrubs (Salix spp., Ledum palustre, Rosa acicularis, Vaccinium uliginosum, and Vaccinium vitis-idaea), black spruce (Picea mariana), and grasses (Festuca spp. and Calamagrostis lapponica) separated by patches of moss in open areas (Polytrichum spp.). In the control site, the canopy overstory consisted of homogeneous stands of black spruce (P. mariana) with a mean canopy height of 4 m and a mean age of 80 years. The mean canopy height was 4 m, and the sparse understory consisted of shrubs (L. palustre, V. uliginosum and V. vitis-idaea). The dominant ground cover was feathermoss (Pleurozium schreberi and Rhytidium rugosum) and lichen (Cladonia spp. and Stereocaulon spp.).

3. Dataset

3.1. Eddy covariance

CO2 fluxes of three stands that were part of a fire chronosequence in interior Alaska (i.e., 1999 burn, 1987 burn, and control sites) were measured using the eddy covariance method (Fig. 1). From 2002 to 2004, eddy covariance measurements of NEE CO2 fluxes were made at each stand and averaged at 30-min intervals along with vertical and horizontal wind velocity, sonic temperature, concentrations of CO2 and water vapor, above-canopy incoming shortwave radiation and photosynthetic photon flux density (PPFD), precipitation, and vapor pressure deficit (VPD). Soil moisture and temperature at 10 cm
depth were also recorded. Instrument configuration was reported by Liu et al. (2005).

3.2. Satellite images, climate, DEM, and fires

Four Landsat scenes from 26 June 1986 (path 67 row 15), 13 July 2004 (path 67 row 15), 5 August 2004 (path 68 row 15), and 6 September 2004 (path 68 row 15) at 30 m resolution were collected. We focused on the fires that occurred during 1987 and 2004; therefore, a prefire Landsat image of 1986 was selected. After very few clouds and shadows were excluded with the method of Jin et al. (2012), the raw digital numbers of Landsat were converted to radiance and reflectance (Huang et al., 2013). A Digital Elevation Model (DEM) at 60 m resolution was collected from the USGS National Elevation Dataset. Monthly average temperature and total precipitation at 771 m resolution were download from “Scenarios Network for Alaska and Arctic Planning’’ of University of Alaska (SNAP, http://www.snap.uaf.edu/). Fire polygons and burn severity derived from Landsat images were downloaded from the Monitoring Trends in Burn Severity (MTBS, http://mtbs.gov).

4. Method

4.1. Overview

Many satellite-based studies have used the light-use efficiency approach to estimate either GPP or NPP (e.g., Field et al., 1995;...
PAR designates the spectral range of solar radiation from 400 to 700 nm that photosynthetic organisms are able to use in the process of photosynthesis. In this study, monthly PAR was calculated as 0.48 of monthly incoming shortwave radiation (INSOLAR), where 0.48 is the ratio of PAR to INSOLAR (McCree, 1972). INSOLAR received during July, August, and September 2004 was calculated from the ArcGIS solar radiation tool. This tool accounts for the effect of atmospheric conditions, site latitude, elevation, slope, aspect, sun angle, and shadows cast by surrounding topography on the amount of INSOLAR. It requires the user input of a spatially explicit DEM as well as transmittivity and diffuse proportion (Huang et al., 2008). The transmittivity and diffuse proportion were calibrated for each month so that the INSOLAR were approximated to measured values from flux towers.

4.3. E\textsubscript{max} of fire chronosequence

Because the land surface changed after a fire disturbance, we classified vegetation from two Landsat Thematic Mapper (TM) scenes, prefire June 1986 and postfire August 2004, using the unsupervised Self-Organization Data Analysis Techniques Algorithm (ISODATA, Mather, 1987). Spectral classes were grouped into three vegetation types: evergreen needleleaf forest, deciduous broadleaf forest, and shrub/grass mixed. Different vegetation types have different E\textsubscript{max} values, but E\textsubscript{max} can be inferred from eddy flux towers based on NEE of CO\textsubscript{2} and PPFD (Goulden et al., 1997). We estimated E\textsubscript{max} from the three flux towers of the 1987 burn, 1999 burn, and the unburned control sites, which represent the local typical ecosystem types of deciduous broadleaf forest, shrub/grass mixed, and evergreen needleleaf forest, respectively. This was achieved through two steps: 1) gap-filling measured measurements and partitioning NEE into GPP and Re, and 2) fitting the Michaelis–Menten function to estimate E\textsubscript{max} as described below.

Data quality control of eddy covariance and meteorological measurements was implemented, gaps in the observations were filled, and half-hourly NEE fluxes were partitioned into Re and GPP. The detailed approach was described by Welp et al. (2006, 2007). Briefly, missing Re was estimated from a temperature-dependent Q10 respiration model that was mathematically equivalent to a Van't Hoff exponential model (Lloyd and Taylor, 1994). During daytime periods of missing NEE observations, GPP was modeled using a Michaelis–Menten model based on Zha et al. (2004) but with the effect of VPD taken into account. Monthly GPP for these three sites was calculated from the half-hourly observations.

There is a near-linear increase in productivity at low light levels and an asymptotic approach to maximum productivity at high light levels; therefore, a rectangular hyperbola function can be used to represent the relation between gross productivity and incident PAR (Frolking et al., 1998). Based on the daytime data within the peak growing season from July 1 to July 31 in 2002–2004, we estimated the nonlinear model between NEE and PAR by fitting the rectangular hyperbolic Michaelis–Menten function (Eq. 2 and Fig. 3) to obtain the E\textsubscript{max} values of the 1987 burn, 1999 burn, and control sites.

\[
\text{NEE} = \frac{E_{\text{max}} \times \text{PPFD} \times P_{\text{max}}}{E_{\text{max}} \times \text{PPFD} \times P_{\text{max}} - R_e} - R_e
\]
where PPFD is the photosynthetic photon flux density of PAR, $E_{\text{max}}$ is the maximum light-use efficiency or apparent quantum yield (as PPFD approaches to 0), $P_{\text{max}}$ is the maximum gross ecosystem exchange, and $R_e$ is the ecosystem respiration. The $E_{\text{max}}$ values are summarized in Table 1.

### 4.4. $T_{\text{scalar}}$

$T_{\text{scalar}}$ is estimated at each month at each grid, using Eq. (3) developed for the CASA model (Potter et al., 1993).

$$
T_{\text{scalar}} = \frac{1.1814 \times (0.8 + 0.02T_{\text{opt}} - 0.0005T_{\text{opt}}^2) \times \left[1 + \exp\left(0.3 \times (T - T_{\text{opt}})\right)\right]}{1 + \exp\left(0.2 \times (T_{\text{opt}} - 10 - T)\right)}
$$

(3)

where $T_{\text{opt}}$ is the optimal temperature defined as the monthly mean temperature in July when vegetation has the maximum canopy. If $T$ is lower than 0 °C, $T_{\text{opt}}$ is set as 0; if $T_{\text{opt}}$ is greater than 1, $T_{\text{opt}}$ is set as 1 (Potter et al., 1993).

### 4.5. $W_{\text{scalar}}$

The effect of water on plant photosynthesis ($W_{\text{scalar}}$) was estimated based on the atmospheric water supply–demand concept. Monthly moisture effects based on the "supply–demand" drought index (SDDI) approach (Rind et al., 1990) were used. For a month of interest $i$, its potential evapotranspiration (PET) was first calculated using Hamon method (Eq. 4, Lu et al., 2005):

$$
\text{PET}_i = 0.1651 \times 216.7 \times d/12 \times (6.108e^{(17.27T_i/(T+273.33))}/(T + 273.33))
$$

(4)

where $d$ is the total daylength in hours and $T$ is the average monthly temperature (°C). Second, for each grid we calculated an index $Z_i$:

$$
Z_i = \frac{[(\text{PET}_i \times \text{PET}_{i-1}) - (\text{PET}_{i-1} \times \text{PET}_{i})]/\text{STD}}{\text{STD}}
$$

(5)

where $\text{PET}_i$ is the precipitation, $\text{PET}_{i-1}$ is the long-term average precipitation, $\text{PET}_{i}$ is the long-term average PET, STD is the interannual standard deviation of the PPT–PET for month $i$. Third, to account for the fact that soil moisture deficit is a cumulative phenomenon, the index for the current month $Y_i$, which is related to the index from the previous month $Y_{i-1}$, was calculated following Rind et al. (1990):

$$
Y_i = 0.897 \times Y_{i-1} + Z_i.
$$

(6)

Last, we converted $Y_i$ to water stress scalar $W_{\text{scalar}}$:

$$
W_{\text{scalar}} = 0.5 + 0.5 \times \left[Y_i - Y_{i \text{ min}}\right]/\left[Y_{i \text{ max}} - Y_{i \text{ min}}\right]
$$

(7)

where $Y_{i \text{ max}}$ and $Y_{i \text{ min}}$ are the maximum and minimum $Y_i$ for month $i$.

### 4.6. $F_{\text{PAR}}$ change between two scenarios

$F_{\text{PAR}}$ depicts how much PAR can be absorbed by vegetation canopy. In our study, the "best" and "local" $F_{\text{PAR}}$–NDVI relationship for all plant functional types was used to estimate $F_{\text{PAR}}$ from Landsat NDVI (Eq. 8, Steinberg et al., 2006).

$$
F_{\text{PAR}} = \max(0, \min((1.26 \times \text{NDVI} + 0.011), 0.95))
$$

(8)

where NDVI was calculated as a normalized ratio between the near-infrared band (B4) and the red band (B3) using Eq. (9) (Tucker, 1979), resulting in three NDVI datasets for 13 July, 5 August, and 6 September 2004.

$$
\text{NDVI} = (B4 - B3)/(B4 + B3).
$$

(9)

One main purpose of our study is to examine the fire impact on GPP at the pixel level; this requires NDVI datasets (and thus $F_{\text{PAR}}$) assuming the fires had not occurred. Huang et al. (2013) had developed an approach to reconstruct the land surface, including NDVI, assuming no fires had occurred (Fig. 4). Briefly, a prefire image was selected as a reference and spectral characteristics of the same location as the fire pixel were first derived from the reference scene; second, spectrally similar pixels were identified within the reference scene; third, pixels that were not burned in the target scene, but were spectrally similar to the fire pixel on the reference scene, were averaged to provide an estimate for the fire pixel. In our study, taking the 26 June 1986 Landsat scene as a reference, we used the same concept to reconstruct 1977–2004 fire scars for 13 July 2004, 5 August 2004, and 6 September 2004. The NDVI was calculated for the reconstructed images, resulting in three NDVI datasets for 13 July, 5 August, and 6 September 2004 for the assuming-no-fire scenario.

### 4.7. GPP comparison and fire impact analysis

GPP under two scenarios (i.e., actual postfire GPP and assuming-no-fire GPP) was calculated using Eq. (1). This calculation resulted

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**Table 1**

Parameters of Michaelis–Menten in three sites.

<table>
<thead>
<tr>
<th>Sites</th>
<th>n</th>
<th>$E_{\text{max}}^{a}$</th>
<th>$P_{\text{max}}^{b}$</th>
<th>$R^2$</th>
<th>F-test</th>
</tr>
</thead>
<tbody>
<tr>
<td>1999 burn</td>
<td>1986</td>
<td>0.0092</td>
<td>0.1104</td>
<td>0.281</td>
<td>P &lt; 0.001</td>
</tr>
<tr>
<td>1987 burn</td>
<td>1614</td>
<td>0.0242</td>
<td>0.2904</td>
<td>0.545</td>
<td>P &lt; 0.001</td>
</tr>
<tr>
<td>Control</td>
<td>2048</td>
<td>0.0209</td>
<td>0.2508</td>
<td>0.448</td>
<td>P &lt; 0.001</td>
</tr>
</tbody>
</table>

---

*a* Maximum light-use efficiency in different units based on an approximate conversion of 4.6 between MJ (10^6 J) and mol PPFD (McCree, 1981) and of 12.001 between mol CO2 and g.

*b* $P_{\text{max}}$ is the maximum gross ecosystem exchange.
2) FPAR: Different vegetation has different NDVI (and thus FPAR). Taking these two scenarios resulted from the change in E_{max} and FPAR as under the assuming-no-

1) E_{max}: Different vegetation has a different E_{max} value (Table 1). For example, for one pixel, the prefire vegetation type in 1986 was evergreen needleleaf forest, but it changed to deciduous broadleaf forest in 2004. Accordingly, the E_{max} of 1.1556 gC/MJ PAR and 1.3336 gC/MJ PAR was used for the assuming-no-fire and actual postfire scenarios, respectively.

2) F_{PAR}: Different vegetation has different NDVI (and thus F_{PAR}). Taking the same example above, the assuming-no-fire NDVI was 0.4 and the actual postfire NDVI was 0.7. According to Eq. (8), the F_{PAR} of 0.515 and 0.893 was used for the assuming-no-fire and actual postfire scenarios, respectively.

At each flux tower location, the mean modeled GPP was compared with GPP based on eddy covariance. Since we have 3 flux towers (1987 burn, 1999 burn, and control sites) and 3 months (July, August, and September 2004), we compared 9 GPP pair values. This comparison helped to evaluate the reliability of our GPP modeling.

Fire impact on GPP was quantified by subtracting actual postfire GPP and assuming-no-fire GPP, aiding us in examining the absolute GPP magnitude change. However, due to cloud cover, only July, August, and September 2004 images were used, which resulted in incomplete GPP analysis of a full growing season. In addition, the 2004 drought resulted in lower GPP than normal years (Welp et al., 2007). A relative recovery rate, which is the ratio of the actual postfire GPP to assuming-no-fire GPP, would reduce the influence of GPP fluctuation caused by interannual climate variability and was thus further examined to aid the analysis.

5. Result

The modeled and eddy covariance based GPP for July, August, and September 2004 is plotted in Fig. 5. The modeled GPP agreed with eddy covariance based GPP well with an R^2 of 0.9437 and a root mean square error (RMSE) of 7.7 gC/m^2/month, indicating the reliability of our GPP modeling.

With the GPP model applied to two scenarios, the spatial distribution of GPP of the actual postfire and assuming-no-fire scenarios and their difference is shown in Fig. 6, where the general spatial GPP pattern affected by fire disturbance is clearly visible. The lower left corner (fire scars of 1990 and 2002) has very close or even slightly higher actual postfire GPP than assuming-no-fire GPP, indicating almost complete recovery. The prefire vegetation of this area was shrub/grass mixed, the same as postfire vegetation. The upper right corner (fire scars of 2003 and 2004) shows the lowest negative GPP difference, indicating less GPP recovery during the earliest succession stage. The prefire vegetation of this area was evergreen needleleaf forest, different from the postfire vegetation of shrub/grass mixed. The lower right corner (fire scars of 1987 and 1994) shows both positive and negative GPP difference, indicating a complex recovery pattern. The prefire vegetation of this area was primarily evergreen needleleaf forest, but postfire vegetation was primarily deciduous broadleaf forest and shrub/grass mixed. This general qualitative assessment could be further quantitatively analyzed based on the statistics of GPP (Table 2).

Table 2 shows the GPP comparison. The actual mean GPPs for the 0-year 2004 fire scar in July, August, and September are 23, 16, and 5 gC/m^2/month, but the reconstructed means are 122, 38, and 26 gC/m^2/month, resulting in a negative GPP difference of −99, −22, and −21 gC/m^2/month. The recovery ratio is 24%. The 2004 Landsat images were acquired immediately after the 2004 fire event; therefore, the low GPP recovery rate (24%) indicates that the most recent fires significantly damaged the vegetation cover. The 1-year 2003 fire scar shows a similar pattern to the 2004 fire scar, but the recovery rate is 43%, a little higher than the 24% of the 2004 fire scar. This rate indicates that the recovery was still at a low level, but the recovery of the 2003 fire scar was better than that of the 2004 fire scar. The actual mean GPPs for the 17-year 1987 fire scar in July, August, and September are 112, 73, and 21 gC/m^2/month, but the reconstructed means are 120, 82, and 25 gC/m^2/month, resulting in a negative GPP difference of only −8, −10, and −4 gC/m^2/month. The recovery ratio is up to 91%. This rate indicates that the GPP almost recovered to prefire level. In those fire scars from burns in 1991, 1995, 1998, 2001, and 2002,
the recovery rates are all greater than 75%. Before the fires, these areas were dominated by shrub/grass (see the land cover in Table 2), indicating shrub/grass might recover faster than evergreen needleleaf forest. The faster recovery rates of shrub/grass can be better observed in Fig. 7, where their values are at high level and all greater than 75%.

The overall assessment based on the mean values in Table 2 helps to understand the general trend as mentioned above; however, the standard deviations within the 1987–2004 fire scars, which were presented in Table 2 for actual and reconstructed GPP as well as their difference, indicate the variability within the same burned area. These standard deviation values imply the spatial heterogeneity, which is related to local site environment and burn severity. Our approach allows for pixel-by-pixel analysis on the impact of fires and succession on GPP and is revealed in Fig. 6c, where isolated patches deviating from the general distribution even within the same fire scars are visible. For example, over 10 patches within the 2004 fire scar show obvious GPP differences compared to their neighboring areas.

To further investigate the spatial variation, a small area was selected for careful examination (Fig. 8). Before the fire in 1998, this area was covered by evergreen needleleaf forest (54%), deciduous broadleaf forest (11%), and shrub/grass mixed (35%) (Fig. 8a). After the fire, their cover percentages changed to 11%, 20%, and 69% for evergreen needleleaf forest, deciduous broadleaf forest, and shrub/grass mixed, respectively (Fig. 8b). Due to this fire disturbance, when we compared the reconstructed GPP (Fig. 8c) with actual postfire GPP (Fig. 8d), the originally forested areas were subject to reduced GPP after 6 years; however, the originally shrub/grass areas had an increased GPP (Fig. 8e). This phenomenon can be better observed in the recovery ratio (Fig. 8f), where the originally forested areas show a ratio of less than 1, while the originally shrub/grass areas show a ratio of close to or greater than 1.

6. Discussion

Postfire vegetation recovery depends on many factors such as fire scar age, prefire vegetation, burn severity, soil, drainage, weather, and seed availability (Li and Potter, 2012). In our study, we revealed different changes in GPP for those fire scars with different ages (Table 2). Kasischke and French (1997) used 2 years of NDVI after fire and found a 50% reduction. Goetz et al. (2006) found that the burned areas displayed a sharp drop in NDVI at the time of the burning, followed by a recovery to pre-burn levels within about 5 years. Epting and Verbly (2005) found NDVI values dropped sharply for 2 years following the fire and then increased until reaching a peak in year 14. Hicke et al. (2003) modeled NPP of the most impacted pixel within each burned area and estimated a mean recovery period for boreal forests of about 9 years, with substantial variability among fires. Bond-Lamberty et al. (2004) measured total NPP and found it was low immediately after fire but highest 12–20 years after fire. Goulden et al. (2011) found an increasing trend in average GPP at stands that are 6, 15, and 23 years old. All these NDVI, LAI, NPP, and GPP changes indicate vegetation damage and recovery on the surface. In general, our GPP showed only 24% and 43% for the 0-year (immediate 2004 fire) and 1-year 2003 fire scar, which coincided with previous observations. However, we found that after 2 years the recovery rate ranged from 54% to 95%. Our study confirmed that fire scar age affects GPP recovery, but its influence is not absolute; spatial heterogeneity (e.g., prefire vegetation type) also played an important role as demonstrated in Fig. 8, where notable spatial variation of GPP recovery even within the same fire scar is obvious.

The approach we demonstrated in this study can quantify fire-induced GPP change at the pixel level. Satellite vegetation index has been used to estimate postfire vegetation recovery (e.g., Kasischke and French, 1997; Epting and Verbly, 2005; Goetz et al. 2006; Cuevas-Gonzalez et al. 2009; Veraverbeke et al. 2012). We further used NDVI as an input for a light-use efficiency GPP model so that the magnitude change in primary productivity caused by fire disturbance (i.e., the change in carbon fixation by vegetation) can be modeled. In this model, the changes in $E_{\text{max}}$ and $F_{\text{PAR}}$ are critical information. Successional trajectory varies in interior Alaska, resulting in a different
vegetation type after fire disturbance (Beck et al., 2011; Johnstone et al., 2010). The \( E_{\text{max}} \) value for different vegetation types can be modeled from the eddy covariance technique, which was demonstrated in our 1987 burn, 1999 burn, and unburned control flux tower sites. After fire, the canopy structure changed, resulting in the \( F_{\text{PAR}} \) change, which was inferred from NDVI change based on the local relationship found by Steinberg et al. (2006). Based on the spatially explicit change in \( E_{\text{max}} \) and \( F_{\text{PAR}} \), the spatial variation of fire impact on GPP, which is caused by site-specific environment and climate variability, can be captured. This was achieved by reconstructing satellite images assuming the fires had not occurred, with details reported in Huang et al. (2013). Our products advanced the work of Randerson et al. (2006), who used a single fire to quantify the various forcing agents, including ecosystem production, and their combined effect on climate warming.

Single fire study is a necessary step toward assessing the impact of a changing boreal fire regime on climate at regional or continental scales, and our spatially explicit GPP change quantification at the pixel level further advanced the estimation of fire effect on climate change. However, there are some limitations in our work as follows.

First, \( F_{\text{PAR}} \) estimation could be biased by non-photosynthetic vegetation (NPV). Vegetation canopies are composed of chlorophyll and NPV, but only the PAR absorbed by chlorophyll is responsible for photosynthesis; therefore, ideally canopy-level \( F_{\text{PAR}} \) should be partitioned into the fraction of PAR absorbed by chlorophyll and by NPV (Xiao, 2006). This may be more important for a fire-disturbed ecosystem because a large portion of coarse woody debris will remain after fire events (Huang et al., 2009; Liu et al., 2011). In this study, we did not consider the NPV effect.

Fig. 8. A selected area (see white box in Fig. 1) burned in 1998. The black areas are water bodies. a) Prefire (1986) Landsat classification, b) postfire (2004) classification, c) total GPP in July, August, and September 2004 assuming no fires had occurred (gC/m²), d) total GPP in July, August, and September 2004 (gC/m²), e) difference between actual and reconstructed GPP (i.e., d–c), f) ratio of actual to reconstructed GPP (i.e., d/c). In a and b, EF is evergreen needleleaf forest, DF is deciduous broadleaf forest, and SG is shrub/grass mixed. Width 10.5 km and height 11.5 km.
Second, the three $E_{\text{max}}$ Values determined in our study may not be sufficient. The $E_{\text{max}}$ is an important parameter that heavily relies on vegetation types but can be estimated from continuous CO$_2$ eddy flux towers (Wofsy et al., 1993). In our study, we used three flux towers to estimate $E_{\text{max}}$ for the local three representative ecosystems associated with fire disturbance. Although our estimations are between the previously reported $E_{\text{max}}$ (Table 3), land use change, disturbance history, and different successional stages of vegetation may result in the spatial variation and temporal changes of $E_{\text{max}}$ within a biome type (Wang et al., 2010a; Xiao, 2006), and a biome-dependent $E_{\text{max}}$ might be inappropriate due to the large inter-site difference (Wang and Zhou, 2012). This problem may be enhanced by the heterogeneity of a pixel, where different vegetation types may coexist and discrete land cover classification might not distinguish the real world vegetation types (Lavoie and Mack, 2012; Wang et al., 2010a). The problem may be also influenced by the quality of the flux measurements themselves. NEE measurements are affected by instrument calibration and data quality control. Perhaps a larger source of uncertainty comes from partitioning NEE into GPP and $R_e$ for $E_{\text{max}}$ calculation by extrapolating the relationship between night-time respiration and soil temperature to daytime respiration. Both NEE and respiration decisions are subjective, and are currently subject to great discussion (Wang et al., 2010a). Third, the GPP change revealed in the current study only reflects the conditions of three Landsat acquisitions in 2004 due to the 16-day repeat frequency and cloud cover. The hottest summer in at least the past 200 years occurred in 2004 (Barber et al., 2004) and the drought resulted in low vegetation production and different drought response sensitivity between aspen and black spruce (Welp et al., 2007). The approach demonstrated in this study using limited images in a limited extent shows promising results for extrapolating site-specific field or flux observations to a regional area; however, a fuller analysis of interannual and seasonal dynamics is desired. Extending this analysis to more Landsat overpasses would be able to address the interannual and seasonal dynamics.

### 7. Summary and conclusion

Boreal wildfires and succession change the land surface, including vegetation type and coverage, and carbon fixation. Due to the importance of fires in the carbon cycle and climate change, it is critical to quantify the effect of fire and succession on the dynamics of GPP. Point-based observations such as eddy covariance help us understand the carbon uptake, but its weakness of spatial representation hampers an analysis over a large area. Satellite-derived data such as NDVI or LAI can provide spatial–temporal vegetation information, but direct vegetation index comparison cannot reveal GPP magnitude. The direct prefire and postfire comparison is widely used, but the recovery identification may become biased due to interannual climate variability. Our approach used an image reconstruction that minimizes the confounding factors of weather variability, seasonal offset, topography, land cover, and drainage. This reconstruction reveals spatially explicit change in NDVI and $F_{\text{PAR}}$ between the actual postfire and assuming-no-fire scenarios (Huang et al., 2013). The information can be incorporated into a light-use efficiency model for estimating GPP. This model requires an important parameter $E_{\text{max}}$ that differs for different vegetation type, which can also be changed by fires and succession. The $E_{\text{max}}$ can be derived from eddy covariance data. By incorporating changes in $E_{\text{max}}$ and $F_{\text{PAR}}$ into the light-use efficiency model, the spatially explicit GPP change and recovery caused by fires could be examined. A future study will apply the approach demonstrated here to multitemporal fire impact on GPP over a large area.

### Acknowledgments

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### References


### Table 3

<table>
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<tr>
<th>Sites</th>
<th>This study</th>
<th>Other studies</th>
<th>Reference/notes</th>
</tr>
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<td>Running et al. (2000)</td>
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<td>Ruimy et al. (1996)</td>
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<td>0.37</td>
<td>Wang et al. (2010b) (for degraded grassland)</td>
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</table>

a Data from Table 1.
b The original unit is in μmol CO$_2$/μmol PPDF, but here converted to gC/mol PAR using a scalar of 12.001.


