Mapping recent burned patches in Siberian larch forest using Landsat and MODIS data

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Abstract
Mapping burned area at relatively high spatio-temporal resolution is important to assess the causes and consequences of landscape fire in forest ecosystems. A simple algorithm, Burned Area Extraction and Dating (BAED) algorithm, was developed to automatically extract burned patches and determine approximate date of fire occurrence for each burned perimeter. Burned perimeters were extracted by a two stage approach, including determining “core burned” pixels and shape of the burned patches, from successive Landsat images. A time series model that has components of seasonality and trend was fitted from MODIS (MODerate-resolution Imaging Spectroradiometer) NDVI (Normalized Difference Vegetation Index) product. The approximate date of fire occurrence for each burned patch was assigned when the difference between the observed NDVI and the predicted NDVI from the time series model exceeded a threshold for three consecutive times. The BAED algorithm was tested in Siberian larch forest, an ecosystem with unique fire regime and considerable contribution to the global carbon balance. The results suggested that correct rate detected by BAED algorithm increases sharply when fire size < 200 ha, and then levels at 90% thereafter. The BAED provides ecologists an easy way to map burned area for assessing ecological effects of landscape fire in Landsat data poor regions.

Keywords: Wildfire, boreal forest, mapping, larch, remote sensing, landscape ecology.

Introduction
Wildfire is an important natural disturbance agent for regulating species composition, influencing the carbon cycle, emission of gases and aerosols to the atmosphere, and affecting the socioeconomic life of humans in boreal ecosystems [Bowman et al., 2009; Shorohova et al., 2011; de Groot et al., 2013]. Mapping burned area at fine spatio-temporal resolution is increasingly important for assessing ecological effects of landscape fire and restoring ecological functions in this era of climate change [Turner, 2010]. Optical remote sensing
is a viable approach to provide timely, cost-effective, and spatially comprehensive view of burned patterns in vegetated areas [Chu and Guo, 2014; Mouillot et al., 2014]. Fire causes a drastic reduction of reflectance in the visible-to-near-infrared wavelengths (≈0.4 – 0.9 μm) due to loss of photosynthetic vegetation and an accompanied increase of reflectance in the short and middle infrared wavelengths (≈1.5 – 2.3μm) due to increased char/ash [Lentile et al., 2006; Miller and Thode, 2007]. Such changes in spectral signatures form the basis to identify spatial and temporal patterns of wildfires by remote sensing approaches [Chu and Guo, 2014; Mouillot et al., 2014].

High spatial resolution (< 30 meters) optical satellite sensors are able to capture changes in ecosystem structure and dynamics, and disturbance patterns at landscape scale [Kennedy et al., 2014], but typically result in smaller image footprints, thereby increasing the revisit time to image the same location on Earth [Roy et al., 2014]. So far, Landsat data is one of the most widely used fine resolution remotely sensed data to detect wildfire patterns [Wulder et al., 2012], and there has been a number of change detection algorithms applied over large spatial scales [Hansen and Loveland, 2012]. Most of these algorithms employ pixel-level time series segmentation techniques to identify abrupt changes or breaks in the temporal trajectory of spectral signatures of the land surface, and attribute the changes to a particular land cover change or disturbance event, including the Landsat-based detection of Trends in Disturbance and Recovery (LandTrendR) [Cohen et al., 2010; Kennedy et al., 2010]; On-the-Fly Massively Multitemporal Change Detection Using Statistical Quality Control Charts and Landsat Data [Brooks et al., 2014]; and Vegetation Change Tracker (VCT) [Huang et al., 2010]. However, a number of constraining factors, including cloud contamination, data receiving and archiving capacity, often result in a dearth of imagery for the desired time interval (e.g., monthly, seasonally, or yearly) in many parts of the world, and therefore compromise the application of these algorithms in Landsat data scant regions.

High temporal resolution sensors typically have more frequent revisit rates and produce wide-area coverage but with lower spatial resolution. Data acquired via the Moderate Resolution Imaging Spectroradiometer (MODIS) on board Terra and Aqua satellites have been widely used to study forest dynamics in tropical regions because of their superior quality in terms of atmospheric correction, accurate geolocation, and near-daily observations [Huete et al., 2002; Hilker et al., 2015]. MODIS was designed with dedicated fire monitoring capabilities, and a suite of standard MODIS products have been systematically generated, including thermal anomalies and fire [Giglio et al., 2003], burned area [Giglio et al., 2009], and associated global emission products [van der Werf et al., 2010]. Due to its high revisit rate and global coverage, several time series segmentation techniques have been developed to detect disturbance events, particularly wildfires, over large areas. Examples include Detecting Breakpoints and Estimating Segments in Trend (DBEST) [Jamali et al., 2015], and Breaks For Additive Season and Trend (BFAST) [Verbesselt et al., 2010b; Verbesselt et al., 2012]. However, the coarse spatial resolution of MODIS impedes its landscape-scale detection of ecosystem processes.

To monitor fire disturbance at both high spatial and temporal resolutions, several approaches have been developed via blending or fusing data with differing spatial and temporal characteristics, such as Landsat and MODIS data. The first approach was to use Landsat pixels to select pure end-members to train MODIS pixels to generate percentage tree cover [Hansen et al., 2003], which can subsequently be used to characterize land cover change or
disturbance event at sub-MODIS pixel resolution [Song et al., 2014]. The second approach was to fuse Landsat and MODIS data to generate high spatio-temporal synthetic images [Hilker et al., 2009a], which can subsequently be used to detect fire disturbance at Landsat pixel resolution [Healey et al., 2005; Hilker et al., 2009b]. Fire disturbance can also be detected by cross checking products from both sensors. For example, Boschetti et al. [2015] developed a rule-based approach to group patches with similar spectral characteristics into candidate burned area objects using Landsat ETM+ derived top of atmosphere reflectance products, and then compared the candidate burned area objects with contemporaneous MODIS Terra 8-day 1 km active fire detection product to discard or retain a burned area object.

In this paper, we introduce a simple two-stage approach, the Burned Area Extraction and Dating (BAED) algorithm, to detect burned patches at both high spatial (30 m) and temporal (<16 days) resolutions by combining Landsat and MODIS data. The first stage aims at extracting burned perimeters from high spatial resolution Landsat data, whilst the second stage detects approximate date of fire occurrence from high temporal resolution MODIS data. The BAED was designed to provide ecologists an easy way to map burned area for assessing ecological effects of landscape fires in Landsat data scant regions. The BAED algorithm was tested in Siberian larch forest; a region with unique fire regime and considerable contribution to the global carbon balance and climate change, yet an understudied ecosystem [Chu and Guo, 2013].

Materials and methods

**Burned Area Extraction and Dating (BAED) algorithm**

**Overview**

The BAED algorithm was designed to automatically extract burned perimeters from Landsat images, and to detect approximate date of fire occurrence from time series MODIS vegetation index data. At the core of the algorithm, normalized multidate Landsat surface reflectance was used to extract burned perimeters, and MODIS time series Normalized Difference Vegetation Index (NDVI) data was used to approximate the date of fire occurrence. To extract burned perimeters, the algorithm first determines “core burned” seeds by selecting pixels with the most significant spectral change, and then grows the seeds into patches by a region growing algorithm. To approximate the date of fire occurrence, the MODIS time series NDVI data was used to fit a time series model, and the model used to predict the expected NDVI at any given time. The predicted NDVI was compared with the observed NDVI from a fire perimeter to find persistent change of spectral signal to approximate fire occurrence date.

The primary inputs to the BAED algorithm are the normalized multi-date Landsat surface reflectance data, and standard MODIS vegetation index product (MOD13Q1). The processing flow included image preprocessing, determining “core burned” pixels, and shaping burned patches, dating burned patches, and post-processing. The primary output of the BAED algorithm is burned patches, and each patch associated with the approximate fire occurrence date (Fig. 1).
**Preprocessing**

*Image selection and radiometric normalization* Cloud-free (<10%) Landsat images in the peak growing season highlight the spectral contrast between unburned and burned forest, and therefore are better at detecting fire-induced spectral space change. In the process of image selection, the absence of clouds was given the highest priority, and then the consistency of seasonality. Radiometric normalization is critical to the BAED algorithm, as normalization facilitates comparison of spectral space through time. No geometric correction was applied, as Landsat data from USGS GLOVIS portal (http://glovis.usgs.gov/) are already well-registered. Atmospheric correction was performed using the Landsat Ecosystem Disturbance Adaptive Processing System (LEDAPS) atmospheric correction tool [Masek et al., 2006], in which the raw digital numbers were converted to surface reflectance. Topographic correction was not applied. The effects from sun-sensors-geometry, phenology, and random error on surface reflectance were further corrected by the iteratively re-weighted multivariate alteration detection (IR-MAD) technique [Canty and Nielsen, 2008]. The IR-MAD technique uses canonical correlation analysis (CCA) to find linear combinations between subject images and reference image to generate a pair of new multispectral images, called canonical variates (CVs). Each pair of CVs is maximally correlated and is orthogonal to (uncorrelated with) other pairs. This means that
the difference between the two newly generated images will show maximum spread in its pixel intensities. Pixels with the least differences between CVs are located as the pseudo-invariant pixels (PIFs) by this technique. The selected PIFs were subsequently used to normalize each image band-by-band to the reference image using an orthogonal regression. Linear regression equations used to spectrally align each of the six bands of an image had an average \( R^2 \) value greater than 0.9 in all Landsat images.

Spectral indices selection Normalization process makes the spectral space relatively consistent among stable land cover targets through time, and highlights the spectral space contrast caused by fire. Following fire, changes in reflectance were evident across all the Landsat reflective bands but were greatest in the near infrared (NIR) and shortwave infrared (SWIR) wavelengths due to their large dynamic range and sensitivity to fire-related change (i.e. loss of photosynthetic vegetation and increased char/ash) (Fig. 2) [Goodwin and Collett, 2014]. Ratio-based spectral indices were selected because they enhance detection of vegetation and also minimize topographic-induced variance [Miller and Thode, 2007]. Spectral indices that have shown to be most sensitive to fire disturbance were carefully selected [Bastarrika et al., 2011; Chu and Guo, 2013] to be used in the BAED algorithm.

These indices included:

NDVI: NDVI is one of the most widely used indices to quantify the amount of photosynthetically active vegetation or greenness on the ground [Carlson and Ripley, 1997]. Therefore, change in NDVI indicates modification of aboveground photosynthetic vegetation. NDVI is defined as:
\[
NDVI = \frac{\rho_{\text{NIR}} - \rho_{\text{red}}}{\rho_{\text{NIR}} + \rho_{\text{red}}} \quad [1]
\]

where \( \rho_{\text{NIR}} \) is reflectance in the NIR wavelength, \( \rho_{\text{red}} \) is reflectance in the red wavelength.

Normalized Burn Ratio (NBR): NBR is sensitive to char, mineral soil, ash, and changes in soil color [Miller and Thode, 2007; Miller et al., 2009]. Change in NBR indicates alternation of soil condition, and char/ash. NBR is computed as:

\[
NBR = \frac{\rho_{\text{NIR}} - \rho_{\text{SWIR1}}}{\rho_{\text{NIR}} + \rho_{\text{SWIR1}}} \quad [2]
\]

where \( \rho_{\text{SWIR1}} \) is surface reflectance in the SWIR 1 wavelength.

Disturbance Index (DI): DI is specifically designed to detect changes in forest cover. The DI is a linear combination of brightness, greenness and wetness indices from Tasseled Cap (TC) transformation [Healey et al., 2005; Masek et al., 2008]. DI takes advantage of the reflectance change in the reflective bands of Landsat data, and therefore is sensitive to land cover change. The brightness (B), greenness (G), and wetness (W) indices are a standard transformation of the original Landsat spectral bands, and the coefficients used to calculated the TC indices for Landsat 5, 7, and 8 were obtained from literature [Huang et al., 2002; Baig et al., 2014]. The DI is calculated as follows:

\[
B_r = \frac{B - \bar{B}}{B_o} \quad [3]
\]

\[
G_r = \frac{G - \bar{G}}{G_o} \quad [4]
\]

\[
W_r = \frac{W - \bar{W}}{W_o} \quad [5]
\]

\[
DI = B_r - G_r - W_r \quad [6]
\]

where \( B_r, G_r, W_r \) are the normalized TC brightness, greenness, and wetness indices respectively, and \( \bar{B}, \bar{G}, and \bar{W} \), and \( B_o, G_o, W_o \) are respectively the mean and standard
deviation of these three TC spaces for mature or undisturbed forest. The re-scaling process normalizes pixel values across TC bands with respect to the overall changes in reflectance, such as seasonal changes or changes induced by directional reflectance effects, thereby effectively minimizing seasonal variability in the imagery. In short, DI records the normalized spectral distance of any given pixel from a nominal “mature forest” class to a “bare soil” class [Healey et al., 2005]. Pixels with NDVI greater than 0.8 were selected as mature forest. A total of 1000 mature forest pixels were selected to calculate mean and standard deviation of the three TC indices, and these statistics were used to calculate DI for each Landsat image.

Cloud and water mask Cloud masking strategies from other algorithms, such as Fmask [Zhu and Woodcock, 2012] or Automated Cloud Cover Assessment (ACCA) system [Irish et al., 2006], may yield better results, but are less easy to be integrated into the BAED algorithm. We identified clouds by applying a number of spectral filters used by Fmask and ACCA system [Zhu and Woodcock, 2012; Irish et al., 2006]. For example, clouds appeared to be white due to their “flat” reflectance in the visible bands. A “whiteness” index of 0.7 was found to be an optimal threshold to capture this property [Zhu and Woodcock, 2012]. Due to the very bright nature of clouds, all kinds of clouds have SWIR2 surface reflectance greater than 0.03 [Zhu and Woodcock, 2012]. Clouds make green wavelength brighter while cloud shadows make NIR and SWIR2 wavelength darker. Therefore, Normalized Difference Snow Index (NDSI) and NDVI should be smaller than 0.8. Based on these rules, a pixel was flagged as a cloud pixel if it met all the following conditions:

\[
\text{Cloud pixel} = \rho_{SWIR2} > 0.03 \text{ and } NDSI < 0.8 \text{ and } NDVI < 0.8 \text{ and Whiteness < 0.7} \quad [7]
\]

Where:

\[
NDSI = \frac{\rho_{green} - \rho_{SWIR2}}{\rho_{green} + \rho_{SWIR2}} \quad [8]
\]

\[
MeanVis = \left(\frac{\rho_{blue} + \rho_{green} + \rho_{red}}{3}\right) \quad [9]
\]

\[
Whiteness = \frac{\sum_{i=1}^{3} |(\rho_i - MeanVis) / MeanVis|}{3} \quad [10]
\]

Where 1, 2, and 3 correspond to blue, green, and red wavelengths, respectively \(\rho_{blue}, \rho_{green}\) and \(\rho_{SWIR2}\) are the reflectance in the blue, green, and SWIR2 wavelengths, respectively. Seasonal water bodies generally decrease surface reflectance for all reflective bands and greenness because there is often a mixture of water and aquatic plants. If un-flagged, most likely they will be mapped as forest disturbance regardless of the actual surface conditions [Huang et al., 2010]. Based on previous reports, a pixel was flagged as water pixel if it met all the following conditions [Zhu and Woodcock, 2012]:
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Water pixel = \((\text{NDVI} < 0.01 \text{ and } \rho_{\text{NIR}} < 0.1) \text{ or } (\text{NDVI} < 0.1 \text{ and } \rho_{\text{NIR}} < 0.05)\) \[11\]

**Determination of “core burned” pixels**

The aim of this step was to identify the most likely burned pixels on the Landsat image to minimize the commission error of potential burned patches. These “core burned” pixels were used as training data in the next step to model the burn probability of each cell based on their spectral characteristics (see next step for details). The “core burned” pixels for burned mapping was based on spectral indices change induced by fire between two successive Landsat images. Fire increases the DI [Masek et al., 2008] and decreases NDVI [Verbesselt et al., 2012] and NBR [Miller and Thode, 2007], and post-fire vegetation regrowth have the opposite effects on these spectral indices. Theoretically, any increase in DI \((\Delta \text{DI} > 0)\) and decrease in NDVI and NBR \((\Delta \text{NDVI} < 0, \Delta \text{NBR} < 0)\) is enough to determine burned pixels from Landsat images. However, this is only true when there are no other types of disturbance on the landscape and the land surface reflectance is free of contamination from factors, such as undetected clouds, cloud shadows, snow, atmospheric haze, smoke, and changes in soil wetness.

Although this step was aimed at identifying the most likely burned pixels with the lowest possible false detection, we also needed to get enough “core burned” pixel samples to increase the accuracy of the statistical model used to generate the burn probability [Hernandez et al., 2006]. Whenever stricter thresholds (larger \(\Delta \text{DI}\), smaller \(\Delta \text{NDVI}\) and \(\Delta \text{NBR}\)) were considered, fewer “core burned” pixels were selected and the commission error was reduced while the omission error of burned pixels increased. We determined spectral indices thresholds (i.e., \(\Delta \text{DI}\), \(\Delta \text{NDVI}\), \(\Delta \text{NBR}\)) iteratively based on the distribution probability of spectral indices change. To do this, we randomly sampled a pixel on every 7 by 7 window based on global Moran’s I to exclude spatial autocorrelation issues. We then used a histogram approach and previous publications to determine the threshold \((\Delta \text{DI} = 1, \Delta \text{NDVI} \text{ and } \Delta \text{NBR} = 0.1)\) that can separate burned pixels from the unburned within our study area [Fang and Yang, 2014; Fang et al., 2015]. Therefore, a pixel was flagged as a “core burned” pixel if it met all the following conditions:

"Core burned" pixel = \(\Delta \text{DI} > 1\) \text{ and } \(\Delta \text{NDVI} < -0.1\) \text{ and } \(\Delta \text{NBR} < -0.1\) \text{ and } \# \text{ cloud} \# \text{ water} \[12\]

Where \(\Delta \text{DI}\), \(\Delta \text{NDVI}\), \(\Delta \text{NBR}\) were calculated from successive Landsat imageries.

**Shaping the burned patches**

This step was aimed at growing “core burned” pixels into patches by applying a region growth algorithm based on the spectral properties of pixels close to the “core burned” pixels. Commonly used region growth approaches include spectral segmentation and contextual region growth. In spectral segmentation approach, pixels with similar spectral characteristics were grouped into an object, and the object attributed to different land cover classes [Boschetti et al., 2015]. In contextual region growth approach, iterative addition of pixels bordering the seed pixels were conducted based on the spatial contingency and spectral similarity [Bastarrika et al., 2011; Morton et al., 2011]. Some other approaches
include threshold based approach [Masek et al., 2008], or probability of burning conditioned on a suite of spectral changes, such as the Burned Area Essential Climate Variable algorithm [Hawbaker et al., 2015].

We combined spectral segmentation and contextual region growth to maximize benefits of the two approaches. The region growth algorithm includes three steps, including burned probability determination, spectral segmentation, and contextual region growth. The burned probability determination step was accomplished by using a case-control binomial boosted regression tree (BRT) ensemble model. In the BRT model, 70% of “core burned” pixels were used as cases and the same number of random points selected as controls. Spectral indices that have dramatic response to fire were used as predictors, and these are $\Delta \text{DI}$, $\Delta \text{NDVI}$, $\Delta \text{NBR}$, $\Delta \rho_{\text{NIR}}$ and $\Delta \rho_{\text{SWIR2}}$. To limit potential overfitting, the BRT ensemble process is controlled by learning rate ($lr$, the rate at which the model is built), tree complexity ($tc$, the level of variable interactions), and number of trees ($nt$) to balance model fit and predictive performance [Elith et al., 2008]. The remaining 30% of “core burned” pixel was used to evaluate the BRT model. Spectral segmentation step was accomplished by finding pixels with similar spectral change as the “core burned” pixels. A threshold value, which maximize kappa statistic, was used to classify continuous burn probability surface into a binary burned/unburned image. Then, a contextual region growth step was applied to the binary burned/unburned image to increase the continuity of burned patches. This was done by applying a $7 \times 7$ pixel moving window. If more than 50% of the pixels within the window were classified as burned, then the central pixel was also classified as burned.

Finally, the binary burned/unburned image was converted to polygons, and holes within burned patches were removed, as we were mainly interested in delineating outer perimeters, not the unburned islands within fire. To increase the accuracy of detection rate and disturbance time in the next stage, the minimum mapping size was set to 6.25 ha (1 MODIS cell at 250 m resolution). Each potential burned patch was assigned to one of three potential cloud conditions based on the spatial relationship between burned patches with cloud, including completely within cloud, partially within cloud, or clear (no cloud presence).

**Dating burned patches**

The basis of our method is to compare expected NDVI trajectory with observed NDVI trajectory within delineated burned patches from the previous step to find when persistent and significant change in NDVI occurred. Expected NDVI trajectory described land surface phenology (LSP) in each day of the year for undisturbed forest. The expected NDVI change, or LSP, were modeled by a time series model with three components: (1) a trend component: caused by gradual change in climate, such as warming or long-term drought, vegetation regrowth after disturbance, such as fire or disturbance; (2) a seasonal component: driven by seasonal patterns of environmental factors like temperature and precipitation; and (3) a remainder component, capturing the remaining variation in the data beyond the seasonal and trend components [Verbesselt et al., 2010a; Zhu and Woodcock, 2014]. We used a time series additive model to capture the seasonality and trend in the LSP change. The model coefficients were estimated by the Ordinary Least Squares (OLS) method because it is faster and more accurate when all the significant outliers have been excluded [Zhu and
Woodcock, 2014].

\[ Y_t = T_t + S_t + e_t \quad [13] \]

\[ Y_t = \alpha \cos \left( \frac{2\pi}{365} t \right) + \beta \sin \left( \frac{2\pi}{365} t \right) + \gamma t \quad [14] \]

Where \( Y_t \) is the observed data at time \( t \), \( T_t \) is the trend component, modeled as linear model; \( S_t \) is the seasonal component, modeled as harmonic model; and \( e_t \) is the remainder component. \( \alpha \) and \( \beta \) are the coefficients for seasonal component, and \( \gamma \) is the coefficient for trend component.

The fitted time series model was used to predict the expected NDVI trajectory for each day of the year (\( t \)), and then compared with the observed NDVI trajectory from each burned patch. Ideally, if observed NDVI is smaller than expected mean NDVI predicted by the time series model, it will be definitive for detecting change. However, noise in the system due to factors like undetected clouds, cloud shadows, snow, atmospheric haze, smoke, and changes in soil wetness will lead to NDVI variations [Zhu et al., 2012]. These noise factors tend to be ephemeral in nature; while fire-induced NDVI decrease is more persistent. Therefore, the BAED algorithm minimizes ephemeral effects by processing a set of dates together as a group for identifying fire disturbance. That is, if a pixel is observed to change in multiple consecutive images, it is more likely to be a real change. In this study, if observed NDVI was smaller than a 5% percentile value of expected NDVI for three successive dates, the first date of NDVI change was assigned as the disturbance time. Otherwise, the fires were likely falsely detection.

**Post-processing**

This step was aimed at removing conspicuous errors from the final output of the BAED algorithm. It was specifically meant to remove fire perimeters with occurrence date outside the Landsat acquisition periods or the fire season.

**Algorithm testing and validations**

The BAED algorithm was tested in Great Xing’an Mountains of Northeast China corresponding to WRS-2 Path 121/Row 24 (122.26-125.71 E, 50.70-52.70 N) for which the fire occurrence dates and locations were known and could be validated using an independent data source described below. Larch forest in this area is in the southern extension of Siberian deciduous coniferous forest. Wildfire is the major natural disturbance agent but has been aggressively suppressed since the 1950s. Large fires only occurred in remote areas under extreme fire weather conditions [Liu et al., 2012]. Landsat images from the Thematic Mapper (TM), the Enhanced Thematic Mapper plus (ETM+), and the Operational Land Imager (OLI) were selected to map the burned area. Six bands from the visible, NIR, and SWIR wavelengths were used to calculate spectral indices, and numbered accordingly to facilitate the radiometric normalization, spectral indices calculation and comparison (Tab. 1). Six cloud-free Landsat images described in Table 2 were selected for burned area mapping during the validation process. These images were acquired during the peak
growing season (from mid-June to late August) from 1999 to 2013. Successive Landsat images were less than 5 years apart, because previous studies have shown that spectral change caused by fire was most apparent within 5 years [Cuevas-Gonzalez et al., 2009].

Table 1 - Spectral bands used in the BAED algorithms for each Landsat sensor [Roy et al., 2014].

|             | Landsat 5 (TM) |         | Landsat 7 (ETM+) |         | Landsat 8 (OLI) |         |
|-------------|---------------|---------|-----------------|---------|----------------|---------|
|             | Band          | Wavelength (μm) | Band          | Wavelength (μm) | Band          | Wavelength (μm) |
| blue        | 1             | 0.45-0.52 | 1               | 0.44-0.52 | 2               | 0.45-0.51 |
| green       | 2             | 0.52-0.60 | 2               | 0.52–0.60 | 3               | 0.53–0.59 |
| red         | 3             | 0.63–0.69 | 3               | 0.63–0.69 | 4               | 0.64–0.67 |
| NIR         | 4             | 0.76–0.90 | 4               | 0.77–0.90 | 5               | 0.85–0.88 |
| SWIR1       | 5             | 1.55–1.75 | 5               | 1.55–1.75 | 6               | 1.57–1.65 |
| SWIR2       | 7             | 2.08–2.35 | 7               | 2.09–2.35 | 7               | 2.11–2.29 |

Note: ETM+: enhanced thematic mapper plus; TM: thematic mapper; OLI: operational land imager

Table 2 - Landsat data and MODIS 16-day NDVI composite data from MOD13Q1 (tile H25V3) used in this analysis.

| Landsat data               | MODIS                        |
|----------------------------|------------------------------|
| Date (YYYY-MM-DD)          | Path/row | sensor          | time span (YYYY-MM-DD) |
| 1999-9-4                   | 121/24  | ETM+ SLC-on     | 2000-2-18 ~ 2013-12-20 |
| 2002-7-27                  | 121/24  | ETM+ SLC-on     |                          |
| 2005-9-13                  | 121/24  | TM              |                          |
| 2007-8-18                  | 121/24  | TM              |                          |
| 2010-8-26*                 | 121/24  | TM              |                          |
| 2013-9-3                   | 121/24  | OLI             | 2010-1-1 ~ 2011-12-19   |
| 2010-8-17*                 | 122/20  | TM              |                          |
| 2011-8-12                  | 122/20  | ETM+ SLC-off    |                          |

Note: * denote reference images used in IR-MAD normalization. ETM+: enhanced thematic mapper plus; SLC: scan liner correction; TM: thematic mapper; OLI: operational land imager; MODIS: Moderate Resolution Imaging Spectroradiometer; NDVI: Normalized Difference Vegetation Index.

We used the 16-day composite NDVI data at 250-meter spatial resolution from the MODIS MOD13Q1 product (collection 5) to fit time series LSP model (Tab. 2). The products were derived from daily NDVI data through maximum value composites method within each 16-day period. These products were computed from atmospherically corrected bi-directional surface reflectance data that have been masked for water, clouds, heavy aerosols, and cloud shadows. The accuracy of this product has been assessed over a widely distributed set of locations and time periods via several ground-truths and validation efforts [Justice et al., 1998]. Data quality labeled as “good” was used to fit time series phenology model
for predicting expected NDVI trajectory. The MODIS NDVI data was obtained from the Land Processes Distributed Active Archive Center (LP DAAC), and was reprojected to the Universal Transverse Mercator projection for consistency with the Landsat data. Validation fire dataset between 2000 and 2013 were obtained from local forest fire prevention agency. Burned patches were manually delineated based on fire ignition locations and date on a remote sensing index, called delta Normalized Burn Ratio (dNBR), which was shown suitable for burned patch delineation in our study area [Fang and Yang, 2014]. Calculation of dNBR images strictly followed the protocol proposed by Miller et al. [2009]. We determined the dNBR threshold (>0.1 in this study) to separate burned pixels from the unburned. A total of 16 fires, ranging from 18.4 ha to 8470.4 ha with a median of 286.0 ha, that burned over 26343.7 ha during the study period were extracted based on this approach. We calculated omission and commission rates on a per-fire polygon basis, rather than per-pixel basis [Foody, 2002]. Per-fire polygon analyses quantified the overlap between BAED-derived fire perimeters and manually-delineated validation fire perimeters. Omission rate quantified the burned pixels that were missed by the BAED algorithm. Commission rate quantified unburned pixels that were falsely detected by the BAED algorithm. An overall correct rate was also calculated as both burned and unburned pixels correctly mapped by BAED algorithm. Correct rate quantified the overall spatial accuracy of the BAED algorithm. We calculated date difference, as the difference between BAED-derived disturbance time and validation disturbance time, to quantify the temporal accuracy of the BAED algorithm. We plotted the validation results with fire size to quantify the scale effects of fire size on the accuracy of the BAED algorithm.

**Results**

Our results showed that spectral indices and band reflectance were not significantly different from each other (t-test, \(p>0.05\)) for stable forest among TM, ETM+, and OLI sensors after radiometric normalization (Fig. 3). This result suggested that the band to band normalization approach by IR-MAD effectively maintained the cross-sensor radiometric integrity, although they had different band wavelength widths, scanning mode, and radiometric resolutions [Roy et al., 2014]. Figure 4 shows an exemplary output from BAED algorithm, which demonstrates that even potentially small fires can be detected. The BAED algorithm also successfully grew the fire perimeter, and matched closely with the burn/unburned boundary. BRT results showed that changes in NDVI and DI alone account for over 85% of variations in the probability of burning (Fig. 5a). Burned probability increases shapely when NDVI drops more than 0.01 and DI increases more than 0.5 after fire, suggesting a drastic contrast between burned and unburned pixels in the boreal forest ecosystems (Fig. 5bandc). It is this sharp spectral space alteration caused by wildfires that form the basis of selecting “core burned” pixels based on a threshold value. However, it is worth to note that these thresholds can be different due to (1) fire characteristics, such as fire severity and size; (2) ecosystems characteristics, such as ecosystem structure and recovery rate; and (3) fire-ecosystems interactions, such as ecosystems fire susceptibility and regeneration strategies. These thresholds may be lower in larch forest than other boreal forest, because mature larch trees are fire-resistant, and burned area tends to be dominated by low severity surface fires [Wooster and Zhang, 2004; Liu et al., 2012; de Groot et al., 2013].
Figure 3 - The reflectance values and spectral indices of stable forest (NDVI >0.8) among normalized multi-date and different Landsat sensors.
Figure 4 - An illustrative example showing that the BAED algorithm extracts burned patches using a two-stage process. Panel a) the background Landsat image (acquired by ETM+ on 2002-7-27) displayed in band 4 (red), 3 (green), 2 (blue) color composite, and overlaid with “core burned” pixels. The extracted burned patch was overlaid on delta disturbance index (b), normalized burn ratio (c), and normalized differenced vegetation index (d). The delta spectral indices were calculated from ETM+ images acquired before (1999-9-4) and after (2002-7-27) fire. The green polygons were associated with invalid disturbance date, and were excluded in the final results.
Cloud contamination is one of the biggest challenges in forest change detection [Huang et al., 2010]. If un-flagged, cloud-contaminated pixels will have lower greenness values, and may be mapped as fire disturbance (Fig. 4). The BAED algorithm minimizes cloud influence at multiple stages. First, the simple cloud mask strategy could detect a significant portion of clouds, and this mask was used in the process of “core burned” pixels selection and patch growth. Second, the dating algorithms only used the significant and persistent change in NDVI trajectory to find disturbance time. Figure 6 shows how time series LSP model can be used to characterize the seasonal circles of NDVI, and to find fire disturbance date. Generally, NDVI trajectory of an unburned pixel is within the 90% confidence interval.
of predicted NDVI, whilst NDVI trajectory of a burned pixel is consistently outside this boundary. This information helps to identify when the persistent change of land cover begins, and therefore forms the basis of disturbance time detection. For example, in Figure 4, many small fires were successfully identified as false detection after the dating procedure (green polygons); even though BAED algorithm had extracted many potential fires from the Landsat images. Third, each burned patch was labelled with different levels of cloud condition, and therefore denoted possible cloud influence. Moreover, the BAED does not rely on very dense stacks of Landsat images and therefore increases the chance of finding cloud-free Landsat images in the growing season.

![Figure 6](image)

**Figure 6** - An illustrative example showing how date of fire occurrence can be determined by comparing the expected NDVI and the observed NDVI trajectories within burned patches. Grey area is 90% confidence interval of unburned forest, overlaid with mean predicted NDVI trajectory for unburned forest (green line), and burned forest (red line).

Figure 7 shows the extracted burned patches and associated fire occurrence time in the test area from the BAED algorithm. Generally, the spatial accuracy of the BAED algorithm is dependent on fire size (Fig. 8). The correct rate increases sharply when fire size < 200 ha, and then leveled at 90% thereafter. Similarly, the omission and commission rates were highly variable when fire size is smaller than 200 ha, suggesting a relative unstable performance with smaller fire sizes. This result is expected because fire-induced change in spectral signature of small fires are more likely to be compensated by the adjacent unburned vegetation, and are therefore more difficult to detect. This result is also consistent with other studies, which suggested that larger fires tend to have higher detection accuracy [Sulla-Menashe et al., 2014]. Generally, the omission rate is higher than commission rate, suggesting that we are conservative in growing fire perimeters. The temporal accuracy of BAED algorithms was generally within 10 days. The temporal accuracy is expected to increase should a finer temporal resolution data be used.
Figure 7 - The burned patches and approximate fire occurrence date determined by BAED algorithm between 1999-9-4 and 2013-9-3 for two chips from test site 1 (panel a), overlaid with validation fire polygons (in light blue polygons). The background Landsat image (acquired by TM on 2010-8-26) was displayed in band 4 (red), 3 (green), 2 (blue) color composite. The dimension of b is 1000 × 1000 cells in 30 m spatial resolution, and c is 1000 × 1500 cells in 30 m spatial resolution.
The BAED algorithm were also tested using a Landsat 7 SLC-off image in a Siberian larch forest corresponding to WRS-2 Path 122/Row 20 (123.30-127.25E, 56.33-58.26N). Two cloud-free (cloud cover < 10%) images were selected to map burned patches, and 35 MODIS NDVI 16-day composites (from May 9th, 2010 to Nov 1st, 2011) were used to date burned patches (Tab. 2). The result show that BAED could correctly identify fire patches. However, data gaps caused by scan line corrector failure result in about 22% loss of the image data. Therefore, burned patches detected by BAED were broken into smaller segments. Because of this constraint, we expected a decreased performance of the algorithm. Our results confirmed that many small burned fragments were not detected. Despite this limitation, the location of most fires could be detected correctly. Our results also indicate that the disturbance times were generally correct by comparing active fire and BAED-derived date (Fig. 9)
Figure 9 - The perimeters and approximate fire occurrence date extracted by BAED algorithm between 2010-8-17 and 2011-8-12 in the central Siberia site (panel a). Panel b, a Landsat image (acquired by TM on 2011-7-19) displayed in band 4 (red), 3 (green), 2 (blue) color composite; showing active fires at the time of satellite overpass. Panel c, fire perimeters overlaid on top of delta NDVI.
Discussion and conclusion

The BAED algorithm was designed to map burned patches at relatively high spatio-temporal resolution using Landsat and MODIS data. The Landsat archive offers the longest, high spatial resolution, global coverage, and freely available data since the 1970s. The 30 meter spatial resolution Landsat data has demonstrated its capability to discriminate anthropogenic and natural changes at local to global scale consistently [Kennedy et al., 2014]. Therefore, ensuring the continuity of Landsat data could provide high spatial resolution, large area, long-term terrestrial data records for landscape scale ecological applications, resource management, and for climate and global change studies [Kennedy et al., 2014]. The BAED algorithm can also potentially use any Landsat-like observations. For example, the Sentinel 2A/2B satellites, which are similar to Landsat in terms of orbit, overpass time, and spatial resolution [Drusch et al., 2012], can potentially be used by BAED algorithm given proper modification of the algorithm (e.g., threshold values). Theoretically, the BAED algorithm can be modified to use any higher spatial and temporal resolution dataset. We used MODIS 16-day NDVI time series as an example to find disturbance time. It is worthy to note that other vegetation indices, such as EVI, from other satellite sensors, such as SPOT, AVHRR can also be used. Increasing the temporal resolution of time series NDVI data can increase the temporal accuracy of the algorithm.

Our ability to characterize landscape processes, including those that are abrupt (e.g., wildfire, clear-cut), subtle trends (e.g., drought or regrowth), cyclical (e.g., phenology), or feedbacks, depends on the number of clear observations and measurement noise [Kennedy et al., 2014; Hilker et al., 2015]. Stimulated by freely available, consistent and robust radiometric and geometrically corrected Landsat data, and advance in computation capacity, more and more algorithms seek to use dense Landsat data to characterize landscape dynamics at larger spatial extent over longer temporal scales, and have produced satisfactory results in detecting forest dynamics [Hansen et al., 2013], land cover change [Zhu and Woodcock, 2014], or disturbance mapping [Kennedy et al., 2012]. Researchers in many areas, however, are still struggling to interpret high resolution satellite data in the presence of cloud cover, aerosol contaminations, and limited good observations. On the other hand, medium resolution (for example, MODIS 250 -500) sensors typically have higher chances of getting clear sky observations due to their high revisit rate. Noise is usually from undetected clouds and cloud shadows, snow and aerosol from biomass burning. Typical techniques to overcome high noise levels include best pixel compositing, which effectively increases the data quality at the cost of a reduced number of observations. In the BAED algorithm, we tried to combine the advantages offered by both high and medium resolution remote sensing data. Therefore, the BAED can be a complement to algorithms based on Landsat or MODIS data. The BAED algorithm has the potential to map wildfire disturbances in highly dynamic landscapes, such as boreal larch forest, where high resolution remote sensing data are limited.

Comparing BAED-derived fire patch with MODIS burned area (MCD45A1, c5.1) and active fire (MCD14ML, c5) products suggested that standard MODIS products often fail to detect burned area and fire occurrence in Siberian larch forests (Fig. S1). This is because larch forest does not support crown fire because of high moisture content of deciduous needles. Most large fires in larch forest occur during spring (March - May), when there are extensive areas of dead light surface fuels (e.g., cured grass, leaf litter) available for
combustion before understory plants green-up and trees leaf-out [de Groot et al., 2013]. Therefore, Siberian larch forest fire regime is characterized by early season, low-intensity surface fires, which are distinctly different from fire regimes in other boreal biomes, which are characterized by high intensity crown fires mainly occurring in summer and autumn [Wooster and Zhang, 2004; de Groot et al., 2013; Rogers et al., 2015]. All things being equal, fires in Siberian larch forest are more difficult to detect using coarse spatial resolution satellite images due to lower energy output and possible obscuration of the fire front by live tree canopy [Wooster and Zhang, 2004; de Groot et al., 2013]. Therefore, the algorithm proposed here provides a useful alternative for detecting fire dynamics in forest ecosystems dominated by low severity fire regimes.

Notwithstanding the promising performance of the algorithm, some limitations should be noted in using BAED algorithm. The BAED was aimed at detecting fires in ecosystems where fire effects were acute and persistent. If the effect of fire on ecosystem structure is short or less severe, such as savanna fire or understory fire in rainforest, the algorithm may not be able to detect burned patches correctly. The BAED algorithm has a decreased accuracy with decreasing fire size. Therefore, this algorithm may be less useful to assess spatial patterns of small fires. However, it can be very useful to assess burned area and its seasonality, as large fires contribute most of burned area. This makes BAED algorithm particularly useful in Siberian larch forest, as studies have shown fire size is larger than Canadian boreal forest [de Groot et al., 2013]. Although the BAED algorithm has proven successful for detecting burned area in Siberian larch forest, it may not be able to differentiate other types of disturbance, such as timber harvesting, insect infestations or low-grade fire events. Further modifications will be required to detect these kinds of disturbances in other boreal ecosystems. Finally, the BAED algorithm is limited to a before and after delineation of each disturbance event, and does not allow for the detection or progression of individual fire events.

Mapping fire disturbances has significant implication for studying the carbon cycle, vegetation-fire-climate interactions, and post-fire recovery. High spatial and temporal resolution fire products may offer the scientific community an opportunity to explore the relationships between disturbance and ecosystem processes at more meaningful spatio-temporal scales. The BAED has the ability to generate fire products at fine spatio-temporal resolution in Landsat-like data scant areas with very limited human interventions. Results from Siberian larch forest provide the evidence of its utility, and the possibility to extend the algorithm to other satellite sensors and boreal regions.

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Figure S1 - Comparison between BAED-derived patch and standard MODIS fire products. MODIS burned area product detects the approximate date of burning and maps the spatial extent of recent fires and not of fires that occurred in previous seasons or years (Roy et al., 2005). MODIS burned area product (MCD45A1, resolution = 500 meter, collection 5.1, temporal coverage: April 2000 – March 2013) were obtained from the Land Processes Distributed Active Archive Center (LP-DAAC) (https://lpdaac.usgs.gov/). The MODIS active fire product detects fires in 1km pixels that are burning at the time of overpass under relatively cloud-free conditions using a contextual algorithm and a set of rule-based rejection algorithms (Giglio et al., 2003). The monthly fire location product (MCD14ML, collection 5, temporal coverage: December 2000 – December 2013) contains the geographic location, date, and some additional information for each fire pixel detected by the Terra and Aqua MODIS sensors on a monthly basis at ASCII (text) file were downloaded from University of Maryland (ftp://fuoco.geog.umd.edu).

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