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Assessment of post-fire vegetation recovery in Southern Siberia using remote sensing observations

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Abstract

Wildfire is one of the main disturbances affecting forest dynamics, succession, and the carbon cycle in Siberian forests. The Zabaikal region in southern Siberia is characterized by one of the highest levels of fire activity in Russia. Time series of Landsat data and field measurements of the reforestation state were analyzed in order to estimate post-fire vegetation recovery. The results showed that the normalized burn ratio time series can be used to estimate forest recovery in the pine- and larch-dominated forests of the Zabaikal region. Multiple factors determine a forest's recovery rate after a wildfire, including fire severity, tree species characteristics, topography, hydrology, soil properties, and climate. Assessing these factors is important if we are to understand the effects of fire on forest succession and to implement sustainable forest management strategies. In this work we used the field data and Landsat data to estimate post-fire vegetation dynamics as a function of several environmental factors. These factors include fire severity, pre-fire forest state, topography, and positive surface temperature anomalies. A regression model showed that fire frequency, fire severity, and surface temperature anomalies are the primary factors, explaining about 58% of the variance in post-fire recovery. High frequency of fire and positive surface temperature anomalies hamper the post-fire reforestation process, while more severe burns are followed by higher recovery rates. Further studies are necessary to consider other important factors such as soil properties, moisture, and precipitation, for better explanation of post-fire vegetation recovery.

1. Introduction

The world's boreal forests cover about 1.2 billion ha in total, of which about 900 million ha are in Russia (FIRESCAN Science Team 1994). Fire is the key factor influencing a boreal region's vegetation dynamics, carbon cycle, and surface energy exchange (Furyaev 1996, Harden *et al* 2000, Amiro *et al* 2006). Currently, several million hectares of forested lands in Russia are exposed to fires every year, with a mean annual burned forested area of about 10 million hectares (Shvidenko *et al* 2011, Ponomarev and Shvetsov 2013, Bartalev *et al* 2015). Satellite-derived fire products show an increasing trend in burned forested areas of Siberia (Kharuk and Ponomarev 2017, García-Lázaro *et al* 2018), including the Zabaikal region (Kukavskaya *et al* 2016).

The Zabaikal region located in southern Siberia is characterized by one of the highest levels of fire activity in Russia (Kukavskaya *et al* 2013). According to analysis of satellite data, the annual burned forested area in the Zabaikal region between 1996 and 2015 varied from 0.04 to 5.6 million hectares (Kukavskaya *et al* 2016). Severe fire seasons generally occur every 3–5 years. The most severe fire seasons (2003, 2007, 2008 and 2015) were characterized by the early beginning of the fire activity (in March) and burned areas exceeding one million hectares of forested lands (Buryak *et al* 2016, Kukavskaya *et al* 2016). Krylov *et al* (2014) reported that the portion of area burned by stand replacement fires in the Zabaikal region varies between 10% and 20%.

Previous studies have examined *in situ* post-fire forest recovery, showing that many areas are characterized by reforestation failure (Buryak *et al* 2011, Gorbunov *et al* 2015, Buryak *et al* 2016, Kukavskaya *et al* 2016). Repeated fires in the Zabaikal region have significantly shorter fire return intervals than is required for the ecosystems to recover to their pre-fire state, thus leading to the transformation of forests to steppe ecosystems (Kukavskaya *et al* 2016). The 'Tsasuchei' Scots pine stand located in the forest-steppe ecozone of the Zabaikal region experienced multiple fires during 2000–13, in which most of its area was burnt (Kurganovich and Makarov 2015). As a result, 90% of its territory experienced total tree mortality as well as steppification (Buryak *et al* 2016). According to on-ground studies of Makarov *et al* (2016), post-fire regeneration in pine stands near Chita (the administrative center of the Zabaikal region) is mostly poor. Using MODIS data, Shvetsov *et al* (2016) found that the southwestern part of the Zabaikal region, which is characterized by the highest wildfire disturbance, experienced reforestation failure on about 11% of the total forested area.

Several studies have used multispectral and hyperspectral remote sensing data, to assess the degree of fire disturbance and to monitor the post-fire dynamics of forest ecosystems (Cuevas-Gonzalez *et al* 2009, Jin *et al* 2012, Mitri and Gitas 2013, Yi *et al* 2013). Fire-induced changes in the surface reflectance in the visible, near-infrared (NIR) and shortwave-infrared (SWIR) or middle-infrared (MIR) portions of the electromagnetic spectrum provide the basis for assessing the extent of the areas disturbed by fire in forest ecosystems, using remote sensing data (Fraser *et al* 2000, Roy *et al* 2005, Loboda *et al* 2007). These spectral bands are sensitive to variations in soil and vegetation color (visible), chlorophyll and water content (NIR and SWIR/MIR), which are significantly affected by fire severity (Tucker 1979, Gao 1996, Miller and Thode 2007).

Remotely-sensed SWIR-based indices such as normalized burn ratio (NBR) have been used to distinguish burned areas in various ecosystems (Gerard *et al* 2003, Loboda *et al* 2007). At the same time, NBR is used for fire severity assessment (Escuin *et al* 2008, Bartalev *et al* 2010). It also can be useful in monitoring the vegetation regeneration in disturbed areas (Lopez-Garcia and Caselles 1991, Cuevas-Gonzalez *et al* 2009) and in some cases could outperform normalized difference vegetation index (NDVI) (Pickell *et al* 2016). NBR demonstrates a greater magnitude of post-fire decrease and requires a longer recovery period to reach pre-fire values compared to NDVI (Gerard *et al* 2003, Cuevas-Gonzalez *et al* 2009).

Depending on forest type, wildfire severity, climate, and the initial post-fire density of tree seedlings, it takes more than a decade for remotely-sensed vegetation indices to recover after wildfire, i.e. to reach pre-fire values (Cuevas-Gonzalez *et al* 2009, Yi *et al* 2013). However, several studies report shorter recovery times for North American boreal forests (Hicke *et al* 2003, Jin *et al* 2012). Full ecosystem recovery to the pre-fire state in Siberia requires 100 or more years (Zyryanova *et al* 2008, Gamova 2014), as the growth of tree canopy occurs much more slowly than vegetation index recovery.

Fire severity is an important variable for prediction of post-fire vegetation recovery and succession (Johnstone and Kasischke 2005), which integrates active fire characteristics and immediate post-fire effects on the local environment (Lentile *et al* 2006). The combination of NIR and SWIR bands appears to provide the best distinction between burned and unburned areas, and an optimum signal for information about variation of burn severity (Key and Benson 2006). The correlation between remotely-sensed indices and field measurements of fire severity depends on various factors, such as the timing of severity assessment, topography, and vegetation characteristics, and can vary between regions and forest types (French *et al* 2008). Several studies attempted to assess fire severity using remote sensing data, mainly Landsat imagery, for various ecosystems (Lopez-Garcia and Caselles 1991, Wagtendonk *et al* 2004, Escuin *et al* 2008). For instance, Epting *et al* (2005) evaluated several remotely-sensed indices and found that the NBR was the best for estimating burn severity in Alaska. However, only a few studies have been conducted in the boreal forests of Siberia. Isaev *et al* (2002) found a linear relationship and a high correlation ($R^2 = 0.82$) between tree mortality and NDVI difference between pre-fire and post-fire images in the mixed conifer and deciduous forests of central Siberia. Bartalev *et al* (2010) compared remotely-sensed indices and tree mortality for southern Siberian regions, including the Zabaikal region. Their results indicate a good correlation between SWIR-based indices and tree mortality ($R^2 = 0.78$). Chu *et al* (2016) found that differenced Normalized Burn Ratio (dNBR) is the most important remotely-sensed index for assessing burn severity in Siberian larch forests of northern Mongolia.

Forest recovery after disturbances is a complex process since it is affected by multiple factors. Although several studies have identified the importance of such factors as fire severity, forest and environmental conditions, hydrology, and topography (elevation, slope, aspect) on tree regeneration (Díaz-Delgado *et al* 2002, Kasischke *et al* 2007, Chu *et al* 2017, Viana-Soto *et al* 2017), very few studies (Buryak *et al* 2016, Kukavskaya *et al* 2016) assessed in detail the role of these factors in vegetation recovery in the

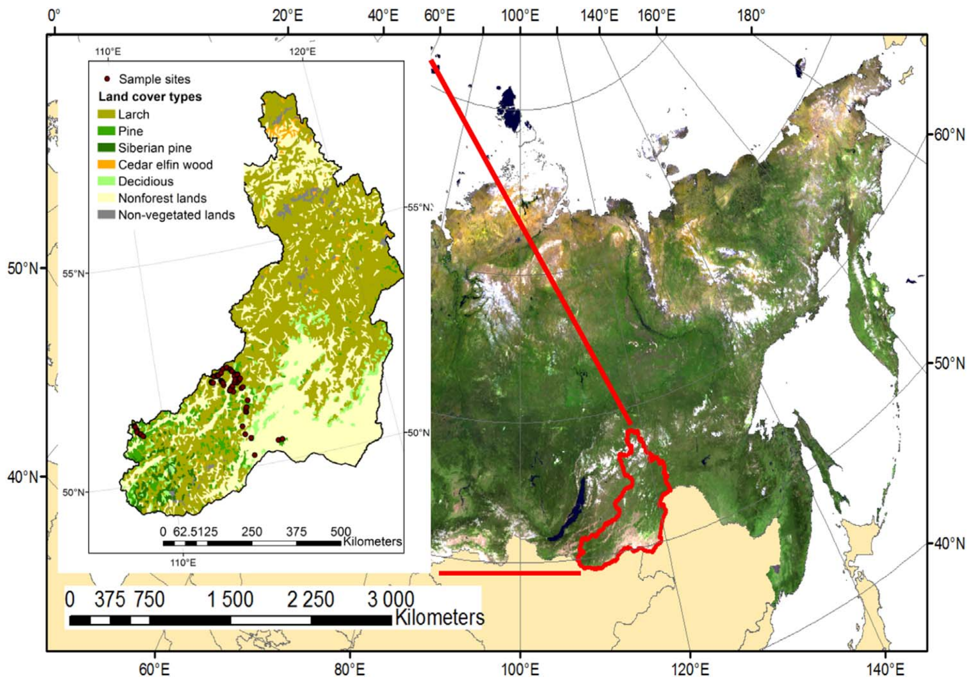

Figure 1. Study region. The inset shows land cover types within the study region, from a USSR vegetation map (USSR Forests 1990). The locations of sample sites are marked with dark dots. The background image of the Russian Federation is taken from the Blue Marble Next Generation dataset (Stockli *et al* 2005).

Zabaikal region in southern Siberia. The main goal of this research is to evaluate the performance of SWIR-based satellite metrics in assessing post-fire vegetation dynamics in the Zabaikal region, and to model the short-term vegetation recovery (7–17 years). Our objectives are: (1) to assess the relationship between 30 m Landsat data and post-fire reforestation dynamics; (2) to analyze the influence of several factors (pre-fire forest state, dominating tree species, landscape slope and aspect, fire frequency and severity, temperature anomalies) on the post-fire reforestation process.

2. Data and methods

2.1. Study area

The Zabaikal region is located to the east of Lake Baikal in southern Siberia (figure 1), occupying an area of 432 000 km^2. Forests account for 68% of the territory, while steppes dominate in the south and southeast (Kalesnik 1969, Forest Plan of the Zabaikal Region 2014). There are more than 50 mountain ridges in the region, with low valleys in between. Altitudes range from 300 m to > 2000 m (Geniatulin 2000, Kulakov 2009).

The climate in the Zabaikal region is strongly continental, with significant seasonal temperature variations (in some areas the annual range is almost 90 °C), low precipitation (from 300 mm in the south and southeast to 600 mm in mountains in the north), and a highly uneven annual distribution of precipitation (up to 80%–90% of precipitation is recorded during the summer–autumn period). Mean annual temperatures are negative for the whole region, varying from −0.5 °C to −11.4 °C. The average temperature in January is −24 °C to −26 °C, and the average July temperature is +15 °C to +18 °C (Geniatulin 2000).

Larch (*Larix gmelinii*, *L. sibirica*) and Scots pine (*Pinus sylvestris*) forests of low to moderate productivity dominate the region, with litter as the dominant ground cover under the forest canopies. Pine stands are widespread on dry and mesic sandy and sandy-loam soils. Larch stands grow in the upper parts of north slopes and in the zone of continuous permafrost in the northern Zabaikal region. Mixed larch and pine stands with some presence of deciduous species are typical on mesic and wet loamy soils (Buryak 2015).

Post-fire succession patterns in the region differ significantly, depending on the site conditions and fire characteristics. The most important factors determining post-fire regeneration are soil productivity, moisture, temperature, post-fire mortality related to fire severity, areal extent of wildfire, ground vegetation, and fire return interval. We investigated processes of post-fire recovery in differing forest types in the Zabaikal region. According to *in situ* data (Buryak *et al* 2016, Kukavskaya *et al* 2016), in undisturbed pine stands growing on dry sandy and sandy-loam soils, regeneration consists of pine seedlings only (on average, 2.2 × 10^3 per ha). Fires of both low and high severities result in a decrease of regeneration to 0.9–0.5 × 10^3 per ha, respectively, due to consumption of the shallow organic layer, soil dehydration, and post-fire grass proliferation (figure 2(a)). No regeneration is observed after severe large fires with no tree survival

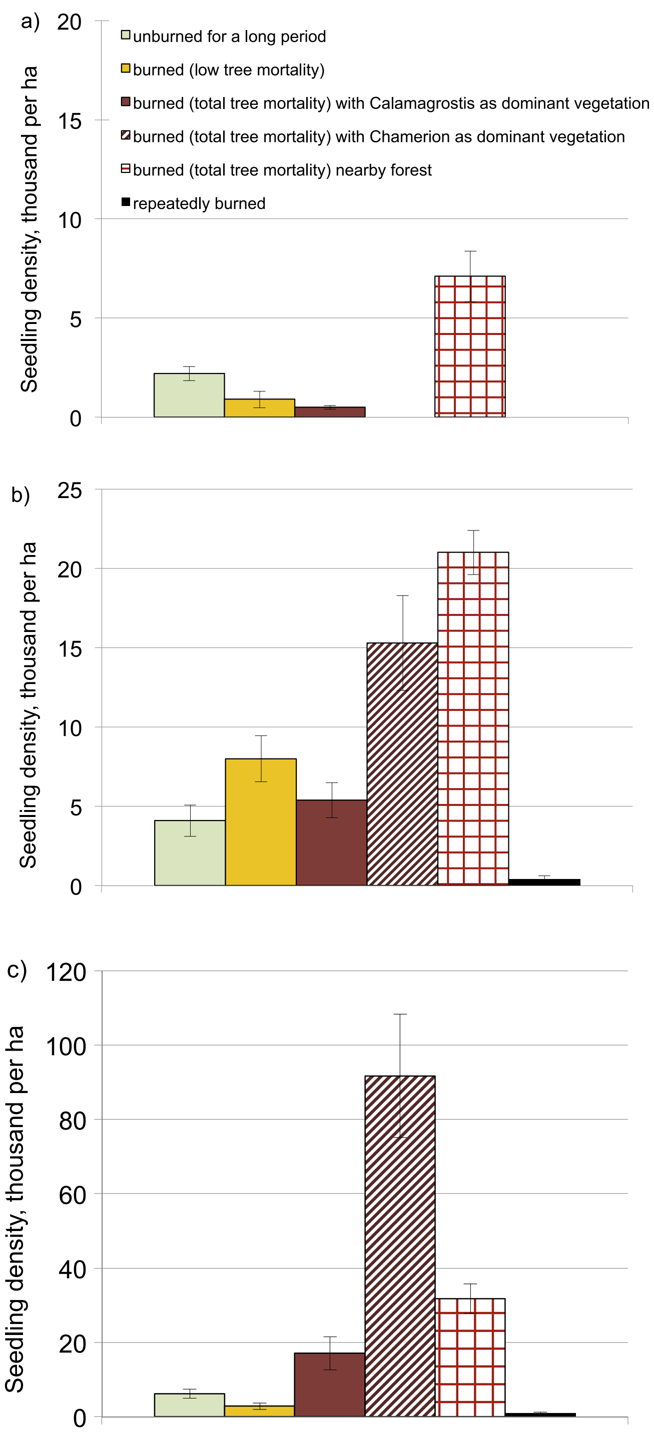

Figure 2. Regeneration density in the light-coniferous forests of the Zabaikal region with respect to site conditions and type of disturbance: (a) pine stands on sandy and sandy-loam dry soils; (b) mixed pine and larch stands and coniferous-deciduous stands on loamy mesic and wet soils; (c) larch stands on loamy wet and very wet soils.

over long distances, resulting in little or no seed source and in soil overheating and erosion.

In undisturbed mixed pine and larch stands and coniferous-deciduous stands on loamy mesic and wet soils, regeneration consists of Scots pine, larch, birch, and aspen. While Scots pine seedlings dominate post-fire at dry pine stands, fires in mixed forests on mesic loamy soils and in larch forests on wet soils usually result in post-fire dominance of deciduous (birch, aspen) seedlings. The post-fire amount of regeneration increases to 5.4–8.0 $\times$ 10^3 per ha at sites with high and low tree mortality (i.e., severity), respectively (figure 2(b)). Here, the deciduous successional stage would take 80–120 years before coniferous species return, in the event of absence of repeated disturbances (Furyaev 1996). While regeneration is sufficient for a forest to recover to its pre-fire state even after severe large fires in mixed pine and larch stands on loamy mesic and wet soils, repeated disturbances (with a fire return interval of less than 20 years) result in an absence of seedlings.

Fires of low severity in larch or mixed larch-deciduous stands growing on loamy wet and very wet soils decrease regeneration density to 2.8×10^3 per ha, due to grass sod formation, while high-severity fires result in a regeneration increase (up to 400×10^3 per ha in 2–3 years after a fire, and up to 73×10^3 per ha after 7–8 years). Scots pine does not grow on these loamy wet and very wet soils; birch and aspen usually dominate post-fire. Repeated fires result in an insufficient density of healthy tree seedlings (figure 2(c)). Conversion from forest to steppe is observed at many sites where repeated disturbances had led to a complete lack of forest regeneration. Little or no regeneration is observed at large burned sites with high tree mortality and *Calamagrostis* spp. dominated in ground cover.

2.2. Field data

Our on-ground survey dataset included 97 sample sites collected from 2004 to 2016. The sample sites were mainly located in central and southern areas of the Zabaikal region (figure 1), where the highest fire activity occurs (Kukavskaya *et al* 2016). The 2–4 ha sites were laid out in the major forest types (Scots pine, larch, and mixed coniferous-deciduous forests) of the region, to cover the range of forest and disturbance conditions (table 1). Every site presented a relatively homogenous burned stand. The diameter at 1.35 m and height by species of at least 100 trees were measured at 3–5 round plots (10 m radius) at each site, to determine stand characteristics. The crown scorch percentage, the presence of fire scars, mechanical injuries, diseases, and stem pest infestation were recorded for each tree. In addition, information on the year of fire, fire type (surface or crown), form (fast-moving or steady) and severity (except for repeatedly burned sites with high tree mortality during the previous disturbance) was recorded (table 1).

The regeneration assessment used the methodology of Pobedinsky (1966). On each site, 15 to 25 sample plots (1×1 m or 2×2 m) were examined 2–16 years post-fire, with all seedlings and saplings counted and categorized by species, age, height, and condition (healthy, weakened, or dead). Scots pine and larch trees fruit heavily every four years in Siberia (Geniatulin 2000), so if no seedlings had appeared in four years since a fire, the site was classified as a regeneration failure. Those sites that were examined in the first post-fire years were revisited 5–10 years later.

Based on the regeneration density (the number of tree saplings higher than 1.5 m per hectare), field sites were grouped into three classes: (1) sites with successful regeneration (> 2000–3000 saplings), (2) sites with poor regeneration (100 to 2000–3000 saplings), and (3) sites with regeneration failure (< 100 saplings) (Decree on reforestation rules 2016). To be able to compare sites burned in different years, where the age of regeneration also differs, the following coefficients were used to convert seedlings to saplings higher than 1.5 m: 0.5 for seedlings less than 0.5 m, and 0.8 for seedlings of 0.6 to 1.5 m in height (Decree on reforestation rules 2016).

2.3. Satellite data

In this study we used Landsat data and MODIS active fire products. Landsat data were downloaded from the archives of the United States Geological Survey (USGS), accessed through the Earth Explorer interface (https://earthexplorer.usgs.gov/). We obtained Landsat 5, 7 and 8 images from 1998 to 2017 (WRS-2 path/row 128/24 and 130/24) to track vegetation dynamics before and after the fire impact. To minimize changes in illumination and phenology we used mostly cloud-free imagery obtained between early July and mid-August. Landsat level 2 raw digital numbers (DNs) were scaled to at-sensor reflectance values (Chander *et al* 2009). Additionally, several post-processing procedures were performed to mask clouds and cloud shadows, and to implement topography and atmospheric corrections (Teillet *et al* 1982, Bodard *et al* 2011, Zhu and Woodcock 2012).

The MODIS active fire products (MOD14A1/MYD14A1) collection 6 data (Giglio 2015), having a spatial resolution of 1 000 m, were used to obtain the locations and dates of active fires. Fire pixels having a detection confidence (Giglio *et al* 2016) of 50 and higher were considered. Comparison between fires detected at this confidence level and on-ground data showed that it is a reasonable threshold from which to determine fire years, if they were not reported in field data. MODIS data were acquired from the Level-1 and Atmosphere Archive & Distribution System (LAADS) Distributed Active Archive Center (DAAC) website (https://ladsweb.modaps.eosdis.nasa.gov/). The surface temperature was estimated from MODIS Collection 6 land surface temperature product (MOD11A1) having high temporal resolution (one day) but low spatial resolution (1 km) (Wan 2013).

We identified prevailing forest types in the study region using the USSR vegetation map of 1:2 500 000 scale (USSR Forests 1990). An ASTER Global Digital Elevation Model (GDEM) version 2 (a product of NASA and METI, available at http://reverb.echo.nasa.gov/reverb/) was used to acquire topographic variables for the study and also for topographic correction of Landsat data.

2.4. Methods

For the analysis, we used the Normalized Burn Ratio (NBR), a satellite-derived spectral index associated with vegetation state (Epting and Verbyla 2005). This index uses reflectances measured in NIR and SWIR wave ranges. In the case of Landsat TM/ETM + these are band 4 (760–900 nm) and band 7 (2080–2350 nm), and for Landsat OLI, bands 5 (851–879 nm) and 7 (2107–2294 nm) respectively. NBR is calculated as:

Table 1. Pre-fire stand structure characteristics and fire regimes.

Forest type and soil	Stand characteristics					Fire characteristics	Post-fire tree mortality (% to pre-fire wood volume
	age (years)	average $D_{1.35}$ [a] (cm)	average height (m)	basal area ($m^2\ ha^{-1}$)	wood volume ($m^3\ ha^{-1}$)		
Pine stands on sandy and sandy-loam dry soils	50–90	10–22	11–21	17.5–35.6	95–260	surface low to high severity, fast-moving fires crown fires	low to moderate (4.0–87.5) total (100.0)
Mixed pine and larch stands and coniferous-deciduous stands on loamy mesic and wet soils	60–120	15–32	16–24	21.3–35.5	160–300	surface low to high severity, fast-moving and steady fires crown fires	moderate to high (6.5–59.5) total (100.0)
Larch stands on loamy wet and very wet soils	70–150	14–28	15–23	14.5–26.2	110–250	surface moderate to high severity, steady fires	moderate to total (82.2–100.0)

[a] - tree diameter at 1.35 m.

$$\mathrm{NBR} = \frac{\mathrm{R_{NIR}} - \mathrm{R_{SWIR}}}{\mathrm{R_{NIR}} + \mathrm{R_{SWIR}}},$$

where R_{NIR} and R_{SWIR} stand for the spectral reflectance measurements acquired in the near-infrared and shortwave-infrared regions of the electromagnetic spectrum, respectively.

NBR and differenced NBR indices are often used to assess fire severity in various forest ecosystems (Wagtendonk *et al* 2004, Epting *et al* 2005, Escuin *et al* 2008). For instance, Bartalev *et al* (2010) reported good results in estimating fire-related vegetation damage using remotely-sensed indices for several regions of Siberia, including the Zabaikal region. In our study we calculated the differenced Normalized Burn Ratio (dNBR) by subtracting the post-fire NBR value from the pre-fire value ($\mathrm{dNBR} = \mathrm{NBR_{pre\text{-}fire}}–\mathrm{NBR_{post\text{-}fire}}$), and used it as a metric to assess the degree of vegetation change. Pre-fire NBR values were calculated using Landsat imagery from the year preceding the fire, and for post-fire NBR calculations we used Landsat data obtained from the year following the fire. According to Bartalev *et al* (2010) the following dNBR thresholds can be used to assess fire severity in the Siberian forests: high severity ($\mathrm{dNBR} > 0.4$), moderate severity ($0.2 < \mathrm{dNBR} \leqslant 0.4$), low severity ($0.07 < \mathrm{dNBR} \leqslant 0.2$), and unburned ($\mathrm{dNBR} \leqslant 0.07$). It should also be noted that Chu *et al* (2017) reported somewhat similar dNBR values with which to distinguish severity classes for northern Mongolia.

Several studies used time series of satellite-derived spectral indices to evaluate post-fire vegetation dynamics (Pickell *et al* 2016, Chu *et al* 2017, Viana-Soto *et al* 2017). For this research we used NBR time series obtained for 97 sample sites from our on-ground survey dataset. Annual NBR values were calculated from the best quality image obtained during July or August. The season of burning for each sample site was generally determined from the field data, but if fire dates were not reported, MODIS active fire products were used to determine the fire season. If the sample site was burned several times, the recovery dynamics were calculated starting from the fire season with the greatest dNBR.

To assess the post-fire vegetation dynamics on each study site we created NBR time series using Landsat data and approximated it by linear fit, using NBR as the dependent variable and the time since burn as the independent variable. We hypothesized that the success of the reforestation process is related to the post-fire NBR increase represented by the slope (rate of change) of the linear fit (figure 3). All the study sites experienced fires before 2011, so at least seven NBR values were used to calculate the linear fit.

For our sample sites we compared the regeneration state (successful, or poor, or failed) reported by field studies with the slope of regression lines. The correlation between the seedling density and the slope of the regression line was calculated. We also calculated several statistical measures (median, standard deviation, 25th and 75th percentiles) of regression slopes for each of the regeneration classes.

The different factors which were used to model the reforestation process were derived from the satellite products and ancillary datasets. These were factors determining forest and landscape conditions (pre-fire NBR value, slope, and aspect), fire characteristics (fire severity, fire frequency), and climate (temperature anomalies during the post-fire period). The rate of change (units—1/year) of the post-fire NBR regression line was considered as a dependent variable (table 2).

Using the vegetation map and field reports, we determined that the dominating tree species on the sample sites were mainly larch and pine-dominated stands. Fire severity expressed via dNBR as well as pre-fire NBR values were acquired from Landsat imagery, and fire frequency was determined from the MODIS active fire product.

The MODIS surface temperature product was used to obtain positive temperature anomalies during recovery periods. First, using daily temperature measurements, 18-year mean temperatures (T_{mean18}) and standard deviations (T_{sdev18}) were calculated, excluding extreme values (outside the 5th and 95th percentiles). We then determined monthly mean temperatures for June, July, and August ($T_{monthly}$), using all temperature measurements. Finally, we obtained the number of months with positive temperature anomalies, which were defined as: $T_{monthly} > T_{mean18} + 2T_{sdev18}$.

Topographic factors including elevation and aspect were generated from ASTER GDEM using ArcGIS software. Elevation was measured in meters and aspect was calculated in degrees from 0 to 359. The aspect value was converted to a categorical variable having a value of 1 for north-facing, shadowed slopes (N, NE, NW and E) or a value of 2 for south-facing slopes (S, SE, SW and W).

Regression analysis is a powerful method that can be used to simultaneously analyze the influence of multiple factors on the variable of interest. The most common estimation method for linear models is Ordinary Least Squares (OLS). In this study we performed OLS analysis using ArcGIS to evaluate the influence of environmental factors on the post-fire reforestation process.

3. Results and discussion

3.1. Comparison of NBR trends to on-ground reforestation data

We compared NBR trends obtained from satellite data to sample site reforestation data reported from on-ground observations. The results show generally satisfactory differences between NBR trends for sample sites with successful reforestation and sites with reforestation failure (figure 4). Sample plots with successful reforestation were generally characterized

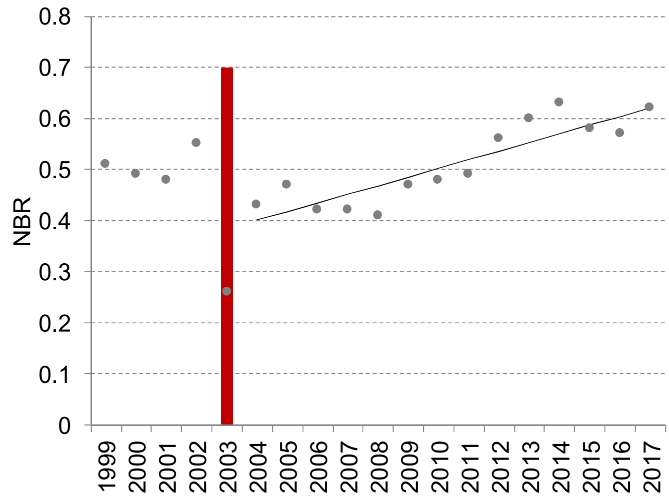

Figure 3. Landsat NBR dynamics for a location reported to have good post-fire regeneration according to ground survey data. Each data point represents an NBR value. The red bar indicates the fire year of 2003. The fitted linear relationship indicates the NBR trend following the fire event.

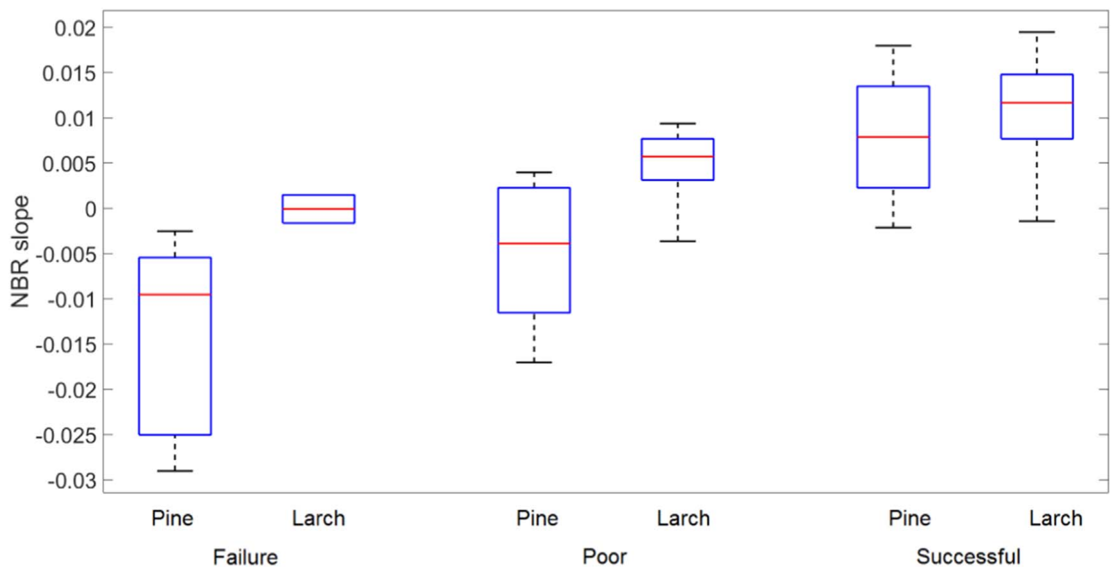

Figure 4. Post-fire NBR slopes for three classes of sample sites according to reforestation state. For each class, pine- and larch-dominated stands are shown separately. The edges of the blue boxes correspond to the 25th and 75th percentiles, and the red lines indicate medians. Black whiskers extend to minimum and maximum data points. The 'regeneration failure' class for larch-dominated stands contains only two data points, so whiskers are not shown.

Table 2. The list of variables used in regression analysis.

Variable group	Variable	Variable type	Description
Dependent	NBR slope	Continuous	Slope of post-fire NBR trend
Explanatory	dNBR	Values of 1 (low/moderate), 2 (high)	dNBR $>$ 0.4 corresponds to high fire severity, and dNBR $\leqslant$ 0.4 to low/moderate severity
	Pre-fire NBR	Continuous (from −1 to 1)	—
	Dominating tree species	Value 1 (pine) or 2 (larch)	—
	Number of fires	Continuous	Total number of fires occurring at the given sample site
	Aspect	Value 1 (north facing) or 2 (south facing)	—
	Elevation	Continuous (meters)	—
	Temperature anomalies	Continuous	Number of months with positive temperature anomalies

by the highest positive values of post-fire NBR trends. The average NBR increase for such sites was 0.011 ± 0.005 (mean value $\pm$ one standard deviation) per year. At the same time, sites with reforestation failure were characterized by negative or near-zero values of post-fire NBR trends (-0.009 ± 0.011 per year). Negative values were often observed for areas that experienced multiple disturbances (fires, logging) during the study period. The class marked as having "poor" reforestation generally has low positive values (0.002 ± 0.008) of NBR trends, corresponding to a slower index increase over time.

We also calculated statistics of NBR slopes for larch- and pine-dominated stands separately. Sample sites located in pine-dominated stands were characterized by lower mean values and higher variability of post-fire NBR slope for all regeneration classes, compared to larch-dominated stands (figure 4). The smallest difference (median values) in post-fire trends between two forest types was observed for sites with successful reforestation. The difference in median values was greater for sites with poor reforestation and reforestation failure. It should also be noted that only two sample sites experienced reforestation failure in larch-dominated stands. The statistical significance of the differences in regression line slopes was tested using a two-way analysis of variance (ANOVA). We considered forest type and regeneration class as independent variables, and the slope of regression line as a dependent variable. The results indicate that these differences could be considered as statistically significant, with a p-value < 0.01.

Finally, the relationships between the slope of the remotely measured NBR regression line and field estimates of seedling density were evaluated. The seedling density varied between zero and 103 000 seedlings per hectare, with a mean value of 10 700. For the successful reforestation class, larch-dominated stands were characterized by higher seedling density comparing to pine-dominated stands: $18\,400 \pm 20\,500$ and $10\,500 \pm 10\,700$ (mean value $\pm$ one standard deviation) for larch- and pine-dominated stands, respectively. For the poor reforestation class, these numbers were 1360 ± 780 and 1640 ± 740. The results of the comparison between the slope of the NBR regression line and seedling density are shown in figure 4, using seedling density as an independent variable and the slope of the NBR line as dependent. The data showed a non-linear relationship between the two variables. However, a fairly strong positive correlation ($R = 0.71$) was observed between log-transformed seedling density and NBR slope (figure 5).

3.2. Influence of environmental variables on post-fire vegetation response

Using regression analysis, we determined the significance of each explanatory variable for post-fire reforestation estimation. The results of regression model performance are reported in table 3.

According to the t-statistic, the main factors influencing post-fire NBR dynamics within the current model include dominating tree species, number of fires, fire severity, and temperature anomalies.

Repeated fires in various forest ecosystems are generally reported to have a negative impact on the reforestation process (Stevens-Rumann and Morgan 2016). In the case of the Zabaikal region, repeated wildfires with fire return intervals of less than 10 years often result in near to complete tree mortality, followed by conversion of forest to steppe (Kukavskaya *et al* 2016, Makarov *et al* 2016). The negative regression coefficient for the number of fires indicates the hampering of the reforestation process at the sites that experienced multiple fires. Analysis of NBR time series also showed that sites that experienced repeated wildfires are generally characterized by decreased post-fire slopes.

The next important factor related to forest recovery is fire severity estimated via dNBR variable. The importance of fire severity for post-fire forest recovery in boreal regions has been shown in several studies (Johnstone and Kasischke 2005, Cai *et al* 2013, Chu *et al* 2017). With regard to boreal forests of Siberia, several researchers (Sannikov and Sannikova 1985, Matveev 2006, Sannikov and Sannikova 2008, Sedykh 2009) noted that fires have a significant effect on reforestation, and their role in post-fire recovery may vary depending on the fire severity. It was found that reforestation is hampered, in the case of low severity fires in larch forests on wet soils, by incomplete moss and duff consumption and grass proliferation (Sheshukov 1979). In the case of high severity fires on dry poor soils in the lichen, Scots pine reforestation failure is also observed. For each forest type there is optimal fire severity, contributing to successful post-fire recovery (Sannikov and Sannikova 1985, 2008).

Our results indicate that on 57% of the sample sites that experienced high severity burns, increasing post-fire trends were observed (generally corresponding to successful regeneration). At the same time, 43% of such sites were characterized by poor regeneration or regeneration failure. In cases of low to moderate severity burns, rapidly increasing trends were noted on 44% of the sites and poor regeneration or regeneration failure was registered on 56% of the sites. In our previous study we found that NBR recovery rates were higher for the more severe fires than for low and moderate severity fires, particularly in larch-dominated and deciduous forests (Shvetsov *et al* 2016).

Several remote sensing-based studies reported that higher burn severity often results in higher vegetation recovery in boreal forests. For instance, Epting and Verbyla (2005) found that post-fire NDVI recovery is the fastest for high severity areas in Alaska. The results obtained by Chu *et al* (2017), who studied post-fire

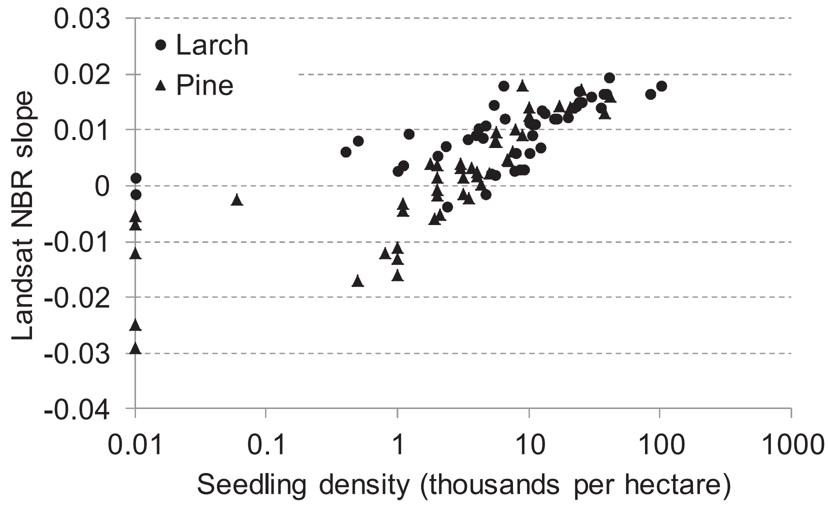

Figure 5. Scatter plot of on-ground estimates of seedling density versus remotely measured NBR slope. Each data point corresponds to one sample site. Data from pine- and larch-dominated stands are shown separately. Sample plots reported as having 'reforestation failure' were assigned a seedling density value of 0.01, using a logarithmic scale for the X-axis.

Table 3. Regression results obtained from Ordinary Least Squares analysis.

Variable	Coefficient	Standard Error	t-statistic	p-value	VIF[a]
Intercept	−0.000 534	0.007 738	−0.068 992	0.493 846	–
Dominating tree species	0.000 789	0.000 388	1.964 942	0.009 636[b]	1.102 743
Number of fires	−0.006 86	0.001 743	−3.935 889	0.004 014[b]	1.487 017
Elevation	0.000 069	0.000 069	1.077 473	0.363 23	1.077 307
Aspect	−0.000 447	0.001 51	−0.267 051	0.835 491	1.667 299
dNBR	0.006 635	0.001 264	3.432 631	0.001 249[b]	1.041 996
Pre-fire NBR	0.009 434	0.007 165	1.274 854	0.161 418	1.029 833
Temperature anomalies	−0.003 402	0.000 738	−3.486 316	0.004 205[b]	1.760 002

[a] VIF is the variance inflation factor, which measures redundancy among explanatory variables.
[b] An asterisk next to a number indicates a statistically significant p-value ($p < 0.01$).
Multiple $R^2 = 0.596\ 205$; adjusted $R^2 = 0.585\ 615$.

regeneration of Siberian larch in northern Mongolia, indicate a positive correlation between remotely-sensed vegetation indices and fire severity in the early stages of forest succession. However, they also found that at later successional stages (> 10 years since a fire) the moderate burn severity sites recover faster. Cuevas-Gonzalez *et al* (2009) analyzed post-fire forest recovery in boreal forests of Central Siberia, using MODIS data, and found that NDVI for the most severely burned forests have the highest recovery rates. Jin *et al* (2012) reported that more severe fires lead to a more rapid increase of the MODIS-derived Enhanced Vegetation Index (EVI) in Canadian boreal forests.

A positive surface temperature anomaly is the third important factor affecting post-fire NBR dynamics. Our results showed that surface temperature anomalies have a negative relationship with post-fire NBR slopes. About 76% of all temperature anomalies, considering all sample sites, were registered within three years: 2007 (39%), 2010 (21%), and 2011 (16%). It was shown that environmental stress after fire significantly controls the succession patterns (Johnstone *et al* 2010b, Boiffin and Munson 2013). High temperatures at the soil surface result in low seedling survival in various environments, including boreal forests (Koppenaal *et al* 1991, Kolb and Robberecht 1996). The effects of high temperatures on seedlings include increased evaporative demand and direct tissue damage where seedlings are in contact with hot surfaces (Gauslaa 1984, Halgren *et al* 1991). Several studies found that heat-induced tissue damage starts at approximately 50 °C for most plant species (Kayll 1968, Weis and Berry 1987, Colombo and Timmer 1992). For our sample sites, the maximum MODIS-derived surface temperature was 49 °C. According to Kukavskaya *et al* (2016) the summer temperature on the burned sites in the Zabaikal region can reach 60 °C, causing thermal stress and limiting seedling regeneration.

A positive regression coefficient for the dominating tree species shows that on larch-dominated sites the process of forest recovery is somewhat more successful than on pine-dominated sites. According to previous studies, larch stands are considered to be more fire-resistant in southern taiga zones of southern Siberia (Buryak *et al* 2003, Wirth 2005, Buryak 2015) and have a rapid post-fire regeneration rate (Melehov 1947). A higher post-fire tree recruitment rate for larch forests is also observed in Mongolian forests (Chu *et al* 2017). These findings generally agree with our field observations.

The less significant factors include the pre-fire NBR value, and topographic variables. We consider the pre-fire NBR to be related to vegetation condition before disturbance, since SWIR-based vegetation indices were shown to be sensitive to canopy structure and vegetation water content (Ceccato *et al* 2001). The pre-fire vegetation state may influence post-fire vegetation dynamics since it is related to burn severity (Johnstone and Kasischke 2005, Whitman *et al* 2018) and seed availability. The results of Chu *et al* (2017) indicate that areas showing an increase of post-fire regeneration metrics were characterized by a higher pre-fire NDVI than the areas of significant decrease. In our case, pre-fire NBR value was also positively correlated with the rate of post-fire reforestation, but its influence was less important than in the study of Chu *et al* (2017). This could possibly be caused by several factors, such as the experiment design (NDVI versus NBR), or related to the fire regime (common repeated fires in the Zabaikal region, large burned area extent) or regeneration conditions.

Our results show that topographic variables were the least important factors in explaining the regeneration rate, in agreement with results reported by Chu *et al* (2017) for larch regeneration in Mongolia. However, several studies conducted in other regions report the significance of such variables. For instance, Daskalakou and Thanos (1996) report that elevation positively influences regeneration in Greece, while Johnstone *et al* (2010a) showed that conifer recruitment in boreal forests is negatively correlated with elevation. Our field observations show that burns located on south-facing slopes often experience hampered reforestation, primarily due to high noon temperatures. However, the use of a surface temperature anomaly factor in our study could possibly obscure the aspect factor as a predictive variable.

Multiple R^2 and adjusted R^2 values show that such variables as fire frequency, fire severity, dominating tree species, and positive surface temperature anomalies, as considered in this study, can explain about 58% of the variance in post-fire NBR trend. This implies the presence of additional factors influencing the reforestation process, which are not considered in the current model. Such factors influencing post-fire regeneration include soil properties and moisture, summer and winter precipitation, and permafrost conditions (Johnstone and Kasischke 2005, Kasischke *et al* 2007, Kukavskaya *et al* 2016). Further investigations focusing on the analysis of other factors affecting post-fire regeneration are required.

4. Conclusions

We have analyzed the performance of SWIR-based remotely-sensed indices in assessing post-fire reforestation in the Zabaikal region of southern Siberia. Landsat-derived NBR time series were compared to field reforestation observations. The results indicate fairly good separability between sites with successful reforestation and those with reforestation failure, considering differences between the change rates of post-fire NBR regression lines. This suggests the possibility of the application of this method to evaluate forest recovery states in the Zabaikal region.

We evaluated the influence of several factors on the post-fire reforestation dynamics described by Landsat-derived time series of the NBR index. From the multiple linear regression model we estimated the explanatory capacity of such environmental factors as fire frequency and fire severity, pre-fire forest state and dominating tree species, post-fire surface temperature anomalies and topographical factors. Fire severity, fire frequency and surface temperature anomalies were the most important factors explaining post-fire forest recovery. The process of post-fire forest recovery is more successful on larch-dominated sites than on pine-dominated sites. Altogether, these variables explain about 58% of the variance in post-fire reforestation. These results improve our understanding of the post-fire vegetation dynamics in southern Siberia, but additional studies are required in order to include other potentially important factors (soil properties, moisture, and precipitation) in the analysis.

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