Monitoring of post-fire forest recovery under different restoration modes based on time series Landsat data

Wei Chen1*, Kazuyuki Moriya1, Tetsuro Sakai1, Lina Koyama1 and Chunxiang Cao2

1Biosphere Informatics Laboratory, Department of Social Informatics, Graduate School of Informatics, Kyoto University, 606-8501, Kyoto, Japan
2State Key Laboratory of Remote Sensing Science, Institute of Remote Sensing and Digital Earth, Chinese Academy of Sciences, 100101, Beijing, China

*Corresponding author, e-mail address: chenwei@bre.soc.i.kyoto-u.ac.jp

Abstract
Forest fire is a common disturbance factor, especially in boreal forests. The detection of forest disturbance and monitoring of post-fire forest recovery are crucial to both ecological research and forest management. The Greater Hinggan Mountain area of China is rich in forest resources, but also has a high incidence of forest fires. After the most serious forest fire in the history of P. R. China, three restoration modes were adopted for local forest recovery, namely artificial regeneration, natural regeneration and artificial promotion. In this study, based on time series Landsat data, we proposed to detect the disturbance and monitor the post-fire forest recovery under the three restoration modes. Disturbance Index (DI) was proven to be an effective approach for the detection and monitoring. The results indicated that the forest under natural regeneration achieved a totally different recovery process with those under the other two modes. In combination with the field survey data analysis, the availability of different remote sensing indices and applicability of the three restoration modes were evaluated and compared. It could provide significant suggestions for local post-fire forest management.

Keywords: Forest fire, post-fire recovery, restoration mode, time series, Landsat.

Introduction
Forests are integrated multi-functional and multi-value terrestrial ecosystems with widely distributed coverage areas, complex composition and high species diversity [Lucas et al., 2000; Flynn and Traver, 2013]. Although they occupy less than 14% of the Earth’s surface, forests and savannas together account for more than 40% of the total solar energy captured each year by green plants, as well as containing the largest concentrations of organic material compared to all other global ecosystems [Weber and Flannigan, 1997; David et al., 2008; Chen et al., 2010]. It serves as an
important component of the land surface ecosystems and plays an irreplaceable role in maintaining ecological balance in terrestrial biosphere [Wood et al., 2012]. Forest fire is a widespread and common disturbance factor, especially in boreal forests [Asselin et al., 2001; Forkel et al., 2012]. It is a complex regime, which organizes the physical and biological attributes of a boreal biome, as well as influences the flow of energy and biogeochemical cycles, with significant implications for both carbon cycle and forest health [Díaz-Delgado and Pons, 2001; Shorohova et al., 2009; Wotton et al., 2010; Chen et al., 2011; Mari et al, 2012; Marzano et al., 2013]. Serious fires will bring great damage to not only the trees, but the whole forest ecosystem. Consequently it is necessary to elucidate the effects of fire on forests as well as identify the spatial and temporal trends in post-fire forest recovery for both ecological research and forest monitoring and management [Bonan, 1989; Schulze et al., 2005; Stueve et al., 2009; Beghin et al., 2010; Kennedy et al., 2012; Otoda et al., 2013].

Forest disturbance and recovery have been regarded as a primary mechanism for transferring carbon between land surface and atmosphere, thus play an important role in both regional and global carbon cycles [Healey et al., 2005; Soja et al., 2007; Cao et al., 2011]. The detection of forest fire disturbances and post-fire recovery is a key process in terrestrial ecosystem research, especially in fields focusing on carbon cycles, and forest monitoring and management [Lucas et al., 2000; Schroeder et al., 2012]. At regional scales and over greater distances, the only feasible and effective means of monitoring forest dynamics continuously and regularly is remote sensing [Cohen and Goward, 2004; Masek et al., 2008; Corona et al., 2012]. Satellite remote sensing offers an affordable and efficient tool for monitoring forest changes over large areas [Townshend et al., 2012]. Optical remote sensing images, particularly the extensive Landsat records, are well suited to the detection of forest disturbances and monitoring of forest changes (post-fire restoration etc.) as they have unprecedented historical coverage (40 years of observations), as well as the necessary spatial (30 m) and spectral (7 bands) resolutions which permit capture of most natural and managed forest disturbance events [Masek et al., 2008; Schroeder et al., 2012; Han et al., 2013].

In the history of P. R. China, there was a most serious forest fire which occurred on May 6th, 1987 in the Greater Hinggan Mountain area of Northeastern China (abbreviated to the “5.6 Fire” hereafter). After this fire, the local forest bureaus took a series of measures to recover the burned forest area. Especially after the implementation of “Natural Forest Protection” program organized by the State Forestry Administration [Yang et al., 2010], more favorable measures were adopted to facilitate local forest recovery and ecological reconstruction. During the recovery process, there were three restoration modes used for the forest regeneration and vegetation recovery, namely artificial regeneration, natural regeneration and artificial promotion. As the name suggested, artificial regeneration comprises salvage logging followed by complete planting by human, while natural regeneration means recovering completely naturally without any human intervention. Artificial promotion means natural regeneration with artificial aids, which include tidying the burned area, weeding, and digging some pits to promote seed germination and growth naturally. Under different restoration modes, the temporal and spatial dynamics of forest restoration are likely to differ [Ascoli et
There have been many cases studying and comparing the effects of different post-fire forest restoration strategies [Moreira et al., 2009; Beghin et al., 2010; Ascoli et al., 2013], while most focused on only the two restoration ways of natural regeneration and direct planting, with the only difference lying in the species selected. In previous studies, little was done aiming at the comparisons among the three different post-fire restoration modes of artificial regeneration, natural regeneration and artificial promotion, especially based on remote sensing data. In addition, the magnitudes of post-fire forest recovery under various restoration modes varied significantly in time, which may translate to interannual variability in forest regrowth process. Thus long-term monitoring appeared to be quite necessary. In this study, taking the forest recovery after the “5.6 Fire” in the Greater Hinggan Mountain area as an example, based on Landsat time series images, we proposed to monitor the post-fire forest recovery and compare the effects of the three different restoration modes. The results can be used to provide significant suggestions for policy decisions in local forest management.

Data and methods

Study area

The Greater Hinggan Mountain, which locates in the northern part of Heilongjiang Province and Inner Mongolia Autonomous Region, is the watershed of the Mongolian Plateau and the flat Songliao Plain. Its geographic coordinates range from 50°10’ to 53°33’ N in latitude, and from 121°12’ to 127°00’ E in longitude (Fig. 1). The region has a total length of over 1200 km, and a width of 200–300 km, as well as an average altitude of 1200–1300 m.

This region is an important climatic zone, having a typical cold temperate continental monsoon climate with warm summers and cold winters. The annual average temperature is -2.8 °C, a minimum temperature of -52.3 °C and an average annual precipitation of 746 mm. The Greater Hinggan Mountain is also China’s largest modern state-owned forest area, with a total ground area of 8.46×10⁴ km² and a forest-covered area of 6.46×10⁴ km². Thus, the forest coverage is around 76.4%, providing a total stand volume of up to 5.01×10⁸ m³, which accounts for around 7.8% of the total national volume. It is a mixed forest area dominated by the coniferous species of Mongolian pine (Pinus sylvestris L.) and Larch (Larix gmelini R.), and the broad-leaved species of Birch (Betula platyphylla S.) and Aspen (Populus davidiana D.).

This region is rich in forest resources, but also in a high incidence of forest fires [Chen et al., 2011]. The annual burned forest area of this region ranks first in China, making it to be the most serious forest fire hazard areas [Tian et al., 2011]. Among all the fires in this region, the most noteworthy one was the “5.6 Fire”. On that day, the four forestry bureaus of Xilinji, Tuqiang, Amuer, and Tahe were on fire at almost the same time, causing the most serious forest fire since the founding of P. R. China. The fire continued to burn for 28 days and caused a great loss of life and property which included a burned area of 1.7×10⁴ km² and a burned forest area of 1.01×10⁴ km² [Zhao et al., 1994]. It made this area to be a key focus for studies of fire prevention and post-fire forest management [Sun et al., 2011].
Figure 1 - Location of the Greater Hinggan Mountain area and the “5.6 Fire” perimeter as well as a sample area in Landsat path 122 row 23. The background is the mosaic of two Landsat TM scenes showing the burned area of the “5.6 Fire” in dark blue.

Data and pre-processing
The burned area and burned forest area of the “5.6 Fire” were extracted in a previous study [Chen et al., 2013]. The entire burned forest area spanned two Landsat scenes (Path 121/122, Row 23), but it was difficult to acquire the two scenes simultaneously in each period. Considering that around 90% of the burned forest area was within the scene of path 122 row 23, we proposed to extract a sample area (Fig. 1) from Landsat path 122 row 23 for the recovery monitoring. For this scene 12 growing season (May-October) Landsat TM (Thematic Mapper) and ETM+ (Enhanced Thematic Mapper plus) images were acquired between 1987 and 2011 to develop the time series (Tab. 1). These data were provided by the USGS-EROS (Earth Resources Observation and Science center).

Table 1 - The Landsat images used to develop the path 122 row 23 time series.

| Date       | Sensor |
|------------|--------|
| 6/15/1987  | TM     |
| 10/5/1993  | TM     |
| 10/24/1994 | TM     |
| 10/11/1995 | TM     |
| 8/11/1999  | ETM+   |
| 9/14/2000  | ETM+   |
| 7/15/2001  | ETM+   |
| 5/15/2002  | ETM+   |
| 7/5/2006   | TM     |
| 8/30/2009  | TM     |
| 9/2/2010   | TM     |
| 7/3/2011   | TM     |
Prior to detection the images were pre-processed using the following steps. Firstly, the images were converted to surface reflectance through geometric and terrain correction, radiometric calibration, as well as atmospheric correction (based on the moderate resolution atmospheric transmission model-4). Then the reflectance images were normalized to a common reference scene to minimize the impact of sun-sensor-view angle effects. This made locating pseudo-invariant features (i.e., temporally stable areas of reflectance) necessary. It was achieved by the iterative multivariate alteration detection algorithm [Canty and Nielsen, 2008]. Areas of cloud and cloud shadow were masked and then filled using an interpolation of the temporally nearest clear observations.

After all these pre-processing work, the sample area of each scene was extracted. Here we first masked the rivers, roads and building area in each scene by visual interpretation and then extracted the burned and unburned forest area from the post-fire detection of the scene on 6/15/1987 [Chen et al., 2013]. The acquired surface reflectance of the sample area in the scene on 9/14/2000 was shown in Figure 2. The boundary of “Serious Forest Area” was extracted from the scene on 6/15/1987 and just for auxiliary understanding of the main burned area of the “5.6 Fire”.

![Figure 2 - The pre-processed surface reflectance image of the sample area in the scene acquired on 9/14/2000.](image)

**Remote sensing indices**

Here we selected two indices of NDVI (Normalized Difference Vegetation Index) and DI (Disturbance Index).

NDVI is one of the oldest, most well-known, and most frequently used vegetation indices. The combination of its normalized difference formulation and use of the highest absorption and reflectance regions of chlorophyll make it robust over a wide range of conditions...
NDVI indicates the amount of green vegetation present within a pixel. It is defined by the following equation:

$$NDVI = \frac{\rho_{NIR} - \rho_{Red}}{\rho_{NIR} + \rho_{Red}}$$  \[1\]

where $\rho_{NIR}$ and $\rho_{Red}$ indicate the reflectance of the near-infrared and red bands, respectively.

DI is derived from the Tasseled Cap transformation [Crist and Cicone, 1984; Healey et al., 2005]. The Tasseled Cap transformation is one type of spectral transformations which turns original, highly covariant data into three uncorrelated indices called Brightness (B), Greenness (G), and Wetness (W). The transformation matrix $T$ used with the Landsat sensor was shown as follows [Zhao, 2003]:

$$\begin{bmatrix} B \\ G \\ W \end{bmatrix} = T \cdot \begin{bmatrix} X_1 \\ X_2 \\ X_3 \\ X_4 \\ X_5 \\ X_6 \\ X_7 \end{bmatrix}$$  \[2\]

The DI calculation is based on the observation that disturbed forest stands typically have a higher Tasseled Cap Brightness value and lower Greenness and Wetness values than undisturbed forest areas [Healey et al., 2005]. It is a linear combination of the three Tasseled Cap indices: Brightness, Greenness and Wetness. However, as there are variations that exist in the acquisition date between images, the detection index adopted should be relatively insensitive to BRDF (Bidirectional Reflectance Distribution Function) variability and phenology. Thus, spectral normalization steps should be taken which use within-image statistics to normalize radiometric change. The normalization was conducted as follows:

$$B_n = \frac{(B - B_\mu)}{B_\sigma}$$
$$G_n = \frac{(G - G_\mu)}{G_\sigma}$$  \[3\]
$$W_n = \frac{(W - W_\mu)}{W_\sigma}$$

where $B_\mu$, $G_\mu$, and $W_\mu$ represent the mean Tasseled Cap Brightness, Greenness and Wetness of the “dense forest for a particular scene”, respectively. $B_\sigma$, $G_\sigma$, $W_\sigma$ are the corresponding standard deviations, and hence $B_n$, $G_n$, and $W_n$ indicate the normalized Brightness, Greenness and Wetness, respectively. As we had extracted the burned and unburned forest area in a previous study, to focus on the burned forest area, here the “dense forest for a particular scene” used for normalization was the same extracted unburned forest area.

After normalization, the three component indices were combined linearly to acquire the DI.
as follows:

\[ DI = B_n - (G_n + W_n) \quad [4] \]

Thus, a disturbed forest area that shows a high positive \( B_n \) and a low negative \( G_n \) and \( W_n \) will give high DI values. Conversely, an undisturbed forest area should present low DI values.

**Field forest survey**

In order to monitor and compare the forest recovery states under different restoration modes, we selected and surveyed 9 typical plots in forests under every type of the three restoration modes of artificial regeneration, natural regeneration and artificial promotion. In these plots, the forest recovery all began from the period of 1987-1988 regardless of the restoration modes. But since the two indices could only be used as a relative description of the overall conditions of forest ecosystems with no corresponding parameters that could be measured by devices, it was difficult to directly compare the results with field survey data. Additionally, as there were already 26 years after the “5.6 Fire”, and we had not collected forest attributes covering such a long period, the ground-based validation synchronized with the time series images appeared impossible.

In spite of this, we conducted a field forest survey in the burned forest area of “5.6 Fire” during July 12th-18th, 2012 to provide some direct demonstration of the effects of different restorations modes. In this survey, we investigated 27 plots in the three forestry bureaus with forests under the three restoration modes. The coordinates of four corners and the centre of each plot were measured using a differential global positioning system. Within plots, the species of each individual tree was recorded and the corresponding structural parameters including tree height, Diameter at Breast Height (DBH), crown width (in the direction of North-South and West-East) were measured using altimeter rod, tape measure and the device of NIKON Forestry pro 550 etc. Leaf Area Index (LAI) of each plot was measured using the LAI-2200 canopy analyzer [Chen and Cao, 2012]. As the forest recovery began at almost the same time, we were able to perform comparison of the parameters among different restoration modes.

**Results**

**Forest recovery in the burned area**

The NDVI time series values of the sample area in all scenes were calculated. As there were 12 scenes which were too many to show all, only that on 9/14/2000 was illustrated (Fig. 3). In this figure, the rivers, roads and building area were extracted by visual interpretation. Then the average NDVI values of the “burned forest” and “unburned forest” area were calculated and developed to be time series (Fig. 4).

From Figure 3 and 4, we found that there were little difference in NDVI between the “burned forest” and “unburned forest” area. To illustrate quantitatively, we performed the analysis of variance (ANOVA) of the two groups of NDVI values and the result was shown in Table 2. We concluded that the difference in NDVI between the “burned forest” and “unburned forest” area was statistically insignificant (Sig. = 0.296 > 0.05). Additionally,
from Figure 4, we could also find that the NDVI was influenced by phyto-phenology as the values in October (1993-1995) and May (2002) were significantly lower than those in the peak growing season of July-September.

Figure 3 - The NDVI image of the sample area in the scene acquired on 9/14/2000.

Figure 4 - The NDVI time series of “burned forest” and “unburned forest” area of the “5.6 Fire”.

Chen et al.  
Post-fire forest recovery monitoring
The DI time series images were also acquired. Here also the DI image on 9/14/2000 was shown in Figure 5, where the rivers, roads, building area were the same as in Figure 3. Then the average DI values were calculated, forming the time series (Fig. 6). Since the “unburned forest” area of this fire was used for normalization in the calculation of DI, the corresponding values all equaled to 0 which appeared to be a green straight line in Figure 6.

From Figure 5 and 6, we could visually find the difference in DI between the “burned forest” and “unburned forest” area, especially for the scene in 1987 which was acquired immediately after the fire. The ANOVA was also conducted (Tab. 3) and the result suggested that the difference in DI between the “burned forest” and “unburned forest” area was statistically extremely significant (Sig. = 0.001 < 0.01). It indicated that the serious “5.6 Fire” caused far-reaching impact on the forest ecosystem. The forest was not completely recovered after even more than 20 years of the fire.

Focusing on the DI of the “burned forest” area (red line in Fig. 6), we could easily conclude the trend of DI which representing the trend of post-fire forest recovery. As forest area with a larger DI had a higher degree of being disturbed and the DI values in the year of 1999-2002 (especially for 1999-2000) were significantly larger than those in other years, the forest definitely suffered a new disturbance during this period for some reasons. But the

| Difference Source | Sum of Squares | df  | Mean Square | F statistics | Sig. |
|-------------------|---------------|-----|-------------|--------------|------|
| Between Groups    | 0.042         | 1   | 0.042       | 1.148        | 0.296|
| Within Groups     | 0.796         | 22  | 0.036       |              |      |
| Total             | 0.838         | 23  |             |              |      |

Table 2 - The ANOVA result of NDVI.

---

**Figure 5 - The DI image of the sample area in the scene acquired on 9/14/2000.**

---
specific causes still remained to be determined.

![DI time series of "burned forest" and "unburned forest" area of the “5.6 Fire”](image)

**Figure 6** - The DI time series of “burned forest” and “unburned forest” area of the “5.6 Fire”.

| Difference Source | Sum of Squares | df | Mean Square | F statistics | Sig. |
|-------------------|----------------|----|-------------|--------------|------|
| Between Groups    | 50.737         | 1  | 50.737      | 16.118       | 0.001|
| Within Groups     | 69.251         | 22 | 3.148       |              |      |
| Total             | 119.988        | 23 |             |              |      |

**Table 3 - The ANOVA result of DI.**

Finally, as there were no available TM images distributed in the period of 1988-1993, we were not able to monitor the forest dynamics immediately after the “5.6 Fire”, when the forest were greatly recovered for natural and managed reasons.

**Forest under different restoration modes**

As DI, but not NDVI, had been proven suitable for the monitoring of post-fire forest recovery, here we selected DI to conduct the comparison of forest recovery under different restoration modes. The DI values of the specific plots under the three restoration modes were extracted and averaged to characterize the forest growth states under different modes (Fig. 7).

The Figure 7 suggested that the forest recovery processes were different among the three restoration modes. Compared with other two modes, forest under natural regeneration (red line in Fig. 7) presented a totally different recovery track. The much higher DI values in the early stage after fire indicated a relatively slower forest regeneration progress during this period. But after about 20 years, the recovery process had a breakthrough and the completely
naturally recovered forest grew better than those under artificially assisted restoration. Some minor difference also existed in the DI values between the modes of artificial regeneration and artificial promotion, which was statistically insignificant. Relatively speaking, the artificial regeneration appeared to be more effective than artificial promotion for the forest recovery, especially in the late-growth phase, while the former compared to be more time and labor-consuming simultaneously.

![Figure 7 - The DI time series of post-fire forest recovery under different restoration modes.](image)

**Comparison with field survey data**

The field survey indicated that there were only coniferous species of Mongolian pine (*Pinus sylvestris* L.) and Larch (*Larix gmelini* R.) in the forest area under artificial regeneration. It was definitely decided by the species selection in the planting process. In the area under natural regeneration, there were both coniferous species (Mongolian pine and Larch) and broad-leaved species (Birch and Aspen), and the latter achieved complete dominance. But for the forest under artificial promotion, the coniferous species became dominant again. The statistics of LAI of forests under the three restoration modes was collected and compared (Fig. 8). The result indicated that the LAI of forest under natural regeneration was the highest which corresponded to the lowest DI value in 2011 (Fig. 7). The LAI of artificial regeneration was higher than that under artificial promotion. It was also consistent with the result from DI comparison. ANOVA results showed that an extremely significant difference was observed among the three restoration modes \( (p = 0.007 < 0.01) \). Multiple comparisons (post-hoc test) further indicated that the forest under natural regeneration achieved a significantly higher LAI than those under the other two modes (label a and b in Fig. 8). It also reflected the overall trends of forests under the three restoration modes characterized by the time series DI values.
Figure 8 - The statistics (mean±S.D.) and comparison of leaf area index (LAI) in different regions under different restoration modes. The letters a and b indicate the results of multiple comparisons (post-hoc test).

Discussion

Availability of different remote sensing indices

In this study, NDVI, one of the most widely used vegetation indices, was considered not suitable for the monitoring of post-fire forest recovery in the Greater Hinggan Mountain area. Actually we had also calculated several other vegetation indices including RVI (Ratio Vegetation Index), SAVI (Soil Adjusted Vegetation Index), ARVI (Atmospherically Resistant Vegetation Index) and EVI (Enhanced Vegetation Index), however, the results were similar with that of NDVI although their characteristics varied. It was probably due to the limited bands (no more than three) used in the acquisition of these simple vegetation indices, making them relatively insensitive to the post-fire forest recovery detection, especially in long time series.

DI was proven to be a relatively effective approach to detect the forest disturbance and monitor its change. It relies on the physical characteristics of reflectance variations rather than statistical generalization from training samples, making it more reliable and widely applicable [Healey et al., 2005; Masek et al., 2008]. The normalization of the spectral components using within-image statistics of unburned forest area makes DI relatively insensitive to BRDF variability and phenology and thus widely extend the data supply. The Tasseled Cap transformation, where DI comes, is a standard transformation of the original Landsat spectral bands and can effectively capture the three major axes of spectral variation across the solar reflective spectrum [Crist and Cicone, 1984]. The Brightness, Greenness and Wetness incorporate the information within a wide range of spectrum, making them widely used in various applications. The Tasseled Cap transformation has even been extended to other sensors including IKONOS [Horne, 2003], MODIS [Lobser and Cohen, 2007] and so on. Consequently, the application of tracking forest disturbance...
and recovery by DI will be more widely expanded across a variety of forest ecosystems using a wide range of data sources.

**Applicability of the three restoration modes**
The analysis results of structural parameters (tree height, DBH and crown widths) suggested that the coniferous species under artificial regeneration regrew significantly faster than those under the other two modes. It probably resulted from the different species composition and the human intervention in the recovery practice. On the other hand, from the measured LAI which reflects the “layers” of leaves at a certain area within various ecosystems and can effectively characterize the canopy-atmosphere interface [Chen et al., 2010], we found that the completely naturally recovered forest had the highest canopy vertical density and relatively more abundant species. It was consistent with the results obtained from the remote sensing indices.

Based on the comprehensive analysis of remote sensing images and field survey data we concluded that the artificial regeneration mode could be adopted in the post-fire forest recovery if the goal is timber production because we can determine the species planted. However, if the aim of forest recovery is to promote species richness in the forest ecosystem, the burned forest area should be allowed to recover under completely natural regeneration conditions without any human intervention. This conclusion can provide a reference for local post-fire forest management.

**Acknowledgements**
The research in this paper was funded by the Japanese Government Scholarship provided by MEXT (Ministry of Education, Culture, Sports, Science and Technology). The authors are grateful to USGS-EROS (Earth Resources Observation and Science center) for providing the study with the time series Landsat data. Thanks to all local forestry technicians and workers for their assistance in the field survey.

**References**
Ascoli D., Castagneri D., Valsecchi C., Conedera M., Bovio G. (2013) - *Post-fire restoration of beech stands in the Southern Alps by natural regeneration.* Ecological Engineering, 54: 210-217. doi: http://dx.doi.org/10.1016/j.ecoleng.2013.01.032.

Asselin H., Fortin M.J, Bergeron Y . (2001) - *Spatial distribution of late-successional coniferous species regeneration following disturbance in southwestern Quebec boreal forest.* Forest Ecology and Management, 140: 29-37. doi: http://dx.doi.org/10.1016/S0378-1127(00)00273-5.

Beghin R., Lingua E., Garbarino M., Lonati M., Bovio G., Motta R., Marzano R. (2010) - *Pinus sylvestris forest regeneration under different post-fire restoration practices in the northwestern Italian Alps.* Ecological Engineering, 36: 1365-1372. doi: http://dx.doi.org/10.1016/j.ecoleng.2010.06.014.

Bonan G.B. (1989) - *Environmental factors and ecological processes controlling vegetation patterns in boreal forests.* Landscape Ecology, 3: 111-130. doi: http://dx.doi.org/10.1007/BF00131174.

Canty M.J., Nielsen A.A. (2008) - *Automatic radiometric normalization of multitemporal satellite imagery with the iteratively re-weighted MAD transformation.* Remote Sensing
of Environment, 112: 1025-1036. doi: http://dx.doi.org/10.1016/j.rse.2007.07.013.
Cao C.X., Chen W., Li G.H., Jia H.C., Ji W., Xu M., Gao M.X., Ni X.L., Zhao J., Zheng S., Tian R., Liu C., Li S. (2011) - The retrieval of shrub fractional cover based on a geometric-optical model in combination with linear spectral mixture analysis. Canadian Journal of Remote Sensing, 37: 348-358. doi: http://dx.doi.org/10.5589/m11-044.
Chen H.W., Hu Y.M., Chang Y., Bu R.C., Li Y.H., Liu M. (2011) - Simulating impact of larch caterpillar (Dendrolimus superans) on fire regime and forest landscape in Da Hinggan Mountains, Northeast China. Chinese Geographical Science, 21: 575-586. doi: http://dx.doi.org/10.1007/s11769-011-0494-9.
Chen W., Cao C.X. (2012) - Topographic correction-based retrieval of leaf area index in mountain areas. Journal of Mountain Science, 9: 166-174. doi: http://dx.doi.org/10.1007/s11629-012-2248-2.
Chen W., Cao C.X., He Q.S., Guo H.D., Zhang H., Li R.Q., Zheng S., Xu M., Gao M.X., Zhao J., Li S., Ni X.L., Jia H.C., Ji W., Tian R., Liu C., Zhao Y.X., Li J.L. (2010) - Quantitative estimation of the shrub canopy LAI from atmosphere-corrected HJ-1 CCD data in Mu Us Sandland. Science in China-Earth Sciences, 53: 26-33. doi: http://dx.doi.org/10.1007/s11430-010-4127-4.
Chen W., Sakai T., Moriya K., Koyama L., Cao C.X. (2013) - Extraction of burned forest area in the Greater Hinggan Mountain of China based on Landsat TM data. Proceedings of the IEEE International Geoscience and Remote Sensing Symposium (IGARSS2013), July 21-26, 2013, Melbourne, Australia.
Cohen W.B., Goward S.N. (2004) - Landsat’s role in ecological applications of remote sensing. Bioscience, 54: 535-545. doi: http://dx.doi.org/10.1641/0006-3568(2004)054[0535:lrileao]2.0.co;2.
Corona P., Cartisano R., Salvati R., Chirici G., Floris A., Di Martino P., Marchetti M., Scrinzi G., Clementel F., Travaglini D., Torresan C. (2012) - Airborne Laser Scanning to support forest resource management under alpine, temperate and Mediterranean environments in Italy. European Journal of Remote Sensing, 45: 27-37. doi: http://dx.doi.org/10.5721/EuJRS20124503.
Crist E.P., Cicone R.C. (1984) - A physically-based transformation of Thematic Mapper data-the TM Tasseled Cap. IEEE Transactions on Geoscience and Remote Sensing, 22: 256-263. doi: http://dx.doi.org/10.1109/TGRS.1984.350619.
David A.P., Ram O., Stephen C.H. (2008) - Forest Ecosystems (second edition). The Johns Hopkins University Press, Baltimore, Maryland, USA.
Díaz-Delgado R., Pons X. (2001) - Spatial patterns of forest fires in Catalonia (NE of Spain) along the period 1975-1995 analysis of vegetation recovery after fire. Forest Ecology and Management, 147: 67-74. doi: http://dx.doi.org/10.1016/S0378-1127(00)00434-5.
Flynn K.M., Traver R.G. (2013) - Green infrastructure life cycle assessment: A bio-infiltration case study. Ecological Engineering, 55: 9-22. doi: http://dx.doi.org/10.1016/j.ecoleng.2013.01.004.
Forkel M., Thonicke K., Beer C., Cramer W., Bartalev S., Schmullius C. (2012) - Extreme fire events are related to previous-year surface moisture conditions in permafrost-underlain larch forests of Siberia. Environmental Research Letters, 7: 044021. doi: http://dx.doi.org/10.1088/1748-9326/7/4/044021.
Han N., Du H.Q., Zhou G.M., Xu X.J., Cui R.R., Gu C.Y. (2013) - Spatiotemporal
heterogeneity of Moso bamboo aboveground carbon storage with Landsat Thematic Mapper images: a case study from Anji County, China. International Journal of Remote Sensing, 34: 4917-4932. doi: http://dx.doi.org/10.1080/01431161.2013.782115.
Healey S.P., Cohen W.B., Yang Z.Q., Krankina O.N. (2005) - Comparison of Tasseled Cap-based Landsat data structures for use in forest disturbance detection. Remote Sensing of Environment, 97: 301-310. doi: http://dx.doi.org/10.1016/j.rse.2005.05.009.
Horne J.H. (2003) - A Tasseled Cap Transformation for IKONOS Images. Proceedings of the ASPRS Annual Conference, Alaska, USA.
Kennedy R.E., Yang Z.Q., Cohen W.B., Pfaff E., Braaten J., Nelson P. (2012) - Spatial and temporal patterns of forest disturbance and regrowth within the area of the Northwest Forest Plan. Remote Sensing of Environment, 122: 117-133. doi: http://dx.doi.org/10.1016/j.rse.2011.09.024.
Lobser S.E., Cohen W.B. (2007) - MODIS tasseled cap: Land cover characteristics expressed through transformed MODIS data. International Journal of Remote Sensing, 28: 5079-5101. doi: http://dx.doi.org/10.1080/01431160701253303.
Lucas N.S., Curran P.J., Plummer S.E., Danson F.M. (2000) - Estimating the stem carbon production of a coniferous forest using an ecosystem simulation model driven by the remotely sensed red edge. International Journal of Remote Sensing, 21: 619-631. doi: http://dx.doi.org/10.1080/014311600210461.
Mari N., Laneve G., Cadau E., Porcasi X. (2012) - Fire Damage Assessment in Sardinia: the use of ALOS/PALSAR data for post fire effects management. European Journal of Remote Sensing, 45: 233-241. doi: http://dx.doi.org/10.5721/EuJRS20124521.
Marzano R., Garbarino M., Marcolin E., Pividi M., Lingua E. (2013) - Deadwood anisotropic facilitation on seedling establishment after a stand-replacing wildfire in Aosta Valley (NW Italy). Ecological Engineering, 51: 117-122. doi: http://dx.doi.org/10.1016/j.ecoleng.2012.12.030.
Masek J.G., Huang C.Q., Wolfe R., Cohen W., Hall F., Kutler J., Nelson P. (2008) - North American forest disturbance mapped from a decadal Landsat record. Remote Sensing of Environment, 112: 2914-2926. doi: http://dx.doi.org/10.1016/j.rse.2008.02.010.
Moreira F., Catry F., Lopes T., Bugalho M.N., Rego F. (2009) - Comparing survival and size of resprouts and planted trees for post-fire forest restoration in central Portugal. Ecological Engineering, 35: 870-873. doi: http://dx.doi.org/10.1016/j.ecoleng.2008.12.017.
Otoda T., Doi T., Sakamoto K., Hirobe M., Nachin B., Yoshikawa K. (2013) - Frequent fires may alter the future composition of the boreal forest in northern Mongolia. Journal of Forest Research, 18: 246-255. doi: http://dx.doi.org/10.1007/s10310-012-0345-2.
Rouse J.W., Haas R.H., Schell J.A., Deering D.W. (1973) - Monitoring Vegetation Systems in the Great Plains with ERTS. Proceedings of Third Earth Resources Technology Satellite-1 Symposium, Greenbelt, MD, USA, pp. 309-317.
Schroder T.A., Wulder M.A., Healey S.P., Moisen G.G. (2012) - Detecting post-fire salvage logging from Landsat change maps and national fire survey data. Remote Sensing of Environment, 122: 166-174. doi: http://dx.doi.org/10.1016/j.rse.2011.10.031.
Schulze E.D., Wirth C., Mollicone D., Ziegler W. (2005) - Succession after stand replacing disturbances by fire, wind throw, and insects in the dark Taiga of Central Siberia. Oecologia, 146: 77-88. doi: http://dx.doi.org/10.1007/s00442-005-0173-6.
Shorohova E., Kuuluvainen T., Kangur A., Jogiste K. (2009) - Natural stand structures,
disturbance regimes and successional dynamics in the Eurasian boreal forests: a review with special reference to Russian studies. Annals of Forest Science, 66: 1-20. doi: http://dx.doi.org/10.1051/forest/2008083.

Soja A.J., Tchebakova N.M., French N.H.F., Flannigan M.D., Shugart H.H., Stocks B.J., Sukhinin A.I., Parfenova E.I., Chapin F.S., Stackhouse P.W. (2007) - Climate-induced boreal forest change: predictions versus current observations. Global and Planetary Change, 56: 274-296. doi: http://dx.doi.org/10.1016/j.gloplacha.2006.07.028.

Stueve K.M., Cerney D.L., Rochefort R.M., Kurth L.L. (2009) - Post-fire tree establishment patterns at the alpine treeline ecotone: Mount Rainier National Park, Washington, USA. Journal of Vegetation Science, 20: 107-120. doi: http://dx.doi.org/10.1111/j.1654-1103.2009.05437.x.

Sun L., Hu H.Q., Guo Q.X., Lv X.S. (2011) - Estimating carbon emissions from forest fires during 1980 to 1999 in Daxing’an Mountain, China. African Journal of Biotechnology, 10: 8046-8053.

Tian X.R., McRae D.J., Jin J.Z., Shu L.F., Zhao F.J., Wang M.Y. (2011) - Wildfires and the Canadian Forest Fire Weather Index system for the Daxing’anling region of China. International Journal of Wildland Fire, 20: 963-973. doi: http://dx.doi.org/10.1071/wf09120.

Townshend J.R., Masek J.G., Huang C.Q., Vermote E.F., Gao F., Channan S., Sexton J.O., Feng M., Narasimhan R., Kim D., Song K., Song D.X., Song X.P., Noojipady P., Tan B., Hansen M.C., Li M.X., Wolfe R.E. (2012) - Global characterization and monitoring of forest cover using Landsat data: opportunities and challenges. International Journal of Digital Earth, 5: 373-397. doi: http://dx.doi.org/10.1080/17538947.2012.713190.

Tucker C.J. (1979) - Red and Photographic Infrared Linear Combinations for Monitoring Vegetation. Remote Sensing of Environment, 8: 127-150. doi: http://dx.doi.org/10.1016/0034-4257(79)90013-0.

Weber M.G., Flannigan M.D. (1997) - Canadian boreal forest ecosystem structure and function in a changing climate: Impacts on fire regimes. Environment Review, 5: 145-166. doi: http://dx.doi.org/10.1139/a97-008.

Wood T.E., Cavalieri M.A., Reed S.C. (2012) - Tropical forest carbon balance in a warmer world: a critical review spanning microbial- to ecosystem-scale processes. Biological Reviews, 87: 912-927. doi: http://dx.doi.org/10.1111/j.1469-185X.2012.00232.x.

Wotton B.M., Nock C.A., Flannigan M.D. (2010) - Forest fire occurrence and climate change in Canada. International Journal of Wildland Fire, 19: 253-271. doi: 10.1071/wf09002.

Yang H.Q., Nie Y., Ji C.Y. (2010) - Study on China’s Timber Resource Shortage and Import Structure: Natural Forest Protection Program Outlook, 1998 to 2008. Forest Products Journal, 60: 408-414. wos:000286080900001.

Zhao K.Y., Zhang W.F., Zhou Y.W. (1994) - The impact of Da xing’an ling forest fires on environment and its countermeasures. Science Press, Beijing, China.

Zhao Y.S. (2003) - Remote sensing applications and its principles. Science Press, Beijing, China.

© 2014 by the authors; licensee Italian Society of Remote Sensing (AIT). This article is an open access article distributed under the terms and conditions of the Creative Commons Attribution license (http://creativecommons.org/licenses/by/4.0/).