Monitoring and assessment of forest cover disturbance in the Middle Volga region of Russia using Landsat images

O N Vorobev, E A Kurbanov, S A Lezhnin, D M Dergunov and L V Tarasova

Center of Sustainable Forest Management and Remote Sensing, Volga State University of Technology, 424000, Yoshkar-Ola, Russia

E-mail: kurbanovea@volgatech.net https://orcid.org/0000-0001-5330-9990

Abstract. The knowledge of the disturbance effect on the forest ecosystems is crucial for sustainable development on the global level. It is important to quantify, map and monitor forest cover resulting from natural and anthropogenic disturbances. This research presents spatiotemporal trend analyses of forest cover disturbance in the Middle Volga region of Russia, using a time series of Landsat images. We generated a series of image composites at different year intervals between 1985 and 2018 and utilized a hybrid strategy consisting of Tasseled Cap transformation, sampling ground truth data and post-classification analyses. For validation of the disturbance maps, we used a point-based accuracy assessment, using local forest inventory reports and ground truth sample plots data for 2016-2018. The produced Landsat 1985, 2001 и 2018 thematic maps for 7 classes of forest cover show that coniferous area decreased by 4%. At the same time, there is a decrease in small-leaved (19%), mixed (8%) and an increase in young stands (23%). A significant disturbed forest area 85,120 ha was observed between 2014-2018, where much of the loss occurs due to severe wildfires. More research is needed with the inclusion of the additional number of anthropogenic and natural factors to increase the accuracy of monitoring and detection of forest disturbance of the region.

1. Introduction

Security of forest ecosystems, as the guarantee for accomplishing sustainable development and promoting public well-being, has come to the foreground of research. The sustainability of forest ecosystems can be affected by natural factors, such as global climate change and natural disasters, and through human activities, such as land use/land cover change [1-3]. Compared to intact ecosystems, degraded forests are usually fragmented, often poorer in carbon sequestration, and lower in canopy cover [4]. The most common natural disturbances affecting forests are fire, drought, floods, insect defoliation, windfall and freezing, or human-induced factors such as and clear cut, selective logging, and mining [5-8]. Such disturbances, especially triggered by natural disasters, threaten human well-being and economic damage [9].

Forest disturbance data can be acquired through field inventory or remote sensing technologies. The latest method due to its long-term data availability, spatially explicit, repeated acquisition capability and often at no cost to the users, has become the key technology for forest monitoring and mapping [10]. A lot of studies have recently been carried out with the use of time series for forest disturbance monitoring at the global scale using coarse spatial resolution images (e.g., AVHRR, MODIS, MERIS) [11–15] and at the regional scale using medium spatial resolution data (e.g., Landsat, Sentinel) [16–18].

Most of the remote sensing algorithms in estimation and monitoring forest disturbance are mainly based on the use of vegetation indices (VI), such as the normalized difference vegetation index (NDVI),
enhanced vegetation index (EVI), soil adjusted vegetation index (SAVI) and many others [19–21]. Disturbance Index (DI) [22], which is based on a linear transformation of the Tasseled Cap indices, is also used in numerous forest cover studies including the Pacific Northwest (USA), Russian Federation, Canada and the United States [23–26].

Detecting and monitoring the causes and scale of forest disturbances at regional and global levels are important for understanding global biogeochemical cycles and developing solutions for effective forest management [27-29]. This is especially true for forests of the Middle Volga region of the Russian Federation, which in recent decades have been exposed to severe fires, droughts, windfalls and windbreaks, which resulted in their diebacks [30]. The objective of this research is spatio-temporal analysis of forest cover dynamics and disturbances in the Middle Volga region of the Russian Federation, based on retrospective estimation of satellite images and the use of geospatial technologies. The spatial structure of forest stands on the estimated area is represented by mixed broadleaf, coniferous and forest-steppe zone.

2. Study area

The study area is a large part of the Mari El and Chuvashia Republics (constituent entities of the Russian Federation) with a total area of over 3 million ha (figure 1). The region is of particular interest because it represents wide areas of natural forests in Europe and Western Russia that are reported to be large terrestrial carbon sinks [31].

The climate of the Middle Volga region is considered to be temperate-continental with relatively stable weather in winter and summer, but considerably changing conditions in spring and autumn. The average amount of precipitation is 450-500 mm, of which 250-300 mm falls during the vegetation period (spring and summer). Rainfall is seasonal, with a dry season from May/June until August, when wildfires are possible, and a wet season from September to November.

The spatial structure of forest stands on the estimated area is represented by different types of vegetation, including mixed broadleaf, coniferous and forest-steppe zone. The forests of the region were severely affected by wildfires in 1972 and 2010 years with thousands of hectares burned [2](figure 1). Although pine stands (Pinus sylvestris L.) are the dominant forest type of the landscape, especially in the Mari El Republic, regeneration of birch (Betula pendula Roth.) and aspen (Populus tremula L.) species after the wildfire is the most common over the study area.

3. Data and methodology

3.1. Remote-sensing data

A set of Landsat (TM, ETM+, and OLI) images with 30 m resolution (Worldwide Reference System path/row (171/21) were used to map the boreal forest cover and burn severity in the entire region. All Landsat images were downloaded from the US Geographic Survey (USGS GloVis portal with Standard Terrain Correction (Level 1T), and systematic radiometric and geometric accuracy corrections (GloVis; http://glovis.usgs.gov, verified 14 October 2021). The satellite images were selected based on the minimal cloudiness over the burnt areas, vegetation season and date of acquisition (table 1). The image selection was aimed at minimising temporal, phenological and sun angle differences between the pairs. All Landsat images were geometrically and atmospherically corrected and converted to radiance using the atmospheric correction model (Flaash) available in the ENVI-5.2 software package.
Figure 1. Location of the study area on the map of the Russian Federation.

Table 1. Landsat Images used in the study (Path 172, Row 21)

| Satellite     | Acquisition date   |
|---------------|--------------------|
| Landsat 4 TM  | 26 August, 1988    |
| Landsat 5 TM  | 10 August, 1985    |
|               | 8 July, 1999       |
| Landsat 7 ETM+| 27 May, 2001       |
|               | 22 May, 2010       |
|               | 01 July, 2011      |
| Landsat 8 OLI | 18 June, 2018      |
3.2. Methodology

The processing flow of the spatio-temporal analyses of the forest cover in the Middle Volga region with the use of time series satellite images is presented in figure 2.

![Figure 2](image)

**Figure 2.** The algorithm of the spatio-temporal analyses of the forest cover.

We used Tasseled Cap (TC) transformation for compressing spectral data of the Landsat TM, ETM+ and OLI reflectance bands (associated with physical scene characteristics) to three indices: Brightness, Greenness, and Wetness (BrGrWt). A detailed assessment of the forest cover disturbance was carried out based on a Landsat p172r21 image. For all 6 Landsat images, a layer of “forest mask” was designed using the unsupervised classification for BrGrWt images. Unsupervised ISODATA classification was carried out in several iterations. During the first stage, the Landsat satellite image was classified into 25 thematic classes, which were subsequently grouped into larger classes: coniferous, small-leaved and mixed forests. Finally, 7 forest classes were distinguished on each Landsat image, differing in species composition, origin, biological productivity of tree species and age (figure 3). These seven classes of land cover should be sufficient for the classification and assessment of disturbance dynamics in forest cover, taking into account all the existing forest ecosystems and vegetation cover in the Middle Volga region (figure 4). Finally, after designing 6 thematic maps, a general “forest mask” was formed, combining all the selected classes (coniferous, deciduous, mixed and young stands) of forest cover.

The Disturbance index (DI) is based on a linear combination of the BrGrWt [22](figure 5). The underlying theory is that recently cleared (disturbed) forest stands typically have a higher TC brightness value and lower TC greenness and wetness values in relation to undisturbed forest areas [23]. Specifically, the different spectral responses of a forest cover will occur with a higher reflectance of brightness and a lower reflectance of greenness and wetness [23]. The resulting disturbance index includes the values in all TC indices, summarized as follows:

\[ DI = Br - (Gr + Wt) \]

Thematic maps of BrGrWt were prepared based on the “forest mask” for 1985-2018 (figure 6).
**Figure 3.** Map of the main forest classes in the Middle Volga region.

| № | Classes of forest cover                      | Color |
|---|----------------------------------------------|-------|
| 1 | Mature and over mature coniferous            |       |
| 2 | Middle aged coniferous                       |       |
| 3 | Small-leaved mature and over mature          |       |
| 4 | Small-leaved middle aged                     |       |
| 5 | Mixed mature and over mature                 |       |
| 6 | Mixed middle aged                            |       |
| 7 | Young forest stands                          |       |

**Figure 4.** Raster image of “Forest mask” on Landsat imagery.
The DI space of transformation divides TC space in a way that segregates pixels between healthy forest and disturbed forest. DI values above zero indicate that the pixel has been disturbed, DI values
below zero indicate a recent flush of vegetation (possibly recovery), and DI values near zero indicate no change in the forest cover.

The assessment of the degree of disturbances for each thematic forest class was carried out based on the training samples (Region of Interest, ROI), extracted from developed thematic classes of Landsat satellite images. On the area under study in the Middle Volga region, we selected the corresponding polygons of forest areas for each assessed period. The sample plots included in the study were exposed to one or another disturbance as a result of a natural anomaly or anthropogenic activity. These polygons were used both for the subsequent classification of satellite images and for the accuracy estimation of thematic mapping.

Based on the combined images, including all time-series DI layers, the Maximum Likelihood classification was conducted to elaborate the general disturbance map. Classifications were trained from a database of disturbances that were prepared earlier. The resulting classifications were compared to the layer received using the ground truth data in an error matrix for each classification. The collection of ground truth data was carried out during field trips to forest plots and visual inspection of the territory of the Middle Volga region. Forest inventory data, plans of afforestation, high-resolution satellite images, and Yandex maps were used as supporting materials. In total, the study used data from 1,215 test plots, including 720 from field trips, 310 from forestry plans, 185 from high-resolution satellite images (Google Earth, Yandex, satellite images ALOS, Rapid Eye, and Canopus-V).

4. Results and discussion
A comprehensive assessment of forest disturbance in the Middle Volga region included remote monitoring of forest burns, clearcuttings, windbreaks, and insect outbreaks during the study period (1985-2018). The integrated disturbance map shows a cumulative increase in the entire forest cover disturbance (figure 7). Historically recurring in extremely dry seasons with approximately equal time intervals wildfires are especially disastrous. The anthropogenic impact is represented by forestry activities in the form of clear cut areas, mainly in mature and over mature coniferous forest stands. The TC image transformations and the DI made it possible to reveal with high accuracy (88%) the dynamics of disturbed forest cover areas in the Middle Volga region.

The general distribution of forest cover disturbances is represented by thematic classes within the studied scene (figure 8). The identified disturbances in forest cover are the result of anthropogenic and natural impacts. As depicted in figure 6, the distribution of forest disturbances is uneven throughout the study area. The total forest disturbance area was estimated at 191,8 thousand ha throughout the entire 1985–2018 period (at an approximate 95% confidence interval), roughly accounting for 10.7% of the total forest area across the Middle Volga region in 1985. The forest disturbance area increased from 1985 to 2018 and had reached its peak in 2014 (figure 8) due to severe wildfires.

The changes in the periods 1985-1988 and 2010-2014 were caused by intensive clear-cutting of forest stands and severe wildfires in 2010. In 2001-2010, there was 2,7617 ha of disturbed areas (table 2), which can be explained by intensive deforestation and drying up of significant areas of spruce plantations. During 2010-2014 the disturbance rate reached 4.8% on the studied scene of the Landsat image, the total area of which reached 85,121 ha. A significant part of such disturbances affected the territory of the Mari El Republic, primarily in connection with the summer abnormally hot weather in 2010. The distribution of disturbed forest areas varies from 6 to 45% throughout the study area (figure 7) of the Middle Volga region. The largest number of changes occurs in the northern part of the Landsat image, where the Mari El Republic is located. The lower part of the Landsat image scene covers small forested areas, which mostly borders on open landscapes (agricultural land, open areas).
Figure 7. Forest disturbance map of the Middle Volga region for 1985-2018.

Figure 8. Dynamics of forest cover disturbances in the Middle Volga region.
Table 2. The estimated area of forest disturbances in the Middle Volga region from 1985 to 2018.

| Change period, years | Area, ha | Disturbance rate, % |
|----------------------|----------|---------------------|
| 1985-1988            | 14750    | 0.83                |
| 1988-1999            | 18836    | 1.05                |
| 1999-2001            | 21024    | 1.18                |
| 2001-2010            | 27617    | 1.55                |
| 2010-2014            | 85121    | 4.77                |
| 2014-2018            | 24456    | 1.33                |

The changes in the class area in 1985-2018 were observed in all forest stands of the Middle Volga region. Among the studied classes, the largest part is covered with coniferous stands (middle-aged, mature, and over mature), as of 2018, the area of which accounted for 29% of the total forest area under study. In general, the area of the small-leaved class forest species (mature, over mature, and middle-aged) decreased by 19%. Due to the transition of stands to other thematic classes of forest cover, a decrease in the class of mixed stands reached 8% by 2018. The produced Landsat 1985-2018 thematic maps for 7 classes of forest cover show that coniferous area decreased by 4%. At the same time, there is a decrease in small-leaved (19%), mixed (8%) stands and an increase in young stands (23%).

5. Conclusion
In this study, Tasseled Cap transformation, which is based on reducing the time series Landsat (TM, ETM+, and OLI) reflectance bands of a single image date to three indexes (Br, Gr, and Wt) from 1985 to 2018, was employed to capture forest disturbances across the Middle Volga region. Using 7 forest classes in the Middle Volga region of the Russian Federation, we found that the developed algorithm of spatio-temporal analysis has high potential in mapping various forested land cover types related to disturbances with an overall accuracy of up to 88%. Approximately 10.7% of forest area was disturbed over the studied period, which implies that these disturbances are contributing to carbon emissions. The largest forest area of 85,121 ha was disturbed during the period from 2010 to 2014 as a result of severe wildfires. Intensive forest disturbance with larger disturbed forest patches occurred in the Mari El Republic in comparison with the Chuvash Republic of the Russian Federation. The results were in good agreement with ground truth data, including high spatial resolution images and data from field trips. The proposed algorithm can greatly improve the application of a variety of time series data used for estimation and monitoring forest ecosystems disturbances. Future studies need to incorporate multisource data for forest disturbance and recovery detection, especially for biogeochemistry simulations to improve forest accounting uncertainties in the region.

Acknowledgments
The reported study was funded by BRICS Multilateral Joint Science and Technology Research Collaboration between South Africa (supported by the National Research Foundation), Russia (supported by Russian Foundation for Basic Research, Research project № 19-55-80010/19) and China (supported by National Natural Science Foundation of China.)
The GIS and Remote Sensing for Sustainable Forestry and Ecology (SUFOGIS) project has been funded with support from the EU ERASMUS+ program. The European Commission support for the production of this publication does not constitute an endorsement of the contents which reflects the views only of the authors, and the Commission cannot be held responsible for any use which may be made of the information contained therein.

References
[1] Cohen W B., Yang Z, Stehman S V, Schroeder T A, Bell D M, Masek J G, Huang C and Meigs G W 2016 Forest Ecol. Manage. 360 242-52
[2] Pflugmacher D, Cohen W B and Kennedy R E 2012 Remote Sens. Environ. 122 146–65
[3] Ramankutty N, Gibbs H K, Achard F, Defries R, Foley J and Houghton R A 2007 Global Change Biol. 13 51–66.
[4] Vorobiev O N, Kurbanov E A, Polevshikova YA, Leznin S A 2016 Sovremennye Problemy Distantionnogo Zondirovaniya Zemli iz Kosmosa 13 124–34
[5] FAO 2016 Global forest resource assessment 2015 (In Food and Agriculture Organization of the United Nations, Rome) p 54
[6] de Groot. W J, Flannigan M D and Cantina A S 2013 For. Ecol. Manage. 294 35–44
[7] Westerling A L, Hidalgo H G, Cayan D R and Swetnam T W 2006 Science 313 940–43
[8] Hicke J A et al. 2011 2007 Global Change Biol. 18 7-34
[9] Stromber D 2007 J. Econ. Perspect. 21 199-222
[10] Hansen et al. 2013 Science 342 850-53
[11] Justice C O et al. 2016 Remote Sens. Environ. 173 3–15
[12] Gits J Z, Mitri G H and Ventura G 2004 Remote Sens. Environ. 92 409–413
[13] Spruce J P et al. 2011 Remote Sens. Environ. 115 427–437
[14] Potapov P, Hansen M, Stehman S, Loveland T and Pittman K 2008 Remote Sens. Environ. 112 3708-3719
[15] Hansen M C and Loveland T R 2012 Remote Sens. Environ. 122 66–74
[16] Vogelmann J E, Tolk B and Zhu Z 2009 Remote Sens. Environ. 113 1739–1748
[17] Huang C, Goward S N, Masek J G, Thomas N, Zhu Z and Vogelmann J E 2010 Remote Sens. Environ. 114 183–198
[18] Löw M and Koukal T 2020 Remote Sens. 12 4191
[19] Fraser R H, Li Z and Cihlar J 2000 Remote Sens. Environ. 74 362–376
[20] Dutrieux L P, Verbssett J, Kooistra L and Herold M 2015 ISPRS J. Photogramm. Remote Sens. 107 112–125.
[21] Masek J G et al. 2015 J. Geophys. Res. Biogeosci. 116 1451–1453
[22] Healey S P, Cohen W B, Zhiqiang Y and Kräger O N 2005 Remote Sens. Environ. 97 301–310
[23] Healey S P, Yang Z, Cohen W B, Pierce D J 2006 Remote Sens. Environ. 101 115–126.
[24] Frantz D, Röder A, Udelhoven T and Schmidt M 2016 Remote Sens. 8 277
[25] Arnett J T T R, Coops N C, Gergel S E, Falls R W and Baker R H 2014 Can. J. Remote Sens. 40 1-14
[26] Sieber A, Kuenmerle T, Prischepov A V, Wendland K J, Baumann M, Radeloff V C and Baskin L M and Hostert P 2013 Remote Sens. Environ. 133 38-51
[27] Barlow J et al. 2016 Nature 535 144–47
[28] Shimabukuro Y E, Arai E, Duarte V, Jorge A, dos Santos E G, Gasparini K A C and Dutra A C 2019 Int. J. Remote Sens. 40 5475-96
[29] Neumann M, Mues V, Moreno A, Hasenauer H and Seidl R 2017 Global Change Biol. 23 4788 – 97
[30] Kurbanov E, Vorobyev O, Leznin S, Polevshikova Y and Demisheva E 2017 Int. J. Wildland Fire 26 772-82
[31] Kurbanov E A and Post W M 2002 Climatic Change 55 157–71