Environ. Res. Lett. 13 (2018) 095008

LETTER

Forest cover and disturbance changes, and their driving forces:
A case study in the Ore Mountains, Czechia, heavily affected by anthropogenic acidic pollution in the second half of the 20th century

L Kupková1,2, M Potůčková1,2, Z Lhotáková1 and J Albrechtová2,3

1 Department of Applied Geoinformatics and Cartography, Faculty of Science, Charles University Prague, Albertov 6, 128 43, Czechia
2 Department of Experimental Plant Biology, Faculty of Science, Charles University Prague, Albertov 6, 128 43, Czechia
3 Shared first authorship.

E-mail: jana.albrechtova@natur.cuni.cz

Keywords: Landsat, time series analysis, air pollution, Disturbance Index, forest decline and recovery, mountainous forest ecosystems, Norway spruce

Supplementary material for this article is available online

Abstract
This study focuses on the assessment of forest cover and disturbance changes in the heavily polluted Ore Mountains (Czechia, Central Europe) during the second half of the 20th century and onward. It analyzes the driving forces of forest changes with reference to environmental, societal and political development in the region. Anthropogenic air pollution, prevalently SO2 from adjacent coal-burning industry, caused extensive forest decline, especially between the 1970s and 1980s. The most affected tree species was the main economical timber species, Norway spruce, which proved to be remarkably pollution-sensitive. We used Landsat time series, and a combination of an integrated forest Z-score and Disturbance Index (DI), to analyze the forest cover change and disturbance development during 1985–2016. In 1994, the forest cover reached its minimum there. The breakdown of communism in the 1990s implied fulfilling EU pollution standards via air protection regulations, investment in power plant desulphurization, and forest management measures, which were the main drivers of the forest recovery. The forest recovery continued till about 2005; however, fluctuations in forest cover and DI have continued during the last decade. Apparently, forests weakened by old loads are prone to new stress factors. Landsat time series represent a powerful data source to monitor the impact of these drivers on forests on a regional scale. Originally, the severely damaged eastern part with heavier acidic load and large forest decline recovered faster after remarkable lowering of air pollution loads compared to the western part, with lower loads and less damaged forests. However, the interactions of persisting driving forces (soil acidification, adverse meteorological events, climate change factors, air pollution, tree species composition and physiological state, pest outbreaks) still threaten the forests there, which remain moderately damaged in both parts of the Ore Mountains. This may lead to unpredictable forest development independently of societal and political driving forces.

1. Introduction

Forest condition has become strikingly important due to forest adaptive carbon sequestration capacity and regional vulnerability, especially in this time of ever increasing greenhouse gas emissions—particularly CO2—climate change, and global loss of forest areas (FAO 2010, Lindner et al 2014, Manan et al 2017). Forests are under tremendous pressure from many disturbances imposed by climate change (Bonan 2008), such as drought and heat waves (Allen et al 2010); increasing fire danger (Flannigan et al 2006) and severity of storms and floods (Lindner et al 2010, 2014); and higher susceptibility to pathogens and pest outbreaks (Ayres and Lombardero 2000). All these factors impair forest productivity and carbon sequestration (Boisvenue and Running 2006, Lindner et al 2014). Anthropogenic air pollution also interacts with climate change factors in
unpredictable ways, affecting many forest ecosystem services (Bytnerowicz et al 2007, Cudlin et al 2013). Air pollution has become a severe problem in many European regions since the second half of the 20th century, exhibiting a range of impairments on forest ecosystems based on the character and strength of the air pollution load (Kauppi et al 1992). Forest stands in the area of the present study, predominantly monocultures of Norway spruce (Picea abies L. Karst.) in the heavily polluted Ore Mountains (Krušně hory, Das Erzgebirge), proved to be very pollution-sensitive during the second half of the 20th century (Materna 1997, Šrámek et al 2008).

Forest ecosystems were reduced globally by 3% during 1990–2015, especially in developing countries (Keenan et al 2015 based on FAO data) due to deforestation. By contrast, there have not been further demands for expansion of agricultural land since the 19th century in European countries with advanced economies and technological advantages. Consequently, forests have started to expand, as explained by the forest transition theory (Mather and Needle 1998). During 1990–2015, after abrupt political changes took place in Central and Eastern Europe, the area covered by forests in Europe increased by 2.1% (Keenan et al 2015).

Territorial expansion of forest ecosystems, however, has not always been connected with improvements in forest condition. Significant political, economic, and social drivers during the 20th century, such as two world wars, the rise of communist regimes in Central and Eastern Europe, economic competition of COMECON states with Western Europe, and finally the collapse of communism and economic transformation in Central and Eastern Europe after 1989 have caused extensive land use/land cover changes (LU/LCC) and influenced forest health conditions in many regions of Central Europe (Kandel and Innes 1995, Lambert et al 1995, Olofsson et al 2011, Kolář et al 2015, Groisman et al 2017, Vejpustková et al 2017). The Ore Mountains are very rich in mineral deposits (various ores and brown coal; Rojík 2015), and thus have been exploited for centuries. In the second half of the 20th century, severe air pollution coming from nearby coal-burning power plants led to unprecedented environmental damage in the area, including large-scale forest decline and dieback (Moldan and Schnoor 1992, Materna 1997) first described on Norway spruce, which have proven to be very pollution-sensitive (Schulze 1989). The whole region was part of the so-called ‘Black Triangle’, comprising Northern Czechia and the adjacent regions of Germany and Poland, where high concentrations of coal-burning power plants and industrial complexes created an area of extreme pollution emissions (Blážková 1996, Bridgman et al 2002, Kolář et al 2015).

In the Czech part of the Black Triangle, forest soils exceeded critical loads of acidity in 75% of the region (Akselsson et al 2004). The prevailing winds from numerous pollution sources generated a west-to-east positive gradient of air pollution, causing an extreme pollution load in the eastern and a remarkably reduced load in the western parts of the Ore Mountains (see table 1). This corresponded to the gradient in the Norway spruce forest condition and health (Campbell et al 2004).

The term ‘forest health’ is frequently used without clear definition. When upscaling to higher hierarchical levels, the definition of forest health becomes even more difficult to assess since physiological status of a single tree does not correspond to overall status of a forest stand, an ecosystem, or a biome (Kolb et al 1994). Existing measures of forest health, e.g. productivity, range from strictly utilitarian, related to human needs, to ecological definitions related to the persistence of forests or stands within biomes (Kolb et al 1994, Trumbore et al 2015). The Food and Agriculture Organization FAO definition of ‘forest health and vitality’ combines these two perspectives by examining how the combined presence of abiotic (e.g. drought and pollution) and biotic stress affect tree growth and survival, the yield and quality of wood and non-wood forest products, wildlife habitat, and recreational, scenic, and cultural value.

The LU/LCC and anthropogenic impacts on forests in Europe from the mid-20th century have been examined by a number of researchers. Studies evaluating forest changes have been based on different data sources: statistical data (Bičík et al 2015, Earth Observation data (Griffiths et al 2014, Olofsson et al 2016), datasets derived from satellite data (Feranec et al 2007, Pekkarinen et al 2009, Kupková et al 2013). The forest LU/LCC analyses often focus on the quantification of forest change (Pekkarinen et al 2009, Potapov et al 2015), forest disturbances and degradation (Healey et al 2005), or methodological issues of the change detection (Mitchel et al 2017). An increasing number of analyses also attempt to determine the driving forces of the changes (Munteanu et al 2014). In addition, FAO (2016) emphasizes the importance to address driving forces in the context of deforestation and forest health and damage in the State of the World’s Forests Report.

Studies dealing with environmental and forest damage in the Ore Mountains and the entirety of North Bohemia have often been based on data collected by foresters, researchers or administrators (e.g. Hadaš 2002, Slodičák et al 2007, 2008, Šrámek et al 2015). Annual reports by the Ministry of Agriculture of Czechia, ‘Information on Forests and Forestry in the Czech Republic’ are issued regularly and the Ore Mountains are often mentioned as the forests in the region are still exhibiting forest damage due to nutrient imbalances caused by previous acidic pollution combined with extreme meteorological events (Ministry of Agriculture of the Czech Republic 2017). Only a few remote sensing studies have focused on
Table 1. Air pollution and atmospheric deposition in data: SO\(_2\) and NO\(_x\) emission load in 1997, 2005 and 2015. Data from the measuring stations of the Czech Hydrometeorological Institute (http://portal.chmi.cz/files/portal/docs/uoco/isko/tab_roc/tab_roc_EN.html). The measuring stations (locations in figure 1) are presented from west to east. W, E—affiliation to the western (West), eastern (East) parts of the study area, respectively.

| Station  | SO\(_2\) \(\mu g\) m\(^{-3}\) | Altitude m a. s. l. | 1997  | 1998  | 1999  | 2000  | 2001  | 2002  | 2003  | 2004  | 2005  | 2006  | 2007  | 2008  | 2009  | 2010  | 2011  | 2012  | 2013  | 2014  | 2015  | 2016  |
|----------|-------------------------------|--------------------|-------|-------|-------|-------|-------|-------|-------|-------|-------|-------|-------|-------|-------|-------|-------|-------|-------|-------|-------|
| Přebuz (W) | 904                          | 13                 | 6     | 5     | 5     | 4.62  | 5.69  | 4.01  | 2.96  | 4.02  | 4.06  | 2.57  | 2.16  | 2.44  | 3.22  | 3.07  | 2.94  | 2.57  | 1.93  | 1     | 1     | 1     |
| Sokolov     | 401                          | 27                 | 13    | 13    | 10    | 6.73  | 7.32  | 6.84  | 7.19  | 6.28  | 9.6   | 6.59  | 6.03  | 6.36  | 6.33  | 7.21  | 6.38  | 6.29  | 5.26  | 5     | 6.18  |
| Měděnec (E) | 827                          | 36                 | 17    | 11    | 10    | 8.14  | 12.62 | 15.88 | 9.75  | 9.66  | 14.22 | 10.88 | 8.55  | 10.45 | 9.57  | 10.37 | 8.25  | 8.1   | 8.83  | 9.36  | 5.96  |
| Přísečnice (E) | 740                     | 25                 | 13    | 6     | 6     | 6.62  | 9.16  | 19.95 |       |       |       |       |       |       |       |       |       |       |       |       |       |
| Výsluní (E)  | 740                          | 19                 | 28    | 17    |       |       |       |       |       |       |       |       |       |       |       |       |       |       |       |       |       |
| Chomutov     | 320                          | 35                 | 17    | 14    | 12    | 9.74  | 11.64 | 12.3  | 8.76  | 7.83  | 9.82  | 10.61 | 10.7  | 9.79  | 10.71 | 8.34  |       |       |       |       |       |       |

| Station  | NO\(_x\) \(\mu g\) m\(^{-3}\) | 1997  | 1998  | 1999  | 2000  | 2001  | 2002  | 2003  | 2004  | 2005  | 2006  | 2007  | 2008  | 2009  | 2010  | 2011  | 2012  | 2013  | 2014  | 2015  | 2016  | 2017  | 2018  |
|----------|-------------------------------|-------|-------|-------|-------|-------|-------|-------|-------|-------|-------|-------|-------|-------|-------|-------|-------|-------|-------|-------|-------|-------|-------|
| Přebuz (W) | 904                          | 15     | 14    | 13    | 12    | 9.8   | 11    | 11    | 10.1  | 9.7   | 9.4   | 9.3   | 9.4   | 9.0   | 9.4   | 8.0   | 7.3   | 8.3   | 7.6   | 6.8   | 5.6   |       |       |
| Sokolov     | 401                          | 39     | 30    | 29    | 26    | 25    | 27    | 28.7  | 24.5  | 24.6  | 26.4  | 24.2  | 23.8  | 22.8  | 21.0  | 19.0  | 19.5  | 19.1  | 19.1  | 19.0  |       |       |       |
| Měděnec (E) | 827                          | 23     | 18    | 17    | 16    | 13    | 11.23 | 19.8  | 14.4  | 15    | 15.8  | 13.9  | 15.3  | 15.1  | 13.6  | 11.5  |       |       |       |       |       |       |       |
| Přísečnice (E) | 740                   | 19     | 17    | 11    | 9     | 11    |       | 9.81  |       |       |       |       |       |       |       |       |       |       |       |       |       |       |       |       |
| Výsluní (E)  | 740                          | 19     | 17    | 11    | 9     |       |       |       |       |       |       |       |       |       |       |       |       |       |       |       |       |       |       |       |
| Chomutov     | 320                          | 50     | 41    | 40    | 39    | 36    | 39    | 40.7  | 36.2  | 34.7  | 39.2  | 33.9  | 33.1  | 33.3  | 34.9  | 29.1  |       |       |       |       |       |       |       |       |       |

Environ. Res. Lett. 13 (2018) 095008
anthropogenic impacts on forest health in the Ore Mountains using Landsat data (e.g. Lambert et al 1995, Ardo et al 1997, Mišurec et al 2016), and there is currently no detailed historic comparison between the eastern and western parts of the Ore Mountains. Our previous hyperspectral studies aimed to detect stand damage on Norway spruce in the western part of the Ore Mountains (Campbell et al 2004) and in the adjacent Sokolov mining region (Mišurec et al 2012, Kopačková et al 2014, Mišurec et al 2016). For these studies, hyperspectral data for only two time horizons were used. A comprehensive study on the whole area of the Ore Mountains using a series of long-term satellite data quantifying changes in forest area, disturbance, and health status in the context of complex driving forces is not available yet. Hyperspectral studies are more efficient for estimating tree or stand physiological status compared to multispectral or moderate/high-resolution data; however, long-term satellite evaluation of forest condition using hyperspectral data is not possible because the historical data is not available.

Our study focuses on dynamics of forest damage and recovery, and their driving forces in the Ore Mountains from the 1980s through the use of a time series of Landsat data. Our goal was to evaluate forest cover and disturbance/health dynamics in connection with acidic pollution loading and its subsequent reduction. In addition to determining tipping points between forest damage and recovery in the region, we wanted to see if the changes in forest health status or disturbance were dependent on any ongoing or new drivers of forest stability and health condition. Our study aimed to verify whether the region is heading towards more sustainable development regarding forest cover and forest condition.

2. Study area

2.1. Biophysical description of the Ore Mountains, forest ownership and management

The Ore Mountains (Krušně hory, Das Erzgebirge) flank the border between North-Western Bohemia and Saxony, forming a range of about 130 kilometers in length. Our study area covers the western part of the Ore Mountains with the highest elevation being 90 kilometers long (figure 1). The Ore Mountains is a Hercynian block formed by metamorphic rocks (Rojík 2015). The study area can be divided into two geologically distinct units separated by the highest elevation, Klinovec (1244 meters a. s. l.). Intrusive rocks (granites, granodiorites) are more acidic, and prevail in the western area—hereinafter termed the West. Metamorphic rocks (gneisses, phyllites or mica-schist) underly the eastern area (Czech Geological Survey http://mapy.geology.cz/geocr_50/). The region 40 km east of Klinovec will be termed the East (figure 1). Despite the different bedrocks, cryptopodzols and podzols prevail across the majority of the forested study area.
Mean annual precipitation often exceeds 1000 mm, making the area humid to perhumid. Horizontal precipitation (fogs and atmospheric icing) enhance the humid character of the climate. Mean annual temperatures range over 4°C–6°C. Prevailing eastward winds together with the position of the main pollution sources resulted in a sharp west-to-east positive air pollution gradient, which persisted even after the desulphurization of the majority of the sources during the 1990s (table 1).

Forest ownership and its effect on forest management has been influenced by the political system in Czechia. During the communist regime (1948–1989) the forests were nationalized. In 1990 about 96% of forests were owned by the state (SVOL 2017). Since 1990 and the return of the democratic system, the amount of private and municipal forests has been persistently increasing (Ministry of Agriculture of the Czech Republic 2017). However, according to ÚHUL (2009) the majority of forests (almost 89%) in the Ore Mountains are state-owned and being managed by Forests of the Czech Republic, a joint-stock company. Thus, the main driver of their management is determined by current legislation.

Before the 1950s, Czech forestry tended mainly to favor the shelter-wood system over even-aged forestry of pure coniferous stands. These shelter-wood stands embraced continual development of structural forest heterogeneity in terms of age and tree species composition, with the primary goal of achieving sustainable forest management (Bednar 2015). However, after the communist system took power in 1948, Czech forestry was negatively affected by the process of nationalization and the formation of a new state forest administration. The Forest Act of 1960 (no. 166/1960) exerted a positive influence, based on detailed theoretical foundations of uneven-aged silviculture within Czech conditions. The Forest Act codified the small-scale shelter-wood system as the main forest management system. However, the 1970s provided a dramatic diversion from that approach to forest management via the application of massive heavy machinery, mainly because of common social and political drivers. This was achieved by the creation of so-called ‘forest harvest units’ and by application of ‘work rationalization’ ideas (Bednar 2015). This negative development was completed in 1977 by an all-new Forest Act (no. 96/1977 Sb.) which enabled the use of a clear-felling system focused on timber production and dramatically restricted application of other forest management systems. Consequently, the 1970s are often regarded as one of the worst periods for Czech forestry (Bednar 2015). Moreover, during the 1970s and 1980s, Czech forests started to exhibit serious damage due to air pollution and large-scale forest dieback. This resulted in emergency logging in many regions of the country (figure 3). Even after 1989 and the return of a democratic regime, Czech forest management remained focused on wood production and neglected other ecosystem services (Fanta 2010). The change in the Forest Act in 1995 (no. 289/1995) theoretically enabled more forest management systems (including a planter system) and emphasized greater tree species diversity. However, even at present, the economic function of the forest takes precedence, and even-aged stands are still planted in the prevailing forest areas (Bednar 2015).

2.2. Forest decline and dieback in the Ore Mountains from the middle of the 20th century till the breakdown of socialism

The primeval mixed forests were largely cleared during the mining era of the 12th century (Melichar and Krása 2009) and replaced by spruce monocultures. These managed forests were heavily damaged by acid pollution in the second half of the 20th century. However, forests are still the dominant landscape feature and have always covered 54% or more of total area of the Ore Mountains (Bičík et al. 2015). Locally mined lignite exhibits high sulphur content (up to 15%, Moldan and Schnoor 1992) and until the 1990s sulphur filters had not been used in socialist Czechoslovakia. Thus, SO2 was the main air pollution agent. Few environmental standards or regulations were present under socialism, and information on environmental issues was often kept secret (Hill 1992, Moldan and Schnoor 1992).

During the 1940s, interaction of emissions and adverse winter inversion events led to irregular patterns of forest damage in the Ore Mountains (Šrámek et al. 2015). The most affected species appeared to be Norway spruce, with the largest area of damaged stands. The first phase of large-scale forest decline in the Ore Mts became apparent in 1947–1965 (Krčmér et al. 1999). In this period, the first intensive multiple stresses of forests were documented (figure 2). The sensitivity of Norway spruce to emissions was not yet known, and so spruce was used repeatedly for afforestation.

During the second phase of forest decline in 1966–1977, the emission load increased together with extensive forest dieback. Starting at that time, emergency logging was applied for the purpose of harvesting recently dead and heavily damaged trees in large quantities. These emergency loggings increased three-fold at the end of this phase and reached their maximum in 1981. The connection between emission loads, forest decline and emergency logging became apparent (Schulze 1989; figure 3). A new forestry management strategy was applied there: substitution of supposedly more tolerant tree species for afforestation—pioneer- tree species (birch, mountain ash) and exotic Colorado blue spruce (Picea pungens). However, regardless of seemingly better needle anatomical adaptations, our reflectance study on the needles of both Norway and Colorado blue spruce revealed the same degree of damage in response to air pollutants (Soukupová et al. 2001), which later proved to be a valid fact.
Figure 2. Periods of forest damage and recovery from the mid of the 20th century and their major drivers. Upper graph: red curve (left axis) corresponds to the mean annual SO2 emissions in Northern Bohemia region between 1963 and 1999 (source CHMI, www.chmi.cz); Blue columns (right axis) estimation of forest area based on iFZ with thresholds of 8 for the Ore Mountains (own data processing, see chapter 3). Red color and its shading symbolize the periods of forest damage and decline (darker = heavier damage), blue color represents periods of forest recovery and orange color current fluctuation of forest area, health state and disturbance. Sources: Alertová 2001, Lomský and Šrámek 2004, Slodičák et al 2007, Klega 2007, Slodičák et al 2008, Šrámek et al 2008, Šrámek et al 2015, Lorenc et al 2017.
The third phase of emission calamity, 1978–1987, was characterized by culmination of SO2 loads leading to an ecological disaster. This remained undisclosed to the general public until the change of political regime after 1989 (Moldan and Schnoor 1992). Between 1975 and 1990 annual SO2 emissions exceeded 800 kt, reaching a maximum in 1984 (1089 kt, figure 3). The reduction of forest area in 1977–1987 was more than 20% (data of the Forestry and Game Management Research Institute, www.vulhm.cz). At that time a new large-scale forestry management measure was applied in the form of airborne liming, usually with crushed dolomite, to impede soil acidification and a loss of basic cations. Only starting in the 1980s were new management measures focused on the gene pool of locally adapted ecotypes of tree species.

3. Data sources and methods

We studied forest change in the last 30 years using Landsat 4, 5, 7 and 8 surface reflectance T1 products. According to the product description (United States Geological Survey https://landsat.usgs.gov/landsat-collections), the applied processing level provides geometrically and radiometrically consistent datasets, which are suitable for direct time-series processing (with root mean square error of the scene-to-scene co-registration up to 12 meters; inter-calibration between Landsat instruments and atmospheric correction). Nineteen scenes were selected, mostly during the vegetation period (May to September) between the years 1985 and 2016 with no cloud cover over the Ore Mountains (for acquisition dates see figure 4).
A modified Vegetation Change Tracker (VCT) algorithm published by Huang et al. (2010) was employed to determine forest area for each year and to discriminate basic change directions, viz. deforestation, afforestation and stable forest. The algorithm is based on observed spectral-temporal characteristics of land cover classes, mainly during the mid-growing season. Unchanged health status forest exhibits relatively stable spectral signatures in visible and some shortwave infrared bands over the years, while other classes vary in their spectra both seasonally and inter-annually. Spectral properties of unchanged health status forest are usually defined by means of supervised classification when field campaigns or existing forest maps are used for delineation of training sites. Due to lack of such data, unsupervised ISO-DATA classification utilizing six Landsat bands (three in visible, one in NIR and two in SWIR spectral bands) and a derived normalized difference vegetation index was carried out first. Comparison with the available archive orthomages revealed that mature coniferous forests in the Ore Mountains represent a homogeneous spectral class. Thus, a mean reflectance \( \bar{b}_i \) and a standard deviation \( SD \), of reflectance in selected spectral bands corresponding to mature coniferous forest were used later for normalizing Landsat scenes when calculating the integrated forest score (see formulas 1 and 2). While \( SD \) are relatively stable in all the scenes and correspond to standard deviations published in Huang et al. (2010), the \( \bar{b}_i \) are influenced by seasonal differences (see figure 4).

Spectral-temporal behavior of water is similar to that of a forest. Water bodies occupied only 3% of the area of interest according to the Corine Land Cover (CLC) 2012 and a change between forest and water classes was not significant during the studied period. Thus, only one water mask was created as a union of water areas in the CLC 2012 database and a result of an unsupervised classification of the Landsat images, and was used for all processed Landsat scenes.

The VCT algorithm discriminates forest disturbances based on evaluation of time series of an integrated forest score (IFZ), which is supposed to be inter-annually stable and below a defined threshold in case of an unchanged health status forest. First, a forest Z-score \( FZ_i \), is calculated for each pixel from the green and two SWIR bands of the LANDSAT sensors (TM, ETM+, and OLI) according to the formula

\[
FZ_i = \frac{b_i - \bar{b}_i}{SD_i} \quad (1)
\]

where \( b_i \) is the spectral reflectance of a pixel in band \( i \), \( \bar{b}_i \) is the mean value and \( SD_i \) the standard deviation of forest pixels in the same band. In our case, \( \bar{b}_i \) and \( SD_i \), values correspond to mature coniferous forest and were derived based on unsupervised classification as described above. An IFZ is then derived for each pixel using the formula

\[
IFZ = \sqrt{\frac{\sum_{k=1}^{3} FZ_k^2}{3}} \quad (2)
\]

Following Huang et al. (2010) we applied a threshold of \( IFZ \leq 3 \). In this way, stands of mainly mature conifers were discriminated. Mean IFZ values from 1990, 2000, and 2006 images were calculated under the forest mask derived from corresponding CLC databases using deciduous (code 311), coniferous (312), mixed (313) and transitional (324) forest classes. This revealed a mean \( \mu_{IFZ} = 5 \) and a standard deviation \( \sigma_{IFZ} = 3 \). Thus, a new threshold of \( IFZ \leq 8 (\mu_{IFZ} + 1\sigma_{IFZ}) \) was used in order to discriminate all forest classes. The time series of derived forest mask were processed using a self-developed MATLAB script according to the scheme shown in Huang et al. (2010 p 189). A pixel with a value of \( IFZ \leq 8 \) over all evaluated images was labelled as a stable forest (isolated outliers in the time series caused by random image errors were ignored).

Because of the variety of forest classes covered by the defined threshold (including both new plantings and declining forest), the IFZ value of pixels marked as non-stable forest was further evaluated and assigned into one of following classes: (i) deforestation (the IFZ value can be divided in two parts where IFZ \( \leq 8 \) is followed by IFZ > 8 and each relation holds for at least three subsequent years with the exception of the very beginning and end of the time series), (ii) afforestation (opposite to i), (iii) deforestation followed by afforestation (at least three subsequent IFZ > 8 exist inside series of IFZ \( \leq 8 \)), (iv) afforestation followed by deforestation (at least three subsequent IFZ \( \leq 8 \) exist inside series of IFZ > 8). A map of forest changes was derived on this basis.

A disturbance index (DI, Healey et al. 2005) based on tasseled cap transformation (TCT, Kauth and Thomas 1976) was calculated for all Landsat scenes in order to evaluate changes in forest damage/recovery over the time period studied. The DI reflects an assumption that recently cleared or declining forest exhibits high brightness and low greenness and wetness values in relation to undisturbed or recovering forest. Methodology described by Healey et al. (2005) and Mišurec et al. (2016) was followed. First, TCT was carried out for all 19 images. Second, DI was calculated for all pixels included in the stable forest and forest change categories as derived from IFZ with the threshold 8 (see above). Due to outliers present in the data, a median value \( m \) and an estimated standard deviation \( \sigma \) based on the mean absolute difference (MAD, \( \sigma = 1.4826 \times \text{MAD} \)) were used. In order to relate the normalization to the forest reflectance, \( m \) and \( \sigma \) of the three TCT components and later on also of DI were derived only from pixels labeled as ‘stable forest’ in the forest change map.

Finally, DI values were divided into three intervals \( \text{DI} = m_{\text{DI}} + 0.5\sigma_{\text{DI}} \), \( \text{DI} \in (m_{\text{DI}} - 0.5\sigma_{\text{DI}}, m_{\text{DI}} + 0.5\sigma_{\text{DI}}) \), \( \text{DI} > = m_{\text{DI}} + 0.5\sigma_{\text{DI}} \), separately for the West and East parts of the Ore Mountains.
In order to evaluate change in DI over the period studied, a linear trend ($T_{DI}$) was calculated from the nineteen time horizons. A similar approach was used by Schneibel et al (2017). Those $T_{DI}$ values close to 0 represent areas with minimal changes. Negative values of $T_{DI}$ indicate a decrease of DI and therefore improvement in the forest condition in general, which includes various aspects such as forest health status, afforestation and young forest growth. On the other hand, positive trend values indicate an increase of DI in connection with a worsening of forest condition, including deforestation. Examples of all three defined cases of DI change are depicted in figure 5. The $T_{DI}$ were visualized in the form of a map presented in Results, figure 9. The procedure described was used instead of simply subtracting the DI value in the first and last year due to obvious outliers in the time series, as visible in the examples in figure 5.

Accuracy of forest classifications (generated for threshold of IFZ $\leq 8$) were evaluated for image classification outputs from three years (2005, 2009 and 2016) using available RGB orthoimages from 2005, 2008 and 2015 with resolutions of 0.5 m (2005 and 2008) and 0.25 m (2015). We used 385 randomly generated validation points for each year. A number of samplings were calculated according to an approach proposed by Foody (2009) for defining the testing set in remote sensing studies. A stratified sampling design was used based on the area fraction of forest and non-forest sub-classes to the total cover area in each year. A confusion matrix approach was employed to validate the classification outputs (Congalton and Mead 1983, Foody 2002).
4. Results

4.1. Estimation of forest area based on Landsat data

Forest area for each year studied was estimated by thresholding IFZ. The results for thresholds 3 and 8 are summarized in figure 6 separately for the West and East of the Ore Mountains. Some fluctuation in forest cover can be detected in both parts of the study area under both IFZ thresholds, particularly between 1985 and 2000. The minimum of forest area (in both IFZ thresholds in West, and IFZ8 in East) was reached in 1994, probably due to previous emergency loggings (see chapter 2). Since 2002 the forested area has been more stable, with smaller fluctuations in both parts of the Ore Mountains, as well documented with simple moving average values in figure 6.

Figure 7. Forest change map for the period 1985–2016 based on evaluation of time series of IFZ masks using the threshold 8. While stable forests dominate in the West part, they are rare in the East part of the Ore Mountains.
There is a striking difference in forest cover change between the West and East from 1985 to 2016 (figures 6 and 7). While in the West part the area of stable forest (i.e. pixels with a record of IFZ ≤ 8 over all evaluated images) remains almost unchanged, the afforestation trend is obvious in the East part. This difference is attributed to the air pollution gradient from west to east (table 1), which led to more serious forest damage in the East and subsequently to the regeneration and afforestation after the pollution drop. These processes across the whole area between 1985 and 2016 are also well represented by the forest change map (figure 7) as the afforestation prevails in the East.

The relative frequency of forest change categories is presented in table 2, which quantifies the trends shown in forest change map (figure 7). Stable forest area between 1985 and 2016 was significantly higher in the West (by 25.3%). The trend of afforestation dominates the East (higher by 20.4% compared to the West); also, deforestation followed by afforestation was higher in the East. Trends of deforestation and afforestation followed by deforestation were recorded in a rather small area.

**Table 2. Relative frequency of forest change categories between 1985 and 2016.**

|                | Whole area | East | West |
|----------------|------------|------|------|
|                | area [ha]  | %    | area [ha] | % | area [ha] | % |
| stable         | 56 704     | 69.2%| 17 421    | 53.9%| 39 282    | 79.2%|
| deforestation  | 3033       | 3.7% | 831       | 2.6% | 2202      | 4.4% |
| afforestation  | 13 475     | 16.4%| 9295      | 28.8%| 4180      | 8.4% |
| deforestation—afforestation | 8060   | 9.8% | 4449      | 13.8%| 3611      | 7.3% |
| afforestation—deforestation  | 655      | 0.8% | 331       | 1.0% | 324       | 0.7% |
| Sum            | 81 926     | 100.0%| 32 327    | 100.0%| 49 599    | 100.0%|

**Figure 8.** Time series 1985–2016 of the relative frequency of DI for the West (a) and East (b) parts of the Ore Mountains. While the West part gradually became more disturbed exhibiting only 30% of most damaged forests in 1985, the East part, where 70% or more forests belonged into the most disturbed class, gradually improved into the proportions of disturbance resembling the west part.
Figure 9. A map of $T_{DI}$ for each pixel of a forest cover (IFZ mask using the threshold 8), where the values of 0 or close to 0 indicate no disturbance, values over zero show increase of disturbance due to deforestation or worsening of forest health, and values below zero indicate afforestation or improvement of forest health. A method of quantiles was used for the construction of disturbance change classes and legend.
This indicates that a thirty-one-year period of forest die-back was replaced by forest recovery, especially in the East where previous forest damage was more serious.

4.2. Estimation of forest health using DI and its linear trends

We used the DI to evaluate changes in forest health status during the study period in the West and East parts of the Ore Mountains. (figure 8). The relative frequency of DI classes clearly shows differences in forest disturbance between East and West parts, particularly in the beginning of the study period. The East showed more fluctuation in DI distribution compared to the mostly stable DI distribution in the West. In the East, a sharp decrease in frequency of the most disturbed class between 1985 and 1995 (figure 8) corresponded with the reduction of the pollution load (refer to the figure 3 and chapter 5). This observation is in accordance with when the forest area minimum was reached (1994), probably when the most damaged parts of forests had been already harvested. Since 2002, the distribution of DI tended to show a reduction in the most disturbed class up to 2016, except 2006. This drop may have been caused by long-term inversion events in 2006 that caused severe air pollution and led to forest damage (Slodičák et al 2008, Šrámek et al 2015). By contrast, there is almost no apparent trend in DI distribution change in the West throughout the whole period.

The map of $T_{DI}$ for each pixel of forest cover (figure 9) confirms the different trends in forest status (disturbance and/or health) changes in West and East from 1985 till 2016. Visual co-localization of stable forest cover class and $T_{DI}$ categories for the whole area (figure 10) were used to distinguish processes of deforestation from forest status decline and afforestation from forest status improvement. In the West, only small regions of extremely increased $T_{DI}$ corresponded to deforestation (e.g. $T_{DI}$ maxima in dark red on the southwestern edge). The main body of stable forests in the central region showed mostly increasing $T_{DI}$ and, thus, forest status decline. Towards the north, scattered areas of $T_{DI}$ decrease were detected, mostly corresponding to afforestation. However, even the stable forest stands showed increasing disturbance there. By contrast, in the East the $T_{DI}$ values mostly documented recovery processes in the stable forested areas. Particularly in the northern and central parts of the region, we can observe more equal distribution of $T_{DI}$ decrease (blue color) among the areas covered with stable forest and the areas afforested during the studied period (consult figures 7 and 9 or maps in figures S1 and S2 in a supplement is available online at stacks.iop.org/ERL/13/095008/mmedia). Similarly, to the west, $T_{DI}$ maxima corresponded to deforestation. A minor area of stable forests showed increased
Table 3. Results of accuracy assessment for classification of Landsat data from 2005, 2009 and 2016.

|                      | 2005     | 2009     | 2016     |
|----------------------|----------|----------|----------|
| Overall accuracy     | 90.4%    | 87.5%    | 91.7%    |
| Kappa coefficient    | 0.78     | 0.74     | 0.82     |
| Producer’s accuracy forest | 93.9%    | 90.1%    | 93.5%    |
| Producer’s accuracy non-forest | 85.2%    | 82.8%    | 89.1%    |
| User’s accuracy forest | 90.4%    | 87.8%    | 92.6%    |
| User’s accuracy non-forest | 90.4%    | 87.1%    | 90.3%    |

disturbance, particularly the southeastern edge facing toward the Chomutov Basin (figure 1) and the areas on the border with the West part. Another rather extensive area of increased disturbance in the East is located in the middle of the East part toward the north. Based on comparison of an orthophoto, stable old stands of dwarf pine (Pinus mugo) were identified there and we attributed their increased disturbance to possible long-term pollution impact.

4.3. Classification accuracy assessment
Results of accuracy assessment using orthophotos are summarized in table 3. In 2005 and 2016 the overall accuracy was around 90%, also the results of Kappa index and Producer’s and User’s accuracies are high. The worst results were recorded for 2009, when the overall accuracy was 87.5% and Kappa coefficient 0.74.

5. Discussion

5.1. Forest recovery after the breakdown of communism and present situation
Figure 2 gives the overview of forest damage periods and its driving forces in the Ore Mountains. The main driving force affecting the physiological status of forest stands there during the second half of the 20th century was atmospheric pollution (Godzik and Sienkiewicz 1990, Moldan and Schnoor 1992, Groisman et al. 2017).

Since 1989 and the political and economic changes in Czechoslovakia, information regarding environmental issues has been disclosed and gradually given attention by governmental institutions and the public (figure 2). The following period of 1988–2005 was characterized by (1) a substantial lowering of emissions due to legislative measures of a new political democratic regime regulating sulphur emissions, and (2) a corresponding decrease in emergency logging (figure 3). The desulphurization of coal power plants started in 1993 based on the project supported in 1992 by the World Bank and by 1998 the overall SO2 emissions were cut to one tenth of their peak values from the 1980s (figure 3). Over one decade (1993–2003) a total reduction from 719 149 t to 58 346 t SO2 was achieved (source CHMI). Great investments into desulphurization and into forest reconstruction from domestic sources and abroad were the main drivers of gradual forest recovery. Our analysis shows a time-lag between positive drivers and forest recovery, due to extreme damage of remaining forest stands and slow growth of new plantations. According to our data, the forest cover reached its minimum in both the West and the East in 1994 (figure 6) and a combination of recovery and fluctuation has been detected since then. The DI shows worsening from 1995 till 2000 and slow improvement since 2002 (figure 8) in the East. The forest vulnerability was proven in the winter 1995/6 when increased air pollution values due to long-term winter inversion events caused extremely severe damage.

Comparing the forest cover and disturbance level in 1985 with the present state (maps on figures 6–10 and table 2), there is significant recovery in forest cover and decrease in forest disturbance mainly in the East but also in the West during the thirty-year period. However, the last period from 2005 till present is characterized by partial forest cover and DI fluctuations, rather than stable recovery. In this period, the SO2 pollution in the Ore Mountains was lowered to EU standards; however, nitrogen-based acidic deposition remains a significant contribution to imbalance in basic cation availability (Šrámek et al. 2015). Ozone concentrations gradually decreased over the last decade; however, ozone still supposedly contributes to tree damage. The less favorable acidic soil conditions remain in the West due to nutrient-poor soils on naturally acidic geological bedrock, and soil acidification remains a serious barrier to the forest recovery process because the effects of liming are not stable and permanent (Šrámek et al. 2015). New problems have arisen for forest stability in the last decade. The pathogen, bud blight (Gemmamyces piceae) specific to substitute species Colorado blue spruce occurred and caused extensive damage. Moreover from 2015, Gemmamyces bud blight occurred on Norway spruce (Lorenc et al. 2017). A combination of aforementioned factors and other miscellaneous factors, in conjunction with possible extreme meteorological events (related to ongoing climate change) remains a serious threat for as-yet unstable forest ecosystems in the Ore Mountains. Our results and the recently introduced Program of complex restoration of forest ecosystems in the Ore Mountains approved by the Czech government, which will last till 2030 (Czech Ministry of Environmental protection https://www.mzp.cz/cz/revitalizace_krusnych_hor) proves that forests in the area are still vulnerable. Significant protective arrangements demanding extensive investments (4.1 billion CZK) must continue in the Ore Mountains Regarding this situation, complex monitoring is very important and remote sensing is a valuable tool for the job.
5.2. Discussion of data sources and methods used, and their validity

The Landsat time series are frequently used to evaluate forest disturbances (e.g. Banskota et al 2014, Griffiths et al 2014, Potapov et al 2015, Gómez et al 2016). In the Ore Mountains, Landsat images were used by Lambert et al (1995) for spectral description of six Norway spruce damage classes and evaluation of models for forest damage prediction; Mišurec et al (2016) studied general trends of forest recovery using DI. In both cases, study areas were smaller, with relatively homogeneous cover of even-aged Norway spruce stands. Thus, the relation between spectral properties of Norway spruce stands and a specific disturbance was investigated.

The time series processed comprised 19 images. The time distribution was not regular (see figure 4), due to the requirement of no cloud cover over the entire study area. Imagery acquired at the very beginning (May 1986) and end (October 1985) of the vegetation season are also present in the dataset in order to cover oldest events possible. The influence of seasonality could not be fully eliminated but is partially suppressed by normalization of image bands of derived products when IFZ and DI are calculated. Referring to figure 6, underestimation of total forest area due to early or late vegetation season is possible in the years 1986, 1999 and 2000 when compared to surrounding forest area values. The low density of time series made it impossible to apply algorithms allowing for modeling of both the trend and seasonal variations as Breaks for Additive Seasonal and Trend (Verbesselt et al 2010).

The forest definition is a crucial point for the interpretation and validation steps. On both a national and international level, forest land cover class definition may use parameters such as tree density, minimum tree height and minimal area covered by trees, such as FAO definition (FAO 1998). Studies using remote sensing data usually define the forest classes in connection of in situ data, e.g. Lambert et al 1995, or existing maps and databases, e.g. Huang et al 2010, or a combination of the two. Supervised classification is then used for discrimination of forest classes (e.g. Griffiths et al 2014). Our aim was to study the forest as one class, comprising all its sub-classes. The results of unsupervised classification were first used to evaluate spectral differences between clusters comprising forest pixels. Mature Norway spruce stands occupying the West part of the study area could be easily discriminated in this way because their spectral properties enabled their assignment into one cluster across all time periods (see also Huang et al 2010). We found that, in order to extend the forest masks to other forest types, it was possible to aggregate clusters from unsupervised classification, or to increase the threshold of IFZ. After comparison with orthoimages, the latter and computationally easier option was chosen. Thus, the forest definition in our study is based purely on spectral properties and ex-post comparison with orthoimages.

A wide range of change detection techniques to evaluate time change of forest or other land cover classes can be applied. Comprehensive reviews of the methods published Lu et al (2004), Banskota et al (2014), Gómez et al (2016) and others. According to Banskota et al (2014), approaches for change detection can be categorized into two main types: image classification and trajectory-based analysis. We used the first approach to determine the forest area in each year. This approach is advantageous because it minimizes the problem of radiometric calibration between dates and is still frequently used (Banskota et al 2014). The methods employed for deriving maps of forest change and TD\textsubscript{DI} follow the trajectory-based approach as the time series of derived parameters (IFZ, DI) for each pixel were analyzed. Our results documenting the forest recovery in the East part of the area and stable or worsening state of forests in the West part during the period from 1985 to 2016 are in agreement with the results published by Mišurec et al (2016), although we analyzed a more extensive area with significant variations in forest age and composition.

As for the results of accuracy assessment of the forest mask, accuracy between 87% and 92% for all years is quite good and comparable with other studies (for example Griffiths et al 2014, Feng et al 2015, Song et al 2016). Nevertheless, the uncertainty of the method should still be considered in drawing conclusions.

5.3. Discussion on forest health assessment

In the present case study, we used the trend in DI derived from Landsat data as a measure of forest health status. We are aware that TD\textsubscript{DI} calculated from spectral properties of a particular cover classified as forest corresponds to a broad range of processes. There are a high number of factors combined in the study area (different species, forest age, types of disturbance). Continuous changes of DI correspond to events like tree growth, canopy closure and tree aging, while abrupt changes indicate changes like harvesting. We used co-localization of the forest change map (figure 7) and the map of TD\textsubscript{DI} (figure 9) for the period 1985–2016 (projected in figures 10 and S1 and S2 in supplement) to distinguish between forest damage and deforestation, and by contrast, forest condition improvement, stable growth, closing the canopy and afforestation. Deforestation was characterized by co-localization of positive TD\textsubscript{DI} values in figure 9 (red color) with deforested areas in figure 7 (yellow class). Positive TD\textsubscript{DI} values in figure 9 (red color) co-localized with stable forest class were interpreted as decreases in forest health condition. Negative TD\textsubscript{DI} values in figure 9 (blue color) co-localized with stable forest class in figure 7 were interpreted as improvements of forest condition.
The analysis showed that the positive and negative extremes in T_{DI} likely correspond to afforestation and deforestation respectively. However, T_{DI} proved to be especially useful in distinguishing more subtle disturbances and recoveries in the stable forest class (figure 10). Trumbore et al. (2015) indicated that Landsat data are suitable for detection of the background forest disturbance level; however, they are not sufficient to document smaller-scale changes due to the insufficient spatial resolution. This is true for remote areas in many countries which lack ground truth inventories, or data from sensors other than Landsat (e.g. Schneibel et al. 2017). As in the present study, DI and pixel-based linear trends of DI over long-term Landsat data series were used for description of dry forest degradation in South-Central Angola (Schneibel et al. 2017). However, the main trends of forest health status in the West and East parts of the Ore Mountains described by T_{DI} corresponded to plot-based research (e.g. Norway spruce crown defoliation, needle chlorophyll content; Lhotáková and Albrechtová 2017) and a hyperspectral airborne study (Mišurec et al. 2016) conducted on Norway spruce. Some negative changes in forest health which were visually detectable at the plot and tree level were not revealed by DI. In 1999, 2000 and 2001, a massive Norway spruce needle yellowing (2,000 ha, 6,500 ha and 9,000 ha respectively) caused by nutrient deficiency was observed in the West part of the Ore Mountains (Lomský and Šrámek 2004), which is not apparent in any significant shift in the distribution between DI classes (figure 8(a)). Although Trumbore et al. (2015) called for linking of the remote sensing data with plot-based information and the combination of various approaches to forest health assessment at several hierarchical levels, this was not completely possible in the present study.

Even though former Czechoslovakia joined the ICP forest monitoring program in 1986, the density of monitoring forest plots was not high enough in the study area, and lacked systematic coverage. Pollution measuring stations (figure 1) were similarly sparse and several years of the study period are missing values (table 1). Moreover, this fact impedes the application of various modelling techniques, e.g. multiple logistic regressions as used, for example, by Schulz et al. (2011). In the area of the former ‘Black Triangle’ it is hard to apply the distance from the pollution source as an explanatory variable because there have been numerous pollution sources and significant contributions of long-range transport of air pollution in Europe. Moreover, the problem of strong horizontal concentration gradients and a strong dependence on wind direction at observed peak concentrations at specific sites comes into play, as discussed by Beyrich et al. (1998).

6. Conclusions

The present case study shows that Landsat time series can be successfully used not only for forest cover changes, but also for forest disturbance and health status evaluation on a regional scale. The Landsat series begins in 1985—after the culmination of air pollution load, the peak of the emergency logging and the major decline of forested area in the early 1980s. The combination of forest area estimation with evaluation of trends in DI provided valuable information on forest cover and forest status (health or disturbance) in the historically polluted area of the Ore Mountains during the last 30 years. Our study further documents that available Landsat series are a useful data source in monitoring the impact of these drivers on forest status on a regional scale, and provide valuable information for forest management and preservation.

Heavy acidic pollution and extreme meteorological events were responsible for large-scale forest decline and dieback in the region. This was exacerbated by the fact that the majority of the forests were monocultures composed of Norway spruce, which is particularly sensitive to air pollution. According to our results, the forest cover reached its minimum in the middle of the 1990s. Significant political and societal changes after the fall of communism in 1989 began the process of recovery, particularly in the eastern, heavily polluted and damaged part of the mountains. The severely damaged eastern part, with heavier acidic load and large forest decline and dieback, recovered faster after air pollution loads diminished compared to the western part, with less damaged forests. Among the most effective factors in the forest recovery were air pollution control legislation, high investment in desulphurization and forest reconstruction, and legislative and forestry management measures, which led to more sustainable tree species composition in the region.

This study shows the transition towards more sustainable forest stands in the region since the 1990s. However, persistent fluctuation in forest cover during the last decade is still apparent. Interactions of persisting specific negative driving forces (soil acidification, adverse meteorological events, climate change factors, air pollution, tree composition and physiological state, pest outbreaks) are still threatening the forests, which remain moderately damaged in both parts of the Ore Mountains. This may lead to unpredictable forest development, regardless of societal and political efforts to stabilize forest stands in the area. Our observation of fluctuations in forest area in the period from 2005 to the present support the need for new high investments to help continue forest recovery in the Ore Mountains (like the abovementioned Program on Forest Recovery in the Ore Mountains by the Ministry of Agriculture of Czechia 2018–2020). Meteorological fluctuations, extreme events due to climate change, and anthropogenic activities cause instability not only for the Ore Mountains but also for other forests in Europe and worldwide. Remote sensing can be an effective tool in providing large-area, time-dense, real-time forest monitoring.
Acknowledgments

This publication was supported by the Ministry of Education, Youth and Sports of the Czech Republic: Project [NPÚ 1LO1417]. We would like to thank our colleagues, namely Pavel Bednář from the Forestry and Game Management Research Institute, Opočno, Czechia and to Lena Hunt, a new American PhD student in our lab, for language proof-reading. We are grateful for very inspiring and helpful comments to three anonymous reviewers from ERL and Garik Gutfman from NASA Headquarters.

ORCID iDs

J Albrechtová https://orcid.org/0000-0001-6912-1992

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