Introduction

In last century, forest decline became a serious ecological problem mainly due to acid rains caused from industry. In the early 1980s, this resulted in a collapse of the most seriously acid-rain exposed forest stands, which were situated in Central Europe in the so-called “Black Triangle” (Poland, former East Germany) and caused mainly by air pollution from coal power stations and chemical plants (Aksellson, Ardo, & Sverdrup, 2004; Blazkova, 1996; Cada et al., 2016; Hruška and Cienciala, 2003). Recently, due to high weather fluctuation, characterized by still more frequent long spells of heatwaves without precipitation and short intensive rain events during which most of the precipitated water runs out, bring about problems with impact of drought on many forest species. Therefore, a need arises to find appropriate indicator of recent forest decline, which can be practically used by forest managers and easily estimated from new informative technologies. Forest decline is interpreted here as a complex disorder involving abiotic and biotic stresses on a forest stand that results in a slow, progressive decrease in growth with loss of health and vigor (Kaennel & Schweingruber, 1995; NAL Glossary 2014).

There are numerous symptoms of deteriorated forest state that can be detected by in situ assessment. Both National Forest Inventory (NFI; Tomppo et al., 2010) and forest health monitoring programs such as ICP Forests in Europe (Michel & Seidling, 2015) may include various forest decline indicators related to crown conditions, tree damage, tree mortality, and stand structure. Whereas some symptoms are easy to detect and follow in situ, the others might be difficult to monitor, especially if the problem is sporadic or at local scale (Gauthier et al., 2015). Remote sensing (RS) offers a unique opportunity for large-scale forest monitoring, which can be superior to conventional plot sampling methods, both in terms of accuracy and speed. Numerous studies dealing with the assessment of selected forest decline indicators based on airborne and satellite data have been published (Lausch, Erasmi, King, Magdon, & Heurich, 2016), where forest decline indicators were measured, explained or predicted (Table 1). Most of them utilize vegetation indices (VIs) extracted from RS to assess forest state (Glenn et al., 2008; Henry et al., 2015; Tuominen, Lipping, Kuosmanen, & Haapanen, 2009). Generally, to establish the relationship between VIs extracted from RS data and the observed forest conditions, researchers use the following forest decline indicators: tree crown condition (discoloration, defoliation), presence of dead trees, and chlorophyll concentration or metal concentration in the leaves. While the indicators of tree crown status were typically used for in situ assessment of tree health conditions (Rullan-Silva, Olthoff, de la Mata, & Pajares-Alonso, 2013), the use of combined indicators is

ABSTRACT

The study is aimed to explore the potential of time-series airborne hyperspectral and satellite multispectral data to track the changes in spruce forest decline expressed by a composite spruce decline indicator. Vegetation indices and exergy of solar radiation extracted from remote sensing data are used to predict the development of the composite spruce health indicator. The canopy-level spectral reflectance properties of spruce stands are investigated to identify categories of spruce stand decline: healthy, initial decline, and initial to moderate decline. The sensitivity peaks for initial decline and initial to moderate decline of spruce are shown. The highest potential for the estimation of the composite spruce health indicator is demonstrated by vegetation indices WBI and NDVI_red_edge from airborne hyperspectral data, and by PSRI, NDII and exergy of solar radiation from Landsat and Sentinel-2 satellite multispectral data. MODIS data show only a poor correlation between the composite spruce stand health indicator and NDII index. The proposed methodology to obtain the distribution of the composite spruce decline indicator using remote sensing (RS) data promisingly suggests its applicability over a large forest area with potential time and economic benefits, since foliar spectral measurements, canopy chemistry, and laboratory analysis are not required.
Table 1. Selected studies on the assessment of forest decline indicators from remote sensing data.

| Field indicator of forest decline | Tree species and location | RS instrument/spatial resolution, m | Detection method | Reference       |
|-----------------------------------|---------------------------|------------------------------------|------------------|-----------------|
| Biochemical parameters            |                          |                                    |                  |                 |
| (chlorophyll concentration)        |                          |                                    |                  |                 |
| Norway spruce, Czech Republic     | HyMAP                     | R718/R704 for Cab, SIPI            | Determination coefficient between measured and estimated (optical indices) values | Misurec et al., 2012 |
| Norway spruce, Czech Republic     | Airborne HS CASI data     |                                    |                  |                 |
| Canada                             | 450–900 nm                |                                    |                  |                 |
| Norway spruce, Bavarian Forest    | Airborne Zeiss RMK camera | Dmax/D704, D714/D704, Dmax/D714 and Dmax/D744 |                  |                 |
| Finland                            | 0.2 m                     |                                    |                  |                 |
| Scots pine, Norway                 | Airborne laser scanner    | Quantile regression analysis for indicating the difference between parameters crown dieback, age, slope, mean annual temperature range, NDMI | Solberg          |
| Pine, Finland                      | Airborne laser scanner    |                                    |                  |                 |
| Norway spruce, Czech Republic     | Landsat TM                |                                    |                  |                 |
| Red oak, Arkansas                  | Landsat TM                |                                    |                  |                 |
| Spruce and birch, Finland          | Airborne AISA dual HS scanner, 2.5 m | Dmax is defined as the maximum value of the first derivative in the 675–740 nm region |                |
| Metal concentration in leaves      |                           |                                    |                  |                 |
| Norway spruce, Czech Republic     | Landsat TM                |                                    |                  |                 |
| Pine, spruce and birch, Finland    | Airborne HS scanner       |                                    |                  |                 |
|                                 | HyMap                     |                                    |                  |                 |
|                                 | 420–2480 nm, 5 m          |                                    |                  |                 |

promising for forest decline assessment from RS data. For example, Entcheva-Campbell et al. (2004) found a strong linear correlation between a combination of three forest decline indicators (DSI, Damage Severity Index) and VIs from satellite Landsat and airborne ASAS (62 spectral bands, 450–900 nm spectral range) data. However, composite forest decline indicators have been little investigated within RS data. Also, there are still research gaps in the potential of VIs for detection of changes in forest decline based on time series RS data since most studies focus on a single time-point observation.

A composite indicator of forest decline may include information about both direct and indirect damage that is visible in the forest, about growth and biomass, and potentially can be estimated with complex characterization of the forest ecosystem status from RS data. Currently, little effort has been done to explore the complex forest ecosystem status by thermodynamic approach estimating the exergy of solar radiation, where forest ecosystem has been suggested as an open thermodynamic system. Exergy is the distance between the present state of the ecosystem and its state in the thermodynamic equilibrium with the environment, measured in the units of energy (Jorgensen & Svirezhev, 2004). A number of studies have been published to estimate and interpret exergy of forest ecosystem from satellite data. It was demonstrated that the changes in exergy were significantly correlated with changes in forest health (Gornyy, Kritsuk, & Latypov, 2010; Lu et al., 2010; Silow & Mokry, 2010). The spectral structure of the reflected solar radiation and incoming solar radiation for each elementary unit of the Earth surface (pixel) makes it possible to estimate the exergy of a forest ecosystem at the moment of the measurement. A series of measurements allow determining the time and space variations with the control parameters, such as forest characteristics. In our study, we contribute to understanding of exergy of forest ecosystem to explore the relationship between exergy of spruce ecosystem from RS data and indicators of spruce decline from field.

This study was initiated to explore the potential of time-series of airborne and satellite data to track the changes in forest decline and to select spectral properties for the composite spruce decline indicator resulting from the repeated observations made in Těšínské Beskydy Mts. Decreased stability of spruce-dominated forests in this region became an issue already during the last century when the area became severely exposed to acidifying air pollution. In the 1990s, there was a significant industrial modernization and the elimination of large emission sources, which positively reflected on the state of the forest. However, the region still belongs to the most polluted in the Czech Republic: legacy of the past is still reflected in disturbed soil chemistry, which is a factor contributing to forest decline. The changing climatic conditions with increased temperature and high precipitation variability in the last decade represents another factor contributing to forest decline. The changing climatic conditions with increased temperature and high precipitation variability in the last decade represents another factor contributing to forest decline in the area (Cienciala et al., 2017; Kmet et al., 2011; Pokorný & Stojnic, 2012). Monitoring of the local spruce forest decline is extremely important and can help to avoid forest productivity reduction (Hlášny & Šitková, 2010) and unfavorable changes in the terrestrial biogeochemical cycle. Specifically, study objectives were: (1) to
determine the indicators of spruce decline from field which will form a composite indicator based on canopy-level spectral reflectance properties of spruce stands; (2) to explore spectral reflectance properties of spruce stands for categories of the composite spruce decline indicator; and (3) to investigate the potential of VIs and exergy of solar radiation extracted from time-series hyperspectral airborne and multispectral satellite data to predict the development of the composite spruce decline indicator.

Methods

Study area

Study area is located in Těšínské Beskydy region of the Czech Republic (TB; 18° 47’ E, 49° 37’ N, altitude ranging from 500 to 900 m a.s.l.) (Figure 1). The forest stands are composed mainly of managed Norway spruce (Picea abies, L.) and European beech (Fagus sylvatica, L.) as the dominant tree species and a scattered admixture of Scots pine (Pinus sylvestris, L.), silver fir (Abies alba, L.), European larch (Larix decidua, L.) and ash (Fraxinus excelsior, L.) (Michalko, 1986). Norway spruce (Picea abies, L.) is grown at the elevations that would not naturally support its dominance among local tree species. It makes the current forest stands specifically vulnerable to various stressors (Spiecker et al., 2004). Soils in the region are still strongly influenced by acidification and nutrient degradation. It is supported by the presence of heavy metals, persistent acidity and very low nutrient content and a high concentration of aluminum (Fiala et al., 2013). The overall conditions of the soil environment in the study area and the extreme droughts in the summers of 2003 and 2007 are implicated in worsening health condition of the forests. (Grodzki, 2010; Zahradniček et al., 2015).

The study workflow (Figure 2) includes five basic steps: analysis of spruce decline indicators from field survey, analysis of spectral reflectance of RS data, determination of composite spruce decline indicator, analysis of composite indicator categories and analysis of changes in composite indicator based on RS data.

Data

Field data

Field data were collected in the middle of vegetation season of 2010, 2013 and 2015 at the Forest Management Unit (FMU) Jablunkov, Forests of the Czech Republic, S.E. The forest inventory targeted young to medium-aged stands up to 60 years of age a 2008 (Figure 3). The inventory consisted of sampling pairs of spruce plots, each circular with an area of 500 m². The pairs of plots were randomly scattered across the forest area of FMU Jablunkov with a distance of about 1 km. Quantification of the observed indicators for each spruce plot was done in a form of a relative share. It was expressed as a number of spruce individuals with the specific indicator relative to all spruce trees in the plot. The following commonly used spruce stand decline indicators were analyzed: dead trees, crown break, resin exudation, discoloration, dry tree tops, reduced increments of tree top shoots, decreased vitality by IUFRO (International Union of Forest Research Organizations) classification (Nieuwenhuis, 2000) (Table 2). Sample plots used for the study were spruce plots or those dominated by spruce with spruce share ≥80%. The number of sample plots used for this study was 62 in 2010, 78 in 2013, and 27 in 2015.

Airborne and satellite data

Airborne hyperspectral data were acquired in 2010, 2013 and 2015 (Table 3). The image preprocessing included radiometric, atmospheric and geometric corrections. The radiometric correction was performed using CaliGeo 4.6.4 (Specim) software and ENVI 4.4. The atmospheric correction was done in ATCOR4 6.0 (ReSe Applications Schlaepfer) and the georectification was done in
PARGE 3.2. Airborne data consisted of three flightlines per year and were processed in ENVI 4.4 using mosaic procedure. The number of sample plots covered by airborne data was 15 in 2010, 16 in 2013 and 20 in 2015.

Radiometrically corrected satellite Landsat-5TM and Landsat-8OLI,TIRS data were downloaded from the US Geological Survey (USGS) data portal [http://earthexplorer.usgs.gov/](http://earthexplorer.usgs.gov/) (Table 3). Atmospheric correction of Landsat satellite images was done in FLAASH module.

Table 2. Indicator values observed in the study area in 2010, 2013 and 2015, n – number of monitoring plots (dash line describes an absence of an indicator).

| Indicator                  | Description                                                                 | Range within study area, % |
|----------------------------|-----------------------------------------------------------------------------|----------------------------|
| Dead trees                 | Fraction of dead trees                                                      | 0.41 6 0.50 7 0.35 11     |
| Break trees                | Trees with mechanical or wind break                                         | 0.43 8 0.44 9 0.35 8      |
| Resin exudation            | Trees with honey fungus resin exudation                                     | 0.18 5 0.44 8 0.21 6      |
| Discoloration              | Decreasing chlorophyll concentration causing color changes in foliage        | 0.33 10 0.33 7 0.23 5     |
| Dry tree top               | Fraction of trees with dry tree tops                                        | 0.40 10 0.33 10 0.18 9    |
| Reduced increment          | Reduced increment of top shoots                                             | - - 0.66 20 0.45 13      |
| IUFRO vitality            | Categorization based on visual classification of 10 trees per plot, distinguishing vital individual trees | 0.50 20 0.33 10 0.67 9    |
of ENVI 4.4 software. Orthorectified top of atmosphere satellite Sentinel-2 data were downloaded from the ESA data portal https://scihub.copernicus.eu/. Atmospheric correction was performed in SNAP software. Finally, time series of satellite MODIS data (MCD43A4 product, ver. 6) were downloaded for the entire vegetation period of 2015 from the USGS data pool https://lpdaac.usgs.gov/data_access/data_pool. Satellite data covered all sample plots used in the study.

**Determination of the composite indicator of spruce stand decline**

To determine components of the spruce stand decline composite indicator, the analysis of spectral reflectance of spruce plots from airborne hyperspectral data was conducted. Each spruce plot was simultaneously influenced by an array of indicators that varied from plot to plot. These indicators could not be “decoupled” or normalized across the sample to allow quantifying an expression of one single indicator. We identified the indicators that most affected spectral reflectance based on unsupervised classification of spruce plots. First, the inverse mask of spruce sample plots was created for hyperspectral images (2010, 2013 and 2015) to confine hyperspectral image processing to spruce sample plots and to ignore other areas in the image. Second, using the inverse mask spruce sample plots were classified by means of unsupervised classification into 4 classes (K-Means clustering algorithm, Forgy, 1965). Various distribution of classes were found in spruce sample plots after classification. Most of plots \( (n = 39) \) were occupied by one dominant class (more than 65% of plot pixels were covered by one class, Figure 4(b–e)). Other plots \( (n = 11) \) were occupied by several classes without dominant class (Figure 4(f)).

The analysis of the distribution of spruce indicators from the field through the classes (Table 4) showed that plots occupied by dominant class 1 (Figure 4(b)) were characterized by high values of the dead tree indicator and low to medium values of dry tree top, IUFRO vitality and discoloration. Plots occupied by dominant class 2 (Figure 4(c)) were characterized by medium values of the dead tree indicator and medium-to-high values of dry tree top, IUFRO vitality and discoloration. Plots occupied by dominant class 3 (Figure 4(d)) tended to low values of the five indicators (except break trees). Plots with dominant class 4 (Figure 4(e)) contained various ranges of each indicator. Crown break and resin exudation had approximately equal values across classified plots, which potentially could not influence spectral reflectance changes. Based on distribution of field spruce indicators through the classes, four indicators were composed to a complex indicator of spruce decline – CI4: dead tree, discoloration, dry tree top and IUFRO vitality. To consider the health state evaluation for living and dead trees, CI4 was calculated as:

| Acquisition date | Sensor | Spectral range, \( \mu m \) | Number of used spectral bands | Spatial resolution, m |
|------------------|--------|-----------------------------|-------------------------------|----------------------|
| 10.8.2010        | HyMap  | 0.45-2.49                   | 125                           | 5                    |
| 8.9.2013         | AISA   | 0.40-1                      | 65                            | 5                    |
| 5.6.2015         | CASI   | 0.37-1                      | 72                            | 1                    |
| 12.6, 14.7, 22.8, 23.9.2010 | Landsat-5TM | 0.45-2.35 | 6 | 30 |
| 19.5, 20.6, 29.7, 7.8, 8.9.2013 | Landsat-8OLI,TIRS | 0.45-2.29 | 6 | 30 |
| 16.5, 12.7.2015  | Landsat-8OLI,TIRS | 0.45-2.29 | 6 | 30 |
| 7.8.2015         | Sentinel-2 | 0.49-2.19 | 9 | 20 |
| 7–10.2015        | MODIS  | 0.45-2.16                   | 7                             | 250                  |

![Figure 4](image-url)  
**Figure 4.** Example of spruce plot on airborne image (single band 550 nm) (a) and examples of spruce plots after unsupervised classification of airborne image (b–f). The (b–f) show the distribution of classes in the plot: green color is class 1, blue is class 2, yellow is class 3, orange is class 4.
In addition to CI₄, we calculated the indicator CI₆ as a combination of all 6 field indicators (dead trees, break trees, resin exudation, IUFRO vitality, discoloration, and dry tree top) (Equation 2). CI₆ was calculated to test a difference between using CI₄ with 4 selected components and using CI₆ with 6 field indicators in RS methods.

Based on ranges of CI₄ values for classes 1, 2 and 3 (Table 4), spruce stand decline level was divided into three categories: healthy I (class 3), initial decline II (class 2 and 4), initial to moderate decline III (class 1). Basically, CI₄ values represent share of trees at a plot level with discoloration, dry tree top, IUFRO vitality and dead tree indicators. These indicators were aggregated according to Equation 1. CI₄ ranges from 0 to 100, where 100 represented a fully declined plot. In our study, CI₄ ranged from 0 to 47. This range did not span to moderate, heavy and full decline categories in our study area at the time of the observations. If CI₄ for plot is <5, the spruce stand was categorized as “healthy”. If CI₄ for plot is >5 and <20, the plot had decline category “initial decline”. If CI₄ for plot was >20, the plot had decline category “initial to moderate decline”. Category boundaries were determined based on distribution of individual decline indicators through the classes of unsupervised classification.

**Vegetation indices**

We selected common VIs from the current relative literature sensitive to the three main categories (structure, biochemistry, plant physiology/stress) both for airborne hyperspectral and satellite multispectral data (Table 5). Mean value of VIs for the plot in each set of RS data was used. The potential of VIs to predict the development of the composite spruce stand decline indicator was investigated.

**Exergy of solar radiation**

Exergy of solar radiation was proven to be a vital parameter describing the status of forest ecosystem while allowing the estimation of severity of anthropogenic damage (Lu, Wang, Campbell, Ren, & Wang, 2010; Puzachenko, Sandlersky, & Sankovski, 2013). Exergy of solar radiation \( E_x \) was calculated using time-series satellite Landsat data (Table 3) based on the thermodynamic theory of ecosystem through Kullback entropy \( K \) and absorbed solar energy \( B \) [3–5] (Jorgensen & Svirezhev, 2004):

\[
E_x = E^{\text{out}} \left( K + \ln \frac{E^{\text{out}}}{E^{\text{in}}} \right) + B \tag{3}
\]

\[
K = \sum_{i=1}^{n} p_{\text{out}}^{\text{in}} \ln \frac{p_{\text{out}}^{\text{in}}}{P_{\text{out}}^{\text{in}}} \tag{4}
\]

\[
B = E^{\text{in}} - E^{\text{out}}, \tag{5}
\]
Table 5. Vegetation indices and data for their calculation (HS: airborne hyperspectral; MS: satellite multispectral data) used in the study.

| VI               | Equation                                                                 | Data used | Reference                  |
|------------------|--------------------------------------------------------------------------|-----------|----------------------------|
| **Structure**    |                                                                          |           |                            |
| NDVI_red_edge    | \( \rho_d(\text{peak}_1) / (\rho_d(\text{peak}_2) + \rho_d(\text{peak}_3)) \) | HS        | Gitelson and Merzlyak (1994) |
| NDVI             | \( \rho_d(\text{peak}_1) / (\rho_d(\text{peak}_2) + \rho_d(\text{peak}_3)) \) | MS        | Rouse, Haas, Scheel, and Deering (1974) |
| SR               | \( \rho_d(\text{peak}_1) / \rho_d(\text{peak}_2) \)                     | MS        | Birth & McVey, 1968          |
| GNDVI            | \( \rho_d(\text{peak}_3) / (\rho_d(\text{peak}_1) + \rho_d(\text{peak}_2)) \) | MS        | Gitelson and Merzlyak (1998) |
| GRVI             | \( \rho_d(\text{peak}_2) / \rho_d(\text{peak}_3) \)                     | MS        | Sripada et al. (2006)       |
| **Biochemistry** |                                                                          |           |                            |
| PSRI             | \( \rho_{2130}(\text{peak}_1) / \rho_{515}(\text{peak}_1) \)             | MS        | Merzlyak, Gitelson, Chivkunova, and Rakitin (1999) |
| WBI              | \( \rho_{700}(\text{peak}_1) / \rho_{850}(\text{peak}_1) \)             | HS        | Penuelas, Baret, et al. (1995) |
| SII              | \( \rho_{850}(\text{peak}_1) / \rho_{800}(\text{peak}_1) \)             | HS        | Penuelas, Fiél, et al. (1995) |
| MSI              | \( \rho_{550}(\text{peak}_1) / \rho_{450}(\text{peak}_1) \)             | MS        | Hunt and Rock (1989)         |
| CARI             | \( \rho_{515}(\text{peak}_1) \times (1/\rho_{350}(\text{peak}_1)) \)     | HS        | Kim (1994)                  |
| ARI_NIR          | \( \rho_{380} \times (1/\rho_{550} - 1/\rho_{700}) \)                    | MS        | Gitelson, Merzlyak, and Chivkunova (2001) |
| NDMI             | \( \rho_{550} - (\rho_{510}(\text{peak}_1) + \rho_{450}(\text{peak}_1)) \) | MS        | Wang et al. (2007)          |
| NDWI             | \( (\rho_{560}(\text{peak}_2) \times \rho_{550}(\text{peak}_1)) / \rho_{510}(\text{peak}_1) \) | HS        | Gao (1996)                  |
| **Plant physiology/stress** |                                                                          |           |                            |
| PRI              | \( \rho_{510}(\text{peak}_1) / \rho_{531}(\text{peak}_1) \)             | HS        | Gamon, Serrano, and Surfas (1997) |
| NDII             | \( \rho_{510}(\text{peak}_1) / \rho_{531}(\text{peak}_1) \)             | MS        | Hardisky, Klemas, and Smart (1983) |
| CRI_550          | \( (1/\rho_{510} - 1/\rho_{531}) \)                                    | HS        | Gitelson, Gritz, and Merzlyak (2003, 2006) |
| CRI_700          | \( (1/\rho_{510} - 1/\rho_{531}) \)                                    | HS        |                            |

where \( E_{\text{int}} = \sum_{i=1}^{n} e_{\text{int}}^i \), incoming solar energy total; 
\( E_{\text{out}} = \sum_{i=1}^{n} e_{\text{out}}^i \), reflected solar energy total; 
n- number of spectral bands; \( e_{\text{int}}^i \), incoming energy in the range \( v_i \); 
\( e_{\text{out}}^i \), reflected energy in the spectral range \( v_i \); 
\( p_{\text{int}}^i = e_{\text{int}}^i / \sum_{i=1}^{n} e_{\text{int}}^i \), fraction of incoming energy in the spectral range \( v_i \); 
\( p_{\text{out}}^i = e_{\text{out}}^i / \sum_{i=1}^{n} e_{\text{out}}^i \), fraction of reflected energy in the spectral range \( v_i \). Spectral reflectance and surface temperature bands of satellite Landsat data were inputs in [3–5]. Exergy of solar radiation was calculated for the study area for vegetation period from May to September of 2010, 2013 and 2015.

**Statistical analysis**

The relationships between VIs from RS data and spruce stand decline indicators from the field survey were evaluated using a simple correlation analysis (Zar, 1996). Regression analysis was applied to explore the relationship between independent spruce decline indicators and composite indicator CI4 (dependent variable), and VIs (independent variable) for the corresponding spruce plots in the individual monitoring years. The general linear model (GLM) was used to assess the strength of these relationships across the entire time period including year as a categorical variable with the above relationships (Equation 6). The intersection of plots was used across the entire time period for GLM (17 plots from satellite data for each year and 13 plots from airborne data for each year).

\[
Y = \beta_0 + \beta_1 X_1 + \beta_2 X_2, \tag{6}
\]

where \( Y \) is modeled composite indicator CI4, \( \beta_0 \) is a constant, \( \beta_1 \) and \( \beta_2 \) are coefficients, and \( X_1 \) and \( X_2 \) are variables. In our case, \( X_1 \) is a vegetation index (WBI, NDVI_v, PSRI, Exergy, NDII or PRI), \( X_2 \) is year and \( i \) is index of the categorical variable “YEAR”.

To test the sensitivity of VIs to decline categories of CI4 ANOVA was applied. VIs showing a good correlation with the composite indicator CI4 were tested for the sensitivity to decline categories (healthy I, initial decline II, and initial to moderate decline III) by means of ANOVA analysis.

**Results**

**Analysis of sensitivity of spectral regions to categories of CI4**

Spectral analysis of airborne hyperspectral data based on decline categories from composite index CI4 showed that increasing canopy reflectance in both visible and red-edge region was linked with the decline of spruce stands (data from HyMap) (Figure 5(a,b)). The opposite trend was observed in near-infrared region, where the healthy forest stands had the highest NIR reflectance for all hyperspectral data. The sensitivity peaks for initial decline were located in 400–530 nm range (all hyperspectral data), and 1415–1430 nm, 1970–2400 nm ranges (HyMap data). Initial to moderate decline, on the other hand, showed highest sensitivity for 640–710 nm, 740–850 nm (all hyperspectral data), 1415–1450 nm and 1800–2430 nm ranges (HyMap data).

**Analysis of VIs**

The highest potential for detection of spruce stand decline indicators (dry tree top frequency and CI4) was demonstrated by PRI (photochemical reflectance index), WBI (water band index), and NDVI_red_edge (narrowband normalized difference vegetation index) from airborne
hyperspectral data, by PSRI (plant senescence reflectance index), and NDII (normalized difference infrared index) from Sentinel-2 satellite data, and exergy of solar radiation from Landsat satellite multispectral data (Tables 6 and 7). Dry tree top and CI4 are considered as independent variables. The correlation between indicators from the field and VIs with the highest potential from time-series RS was shown together with the corresponding coefficient of determination ($R^2$) from GLM for forest plots with repeated field measurements in 2010, 2013 and 2015 (17 plots from satellite data for each year and 13 plots from airborne data for each year) (Figure 6). Coefficients for GLM is presented in Table 8. From MODIS data, only a poor correlation between composite index CI4 and NDII index was found ($R^2 = 0.21$). There was a lack of correlation between the other examined VIs from airborne and satellite data, and spruce stand decline indicators.

ANOVA null hypothesis (the means of three decline categories are equal, $\alpha = 0.05$) was rejected for NDVI$_{red\_edge}$ index from airborne hyperspectral data, which was found sensitive to decline categories of spruce. T-test showed that the observed difference between decline category I and category II was not statistically significant; while the differences between category I and
category III, as well as category II and category III were statistically significant ($p$-value ≤0.05). The difference between means of I, II and III decline categories from satellite PSRI, NDII and exergy were not significant.

**Discussion**

*Analysis of airborne hyperspectral data*

The region between 520 and 550 nm is associated with a decrease in reflectance which is characteristic of stressed plants (Thenkabail, Lyon, & Huete, 2011). In our study, spruce canopies of category III (initial to moderate decline) had an increasing reflectance in this spectral region, and the category III reflectance was higher than the reflectance of categories I (healthy) and II (initial decline). This may be explained by the sensitivity of the components of composite index CI4 (dead tree, discoloration, dry tree top and IUFRO vitality) to changes in the green spectral region. However, the spectral characteristics of CI4 are in agreement with spectral trends of damaged trees observed in 600–720 nm range as reported in earlier studies (Ekstrand, 1996; Entcheva, 2000). Category III has a higher spruce canopy reflectance intensity compared to categories I and II in the red and red-edge spectral regions (from CASI and AISA data).

The forest canopy reflectance around 1500 and 2400 nm is associated with water absorption in leaves. Healthy canopy has a deeper water absorption feature (higher water content) in this region (Roberts et al., 2004) than decline trees. Our results confirm this by showing that spruce canopies of category III have a higher canopy reflectance than spruce of categories I and II in the short infrared spectral region 1140–2485 nm (from HyMap data). Ustin (2008) found the highest reflectance of decaying pine canopies at 2400 nm in Georgia forest site using airborne HS data (350–2456 nm, 2 m). Huber, Kneubühler, Psomas, Itten, and Zimmermann (2008) reported absorption features at 2223–2388 nm related to estimation of nitrogen, lignin and cellulose in spruce and pine canopy using airborne HS data (350–2400 nm, 5 m).

The sensitivity peaks for decline category II were located in 400–510 nm, 610–710 nm ranges (CASI and AISA data), and 1415–1430 nm, 1970–2400 nm ranges (HyMap data), while for decline category III, the peaks were in the 410–510 nm, 740–850 nm (CASI and AISA data), and 1415–1450 nm, 1800–2020 nm, 2300–2485 nm ranges (HyMap data). Entcheva-Campbell et al. (2004) reported the sensitivity peaks for initial decline spruce trees in the 695–720 nm range, for moderate damage the peaks were in the broader 580–705 nm range in spruce canopies of the Czech Republic using airborne hyperspectral data (450–900 nm, 2 m), where the decline stages were assigned based on the field measured concentration of chlorophyll.

**VIs and exergy**

Composite spruce decline indicator CI4 was found as a promising field characteristic with a high potential for estimation from both hyperspectral airborne and multispectral satellite RS data.

The NDVI$_{red\_edge}$ based on airborne HS data showed a strong fit with the CI4 ($R^2$ from 0.61 to 0.78). Moreover, NDVI$_{red\_edge}$ was found sensitive to initial decline categories of CI4. These results agree with the recently published studies, where the “red edge” index was demonstrated as very sensitive to
small changes in canopy chlorophyll content. Tuominen et al. (2009) and Ustin (2008) detected initial pine defoliation in mixed coniferous forests. Misurec et al. (2012) assessed the decline of spruce utilizing NDVI_{red} from HS data. NDVI_{red} from satellite Sentinel-2 data showed a weaker fit with CI4 ($R^2 = 0.57$).

The PRI from HS data showed $R^2$ from 0.52 to 0.61 with Dry tree top indicator from field observations, which indicates the applicability of PRI for canopy initial water stress detection in coniferous forest (Entcheva-Campbell et al., 2004; Hernández-Clemente et al., 2011). The WBI from HS data was also found sensitive to changes in composite spruce

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**Figure 6.** Correlation between indicators from field and vegetation indices from time-series HS (13 plots for each year) (a, b, c), MS Landsat (17 plots for each year) (d, e, f) and MS MODIS data (144 plots) (g), $p$-value $≤ 0.01$ (HS – airborne hyperspectral data, MS – satellite multispectral data; CI4 – composite index; PRI, WBI, NDVI_{red}, PSRI and NDII – vegetation indices from Table 5).
Table 8. Coefficients for general linear model (GLM, Equation 6).

| Y   | CH4  | Dry tree top |
|-----|------|--------------|
| β₀  | -835.5 | 95.14 | 59.6 | -48.15 | 51.46 | -45.21 |
| β₁  | 909.67 | -124.62 | -12.35 | 0.09 | -163.02 | 388.53 |
| βᵢ  | i = 1 | -2.35 | -10.34 | -7.33 | 1.96 | -4.07 | 5.52 |
| βᵢ  | i = 2 | -10.77 | 4.19 | 3.98 | -0.65 | 0.81 | -2.216 |

The use of satellite Sentinel-2 data was shown beneficial when estimating CI4 with NDII (R² = 0.52) comparing the use of Landsat data (R² from 0.42 to 0.45), though PSRI from satellite data was in high agreement with CI4 for both Sentinel-2 and Landsat data (R² = 0.71).

A second composite indicator CI6 (dead trees, break trees, resin exudation, IUFRO vitality, discoloration, and dry tree top), which was calculated in addition to CI4, demonstrated a weaker correlation with VIs considered in the study. As shown (Section 2.3), crown break and resin exudation changes did not influence the spectral reflectance changes of spruce plots. The presence of these two parameters might affect uncertainties in CI6. Exergy of solar radiation was shown to be in a somewhat tighter agreement with CI6 (R² from 0.47 to 0.58) compared to that with CI4 (R² from 0.42 to 0.57). GLM assessed the strength of the relationships between CI4 and selected VIs and exergy across the entire time period. Using year as a categorical variable with the above relationships was statistically significant (p-value ≤ 0.01). The regression analysis demonstrated the relative robustness of NDVIred_edge and WBI from airborne HS data, and PSRI, NDII and exergy of solar radiation from MS satellite data to identify changes in composite spruce health indicator CI4 (Figure 6). Interposition of lines 2010, 2013 and 2015 are similar in charts with NDVIred_edge, PSRI, NDII and exergy. Lines 2013 and 2015 are almost identical, whereas line 2010 departs from the 2013 and 2015 trends. In general, there is no reason why the relationship should change between years over such a short period. There is a minimum difference in spectral reflectance for spruce plots between June, August and early September (airborne data acquisition dates), which potentially could affect this relationship. A differentiation of line 2010 can be explained by the fact that the method is not that robust and/or involvement of some additional factors affecting the relationship between the health indicator CI4 and VIs. Specifically, year 2010 had the highest seasonal (April–September) precipitation in the area. It reached 1293 mm in 2010 as compared to 620 and 514 mm in 2013 and 2015, respectively (data from the meteorological station at the study area). Hence, these differences could affect the observed trends in the individual years.

Conclusions

A composite spruce decline indicator (CI4) was formed in the study. Dead tree, discoloration, dry tree top and IUFRO vitality were composed to CI4. The assessment of spruce stand decline from time-series of hyperspectral airborne and multispectral satellite RS data was explored. The use of airborne hyperspectral VIs was shown to be more efficient in matching composite decline indicator CI4 (R² from 0.63 to 0.75). Based on good positive correlation between PRI and CI4, and WBI and CI4 we can assume the canopy water content as an important covariate of composite spruce decline indicator CI4, which can be estimated from airborne HS data.

Exergy of solar radiation from satellite Landsat data demonstrated a good potential to estimate CI4 (R² from 0.42 to 0.57). Based on the interpretation of exergy for forest ecosystems in recent studies (Silow & Mokry, 2010; Lu et al., 2011), the exergy of solar radiation could be recommended for the assessment of a composite spruce decline indicator. However, additional research is required to test the exergy in the forest ecosystem with various species and growth conditions. Identification of decline categories of CI4 was not achieved from satellite multispectral data. We believe that Landsat broad spectral bands with 30-m pixel size and Sentinel-2 narrow spectral bands with 20-m pixel size are inapplicable to differentiation between healthy, initial decline, and initial to moderate decline categories of spruce health. Moderate and heavy spruce decline categories, potentially, can be identified from Landsat and Sentinel-2 data on study area. Lambert et al. (1995) declared the ability of Landsat TM red band to distinguish healthy, moderate and heavy damage categories in a spruce forest of the Ore Mountains.

The NDII from satellite Sentinel-2 data showed a moderate correlation with composite spruce decline indicator CI4 (R² = 0.52). De Beurs and Townsend (2008) concluded that NDII performed significantly better than commonly used VIs (NDVI and EVI) for monitoring of forest defoliation on an annual time scale. Only weak correlation was found between the temporal composite of NDII from MODIS and composite spruce decline indicator CI4 from the field (R² = 0.21) due to coarse spatial resolution of the satellite sensor (250 m), whereas Jepsen et al. (2009) and Spruce et al. (2011) demonstrated the applicability of coarse spatial resolution MODIS time-series data to long term forest monitoring. They proposed the combination and ratio of NIR and SWIR MODIS bands for the identification of heavy disturbances in a broadleaved forest area. MODIS NDVI proved sufficiently sensitive as a stand-level indicator of stress in temperate broadleaf forests improving parameterization of forest stress indices (Hlásny et al., 2015).
spruce decline indicator CI4 than the satellite VIs, due to the ability of the hyperspectral data to identify initial decline categories. However, when airborne data are unavailable or limited, PRSI, NDII and exergy of solar radiation from satellite (Landsat and Sentinel-2) data can be successfully utilized to obtain the distribution of the composite spruce decline indicator CI4 over a large forest area. The proposed methodology is potentially timely and economically expedient, since foliar spectral measurements, canopy chemistry, and laboratory analysis are not required. Further research will aim to explore the application of RS data for estimation of the composite decline indicator for pine and beech forest stands.

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References

Akselsson, C., Ardo, J., & Sverdrup, H. (2004). Critical loads of acidity for forest soils and relationship to forest decline in the Northern Czech Republic. Environmental Monitoring & Assessment, 98(363-379)

Birth, G., & McVey, G. (1968). Measuring the color of growing turf with a reflectance spectrophotometer. Agronomy Journal, 60, 640–643. doi:10.2134/agronj1968.0002196200600060016x

Blazkova, M. (1996). Black triangle – the most polluted part of central Europe. In P.E. Ritjema & V. Elias (Eds.), Regional approaches to water pollution in the environment (pp. 227–249), Kluwer Academic Publishers.

Cada, V., Santruckerova, H., Santrucek, J., Kubistova, L., Seedre, M., & Svoboda, M. (2016). Complex physiological response of Norway spruce to atmospheric pollution – decreased carbon isotope discrimination and unchanged tree biomass increment. Frontiers in Plant Science, 7. doi:10.3389/fpls.2016.00805

Carter, G.A. (1994). Ratios of leaf reflectances in narrow wavebands as indicators of plant stress. International Journal Of Remote Sensing, 15, 697-703

Cienciala, E., Tumajer, J., Zlatokulak, V., Beranová, J., Holá, Š., Hůnová, I., & Russ, R. (2017). Recent spruce decline with biotic pathogen infestation as a result of interacting climate, deposition and soil variables. European Journal of Forest Research, 136, 307–317. doi:10.1007/s10342-017-1032-9

Crosby, M.K., Fan, Z., Spetch, M., Leininger, T.D., & Fan, X. (2012). Remote sensing of forest health indicators for assessing change in forest health. In Proceedings of the 8th Southern Forestry and Natural Resources GIS conference, K. Merry, P. Bettinger. J. Siry (eds.) Warnell School of Forestry and Natural Resources, University of Georgia, Athens, GA

De Beurs, K.M., & Townsend, P.A. (2008). Estimating the effect of gypsy moth defoliation using MODIS. Remote Sensing of Environment, 112, 3983–3990. doi:10.1016/j.rse.2008.07.008

Ekstrand, S. (1996). Landsat-TM forest damage assessment: Correction for topographic effects. Photogrammetric Engineering and Remote Sensing, 62, 151-161.

Entcheva, P.K. (2000). Remote sensing of forest damage in the Czech Republic using hyperspectral methods (Dissertation). University of New Hampshire, Durham, NC.

Entcheva-Campbell, P.K., Rock, B.N., Martin, M.E., Neeffus, C.D., Irons, J.R., Middleton, E.M., & Albrechtova, J. (2004). Detection of initial damage in Norway spruce canopies using hyperspectral airborne data. International Journal of Remote Sensing, 25(24), 5557–5584. doi:10.1080/01431160410001726058

Fiala, P., Reiningter, D., Samek, T., Nemec, P., Susil, A. (2013). Průzkum vyzvy lesa na uzemi České republiky (Forest nutrition survey in the Czech Republic)1996 – 2011 (p. 149). Ustredni kontrolni a zkusebni ustav zemedelsky, Brno, Czech republic.

Forgy, E.W. (1965). Cluster analysis of multivariate data: Efficiency versus interpretability of classifications. Biometrics, 21, 768–769.

Gamon, A.L., Serrano, L., & Surfus, S. (1997). The photochemical reflectance index: An optical indicator of photosynthetic radiation use efficiency across species, functional types, and nutrient levels. Ecologia, 112, 492–501.

Gao, B. (1996). NDWI A normalized difference water index for remote sensing of vegetation liquid. Water From Space, 266, 257–266.

Gauthier, S., Bernier, P., Kuuluvainen, T., Shvidenko, A.Z., & Schepaschenko, D.G. (2015). Boreal forest health and global change. Science, 349, 819–822. doi:10.1126/science.aaa9092

Gitelson, A., & Merzlyak, M. (1998). Remote sensing of chlorophyll concentration in higher plant leaves. Advances in Space Research, 22, 689–692. doi:10.1016/S0273-1177(97)01133-2

Gitelson, A.A., Keydan, G.P., & Merzlyak, M.N. (2006). Three-band model for noninvasive estimation of chlorophyll, carotenoids, and anthocyanin content in higher plant leaves. Geophysical Research Letters, 33. doi:10.1029/2006GL026457
Puzachenko, Y., Sandlersky, R., & Sankovski, A. (2013). Methods for evaluating thermodynamic properties of landscape cover using multispectral reflected radiation measurements by the Landsat satellite. *Entropy, 15*, 3970–3982. doi:10.3390/e15093970

Roberts, D.A., Ustin, S.L., Ogunjemiyo, S., Greenberg, J., Dobrowski, S., Chen, J., & Hinckley, T.M. (2004). Spectral and structural measures of northwest forest vegetation at leaf to landscape scales. *Ecosystems, 7* (5), 545-562.

Rullan-Silva, C.D., Olthoff, A.E., de la Mata, D., & Pajares-Alonso, J.A. (2013). Remote monitoring of forest insect defoliation. A review. *Forest Systems, 22*(3), 377-391.

Solberg, S. (2010). Mapping gap fraction, LAI and defoliation using various ALS penetration variables. *International Journal of Remote Sensing, 31*, 1227–1244. doi:10.1080/01431160903380672

Zahradníček, P., Trnka, M., Brázdíl, R., Možný, M., Štěpánek, P., Hlavinka, P., … Řezníčková, L. (2015). The extreme drought episode of August 2011-May 2012 in the Czech Republic. *International Journal of Climatology, 35*, 3335–3352. doi:10.1002/joc.4211

Zar, J. (1996). *Biostatistical analysis*. Upper Saddle River, NJ: Prentice Hall.

Zarco-Tejada, P.J., & Miller, J.R. (1999). Optical indices as bioindicators of forest condition from hyperspectral CASI data. In *Proceedings of the 19th EARSeL symposium*. Valladolid, Spain.