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Remote Sensing of Forest Health

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1. Introduction

Global forest health is declining. The main reasons for this unfortunate development include climate change, air pollution and increased human activities. There is a need to monitor and quantitatively measure the change in forest health. Forest health can be defined in many different ways depending on the perspective one takes. The relationship between the cause and the symptom of forest health deterioration is complex mainly because the same symptom can often be induced by multiple different stressors.

Modern state of the art remote sensing technologies provide the means for wide coverage measurement of forest health with reasonable accuracy. In the assessment of forest health by means of remote sensing, features called Vegetation Indices (VIs) are usually extracted from the data. VIs are combinations of surface reflectances at two or more wavelengths designed to highlight a particular property of vegetation. In addition to specific VIs some attempts to develop a general forest health index combining the assessments of the various properties have been published.

In this chapter we first discuss the term 'forest health' as well as the various causes and symptoms of forest health deterioration. We then argue about the role of remote sensing in forest health monitoring and present the most common VIs used for the assessment of forest health. The VIs' capability to detect different types of forest damage is assessed in case studies; the results for Ni contaminated and pest inflicted forest areas are presented in sections 7 and 8, respectively. Finally, future possibilities in applying the remote sensing technologies to forest health monitoring are discussed.

2. Forest health

Despite its widespread use, the term "forest health" is vaguely defined in the literature, making its application to forest management difficult (Kolb et al., 1994). The definition of forest health is always a matter of perspective. Social, economic and ecological perspectives

are taken most frequently. Looking from different perspectives the definitions of healthy forest can even appear contradictory.
Social perspective emphasises people's needs for healthy living and recreational environment. In many countries people are becoming more and are more concerned about their environment. Since the 1960s, people have become more concerned about their environment, due to intensified management of natural resources, increased availability of information and structural changes in the society, i.e. decreased importance of primary production and increased leisure time. Healthy forests are needed for aesthetical pleasure and variety of outdoor activities. Economical perspective is quite complex. Historically short-term needs have usually exceeded long-term needs in forest industry. Production of commodities and services has outweighed ecological considerations in the past. Nevertheless, long-term economical benefits can only be obtained by practicing sustainable forest management. Ecological perspective is focused on ecosystems instead of human needs. This perspective emphasises the fact, that counterproductive interaction between ecosystems and humans should be minimized. The potential should exist for all biotic and abiotic elements to be present with sufficient redundancy at appropriate spatial and temporal scales across the landscape. Human intervention should not impact ecosystem sustainability by destroying or significantly degrading components that affect ecosystem capabilities.
Utilitarian perspective versus ecosystem perspective is another categorization presented in literature (Kolb et al., 1994). The utilitarian perspective emphasizes forest conditions that directly satisfy human needs. The ecosystem perspective emphasises the maintenance of sustainable ecosystems over the landscape. Often different perspectives do overlap, however, on occasions they may be contradictory. Depending on the perspective, the condition of the same forest can be viewed as healthy or unhealthy. For example, a common component in ponderosa pine forests is dwarf mistletoe. It reduces the growth of ponderosa pine and increases its mortality. The existence of dwarf mistletoe is harmful from economical perspective. However, abundance and species richness of birds is higher when dwarf mistletoe is present. Thus, the existence of dwarf mistletoe is desirable from the ecological perspective (Kolb et al., 1994).
The first definition of forest health usually cited in the scientific literature is by Aldo Leopold (1949): "Health is the capacity of the land for self-renewal. Conservation is our effort to understand and preserve this capacity." Although Leopold's definition is concerned also with other issues than forest health, it has founded the basis for all later definitions. Since Leopold's definition many new ones have been presented in the scientific literature. Some of these definitions deserve more in-depth consideration.
O'Laughlin et al. (1994) defined forest health in the following way: "Forest health is a condition of forest ecosystems that sustains their complexity while providing for human needs". This definition is an effort to take all the different perspectives of forest health, i.e., social, ecological and economical, into account. The question often asked when discussing forest health is: 'Can forest health be measured?': According to O'Laughlin et al. (1994) the answer is: "Objective indicators of forest condition can be specified and measured, but forest health assessments contain subjective value judgements which must be clearly recognized."
Some definitions of forest health like that by Monnig&Byller (1992), for example, emphasize ecological perspective: "A healthy forest is an ecosystem in balance"(Monnig&Byler, 1992). Human social and economical needs are not accounted for and the condition of ecosystems

matters for its own sake. Kolb, Wagner & Covington (1994) defined forest health as follows: “The term forest health should be restricted to the examination of the role of biotic and abiotic agents in ecosystem processes.” Several characteristics for such a system were mentioned: resistance to dramatic change in populations of important organisms within the ecosystem not accounted for by predicted successional trends; a functional balance between supply and demand of essential resources; and a diversity of seral stages, cover types and stand structures that provide habitat for many native species and all essential processes.

Climate change, in particular increased temperatures and levels of atmospheric carbon dioxide, as well as changes in precipitation and the occurrence of extreme climate events, is having notable impacts on the world’s forest health. Increased temperatures may relieve forest stress during colder seasons but increase it during warmer seasons. Impacts of increased temperatures vary widely among different climatic zones. Climate change has both direct and indirect impacts on forest health (Moore&Allard, 2008). For example, climate change has strong influence on forest pests which can be considered as a direct impact. Pests can rapidly react to changing climate because of their short generation times. Drought is a good example of a cause that is influencing forest indirectly. Drought can change tree physiology in a way that it is more vulnerable to certain insect and pest species. Such changes are, e.g., sugar content of foliage, changes in leaf colour, change of leaf thickness and structural changes of foliage.

3. Causes and symptoms of deteriorated forest health

In the scope of this chapter it is only possible to address the complex relationship between causes and symptoms of deteriorated forest health briefly. The relationship is complex mainly because there are often multiple stressors causing a certain symptom (Ferretti, 1997).

One of the major causes of deteriorated forest health is air pollution, particularly acid rain and ground-level ozone. There are two major types of pollutant threatening forest health: photochemical oxidants of which ozone is the primary compound, and nitrogen pollutants. Ozone is toxic (plant-killing) to sensitive plant species. Nitrogen is the primary growth-limiting nutrient, yet it is also a pollutant when in excess. The emission levels of these two pollutants are expected to increase significantly globally (Moore&Allard, 2008).

Some causes of deteriorated forest health are controversial. Depending on the perspective they can be seen as beneficial or negative. The role of disease agents (pathogens) and insects, for example, is controversial. They are essential to the function of dynamic ecosystems as they recycle nutrients and create habitats for different species. They can also negatively affect forest health, increase mortality and create growth losses. Diseases and insects influence the health of forests, trees outside forests and other wooded lands. Globally, all ecosystems with tree cover are under increasing threat, as the periods between sequential outbreaks are rapidly decreasing because of a range of factors including climate change and lack of proper forest management (Moore&Allard, 2008).

The impact of forest fires may also be controversial. Although they are usually seen as a threat to forest health, these natural events are key elements in many forest ecosystems as well. Another major cause for deteriorated forest health is posed by droughts. The consequences of a long-lasting drought can be very severe. In addition to direct impacts, they have indirect ones, for example pest outbreaks are associated with droughts. Drought can also increase the risk of forest fires.

Another cause of forest health deterioration is invasive species. Any species non-native to a particular forest ecosystem and whose introduction and spread causes deteriorated forest health can be considered invasive species. A major cause of increasing number of invasive species is increaced human activity. Transport vechiles act as carriers of seeds and plants. Sometimes invasive species can be intentionally introduced to an ecosystem to provide economic or environmental benefits. These species have later spread and caused serious problems in forests ecosystems.

There is an abundance of symptoms of deteriorated forest health. Some symptoms are easy to detect and follow while others might be very difficult to monitor. Discoloration is a good example of a symptom, which is relatively easy to monitor. Discoloration is usually also a very useful index of forest health. Growth losses, in turn, are difficult to measure from large forest areas. Usually sample plots are used, but, as the problem may be sporadic and local, it may not be caught with the sampling design. The new remote sensing technologies offer possibilities to large-scale forest growth monitoring.

Needle or leaf loss is a common symptom, which is also difficult to monitor unless the loss is severe. The needle loss symptom is often observed from needle retention. Needle retention provides an index of the number of years that needles are retained. It is only useful as a measure of needle loss if the loss occurs progressively from the oldest to the youngest needles (Innes, 1993). Defoliation can be estimated by observing the form of the tree crown. Mechanical damage to the crown is usually caused by wind. Butt and stem damage is another mechanical damage usually caused by animals like rabbits and squirrels, for example. A common nominator for most of the causes and symptoms of deteriorated forest health is, that almost all are expected to become more frequent.

4. The role of remote sensing in forest health monitoring

First attempts to introduce aerial photographs as a remote sensing tool in forestry were made in 1887. An airborne balloon was used as a photographic platform to produce photographs of forests in the vicinity of Berlin (Van Laar & Acka, 2007). The objective was to examine the possibility of preparing forest maps from aerial photographs. The forest was classified and described on the basis of visual examination of the photographs. Airborne photography from aircraft was introduced during World War 2. After the war the techniques developed for military use became available for civil applications. Since then aerial photography has been widely used in forestry applications. Forest inventory and measurement has been the most widely used application in forestry remote sensing. Earlier, stereo imagery consisting of pairs of oriented aerial images was used to measure individual trees. Today LiDAR based 3D-measurements have made stereo images obsolete (Clement, 2004).

Storm damage studies using aerial photographs were probably the first forest health applications using remotely sensed data. After the introduction of false colour photographs and early multispectral satellites it was possible to study red edge related observables (Barret & Curtis, 1997). By the red edge the difference between the reflectance maximum at near-infrared region and corresponding minimum at visible red region typical for all green vegetation due to chlorophyll absorption is meant. Red edge related indices such as normalized difference vegetation index (NDVI) and leaf area index (LAI) were applied. The introduction of hyperspectral sensors and the increased spatial resolution of multispectral data available enabled new forest health applications: detection of root diseases (Leckie et al., 2004), detection of pest inflicted damages (Vogelmann & Rock, 1989) and assessment of photosynthetic efficiency (Gamon et al., 1992).

Recent advances in high spectral resolution hyperspectral technology have enabled a whole new approach to forest health studies - the remote chemistry. The most advanced technology to study the health of forest is foliar chemistry. Estimates of the foliar chemistry of canopies allow a better understanding of the functioning of forest ecosystems since many biochemical processes such as photosynthesis, respiration and litter decomposition, are related to the foliar chemistry of trees (Huber et al., 2008). The use of high spectral resolution data has enabled to study many forest health relevant observables, such as the concentration of nitrogen (Fourty et al., 1996), carbon (Daughtry et al., 2001) and leaf pigments (Gitelson et al., 2002).

In the concept of forest health remote sensing nowdays means airborne or satellite imaging of forest areas. Depending on the number of wavelength channels used images obtained by remote sensing are categorized into aerial photographs, multi- and hyperpectral images. Other methodologies such as radar and Light Detection and Ranging(LIDAR) also used in remote sensing of forests. It has been shown that remote sensing can provide useful and relevant forest information (Solberg, 1999). Historically, the potential of remote sensing for forest health studies remained limited for a variety of reasons. Most of the remote sensing data suffered from insufficient spatial, spectral, or temporal resolution. Modern remote sensing instruments have overcome these problems opening new possibilities for forest health assessment. Especially promising is the modality of hyperspectral imaging.

Traditionally, forest health monitoring is performed by means of field studies. In many cases systematically monitored sample plots are used. There is no conflict between field studies and remote sensing. Both techniques are needed and they have their own important role in forest health monitoring. The advantages of remote sensing over conventional field studies include better spatial coverage, shorter sampling intervals, efficiency of data acquisition as well as access to remote or restricted areas. Climate change and increasing pollution set new requirements to forest health monitoring. State of the art remote sensing technology and methods offer an efficient solution to meet those requirements.

Disadvantages of remote sensing in forest health assessment mainly arise from quality and interpretation issues. The quality of modern remote sensing instruments has improved remarkably, however, unfortunately the advancements in algorithm development and verification are not at the same level. Algorithms used to retrieve end-user products such as chlorophyll content have to be validated using field measurements. Algorithms are used worldwide, but the field measurements used in their validation often cover only some specific area. Therefore it is not unusual that algorithms fail to produce reliable results at certain climate zone or geographic location. Remote sensing data products are sometimes difficult to interpret and that makes otherwise reliable data useless. Reliable verification of airborne remote sensed data can only be done using adequate ground truth measurements during the flight operation.

Practically all remote sensing algorithms require the data to be atmospherically corrected. Atmospheric correction is a procedure where the filtering effects of the atmosphere are compensated for. Optical properties of the atmosphere are time and place variant making correction procedure complex and difficult. Atmospheric models used in the correction procedure are not precise enough to ensure correct results in all cases. Atmospheric

correction should be made with utmost care in order to produce quality results. Results should always be verified using known ground targets.
Another remarkable difficulty is the so called "mixed pixel problem". This means that usually in remote sensing data one pixel represents many different materials. In forest areas one pixel often represents tree canopy, soil and some other materials like rock, for example. Then vegetation indices measuring certain forest property can give false results because the percentage of tree canopy is too low. In dense tropical forest the problem is not so serious as in boreal forest areas with low tree density. Because of the mixed pixel problem remote sensing usually provides general estimate of forest health over larger area rather than precise condition of a single tree.

5. Vegetation indices

In the assessment of forest health by means of remote sensing, features called Vegetation Indices are usually extracted from the data. VIs are combinations of surface reflectances at two or more wavelengths designed to highlight a particular property of vegetation. They are derived using the reflectance properties of vegetation. Each of the VIs is designed to accentuate a particular vegetation property. VIs are usually developed by means of empirical laboratory measurements of the property to be studied as well as correlation analysis of remotely sensed data. VIs can be categorized into narrow or broadband ones according to the bandwidth of used wavelength channels. The use of narrowband VIs requires data of high spectral resolution, i.e., hyperspectral data. The use of many VIs is limited because they saturate in dense vegetation areas (Mutanga & Skidmore, 2004). Some narrowband VIs can overcome this problem. Another problem with VIs is nonlinearity (Jiang et al., 2006). The relationship between VI value and measured property is nonlinear which makes the use of VI somewhat difficult. Here we present the most important categories of VIs and some examples of VIs for each category. The ability of the VIs to detect different types of stressed forest areas are tested by means of two case studies presented in sections 7 and 8.

5.1 Greennes (chlorophyll concentration) VIs

Greennes VIs are designed to measure the general quantity and vigor of green vegetation. They measure many different aspects: chlorophyll concentration, canopy area and canopy structure. VI value is always determined by the combination of these different effects. Greennes VIs are based on the measuring of reflectance peak in near-infrared region (NIR). Red wavelength where the chlorophyll absorption is strongest is used as a reference.
Normalized difference vegetation index (NDVI) is the most frequently used and most well know VI. It simply measures the reflectance peak at NIR region. NDVI is a good overall measure of green vegetation, but it has problems with saturation and non-linearity (Jiang et al., 2006). NDVI is defined according to the equation

$$NDVI = \frac{\rho_{NIR} - \rho_{RED}}{\rho_{NIR} + \rho_{RED}} , \tag{1}$$

where ρ_x represents reflectance at wavelength band x (Tucker, 1979).

Enhanced Vegetation Index (EVI) is designed to be used in dense vegetation areas. NDVI saturates in densely vegetated areas (Huete et al., 1997). In order to overcome this problem blue reflectance is used to compensate the effects of background soil and atmospheric scattering effects. EVI is defined according to the equation

$$EVI = 2.5\left(\frac{\rho_{NIR} - \rho_{RED}}{\rho_{NIR} + 6\rho_{RED} - 7.5\rho_{BLUE}}\right). \tag{2}$$

The Red Edge Normalized Difference Vegetation Index (RENDVI) is a broadband version of the NDVI. While NDVI uses the minimum and maximum reflectances of the red edge region, the RENDVI employs wavelength bands along the red edge (Sims&Gamon, 2002). RENDVI is very sensitive to small changes in canopy chlorophyll content. It can only be calculated based on hyperspectral data. RENDVI is defined according to the equation

$$RENDVI = \frac{\rho_{750} - \rho_{705}}{\rho_{750} + \rho_{705}} . \tag{3}$$

Malenovsky et al. (2006) presented a new approach to canopy chlorophyll content measurement in the form of an index called Area under curve Normalized to Maximal Band depth between 650-725 nm (ANMB). Most of the VIs use simple band ratios to calculate the measured property. In ANMB the surface integral and maximum band depth are calculated. In that way the whole red edge region is estimated instead of a few bands. In the first phase the area under the reflectance curve between 650 and 750 nm is integrated according to the equation

$$AUC_{650-725} = \frac{1}{2}\sum_{j=1}^{n-1}(\lambda_{j+1} - \lambda_j)(\rho_{j+1} + \rho_j) , \tag{4}$$

where ρ_j and ρ_{j+1} are reflectances at the j and $j+1$ bands, λ_j and λ_{j+1} are wavelengths of the j and $j+1$ bands, and n is the number of the used spectral bands. The ANMB index is computed according to

$$ANMB_{650-725} = \frac{AUC_{650-725}}{MBD_{650-725}} , \tag{5}$$

where $MBD_{650-725}$ is the maximal band depth of the reflectance, placed at one of the spectrally stable wavelengths of the strongest chlorophyll absorption peaks around 675-680nm.

5.2 Water content VIs

Water content VIs are designed to provide an estimate of canopy water content. Water content is an important vegetation property which correlates with vegetation health. Water content VIs are based on the fact that there are well known water absorption features in the near-infrared and shortwave infrared regions. The use of water content VIs requires high spectral resolution data.
The Water band index (WBI) is a simple reflectance measurement that is sensitive to changes in canopy water content. WBI is utilizing well know water absorption feature at 970nm. The ratio of the reflectance at 970nm to that at 900nm is measured (Penuelas et al., 1995). WBI is defined according to the equation

$$WBI = \frac{\rho_{900}}{\rho_{970}} \ . \tag{6}$$

Normalized difference water index (NDWI) is sensitive to changes of canopy water content. It uses two different bands, 857 and 1241 nm having similar but slightly different water absorption properties (Gao, 1995). The scattering of light by canopy enhances the weak water absorption at 1241nm. NDWI is defined according to the equation

$$NDWI = \frac{\rho_{857} - \rho_{1241}}{\rho_{857} + \rho_{1241}} \ . \tag{7}$$

The Moisture Stress Index (MSI) is a simple reflectance measurement that is sensitive to increasing canopy water content. The strength of the absorption at 1599 nm increases when the canopy water content increases. The absorption at 819 nm is used as a reference because it is nearly unaffected by changing water content in the canopy (Ceccato et al., 2001). MSI is defined according to the equation

$$WBI = \frac{\rho_{1599}}{\rho_{819}} \ . \tag{8}$$

5.3 Leaf pigment VIs

Leaf pigment VIs are measuring the amount of stress-related pigments in vegetation. Carotenoids and anthocyanins are pigments which are present in higher concentrations in stressed vegetation. Carotenoids are pigments that protect vegetation from high light condition. Anthocyanin pigment content is high in senescence and in new leafs.

Anthocyanin reflectance index 700 (ARI_700) is sensitive to anthocyanin amount in vegetation (Gitelson et al., 2001). ARI_700 is defined according to the equation

$$ARI\_700 = \left(\frac{1}{\rho_{550}}\right) - \left(\frac{1}{\rho_{700}}\right) . \tag{9}$$

Anthocyanin reflectance index NIR (ARI_NIR) is similar to ARI_700, but it uses one additional NIR band (Gitelson et al., 2001). ARI_NIR is capable in detecting higher anthocyanin concetrations than ARI_700. ARI_NIR is defined according to the equation

$$ARI\_NIR = \rho_{800}\left(\frac{1}{\rho_{550}}\right) - \left(\frac{1}{\rho_{700}}\right). \tag{10}$$

Carotenoid Reflectance Index 550 (CRI_550) measures the amount of carotenoids in canopy. CRI_550 calculates the difference of two bands sensitive to carotenoid amount (Gitelson et al., 2002). CRI_550 is defined according to the equation

$$CRI\_550 = \left(\frac{1}{\rho_{510}}\right) - \left(\frac{1}{\rho_{550}}\right). \tag{11}$$

Carotenoid Reflectance Index 700 (CRI_700) is a similar reflectance measurement as CRI_550, but it uses NIR band instead of the green one. CRI_700 is designed to measure higher caroteinid concentrations compared to CRI_550. CRI_770 is defined according to the equation

$$CRI\_550 = \left(\frac{1}{\rho_{550}}\right) - \left(\frac{1}{\rho_{700}}\right). \tag{12}$$

5.4 Carbon VIs

Vegetation contains many types of carbon: cellulose, lignin, sugar and starch. Cellulose is used to form cell walls of vegetation tissues. Lignin is used in structurally strong parts in vegetation. There is large amount of carbon in dead or senescent vegetation. These VIs can be used to observe the state of senescence of vegetation.

Normalized Difference Lignin Index (NDLI) is designed to estimate the amount of lignin in vegetation. Reflectance at 1754 nm is primarily determined by lignin concentration of the canopy (Serrano et al., 2002). Reflectance at 1680 nm is used as a reference. NDLI is defined according to the equation

$$NDLI = \frac{\log(1/\rho_{1754}) - \log(1/\rho_{1680})}{\log(1/\rho_{1754}) + \log(1/\rho_{1680})}. \tag{13}$$

The Cellulose Absorption Index (CAI) is a vegetation index indicating surfaces containing dry wood material. Absorptions in the 2000 nm to 2200 nm range are sensitive to cellulose (Daughtry et al., 2004).

CAI is defined according to the equation

$$CAI = 0.5(\rho_{2000} + \rho_{2200}) - \rho_{2100}. \quad (14)$$

5.5 Light Use Efficiency VIs

The light use efficiency VIs are providing a measure of the efficiency with which vegetation is able to use incident light for photosynthesis. Light use efficiency correlates with carbon uptake efficiency and growth rate. Light use efficiency VIs can be used in precision forestry to estimate growth rate and production.

The Photochemical Reflectance Index (PRI) is a reflectance measurement that is sensitive to changes in carotenoid pigments in canopy. The amount of carotenoid pigments indicates photosynthetic light use efficiency and the rate of carbon dioxide uptake (Gamon et al., 1992). It can be used to estimate vegetation productivity and stress. PRI is defined according to the equation

$$PRI = \frac{\rho_{531} - \rho_{570}}{\rho_{531} + \rho_{570}}. \quad (15)$$

The Structure Insensitive Pigment Index (SIPI) is a reflectance measurement designed to maximize the sensitivity to the ratio of bulk carotenoids to chlorophyll while minimizing the affects of variation in canopy structure (Penuelas et al., 1995). SIPI uses three bands: blue, NIR and the maximum chlorophyll peak at 680 nm. SIPI is defined according to the equation

$$SIPI = \frac{\rho_{800} - \rho_{445}}{\rho_{800} - \rho_{680}}. \quad 16)$$

The Red Green Ratio (RG Ratio) index is a reflectance measurement that indicates the relative expression of leaf redness caused by anthocyanin to that of chlorophyll. The Red Green Ratio has been used to estimate the course of foliage development in canopies. The RG Ratio index is an indicator of stress, leaf production and may also indicate flowering in some cases. The ratio is calculated as the mean of all bands in the red range divided by the mean of all bands in the green range. RGRI is defined according to the equation

$$RGRI = \frac{\rho_{RED}}{\rho_{GREEN}}. \quad (17)$$

6. General forest health indices

Forest health is likely to deteriorate due to climate change, pollution and increased human activities. This unfortunate development sets new demands for forest health assessment. There is a need to obtain a quantitative and reliable assessment of the general condition of forest health. Most of the VIs measure a certain property of forest that doesn't necessarily represent the general condition of the forest. A general forest health index capable of detecting a variety of different damage types would be very desirable. Several methods for obtaining general forest health index have been proposed in the literature.

NDVI index is generally used as a forest health index. Xiao&McPherson (2005) presented a method using NDVI with multispectral data to asses tree health in urban environment. Although NDVI is usually a good VI for general assessment of forest health it leaves opportunities for improvement. NDVI can detect chlorophyll content and defoliation, but there are problems regarding saturation with dense vegetation and non-linearity.

Solberg et al. (2005) presented a method based on combining the LiDAR and hyperspectral data. Variation of canopy chlorophyll mass per area is used to measure forest health. NDVI calculated from hyperspectral data is used as a measure of chlorophyll mass while the Leaf area index (LAI) calculated from the LiDAR data is used as a measure of canopy area. The proposed method produced promising results.

In hyperspectral data analysis the ENVI software package is widely used. ENVI features a forest health tool, which creates a spatial map showing the overall health and vigor of a forested region. The spatial map is showing health index using 9 different classes. Forest health tool uses three different vegetation indices in the classification process. Each VI represents one of the following VI categories: greennes, leaf pigments, canopy water content and light use efficiency. Forest health tool has produced good results in the detection of contaminated forest areas (Tuominen et al., 2008). It constitutes a promising effort to develop a tool to calculate general forest health index using combined VIs.

Forest health can be evaluated using remote sensing by measuring chlorophyll content, defoliation and content of certain pigments (Solberg, 1999). A good general forest health index should measure at least those variables. In addition, water content and photochemical indices could be used. Even advanced foliar chemistry indices yet in experimental phase could be utilized. General forest health index integrating across different damage types is feasible, but a lot of research has to be done. Comprehensive algorithm verification with different forest and damage types would be required.

7. Case study 1: Detection of talc dust contaminated forest areas

The objective of this study was to evaluate how well talc dust contaminated forest areas can be detected using the various vegetation indices. Contamination is one of the major causes of deteriorated forest health. The level of contamination in forest areas can be influenced byrelated to industrial enterprises. Therefore, it is important to provide reliable forest health information in order to support decision making in all administrative levels.

7.1 Test area

The test area contains Boreal forest around the Lahnaslampi talc mine in North-East Finland. Geographic location as well as the true colour image of the test area are shown in Fig1. Forest in the test area is dominated by Pine, Spruce and Birch trees. Due to large scale mining of crumbly ore, talc, carbonate etc. dust from the rock piles and tailings is carried by the wind to the environment (Kuosmanen et al., 2004). Magnesium and nickel are components of dust emitted from the Lahnaslampi talc plant and mine. Magnesium is bound to talc and magnesite, whereas sources of Ni are both sulphides and Ni bearing Mg-silicates, e.g. talc. Elevated concentrations of Ni and Mg in both moss and humus samples reflect the amount of precipitated talc dust along the prevailing wind direction (Helminen&Räisänen, 2002). Another source of environmental impact is constituted by the seepage of acid waters through rock piles and tailing ponds. Generally, the level of vegetation stress around the Lahnaslampi mine is low, i.e. the mine does not restrict forestry or other utilization of nature except in the mining area itself. Although talc is not the only source of contamination, it can be assumed that there is strong correlation between Ni concentration and forest stress level.

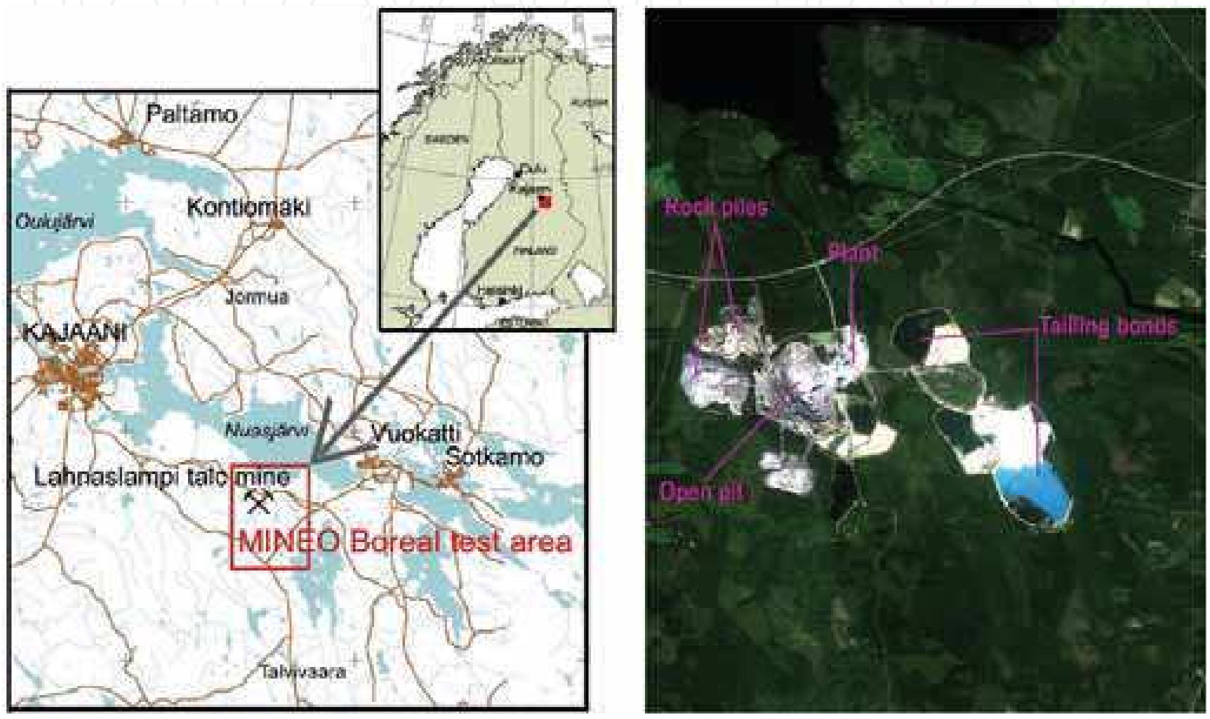

Fig. 1. Geographic location of the test area (Kuosmanen et al., 2004) (left), true colour image of the test area (right).

7.2 Data acquisition

The data acquisition was part of the EU-funded MINEO project, which aimed at the development advanced methods for the extraction of information and knowledge from earth observation data. This study utilized imagery from the HyMap airborne hyperspectral scanner recorded at 28th of July 2000. During the data acquisition cloud cover was non-existent. The HyMap sensor collects reflected solar radiation in 126 bands covering the wavelengths from 420 to 2480 nm. This includes visible, near infrared and short-wave infrared regions of the electromagnetic spectrum. The ground resolution of one pixel was 5*5 meters (Kuosmanen et al., 2004). Hyperspectral data was atmospherically corrected using ATCOR software. ATCOR uses MODTRAN 4 atmospheric model and parameters describing atmospheric type, solar geometry and hyperspectral sensor.

7.3 Methods

In order to remove non-forest pixels from hyperspectral data, a mask image was constructed. Masked pixels were not accounted when test results were calculated. Non-forest pixels were detected by calculating the forest discrimination index (FDI)

$$FDI = \rho_{838} - (\rho_{714} + \rho_{446}) \tag{18}$$

where ρ_x represents reflectance measured in the spectral band centred at x nm (Lucas et al., 2008). All pixels whose FDI-value was under certain threshold were removed from hyperspectral data. It is quite difficult to separate different types of green vegetation reliably. Therefore it was necessary to remove pixels representing green agricultural fields and grasslands manually when they were located near the sites where moss samples were collected. High albedo of the ore minerals causes an atmospheric scattering halo effect around the mining area, a halo which is clearly visible in HyMap imagery especially at VNIR-wavelengths. In order to avoid the influence of halo effect on the test results, 50 meters wide buffer zone was masked around bright ore material. The mask image used to remove non-forest pixels is shown on the left panel of Figure 2.

During the flight campaign 51 moss samples were collected from the test area around Lahnaslampi talc mine. Moss samples were collected by hand using contamination-free gloves. The samples were stored at low temperature and the concentrations of heavy metals were measured in the Geolaboratory of the Geological Survey of Finland (Helminen&Räisänen, 2002). Measurements of nickel concentration were utilized in this case study. Sample sites were divided into six classes according to measured nickel concentration as follows:

- Class 1 Ni concentration 0-5 mg/kg
- Class 2 Ni concentration 6-16 mg/kg
- Class 3 Ni concentration 17-30 mg/kg
- Class 4 Ni concentration 31-60 mg/kg
- Class 5 Ni concentration 61-90 mg/kg
- Class 6 Ni concentration 91-130 mg/kg

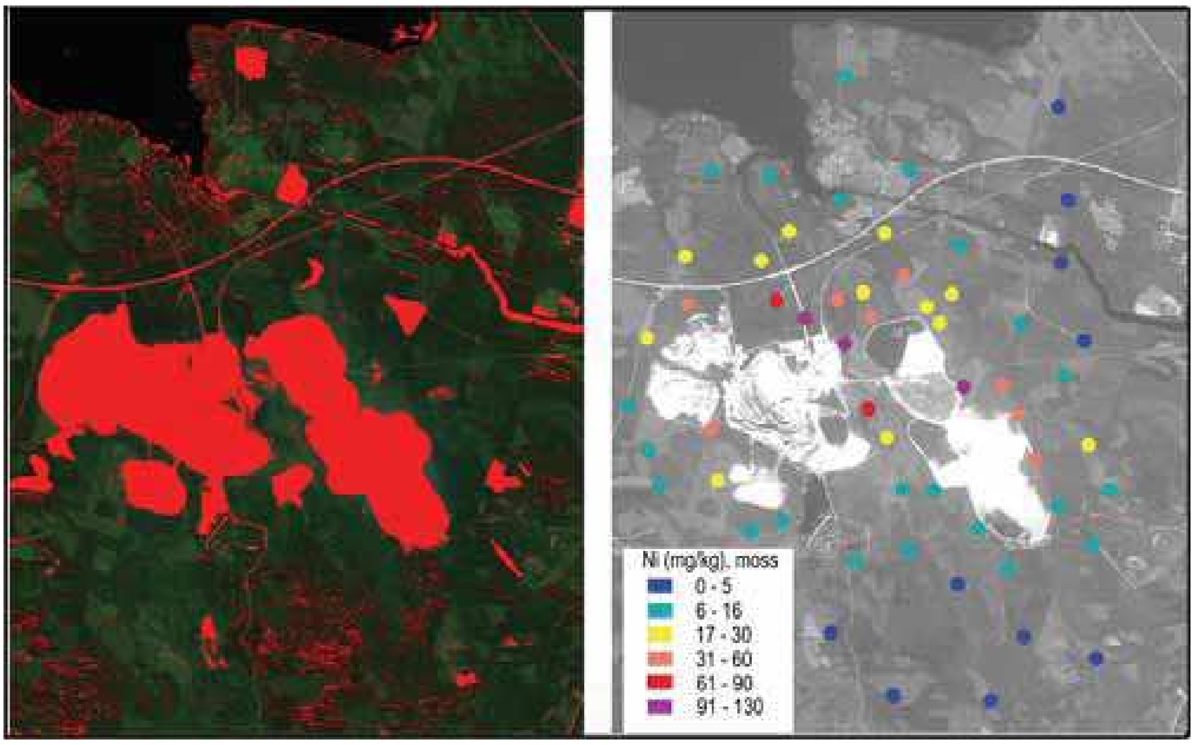

Fig. 2. Mask image used to eliminate non-forest pixels (left), ground truth map indicating Ni-content (mg/kg) of collected moss samples (right).

It is safe to assume that Ni concentration varies slowly within immediate neighborhood of the sampling site. Circular neighborhoods (radius 50 m) were created around each sampling site. These circular areas were color coded according to their Ni concentration levels. Resulting color coded map was used as a ground truth map in the testing process of Vegetation Indices. Color coded ground truth map is shown on the right panel of Fig 2. Correlation between the values of VIs and the measured Ni concentration as well as separability of the classes were considered as the evaluation criteria for Vegetation Indices. Both measures were calculated for each VI using all pixels situated within the 50 m circular neighborhood around the sample sites. Computation of tested VIs is described in section 5.

7.4 Results and discussion

The coefficients of determination r^2 for each VI are shown in table 1. Separability between two classes was calculated using the following simple and robust measure

$$d_{norm} = \frac{|\mu_1 - \mu_2|}{\sigma_1 + \sigma_2} \tag{19}$$

where mu and sigma are the mean and standard deviation of the particular class, respectively (Landgrebe, 2003).

Overall separability between all different class combinations is then

$$S = \frac{1}{15} \sum_{i=1}^{5} \sum_{j=i+1}^{6} \frac{\left| \mu_i - \mu_j \right|}{\sigma_i + \sigma_j} \tag{20}$$

where i and j denote the classes. Separability values for the vegetation indices are shown in table 1.

Vegetation Index	R^2	S
Normalized Difference Vegetation Index (NDVI)	0.9027	0.4866
Enhanced Vegetation Index (EVI)	0.6405	0.2953
Red Edge Normalized Difference Vegetation Index (RENDVI)	0.8135	0.3110
Area Normalized to Maximum Band depth (ANMB)	0.8101	0.3036
Water Band Index	0.4092	0.1514
Normalized Difference Water Index (NDWI)	0.2403	0.0925
Moisture Stress Index (MSI)	0.40141	0.2026
Anthocyanin Reflectance Index 700 (ARI_700)	0.8704	0.3242
Anthocyanin Reflectance Index NIR (ARI_NIR)	0.8098	0.1653
Carotenoid Reflectance Index 550 (CRI_550)	0.7490	0.2868
Carotenoid Reflectance Index 700 (CRI_700)	0.7785	0.3223
Normalized Difference Lignin Index (NDLI)	N/A	N/A
Cellulose Absorption Index (CAI)	N/A	N/A
Photochemical Reflectance Index (PRI)	0.8141	0.2707
Red Green Ratio Index (RGRI)	0.6258	0.1411
Structure Intensive Pigment Index (SIPI)	0.0023	0.1146

Table 1. Coefficients of determination and separability values for different vegetation indices (N/A means not applicable).

In general, correlation and separability values obtained for greenness VIs were relatively high. Highest correlation and separability values were obtained for the NDVI index. Narrow band indices (RENDVI, ANMB) produced better results than the broad band EVI. Test results of water content indices were rather poor. Among these indices best separability of classes was achieved by the MSI index. The separability of NDWI index was the worst of all tested VIs. The value of the WBI index is almost the same for all classes; this can clearly be seen from Figure 3 where the median as well as upper and lower quartiles values are shown for each class.

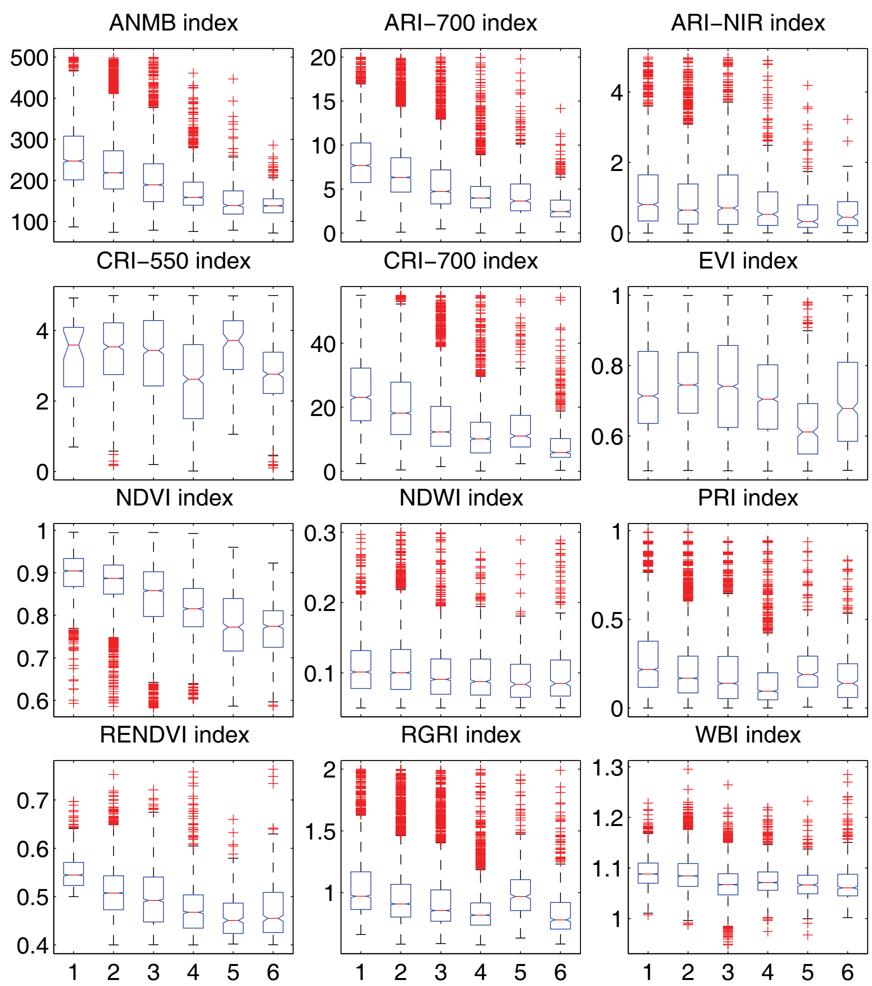

Fig. 3. Median, upper and lower quartile values of classes for tested vegetation indices.

Leaf pigment indices that measure the carotenoids and anthocyanins concentration produced quite good test results. Among these indices the best separability and correlation values were obtained by the ARI_700 index. The separability of classes was poor using the ARI_NIR index. VIs designed to provide an estimate of the amount of carbon, i.e., NDLI and CAI were totally useless in the detection of Ni contaminated forest areas. The test results of VIs used to estimate light use efficiency varied a lot. The PRI index produced good results while the results of the SIPI index were very poor.

7.5 Conclusions

Most of the tested VIs could not detect Ni contaminated forest areas with adequate accuracy. However, three VIs, the NDVI, the ARI_700, and the PRI, produced good results. When the spatial distribution of the ARI_700 index is studied from Figure 4, it is easy to see that the more contaminated areas are stretched into North East direction from the mine. From this we can correctly conclude that North East is the prevailing wind direction in the area as the dust emitted from the talc plant and mine is transported by the wind. Poor separability of classes was the common problem for almost all VIs. This can be seen clearly in Figure 3. The major cause of poor separability is the mixed pixel problem. One pixel is usually representing canopy, shadow and soil. In this Boreal test site the forest is so dense that soil is not present in the pixels normally. The basic problems of the VIs i.e., non-linearity and saturation at high levels can be seen when the test results are analyzed. When Fig 4. is studied, it is easier to detect stressed forest areas by analyzing the spatial distribution of the ARI_700 index, although the NDVI index had better correlation and separability values in the test. This is due to non-linearity and high-end saturation of the NDVI index. The carbon concentration Vis, the CAI and the NDLI failed to produce any meaningful test results. It is understandable because Ni contamination is not assumed to increase carbon content of the tree unless the contamination level is very high.

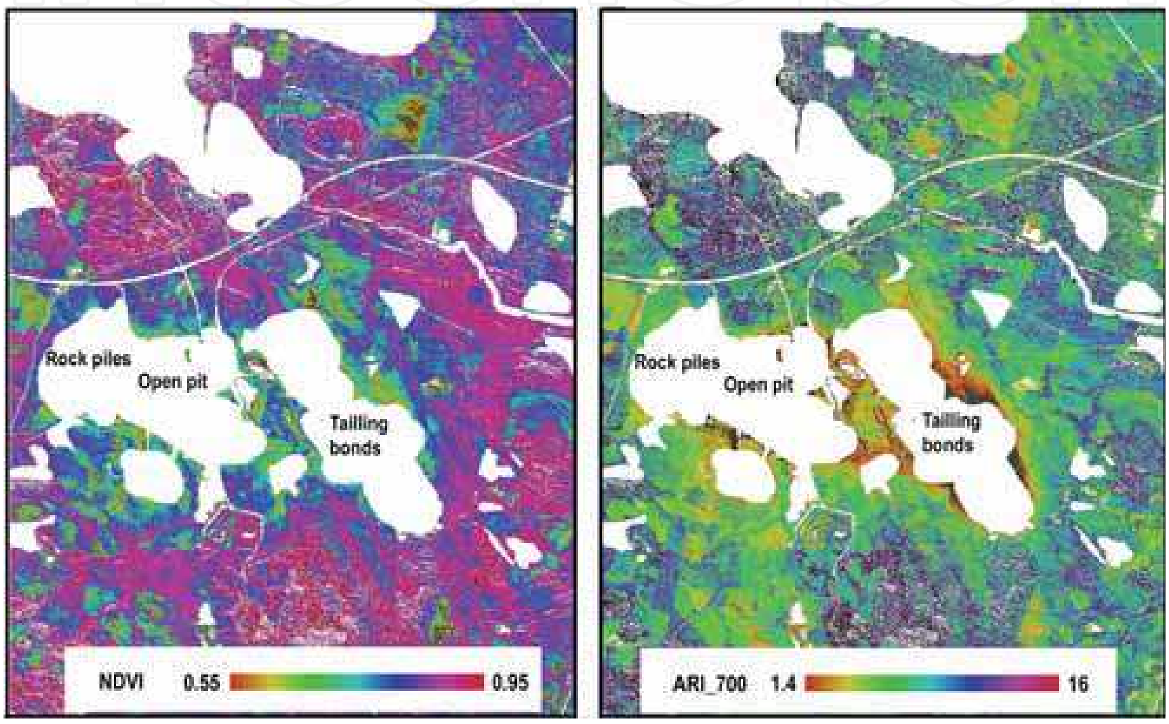

Fig. 4. Spatial distribution of the NDVI and the ARI_700 indices.

VIs estimating canopy water content had only very weak correlation with Ni concentration. Water absorption regions of hyperspectral data are very difficult to measure as often data in those regions is just noise. Light use efficiency indices produced mixed results. PRI had rather good correlation and separation values, but SIPI did not have any correlation with Ni concentration. A probable cause of this is the high noise level in one channel in the blue region of the spectrum. Test results of SIPI index were not excluded from this study, but they should be interpreted with cautious mind. As an overall conclusion from this study it can be said that the deterioration of forest health due to Ni contamination can be detected using carefully selected VIs.

8. Case study 2: Detection of pest inflicted defoliation

The objective of this study was to evaluate how well defoliated tree crowns can be separated from healthy tree crowns using different vegetation indices. Pest inflicted stress is globally one of the most important threats to forest health. Pest inflicted damages can be sometimes avoided or reduced with proper countermeasures. Therefore it is important to be able to monitor and detect early stage pest damages in forest areas.

8.1 Test area

The test area constituted a sand soiled boreal forest area in South-West Finland. Forest in the test area is dominated by Pine with some occasional Spruce and Birch trees. In the summer of 2006 a seriously damaged pine forest area was found in South-West Finland.

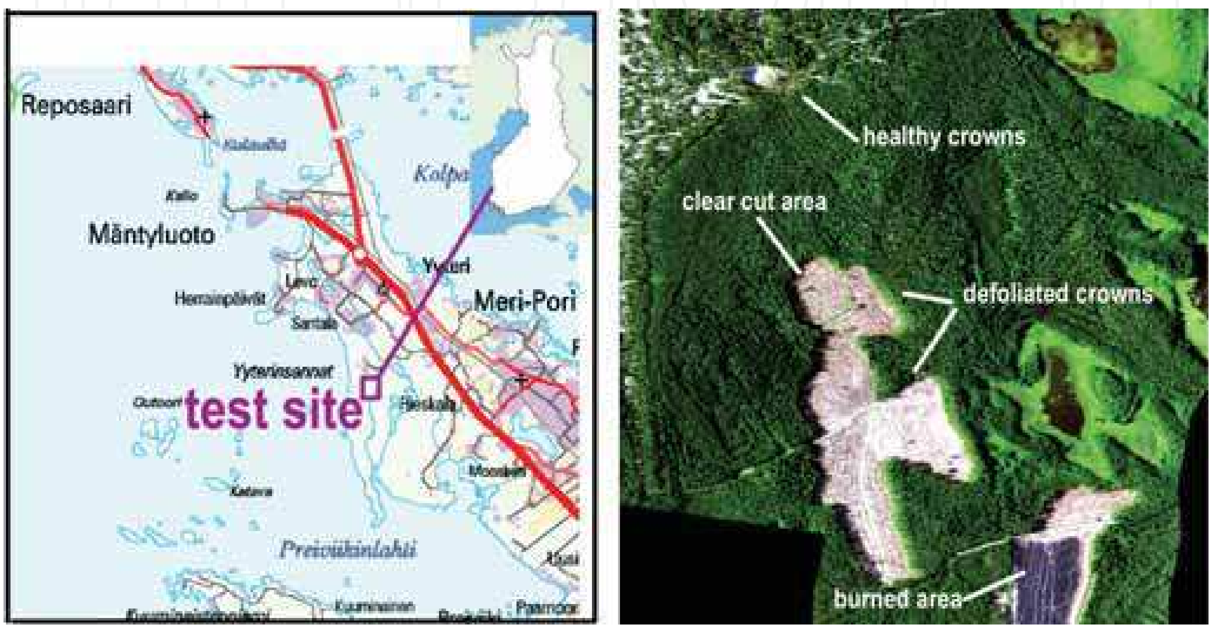

Fig. 5. Geographic location of the test area(left), true colour image of the test area(right).

Studies showed that the cause of the damage was the great webspinning pine sawfly (acantholyda posticalis). Great webspinning pine sawflies have been found in Finland before, but they have not caused any forest damage before. This time recent warm weathers and sandy soil of the area have made it possible for the sawflies to reproduce and cause damage. It is very possible that forest damage caused by great webspinning pine sawfly will be more frequent due to climate change. The tree mortality in the area was so high that is was necessary to clear cut 30 hectares of forest. 10 hectares were burned in order to decrease future damage. Most of the damaged trees were successfully clear cut, but there were still some left.

8.2 Data acquisition

This study utilized data from the AISA dual airborne hyperspectral scanner recorded at 13th of July 2008. During the acquisition the cloud cover was non existent. The AISA dual spectrometer collects reflected solar radiation in 481 bands covering the wavelengths from 399 to 2452 nm. This includes the visible, near infrared and short-wave infrared regions of the electromagnetic spectrum. The ground resolution of one pixel was 2.5*2.5 meters. Hyperspectral imagery was atmospherically corrected using ATCOR software. This study utilized also LIDAR data acquired on May 1st, 2008, by a small aircraft carrying Leica ALS50-II LIDAR scanner. Acquisition was carried out in early spring, so deciduous trees were still without leafs. The point density of the LIDAR data was 0.76 points per sq. m. Measurement accuracy of elevation data was 0.15 m.

8.3 Methods

Ground truth data was collected by doing an extensive field study in the test area. Moderately defoliated tees were located using visual inspection. Heavily defoliated trees were excluded because in this case most of the reflected radiation actually comes from the soil. Geo-coordinates of promising candidates were recorded using a GPS-instrument. Candidates for healthy trees were also collected. Final selection of the trees included in the study was done using LIDAR data.

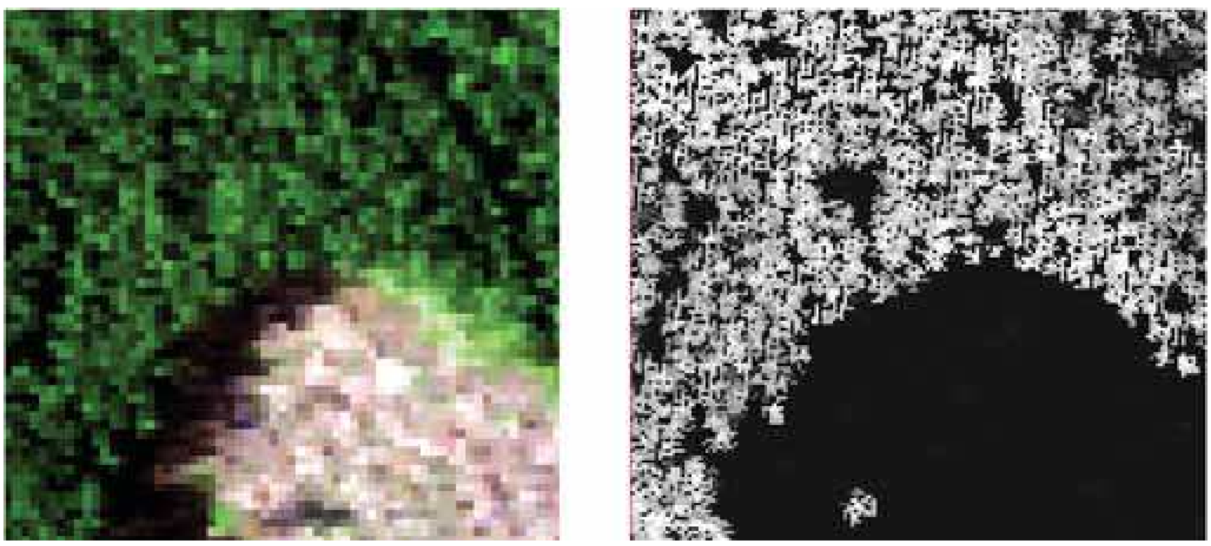

Fig. 6. True colour image of the hyperspectral data(left), DSM image from the same area(right).

The reason for using LIDAR data is mixed pixel problem. Usually spectral signature imaged from the test area represents the mixture of canopy, soil, shadow and maybe some other materials too. In order to test VIs reliably it was necessary to select final tree crown using digital surface model (DSM). DSM was generated by rasterizing and interpolating raw LIDAR data using ENVI software. DSM was geo-referenced to same coordinate system as the hyperspectral data using polynomial triangulation of ERDAS software. Both data sets were linked in ENVI software and the neighborhood of each tree crown candidate were studied. The tree crowns for which the DSM of the tree top neighborhood showed full canopy coverage in the corresponding hyperspectral pixel were chosen for VI testing. Geo-referenced DSM image is shown on the right panel Fig 7. White pixels show laser beam returns from tree tops. As a result altogether 20 hyperspectral pixels representing 10 healthy tree crowns and 10 partly defoliated tree crowns were selected for the analysis.

8.4 Results and discussion

VIs were calculated for all 20 test pixels. Mean and standard deviation values for both healthy and defoliated classes are shown in table 1. Separability S between healthy and defoliated classes was calculated using the formula

$$S = \frac{|\mu_1 - \mu_2|}{\sigma_1 + \sigma_2} \tag{21}$$

where mu and sigma are the mean and standard deviation of the particular class, respectively.

Vegetation index	Healthy		Defoliated		
	Mean	std.	Mean	std.	S
NDVI	0.934	0.0219	0.791	0.035	2.513
EVI	N/A	N/A	N/A	N/A	N/A
RENDVI	0.502	0.0139	0.4823	0.01844	0.5820
ANMB	232.7	50.69	139.8	28.79	1.168
WBI	N/A	N/A	N/A	N/A	N/A
NDWI	N/A	N/A	N/A	N/A	N/A
MSI	0.3865	0.0810	0.2805	0.0872	0.6302
ARI_700	0.0059	0.0011	0.0030	0.0009	1.4500
ARI_NIR	1.654	0.433	3.487	0.611	1.7471
CRI_550	0.0101	0.0144	0.0023	0.0031	0.7936
CRI_700	0.0143	0.0021	0.0177	0.0024	0.7348
NDLI	N/A	N/A	N/A	N/A	N/A
CAI	N/A	N/A	N/A	N/A	N/A
PRI	N/A	N/A	N/A	N/A	N/A
RGRI	0.8574	0.1078	0.70838	0.1540	0.5692
SIPI	1.003	0.0174	1.0280	0.0189	0.6887

Table 2. mean, standard deviation and separability values for each tested Vis (N/A means not applicable).

Many of the tested VIs did not produce any meaningful results. PRI used one wavelength channel that appeared to be noisy and therefore the results for this index are not valid. NDLI and CAI probably failed because they use SWIR channels. Most VIs were calculated using ENVI software VI calculator and some using MATLAB codes. Best separability value was obtained using NDVI. NDVI correlates well with reduced chlorophyll content, so its good performance could be expected the result is understandable. ARI_700 and ARI_NIR produced also rather good results. Recently published ANMB produced clearly better separability than the well established EVI and RENDVI VIs

8.5 Conclusions

The objective of this study was to determine if defoliated tree crowns can be detected using vegetation indices. Widely used and tested NDVI proved to be the best VI in detection of defoliation. Separability was calculated using standard deviation. The number of tested pixels in each class was rather small for accurate statistical analysis. The results show that some of the VIs can detect defoliated tree areas rather reliably. Results also indicated that reduced chlorophyll content and increased anthocyanoid pigment levels are good indicators of defoliation.

9. The future of forest health related remote sensing

High spatial resolution remote sensing for forestry applications has reached an almost mature phase with wide range of applications available. However, numerous opportunities and challenges remain. The robustness of the data processing methods is one of the issues to be considered. Processing methods currently in use often need extensive calibration and adjustment for each new imaged forest area. Processing methods should be able to handle different types of forest areas in routine fashion despite the variation of climate zone, soil type or forest structure. A lot of research has still to be done to fully utilize the potential of high spatial and spectral resolution data.

In the forest health assessment, most studies are characterized by a limited geographic extent concentrating on test sites were the complexity of forest environment is low. The methods are mostly empirical and require local calibration. Expanding forest health studies over wide geographic regions is a challenge because the added complexity of varying vegetation types can hide the relatively weak signal feature associated with forest stress. One possible solution to overcome this problem is to identify forest health change using data obtained at different times as it may be easier to identify stress from spectral change, rather than from the spectral properties of stress itself (Brandberg & Warner, 2006).

It would be highly desirable to be able to use satellite data, instead of airborne data for remote sensing of individual trees. Airborne remote sensing campaigns are very costly limiting the accessibility of data. Airborne hyperspectral instruments offer superior signal quality and spatial resolution, however, wide coverage multi-temporal forest health monitoring using airborne data is not feasible. Satellite data has the advantage of a relatively uniform illumination and view angle over large regions, thus minimizing problems associated with combining data from individual flight lines. Satellite-borne high spatial resolution hyperspectral data is not available at the moment, but can be anticipated in the future as the development of space technology continues. Spatial resolution of the hyperspectral imager currently in space (EO1 Hyperion), at 30 m, is too coarse for studying individual trees. OrbView-4 which failed to reach orbit after launch in 2001, would have offered 250 band hyperspectral data at 8 m spatial resolution. Specifications of Orbview-4 provide some kind of reference on what can be expected from the capability of future sensors (Castro-Esau & Kalashka, 2008).

Data fusion where several data sources are used together has the potential for revolutionary impact on forest health measurement. For example, with LiDAR data it is possible to directly measure the structural attributes of trees. The data fusion of high spectral resolution LiDAR and high spectral resolution hyperspectral data can raise forest health studies on a new level: precise information on foliar chemistry pin pointed to a single tree. Data fusion of LiDAR and hyperspectral data has already showed promising results (Solberg et al., 2005).

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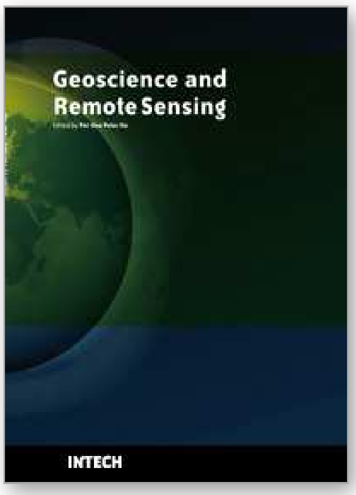

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Remote Sensing is collecting and interpreting information on targets without being in physical contact with the objects. Aircraft, satellites ...etc are the major platforms for remote sensing observations. Unlike electrical, magnetic and gravity surveys that measure force fields, remote sensing technology is commonly referred to methods that employ electromagnetic energy as radio waves, light and heat as the means of detecting and measuring target characteristics. Geoscience is a study of nature world from the core of the earth, to the depths of oceans and to the outer space. This branch of study can help mitigate volcanic eruptions, floods, landslides ... etc terrible human life disaster and help develop ground water, mineral ores, fossil fuels and construction materials. Also, it studies physical, chemical reactions to understand the distribution of the nature resources. Therefore, the geoscience encompass earth, atmospheric, oceanography, pedology, petrology, mineralogy, hydrology and geology. This book covers latest and futuristic developments in remote sensing novel theory and applications by numerous scholars, researchers and experts. It is organized into 26 excellent chapters which include optical and infrared modeling, microwave scattering propagation, forests and vegetation, soils, ocean temperature, geographic information , object classification, data mining, image processing, passive optical sensor, multispectral and hyperspectral sensing, lidar, radiometer instruments, calibration, active microwave and SAR processing. Last but not the least, this book presented chapters that highlight frontier works in remote sensing information processing. I am very pleased to have leaders in the field to prepare and contribute their most current research and development work. Although no attempt is made to cover every topic in remote sensing and geoscience, these entire 26 remote sensing technology chapters shall give readers a good insight. All topics listed are equal important and significant.

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