Remote sensing of spruce budworm defoliation using EO-1 Hyperion hyperspectral data: an example in Quebec, Canada

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Abstract. Each year, the spruce budworm (SBW) causes severe, widespread damage to spruces and fir in east coast Canada. Early estimation of the defoliation can provide crucial support to mitigate the socio-economic impact on vulnerable forests. Remote sensing techniques are suitable to investigate the affected regions that usually consist of large and inaccessible forestry areas. Using satellite images, surface reflectance values at two or more wavelengths are combined to generate vegetation indices (VIs), revealing a relative abundance of features of interest. Forest health analysis based on VIs is considered as one of the primary information sources for monitoring vegetation conditions. Especially the spectral resolution of Hyperion hyperspectral satellite imagery used in this study allows for a detailed examination of the red to near-infrared portion of the spectrum to identify areas of stressed vegetation. Several narrow-band vegetation indices are used to indicate the overall amount and quality of photosynthetic material and moisture content in vegetation. By integrating the information from VIs that focus on different aspects of overall health and vigour in forested areas, the study aims at detecting defoliated condition in a forested region in the Province of Quebec, Canada. In June and August of 2014 two Hyperion images were acquired by NASA’s EO-1 satellite for this study. Changes in vegetation health and vigour are observed and quantitatively compared using the multi-temporal remote sensing images. The experimental results suggest that the VI-based forest health analysis is effective in estimating SBW defoliation in the study area.

1. Introduction

The spruce budworm (SBW) is arguably the most damaging insect of North America’s forest. In Canada, it occurs throughout most of the range of spruce and balsam fir [1]. In the Province of Quebec, Canada, the government has conducted surveys and released annual reports on SBW defoliation. They concluded that, in 2014, SBW defoliation continued to rise significantly in the Province. In 2014, the affected areas totalled 4,275,065 hectares compared to 3,200,348 hectares in 2013 [2]. Conventional strategies to eliminate or slow the spread of these destructive pests, such as pesticide spraying, can be costly, time consuming and less effective, especially when an accurate estimation of defoliated regions is not available. The sizes and locations of defoliated regions make field investigation difficult. Aerial survey is considered an option to provide relative accurate maps, as investigators have a relatively close look at the trees at suitable flying altitudes. This kind of operation has been conducted in Quebec, directed by the Ministry of Forests, Fauna and Parks (MFFP), Government of Quebec, and has resulted in defoliation maps across the province. However, the operation calls for considerable involvement of manpower; it is also time-consuming. Alternatively,
remote sensing techniques, especially the utilization of satellite images, provide wide area coverage, high temporal repeatability and high spatial resolution, making them suitable for such investigations. Previous studies have derived vegetation indices from remote sensing data and applied them to estimate and map field forest ecosystem variables or properties [3], [4]. Healthy vegetation will absorb most of the visible light and reflects a large portion of the near-infrared light. The defoliated forest, due to unhealthy or sparse vegetation, reflects more visible light and less near-infrared light. The widely applied broad spectral band indices are thus usually constructed with near-infrared (NIR) and red (R) bands and use average spectral information over broad bandwidths [5]. However, the broad-band VIs have limited information content concerning the significant spectral of response at specific and relatively narrow spectral wavelengths. As an alternative, more refined VIs can be constructed through the use of distinct narrow bands from hyperspectral images. Instead of indicating general health or greenness, the narrow-band VIs provide more specific information regarding the overall amount and quality of photosynthetic material and moisture content in vegetation. Thus, they have advantage over broad-band VIs in quantifying different biophysical characteristics of vegetation [3]. It is also expected that the hyperspectral data can be useful in early stress detection, as spectral differences can be identified only from certain wavelengths, while existing remote sensing studies on SBW defoliation use mostly broadband VIs or limited narrow band VIs [4]. However, little evidence has been found while mapping SBW defoliation with the help of hyperspectral VIs [4].

The hyperspectral data from the Hyperion sensor on the Earth Observing-1 Mission (EO-1) satellite is used in this study. NASA provided the Hyperion hyperspectral images free of charge. Despite of their coarse resolution of 30 m, they provide a 10 nm spectral resolution across spectral bands from 0.4 to 2.5 µm [6]. The fine spectral resolution increases the capability to distinguish structures and objects in the image scene [7]. Further, access to multi-temporal images captured by the same hyperspectral sensor allows for assessment of SBW related changes that occur during the time intervals of data acquisition. In this study measurements are carried out by observing the spectral changes on hyperspectral images by means of VIs. Seven VIs derived from the Hyperion images representing different bio-physical properties are used to measure the change during SBW defoliation. Three different VIs are combined to assess the forestry health for estimation of SBW defoliation magnitudes. An aerial survey map provided by MFFP is used as reference.

2. Proposed Method
In order to process acquired image data for SBW defoliation analysis, the method used in this study consists of three major parts: data pre-processing, VI-based change detection, and forest health analysis. The pre-processing of Hyperion data includes the following steps: band selection, abnormal pixels removal, vertical stripe removal [8], smile effect correction [9], atmospheric correction [10], and geometric correction.

Four broad band VIs together with nine narrowband VIs, which are only available from hyperspectral data, were applied for analysis. The VIs used in this study can be divided as broadband and narrowband vegetation indices while the narrowband VIs can be further categorized into three classes. They are summarized in table 1.

The VIs based change detection includes the following steps: construction of individual VIs from multi-temporal images, change detection based on each VI images, synthesis of several VIs to generate forest health map, and change detection based on the health map. The whole process of the proposed method is presented as a flowchart in figure 1.

After suitable pre-processing and alignment of the images, we will be able to monitor the changes of VIs values at the pixel level. This will allow for quantitative analysis on the influence of SBW defoliation on different aspects of forest health. Pixel level change detection will be applied for each VI image derived from two multi-temporal images (figure 1). $\text{VI}_{\text{before}}$ represents the value of a vegetation index at the high point before defoliation, and $\text{VI}_{\text{during}}$ represents the value of the vegetation index at the low point during the defoliation event. In this study, $\text{VI}_{\text{before}}$ was derived from
| Abbreviation | Formula | Name | Category |
|--------------|---------|------|----------|
| SR           | \( \frac{NIR}{RED} \) | Simple Ratio. | Broadband Greenness |
| NDVI         | \( \frac{NIR - RED}{NIR + RED} \) | Normalized Difference Vegetation Index | |
| EVI          | \( 2.5 \times \frac{NIR - RED}{NIR + 6 \times RED - 7.5 \times BLUE + 1} \) | Enhanced Vegetation Index | |
| ARVI         | \( \frac{NIR - [RED - \gamma(BLUE - RED)]}{NIR + [RED - \gamma(BLUE - RED)]} \) | Atmospherically Resistant Vegetation Index | |
| RENDVI       | \( \frac{\rho_{705} - \rho_{705}}{\rho_{705} + \rho_{705}} \) | Red Edge Normalized Difference Vegetation Index | |
| MRESR        | \( \frac{\rho_{705} - \rho_{445}}{\rho_{705} + \rho_{445}} \) | Modified Red Edge Simple Ratio | Narrowband Greenness |
| MRENDVI      | \( \frac{\rho_{705} - \rho_{705} - 2 \times \rho_{445}}{\rho_{705} + \rho_{705} + 2 \times \rho_{445}} \) | Modified Red Edge Normalized Difference Vegetation Index | |
| MSI          | \( \frac{\rho_{599}}{\rho_{819}} \) | Moisture Stress Index | |
| WBI          | \( \frac{\rho_{970}}{\rho_{900}} \) | Water Band Index | Canopy Water Content |
| NDWI         | \( \frac{\rho_{857} - \rho_{1241}}{\rho_{857} + \rho_{1241}} \) | Normalized Difference Water Index | |
| PRI          | \( \frac{\rho_{531} - \rho_{570}}{\rho_{531} + \rho_{570}} \) | Photochemical Reflectance Index | |
| SIPI         | \( \frac{\rho_{800} - \rho_{445}}{\rho_{800} + \rho_{680}} \) | Structure Insensitive Pigment Index | Light Use Efficiency |
| RDRI         | \( \frac{\sum_{i=500}^{600} R_i}{\sum_{i=500}^{599} R_i} \) | Red Green Ratio Index | |
the June image whereas $V_d$ was derived from the August image. In order to make the change detection of other VIs more efficient and accurate, the Normalized Difference Vegetation Index (NDVI) values derived from both images were used as masks. To be specific, an NDVI value of 2 was used to delineate only vegetation pixels on which change detections will be conducted. The change rate of each VI was also summarized at a regional level. Using the aerial survey map as a reference, the change rates at each defoliation magnitude level, i.e., light, moderate and severe, were averaged from pixels within each region. VIs with high change rates are considered sensitive and relevant to spruce budworm defoliation and will be selected for further process.

Furthermore, three selected VIs were synthesized to analyze forest health in order to estimate the spread of defoliation. This was done using the “Forest Health Tool” provided by ENVI software (ITT Visual Information Systems, 2006). A spatial map was generated to show the overall health and vigour of a forested region. Forest health mapping was useful for detecting pest and blight conditions in a forest, and it was useful in assessing areas of timber harvest. A forest exhibiting low stress conditions was usually made up of healthy vegetation, whereas a forest under high stress conditions shows signs of dry or dying plant material, very dense or sparse canopy, and inefficient light use. The spatial maps generated for two multi-temporal images will then be aligned with aerial survey map for comparison.

3. Experimental Results and Discussion

3.1 Study site and data
Several EO-1 campaigns were established during June, July and August, 2014 on a selected site centred at 48°14'32.69"S / 67°25'45.77"W in the southern part of the Bas-Saint-Laurent region of Quebec. A set of two EO-1 Hyperion images was acquired from NASA in June and August of 2014. They were targeted to cover the above mentioned study area. After pre-processing, 162 bands were selected bands from 242 bands, with 10 nm spectral resolution across the visible near-infrared (VNIR) and shortwave-infrared regions.

3.2 Results of the proposed technique
The VI-based change detection results are based on the four VI images derived from June and August images respectively. The pixel-level changes are calculated for each VI and expressed as percentages. The change rates for different defoliation magnitude regions are summarized in table 2.

We use the “Agricultural Stress Vegetation Analysis” tool provided by ENVI [11] to synthesize the VIs and generate a spatial map showing the distribution of the forest stress in the study site. For calculation, the tool chooses the band nearest 650 nm for the Red term and the band nearest 860 nm for the NIR term. In addition to the hyperspectral image, the tool takes in three VIs from different
Table 2. Change rate detected from vegetation indices of different defoliation regions

| VI        | Light | Moderate | Severe |
|-----------|-------|----------|--------|
| SR        | 25%   | 23%      | 24%    |
| NDVI      | 4.4%  | 4.1%     | 3.7%   |
| EVI       | 19%   | 18%      | 19%    |
| ARVI      | 23%   | 20%      | 17%    |
| RENDVI    | 5.6%  | 6.3%     | 5.7%   |
| MRESR     | 16%   | 16%      | 17%    |
| MRENDVI   | 12%   | 12%      | 11%    |
| MSI       | 13%   | 14%      | 13%    |
| WBI       | 8.8%  | 8.2%     | 7.6%   |
| NDWI      | 9.3%  | 7.5%     | 13%    |
| PRI       | 6.0%  | 4.8%     | 3.2%   |
| SIPI      | 8.8%  | 8.0%     | 7.2%   |
| RDRI      | 43%   | 41%      | 43%    |

categories as input, namely Greenness Index, Canopy Water or Nitrogen Index, and Light Use Efficiency or Leaf Pigment Index. In our case, SR, NDWI and RDRI are used for these three inputs. The VIs from the June and August Hyperion images are used to implement the stress analysis. The

Figure 2. Stress maps generated for the June (a) and August (b) images of the study area; both image map show different levels of stress, as per scale shown in (c).
Figure 3. Most stressed regions extracted from stress maps and aligned with aerial survey maps as reference shown as new spatial map for the June (a) and the August (b) images. The stress levels range from light blue, dark blue to black (from level 7, 8 to 9, with 9 being the highest).

results from both images are aligned with the aerial survey map for comparison. The Agricultural Stress Tool divides the input scene into nine classes, from lowest stress to highest stress. The resultant spatial maps generated for June and August image are shown in figure 2.

Most stress-related pixels range from light blue, dark blue to black. In order to better illustrate their distribution and compare the two maps, we extract only these three levels and aligned with the aerial survey map. The new maps are shown in figure 3. It is noticeable that, from June to August, the severe defoliated (red) region and light defoliated (green) region, transferred more light blue blocks to black or dark blue colour, suggesting that the stress level is increasing. In the moderate defoliated region (yellow), it appears that less highly stressed pixels are identified predominantly in the August image than in the June image. However, it also appears that the stressed regions have expanded, as some isolated stressed pixels in the June image tend to form clusters in August. As a result, the forest stress map generated from VIs generally matched the aerial survey result for defoliation.

4. Conclusion
In this study, we investigate the potential of using remote sensing and vegetation indices derived from Hyperion hyperspectral images to analyze the defoliation caused by spruce budworm for a study area in Quebec, Canada. The VI based change detection is applied to quantify the change of different VIs between Hyperion images acquired in June and August of 2014.

We investigate the VIs from four different categories with the aim to find the VIs with most significant changes in response to the increasing defoliation from June to August. The change rates of different VIs generated from these two images are calculated, and the VIs with high change rates are then considered as more relevant to the SBW defoliation. Finally, maps of forest stress are generated for two images using the selected VIs. The result suggests the forest stress distribution generated using remotely sensed hyperspectral images and VIs have potential for estimating SBW defoliation, in terms of its spread and severity.
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