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Remote monitoring of forest insect defoliation. A review

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Abstract

Aim of study: This paper reviews the global research during the last 6 years (2007-2012) on the state, trends and potential of remote sensing for detecting, mapping and monitoring forest defoliation caused by insects.

Area of study: The review covers research carried out within different countries in Europe and America.

Main results: A nation or region wide monitoring system should be scaled in two levels, one using time-series with moderate to coarse resolutions, and the other with fine or high resolution. Thus, MODIS data is increasingly used for early warning detection, whereas Landsat data is predominant in defoliation damage research. Furthermore, ALS data currently stands as the more promising option for operative detection of defoliation.

Vegetation indices based on infrared-medium/near-infrared ratios and on moisture content indicators are of great potential for mapping insect pest defoliation, although NDVI is the most widely used and tested.

Research highlights: Among most promising methods for insect defoliation monitoring are Spectral Mixture Analysis, best suited for detection due to its sub-pixel recognition enhancing multispectral data, and use of logistic models as function of vegetation index change between two dates, recommended for predicting defoliation.

Key words: vegetation damage; pest outbreak; spectral change detection.

Remote Monitoring of Forest pests

A major concern in forest management is the control of pests threatening forest survival. Pest management usually relies on an appropriate detection, allowing for a suitable estimation of the infestation episode, but this is not an easy task, as visual detection of an infested stand is not straightforward in many cases. This situation is particularly complicated in large and inaccessible forests, where on site monitoring would be too unaffordable. RS technology has been called to address this issue, mainly due to two reasons: first, remote sensors have spectral abilities for checking the health of forest vegetation beyond our own eyes, in a wider spectral range. And second, they have an aerial or satellite vision that allows assessing extensive forest areas at different scales and constant time periods.

Scale is a fundamental issue if we are studying RS application in forest health. Detecting, mapping, and monitoring forest damage must consider a hierarchy of data sources ranging from coarse to finer-scale (Wulder *et al*., 2006; Coops *et al*., 2009). The wide range of spatial resolutions in the currently available sensors enables, potentially, the implementation of multi-scale approaches. These are suitable for detection and discrimination of all space objects composing a complex nature scene, like the dynamics of forest disturbances (Marceau and Hay, 1999).

Each Earth's cover material irradiated by solar energy absorbs, transmits and reflects back to the atmosphere, as a result of its intrinsic spectral pro-

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Abbreviations used: ALS (Airborne Laser Scanning); ASTER (Spaceborne Thermal Emission and Reflection Radiometer); ETM+ (Enhanced Thematic Mapper Plus, Landsat 7 satellite); LAI (Leaf Area Index); LiDAR (Light Detection and Ranging); MODIS (Moderate Resolution Imaging Spectroradiometer); NDVI (Normalized Difference Vegetation Index); TM (Thematic Mapper, Landsat 5 satellite); RS (Remote Sensing); SPOT (Satellite Probatoire d´Observation de la Terre); SPOT-VEG (Satellite Probatoire d´Observation de la Terre-Vegetation); VI / VIs (Vegetation Index / Vegetation Indices).

perties (Hunt, 1977), the different solar radiation wavelengths in a way that generates a particular signal pattern of reflectance. This specific signal, known as a spectral signature, allows to detect, identify and classify different forest covers suffering crown damage by insects, diseases or other factors (Ciesla *et al*., 2008).

Tree crown is the main forest component to be observed for estimating health condition by assessing two particularly important variables, foliage discoloration and defoliation. These are related to stress factors and are considered reliable parameters to assess forest damage (Innes, 1993). Damaging factors can be abiotic, as pollution, winds, hails and droughts, or biotic when pathogens (diseases) and insect pests are involved. Furthermore, forest damage such as defoliation can be the result of a complex combination of the two mentioned kind of factors causing decline and dieback, often followed by tree mortality. So, there are several agents causing loss and colour alteration of foliage, though it is assumed that insects are the most common cause of defoliation (Ciesla *et al*., 2008). Due to its multiple causes, detecting and mapping forest defoliation by insects is still a challenge.

In many forested ecosystems, insect defoliation has been the major cause of disturbance leading to important timber and carbon losses (Fraser and Latifovic, 2005). Defoliators are in many occasions the main factor responsible for the annual losses in forest yield (Fleming and Volney, 1995), and frequently increase susceptibility to secondary host infection, driving direct changes in stand dynamics (Wulder and Franklin, 2007).

Considering the ongoing climate warming, several empirical studies have forecasted for the not-too-distant future dramatic changes in the forest landscapes and in the insect populations inhabiting them, including expansion of insect defoliators (Williams and Liebhold, 1995; Volney and Fleming 2000; Battisti *et al*., 2005; Kharuk *et al*., 2009; Jepsen *et al*., 2008, 2009; Karjalainen *et al*., 2010; Seixas *et al*., 2011; Paritsis *et al*., 2011). Furthermore, the known difficulty for trees to quickly adapt to environmental changes adds a special vulnerability to any forest ecosystem facing climatic change, rending it more susceptible to pest attacks (García-López and Allué-Camacho, 2010; Pajares, 2009).

Nevertheless, the major current pest related threat is not global warming but global trade (MacLeod *et al*., 2002; Vanhanen *et al*., 2007). The greater volume, speed and frequency of trade eases dispersal of organisms from one region to another, making much more likely for potential exotic invasive pests to be introduced undetected in new ecosystems. This situation is posing a high risk to natural forests and forest plantations in the last decades, despite considerable international efforts in trade regulation and border surveillance. Thus, these present and future pest threats to forest are becoming practically too complex and "Hence, the most promising strategy will rely on a judicious interdisciplinary mix of available research approaches" (Fleming and Volney, 1995), one of which should be the RS approach.

Remote Sensing has had difficulties in the past to be successfully applied in monitoring forest health. In 1999, Peterson *et al*., evaluating the feasibility of RS on forest health monitoring, concluded that satellite RS was oversold and had often been of little utility. It was perceived insufficient in their technological capabilities, too expensive to acquire and interpret satellite data, compared to aerial detection surveys, and its scale was seen inappropriate for answering most operational forest management questions. However, eight of the nine current major satellite sensors used in forest health research have been launched since then (Wang L. *et al*., 2010) and the RS has continued to develop new technologies until today.

To put this technological evolution within a context, Melesse *et al*. (2007) have differentiated three different periods: The "Earth Observing System Era", comprising the launching of the MODIS coupled with ASTER and the Landsat 7 (ETM+) satellites in 1999, and the second MODIS in 2002. In the second, "New Millennium Era", the next generation of satellites and sensors, like the Earth Observing-1 carrying the first spaceborne hyperspectral sensor and the Advanced Land Imager (ALI), were launched. Finally, the "Private Industry Era", started when the first very high resolution (<10 meter) sensors, like IKONOS and QuickBird satellites, were launched in 1999 and 2001 respectively. It is also to remark the introduction of micro satellites in several countries, all of them designed and launched by the private industry, as the Spanish commercial satellite DEIMOS-1, launched in 2009, and the next DEIMOS-2 with sub-meter resolution to be launched in 2013 (Casal and Freire, 2012).

Therefore, in less than fifteen years since Peterson *et al.* (1999) remarks, the availability of remote technology has enormously increased and the traditionally high costs have fallen to more affordable prices, particularly for coarse and medium resolution

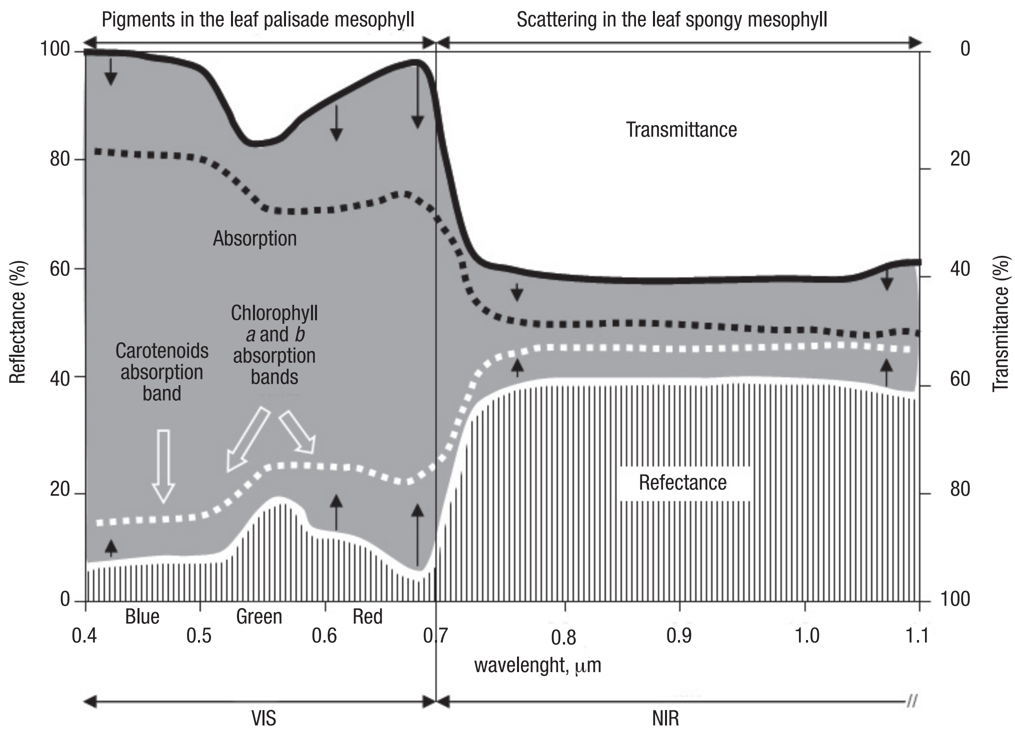

Figure 1. Change in canopy absorption, reflectance and transmittance. A healthy leaf absorbs, reflects and transmits the incident sunlight in a typical spectral signal pattern (white line). Chlorophyll pigments in the leaf palisade mesophyll produce a reflectance peak in the visible (VIS) portion, whereas the spongy mesophyll layer strongly reflects in the near-infrared (NIR) portion of the sunlight spectrum. An unhealthy leaf will show an increase and flattening of the reflectance signal (dotted line) due to the leaf stress response. Reflectance and transmittance curves are almost mirror images of each other in the VIS and NIR portion of the electromagnetic spectrum (modified after Jensen, 2005).

data (Wang *et al*., 2010). Nowadays, RS industry is aiming to reduce the cost of their products and this may be the general trend during the next years for medium spatial resolution imagery (with Landsat-8 and Sentinel-2, for example as free cases) but expectations for high spatial resolution are more reduced.

This paper is aimed to provide a comprehensive review of the research published during the last 6 years (2007-2012) on the sate, trends and potential of airborne and spaceborne RS applications for detecting, mapping and monitoring forest insect defoliation.

The next section shows some main RS concepts to better comprehend the physical interactions of light on vegetation that are applied in RS defoliation studies.

Remote sensing indicators of defoliation

Plotting the wavelengths of the electromagnetic spectrum versus the corresponding reflectance percentage from healthy and green vegetation results in a well known pattern of spectral signature (white line in Fig. 1). This pattern shows highest absorption and lowest reflectance in the visible portion (VIS) of the continuum sunlight spectrum, followed by an opposite behaviour in the nearest-infrared portion (NIR), where highest reflectance of vegetation forms a plateau.

Inside the VIS interval and between chlorophyll a and b absorption bands (0.43 μm and 0.66 μm respectively), a reflectance peak occurs in the middle of the green band (0.54 μm) that is the responsible for the green colour of healthy foliage. Moreover, the strong light absorption in the VIS interval primarily depends on the pigments (chlorophyll a and b, carotene, xanthophyll, anthocyanin, etc.) present in the leaf palisade mesophyll (Fig 1).

In healthy plant leaves, the abundant chlorophyll pigments have a major role in the absorption of the blue and red wavelengths and in the photosynthesis rate across the Photosynthetically Active Radiation (PAR) region. Therefore, chlorophyll content has

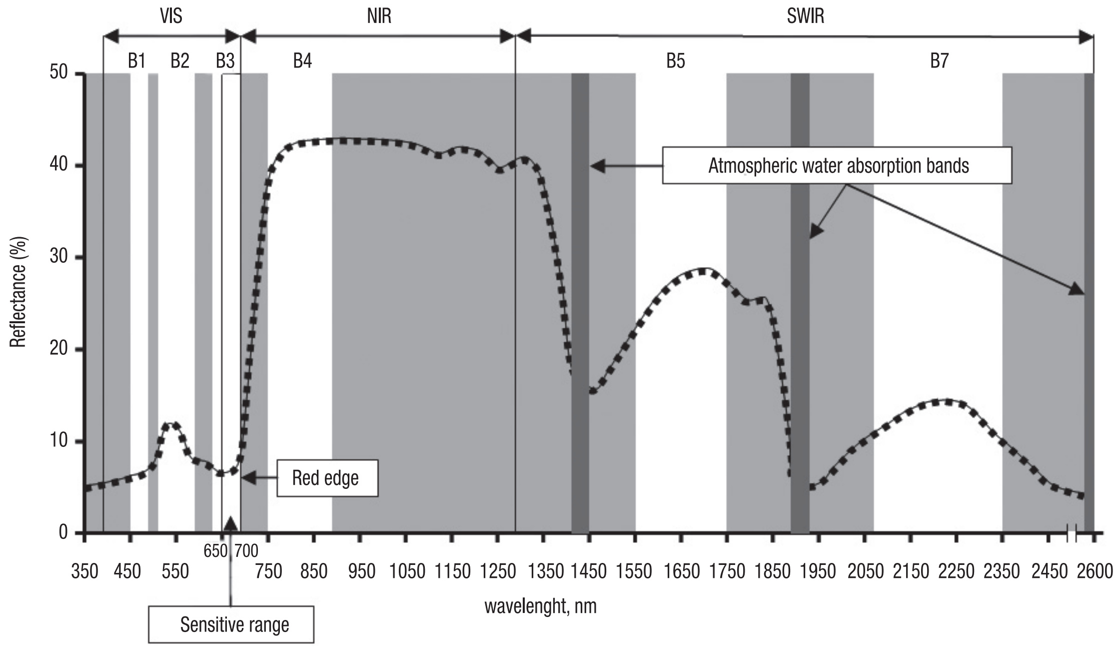

Figure 2. Differences between multispectral and hyperspectral data. The typical spectral reflectance pattern of a healthy green leaf is showed as a continuous black line across the 350-2600 nm wavelength interval. Black dots along the line represent the contiguous large number of narrow, less than 2 nm, wavelength bands of a hypothetical hyperspectral sensor. The six white strips depicted on the reflectance plot represent six of the seven non-contiguous bands (B1-B5, B7) of the multispectral sensor Landsat ETM+ The sensitive range and the red edge of the red band (600-700 nm) are also shown (modified after Jensen, 2005 and Mutanga *et al.*, 2009).

become an important biophysical variable to be assessed. The LAI is defined as the amount of chlorophyll by ground area in the forest canopy. As a proxy for crown density, LAI variation is significant of changes occurring in forest health (Solberg *et al.*, 2007). Thus, a significant loss of foliage is expected to be shown by the corresponding decrease of LAI. It is said that a plant is under stress when there is a change in the health condition of the plant foliage. Under such condition, plants increase their reflectance in the green and red portions as leaves become yellowish or chlorotic. This fact has lead to suggest that the VIS portion is the most consistent leaf reflectance indicator of plant stress (Carter, 1993; Jensen, 2005). On the other hand, NIR reflectance increase appears only consistent with extreme stress levels, like significant damage by dehydration (dotted line in Fig. 1).

Moreover, the stress induced increase of reflectance in the VIS interval may first be noted near 0.7 µm wavelength, the red edge, shifting then towards shorter wavelengths in the so called "blue shift of the red edge" (Jensen, 2005). Thus, the 0.65-0.7 µm portion of the red band within the VIS is a sensitive range (Fig. 2) to detect any initial increase of reflectance due to vegetation stress, suitable for early forest damage detection. Hence, the ability to analyse such narrow sensitive range may improve the capacity to detect vegetation stress, scaling from plant leaves to densely vegetated canopies (Carter, 1993; Carter *et al.*, 1996; Jensen, 2005). Actually, this may be possible using high spectral resolution imaging or hyperspectral data. This data has large number of narrow width bands (less than 2 nm) and contiguous coverage (Mutanga *et al.*, 2009), whereas multispectral data has commonly few bands with non-contiguous coverage (Fig. 2). Hyperspectral data may also measure chlorophyll absorption and reflectance in the PAR to assess vegetation damage such as insect defoliation (Jensen, 2005).

Healthy vegetation reflects 40-60%, transmits 40-60% through the leaf onto underlying leaves, and absorbs the 5-10% of the incident solar energy in the NIR interval. Reasons for the strong reflectance of NIR energy by healthy plant canopies are first, the scattering of the wall-air interfaces in the leaf spongy mesophyll, and second, the leaf additive reflectance occurring when the remaining energy is transmitted through the leaf and can be reflected once again by the leaves below it

(Jensen, 2005). Therefore, is known that changes in the NIR spectral properties may be useful in detecting loss of foliage by senescence or stress.

In the shortwave infrared interval (SWIR) reflectance of healthy vegetation presents two peaks, at about 1.6 μm and 2.2 μm respectively, between the two atmospheric water absorption bands crossing the middle-infrared interval (Fig. 2). Water is a good absorbent of the middle-infrared energy, thus, this SWIR band reflects leaf moisture content, turgidity, which is the amount of plant water occupying the intercellular air spaces. Moisture content of plant canopies is correlated with transpiration rates. When this content decreases, the middle-infrared energy becomes scattered and its reflectance increases (Jensen, 2005). Thus, this band can be useful in assessing water stress.

Chlorophyll content, LAI, absorbed photosynthetically active radiation (APAR), moisture content, evapotranspiration, etc., are then fundamental biophysical variables to be extracted by means of remote sensing, and to be modelled for measuring changes in vegetation condition. Several VIs indicating relative abundance and activity of green vegetation have been developed for this purpose. The VIs are single dimensionless radiometric measures, based on algorithms of several spectral values (Jensen, 2007; Wang *et al*., 2010), directly or indirectly linked to the behaviour of a biophysical variable of interest. For example, defoliation, a general plant response to stress, is intimately related to LAI (Solberg *et al*., 2007), or the APAR can be linked to chlorophyll content in the foliage. There are many VIs with redundant functions and some that provide unique biophysical information.

Current contributions to remote monitoring of insect defoliation

There are many studies where RS techniques have been applied to detect, map and monitor forest insect damage in the past decades. However, current availability and development of RS have notably increased research of potential applications of RS to the complex challenge of monitoring forest damages caused by pests, particularly by insect defoliators, and even more in the context of climate change. This section reviews the main outcomes in remote monitoring of forest insect defoliation achieved during the past six years. Aimed to facilitate a comprehensive overview, research topics covered by these studies are grouped in four main subsections based in Zhang *et al.* (2010) classification (Table 1).

Remote detection of forest defoliation

Remote detection of insect defoliation is thought to be at initial stages (Zhang *et al*., 2010) and the processes involved in the spectral response of forest pest damaged vegetation are still far away to be fully understood (Wang L. *et al*., 2010). In this sense, as pointed out by Jepsen *et al*. (2009), operational RS "has yet to find its way".

Remote defoliation monitoring is asked for an early and adequate detection of outbreaks. That means a continuous RS system able to detect ephemeral forest defoliation episodes across large regions. Early warning is crucial for a sound forest management, more even so for forest health. Developing early warning systems is thus a much desirable goal (Lange and Solberg, 2008), as they are key tools for effective pest control and outbreak suppression (Kharuk *et al*., 2009). For such a system, it is necessary the aggregation of temporal composite images, allowing for a wall to wall cloud-free observational coverage (Prados *et al*., 2006), and the improvement of the signal to noise ratio (Cohen *et al*., 2010) (e. g. the increasing application of time-series and algorithms used with them, such as Landsat time-series (LTS) or MODIS time-series products.

The scale of study is another important aspect to bear in mind if we are to keep remote monitoring cost effective. Two operational scales should be considered: a national or regional scale at an early warning level, with coarse resolution satellite-based monitoring for identifying locations of disturbances where they are suspected, and a second local, tactical scale, with finer resolution for assessing the validity and nature of warnings coming from first level, using finer satellites or even overflights and on-the-ground monitoring (*e.g.* sketch maps produced by the US Forest Service Aerial Detection Surveys (ADS) overflight program for forest disturbances; Spruce *et al*., 2011). Sketch mapping is to date the most commonly used technique for detection and assessment of forest damage caused by biotic factors (Ciesla *et al.,* 2008), and has been an integral part of forest health protection programs in Canada and the United States since the end of World War II (Ciesla, 2000). Unfortunately, information from

Table 1. Recent (2007-2012) remote monitoring studies of insect defoliation

Study area	Insect defoliator/Host	Remote sensor[1] t-s = time-series	Topic[2], Method[3]	Prepro[4], class/Con[5]	Analysis and Techniques[6]	Reference
Russia	*D. sibericus/Abies siberica*	SPOT-VEG	D, i	Ac, 2 class	Supervised & threshold classification, correlation	Kharuk *et al.,* 2009
Finland	*D. pini/Pinus sylvestris*	TM, DAP	B, i	Ac, 2class	Supervised & unsupervised, regression & mixed model	Ilvesniemi, 2009
Finland	*D. pini/Pinus sylvestris*	SAR t-s	B, i	—, 2class/Con	3- Nearest neighbour classification	Karjalainen *et al.,* 2010
Finland	*D. pini/Pinus sylvestris*	ALS-DAP	B, i	—, 2 class	Tree feature extraction, regression tree classifiers	Kantola *et al.,* 2010
Finland	*D. pini/Pinus sylvestris*	ALS	B, m	—, 2class/Con	Area based & tree feature extraction, regression tree classifier	Kantola *et al.,* 2011
Norway	*N. sertifer/Pinus sylvestris*	SPOT, MODIS t-s	A, m	Nc, Con	LAI regression analysis, correlation	Solberg *et al.,* 2007
Norway	*N. sertifer/Pinus sylvestris*	ALS	C, o	Ac, —	LAI regression analysis, tree segmentation, PC, correlation	Lange, Solberg, 2008
Norway	*N. sertifer/Pinus sylvestris*	ALS	A, m	— , 2 class/Con	LAI regression analysis, regression, correlation	Solberg, 2010
Norway	*N. sertifer/Pinus sylvestris*	MODIS t-s	B, m	Ac, Con	LAI regression analysis, VI profiles, regressions	Eklundh *et al.,* 2009
Norway	*E. autumnata/B pubescens*	TM	D, o	Ac, Con	Supervised, image differencing, tree-ring detection, PC	Babst *et al.,* 2010
Sweden	*E. autumnata/B pubescens*	MODIS t-s	D, v	Ac, 2 class	Correlation, logistic regression	Jepsen *et al.,* 2009
Spain	*G. scutellatus/E.globulus*	TM	A, m	Nm, 2 class	Discriminant analysis, stand density	Alvarez *et al.,* 2007
Spain	*T. pityocampa/Pinus Pinea*	AHS	C, s	Ac, 2 class	Regression & correlation, threshold segmentation	Cabello *et al.,* 2011
Canada	*C. fumiferana/Populus.spp.*	TM t-s	A, d	Nc, 2 class	Image differencing, threshold segmentation	Thomas *et al.,* 2007
USA	*D. elongate/Tamarix spp.*	ASTER, MODIS t-s	A, v	Ac, 2 class	ET estimation function of VI, ET-VI profiles, histogram threshold	Dennison *et al.,* 2009
USA	*L. dispar/Oaks spp.*	MODIS	C, v	Ac, Con	Regressions and statistic comparison	De Beurs,Townsend, 2008
USA	*L. dispar/Oaks spp.*	MODIS t-s	A, i	Ac, Con	Unsupervised & threshold classification, temporal processing	Spruce *et al.,* 2011
USA	*L. dispar/Oaks spp.*	TM	B, m	Ac, Con	Model regression as change in VI, comparison of VI	Townsend *et al.,* 2012
Argentine	*O. amphimone/N. spp.*	MSS,TM, ETM+	D, m	Nm, Con	Supervised classification, overlay analysis-GIS, model regression	Paritsis *et al.,* 2011
Australia	*Several/E. globulus*	TM, Hyperion	A, o	Ac, —	Statistic comparison of spectral mixture analysis methods	Somers *et al.,* 2010
China	*Pine moths/Larix spp.*	TM,ETM+, MODIS	A, m	Ac, 2 class	Forest physical model & NN based in decision rules & fixed VI	Wang L. *et al.,* 2010

[1] Active: ALS = airborne laser scanner, SAR = synthetic aperture radar. Passive: Multispectral = Landsat (MSS, TM, ETM+), MODIS, ASTER, SPOT, DAP = digital aerial photography, SPOT–VEG and Hyperspectral = AHS (Airborne Hyperspectral Scanner), Hyperion. [2] A. Remote detection of forest defoliation; B. Classification of damage degree; C. Research on forest vegetation index; D. Tempo-spatial distributions and prediction of forest pests (based Zhang *et al.,* 2010). [3] (i) Image classification method; (v) Different types of vegetation index and ratio method; (d) Difference method; (o) Other image processing method; (s) Spectrum analysis technology; (m) Mathematical statistical methods and GIS technology (based Zhang *et al.,* 2010). [4] Pre-processing: Ac = atmospheric corrected; Nm = atmospheric correction not mentioned; Nc = mention not doing atmospheric correction. [5] Defoliation intensity as a discrete class data (# class) or continuous data (Con). — Not data or not needed. [6] ET = evapotranspiration; GIS = Geographic Information System; LAI = Leaf Area Index; NN = Neural Network; PC = principal component; VI = vegetation Index.

sketch maps is subjective and is extracted primarily through manual processes, so it is not copping with the increasing need for a more detailed and frequent information for sustainable forest management.

Developing a fully operational system for multi-scale RS monitoring of insect damage will require a combination of data from different sources. Whereas coarse-resolution time-series will enable low-cost detection and mapping of large areas, high resolution data and field surveys will be necessary for pinpointing the cause and exact location of damage (Eklundh *et al*. 2009). In other words, fine scale sources, such as ALS (where area mapping relies on a laser beam, mostly pulsed, emitted at fixed time intervals and attached to an airborne scanning mechanism), hyperspectral and hyperspatial data, coupled with reference data from ground-based assessments and ancillary information, may improve accuracy and become an effective means to monitor forest pests, reducing the interference factors unrelated to defoliation (Zhang *et al*., 2010). However, its must be bare in mind that forest extension limits the use of these sensors. For example the use of MODIS requires large continuous forests (as in the Scandinavian forests), as noted Eklundh *et al.* (2009) and Wang *et al.* (2010). In the case of fragmented forests, as Mediterranean forests, moderate or coarse resolution sensors are difficult to work with.

Classification of damage degree

In 1989, Ciesla *et al*. pointed that whereas defoliated areas could be identified, the intensity of defoliation was not yet reliably classified. The inherent complexity

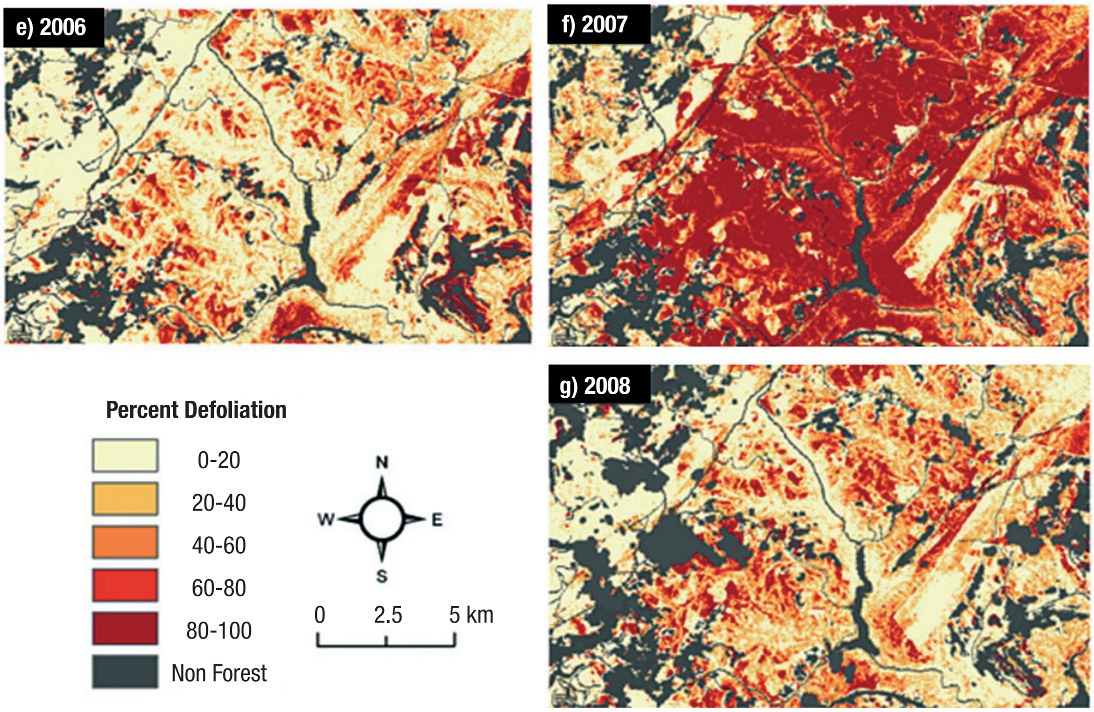

Figure 3. Damage mapping of an oak-forested area affected by a *Lymantria dispar* outbreak during 2006-2008 in the central Appalachian ecoregion of the USA. Severity of defoliation damage has been successfully classified into five degrees. Reprinted from Remote Sensing of Environment, Vol. 119, Townsend, Philip A., Singh, Aditya, Foster, Jane R., Rehberg, Nathan J., Kingdon, Clayton C., Eshleman, Keith N., Seagle, Steven W., A general Landsat model to predict canopy defoliation in broadleaf deciduous forests, Pages 255-265, Copyright 2012, with permission from Elsevier.

of this issue has long challenged research. The difficulties for classifying damage severity using traditional methods may be underlined by the fact that less than half of the studies in this review were able to map defoliation above two severity classes in a continuous manner (see Table 1), and in two of these significant accuracy was attained only for two classes (Ilvesniemi 2009; Kantola *et al*., 2010). Nevertheless, accuracy of 80% or above and Kappa values ≥ 0.6 were achieved in one third of the cases using a dichotomous classification.

One of the most outstanding studies assessing damage severity and detecting location of hazards is the recent work by Townsend *et al*. (2012) in which defoliation severity was recorded as a five continuous variables (Fig. 3). They used Landsat data to predict defoliation severity caused by *Lymantria dispar* in deciduous forests, applying a straightforward and robust logistic model as a function of the change in the Normalized Difference Infrared Index (NDII) (mean absolute error of 10.8% and $r^2 = 0.802$).

Moreover, the work by Eklundh *et al*. (2009) also deserves to be highlighted. These authors successfully assessed defoliation by *Neodiprion sertifer* in pine forests using MODIS time-series data with 71-82% accuracy, testing it against the change in LAI estimated from ALS data. However, even if they outlined the obvious potential of data from MODIS time-series for early detection of forest insect defoliation, they also warned that MODIS approach should not be recommended for estimating defoliation intensity.

Another successful study was carried out by Solberg (2010) for detecting pine forest defoliated by *N. sertifer*, using penetration variables derived from high density ALS data strongly related to field-measured gap fraction. They estimated outbreak defoliation by temporal changes in the LAI variable derived from ALS data during a summer season, with $r^2 = 0.82 – 0.95$, thus demonstrating that combining ALS data penetration variables in an alternative manner may differentiate defoliation from felling. However, these authors suggested that ALS data alone cannot provide the monitoring accuracy required to assess damage degree. Even though light defoliation is difficult to monitor (Zhang *et al*., 2010), current pest caused defoliation monitoring is achieving 70% to 80%

accuracy for three defoliation levels (light, moderate and severe). Remote detection of defoliation in sparse cover vegetation is still much more difficult to assess (Dennison *et al*., 2009). Nevertheless, Kantola *et al*. (2010) found that combining (in a fusion approach) different sensor data, like spectral features from digital photographs with those from high density ALS data, can enhance mapping accuracy for two defoliation classes to higher values (88.1%) than obtained by each method separately (80.7% and 87.4% respectively).

Correct assessment of defoliation by detection of changes much depends on obtaining data relatively free of exogenous noise, so an adequate pre-processing of image data is critical. Measurement of site features provided by sub-pixel georeferencing is needed for change detection techniques to avoid geolocation inaccuracies that might result in anomalous measuring of even the most stable land features (Townshend *et al*., 1992; Lambin and Linderman, 2006). Accurate links between data and image processing require quality data relatively uncontaminated by noise and extraneous effects derived from viewing, light conditions, cloud and atmospheric contamination, etc. Thus, sufficient cloud-free temporal composites across the defoliation period and effective noise reduction of residual atmospheric contamination (Spruce *et al*., 2011) or background influences, such as soil or understory in open forest stands (Lambin and Linderman, 2006), are required for useable imagery detecting defoliation.

The *biological window* (bio-window) period, defined as "the optimum for visual expression of major forest pests and related damage" (B.C. Ministry of Forest, 2000; Wulder *et al.,* 2004), is another key factor for successful detection of defoliation by a particular pest. It is a varying period depending on several factors (*e.g.* host phenology, climate conditions, predators, etc), often synchronized with the maximum foliation period in the host tree. The bio-window is usually open within a relative short period in relation to the temporal resolution of the satellite sensor and to the quantity of sensing images during the period. Therefore, historical and field data on pest occurrence, or predictions of defoliation phenology using climatically driven insect population models, as the BioSIM (Régnière *et al*., 1995), are critical to establish the pre-defoliation and peak defoliation periods, before post-outbreak refoliation.

In this sense, sensors suitable to encompass a bio-window have high temporal resolutions of 1-3 days (*e.g.* satellites as the coarse resolution AVHRR and SPOT-VEG, the moderate resolution MODIS, the fine resolution SPOT or the very high resolution IKONOS and Quickbird-2). By contrast, sensors with low temporal resolution of 16 days (*e.g.* satellites with fine resolution ASTER, ALI and Landsat) can rarely obtain more than one or a few images during a growing season (Jepsen *et al*., 2009), severely limiting its use in the seasonally ephemeral forest defoliator outbreaks (de Beurs and Townsend, 2008). Commercial very high resolution sensors are currently prohibitive for practical monitoring of insect outbreaks on a regional scale due to the high costs of obtaining, processing and calibrating large numbers of fine resolution images (Jepsen *et al*., 2009). On the other hand, MODIS sensor is free and the MODIS-based Vegetation Continuous Fields products can be used for measuring changes in the forest cover over time. Today, MODIS is regarded as an important tool for insect damage detection at regional scale (Hayes *et al*., 2008; Adelabu *et al*., 2012). It is strongly recommended for physical and physiological modelling and has been considered the best sensor for forest health RS (Wang *et al*., 2010). However, lack of spatially explicit reference data for producing damage maps is a MODIS major limitation (Adelabu *et al*., 2012).

A new promising approach when assessing defoliation is the Spectral Mixture Analysis (SMA). This method quantifies the proportion of each pixel that is occupied by individual image components and, considering defoliation as the absence of leaves, estimates stress severity as the relative proportion of leaves in the image pixels (Somers *et al*., 2010). Coupled, with high resolution multispectral data, SMA is able to detect low and fragmented vegetation cover and offers advantages over simple regression using spectral indices and other transformation methods (Goodwin *et al*., 2005; Somers *et al*., 2010). In 1998, Robert *et al* were able to improve SMA by the Multiple Endmember Spectral Mixture Analysis (MESMA) and later Somers *et al*. (2010) further improved it in a weighted Multiple Endmember Spectral Mixture Analysis (wMESMA), a novel spectral unmixing technique. These authors were able to detect defoliation by *Gonipterus spp* in *Eucaliptus globulus* stands in Australia using hyperspectral (Hyperion) and multispectral (Landsat) satellites. The SMA technique performed better with the last sensor, pointing to a higher potential for multispectral data.

Another relevant advantage of linear mixture model techniques is that they can estimate the sub-pixel spectral composition of plant cover, as regression techniques do for modelling biophysical continuous variables. They can extract major information on key variables in the spectral signal when the targeted processes operate at scales below the sensor resolution. This will often be the case when studying land cover changes with coarse resolution imagery, such as MODIS data sets (Hayes *et al*., 2008). They may also assess degree of defoliator damage in finer scales, as those from Landsat.

Forest vegetation indices

Presence and condition of leaf foliage are reliable indicators of tree health, similarly as canopy foliage is of the forest stand. Research on forest VIs is aimed to the spectral identification, detection and quantification of forest health. Thus, defoliation and discoloration, not related to plant phenology, are taken as indicators of the plant stress that may be caused by insect defoliators. In addition, water loss suffered by the host is another important, but not visually evident, stress indicator (Wang L. *et al*., 2010). Many RS studies have detected differences in spectral responses between forest discoloration, like chlorosis or canopy reddening, and insect defoliation, (Jepsen *et al*., 2009; Kantola *et al*., 2011). Biophysical variables, such as the LAI, chlorophyll content and evapotranspiration, or any other VI correlated with ground based data, are aimed to quantify defoliation, discoloration and water loss. Therefore, analyses of these variables would provide insight into the nature and development of forest defoliation and may allow monitoring and damage mapping with significant accuracy. There are certain requisites that the biophysical variables or VI related to them, must fulfil: they must present high sensitivity and linear relationships with the forest vegetation variables to be estimated, and they must have high dynamic ranges and minimal saturation effects. Furthermore, biophysical variables, or VIs, must be scale-independent, so they can be transferred across scales even to more heterogeneous landscapes (Lambin and Linderman, 2006).

In general, remote detection methods are usually based on differences among the red (R), NIR, and SWIR wavelengths. Mathematic algorithms of these bands conform the VIs that are closely related to the biophysical variables of foliage vigour associated to plant health. Thus, these algorithms account for the morphological and physiological changes in the forest canopy occurring before, during and after insect outbreaks.

De Beurs and Townsend (2008), mapping the magnitude of defoliation by *L. dispar* during two consecutive years in a largely broadleaved and oak-dominated forest area in the USA central Appalachian range, used MODIS images within a single year that corresponded to the pre-defoliation and peak defoliation periods. The bio-window period was previously determined by the BioSIM model. They used both images to develop a MODIS index of defoliation as a function of a VI. Besides the commonly used NDVI and Enhanced Vegetation Index (EVI) (that uses the R and NIR bands), the authors also tested three VIs that use the R, NIR, SWIR and mid-infrared (MIR) bands. SWIR reflectance is very sensitive to the amount of water in the vegetation, increasing when leaf water content decreases, as happens in vegetation stressed by pest defoliators. They concluded that Normalized Difference Infrared Index bands 6 and 7 (NDIIb6 and NDIIb7, both using the SWIR band) performed significantly better than NDVI and EVI, in daily MODIS 250m data, for monitoring insect defoliation in large patches (>0.6 km^2) on an annual time scale.

Spruce *et al*. (2011), however, obtained similar accuracy in mapping defoliation for the same region and pest using NDVI derived from MODIS (MODIS-NDVI) to a minimum patch size of 0.25 km^2. They recommended this product by its higher inherent spatial resolution compared to alternative indices as the NDII proposed by De Beurs and Townsend (2008). Temporal compositing using any VI combining NIR and SWIR bands from MODIS data would be difficult, since these bands have different spatial resolution (*i.e.* 250 m versus 500 m) and noise mitigation can be complicated. Furthermore, Jepsen *et al*. (2009) showed, for the same region, that MODIS-NDVI time-series were more reliable than daily MODIS products for long term monitoring of ephemeral forest disturbances, due to significant cloud coverage during the defoliation period of daily products.

Moreover, Townsend *et al*. (2012), working with Landsat TM, were able to successfully classify and map, in a continuous way, defoliation severity using NDIIb5 in combination with a logistic regression model. Long before, Vogelmann (1990) had obtained a better performance of the SWIR/NIR ratio over NDVI in identifying low versus high forest damage in balsam fir forests. On the contrary, Spruce *et al*. (2011) noted that NDVI was better in separating medium from low damage within a deciduous forest. Thus, as the VIs performance may vary from site to site, it is always recommendable to explore and test several robust VIs for selecting the best index for a particular case. For example, NDVI has been shown to have a robust positive linear correlation with vegetation coverage between 25% and 80%, but its performance was reduced significantly below or above this range (Zhang *et al*., 2010).

Hyperspectral data is becoming very important for early stress detection and may be useful for identifying tree-level pre-visual reductions in LAI, chlorophyll (Pontius *et al*., 2008) and water contents. Early detection means detecting subtle changes in foliage canopy occurring as physiological or biochemical host defence responses to infestation. Hyperspectral sensors operate with hundreds of narrow wavelength bands. Thus, there are specific VIs for hyperspectral data, such as the Vogelmann "red edge" index or Vog 1 (R_{740}/R_{720}; Vogelmann *et al*., 1993) proposed for assessing chlorophyll content, or the simple ratio or SR (R_{NIR}/R_{red}; Rouse *et al*., 1973) for LAI. Both of them have recently been used to preliminary detect and map defoliation caused by *Thaumetopoea pityocampa* in *Pinus pinea* stands in Spain (Cabello *et al*., 2011). Further results from this advanced methodological proposal could provide valuable insight into forest VIs and monitoring defoliation issues.

Adelabu *et al*. (2012), following Coops *et al*. (2003) and Santos *et al*. (2010), have stressed the need for research monitoring defoliation on broadleaved forest by applying multi and hyperspectral sensors. Complexity and costs of pre-processing (correction and calibration) and information extraction are current constraints of hyperspectral data. Nevertheless, continuous estimates of variables such as LAI, and several others, from multispectral or hyperspectral data can be provided by regression analysis, the most popular empirical method linking ground-measured biophysical variables to RS data, or by any other empirical model (Cohen *et al*., 2003).

Tempo-spatial distribution and prediction of forest pests

Remote detection and mapping of defoliation inform on spatial distribution and intensity of damage, but does not provide insight into its temporal component. Temporal distribution is relevant to fully understand the dynamics of pest outbreaks and therefore to predict its potential behaviour. Time-series analysis may allow for predicting annual distribution of defoliated areas and can provide indications of outbreak history in periods where field records are unavailable (Jepsen *et al*., 2009). Using MODIS-NDVI 16-day data, orthophotos and sketch maps of defoliated polygons, these authors succeed in using defoliation scores to classify defoliation and estimate *Epirrita autumnata* larval density. They were able to capture the spatial and temporal patterns of this pest and concluded that data obtained this way may allow for the development of monitoring at relevant regional scales. Kharuk *et al*. (2009) analyzed the spatial and temporal dynamics of a *Dendrolimus sibiricus* outbreak using NDVI derived from SPOT-VEG data coupled with a digital elevation model (DEM). They found strong relationship between outbreak patterns and topographic features (elevation, azimuth, slope steepness) and confirmed the suitability of this satellite for remote pest monitoring.

Supported by natural proxy data (pine and birch chronologies, temperatures, documented outbreaks) and using Landsat-based detection, Babst *et al*. (2010) succeeded in reconstructing *E. autumnata* outbreaks over the 19th and 20th centuries in the Scandes Range. They observed that microclimate, topography, site conditions and vegetation type strongly influenced distribution of pest damage. Applying dendrochronological techniques, they found a significant non linear relationship between standardized radial growth reductions due to *E. autumnata* outbreaks and NDVI variations. They also observed that outbreaks appeared clearly related to regional climate change (frequency of egg-killing minimum winter temperatures).

Zhang *et al*. (2010) stressed that a health monitoring system should be aimed to gathering information for monitoring, prediction and disaster loss assessment decision. In this sense, Alvarez *et al*. (2007) have proposed a forest health monitoring system prototype for predicting *Gonipterus scutellatus* damage on *E. globulus* stands in Galicia (Spain), based in the combined application of satellite remote sensing, GIS and forest growth models. Unfortunately, this prototype has not yet produced conclusive results. Recently, Paritsis *et al*. (2011) have succeeded in predicting susceptibility to defoliation by *Ormiscodes amphimone* in *Nothofagus* forests in two areas of Patagonia (Argentine). They applied straightforward patch detection, false-colour visually evident and composite Landsat image, together with logistic regression model generated maps, to assign the areas to defoliated and non-defoliated classes. These authors concluded on the need of knowing how vegetation heterogeneity and abiotic sources of landscape heterogeneity affect susceptibility of *Nothofagus* stands to *Ormiscodes* attack.

Trends in remote monitoring of forest insect defoliation

Recent research in RS of forest insect defoliation shows a trend of specialization in a particular pest for certain area. Thus, current research might be grouped in relation to the insect and the area most frequently studied. In the United States, studies are focused on oak forests affected by *L. dispar*, whereas Northern European research is mostly dealing with Scots pine forests affected by *N. sertifer* (Norway) and *Diprion pini* (Finland). There is also research on *E. autumnata* outbreaks in Fennoscadian birch-coniferous forests. In Southern Europe, research has been addressed to *E. globulus* defoliation by *Gonipterus* beetles and to pine defoliation by processionary moths in Spain.

Collaborative national RS for developing nation wide forest health monitoring systems tackling climate change is another currently observed research trend (Solberg *et al*., 2004). It may be exemplified by the U.S. National Early Warning System (EWS) (Spruce *et al*., 2011), the Norwegian REMote sensing of FORest health project (REMFOR) (Solberg *et al*., 2007), or the National Environmental Disturbances Framework (NEDF) in Canada (Thomas *et al*., 2007).

Although to date multispectral sensors Landsat, MODIS and SPOT are still the most used in studies of insect defoliation (Hall *et al.,* 2007, Wang, L. *et al.,* 2010; Adelabu *et al.,* 2012), it is to remark the increasing use of LiDAR technology in the relatively new ALS sensors by Northern European research teams. ALS data has proven efficient for determining important forest parameters; it is increasingly used in forest inventory (Kantola *et al*., 2010) and would provide a good basis for detection of defoliation (Solberg *et al*., 2006). On the contrary, Synthetic Aperture Radar (SAR) data seems to contribute modestly to remote detection of defoliation.

All the studies here reviewed were multitemporal and considered the pest period as the criterion for image selection. Individual images were taken before, during and after the outbreak episode, like time-series data from MODIS, Landsat or SPOT, for the detection and temporal analysis of pest outbreak. Satellite-derived time-series of outbreak dynamics is a promising tool with many applications (*e.g.* as a basic large scale and cost effective monitoring) (Jepsen *et al*., 2009).

In 2007, Hall *et al*. reported that half of the studies reviewed in North America, most of them after 1998, employed pre-processing procedures, such as image normalization or atmospheric correction. This may signal an increasing use of pre-processing image procedures, such as georeferencing or radiometric and atmospheric correction, prior to any change detection analysis (Lu *et al*., 2004; Hall *et al*., 2007). In this sense, we have found that at least 75% of the studies here reviewed used atmospheric correction when it was necessary. Furthermore, these authors observed that about 20% of the studies employed continuous estimates of insect defoliation damage, whereas in the present review this figure has been doubled (Table 1). This may point to a trend for finer limits more suited to the nature of the spectral response to defoliation than the subjective and broad defoliation classes (Hall *et al*., 2007) obtained from visual estimates on field or aerial surveys.

Another interesting trend in remote insect defoliation monitoring is the development of temporally processed time-series data. This technique may provide alternatives to overcome the need of cloud-free data for operational monitoring (cloud contamination is a main problem inherent to all electro-optical sensors), allowing for a wall to wall assessment of defoliation towards an early warning system (Dennison *et a*l., 2009; Spruce *et al*., 2011). In this sense, it can be observed in Table 1 that at least one third of the studies have applied time-series or temporal composite images, mostly for "Remote detection of forest defoliation" topic, with several methods and sensors, in North America and Fennoscandia. In fact, both regions suffer in their northern latitudes from high cloud coverage that frequently precludes the use of daily satellite images for operational monitoring (Jepsen *et al*., 2009; Spruce *et al*., 2011). Furthermore, global coverage and the cluster of historic images of Landsat time-series (LTS), free available now, along with the growing need for detailed information on disturbances over large areas, have generated new automated algorithms for exploiting these data. Temporal aggregation of LTS high-density data improves the signal to noise ratio and therefore requires new mapping algorithms. LandTrendr and

Vegetation Change Tracker (VCT) with new calibration and validation, and TimeSync algorithms (Kennedy *et al*., 2010; Huang *et al*., 2010; Cohen *et al*., 2010) were created for that purpose. These algorithms may lead to new methods to be tested or incorporated (Deel *et al.,* 2012), for characterizing annual changes in disturbed vegetation of large areas, offering interesting potential for assessing pest patterns and history of affectation and recovery of forests.

There is a wide variety of remote change detection methods being applied to a given range of damage pattern, from traditional classification to mathematic modelling (Table 1). This diversity makes difficult to select a particular approach for mapping defoliation and some are becoming more sophisticated image processing techniques (*e.g.* the five-scale model coupled with neural network from Wang L. *et al*., 2010). This may be evidenced by the higher frequency of application (38%) of "Mathematical statistical methods and GIS technology" (m) over the other methods shown in Table 1, as expected by Zhang *et al*. (2010). These (m) methods have been applied mainly for topics A and B and have similarly used Landsat and MODIS data, followed by the significant rise of ALS data applications (20%). In this respect, several promising studies reveal a trend towards an increasing contribution of this sensor to remote monitoring of defoliation: LAI mapping in Solberg *et al*. (2007) and Solberg (2010), defoliation predicting in Kantola *et al*. (2010, 2011) and satellite image analysis in Eklundh *et al*. (2009). Solberg *et al*. (2007) found a close to 1:1 correlation between satellite-borne LiDAR data (ICESAT sensor) and penetration rates of airborne LiDAR data (ALS sensors), pointing to the feasibility of exploiting the potential advantages of LiDAR satellite monitoring.

Development of hyperspectral capacities has lead to new powerful indices for analyzing the "red edge" zone, to detect subtle changes in plant health, as occurs in early stages of insect damage (Zhang *et al*., 2010). Moreover, it has been shown the capacity of hyperspectral analysis to assess defoliation intensity with a highly significant accuracy (Pontius *et al*., 2005).

Conclusions

Remote sensing is a dynamic technology continuously improving sensors, methods, products and availability. Though, it is increasingly being used in forest health monitoring RS of insect defoliation is still at an early stage. RS of defoliation is a complex and multifactorial task, dependent on several factors such as physiographic conditions or host and pest phenologies. Forest defoliation does not mean a simple change in foliage condition, so each case should be treated as unique, testing different sensors and combining different techniques that may produce the best results.

There is increasing evidence suggesting that recent changes in distribution and duration of pest outbreaks can be attributed to climate warming. These changes could be cost effectively monitored in large areas using satellite derived spatio-temporal time-series, to predict population build ups and prevent harmful consequences to forest ecosystems.

Remote monitoring of forest health may allow for effective pest control and outbreak suppression. It has been suggested that an operative nation or region wide monitoring system will depend on two scale levels, one using time-series with moderate to coarse resolutions (*e.g.* MODIS or SPOT-VEG data) and the other with fine or very high resolution (*e.g.* Landsat or Quickbird-2 data) supported with reference ground-based data, digital elevation models and other ancillary data. ALS and hyperspectral data analysis may be included in this second level.

MODIS capabilities place it as the most suitable sensor for early warning detection and physical and physiological modelling, whereas Landsat is especially suited for defoliation damage research, but not for operative monitoring due to its coarse temporal resolution. ALS data currently stands as the more promising option for operative detection of defoliation using several data sources in a fusion approach.

A general straightforward method is applying multispectral fine resolution satellite data (Landsat imagery) to assess percent defoliation as a function of the change in a VI. This approach has been shown to allow for continuous, rather than categorical, defoliation scoring, and to produce appropriate insect defoliation maps across years.

Proper estimation of defoliation phenology of an insect pest, or bio-window, is another key requisite for acquisition of spectral images suitable for effectively detecting the seasonally ephemeral outbreak of the forest defoliators. Climatically driven insect population models are currently providing accurate bio-window estimations.

Remote spectral characterization of forest defoliation accounts for detecting morphological changes in tree crown coverage for a given period of time using adequate change detection methods. These methods are usually especially sensitive to pre-processing techniques, such as precision georeferencing or radiometric and atmospheric correction among others. Thus, pre-processing may largely determine the reliability and accuracy of insect defoliation damage detection and mapping.

Vegetation indices are derived from its reflectance properties and are designed to highlight a particular vegetation feature or change. To date, NDVI has been the most used and so proven VI for mapping insect pest defoliation, although those indices combining SWIR and NIR bands, as SWIR/NIR-based indices, seem more promising. The loss of foliage is intimately related to the biophysical variable LAI which has been significantly used for defoliation mapping. Furthermore, since decrease of moisture content is a general plant stress response, moisture content indicators should be also considered for remote detection of defoliation.

Two promising methods for insect defoliation monitoring are to be highlighted. One, the Spectral Mixture Analysis approach is best suited for detection due to its sub-pixel recognition and analysis capacity. The second approach attempts classification damage degree using logistic models as a function of the VI change difference between two dates, and is recommended for predicting defoliation.

Research on remote monitoring of insect defoliation can be considered still rare compared to other RS applications to forest health management. There is an evident need, though, for facing present and future forest pest threats in a multidisciplinary way. A clear research opportunity for RS of defoliation arises, posing a challenge for improving defoliation intensity detection, improving early stage outbreak detection, developing more generalist models, increasing robustness of data processing and analytical methods, and extending results to more heterogeneous and complex forests.

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