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# A Review of Remote Sensing of Insect Defoliation and its Implications for the Detection and Mapping of *Imbrasia belina* Defoliation of Mopane Woodland

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## ABSTRACT

Forest health, especially insect defoliation monitoring in forest using direct sampling and visual estimation has been only moderately successful due to its cost, time required for sampling, and most importantly the need to collect data immediately before and after an extreme event. However, remote sensing techniques offer timely, up-to-date, and relatively accurate information for sustainable and effective management of forest health. In this paper, we discuss the different approaches including the remote sensing platforms and techniques that have been used for assessing insect defoliation and its implications for detecting and monitoring mopane worm defoliation of mopane woodland, highlighting their strengths and weakness. Research gaps in the detection of insect defoliation with remote sensing are highlighted and future directions of research are also proposed.

**Keywords:** chlorophyll content, forest health, hyperspectral, mopane worm, multispectral

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## INTRODUCTION

An important component of forest ecosystem is its health status and the impact it has on sustainable growth. Recent evidence suggests that new damaging agents are appearing at an increasing rate which could affect the future sustainability of forest industries (Wulder and Franklin 2003). While many of the past impacts of damaging agents such as insects on forest woodland have been disastrous, mopane worm, an important defoliator of mopane woodland in Southern Africa exhibit a different scenario. As a result, *Imbrasia belina* (mopane worm) is widely distributed (**Fig. 1**) and consumed in Southern Africa because of its nutritional values and sold to generate income (Timberlake 1996).

However, while the depletion of worms derived from mopane woodland have been reported in different areas, none of these depletions have been attributed to the impacts of the worms on the vitality and productivity of their host. Mopane defoliation is one of the serious impacts of the worm on its host. Furthermore, the absence of mopane worms from certain regions of mopane veldt has not been satisfactorily explained. It may be due to the absence of necessary nutrients that attract the worms to the leaves of the tree. Defoliation process as a result of the worms if not well managed can in the long run lead to the extinction of the tree and hence the worms within the region. In an effort to minimize the potential loss of *I. belina* (hereafter referred to as mopane worm) in mopane woodland of Southern Africa, an integrated management strategy is needed combining detection, mapping and monitoring methods. Moreover, resource managers need to know the impacts, vulnerability and suggest possible management practices

Received: 6 August, 2011. Accepted: 1 December, 2011.

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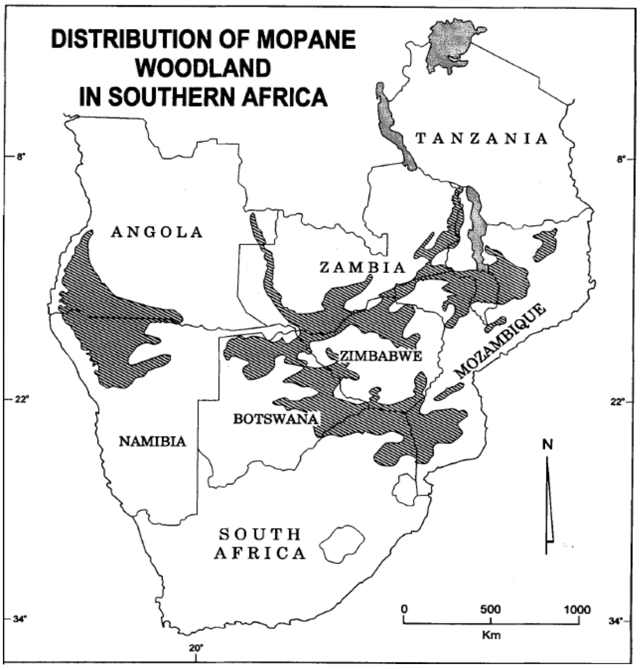


**Fig. 1 The distribution of mopane woodland in southern Africa.** Source Marias (1996), with kind permission of the author.

that will enable efficient and sustainable use of the resources emanating from mopane woodland.

Information on the extent and severity of mopane defoliation is required for a wide variety of forest planning, management, and modeling activities. Mapping mopane defoliation will also aid sketch mapping surveys and also help in reporting and assessing the impacts of the defoliation on the health and productivity of the woodland. Currently, there are no specific methods of mapping mopane defoliation.

The objective of this paper therefore is to discuss the different approaches including the remote sensing platforms and techniques that have been used for assessing insect defoliation and its implications for detecting and monitoring mopane worm defoliation of mopane woodland highlighting their strengths and weakness. Firstly, we review the effects of insect defoliation on trees and the conventional ways in which they are assessed. Thereafter we consider different remote sensing platforms that have been used in detecting insect defoliation, highlighting the strengths and weaknesses in detecting, mapping and monitoring mopane woodland defoliation. Thirdly, the remote sensing techniques that can be used for accurate monitoring are presented. Finally, we discuss various challenges that might occur while using remote sensing to detect, map and monitor defoliation in mopane woodland by mopane worms suggesting possible solutions to them.

## EFFECTS OF INSECT-CAUSED TREE DEFOLIATION ON VEGETATION PRODUCTIVITY

The primary function of leaves in plants is to manufacture sugars and carbohydrates (Morgan *et al.* 2010). Sugars and carbohydrates are the basic food or energy that plants use for all metabolic activities such as growth, root development, flower and seed production, disease resistance etc. Leaves also provide many indirect benefits such as emitting oxygen, screening out particulates and other air pollutants, intercepting precipitation to minimize erosion and shading the ground to modify surface temperatures (Morgan *et al.* 2010). When insect defoliation occurs in a particular tree, the effects range from a slight reduction in vigor to total death (Hall *et al.* 2003). Insect defoliation harms plants by eliminating or limiting their food production capability (Hall *et al.* 2003). The refoliation process, which frequently occurs immediately after defoliation, also requires energy for budbreak and leaf expansion, which causes further depletion of stored food reserves (Hall *et al.* 2003).

The inability of the tree to manufacture food (energy) together with the depletion of stored food weakens the tree and results in reduced growth, stunted, pale-green new leaves and possibly twigs and branch dieback (Kantola *et al.* 2010). Insect defoliation also affects the morphological and physiological characteristics of trees, and it is these characteristics that govern how trees absorb and reflect light (Hall *et al.* 2003). The production of protective substances that aid in disease resistance may be inhibited (Hall *et al.* 2003). It is predicted that the frequency and severity of insect defoliation outbreaks could increase in response to climatic warming, further magnifying their effects (Fraser and Latifovic 2005).

Mopane tree defoliation follows the same pattern as other insect defoliators and when the outbreak occurs, about 200 mopane worms feed on a single tree leading to 90% of mopane trees if not all left without leaves within a mopane woodland (Ditlhogo *et al.* 1996). Moreover, Stack *et al.* (2003) observed that mopane trees do not contain any hydrolysable tannin which is widely accepted as being the primary defence compounds against insects. This explains the close association between mopane worms and mopane trees. While mopane woodland often recover within a relatively short period after defoliation with little mortality, continuous defoliation may lead to deplorable long term effect that may be fatal.

Although, no report of eradication of mopane trees as a result of defoliation in any region of mopane veldt is known yet, studies have proved that there are long term effects. Hrabar *et al.* (2009) noted that at present, defoliation has no effect on mopane plant size; however, it has potential negative effects on stored resources which characteristically result in regrowth with smaller and or fewer leaves. Styles and Skinner (2000) further explained that heavily defoliated mopane trees tend to lose nutrient and greatly reduced in age over years. Having discussed the (possible) effects of mopane worm defoliation on mopane woodland, it is important to highlight the linkage between (biophysical and biochemical) indicators of mopane woodland productivity and remote sensing. Knowledge of this will help for accurate detection of defoliation level within the woodland.

## CONVENTIONAL METHODS OF ASSESSING AND MONITORING OF INSECT-CAUSED TREE DEFOLIATION

Defoliation is a general stress response, and it is closely linked to biophysical and biochemical indicators hence they are used as conventional methods of detecting insect defoliation (Lee *et al.* 2010). Measuring forest biophysical characteristics aims at documenting forest integrity in many aspects, such as structural, functional and species diversity (Kumar *et al.* 2001). However, these measurements often depend on extensive and expensive fieldwork, encompassing a restricted study area. Remote sensing enables monitoring studies in a wide area at constant time periods (Seidl *et al.* 2011).

The alliance between remote sensing techniques and biophysical indicators could be valuable to studies on detecting, mapping and monitoring defoliation process in forests. To fully understand how remote sensing can be used for detecting, mapping and monitoring insect defoliation especially the mopane woodland defoliation, we need to discuss the biophysical and biochemical variables that affect mopane trees focusing on the two main ones: Leaf Area Index (LAI) and chlorophyll content. Understanding these biophysical indicators could help in providing more information on the techniques and platforms of remote sensing that can be applied.

## Leaf Area Index

The use of biophysical change metrics, such as LAI change, has been proved to provide a more flexible and general defoliation mapping method (Hall *et al.* 2003). Moreover researchers have stated that insect defoliation thresholds that are based on LAI rather than percent defoliation are more meaningful (Malone 2001). LAI is an important variable explaining canopy primary production and can be used to infer processes such as photosynthesis, transpiration, evapotranspiration and estimate net primary production (NPP) of terrestrial ecosystems (Yao *et al.* 2008). LAI is defined as one-half the total surface area of leaves per unit ground area. The estimation of LAI from remote sensing measurements has received much attention. For example, a simplified semi-empirical reflectance model for estimating LAI of a green canopy was introduced by Clevers (1997). The widely used crown condition variables are closely related to LAI, but this has received little attention. As such, LAI is increasingly desired as a spatial data layer (i.e., map), to be used as input for modeling biogeochemical processes (Thenkabail *et al.* 2000).

The LAI measurements are relevant for comparing the condition of differently damaged stands and can therefore be used in forest monitoring practice (Thenkabail *et al.* 2000). Measuring LAI on the ground is difficult and requires a great amount of labor and cost (Kumar *et al.* 2001). To produce a LAI map of a large area, a model relating field data with remote sensing data is typically developed, the model is inverted, and the remote sensing data are then used to extrapolate that relationship to the landscape (Hall *et al.* 2003). Many studies have sought to establish relationships between LAI and remote sensing data (Thenkabail *et al.* 2000; Kumar *et al.* 2001; Yao *et al.* 2008). Most of these studies have relied on empirical relationships between the ground-measured LAI and observed spectral responses, although several have used canopy reflectance models (Thenkabail *et al.* 2000; Kumar *et al.* 2001).

Although, LAI has not been used in detecting and mapping the forest health levels of mopane woodland, especially during mopane defoliation, it is hypothesized that data from LAI could evaluate the vegetation levels before, during and after defoliation. When forest health deteriorates and the deterioration is affecting canopy volume it would be detected as LAI change. Therefore, the healthier the vegetation, the higher the LAI since LAI increases with healthy status of plants (Sanz-Cortiella *et al.* 2011). Hence, a forest that is highly defoliated is expected to have low LAI. LAI during the healthy state of mopane woodland (without defoliation) is expected to be high since its canopies at this stage are still very green and have not been attacked by the worms. However it may be difficult to differentiate the early defoliation stage of mopane woodland from the healthy state using LAI since the canopy at this stage are visually indistinguishable from healthy trees of the green stage (Ismail *et al.* 2008). Combination of LAI as well as the variation in biochemical concentration in leaves could help in dissociating this level. On the basis of the above discussion, measurement of LAI can help develop a background to which remote sensing techniques could be applied for detecting, mapping and monitoring defoliation process in mopane woodland.

## Chlorophyll content

Chlorophyll (Chl) content is another biophysical variable for detecting insect defoliation on forest (Thomas *et al.* 2008). Chl content is a good indicator of vegetation status and gross primary productivity because of its direct role in photosynthesis (Gitelson *et al.* 2006). Results in the past have showed that Chl content was much lower in woodlands that have insect defoliation when compared with healthy woodland (Gitelson *et al.* 2002). When forests are subjected to insect defoliation, many physiological changes occur, including: reductions in photosynthetic activity (Zarco-Tejada *et al.* 2000), inhibition of Chl formation (Sims and Gamon 2002), and an increasing breakdown of the chlorophyll molecule (Gitelson *et al.* 2006). Efficient field measurements of these Chl related changes have been approximated using measures of Chl fluorescence (a measure of photosynthetic activity (Zarco-Tejada *et al.* 2000).

However, this has been costly and time consuming. Recently, a relatively cheaper and less time consuming approach of detecting defoliation using Chl content over large areas involves remote sensing technology (Thomas *et al.* 2008). Narrow wavebands near 700 nm where changes in Chl absorption are easily detectable have been recommended for early detection of forest damage (Pontius *et al.* 2005).

The Chl in green leaves absorbs light for photosynthesis at wavelengths from 650–660 nm (Thomas *et al.* 2008). For this reason, the red region of the spectrum is most useful for detecting the absorption of visible light by the Chl pigments. The healthiest vegetation will perform photosynthesis efficiently, which requires an abundance of Chl pigments. The healthiest vegetation, hence, will absorb the greatest amount of red light. Most of the infrared light incident on a green leaf is reflected at wavelengths from 0.7–1.2 μm due to leaf internal scattering. The near-infrared region of the spectrum is most useful for detecting the reflection of infrared light by the leaves (Pontius *et al.* 2005). The healthiest vegetation will have many leaves and will, therefore, reflect the greatest amount of near-infrared light. Hence, healthy vegetation is highly reflective in the near infrared region and highly absorbent in the red region.

Also narrow-band hyperspectral instruments have the capability to identify early signs of defoliation in some cases even when symptoms are not visible to the human eye (Mohammed *et al.* 1995; Zarco-Tejada *et al.* 2000; Pontius *et al.* 2005). Physiologically, this can be explained by the tendency of defoliated forest to reduce photosynthetic activity and hence Chl content. Even subtle changes in Chl content can alter reflectance patterns in the visible and near-infrared (NIR) portions of the spectrum (Pontius *et al.* 2005).

While Chl content can be measured directly using Chl meter such as Minolta SPAD-502 (Konica Minolta, Osaka, Japan), most studies using Chl content in monitoring defoliation make use of models that are derived from empirical relationships between the ground-measured Chl content and observed remote sensing variables. Moreover, with high forest canopy cover such as mopane woodland, relationships between the reflected electromagnetic radiation and leaf chemistry tend to break down (Pontius *et al.* 2005). However Chl content derived from hyperspectral remote sensors may be a good indicator of defoliation at the green stage of defoliated mopane woodland since the photosynthesis activities at this stage is relatively higher than when they are totally defoliated.

Changes in Chl content and LAI have been related to variation in photosynthetic activities of deciduous trees (Koike 1987). Although they (LAI and Chl content) are not direct measurements of vegetation productivity and physiological activities, they represent important determinants of productivity and physiological capacity of plants (Sims and Gamron 2002). Infact, relationship between the two can actually provide information on the health status of a particular tree (Kodani *et al.* 2002). It is expected that the knowledge about the dynamics will establish the impact of defoliation on the tree.

## RELEVANCE OF REMOTE SENSING IN ASSESSING AND MONITORING INSECT-INDUCED TREE DEFOLIATION

The most reliable method of measuring defoliation is by direct sampling (ground based measurement), which is obviously unreasonable because of its cost, time required for sampling, and most importantly the need to collect data immediately before and after an extreme event (de Beurs and Townsend 2008). For large areas, aerial survey is more efficient than ground-based measurement. However, ground-based estimates provide better tree specific information (Ciesla and Acciavatti 1982). Information on defoliation prior to 1947 was limited to records from ground observations, memoranda and letters (Dolph 1980). Since 1947, when an aerial survey program was initiated, detailed information and forest pests especially in North America and Europe have been collected annually. The remote sensing approach in assessing and monitoring insect defoliation has been to relate differences in spectral response to chlorosis (yellowing), foliage reddening, or foliage reduction over time, assuming that these differences can be interpreted, classified, or correlated to damage caused by insect activity (Franklin 2001). Remote sensing has been used to generate more spatially precise and detailed defoliation maps from which its impact on the forest resource could be determined.

The range of remote sensing applications has included detecting and mapping defoliation, characterizing patterns of disturbance, modeling and predicting outbreak patterns, and providing data to pest management decision support systems (Lee *et al.* 2010). The possibility of forecasting the susceptibility and vulnerability of forested areas to insect defoliation has also been reported as a tool to provide mitigation options to forest managers (Luther *et al.* 1997). These applications were intended to produce information products that support pest management planning. The advantages of applying remote sensing for monitoring insect defoliation includes the ability to acquire relatively cheap and rapid method of acquiring up to date information over a large geographical area (de Beurs and Townsend 2008). Also remote sensing has an edge over other methods because it is the only practical way to obtain data from inaccessible regions; it has ability to be in the form of both small and large scales for easy identification and its ability to image defoliation in different spectral forms.

One of the earliest research of using remote sensing to monitor defoliation was conducted in north central Washington and central Idaho in USA using aerial photographs (Heller *et al.* 1981). Ciesla and Acciavatti (1982) determined that high altitude panoramic color infrared photography acquired during the time of peak defoliation could consistently differentiate between heavy defoliation, moderate defoliation, and no defoliation. Ever since then, the use of remote sensing technology to detect, map and manage forest defoliation over large region has been a subject of intense interest (de Beurs and Townsend 2008).

In mapping areas covered with mopane woodland, Sebego and Arnberg (2002) used coloured infrared photographs and they discovered that though mopane woodland extent and distribution can accurately be mapped using colour infrared photographs, it may however not be able to discriminate defoliated from undefoliated mopane woodland. Moreover, using aerial photographs alone will also be time consuming and expensive since photographs need to be taken for every events of the defoliation process. It must however be noted that aerial photographs can form a bases on which other forms of remote sensing platform can be used in monitoring mopane defoliation.

## DEVELOPMENTS IN THE REMOTE SENSING OF INSECT-INDUCED TREE DEFOLIATION

The increasing availability of remote sensing and geographic data has not only helped the detection, mapping, monitoring and management of the health of forest ecosystems especially those affected by insect defoliation, but also proved to be important for the protection of natural resources and the economy worldwide (Kantola *et al.* 2010). Different platforms of remote sensing have been used in the past for forest defoliation monitoring with varying success. A review of the remote sensing methods and platforms that have been used for insect defoliation illustrates the degree that they have been successful in obtaining information of operational relevance (i.e., used by those in forest management) (**Table 1**). We discuss the various platforms and their implications in mapping mopane woodland.

### Broadband sensors

Various images from remote sensing broadband sensors have been found to effectively monitor insect defoliation in woodland (**Table 1**). The resulting data usually classify defoliation in terms of light, moderate and heavy defoliation. It has been demonstrated that data from Landsat and other synoptic scale sensors have an appropriate spatial resolution for monitoring many types of insect defoliation. The advantages and pitfalls of Landsat data were recognized early. Williams (1975) expressed concerns about Landsat-1's ability to effectively monitor insect defoliation with only 18-day temporal coverage and the greater than 50% chance of cloud cover during an acquisition over Pennsylvania. Williams and Stauffer (1978) used Landsat imagery acquired before and during gypsy moth defoliation. The investigators recognized that agricultural features could be mistaken for insect defoliation. Moreover, Williams *et al.* (1979) evaluated different types of vegetation indices on Landsat imagery acquired before and during peak defoliation to differentiate between defoliation and healthy forest, however, they could not be distinguished from healthy forest. Radeloff *et al.* (1999) used Landsat Thematic Mapper (TM) TM data to identify the forest attributes that affect jack pine budworm population levels and separate the spectral signatures of these attributes from those of actual jack pine bud-worm defoliation in Wisconsin.

Hall *et al.* (2003) also used Landsat multi-temporal change detection approach to map defoliation in insect defoliated forest of Canada with results showing consistency with other studies earlier carried out using the same platform. The various studies have shown the utility of Landsat multi-temporal imageries to identify those characteristics of a forest that make it susceptible to insect defoliation, as well as to identify the actual insect defoliation but could not clearly differentiate defoliation where vegetation is highly saturated. Therefore, it may be difficult for Landsat images to detect defoliation in heavily populated mopane woodland due to the short window for monitoring and the coarse temporal resolution of Landsat relative to cloud cover.

As an alternative, other remote sensing platforms have been demonstrated since the early-1990s to be effective for insect defoliation detection and mapping. Two of those are the Systeme Probatoire d'Observation de la Terre (SPOT) and National Oceanic and Atmospheric Administration Advance Very High Resolution Radiometer (NOAA AVHRR) imageries (Fraser and Latifovic 2005; Kovacs *et al.* 2005). Clerke and Dull (1990) determined the extent and severity of gypsy moth defoliation in Virginia using imagery acquired by SPOT. SPOT data acquired before and during defoliation was used to classify insect defoliation. Based on ground truth data and aerial photography, the range of ratio values corresponding to heavy, moderate, and light defoliation were defined. Clerke and Dull (1990), however, raised questions regarding the completeness of this classification, citing the unknown effects of terrain and forest type on the extent and severity of gypsy moth defoliation.

Dull *et al.* (1990) used SPOT imagery, high altitude panoramic color infrared photography, and traditional aerial sketch-mapping results to determine the extent of gypsy moth defoliation in northern Virginia. This study illustrated the importance of maintaining a GIS database to track defoliation extents, spray block extents, pheromone trap data, and egg mass survey results. This database could be used to efficiently determine the defoliated area of each county, the defoliated area of each property owner, and the defoliated area of each spray block. This

**Table 1** Sample of multispectral remote sensing studies applied in defoliation.

| Sensor | Study area | Image data date | Defoliators | Comment | Reference |
|---|---|---|---|---|---|
| Landsat-1 | Pennsylvania, USA | 1975 | Gypsy moth | Classification results were subjectively analysed and found to be representative of actual ground cover. However, errors of commission in which agricultural cover types were classified as heavy defoliation decreased classification performance. | Williams 1975 |
| Landsat TM | Wisconsin, USA | 1990-1995 | Jack pine budworm | Classification was successful with single-date imagery but was not tested with other methods such as change detection. | Radeloff *et al*. 1999 |
| MODIS EVI | Siberia | 2002 | Silk moth | Very effective in mapping large-scale conifer mortality and also for near real time monitoring but does not provide links with finer resolution validation data | Kovacs *et al*. 2005 |
| SPOT | Virginia | 1989 | Gypsy moth | Questions regarding the completeness of this classification, citing the unknown effects of terrain and forest type were raised. | Clerke and Dull 1990 |
| Landsat TM | Canada | July (1999, 2001) | Aspen | Good for identification but could not differentiate defoliation where vegetation is dense. | Hall *et al*. 2003 |
| Landsat TM & SPOT | Michigan, USA | June 1988 | Gypsy moth | Both can classify defoliation only on a large scale | Joria *et al*. 1991 |
| MODIS | Norway | 2000-2002, 2005 | Scots pine | Good for regional scale analyses but still coarse for effective defoliation monitoring | Eklundh *et al*. 2009 |
| SPOT VGT | Canada | 1998-2000 | Hemlock looper | Good for near real-time and identifying occurrence of defoliation but less reliable for classifying intensity of defoliation | Fraser and Latifovic 2005 |
| Landsat TM | Australia | March 2008 | Beetles and sawfly | Improved accuracy when advance analytical techniques was applied but still coarse for small scale monitoring | Somers *et al*. 2010 |
| SPOT HRV | USA | August 1991 | Spruce budworm | Can classify effectively but cannot monitor defoliation in real time | Franklin and Raske 1994 |
| MERIS | Canada | 2003-2005 | Aspen | Better than Landsat, SPOT, MODIS but unable to evaluate small scale details | van der Sanden *et al*. 2006 |
| MODIS | USA | 2000-2001 | Gypsy moth | Demonstrated significant relationships between defoliation and vegetation indices estimated at the plot scale. | Beurs and Townsend 2008 |

information could make the evaluation of treatment success, as well as any treatment decisions, very simple. Joria and Ahearn (1991) used a digitized USGS map to determine the locations of forested areas in Michigan and concentrated the study on only those forested areas using both Landsat TM and SPOT imageries. Landsat TM was found to be better than SPOT for differentiating between the defoliation classes.

Data from SPOT Vegetation (VGT) at 1 km resolution was used for mapping defoliation and mortality of coniferous forests due to the eastern hemlock looper, with commission errors of 60% and omission errors of 33% respectively, and with reduced errors when aggregating the data into larger mapping units (Fraser and Latifovic 2005). The authors also indicated the potential for near real-time monitoring, however with potentially greater errors. Fraser and Latifovic (2005) suggested the combination of SPOT VGT and NOAA AVHRR data for establishing a general system for large-scale (5–10 $km^2$) forest change detection. While the general occurrence of defoliated areas can be identified, the classification of the intensity of defoliation has been less reliable using SPOT and NOAA AVHRR (de Beurs and Townsend 2008).

Insect defoliation outbreaks have also been investigated using Moderate Resolution Imaging Spectroradiometer (MODIS) data (Kharuk *et al.* 2007). de Beurs and Townsend (2008) conducted a thorough analysis of MODIS daily, 8-day and 16-day composite data for detecting gypsy moth defoliation in oak forests. Their study demonstrated significant relationships between defoliation and vegetation indices estimated at the plot scale. They concluded that MODIS data represent an important tool for insect damage detection at the regional scale. Furthermore, Cook *et al.* (2008) studied the effect of insect defoliation on forest production efficiency and net carbon exchange using models driven with MODIS data. In contrast to other multi spectral remote sensing platforms, MODIS data have a lower spatial resolution, and are therefore more appropriate for regional-scale analyses. In addition, MODIS data are available at a significantly higher temporal resolution (daily) while preserving the spectral bands that are available in the Landsat data.

However, a common problem in using MODIS data is that evaluation of coarse-resolution damage maps is difficult due to the general lack of spatially explicit reference data. Many of the cited studies have evaluated their classifications against sketch maps from aerial surveys or Landsat change maps. These are themselves estimates that may be limited in temporal and attribute accuracy.

Relatively new Medium Resolution Imaging Spectrometer (MERIS) data according to Van der Sanden *et al.* (2006) proved to be better in detecting and monitoring insect defoliation than Landsat, MODIS and SPOT because of its ability to image large areas at medium spatial resolution. MERIS data were concluded to generally depict areas of tent caterpillar defoliation in Canadian aspen forests (van der Sanden *et al.* 2006), however, no formal evaluation was made due to lack of accurate ground data.

Recently, a new satellite platform known as World View-2 was launched. WorldView-2 is Digital Globe's second next-generation satellite, built by Ball aerospace, and leveraging the most advanced technologies (Cheng and Chaapel 2008). Like WorldView-1, WorldView-2 is equipped with state of the art geolocational accuracy capabilities and will be only the second commercial spacecraft after WorldView-1 equipped with control moment gyros, which enable increased agility, rapid targeting and efficient in-track stereo collection (Cheng and Chaapel 2008). This advanced agility combined with an operating altitude of 770 km enables it to collect nearly 1 million $km^2$ of high-resolution imagery per day, and offer average revisit times of 1.1 days around the globe. Currently, WorldView-2 is the only commercial multispectral satellite to provide global, high-resolution access to the Red-Edge spectral band as part of its 8-band multispectral capabilities (Cheng and Chaapel 2008). This Red Edge band has been used to track stress-induced changes in plants, hence it is very important band to consider when detecting and monitoring the health of forest. Until now, the only satellite imagery available that contains Red-Edge data is MERIS with medium spatial resolution (300 m) (van der Sanden *et al.* 2006). MERIS can provide some insights into the conditions of an entire field, but is unable to provide the segmentation necessary to evaluate small scale details, like the health of individual trees in an orchard, hence the advantage of World View-2 with higher spatial resolution

**Table 2** Sample of hyperspectral remote sensing studies applied in defoliation.

| Sensor | Study area | Defoliators | Comment | Reference |
|---|---|---|---|---|
| AISA EAGLE | USA | Hemlock looper | Good for identifying defoliation at tree level using biophysical indicators such as chlorophyll content | Pontious *et al.*2005 |
| HYPERION | Australia | Beetles and sawfly | Good results with ground measurement | Somers *et al*. 2010 |
| HYPERION | Chile | Aphid | Able to detect defoliation also at tree level | Peña and Altmann 2009 |

(1.84 m) (Cheng and Chaapel 2008).

Although images from SPOT, MODIS and MERIS proved a better alternative to Landsat in terms of the spatial, temporal and spectral resolution, they are also limited in that they do not contain specific windows such as red–edge (except for MERIS but still has low spatial resolution) which is a very important band in studying defoliation (Pu *et al.* 2003). Moreover, most of the researches on insect defoliation using multispectral images have been carried out in coniferous forest. Therefore, there is need to test the effectiveness of these multispectral sensors for monitoring insect defoliation in broadleaved forests.

## Hyperspectral remote sensing

Further advances in satellite remote sensing and imaging spectrometry have given rise to hyperspectral imagery, which has been demonstrated to be a reliable and relatively accessible technology to study forests damaged by insects (Coops *et al.* 2004; Stone and Coops 2004; Mutanga *et al.* 2009). Hyperspectral sensors also known as imaging spectrometers are instruments specifically made to acquire data at high spectral and moderate spatial resolution thereby allowing reflectance, radiance and emittance spectra to be constructed in such a way that it permits physical measurements of the Earth's surface. Unlike multispectral imagery, a hyperspectral image provides hundreds of contiguous bands across the visible (VIS), near-infrared (NIR) and shortwave infrared (SWIR) regions of the electromagnetic spectrum, offering unprecedented detailed spectral reflectance data from land surface features. Since major leaf components (e.g. pigments, water, carbon, nitrogen) produce distinctive reflectance signals at specific wavelengths of the aforementioned regions, hyperspectral imagery allows for the measurement of biochemical and biophysical attributes of the plant, associated with its structure, physiology and phenology, and therefore with its health status (Asner 1998; Treitz and Howarth 1999; Lucas *et al.* 2004; Mutanga and Skidmore 2004; Mutanga *et al.* 2004; Cho and Skidmore 2006).

There is mounting evidence that hyperspectral instruments have the capability, not only to assess defoliation, but also to identify the early signs of defoliation; in some cases before visual symptoms are apparent (Mohammed *et al.* 1995; Ismail *et al.* 2007, 2008). This can be explained by the tendency of defoliated leaves to undergo reduction in photosynthetic activity and to lose chlorophyll. These changes alter reflectance at chlorophyll-sensitive wavelengths (Vogelmann *et al.* 1993). Researches on defoliation conducted using hyperspectral sensors are not limited in the literature (**Table 2**). Although broad-band sensors detect defoliated and non-defoliated plants, hyperspectral imagers, have the spectral detail to potentially distinguish between soil, dead, and senescent trees. Hyperspectral data are demonstrated to discriminate plant physiological condition (Pontius *et al.* 2005), even at early phases of senescence (Campbell *et al.* 2004).

Some previous studies have used hyperspectral remote sensing to detect plant defoliation due to water deficit (Stimson *et al.* 2005), insect damage (Radeloff *et al.* 1999), pest outbreaks (Wolter *et al.* 2008), and pollution (Campbell *et al.* 2004). For instance, Pontius *et al.* (2005) used AISA Eagle sensor to map hemlock decline in USA. They found out that unlike multispectral sensors, hyperspectral sensors were able to classify defoliation in a given forest to 11-class rating system with 88% accuracy making it possible for land managers to assess and monitor detailed changes in forest health. Others such as Somers *et al.* (2010) used Hyperion sensor to monitor forage defoliation in southern Australia and observed a good relationship with ground measurement. Additionally, the high spatial resolution data from hyperspectral sensors gives the ability to detect tree-level (rather than stand level) characteristics, which reduce confusion caused by mixed pixels (e.g. crown shading, soil, non-tree vegetation, etc.) (Greenberg *et al.* 2006). While some of these studies reveal substantial improvement over multispectral sensors, others believe that for accurate detection and monitoring, there will be need for the combination of both sensors.

However, just like multispectral sensors, only a few studies have used hyperspectral sensors to monitor defoliation in broadleaved forests (Coops *et al.* 2003; Santos *et al.* 2010). To the best of our knowledge, no studies have been carried out to map and monitor mopane woodland defoliation using hyperspectral scanners. Hyperspectral sensors could actually provide more information of insect defoliation in broadleaved forest because of the presence of high spatial and different bands to which defoliation can be monitored. Therefore, further research need to be conducted on the use of Hyperspectral remote sensors for effective management of insect defoliation in broadleaved forests such as mopane woodland.

## Trade-offs between sensor resolutions for monitoring insect defoliation

We have shown that remote sensing is effective for mapping insect defoliation. However, three issues appear fundamental to the successful use of remote sensing to assess and monitor insect defoliation: the spectral, spatial characterization of defoliation and the timing of image acquisition.

First, a remote sensing spectral basis for damage class limits (e.g., light, moderate, and severe) is required to achieve consistent detection and mapping of defoliation severity. Field and aerial surveys tend to rate areas defoliated into categories that remote sensing studies have attempted to emulate. Broad damage class limits are not conducive for consistent defoliation mapping because they may not correspond to differences in spectral response values that are spectrally or statistically separable on the image. The two factors that drive the spectral response of a sensor include its radiometric resolution and the range of sensitivity to the electromagnetic spectrum. Defoliation tends to result in either physical loss of leaf area or leaf color change, which results in physical differences in spectral response when compared to pre-defoliation images. Several consecutive years of defoliation, however, tend to result in physiological weakening, top kill, and mortality for some defoliators. Understanding the role these factors may play in the resulting spectral responses recorded in the image is important to successful use of remote sensing for mapping defoliation. Thus, remote sensing observations from airborne or satellite sensors that can be used for monitoring defoliation must be over a more continuous scale of spectral responses that can potentially capture a finer scale of defoliation levels rather than the broad classes that are typically used (Franklin 2001; Hall *et al.* 2003) hence the recent use of hyperspectral sensors.

In addition to the spectral observations of defoliation, the size of the outbreak area must also be large enough to be detectable with the airborne or satellite sensor employed. The spatial resolution of the sensor and the areal coverage of an image are also important considerations in the selection of the appropriate sensor. As a result, with both sensor spectral and spatial resolution considerations, the remote sensing of a defoliation problem is more complex than a simple change in foliage condition.

Thirdly, the timing of image data acquisition should coincide with the period when spectral changes resulting from defoliation are most observable; for timing of data acquisition is notably one of the most difficult to achieve with satellite remote sensing because of the need for cloud-free conditions during the suitable range of dates for image acquisition. Most remote sensing studies tend to rely on pre- and post-outbreak images to detect spectral response differences resulting from insect defoliation. The opportunities to acquire imagery ranging from high (e.g., submeter pixel size) to low spatial resolution (e.g., 1-km pixel size) are obviously increasing at an unprecedented rate that should help ensure that future image data will be available during the narrow time periods necessary to capture damage from insect defoliation.

This section has outlined the remote sensing data used in monitoring defoliation from inception highlighting the strengths and weaknesses and its implications in mapping and detecting defoliation within mopane woodland. Logical questions that follow include: What has been the primary methods used in defoliation surveys and which remote sensing methods have been employed in mapping defoliation and to what extent have they been successful?

## DEVELOPMENTS IN REMOTE SENSING TECHNIQUES FOR ASSESSING INSECT DEFOLIATION

A number of studies have demonstrated the potential of measuring defoliation from remotely sensed observations using different techniques (Coops *et al.* 2004; Stone and Coops 2004). The studies use map sketching and linear regression modeling between field assessments of vegetation characteristics related to biophysical variable indicators of defoliation such as LAI and Chl content. They also relate the field measurements with vegetation indices calculated from the images to detect and monitor defoliation from a range of damaging agents including fungal infections and insect predation. Therefore, we discuss the different analytical approaches that have been used for detecting, mapping and monitoring insect defoliation and their implications in mopane defoliations monitoring.

### Vegetation indices

Most of the vegetation indices developed to detect defoliation in woodlands are based on Chl and water content. Vegetation indices can be used to measure changes in leaf area resulting from defoliation (Nelson 1983). Previous studies have used vegetation indices or other measures to examine canopy defoliation by a variety of insects. Nelson (1983) calculated the difference between vegetation indices on two Landsat dates using simple ratio indices such as red-green ratio index, and then empirically determined a threshold to separate defoliated from non-defoliated pixels. This technique was found to be superior to competing techniques for the most accurate assessment of defoliated areas. It has been reported that plants under defoliation display a decrease in canopy reflectance in the lower portion of the near infrared, a reduced absorption in the Chl active region, and subsequently a shift in the red edge (Carter and Knapp 2001).

One simple vegetation index that has also been used in the past is the Normalized Difference Vegetation Index (NDVI) (Rouse *et al.* 1973). As defoliation occurs and leaf area decreases, the NDVI value will also decrease. It has recently been shown that the Wide Dynamic Range Vegetation Index (WDRVI) performs better than the NDVI in estimating defoliation in high-density vegetation (Gitelson *et al.* 2002; Gitelson *et al.* 2006). While the NDVI becomes saturated with high densities of photosynthetic green biomass and the relationship between NDVI and LAI is non-linear (Mutanga and Skidmore 2004), the WDRVI increases the sensitivity of the NDVI, and hence makes the WDRVI - LAI relationship linear. More complex vegetation indices correct for variations in soil background and for atmospheric scattering. The Enhanced Vegetation Index (EVI) (Huete *et al.* 2002) is the standard vegetation index for MODIS. EVI will decrease in response to defoliation (Huete *et al.* 2002).

However, due to errors (saturation in areas with significant forest cover) encountered when using these indices, scientist have developed better indices which includes the short wave infrared band (SWIR). Water strongly absorbs radiation in SWIR portion of electromagnetic spectrum making SWIR reflectance to be very sensitive to the amount of water in vegetation. SWIR reflectance is generally low for high leaf water content and increases with decrease in water content. The sensitivity of the SWIR has led to the development of a number of vegetation indices that are responsive to vegetation defoliation based on SWIR and NIR reflectance.

Normalized Differential Water Index (NDWI) and Normalized Differential Infrared Index (Gao 1996) were developed from hyperspectral data as the difference between NIR reflectance and a SWIR band and were found to be good detectors of defoliation. In most cases however, most of these indices have been modified to meet the need of researches into insect defoliation in modern times. All of these indices have been used in mapping and detecting defoliation of different insect defoliator with varying outcomes (Pu *et al.* 2003; Coops *et al.* 2004). While some have reported success, some of the indices have failed to efficiently discriminate defoliated areas from other spectrally active end members within particular

**Table 3** Summaries of indices proposed for mapping and monitoring defoliation.

| Category | Notation | Formula | | | Description | References |
|---|---|---|---|---|---|---|
| | | MODIS | World View-2 | Hyperion | | |
| Multiple ratio | NDVI | $(B_3-B_2)/(B_3+B_2)$ | $(NIR_1-Red)/(NIR_1+Red)$ | $(R_{750}-R_{705})/(R_{750}+R_{705})$ | Chlorophyll content and LAI | Giltelson and Merzlyak 1994 |
| | mNDVI | $(NIR_1-Red)/(NIR_1+2CB)$ | | $(R_{750}-R_{705})/(R_{750}+R_{705})$ | Chlorophyll content | Sims and Gamon 2002 |
| Red edge | VRE | | $NIR_1$/Red Edge | $(R_{740}/R_{720})$ | Chlorophyll absorption | Vogelman *et al.* 1993 |
| | CUR | | | $R_{675}-R_{690})/R_{683}^2$ | Chlorophyll content | Zarco-Tejada *et al.* 2000 |
| | REIP | | | $700 + 40 ((R_{667}+ R_{782})/2) -R_{702})/R_{738}-R_{702}$ | LAI | Guyot and Baret 1988 |
| Pigment C | PRI | | (Green-Yellow)/(Green+Yellow) | $(R_{531}-R_{570})/(R_{531}+R_{570})$ | Xantophyll pigment | Gamon *et al.*1992 |
| | CRI | | | $(R_{510})^{-1}-(R_{700})^{-1}$ | Chlorophyll absorption | Gitelson *et al.*2002 |
| Simple ratio | RDRI | | $(R_{G+Y})/(R_{red})$ | $(R_{500-599})/(R_{600-699})$ | Chlorophyll content and LAI | Peñuelas *et al*. 1995 |
| | RNI | | Red/ $NIR_1$ | | Chlorophyll content and LAI | Zhang *et al*. 2009 |

wood-lands. A common problem in dense vegetation stands is the high degree of light absorption making vegetation indices insensitive to biomass changes. Knowing fully the limita-tion of vegetation indices, scientists have developed and improved techniques that can accurately estimate biomass in more densely vegetated areas using hyperspectral derived vegetation indices rather than focusing on the red and NIR bands alone (Mutanga and Skidmore 2004). For detecting and mapping defoliation in mopane, we suggest the use of three categories of vegetation indices which are described below and presented in **Table 3**.

### *1. Multiple ratio indices*

Multiple ratio indices such as Normalized Differential Vegetation Index (NDVI), modified normalized difference vegetation index (mNDVI) have been found to be good detectors of defoliation (Sims and Gamon 2002). While, NDVI is a vegetation index derived from the ratio of red and NIR bands and has been found to be highly correlated with biophysical indicators that depicts defoliation (LAI and Chl content) (Dye and Tucker 2003; Zhou *et al.* 2003), mNDVI modifies NDVI by including the reflectance at high 445 nm (at which Chl absorption produce minimal reflectance) (Sims and Gamon 2002). The mNDVI compensates for high leaf surface scattering that NDVI does not account for (Peña and Altmann 2009). It is our opinion that mopane worm defoliation of mopane woodland is expected to yield a decrease in NDVI, mNDVI during the defoliated stage when the leaves are almost absent. The limitation of these indices in the context of detecting and mapping defoliation of mopane woodland will be their sensitivity to optical properties of reflecting soil background since for a given amount of vegetation, soil substrates results in higher vegetation index values which may not necessarily mean lack of defoliation (Sims and Gamon 2002). To minimize the effect of soil background, other vegetation indices have been pro-posed.

### *2. Simple ratio indices*

Simple ratio indices were developed to reduce or eliminate soil influence on solar reflectance values when monitoring forest health (Huete *et al.* 2002; Peñuelas *et al.* 1995). The simple ratio indices measured with sufficient precision is quite sensitive to vegetation changes during the time of peak growth. However, an inherent drawback of these indices is the loss of uniqueness in information due to the fact that different leaves can have different spectral responses, but have band ratio values that are similar. The introduction of multiple ratios such as NDVI has covered the limitations of simple ratio although they both saturate when LAI is very high. For monitoring mopane defoliation, two simple ratios have been suggested, the Red Green Ratio Index (RGRI) and Red NIR Index (RNI). The two indices have been found to accurately determine the defoliation level of forest to a certain level since they include the combination of bands where healthy and unhealthy vegetation can be easily differentiated (Peñuelas *et al.* 1995). They also eliminate topographic (irradiance) and atmospheric effects (Peñuelas *et al.* 1995). For mopane defoliation, the ratio is expected to be high when the woodland is photosynthetically active i.e., the healthy stage and *vice versa*.

### *3. Red edge indices*

Recently, new vegetation indices based on red-edge region have been used to track insect defoliation (van der Sanden *et al.* 2006). Red-edge is defined as the rise of reflectance at the boundary between the chlorophyll absorption feature in VIS red wavelengths and leaf internal structure scattering in NIR wavelengths. The position of the red edge is consistent among different species and generally ranges from 680 to 780 nm (Cho and Skidmore 2006). Red edge indices are constructed with bands sensitive to the Chl content and internal structure of the leaf, and therefore have proven to be closely related to foliage biomass quantity, growth and developmental stage and health status of the plant (Gitelson and Merzlyak 1994; Sims and Gamon 2002). Zarco-Tejada *et al.* (2000) describe Chl content as a potential indicator of defoliation process because of its direct role in the photosynthetic processes of light harvesting and initiation of electron transport and its responsiveness to a range of changes in plant health status at any particular time.

Red edge indices such as Curvature index, Vogelman index and the red edge inflection points have been used to relate biophysical indicators that are used to measure the health status of woodland (Zarco-Tejada *et al.* 2000). Vogelman red edge index was discovered to be associated with leaf area and chlorophyll content while curvature index was used to track changes in Chl content and it was found to be strongly correlated with Chl index (Zarco-Tejada *et al.* 2000). The red edge inflection point (REIP) has also been found to correlate significantly with LAI and hence could be used for monitoring the health status of woodland (Hermann *et al.* 2010).

In monitoring mopane worm defoliation of mopane woodland therefore, it is expected that the changes in the values of the red edge indices mentioned above will indicate the changes in the health status of the canopy at the different stages of defoliation. For instance, decrease in the values of the red edge indices is expected during the defoliated stage when the leaves are almost absent.

### *4. Pigment content indices*

When the rate of photosynthesis decreases due to plant stress, the foliage exhibits higher concentrations of carotenoid relative to chlorophyll pigments, while higher foliar investments of xanthophyll cycle pigments result as a response to low light use efficiency. Vegetation indices based on bands sensitive to these leaf pigments have also been demonstrated to be closely correlated with vegetative growth stage and the degree of stress of vegetation (Gamon and Surfus 1999; Gitelson *et al.* 2002; Sims and Gamon 2002). In stressed plants, the proportionally stronger decline of green pigments (i.e. Chls) can be used to detect defoliation. The two major pigment indices that have been found to be an indicator of plant stress are photochemical reflectance index (PRI) and Carotenoid Reflectance Index (CRI) (Gitelson *et al.* 2002). The PRI and CRI were developed as a remotely-sensed indicator of Light Use Efficiency (LUE) (Gamon *et al.* 1992). They use narrow spectral bands to detect changes in leaf reflectance at 531 nm relative to a reference band that is usually located at around 570 nm and is not affected by changes in short-term stress events.

Carotenoid pigments have multiple functions, but they are generally found in higher concentrations in plant leaves that are either stressed or dead. PRI and CRI have been correlated with plant stress in several field studies at the leaf and ecosystem levels (Peñuelas *et al.* 1995). They provide a quick and non-destructive assessment of leaf physiological properties (Peñuelas *et al.* 1995) and may be used for wide range of species (Gamon *et al.* 1992). The limitation of these indices for defoliation mapping occurs when they are related to plant water status (Peñuelas *et al.* 1995) especially during wilting of leaves in dry periods. It must be noted that PRI is sensitive to soil background reflectance (Peñuelas *et al.* 1995). However, they may be integrated with other vegetation indices that exploit biophysical variables to provide strategic remote sensing monitoring of defoliation. In mapping defoliation within mopane woodland, it is believed that defoliation will result in low green pigments hence low values of PRI and CRI based on leaf pigments during the peak of defoliation since photosynthesis activities is low or even non-existent. Narrow-band spectral reflectance may also provide information on the ratio of carotenoid to Chl for detec-ting stress effects.

## Change detection

Other studies have approached defoliation in terms of change detection methods (Collins and Woodcock 1996). Relative robust change detection methods include image differencing and ratio differencing. Image differencing is probably the most widely applied change detection algorithm for a variety of geographical environments (Coppin *et al.* 2004). It involves subtracting one date of imagery from a second date that has been precisely registered to the first. With "perfect" data, this would result in a data set in which positive and negative values represent areas of change and zero values represent no change. Nelson (1983) delineated forest canopy changes due to Gypsy Moth defoliation in Pennsylvania more accurately with vegetation index differencing than with any other single band difference or band rationing. Image ratio differencing on the other hand is one of the simplest and quickest change detection methods in insect defoliation monitoring where data are rationalized on a pixel-by-pixel basis. A pixel that has not changed will yield a ratio value of one. Areas of change will have values either higher or lower than one. The major drawback for these two change detection algorithms is that they do not adequately address differences in sun elevation angles or phenological changes between images recorded at different dates (Radeloff *et al.* 1999). In fact, Riordan (1981) criticized the ratio change detection algorithm in combination with an empirical threshold definition as being statistically invalid.

More sophisticated change detection methods perform transformation of the image space such as Gramm-Schmidt transformation, data reduction techniques such as principal component analysis and Tasseled Cap transformation.

Image transformation techniques are frequently applied to multidate imagery that has been stacked in 2n-dimensional space (where n is the number of input bands per image): principal component analysis (PCA) and tasseled cap (Radeloff *et al.* 1999). Using multi-date Landsat TM data, Collins and Woodcock (1996) compared Kauth-Thomas and Principal Components transforms with Gramm Schmidt orthogonalization for mapping pest-induced forest mortality in the Lake Tahoe Basin, concluding that the KT transform was most sensitive to changes in vegetation condition. Muchoney and Haack (1994) also examined merged principal components analysis, image differencing, spectral-temporal change classification, and post classification differencing for detecting forest defoliation. Their results indicated that of the entire algorithm employed, defoliation was best determined by image differencing and principal components analysis. The exact nature of the principal components derived from multi-temporal data sets is difficult to ascertain without a thorough examination of the structure of the data and a visual inspection of the combined images. To avoid drawing faulty conclusions, the analysis should not be applied as a change detection method without a thorough understanding of the study area (Diago *et al.* 2010). Moreover, the vegetation indices and most of the transformation methods used for monitoring defoliation are limited however by their dependence on the visibility of leaves in image pixels since for defoliation, it is the absence of leaves that determines the severity of the stress (Stone and Coops 2004).

By using combined registered data sets, or corresponding subsets of bands, collected under similar conditions, researchers have come up with another algorithm for monitoring change detection in forest health known as composite analysis (Coppin *et al.* 2004). They came up with classes where forest canopy change would be expected to have statistics significantly different from those where no change has occurred, and could be identified as such. The method can incorporate multistage decision logic and is sometimes referred to as "layered spectral / temporal change classification", "multidate clustering", or "spectral change pattern analysis". While this technique necessitates only a single classification, it is a very complex one, in part because of the added dimensionality of two dates of data.

In numerous cases it requires many classes and many often redundant features when no discriminant analysis has preceded the process. It furthermore demands prior knowledge of the logical interrelationships of the classes and should only be used when the researcher is intimately familiar with the study area (Coppin *et al.* 2004). Burns and Joyce (1981) found the method to produce only change in forest cover per se without providing accurate information on the character of the change. Coppin *et al.* (2004) remarked that, since spectral and temporal features have equal status in the combined data set, they cannot be easily separated in the pattern recognition process. As a consequence, class labeling using this algorithm may be difficult.

A mathematical model that best describes the fit between two multidate images of the same area can be developed through stepwise regression and also use to detect defoliation in forest. The algorithm assumes that a pixel at time is linearly related to the same pixel at a later time in all bands of the electromagnetic spectrum acquired by the sensor. This implies that the spectral properties of a large majority of the pixels have not changed significantly during the time interval (Coppin *et al.* 2004). The dimension of the residuals is an indicator of where change occurred. The regression technique accounts for differences in mean and variance between pixel values for different dates. Simultaneously, the adverse effects from divergences in atmospheric conditions and/or sun angles are reduced. The critical part of the method is the definition of threshold values or limiting dimensions for the no-change pixel residuals. Singh (1989), on the other hand, reported the highest change detection accuracy for tropical forest change detection with the regression method.

Change Vector Analysis (CVA) is another multivariate statistical analysis that has been used extensively to identify changes in forest as a result of insect defoliation between image dates and is widely discussed in the remote sensing literature (Collins and Woodcock 1996; Townsend *et al.* 2004). Generally, users rely upon two outputs of CVA to represent the magnitude of change, computed as the absolute geometric difference in the soil brightness (B), vegetation greenness (G), and surface wetness (W, collectively BGW), between dates, and an eight-level classification representing all possible directions of change bounded by BGW all increasing between dates and BGW all decreasing between dates (Allen and Kupfer 2000). As noted in numerous studies (Cohen and Fiorella 1998; Allen and Kupfer 2000; Townsend *et al.* 2004), the limitation to this approach for mapping defoliation is that it requires the user to identify a threshold level in magnitude change that represents actual change between dates rather than changes within a date. This becomes very difficult to use when defoliation is rapid and can only be applied with imageries of high temporal resolution.

Radeloff *et al.* (1999) developed an approach for monitoring defoliation in terms of the relative proportion of leaves in image pixels using linear spectral mixture analysis (SMA) which can quantify the proportion of each pixel that is occupied by individual image component (Sims *et al.* 2007). These methods have previously been used to measure defoliation in *Pinus radiata* plantations using high-resolution multi-spectral images but methods for calculating image fractions from hyperspectral image data are in their developmental infancy. The application of SMA for the assessment of defoliation offers several advantages over simple regression methods using spectral indices and other transformation methods in that it is capable of detecting vegetation cover at low and fragmented levels, and has the ability to reference a small number of spectrally stable endmembers (vegetation, soil, water, etc.) (Goodwin *et al.* 2005). The technique decomposes the reflectance of each pixel into the relative contribution of a limited number of surface endmembers making it easy to separate image components (Somers *et al.* 2010). SMA methods have been used to monitor insect defoliation in broadleaved forest (Goodwin *et al.* 2005; Somers *et al.* 2010). However and to date, the full potential of SMA for forest defoliation assessment has not yet been achieved. Residual error in fraction estimates provided by SMA is often introduced by the natural variability in the conditions of scene components, i.e., soil, plant, etc. inherent in remote sensing data. Recently, a number of solutions have been developed to reduce this effect (Asner 1998). Somers *et al.* (2010) found out that the SMA techniques gave improved accuracy in monitoring defoliation.

## POTENTIAL OF MAPPING MOPANE DEFOLIATION USING REMOTE SENSING

The current method used to spatially map the mopane worm defoliation of mopane woodland is by field-based exercises. The effectiveness of this method is questionable because the method is qualitative, subjective, and dependent on the skill of the surveyor (Stone and Coops 2004). However, the ability of remote sensing to successfully detect and map forest health has been given great attention with diverse range of imageries and modeling techniques (Radeloff *et al.* 1999; Stone and Coops 2004; Pontius *et al.* 2005). Thus remote sensing has the potential to ensure that the detection, mapping and monitoring of mopane worm defoliation is a possible task provided a sound understanding of the progression and patterns of defoliation are known. Knowledge of these defoliation processes allows for the development of algorithms to detect changes in foliar characteristics using remotely sensed data. Digital remote sensing technologies measure the amount of electromagnetic energy reflected from the leaves and canopy of the tree using a number of wavelengths which can range from 350 to 2500 nm. Researchers have used this spectral information, in the form of individual bands, band combinations, and vegetation indices to detect and map forest health (Coops *et al.* 2004; Pontius *et al.* 2005).

Additionally, remote sensing technology can image large areas and allow for the repetitive monitoring and assessment of tree damage and mortality (van der Sanden *et al.* 2006).

A combination of both multispectral and hyperspectral imageries will give more insight for detecting and monitoring the defoliation process within mopane woodland in order to determine the best spatial and spectral resolution to which it can be monitored. In mapping and monitoring mopane defoliation using satellite remote sensing platforms therefore, spatial, spectral and temporal resolution must be of great importance. We therefore suggest the use of SPOT, World View-2 and Hyperion imageries for monitoring the defoliation process. The primary strengths of Word View-2 are its high temporal resolution (1.1 days), the presence of windows (red edge) for monitoring defoliation, its ability to image large areas at a relative high spatial resolution (1.84 m). Also, SPOT and Hyperion images are suggested not only due to their relatively high resolutions (spatial, spectral and temporal) with respect to other multispectral and hyperspectral images respectively, but also for their easy accessibility. The view of these authors is that with the relatively high resolution images of World View-2 and Hyperion and relatively coarse SPOT images, we can not only be able to map but also determine the extent to which spatial, spectral and temporal resolution of satellite imageries play in the detection and monitoring of defoliation from mopane woodland at different stages i.e. undefoliated, early defoliated and late defoliated stages.

Given the success and limitations of the different techniques used in monitoring insect defoliation discussed above, we recommend the combination of different techniques with the aim of determining the best approach to mapping and monitoring defoliation within mopane woodland. For instance the use of vegetation indices will provide the spatio-temporal patterns of mopane defoliation while more sophisticated image classification techniques such as SMA and CVA which have been previously associated with biophysical indicators that are related to defoliation (Rade-loff *et al.* 1999; Somers *et al.* 2010) will reduce the limitations encountered with the use of vegetation indices.

## CHALLENGES OF REMOTE SENSING IN MAPPING MOPANE DEFOLIATION

Despite all the efforts of applying remote sensing, insect defoliation monitoring has been only moderately successful. Reliable insect defoliation monitoring has often been limited to three classes (e.g., heavy, medium, and light) with accuracies around 70–80%. Low defoliation levels remain difficult to detect. Consequently, the challenge would be to assess the different characteristics and defoliation process within mopane woodland, and then associate each level of observation with different remote sensing data types in order to provide the appropriate level of detail and accuracy for detection and mapping purposes.

Three challenges may make it difficult to monitor mopane defoliation with remote sensing. First, mopane worm-mopane tree interactions are dynamic and periods where defoliation can be detected are often short. For instance, mopane worm defoliation of mopane woodland are bivoltine across most of its distribution with the first defoliation in November to December and the second in February to March, except in more arid areas where it is univoltine. This restricts the time period when defoliation can be detected to about 2 months. However, during the early stages of defoliation (when the worms are feeding on the tree), the canopy of the tree appears green and visually indistinguishable from healthy trees (Ciesla 2003). Leaves become pale green gradually leading to total defoliation. At this stage, discriminating the defoliated part of the tree using remote sensing is dependent on detecting the little changes that might have occurred in the spectral reflectance of the tree. The subtle changes in the reflectance of defoliated vegetation, when measured by various broad band sensors, are often masked by the high degree of variation in reflectance caused by factors such as varying view geometry, illumination, and canopy density (Lucas *et al.* 2004). Moreover, because mopane worm is a wasteful feeder, its feeds on the entire leaflets of mopane tree giving the trees their characteristic red brown color (Ditlhogo *et al.* 1996).

Given these challenges, there is strong possibilities of using high spectral resolution data (hyperspectral) for effective detection, mapping and monitoring early stages of mopane defoliation because the data allow for the detection of detailed features using many narrow bands which would have been otherwise masked by broad band sensors (Kumar *et al.* 2001; Mutanga *et al.* 2004, 2009).

The second challenge is the presence of other end members in mopane woodland. Most mopane woodland contain an understorey of grasses and herbs that are always present during the mopane worm defoliation making it very difficult to distinguish defoliation of mopane from reflectance of other end members (mostly grasses and herbs) (Vogelmann *et al.* 1993). Infact, reflectance of heavily defoliated mopane tree may be mistaken for the end members. To resolve this, two things are suggested. Firstly, it will be important to use spectrometer to characterize the reflectance of end members in other to distinguish them from actual defoliation (Somers *et al.* 2010). This can then be applied to satellite images. Secondly, high resolution imageries such as hyperspectral sensors will be accurate for detection and mapping purpose at canopy level and able to distinguish different understoreys using advance image transformation techniques such as SMA (Radeloff *et al.* 1999).

The third challenge may occur when an image at the peak of an outbreak is being analyzed; it is unclear if an effect (changes in chlorosis, nutrient content or tree vitality) or a determining factor (e.g., stand age) of the insect population drives the satellite image classification (Somers *et al.* 2010). Effects and determining factors can both lead to reasonable classification accuracy peak-outbreak satellite imageries are analyzed. Effects and determining factors may not be important for a forest manager mainly interested in a quick assessment of insect outbreak. However, separating the two and being able to identify actual defoliation is crucial for a scientist who may want to study the relationship between stand age and defoliation. To achieve this, there may be need to relate the effects with the determining factors. For example, the fraction (proportion of each end member) images from image transformation techniques such as SMA can be correlated with population measurements of mopane worms at sampling location to detect if there are any relationships with effects and determining factor of mopane defoliation.

## SYNTHESIS AND RECOMMENDATIONS FOR REMOTE SENSING OF MOPANE DEFOLIATION

Remote sensing is an integral and essential tool for the collection of data needed to support decisions and action programs to improve forest health (Zhou *et al.* 2010). While not all attempts to use remote sensing in forest health protection have proven successful, many have been shown to meet data requirements, and have proven to be cost-effective alternatives to ground data acquisition. At the present time, there are two classes of remote sensing tools that have been shown to be effective in meeting forest health protection data requirements: aerial sketch mapping and imagery (satellite and airborne). Each have their individual strengths and weaknesses, and all should be considered a collective set of tools available to the forest health specialist.

The capabilities of the various sensor systems presently available to the forest health protection specialist are a key factor in the type of sensor selected for a specific application. Aerial sketch mapping, for example, is an excellent tool for background mapping, but subjective and their reliability is difficult to assess hence not suitable for the assessments of forest health. Today's Earth-orbiting satellites and airborne sensors offer the advantage of image acquisition at regular intervals provided that the targets of interest are not under cloud cover. They also provide a range of spectral sensitivity across the electromagnetic spectrum. Initial satellite sensors have a poor spatial resolution, however, when compared to airborne sensors. This limits their ability to resolve all but the most severe of forest damage signatures. However, remote sensing is a dynamic technology. New and improved methods of data collection, with superior resolution, are continuously becoming available. For instance, high spatial resolution remote sensing for forestry applications has reached an almost mature phase with wide range of applications. Numerous opportunities and challenges such as the robustness of remote sensing data processing and analytical methods remain.

With increasing availability of high resolution remote sensing data like hyperspectral scanners and Digital Multispectral Image (DMSI) in Southern African sub-region which offers a potential source for the effective collection of spatially accurate, consistent, and timely imagery, it is essential to study the impacts of *Imbrasia belina* on mopane woodland. High resolution remote sensing data is capable of achieving higher mapping accuracies by identifying individual crowns (Wulder and Franklin 2003). This is an important benefit for mapping and monitoring *Imbrasia belina* in mopane woodland as it helps to dissociate insect defoliation from other events, such as climate disturbance and phenology of forest type (Stone and Coops 2004). Given this development, it is prudent to assess what remotely sensed methods or data sources may have potential for detecting, mapping and monitoring defoliation in mopane woodland. Since defoliation of mopane woodland by mopane worms occurred in the past and will likely occur again in the future, lessons learned from this research may be applied in future mopane woodland management. As such, a lot of research has still to be done to fully understand the potential of high spatial and spectral resolution data in insect defoliation especially in broadleaf forest defoliation such as mopane woodland.

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