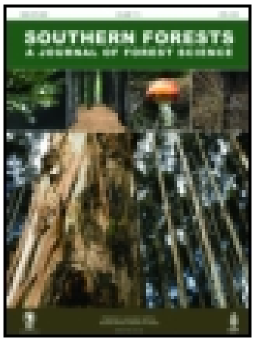

Southern Forests: a Journal of Forest Science

ISSN: 2070-2620 (Print) 2070-2639 (Online) Journal homepage: http://www.tandfonline.com/loi/tsfs20

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To cite this article: Sifiso Xulu, Michael T Gebreslasie & Kabir Y Peerbhay (2018): Remote sensing of forest health and vitality: a South African perspective, Southern Forests: a Journal of Forest Science, DOI: 10.2989/20702620.2018.1512787

To link to this article: https://doi.org/10.2989/20702620.2018.1512787

Published online: 28 Nov 2018.

Southern Forests 2018: 1–12
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This is the final version of the article that is published ahead of the print and online issue

SOUTHERN FORESTS
ISSN 2070-2620 EISSN 2070-2639
https://doi.org/10.2989/20702620.2018.1512787

Review Paper

Remote sensing of forest health and vitality: a South African perspective

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Commercial forestry plantations are an important and valuable segment of the South African economy and forest managers are required to maximise and sustain forest productivity. However, various factors such as the outbreak of damaging agents are constantly hampering forest health and thus decrease productivity. It is therefore important to detect the presence and spread of these agents within plantation forests, a task efficiently achieved using remote sensing technology. A wide assortment of sensors with varying resolutions are available and have been extensively used for this purpose. This paper reviews the current status of remote sensing of forest health in South Africa by providing insight on the latest developments on the use of the technology in forest plantations. A systematic search was executed on Google Scholar, ScienceDirect® and EBSCO*host*® databases that identified 627 articles of which 29 made reference to remote sensing of forest health in South Africa. Four key results were found: (1) the latest technology is capable of detecting and monitoring forest health with great accuracy, especially with the adoption of machine learning methods; (2) studies employing remote sensing to characterise forest health have burgeoned since 2006 with even more applying hyperspectral data; (3) most studies were spatially concentrated in the KwaZulu-Natal Midlands region around Pietermaritzburg with only a few over the Western Cape; and (4) the remote detection of pest outbreaks and pathogens have received much attention followed by alien invasive plants and a few studies directed to fragmentation. Present and future partnerships may open up opportunities for exploiting remote sensing further; this should address growing expectations from government and industry for more detailed and accurate information concerning the health and condition of South Africa's plantation forests.

Keywords: alien invasive plants, forest health, fragmentation, pest and pathogens, remote sensing

Introduction

Forest health has become an increasingly important concept for sustainable forest management. This concept, however, lacks universal meaning, because it comprises subjective judgements as a result of differing socioeconomic and ecological viewpoints that have yielded a variety of indicators used to measure forest health (Ferretti 1997; Stone and Mohammed 2017). Most scientists agree, however, that forest health essentially describes the capacity of forests to maintain and preserve constantly high-quality supply of environmental products and services (Coyle and Megalos 2016). In this review, the emphasis is on tree health, particularly tree crowns that have been affected by tree-damaging insect pests and disease, invasive alien plants and fragmentation in South Africa's planted forests.

In recent years, there has been increasing attention on the susceptibility of forests to various damaging agents that may be regulated by climate (FAO 2010) and these are expected to grow with global warming and climate change (Bentz et al. 2010). Factors such as insects and disease outbreaks, alien species invasion and fragmentation warrant particular concern (Tkacz et al. 2008) as they have been reported to cause substantial forest deterioration where they occur. These factors, if not properly monitored, could have devastating effects in the forestry sector, particularly for those markets dependent on timber and its allied products. More recently, concerns over these forest-disturbing agents have led to increased collaborative research by foresters, government and academic institutions, a practice that is widely used to address the decline in forest health. For instance, in South African forestry, a concerted research approach has been applied to combat the escalating damage to resources from pests (Ismail et al. 2012; Lottering et al. 2018), pathogens (McTaggart et al. 2015), alien invasive plants (Peerbhay et al. 2015, 2016b) and, more recently, the damage to pine trees by bark-stripping baboons (Germishuizen et al. 2017). Information on the spatial extent and severity of such forest-damaging disturbances is perceived to require management planning (Westfall and Ebata 2014) to reduce forest damage to acceptable levels (Coulson and Stephen 2008).

Forest protection strategies typically depend on timely detection of threats to permit the accurate assessment and introduction of effective mitigation measures; however, the

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traditional visual detection of affected trees is labourious and not straightforward (Rullan-Silva et al. 2013). The process is dubious because it is subjective, qualitative and hinges on the assessor's expertise (Stone and Coops 2004). The monitoring of large and unreachable areas further exacerbates this quandary, especially when using costly and spatially restrictive field surveys. The need for an affordable and spatially comprehensive approach has stimulated much research into extracting the necessary forest health information from airborne and satellite-based remote sensing (Trotter et al. 1997). Several studies have demonstrated that forest health is efficiently assessed by exploiting remote sensing capabilities (Wulder et al. 2006; Ismail and Mutanga 2010; McDowell et al. 2015).

Remote sensing has gained wide acceptance and plays a growing role in forest management; its application introduces new opportunities for improving the assessment of forest-disturbing agents, their location, nature, areal extent and frequency (Ciesla 2000). Moreover, it offers forestry researchers and managers a flexible and spatially exploratory tool to augment other methods and extends monitoring capabilities (McDowell et al. 2015). However, to detect the impacts of disturbance on forest trees, the variation in reflectance must be great enough to respond to sensitivity of the imaging sensor (McGowen et al. 2001). Key vegetation attributes, such as size, shape, distribution and phenology, contribute to the detection of tree health using remote sensing (Lawley et al. 2015). Hitherto, great strides in remote sensing have been made with the early sensors recording features at relatively coarse resolution (Melesse et al. 2007). As space- and air-borne platforms with improved sensor capability became available, so did the means to collect images across a wide range of spatial, spectral and temporal resolutions (Jakubowski 2012). These advances from contemporary high-resolution sensors permit data quality close to that of aerial photography (Chuvieco 2016), so that the use of aerial photographs has since become largely overtaken – but not entirely – by remote sensing. The latest generation of sensors that generate high-spatial, hyperspectral and multispectral resolution data, allows automated image computation and holds much promise to obtain even more information related to forest health more efficiently (Jia et al. 2006).

In summary, this paper provides a review of different remote sensing applications in South African commercial forestry and discusses their unique contributions in assessing forest health. The algorithms applied to process remotely sensed data when interpreting forest health indicators are also considered. While this paper is limited to a South African context, studies that explain the application and ability of remote sensing to evaluate forest health in other parts of the world were considered for completeness and to guide future research focus.

The remainder of the paper proceeds as follows. Firstly, the search strategy and the study area is described. Secondly, remote sensing for characterising forest health is explained. Then, tree-damaging agents that have been studied remotely in South Africa and their spatiotemporal aspects are provided. Finally, concluding remarks and future research directions are presented.

Materials and methods

Systematic review

Unlike general research reviews (e.g. Rullan-Silva et al. 2013), which typically do not provide a detailed account of the review procedures applied (e.g. databases searched, articles excluded and search words used) – and with a dearth of such information – it is difficult to replicate the study to confirm the completeness of the analysis (Ford et al. 2011). In principle, systematic reviews employ literature search methods to select relevant studies that meet explicit criteria that reasonably confirm the strength of the evidence produced by previously published studies (Ham-Baloyi and Jordan 2015). Thus, the systematic review in this case is expected to provide the foundation of an evidence-based account of remote detection of forest health, emerging practices and knowledge gaps in the South African context.

Method

A systematic literature search was carried out using the Google Scholar, ScienceDirect® and EBSCO*host*® databases for published articles on the remote detection of plantation forest health in South Africa. The following combinations of keywords and Boolean operators were entered into the database to retrieve relevant publications: remote sensing OR satellite imagery OR earth observation OR forest health OR forest disturbance OR forest damage OR insect pest infestation OR insect outbreak OR alien invasive plants OR machine learning algorithm OR forest plantations OR commercial plantations OR South Africa. As illustrated in Figure 1, the search identified 627 articles, and for the purposes of this paper, articles were narrowed down to 29 that made a direct reference to 'remote sensing of forest health in South Africa's plantation forest'. The selected studies were considered based on a number of criteria as illustrated in Figure 1. First, they had to apply remote sensing to detect forest health. Second, they had to be restricted to commercial forestry plantations. Third, they had to be based in South Africa for analysis, or elsewhere for accurate reporting and completeness.

Reviewed articles were vetted using the following stratification: forest-disturbing agent tackled, methods applied, study site location, and year of publication. Further details on each application can be found in Table 1.

Study area

Plantation forests in South Africa cover approximately 1.2 million ha of the total land area (1.2%), stretching from the Western Cape and traversing the eastern seaboard to Limpopo in the north (Figure 2). These fast-growing trees consist overall of 50% pine, 43% *Eucalyptus* and 7% wattle, most of which are spatially concentrated in Mpumalanga (40%), KwaZulu-Natal (40%), Eastern Cape (12%), Limpopo (4%) and Western Cape (4%) provinces. Generally, commercial forestry plantations follow dryland cropping practices and grow most productively in environments receiving more than 800 mm rainfall y^{-1}. All plantation sites are restricted to relatively high rainfall areas exceeding 750 mm y^{-1} (van der Zel 1995); these are favourable conditions for forestry plantations (DWAF 2004).

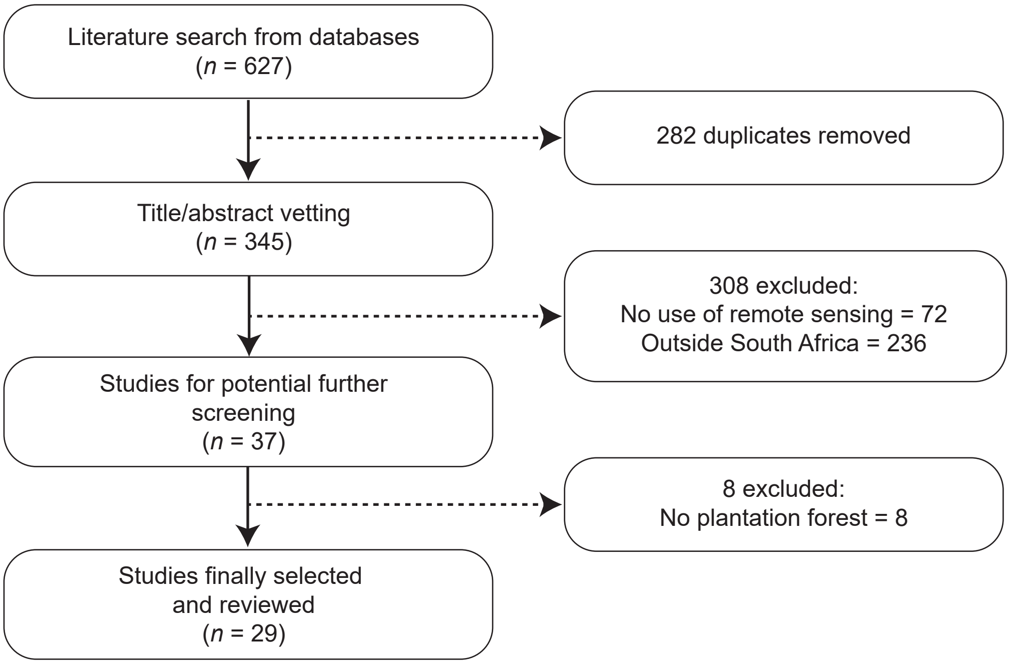

Figure 1: Schematic flow chart demonstrating the literature search process using the various databases

Table 1: Summary of studies that applied remote sensing to assess forest health in South Africa. KZN = KwaZulu-Natal

Reference	Study area	Data	Approach	Accuracy (%)
Ismail et al. (2006)	SAPPI Pinewoods, KZN	LrEye	Analysis of variance	69–84
Ismail et al. (2007)	SAPPI Pinewoods, KZN	LrEye	Analysis of variance	69–84
Mutanga et al. (2007)	SAPPI Pinewoods, KZN	ASD	Analysis of variance	99
Dye et al. (2008)	SAPPI Richmond, KZN	LrEye	Image texture analysis	70
Ismail et al. (2008)	SAPPI Pinewoods, KZN	ASD	Analysis of variance	99
Ismail et al. (2008)	SAPPI Pinewoods, KZN	LrEye	Minimum variance	–
Ismail and Mutanga (2010)	SAPPI Pinewoods, KZN	ASD	Random forest, bagging and boosting	68–73
Mutanga and Ismail (2010)	SAPPI Pinewoods, KZN	ASD	Analysis of variance	84
Oumar and Mutanga (2010)	Richmond, KZN	ASD	Artificial neutral networks	67–74
Ismail and Mutanga (2011)	SAPPI Pinewoods, KZN	ASD	Random forest and boosting trees	–
Oumar and Mutanga (2011)	–	–	Review article	–
Lottering and Mutanga (2012)	New Hannover District, KZN	SPOT-5	Artificial neutral networks	89
Poona and Ismail (2012)	Tokai plantations, Western Cape	ASD	Random forest	81
Oumar and Mutanga (2013)	Richmond, KZN	WorldView-2	Partial least squares	65
Oumar et al. (2013)	Pietermaritzburg	ASD	Partial least squares	63–74
Poona and Ismail (2013)	Tokai plantations, Western Cape	QuickBird	Artificial neural network	82
Adam et al. (2013)	Helvetia plantations, Mpumalanga	–	Random Forest	82
Abdel-Rahman et al. (2014)	Greytown, KZN	AISA	Random forest and support vector machine	74–78
Atkinson et al. (2014)	SAPPI Hodgsons, KZN	AISA	Support vector machine	93
Oumar and Mutanga (2014)	Richmond, KZN	WorldView-2	Artificial neural network	71
Oumar and Mutanga (2014)	Pietermaritzburg, KZN	ASD	Artificial neural network	88
Peerbhay et al. (2014)	SAPPI Hodgsons, KZN	AISA	Partial least squares	82
Poona and Ismail (2014)	Tokai plantations, Western Cape	ASD	Botura algorithm	75
Peerbhay et al. (2015)	SAPPI Hodgsons, KZN	AISA	Random forest	89–95
Lottering and Mutanga (2016)	SAPPI Pinewoods, KZN	WorldView-2	Artificial neural network	80
Peerbhay et al. (2016)	SAPPI Hodgsons, KZN	WorldView-2	Random forest	67–91
Peerbhay et al. (2016)	SAPPI Hodgsons, KZN	WorldView-2, AISA and LiDAR	Partial least squares	68–98
Peerbhay et al. (2016)	–	–	Review article	–
Lottering et al. (2018)	Greytown, KZN	WorldView-2	Artificial neural network	83

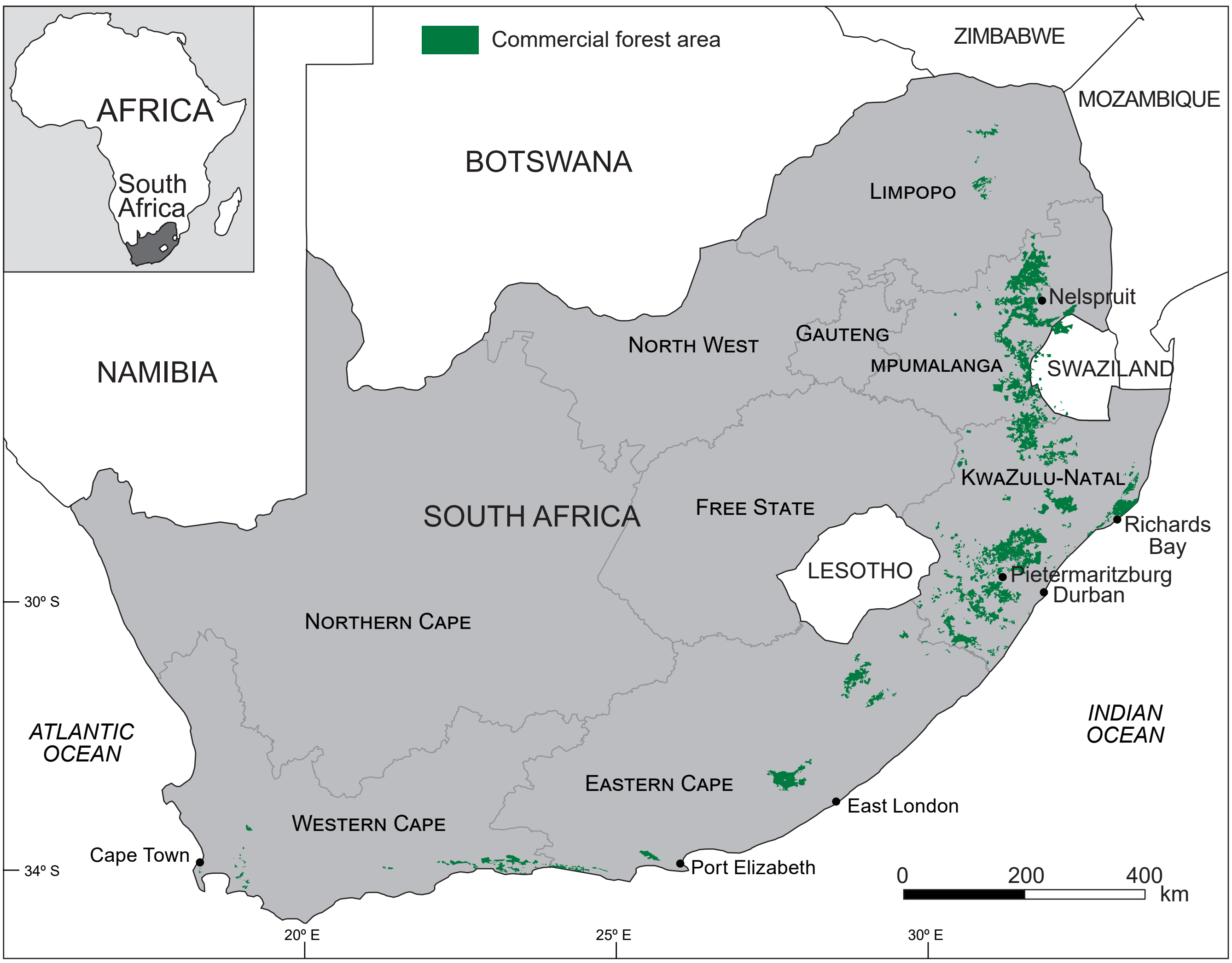

Figure 2: Distribution of plantation forests in South Africa

Conceptualising pests and pathogens as remotely sensed forest health indicators

Remote detection of diseased or stressed trees typically involves the use of leaf chlorophyll (Mutanga et al. 2007; Dye et al. 2008) and moisture content (Ismail and Mutanga 2010, Oumar and Mutanga 2014b) as acute indicators. These indicators are consistently related to spectral information, in that spectral characteristics change when trees are exposed to any source of stress (Chuvieco 2016). Therefore, the details of reflectance spectra provide the most suitable and accurate means for detecting tree stress. Their measurement entails contrasting the chlorophyll absorbing (red band; 0.6–0.7 μm) and non-absorbing near-infrared (NIR; 0.7–1.1 μm) spectral regions to determine tree health status (Mutanga et al. 2007). In this regard, healthy trees exhibit greater reflectance in the NIR portion and absorb most of the visible light as illustrated in Figure 3. In contrast, reflectance decreases when tree health deteriorates (Dye et al. 2008). It is well established that stressed trees generally reduce chlorophyll activity, which consequently causes increased reflectance in the red band (Chuvieco 2016).

The contrast between the NIR and short-wave infrared (SWIR) regions of the spectrum has been used widely to estimate leaf moisture content (Oumar and Mutanga 2010; Yebra et al. 2013) as illustrated in Figure 3. Variations in strategic bands located at 1.4 and 1.9 μm within the SWIR region form the foundation for the insect pest-induced water stress detection because water in the leaf absorbs strongly at these wavelengths (Lillesand and Kiefer 1994). On the basis of this evidence, several studies have progressively evaluated the utility of different sensors and ways to improve stress detection.

It is important to note that many damaging agents confront South African forestry plantations but for the purpose of this paper, only those that have been investigated using remote sensing technologies will be reported. Overall, it was found convenient to divide the remote sensing applications in forest health into three broad categories: insect pest and pathogens, alien invasive plants, and fragmentation.

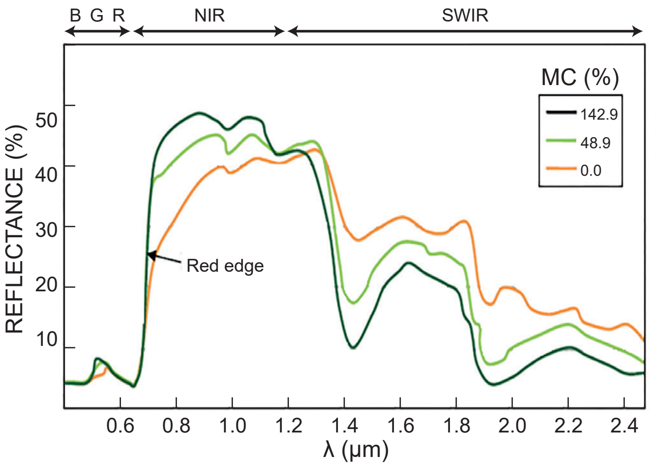

Figure 3: Leaf spectral reflectance signatures in terms of moisture content (MC) (modified from Chuvieco 2016)

Insect pest and pathogens

In South African forest plantations, over the past decade, pests and pathogens have been the dominant cause of serious damage to forest trees, affecting future forest resource sustainability. The Siricid wasp (*Sirex noctilio*) is among the insect pests that have had a great impact on commercially planted pine species (Ismail et al. 2007). Its periodic outbreaks have caused extensive tree mortality in KwaZulu-Natal, threatening more than 72 000 ha of forest (Ismail et al. 2008b) with a 6% infestation rate (Hurley et al. 2007). Ismail et al. (2006) used a selection of vegetation indices derived from high-resolution imagery to distinguish different stages of *S. noctilio* infestations in pine plantations. They applied canonical variate analysis, which discriminated the red from the grey infestation stage with an accuracy of 84% and 69%, respectively. A key priority among foresters is detecting the red infestation stage, which reflects the degree of infestation (Leckie et al. 2005; Ismail et al. 2007). The difficulty in discerning the green infestation stage was noted and still remains a challenge in related studies using other criteria (Leckie et al. 2005). Using hyperspectral imagery, Mutanga et al. (2007) established that most (77%) wavebands within the visible region distinguished three levels of *S. noctilio* attack. This is attributed to the sensitivity of wavebands located within the visible region to reduced leaf chlorophyll content (Ismail et al. 2008a). Dye et al. (2008) applied texture analysis and found that the NIR and blue bands correlated well with *S. noctilio* infestations compared with green and red bands, which had weak correlations. The study confirmed that the integration of spectral and textural information improves the discrimination between different insect pest infestation stages (Wang et al. 2015).

Mutanga and Ismail (2010) analysed the relationship between plant water content and different classes of *S. noctilio* infestations using analysis of variance (ANOVA). These authors found that variation in leaf water content correlated well with variation in spectral reflectance across three classes (59% for healthy, 46% for the green and 15% for the red). These results corroborate earlier studies (Carter 1991; Eitel et al. 2006) in which wavebands within the SWIR part of the spectrum were more sensitive to plant water variations than wavebands in the NIR region. In the same area, Ismail and Mutanga (2010) tested the performance of three regression tree ensembles for predicting *S. noctilio*-induced water stress in *Pinus patula* plantations. The results showed random forest (RF) to have relatively superior predictive accuracy (73%) than boosting (68%) and bagging (69%). RF seems consistently to achieve better accuracy than bagging, with exceptions when a modified form of bagging, termed adaptive bagging, was applied, which surpassed RF (Ismail and Mutanga 2010).

More recently, Abdel-Rahman et al. (2014) applied RF and support vector machine (SVM) to distinguish between healthy, *S. noctilio*-infested and lightning-damaged pine trees from airborne hyperspectral data. Both RF and SVM performed relatively well in discriminating healthy, *S. noctilio*-attacked and lightning-damaged classes, attaining an accuracy of 75% and 74%, respectively. Following Ismail and Mutanga (2011), RF was implemented to select discriminatory bands and the accuracy shifted to 78% for RF and 77% for SVM. Similarly, Adam et al. (2013) used RF to model climatic and topographical variables to determine susceptibility of *E. nitens* to cossid moth (*Coryphodema tristis*) attack in Mpumalanga province, and the model produced good accuracy (82%) results. *Coryphodema tristis* is a native wood-boring insect to South Africa that only feeds on *Eucalyptus nitens* trees (Gebeyehu et al. 2005), threatening products and markets associated with *E. nitens* (Boreham 2006).

The recent appearance of *Thaumastocoris peregrinus* (bronze bug) pest in South Africa (Jacobs and Neser 2005), that affects *Eucalyptus* plantations, is another concern to timber production in the country. This is a sap-feeding insect pest from Australia, which has almost achieved ubiquitous distribution in South African plantation forests on 26 *Eucalyptus* genotypes (Laudonia and Sasso 2012). The insect constitutes a major threat to the forestry industry by affecting the trees' photosynthetic ability, causing much reduced growth and even mortality of severely affected trees (FAO 2010). Jacobs and Neser (2005) studied *T. peregrinus* extensively and found infestation symptoms to include the reddening and dropping of leaves, branch dieback and tree mortality in severe cases. The current pest detection methods involve time-consuming and costly field surveys as well as cost-effective remote sensing. Considerable progress has been made to detect *T. peregrinus* occurrence remotely in South Africa and elsewhere in the world.

In the KwaZulu-Natal Midlands region, Oumar et al. (2013) used narrow indices calculated from normalised difference vegetation index ratios to predict the presence of *Thaumastocoris peregrinus* using ASD field spectrometer (0.35–2.5 μm). The indices produced an accuracy of 59%. Subsequently, a partial least squares (PLS) algorithm was applied for spectral data reduction so as to identify spectral bands with high predictive power. The resultant top 20 indices (located in the NIR at 0.80–0.89 μm) increased the accuracy to 63%. Overall, the accuracy increased to 65%. Oumar et al. (2013) further tested a greedy backward variable selection model, which identified three indices (anthocyanin, carotenoid and normalised [0.86–0.88 μm]), resulting in improved (74%) accuracy.

In an alternate study, Oumar and Mutanga (2013) developed PLS models from multispectral WorldView-2 bands and indices to predict *T. peregrinus* infestations. The performance of these data sets was tested individually and combined using a PLS regression. WorldView-2 bands outperformed vegetation indices in predicting *T. peregrinus* infestation with an accuracy of 63% against 42%. Both bands and indices identified performed well in all PLS models with 65% accuracy. Much predictive strength for Worldview-2 bands was vested in the red edge and NIR portions of the spectrum. Oumar and Mutanga (2014a) reaffirmed this finding, reinforcing the power of the red edge and NIR bands. These wavebands have been found useful for detecting forest stress as tress undergo chlorosis, resulting in alterations in reflectance from the trees affected (Zarco-Tejada et al. 2002).

More recently, Oumar and Mutanga (2014a) combined environmental variables with WoldView-2 data to enhance the prediction of *T. peregrinus* infestation using a PLS algorithm. Among the environmental variables, rainfall significantly correlated with *T. peregrinus* presence, with accuracy ranging from 62% to 76%. NIR-1 and NIR-2 as well as the red-edge band produced significantly ($p < 0.05$) high correlations with *T. peregrinus* damage (60% to 74%). In a subsequent study, these authors successfully predicted water stress induced by *T. peregrinus* damage from field spectral data using an artificial neural network (ANN) (Oumar and Mutanga 2014b).

Eucalyptus snout beetle (*Gonipterus scutellatus*) is another important insect pest in the South African forestry sector. This is a leaf-feeding weevil that is a major defoliator of *Eucalyptus* species (Newete et al. 2011). The weevil has caused extensive damage in *Eucalyptus* plantations, particularly over the eastern areas of South Africa (Lottering et al. 2018). An understanding of *G. scutellatus* is essential for effective management and to maximise the productivity of *Eucalyptus* species due to its widespread damage. In this regard, Lottering and Mutanga (2016) determined the optimal spatial resolution for predicting different levels of *G. scutellatus*-infested *Eucalyptus* trees using a minimum variance technique. They established that low to medium defoliation levels can be detected at 2.5 m resolution, whereas high and severe defoliation levels can be detected at 3.5 and 4.5 m resolution, respectively. Moreover, these authors modelled the relationship between weevil-induced defoliation and leaf area index (LAI) from WorldView-2 imagery. The results showed strong correlation between these variables at 72% accuracy. The authors further applied ANN to optimised vegetation indices and the accuracy improved to 83% (Lottering et al. 2018).

Similar to tree-damaging insect pests, some studies have remotely detected diseases caused by fungal pathogens that attack commercial trees in South Africa. While numerous pathogens have been recorded to date, the fungus *Fusarium circinatum*, known to cause pitch canker disease (Wingfield et al. 2008), is currently the most remotely detected pathogen in the country. This disease has become widespread in pine species, causing extensive mortality in plantations and nurseries across South Africa (Porter et al. 2009) and resulting in significant economic losses. Poona and Ismail (2012) determined hyperspectral wavebands for discriminating healthy and diseased seedlings using the RF algorithm. They found wavebands in the red-edge and NIR regions to be highly capable for separating healthy and infected classes. Poona and Ismail (2013) undertook a similar study using QuickBird imagery and an ANN approach, and found QuickBird imagery (0.6–2.44 m, 0.44–0.93 μm resolution) to be capable of discriminating diseased from healthy classes with an 82% accuracy. The authors concluded that wavebands in the red-edge and NIR portions of the spectrum are useful for detecting *F. circinatum* infection prior to the noticeable visual symptom stage.

Recently, a new pathogen, wattle rust (*Uromycladium acaciae*) emerged in KwaZulu-Natal and southern Mpumalanga (Little and Payn 2016), threatening the productivity of black wattle (*Acacia mearnsii*) plantations in South Africa (McTaggart et al. 2015). The pathogen affects all age classes and has currently spread throughout wattle growing areas in KwaZulu-Natal with the Midlands region being the worst-affected area (Little and Payn 2016). The rust seems to be favoured by moist and low-light conditions, making spring and early summer months appropriate for the spread of this disease. In their empirical study, McTaggart et al. (2015) studied key characteristics of the wattle rust and concluded that it causes gummosis of the bark on trunks, stems and matted leaves. Infection occurs when spores germinate on a leaf or branch and penetrate the surface, resulting in spots of diseased tissue on the tree (Little and Payn 2016). As yet, only laboratory work has been done and there is an urgent need for the spatial detection of this rust fungus to monitor the spread and impact at a landscape level.

On the basis of this account, it has proved possible to apply remote sensing for successful detection and mapping of insect pests and pathogen-infected trees. The integration of machine learning has greatly increased the accuracy of detecting affected trees, making remote sensing a more practical tool for effective forest management.

Invasive alien plants

Invasion alien species (IAS) and their effects on forestry plantations are another serious management concern. In South Africa, the proliferation of the aggressive weed, *Solanum mauritianum* (bugweed), has received much attention. This is currently the most insidious, densely growing and highly resilient invasive plant species in the country as recorded by the *South African Plant Invaders Atlas* (Henderson 2007). The grey-green-leaved plant, with a roughly 30-year life span, is a major forestry plantation invader in South Africa (Peerbhay et al. 2016a). As such, continuous evaluation and monitoring of IAS has been accepted as a research necessity (Johnson 1999) that South Africa is progressively addressing.

Several studies have demonstrated remote sensing technology as highly capable for mapping IAS. The practice has evolved from using images with low spectral but high spatial resolution (i.e. aerial photographs) to digital images comprising mature spectral with medium to high spatial resolution (Underwood et al. 2007). The emergence of multispectral data has amplified the detection ability of IAS by recording up to eight wavebands (Groeneveld and Watson 2008). Locally in South Africa, WorldView-2 is currently the most used source of multispectral data for this purpose. In part, this is because Oumar and Mutanga (2013) acclaimed WorldView-2 as having superior bands located strategically in the visible and NIR regions with 1.8 m resolution, which outstrips those of other multispectral sensors, such as GeoEye, IKONOS and QuickBird. The sensor's newly incorporated red-edge (0.68–0.75 μm), coastal (0.40–0.45 μm), yellow (0.58–0.62 μm) and NIR-2 (0.86–1.04 μm) bands are strongly correlated with variations in plant health, which makes it useful for detection purposes (DigitalGlobe 2010; Oumar and Mutanga 2014a; Stone and Mohammed 2017).

Peerbhay et al. (2016b) tested the ability of WorldView-2 and a unique unsupervised RF method to detect bugweed occurrences in forest margins, open areas and riparian sites in the KwaZulu-Natal Midlands. Their results showed high competency for WorldView-2 imagery to discriminate bugweed as they achieved respectively high (91%, 85% and 68%) accuracies. Despite these successes, McGowen et al. (2001) noted limitations with recent multispectral data to include inability to distinguish light and scattered weed occurrences. The sensor is able to detect weeds when they become heavy and widespread (Ghiyamat and Shafri 2010) and this has serious economic implications. Alternatively, the use of hyperspectral data with many narrow contiguous spectral bands that are sensitive to phenological changes is a promising option (Zeng et al. 2017). Hyperspectral remote sensing offers greater spectral resolving power than multispectral data, making it well-suited for extracting weeds' biochemical and structural attributes at fine scales (Underwood et al. 2003). This further permits detection of the weed at an early stage of establishment, which adds to a suppression campaign for weed control. Early weed control cuts the effects that may affect tree productivity, which enhances the success of prevention and eradication measures (Peerbhay et al. 2016a). In the KwaZulu-Natal Midlands, Atkinson et al. (2014) successfully detected bugweed within mature *P. patula* stands using 2 m AISA hyperspectral imagery (0.3–0.99 μm) with overall accuracy of 93%. This accuracy was influenced by the adoption of SVM, which selected 17 optimal bands from 272 original AISA bands. Peerbhay et al. (2015) also reported an excellent accuracy of 95% through using an AISA and RF approach. Peerbhay et al. (2016c) used AISA imagery to compare with LiDAR data collected over the same period to detect bugweed abundance. The AISA and LiDAR data individually produced an overall accuracy of 63% and 64%, respectively. The integration of these data sets improved the accuracy to 78%. This improvement ascribes to the synergetic effect of very highly detailed spatial and spectral data that provide complementary abilities for vegetation classification (Lim et al. 2003).

The use of multispectral and hyperspectral remotely sensed data for IAS detection and mapping has been improved by the incorporation of machine learning, especially RF and SVM. These algorithms are instrumental in IAS detection using hyperspectral data, which suffers from several caveats, including data dimensionality. Nonetheless, the issue of dealing with high data dimensionality has been eased by applications selecting and processing a subset of important bands that best characterise a feature of interest (Atkinson et al. 2014). This holds much potential for detecting IAS with high accuracy.

Fragmentation

Forest fragmentation is one of the broad spectrum of factors that affect forest health, involving the division of forest stands into smaller and more isolated patches. Lindenmayer and Fischer (2006) note that fragmentation is responsible for long-term changes to the composition and function of forests, an aspect that disrupts silvicultural management and forest productivity. In South African forestry landscapes, attempts have been made to record such manifestations remotely. For instance, Lottering and Mutanga (2012) used SPOT-5 imagery to estimate road-edge effects on *Eucalyptus* plantations in KwaZulu-Natal. They applied ANN to select ideal texture measures. The results demonstrated that structural differences existed from forest road edges towards the interior. They subsequently applied an ANOVA to verify the results, and the outputs confirmed a decrease of forest structural attributes from the road edge towards the interior. The overall accuracies ranged from 69% to 89%.

Having highlighted the utility of various sensors in tacking the myriad of forest health conditions, the narrative now turns to a spatiotemporal account of these studies across South African landscapes.

Spatiotemporal account of remote sensing application to forest health

Overall, the remote sensing of forest health in South Africa is a growing research area with much attention devoted to pest and pathogen outbreak as they constitute the majority (19 of the total of 28) of the articles. This is followed by the detection of alien plant species (totalling seven articles) with relatively little focus (two articles) devoted to fragmentation (Table 2). Insect pests and pathogens were combined as they are often mutually dependent. The search results encapsulated in this table also showed that in South Africa, as in other forest-growing countries, remote detection of forest health is largely restricted to optical platforms because of their reflectance spectra that enables detection of vegetation stress. Notably, hyperspectral (Analytical Spectral Device [30%], AISA [17%] and LrEye [14%]) and multispectral data (WorldView-2 [24%]) have dominated the forest health assessment practice. The use of LiDAR has been limited due to its high cost, but it is hoped that growing research partnerships may increase its application.

Spatially, most studies (80%) were spatially concentrated in the province of KwaZulu-Natal, particularly in the Midlands region, around Pietermaritzburg. The Western Cape accounts for about 10% with Mpumalanga having 3% of the articles, while the remainder featured reviews on specific damaging agents (Figure 4). Should studies that have remotely detected forest plantation health elsewhere in South Africa exist, then such studies have not been

Table 2: Summary of remote sensing applications for forest health in South Africa (2006–2018)

Forest-disturbing or -damaging agent	Imaging sensor								Overall application (%)
	AISA	WorldView-2	Spectrometer (Fieldspec3 Pro)	LrEye (DMSI)	SPOT	Quick Bird	LiDAR	Total	
Sirex noctilio	1	–	5	4	–	–	–	10	68
Thaumastocoris peregrinus	–	2	2	–	–	–	–	4	
Gonipterus scutellatus	–	2	–	–	–	–	–	2	
Pitch canker	–	–	2	–	–	1	–	3	
Solanum mauritianum	4	2	–	–	–	–	1	7	25
Road edge	–	–	–	–	1	–	–	1	7
Moisture content	–	–	1	–	–	–	–	1	
Total application	5	6	10	4	1	1	1	28	100

Insect pests and pathogens
Invasive alien species
Forest fragmentation

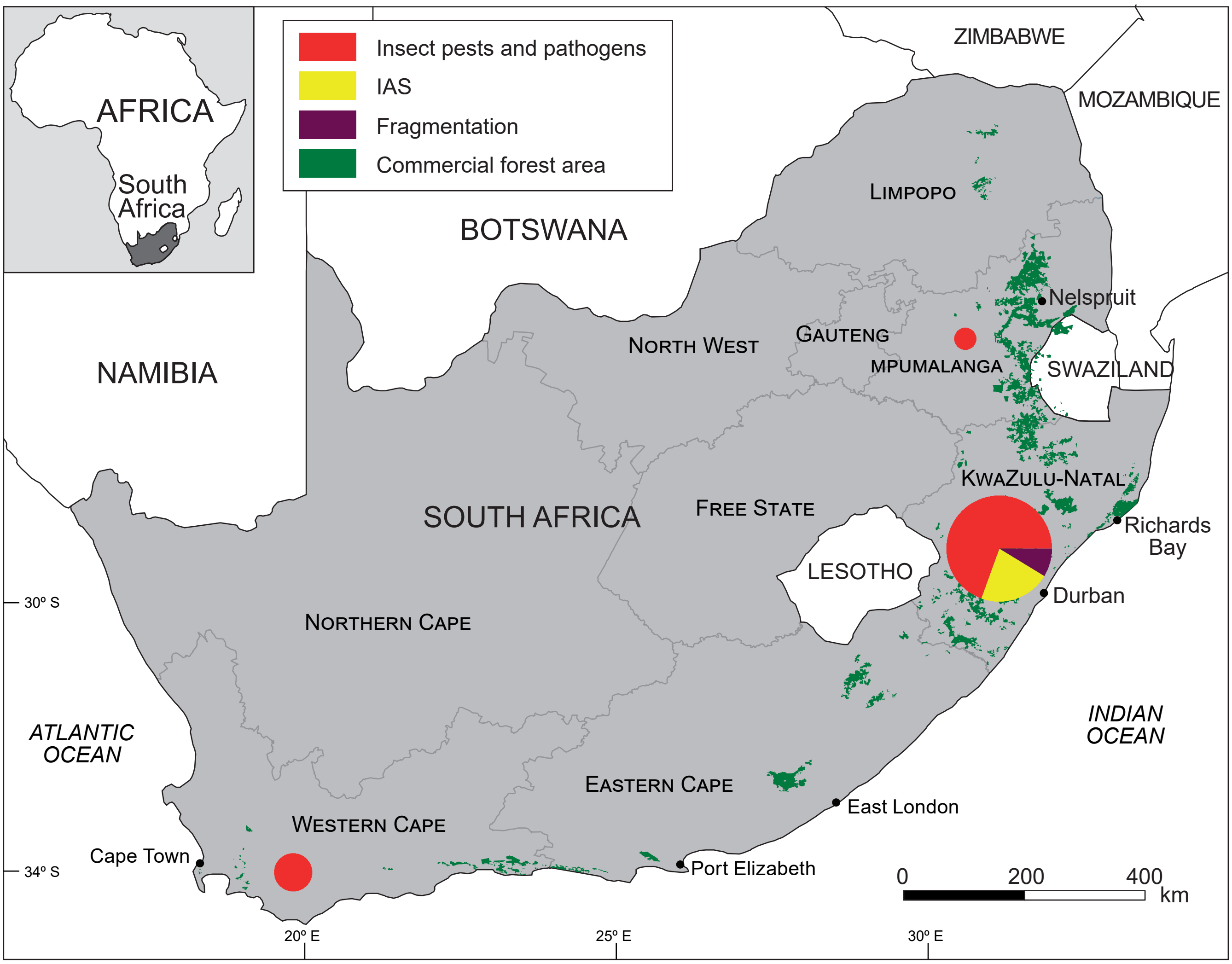

Figure 4: Spatial distribution of remote sensing of forest health studies in South Africa

published and this review solely considered the published surveys as required.

Regarding developments in remote sensing as publication records indicate, the history of remote sensing of forest health in South Africa is slightly more than a decade long with 2006 recording the first publication. Since then, there has been a gradual increase over the years, yielding a total of 29 publications by 2017. Mutanga et al. (2016) credit this progress to data availability and the increase in Earth observation and geographic information systems (GIS) programmes at various institutions locally.

The research partnerships, such as between SAPPI, the Department of Science and Technology, the Council for Scientific and Industrial Research, and the University of KwaZulu-Natal (Ismail et al. 2012), are also adding to this increasing output. Furthermore, Köhl et al. (2006) note improved access to remotely sensed data, constant data cost reduction and better-quality resolution from imaging sensors is stimulating the utility of remote sensing further.

Discussion

Studies of remote sensing for forest health have shown that tree stress by different damaging agents alter biochemical and structural properties so that the resultant variations in leaf reflectance can be recorded by imaging sensors. This review has demonstrated that information generated by means of remote sensing platforms are essential for developing spatial maps that will expose the occurrence and the extent of tree damaging agents so that early warning systems and effective monitoring measures can be established. The benefits of early forest stress detection are that they reduce costs and enhance the success of prevention measures, which consequently maximise forest productivity, as expected.

The continuous developments in imaging sensors has made remote sensing a desired and practical tool for characterising the state of forest health in various respects with great fidelity. High-resolution multispectral data, such as WorldView-2 (Lottering et al. 2018) and QuickBird (Poona and Ismail 2013), have been used with success to detect tree-damaging insects and to discriminate affected from healthy trees. WoldView-2 has also been found useful for detecting weeds, particularly those that have become dense and widespread (Peerbhay et al. 2016a). The monitoring of early weed invasions, however, has not yet been successful. The appearance of hyperspectral data with many contiguous narrow spectral bands overcomes this problem by proving highly capable of recording weeds at their early stages (Houborg et al. 2015). Studies have also shown high competency of hyperspectral data to classify different levels of trees exposed to several tree-damaging insects (Dye et al. 2008; Oumar et al. 2013) and pathogens (Poona and Ismail 2012; Poona and Ismail 2014).

More recently, Peerbhay et al. (2016c) demonstrated that the integration of either hyperspectral or multispectral data with LiDAR data deliver better accuracies for weed detection than using these data sets on their own. Moreover, the combination of LiDAR with hyperspectral data in particular prevails over that with multispectral data. While hyperspectral data can afford detailed information on the spectral properties associated with varying levels of stresses, the immanent high dimensionality of the data makes the analysis challenging (Kursa et al. 2010). Several algorithms have been applied to reduce data dimensionality of hyperspectral data and most studies found that RF stood out as the best approach for this purpose (Abdel-Rahman et al. 2014).

Several studies have produced satisfactory accuracies for numerous forest health conditions using satellite imagery, but better accuracies were mostly achieved when competent machine learning algorithms were employed. Overall, several studies have demonstrated RF, and to some extent ANN, as highly suitable for characterising forest health parameters. These algorithms have been applauded in particular for their strength not only in amplifying classification accuracies or reduce data dimensionality but also in selecting useful variables with high discriminatory power (Ismail and Mutanga 2010). As a result, the prevalence of these algorithms in remote sensing of forest health research is to be expected. Peerbhay et al. (2016a) advised that further investment should now be directed toward the development of accurate automated and semi-automated algorithms that are capable of exploiting the massive amounts of information associated with remotely sensed data sets in order to sort out spectral complexities.

This review has also shown that studies on remote sensing of forest health have been almost entirely limited to the KwaZulu-Natal Midlands, and few undertaken within Tokai plantations over the Western Cape and Mpumalanga province. With the advent of freely available sensors, such as Landsat and Sentinel, and increase in access to data along with abreast and rapid advances in computer applications, forest health studies are expected to spread across the forestry landscape of South Africa. In addition, the state-of-the-art synthetic aperture radar (SAR) appears to have great potential for characterising the structure and detecting subtle changes within forest stands (Verhegghen et al. 2016). Imminent SAR developments are anticipated with much capability for recording disturbance manifestations that are concomitant with canopy structure, such as canopy gaps. Ultimately, the monitoring of forest canopy disturbances will expand since SAR is capable of imaging forests throughout the year regardless of cloud conditions (Siegert and Ruecker 2000).

Given that forest health, like all forestry applications, requires accurate analysis, the modifications of forest conditions due to climate change and other drivers make forest characterisation an extremely important consideration for management planning in order to maximise forest productivity. For this assessment, spatially explicit risk models with scenario capability are required to fully understand current and future potential of insect pests and other damaging agents on the plantation forestry industry. This may also facilitate the economic evaluation of the impact of forest stressors within plantations and provide the industry with measures to mitigate financial losses.

Further studies on forest health employing multitemporal with medium to high spatial and temporal resolution images are essential to expose disturbance pattern. Future airborne and satellite sensors are anticipated to bring far more capable observations to detect forest stressors, allowing for the separation of impacts of multiple stressors in support of a comprehensive forest protection and monitoring framework.

Conclusion

This review has demonstrated the use of remote sensing as a practical tool for extracting forest health information in South Africa. Studies have applied a range of data sets, the majority of which are hyperspectral data followed by multispectral and lately incorporating LiDAR and machine learning techniques. Thus far, studies are restricted to few areas, much of which are based in the KwaZulu-Natal Midlands region, probing insect pests and disease, invasion alien species and forest fragmentation. While South Africa's plantation forests are confronted with a multitude of tree-damaging agents, only few, thus far, have been explored using remote sensing technology. With the advent of cloud-based remote sensing platforms such as Google Earth Engine that afford access to freely available and processed satellite data, it is hoped that full potential of this technology will be explored in order to meet the government and industry's growing expectations for more updated and accurate information on forest conditions and timber procurement potential. There is also potential to further increase the utility of remote sensing by shifting towards long-term time-series analyses, as part of an effective management framework to monitor several other tree-damaging instances, such as forest drought, forest fires or anthropogenic disturbance. Otherwise, remote sensing of forest health in South Africa is very much in its infancy, and with improving research partnerships there are promising developments in this regard.

Acknowledgements — We would like to thank the South African National Space Agency and the National Research Foundation of South Africa (grant number 114898) for partly funding this work and Sappi Forests-SA for providing the necessary support and information to make this study a success. We also thank the editors of the journal and anonymous reviewers for constructive comments.

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References

Abdel-Rahman EM, Mutanga O, Adam E, Ismail R. 2014. Detecting *sirex noctilio* grey-attacked and lightning-struck pine trees using airborne hyperspectral data, random forest and support vector machines classifiers. *ISPRS Journal of Photogrammetry and Remote Sensing* 88: 48–59.

Adam E, Mutanga O, Ismail R. 2013. Determining the susceptibility of *Eucalyptus nitens* forests to *Coryphodema tristis* (cossid moth) occurrence in Mpumalanga, South Africa. *International Journal of Geographical Information Science* 27: 1924–1938.

Atkinson JT, Ismail R, Robertson M. 2014. Mapping bugweed (*Solanum mauritianum*) infestations in *Pinus patula* plantations using hyperspectral imagery and support vector machines. *IEEE Journal of Selected Topics in Applied Earth Observations and Remote Sensing* 7: 17–28.

Bentz BJ, Regniere J, Fettig CJ, Hansen EM, Hayes JL, Hicke JA. 2010. Climate change and bark beetles of the western United States and Canada: direct and indirect effects. *BioScience* 60: 602–613.

Boreham G. 2006. A survey of cossid moth attack in *Eucalyptus nitens* on the Mpumalanga Highveld of South Africa. *Southern African Forestry Journal* 206: 23–26.

Carter GA. 1991. Primary and secondary effects of water concentration on the spectral reflectance of leaves. *American Journal of Botany* 78: 916–924.

Ciesla WM. 2000. Remote sensing in forest health protection. FHTET Report no. 00-03. Fort Collins: US Department of Agriculture, Forest Service.

Chuvieco E. 2016. *Fundamentals of satellite remote sensing: an environmental approach* (2nd edn). Boca Raton: CRC Press.

Coulson RN, Stephen FM. 2008. Impacts of insects in forest landscapes: implications for health management. In: Paine TD (ed.), *Invasive forest insects, Introduced Forest Trees and Altered Ecosystems*. Dordrecht: Springer. pp 101–125.

Coyle D, Megalos M. 2016. Promoting a healthy forest on your land. SREF-FH-001. Athens, GA: Southern Regional Extension Forestry.

DigitalGlobe. 2010. *The benefits of the eight spectral bands of WorldView-2*. Westminister: DigitalGlobe.

Dye M, Mutanga O, Ismail R. 2008. Detecting the severity of woodwasp, *Sirex noctilio*, infestation in a pine plantation in KwaZulu-Natal, South Africa, using texture measures calculated from high spatial resolution imagery. *African Entomology* 16: 275–289.

DWAF (Department of Water Affairs and Forestry). 2004. Water resource protection and assessment policy implementation process. Resource directed measures for protection of water resource: methodology for the determination of the ecological water requirements for estuaries. Pretoria: DWAF.

Eitel JUH, Gessler PE, Smith AMS, Robberecht R. 2006. Suitability of existing and novel spectral indices to remotely detect water stress in *Populus* spp. *Forest Ecology and Management* 229: 170–182.

FAO (Food and Agriculture Organization of the United Nations). 2010. *Global forest resources assessment 2010 – main report*. Rome: FAO.

Ferretti M. 1997. Forest health assessment and monitoring—issues for consideration. *Environmental Monitoring and Assessment* 48: 45–72.

Ford JD, Berrang-Ford L, Paterson J. 2011. A systematic review of observed climate change adaptation in developed nations. *Climatic Change* 106: 327–336.

Gebeyehu S, Hurley BP, Wingfield MJ. 2005. A new lepidopteran insect pest discovered on commercially grown *Eucalyptus nitens* in South Africa: research in action. *South African Journal of Science* 101: 26–28.

Germishuizen I, Peerbhay K, Ismail R. 2017. Modelling the susceptibility of pine stands to bark stripping by Chacma baboons (*Papio ursinus*) in the Mpumalanga province of South Africa. *Wildlife Research* 44: 298–308.

Ghiyamat A, Shafri HZ. 2010. A review on hyperspectral remote sensing for homogeneous and heterogeneous forest biodiversity assessment. *International Journal of Remote Sensing* 31: 1837–1856.

Groeneveld DP, Watson RP. 2008. Near-infrared discrimination of leafless saltcedar in wintertime Landsat TM. *International Journal of Remote Sensing* 29: 3577–3588.

Ham-Baloyi W, Jordan P. 2015. Systematic review as a research method in post-graduate nursing education. *Health SA Gesondheid* 21: 120–128.

Henderson L. 2007. Invasive, naturalized and causal alien plants in southern Africa: a summary based on the Southern African Plant Invaders Atlas (SAPIA). *Bothalia* 37: 215–248.

Houborg R, Fisher JB, Skidmore AK. 2015. Advances in remote sensing of vegetation function and traits. *International Journal of Applied Earth Observation and Geoinformation* 43: 1–6.

Hurley BP, Slippers B, Wingfield MJ. 2007. A comparison of control results for the alien invasive woodwasp, *Sirex noctilio*, in the Southern Hemisphere. *Agricultural and Forest Entomology* 9: 159–171.

Ismail R, Mutanga O. 2010. A comparison of regression tree ensembles: predicting *Sirex noctilio* induced water stress in *Pinus patula* forests of KwaZulu-Natal, South Africa. *International Journal of Applied Earth Observation and Geoinformation* 12(Suppl. 1): S45–S51.

Ismail R, Mutanga O. 2011. Discriminating the early stages of *Sirex noctilio* infestation using classification tree ensembles and shortwave infrared bands. *International Journal of Remote Sensing* 32: 4249–4266.

Ismail R, Mutanga O, Ahmed F. 2008a. Discriminating *Sirex noctilio* attack in pine forest plantations in South Africa using high spectral resolution data. In: Kalacska M, Sanchez-Azofeifa GA (eds), *Hyperspectral remote sensing of tropical and subtropical forests.* Boca Raton: CRC Press. pp 161–174.

Ismail R, Mutanga O, Bob U. 2006. The use of high resolution airborne imagery for the detection of forest canopy damage caused by *Sirex noctilio*. In: Ackerman PA, Längin DW, Antonides MC (eds), *Precision forestry in plantations, semi-natural and natural forests: proceedings of the International Precision Forestry Symposium, Stellenbosch University, South Africa, 5–10 March 2006*. Stellenbosch: Department of Forestry and Wood Science, Stellenbosch University. pp 119–134.

Ismail R, Mutanga O, Bob U. 2007. Forest health and vitality: the detection and monitoring of *Pinus patula* trees infected by *Sirex noctilio* using digital multispectral imagery (DMSI). *Southern Hemisphere Forestry Journal* 69: 39–47.

Ismail R, Mutanga O, Kumar L, Bob U. 2008b. Determining the optimal spatial resolution of remotely sensed data for the detection of *Sirex noctilio* infestations in pine plantations in KwaZulu-Natal, South Africa. *South African Geographical Journal* 90: 22–31.

Ismail R, Norris-Rogers M, Ahmed F, Mutanga O. 2012. Geographic information systems and remote sensing applications in forest management. In: Bredenkamp BV, Upfold SJ (eds), *South African forestry handbook* (5th edn). Pretoria: Southern African Institute of Forestry. pp 229–238.

Jacobs DH, Neser S. 2005. *Thaumastocoris peregrinus* Kirkaldy (heteroptera: Thaumastocoridae): a new insect arrival in South Africa, damaging to *Eucalyptus* trees. *South African Journal of Science* 101: 233–236.

Jakubowski MK. 2012. Using LiDAR in wildlife ecology of the California Sierra-Nevada forests. PhD thesis, University of California, Berkeley, USA.

Jia GJ, Burke IC, Goetz AF, Kaufmann MR, Kindel BC. 2006. Assessing patterns of forest fuel using AVIRIS data. *Remote Sensing of Environment* 102: 318–327.

Johnson DE. 1999. Surveying, mapping, and monitoring noxious weeds on rangelands. In: Sheley RL, Petroff JK (eds), *Biology and management of noxious rangeland weeds*. Corvallis: Oregon State University Press. pp 19–35.

Köhl M, Magnussen SS, Marchetti M. 2006. *Sampling methods, remote sensing and GIS multiresource forest inventory*. Heidelberg: Springer.

Kursa MB, Jankowski A, Rudnicki WR. 2010. Boruta–a system for feature selection. *Fundamenta Informaticae* 101: 271–85.

Laudonia S, Sasso R. 2012. The bronze bug *Thaumastocoris peregrinus*: a new insect recorded in Italy, damaging to *Eucalyptus* trees. *Bulletin of Insectology* 65: 89–93.

Lawley V, Lewis M, Clarke K, Ostendorf B. 2015. Site-based and remote sensing methods for monitoring indicators of vegetation condition: an Australian review. *Ecological Indicators* 60: 1273–1283.

Leckie DG, Cloney E, Joyce S. 2005. Automated detection and mapping of crown discolouration caused by jack pine budworm with 2.5 m resolution multispectral imagery. *International Journal of Earth Observation and Geoinformation* 7: 61–77.

Lillesand TM, Kiefer RW. 1994. *Remote sensing and image interpretation* (4th edn). New York: Wiley.

Lim K, Treitz P, Wulder M, St-Onge B, Flood M. 2003. LiDAR remote sensing of forest structure. *Progress in Physical Geography* 27: 88–106.

Lindenmayer DB, Fischer J. 2006. Habitat fragmentation and landscape change: an ecological and conservation synthesis. Washington, DC: Island Press.

Little KM, Payn RG. 2016. Screening of fungicides for the management of wattle rust (*Uromycladium acaciae*) in *Acacia mearnsii* plantations, South Africa. *Southern Forests* 78: 151–158.

Lottering R, Mutanga O. 2012. Estimating the road edge effect on adjacent *Eucalyptus grandis* forests in KwaZulu-Natal, South Africa, using texture measures and an artificial neural network. *Journal of Spatial Science* 57: 153–173.

Lottering R, Mutanga O. 2016. Optimizing the spatial resolution of WolrdView-2 pan-sharpened imagery for predicting levels of *Gonipterus scutellatus* defoliation in KwaZulu-Natal, South Africa. *ISPRS Journal of Photogrammetry and Remote Sensing* 112: 13–22.

Lottering R, Mutanga O, Peerbhay K. 2018. Detecting and mapping levels of *Gonipterus scutellatus*-induced vegetation defoliation and leaf area index using spatially optimized vegetation indices. *Geocarto International* 33: 277–292.

McDowell NG, Coops NC, Beck PSA, Chambers JQ, Gangodagamage C, Hicke JA, Huang CY, Kennedy R, Krofcheck DJ, Litvak M et al. 2015. Global satellite monitoring of climate-induced vegetation disturbances. *Trends in Plant Science* 20: 114–123.

McGowen IJ, Frazier P, Orchard P. 2001. Remote sensing for broad scale weed mapping – is it possible? In: Geospatial information and agriculture: Incorporating Precision Agriculture in Australasia 5th Annual Symposium, 16–19 July, Sydney, Australia. Orange: NSW Agriculture.

McTaggart AR, Doungsa-ard C, Wingfield MJ, Roux J. 2015. *Uromycladium accaciae*, the cause of a sudden, severe disease epidemic on *Acacia mearnsii* in South Africa. *Australian Plant Pathology* 6: 637–645.

Melesse AM, Weng Q, Thenkabail PS, Senay GB. 2007. Remote sensing sensors and applications in environmental resources mapping and modelling. *Sensors* 7: 3209–3241.

Mutanga O, Dube T, Ahmed F. 2016. Progress in remote sensing: vegetation monitoring in South Africa. *South African Geographical Journal* 98: 461–471.

Mutanga O, Ismail R. 2010. Variation in foliar water content and hyperspectral reflectance of *Pinus patula* trees infested by *Sirex noctilio*. *Southern Forests* 72: 1–7.

Mutanga O, Ismail R, Ahmed F, Kumar L. 2007. Using *in situ* hyperspectral remote sensing to discriminate pest attacked pine forest in South Africa. In: Proceedings of the 28th Asian Conference on Remote Sensing (ACRS 2007), Kuala Lumpur, Malaysia, 12–16 November 2007, Red Hook, NY: Curran Associates.

Newete SW, Oberprieler RG, Byrne MJ. 2011. The host range of the *Eucalyptus* weevil, *Gonipterus* “*scutellatus*” Gyllenhal (Coleoptera: Curculionidae), in South Africa. *Annals of Forest Science* 68: 1005–1013.

Oumar Z, Mutanga O. 2010. Predicting plant water content in *Eucalyptus grandis* forest stands in KwaZulu-Natal, South Africa using field spectra resampled to the Sumbandila satellite sensor. *International Journal of Applied Earth Observation and*

Geoinformation 12: 158–164.
Oumar Z, Mutanga O. 2011. The potential of remote sensing technology for the detection and mapping of *Thaumastocoris peregrinus* in plantation forests. *Southern Forests* 73: 23–31.
Oumar Z, Mutanga O. 2013. Using WorldView-2 bands and indices to predict bronze bug (*Thaumastocoris peregrinus*) damage in plantation forests. *International Journal of Remote Sensing* 34: 2236–2249.
Oumar Z, Mutanga O. 2014a. Integrating environmental variables and WorldView-2 image data to improve the prediction and mapping of *Thaumastocoris peregrinus* (bronze bug) damage in plantation forests. *ISPRS Journal of Photogrammetry and Remote Sensing* 87: 39–46.
Oumar Z, Mutanga O. 2014b. Predicting water stress induced by *Thaumastocoris peregrinus* infestations in plantation forests using field spectroscopy and neural networks. *Journal of Spatial* Science 59: 79–90.
Oumar Z, Mutanga, Ismail R. 2013. Predicting *Thaumastocoris peregrinus* damage using narrow band normalized indices and hyperspectral indices using field spectra resampled to the Hyperion sensor. *International Journal of Applied Earth Observation and Geoinformation* 21: 113–121.
Peerbhay KY, Mutanga O, Ismail R. 2014. Does simultaneous variable selection and dimension reduction improve the classification of *Pinus* forest species. *Journal of Applied Remote Sensing* 8: 085194.
Peerbhay KY, Mutanga O, Ismail R. 2015. Random forests unsupervised classification: the detection and mapping of *Solanum mauritianum* infestations in plantation forestry using hyperspectral data. *IEEE Journal of Selected Topics in Applied Earth Observations and Remote Sensing* 8: 3107–3122.
Peerbhay KY, Mutanga O, Ismail R. 2016a. The identification and remote detection of alien invasive plants in commercial forests: an overview. *South African Journal of Geomatics* 5: 49–67.
Peerbhay KY, Mutanga O, Lottering R, Bangamwabo V, Ismail R. 2016c. Detecting bugweed (*Solanum mauritianum*) abundance in plantation forestry using multisource remote sensing. *ISPRS Journal of Photogrammetry and Remote Sensing* 121: 121–176.
Peerbhay KY, Mutanga O, Lottering R, Ismail R. 2016b. Mapping *solanum mauritianum* plant invasions using WorldView-2 imagery and unsupervised random forests. *Remote Sensing of Environment* 182: 39–48.
Poona NK, Ismail R. 2012. Discriminating the early stages of *Fusarium circinatum* infection of *Pinus radiata* seedlings using high spectral resolution data. In: 9th International Conference of the African Association of Remote Sensing and the Environment (AARSE 2012): Earth observation and geo-information sciences for environment and development in Africa: global vision and local action synergy, El Jadida, Morocco, October 29 – 2 November 2010. p 77 [abstract only].
Poona NK, Ismail R. 2013. Discriminating the occurrence of pitch canker fungus in *Pinus radiata* trees using QuickBird imagery and artificial neural networks. *Southern Forests* 75: 29–40.
Poona NK, Ismail R. 2014. Using Boruta-selected spectroscopic wavebands for the asymptomatic detection of *Fusarium circinatum* stress. *IEEE Journal of Selected Topics in Applied Earth Observations and Remote Sensing* 7: 3765–3772.
Porter B, Wingfield MJ, Coutinho TA. 2009. Susceptibility of South African native conifers to the pitch canker pathogen, *Fusarium circinatum*. *South African Journal of Botany* 75: 380–382.
Rullan-Silva CD, Olthoff AE, de la Mata JD, Pajares-Alonso JA. 2013. Remote monitoring of forest insect defoliation. A review. *Forest Systems* 22: 377–391.
Siegert F, Ruecker F. 2000. Use of multitemporal ERS-2 SAR images for identification of burned scars in South-East Asian tropical rainforest. *International Journal of Remote Sensing* 21: 831–837.
Stone C, Coops N. 2004. Assessment and monitoring of damage from insects in Australian eucalypt forest and commercial plantations. *Australian Journal of Entomology* 43: 283–292.
Stone C, Mohammed C. 2017. Application of remote sensing technologies for assessing planted forests damaged by insect pests and fungal pathogens: a review. *Current Forestry Reports* 3: 75–92.
Tkacz B, Moody B, Villa Castillo J, Fenn ME. 2008. Forest health conditions in North America. *Environmental Pollution* 155: 409–425.
Trotter CM, Dymond JR, Goulding CJ. 1997. Estimation of timber volume in a coniferous plantation forest using Landsat TM. *International Journal of Remote Sensing* 11: 2209–2223.
Underwood EC, Ustin SL, DiPietro D. 2003. Mapping nonnative plants using hyperspectral imagery. *Remote Sensing of Environment* 86: 150–161.
Underwood EC, Ustin SL, Ramirez CM. 2007. A comparison of spatial and spectral image resolution for mapping invasive plants in coastal California. *Environmental Management* 39: 63–83.
van der Zel DW 1995. Accomplishments and dynamics of the South African afforestation permit system. *South African Forestry Journal* 172: 49–58.
Verhegghen A, Eva H, Ceccherini G, Achard F, Gond V, Gourlet-Fleury S, Cerutti PO. 2016. The potential of Sentinel satellites for burnt area mapping and monitoring in the Congo Basin forests. *Remote Sensing* 8: 986.
Wang H, Pu R, Zhu Q, Ren L, Zhang Z. 2015. Mapping health levels of *Robinia pseudoacacia* forests in the Yellow River delta, China, using IKONOS and Landsat 8 OLI imagery. *International Journal of Remote Sensing* 36: 1114–1135.
Westfall J, Ebata T. 2014. *Summary of forest health conditions in British Columbia.* Victoria: British Columbia Ministry of Forests, Lands and Natural Resources Operations, Forest Practices Branch.
Wingfield MJ, Hammerbacher A, Ganley RJ, Steenkamp ET, Gordon TR, Wingfield BD, Coutinho TA. 2008. Pitch canker caused by *Fusarium circinatum* – a growing threat to pine plantations and forest worldwide. *Australasian Plant Pathology* 37: 319–334.
Wulder MA, White JC, Bentz BJ, Ebata T. 2006. Augmenting the existing survey hierarchy for mountain pine beetle red-attack damage with satellite remotely sensed data. *The Forestry Chronicle* 82: 187–202.
Yebra M, Dennison PE, Chuvieco E, Riaño D, Zylstra P, Hunt ER, Danson FM, Qi Y, Jurdao S. 2013. A global review of remote sensing of live fuel moisture content for fire danger assessment: moving towards operational products. *Remote Sensing of Environment* 136: 455–468.
Zarco-Tejada PJ, Miller JR, Mohammed GH, Noland TL, Sampson PH. 2002. Vegetation stress detection through chlorophyll a+b estimation and fluorescence effects on hyperspectral imagery. *Journal of Environmental Quality* 31:1433–1441.
Zeng C, King DJ, Richardson M, Shan B. 2017. Fusion of multispectral imagery and spectrometer data in UAV remote sensing. *Remote Sensing* 9: 696–716.

Received 7 January 2018, revised 4 July 2018, accepted 26 July 2018