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CASE STUDY: USE OF REMOTE SENSING DATA TO DERIVE SPATIAL AND TEMPORAL EXPLICIT FUEL ACCUMULATION CURVES ACROSS DEFENCE LANDS

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Cover: Overview of the location and scale of the five defence lands with true colour Landsat imagery insets. Source: Vivid Australia.

TABLE OF CONTENTS

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EXECUTIVE SUMMARY

Fuel loads are a main driver of fire rate of spread. Therefore, a spatially explicit estimation of fuel loads, coupled with their variation through time may improve wildland fuel management and contribute to the design of more efficient active fire response strategies. However, the high frequency of planned and unplanned fires in large wild areas linked to varying fire severity levels that affect the rate at which fuels re-accumulate, make the continuous monitoring of wildland fuels challenging with field-based survey methods. Here we propose the use of satellite remote sensing to map fuel loads with a revisit time of 16 days. Fuel load maps are produced for five Defence Lands using Landsat and Sentinel-2 optical remote sensing data available at Digital Earth Australia and the National Computation Infrastructure. The fuel load maps are obtained by calculating the time series of the Vegetation Structure Perpendicular Index, an index that measures post-fire disturbance, and fitting these to fuel accumulation curves derived from literature.

END-USER STATEMENT

Frederick Ford, *Australian Department of Defence, ACT*

The Australian Department of Defence manages millions of hectares of bushfire prone land across Australia. Empirical knowledge of fuel load is a key aspect of Defence management, both as a trigger for hazard reduction activities, and in assessing the current suitability of an area for an activity with an inherent risk of ignition to occur. Even in smaller properties, ongoing active use by Defence means that on-ground access for fuel load monitoring is problematic. However, some northern Australian Defence properties are hundreds of thousands of hectares in size, and it is practically infeasible to establish an accurate on-ground fuel load monitoring program. Reasonable estimates of fuel load and management requirements can be gleaned from fire history. However, Defence sought a remote sensing method that could potentially overcome the contraints to fuel load monitoring, and ideally be available as an input into real- time decision making tools that incorporate empirical fuel load and fuel state data with terrain, weather and other variables. Defence also sought a method to provide calibrated, spatially explicit, estimates of fuel accumulation rate for slower-developing southern fuels such that intensively managed fuel zones (e.g. Strategic Fire Avantage Zones) could be reasonably scheduled for management without an ongoing requirement for ground-based fuel load monitoring as a trigger for management.

INTRODUCTION

The estimation of spatially and temporally explicit post-fire fuel accumulation is key in fire management. Fuel loads are a main driver of fire behaviour, affecting particularly the rate of spread (Anderson et al. 2015; Garnica 2009; Gill and Zylstra 2005; Sullivan 2009). Therefore, knowing the fuel load at different locations can help design more effective fuel treatment strategies, and plan firefighting operations during active fires (Boer et al. 2009). The monitoring of the processes of fuel accumulation based on traditional field surveys is very challenging. This is due to the high variability in both space and time of these processes across fuel types and different levels of fire severity that would require frequent field campaigns. In most cases, this is not feasible due to the inaccessibility and large extension of wild areas. For example, extensive areas are dedicated to military training by the Australian Department of Defence (Defence Lands). The Defence Lands are for the most part wild. However, there is a need to strategically manage fuel loads in order to reuce risk to neighbouring communities and assets, and to maintain some areas in a low-fuel state to mitigate the risk from unintentional ignitions that may derive from military activity.

Satellite-based sensors allow for a deep understanding of the Earth surface processes by capturing the evolution of different land covers at relatively high spatial and temporal resolutions (Xie et al. 2008). These provide the unparalleled opportunity to map fuel condition as it changes seasonally (Yebra et al. 2018) and fuel load as it changes in a longer time frame because of disturbances such as fires (Massetti et al. 2019). The spatial resolution of Landsat satellites (30 m) allows resolving changes at the forest stand scale while covering all Australia's surface with a revisit time of about 16 days. In combination with the more recent Sentinel-2 satellites, the revisit time can be improved to 3-5 days. Furthermore, the shortwave infrared electromagnetic radiation reflected by plants and acquired by these sensors is related to fuel load, fuel structure and condition (Asner et al. 2015; Elvidge 1990). The Vegetation Structure Perpendicular Index (VSPI) is a metric that relates to post-fire fuel accumulation based on the shortwave infrared channels. The VSPI can be used to map fuel accumulation in Australian environments that burn frequently. Here, we propose as a study case the estimation of maps of fuel loads of every available Landsat and Sentinel-2 satellites acquisition at five priority Defence Lands.

BACKGROUND

DEFENCE LANDS

Five areas were selected as study cases to estimate the fuel load and post fire accumulation. These Defence Lands are scattered across the Australian territory: Mount Bundey is in the Northern Territories, Shoalwater Bay and Wide Bay are in Queensland, Holsworthy Barracks is in New South Wales and Puckapunyal is in Victoria (Fig. 1). Mt Bundey surface is 105,398 ha and the fuels range from low woodland to open eucalypt forest. Shoalwater Bay surface is 269,100 ha most of which characterized by eucalypt forest and woodlands, heath and mangroves and a few pockets of rainforest. Wide Bay surface is 19,596 ha and is characterized by eucalypt forest and palustrine wetland. Holsworthy Barracks surface is 18,931 ha (including two minor Lands: Camp Sapper Training Area and Moorebank Area) and is mostly characterized by eucalypt forest. Puckapunyal surface is 42,071 ha characterized by box-ironbark forest and grassland.

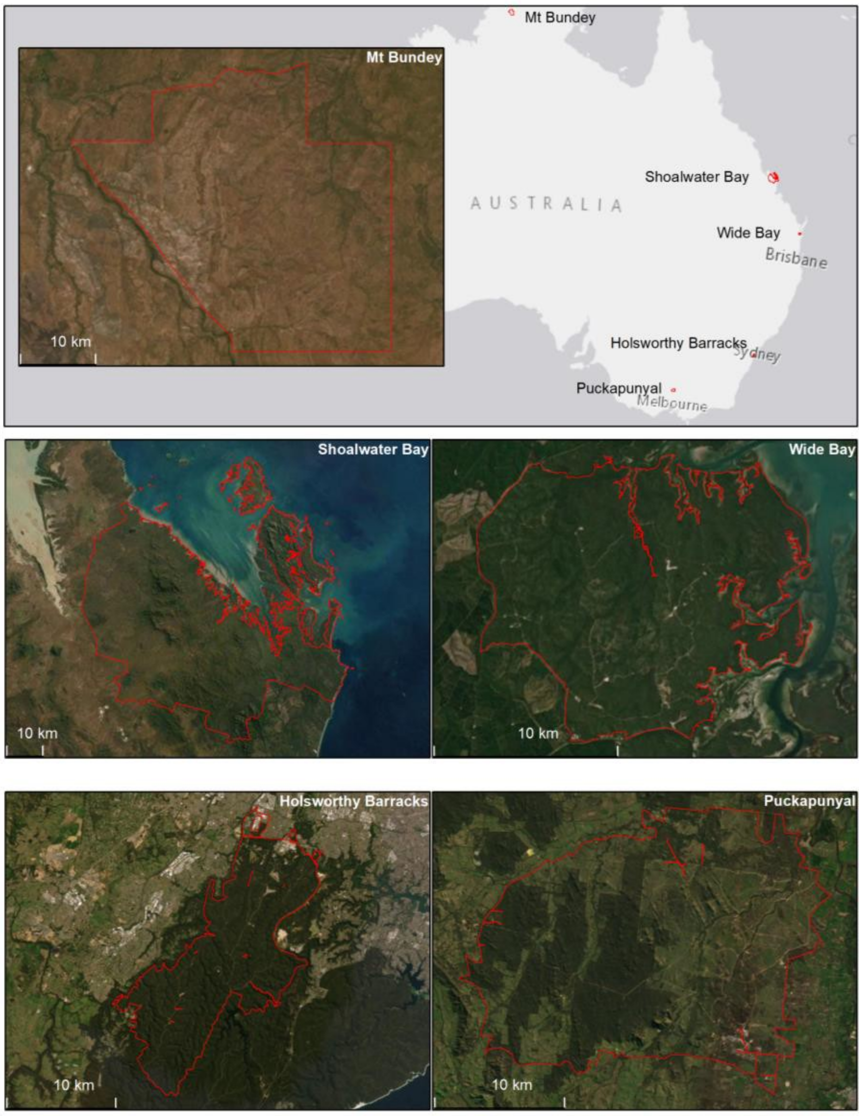


FIGURE 1 OVERVIEW OF THE LOCATION AND SCALE OF THE FIVE DEFENCE LANDS WITH TRUE COLOUR LANDSAT IMAGERY INSETS. SOURCE: VIVID AUSTRALIA.

RESEARCH APPROACH

The Landsat data, available at Digital Earth Australia (link) was used to compute the VSPI that represents a measure of fuel load depletion (Fig 2). The Python code used in this work is available in a GitHub repository (link). The VSPI measures a disturbance from the steady-state represented by a vegetation line and is close to zero for undisturbed forest-stands while increasing when a wildfire decreases the amount of vegetation (Fig 3). Consequently, the VSPI was calculated at each study area as the perpendicular distance from the vegetation line (Massetti et al. 2019).

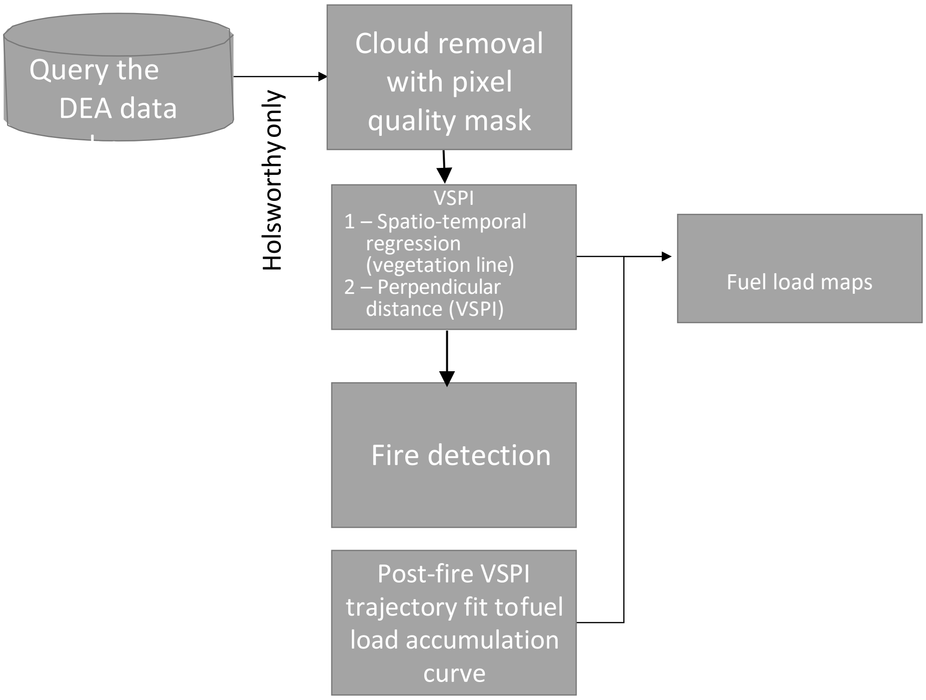


FIGURE 2 METHODOLOGY OVERVIEW

$$VSPI = \frac{1}{\sqrt{a^2 + 1}}(SWIR_2 - aSWIR_1 - b) \qquad Eq\ 1$$

In Eq 1, *a* and *b* are the slope and the intercept of the vegetation line, respectively; and *SWIR1* and *SWIR2* are the values of the top-of-canopy reflectance of the short-wave infrared Landsat bands at 25m spatial resolution, that are centred at wavelengths of 1.6 and 2.2 µm of the electromagnetic spectrum. Different vegetation lines were derived for each study area by selecting an area undisturbed from fires for at least ten years and derived as the linear regression of the reflectance values in the shortwave infrared bands across time 10 years.

Given that the VSPI is a disturbance metric, a model that linked fuel load and VSPI time series is needed to obtain a quantitative estimation of fuel load. To this end, the exponential decay model developed by Gould et al (2011), that describes surface and near-surface fuel accumulation as a function of time after fire *t* (Eq 2) was fitted to the VSPI value at *t* months after fire (*VSPIt*) using three regression values *a*, *b* and *c* (Eq 3).

$$FUEL\ LOAD\ \frac{kg}{m^2} = 1.60\ (1 - e^{(-0.22\ t)}) \qquad Eq\ 2$$

$$FUEL\ LOAD\ \frac{kg}{m^2} = e^{(\frac{-c}{a^b} VSPI_t)} \qquad Eq\ 3$$

Eq 3 describes the exponential decay of fuel load in function of the increase of VSPI disturbance. A least-squares minimization function was used to optimize the regression values *a, b* and *c* in Eq 3 to the fuel loads obtained from "time since fire" from Eq 2. This optimization was performed on the post-fire time series of the geo-median of the VSPI after a wildfire in Holsworthy Barracks, and then used for all the areas. Firstly, the dates of all the fires in the historical time series were determined by finding the local maxima of the VSPI; the latest fire with at least 3 years of uninterrupted recovery was chosen and the time in months *t* after the VSPI maximum was used in Eq 2 to obtain fuel loads which were then used to optimize the regression values *a*, *b* and *c* in Eq 3 for all *VSPIt* in the time series.

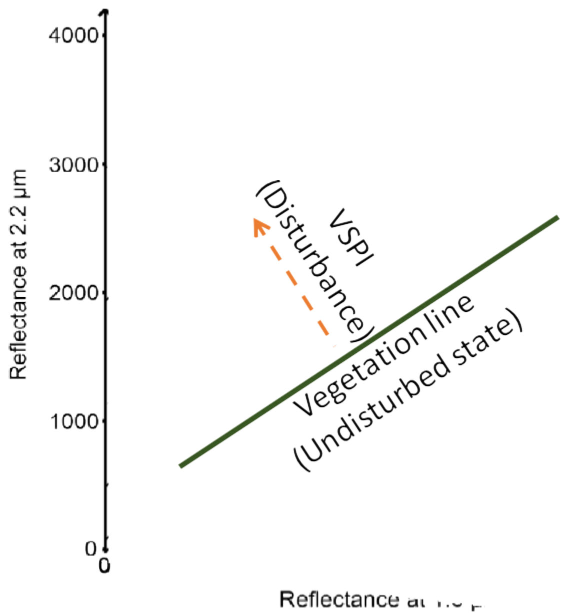


FIGURE 3 THEORETICAL BASIS OF THE VSPI

RESULTS

Two historical fires were identified by selecting the VSPI local maxima of each pixel in Holsworthy Barracks area (Fig 4). A fire in 2003 affected the northern area (red), while a fire in 2001 affected the southern and eastern areas (orange). The gullies and small valleys were affected to a lesser extent and were not detected in any of the fires by the VSPI. The 2003 fire was selected for fitting the fuel load model.

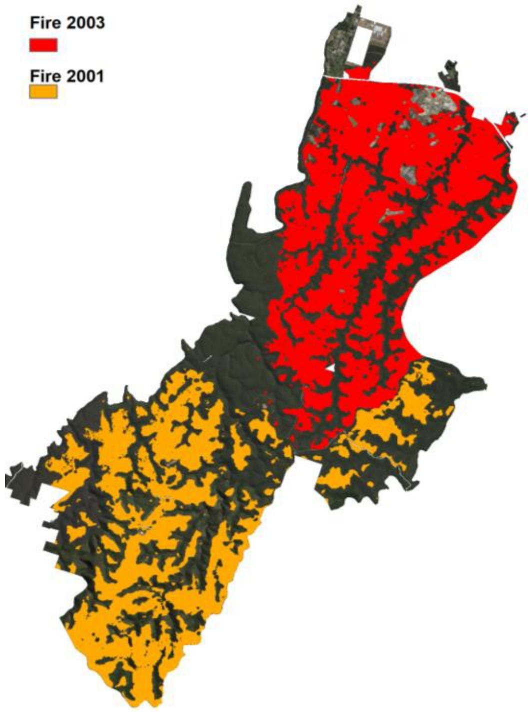


FIGURE 4 HISTORICAL FIRES DETECTED AT HOLSWORTY BARRACKS BY IDENTIFYING THE LOCAL MAXIMA OF VSPI FOR EACH PIXEL

The regression values obtained by the least-squares' optimization were a=351, b=1.09 and c=-4.94, which, simplifying Eq 3 equal to:

$$FUEL\ LOAD\ \frac{kg}{m^2} = e^{(-0.008\ VSPI_t)} \qquad Eq\ 4$$

Eq 4 was used to estimate fuel loads as a function of the observed VSPI value. This allowed producing fuel load maps for the study areas. Follow a few examples of fuel load maps obtained at different study areas. Access to the fuel maps animations is available through the following link.

At Holsworthy Barracks, just before the 2003 fire, the fuel loads were low, (<0.4 t/ha) in the southern section of the area (Fig 5.A) due to the fire that occurred in 2001 (Fig 4). The fire in January 2003 (identified in Fig. 4) consumed most of the fuels (≈0 t/ha) in the northern part of Holsworty Barracks, while did not spread in the southern area due to the low fuels and potentially effective suppression efforts (Fig 5.B). Four years later, in January 2007, some of the fuels in the north-western area recovered to over 10 t/ha of fuel (Fig 5.C) which is similar load to what it was observed before the 2003 fire (Fig 5.A). However, at that time, some residual patches of lower fuels are still visible (6 < fuel load < 8t/ha) from both the 2003 and the 2001 fires (Fig 5.C).

Several planned fires were detected during the early dry season of 2019 in the Mt Bundey training area (reds in Fig 6.B) which consumed most (remaining <2 t/ha) of the very high fuel loads previously in place (> 16 t/ha, dark greens in Fig 6.A). Towards the end of the dry season, almost all the Mt Bundey area underwent fuel load loss (Fig 6.C) due to fuel reduction practices, probably favoured by the dry weather and the seasonality of the low woodland to open eucalypts forest in the area. However, some of the areas that burnt in May with lower severity (6-8 t/ha, yellows, arrow in Fig 6.B) already started to accumulate fuels (8-10 t/ha, yellow to pale green, arrow in Fig 6.C).

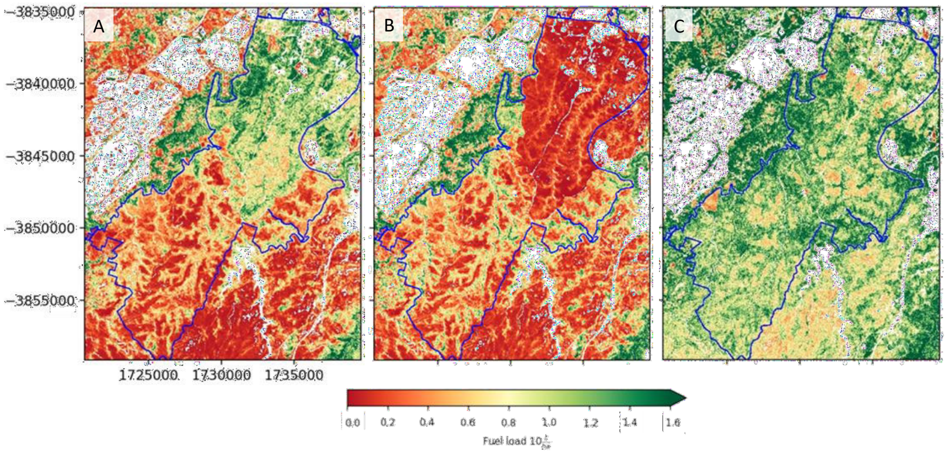
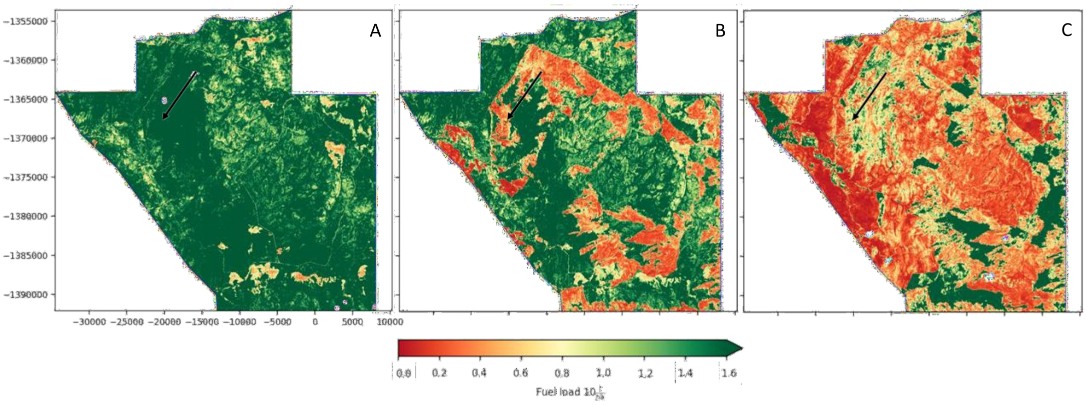


FIGURE 5 FUEL LOAD MAPS AT HOLSWORTHY BARRACKS JUST BEFORE (A), SOON AFTER (B) AND 4 YEARS AFTER (C) THE 2003 FIRE. LOW FUEL LOADS ARE REPRESENTED IN RED, HIGH FUEL LOADS ARE REPRESENTED IN GREEN



FI GURE 6 FUEL LOAD MAPS DURING THE DRY SEASON OF 2009 AT MT BUNDEY TRAINING AREA

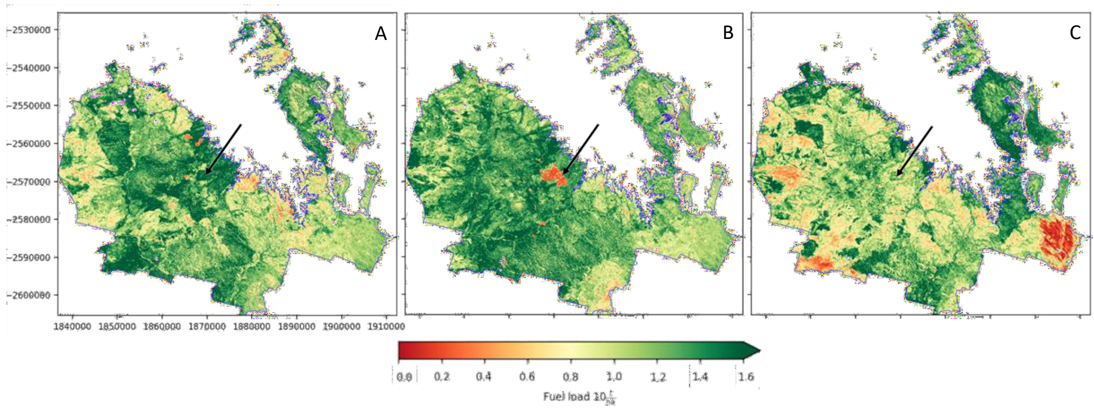


FIGURE 7 FUEL LOAD MAPS AT SHOALWATER BAY DURING THREE DIFFERENT YEARS

At Shoalwater Bay, a fire in April 2017 (red area indicated by an arrow in Fig 7.B) consumed all the fuel loads visible 11 months before (16 t/ha, area in green indicated by an arrow in Fig 7.A). The re-accumulation captured in February 2018 for the same area (arrow in Fig 7.C) showed a radial pattern with higher fuel loads at the perimeter (green >10 t/ha) and lower in the centre (yellow 7 t/ha). This different load accumulation occurred despite observed homogeneous severity (red at arrow in Fig 7.B) and pre-fire distribution (green at arrow in Fig 7.A)

When compared to the other 4 areas, Wide Bay presented the lowest fuel loads with an average of 8 t/ha and maximum values not exceeding 10 t/ha (Fig 8). A fire in May 2017 reduced the loads from values between 8-9 t/ha in July 2016 (yellow to pale greens indicated by the arrow in Fig 8.A) to <2 t/ha (reds areas in Fig 8.B). 25 months later (June 2019) the area appeared to have re-accumulated most of the fuels seen in 2016, but a few areas remaining with low fuels (reds and yellows area indicated by the arrow in Fig 8.C).

Finally, the forests mapped at Puckapunyal showed loads ranging between 8 and 10 t/ha (pale greens and yellows in the central and western sections of Fig 9, in correspondence of the dark green covers visible in Fig 1). Observing the January fuel load maps of three consecutive years, a lower loading is noticeable in 2018, when compared to the previous year (grees becoming yellow in correspondence of the arrows in Fig 9.A and 9.B). In January 2019, the load generally increased without reaching the initial levels seen in 2017 (Fig 9.C). Generally, the areas of forest bordering with the grassland (the red areas in the north-east) showed lower loads than the central and western areas in which the rivers may provide higher moisture availability in dryer years contributiong to higher fuel build-up. For example, in 2018, only a limited area of forest near the river to the center showed loads >10 t/ha (in deeper green Fig 9.B), while surrounded by loads <8 t/ha.

Since the fuel load model in function of VSPI was calibrated in a forested area of Holsworthy Barraks, the maps do not represent well grasslands loading. The red areas on the north east of Puckapunyal, for example, showed very low values in the maps presented (Fig 9), while showing unlikely extremely high values in other dates (not presented; available at the link above).

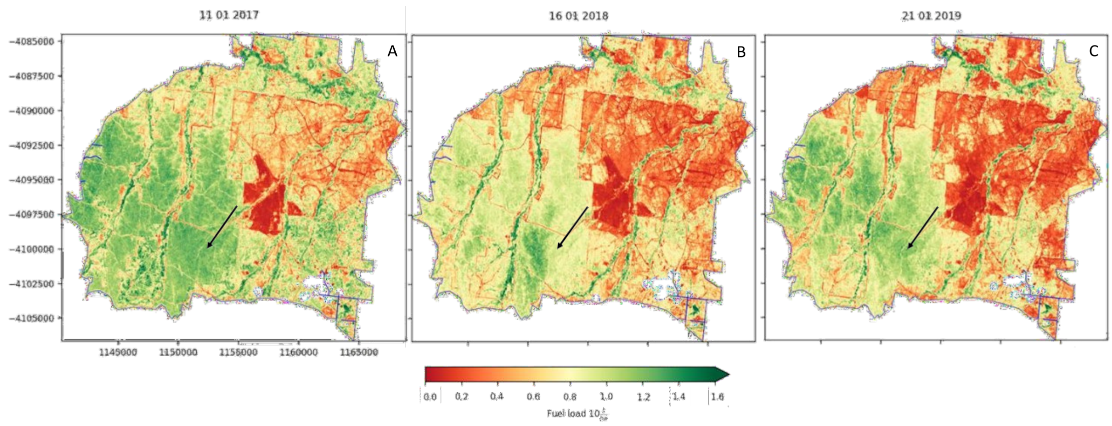


FIGURE 9 FUEL LOAD MAPS AT PUCKAPUNYAL BETWEEN SEPTEMBER 2016 AND JUNE 2017

DISCUSSION

The case studies presented in the previous section demonstrate that VSPI is highly sensitive to fuel loads in different biomes. The recovery observed at Holsworthy shows that the fuel load reduction caused by the 2003 fire left the forest with a very patchy distribution of fuel loads up to 4 years later (Fig 6). A similar phenomenon was captured in the fire seen in Shoalwater Bay (Fig 7), in which a consistently burnt fuel showed a discontinuous spatial distribution of the fuels accumulated in the following year. At Wide Bay it is also observed a discontinuous fuel reaccumulation 25 months after a fire (Fig 8).

A discontinuous post-fire fuel loading is due to compound effects that influenced the pace of fuel re-accumulation, such as, 1 – fire severity; 2 – fuel moisture contents and topographical ubication (for example, the higher humidity levels in the bottom of the gullies may boost recovery rate) and 3 – seed bank and plant species present (i.e. the presence of obligated seeders species vs sprouters species).

The availability of such fuel load maps may prove pivotal in the design of new controlled burns, for example, by targeting only the areas with higher loads, or prioritizing treatment of areas that present spatially consistent high fuel loads. Moreover, as seen in Puckapunyal, the fuel load maps we propose capture fluctuations in fuel loads from one season to another even in absence of fire events (Fig 9). In this context, these maps can be of great value to calculate the potential rate of spread of active fires allowing timely intervention.

Furthermore, Mt Bundey maps demonstrate the possibility to assess the effectiveness of controlled fires to reduce fuel loads. Some of the fuels that were burnt earlier in the year and at low severity accumulated a substantial amount of fuel within only 4 months from the fuel reduction burning.

The load can be very different depending on the type of fuel. For example, Shoalwater Bay and Wide Bay showed different overall loading (>16 and <8 t/ha, respectively in Figs 7 and 8) due to different forest density and type. While these differences were captured in relative terms, they may not be quantitatively relevant due to the calibration of the model having been made at Holsworthy Barracks, where very specific forest loading and type were in place. In turn, the values for grassland shown are not valid due to different reaccumulation and fuel loading of this fuel type, that would require a dedicated accumulation model.

CONCLUSIONS AND RECOMMENDATIONS

The Landsat and Sentinel-2 time series available at Digital Earth Australia can be used to compute VSPI and detect fires and fuel load depletion and re-accumulation processes. The VSPI uses the shortwave infrared channels to detect structural changes to the fuels. We fitted the VSPI post-fire time series to available fuel accumulation curves, capturing the changes in fuel loads at five Defence Lands locations. The fuel accumulation processes were thus highlighted in a spatially and temporally explicit way.

As a proof of concept, due to the limited availability of fuel re-accumulation curves and ground truth data collected for different Australian biomes during post-fire recovery, we calibrated only one accumulation model. The model was based on Holsworthy Barracks area, which presented similar vegetation to the one used to calibrate the original accumulation curve by Gould et al (2011). Inevitably, this causes inaccuracies for different vegetation types and the quantitative results presented here should be used with caution. Therefore, as a follow up, it is recommended the design of different models calibrated with fuel load post-fire accumulation data collected for specific forest types.

Additionally, the computation of vegetation lines that are specific for different vegetation cover types may reduce inaccuracies. For example, the results shown here cover well open to dense woodlands and forests, but do not represent well grasslands, whose values might not be valid.

However, in order to calibrate vegetation lines for different fuel types, study areas with samples of these fuels that remain undisturbed for several years must be identified. In Australia, locating such areas is challenging due to the variability of fuels deriving from frequent fires and it would require fuel cover maps with at least yearly repetition.

Better estimating spatial and temporal variations of fuel load is critical for fire prevention and response. In this regard, the fuel load maps generated in this report are vitally important for strategic planning. Additionally, this information is useful to locate containment lines and help with the firefighting strategies (e.g. to locate sites free of trees to winch specialist firefighters in, to try to pick the easiest line to construct walking tracks or highlighting low fuel loads areas where it is safer to intervene and relatively easier to put off a fire). This information can equally be used as part of pre-season planning when fire agencies and land management departments formulate their seasonal outlook for fire and map at-risk areas as well as for planning and undertaking prescribed burns.

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