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FUELS3D

Quantifying surface and near-surface fuel hazards using image-based point clouds

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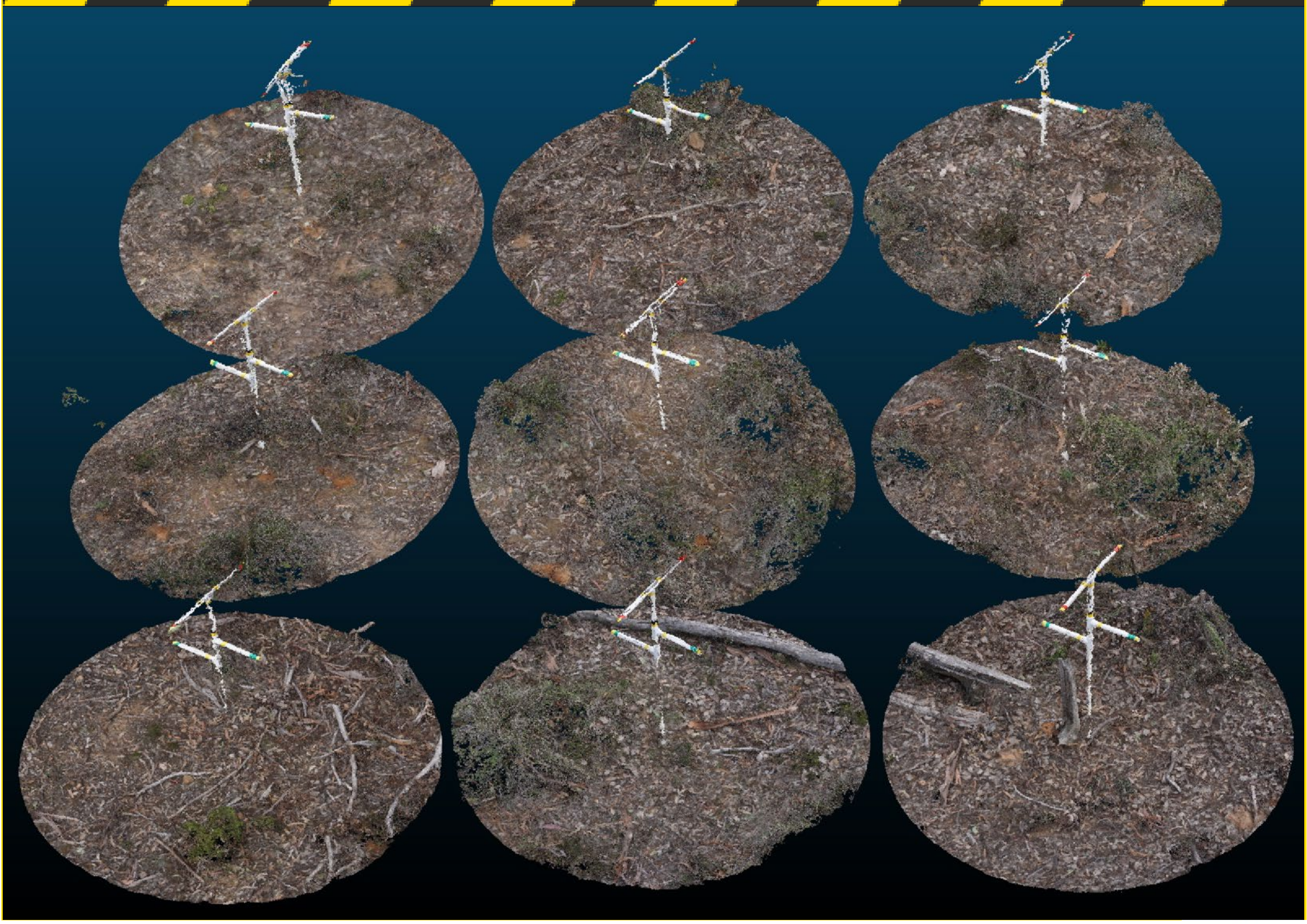
RMIT University & Bushfire and Natural Hazards CRC



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EXECUTIVE SUMMARY

Understanding fuel hazard is essential. Effective management of Australia's fire prone landscapes relies on accurate consistent and up-to-date fuel characterisation. This project seeks to create a quantitative methodology for calculating fuel hazard, in surface and near surface fuel layers, using affordable consumer grade equipment. It is hoped that this methodology will enhance and supplement existing visual estimation methods used by land management agencies across Australia and demonstrate the utility of moving towards new approaches capable of creating quantitative outputs. The method uses a series of systematically acquired photographs to create a 3D point cloud that captures vegetation elements in the surface and near surface vegetation layers and their horizontal and vertical structure. These point clouds are then processed to create the metrics for deriving fuel hazard estimates.

The project methodological tool-chain is divided into five major components:

- Data Collection;
- Image and Metadata Upload;
- Point Cloud Generation;
- Feature Classification;
- Hazard Metric Extraction and Quantification.

Each of these methods are embedded in an AWS workflow. The aim being to provide firefighting and land management agencies with an end-to-end semi-automated methodology for collecting, analysing and visualising fuel hazard information.

Although a viable methodology was developed and implemented, results varied by ecosystem. Woodlands, plantations, low open forest, open grasslands and low open shrublands systems all had good image matching and end metric conversion rates (>90%). In contrast, closed and other grasslands, shrublands and tall closed forest fuel types all had sample conversion rates below 65%. The explanation of these large variances in success rates were explored with a number of image acquisition and processing factors identified.

There are many benefits to standardising data collection and harmonising metrics for reporting fuel hazard. Unlike visual assessments the reference photographs and associated point clouds exist in perpetuity and can be re-processed when new techniques emerge for their analysis. Comparing data gathered in different states, territories and jurisdictions also becomes much easier.

Feedback from end users was mixed. While many land managers felt this quantitative methodology had much merit others commented it was too time-consuming to replace current practices. Other (more costly) point cloud collection methods (Terrestrial Laser Scanners and Mobile Laser Scanners (LiDAR) as well as optical depth camera systems) have presented themselves as alternatives during the course of the project. With this in mind the research team has enabled the AWS tool chain to ingest other point cloud data into the fourth and fifth workflow elements.

END-USER PROJECT IMPACT STATEMENT

Danielle Wright and Thomas Duff, *Country Fire Authority, Victoria*

The Fuels3D project identified that the current system of fuel hazard assessment has an exceptionally high degree of subjectivity. A key outcome of RMIT's work is the identification of the need to review the overall fuel hazard assessment system to ensure it is robust, represents the properties of fuel that influence fire behaviour, and is compatible with future technological developments. The Fuels3D solution was designed to determine surface and near-surface fuel hazard in an objective and repeatable way, that would be available to all CFA members. Working with RMIT researchers we were taken through the workflow. From the trial we learnt that smartphone cameras did not provide the level of quality needed to create a 3D fuel hazard environment, however consumer mirrorless cameras could. We also learnt that the Fuels3D method cannot capture fuel hazard accurately in grasslands, but can in woody vegetation. Overall, the ability of the solution to adapt to different terrestrial sensing technologies, and the modular design of the automated processing back-end, has created a valuable foundation for future utilisation into fuel hazard assessment approaches.

PRODUCT USER TESTIMONIALS

Simeon Telfer, *Department for Environment and Water, South Australia*

Fuel3D uses photos collected in field to create 3D models of vegetation which can be used to determine bushfire fuel hazard. SA National Parks and Wildlife Service have used Fuels3D to collect information before and after prescribed burns and bushfires across the state including Mt Lofty Ranges, Kangaroo Island and Eyre Peninsula. Using Fuels3D allows us to make quantitative measurements of fuel in a variety of vegetation types, from woodlands to semi-arid mallee. Using Fuels3D is more repeatable than the subjective fuel hazard estimates which we routinely collect, and much faster than destructive sampling of fuel loads. The previous version of Fuels3D provided results, but required lots of manual intervention in order to process. The new workflow has streamlined the upload, processing and results workflows for end users. Future improvements could include more fuel metrics, automation of workflow and feedback on photo points that weren't successfully processed.

INTRODUCTION

Fuel hazard assessments inform the management and mitigation of wildfire risk in fire-prone landscapes by describing the presence and condition of fuel in the environment. Physical characteristics of fuel such as arrangement, volume, connectivity, and height above ground play a significant role in the intensity of fire events, potential for spread across the landscape, and probability of success in suppression efforts [1]. Fuel hazard assessment provides a means for the observation of these characteristics and enables land managers to quantify and monitor fuel presence in the field over time. Current standards and protocols for describing fuel hazard (for example, "Overall Fuel Hazard Assessment Guide", Victorian Department of Sustainability and Environment) and post-burn severity (for example, "Fire Severity Assessment Guide", Victorian Department of Sustainability and Environment) are the culmination of decades of work across a diverse array of Australian environments, and the metrics described in these guides remain the measures of key drivers of fire risk. It is difficult to estimate fuel hazard using visual assessments in a repeatable and quantitative way thereby limiting the reliability with which the data can be integrated with modern risk assessment and fire behaviour tools. Although, it is acknowledged these guides were written to utilise rapid descriptions of the landscape, rather than to facilitate the quantitative measurement of fuel metrics [2]. As a result, a misalignment exists between the experience and expertise of land managers in monitoring fuel, and the collection of data inputs applicable for fire modelling. Quantitative data-rich methods of measuring and assessing fuel load and structure are the missing link between the knowledge of land management personnel in the field, and the model drivers and decision makers at organisational level.

Remote sensing offers new opportunities for the way in which fuel can be measured and characterised. Whilst technologies such as laser scanners (LiDAR systems) are the gold standard for 3D reconstructions of environments, passive remote sensing using new algorithms in photogrammetry and computer vision yield a new opportunity for image-based approaches to be explored. Consumer grade digital cameras coupled with structure from motion software such as Agisoft Metashape Professional and Pix4D Professional can provide a low-cost method for the capture, reconstruction, and subsequent extraction of quantitative fuel hazard metrics [3]. Images captured provide a permanent snapshot of the landscape in time, and when collected using the Fuels3D approach, provide a data rich legacy for new structure, allowing for reanalysis as new tools are developed, from motion methods and/or fuel hazard calculations to be applied.

This project investigated the use of passive remote sensing and structure from motion techniques to improve the quantification and assessment of surface and near surface fuel hazard in the field. A sampling method that was optimised for repeatability, redundancy, accuracy whilst remaining sympathetic to current fuel hazard assessment operational practices evolved through consultation with land management agencies. Python code was built to ingest 3D point clouds and classify these into fuel categories to derive fuel hazard metrics such as percentage cover and height of fuel in surface and near surface fuel layers.

BACKGROUND

Recent advancements in the modelling of fire spread across Australian landscapes are enabling increased understanding of fire behaviour before, during, and following significant fire events. The Australian Fire Danger Rating System trialled in 2019, is designed to categorise locations by expected fire behaviour. Forecasts are made through the combination of fire spread models developed for eight models across Australia [4, 5, 6, 7, 8, 9, 10] with meteorological data from the Bureau of Meteorology to predict fire behaviour characteristics such as rate of spread, intensity, flame height, and spotting distance. Quantitative metrics describing fuel load and condition at a given location are necessary to drive this modelling, generally requiring advanced fuel hazard surveys and techniques such as destructive sampling to collect and ensure they accurately reflect the landscape. The metrics used to describe the fuel in each landscape vary, and are likely to change over time, as older models are improved, and newer models replace legacy methods. Indeed, new ways to categorise fuel types are evolving and demonstrated in the AFAC bushfire classification scheme [11] that bases classes on structural characteristics rather than species composition. Robust modelling requires input metrics that are known to be accurate and consistent between sources (and flexible to accommodate new classifications) and as such, there is an opportunity to create an improved fuel hazard assessment approach that can quantify fuel hazard in a repeatable, and objective manner.

Visual estimation is the standard practice for land management agencies across Australia for generating fuel hazard assessments. Visual assessment provides a low-cost and efficient method to rapidly describe and estimate the quantity and arrangement of fuels within individual fuel layers [12]. In South Eastern Australia, this process is often guided by the Overall Fuel Hazard Assessment Guide [1] (OFHAG) which provides descriptors to the structure of fuels occurring within the surface, near surface, and elevated fuel layers including the canopy and requires assessment to be completed in the field using mostly visual estimates. The significant rate of utilisation of the OFHAG in Australian land management practices is reflective of its practicality in enabling fuel hazard assessment across vast geographic space, to occur rapidly, and with minimal economic investment required by the user. However, it is well known and documented in the literature that visual assessments are subjective and can vary greatly between assessors [12, 13, 14, 15]. In addition, visual assessment using the OFHAG is designed only for a hazard rating to be determined between five ratings; low, moderate, high, very high, and extreme, and not to facilitate the precise capture of various quantitative fuel metrics. As such, it cannot easily reconcile with modern hazard assessment methods guided by fire spread modelling.

Remote sensing methods provide an encouraging alternative to visual assessments for the non-invasive observation and quantification of fuel hazard in the field [2]. Ground based remote sensing methods have proven to be successful in accurately capturing the 3D structure of under-storey vegetation in the environment at a level of detail that enables fuel metrics to be observed and measured when interrogating the corresponding point data [16, 17]. Typically, terrestrial laser scanners (TLS) have been used to survey environments in the field, however recent advancements in photogrammetric algorithms, in particular structure from motion (SfM), are providing an alternative low-cost approach using passive sensors such as digital cameras.

Terrestrial laser scanners record the time taken for a laser pulse emitted from the device to be reflected off an object and back to the sensor to determine the 3D geometry of a scene. TLS sensors can provide high resolution, high accuracy point clouds of the local environment and have a range between 10 and 1500 m from the sensor depending on the device. In addition, as an active sensing technology, the laser pulses from a TLS platform have some penetrative ability through less dense or loosely arranged vegetation. By detecting concurrent returns from the scanner, more information is captured from the sensor's surroundings, increasing the detail of resulting point clouds particularly in natural environments. TLS derived point clouds are of sufficient detail to facilitate the observation of fine scale vegetation characteristics [18, 19, 20] and have a demonstrated ability for use in providing accurate estimates of fuel hazard properties [16, 17] and detecting changes in near surface fuel [21, 22]. Despite the strengths of TLS, the technology remains relatively expensive with sensor costs between $10,000 and $100,000 USD [18], delaying its widespread use in fuel hazard monitoring. In addition, the expertise required for both the operation of equipment while surveying in the field, and for the processing of collected point clouds is considerable [23]. As a result, the incorporation of TLS into existing fuel hazard assessment practices may prove difficult until such limitations are resolved.

In contrast to TLS, image-based 3D reconstruction is possible using data acquired from <$2,000 digital cameras when coupled with Structure from Motion (SfM) software. Structure from Motion is a photogrammetry method used to estimate the geometry of a scene in 3D, using the input of multiple highly overlapping 2D images of the scene taken from multiple angles [24]. Advances in processing algorithms have made this possible using images from the natural environment, despite the level of detail and complexity present [3, 25]. Image-based point clouds have proven successful in resolving woody [26] and near surface vegetation [27, 28, 29], and the results presented by Bright et al. [27], Hillman et al. [28], Cooper et al. [29] and Wallace et al. [30] indicate that the collection of imagery and use of computer vision to derive dense point clouds could be an effective method in quantifying fuel hazards.

The use of computer vision and photogrammetry to derive geometry is not without limitations. Unlike active sensors such as TLS, which detect light rays actively generated by the device, passive sensors can only detect light rays from other sources. As a result, passive sensors are reliant on a scene being illuminated from other potentially less consistent sources such as the sun, demanding consideration by the operator to ensure minimum light requirements are met, and the effects of shadowing are mitigated [31]. In addition, passive sensors do not provide any penetrative ability through less dense objects such as vegetation, limiting the potential scene size to reduce possible obscuration of features. Fortunately, 3D photogrammetry also offers some advantages over the use of TLS for assessing fuel hazard. The ability to use passive sensors allows data capture to be completed with off the shelf digital cameras that do not require extensive training to operate. Recent advancements in consumer camera technology have also improved the affordability and accessibility to devices with high resolution, large format sensors. In addition, image-based point clouds also contain the spectral information captured by the camera [32]. Spectral reflectance provides a substantial source of data in natural environments that can guide processes of object delineation, feature classification, with potential to identify whether vegetation is live or dead. This information is not typically captured in surveys with laser scanners as additional equipment and surveys are required, although recently emerging systems such as the Hovermap now provides colourised point clouds. Still, substantial care must be taken to accurately align the spectral and spatial datasets. The combination of low cost, easy to use survey equipment, and the ability to collect spectral information from the scene provide benefits over the use of TLS and allow for a substantially cheaper and simpler incorporation into existing fuel hazard assessment survey approaches.

RESEARCH APPROACH

The Fuels3D project has created a suite of scripts, tools, and methods for image capture in the field during fuel hazard assessments. 3D point clouds are generated using computer vision and photogrammetry techniques as built into existing available SfM software. From these 3D point clouds, scale is added and decision rules are programmed to calculate quantifiable surface / near-surface metrics that replicate those used in current fuel hazard visual assessment guides. The key steps in the strategy followed:

- New opportunities and proof of concept
- Validation and inter-comparison of point clouds
- Design and development of Fuels3D methods

NEW OPPORTUNITIES AND PROOF OF CONCEPT

Summary

The research approach employed for the development of Fuels3D began with a review of remote sensing technologies suited for capturing vegetation structure. Remote sensing captured from airborne and satellite platforms has long been used as a viable option for mapping vegetation in the landscape. However, estimates of fuel structure and hazard made using remote sensing data still requires input at the local, or plot, scale for calibration and validation purposes. Terrestrial remote sensing techniques can provide an alternative or complementary source of information to traditional field assessments and support large scale remote sensing used to quantify and describe vegetation properties. Early work using TLS showed the potential for 3D reconstructions of landscapes and was the inception to explore low-cost approaches for mapping understorey vegetation and fuel hazard.

Method and Key Findings

Early work was completed to understand the utility of point cloud products in facilitating the accurate observation and quantification of fuel hazard metrics in the forest understory [2, 21]. Each study utilised TLS in fixed survey plots prior to, and following a planned burn, to measure changes in fuel hazard resulting from the fire to provide an indication of measurement sensitivity and precision required. In addition, control plots not exposed to fire events were measured to allow for a benchmark and to exclude other non-fire drivers of change. Both permanent and temporary field survey markers were used to co-register the multitemporal point clouds, and up to eighteen metrics describing different elements of fuel structure including fuel height, volume, and fragmentation/cover were investigated. The study demonstrated that TLS and the methods used to measure the fuel environment were able to detect changes in different fuel hazard metrics, and with no corresponding change occurring between control plots indicating that the approach could provide the precision required to monitor fire-induced change in fuel hazard. Metrics extracted from corresponding point clouds were comparable to those determined via synchronous on ground visual assessment. These results highlight the capabilities and potential of multitemporal TLS data for measuring and mapping changes in the 3D structure of vegetation. Metrics from point clouds can be derived to provide quantified estimates of surface and near-surface fuel loss and accumulation, and inform prescribed burn efficacy and burn severity reporting. However, using TLS to create 3D representations is costly, lacks portability, and requires user expertise to conduct data capture and pre-processing of data.

As a result of identifying the value and utility of point clouds for reconstructing and deriving quantitative estimates for fuel hazard assessment an investigation into low-cost options for mapping fuel hazard was explored. Using consumer grade cameras and smartphones with Structure from Motion software was proposed as offering a suitable option. An image collection (photo taking and sampling) protocol was designed and tested by researchers and developed into a protocol to provide instructions on how to capture an image network with strong geometric properties and sufficient overlap to achieve an accurate reconstruction of the fuels 3D structure. In parallel, methods to extract fuel layers based on simple height thresholds, and calculation of fuel hazard input metrics were developed.

To test the proof-of-concept of the approach, end-users users from SA DEWNR, ACT Parks and Wildlife, VIC DELWP, VIC CFA, Melbourne Water and Parks Victoria were invited to a testing day in areas of lowland forest at Cardinia Reservoir, Victoria, Australia. The field day aimed to introduce end-users to the Fuels3D collection protocol and to assess its ease of use and repeatability between data collectors in comparison to traditional visual assessment techniques. Participants were asked to undertake a visual assessment and collect Fuels3D data at three plots as shown in Figure 1. Following, the data collection, participants were asked to complete a survey evaluating the Fuels3D data collection workflow.

The results of the field trial indicated that surface and near-surface metrics related to fuel hazard can be measured with greater repeatability between different observers. Variability was observed within point cloud estimates but was on average two to eight times less than that seen in visual estimates, indicating greater consistency and repeatability of this method. This is further demonstrated in Figure 2, where the range of surface cover and height is significantly lower across all plots than seen in the visual assessment approach. The results, published in Sensors in 2017 [15], indicated that surface and near- surface metrics relating to fuel hazard can be measured with greater repeatability between observers using the Fuels3D method when compared to the same assessment using the OFHAG. Even more critical was the propagation of this error when the metrics were combined to calculate hazard ratings. This is demonstrated in Figure 2, where the range of surface cover and height is significantly lower across all plots than seen in the visual assessment approach, spanning across almost four hazard rating classes.

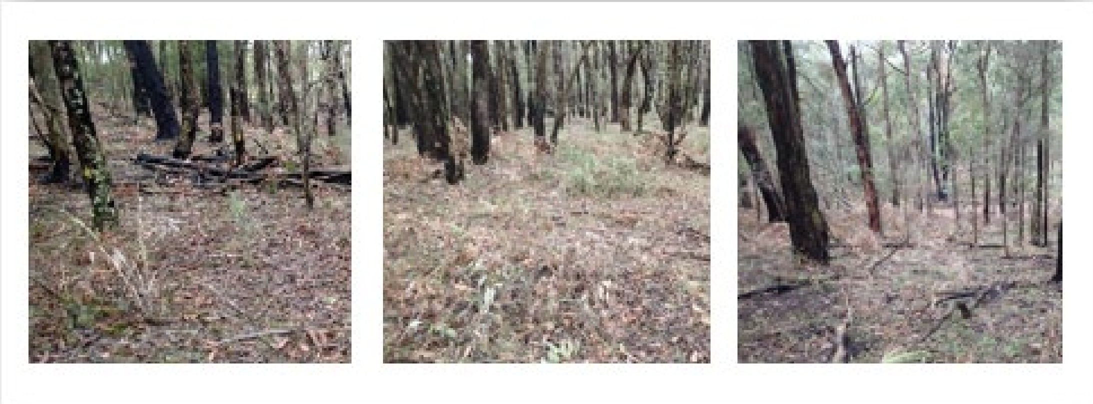


FIGURE 1. EXAMPLES OF THE THREE SITES FROM WHICH PLOT LEVEL FUEL HAZARD ASSESSMENTS WERE CONDUCTED.

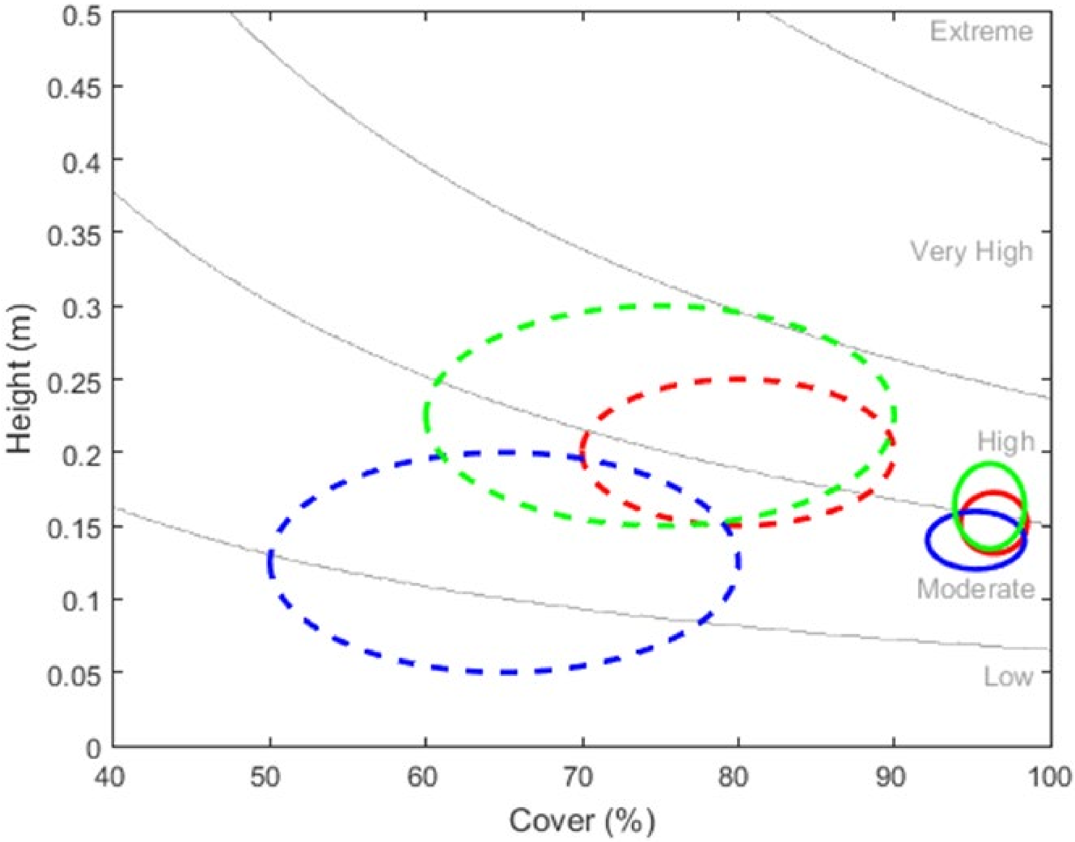


FIGURE 2. RANGE OF SURFACE FUEL HAZARD RATINGS ACROSS THREE PLOTS AS ASSESSED VISUALLY (DASHED LINES) AND USING FUELS3D METICS (SOLID LINES).

Overall, the survey indicated that the participants found the Fuels3D protocol easy to follow. This was further indicated by the collected data of which more than 90% of the image sets were able to be used in the Fuels3D processing method. From the results of this study several areas of improvement in the data collection and processing methods were identified, indicating the potential for this approach to have utility in fire management practices where quantitative and repeatable data is essential.

Outputs

Gupta V, Reinke KJ, Jones SD, Wallace L, Holden L. *Assessing metrics for estimating fire induced change in the forest understorey structure using terrestrial laser scanning*. Remote Sensing. 2015; 7(6): p.8180-201.

Wallace L, Gupta V, Reinke K, Jones S. *An assessment of pre-and post fire near surface fuel hazard in an Australian dry sclerophyll forest using point cloud data captured using a terrestrial laser scanner*. Remote Sensing. 2016; 8(8): p.679.

Spits C, Wallace L, Reinke K. *Investigating surface and near-surface bushfire fuel attributes: A comparison between visual assessments and image-based point clouds*. Sensors. 2017; 17(4): p.910.

VALIDATION AND INTERCOMPARISON

Summary

Initial assessment of the solution demonstrated the repeatability of measures possible through the Fuels3D approach. Subsequently, an assessment of the accuracy of the solution was conducted by comparing reconstructed 3D point clouds to sources of ground-truth, validation against dry weights and through intercomparison with other "gold-standard" technologies such as TLS. This approach of benchmarking image-based point cloud accuracy and performance against TLS was conducted and reported as an ongoing practice during the development phase.

Method and Key Findings

A critical gap in developing point clouds for estimating fuel hazard metrics was the absence of a standard validation method. At the time of the study, no standards or methods for the ground truthing of remotely sensed point clouds were present in the literature. As such, a validation framework was designed to allow point intercept measurements to be co-registered with point cloud data enabling a direct validation approach to be applied [17]. Upon applying the approach, validation results showed a high correlation of point matching in forests with understory vegetation elements of large mass and/or surface area, typically consisting of broad leaves, twigs, and bark 0.02 m diameter or greater in size (SfM, Matthews Correlation Coefficient (MCC) 0.51–0.66; TLS, MCC 0.37–0.47) using consumer grade digital cameras with SfM software. In contrast, complex environments with understory vegetation elements with low mass and low surface area showed lower correlations between validation measurements and point clouds (SfM, MCC 0.40 and 0.42; TLS, MCC 0.25 and 0.16). The results of the study demonstrated that the validation framework provides a suitable method for comparing the relative performance of different point cloud generation processes, and for the validation of Fuels3D generated point clouds.

The second approach for validation used destructive sampling to measure dry weight fuel loads. At the same time, data captured using TLS as the gold standard was also collected and compared to image-based techniques. Accuracy of biomass estimates were assessed using these two techniques. Case study environments are depicted in Figure 3. Results indicated that both TLS and image-based point clouds accurately estimate surface biomass in the dry grassy forest (image-based, r^2 = 0·87, rRMSE = 9·4% and TLS, r^2 = 0·73, rRMSE = 13·4%), lowland forest (image-based, r^2 = 0·59, rRMSE = 20·7% and TLS, r^2 = 0·74, rRMSE = 16·3%) and pasture environments (image-based, r^2 = 0·78, rRMSE = 19·5% and TLS, r^2 = 0·81, rRMSE = 17·8%) when compared to their actual biomass. However, for the woodland site, the vertical complexity and density of the vegetation resulted in less reliable estimates (r^2 = 0·5, rRMSE = 41·2%) for the TLS. Higher correlation was found at this site between biomass and image-based point cloud estimated volume (r^2 = 0·90, rRMSE = 15·7%), however, this was based on a limited number of samples (n = 4). Generally, with comparable point cloud estimations to TLS, image-based techniques show potential as a viable, cost-effective, non-subjective alternative to techniques currently used to assess surface biomass. Whilst some strong correlations were observed in many of the case studies, the use of point clouds to accurately estimate fuel load is recognised as being highly dependent upon specific environments, condition, and the density and mass of local vegetation.

FIGURE 3. THE LOCATION OF THE STUDY AREA (A) AND THE FIVE PLOTS USED TO DEMONSTRATE THE UTILITY OF IMAGE-BASED POINT CLOUDS FOR MEASURING THE 3D PROPERTIES OF NEAR-GROUND VEGETATION IN (B) MANICURED TURF, (C) NATIVE TALL GRASS, (D,E) DRY SCHLEROPHYLL FOREST, AND (F) LOW SHRUB ENVIRONMENTS.

Outputs

Wallace L, Hillman S, Reinke K, Hally B. *Non-destructive estimation of above-ground surface and near-surface biomass using 3D terrestrial remote sensing techniques*. Methods in Ecology and Evolution. 2017; 8(11): p.1607-16.

Hillman S, Wallace L, Reinke K, Hally B, Jones S, Saldias D. *A method for validating the structural completeness of understory vegetation models captured with 3D remote sensing*. Remote Sensing. 2019; 11(18): p.2118.

DESIGN AND DEVELOPMENT OF FUELS3D SOLUTION

Summary

The design and development of Fuels3D covered steps including sampling, photo-taking protocol, point cloud generation, fuel layer separation and fuel hazard metric calculations. The most recent iteration of the Fuels3D project is designed to capture and ingest information from field assessments of fuel hazard to provide an augmentation of associated metrics to existing subjective assessments of fuel load. The process involves major steps relating to the sampling and acquisition of field data in a systematic and consistent manner, and the processing of imagery to provide accuracy and consistency in resultant metrics. The process and key decisions around method development and implementation are described below. An overview of the data processing chain is illustrated in Figure 4.

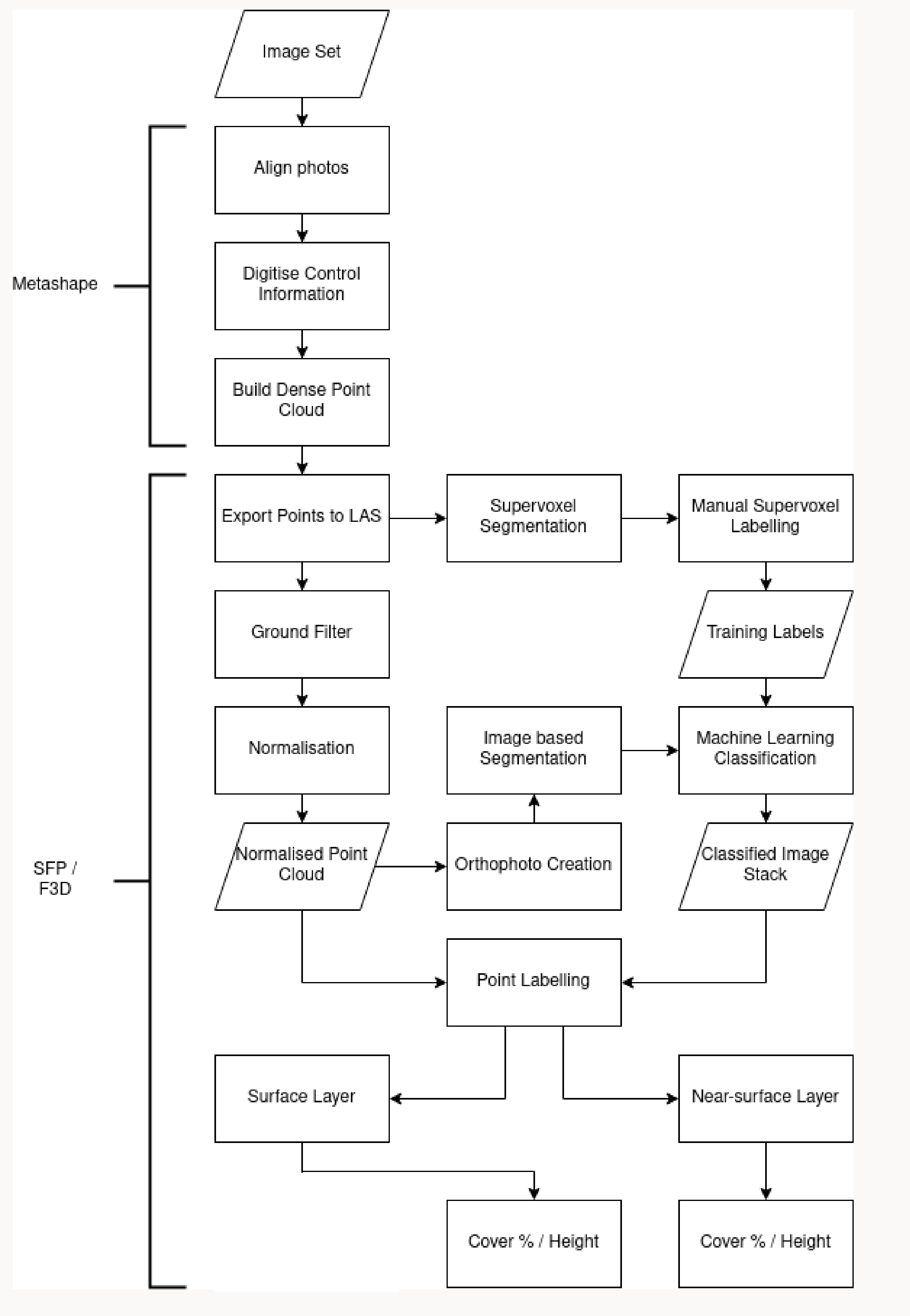


FIGURE 4. OVERVIEW OF PROCESSING STEPS FOR EXTRACTING FUEL HAZARD METRICS FOR SURFACE AND NEAR-SURFACE FUEL LAYERS.

Method and Key Findings

Sampling and Data Capture

Initially the sampling approach utillised 0.5m x 0.5m samples at 2m intervals across the diameter of a 20m diameter plot which were able to produce 3D reconstructions of the landscape using such a sampling strategy. To enable larger, continuous plots to be supported, and to speed up data collection, a linear transect of varying distances (>10m) was used to drive the acquisition of images, with marker posts placed at regular 2m intervals along said transect. Upon further application and testing, this technique had two shortcomings. Firstly, the marker posts or targets were required to be placed at regular measured intervals along the transect. This meant operators would have to take extra steps to ensure that targets are measured out correctly, regardless of slope and terrain conditions. This can prove difficult even with specialist measuring equipment and trained operators, and minimising errors of scale in these transects would require specialist training. Secondly, the transects themselves resulted in point clouds which were less comprehensive than required for accurate estimation. The use of image-based techniques prescribes that adjacent photos should have sufficient overlap to provide for feature detection between photos. The transect method resulted in photo trails that contained sufficient overlap between images on each side of the transect but still proved inadequate for point matching across the transect – in other words, photos that were adjacent on the opposing sides of a transect would not end up with commonly shared features, which is an integral part of point cloud reconstruction. Also, the resultant point clouds tended to provide planar surfaces on each side of the transect that would not match with each other. In order, to provide accurate and comprehensive feature spaces to reconstruct the targeted environment, a circular photo trail surrounding a 1m x 1m sample of interest (based upon the initial success using 0.5m x 1.5m) was decided upon, to maximise the likelihood of photo matching and point cloud construction.

The provision of sufficient coverage within a fuel assessment plot was also a consideration for the sampling method. A typical fuel assessment plot as defined by the OFHAG is a 10m radius plot, and the subjective analysis of features is undertaken across that area. Plot design had to accommodate provision of a representative sample of the plot space, bearing in mind that each sample can only capture 1% of the plot. Sampling design also had to consider that image taking is an invasive process – operators taking photos may disturb/trample vegetation, which may lead to under-estimations of volume in areas of compacted vegetation. As such the sampling scheme decided upon had to also allow for separation between samples, to minimise the disturbance within any particular sample, and to minimise the likelihood of adjacent photo taking impacting upon samples. This led to the adoption of the nine-sample cross pattern for plot capture. Additional samples could be taken to bulk up the representative sample space, but this comes at the price of potential disturbance of each of those samples before capture. The time constraints of adding extra samples were a concern also – skilled operators with training of sample capture achieved capture times of five minutes or less, but this procedure still must be conducted nine times per plot, resulting in total acquisition times of around an hour per plot. It is difficult to envision how this constraint of the method could be overcome – the image sampling configuration is already pared back to a minimum number of photos in order to still provide comprehensive capture, and the use of still imagery is required to ensure that factors that affect video capture such as motion blur and dynamic adjustment in response to lighting conditions do not add to the error budget of object determination within the point cloud.

In-field Targets

To ensure accuracy of resultant point clouds and derived metrics, image-based point cloud processing requires a measure of scale within plots and samples. This is often provided in the form of custom targets like those used to coordinate aerial photography. In cases such as those, extra work is done to provide external measurements (survey using GNSS or traditional survey methods) to provide a basis for reduction to a coordinate system, which of course has an inherent scale. Again, due to the nature of utilising field personnel without specialist training in measuring to external coordinate datums, it was decided that samples within plots would be coordinated in a local reference frame for ease of use. This per-sample coordinate system still requires a scale object to be embedded in the images, but given the scale of each of the samples, the scale object in this case can span far less of the sample to provide sufficient scaling accuracy. Originally, designs were put in place to manufacture a custom scaling object specially manufactured for the task, with fixed scaling points that could be easily discovered by manual control processes, and potentially allowing for the automatic detection of target information from images. Ultimately, circumstances surrounding the timing of the project halted the development of this custom target setup, which would have required extensive calibration to fulfil this potential. In lieu of a properly engineered control target, the current design of the polytarget used in this project was brought to life. The design needed to be simple to construct, yet at the same time be robust and durable with sufficient control information inherent to the geometry of the construction to provide redundancy of measurements. Testing and trials have shown the the target (see Figure 5) as a control source, was able to achieve accuracies of scale in the photo matching process typically in the order of < 2mm. Of course, the device is not without potential shortcomings – the taped sections that constitute the control targets can be torn or moved unwittingly by operators, the target itself can be constructed in a non-standard manner, and the whole target is reliant on a stable fixing to the ground to maintain coordination integrity (up is up, left is left, etc) throughout the image taking process.

Image-based 3D Point Cloud Creation

The production of point cloud information using SfM techniques is reliant upon the matching of features within adjacent images. This feature matching provides a framework for the estimation of camera (image acquisition) locations, and if sufficient overlap in feature spaces is found, the process in question can use this geometrical representation to refine a more comprehensive depth mapping process, over which resultant point clouds are built. The commonly used SfM processing software Agisoft Metashape (Professional), was used to construct image-based point clouds for this process. This decision came on the back of extended use of this software since the inception of the project to provide image-based point clouds throughout other work in similar landscapes and for similar applications that the research team had encountered in the past. Unfortunately, a shortcoming when using closed-source software, is that not much is known about proprietary processes used within the workflow. The program appears to be using a form of the SIFT algorithm for provision of feature matching between images, but the settings that are available to the user to alter this process seem to have limited or counter-intuitive effects given the results derived. Without greater knowledge of what occurs internal to the program and algorithms used to construct the sparse point cloud matches, it is difficult to forsee how improvements could be made to image reconstruction rates through tweaking of what few parameters are available to users. Metashape is not the only player in this space – other commercial software providers such as Pix4D and 3DF have applications that can construct point clouds from images, but of course use of these would come at the cost of familiarisation of workflows, and the adoption of new variables to alter point cloud reconstruction and similar issues using commercial closed-source software. One advantage that Metashape has over competitors in the field is the integrated Python library, which has allowed for the seamless adaptation of the specific Metashape processes within our preferred Python workflow; this ability eased development and adoption times significantly throughout the life of the project.

SfM relies on the accurate rendition of feature spaces within images, and the subsequent matching of these features to produce a product. The determination of a feature space within an image has been the topic of much research within the image processing and computer vision communities for decades, but little work has done to reconcile errors in more complex feature spaces, such as those inherent to images of vegetation as featured in this project. Certain landscapes will confound feature detection processes – computer vision and photogrammetry techniques were developed in laboratories and built environments, where sharp contrasts between surface geometry and reflections exist, and prominent features make for strong reconciliation of feature importance within image feature spaces. This is not the case in a lot of the natural environment – many of the environs and land cover types covered by this project encompass regions that for an image feature detection process constitute noise. Reconciliation of features in a space such as surface leaf litter of coarse woody debris may be relatively easy, as the colour space of images of these types of features provide marked contrast between adjacent objects, and this leads to high confidence in the resultant matches. (A benefit lacking in non-colorised point clouds.)

Despite these shortcomings, the processes developed have managed to construct 3D point clouds in a number of different plots in different landscape types. Issues remain regarding occlusion of features and volume underestimation, as the SfM technique tends to cluster points upon surfaces, and neglects spaces that require penetration below the surface. This is not a problem image-based point clouds face by themselves – point clouds derived from active light sources also face issues with layering and penetration, and the deeper a layer of material is, the more likely it is to have its volume underestimated by any remote sensing technique.

Fuel Layer Extraction and Metric Calculation

As per traditional methods for describing overall fuel hazard, and input requirements for new fire behaviour models, separating the vegetation into fuel layers, or strata, is a key requirement. For this project, the separation was primed for extracting surface and near-surface fuel from the local environment. No clear interpretation existed for constituting each of these layers means that simple geometry is not enough to provide a clear and consistent delineation. If these two layers were treated as one for the purposes of fuel assessment, the procedures used to produce measures of fuel would be simplified greatly (noting that this follows the fuel layer definitions implemented in Vesta V2.0) but given the desire to follow existing protocols within the Overall Fuel Hazard Assessment Guide separating these two layers to inform assessment was required. The simplest fuel layer separation approach employs fixed-height thresholds which are, of course, flawed by breaking natural connectivity between the fuels. More recent and comprehensive solutions are arising, such as raster pouring [33], that maintains both horizontal and vertical connectivity. Other approaches, such as the one implemented for Fuels3D, makes use of a machine-learning classification technique for separating specific elements from each other in the point cloud and is based on indicative positive results of classification accuracy reported in [34]. Using a machine-learning approach required point clouds to be segmented in a fashion that allowed for systematic classification of vegetation elements, and subsequently for a number of samples to be manually classified to provide training data. Finally, these classifications needed to be applied to whole point clouds with the use of a Random Forest classifier and verified for accuracy.

Segmentation of the point clouds was achieved with the use of the SLIC segmentation technique, a process where an aggregated voxel space of transformed spectral information was carved up into blobs of a specified size. The voxel space of each point cloud is a representation of the coverage and characteristics at a coarser geometric scale, enabling larger datasets such as point clouds to be processed using fewer resources. The median of all points in the CIElab colour space in each voxel was the aggregation used, as this particular spectral transformation technique provides more depth of resolution in the red-green colour space, which of course is our focus when assessing vegetation. As with any algorithm there are a number of parameters to adjust in order to optimise the results. The compactness of the segmentation dictates the potential elongation of resultant segments from the process. There is a trade-off here made between providing realistic looking segments of common objects and allowing the segmentation to group spatially disparate objects. The segment size was determined by the processing capabilities of the hardware used to produce results – dropping the segment size further would have increased the processing requirements of the hardware used to produce results to a point where additional resources would have been required during prototyping. Dropping segment size further would have also made validation of subsequent classification more difficult - often the segments produced consisted of very few points, requiring the use of a noise class within the classification to eliminate segments of this type.

Once segmentation was achieved, a table of features had to be constructed for the simplification of point elements in each segment. A number of features was selected, as documented in the code accompanying this document. The source code and installation instructions and dependices for the project is hosted at: https://gitlab.com/janomecopter/f3d_meta and README file. The metrics calculated were a combination of commonly used features and indexes for differentiation of RGB and LAB colour spaces, along with texture information, structural information, and indices of transformations of both these spaces and those of surrounding segments. The nature of using a Random Forest classifier means that feature importance is not critical for algorithm outcomes, and as such no available features were eliminated from the final classification. Two sets of RF classification were undertaken - one with all segments that had textural features available, and one classification of all segments with no textural information, with the results of that classification only applied to segments not attributed in the first instance. In this way, and with a lower bound point cut-off designed to capture noise segments, the bulk of segments were classified into the determined classes.

The classification accuracy is affected by a number of factors, not the least being the quality of training data used to drive the classifier. Training data derivation occurred using a random selection of segments from each of the samples assessed – this of course results in heavy weighting of training data to predominant classes such as leaf litter and grass, and the sample space for the smaller classes is low. Acquisition of training segments to be added to the classification library should look to target these fringe classes more readily, in order to sure up the accuracy of delineation of features such as woody debris. Additionally, classifier accuracy is a major component of success rates in subsequent classification tasks. If sufficient care is not taken in the clear delineation of classes, or an operator's definition of what constitutes a particular class changes over time, the accuracy of the resultant classification may deteriorate. To mitigate this, the training data used in this project is verified as correct by two operators – if the operators agree on the class of an assessed object, it is used in subsequent classification. This has resulted in a better set of segments for training and a more accurate resulting classifier than any one operator alone.

The last step of the process constitutes metric calculation, a simple step considering the previous processes outlined. Metrics are generated by aggregation of point cloud information in segments classified in the surface and near-surface layers, as defined by class in the documentation. The classes used in the classification have been identified as those most likely to provide feature space separation to aid with classification, whilst also enabling assessment at the surface and near-surface level. These metrics are derived from various studies into fuel hazard and fuel assessment and are predominantly made up of cover and height calculations. Due to occlusion of under-surface material in the image-based point clouds, volumetric estimates of material have not been provided, as they are likely to significantly underestimate fuel load, and other issues surrounding differences in density and mass of vegetation albeit with similar volumes.

Outputs

Wallace L, Hally B, Reinke K, Jones S, Hillman S. *Leveraging smart phone technology for assessing fuel hazard in fire prone landscapes*. In Proceedings of the 5th International Fire Behaviour and Fuels Conference, Melbourne, Australia. 2016: p.11-15

Wallace L, Saldias D, Reinke K, Hillman S, Hally B, Jones S. *Using orthoimages generated from oblique terrestrial photography to estimate and monitor vegetation cover*. Ecological Indicators. 2019; 101: p.91-101.

Wallace L, Hally B, Hillman S, Jones S, Reinke K. *Terrestrial Image-Based Point Clouds for Mapping Near-Ground Vegetation Structure: Potential and Limitations*. Fire. 2020; 3(4): p.59.

Hillman S, Wallace L, Lucieer A, Reinke K, Turner D, Jones S. *A comparison of terrestrial and UAS sensors for measuring fuel hazard in a dry sclerophyll forest*. International Journal of Applied Earth Observation and Geoinformation. 2021; 95: p.102261.

KEY MILESTONES

2015 – 2016

Pre and post burn TLS data was collected for three Victorian prescribed burn events to investigate the utility of 3D point clouds for observing change in fuel hazard. From this, options for low-cost alternatives were proposed and tested by researchers.

Key milestones and highlights included:

- Pre and post burn data collected for three Victorian prescribed burn events and assessment of TLS utility and operational feasibility. Low-cost options explored.
- A workshop was held in December 2015 with various project end-users to convey findings and propose a low-cost solution using digital cameras and smartphones. Subsequently, end-users have collected close to 100 Fuels3D samples. This information is being used to refine the processing workflow and calibrate an Android app.
- Research featured in Australia Fire magazine and Asian-Pacific Fire magazine.
- One poster [AFAC 2016].
- Three conferences and/or invited presentations [BNH CRC Research Advisory Forum 2015; AFAC EMSINA PDP 2016; International Fire Behaviour and Fuels Conference 2016]
- One peer-review paper published [21]

2016 – 2017

A field day was held demonstrating the Fuels3D as a proof of concept including sampling approach and image taking guidelines in July 2016 with participants attending from SA DEWNR, ACT Parks and Wildlife, Vic DELWP, Vic CFA, Parks Victoria and Melbourne Water. DELWP representatives provided a walk-through using the Overall Fuel Hazard Assessment guide as a method for later evaluation to compare visual versus Fuels3D collected data. Trials with end users identified that infield scaling required improvements to enhance accuracy and user friendliness, and an automated approach to application of the scale during processing.

Key milestones and highlights included:

- Develop sampling protocol and image taking methods to support novice end users.
- Field day with end-users to trial Fuels3D data collection methods and provide feedback of approach and suggestions for improvements.
- Field data collection with end-users (to run simultaneously during field day trials) to investigate the repeatability or variability in measures that may

exist between different data collectors when using Fuels3D, and compare the accuracy of Fuels3D outputs and traditional visual assessments.

- Python script to extract fuel hazard layers from point cloud information.
- Ongoing evaluation of the accuracy of Fuels3D metrics against TLS data.
- Testing of a new in-field targets and scaling method.
- Extension and testing of Fuels3D methods into other landscapes identified by end-users as priority landscapes.
- Development of a Fuels3D android app.
- One poster [AFAC 2016].
- Two conferences and/or invited presentations [BNH CRC Research Advisory Forum 2016; GEOSAFE 2016]
- Three peer-review papers published [2, 15, 30]

2017 - 2018

The Fuels3D mobile phone application for in field data collection was created for both Android and iOS operating systems, and instructional documentation supporting their use was generated. Further development around the in-field targets used to apply scale to scenes was trialled. End user trials were completed in South Australia, Victoria, and ACT, where users were provided with the Fuels3D app, in-field targets, and instructional material to facilitate data collection. Feedback on the data collection process and any issues were captured from end users.

Key milestones and highlights included:

- Fuels3D app adapted for iPhones and distributed for end-user field trials commence in Victoria, South Australia and ACT with new field in-field sampling targets trialled.
- Ongoing evaluation of the accuracy of Fuels3D metrics against TLS data and destructive sampling validation.
- One poster [AFAC 2017].
- One conferences and/or invited presentations [BNH CRC Research Advisory Forum 2017, AFAC 2017]
- Three peer-review papers published [2, 15, 30]
- Fuels3D wins the 2017 Victorian Spatial Industries Award for Environment and Sustainability.

2018 - 2019

End-user trials produced image datasets collected by end-users in their nominated priority areas. As part of this process automated processing of target identification, fuel hazard layer extraction, and quantification of fuel hazard metrics was completed using research-grade Python code. Following the trial, image quality control was completed to assess suitability of smartphones and the new transect method for producing 3D point clouds of fuel hazard.

Key milestones and highlights included:

- End-user trials using Fuels3D iPhone and app delivered and completed across south-eastern Australia and new sampling transect method assessed to increase rate of in-field image capture of surface and near-surface fuels.
- Ground-truthing and validation of 3D point clouds.
- Ongoing evaluation of the accuracy of Fuels3D metrics against TLS data.
- Determination of existing fuel hazard metrics and burn severity metrics used by fire and land managers that can be "measured" using image-based techniques.
- One poster [AFAC 2018].
- Five conferences and/or invited presentations [BNH CRC Research Advisory Forum 2018; AFAC 2018; BNH CRC Bushfire Mitigation Research Advisory Forum 2019; NSW FBAn Workshop 2018; AFAC Predictive Services Group Meeting 2019]
- Three peer-review papers published [34, 35, 36]

2019 - 2020

Workshops with end users were completed to understand and document requirements of Fuels3D system between agencies. Redesign of the in-field target, initially planned for manufacture via 3D printing but halted due to COVID-19, was completed to allow for DIY manufacture using low-cost materials. Test deployments completed for image upload portal in an AWS environment, and processing of datasets via local machines.

Key milestones and highlights included:

- AFAC and Predictive Services Group Workshop with end users to determine Fuels3D requirements.
- Developent and manufacture of redesigned in-field target.
- Web application build for data handling and notifications to system administrator within AWS environment.
- Three presentations [Silvilaser 2019; BNH CRC Research Advisory Forum 2019; BNH CRC Northern Australia Research Engagement Forum 2019; AFAC 2019].
- One peer-review paper published [3].
- The International Association of Wildland Fire (IAWF) awarded Sam Hillman IAWF 2020 scholarship toward his PhD with the Remote Sensing Centre at RMIT University.

2020 - 2021

Additional field trials involving the use of the redesigned in-field target, and the newly deployed Fuels3D upload portal was completed by participating end users from Queensland, South Australia, Victoria, and ACT. Online surveys and interviews were completed to obtain feedback from end users regarding the collection of data via the updated approach, and the transfer and utility of datasets for processing via the upload portal. As per suggestions within the feedback, adjustments were made to the supporting material provided to end users, including the creation of two instructional videos as a visual guide to the processes. Handling and processing of data was successfully transitioned to AWS infrastructure providing a semi-automated workflow.

Key milestones and highlights included:

- Distribution of updated in-field targets, digital cameras, and instructional material to end users in Queensland, South Australia, Victoria and ACT, for trials of updated workflow.
- Deployment of AWS hosted Fuels3D image upload portal. Technical instructions for replication of AWS implementation prepared as a significant body of work (100 page + 50-page document).
- Workshop with end user agencies from QFES, DEWNR, CFA, DEWLP, ACT Parks, presenting initial insights and delivering metrics from processed plots submitted during the 2019-2020 end user trials.
- Migration of data processing from local RMIT equipment to AWS hosted infrastructure.
- Collection of additional datasets from landscapes not captured or under-represented in the end user trials.
- Two peer-review papers published [33, 37].
- Graduation of PhD student Sam Hillman and awarded a postdoctoral Fulbright Future Scholarship (Funded by The Kinghorn Foundation).

UTILISATION AND IMPACT

SUMMARY

The Fuels3D approach for the assessment of surface and near-surface fuel hazard in the field was designed as a series of stages and built in a modular fashion to facilitate flexibility in the solution to accommodate different assessment requirements, improved techniques and algorithms, and/or alternative technologies. Each stage is described below with the outputs listed and is followed by an evaluation of each based on feedback from end-users and lessons learnt by researchers.

SOLUTION DESCRIPTION AND OUTPUTS

Data collection

Stage 1: sampling and image-taking

Stage 1 of the workflow involves the collection of data in the field by the user. Data collection consists of repeated imaging of nine sample locations in the field, each sample 1m in diameter, with a digital camera to create an overlapping, multi angle view of the sample area. Samples are consecutively photographed from multiple angles and heights in a circular manner to capture a 360° hemispherical view of the area and when aggregated are representative of a single plot of 10m diameter following the Overall Fuel Hazard Assessment Guide. Images with respective site metadata are then uploaded for processing through the Fuels3D online upload portal.

Associated Outputs:

- The following outputs are made available from within the Fuels3D web app (www.fuels3d.net).
- Fuels3D Quick Guide Image Capture
- Fuels3D Quick Guide Polytarget Assembly
- Image capture instructional video:

  https://www.youtube.com/watch?v=SA8Pc9slz9c

FIGURE 5. EXAMPLE IMAGE COLLECTED DURING FIELD SURVEY. IN-FIELD TARGET CENTERED IN FRAME.

Data Upload

Stage 2: Data Upload

The Fuels3D upload portal was created via a static website hosted in an AWS S3 bucket to enable user driven submission of collected datasets and metadata. Navigation to the Fuels3D website presents the user with a HTML/Javascript/Bootstrap form, enabling the registration and login to the Fuels3D system, and finally the upload of collected images. Prior to upload, the user is prompted to enter information describing the surveyed location, including time of data collection, location name and coordinates, and landscape description. Data entered in the form's controls are used to create a JSON metadata file, also uploaded to the S3 bucket, which drives some functionality of the Fuels3D processing method. Successful upload of imagery triggers the subsequent ingestion of data and processing of the plot. Further details can be found in the document 'Fuels3D Uploader Technical Overview.doc'. For more detailed specifications see the CloudFormation 'fuels3d-website-cf.template' template.

Associated Outputs:

- Technical instructions, architecture, and templates for replicating and implementing the image-uploader within an AWS environment.
- The following user outputs are made available from within the Fuels3D web app (www.fuels3d.net).
- Fuels3D Quick Guide Image Upload
- Image upload instructional video:

  https://www.youtube.com/watch?v=ibU4oPX1YLU

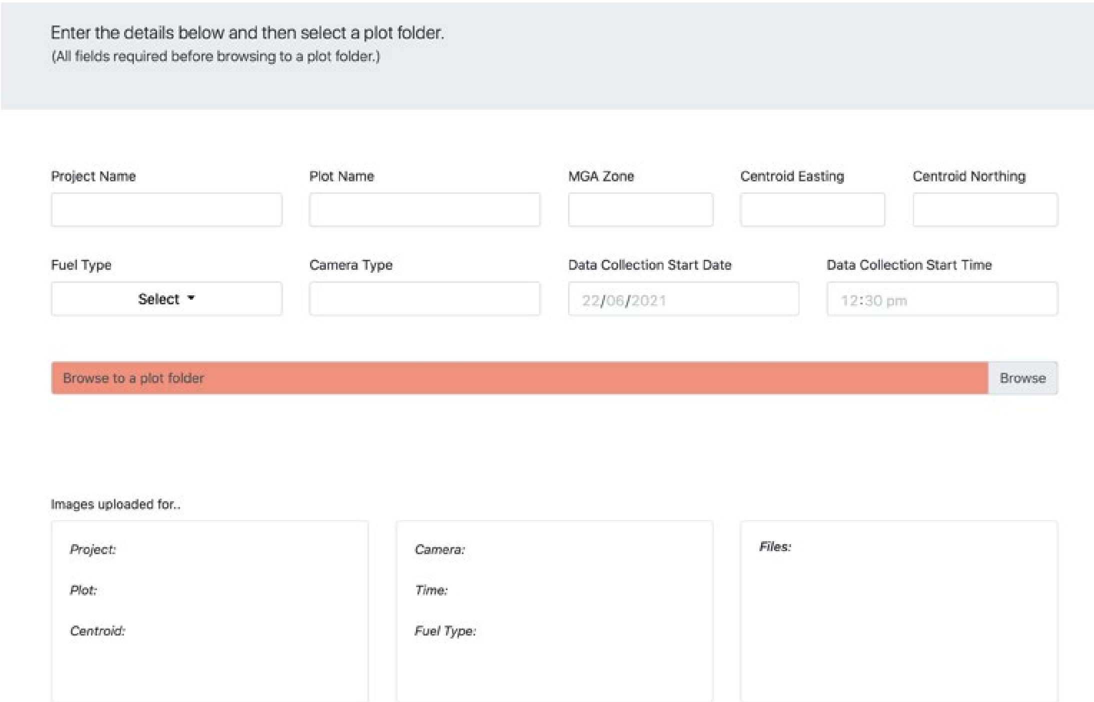


FIGURE 6. FUELS3D UPLOAD PORTAL WITH PRE-SET FIELDS FOR METADATA CAPTURE.

Point Cloud Creation

Stage 3: Image matching and point cloud generation

Stage 3 is the first stage of processing in the Fuels3D workflow and reconstructs the sample in 3D from the captured images. Agisoft's Metashape Pro is used to analyse the images and locate feature points appearing in multiple frames. The geometry of these points is then used to estimate the origin and orientation of the camera for each image, and generate a dense point cloud of the sample. Manual intervention by the user is required at this stage to digitise points on the in-field target, providing the scene with a coordinate system for scale.

Associated Outputs:

- Dense point cloud coordinated in local reference frame internal to workflow.

Associated Fuels3D Python Modules:

- meta_processing.py – import_and_align()
- meta_processing.py – build_clouds()
- For more details see 'f3d_meta_user_guide.docx' pages 2 - 3.

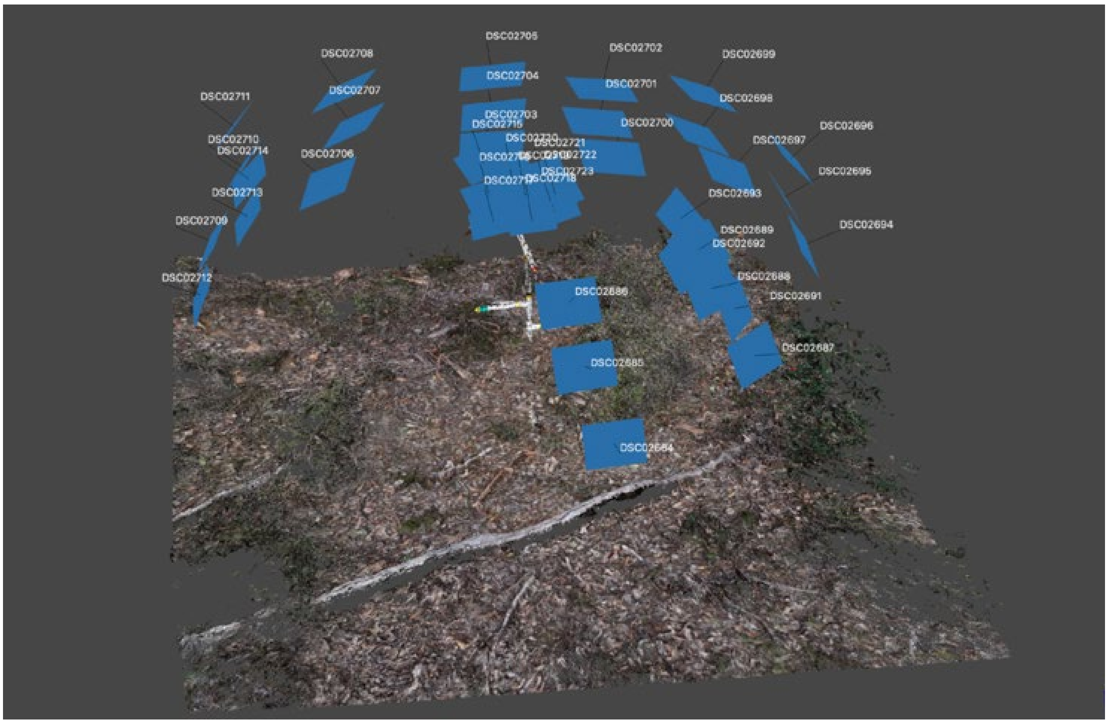


FIGURE 7. VIEW OF DENSE POINT CLOUD, WITH ASSOCIATED CAMERA GEOMETRY WITHIN METASHAPE PRO.

Feature Classification

The feature classification phase encompasses the processing and analysis of an output point cloud, to enable the classification and attribution of fuel layers. Stages 4 and 5 prepare the dataset for the final classification of features within stage 6. This phase is not dependent on the data collection and point cloud generation phases of the Fuels3D workflow, however, it does require a point cloud dataset to contain spectral information.

Stage 4: 3D voxel space generation

Stage 4 of the Fuels3D workflow is designed to ingest a point cloud product containing RGB spectral information and stratify the points within a 5 mm voxel space. This simplifies the dense point cloud, reducing computational demand in later processing.

Associated Outputs:

- Voxelised dense point cloud coordinated in local reference frame internal to workflow.

Associated Fuels3D Python Modules and Functions:

- segmentation.py – segment_main_process()
- For more details see 'f3d_meta_user_guide.docx' pages 3 – 4.

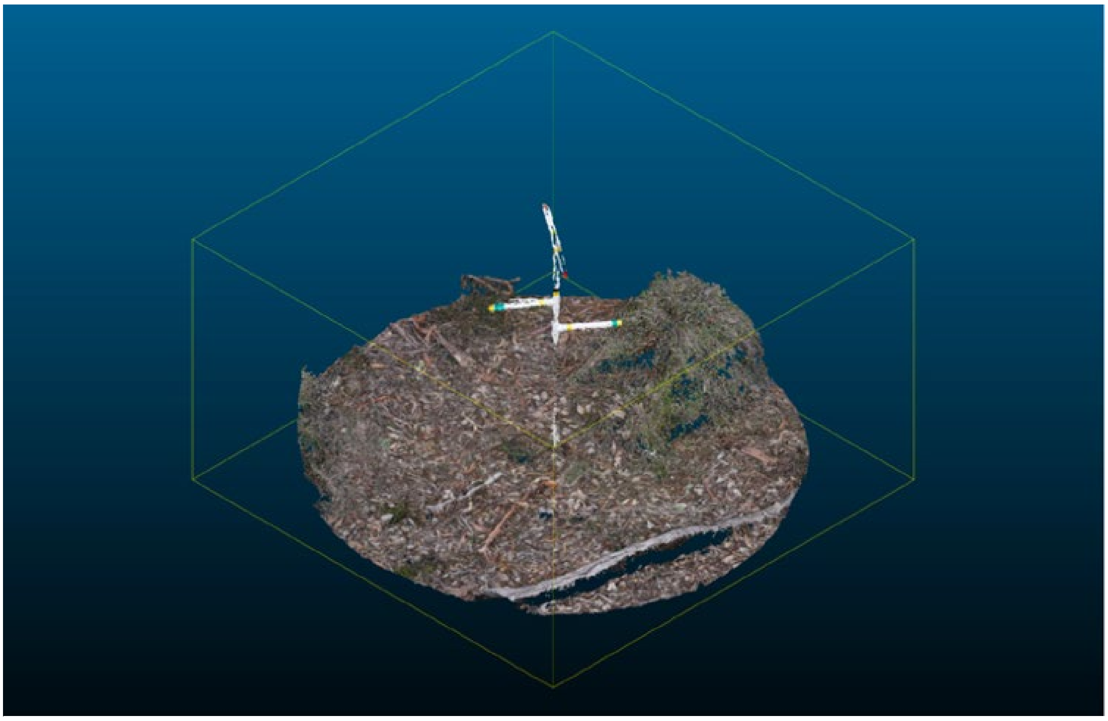


FIGURE 8. VOXELLISED DENSE POINT CLOUD IN POINT CLOUD PROCESSING SOFTWARE CLOUDCOMPARE.

Stage 5: Segment generation

Neighbouring voxels with similar spectral and textural characteristics are grouped, segmenting the voxel space. Segments typically reflect a portion of a feature within the scene and are used to train a random forest classification model.

Associated Outputs:

- Segmented dense point cloud coordinated in local reference frame internal to workflow.

Associated Fuels3D Python Modules and Functions:

- segmentation.py – segment_main_process()
- For more details see 'f3d_meta_user_guide.docx' pages 3 – 4.

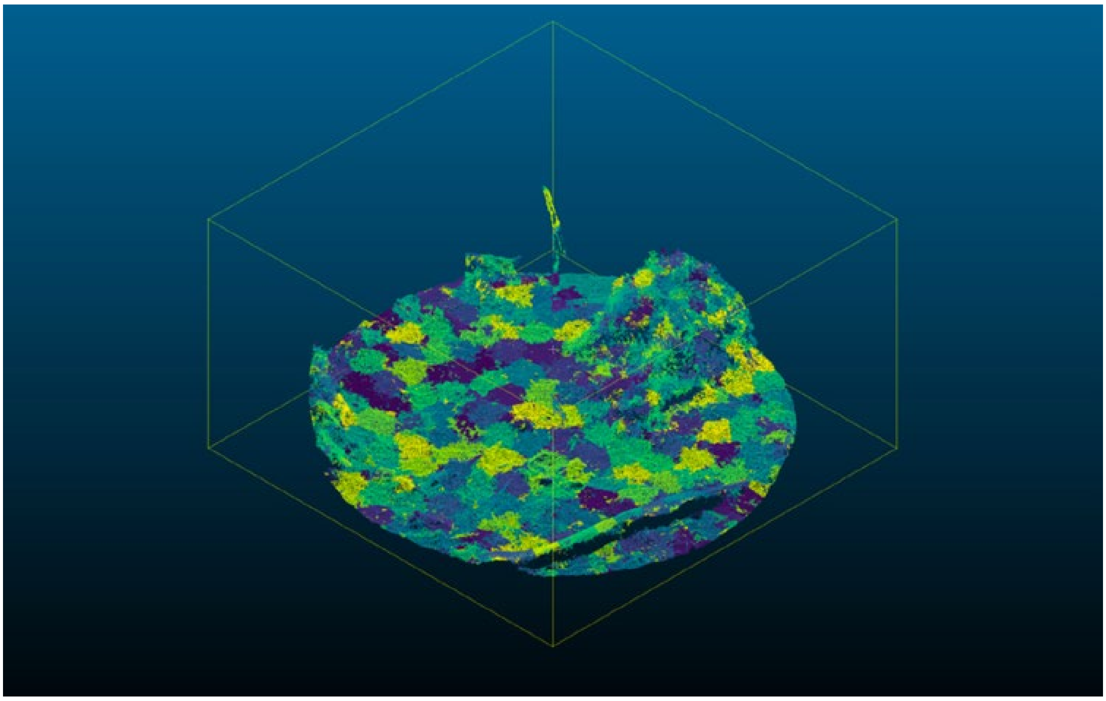


FIGURE 9. VOXELLISED DENSE POINT CLOUD FOLLOWING SEGMENTATION IN POINT CLOUD PROCESSING SOFTWARE CLOUDCOMPARE. SEGMENT COLOURS USED FOR VISUALISATION PURPOSES ONLY.

Stage 6: Fuel type classification

Stage 6 involves the classification of each segment defined in stage four into representative classes such as leaf litter, grasses, and bare earth, using a random forest classification model. Classified segments are allocated to surface or near surface fuels based on their class, providing a dense point cloud with class attributes.

Initial training of the classification model requires the manual annotation of segments from exemplar environments as training data. Re-training of the random forest model is recommended where there is significant variation in the visual appearance of fuels between locations.

Associated Outputs:

- Segmented dense point cloud with associated class attributes internal to workflow.

Associated Fuels3D Python Modules and Functions:

- classification.py – create_feature_table_from_points()
- random_forest.py – get_training_labels()
- random_forest.py – get_classifier()
- random_forest.py – classify_clouds()
- For more details see 'f3d_meta_user_guide.docx' pages 4 – 6.

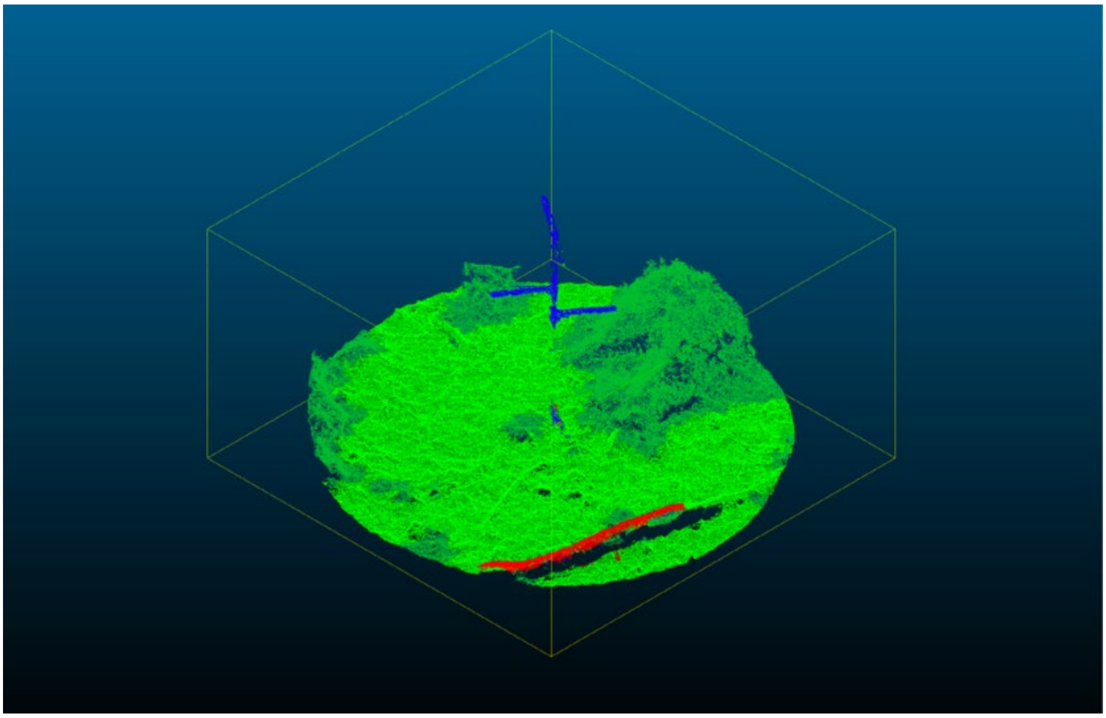


FIGURE 10. CLASSIFIED DENSE POINT CLOUD. COLOURS USED FOR VISUALISATION PURPOSES ONLY.

Hazard Metric Extraction and Quantification.

Stage 7: Fuel hazard metric extraction

The final stage of processing involves the analysis of a classified point cloud for the quantification of fuel hazard metrics. Classified segments are split into surface and near surface fuel layers. Currently, the Fuels3D workflow determines the values of two hazard metrics for each fuel layer: fuel height, and percentage cover; by calculating the volume and surface area of corresponding voxels. Calculation of additional or alternative metrics is achieved via modification to the processing code. Fuel hazard metrics are output and sent to the user via an automated email service.

Associated Outputs:

- Spreadsheet of fuel hazard metric values in .csv format, available as a data product for end users.

Associated Fuels3D Python Modules and Functions:

- calc_metrics.py – calc_metrics()
- For more details see 'f3d_meta_user_guide.docx' pages 6 - 7

Sample No	Mean Near Surface Fuel Height (m)	Near Surface Fuel Height STD (m)	Near Surface Fuel Height 90th Percentile (m)	Near Surface Fuel Height 10th Percentile (m)	Near Surface Fuel Cover (%)	Surface Fuel Cover (%)	Surface Fuel Thickness (m)
S1	0.008	0.017	0.051	0.000	0.75	0.25	0.007
S2	0.012	0.050	0.054	0.000	0.76	0.23	0.007
S3	0.006	0.023	0.045	0.000	0.90	0.10	0.007
S4	0.024	0.093	0.159	0.000	0.88	0.14	0.009
S5	0.008	0.026	0.071	0.000	0.83	0.14	0.008
S6	0.035	0.050	0.146	0.001	0.87	0.10	0.009
S7	0.015	0.045	0.061	0.000	0.98	0.05	0.010
S8	0.017	0.063	0.234	0.000	0.93	0.06	0.008
S9	0.024	0.068	0.146	0.000	0.61	0.38	0.007
Plot Statistics	0.017	0.048	0.108	0.000	0.84	0.16	0.008

FIGURE 11. EXAMPLE FUELS3D OUTPUT CONTAINING FUEL HEIGHT (MM) AND FUEL COVER (%) FOR SURFACE AND NEAR SURFACE FUELS.

Evaluation of Utilisation Potential

Comments, suggestions, and general feedback was collected from volunteers representing four government agencies participating in the 2020 Fuels3D end user trials. Leading up to this trial, a number of other experimental trials were conducted with end-users to investigate proof-of-concept, trialling of smart phones and different sampling methods. It should be noted that issues or improvements in the system occurred throughout the trial as bugs or points of clarification were raised by end-users. Identified issues were resolved as part of ongoing development and refinement. Upon completion of the completed trial additional feedback of the overall process was sought. Feedback was completed via a combination of face-to-face interviews, phone conversations, online surveys, and group workshops. Participants were encouraged to provide any thoughts they considered relevant, in addition to answering more specific questions regarding aspects such as:

- The ease of understanding what was required at the various workflow stages.
- The relevance and effectiveness of instructional material.
- The operational suitability of Fuels3D.

Extent of use

The development of a final Fuels3D workflow for utilisation trials included an updated data collection strategy, Fuels3D image upload portal, and semi-automated processing via AWS infrastructure during 2020 and 2021, with participating end users from Queensland Fire and Emergency Services, Department for Environment and Water SA, Country Fire Authority Vic, and ACT Parks and Conservation.

Data was captured and uploaded using the AWS Fuels3D uploader app. Submitted datasets were categorised based on their corresponding fuel type as described in the AFAC Bushfire Classification Overview. Datasets reflecting all top tier codes (Forest, Woodland, Plantation, Shrubland, Hummock Grassland, and Grassland) were collected throughout the trial both by submission from participating end users, and by RMIT researchers.

End-user organisation	End-user representative	Extent of engagement
Country Fire Authority Victoria (CFA)	Thomas Ellingworth Danielle Wright Thomas Duff	Data collection and feedback submission.
Queensland Fire and Emergency Services (QFES)	Francis Hines	Data collection and feedback submission.
Department or Environment and Water South Australia (DEWNR)	Simeon Telfer Ian Colquhoun Alex Otterbach	Data collection and feedback submission.
ACT Parks and Conservation Service	Adam Leavesley Bethany Dunne	Data collection and feedback submission.

TABLE 1. ORGANISATIONS AND REPRESENTATIVES PARTICIPATING IN THE 2020 – 2021 FUELS3D END USER TRIALS.

AFAC Fuel Type	Total Number of Samples	Number of Successfully Processed Samples	Sample Conversion %	Total Number of Plots	Number of Successfully Processed Plots	Plot Conversion %
Open Grassland	9	6	**67**	1	1	**100**
Grassland	41	9	**22**	6	0	**0**
Closed Grassland	81	13	**16**	9	0	**0**
Hummock Grassland	12	9	**75**	2	1	**50**
Low Open Shrubland	12	11	**92**	2	2	**100**
Low Shrubland	45	19	**42**	5	1	**20**
Low Closed Shrubland	5	0	**0**	1	0	**0**
Tall Open Shrubland	14	5	**36**	2	1	**50**
Tall Shrubland	39	18	**46**	5	2	**40**
Tall Closed Shrubland	9	0	**0**	1	0	**0**
Low Woodland	80	68	**85**	10	9	**90**
Low Open Forest	27	24	**89**	3	3	**100**
Low Closed Forest	9	1	**11**	1	0	**0**
Open Forest	27	11	**41**	3	1	**33**
Tall Closed Forest	9	0	**0**	1	0	**0**
Conifer Plantation	90	70	**78**	10	7	**70**

TABLE 2. STATISTICS OUTLINING THE SUCCESSFUL EXTRACTION OF FUEL HAZARD METRICS FROM PLOTS SUBMITTED BY END USERS DURING THE 2020 - 2021 END USER TRIALS. RESULTS ARE GROUPED BY GROWTH FORM AS DEFINED IN THE AFAC BUSHFIRE CLASSIFICATION OVERVIEW.

Table 2 reports the success rate of converting different fuel types into quantitative fuel hazard metrics. Conversion rates were reported at the sample scale, and at the plot scale (ie up to 9 samples collected for a plot and requiring more than 60% of the samples to be successfully processed to equate to a successful plot). Open grassland, hummock grassland, low open shrubland, low woodland, low open forest, and conifer plantation fuel types all had sample conversion rates above 65%. In contrast, grassland, closed grassland, low shrubland, low closed shrubland, tall open shrubland, tall shrubland, tall closed shrubland, low closed forest, open forest, and tall closed forest fuel types all had sample conversion rates below 65%, ranging from 0% - 46%.

Manual interrogation of all datasets was completed in order to identify factors which may be influencing conversion rates. This identified that failures in the processing of samples was occurring only during the image matching and point cloud generation phase within Agisoft Metashape, and commonly as a result of factors relating either to the collection of data in the field by the user, environmental conditions, and/or the physical characteristics of the features within the landscape itself.

Lessons learned from the utilisation trial and identified limitations include:

- Poor image capture by end users.
    - Image-based point cloud reconstruction via SfM requires significant overlap between images to ensure accurate estimation of object geometry. Factors during image capture such as poor camera focus and poor framing of the sample quickly resulted in

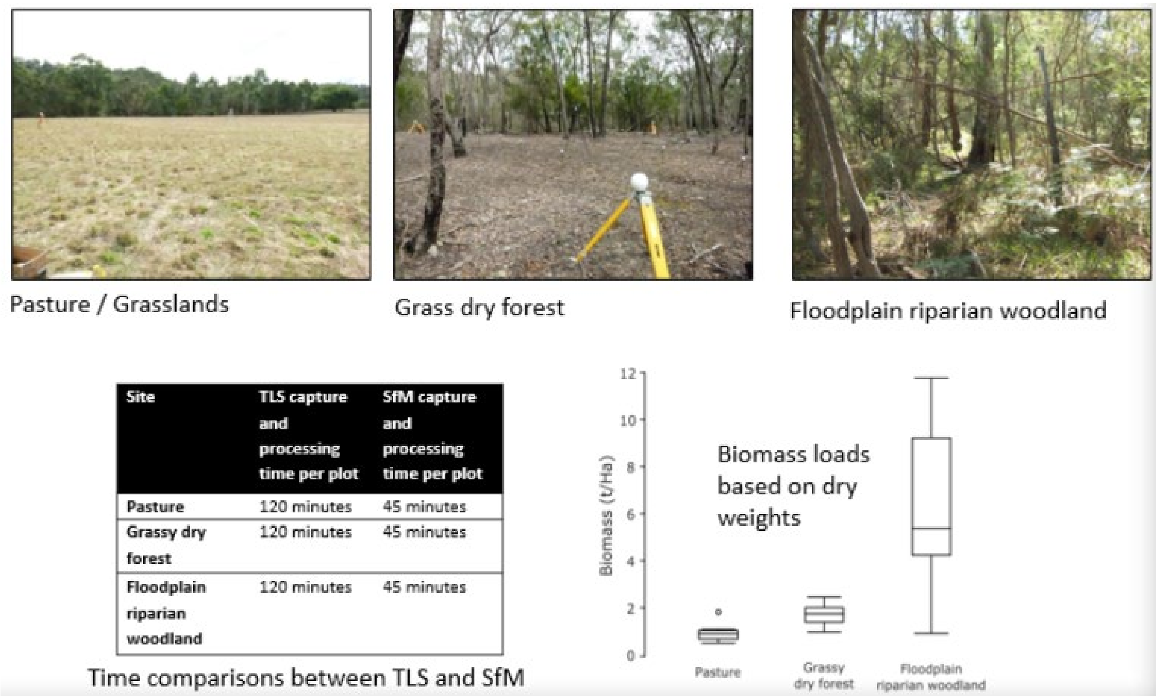
images becoming unusable during processing, leaving significant gaps in viewpoints. Out of focus images do not provide the detail required during processing, and images that are not appropriately framed often do not capture the entire sample area, which should be fully visible in the foreground of each photo. This can be mitigated by users taking greater care when image taking, noting some users commented that they did not read / view instructional material.

- Sample illumination.
    - Between photos, extreme changes in dynamic range of objects resulting from the presence and/or movement of shadowing make the identification of persistent features difficult during processing. The spectral signature of candidate features is one of many characteristics that are utilised to determine matching pairs between images. Extreme changes in the feature's appearance confounds this approach. Inconsistent shadowing is most extreme under conditions of direct sunlight, and is likely to occur as a result of factors such as canopy movement under wind, or by the user when standing between the sun and the sample. This can be mitigated by specifying particularly favourable conditions for capturing images for structure from motion. Recommendation: images are collected early or late in the day - after sunrise / just before sunset (similar to the LAI2200 plant canopy analyser that collects LAI information).
- Sample obscuration.
    - Data collected from locations with a high vegetation density were complicated by the resulting obscuration of features within the sample, limiting the capture of information in the centre of the sample. Obscuration reduces the visibility of candidate matching features between images, in turn reducing their potential to be identified. High vegetation density was also identified as a primary factor in poorly focused images, with vegetation outside of the sample area drawing the attention of the cameras auto-focus system. This is a limitation of hand-held cameras and image-based point clouds.
- Structural characteristics.
    - Objects such as grasses presented such fine features that they could not be accurately resolved during reconstruction. Prone to movement, even where features could be identified between viewpoints, changes in their location / orientation, due to wind for example, increased margin of error when estimating camera geometry and orientation, reducing the accuracy of the reconstruction. This is a limitation of image-based point clouds.

Feedback and Potential of Methodology

Primary benefits to the Fuels3D method for data collection revolved around the consistency of data generated, and the potential for increased understanding of site fuel loads and structure/arrangement. In addition, the ability to capture and store a larger quantity of quantitative data for use in future applications.

Three primary drawbacks to the Fuels3D methodology were noted by participants. Firstly, method complexity and the amount of time required to capture a plot was too great in comparison to that of existing visual methods. Users reported that capture of a single plot took on average 60 minutes to capture the surface and near-surface layers, compared to an average of 10 minutes when making a visual assessment (Figure 12). Secondly, the plot was at times not representative of the surrounding environment due to its limitation in size (although it is noted that plot size used in this trial follows that of current visual assessment guidelines but is easily changed to be samples that are placed along a transect of any length). Finally, the indicative low conversion rates observed in certain fuel types coupled with the time taken for capture reduces the operational applicability where quick assessments are required. It was noted however that the solution offers an approach where data is required for calibration and validation with other data sources.



Site	TLS capture and processing time per plot	SfM capture and processing time per plot
Pasture	120 minutes	45 minutes
Grassy dry forest	120 minutes	45 minutes
Floodplain riparian woodland	120 minutes	45 minutes

FIGURE 12. CAPTURE AND PROCESSING TIME COMPARISONS BETWEEN FIELD SURVEYS EMPLOYING TLS AND SFM APPROACHES IN PASTURE, GRASSY DRY FOREST, AND FLOODPLAIN RIPARIAN WOODLAND SITES.

Feedback on Instructional Material

Several suggestions were provided to improve the image capture quick guide, primarily requesting an increase in the clarity of methodological instructions to boost user confidence during image capture. Responders indicated the required layout of samples within each plot, in addition to the location from which each image should be captured from, was well understood however could have been aided through the inclusion of additional diagrams or example images. Image framing and orientation was not well understood however, with responders again noting additional diagrams and/or example images would aid understanding. With the feedback in mind, an instructional video was created and distributed as a visual guide to supplement the written material (Quick Guides). The video received positive response from users, with comments primarily noting better understanding of framing and orientation of images during capture, or more complex steps such as overheard image capture.

Feedback and Potential of Equipment

Short camera battery life was identified as a cause or potential cause of issue during data collection. In some instances, this resulted in an incomplete capture of a plot, with fewer than the required 9 samples collected. In particular, the inability of most users to charge camera batteries in field was flagged as limiting, as data collection of multiple plots are often arranged for a single day in the field.

Feedback and Potential of Fuels3D Portal GUI

Two points of feedback were provided regarding the user experience uploading imagery. Firstly, the time required to upload a plot was longer than expected, and at times needed to be left to complete overnight. Secondly, in the event that an upload was interrupted, previous progress was lost requiring the process to be restarted.

Utilisation potential impact

Utilisation potential impact has been captured as a SWOT analysis to summarise both the advantages and disadvantages of the Fuels3D solution.

Phase	Stage	Strengths	Weaknesses	Opportunities
Data Collection.	**Stage 1: Data collection.**	Low economic investment for equipment. Portable. Accumulation of site imagery over time and a permanent snapshot in time. Image data includes spectral information without the need for co-registration of multiple datasets. Repeatable.	Data collection of one plot took users 1 hour on average, to capture surface and near surface layers compared to an average of 10 minutes for an entire visual assessment. Successful processing of image to point clouds significantly influenced by errors in data collection such as poor focus/image framing. Difficult to collect data in densely vegetated environments (obstructed movement). Potential for disturbance of the surrounding landscape during data collection.	Data collection using alternative camera sensors such as new MLS options which capture colorised point clouds. Data collection via active sensors. As this stage of the workflow has been developed with the creation of image-based point clouds in mind, This processing step may be switched out if other point cloud generation methods are implemented.
Data Upload	**Stage 2: Data Upload.**	Provides a user driven approach to the upload of datasets. Ease of use. Capture of metadata provides consistent format.	Size of datasets can result in slow upload depending on connection speed. Requires user to have stable internet access.	Metadata provided by users could be used to adjust processing, such as using specific classification models for different landscapes.
Point Cloud Generation.	**Stage 3: Image matching, scaling, and point cloud generation.**	Agisoft Metashape supporting Python scripting. Fully supported commercial software (technical issues).	Limited flexibility of proprietry software and inability to access information regarding processing algorithms used. Use of Agisoft Metashape creates a break in the automation of the Fuels3 workflow, requiring manual user intervention to provide scale. Agisoft Metashape created to map built environments and may not be optimised to natural environments. Successful point cloud generation strongly influenced by image quality/characteristics such as focus and image framing. Successful point cluod generation strongly influenced by obscuration of sample centre in densely vegetated environments.	Assessment of alternative software solutions for image-based point cloud generation. Can be replaced by alternative methods of generating point clouds (active sensors/depth cameras) removing need for this step. (Potential) for automated registration of in-field target if mm accuracy can be attained.
Feature Classification.	**Stage 4: 3D voxel space generation.**	Capable of ingesting any point cloud dataset and is not dependent on previous stages or data capture technologies.		
	Stage 5: Segment generation.		Processing requires substantial CPU and GPU resources,, however, no AWS instances are currently able to provide both.	Optimisation of Python code to reduce processing times and to better utilise AWS instance specifications further reducing processing times and costs..

	Stage 6: Fuel type classification.	Machine learning training samples can be tailored for specific landscapes and features of interest to increase classification accuracy. Trained models can be shared between users.	Requires collection of spectral information to drive classification. Classification accuracy influenced by variable lighting effects such as shadowing.	
Hazard Metric Extraction and Quantification.	**Stage 7: Fuel hazard metric extraction.**	Potential to calculate alternative metrics where required. Ability to extract alternative hazard metrics from legacy datasets accumulated over time.	Accuracy of metrics dependent on the performance of segment classification.	Extration of data such as live/dead ratio possible using spectral information.

TABLE 3. SUMMARY OF THE STRENGTHS, WEAKNESSES, AND OPPORTUNITIES RELATING TO EACH STAGE OF THE FUELS3D WORKFLOW.

Utilisation and impact evidence

The development of Fuels3D moved from concept to end-user trials with the first end-user field day workshop held in July 2016. Participants included staff from SA DEWNR, ACT Parks and Wildlife, VIC DELWP, VIC CFA, Melbourne Water and Parks Victoria. The field day aimed to introduce end-users to the Fuels3D collection protocol and to assess its ease of use and repeatability between data collectors in comparison to traditional visual assessment techniques. Participants were asked to undertake a visual assessment as well as use the Fuels3D app. At the completion of the day, the data collection participants were asked to complete a survey evaluating the Fuels3D data collection workflow providing an early insight into the potential for uptake by end-users.

The survey indicated that the participants found the Fuels3D protocol easy to follow. This was further indicated by the collected data of which more than 90% of the image sets were able to be used in the Fuels3D processing method for the study environment. From the results of this study several areas of improvement in the data collection and processing methods were identified and incorporated into the ongoing development of the Fuels3D solution.

Since the first workshop, various in-field scaling methods have been assessed for accuracy, reliability and user friendliness. Initially the team developed a smartphone Fuels3D app to provide a complete in-field mapping approach for surface and near-surface fuels. The Fuels3D app was made available for both Android and iPhone devices and extensive in-field trials were conducted with end-users from Victorian CFA, Victorian Department of Environment, Land, Water and Planning, South Australian Department for Environment and Water, and ACT Parks and Conservation. End users are provided with access to the Fuels3D app and provided with portable vertical targets necessary for image scaling. Quick Guide documents have been provided to instruct end-users through the solution, and an open spreadsheet for end-user feedback and issue reporting is also given.

This second set of trials demonstrated a lack of consistency in reconstructing image-based point clouds using smartphones. This was due at least in part to the new generation smartphones moving towards increasing the number of camera sensors rather than increasing camera sensor spatial resolution. As such, a move was made to replace phone cameras with off-the-shelf digital cameras.

Ongoing research investigations into improving image-matching continued to run in parallel to the development of the other workflow components. A modular workflow allowed for elements to be "switched out" as new and improved solutions would come to hand. Whilst the Fuels3D workflow has been developed with the creation of image-based point clouds in mind, it is possible to replace this step with other point cloud generation technologies and methods (TLS and MLS LiDAR), effectively being ingested into stage 4 of the workflow. At the same time, samples across different fuel types were captured for assessment of utility. Table 2 in this document reports the success rate of converting different fuel types into quantitative fuel hazard metrics.

Utilisation and impact evidence of the approach has been communicated throughout the life of the project via:

- BNH CRC Research Advisory Forums (annually)
- BNH CRC reports (e.g. Wallace L, Reinke K, Jones S. Emerging technologies for estimating fuel hazard. Melbourne: Bushfire and Natural Hazards CRC. 2017.)
- AFAC conferences (e.g. Wallace, L, Reinke, K., Jones, S. Hillman, Leavesley, A., Telfer, S., Bessel, R. and Thomas, I Experiences in the in-field utilisation of Fuels3D. AFAC, September 5-8, 2018, Perth, Australia.
- International Fire Behaviour and Fuels Conference (e.g. Wallace, L., Hally, B., Reinke, J.K., Jones, D.S. and Hillman, S., 2016, April. Leveraging smart phone technology for assessing fuel hazard in fire prone landscapes. In Proceedings of the 5th International Fire Behaviour and Fuels Conference, Melbourne, Australia (pp. 11-15).)
- Peer-review publications (e.g. Wallace L, Hally B, Hillman S, Jones S, Reinke K. Terrestrial Image-Based Point Clouds for Mapping Near-Ground Vegetation Structure: Potential and Limitations. Fire. 2020; 3(4): p.59.)

CONCLUSION

This report summarises the inception, design, and development of the Fuels3D project. This work considers the lack of repeatability and reliability with current field fuel hazard assessments and looks to opportunities in photogrammetry and computer vision to create an affordable yet accurate alternative and package this in an end-to-end workflow and scaleable solution. A tool chain and suite of computer vision and photogrammetric algorithms that use images captured in the field to produce 3D point clouds from which fuel hazard metrics are calculated. The developed technique is adaptive to 3D point clouds captured from other terrestrial technologies and can allow for changes in data collection technologies.

Due to time constraints and issues revolving around COVID and associated impacts, the utilisation model saw development and utilisation conducted in parallel rather than sequentially. During the project, adaptions were made to the site capture procedure to work towards the reliability of site reconstruction and accuracy of fuel metrics extracted. For the majority of 2020 and 2021, a comprehensive evaluation of fuel types that were a priority or a landscape of interest to end-users was conducted. Under-represented fuel types were also collected by researchers to provide a clear and comprehensive picture of the performance of the solution.

Factors such as poor image capture, and inconsistent sample illumination can be resolved through additional information and direction within the instructional materials guiding image capture, such as specifications to appropriate data capture times throughout the day, or the use of manual camera controls. Evolution of instructional materials throughout the development of Fuels3D has proven effective in mitigating similar limitations by increasing understanding of end users to the problem. For other factors such as fuel obscuration and fine features such as those found in grasslands the solution is compromised and alternative but significantly more costly technologies will need to fill in these gaps. The time taken to capture a plot (using a nine-sample method) was considered too time consuming an investment to warrant capture of the surface and near-surface layers only. This was identified by all end-users as a distinct barrier to operational uptake.

NEXT STEPS

Evaluation of the Fuels3D workflow has highlighted several limitations and opportunities for further development. It also emphasised the need for quantitative measures of fuel to be able to be collected operationally, and across the landscape for all fuel layers.

Structure from Motion as the primary method of 3D point generation for Fuels3D image reconstruction is a stress-point in the solution. Around half of the sample landscapes were reconstructed successfully and a number of others could be mitigated by for example increased training and user care in acquiring images. Other issues such as obscuration or very fine and complex fuel features require exploration of alternative software packages and/or point cloud capture technologies. Investigation into alternative software packages or open-source offerings of image-based point cloud reconstructions tailored for vegetation may enhance the low-cost point of the solution to proposed here. From a technology perspective more expensive LiDAR-derived point clouds (incl. MLS) containing spectral information may prove effective in circumventing some of the shortfalls of image-based only solutions whilst still retaining the benefits associated with having spectral information for fuel attribution. However, these technologies come at a significant jump in price point.

Another conceptual challenge remaining is the identification of a consistent definition and decision tree to identify the different vertical fuel layers across landscapes and jurisdictions. These are needed to consistently program and compute hazard metrics from 3D point clouds. The options range from the simple (using fixed height thresholds) through to the more complex such as implemented here using machine-learning approaches or through 3D network analysis based on vertical and horizontal connectivity constraints.

Decreases to the total processing times of datasets is recommended to improve the viability of the Fuels3D approach at larger scales. End to end processing of imagery from the field to the quantification of fuel hazard metrics also demands substantial CPU and GPU processing performance. Currently, no AWS computing instances offer hardware that can support both, with individual instances geared towards one or the other. As such, further development of the Fuels3D Python code to support parallel processing across multiple instances could reduce processing times dramatically. In addition, optimisation of the code to support multi-threaded processing and faster Python libraries is recommended.

PROJECT OUTPUTS LIST

PEER-REVIEWED JOURNAL ARTICLES

1 Gupta V, Reinke K, Jones S, Wallace L, Holden L. *Assessing metrics for estimating fire induced change in the forest understorey structure using terrestrial laser scanning*. Remote Sensing. 2015; 7(6): p.8180-8201.
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Dr Vaibhav Gupta
Ms Ritu Taneja
Ms Christine Spits

END-USERS

End-user organisation	End-user representative	Extent of engagement (Describe type of engagement)
Country Fire Authority Victoria (CFA)	Alex Chen Danielle Wright David Nicholls Rachel Bessel Thomas Duff Thomas Ellingworth	Data collection, field testing, and feedback submission.
Queensland Fire and Emergency Services (QFES)	Francis Hines	Data collection, field testing, and feedback submission.
Department or Environment and Water South Australia	Alex Otterbach Ian Colquhoun Simeon Telfer	Data collection, field testing, and feedback submission.
ACT Parks and Conservation Service	Adam Leavesley Amanda Johnson Bethany Dunne Tony Scherl	Data collection, field testing, and feedback submission.
WA. Department of Biodiversity, Conservation and Attractions	Lachlan McCaw	Facilitating utilisation requirements.
Melbourne Water	Tim Sanders	Data collection, field testing, and feedback submission
Vic. Department of Environment, Land, Water and Planning (DELWP)	Natasha Schedvin	Data collection, field testing, and feedback submission

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