TREE-LEVEL FUEL CONNECTIVITY TO ASSESS CROWN WILDFIRE POTENTIAL BY UAS-BASED PHOTOGRAMMETRY

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ABSTRACT:

Evaluating the potential for crown fires remains a pivotal concern in wildfire management because it affects fire behavior, causing them to spread further. In this work, we propose a methodology to assess crown fire potential based on the tree connectivity at crown level from UAS (Unmanned Aircraft Systems)-based Structure-from-Motion Photogrammetry. The approach is usable in a large landscape with the aim of reducing crown fire potential by considering the spatial variability of fuels within a stand. The utilization of UAS for photogrammetry holds immense promise in transforming the approach to assessing and managing forest fires. This cutting-edge technology offers the potential to deliver highly precise and comprehensive data concerning forest structure and connectivity, thereby presenting a groundbreaking opportunity for enhanced forest fire analysis and control.

1. INTRODUCTION

Forests are biodiversity hotspots that store huge amounts of carbon in their above- and below-ground biomass (Ameray et al., 2021). Climate change and environmental degradation contributes to the increased occurrence and severity of wildfires (Abraham et al., 2021). Consequently, fire behavior and simulation models (Ford et al., 2021; Bakhshaii and Johnson, 2019) have become essential tools for land managers and decision makers. These models are utilized to anticipate fire potential, pinpoint areas with a high risk of wildfires, and effectively allocate resources for fuel treatments (Pham et al.,2020). Concretely, crown fires occur when fire spreads into the forest canopy, and they can be particularly dangerous and difficult to control. Assessing crown fire potential is a critical issue in wildfire management. The number of tree-level fuel connections, the average number of fuel connections per tree or average trees forming a cluster of connected tree fuels as measures of fuel connectivity can be the key to alter fire behavior and reduce fire spread at the landscape level (Contreras et el., 2012). Traditional approaches have focused on the vertical structure of forests, such as tree height, stand density, and ladder fuels, to predict the likelihood of crown fire initiation and spread. A clear example is FlamMap wildfire model (Finney, 2006), which uses the average attribute values of a forest stand for stand-level predictions without considering spatial variability in fuels and vegetation within a stand. However, recent studies have shown that horizontal connectivity at the crown level may also play an important role in determining crown fire behavior (Gu et al., 2020, Jaskierniak et al., 2021). The concept of horizontal connectivity refers to the spatial arrangement and distribution of tree crowns in a forest. Trees with overlapping crowns can allow fire to spread quickly and easily from one tree to another, leading to a rapid spread of crown fires. On the other hand, gaps between trees can limit the spread of fire, making it easier to control and suppress. As well, crown fire propagation shows that weather conditions largely affect the ranges of tree spacing that allow fire propagation between adjacent trees. Several methods have been proposed to assess connectivity at the tree level using airborne LiDAR (Light Detection and Ranging) data to create 3D (three-dimensional) models of forest canopies and analyze the spatial arrangement of tree crowns (Karna et al., 2019). Other methods include using satellite imagery and ground-based measurements to estimate canopy cover and crown spacing (Rocha et el., 2023).

Recent advances in UAS (Unmanned Aircraft Systems) show its ability to capture high-resolution images of the forest canopy from different angles and perspectives, allowing for a more complete and comprehensive analysis of 3D tree crown structure and connectivity (Gu et al., 2020, Jaskierniak et al., 2021).

In this work, we propose a methodology to assess crown fire potential based on the tree connectivity at crown level from UAS-Based Structure-from-Motion Photogrammetry. This approach involves analyzing the arrangement and spacing of tree crowns, as well as the distribution of fuel loads, to estimate the likelihood of crown fire ignition and spread. The Connected Components algorithm is used to identify clusters of points that are connected to each other in forested point clouds. The algorithm works by starting at a given vertex and traversing all the vertices that are directly or indirectly connected to it. The process is repeated for any remaining vertices that are not yet part of a connected component until all vertices have been visited. The octree level is used as a limit. Octree level refers to a specific level of detail in the hierarchical subdivision of the 3D space. At each level, the space is divided into smaller cubic regions (octants), and points from the point cloud are assigned to these regions. Higher octree levels represent larger cubic regions with fewer details, while lower levels represent smaller regions with more detailed point information. Usually, octree levels allow for efficient data organization, storage, and analysis in point cloud datasets.

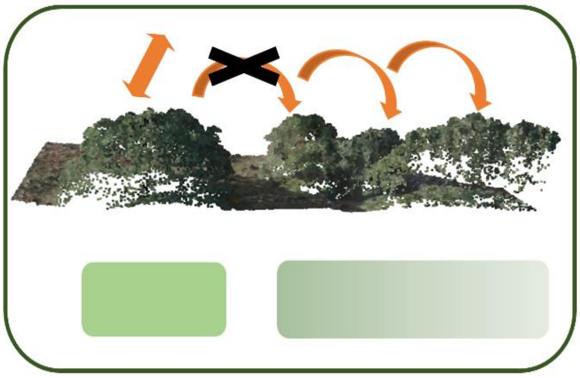

Figure 1. Conceptual workflow of the proposed methodology: canopy connectivity related to direction of fire propagation and canopy density.

Figure 1 illustrates the conceptual aim of the proposed methodology, where the effect on fire behavior due to connected stand mass is drawn: how easy is it to jump the vegetation gaps represented by the canopy connectivity and the fuel quantity of each cluster (represented by the color darkness of the rectangles, that signifies each cluster formed by connected canopies, on the bottom).

In essence, the implementation of UAS-based photogrammetry holds the transformative potential to revolutionize forest fire assessment and management practices. By furnishing intricate and precise information on forest structure and connectivity, it opens up unprecedented opportunities for fire managers and policymakers engaged in wildfire prevention, suppression, and mitigation (Keefe et al., 2022). While this technology is relatively nascent and demands further investigation, its implications are captivating as it promises to significantly enhance our capacity to anticipate and control crown fires in the future.

2. MATERIALS AND METHODS

2.1 Experimental site

The study took place in a holm oak forest, situated in Southern Catalonia (NE Spain) at coordinates 41° 19′ N, 1° 2′ E, and an elevation of 945 meters. The forest covers a south-facing slope with a gradient of 25 per cent. The soil in this area is a Dystric Cambisol over Paleozoic schist, with a depth ranging from 40 to 85 cm. This particular holm oak forest is characterized by a densely packed multi-stem canopy, containing approximately 17 stems per hectare. The dominant tree species include *Q. ilex*, *P. latifolia* and *A. unedo*. Additionally, the forest exhibits a variety of other evergreen species well adapted to dry conditions, such as *Erica arborea L.*, *Juniperus oxycedrus L.*, and *Cistus albidus L.* Occasional individuals of deciduous species, namely *Sorbus torminalis (L.) Crantz* and *Acer monspessulanum L.*, are also present.

2.2 Aerial image acquisition and processing

Automated image acquisition occurred at 2-second intervals, following a predetermined flight plan designed to achieve 80% longitudinal and 50% side overlap, which was computed using the Microdrones Photogrammetric Flight Planning software (MFLIP). The software played a pivotal role in defining the flight project parameters, including the area of interest, flight direction, camera specifications and coordinate system. Moreover, it facilitated the creation of the flight plan, considering Ground Sample Distance (GSD), overlap, UAV flight, and image acquisition parameters, while also providing essential controls for geo-referencing, vertical image deviation, scale, overlap, and drift effect (Hernandez-Lopez et al., 2013). The UAV flights were consistently scheduled near solar noon, maintaining a flight altitude of 80 meters above ground level. Employed in the study was a quadcopter md4-1000 from Microdrones Inc., Kreuztal, Germany, equipped with an RGB SONY ILCE-5100 digital camera from Sony Corporation, Tokyo, Japan, capable of capturing imagery at an impressive 0.02-meter GSD. The technical specifications of this photogrammetric sensor are illustrated in Table 1. To ensure precise georeferencing and camera geometric calibration, eight targets were strategically distributed throughout the flying area. The positions of these targets' centroids were accurately determined using a Leica Global Positioning System (GPS) 1200, linked to a Global Navigation Satellite System (GNSS) permanent reference station. The real-time kinematic (GNSS-RTK) capabilities of the system boasted an estimated accuracy of 0.01 meters in planimetry and 0.015 meters in altimetry. To optimize the photogrammetry process, any blurred images were swiftly detected and removed automatically (Ribeiro-Gomes et al., 2016), thereby preventing artifacts in the final output. Geomatic products were then generated using version 1.6.1 of the Agisoft Metashape Professional software, developed by Agisoft LLC, St. Petersburg, Russia. This advanced software played a crucial role in generating dense point clouds from the aerial images acquired by the UAVs, thus facilitating the extraction of valuable information for further analysis and applications.

	Sony ILCA-5100
Sensor	23.5*15.6 mm CMOS
Pixel size (µm)	4*4
Image resolution (pixel column & row)	6000*4000
Focal length (mm)	20

Table 1. Technical specifications of the photogrammetric sensor.

2.3 Methodology

We consider the importance of horizontal fuel connectivity to significantly affect crown fire propagation. This variable can predict crown fire propagation from a burning tree crown to an adjacent tree crown in front of the flaming front. Being able to quantify it, crown fire potential can easily be deduced. For that, we propose a methodology that analyses the crown structure and the connectivity in forest, a component which alters the fire spread, in terms of direction and speed (fuel load), directly useful for wildfire management. Figure 2 represents the workflow of the proposed methodology.

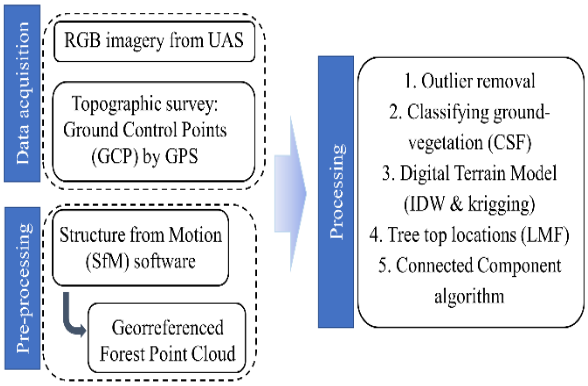

Figure 2. Workflow of the proposed methodology.

The processing steps are described below. After the image acquisition from the UAS and the topographic survey carried out, a SfM software (the Agisoft Metashape Professional software) is run to reach the point cloud of the forest already georeferenced (Over et al.,2021). The imagery dataset is handled by a framework based on camera calibration, image orientation and dense point cloud extraction (Herrero-Huerta et al., 2023). Next, the point cloud is processed as follow:
(i) Outlier removal: The sample point cloud can be susceptible to outliers and noise, often caused by interference from various sources like people, vehicles, and more. These points are not representative of actual trees and must be eliminated from the point cloud in the initial step. To achieve this, a statistical analysis is conducted on the neighborhood of each point, assuming a Gaussian distribution of distances (d) between neighbors. The distances are adjusted based on the variable point densities, accounting for factors such as distance to the sensor, occlusions, and driving speed. For every Moving Least Squares (MLS) point, the average distance to its k-nearest neighbors is computed and compared to the Upper Confidence Limit (UCL) derived from a normal error distribution. If the ratio between the distance of a given j^{th} point (j = 1…k) and the UCL, considering a specific confidence level (p), exceeds 1, then that point is considered an outlier and excluded from the analysis, as represented in (1).

$$thereshold = \frac{d_j}{\bar{d}+p*\sigma_d} > 1 \quad (1)$$

Here, $\bar{d}$ represents the mean, and σ_d indicates the standard deviation of the distances to the k-nearest neighbors within the evaluated point's vicinity (j = 1…k), respectively. The confidence level (p) is denoted as the critical value associated with the standard normal density curve. This approach was developed by (Herrero-Huerta et al, 2020).
(ii) Classify ground/non ground: In this step, Cloth Simulation Filter (CSF) is used to classify ground- non ground (Zhang et al., 2016). This filtering method requires only a few simple integer and Boolean parameters for configuration. The point cloud is inverted, and a rigid cloth is employed to envelop the inverted surface. Through analyzing the interactions between the cloth nodes and their corresponding points, the positions of the cloth nodes are determined to generate an approximate representation of the ground surface. Subsequently, the ground points are extracted from the point cloud by comparing the original points with the generated surface.
(iii) Creating the Digital Terrain Model (DTM): The process of DTM computation begins with sampled ground points and employs various spatial interpolation techniques to infer ground points at unsampled locations. To initiate this process, we use the inverse distance weighting algorithm (IDW) due to its speed, accuracy, and robustness as a triangulation algorithm. IDW is a deterministic method for multivariate interpolation, ideal for dealing with a scattered set of points. It operates under the assumption that the value at an unsampled point can be approximated as a weighted average of values at points from the nearest neighbors. These weights are inversely proportional to a power of the distance between the location and its neighbors. Afterward, the kriging algorithm is employed to interpolate the coarse DTM, achieving a high-resolution DTM. Kriging represents a more advanced approach, utilizing geostatistical interpolation methods that take into account the spatial relationships between the points and their respective distances from one another. This process can be understood as a two-step approach: first, the spatial covariance structure of the sampled points is determined by fitting a variogram using exponential, spherical, or Gaussian curves; and second, the derived weights from this covariance structure are used to interpolate values for unsampled points or blocks across the spatial field.
(iv) Tree top locations: The process of individual tree detection involves locating trees in their spatial positions and extracting their height information. To achieve this, a point cloud-based algorithm called the Local Maximum Filter (LMF) is applied to the loaded dataset, utilizing a flexible window size (Bonnet et al., 2017). This algorithm examines neighboring points within the defined window size to determine if the processed point represents the highest point in that local region. The number of detected trees is indirectly linked to the chosen window size. As a result, the window size is dynamically adjusted based on the height of the trees. Taller trees with larger crowns require larger window sizes to accurately detect their treetops. This adaptability in window sizes is particularly beneficial for areas with complex forest structures and heterogeneous landscapes. Additionally, it proves useful for covering extensive regions effectively.
(v) Applying connected component algorithm at different octree level: This is a method used to group points in a point cloud into connected clusters at different levels of detail within an octree data structure. The algorithm organizes the points spatially into smaller regions (depending on the octree level value) and identifies groups of nearby points as connected components. By traversing the octree at various levels, the algorithm achieves different levels of roughness in the point cloud representation.

3. RESULTS

We manually segmented an area of 150*100 m to run the proposed methodology. Figure 3 shows the forested point cloud generated by UAS-Based Structure-from-Motion Photogrammetry from the segmented study area in RGB colors (Figure 3.a) and colorized by height (Figure 3.b). The point cloud after the outlier removal process has 2,626,195 points, with a density of more than 175 points / m^2. Once it is classified, the non-ground point cloud has 1,108,676 points. Figure 3.c illustrates the tree tops extracted from the non-ground points with a red point. This point cloud is colorized as well depending on heights. Furthermore, the DTM is added in grey color. A total of 133 trees are accurately localized.

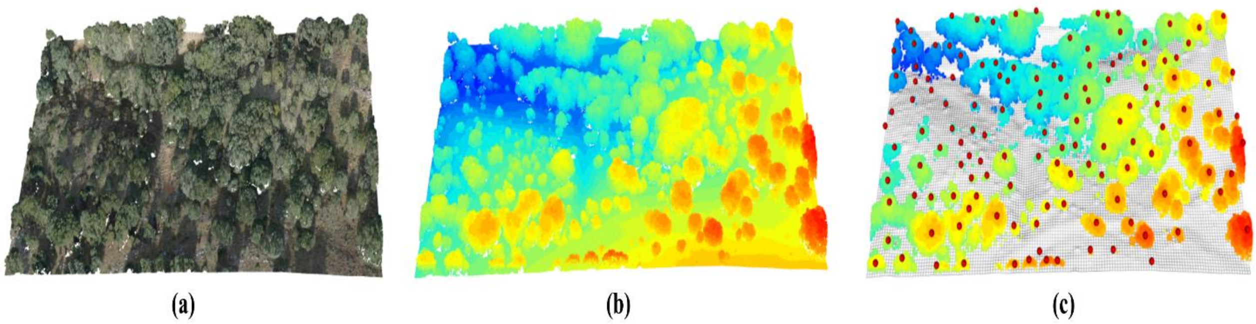

Figure 3. Point cloud of the study site in RGB colors (a) and colorized by height (b); non-ground point cloud colorized by height, the computed tree tops with a red point and the DTM in grey color (c).

Next, connected component algorithm is computed at 4 octree levels. Figure 4 shows the results of the tree connectivity in random colors each cluster. Table 2 summarizes these results.

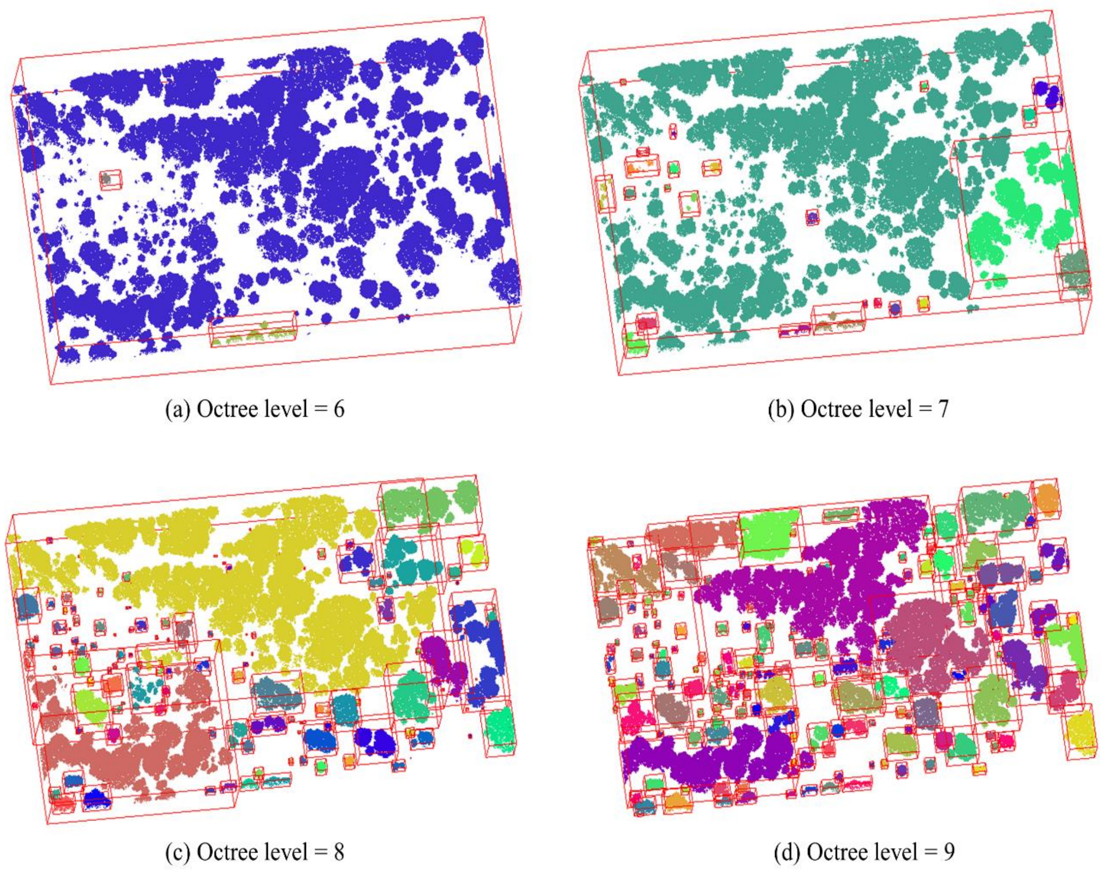

Figure 4. Forested point cloud generated by UAS-based Structure-from-Motion photogrammetry with the connectivity approach at 4 octree levels with random colors per cluster (a, b, c, d).

The octree-level parameter is affected by the climatic parameters. The explanation come from (Contreras et al., 2012) that affirms the results for crown fire propagation are largely affected by the weather conditions which determine the ranges of tree spacing that allow fire propagation between adjacent trees.

Octree level	Grid step (m)	# Connected component	Max. connected trees
6	2.320	3	129
7	1.160	25	81
8	0.580	90	59
9	0.290	167	24

Table 2. Results from the connectivity analysis.

4. CONCLUSION

The integration of advanced physics-based fire behavior analysis with precise vegetation mapping technologies has allowed us to examine individual tree-level fuel characteristics, leading to a better understanding of crown fire risks. Furthermore, we assessed the count of trees susceptible to ignition and the number of trees that could potentially facilitate fire propagation upon reaching the canopy fuels. However, it is essential to take into account weather parameters and conditions for accurate analysis. When applying these methods in drier, hotter, and windier regions, there is a potential risk of underestimating the distance over which fire can spread through adjacent crowns. To validate and broaden the scope of our approach, further research is necessary. Our current work represents a preliminary step, exploring the feasibility of constructing regression models based on detailed three-dimensional fire simulations for application in forest stands.

Overall, UAS-based photogrammetry has the potential to revolutionize the way we assess and manage forest fires by providing more detailed and accurate data on forest structure and connectivity. In addition, this is particularly interesting for fire managers, and policymakers who are involved in wildfire prevention, suppression, and mitigation. While this technology is still relatively new and requires further research, it shows great promise for improving our ability to predict and manage crown fires in the future.

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