INFLUENCE OF VOXEL SIZE AND VOXEL CONNECTIVITY ON THE 3D MODELLING OF AUSTRALIAN HEATHLAND PARAMETERS

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Commission IV, WG IV/9

KEY WORDS: Voxel Connectivity, Voxel Size, Segmentation, Point Clouds, Heathland, 3D Modelling

ABSTRACT:

Point clouds acquired through laser scanning techniques are applied in the three-dimensional modelling of vegetation. They provide the three-dimensional coordinates of geometric surfaces with attributes. However, raw point clouds are unstructured and do not provide semantic, geometric, or topological information about an object. Voxelisation is a method for structuring point clouds. It is a generalisation of point clouds and therefore the voxel size and the voxel neighbourhood play a critical role in the processing. This research explores the influence of voxelisation of point clouds acquired of heathland in Australia and how it influences the three-dimensional modelling and the representation of important heathland structure using different voxel sizes and voxel connectivities. Voxel sizes of 0.4 m, 0.6 m, 1.0 m, 1.2 m and 1.6 m with a voxel neighbourhood connectivity of 6, 18 and 26 are examined for three-dimensional modelling and segmentation of heathland vegetation in Australia. The results indicate that the choice of voxel size and the voxel connectivity influence the representation of important heathland parameters. A smaller voxel size of 0.4 m provides a detailed representation of mallee structure while the the processing time is longer compared to a larger voxel size. While a larger voxel size produces blobs while the processing speed is shorter. The results from the voxel neighbourhood connectivity represent a stronger voxel connectivity of 26-connected voxels suitable for heathland modelling rather than a 6-connected voxels.

1. INTRODUCTION

Australia has a diverse range of vegetation, thus potential fuel types, in which a bushfire can burn. Fuel along with other important factors such as weather and topography determine fire behaviour, severity of the fire in terms of suppression difficulty, and its physical impact on the forest (Brodu and Lague, 2012). Knowledge of relevant fuel types is necessary as they affect fire propagation and behaviour differently. Australia has a rich and diverse range of vegetation with distinct fuel arrangements, quantities, and combustion characteristics (Hollis et al., 2015). One fuel type found in Australia is heathland. Heathland is dominated by shrubs, with emergent trees or mallee, a multistemmed eucalyptus. This vegetation environment is highly flammable and the ladder-type structure of heathland can facilitate the transition of a surface fire to a crown fire. Traditionally, methods for measurement of fuel types, attributes and characteristics included field surveys using handheld instruments, or through image interpolation using satellite and aerial imagery. But these methods of data acquisitions face limitations (Lillesand et al., 2015). Field surveys are bias and result in errors while satellite and photogrammetry methods are not suitable to provide accurate three-dimensional vegetation structural details.

Recently, light detection and ranging (lidar) with laser scanners has emerged as a powerful tool for direct three-dimensional measurement of objects on the earth surface. Point clouds acquired through laser scanners such as airborne laser scanners (ALS), mobile laser scanners (MLS), and Terrestrial laser scanners (TLS), have proven to be an optimal source for three-dimensional vegetation modelling and mapping within forested and city environments (Yebra et al., 2015; Trochta et al., 2017; Xu et al., 2021a). However raw point clouds have drawbacks. Raw point clouds are usually unstructured and they do not contain semantic, topological or geometric details about an object (Otepka et al., 2013). But voxels overcome current drawbacks encountered by point clouds through the structuring of the three-dimensional discrete point.

Voxels are the 3D analogue to 2D pixels. They provide a convenient unified geometrical structure for organising point clouds by providing the means to implicitly represent neighbourhood topology in a three-dimensional array. Voxels have many different geometry shapes. They can be represented as cubes, cuboids, spheres, cylinders etc (Poux, 2021). But their conventional geometry shape is a cubic geometry shape that consists of six faces, eight vertices, and twelve edges. While the storage of voxels is either based on the voxel mass centre or the voxel corner vertices. To be able to work with voxels it is important to convert discrete lidar point clouds into a volumetric structure. During the voxel generation and processing, there are two important voxel properties to consider, the voxel size, and the voxel neighbourhood connectivity (Xu et al., 2021b). These two voxel properties impact the voxelisation output.

The voxel size is important for the representation of voxelised point clouds (Griffioen, 2018). It is also significant for the geometric representation of objects. A too fine voxel resolution can result in too many voxels that are no different to the number of existing point clouds. This results in data redundancy and reduced computational efficiency. The voxelisation computational time can be minimised by introducing a large voxel size. However, a large voxel size can result in the loss of important geographic data due to the overestimation or misrepresentation of vegetation structural components. For example, a too coarse voxel resolution may result in the classification of separate objects as a single object. This is particularly significant for the modelling of mallee so that the stems are modelled and represented correctly. Indeed,

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the optimal voxel size varies depending on research objectives, object structure, and lidar platform. Therefore, the voxel size selection remains an active area of research.

The voxel neighbourhood connectivity is another important voxel property of voxelisation. Connectivity is a measure of the way that voxels are linked to their neighbouring voxels (Aleksandrov et al., 2021). In three-dimensional space, neighbouring voxels are connected through either 6, 18 or 26 voxel neighbourhood connectivity (Figure 3). Voxels connected to neighbouring voxels based on this predetermined neighbourhood connectivity define a region (an object). The size of the neighbourhood is determined based on the image parameters and the desired features for extraction.

Thus, it is important to examine how voxel size and neighbourhood connectivity impact the three-dimensional modelling of heathland while identifying the pros and cons of different voxel properties on heathland modelling. To our knowledge, there are currently no papers examining the impact of voxel size and neighbourhood connectivity on the three-dimensional modelling of heathland. Therefore this paper examines how different voxel sizes can impact the representation of heathland parameters. This paper begins with a literature review on voxel-based point cloud representations in section 2. Section 3 provides a description of the workflow methodology for the voxelisation and segmentation of the heathland point clouds. This is followed by section 4 which provides the results and findings from the different voxel sizes and neighbourhood connectivities in three-dimensional heathland modelling. Finally, this paper concludes with the conclusions and future work in section 5.

2. LITERATURE REVIEW

The word voxel stems from the words "volume" and "element" (Foley, 1990), or VOlumetric piXELs Gebhardt et al. (2009). Voxel representations are commonly implemented in scientific computation and medical imaging. They have become increasingly popular in the field of geospatial (Gorte et al., 2019; Aleksandrov et al., 2019; Homainejad et al., 2022a). After the widespread use of point cloud applications, voxel-based representation have experienced a significant boost. There are a wide variety of applications using voxel-based point cloud representations, including pre-processing, segmentation and classification, registration, and modelling. They are increasingly applied in three-dimensional city modelling and analysis(Gorte et al., 2019; Aleksandrov et al., 2019). They are also becoming favourable in three-dimensional vegetation modelling (Barton et al., 2020; Gorte and Pfeifer, 2004; Hancock et al., 2017; Homainejad et al., 2022a).

In three-dimensional vegetation modelling, Gorte and Pfeifer (2004) developed an algorithm for the voxelisation, modelling and reconstruction of (real world) trees based on terrestrial laser scans. The methodology for this work included applying morphological operations such as closing and opening to close the gaps and holes. This is followed by a 3D skeletonisation. The 3D skeletonisation is an iterative process of removing voxels until the final layer of voxel is reached. Finally, Dijkstra's minimum spanning tree algorithms is applied to ensure that the skeleton from the previous step becomes a tree. While, Vonderach et al. (2012) applied a voxel-based method for the modelling of urban vegetation acquired using a TLS. A voxel-based method using a 26-neighbourhood connectivity is applied for the modelling of urban trees to model the tree branch volume, DBH (diameter at breast height) and height of a single tree.

During a standard voxelisation process, selecting the best fitting voxel size is important and can influences the voxelised reconstruction. Ross et al. (2022) evaluated the impact of voxel size and assessed it in terms of canopy structure variability and its influence on the canopy gap at six vertical transects. Voxel lenghts of 10 cm, 25 cm, 50 cm, 100 cm, and 200 cm are tested. The results indicated that the optimal voxel size varied with LiDAR platform—which may relate to laser penetration and occlusion compensation between the two platforms. Puletti et al. (2021) applied voxel method for the estimation of canopy cover. Voxel sizes ranging between 5 cm - 20 cm with voxel point cloud densities ranging between 1-9 $points/dm3$ are tested to identify their influence on the retrieval of canopy cover. The results indicated that the choice of voxel size and point density is critical while a voxel size of 10 cm and point density of 8 $points/dm3$ is recommended for this dataset.

Additionally, Wang et al. (2020) examined the influence of voxel sizes on the precision of canopy height. A range of voxel sizes ranging from 10 m to 40 m with a 2 m interval in the horizontal and a vertical size of 0.15 m were tested. The influence of voxel size on the precision of canopy heigh was noted and a voxel size of 18 m was identified as the most fitting voxel size for this work. While Eusuf et al. (2020) presented an automated method for measuring fuel load in a multi-layered forest in Newcastle, Australia. In this work a voxel size of 0.4 m was selected for the representation of the fuel load and classification of the near-surface fuel.

3. METHODOLOGY

This work is a continuation from (Homainejad et al., 2022a). The method for the processing and voxelisation of heathland environment follows Homainejad et al. (2022b). It includes the identification of important heathland parameters for its application in the Anderson et al. (2015) bushfire behaviour model. The next phase of this work consists of point cloud processing. This is followed by the voxelisation of the processed point clouds. The voxelisation phase consists of defining the voxel size and the voxel connectivity, followed by the segmentation and the classification of the voxelisation data.

3.1 Heathland parameters

Heathland occupy a relatively small portion of the Australian continent, covering 10-20 million ha (Lindenmayer et al., 2014). They grow on rock benches in exposed situations, usually ridge tops in nutrient-poor and sandy soil. This environment is dominated by shrubby, treeless communities with co-occurring undershrubs, sedges, forbs, and a few types of grass (Lindenmayer et al., 2014). Trees are seldom present in this environment or present as mallee, a group of multistemmed eucalyptus. The absence of trees in this environment exposes the dominated shrubby region to sun and wind causing the rapid drying of fine dead fuels a short time after substantial rain while the presence of flammable terpenes and waxes in the foliage of some shrubs promotes the combustion of live fuel components. This makes heath environment highly flammable and fire-prone throughout much of the year.

In the absence of fire, the vegetation structure in this region can transform from an open heath to a closed heath making it more flammable. The heath shrubs in this environment are generally between 0.5 m to 2 m. While mallee trees grow between 5 m-10 m and have an umbrella-like leaf canopy that shades 30-70 % of the ground. Mallee is extremely flammable with fire-prone features and the ability to support intense fires while the ladder-type

https://doi.org/10.5194/isprs-annals-X-4-W2-2022-113-2022

Figure 1. Heathland environment with multistemmed mallee in the Blue Mountains, New South Wales, Australia

pattern of heathland can transition surface to crown fire which is the most intense and dangerous type of bushfire. Thus it is important to predict the spread and movement of a fire through a bushfire behaviour model.

To predict the movement of heathland bushfires, accurate 3D modelling of heathland parameters is required. These parameters should meet the parameters outlined in the Anderson et al. (2015) model. Anderson et al. (2015) is the fire behaviour model utilised in Australia for the fire behaviour modelling of heathland. Important heathland parameters include the continuity and discontinuity of heath shrubs, the height of heath shrubs, the height of emergent trees and mallee, and the density of the trees (Homainejad et al., 2022b).

3.2 Voxelisation of Point Clouds

Point clouds are usually delivered as a set of unstructured 3D points in Euclidean space with x,y,z coordinate values with Cartesian coordinates x, y, z of a point $p_i, i = 1, \ldots, n$. Each point cloud can contain additional attributes such as R, G, B, amplitude, echo width, number of echo returns as attributes. The first step for the voxelisation of the point clouds begins by determining a minimum cubic bounding box $((X_{min}, X_{max}, Y_{min}, Y_{max}, Z_{min}, Z_{max}))$ enclosing P, such that is a set of points p_i with N the number of points in $R^3 \times 1$. A voxel V_k contains several points in one cloud such that k is the voxel index in the voxelised space and $V = V_1, \ldots, V_M, M$ is the number of generated voxel cubes. While the bounding box and the voxel size (V_{Size}) define the dimensions of the voxel space. Each voxel contains other measurable properties such as volume and attributes. The voxel volume is the number of point clouds that occupy each voxel. The attributes of a voxel V are described by the geometric appearance of the point clouds inside the voxel cubes V. These attributes consist of the spatial position of the point clouds, the normal vectors along with the geometric features calculated from the point clouds.

3.2.1 Voxel size : The voxel size is a significant part of the voxelisation phase. In heathland environment, voxels can impact the representation of finer heathland parameters such as the representation of mallee stems. Mallee has fine stems and is multistemmed from the ground up. A large voxel size can result in the aggregation of objects resulting in the misrepresentation of objects (Figure 2). For example, a too large of a voxel size can result in the representation of different tree elements (eg: tree branches or tree stems) as a single element. Thus different voxel size are tested on this dataset to explore the results the influence of the voxel size on the dataset and the representation of the heathland

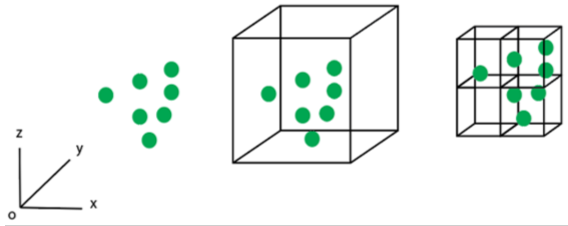

Figure 2. The impact of voxel size on point cloud voxelisation

shrubs and mallee. Voxel sizes of 0.4 m, 0.6 m, 1.0 m, 1.2 m and 1.6 m are experimented on the dataset to explore the influence of the different voxel size.

3.2.2 storage : Voxels can be stored in two different approaches: a dense array and a spars array (Gebhardt et al., 2009). A dense array behaves as a typical $M \times N \times O$ matrix where each cell in the array represents a value. This includes vacuum cells such that every cell has a row and column number. As a result this increases the processing time because all cells in a voxel model store values such as red, green, blue and opacity so do vacuum cells. Vacuum cells have a storage value of zero eg: (0,0,0,0). This increases the storage space and in return increases the processing time.

To reduce storage space and decrease processing time vacuum cells can be separated from occupied cells containing point clouds. The extracted occupied cells form a sparse voxel array. Thus, a sparse voxel array referred to an array where vacuum voxels are removed with only voxels that contain non-zero information remaining. This method is more efficient compared to dense arrays.

A variety of algorithms are available for dense and sparse voxelisation of the ALS point clouds (Nourian et al., 2016; Zhou et al., 2018). For this study, the Poux (2020) voxelisation code is applied. During the voxelisation phase, the voxel size can be altered. After defining the voxel size a dense or sparse voxel array can be generated.

3.3 Voxel connectivity

For the segmentation of the voxels the seeded region growing algorithm is implemented. The seeded region growing algorithm in a voxel 3D space is based on voxel neighbourhood connectivity and the identification of a common trait between the neighbouring voxels. The algorithm searches for connected voxels based on their neighbourhood connectivity with the additional specification of a common trait, if necessary.

The connectivity of a voxel is based on a predetermined neighbourhood so that all voxels that belong to the same connected region may have the same region number. In a three-dimensional grid each voxel has 26 neighbouring voxels; eight voxels at each corner, 12 voxels at each edge, and six voxels at each surface and thus three voxel connectivities, 6-, 18-, or 26 connectivity (Figure 3). The three different voxel connectivities are further explained below.

- 6- connected - every voxel that shares a common face with an adjacent voxel is considered a neighbour in this voxel neighbourhood. These voxels are connected on one of the primary axes such that each voxel with coordinates $((x \pm 1, y, z), (x, y \pm 1, z))$ or $((x, y, z \pm 1))$ is connected to the voxel at $((x, y, z))$.

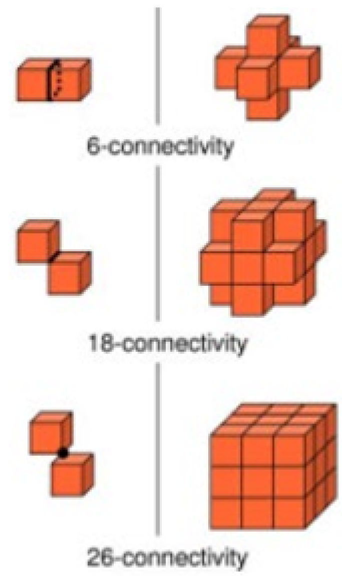

Figure 3. voxel connectivity, 6 neighbourhood, 18 neighbourhood and a 26 neighbourhood connection

- 18- connected - every voxel that shares a common faces and at least on edges is considered a neighbour in this voxel neighbourhood. These voxels are connected on one or two of the primary axes such that each voxel with coordinates $((x \pm 1, y \pm 1, z), (x \pm 1, y \mp 1, z), (x \pm 1, y, z \pm 1), (x \pm 1, y, z \mp 1), (x, y \pm 1, z \pm 1))$ or $((x, y \pm 1, z \mp 1))$ is connected to the voxel at $((x, y, z))$.

- 26- connected- every voxel that shares a voxel face and at least one edge and one vertex with an adjacent voxel is considered a neighbour in this voxel neighbourhood. These voxels are connected on one or two or three of the primary axes such that each voxel with coordinates $((x \pm 1, y \pm 1, z \pm 1), (x \pm 1, y \pm 1, z \mp 1), (x \pm 1, y \mp 1, z \pm 1))$ or $((x \mp 1, y \pm 1, z \pm 1))$ is connected to the voxel at $((x, y, z))$.

The voxel neighbourhood connectivity is based on the data and the desired output and it can be changed in the segmentation algorithm. When a 6-connected voxel neighbourhood is defined only voxels sharing a common face are selected resulting in the exclusion of all other neighbouring voxels. It results in a larger number of voxel clusters. While the specification of an 18 or 26- connected searches for neighbouring voxels with a common face, and a common edge with the addition of a voxel corner connection for the 26- connection. This results in strongly connected voxel connections in a 3D voxel array. The specification of such voxel connectivities results in thinner objects with shorter lengths or areas compared to a 6 voxel neighbourhood connection (Aleksandrov et al., 2021).

For the segmentation of the voxels the region growing is applied. Hancocka (2017) is selected because it is based on voxel 3D array. In this code the voxel neighbourhood connectivity can be altered to explore the results from the different connectivities. Changes were additionally applied to this code to make it specific for this work. For example, a point cloud density threshold specification is added. This allows for the specification of a minimum point cloud density to speed up the segmentation process.

4. RESULTS

For this study lidar point clouds collected over Kelly Hills Cave, Kangaroo Island, South Australia are utilised. Kangaroo Island is 4,405 km² in the area and is dominated by heath and mallee vegetation. The Kelly Hills Cave lidar data is collected and supplied by Airborne Research Australia (ARA) (Airborne Research Australia, 2020). The scan for this region was carried out following the 2019-2020 bushfires. The data includes hyperspectral data in addition to geometric and radiometric attributes (xyz, intensity, Echo Number and Number of Echoes). The point clouds are discrete return point clouds, and the data is compressed and supplied in laz format, a compressed version of las. The data covers 1200 Hectare (ha) and is split into 6 strips. The strip used for this study is 190 ha in area with a point density of 120 points per square meter (ppsm).

4.1 Voxelisation of point clouds

The result of the voxelisation is a voxel mesh of all occupied voxels. The voxel mesh is imported into MeshLab (Cignoni et al., 2008) and CloudCompare (CloudCompare, 2020) for visualisation. MeshLab is an open-source system for the processing and editing of 3D triangular meshes. While CloudCompare is an open-source software for the processing and visualisation of three-dimensional data.

The results from the different voxel sizes indicate a larger voxel count for a smaller voxel size. For example the 0.4 m voxel size has a larger voxel count compared to the 1.6 m voxel size. As the voxel size increases the voxel count reduce but this impacts the object representation. This is specifically noticeable in mallee (Figure 4). The results from the 0.4 m voxel size provide a better representation of the different mallee elements such as the mallee stems. As the voxel size increases the representation of the different tree elements becomes difficult to distinguish with the two larger voxel sizes, the 1.2 m and the 1.6 m voxel size, causing a blob-like representation of mallee Table 1

4.2 Voxel connectivity

Following, the voxelisation, seeded region growing is performed on the spare voxel array. In this study, the region growing is only based on the voxel neighbourhood connectivity. A minimum point cloud threshold of zero points per voxel was set in the region growing algorithm. This is to avoid connectivity loss in the smaller voxel size. Voxel connectivity can be lost by applying a threshold for the lower voxel resolutions thus impacting the final segmentation result.

The results of the three different voxel neighbourhood connectivity are presented in Figure 5. A change in the voxel neighbourhood connectivity can impact the shape and size of the resulting clusters. For example, the change in the voxel neighbourhood connectivity is noticeable in mallee. The mallee stems and branches lose connectivity with a smaller voxel size compared to a larger voxel size of a similar voxel neighbourhood connectivity. The processing time for the different voxel neighbourhood connectivities is variable. A 26-connected voxel neighbourhood connectivity usually requires a longer processing time and occupies a larger memory size compared to a 6-connected voxel.

5. CONCLUSION AND FUTURE WORK

This paper demonstrated the impact of voxel size and voxel connectivity on point cloud data acquired of heathland from South

Voxel Size (m)	Voxel Count	Connectivity	Segment Count	Processing Time (second)
0.4		6	367143	22
0.4		18	171858	45
0.4	2598448	26	111400	165
0.6		6	117959	12
0.6		18	50357	27
0.6	1632854	26	32715	105
1.0		6	19002	17
1.0		18	7132	14
1.0	803965	26	4664	54
1.2		6	8898	13
1.2		18	3321	10
1.2	604229	26	2151	40
1.6		6	2485	7
1.6		18	929	6
1.6	371803	26	620	23

Table 1. Impact of voxel size and voxel connectivity on the point cloud dataset for the modelling of heathland

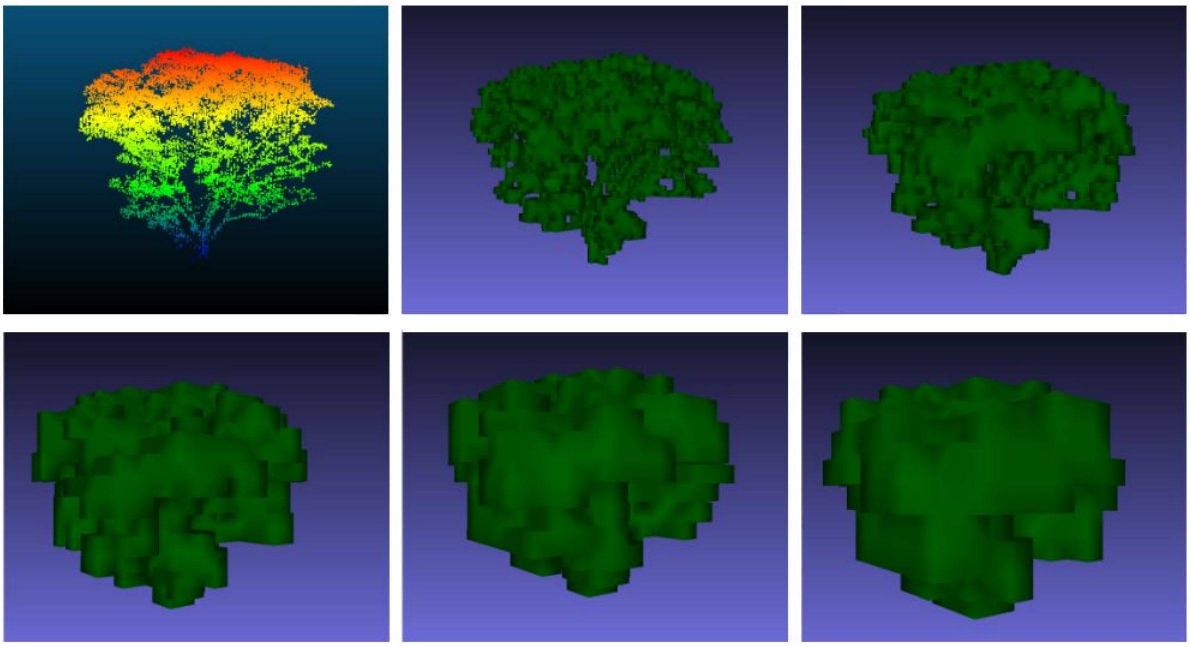

Figure 4. Impact of voxel size on mallee modelling. From right to left - a) point cloud model of a mallee tree in CloudCompare, b) voxel model of the mallee tree with 0.4 m voxel size, c) voxel model of the mallee tree with 0.6 m voxel size, d) voxel model of the mallee tree with 1.0 m voxel size, e) voxel model of the mallee tree with 1.2 m voxel size, f) voxel model of the mallee tree with 1.6 m voxel size

https://doi.org/10.5194/isprs-annals-X-4-W2-2022-113-2022

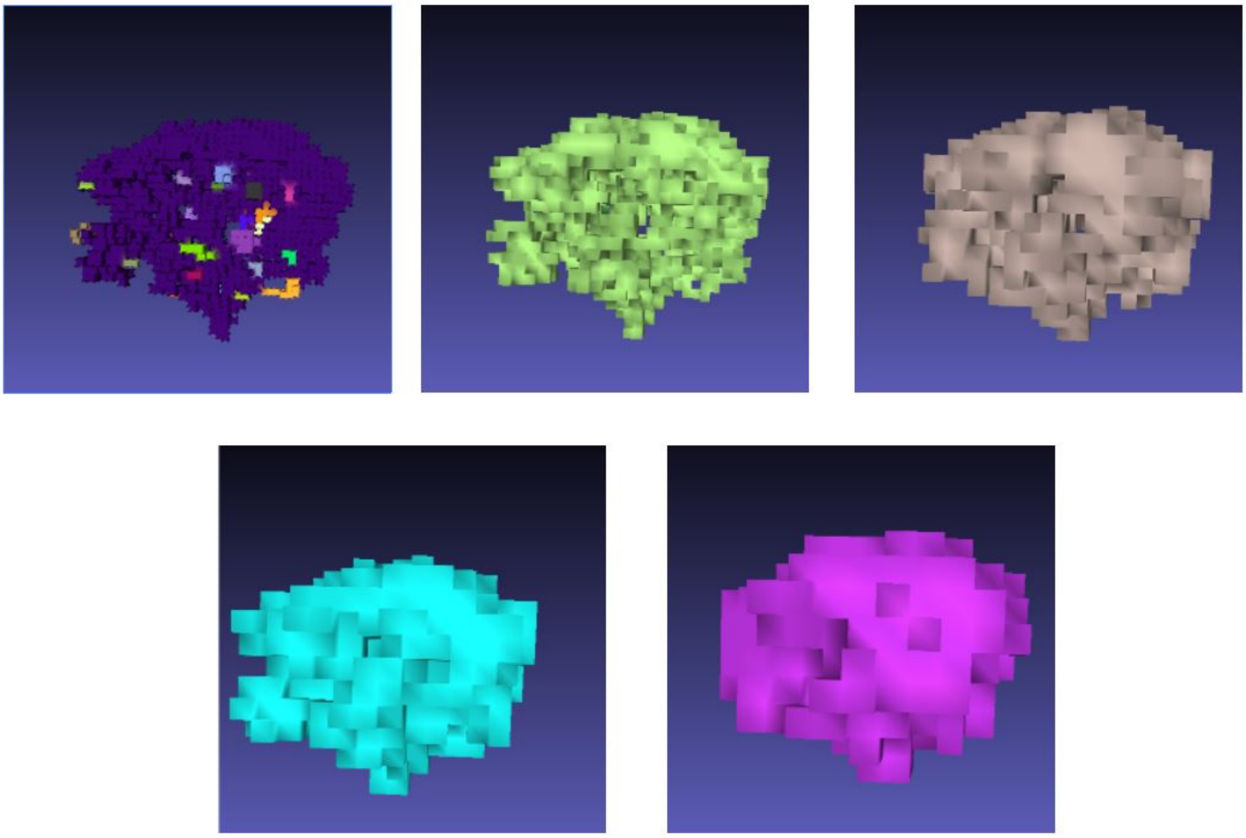

Figure 5. Voxel connectivity of 6 connected neighbourhoods

Australia. The results from the voxelisation demonstrate that a 0.4 m voxel size is a suitable voxel size for the representation of heath shrubs and mallee structure. As the voxel size increases the representation of the mallee becomes more blob type. Although the 0.4 m voxel size was the most suitable voxel size for the representation of mallee structures a smaller voxel size such as 0.2 m is recommended for the representation of mallee. A finer voxel size allows for a better representation and modelling of mallee stems. This is due to how thin mallee stems and branches are and the fact that they are multistemmed. In such a case morphological operations are recommended to remove any gaps and holes in the stems and to build the tree stem connectivity. Thus the voxel size needs to be selected based on specific requirements. For example, if the representation of different vegetation structures is important then a smaller voxel size is recommended.

As heathland is comprised of heath shrubs and mallee the voxel neighbourhood connectivity for both heath shrubs and mallee was examined. Based on the analysis a 6-connected voxel is not appropriate for the modelling of heathland. Both mallee trees and heath shrubs do not have vertical connectivity thus a 6-connected is not recommended while a 18-connected or 26-connected is recommended for the three-dimensional modelling of heathland and heathland parameters. For the representation of finer heathland elements such as the leaves 26-connected voxel connectivity is also recommended. Future work for this research will cover quantitative analysis of the data with respect to training data.

ACKNOWLEDGEMENTS

We would like to acknowledge and thank the Australian Commonwealth Government for supporting Nina Homainejad with the Australian Government Research Training Program (RTP) Scholarship.

We would also like to acknowledge and thank Prof. Jorg Hacker and Airborne Research Australia (ARA) for supplying the Kelly Hills Cave data for this research.

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