MAUP AND LIDAR DERIVED CANOPY STRUCTURE (A CRCSI 2.07 WOODY ATTRIBUTION PAPER)

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ABSTRACT

MAUP theory is applied to a LiDAR dataset acquired over a forested scene. The Weibull Probability Density Function (PDF) has been fit to LiDAR derived canopy height profiles for plots covering the complete 1 x 1 km scene. Ten plot sizes are tested from 10 – 300 m. Parameters describing the location and scale of the PDF are used as analogous of canopy height and canopy length respectively. Results suggest that, for a structurally homogenous forested scene, localised variance decreases for canopy height with increasing plot dimensions. The opposite is apparent for canopy length, it is suggested this is a result of a spatially heterogeneous understorey layer negatively skewing the distribution.

***Index Terms*—** MAUP, LiDAR, canopy structure, probability density function, forest characterisation.

1. INTRODUCTION

LiDAR derived apparent Canopy Height Profiles (CHP) [1] have allowed researchers to penetrate a forest's upper canopy layer and illicit information on the spatial organisation and relative proportions of the vegetative strata below [2]. This additional information can be used to improve modelled estimates of forest biomass [3], [4], evapotranspiration [5], [6] and classification [7]. Spatially explicit modelling, of for example forest attributes, often requires the assignment of sampling units with arbitrary dimensions that may not be appropriate for the input data or desired analysis, this phenomena is known as the Modifiable Area Unit Problem (MAUP) [8–10]. Unlike passive optical remote sensing, the spatial resolution at which LiDAR data is analysed is not predetermined by the sensor or data provider [11]. This allows an appropriate resolution to be (a) determined by the objects and characteristics of a scene/forest type [12], (b) conducive with other remote sensing products such as satellite imagery; and (c) meet the requirements of end-users, for example land managers. The MAUP is demonstrated below using aggregated point-cloud data to derive CHP parameters which are subsequently used to calculate localised variance across a structurally and compositionally homogenous forested scene. The application of MAUP theory to the analysis of LiDAR data is not widely reported in the literature.

2. METHOD

LiDAR data was captured over 1 km^2 of Box Iron Bark forest (BIB) in central Victoria, Australia (-36° 45' 11", 144° 57' 56") on the 15/04/2012. The BIB forest site is designated a Reference Area by the Victorian Department of Sustainability and Environment (DSE) and is representative of an undisturbed BIB forest that is endemic to S.E. Australia. Forest inventory shows the BIB site is dominated by *Eucalyptus tricarpa* (Red Ironbark), *Eucalyptus polyanthemos* (Red Box) and *Eucalyptus macrorhyncha* (Red Stringybark) with a dominant canopy height [13] of ~17 m. Forest structure is characterised by a single canopy with a sparse and intermittent understorey layer. The BIB site was chosen for this study as species composition and forest structure are relatively homogenous and therefore apparent variance should be due to manipulating sampling unit dimensions [12].

A Rigel LMS-Q560 laser scanner (Horn, Austria) was used to capture waveform returns with a footprint of ~30 cm. Data was captured at a flying height of <600 m and with a maximum off-nadir angle of 22.5°, resulting vertical and horizontal accuracies were ±20 cm and ±30 cm respectively. Waveform recorded return pulses were decomposed using a Gaussian Pulse Fitting method to derive a dataset analogous with discrete return LiDAR [14]. A discrete return dataset was considered more appropriate for this investigation as full waveform data is yet to be considered operationally viable by land management agencies [15]. Decomposition resulted in a mean point density of ~17 points m^{-2} across the scene. Points from overlapping flight lines were subsequently removed as well as returns with a vertical height of <0.3 m, this was done to remove potential distortion of CHP [5] and to remove misclassified ground returns [16] respectively.

Post-processed data was then aggregated into square "plots" with increasing dimensions (10, 20, 30, 50, 80, 100, 120, 150, 200, 300 m). A number of techniques have been applied to characterise vertical forest structure from point-cloud data including cluster analysis [7], [17] and the fitting of probability distribution functions (PDF) to CHP [5], [6], [13], [18]. The two-parameter Weibull PDF has proved appropriate for a single canopy and is therefore utilised in this study [5], [6], [13], [18]. The Weibull α and β parameters describe the vertical location e.g. canopy height, and scale or breadth e.g. canopy length, of the fitted distribution respectively [6], [18]. Weibull α and β and the 80th percentile of return height as a measure of Canopy Height (CH) were calculated for each plot and recorded as a spatially explicit raster. Localised variance was then calculated as the arithmetic mean of standard deviation values calculated for a moving 3 x 3 window over the entire image for both the α, β and CH raster layers [12].

3. RESULTS AND DISCUSSION

Local variance as a function of spatial resolution for CH and Weibull α and β parameters is presented in Figure 1. A general trend of decreasing variance is evident for CH and α, correlation between the two parameters is expected as α is analogous with CH [18]. Woodcock and Strahler [12] observed a similar trend when analysing passive optical imagery across a forested scene, they concluded this was a result of the sampling unit being greater in size than any scene elements e.g. tree crowns. The inverse trend is apparent for the β parameter, β is analogous with canopy length [18] and this would suggest that canopy length is heterogeneous across the scene. An explanation may be the presence of a horizontally intermittent understorey layer that distorts the single mode PDF intended for a single canopy layer. Evaluating the goodness-of-fit across the scene may infer the location of understorey where a bimodal PDF would be more appropriate. An anomaly to the general trends is evident at a resolution of 120 m, here an increase in local variance is apparent. This could again be explained by the clumping of species into stands with an approximate area of slightly greater than 100 m^2 [12].

4. CONCLUSION

Early results suggest application of MAUP theory to LiDAR data captured over a forest reveals features of spatial structure that may not be apparent in a similar analysis using passive optical imagery. Furthermore, the use of PDF fitted to CHP yields more information regarding the spatial

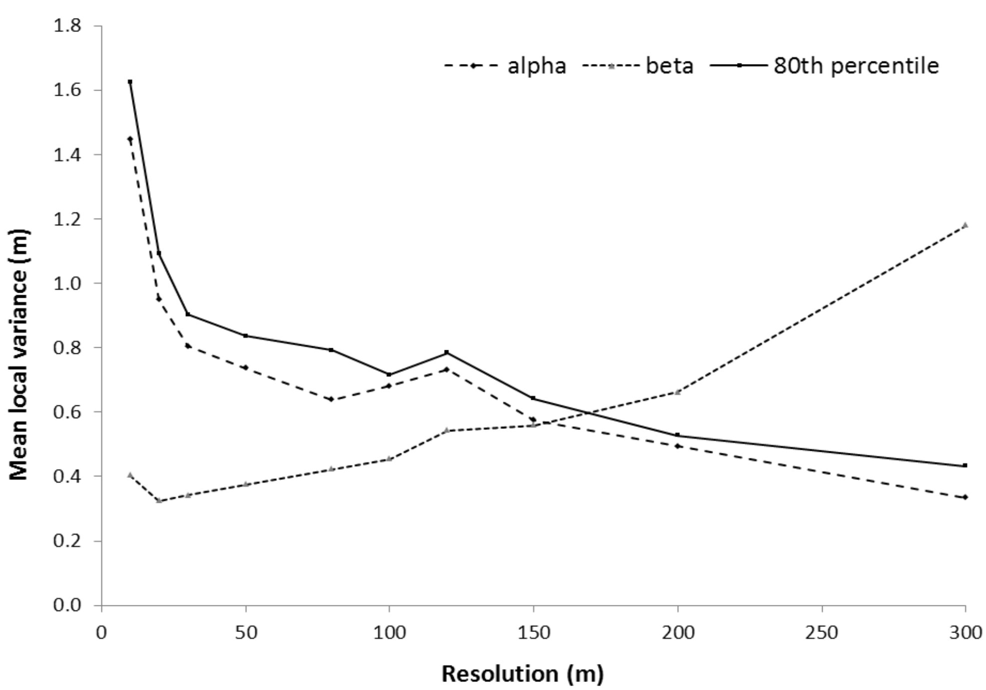

Figure 1. Local variance of CH and Weibull α and β parameters fit to LiDAR derived CHP at different trap sizes across a 1 km2 forested scene.

structure of forests than simple descriptive statistics e.g. canopy height. In particular, the utilisation of the Weibull PDF α and β parameters describes two components of forest structure which are vertical canopy height and horizontal structural complexity respectively. The trend of decreasing variance with α is expected in a forest ecosystem with a homogeneous species composition where the influence of canopy gaps and individual tree structural variability decreases with aggregation into larger groups. The trend of increasing spatial variance observed with β may indicate a non-uniform vertical structure across the scene attributed to a horizontally intermittent understorey, this results in increased vertical structural variability with increasing resolution.

11. REFERENCES

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