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Spatial complexities in aboveground carbon stocks of a semi-arid mangrove community: A remote sensing height-biomass-carbon approach

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Abstract

Mangroves are integral to ecosystem services provided by the coastal zone, in particular carbon (C) sequestration and storage. Allometric relationships linking mangrove height to estimated biomass and C stocks have been developed from field sampling, while various forms of remote sensing has been used to map vegetation height and biomass. Here we combine both these approaches to investigate spatial patterns in living biomass of mangrove forests in a small area of mangrove in north-west Australia. This study used LiDAR data and Landsat 8 OLI (Operational Land Imager) with allometric equations to derive mangrove height, biomass, and C stock estimates. We estimated the study site, Mangrove Bay, a semi-arid site in north-western Australia, contained 70 Mg ha⁻¹ biomass and 45 Mg C ha⁻¹ organic C, with total stocks of 2,417 Mg biomass and 778 Mg organic C. Using spatial statistics to identify the scale of clustering of mangrove pixels, we found that living biomass and C stock declined with increasing distance from hydrological features (creek entrance: 0-150m; $y = -0.00041x + 0.9613$, $R^2 = 0.96$; 150-770m; $y = -0.0008x + 1.6808$, $R^2 = 0.73$; lagoon: $y = -0.0041x + 3.7943$, $R^2 = 0.78$). Our results illustrate a set pattern of living C distribution within the mangrove forest, and then highlight the role hydrologic features play in determining C stock distribution in arid zone.

1. Introduction

Mangrove forests are estimated to cover 137,760 km² globally and are of high economic and ecological importance due to the ecosystem services they provide (Barbier et al., 2011; Giri et al., 2011). This includes habitat for commercial fisheries, coastal protection, and organic C (carbon) storage (Barbier et al., 2011). Total ecosystem services provided by mangroves and saltmarsh are estimated to be equivalent to US\$194,000 ha⁻¹yr⁻¹ (Costanza et al., 2014). Mangrove forests are one of the largest reservoirs of C, with an average estimated at 1023 Mg C ha⁻¹ for mangroves in the tropics (Donato et al., 2011).

There are four mangrove forest C pools recognised; I] above-ground living biomass (AGB), II] below-ground biomass (BGB), III] above-ground dead biomass (e.g., dead wood, litter), and IV] soil organic C (Howard *et al.*, 2014). Soil C contributes the greatest to mangrove C storage, followed by tree carbon stocks including above-ground and belowground biomass (Kauffman and Donato, 2012). AGB of mangroves contributes significantly to overall C storage, noticeably in the tropical region, where mangrove cover accounts for 0.7% of tropical forest cover (Giri et al., 2011) and 1.2% of total tropical forest C stocks from AGB (Saatchi et al., 2011). Unfortunately, mangrove deforestation is leading to a global loss of this habitat, at rates estimated at 0.39% per year, primarily due to anthropogenic impacts (Hamilton & Casey, 2016). Hence, while mangroves account for only 0.7% of global tropical forest area, CO₂ emissions from mangrove reclamation and degradation is equivalent to 10% of global deforestation emissions (Donato et al., 2011), with damages estimated at US\$6-42 billion annually (Pendleton et al., 2012). Recent estimates suggest the global potential CO₂ emissions from soils due to mangrove loss is 7 Tg CO₂ e yr⁻¹ (Atwood et al., 2017).

Carbon policy and market-based approaches provide an avenue to reduce mangrove loss and provide mitigation in a changing climate (Hutchison, Manica, Swetnam, Balmford, & Spalding, 2014). Carbon storage and sequestration is an ecosystem service that is also intricately linked to other ecosystem services such as coastal protection and provision of fisheries habitat (Rogers et al., 2016), all of which depend on the existence of substantial AGB. However, biomass and C within the

forest is variable (Saenger & Snedaker, 1993; Soares & Schaeffer-Novelli, 2005). The structure of the forest reflects variation in AGB, with latitude (Saenger & Snedaker, 1993; Tam et al., 1995), species composition (Day, Conner, Ley-Lou, Day, & Navarro, 1987), salinity (Saintilan, 1997; Sherman, Fahey, & Martinez, 2003), and geomorphic setting, or a combination of these, all shown to influence biomass values (Costa et al., 2015).

Managing mangrove ecosystems for climate mitigation and adaptation, and related services requires accurate methods for estimating biomass of mangroves, and their stored C. These estimates are necessary for mangrove ecosystems within national or global market-based C regulation and trading schemes. Current *in-situ* measurements used to measure biomass and C stocks can be costly, time consuming, and as such tend to be restricted to plots that may not be representative of a whole forest (Simard et al., 2006). Systematic methods to scale from point and plot measurements of C stocks to regional and global C estimates are in the form of allometric equations (Fatoyinbo & Armstrong, 2010; Saenger & Snedaker, 1993). These equations have been developed based on *in-situ* measurements including wood density, diameter-at-breast height (DBH), and tree height.

Allometric approaches for biomass estimation encounter limitations when attempting to scale up estimates over site, region, national or global areas, as the necessary point measurement input parameters can be difficult to obtain. Moreover, allometric equations are site- and species-specific, which renders their global application cumbersome (Calders et al., 2015; Komiyama, Ong, & Pongparn, 2008). However, Saenger and Snedaker (1993) developed global and generic (all species) mangrove allometric equation based on height. As tree height can be derived with remote sensing techniques (Lagomasino et al., 2016), these equations provide an avenue to derive biomass estimates across the large scales required to monitor mangrove changes with climate, and manage ecosystem services. Remote sensing approaches have typically relied on estimating mangrove forest biomass using either passive optical data, or active airborne and spaceborne datasets (Fatoyinbo &

Simard, 2013). Whilst remote sensing has been used to determine forest biomass and C stock estimates across the globe, these studies have predominantly focussed on the use of optical (Landsat) data, which resolves their horizontal but not vertical extent, relying on (Normalised Difference Vegetation Index) NDVI as an indicator of biomass. Advancement of data from which vegetation structural properties can be estimated, e.g. LiDAR (Light Detection and Ranging) data provides highly accurate elevation information and can be considered the most accurate and reliable measure of mangrove vertical structure (Fatoyinbo & Armstrong, 2010). Remote sensing combined with modelling and field survey provides an avenue to systematically map the horizontal (spatial) and vertical (three-dimensional) structure of mangroves that is otherwise challenging (Fatoyinbo & Simard, 2013; Fatoyinbo, Simard, Washington-Allen, & Shugart, 2008; Lucas et al., 2007; Simard et al., 2006). Here we explore a novel approach to elucidate spatial heterogeneity of living C within the mangrove canopy that could be applied in conservation, management, to inform representative field sampling, and carbon accounting to highlight areas of C spatial disparity, both improving and increasing C estimates.

We combine a passive and active data combination to map biomass and C stocks for a relatively small arid zone mangrove forest in north-west Australia. Specifically, we combine passive optical data, derived from Landsat 8 OLI, used to determine the horizontal distribution of a mangrove forest with data from airborne LiDAR, used to determine the vertical structure (canopy height) of the mangrove forest at Mangrove Bay (northern Western Australia, Fig. 1). We then use these estimates to calculate biomass and C stocks. Further, we use a spatial statistical assessment of the derived C stock of the living biomass to determine where areas of low and high biomass occur in relation to the hydrology of the wetland area.

2. Methods

This study firstly determined the mangrove forest extent from Landsat 8 OLI through NDVI values. LiDAR data was then used to determine the canopy height within this extent. These data informed

allometric equations to estimate biomass and C stock across the site. Variation of pixel biomass [and hence C] within the forest was then explored using spatial statistics. An accuracy assessment was then undertaken through Cohen's kappa statistical analyses with high resolution orthorectified aerial imagery.

2.1 Study Area

Mangrove Bay is a small (35ha) back barrier lagoon, fronted by fringing reefs, with two separate mangrove sites divided by a small stretch of sandy coastline (Fig. 1). Located in a semi-arid environment on the Pilbara Coast in north-western Australia, mean annual temperature ranges from 18°C to 32°C, and rainfall averages 261 mm annually (BOM, 2017). Cyclones and floods are common annual occurrences between December and April, with a rainfall minimum July-September (BOM, 2017). The site is legislatively protected by its location in the Ningaloo Marine Park and Cape Range National Park. The region is sparsely populated (BOM, 2017), though it does experience seasonal increases in tourist visitation. *Avicenna marina*, is the dominant species in this mangrove ecosystem, although *Rhizophora stylosa* also occurs (Lovelock et al., 2017).

Whilst a small mangrove forest compared to global mangrove stands, the site is of high ecological importance due to its role in supporting biodiversity in the region (Cassata & Collins 2008; Van Keulen & Langdon, 2011; Reef et al. 2014). Coupled with its position within surrounding terrestrial vegetation that is dominated by grasses, this site provides an opportunity to explore mangrove forest structural complexities in a semi-arid climatic zone.

2.2 Biomass and Carbon Estimates

2.2.1 Horizontal Structure of Mangroves

Cloud-free Landsat 8 OLI imagery (path 115, row 75) were acquired for October 2015 to coincide with the LiDAR collection at Mangrove Bay. ArcPy within ArcGIS was utilised to perform atmospheric corrections to convert the pixels (30m) to top of atmosphere reflectance (corrected for sun angle)

(Chander, Markham, and Helder, 2009; Landsat 7 Science Data Users Handbook, 2011; Landsat 8 Science Users Handbook, 2015). ESRI ArcGISv10.3 was used to calculate the NDVI (Equation 1) which was applied to the study region to visually interpret and identify the mangrove forest. True and false colour scene composites were used to visually determine NDVI minimum and maximum thresholds to categorise pixels as either (predominately mangrove) mangrove community or not (other). High resolution aerial imagery (40cm) was used to assess accuracy through visual determination of the mangrove community from 30m grid cells across the region. Agreement was assessed through Cohen's kappa statistical analysis. The site has a small saltmarsh zone, and whilst not explicitly mapped, the pixels representative of a transitional zone may include some saltmarsh plants, particularly in the outer zones. Agreement was assessed through Cohen's kappa statistical analysis. The site has a small saltmarsh zone, and whilst not explicitly mapped, the pixels representative of a transitional zone may include some saltmarsh plants, particularly in the outer zones.

NDVI is strongly correlated to canopy closure in mangroves ($r = 0.91$) (Jensen et al., 1991) as it measures the absorbance of chlorophyll in the red band and the reflection of the mesophyll in the near-infrared band (Pettorelli et al., 2005). Hence its use as a proxy for measuring mangrove canopy cover in remote sensing studies that monitor changes in mangrove forests; from deforestation and degradation (Chandra Giri, Pengra, Zhu, Singh, & Tieszen, 2007; Satyanarayana et al., 2011), sea level (Lovelock *et al.*, 2017), and cyclone events (Cornforth, Fatoyinbo, Freemantle, & Pettorelli, 2013; Long, Giri, Primavera, & Trivedi, 2016). Values range from -1 to $+1$, where green vegetation corresponds to values above zero, and dense closed canopy forests are closer to 1 (Long et al., 2016). Here, we use this index to identify the mangrove forest extent. We then use this extent as a boundary for the LiDAR data.

$$\text{NDVI} = \frac{\text{NIR} - \text{Red}}{\text{NIR} + \text{Red}} \text{ (Equation 1)}$$

Where NIR and red refer to the near-infrared and red bands respectively. For Landsat 8 OLI this refers to band 5 (NIR) (0.851-0.879 μm) and band 4 (red) (0.636-0.673 μm).

2.2.2 Vertical Structure of Mangroves

Canopy height was mapped from LiDAR data (sensor LiDAR RIEGL Q680i-S; laser wavelength: 1064nm; footprint: 15cm at 500m flying altitude; pulse rate: 400kHz; scanning rate 135LPS; 10cm vertical accuracy; 15cm horizontal accuracy; scan angle: 60°). LiDAR point clouds were obtained classified (LAStools - rapidlasso GmbH (<https://rapidlasso.com>)) as vegetation (first return points) and ground points (last return points). In ESRI ArcGIS LiDAR points were interpolated to a pixel size of 3 metres, which was selected to represent a minimum mangrove crown diameter (Wannasiri, Nagai, Honda, Santitamnont, & Miphokasap, 2013). A Digital Surface Model (DSM) was created from the first return points, and a Digital Elevation Model (DEM) was then created from ground points. The Canopy Height Model (CHM) was derived by subtracting the DEM from the DSM. The CHM was limited to the 35ha area identified as mangrove forest from the Landsat 8 OLI NDVI analysis.

2.2.3 Above Ground Biomass (AGB)

Mangrove AGB is strongly correlated to tree size, in particular DBH (Chave et al., 2005). A global stand height-biomass allometric equation calculated by Saenger and Snedaker (1993), applied in remote sensing derived mangrove AGB studies (Fatoyinbo & Simard, 2013; Fatoyinbo et al., 2008) was used in this study. The equation,

$$\text{AGB} = 10.8 \times H + 34.9 \quad R^2 = 0.77 \quad \text{RMSE } 43.8, n=43 \quad (\text{Equation 2})$$

predicts AGB, in Mg DW ha⁻¹ from tree height, H, in metres. Eq. 2 was derived from 43 field data sets distributed globally ($R^2 = 0.59$, RMSE = 43.8) and was applied in this study to the CHM. Height derived from field measurements at 21 sites (4mx4m quadrats) was used to assess the accuracy of the remote sensing techniques. GPS coordinates of field sites was used to link the location to pixels in ESRI ArcGIS v.10.3.1.

2.2.4 Below Ground Biomass (BGB)

Below ground biomass is directly measured through destructive measurements including excavating root material. However, non-destructive estimates can be derived from the allometric equation (equation 3) developed by Hutchinson and colleagues (2014), from 41 sites across the globe where both AGB and BGB data had been directly derived ($R^2 = 0.712$, $F_{1,39} = 100$, $P < 0.001$). Total BGB were derived from the AGB values calculated above.

$$\text{BGB Mg DW ha}^{-1} = 0.073 \text{ AGB}^{1.32} \text{ Mg DW ha}^{-1} \text{ (Equation 3)}$$

2.3 Carbon Stock Estimates

Carbon stock estimates for total biomass (AGB and BGB) were derived assuming C to be 50% of dry weight (Howard et al., 2014).

2.4 Spatial Structure in aboveground biomass and carbon stocks

The Getis-Ord G_i^* spatial statistic was utilised in ESRI ArcGIS v10.3 to identify statistically significant spatial trends (degree of clustering of high or low mapped values) of AGB [hence C] in the mangrove canopy to assess if there were clusters in structural complexity of the forest canopy, resulting in clusters of mangroves with high biomass areas of 'hot spots' and clusters of biomass with low values 'cold spots'.

Such hot and cold spots represent places where a geographical area exhibits statistically significant spatial clustering of high values (hot spot) or low values (cold spot) (Getis & Ord, 1992). As such a single high or low value does not represent a hot or cold spot, respectively. For example, for this study, for areas to be classified as a statistically significant hot spot, an area (3m cell) of biomass will have a high value and be surrounded by other high (3m) cells. The values of this high biomass area is then compared to all surrounding cells, if the difference is such that is shown to not be random, a hot spot is assigned. The G_i^* statistic is calculated as the sum of the feature and surrounding features (neighbours) compared to the sum of all features, and is standardised as a z-score (equation 4). For statistically significant z-scores, the larger the absolute value, the more

intense the spatial clustering, with positive values representing hot spots, and negative values representing cold spots.

Hot spot analysis has been used in ecological studies to depict areas of high or low land use change to aid in management and conservation efforts (Harris et al., 2017). Here we apply this measure to AGC stock to examine structural trends in the forest.

$$G_i^* = \frac{\sum_{j=1}^n w_{ij} x_j - \bar{X} \sum_{j=1}^n w_{ij}}{\sqrt{\frac{n \sum_{j=1}^n w_{ij}^2 - (\sum_{j=1}^n w_{ij})^2}{n-1}}} \quad (\text{Equation 4})$$

Where;

$$\bar{X} = \frac{\sum_{j=1}^n x_j}{n} \quad (\text{Equation 4) Part I}$$

$$S = \sqrt{\frac{\sum_{j=1}^n x_j^2}{n} - (\bar{X})^2} \quad (\text{Equation 4) Part II}$$

Where, x_j is the value for feature j ; w_{ij} is the spatial weight between feature i and j , and n is the number of features.

The Euclidean distance of pixel (3m) centroids were calculated, and their distances to the inner lagoon and creek entrance of the larger northern site measured. Linear regression were then performed between; percent C stock and distance to the creek entrance [10 m interval]; and percent C stock and distance [10 m intervals] to the lagoon.

3. Results

3.1 Accuracy Assessment

Due to the aridity of the coastline here vegetation is sparse and mangroves were easily distinguishable from surrounding vegetation at the site from the NDVI [NDVI_{mangrove} 0.36-0.69, mean (±S.D) 0.52 (±0.009); NDVI_{region} -0.58 – 0.69, mean (±S.D) 0.24 (±0.11)]. Using NDVI and aerial imagery assessment mangrove forests were calculated to cover an area of 35 ha at Mangrove Bay (Fig. 1).

Cohen's kappa showed agreement between visual determination of mangrove area, and area identified through NDVI values, $k = 0.83$, $p < 0.0005$. Furthermore overall accuracy of mangrove extent determination from error matrices showed 98% agreement, with an omission (missed pixels) of pixels calculated at 1.6%, and commission (added pixels) of 0.2%.

AGB from remote sensing measurements (CHM) were compared to AGB from field measurement to check accuracy. We found that AGB derived from the CHM (mean ($\pm$ S.D); $48.7 (\pm 7.8)$ Mg AGB ha^{-1}) and AGB derived from field measurements (mean ($\pm$ S.D); $46.5 (\pm 5.4)$ Mg AGB ha^{-1}) were not statistically different (d.f. =20, $t = 1.0$, $p = 0.3$), ensuing methods were suitable to implement across the site.

3.2 Biomass and Carbon Estimates

The average ($\pm$ SD) height of the mangrove canopy at Mangrove Bay derived from the CHM was 3.3m (± 1.6 m), ranging from 0.01m, corresponding to the smallest seedlings, to a maximum value of 8.7m.

AGB for the mangrove stand at Mangrove Bay was calculated to total 2,417 Mg (70 Mg ha^{-1}). BGB across the mangrove stand at Mangrove Bay was estimated at 697 Mg (20 Mg ha^{-1}). Hence, a total of 1557 Mg of C or 45 Mg C ha^{-1} was calculated to be stored as biomass in this mangrove forest.

3.3 Spatial variation in aboveground biomass and carbon stocks

Mangrove tree height displayed significant patterns in spatial variation that influenced biomass and carbon estimates (Fig. 1). Particularly evident was the clustering of high biomass around the creek entrance and lagoon area, where tree height was higher (Fig. 1). Consequently, areas of low biomass were located further away from the water bodies, where tree height was lower (Fig. 1). The high biomass hot spots, those areas identified to be of high significance ($p < 0.01$), exhibited higher total living (AGB+BGB) C values, averaging ($\pm$ S.D) $57 \text{ Mg C ha}^{-1} (\pm 6.8)$, while the low biomass, cold spots, that were highly spatially clustered ($p < 0.01$) had a much lower average biomass ($\pm$ S.D) with 33 Mg C

ha⁻¹ (± 6.8) (Fig. 1). Areas identified as not having significant spatial clustering, exhibited an average ($\pm$ S.D) of 45 Mg C ha⁻¹ (± 6.1), which was the same as the whole site average C.

At the northern site, the relationship of mangrove above-ground C and (pixel centroid) distance from the creek entrance was complex, in that a positive linear relationship was evident from the creek entrance (seaward zone) until approximately 150m landward (mesozone) ($y = 0.00041x + 0.9613$, $R^2 = 0.96$), where the %C peaked before the linear relationship then became negative ($y = -0.0008x + 1.6808$, $R^2 = 0.73$) (landward zone). The top 10% of above-ground C stock [at 10m intervals] occurred between 130-210 m of the creek entrance within the mesozone, (Fig. 2A) as would be expected based on the Gi* statistics (Fig. 1) and linear regression results. A strong linear correlation overall was apparent between percentage of above-ground C stock and (pixel centroid) distance from the lagoon ($y = -0.0041x + 3.7943$, $R^2 = 0.78$) (Fig. 2B). Here, the top 10% of C [at 10 m intervals] occurred between 10-50 m of the lagoon entrance (Fig. 2B). The lowest 10% of distances from the creek entrance for % C [from AGB] occurred at both the closet (0-40m) and farthest (740-770m) pixels, while the lowest 10% of % C [from AGB] for distance from proximity from the lagoon was in those areas farthest from the lagoon (290-320 m) (Fig. 2B).

4. Discussion

The method we present here is novel in its combination of spatial statistics [Getis Ord Gi* Spatial Statistic] and remotely sensed data to explore living C estimates and spatial heterogeneity within the canopy. Through its utilisation we have been able to identify significant spatial variability in C stocks in the forest canopy studied, which corresponded to variability in height and biomass across the forest as clearly defined clusters.

Particularly evident was the significant clustering of the higher AGB [and hence C] proximal to an inner lagoon, and conversely the significant clustering of the lower AGB stands [C values] further from the lagoon (Fig. 1). This site has minimal constant fluvial input due to its semi-arid location, which may account for a greater canopy height closer to a hydrological feature (lagoon or

creek), resulting in greater C stock in these microhabitats. In fact, the most significant hot spots ($p < 0.01$) were located close to the intersection of the lagoon and creek entrance (Fig. 1). These hot spots also contained the highest average ($\pm$ S.D) tree height, 5m ($\pm$ 0.89), suggesting hydrological constraints to tree height and canopy development result in constraints on C stocks within living biomass. While further field studies measuring tidal flux would be required to investigate the role of hydrology in constraining stand structure here, changes in hydrology have been shown to influence mangrove dieback (Ellison, 1993), and recruitment events elsewhere (Eslami-Andargoli, Dale, Sipe, & Chaseling, 2010; Krauss, From, Doyle, Doyle, & Barry, 2011). At Mangrove Bay low sea level events are associated with canopy dieback (Lovelock *et al.*, 2017), further suggesting benefits for mangrove trees located in the lower limit of the stand.

Understanding the spatial heterogeneity within mangrove forests is essential for mangrove forest conservation, rehabilitation, field sampling strategies, and the ecosystem services provided (Koch *et al.*, 2009; Ribeiro, Metzger, Martensen, Ponzoni, & Hirota, 2009). Through the adaptation of the LiDAR derived CHM with the spatial statistics this study was able to determine the importance of habitat features for mangrove C, in particular that higher mangrove C coincides with proximity to hydrological feature (creek entrance, lagoon). Canopy located between 10 and 50 m of a lagoon was comparatively higher than in the area further away. This distance increased to 140-210 m for the creek entrance. The direction of the linear relationship between C and distance also varied between hydrological feature, with it being positive for the lagoon, this was also evident with the lowest 10% of average C located at both the closest (0-40m) and farthest (740-770m) distance from the creek. The complex relationship of C in relation to distance from the creek entrance, showed two distinct linear profiles, with the positive linear relationship occurring with those pixels on the seaward side of the lagoon and also proximal to the intersection of the creek and lagoon (Fig. 2A), whilst those pixels further from the entrance and intersection of the lagoon exhibited a strong negative linear relationship with C (Fig. 2A). This is a similar zonation profile to that described by Tomlinson and

colleagues (1986, p.14) for north-eastern Australian mangroves, with shorter mangroves at the seaward edge, increasing and peaking in height in the mesozone, before decreasing landward.

The height and hence AGC] and distance relationship may reflect the tidal influence on the site, with those areas that have more frequent tidal inundation having trees with greater height and hence AGC, possibly indicating that soil porewater salinity is a constraining factor here. Whilst salinity was not measured within this study, other studies have shown tree height gradients (Robertson & Alongi, 1992) are related to soil and salinity conditions, such as in Panama where taller trees were observed at low salinity which decreased as salinity increased toward the forest interior (Lovelock, Feller, McKee, & Thompson, 2005), and in the Everglades where the tallest trees were found along tidal creeks, and shorter scrub mangroves on the landward edges (Simard et al., 2006). Within Australia, the negative effect of high salinity on tree height has been reported for *A.marina* at temperate sites (Saintilan, 1997). The methods applied in this study were able to elucidate that proximity to the creek entrance or lagoon appear to be important in determining the spatial heterogeneity of mangrove forest structure. However further investigation is now warranted to investigate the role of tidal inundation and groundwater to ascertain their role in influencing hydrology here. With mangrove forest structure an important variable influencing C stocks within living biomass, understanding its association is important in further developing C biomass models, and in forest ecosystem management where hydrology is often considered (Lewis, 2005).

Variability in canopy height across mangrove stands has also been shown to be related to age, with taller canopies correlating with older forest age (Bulmer, Schwendenmann, & Lundquist, 2016). As allometric equations utilised are based on canopy height, changes in C stock associated with stand age would also be captured by this approach.

At our study site C within the hot spots compared to C within the cold spots equated to an average difference of 24 Mg C ha⁻¹, and a positive (hot spot) and negative (cold spot) difference of 12 Mg C ha⁻¹ compared to the whole site average (45 Mg C ha⁻¹). Ensuing that spatial heterogeneity of

the canopy should be considered in management, conservation, and carbon accounting to ensure estimates are not underrepresenting biomass due to field sampling in inherent cold spots of lower canopy heights, which in this study occurred on the landward and seaward edges of the site where mangroves are more accessible for field sampling. Whilst the site used within this study is small, the methods we utilise are able to be implemented at larger sites due to the systematic approach and application of high resolution remotely sensed data that enables fine scale measurements (3 metres) across the entire site.

This study demonstrated how remotely sensed data combined with general mangrove allometric equations can provide detailed estimates of the C stored in mangrove living biomass and revealed microhabitat features within mangrove stands. The biomass derived in our study was slightly lower but not unlike those reported by Alongi and colleagues (2000) from field measurements of AGB (90.5 t DW ha⁻¹) and BGB (16.1 t DW ha⁻¹) at the site. Information on C stores is increasingly required in support of conservation policies. The method we present here provides an approach that can be applied to forests of various spatial scales to provide improved C estimates, especially in areas where field data is not available, or coverage is poor. Further the method we present here allows for spatial heterogeneity to be considered. This provides an avenue to develop field C sampling strategies to ensure representative sampling of the mangrove canopy, ensuing sampling is appropriately stratified and therefore not concentrated in hot or cold spots for C stocks from living biomass, such that areas clustered by height, or in similar distances from hydrological features are not inherently solely sampled. In doing so, allometric equations can be further improved from these field data.

Conclusion

Further developments in remote sensing [alongside verification using field sampling methods] will allow more estimates on mangrove height and biomass across a range of geomorphic settings, latitudinal extents and mangrove species to be developed. Australia contains a significant fraction of

the world's mangrove forests [3rd largest area per country (Giri et al., 2011)], and yet, many of these stands have never been studied. The combination of remote sensing and allometric equations used here provides an approach to assess the C stored in living biomass that can be applied in extensive forests as well as in relatively small, sparse and relatively short mangrove stands, such as the NW Australian stand studied here. Applying these methods and the results to analyse the spatial complexity of the forest has provided further insight into the spatial structure of mangrove C stores.

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Figures

Figure 1: Mangrove Bay, a small lagoon fringing coral reef lies within the Ningaloo Marine Park and Cape Range National Park, in north-western Australia (inset map). Results of the Getis-Ord G_i^*

spatial statistic are depicted showing clusters of mangroves with high biomass areas (hot spots) and clusters of biomass with low values (cold spots). Spatial clustering illustrates higher carbon stock proximal to lagoon and creek entrance, and cold spots of lower carbon stocks further away. Spatial clustering illustrates higher carbon stock proximal to lagoon and creek entrance, and cold spots of lower carbon stocks further away. The mangrove extent shown represents the 35ha area. Aerial image provided by © 1995–2016 Esri (Service Layer Credits: Source Esri, Digital Globe, GeoEye, Earthstar Geographics, CNES/Airbus DS, USDA, USGS, AEX, Getmapping, Aerogrid, IGN, IGP, swisstopp, and the GIS User Community).

Figure 2: At the northern site the relationship between percentage (%) carbon stock from living biomass at 10m intervals, and distance to hydrological feature (m) was significant for (A) distance to creek; and (B) distance to lagoon. The percentage carbon stock and distance to creek entrance showed two distinct linear profiles (A), with a positive linear relationship occurring with those pixels proximal to the creek entrance, a strong negative linear relationship with those pixels further from the entrance.