Changes in foliage projective cover and its implications for mapping groundwater dependent vegetation across a precipitation gradient

Running Head : Changes in biomass of groundwater dependent vegetation across rainfall gradient.

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Abstract

Adequate protection of groundwater dependent vegetation (GDV) at the landscape scale ($> 10^4 \text{ km}^2$) is often hampered as their extent is poorly mapped. Remote sensing datasets have previously been used to delineate GDV by analysing both actual, and changes, in green biomass over space and time. The rationale behind such approaches is based on the phenological characteristics of GDV, which often retain greater mean green biomass during dry periods, in comparison to vegetation with access to soil moisture only. However, such methods are hampered by inadequate knowledge about how average annual precipitation, seasonality and differing water regimes of vegetation communities within a landscape influence green biomass. Therefore, we aimed to test for amount of foliage projective cover (FPC), and variation in FPC as indicators of GDV presence. We assessed differences in the FPC of GDV at three sites across a $1500 \text{ mm}^{-1} \text{ year}^{-1}$ precipitation gradient, ranging from arid inland to humid coastal environments in Southern Queensland, Australia. Overall, we found that average annual precipitation had the largest influence on predicting FPC, followed by seasonality. During winter in the semi-arid and humid environments (season with least precipitation) FPC for non-GDV was higher than subsurface GDV. For our study area, GDV delineation based on higher green biomass than surrounding vegetation was effective when average annual precipitation was less than $\sim 600 \text{ mm}^{-1} \text{ year}^{-1}$.

Keywords: Landsat; remote sensing; water limitation; NDVI; greenness; spatial extent

1. Introduction

A diverse array of vegetation communities use groundwater to supplement their water requirements, with recent estimates suggesting 22-32% of all global vegetation uses groundwater to some extent (Fan et al., 2013). Vegetation can become dependent on groundwater in water limited environments, in areas with climates characterised by dry and hot summers, and during times of drought in areas with persistently wet climates (Scott, Lines, and Auble 2000; Froend and Sommer 2010; Tomasella et al., 2008). Groundwater accounts for 96% of all freshwater, however, globally it is extensively pumped for agricultural, industrial and municipal use (Shiklomanov, 1998). In many environments, groundwater withdrawal regularly exceeds recharge which can put considerable strain on GDV communities (Giordano, 2009). Many land management agencies aim to protect GDV. However, identification of GDV presence over large landscapes is challenging and beyond the scope of field surveys (reviewed in Pérez Hoyos et al., 2016).

Remote sensing analysis of green biomass is gaining popularity as a tool to delineate and monitor GDV across large landscapes. In water limited ecosystems, the general assumption is that vegetation communities with access to groundwater produce greater amounts of green biomass (i.e. photosynthetically active leaf area and foliage projective cover) than communities solely reliant on soil moisture (Eamus et al., 2006; Hatton et al., 1998). GDV communities have been delineated from surrounding non-GDV communities using remote sensing measures to identify vegetation with greater green biomass (Barron et al., 2014; Eamus et al., 2006; White et al., 2015). Smaller seasonal changes in green biomass have also been used to delineate GDV, with the assumption that GDV retains green biomass during dry periods (Tweed et al., 2007). Although, such relationships are not so straight forward, and vegetation communities within the same landscape can show vastly different phenological responses to the local hydrological cycle (ie. soil moisture, rainfall, flooding and groundwater) (Richard and Pocard, 1998; Shilong, et al., 2006). Remote sensing methods are still in their infancy and require further assessment to determine their appropriateness, especially for environments that are not water limited (i.e. precipitation is greater than evaporation), and between differing functional groups of GDV. To our knowledge there has not been any comparative studies that assess the utility of such green

biomass measures across precipitation gradients, across seasons and for a variety of GDV communities with different hydrological regimes.

Green biomass is strongly influenced by parameters related to water availability, such as mean annual precipitation, water holding capacity of soil and access to groundwater, and increases in strength with increasing aridity (Eamus et al., 2006; Gholz, 1982; Hatton et al., 1998; Lv et al., 2013; Schulze et al., 1996). Furthermore, different vegetation communities use a range of different water sources over differing temporal patterns (i.e. soil moisture, surface water and groundwater) (O'Grady et al., 2006). Over decadal timeframes, increasing depth to groundwater can lead to a progressive change in community composition to include more drought tolerant species (Pritchett and Manning, 2012; Froend and Sommer, 2010), and wetland species under reduced depth to groundwater (Kozlowski, 2002). Yet, in general, at the landscape scale relationships of decreasing green biomass with increasing aridity are observed (Justice et al., 1985).

Water limited environments have received the greatest attention for methods to delineate GDV, and are characterised by high potential evapotranspiration, low precipitation, and regular droughts (Newman et al., 2006). In such ecosystems, water is the major limiting factor for vegetation growth (Eamus, 2003). Owing to the importance of groundwater in water limited environments, research into GDV has mostly focused on water limited systems, such as those found in arid and semi-arid landscapes (eg., Miller et al., 2010; Stromberg, Tiller, and Richter 1996). While humid landscapes are rarely assessed for groundwater dependence, they contain culturally and ecologically significant GDV, such as rainforest vegetation of floodplains and wetlands (Chui et al., 2011; Miguez-Macho and Fan, 2012). However, delineating GDV in humid environments poses greater challenges than in arid environments. This is because factors other than water availability (e.g. soil type and fire regime) may have the stronger influence on green biomass. Thereby, greater mean green biomass, and smaller change in green biomass, may not be associated with groundwater use. In humid climates water is less of a limiting factor for green biomass production and retention, therefore, those methods used to delineate GDV in arid and semi-arid environments (i.e. water limited) may not be appropriate for humid environments (i.e. not water limited). In order to maximise the potential of GDV delineation, remote sensing studies

commonly analyse images captured during periods of water deficit, supposedly when green biomass of GDV and non-GDV are best differentiated (Barron et al., 2014; Münch and Conrad, 2007).

The level of dependence that GDV have on groundwater is likely to influence the methods capable of GDV delineation. Dependence will vary within and across landscapes, for instance, at the landscape scale (i.e. 10km^2 - 10^4 km^2) precipitation is a major driver, while at local scales (i.e. $< 10\text{km}^2$), groundwater dependence varies with geology, topography and proximity to permanent surface water (O'Grady et al., 2006; Sear and Dawson, 1999; Toth, 1970; Zolfaghar et al., 2015). The water regime (ie. prevailing pattern of surface and groundwater flow) can have a significant influence on FPC. For example, vegetation communities that inhabit wetter environments are more susceptible to water stress (Liancourt et al., 2013). At fine scales GDV that inhabit environments with naturally large fluctuations in groundwater depth are less dependent on groundwater than those occupying environments where there is little fluctuation. The accuracy of methods used to delineate GDV across landscapes is therefore likely to be influenced by the hydrological regime of the water resources supporting individual GDV communities.

Previously, remote sensing studies have used vegetation indices to delineate GDV (Barron et al., 2014; Lv et al., 2013), and evapotranspiration models to monitor GDV response to groundwater drawdown (Yang et al., 2011; Scott et al., 2008). Most remote sensing studies employ band ratio indices such as the normalised differenced vegetation index to provide indirect estimates of vegetation green biomass. Even though vegetation indices are easy to implement, they are known to saturate when vegetation cover is high and can be strongly influenced by features that are not associated with green biomass (i.e. soil colour and moisture content) (Rondeaux, Steven, and Baret, 1996; Huete, 1988). Biophysical models can be used to directly estimate characteristics of vegetation green biomass with better results than broad band-width vegetation indices (Armston et al., 2008; Powell et al., 2010; Zhu and Liu, 2015). The foliage projective coverage (FPC) measure is one such biophysical parameter estimated from Landsat remote sensing datasets, and is defined as the vertically projected percentage of photosynthetic foliage cover over all vegetation strata (Armston et al., 2008; Specht, 1983). In Australia, FPC has been adopted as the standard for vegetation classification frameworks, due in large to the low density

structure of Australian vegetation and ease of field measurements (Specht and Specht 1999). FPC is one of many biophysical parameters used to characterise the photosynthetic structure of vegetation communities, other common ones include: leaf area index (LAI), defined as the ratio of one sided photosynthetic leaf area per ground unit; and the fraction of photosynthetically active radiation (Fpar) absorbed by green vegetation (Gill et al., 2006; Lu et al., 2003). The Joint Remote Sensing Research Program estimates seasonal FPC using the Landsat archive for the state of Queensland using methods described in (Armston et al., 2009). This dataset is ideal for assessing temporal characteristics of GDV and non-GDV green biomass over large landscapes that fall across multiple Landsat scenes. The dataset is particularly useful because it is radiometrically consistent across a large environmental gradient and at a pixel size of 30 meters. Therefore, narrow riparian vegetation communities can be targeted and differences in FPC between images are more likely to represent actual change in FPC and less likely to be associated with atmospheric variability across the time-series.

In this study, we tested the amount of FPC, and variation in FPC as indicators of GDV. Specifically we tested for differences in mean FPC across a precipitation gradient, across seasons and between GDV communities with differing hydrological regimes. We identified the utility of FPC amount and changes in FPC for identifying GDV in a humid environment. Finally, we defined a maximum average annual precipitation threshold to indicate the spatial extent for effectively delineating GDV within our study area.

2. Methods

2.1 Study Area

To answer the question about how average annual precipitation influences FPC of GDV and non-GDV communities, we selected three study sites across a $1500 \text{ mm}^{-1} \text{ year}^{-1}$ precipitation gradient and $1700 \text{ mm}^{-1} \text{ year}^{-1}$ potential evapotranspiration gradient. This study was completed in southern Queensland, Australia. This broad area was stratified into three regions: 1) a humid coastal environment, with a precipitation range of $1600\text{-}1700 \text{ mm}^{-1} \text{ year}^{-1}$; 2) a semi-arid environment, $500\text{-}700 \text{ mm}^{-1} \text{ year}^{-1}$; and 3) an arid environment, $200\text{-}300 \text{ mm}^{-1} \text{ year}^{-1}$ (Figure 1), with potential evapotranspiration of 1400 mm^{-1}

year⁻¹, 2500 mm⁻¹ year⁻¹, and 3300 mm⁻¹ year⁻¹, respectively. Precipitation and greatest evapotranspiration rates were dominant in summer (December – February) for the humid and semi-arid areas, and precipitation was highly intermittent at the arid site.

2.2 Study Design

We used a long-term dataset of FPC estimates derived from the Landsat remote sensing archive to assess mean FPC, and variation in mean FPC. Mean FPC values were spatially grouped into three discrete environments based on average annual precipitation (*Study Area*). Each environment contained four vegetation classes that were repeatedly measured over four seasons for each year of the study period (1987-2015). Vegetation was broadly grouped into four different classes (three GDV and one non-GDV). Vegetation followed two classes proposed by Eamus et al. (2006) which are based on where GDV access groundwater: 1) surface expressions of groundwater (i.e. wetlands and riparian zones), and 2) subsurface expressions of groundwater (i.e. the saturated soil profile below the surface). We divided the surface expression class into two discrete sub-classes based on the hydrological regime: one that experiences flooding events within its water regime (floodplain riparian zones), and one with intermittent water sources (headwater riparian zones). The resulting four classes of vegetation used in this study are as follows: 1) subsurface GDV; 2) floodplain riparian GDV; 3) headwater riparian GDV; and 4) non-GDV. Finally, a threshold describing the maximum average annual precipitation for effective delineation of GDV using remote sensing measures of green biomass was defined.

2.3 Datasets and FPC Extraction

Within each precipitation zone, point shapefiles were created to sample FPC, with at least 50 points for each of the four vegetation classes. Subsurface and surface expression GDV were identified using GIS shapefiles about GDV vegetation distribution (Queensland Groundwater Dependent Ecosystems and Potential GDE Aquifer Mapping shapefiles: V6.13). Methods for GDV shapefile creation can be found in Glanville et al. (2015). Headwater riparian GDV intersected first and second order streams, and floodplain riparian GDV were located alongside high order (3 and 4) streams in floodplains. Subsurface GDV and non-GDV were located at least 120 m away from streams. The native non-GDV vegetation

was identified using the regional ecosystem GIS dataset (Accad et al., 2008). The maximum average annual precipitation to delineate GDV with remote sensing green biomass measures was assessed using 1250 points spread evenly between $160 \text{ mm}^{-1} \text{ year}^{-1}$ and $1900 \text{ mm}^{-1} \text{ year}^{-1}$. The threshold points used to define maximum average annual precipitation contained the same four vegetation classes as above.

The FPC data was calculated by the Joint Remote Sensing Research Program from all images collected with Landsat TM, ETM+ and OLI sensors (spatial resolution of 30 meters, temporal resolution between 7 – 14 days) for Australia. FPC data is available for download from the Auscover ftp server (2016). Prior to FPC estimates, raw Landsat images are pre-processed to surface reflectance to reduce between image errors associated with atmospheric contamination, and to correct for bi-directional reflectance, cloud and shadow masking, topographic shadowing, and water masking, a full description of methods are available (Armston et al., 2009; Danaher and Collett, 2006; Flood et al., 2013). Seasonal FPC estimates were calculated using all available images for four seasons (December-February, March-May, June-August, and September-November) which correspond to summer, autumn, winter and spring in the southern hemisphere.

2.4 Statistical Analysis

In this study, we aimed to test for amount of FPC, and variation in FPC as indicators of GDV presence. We tested the influence of average annual precipitation, seasonality, and vegetation class on FPC (%) using linear mixed-effects models. The sample design was unbalanced, therefore regression models were calculated using restricted maximum likelihood and p-values were calculated using F tests (Bolker et al., 2009; Zuur, 2009). Three linear mixed-effects models were explored, each focusing on a different set of predictor variables to explain FPC (Equation 1, 2 and 3). For all models, location was assigned a random intercept between FPC sampling sites within each of the four vegetation classes (*section Study Design*). This was to account for variation associated with different soils, and for differences in the structure, and response to the hydrological regime of individual vegetation communities. Year was assigned as a random intercept to account for climatic variability, such as those associated with the El Nino-Southern Oscillation. First we fitted a global model with all predictor variables to identify the variable with the greatest influence on mean FPC (Equation 1). In the following two models, different

predictor variables were dropped and the dataset was subset to assess the influence of the remaining predictors for explaining mean FPC. The second model was developed to assess the influence of vegetation class and season on FPC within each individual precipitation zone (Equation 2). The utility of using mean FPC to identify GDV communities during maximum seasonal stress was assessed using Equation 3. Equation 3 assumed that maximum seasonal stress occurred when FPC was lowest for all vegetation communities, as determined using the Equation 2 model output.

$$\text{Mean FPC} = \text{FPC} \sim \text{zone} + \text{vegetation class} + \text{season} + \text{random intercepts for location and year} \quad (1)$$

$$\text{Mean FPC within zone} = \text{FPC (within zone)} \sim \text{vegetation class} + \text{season} + \text{random intercepts for location and year} \quad (2)$$

$$\text{Mean FPC during dry season} = \text{FPC (July-September)} \sim \text{vegetation class} + \text{random intercepts for location and year} \quad (3)$$

Coefficients of variation (CV) of FPC were computed for all vegetation communities in each precipitation zone to assess the utility of measures of change in FPC. The maximum average annual precipitation thresholds for delineating GDV were developed by fitting first order polynomial regression equations with 95% confidence intervals to each of the four vegetation classes. The maximum average annual precipitation for effective GDV delineation were identified as the points of intercept between the upper non-GDV 95% confidence interval and the lower 95% confidence intervals for each GDV class. All data analysis was completed using R Statistics (R Development Core Team, 2016) and linear-mixed effects models was developed using the lmer function in the lme4 package (Bates et al, 2011).

3. Results

2.5 Descriptive Results

Overall, an increase in FPC was predicted from arid to humid precipitation zones (Figure 2). Within each zone, FPC differed between seasons, and between vegetation classes. Non-GDV in the arid zone was the exception, where the mean FPC was constantly near 0%. Non-GDV communities in the arid zone retained the lowest FPC relative to other vegetation classes, whereas non-GDV was greater than floodplain GDV in the semi-arid zone, and retained the greatest FPC in the humid zone. Seasonal

patterns were present in semi-arid and humid vegetation communities, while arid vegetation classes were less seasonally defined (Figure 2).

2.6 Linear Mixed-Effects Models

Precipitation zone, vegetation class and seasonality showed statistically significant ($P < 0.001$) impacts on changes in FPC. Precipitation zone explained the largest variation in FPC, ranging from 9.5% in the arid environment to 75.5% in the humid environment (Table 1).

The largest change in FPC within individual precipitation zones was associated with vegetation class (Table 2). However, non-GDV FPC was not always lowest. In the arid environment, non-GDV had the lowest FPC, while in the semi-arid environment non-GDV was higher than subsurface GDV, and in the humid environment FPC of non-GDV was higher than all other vegetation classes. For seasonality, winter was associated with the lowest FPC across all precipitation zones, while summer was associated with the highest FPC across all precipitation zones. Seasonal variability in FPC was largest in the semi-arid environment (Table 2).

For all precipitation zones, winter was the season when FPC values were lowest (Table 2). During winter only (Table 3), FPC of headwater riparian GDV was higher than non-GDV, however, FPC of subsurface and floodplain riparian GDV were lower and the same respectively.

The coefficients of variation (CV) were low in humid and semi-arid environments, relative to the arid environment (Table 4). For all vegetation communities in semi-arid and humid environments, CV's were lower in winter, compared to those across all seasons. Within the humid and arid environments, the highest CV's were detected in non-GDV. Although, there was little difference between CV's for each of the vegetation communities in semi-arid and humid environments (Table 4).

2.7 Precipitation threshold for effective use of remote sensing green biomass measures

The 95% confidence intervals for the relationship between mean FPC and annual precipitation intercepted the x-axis (average annual precipitation) at $\sim 800 \text{ mm}^{-1} \text{ year}^{-1}$ for both the upper non-GDV and lower GDV (Figure 3). When was separated into its individual classes (Figure 4) the upper non-

GDV and lower subsurface GDV 95% confidence intervals intercepted the x-axis (average annual precipitation) at $\sim 600 \text{ mm}^{-1} \text{ year}^{-1}$. While the 95% confidence intervals for the upper non-GDV and lower floodplain GDV intercepted the x-axis (average annual precipitation) at $\sim 850 \text{ mm}^{-1} \text{ year}^{-1}$. The non-GDV and headwater GDV 95% confidence intervals were not differentiated.

4. Discussion

Our study indicates that precipitation, seasonality and hydrological regime of GDV communities should be considered when using remote sensing derived green biomass measures to delineate GDV. Most importantly, in our study area we found that vegetation with access to groundwater did not necessarily have greater green biomass when compared with vegetation solely reliant on soil moisture. This was evident in the semi-arid and humid environments, where FPC of subsurface GDV was lower than non-GDV. We therefore conclude that remote sensing analysis is ideal for delineating GDV in our arid environment study area based on the assumption that GDV green biomass is greater than non-GDV.

For our study area, GDV could be delineated from non-GDV when average annual precipitation was less than $800 \text{ mm}^{-1} \text{ year}^{-1}$. If separate GDV class are to be delineated then this threshold can be as low as $600 \text{ mm}^{-1} \text{ year}^{-1}$, i.e. for delineating subsurface GDV. We suggest that measures of increased green biomass may not be suitable for delineating GDV in semi-arid and humid environments. Rainforest and other vegetation communities with generally high amounts of green biomass were common in our humid climate study site and thus were likely to attribute to the high FPC of non-GDV. However in humid environments, it may be possible to delineate GDV based on measurements of lower variability (i.e. CV) in green biomass, although more research, including ground-truthing, is required as CV values for all humid vegetation communities were clustered close together. Our finding will likely be globally relevant for the tropics and mid-latitudes with similar climates to our study area. Although further work is required to identify such a level of generalisation. Furthermore, we note that the precipitation threshold is likely to differ under other climates and with differing sample sizes.

Through this study we revealed interesting trends about increasing FPC and decreasing variation in FPC as aridity decreased. In the humid environment FPC was not limited by water availability; i.e.,

groundwater access did not increase FPC relative to soil moisture only. This is consistent with water limitation theory, which shows that in arid environments water is the greatest limiting factor to vegetation growth (Djebou et al., 2015; Stephenson, 1990; Wen et al., 2012). However as precipitation increases, other variables (e.g. nutrient availability) can limit vegetation growth. For example, in a humid environment in Malaysia, Dent et al. (2006) found that vegetation productivity decreased along a gradient of decreasing soil nutrients. In environments with high precipitation and wet summers, vegetation is not limited by water availability and can rely on soil moisture during periods of low precipitation. Furthermore, during the early growing season soil moisture can better explain variation in vegetation greenness (Djebou and Singh, 2015). We did not include soil moisture in our regression models, and the inclusion of such parameters may have improved our understanding of GDV greenness across seasons, climates and vegetation types. Measures of CV identified that variability in FPC exponentially increased as aridity increased. In Australia, green-up of vegetation in arid climates is highly precipitation dependent and has been previously found to follow long-term cycles associated with the El Nino southern oscillation (Broich et al., 2014). Our arid study site had the greatest variation in FPC, and was likely associated with intermittent precipitation in this environment.

In humid environments, water limitation occurs to a lesser extent in severity and in temporal frequency, than in arid environments (Rodriguez-Iturbe et al., 2007; Tromp-van Meerveld and McDonnell, 2006; Cassel and Nielsen, 1986). In our arid study area, the temporal variation of FPC within each vegetation community was well separated and probably reflected differences in water availability for each of the studied vegetation classes. For example, in the arid study area CV values were lowest for subsurface and riparian floodplain GDV, which were more likely to have constant access to groundwater and thereby better retain green biomass. Conversely, CV values were highest for non-GDV in the arid study area. These communities are known to retain lower FPC, with short lived greening of vegetation driven by precipitation events. Such patterns in changes in green biomass have been previously documented in other arid environments (White et al., 2015). In contrast, temporal variation in FPC was low and similar between vegetation communities in our humid study area. Again, this is likely a reflection of more consistently high available soil moisture across humid landscapes. Other authors have identified

similar patterns of higher inter-annual variability of above ground biomass for grasslands in low precipitation environments and lower variability for forest ecosystems in higher precipitation environments (Fang et al., 2001; Kanniah et al., 2013; Lee et al., 2002).

We have established that estimates of biomass amount and change in biomass, may not be suitable as indicators of GDV presence in semi-arid and humid environments. However, we acknowledge that we did not assess the contribution of variables not related to water availability that can significantly influence FPC of GDV. For example, soil type, topographic positions, past fire regimes and soil moisture content can significantly influence vegetation biomass (Briggs and Knapp, 1995; Shafroth et al., 2000). Therefore, future research should identify the influences of such environmental factors on FPC of GDV and non-GDV. Furthermore, our study area was limited to southern Queensland, Australia, and did not contain Mediterranean climates, which may be easier to delineate GDV using biomass estimates. In environments characterised by Mediterranean climates vegetation experiences greater evaporative demand and seasonal stress during the dry and hot summers. In future research, other remote sensing methods may be more appropriate for delineating GDV in semi-arid and humid environments. For example, Gow et al. (2016) successfully used evapotranspiration model-data techniques to assess the frequency and duration of groundwater use in a semi-arid woodland in southern Queensland.

5. Conclusion

We have shown that green biomass measurements derived from analysis of time-series remote sensing datasets can be used to accurately delineate GDV in environments of our study area where average annual precipitation is less than $600 \text{ mm}^{-1} \text{ year}^{-1}$. However, such measures were not suitable for use in the semi-arid and humid environments. This was because subsurface GDV could not be differentiated from non-GDV. Measures of green biomass may prove useful for semi-arid and humid environments if subsurface GDV can first be delineated using other methods, including measures of evapotranspiration. We identified that average annual precipitation had the greatest influence on FPC and that seasonal FPC was lowest during winter across all three precipitation zones. The underlying trends of decreasing FPC

and increasing CV with increasing aridity backed up current understandings about water limitation of vegetation communities across precipitation gradients.

Accepted Article

6. Reference

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Table 1. The influence of precipitation zone, vegetation class and season on FPC (mean $\pm$ SE) were assessed using linear mixed-effect models. All values in the estimate column indicate the mean change in percentage of FPC against the intercept estimate.

Fixed Effect	Class	Estimate	<i>t-value</i>
	Intercept	9.5 $\pm$ 0.88	11
Precipitation	Humid	66 $\pm$ 1.06	62
(Ref: Arid n=16053)	Semi-Arid	31 $\pm$ 0.99	32
Vegetation Class	Floodplain	13 $\pm$ 1.27	11
(Ref: Sub n=9565)	Headwater	5 $\pm$ 1.29	4
	Non-GDV	3 $\pm$ 1.09	3
Season	Autumn	-3 $\pm$ 0.10	-33
(Ref: Summer)	Winter	-7 $\pm$ 0.10	-75
	Spring	-3 $\pm$ 0.11	-30

Ref is the reference variable that all other variables in that class are compared against (ie. change is 0%).

Table 2. Summary of statistic results (linear mixed-effects models) for the influence of vegetation class and season on foliage projective cover (FPC) (mean $\pm$ SE) within each precipitation zone. All values in the estimate column indicate the mean change in percentage of FPC against the intercept estimate.

Fixed Effect		Arid		Semi-Arid		Humid	
		Estimate	<i>t-value</i>	Estimate	<i>t-value</i>	Estimate	<i>t-value</i>
	Intercept	9.8 $\pm$ 0.95	10	40 $\pm$ 1.47	27	76 $\pm$ 1.21	63
Vegetation (Ref: Sub)	Floodplain	1.30	11	15 $\pm$ 1.57	9.6	6.1 $\pm$ 1.58	3.9
	Headwater	-1.1 $\pm$ 1.29	-0.9	10 $\pm$ 1.77	5.7	5.6 $\pm$ 1.35	4.1
	Non-GDV	-6.6 $\pm$ 1.31	-5	3.6 $\pm$ 1.48	2.4	7.4 $\pm$ 1.51	4.9
Season (Ref: Summer)	Autumn	-1.6 $\pm$ 0.11	-14	-1.4 $\pm$ 0.15	-9.4	-4.4 $\pm$ 0.13	-33
	Winter	-2.7 $\pm$ 0.11	-24	-1.1 $\pm$ 0.16	-73	-8.5 $\pm$ 0.13	-63
	Spring	-1.6 $\pm$ 0.11	-13	-5.1 $\pm$ 0.16	-31	-3.4 $\pm$ 0.17	-21

Ref is the reference variable that all other variables in that class are compared against (ie. change is 0%).

Table 3. Summary of statistic results (linear mixed-effects models) for influence of vegetation class during the driest season, winter, on foliage projective cover (FPC) (mean $\pm$ SE) within each precipitation zone. All values in the estimate column indicate the mean change in percentage of FPC against the intercept estimate.

Fixed Effect		Arid		Semi-Arid		Humid	
		Estimate	<i>t-value</i>	Estimate	<i>t-value</i>	Estimate	<i>t-value</i>
Vegetation (Ref: Sub)	Intercept	7 $\pm$ 1.14	6	37 $\pm$ 1.7	22	72 $\pm$ 1.21	58
	Floodplain	18 $\pm$ 1.5	-0.9	18 $\pm$ 1.9	5.7	4.1 $\pm$ 1.58	3
	Headwater	-1.4 $\pm$ 1.5	-3.2	11 $\pm$ 1.6	3.2	7.3 $\pm$ 1.35	4.7
	Non-GDV	-5 $\pm$ 1.5	-12	5.3 $\pm$ 1.7	11	4 $\pm$ 1.51	2.5

Ref is the reference variable that all other variables in that class are compared against (ie. change is 0%).

Table 4. Summary statistics for coefficients of variation for foliage projective cover in winter (June-August) and year round (all seasons) for each vegetation class and each precipitation zones.

	Arid	Semi-Arid	Humid
Floodplain			
All seasons	68.4	27.3	13.8
Winter	88.8	24.1	12.6
Headwater			
All seasons	111	19.6	12.3
Winter	117	16.5	11.9
Subsurface			
All seasons	55	25.5	10.7
Winter	55.5	22.3	10.1
Non-GDV			
All seasons	228	25.7	14.4
Winter	239	21.3	13.7

	Floodplain	headwater	Non-GDV	Riparian
Arid	4760	3945	3662	3686
Coastal	2512	5983	3254	2836
Semi-Arid	2293	2152	5668	3894

X² = 3897, p-value = < 0.001

Figure 1. Mean FPC was assessed for three environments with varying average annual precipitation: 1) a humid coastal environment, with a precipitation range of 1600-1700 $\text{mm}^{-1} \text{ year}^{-1}$; 2) a semi-arid environment, 500-700 $\text{mm}^{-1} \text{ year}^{-1}$; and 3) an arid environment, 200-300 $\text{mm}^{-1} \text{ year}^{-1}$ across a 1500 $\text{mm}^{-1} \text{ year}^{-1}$ precipitation gradient and 1700 $\text{mm}^{-1} \text{ year}^{-1}$ potential evapotranspiration gradient in southern Queensland, Australia. The maximum annual average precipitation threshold where remote sensing biomass measures are effective for delineating groundwater dependent vegetation was defined using data from 1250 threshold points across the precipitation gradient.

Figure 2. Distributions of foliage projective cover within four seasons for subsurface groundwater dependent vegetation (GDV), floodplain riparian GDV, headwater riparian GDV and non-GDV classes growing in arid, semi-arid and humid environments.

Figure 3. First order polynomial regression lines with 95% confident intervals were fitted to groundwater dependent vegetation (GDV) ($n = 1248$) and non-GDV data ($n = 810$). The red vertical line indicates the point of intercept ($\sim 800 \text{ mm}^{-1} \text{ year}^{-1}$ x axis average annual precipitation) between the upper non-GDV and lower GDV 95% confident intervals.

Figure 4. First order polynomial regression lines with 95% confidence intervals were fitted to three classes of groundwater dependent vegetation (GDV) (floodplain riparian ($n = 401$), subsurface ($n = 432$), and headwater riparian ($n = 404$)) and one non-GDV class ($n = 810$). The upper non-GDV and lower subsurface GDV 95% confidence intervals intercepted the x axis (average annual precipitation) at $\sim 600 \text{ mm}^{-1} \text{ year}^{-1}$, as indicated with the red vertical line. While the upper non-GDV and lower floodplain GDV 95% confident intervals intercepted the x axis (average annual precipitation) at $\sim 850 \text{ mm}^{-1} \text{ year}^{-1}$, as indicated with the green vertical line. The 95% confidence intervals for non-GDV and headwater GDV were not differentiated.