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Correlating rainfall and simulated pasture growth for developing sustainable grazing insurance products in northern Australia

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Abstract: Marine ecosystems, such as the Great Barrier Reef, are under threat from the impacts of sediment and particulate nutrient runoff. Overgrazing in rangelands reduces ground cover and exacerbates the export of these fine sediments. Australian graziers are challenged year-by-year with adjusting their stocking rate in anticipation of weather forecasts that may be inaccurate. To maximise profitability, graziers balance stock numbers with anticipated pasture growth. However, low rainfall will not produce enough pasture growth to feed their cattle leading to over-grazing and reduced ground cover. Insuring against inaccurate forecasts of low rainfall may encourage graziers toward more adaptive and sustainable grazing practices. In this study, Spearman's rank correlation coefficients between different rainfall windows and simulated pasture growth were calculated to determine whether rainfall is an effective surrogate for biomass in an agricultural insurance product in 3 IBRA (Interim Biogeographic Regionalisation for Australia) subregions: Cape-Campaspe Plains in Queensland, Sandover in Northern Territory, and McLarty in Western Australia. 1- and 3-month periods of peak median simulated pasture growth were identified to be the same in all three regions: February as the peak growth month, and January-March as the peak growth quarter. Single-month and cumulative month rainfall windows were correlated with both February and January-March quarter growth periods. Additionally, overlapping 2-, 3-, and 4-month rainfall windows were correlated with the peak growth quarter period. Pasture growth in February was most strongly correlated with rainfall window November–February (4-month) for Cape-Campaspe Plains, and January–February (2-month) for Sandover and McLarty. Pasture growth during the peak quarter of January–March exhibited the strongest correlations with both the four-month (December–March) and three-month rainfall (January–March) windows across all three regions, with minimal differences between the two. Identification of rainfall windows most correlated to pasture growth allows for the design of region—specific payout indexes for agricultural insurance products. For example, graziers in Cape-Campaspe Plains can insure against inaccurate forecasts during the 4-month window from November-February. This analysis aimed to provide insight into the temporal dynamics of region-specific relationships between rainfall and simulated pasture growth, and to assess whether rainfall alone could serve as an effective surrogate for biomass. The findings are intended to inform the design of agricultural insurance products that support sustainable grazing practices.

Keywords: *Correlation analysis, simulated pasture growth, rainfall-index insurance, graziers, Northern Australia*

1. INTRODUCTION

Marine ecosystems are currently facing numerous threats in many parts of the world. These include natural pressures from the cumulative effects of climate change, such as warmer temperatures and increased extreme weather events, and anthropogenic pressures such as overfishing, coastal development and, importantly, discharge of sediments, pesticides, and nitrogen in agricultural catchments draining into ocean waters (Healey 2018). The Great Barrier Reef (GBR) and its catchment areas provide one high profile example of this issue. The GBR is the most extensive coral reef system in the world, covering approximately 348,000 km^2 and extending 2,000 km along the north-east coastline of Australia. The GBR is of great ecological and conservation importance as it supports half of the world's diversity of mangroves and seagrass species, thirty species of whales and dolphins, as well as species of dugong and large green turtle threatened with extinction (UNESCO n.d.).

Approximately 60% of sediment comes from erosion of hillslopes and gullies in grazing land areas in GBR catchments (Bartley and Murray 2024). Overgrazing significantly contributes to hillslope erosion by reducing vegetation cover and soil structure. Reduced vegetation exposes the surface bare to the eroding impacts of rainfall washing sediment to waterways and marine environments (Thorburn and Wilkinson 2013). Reducing soil structure results in decreased land productivity, soil compaction, lower water filtration and increases surface runoff (Donovan and Monaghan 2021; Ash et al. 2011). Consequently, the QLD (Queensland) Government has regulated grazing lands in GBR catchments to meet water quality targets. These regulations require graziers to undertake activities to improve land condition which is defined by the ground cover at the end of the dry season (30th September). Ground cover is defined as plants, plant litter, tree leaf litter, twigs and woody debris covering the soil surface. Areas with less than 50% ground cover are considered in poor condition and those with less than 20% as degraded (Office of the Great Barrier Reef 2022). The GBR catchments in QLD represent just one of many agricultural regions across northern Australia where effective management of ground cover is essential to minimise the environmental impacts of runoff in marine ecosystems.

Graziers manage land condition and ground cover primarily by adjusting pasture utilisation rate, which is the proportion of above-ground pasture biomass consumed by livestock (Thorburn and Wilkinson 2013). Pasture utilisation needs to be balanced with pasture supply (i.e. growth) to guide appropriate and sustainable stocking rate decisions (Hunt 2008). High utilisation rates are acceptable while ground cover is greater than 50%–20% but are unacceptable if cover is less than 20% (Thorburn and Wilkinson 2013). However, pasture growth differs greatly between years in GBR catchments because of highly variable rainfall. There are a number of management strategies such as allocating low stocking rates where pasture utilisation rate is maintained at 15% of pasture grown annually and adjusting stocking rates through buying and selling (Cobon et al. 2019). Graziers who rely on pasture biomass to feed their cattle need to continually adjust stocking rates in anticipation of the coming climate and pasture growth (Thorburn and Wilkinson 2013). The problem with this strategy is that forecasting seasonal rainfall is difficult. If graziers destock their property in the face of forecast low rainfall, they risk having low stock numbers and reduced profitability if the forecast was incorrect. In the face of this uncertainty, graziers may maintain stock numbers in which case ground cover and land condition will be reduced and the potential for erosion increased if the forecast of low rainfall is correct. Graziers may be more willing to adjust stock numbers to seasonal rainfall forecasts if there was a way to mitigate the cost and risk of an inaccurate forecast.

Agricultural insurance provides a form of risk management and income security from climate-driven perils (Roberts et al. 2023). There are many products available, generally known as rainfall index insurance, that let farmers or graziers protect against the impacts of low or high rainfall. However, these products have not yet been used to help graziers manage the risk of reduced profitability after destocking their herd at time of low rainfall forecasts. In this context, for rainfall index insurance products that cover this to be operational, the grazier requires three things before investing: they need to be convinced that rainfall and pasture growth are strongly correlated, to know over what time period rainfall and pasture growth are most correlated, and to estimate the pasture system's productivity per unit of rainfall (i.e. water use efficiency). In this scoping study, we investigated the correlations between rainfall and simulated pasture growth in Northern Australia to determine whether rainfall could be used as an effective surrogate for biomass in a rainfall index insurance product. The establishment of rainfall and pasture growth correlations may assist graziers using agricultural insurance products to protect their livelihoods and encourage sustainable grazing practices that mitigate sediment and nutrient runoff that threaten marine ecosystems.

2. DATA AND METHODS

2.1. Data

This analysis used two variables from the AussieGRASS data set: monthly rainfall (mm), and monthly simulated pasture growth (kg/ha) for the period from January 1890 to August 2024. These data were accessed from the *Long Paddock: AussieGRASS* website (Stone et al. 2019) for each of the 3 IBRA subregions. Pasture growth in AussieGRASS is defined as new plant material (kg/ha) produced during the period of interest. It is calculated daily and summed to monthly totals (Department of Science Information Technology and Innovation 2015). AussieGRASS, as documented by Carter et al. (2000), is a simulation model that captures key biophysical processes associated with pasture growth. The model integrates SILO (Scientific Information for Land Owners) climate data (Jeffrey et al. 2001), such as rainfall, maximum and minimum temperature, radiation, evaporation, and humidity, with soils, pasture type, stocking rate, and tree cover data to create outputs such as simulated pasture growth and soil moisture (Department of Science Information Technology and Innovation 2015). This provides long-term spatio-temporal series of rainfall and pasture growth that are separated into IBRA (Interim Biogeographical Regionalisation of Australia) subregions. IBRA classifies Australia's landscapes into 89 large geographically distinct bioregions based on unifying climate, geology, landform, native vegetation, flora and fauna, and land use (Thackway and Cresswell 1995). This analysis used IBRA version 7, outlining 89 IBRA regions that are further refined into 419 localised subregions forming homogenous geomorphological units (Department of Agriculture Water and the Environment n.d.).

Three IBRA subregions were selected for this analysis to capture variation in northern Australia's landscapes and climates: Cape-Campaspe Plains, a QLD region within the GBR catchment, Sandover in NT (Northern Territory), and McLarty in WA (Western Australia) (Figure 1). These regions were chosen to determine whether rainfall and simulated pasture growth correlations would differ under different climatic and environmental conditions.

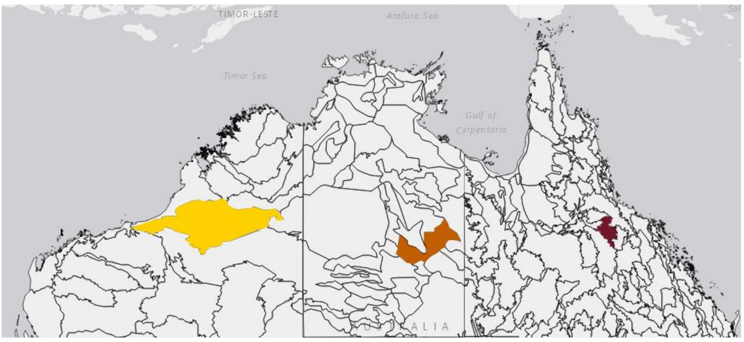

Figure 1. Snapshot of sub-IBRA Map of Northern Australia (Queensland Government n.d.). Highlighted sub-IBRA (Interim Biogeographic Regionalisation for Australia) regions investigated for this analysis: Cape-Campaspe Plains in QLD (maroon), Sandover in NT (orange), and McLarty in WA (yellow).

2.2. Methods

Correlation Analysis

The nonlinear relationship between rainfall and pasture growth is well documented (Cobon et al. 2019; Kumar et al. 2023; Birrell and Thompson 2006). There are various reasons for this relationship including low rainfall not producing pasture growth in dry and heavier textured soils, water runoff from high-intensity rainfall, water drainage due to full soil profile, and lack of nutrients (Cobon et al. 2019). Spearman's rank-order correlation was used to analyse correlations between pasture growth and rainfall in different time periods. Spearman's rank-order correlation assesses the monotonicity of the relationship between two variables and is appropriate when assumptions of normality and homoscedasticity cannot be met (Hauke and Kossowski 2011). All analyses were conducted in R version 4.4.1 (R Core Team 2024).

Determine Peak Growth

We initially identified the 1- and 3-month (termed quarter) time periods when simulated pasture growth was greatest in each region using descriptive statistics and computed correlations between growth in these periods with rainfall.

Peak Growth Month Correlations

Correlations were calculated between the pasture growth and total rainfall both within the same 1-month period and in the preceding months. This was done by calculating correlations between growth and rainfall in singular monthly time windows (e.g. February, January, December, etc.) and cumulative monthly time windows (e.g. February, January–February, December–February, etc.) until there was no change in cumulative monthly time window correlations.

Peak Growth Quarter Correlations

The same approach was used for the peak growth in a quarter period. Correlations were calculated between pasture growth and total rainfall both within the same 3-month period and in preceding quarters singularly (e.g. Q1, Q2, Q3, etc.) and cumulatively (e.g. Q1, Q1–Q2, Q1–Q3, etc.). We also correlated the peak growth quarter period with overlapping 2-month (e.g. February–March, January–February, December–January, etc.), 3-month (January–

March, December–February, November–January, etc.), and 4-month rainfall windows (e.g. December–March, November–February, October–January, etc.), extending the lag until correlations declined to approximately 0.5.

3. RESULTS

3.1. Peak Growth

1-month median simulated pasture growth was highest in February for all three IBRA subregions. January, February, and March (Q1) had the highest median simulated pasture growth months for all three regions (Figure 2).

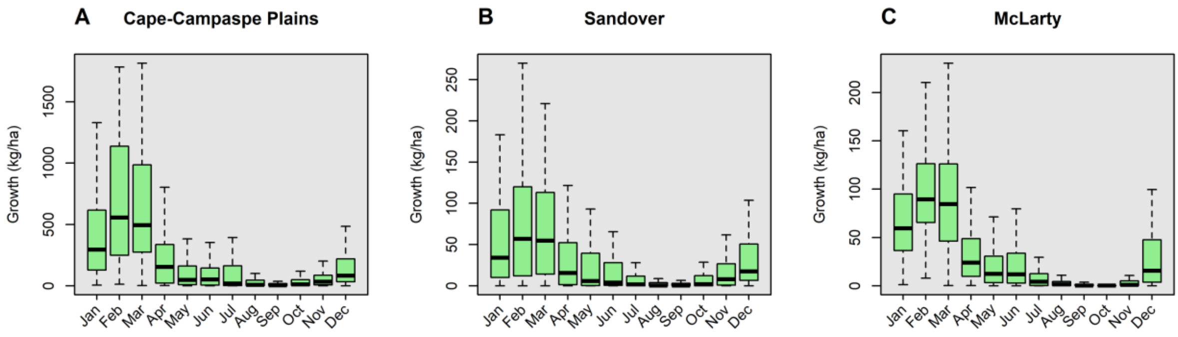

Figure 2. Monthly simulated pasture growth boxplots from January 1890 to August 2024 for Cape-Campaspe Plains (A), Sandover (B), and McLarty (C).

3.2. Correlations between Peak Growth Month and Rainfall

Rainfall in February was most highly correlated with simulated growth in February for all three regions. Spearman's coefficients for Cape-Campaspe Plains, Sandover, and McLarty were 0.63, 0.76, and 0.71, respectively (Figure 3). The correlation between pasture growth and monthly rainfall progressively declined with increasing lag for all three regions.

For cumulative monthly rainfall over multiple monthly time windows, Spearman's coefficients stabilised around November–February for Cape-Campaspe Plains (0.87), and January–February for Sandover (0.88) and McLarty (0.80) (Figure 3). The rainfall window with the highest correlation was October–February for Cape-Campaspe Plains (0.88), December–February for Sandover (0.89), and July–February for McLarty (0.85). Correlations in McLarty exhibited a gradual increase with extended lags without reaching a peak within the months analysed.

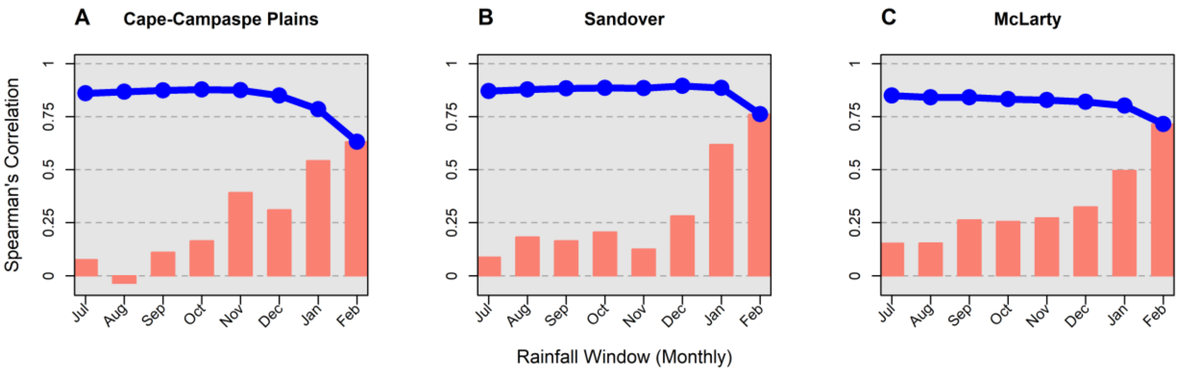

Figure 3. Spearman's rank correlation graphs between simulated pasture growth month in February with total rainfall in single monthly periods in red bar graphs (Feb, Jan, Dec, etc.) and cumulative monthly periods in blue line graphs (Feb, Jan–Feb, Dec–Feb, etc.) for Cape-Campaspe Plains, Sandover, and McLarty IBRA subregions. For example, the cumulative point at July will be the correlation between total rainfall in July–February period with pasture growth in February.

3.3. Correlations between peak growth quarter and rainfall

Q1 simulated pasture growth had the highest correlation with Q1 rainfall for all regions (Figure 4) with values of 0.81, 0.86, and 0.91 for Cape-Campaspe, Sandover, and McLarty, respectively. Correlations for singular quarterly rainfall windows progressively declined as the lag extended. The cumulative quarterly rainfall for the window Q4–Q1 (October to March) had the greatest correlation with pasture growth for Cape-Campaspe Plains (0.90) and Sandover (0.89), and Q3–Q1 (July to March) for McLarty (0.90). Correlations for McLarty show a gradual increase with extended lag.

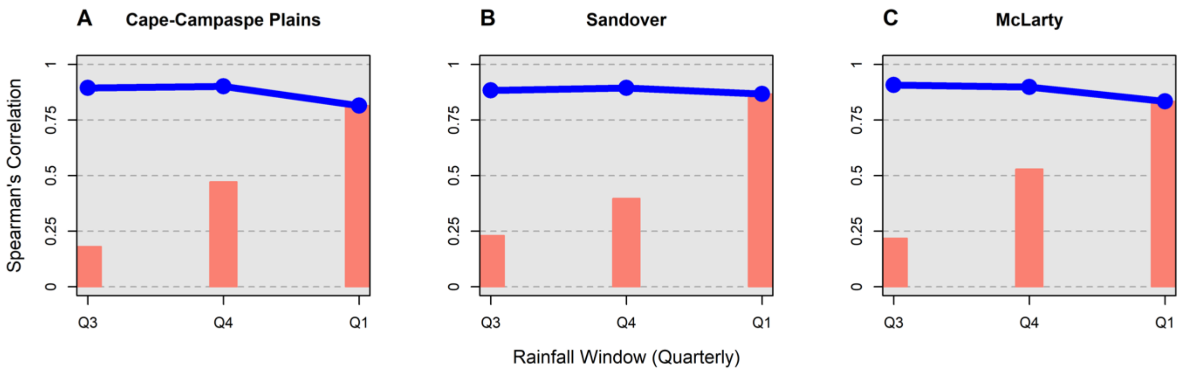

Figure 4. Spearman's rank correlation graphs showing the relationship between simulated pasture growth period in Q1 (January–March) and total rainfall in single (red bar graphs) and cumulative (blue line graphs) quarterly rainfall windows. Q2 = April–June, Q3 = July–September and Q4 = October–December. Results are shown for Cape-Campaspe (A), Sandover (B), and McLarty (C) IBRA subregions.

Rainfall in February showed the strongest correlation with Q1 simulated pasture growth in Cape-Campaspe Plains (Figure 5A), whereas in Sandover, the highest correlation occurred with January rainfall (Figure 5B). In McLarty, both January and February rainfall were equally most correlated with Q1 simulated pasture growth (Figure 5C). For monthly rainfall within the growth period, March rainfall had the lowest correlation for all three regions, Sandover being particularly low at 0.17. Cumulative monthly rainfall window correlations stabilised around December for all regions, coinciding with a decline in singular monthly correlations. At this point, Spearman's correlation coefficients were 0.88, 0.90, and 0.89 for Cape-Campaspe Plains, Sandover, and McLarty, respectively.

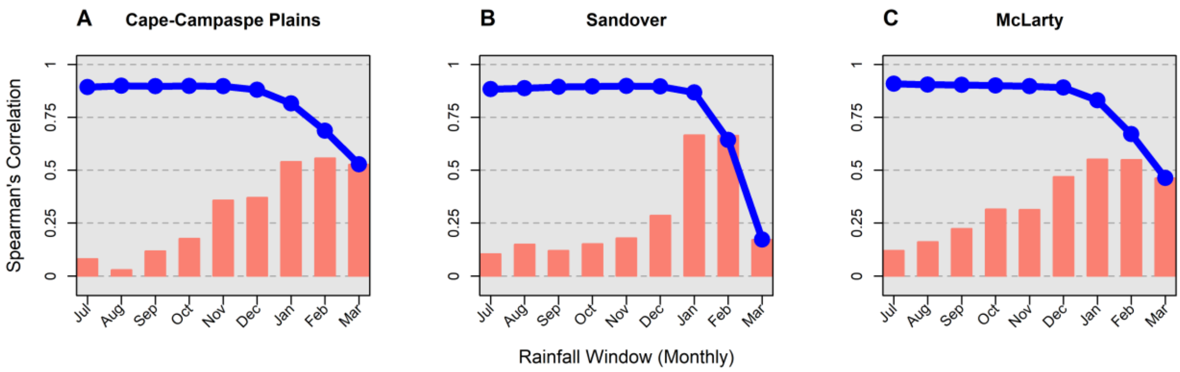

Figure 5. Spearman's rank correlation graphs between simulated pasture growth period in Q1 (January–March) with total rainfall in single (red bar graphs) and cumulative (blue line graphs) monthly rainfall windows for Cape-Campaspe Plains (A), Sandover (B), and McLarty (C) IBRA subregions.

The highest correlations between simulated pasture growth in Q1 and total rainfall across multiple months occurred for the four-month rainfall window from December–March for all three regions (Figure 6). As the window over which rainfall was summed moved earlier, correlations tended to reduce, although they initially increased in the two-month window (i.e. January–February higher than February–March) before reducing (Figure 6A). While the correlations for the four-month window were higher than the three-month window for the windows closest to the time of peak pasture growth, the differences in the correlations were small. For example, the correlations for the December–March window ranged from 0.88 to 0.90 across the three regions (Figure 6C) compared to 0.82 to 0.87 for the January– March three-month window (Figure 6B).

4. DISCUSSION

Graziers in northern Australia need to balance their stocking rates and pasture growth to avoid over-grazing and resultant erosion and degradation of soil health. Uncertainty in seasonal rainfall forecasts hamper this process. However, if rainfall and pasture growth were well correlated, graziers could potentially insure against the adverse outcomes of incorrect seasonal forecasts. Thus, in this scoping study we investigated the correlations between rainfall in various months and times of peak simulated pasture growth across three IBRA subregions in northern Australia. Our results indicate that rainfall alone during and directly preceding the peak pasture growth period is strongly correlated with simulated pasture growth and has potential to be an effective surrogate for biomass. For February, the month when median simulated pasture growth is highest, pasture growth was most strongly

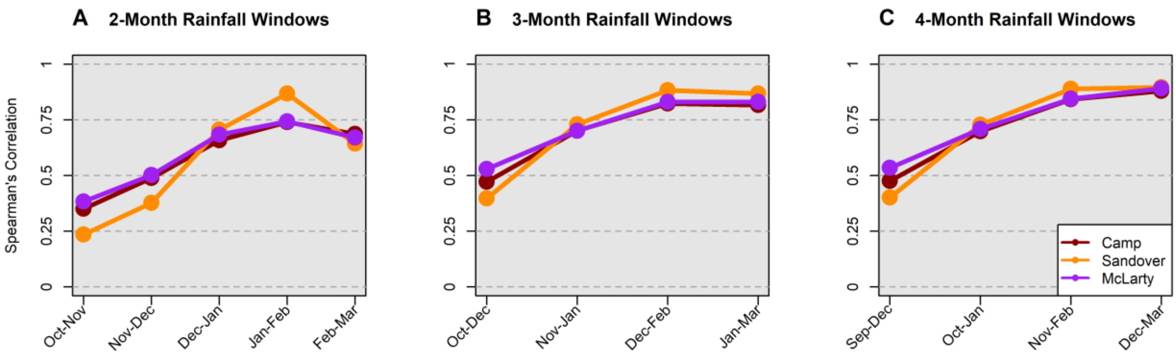

Figure 6. Spearman's rank correlation line graphs between simulated pasture growth in Q1 (January–March) and total rainfall in 2-month (A), 3-month (B), and 4-month (C) overlapping windows for Cape-Campaspe Plains (maroon), Sandover (orange), and McLarty (purple).

correlated with rainfall in November–February (four-month rainfall window) for the Cape-Campaspe Plains regions, and January–February (2-month rainfall window) for Sandover and McLarty (Figure 3). Quarterly simulated pasture growth was greatest in January–March (Q1) and was most correlated with rainfall in December–March (4-month rainfall window) for all three regions (Figure 6). The results are broadly consistent with the understanding that the majority of rainfall and pasture growth typically occur from November to March (Brown et al. 2019). However, they highlight that there are potential temporal differences in the correlations across different IBRA subregions.

Knowing that rainfall periods that are strongly correlated with peak simulated pasture growth in different regions can help graziers use rainfall index insurance to mitigate weather-related risks as they manage stock numbers. For example, if January–March is forecast to be dry graziers in the Cape-Campaspe Plains region may destock to match the anticipated lower pasture supply. However, if actual January–March rainfall is normal their productivity and profitability will be lower than if they kept their stock. These possible losses may make graziers reluctant to destock and risk overgrazing if the forecast is correct. Using rainfall insurance to offset the potential loss of income could thus promote sustainable grazing practices.

Some limitations of this study included the reliance on simulated pasture growth data from the AussieGRASS model. Two limitations that may be relevant for future work include upper pasture growth limits (i.e. maximum biomass productivity under ideal conditions) not being well modelled due to inadequate representation of nitrogen dynamics and the reduction in growth and death of plants due to flooding not being simulated (Department of Science Information Technology and Innovation 2015). The use of Spearman's rank correlation coefficient may not be appropriate due to potentially non-monotonic relationships not captured in the AussieGRASS model. More advanced statistical and machine learning approaches could be explored to improve correlations.

While correlation trends were largely similar across the three regions analysed in this study, the implications of space-time variation across the broader northern Australia mean that the strength and timing of these correlations may greatly differ, requiring region-specific analyses and subsequent insurance products. Pasture growth is impacted by factors other than rainfall, but this varies throughout the year. Our analysis indicates that rainfall alone is sufficiently correlated with simulated pasture growth to serve as an effective proxy for biomass during peak growth periods in three IBRA subregions. This enables use of rainfall index insurance products that are currently available to graziers. While this analysis included only three IBRA subregions, the methodology can be automated to any IBRA subregion as provided by AussieGRASS datasets. Therefore, future directions for this study will include the extension of rainfall correlation analysis to all IBRA subregions in northern Australia and further actuarial methodology to quantify risks and determine the value of a grazier's lost production (e.g. pasture system's productivity per unit of rainfall through statistical modelling). This would serve as a basis for compensation payouts in an agricultural insurance product.

5. CONCLUSION

Quantifying the temporal correlations between rainfall and simulated pasture growth across Northern Australia is an important step in understanding the potential for rainfall index-based insurance products to protect graziers from weather-related risks in managing their stock numbers. Our scoping study identified rainfall time windows most correlated with peak pasture growth periods. This analysis may inform the design of more accurate, region-specific rainfall triggers for climate-smart risk management and insurance products that support adaptive stocking decisions rather than providing compensation after a pasture loss event. Future work could include an analysis of other variables including the use of AI (Artificial Intelligence) to strengthen the correlation with simulated pasture growth, but this would mean creating more complex insurance products.

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REFERENCES

Ash AJ, Corfield JP, McIvor JG and Ksiksi TS (2011) Grazing Management in Tropical Savannas: Utilization and Rest Strategies to Manipulate Rangeland Condition. Rangeland Ecology & Management 64(3), 223–239.

Bartley R and Murray B (2024) Question 3.5 What are the most effective management practices (all land uses) for reducing sediment and particulate nutrient loss from the Great Barrer Reef catchments, do these vary spatially or in differenct climatic conditions? What are the costs and cost-effectiveness of these practices, and does this vary spatially or in different climatic conditions? What are the production outcomes of these practices? Viewed 20/06/2025.

Birrell HA and Thompson RL (2006) Effect of environmental factors on the growth of grazed pasture in south-western Victoria. Australian Journal of Experimental Agriculture 46(4), 545–554.

Brown JN, Ash A, MacLeod N and McIntosh P (2019) Diagnosing the weather and climate features that influence pasture growth in Northern Australia. Climate Risk Management 24, 1–12.

Carter JO, Hall WB, Brook KD, McKeon GM, Day KA and Paull CJ (2000) Aussie Grass: Australian Grassland and Rangeland Assessment by Spatial Simulation. In: Hammer GL, Nicholls N and Mitchell C (eds), Applications of Seasonal Climate Forecasting in Agricultural and Natural Ecosystems. Springer Netherlands, Dordrecht, 329-349. 10.1007/978-94-015-9351-9_20.

Cobon DH, Kouadio L, Mushtaq S, Jarvis C, Carter J, Stone G and Davis P (2019) Evaluating the shifts in rainfall and pasture-growth variabilities across the pastoral zone of Australia during 1910–2010. Crop and Pasture Science 70, 634–647.

Department of Agriculture Water and the Environment (n.d.) Australia's bioregions (IBRA) Australian Government. Viewed 05/08, https://www.dcceew.gov.au/environment/land/nrs/science/ibra.

Department of Science Information Technology and Innovation (2015) AussieGRASS Environmental Calculator – Product Descriptions v1.5. In: Department of Science Information Technology and Innovation (ed.). State of Queensland.

Donovan M and Monaghan R (2021) Impacts of grazing on ground cover, soil physical properties and soil loss via surface erosion: A novel geospatial modelling approach. Journal of Environmental Management 287.

Hauke J and Kossowski T (2011) Comparison of Values of Pearson's and Spearman's Correlation Coefficients on the Same Sets of Data. Quaestiones Geographicae 30(2), 87–93.

Healey J (2018) Saving the Great Barrier Reef. The Spinney Press, Thirroul, NSW.

Hunt LP (2008) Safe pasture utilisation rates as a grazing management tool in extensively grazed tropical savannas of northern Australia. The Rangeland Journal 30(3), 305–315.

Jeffrey SJ, Carter JO, Moodie KB and Beswick AR (2001) Using spatial interpolation to construct a comprehensive archive of Australian climate data. Environmental Modelling & Software 16(4), 309–330.

Kumar R, Lal MK, Tiwari RK, Kumar A, Behera B, Nayak L, Dash GK, Sahoo SK, Jena J, Lal P and Altaf MA (2023) Traditional and Emerging Climate-Resilient Agricultural Practices for Enhancing Food Production and Nutritional Quality. In: Aftab T (ed), New Frontiers in Plant-Environment Interactions Environmental Science and Engineering. Springer Cham, 551–570.

Office of the Great Barrier Reef (2022) Grazing Guide : Version 2. In: Department of Environment and Science (ed.). State of Queensland, State of Queensland.

R Core Team. (2024). R: A Language and Environment for Statistical Computing. Vienna, Austria: R Foundation for Statistical Computing.

Roberts J, Thorburn P and Mehmet R (2023) Agricultural Insurance: can innovation provide better risk management? Farm Policy Journal 20(1), 24–32.

Stone G, Pozza RD, Carter J and McKeon G (2019) Long Paddock: climate risk and grazing information for Australian rangelands and grazing communities. The Rangeland Journal 41, 225–232.

Thackway R and Cresswell I (eds) (1995) An Interim Biogeographic Regionalisation for Australia: a framework for establishing the national system of reserves, Version 4.0. Australian Nature Conservation Agency.

Thorburn PJ and Wilkinson SN (2013) Conceptual frameworks for estimating the water quality benefits of improved agricultural management practices in large catchments. Agriculture, Ecosystems & Environment 180, 192–209.

UNESCO (n.d.) Great Barrier Reef. Viewed 18/06/2025, https://whc.unesco.org/en/list/154/.

