Three regionalised analyses of a time-series of annual pasture production for southwest Western Australia

Handcock, R.N., Donald, G. E., & Gherardi, S.G.
Commonwealth Scientific and Industrial Research Organization
Floreat, Western Australia, 6014, Australia, Rebecca.Handcock@csiro.au

***Abstract*— A thirteen year time-series (1994 to 2006) of gross annual pasture production (GAPP; representing both pasture and crop) was created for the Mediterranean-climate area in the southwest of Western Australia (SWWA) using a light-use efficiency model, incorporating NOAA-AVHRR and NASA-MODIS images in combination with climate data. Trends across the GAPP time-series were quantified by aggregating pixels to spatial regions (called a partition, unit, or spatial support) so that the effects of local spatial noise were minimized. We compared the GAPP analysis using the three spatial partitioning schemes (precipitation zones, Interim Biogeographic Regionalisation for Australia (IBRA) eco-regions, and Statistical Local Areas), and showed that the aggregation unit's size & shape impacted on the analysis. Our results demonstrate trends in GAPP that may be indicative of broader trends in climate change for the SWWA.**

Keywords- Agriculture; time-series; gross annual pasture production; GPP; climate-change

I. INTRODUCTION

Monitoring vegetation within agricultural regions is critical because fluctuations in the amount, extent, and productivity of vegetation often occur in response to changing environmental conditions. The type of agriculture found in a region depends on the prevailing environment, and changes in both the short-term (e.g. drought), or long-term (e.g. climate change) can result in the reduced viability of particular agricultural practices and systems. This in turn impacts on the livelihoods of individual farmers and rural communities, as well as having economic, social and food supply issues.

Vegetation biomass and growth is influenced by eco-climatic factors which include available nutrients, temperature and precipitation, and more indirectly soil-water characteristics. The growth rate of pastures is additionally influenced by the density of plants and their phenological growth stage.

There has been extensive work on the remote-sensing of vegetation, and its monitoring using the widely-used Normalized Difference Vegetation Index (NDVI) [1][2][3]. Other vegetation indices are available [4] but the advantage of NDVI is that it can be calculated from sensors, such as the NOAA-AVHRR [5], which have longer time-series of images. Such datasets provide monitoring of vegetation characteristics such as gross primary production (GPP) [2][6] across large geographical extents. There has been other work on the remote sensing of pastures [7], but this has tended to focus on crops [8], or on rangeland remote sensing [9].

While a time-series of images can be examined at an individual pixel location, local noise (fine-scale spatial heterogeneity) makes it difficult to compare adjacent pixels, and it is useful to aggregate pixels to some spatial region (called a partition, unit, or spatial support). The choice of aggregation unit is critical because its size and shape will impact on the analysis [10]. However, for ease of processing the aggregation regions are often simple regular squares, or anthropological boundaries such as census collection units, which bear little relationship to the physical landscape. There has been recent interest in the analysis of time-series of satellite images using eco- or landuse-regions [6][11][12]. These regions are derived from landscape variables such as temperature, precipitation, soil and geological units, as well as frequently being used in regulatory contexts for reporting data. In some environments the key landscape partition may be based on a single variable, such as for precipitation zones.

In this paper we use NOAA-AVHRR Pathfinder [5] and NASA-MODIS [13] images in combination with climate data and a light-use efficiency model to derive a 13-year time-series (1994 to 2006) of Gross Annual Pasture Production (GAPP) for the Mediterranean-climate areas in the south-west of Western Australia (SWWA). We use three different spatial partitioning methods, being zones from a classification of precipitation data, the Interim Biogeographic Regionalization for Australia (IBRA) [14], and Statistical Local Areas (SLAs) [15], to examine trends across the time-series of GAPP and precipitation.

II. APPROACH

A. *Time frame and study area*

The images, model predictions, and spatial data presented here span the period from 1994 till 2006 over SWWA (Fig. 1). This area is a mixture of cropping (predominantly wheat) and sheep (extensive grazing management regime), and annual pastures. Pastures consist of predominantly subterranean clover (*Trifolium subterraneum*), annual grasses (*Lolium rigidum*), and broadleaf weeds (*Arctotheca calendula*).While the region has areas of native forest, most areas are cleared with scattered remnant vegetation. Soils in the study area can be coarsely divided into clay, loam and sandy, with sandy soils dominating [16].

This region experiences a Mediterranean climate, with the peak growing season for annual pastures having a well-defined start (initialized by plant germination) and finish (defined by plant senescence). Vegetation in the region is strongly driven by precipitation timing, with the peak precipitation occurring in the southern-hemisphere winter months. Total annual precipitation across the study period and region ranged from

400 – 900 mm, the average annual temperature minimum ranged from 7 – 14 ^{o}C, and the maximum is ranged from 19 – 26 ^{o}C [17].

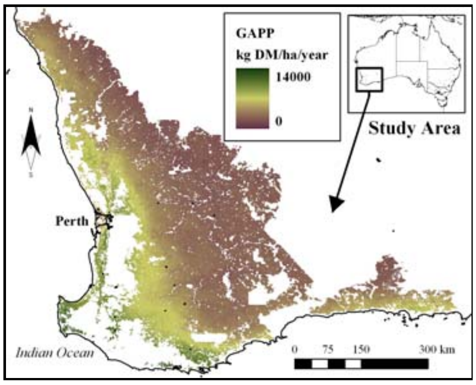

Figure 1. Study area, showing GAPP averaged across the time-series.

B. *Image and Climate Data*

From 1994 the project used data from the NOAA-AVHRR Pathfinder sensor [5] (1 km spatial resolution), and from June 2002 and 2004 images from the NASA-MODIS sensor [13] (250 m spatial resolution). Although AVHRR images were available prior to 1994 there were quality issues with the Australian datasets which prevented their inclusion. A correction for degradation of the AVHRR sensors was determined from observations of invariant targets within scenes. Images were cloud-masked and geo-referenced. NDVI [1][3] was calculated from the top-of-atmosphere reflectance, before determining maximum-value composites at the weekly time-step suitable for agricultural applications. If a pixel was consistently cloudy over the week then the prior week's NDVI, if available, was substituted.

Daily gridded climate surfaces of precipitation and minimum and maximum temperature at 20 km (prior to 2002) and 10 km (from 2002) spatial resolution were obtained from the Bureau of Meteorology [17] and re-sampled to 1 km spatial resolution using a cubic-convolution interpolation.

C. *The GAPP model*

GAPP values for 1994 to 2006 were calculated from weekly estimates of pasture growth rate (PGR) derived using satellite images, climate data, and a light-use efficiency (LUE) model [18], as described in detail by [7]. This method is distinguished by LUE values which are constrained by climate indices. PGR was validated within the study area by the Department of Agriculture and Food WA (DAFWA) using approximately 25-30 ground sites per year since 1995 [19].

PGR calculated at 1 km and 250 m spatial resolution from the AVHRR and MODIS NDVI datasets was masked for pixels which contained greater than 30% woody vegetation as determined from the 25 m landuse dataset [20]. The Perth metropolitan region was also masked using the appropriate SLAs. PGR was not masked explicitly for urban areas, rivers or roads, as visual examination of the dataset showed that these land classes typically contain a high proportion of woody-vegetation and so were captured by the woody vegetation mask, or are assumed to be small and have minimal impact on the PGR. The resulting PGR represents the mixed pasture and crop (e.g. wheat) agriculture typical to the study area. Weekly PGR was summed across each year to derive GAPP (Fig. 1).

D. *Spatial Partitions*

The three different spatial partitioning schemes for aggregating pixels values within an individual image to coarser regions are as follows:

1. Biogeographic regions for the study area were determined from the IBRA dataset from the Australian Government Department of the Environment and Water Resources [14], which divides Australia into 85 regions and 404 sub-regions based on major geomorphic and environmental features.

2. SLAs are artificial boundaries that are not derived from environmental parameters. The Australian SLA dataset [15] are created based on population statistics, and generally follow local government boundaries.

3. Regions with similar total annual precipitation were determined from the time-series of total annual precipitation by applying a clustering algorithm and a maximum-likelihood classification. The 18 parent classes were further classified into 4 coarser classes based on the minimum distance between classes. The results of this statistical classification are not spatially contiguous.

E. *Spatio-temporal analysis*

The three spatial partitioning schemes were used to aggregate pixel values from each of the 13 GAPP images, (1994 to 2006) resulting in a time-series of GAPP statistics (i.e. mean, standard deviation, and the coefficient of variation) for each region in each partitioning scheme. Individual pixel time-series were not examined because the spatial heterogeneity makes these trends too noisy, and so negates the benefits of using an aggregation method.

To identify whether a positive or negative monotonic trend existed in the aggregated time-series data we used a Kendall's Tau test [6][11] which is non-parametric and insensitive to outliers, and does not assume that the data are normally distributed [21]. The statistic is calculated on the rank correlation between successive pairs of values in the time-series. Values of Kendall's Tau around zero indicate that no trend exists, positive values indicate that a positive trend exists, and negative values indicate that a negative trend exists.

III. RESULTS AND DISCUSSION

A. *Spatio-temporal analysis of GAPP and precipitation*

The coefficient of variation of GAPP (Fig. 2a) and precipitation (Fig. 2b) within each of the IBRA regions was used to compare data between disparate regions. From approximately 2002 there is a distinct change in behaviour of the coefficient of variation in GAPP in many of the regions within the SWWA (Fig. 2a). It is possible that these trends have environmental source or anthropological causes due to shifts in landuse, although this can not be determined from these datasets. A possible source of the change of behaviour in

GAPP was the introduction of the MODIS dataset in 2002. The spectral sensitivity of MODIS to chlorophyll is significantly greater than that for AVHRR. However, rather than moving to a new and constant state, the GAPP trends that start around this time continue to change throughout the time-period when MODIS data is used, so this is unlikely to explain the change.

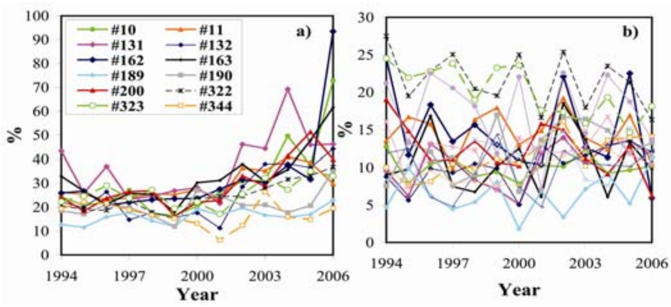

Figure 2. Time-series of the coefficient of variation of (a) GAPP and (b) precipitation, calculated within each of the IBRA regions.

Fig. 2b highlights that individual regions have different inter-annual behavior of total annual precipitation, without the consistent temporal pattern that was seen for GAPP (Fig. 2a). While total annual precipitation will capture coarse differences between regions (as seen in the precipitation classification), for pasture growth it is the intra-annual timing and amount of the precipitation that is important. Future analysis should examine seasonal precipitation patterns and trends.

Figs. 3-5 allow visualization of spatial-temporal patterns across the study area by mapping the Kendall's Tau statistic calculated from the time-series of region average and region standard-deviation of GAPP and precipitation. The trends in GAPP and precipitation are not distributed evenly across the landscape (Figs. 3a-d). Across most of the inland and more northern coastal regions there are decreasing trends in GAPP, whereas for most south-western and south coastal regions there were increasing trends in GAPP (Fig. 3a). Except for one south-west coastal region, all regions displayed an increase in variability of GAPP over the study period (Fig. 3b).

Except for south eastern regions there were negative trends in precipitation, with the greatest declines being on the west coast and the south west corner (Fig. 3c). The trends in precipitation did not mirror trends in GAPP, but regions with decreasing trends in GAPP (Fig. 3a) generally had increasingly variable precipitation (Fig. 3d).

Pasture growth in the SWWA is heavily influenced by the amount and timing of seasonal precipitation but the water-logging common in this area [16] can also limit growth. A reduction in water-logging is a possible explanation for the south-west regions that have increasing trends in GAPP but decreasing trends in total annual precipitation.

B. Spatial Partitioning Schemes

In addition to using the IBRA regions and sub-regions the GAPP time-series was also analysed using the classification calculated from precipitation (Fig. 4) and SLAs (Fig. 5). The three aggregation schemes reveal how the size and shape of regions affects the resulting analysis; all schemes show the same general patterns, but alter how the trends can be related to the underlying landscape processes.

For example, the coarse-scale 4-region precipitation classification (Fig. 4) divides the landscape up into zones of similar total annual precipitation that roughly correspond to the distance from the coast. Within these coarse-scale precipitation zones the aggregated GAPP has distinct trends, but the coarse-scale zones do not capture more localized variables such as the water-holding capacity of the soils. This highlights the benefit of using a multi-level ecoregionalizations such as the IBRA which integrates both landscape and climatic factors, as well as using aggregation regions at the appropriate spatial scale for the analysis. However, the GAPP analyzed using precipitation classes (Fig. 4a) shows that the northern coastal IBRA regions cut across precipitation zones in the north, so finer-scale regions are needed.

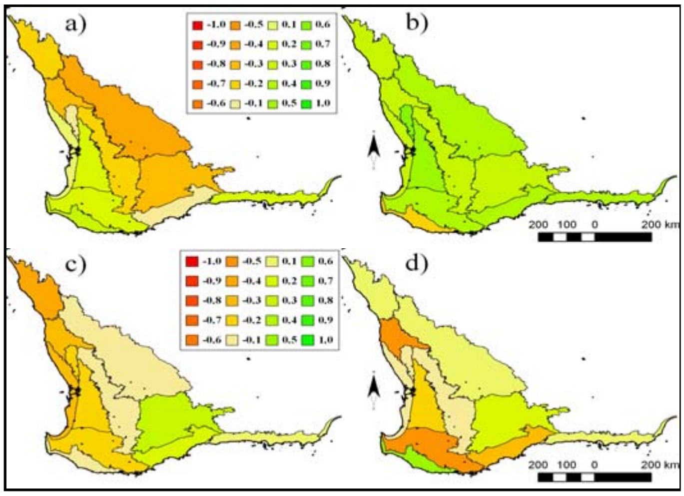

Figure 3. Map of the Kendall's Tau statistic for each IBRA sub-region calculated from the time-series of a) region-average GAPP, b) within-region standard-deviation of GAPP, c) region-average precipitation, d) within-region standard-deviation of precipitation.

When the GAPP dataset was analysed using the SLAs (Fig. 5) the fine-scale of the regionalization is more appropriate to capture fine-scale landscape processes and the data can be more easily related back to the legal and administrative boundaries frequently used for decision making. The spatial-scale of the SLAs is fine-enough to see local regional detail; ideally ecoregions at the same spatial scale would be used, but the IBRA regions only go to the scale of the sub-regions used here. However, anthropological boundaries of SLAs should be used with caution in environmental analyses because they may not match up with landscape processes. For example, in the SWWA study area the SLAs often are orientated west-east based on settlement patterns, and frequently contain large environmental differences dominated by changes in the precipitation distribution inland from the coast.

One aggregation scheme that was not used here were the Agro-Ecological regions for Australia which represent both eco-climatic factors and farming systems [22]. These regions are calculated by amalgamating SLAs to coarser regions using climate, landform, lithology, soil, natural vegetation, land cover, and information such as the major farming system.

While these regions do combine environmental and anthropological variables, they are still restricted by the underlying SLAs. An alternate approach to generate regions for agricultural analysis would be to include the time-series of GAPP in addition to the eco-climatic variables that are used in many schemes.

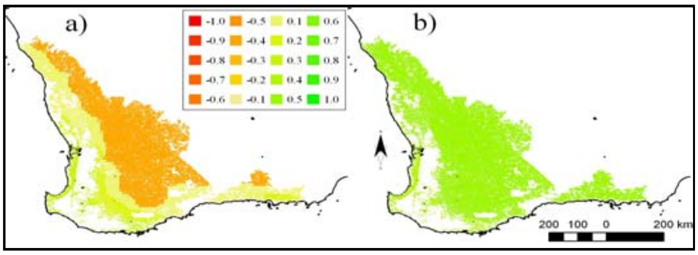

Figure 4. Map of the Kendall's Tau statistic calculated from the time-series of a) region-average GAPP, b) within-region standard-deviation of GAPP, for the precipitation-classification regions

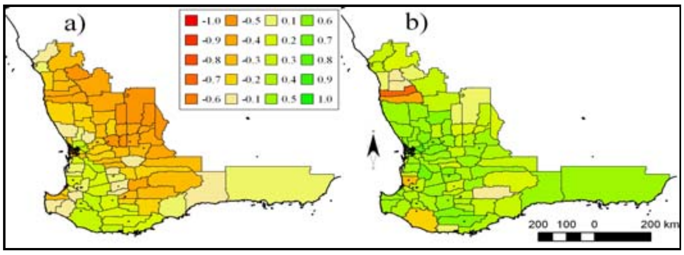

Figure 5. Map of the Kendall's Tau statistic calculated from the time-series of a) region-average GAPP, b) within-region standard-deviation of GAPP, for SLAs

IV. CONCLUSIONS

Our results demonstrate trends in GAPP that may be indicative of broader trends in climate change for the SWWA. The GAPP time-series showed a distinct change in behaviour starting around 2002 associated with a corresponding increase in the within-region variability of GAPP over the same period. Across many northern-coastal and inland cropping (wheatbelt) regions there were decreasing trends in GAPP, whereas for the south-western regions GAPP tended to increase.

GAPP is calculated from observations of vegetation, so it is a good indicator of what actually occurred in the landscape. Further analysis of these data at finer spatial scales would highlight regions of similar circumstances; some declining, some improving, and others with large GAPP fluctuations. These changes may be due to climate changes, whether increasing, decreasing, or more variable, but changes in GAPP may also be due to the modification of farming practices to suit shifts in economic conditions. Future work will look at sub-annual time-steps so that the seasonal profile of GAPP and the sub-annual timing of precipitation events can be more closely linked, as well as exploring the optimum regionalization for GAPP analysis..

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REFERENCES

[1] M. Kumar and J.L. Monteith, "Remote Sensing of plant growth. In Plants and the Daylight Spectrum," H. Smith, Eds. London: Academic Press, 1981, pp. 133-144.

[2] A. Ruimy, B. Saugier, and G. Dedieu, "Methodology for the estimation of terrestrial net primary production from remotely sensed data", J Geophys Res, vol. 99, pp. 5263-5283, 1994.

[3] C.J. Tucker, "Red and photographic infrared linear combinations for monitoring vegetation", Remote Sens Environ, vol. 8, pp 127-150, 1979.

[4] P.S. Thenkabail, R.B. Smith, and E. De Pauw, "Hyperspectral vegetation indices and their relationships with agricultural crop characteristics," Remote Sens Environ, vol. 71, pp. 158-182, 2000.

[5] K. Kidwell, "NOAA Polar Orbiter Data User's Guide. NCDC/SDSD," National Climatic Data Center, Washington, DC, 1998.

[6] R.N. Handcock and F. Csillag, "Ecoregionalization assessment: spatio-temporal analysis of net primary production across Ontario," Ecoscience, vol. 9, pp. 219-230, 2002.

[7] M.J. Hill, G.E. Donald, M.W. Hyder, and R.C.G. Smith, "Estimation of pasture growth rate in south Western Australia from NOAA AVHRR NDVI and climate data," Remote Sens Environ, vol. 93, 528-545, 2004.

[8] S.K. Seelan, S. Laguette, G.M. Casady, and G.A. Seielstad, "Remote sensing applications for precision agriculture: A learning community approach," Remote Sens Environ, vol. 88, pp. 157-169, 2003.

[9] S.W. Todd, R.M. Hoffer, and D.G. Milchunas, "Biomass estimation on grazed and ungrazed rangelands using spectral indices", Int J Remote Sens, vol. 19, pp. 427-438, 1998.

[10] C. Armhein, "Searching for the elusive aggregation effect: Evidence from statistical simulations", Environ Plann A, vol.27, pp.105-119, 1995

[11] R.N. Handcock and F. Csillag, "Spatio-temporal analysis using a multi-scale hierarchical ecoregionalization", Photogramm Eng Rem S, vol. 70, pp. 101-110, 2004.

[12] K.M. de Beurs and G. M. Henebry, "Land surface phenology and temperature variation in the International Geosphere–Biosphere Program high-latitude transects", Glob Change Biol, vol. 11, pp. 779-790, 2005.

[13] V.V. Salomonson, W.L. Barnes, P.W. Maymon, H.E. Montgomery, and H. Ostrow, "MODIS: Advanced facility instrument for studies of the earth as a system", IEEE T Geosci Remote, vol. 27, pp. 145-153, 1989.

[14] "IBRA Version 6.1", Australian Government, Department of the Environment and Water Resources, Canberra, Australia, 2007.

[15] "Australian Standard Geographical Classification (ASGC)", Cat. 1216, Australian Bureau of Statistics, Canberra, Australia, 2006.

[16] N. Schoknecht, "Soil groups of Western Australia - a simple guide to the main soils of Western Australia, 3rd Ed", Technical Report No. 246. Department of Agriculture Western Australia, 2002, pp. 122.

[17] Australian Bureau of Meteorology, http://www.bom.gov.au/weather/

[18] J.L. Monteith, "Climate and the efficiency of crop production in Britain", Philos T Roy Soc B, vol. 281, pp. 277-294, 1977.

[19] G.E. Donald, A. Edirisinghe, R. Craig, D.A. Henry, S. Gherardi, and R. Stovold, "Advantages of TERRA MODIS imagery over AVHRR to quantitatively estimate pasture growth rate in the south west region of Western Australia", Proc. 12th Aust. Remote Sensing & Photogrammetry Conference, Fremantle, October 18-22nd 2004, pp. 917-926, 2004.

[20] S. Furby, "Land Cover Change: Specification for remote sensing analysis", National Carbon Accounting System, CSIRO, Technical report No. 9, 2002, pp. 402.

[21] C. Leach, Introduction to Statistics: A nonparametric approach for the social sciences. New York: Wiley, 1979, pp. 330.

[22] J. Williams, R.A. Hook, and A. Hamblin, "Agro-ecological regions of Australia: methodologies for their derivation and key issues in resource management", CSIRO Land and Water, Canberra, 2002, pp. 84.