Final Report Biomass Business – Activity 2a “Pasture Use Efficiency-East Coast”

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Executive summary

There has been relatively widespread adoption of innovations such as guidance and auto-steer and to a lesser extent yield monitoring, remote sensing and site specific management (SSM) of inputs in the grains and horticultural industries. In contrast, the grazing-based livestock industries, primarily the red-meat, wool and milk production systems, have yet to fully explore the potential of similar "precision agriculture" (PA) technologies.

There are a number of reasons for a lack of development and adoption of these innovations. One standout issue is the complexity that graziers face when managing the interactions between soil, plant and animal systems that make up pasture and rangeland operations. In those industries which have taken up PA innovations, the focus is largely on monitoring and managing the spatial and temporal variation found in the soil and plant systems. Pasture and rangeland livestock producers have to deal with variability in the soil and plant systems, but also face the added complexity that the animal system brings as it interacts with these factors. Monitoring and managing the spatial and temporal variability in the animal system in terms of its interaction with the landscape remains one of the most challenging issues for graziers, however it also offers an opportunity to increase operational efficiency. Furthermore, PA livestock systems provide opportunities to increase production through increased monitoring of individual animal productivity and better management of animal health and nutrition.

This project within the CRCSI sought to address several of these challenges.

As part of the CRCSI Biomass Business Project the "Pasture utilization – high rainfall high input pastures" project sits within the Activity 2 "Tools for improved pasture use efficiency" section. This project sought to explore the following broad objectives and research questions:

Objective (#2 of BB) - Create large and small scale, spatially-enabled, measurement and interpretation protocols, and a knowledge/data access system, for managing stocking rate on monoculture and composite grazing lands (including rangelands) based on measures of pasture growth and availability, as well as time-based growth and grazing demand models.

Question (#2 of BB) - How may remote and proximal biomass sensing technologies, spatially-referenced livestock grazing behaviour data, and pasture production/grazing demand models be deployed to improve whole of landscape management efficiency, productivity and sustainability in high-rotation/high-input and rangeland pastures?

To address these broad objective a coordinated series of projects were developed based around three key work packages:

1. Spatial variability in grazing systems and the implications for management;
2. Spatially enabled livestock management; and
3. Calibration of Active Optical Sensors for pasture biomass.

The following summary outlines the research questions, key findings, industry relevance and future directions of each work package.

1. Spatial variability in grazing systems and the implications for management

Research question

What is the spatial variability in key soil nutrients in grazing systems?

Key outcomes

Substantial variation was found in key nutrients (P, K & S) with CV ranging from 35 to 66%. While average nutrient levels appeared adequate up to 55% of the improved paddock and 78% of the native pasture was potentially responsive to fertiliser.

Industry relevance

There is a significant opportunity for site specific fertiliser management in pastures to improve the efficiency of use of fertilisers. Given that both field surveyed in this study had large areas that did not require nutrient addition the blanket application of fertiliser is clearly inefficient.

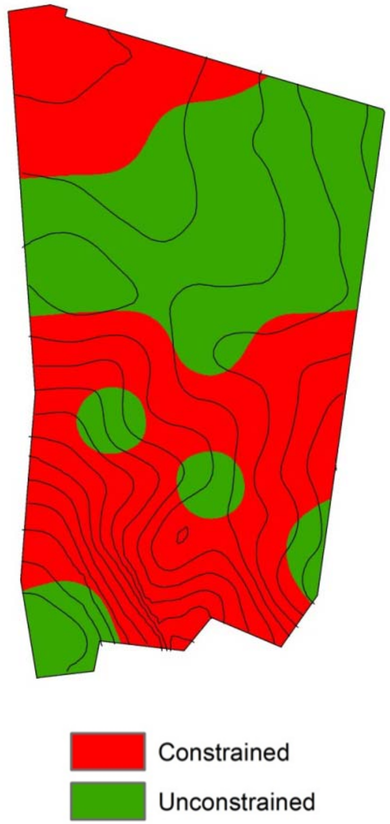
"I believe the potential for variable rate fertiliser and lime in pastures is even greater than in cropping lands"

Tim Neale (PrecisionAgriculture.com.au)

Future directions

More research is require to quantify the extent of variation in nutrients across different pasture types and evaluate the economic benefits of developing site specific management strategies for grazing systems.

UNE currently has research projects underway investigating similar issue in the dairy industry which may have even bigger opportunities.



A nutrient constraint map for a typical field on Sundown Valley. 55% requires fertiliser whilst the remainder does not need nutrient input. Understanding this variation and accounting for it in fertiliser application could result in significant savings

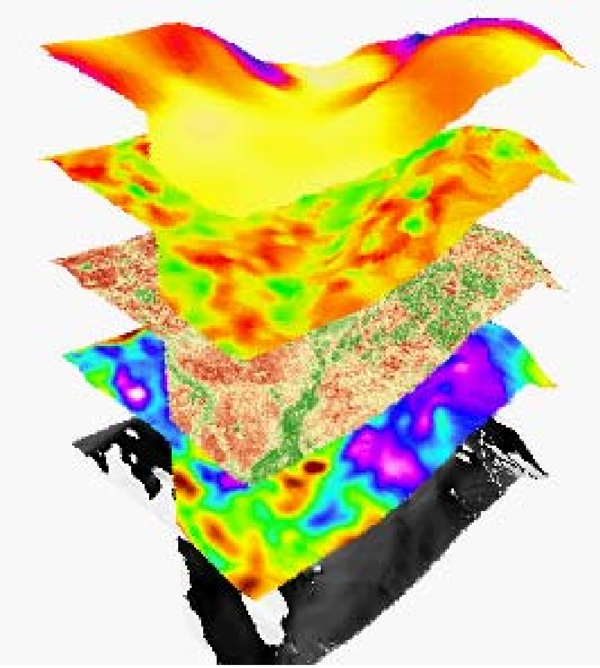
Research question Can PA sensors be linked to key soil nutrients to enable site specific management?

Key outcomes Numerous sensors including EM38, NDVI derived from Active Optical Sensors, elevation mapping and GPS livestock tracking were correlated with soil nutrient status. Single sensor correlations achieved R2 of up to 0.42 (K using elevation), multiple regressions of combined sensors achieved correlations of up to R^2 = 0.58 (K using elevation, EM38 and GPS livestock tracking).

Industry relevance Understanding which sensors provide the key information about soil nutrients will enable the development of zonal fertiliser management strategies. This could result in substantial savings for the grazing industry for which fertiliser is one of the largest inputs.

Research into the development of site specific management strategies for fertiliser in pastures was listed as the number 1 priority in a recent MLA report (B.GSM.0004) in to the potential for information technologies in grazing systems.

Future directions Whilst this study has demonstrated that some relationships exist between common PA sensors a substantial body of research will be required to continue this. The focus of future research should be on identifying the spatial variation in response to fertiliser addition and how sensors can be used to detect and manage this.



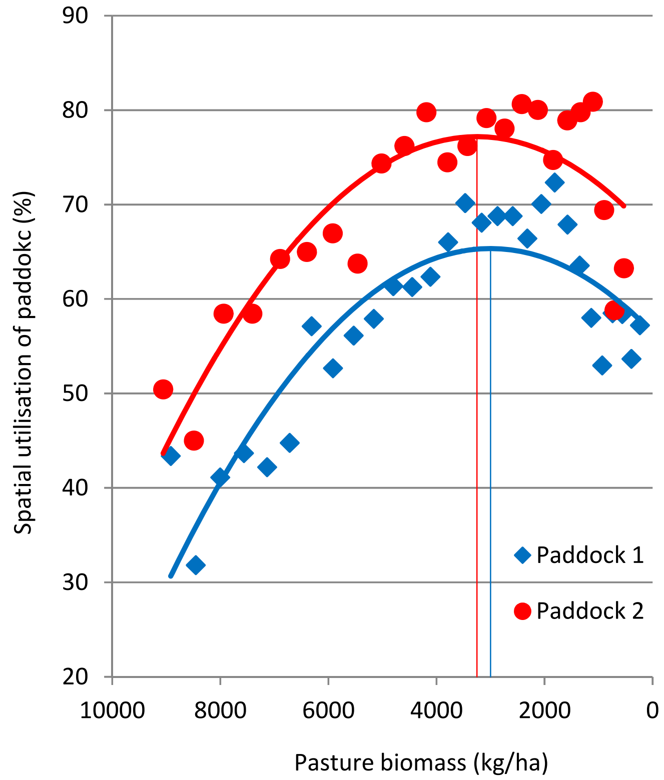
Data from numerous sensors including GPS tracking of livestock can help understand nutrient concentration areas. Correlations (R^2) of up to 0.58 where found between modelled sensor data (shown above) and key soil nutrients in this naturalised pasture paddock.

2. Spatially enabled livestock management

Research question Can spatio-temporal data be used to understand the relationship between animal behaviour and available pasture biomass?

Key outcomes Several key behavioural metrics have been developed that can be applied in commercial livestock monitoring system. These include: grazing time – as derived from a speed based model; spatial landscape utilisation – as derived from mapped positional data; and social Interaction – as derived from either MCP or IHD analysis.

Industry relevance Integration of these models into real-time livestock monitoring systems could revolutionise animal production systems. Both Twynam Agriculture and Sundown Pastoral will be investing in systems when they become commercially available (pers comm. Luke Gleeson and Matthew Monk).



Behavioural models such as the spatial utilisation of paddock have a strong relationship with the amount of pasture biomass available. Linking these models with real-time GPS data from ear tag tracking systems will provide key information for graziers seeking to optimise pasture use efficiency.

Future directions While it is unlikely that the actual values and thresholds developed in this study will be transferable to other situations and commercial tools these models will be. If commercial systems can be developed that provide the data (spatio-temporal) then these models could be implemented and the thresholds customized for the particular property on which it is deployed. Research will be required into how these system can be implemented and optimised on farm.

Research question Can we determine key animal behaviours from spatio-temporal data?

Key outcomes The development of cattle and site specific speed models was found to be feasible in research settings. A speed based model was developed classifying behaviours above 0.025 m/s as grazing and below this threshold as non-grazing. The process developed here could be adapted to produce behavioural models for commercial tracking systems when they are made available.

Industry relevance As well as modelling grazing behaviour producers are also interested in the development of models that provide alert status to disease, predation and stock theft. An estimation by Meat and Livestock Australia has suggested that real-time monitoring of a disease such as ryegrass toxicity could save producers up to $120 / ha. Livestock theft costs the industry $72m and predation costs $80m per year, spatially enabled livestock management systems could significantly reduce the impact of these challenges.

Future directions Research in this field is expanding rapidly as both technology developers and research institutions seek to take advantage of the developments in GPS and other positioning systems. UNE has several flow on projects looking at the use of animal behavioural modelling for disease detection in sheep and landscape productivity mapping in grazing systems.

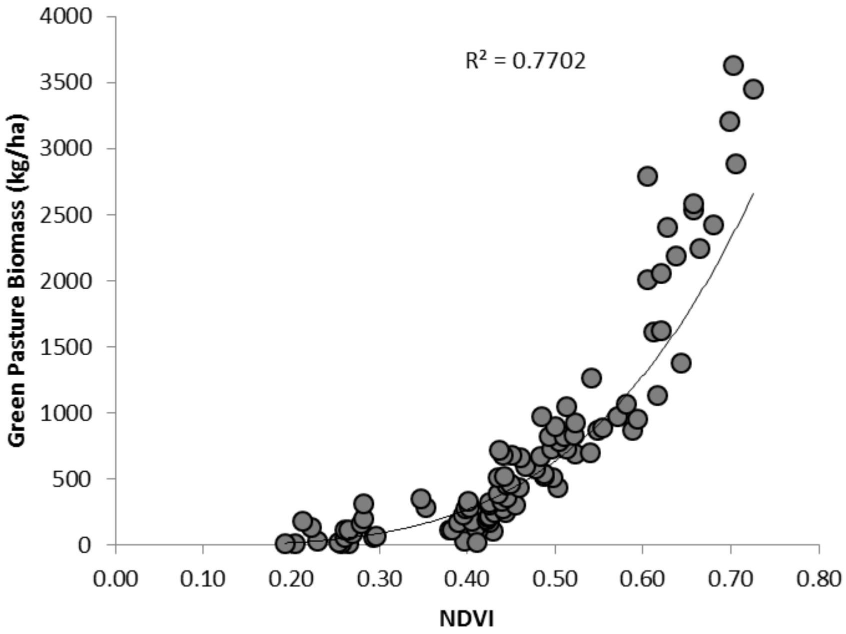
Significant private and public funding is likely to spent on the development of technologies and modelling in the next few years.

Real-time spatially enabled livestock management technologies such as this Taggle System are being developed. The challenge is to take the raw data and turn it into meaningful metrics. This study found that simple speed data could be used to accurately model the grazing behaviour of cattle.

3. Calibration of Active Optical Sensors for pasture biomass

Research question Can active optical sensors (AOS) be used to provide a measure of pasture biomass?

Key outcomes Active Optical Sensors (AOS) were found to measure green dry biomass with accuracies (RMSE) of between 216 and 288 kg/ha. This compares favourably with many of the 'traditional' non-destructive pasture measurement techniques. AOS provide the added benefit of being able to be deployed as on the go sensors in difficult terrain where other sensors will struggle.



Active Optical Sensors generate spectral indices such as NDVI which can be calibrated to the green fraction of the pasture sward. The accuracy of these sensors has so far proven similar or better than other more traditional pasture sensing systems.

Industry Relevance A recent MLA report (B.GSM.0004) concluded that the accurate and objective measurement of pasture biomass is a key requirement for producers seeking to increase grazing system productivity. Provision of accurate estimates of pasture biomass allows graziers to better meet the feed requirements of their livestock, directly increasing red meat production. The recently commenced Biomass Business 2 project had over 20 producer groups express interest in being involved in the development of AOS for pasture biomass assessment.

Future directions The CRCSI has recently established a project co-funded by Meat and Livestock Australia examining the potential for AOS in red-meat grazing systems. Dairy Australia have expressed interest in extending this project.

Research question

What is the potential for active optical sensors to provide biomass estimation in improved and native pastures across different seasonal conditions?

Key outcomes

Seasonal variation was found to be an important factor in the calibration accuracy of AOS. This project evaluated the effects of extreme variation in the green to dead composition on AOS calibrations. When swards contained high dead fraction (>85%) AOS was unable to accurately estimate the green fraction. Although previous research had suggested that this sensor may struggle on native swards this study found better than expected relationships could be achieved.

Industry relevance

For a sensor to be practically useful to graziers the limitations under which it can be deployed must be established. This project has confirmed that swards with a high proportion of senescent material will not be suitable for deployment of AOS. This project has also demonstrated that the sensor may be suitable for native pastures given appropriate guidelines.

Future directions

The new CRCSI "BB2" project is investigating and quantifying the limitations of AOS. This project has highlighted the potential need for seasonal calibrations and this is a key focus of the new research going forward.

Recent developments in technology have evolved active optical sensors at a price point within the reach of grazing producers. The new Trimble Greenseeker handheld is being evaluated for its potential use in pastures.

Research question How accurate can an Active Optical Sensor theoretically be in predicting pasture biomass?

Key outcomes

This exercise has demonstrated that there is a very strong relationship between an AOS sensor and green dry biomass under constrained conditions. For both oats forage and fescue pasture the relationship between NDVI and GDM was regularly found to be higher than an r-square of >0.95 and when considering the predictive capabilities of the models an accuracy of COV = 15% was achieved.

Industry relevance

Testing an evaluating AOS under these conditions provides firm evidence that these sensor have the potential to provide accurate estimates of pasture biomass. The challenge now remains to determine how repeatable these relationships are across different sites and different seasons where plant morphology can vary.

These sensors also have significant potential in the development of productivity maps for integration into site specific management of nutrients

Sampling protocols were developed to evaluate the theoretical accuracy of AOS. Under these constrained conditions correlations (R^2) over >0.95 were achieved for forage oats and up to 0.99 for fescue pastures.

Future directions

The new CRCSI "BB2" project is building on the research undertaken in this study to evaluate the potential accuracy of new AOS including theTrimble Greenseeker handheld device.

Contents

Project overview, scope of works and partner involvement

Activities and Outcomes

The "Pasture utilization – high rainfall high input pastures" project sits within the Activity 2 "Tools for improved pasture use efficiency" section of Biomass Business. This project sought to explore the following objectives and research questions:

Objective (#2 of Biomass Business)

Create large and small scale, spatially-enabled, measurement and interpretation protocols, and a knowledge/data access system, for managing stocking rate on monoculture and composite grazing lands (including rangelands) based on measures of pasture growth and availability, as well as time-based growth and grazing demand models.

Question (#2 of Biomass Business)

How may remote and proximal biomass sensing technologies, spatially-referenced livestock grazing behaviour data, and pasture production/grazing demand models be deployed to improve whole of landscape management efficiency, productivity and sustainability in high-rotation/high-input and rangeland pastures?

Work packages

To achieve these objectives a series of three work package were developed with specific objectives:

1. Spatial variability in grazing systems and the implications for management

Original detail from Gantt chart

2a. An understanding of the impact of cattle grazing behaviour (biomass consumption, nutrient redistribution) on pasture utilisation and management (rotation frequency, fertiliser management) in high-input/high-rainfall systems; 2a.i Establish field sites (baseline EM38, soil nutrients, biomass; weather station) 2a.ii GPS collar (i) fabrication, (ii) deployment, (iii) calibration to grazing behaviour, and (iv) ongoing data analysis 2.a.iii Integration of baseline paddock and GPS tracking data , spatial nutrient maps (i) derived and (ii) variable rate prescription fertiliser maps delivered, final report

2. Spatially enabled livestock management: increasing pasture utilization in rotational grazing systems

Original detail from Gantt chart

2.1 PhD: Pasture utilisation/nutrients (Jess Roberts) (Commenced early 2010)

3. Calibration of Active Optical Sensors for pasture biomass

Original detail from Gantt chart

2b. Calibration of NDVI to pasture biomass (including temporal dynamics) for key pasture species in eastern Australia 2b.i (i) Fieldsites established, (ii) build sensor rig, (iii) field surveys for biomass, energy content/digestibility, (iv) calibrations derived/refined, final report

Partner and Student Involvement

Activity work packages are divided amongst project partners as summarized in Table 1 with the geographic extent of activities depicted in Figure 1. PhD and Honours research students involved in the project are listed, along with supervisors and their current status in Tables 2 and 3.

Work package distribution amongst partners

Project Manager/Coordinator:	Dr Mark Trotter (UNE-PARG)
Industry Coordinator:	Matthew Monk (Sundown Pastoral Company)
1. Spatial variability in grazing systems and the implications for management	Dr Mark Trotter (UNE-PARG) Matthew Monk (Sundown Pastoral Company) Prof David Lamb (UNE-PARG) Dr Greg Falzon (UNE-C4D) Dr Chris Guppy (UNE-PARG) Graham Donald (UNE-PARG) Peter Morrison (Twynam Agriculture)
2. Spatially enabled livestock management: increasing pasture utilization in rotational grazing systems	Dr Mark Trotter (UNE-PARG) Prof David Lamb (UNE-PARG) Matthew Monk (Sundown Pastoral Company) Dr Greg Falzon (UNE-C4D) Prof Geoff Hinch (UNE-PARG)
3. Calibration of Active Optical Sensors for pasture biomass	Dr Mark Trotter (UNE-PARG) Prof David Lamb (UNE-PARG) Graham Donald (UNE-PARG)

	Luke Gleeson (Twynam Agriculture)

PhD research students

Research Student & Status	University and Industry Supervisors:
1. Jess Roberts PhD (UNE-PARG) – *In progress* (UNE/APA Scholarship)	Dr Mark Trotter (UNE-PARG) Prof Geoff Hinch (UNE-PARG) Prof David Lamb (UNE-PARG) Prof Geoff Hinch (UNE) Dr Greg Falzon (UNE-C4D) Matthew Monk(Sundown Pastoral Company)

Honours research students

Research Student & Status	University and Industry Supervisors:
Jamie Barwick B.Rural Science (Honours) Graduated 2012	Dr Mark Trotter (UNE-PARG), Prof Geoff Hinch (UNE-PARG)
Sam Anderson B Agricultural Science (Honours) (UniMelb/UNE) (CRCSI Travel Scholarship 2012) Graduated 2013	Dr Mark Trotter (UNE-PARG) Dr John Stanley (UNE-PARG) Dr Chris Guppy (UNE-PARG)
Josh Barron B Rural Science (Honours) (CRCSI Travel Scholarship 2012) Graduated 2013	Dr Mark Trotter (UNE-PARG) Dr Chris Guppy (UNE-PARG)
Mark Yerbury B Rural Science (Honours) Graduated 2013	Dr Mark Trotter (UNE-PARG) Professor Steve Walkden-Browne
Zac Economou B Rural Science (Honours) Graduated 2014	Dr Mark Trotter (UNE-PARG) Dr Robin Dobos (NSW DPI)
Sean Dickson B Rural Science (Honours) Graduated 2014	Dr Mark Trotter (UNE-PARG) Dr Robin Dobos (NSW DPI)

1. Spatial variability in grazing systems and the implications for management

Introduction

Spatially enabled agriculture in the form of Precision agriculture (PA) has been widely applied in the cropping and horticultural industries for decades. In contrast, there has been little development of similar strategies for the grazing industries. However, both researchers and producers can see potential benefits from increased productivity and pasture use efficiency that may arise from applying PA tools to grazing systems (Schellberg & Lock, 2009; Virgona & Hackney, 2008).

Conceptual frameworks have been developed for precision livestock (Emilio A. Laca, 2009) and precision grassland systems (Schellberg, Hill, Gerhards, Rothmund, & Braun, 2008) and, to lesser extent, integrated animal-plant systems (Hacker, Thompson, Murray, Alemseged, & Timmers, 2008) however these do not adequately integrate the range of contemporary and emerging PA technologies that can be used to monitor and manage the spatial variability in the soil, plant and animal components of a grazing system. This project sought to apply sensors and technologies available for monitoring the soil, plant and animal components systems in a grazing enterprise with a view to integrating datasets from these sensors to better inform PA management technologies in grazing systems.

This project focussed on understanding the potential that PA technologies might hold for better nutrient management in pastures and how the various sensors investigated might enable more efficient management of fertiliser applications.

This report is divided into two research questions:

1. What is the spatial variability in key soil nutrients in grazing systems?; and
2. Can PA sensors be linked to key soil nutrients to enable site specific management?

1. Evaluating the spatial variability of key soil nutrients in grazing systems

Introduction

Nutrient use efficiency has been identified as a key issue for Australian grazing systems (Simpson *et al.* 2011). The spatial variability of soil characteristics has been documented in pasture fields in other countries (McCormick *et al.* 2009; Fu *et al.* 2010) but has not been widely studied in Australian grazing systems (King *et al.* 2006). Furthermore, there are very few studies that have investigated the spatial variability of soil characteristics in relation to the constraints that they may have on pasture productivity (Stefanski and Simpson 2010). Understanding the spatial variability in soil nutrient and pH constraints could provide valuable insights into the potential for fertiliser management strategies on a landscape and sub-paddock scale. Of particular interest is the potential for site specific management (SSM) of fertiliser or ameliorants (Plant 2001). Historically, fertiliser has been applied uniformly over pastures with little consideration of the spatial variability that might exist in nutrient levels and potential response. SSM seeks to target inputs to those areas which are below critical thresholds or which will provide the greatest return per unit input. This technique is now commonly used in the cropping and horticultural industries (Cook and Bramley 1998; Plant 2001), however questions remain regarding how this management strategy might be implemented in Australian grazing systems (Trotter 2010; Trotter *et al.* 2010a; Simpson *et al.* 2011) and its potential benefits. This paper presents two spatial surveys of pasture fields for pH, phosphorus (P), potassium (K) and sulfur (S) with a particular focus on the effect that spatial variability of these factors may have on production, and discusses the potential implications for SSM of fertiliser in these grazing systems.

Materials and Methods

Site characteristics

The "improved" site was a 41ha field located near Kingstown NSW, Australia (30°28'S, 151°0'E). Soils were derived from granite parent material and the average annual rainfall is 766mm. The field has been sown and was dominated by introduced pastures species tall fescue (*Lolium arundinaceum Schreb*.syn and *Festuca arundinacea*). The field is currently used as a backgrounding enterprise (grazing steers prior to entering the feedlot) and is grazed as part of a rotational system. This field had a long history of being grazed by sheep prior to the implementation of a cattle only system. Long term fertiliser history was not available for this field however the general management strategy has involved high levels of P and S in previous years. The current management strategy involves the application of nitrogen fertiliser only.

The "native" site was a 47 ha field located near Armidale NSW, Australia (30˚25'S, 151˚38'E). Field elevation ranged from 1,050 to 1,100m with soils derived from granite parent material. The average annual rainfall is 800mm (BOM 2012). Native and naturalised pastures dominated the sward including *Microlaena stipoides* [(Labill.) R.Br.] , *Bromus* spp, *Vulpia* spp, *Imperata cylindrica*, and *Austrodanthonia* spp. The field has primarily been grazed by sheep and, to a lesser extent, cattle for all of its known history. Long term fertiliser history was not available for this field however the current management plan schedules an application of 125kg/ha of single superphosphate every second year.

Improved field
(a)

Native field
(b)

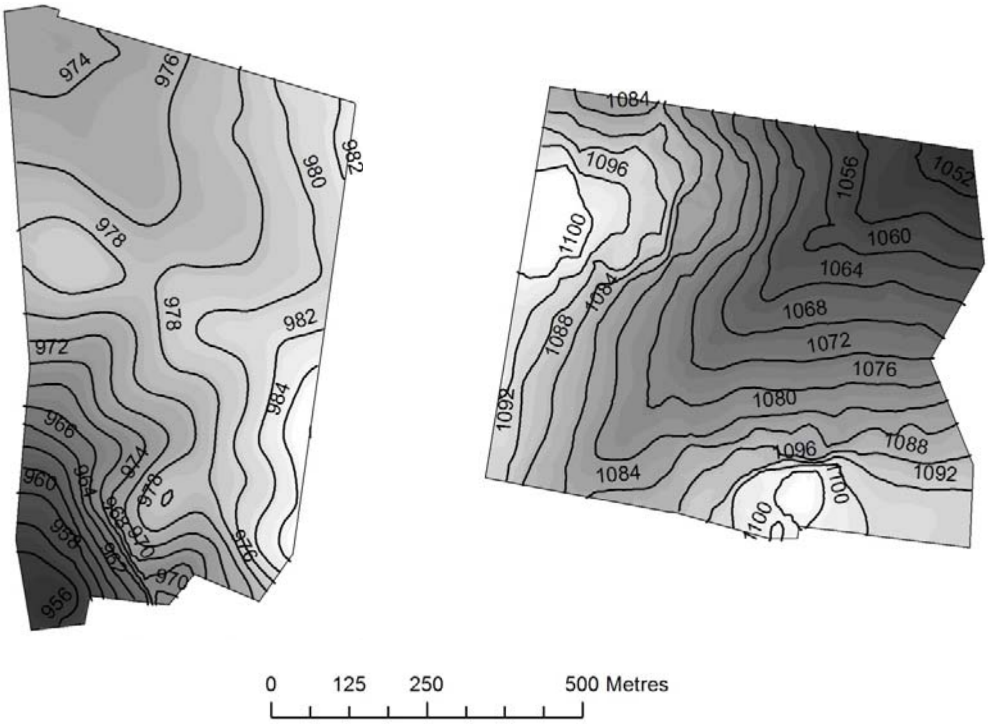


Figure 1 Interpolated elevation derived from Differential GPS survey of (a) an improved field (2 metre contour) and (b) a native pasture field (4 metre contour).

Elevation survey, interpolation and mapping

Both fields were surveyed for elevation using a differential GPS system (Trimble®) mounted on a quad bike. The improved field was surveyed on the 12 May 2011 and the native field on the 13 December 2012. Interpolation of the survey data was undertaken in Vesper (Whelan *et al.* 2001). Both fields were interpolated to a 1m grid using an exponential kriging model, with variable search radius and a neighbourhood of between 90 and 100 points. The Parkers field was surveyed at a transect width of 40 metres and a block size of 50 metres was used for calculation of the local variogram. The improved field was surveyed at a transect width of 25m and a block size of 30m was used for calculation of the local variogram. Both fields were subsequently converted to a 10 metre raster (mean) from which contour layers were developed (Parkers = 2m and Kirby = 4m). Map displays were created from the 1 metre grid (Figure 1).

Field sampling and laboratory analysis

Soil sampling of both fields were undertaken in May 2012 across a 100 m grid providing a total of 40 samples for the improved field and 41 samples for the native field. At each site 20 soil cores (20 mm wide and 100mm deep) were collected within a 1 metre radius of the sample point. Cores were homogenised and then a sub-sample taken for analysis. Soil samples were subsequently dried in an oven at 40oC and then ground to <2mm. Soil pH(1:5) was measured in water using a pH probe (Rayment and Lyons 2010). Phosphorus was assessed using the Colwell extraction method (Colwell 1963). Potassium was assessed using a standard 1M NH4Cl (pH 7) extraction (Rayment and Lyons 2010). Sulfur was assessed using the hot KCl40 method (Blair *et al.* 1991).

Analysis and mapping of soil test data

Descriptive statistics and frequency distributions of soil test data were developed for both fields including minimum, maximum and mean. Standard deviation was calculated for each field and soil characteristic along with a coefficient of variation (CV% = standard deviation/mean). The CV% provides a better measure of variability for comparing different fields and different soil analyses.

For the purposes of visualising the spatial variability of characteristics the soil test values were interpolated using spline fit with barrier (output cell size 1m, barrier was 50 m buffer on paddock boundary) in ArcGIS (ESRI, Redlands California). It should be noted that this interpolation process resulted in variations in minimums and maximums that in some cases exceed the actual sampled values. As a consequence the interpolated maps have been produced to explore general trends in spatial variability and not to provide accurate estimates of key soil attributes at un-sampled locations.

Determining the value of SSM

A simple approach for evaluating the potential of SSM of nutrients and ameliorants in pastures is to determine the variability against pre-determined thresholds. The value of SSM for these fields was assessed by comparing individual site soil test results with critical values. The following critical values were applied for each soil characteristic: P = 30 mg/kg (Holford and Crocker 1988), K = 0.2 cmol+ kg-1 (Peverill *et al.* 1999), S = 8 mg kg-1 (Blair *et al.* 1991) and pH (water) = 5.5 (Peverill *et al.* 1999). The proportion of the fields under the critical value was then calculated for each soil characteristic.

In addition to evaluating each soil factor individually the Sprengel-Liebig Law of the Minimum (LM - van der Ploeg *et al.* (1999)) was applied to this data to evaluate what proportion of the fields would be limited by one or more nutrients. We calculated the number of sample sites where soil characteristics were below the critical thresholds. Spatial representations of the LM were derived for each field and mapped on a 1 metre grid to enable visualisation of trends in constraint across each field.

Results and discussion

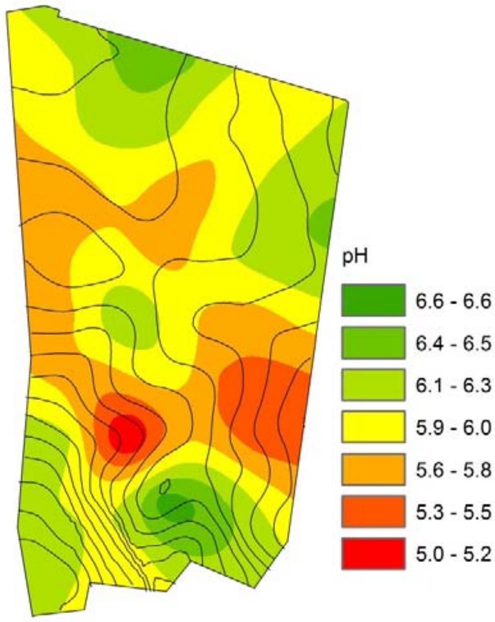
pH

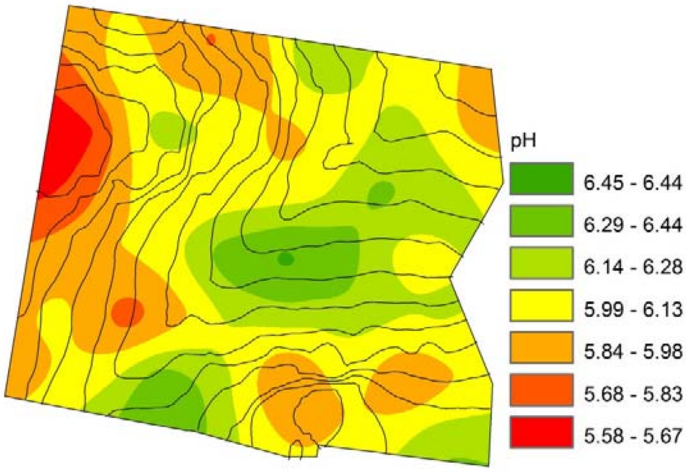
The pH across the two fields ranged from 5.0-6.6 and 5.7-6.4 for the improved and native sites, respectively. This range is generally less than that reported in other studies with King *et al.* (2006) finding a range of 4.4 to 6.8 in a naturalised pasture field in the southern highlands of NSW. Of all the soil characteristics assessed, pH demonstrated the lowest degree of variability with the CV of the improved and native fields below 5% (Table 1). This is similar to that reported by (Merry *et al.* 1990) who found the pH of numerous pasture fields to have a CV below 5%. However, the log transformation of the pH scale artificially lowers the CV (Merry *et al.* 1990). Back transformation of the pH to hydrogen ion concentration is likely to result in a CV similar to the other soil characteristics evaluated in this study. There does not appear to be any clear spatial trends in pH in the improved field with isolated areas of low pH occurring through the middle of the field. There is a more obvious spatial trend in the native field with lower pH evident at higher elevations, particularly on the hill on the western boundary of the field (Figure 2).

The mean soil pH values for the improved and native fields were 5. 9 and 6.1, respectively, and were above the critical pH value of 5.5 (Table 1). Lime would not be recommended if the assessment was based on these averages of each paddock. This is a valid assessment for the native field, in which, no individual sample had a pH below the critical value. However, in the improved field, 10% of the samples were below the critical pH value, which suggests a potential benefit from the addition of lime to these areas. It must also be considered that the measurements in the present study were from samples taken from surface soil, and pH values below the critical threshold might occur at depth. Both Stefanski and Simpson (2010) and Merry *et al.* (1990) recommended that SSM of lime would be of value in the pasture fields that they surveyed. The challenge remains in developing tools that can be used as predictors for pH, particularly at depth.

Improved field
(a)

Native field
(b)





(c)

(d)

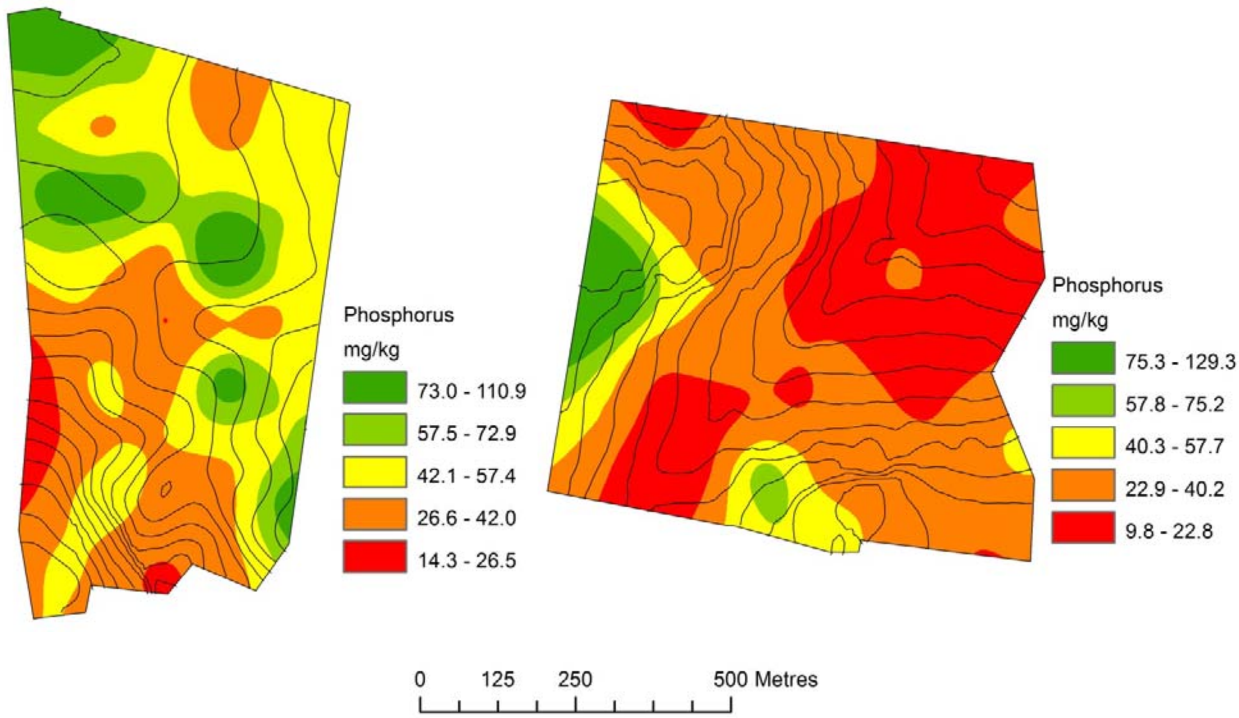


Figure 2 Spatial variability in (a, b) pH and (c, d) phosphorus across an improved and a native pasture paddock

Phosphorus

The range of P across each of the fields was similar with the native field having a marginally larger range (13.0-121.1 mg kg-1) than the improved field (19.3 – 110.6 mg kg-1) (Table 1). The CV of the native field was also higher at 58.5% compared to the improved field at 36.6%. The CV for the native field is comparable to other studies; Fu *et al.* (2010) and McCormick *et al.* (2009) reported a CV of 63% and 57%, respectively. While the CV for the improved field was relatively low, similar degrees of variability have been reported in other productive temperate grasslands (e.g. CV=24% by Shi *et al.* (2000)).

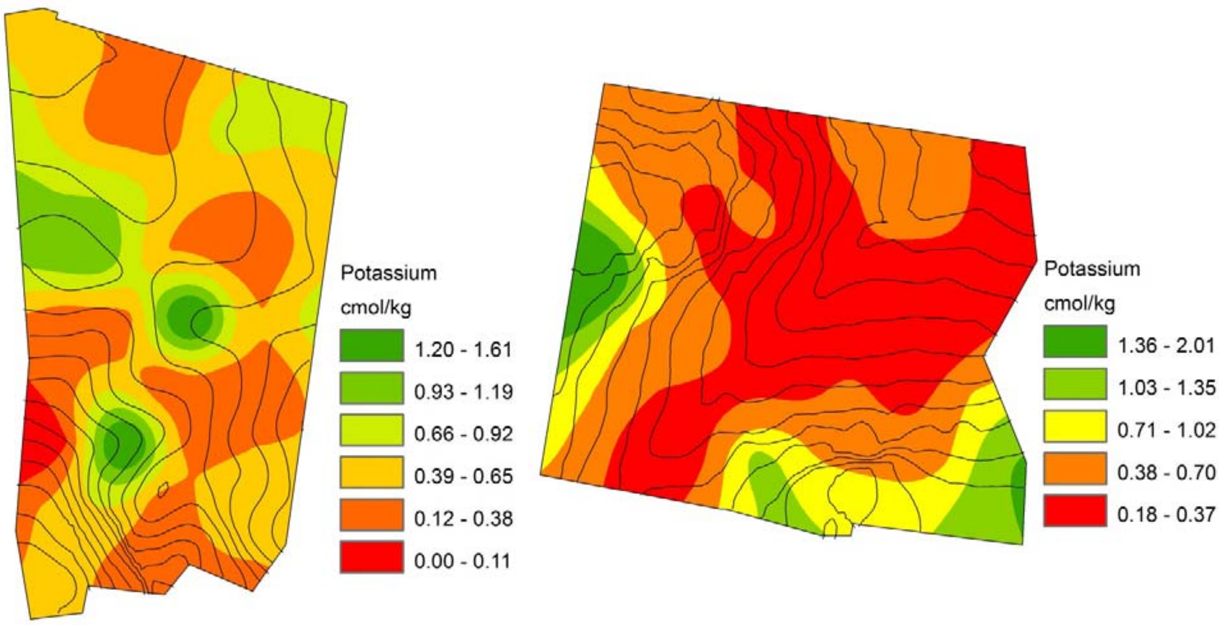
Lower P levels were associated with lower elevation in the native field (Figure 2). Also evident were concentrated patches of P at the highest elevations in this field (Figure 2). Similar elevation related trends have been reported previously (Robinson *et al.* 1983; McCormick *et al.* 2009; Schnyder *et al.* 2010). (Schnyder *et al.* 2010) examined the role that animals play in nutrient re-distribution and concluded that livestock are a key driver in the spatial variability of P, particularly the concentration of P at elevation. In Australia, concentrated zones of P at higher elevations in a field are commonly associated with livestock camping activities (Hilder 1964; Robinson *et al.* 1983; Taylor *et al.* 1987). This was supported in this study with sheep camping behaviour observed in areas of higher elevation in the native field.

In contrast, the association between elevation and soil P was less pronounced in the improved field with little observed influence of animal camping behaviour on soil P (Figure 2). A combination of higher stocking rates, rotational grazing, and the lower tendency of cattle to concentrate their camp areas is likely to have resulted in less pronounced zones of concentrated P at higher elevations. The higher soil P levels in the north western corner of the field might be a result of run-off and soil particle movement from the large and relatively steep catchment area above it (McCormick *et al.* 2009).

The mean soil P value for each field was above the critical P value (Table 1). However, a significant number of sites in each field had P values well above or below the critical threshold, and suggests potential for SSM of P inputs for both fields. The proportion of each field that was below the critical P value was markedly different. The improved field had only 7.5% of sites, whilst the native field had 56% of sites below the critical P value (Table 2). This is most likely explained by the fertiliser history of the two fields with the improved field subject to a higher and more frequent nutrient applications over many years. The result for the improved field suggests scope for SSM for maintenance applications of P; this would reduce wasteful applications in areas where the P status is well above the critical P value. Meanwhile the result for the native field suggests value in SSM of P additions beyond maintenance rates possibly suggest a significant opportunity to increase P use efficiency and productivity. As Simpson *et al.* (2011) has suggested this study does indicate a significant opportunity to increase P use efficiency and productivity in these grazing systems.

Improved field
(a)

Native field
(b)



(c)

(d)

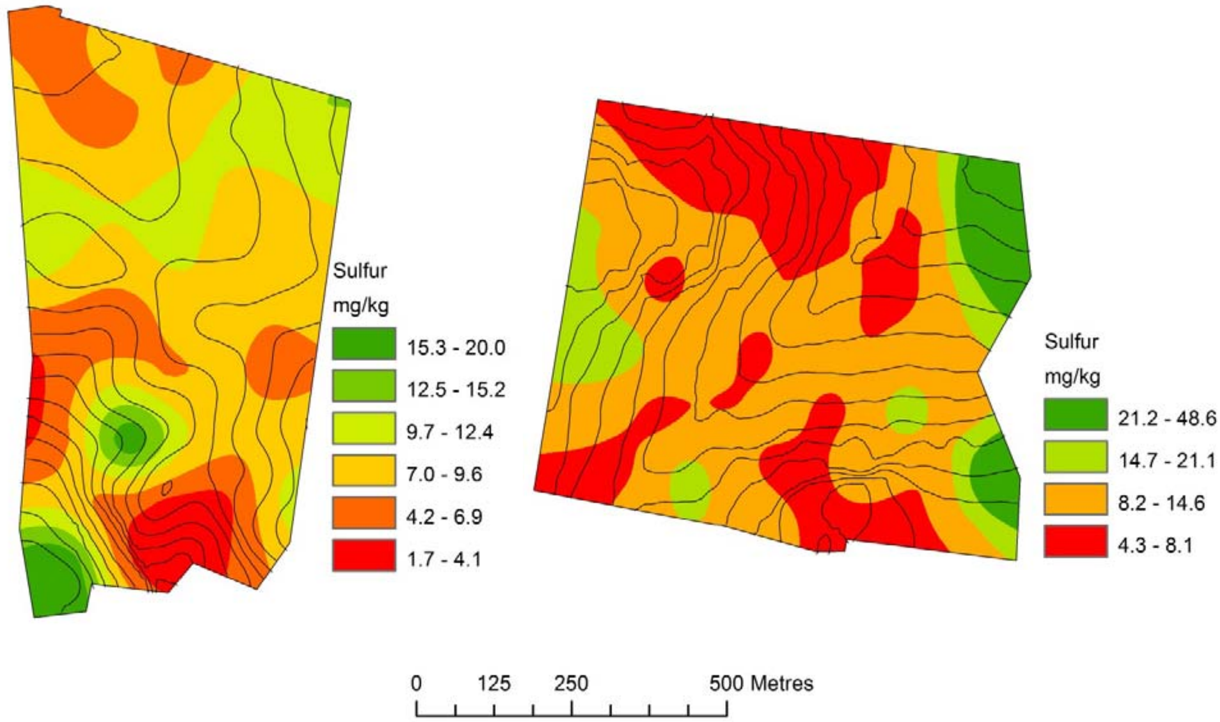


Figure 3 Spatial variability in soil (a,b) potassium and (c,d) sulphur across an improved and a native pasture paddock.

Potassium

The K values ranged from 0.11 to 1.61 cmol+ kg-1, and 0.19 to 1.89 cmol+ kg-1 for the improved and native fields, respectively. This was similar in range to that reported by Stefanski and Simpson (2010) although their maximum (~ 1.1 cmol+ kg-1) was lower. The CV for K in both fields was the highest of all the soil characteristics evaluated at 66.2% and 66.0% for the improved and native, respectively (Table 1). This is almost twice the CV reported for K by (Shi *et al.* 2000).

Of the four soil characteristics that were assessed, K had the strongest observable relationship with elevation in the native field. There was a clear trend between increasing K levels and increasing elevation (Figure 3), which was also reported by (Stefanski and Simpson 2010). Similar to P, particularly high K values were associated with sheep camps. In contrast to the native field, the improved field demonstrated a lower degree of association between elevation and K values (Fig. 3). There were some isolated areas of high k, however, there were no apparent causes. Several international studies have noted an increase in K levels around cattle watering points, shade trees and other points of attraction (Schomberg *et al.* 2000; Sanderson *et al.* 2010). Similar congregational behaviours have been observed in Australian grazing systems (Trotter *et al.* 2010b; Taylor *et al.* 2011). It is possible that these isolated areas of high K are related to the historical location of supplementary feed troughs which are moved randomly around this field. These supplementary feed sites provide two sources of K with increased deposition through concentration of urine and faeces and the direct loss of K from the actual feedstock. Potassium accumulates in hay and is easily washed out by rain, hence transfer to the soil is rapid from hay piles.

Similar to pH, only small areas of each field (7.5% and 2.4% of the improved and native, respectively) had K values below the critical threshold. This is in contrast to some of the fields surveyed by (Stefanski and Simpson 2010) where the majority of samples had K values below the critical level. Based on the survey values of the two fields in the present study, K appears to have the least potential for SSM. However, the strong relationship between K and elevation would otherwise have been a useful tool for creating SSM zones. Nevertheless, elevation might be a useful tool to identify zones for SSM of K in other fields, such as that reported by (Stefanski and Simpson 2010), in which there was both a strong trend between elevation and K, and K values were largely below the critical threshold.

Table 1 Descriptive statistics of key soil attributes for the improved and native pastures fields

Field	Soil characteristic	Minimum	Maximum	Mean	Standard deviation	CV
Improved	pH	5.0	6.6	5.9	0.30	5.0%
	Phosphorus (mg kg^{-1})	19.3	110.6	49.9	18.2	36.6%
	Potassium (cmol+ kg^{-1})	0.11	1.61	0.52	0.34	66.2%
	Sulfur (mg kg^{-1})	3.7	17.0	8.3	2.9	35.0%
Native	pH	5.7	6.4	6.1	0.17	2.8%
	Phosphorus (mg kg^{-1})	13.0	121.1	30.5	17.8	58.5%
	Potassium (cmol+ kg^{-1})	0.19	1.89	0.50	0.33	66.0%
	Sulfur (mg kg^{-1})	7.1	41.8	11.0	6.6	59.9%

Sulfur

S levels in the improved field range from 3.7 to 17 mg kg-1 whilst the native field had a larger range of 7.1 to 41.8 mg kg-1 (Table 1). The extent of variation in the improved field is comparable with the results from transect surveys (~3 to 16 mg kg-1) undertaken by Stefanski and Simpson (2010), however, the maximum values are much higher in the native field. There appears to be little information on the scale of variability of S in pastures. Compared to the variability reported for cropped fields (2-3% Vaněk *et al.* (2008)), the CV was larger in the pasture fields with a CV of 50% and 59.9% for the improved and native fields, respectively. Spatial trends between S and elevation were observed in both fields with high levels of S associated with the lowest elevations. There were also some isolated sites with high S concentration in other areas of the improved field, and some sites with high S associated with the sheep camps in the native field (Fig. 3). The high S levels at the very lowest elevations are mostly likely the result of accumulation through leaching (Eriksen *et al.* 1998).

Although the mean S values for both fields were above the critical value (8.1 and 11.0 mg kg-1 for the improved and native, respectively, Table 1 and 2), variability on the sub-paddock scale was considerable and suggests potential value for SSM of S fertiliser. Sulphur deficiency has long been known to be problem in soils in this region (Hilder 1954; Guppy *et al.* 2013). For the improved field, 50% of the field was considered to be S deficient, which was larger than any of the other soil characteristics measured. In the native field, P was considered deficient in the largest proportion of the field at 56.1 %, but 31.7% of the area was also considered S deficient. However, the minimum S value recorded for the native field was only 7.1 mg kg-1 and therefore these areas might be considered only marginally deficient. Stefanski and Simpson (2010) found similar results in their transect surveys; of the three fields analysed, 9 of the 12 sites were below the critical S levels. Given the large areas potentially limited by S the potential value of SSM of S for improving productivity could be significant.

Table 2 Critical values applied and areas of field subsequently falling above or below thresholds for the improved and native pastures fields

Field	Soil characteristic	Critical value	Proportion of sites below critical value
Improved	pH	5.5	10.0%
	Phosphorus (mg kg^{-1})	30	7.5%
	Potassium (cmol kg^{-1})	0.2	7.5%
	Sulfur (mg kg^{-1})	8	50.0%
Native	pH	5.5	0.0%
	Phosphorus (mg kg^{-1})	30	56.1%
	Potassium (cmol+ kg^{-1})	0.2	2.4%
	Sulfur (mg kg^{-1})	8	31.7%

Constraint interactions and extent

In addition to considering the proportion of each field falling under a single nutrient constraint (as determined by a critical value) it is worth evaluating the interactions between the different soil characteristics. At each sample site it is possible to have more than one soil characteristic falling below the critical value. Table 3 outlines an analysis of this multiple factor constraint. The native field had a greater proportion of sites with only one constraint (51.2%) as opposed to the improved field (37.5%). The native field did have a higher proportion of sites constrained by two characteristics (19%) as opposed to the improved field (15.0%) although the latter did report the only site with three constraints. A closer examination of the detail of which soil characteristics interact to cause sites with multiple constraints reveals that very few are related to a combination of pH and a soil nutrient, with only 7.5% of all sites on the improved field revealing a pH:S interaction (Table 4). By far the most commonly found interaction was the combination of P:S constraint occurring on 17.1% of the native field (Table 4).

Perhaps the most significant result is the proportion of the field limited by one or more soil characteristics. This analysis involves the application of the Sprengel-Liebig Law of the Minimum. Each site is characterised as either constrained based on it failing to meet the minimum threshold for any one of the factors assessed or unconstrained if it reports satisfactory levels for all characteristics. Although this methodology is used in spatial analysis of animal and crop species distributions (Hijmans and Graham 2006; Stehfest *et al.* 2007) there appears to be very few if any applications of it in a spatial context in its originally developed field of plant nutrition. When considering single factors only, the largest constrained area was for P in the native field (56.1% - Table 2). If an analysis of the proportion of sites that are constrained by 1 or more soil factors is undertaken a substantial increase in the total constrained area is observed with 70.7% of the native field and 55% of the improved field falling into this category (Table 4). A spatial representation of constrained and un-constrained areas is provided in Figure 4. These maps demonstrate some clear spatial trends in both fields. The improved field is characterised by an un-constrained area through the upper half of the field although the very north western corner remains constrained. There are isolated un-constrained areas throughout the southern part of the field which may relate to erosion, leaching (the low elevation area in the south eastern corner) or concentration by livestock (the remaining isolated unconstrained single points), (Figure 4). The native field demonstrates a strong association between elevation and constraint with lower elevations (below 1072m) essentially all subject to a deficiency in one or more of the key factors. The higher elevations are effectively the only areas that are consistently unconstrained. These areas are characterised by sheep camps at the highest peaks which are clearly influencing the area around them most likely through nutrient transfer by livestock (Hilder 1964; Robinson *et al.* 1983; Taylor *et al.* 1987).

These results highlight the opportunities to improve production from these grazing systems with large proportions operating under constrained conditions. However, the extent of nutrient interactions does pose a significant challenge when considering the development of SSM strategies for grazing systems. The obvious nutrients of interest in these particular fields are P and S, however targeting SSM strategies at any one of these individually will not solve the constraint problem in its entirety, a challenge which has been noted by both (Stefanski and Simpson 2010) and (Simpson *et al.* 2011). Furthermore, interactions at depth add a further degree of complexity when interpreting the relative importance of these constraints.

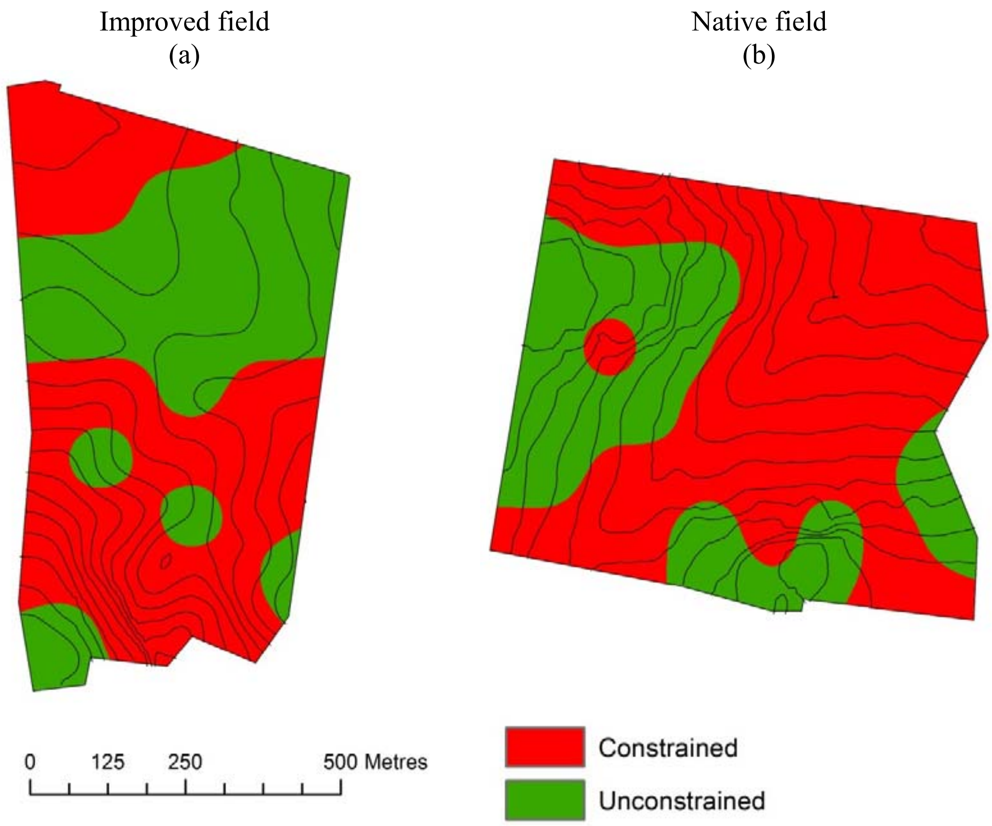


Figure 4. Spatial variability in constraint as derived from applying the Sprengel-Liebig Law of the Minimum to pH, Phosphorus, Potassium and Sulphur across all sample sites

Table 3 Proportion of fields limited by increasing number of soil constraints

Number of limiting factors	Field	
	Improved	Native
0	45.0%	29.3%
1	37.5%	51.2%
2	15.0%	19.5%
3	2.5%	0.0%

Table 4 Detail of the proportions of each field limited by specific soil factor interactions

Limiting interaction	Field	
	Improved	Native
pH:P	0.0%	0.0%
pH:K	0.0%	0.0%
pH:S	7.5%	0.0%
P:K	2.5%	2.4%

P:S	5.0%	17.1%
K:S	7.5%	0.0%
P:K:S	2.5%	0.0%
Proportion of field limited by 1 or more factors	55.0%	70.7%

Implications for management

There are two standard practices used by producers when undertaking soil sampling in order to guide fertiliser application in pastures. The first is to undertake soil sampling at a single key monitoring site which they consider representative of the field to enable monitoring of change over time (Rayment and Lyons 2010). Given the degree of variability found in these two typical pastures using a soil test from any one site could grossly misrepresent the actual fertility levels across the field and the selection of temporal monitoring sites needs to be carefully considered. There are common guidelines that direct the selection of these sites (e.g. avoiding sheep camp sites and vehicle tracks), however, the development of SSM strategies which incorporate measures of paddock variability may refine these further. The development of SSM strategies for pastures may also require the development of new protocols for monitoring temporal variability, if a zonal system was to be developed it would require monitoring sites in each zone.

The second technique is the transect sampling of a field followed by analysis of a sub-sample of the bulked soil cores. It is generally understood that, similar to sampling using a single monitoring site, transect surveys target representative areas of the paddock and avoid sheep camps, drains and other areas likely to bias results. The gridded soil survey, as undertaken in this study, is hence likely to have a greater range of extremely high and low values compared to the standard approach. This may mean that management implications would vary if a targeted transect was used rather than a grid. Despite this difference it is worth considering the management implications if commercial decisions were based on the random grid used in this study. For all soil characteristics assessed the mean values of the grid sample were above the critical levels. In the case of these two fields this means that the recommendation would be to avoid further fertiliser and lime addition. However, when the results for individual sites within a field are considered, the results suggest that a large proportion of each field was subject to constraint and did require amelioration. On the other hand there are also areas that hold considerably high levels of nutrients which do not require any further additions. As has been suggested by numerous authors (Stefanski and Simpson 2010; Trotter *et al.* 2010a; Simpson *et al.* 2011; Trotter 2013) there does appear to be a significant opportunity for a SSM approach to increase productivity and potentially reduce the amount fertiliser and or ameliorant costs in grazing systems.

This study has considered pH and three key soil nutrients as limiting factors for pasture productivity. These are however only a few of the potential limitations that influence the productivity of a grazing system. Numerous other factors including species composition, soil water holding capacity, micro-climate, micronutrients and solar loading all play a critical role in pasture productivity at any given location within a field. Hence increasing the fertility in a given area might not necessarily increase productivity. Furthermore this study has focussed on surface (0.1 m) soil characteristics and has not investigated nutrient or pH levels beyond this depth. Soil pH is known to vary through the profile and is frequently a constraint in the subsoil. Hence the development of any SSM strategy needs to consider more than just the critical levels of surface nutrients and pH. Emphasis needs to be on the potential response to nutrient or ameliorant addition as well as careful consideration around the potential to amend other limiting factors.

Conclusions

This study has demonstrated the variability in key soil characteristics across two typical pasture fields. While mean values for pH, P, K and S all exceeded the critical levels across the two fields, variability on the sub-paddock scale revealed that large areas had one or more parameters that were below the accepted critical levels. Areas potentially constrained by one or more of the measured characteristics were 55% for the improved field and 71% for the native field. The key constraints in both fields, on an area basis, were P and S. Given the scale of variability found in these fields and that reported in the limited number of other studies reviewed there does appear to be a significant opportunity for SSM of key nutrients and pH in grazing systems. The challenge will be in developing SSM systems that take into account interaction between soil factors along with the other drivers of productivity. Research is required into understanding the scale of variability of these various drivers in grazing systems and the development of SSM strategies to take advantage of this variability.

2. Examining the potential for sensors to predict the nutrient status of soils in pastures

Introduction

Precision agriculture (PA) is a management concept that is based on observing and responding to sub-paddock variation with the goal of optimising returns on inputs and minimising the use of resources. The implementation of PA management involves the use of tools and sensors that can be record variation such as a change in soil type or plant biomass within the collected data to a precise position within a field using satellite positioning systems. Use of precision agriculture (PA) has been shown to increase the resource use efficiency within agriculture, particularly in cropping and horticultural systems.

One of the traditional approaches to SSM of fertiliser in cropping systems is the use of remote or proximal sensors to zone up areas of homogeneous nutrient status. This assumes that a relationship between the sensor and the nutrient of interest exists. This is commonly the case in cropping systems but remains largely unexplored in pastures.

Compared to cropping, a grazing system has an increased variability with the introduction of livestock which have the potential to alter the spatial heterogeneity of the vegetation through grazing (Adler, Raff *et al.* 2001). Livestock also introduce variability into a grazing system with the redistribution of nutrients into concentrated discrete locations throughout the field (Betteridge, Kawamura *et al.* 2008).

This project explored the relationship between various sensing platforms and available nutrient status in pasture soils. As well as commonly used sensors (e.g. EM38 and AOS), the potential for GNSS tracking data from livestock was also explored.

Materials and methods

The fields used in this study were the same as those assessed in the previous section. Soil test data was collected as per materials and methods section of previous section and then compared to results from various sensing platforms. As well as elevation, EM38 point and survey data were collected along with NDVI from an active optical sensor (AOS).

EM38 soil survey and point sampling

Soil electrical conductivity was measured by a Geonics Limited, Ontario EM38TM across both paddocks to show the variability within the soil at each site. The paddock at Sundown was surveyed using the EM38TM on 13th of March 2012 and was towed on a rubber mat along the soil surface using an all-terrain vehicle (ATV). Similarly the surveys for Kirby were carried out using the same process on the 27th of March 2012 with the EM38TM mounted on the ATV to ensure that the whole of the paddock was covered including through the trees and over the exposed granite. Additional to the continuous surveys, point survey data was also undertaken at predetermined locations in order to correlate to soil samples.

The EM38 required calibration on site at the area identified as having the lowest soil electrical conductivity. The sensor was allowed to adjust to the temperature and humidity and calibration was carried out as directed by the manufacturer’s operation manual. Once calibrated the sensor was connected to the DGPS and a Trimble ProXRS receiver coupled to a TSCe data logger, trimble ranger field computer (Trimble, Sunnyvale CA) and mounted on a purpose built sled. The EM38TM provides a rapid measure of the apparent electrical conductivity (ECa) and data points were collected every second at a constant speed of 10 km h-1 and geo-referenced by the DGPS. The EM38TM was placed on the sled in the vertical dipole orientation which allowed for the electrical current to penetrate 1.5m into the soil.

At each site for the point survey data the EM38 was also placed at the central point to obtain the soil conductivity for each site (the selection of sites is detailed below). The EM38 -MK2 which has a secondary coil at 0.5 m and 1 m from primary coil was used to record a reading in both the vertical and horizontal orientations. This allowed for 4 different ECa surveys for each site. The EM38 was not connected to the DGPS however each site was labelled within the data logger and later matched up with the corresponding spatial reference.

NDVI survey and point measures

To measure the amount of biomass within each trial site it was determined that the use of NDVI measurements would be the most appropriate biomass index available. This was carried out using a Holland Scientific CropCircle multi-spectral crop canopy sensor. A CropCircle multi-spectral crop canopy sensor (Holland Scientific Inc., Lincoln, NE, USA) was used to estimate the pasture biomass across each paddock. The paddock located at Sundown was surveyed for NDVI data on the 27th of February 2012 using 20 m tram lines with the CropCircle mounted on the bulbar of a Toyota Prado at a height of 0.90 m. For the paddock located at Kirby the CropCircle was mounted on the ATV and the surveys were carried out as well as point surveys using the same process as detailed for the EM38TM surveys.

The CropCircle was also used to survey predefined sites which were also the location of the soil samples and termed ‘point surveys’. The CropCircle was used to survey a 1m radius around each site. This process enabled approximately 130 NDVI readings and an average was calculated for each site. The CropCircle was not connected to the DGPS, however, each site was labelled within the data logger and later matched up with the corresponding spatial reference.

Elevation

The elevation data was collected using a Trimble ProXRS receiver coupled to a Trimble Ranger field computer (Trimble, Sunnyvale CA) using an Omnistar differential correctional signal. The elevation data was recorded continuously over the paddock travelling in a north-south direction creating tram lines with 20 metre spacings.

Spatio-temporal livestock data

Cattle designated to graze the paddock at Sundown was chosen using a strategic selection method. The collars were fitted to the steers on the 27th of February, 2012. Twenty steers within a mob of 250 were selected on race order. This involved placing the collar on 1 out of every 12 steers, this was done to reduce the effect of social cohesion. The selected steers were placed in a cattle crush and the UNEtracker collars were fitted. The collars were programed to log a location every 20 minutes due to the battery life and the required deployment period. This would allow the collars to be on the steers for 3 months to fit in with the management of the property. The steers were rotated through 5 paddocks including the ‘Parkers 3’ paddock. After 3 months the steers were moved off the rotation and the collars were collected. The data was transferred to a computer and stored.

GPS collars were attached to the superfine Merino wethers at Kirby on the 20th of February 2012. The flock had a mean age of 18 months old and were run as part of the commercial flock at Kirby. The selection criteria involved selecting 20 wethers from a mob of 347 based on the race order and live weights of the individual animals. The wether’s, were run through the yard race and the weight of each individual animal was recorded using a Pratley® Autodraft, equipped with a Tru-test XR-3000 data logger. The wethers were put through the Pratley® Autodraft in groups of 50 with the maximum, minimum and medium animals selected on their weights.

GPS collar data processing

The raw point GPS data was transferred to a computer after the deployment period for analysis. This point data was stored on the computer in the form of a text file. The raw data was converted to a useable format using a PARG GPS converter within a Microsoft Excel 2010 spreadsheet. The converted data was transferred to new Excel spreadsheet, labelled and saved in an appropriate folder. The data was then opened in ARCmap (ESRI, Sunnyvale CA) by adding the xlsx file.

A vector grid was required for both paddocks in order to determine to the utilisation by the livestock of specific areas. In order to generate a vector grid the software program Geospatial Modelling Environment (GME) was used. The command option ‘genvecgrid’ was selected and the dimensions for the grid size were specified as a 10 m x 10 m grid. The output was saved in an appropriate folder destination. The vector grid was opened within ARCmap and the grid was clipped to fit in each paddock boundary.

Calculating Livestock Residence Index (LRI)

The frequency of the livestock within each cell of the vector grid was used as an indication of the preference of the herd for a specific area. Files containing collar point data and the vector grid were opened within GME once the command option ‘countpntsinpoly’ was selected and the corresponding collar number was then entered in the ‘field’ address bar. The output was saved automatically within the vector grid .dbf file under the title entered in the field address bar. Another column was created next to the output data titled as the equivalent collars LRI. The LRI was then calculated using the following shown in Figure 4.

The LRI was further broken down into grazing, travelling and stationary behaviour using the velocity of the livestock movement (Putfarken, Dengler *et al.* 2008). The model proposed by (Putfarken, Dengler *et al.* 2008) model describes that grazing behaviour can be categorised as a velocity of between 0.02 m s-1 and 0.33 m s -1. Consequently travelling behaviour can be categorised as a velocity greater than 0.33 m s -1 , and stationary behaviour less than 0.02 m s-1 to account for GPS error. The GPS logs that fell into each category were selected and exported to create a separate shape file for travelling, stationary and travelling behaviour. This process was repeated for both paddocks.

Statistical analysis

The statistical software package JMP was used to investigate relationships between the survey data platforms and the nutrients values. To do this an .xlsx file was created in Microsoft Excel which had the soil sample site number, the values for each soil analysis and then the sensor information for each paddock. The soil sample data included pH, EC, C, N, NO3, NH4, S, P, Ca, K, Mg and Na. The sensor data included the average NDVI for each site (Point NDVI), the survey NDVI (Survey NDVI), the point EM38TM values at 0.5 m horizontal and vertical dipole positions (EM .5m H & EM .5m H) and 1 m horizontal and vertical dipole positions (EM 1m H & EM 1m V), survey elevation, total LRI, Grazing LRI (Graz LRI), stationary LRI (Stat LRI) and travelling LRI (Trav LRI).

Data transformation and outlier detection

The data files for each paddock were copied into a data table in JMP and a test for normal distribution was conducted using an outlier box plot and a normal quartile plot. The soil test results were initially analysed and found that data transformations were required to make the skewed distributions more symmetric and stabilise the spread of the data. It was also found that the NDVI values and all of the soil test data except for the pH values did not conform to a normal distribution. Therefore cube root transformations were applied to the point NDVI data, and all forms of point EM data sets as well as S, P, and K. It was determined that log transformations were required for all LRI data sets to ensure normal distribution. An outlier was detected in the Kirby native pasture field. This was the extremely high nutrient point located on the Western boundary. This point was deliberately excluded from the analysis as initial testing found that it created unrealistically favourable correlations. This point was identified as a sheep camp and so its removal from the data set is not unreasonable as many producers would already know the fertiliser addition to these areas is not required.

Single sensor correlation with nutrients

The soil sample data was correlated against the sensor data using a pairwise comparison. A multivariate pairwise comparison was used to analyse each of the sensor data sets against each of the soil nutrients. A table for each type of sensor for each paddock was created showing the correlation r-squared values.

Multiple sensor correlation with nutrients

A stepwise regression was fitted to the P, K, S and N against each of the sensors. All possible models were ordered up to the best 56 models and up to 8 sensor terms per model were included in the analysis. The correlations were significantly improved by adding multiple sensor data sets, however the trend was found to plateau after a number of terms were added. The last correlation before it was determined to plateau was further analysed to determine which sensor platforms were required to improve the sensors ability to predict the variation of soil nutrients within the soil.

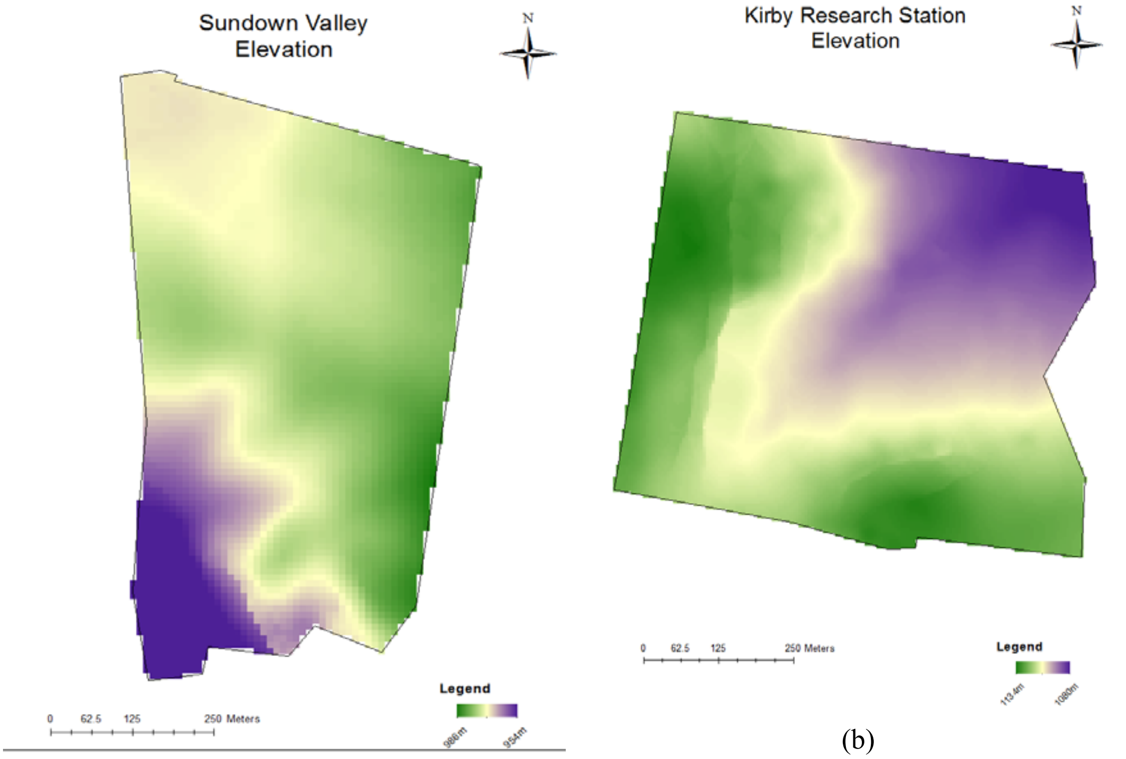
Results

The PA tools survey results

The PA tools examined in this study include a DGPS; used to log the elevation, a Geonics EM38 to measure soil ECa, a CropCircle which measures NDVI and data on the spatial landscape utilisation of animals derived from UNEtracker GPS livestock tracking collars. The results were tabulated and mapped in order to show the variation in each paddock measured by each sensor platform.

Elevation mapping

Elevation data was collected at both Sundown and Kirby with the results displayed in Figure 5. The green areas in represent areas of higher altitude and the areas represented by purple signify the areas of low altitude within each paddock. There is less variation in elevation at Sundown compared to Kirby, with ranges in elevation of 32 and 54 m, respectively.



(b)

(a)

Figure 5 Elevation map for the improved field at Sundown (a) and the native field at Kirby (b)

Electromagnetic induction survey

Results from the Geonics EM38TM survey conducted on 27/3/2012 are presented in Figure 6. The ECa values for the survey conducted at Kirby range from 2 mS m-1 to 37 mS m-1 (Figure 6) and at Sundown the values range from 2 mS m-1 to 17 mS m-1 (Figure 6b) indicating a large range of variability in the ECa in both paddocks. The high values of soil ECa at Kirby are located in the south-west corner of the paddock where a small creek runs towards the north-east corner; at the time of the survey there was water on the surface. No physical soil classification was undertaken over the duration of this trial, however observational analysis suggested that light granite soils corresponded with the low ECa values in the south-east and north-east corners of

Kirby and the southern end at Sundown. The areas of high ECa were observed to have higher clay content relative to the other areas of each paddock.

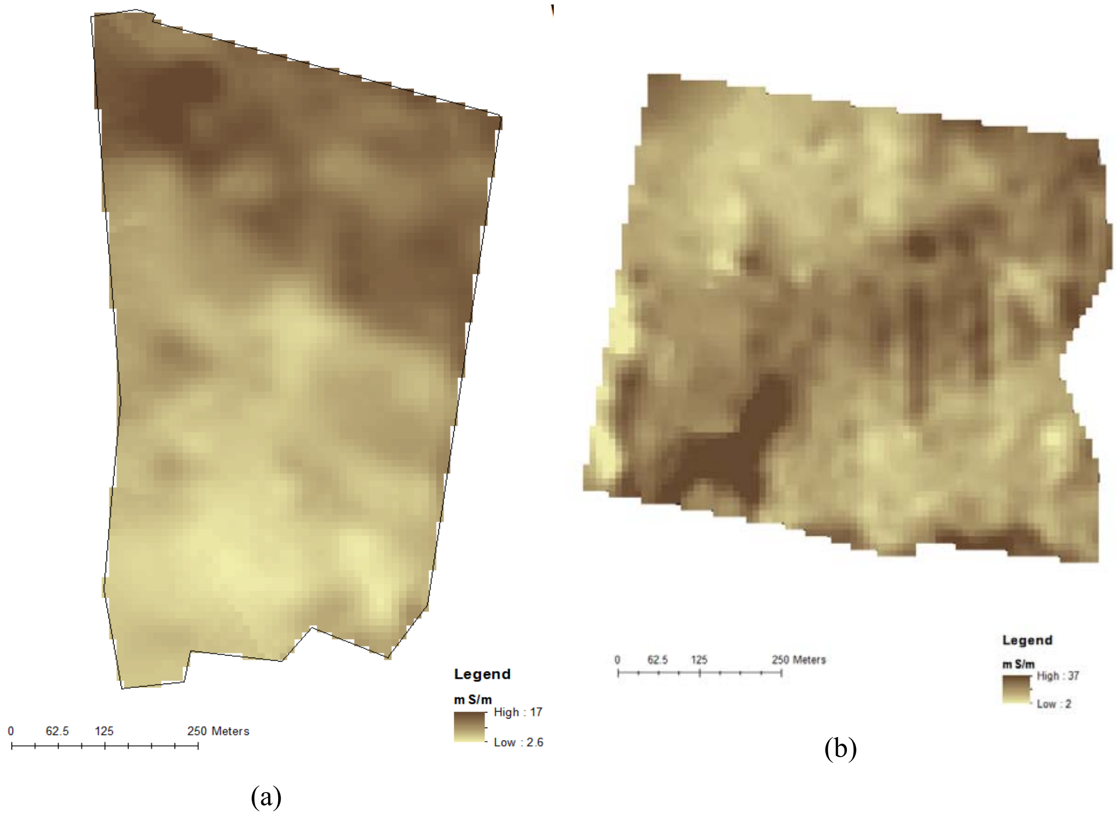


Figure 6 EM38 map for the improved field at Sundown (a) and the native field at Kirby (b)

NDVI survey

The surveys conducted at both Sundown and Kirby are presented in Figure 7 and demonstrate a large range of variability within the pastures. The NDVI values range from 0.34 to 0.78 at Kirby and 0.26 to 0.89 at Sundown (Figure 7). The larger areas of high NDVI on the higher elevations at Kirby were associated with sheep camps.

The NDVI values calculated for Sundown show areas where there was little biomass on the ground caused by exposed granite rock and shading from the dense tree canopy. There is also an area with low NDVI caused by a dam in the north west corner of the paddock.

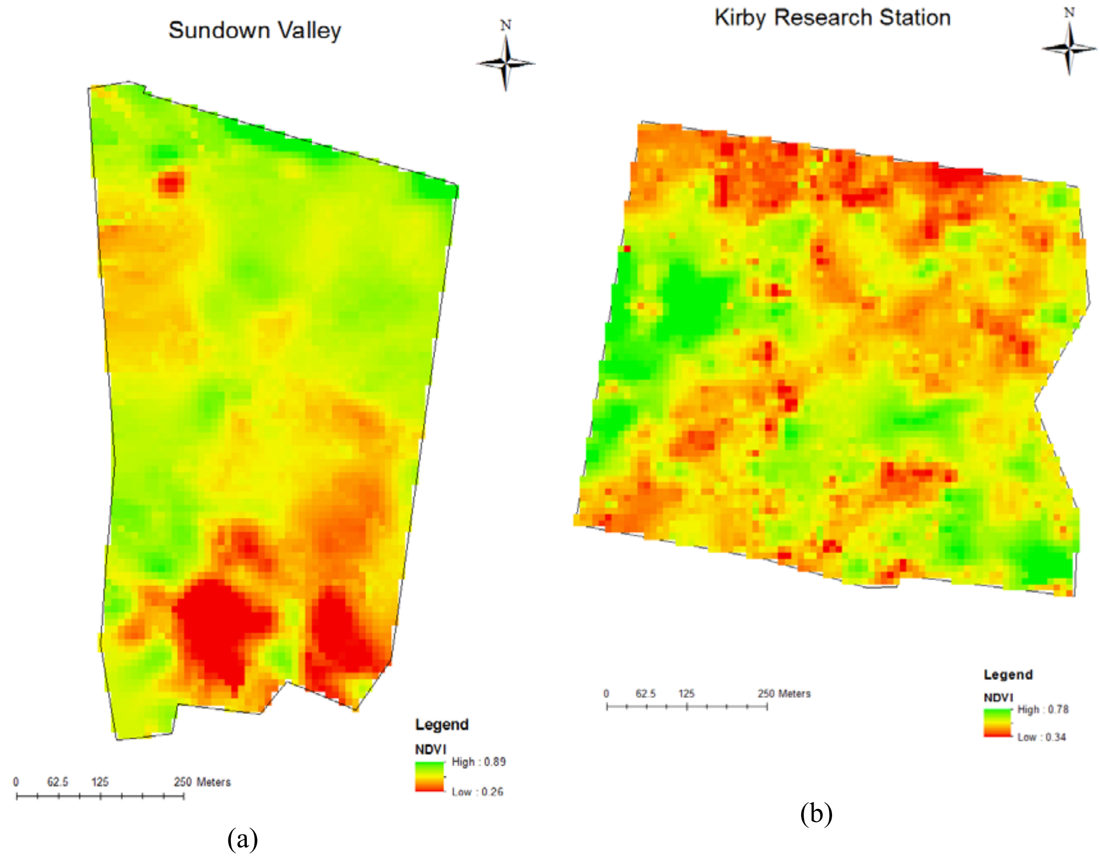
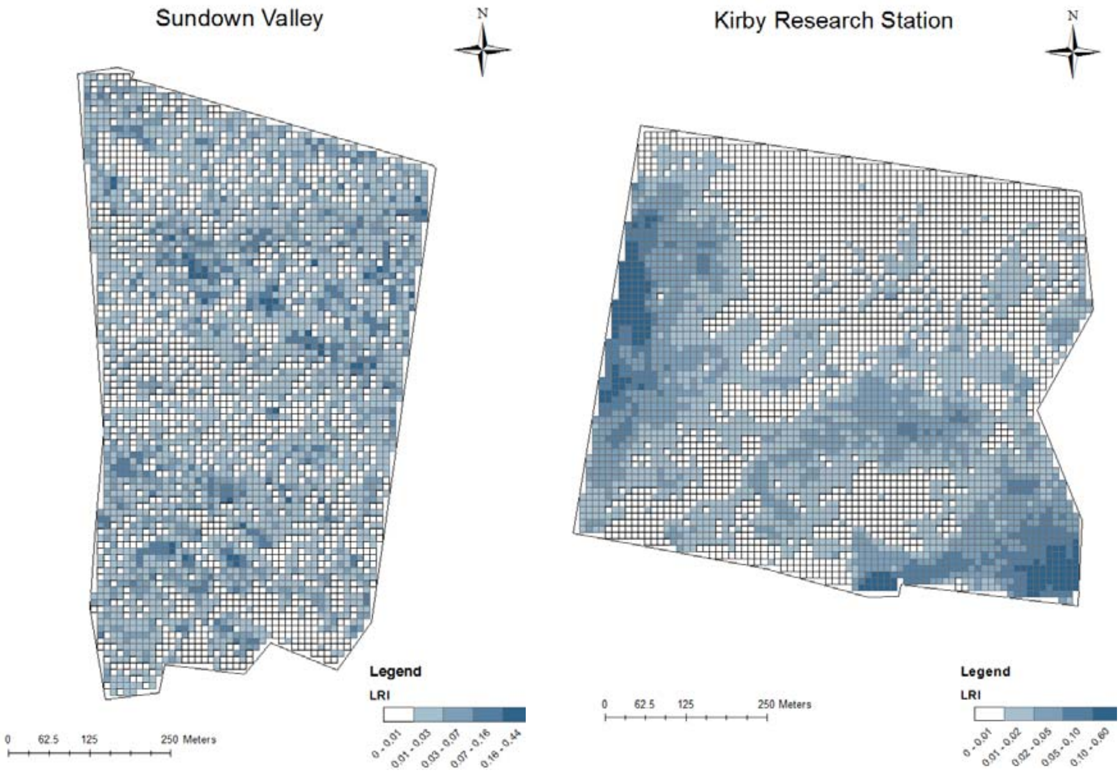


Figure 7 NDVI map for the improved field at Sundown (a) and the native field at Kirby (b)

Livestock Residence Index (LRI) Maps

The LRI shown in Figure 8 highlights the different landscape use between the sheep at Kirby and the cattle at Sundown. The LRI in Figure 8 ranged from 0 to 60 at Kirby (Figure 8) and from 0 to 0.44 at Sundown. The wethers at Kirby showed a preference for specific areas of the paddock over the trial. The areas where the wethers spent most time as indicated by the LRI were determined to be the 'sheep camps' in a study using the same data (Yerbury, Walkden-Brown *et al.* 2012). The LRI for Sundown show a more consistent landscape use by the livestock; this was likely associated with the density and class of livestock.



(a) (b)

Figure 8 Livestock residence index map for (a) Kirby and (b) Sundown

Single sensor correlations to the nutrients

Only the key nutrients P,K and S were selected for analysis. Whilst pH was initially evaluated in the previous section it was not deemed an important constraint of either fields. This is not the case for many other regions in Australia where pH is a critical problem and would warrant investigation in terms of the potential for SSM.

Correlation of elevation mapping to key soil nutrients

The elevation data that was obtained during the initial paddock surveys was included as a sensor platform. The elevation data was tested for the ability to predict the spatial variability of soil nutrients. Table 5 shows the relationship between the elevation and soil nutrients at Kirby and Sundown. The best correlations for elevation data were found with P at both sites and at Kirby the relationship with potassium. The relationship between the key nutrients and elevation at Sundown were considerably less than those found at Kirby.

Table 5 Coefficient of determination for relationship between soil nutrients and paddock elevation at Kirby and Sundown

	Kirby Elevation (R^2)	Sundown Elevation (R^2)
pH	0.09	0.01
Sulphur	0.01	0.01
Potassium	0.32	0.03
Phosphorus	0.33	0.12

Correlation of electromagnetic induction to key soil nutrients

The EM38 data was collected using two sampling techniques; a whole paddock survey which was interpolated to show the spatial variability and a second method involving the collection of point ECa readings at each of the soil sample sites. The point surveys also included ECa reading in both horizontal and vertical modes.

Table 6 shows the relationship between the soil nutrients and the ECa data for Kirby. The ECa proved to be a poor predictor of soil nutrient levels. The strongest relationship with the ECa data was P across each of the EMI surveys with the best relationship between P and the EM38 in the vertical orientation at 0.5 m spacing.

Table 6 Correlations between soil nutrients and apparent electrical conductivity at Kirby

	Point survey 0.5m Vertical (R^2)	Point survey 0.5m Horizontal (R^2)	Point survey 1m Vertical (R^2)	Point survey 1m Horizontal (R^2)	Paddock Survey EM (R^2)
pH	0.01	0.00	0.02	0.01	0.01
Sulphur	0.02	0.03	0.02	0.03	0.05
Potassium	0.12	0.03	0.14	0.10	0.15
Phosphorus	0.29	0.14	0.27	0.24	0.21

Table 7 indicates the correlation between the soil nutrients and the ECa data for Sundown. The best relationship across all EMI surveys (except the 0.5 m survey in the horizontal orientation) was with P; however these R2 values do not reflect a sufficient predictor of soil P. The strongest single correlation to ECa data was for P using data obtained for the whole paddock survey (R2 = 0.23). The EC also produced a stronger relationship with the EM in the horizontal orientation at 0.5 m spacing (R2 = 0.20), although the reality is that all relationships are relatively weak.

Table 7 Correlations between soil nutrients and apparent electrical conductivity at Sundown Valley

	Point survey 0.5m Vertical (R^2)	Point survey 0.5m Horizontal (R^2)	Point survey 1m Vertical (R^2)	Point survey 1m Horizontal (R^2)	Paddock Survey EM (R^2)
pH	0.09	0.04	0.07	0.06	0.04
Sulphur	0.00	0.01	0.01	0.00	0.01
Potassium	0.04	0.01	0.02	0.02	0.00
Phosphorus	0.18	0.04	0.22	0.19	0.23

Correlation of NDVI and key soil nutrients

Pasture biomass measurements using NDVI values were correlated with the soil nutrients using two sampling methods. Similarly to the EM38 data, the NDVI data collected during the paddock surveys was used in addition to the point surveys taken at each soil sample location. Table 8 shows the relationship between NDVI and soil nutrients at Kirby and Sundown.

The strongest relationships at Kirby were found using point surveys directly at the soil sample site with pH and K, and the best relationship for the survey NDVI was for P. The NDVI data for Sundown in Table 7 indicates there was a reasonable correlation at Sundown between Na and the point NDVI survey; however there was no relationship found between Na and survey NDVI. Similarly there is a relationship between NO3 and the point NDVI but no relationship for the survey NDVI.

Table 8 Coefficient of determination for relationship between soil nutrients and Normalised Difference Vegetation Index values

	Kirby		Sundown	
	Point NDVI* (R^2)	Survey NDVI (R^2)	Point NDVI* (R^2)	Survey NDVI (R^2)
pH	0.34	0.07	0.01	0.04
Sulphur	0.04	0.02	0.17	0.02
Potassium	0.25	0.18	0.02	0.03
Phosphorus	0.09	0.23	0.02	0.00

Correlation of livestock residence index with key soil nutrients

Details of the relationships between key soil nutrients and the various LRI's calculated for Kirby are shown in Table 9. There are some weak relationships between the LRI's for grazing and stationary for both pH and K. It should be noted that the removal of the outlier impacted strongly on this relationship. The outlier was located in the camp area which resulted in both high stationary LRI and elevated nutrient levels and gave a much stronger coefficient of determination. Whilst this might be important when considering environmental losses (where concentrated nutrient sources areas are important) the removal of the outlier does provide a realistic situation in which we would like a sensor to provide a prediction for use in SSM. There was no relationship found between LRI and key soil nutrients at Sundown (Table 10).

Table 9 Coefficients of determination for relationship between Livestock Residence Index and key soil nutrient levels at Kirby

	LRI Total (R^2)	LRI Grazing (R^2)	LRI Stationary (R^2)	LRI Travelling (R^2)
pH	0.25	0.28	0.34	0.08
Sulphur	0.06	0.08	0.09	0.01
Potassium	0.20	0.22	0.28	0.09
Phosphorus	0.07	0.08	0.09	0.07

Table 10 Coefficients of determination for the relationship between LRI and key soil nutrients at Sundown.

	LRI* (R^2)	LRI Graz* (R^2)	LRI Stat* (R^2)	LRI Trav* (R^2)
pH	0.02	0.00	0.00	0.03
Sulphur	0.02	0.00	0.01	0.04
Potassium	0.01	0.00	0.00	0.02
Phosphorus	0.00	0.02	0.06	0.04

Correlation of a combination of multiple sensors to key soil nutrients

We hypothesised that a combination of more than one sensor might provide better relationships with key soil nutrients. A deliberately simple analytical approach was taken using a step-wise multiple regression.

For the native field at Kirby the coefficients of determination were found to plateau after the use of three sensors as model inputs (Table 11). The coefficient of determination is increased from 0.35 to 0.53 for P by the addition of more sensors. The highest r-squared was achieved in K. The details of the sensors used in the multiple regression are shown in Table 12. The most commonly used term is the elevation model which appears in all three.

Table 11 Coefficient of determinations for regression models with increasing number of sensor terms at Kirby

Model input terms (number of sensors)	P (R^2)	K (R^2)	S (R^2)
1	0.35	0.42	0.11
2	0.48	0.53	0.19
3	**0.53**	**0.58**	**0.24**
4	0.54	0.60	0.26
5	0.55	0.60	0.26
6	0.56	0.60	0.27

7	0.56	0.60	0.28
8	0.56	0.60	0.28

Table 12 Details of regression models and their coefficients of determination for key soil nutrients for Kirby

Nutrient	R^2	Sensors
P	0.53	Survey NDVI, EM 0.5 V & Elevation
K	0.58	EM 1m H, Elevation, LRI Stationary
S	0.24	Elevation, LRI Total, LRI Grazing

For the improved field at Sundown the coefficients of determination were found to plateau at a variety of model inputs (Table 13). The increase in R-squared is clearly lower than that achieved for the Kirby field. Like the Kirby field the elevation is the most commonly used however the point NDVI sensor was also used in both the K and S models.

Table 13 Coefficient of determinations for regression models with increasing number of sensor terms at Sundown Valley

Terms	P (R^2)	K (R^2)	S (R^2)
1	0.23	0.04	0.17
2	0.28	0.08	**0.21**
3	**0.32**	0.12	0.22
4	0.34	**0.16**	0.24
5	0.35	0.18	0.27
6	0.35	0.19	0.29
7	0.35	0.2	0.3
8	0.35	0.2	0.31

Table 14: Details of regression models and their coefficients of determination for key soil nutrients for Sundown Valley

Nutrient	R^2	sensor
P	0.32	EM 1m V, Elevation, LRI Grazing
K	0.16	Point NDVI, Survey NDVI, EM 1m V & Elevation
S	0.21	Point NDVI & Elevation

Discussion

The correlation of soil nutrients to the various sensors provided variable results, some relationships were low or non-existent. The greatest correlation achieved for any single sensor was the relationship between K and elevation on the Kirby property (R2=0.42). In general terms the correlation of the sensors on the improved paddock at Sundown was less than that achieved for Kirby. There are numerous possible reasons for this however it is worth noting that the increased diversity of landscape and pasture type in the Kirby field may have enabled this distinction to occur. The combination of sensor through a stepwise multiple regression improved the correlation of sensors and key soil nutrients with the highest correlation being achieved for K in the Kirby field again (R2=0.58). The relationship with P was similar on the Kirby field (R2=0.53) however it was lower on the Improved sundown field (R2=0.32). Sulphur remained the most challenging nutrient with low coefficient of determination achieved for both fields in both single nutrient and multiple regression models (R2<0.24).

At first pass it would appear that the predictive power of these models may be insufficient to enable the development of site specific fertiliser management strategies. However it is worth comparing these to the results of similar studies undertaken in cropping systems as this sector is now a widespread user of similar sensors (excluding the GPS tracking) for zonal fertiliser management. Heiniger, McBride, and Clay (2003) reported coefficients of determination of soil nutrients with EM38 of less than 0.5 for numerous key nutrients in cropping soils. reported correlation coefficients (R) of only 0.08 with Bray P at shallow depths (0-15cm) whilst correlation coefficients (R) of up to 0.66 where found at depths between 15-30cm. The R of 0.66 is actually marginally lower than the R2 of up to 0.53 achieved in this study for the Kirby field. Although there is not extensive research in the area it does appear that the correlations achieved in this study are not dissimilar from those reported in cropping fields.

These results are reflected in the attitude of commercial PA service providers. Tim Neale (PA.com) has suggested that whilst he is more comfortable with R2 values of 0.6 to 0.7 (very rarely getting any higher) they are still able to develop site specific management strategies where correlations fall between R2 of 0.5 to 0.6. While it would have been ideal to have achieved higher degree of correlation between the various sensors and soil nutrient levels we would suggest that there is sufficient relationship to warrant further investigation.

Tim believes the potential for variable rate fertiliser and lime in pastures is even greater than in cropping lands. This is due to several reasons, being:

1. There is typically more soil variability in pasture lands than cropping lands due to the inherent nature of the livestock industries and their location in the landscape

2. There are a lot more livestock producers (covering a much greater area of Australia) than cropping producers. This means there is massive potential for making big industry changes.

3. Fertiliser and lime application methods are less precise than in a cropping scenario (e.g. aerial application cf precise placement from a seeder) therefore leading to more variability

4. Re-distribution of nutrients through manures/stock camps doesn't occur in cropping lands (unless they are in a mixed system)

5. The margins in livestock are often, not always!, much tighter than in cropping; so livestock producers need to ensure that every $$ spent on fert/lime inputs is going to the right areas and at the right amount and provide the biggest bang for their buck

6. We don't yet have a good handle of the extent of variability in pasture lands, so more extensive work needs to be done to quantify the problem and benefit:cost scenarios developed

One of the key limitations of this study was the limited data sets used. Only single EM38 and NDVI surveys were undertaken. Multiple surveys particularly using NDVI sensors (either remote or proximal) might provide differential growth data that could relate better to soil nutrient status. In addition the GPS tracking data was collected over a relatively short time frame and may benefit from longer term deployments. The nutrient re-distribution that has occurred in these fields has happened over the past 150 years and short term tracking may not capture the detail required.

Another key challenge when considering site specific management strategies for nutrient addition in pastures is the challenge of determining the potential response to nutrient addition. This project has simply investigated how a sensor might be correlated to a soil nutrient but it is more important to understand how a specific area in a pasture might respond to the addition of a nutrient in the form of fertiliser.

This is an extension of the Sprengel-Liebig Law of the Minimum proposed in the previous section, however it takes into account not just the limitation of key nutrients but also other limiting factors such as variation in soil moisture, local climate and the numerous other biotic and abiotic factors that affect plant growth. Further research is required to understand how response to nutrient addition might be characterised across grazing landscapes.

Conclusions

The best correlation for any single sensor was an r2 of 0.42 (elevation). Combining multiple sensors in a step wise regression improved this relationship to and r2 of 0.58 which is analogous with results reported for cropping fields and the results frequently found by commercial PA service providers (Tim Neale, PA.com). Further research is required to understand the true nature of the variability of soil nutrients in grazing systems but also how pastures might respond to fertiliser addition.

2. Spatially enabled livestock management

Introduction

One of the technologies of most interest to graziers is the development of spatially enabled livestock management systems. The dairy, red-meat and wool industries are increasingly interested in the potential of this class of technology to provide a 24-hour-a-day, 7-dayweek (24-7) monitoring system to generate information on the behaviour and location of their animals. Ear-tag systems (Figure 8) are currently in development and likely to be commercially available in the next few years (Trotter 2012). The development of SELMS would directly and significantly increase labour use efficiency for graziers. Where livestock monitoring is undertaken reductions in time spent locating animals is likely to have a significant benefit for many pastoralists. In place of routine stock observation, more targeted and strategic monitoring could be undertaken in response to analysis of the animal movement data. The constant 24-7 surveillance provided by SELMS would enable rapid responses to livestock theft, potentially eliminating this problem which costs the industry over $72m (Mcall 2003).

The key research challenge is the development behavioural modelling systems that use the information generated by SELMS and deliver meaningful information to producers. There is enormous potential value if this can be achieved. The provision of remote alerts for disease is may well be possible and would enable producers to undertake strategic actions to validate the symptoms (e.g. targeted diagnostic sampling) and/or implement more timely control actions. An example of a disease that might be readily managed using an SELMS is ryegrass toxicity. If a system could be developed to alert producers to the sub-clinical symptoms of this disease the economic impact of sheep deaths from this disease for the industry estimated at $33.6m (Sackett and Francis 2006) may be reduced. Remote monitoring of calving and lambing activity would also provide producers with considerable labour savings and allow more timely intervention in the case of birthing difficulties. The automatic recording of birth dates enabled by ALMS would be valuable information for producers seeking to record individual animal productivity. There are numerous other animal production issues which could be addressed through the development of behavioural modelling from SELMS.

This project focussed on several key issues facing the grazing industry and aimed at developing metrics and models that could be applied to increase efficiency. The initial objective as to develop behavioural models that related animal movement to biomass conditions to increase pasture use efficiency. In addition to investigating this key objective we also undertook several studies looking at how SELMS might be used to model key animal behaviours.

This report is broken down into three main research questions:

1. Can spatio-temporal data be used to understand the relationship between animal behaviour and available pasture biomass?
2. How accurately can we determine key animal behaviours from spatio-temporal data?
3. Can we determine animal disease status from spatio-temporal data?
4. Can we determine birth events from spatio-temporal data?

Figure 8 A cow fitted with Taggle ear tag allowing real-time location of the animal

1. Can spatio-temporal data be used to understand the relationship between animal behaviour and available pasture biomass?

Introduction

Pasture utilisation is a limiting factor in Australian rotational grazing production systems. Adequate monitoring of pasture biomass for decision making purposes is crucial for improving utilisation. The objective of this study was to explore and understand the basic data produced by GPS tracking devices. This research examines specific movement metrics that might be derived from the positional data recorded by GPS devices and how these might be related to the key behaviours identified.

This study comprised two parts, (A) the first involved an investigation of the value of GNSS data for understanding animal behaviour in relation to pasture biomass and the second study (B) investigated specific behavioural models that might be used in this context.

Part A - Preliminary investigation of the use of GNSS data for monitoring livestock

The specific objectives of this trial were to: 1. Gain an understanding of the basic data processing requirements and opportunities for quantifying grazing metrics gained from GPS tracking of livestock; and 2. Explore methods of turning positional logs of cattle to metrics of value.

Materials and Methods

Study Site

The study site was a 51 ha paddock located at the Douglas McMaster Research Station, a 1500ha mixed cattle and cropping enterprise located in the Northwest Slopes region of New South Wales, Australia (150°36’0”, 29°17’6” WGS84). The study began on the 8th of August 2008 and finished on the 24th of September 2008, a duration of 48 days.

The herd was managed as part of a ‘normal commercial system’ during the study period, not as a controlled experiment. As such, the study period was interrupted by management operations (31 August to 5 September 2008) in which the herd was removed and returned to the paddock. This period, hitherto referred to as ‘the exclusion Period’, coincided with a major rainfall event. Prior to the exclusion Period cattle had access to a water trough located in the south eastern corner of the paddock and following the exclusion Period an additional water trough was made available in the north eastern corner of the paddock. As a consequence of the break in the natural grazing cycle (the rainfall events and variation in cattle and water management) the total grazing duration was divided into four periods; Periods 1 and 2 before, and Periods 3 and 4 after the exclusion Period. Period 1 spanned from the 12th to the 21st of August inclusive, Period 2 from the 22nd to the 30th of August inclusive, Period 3 from the 6th to the 14th of September inclusive and Period 4 from the 15th to the 23rd of September inclusive. For the purposes of this study the changes in livestock behaviour were compared between Periods 1 and 2 and then Periods 3 and 4. This enabled a simple comparison of how behaviour might have changed in relation to reducing biomass whilst the cattle had access to relatively similar resources. Due to the change in management and landscape access, it was not deemed feasible to make a comprehensive comparison between periods that occurred before (Period 1 and 2) and after (Periods 3 and 4) the exclusion Period although some notable trends will be discussed.

Pastures

Paddocks were sown to forage oats (*sp. Avena Sativa var. Warrego*) on the 9th of May 2008. The forage oat crop was monitored for biomass quantity using an active optical sensor (AOS) along with calibrating cuts.

Figure 9 The study paddock showing the forage oats at the commencement of the trial.

Figure 10 The paddock during the study showing cattle and forage oats.

Cattle

The paddock was stocked with a herd of 151 cattle consisting of 3 different cohorts; small steers, large steers and in-calf cows (Table 15).

Table 15 Livestock cohorts including weight before entry to the study and standard deviation, and the DSE in the paddock. Note the total DSE in the paddock during the study is 1,770.

Cohort	Number of animals	Initial Average Weight (kg)	Weight Standard Deviation (kg)	DSE/animal	Total DSE
Small Steers	99	243	28	10	990
Cows	30	569	71	15	450
Large Steers	22	450	74	15	330
Total	151				1770

Six UNETracker GPS collars (M. Trotter & Lamb, 2008) were deployed on animals in the herd from 9 August to 23 September 2008, as shown in Figure 11. As the cattle were newly introduced to the paddock, the first three days (9-11th August) of the data collection were excluded from analysis as this was considered an exploration phase where the cattle were adjusting to the new paddock (Vallentine, 2001). Collars were programmed to log a positional record every 10 minutes. In this study, six of 151 animals were tracked. The collars were also programmed to undertake "over determination", meaning that the positional fix was not recorded based on the minimum of 3 satellites but only recorded after a larger number of satellite signals were recorded (Trotter & Lamb 2008).

Figure 11 Four of the livestock in the study on the 28/08/2008 Note, the small steer on the left is fitted with a UNETracker collar around the neck.

Upon completion of the experiment, the collars were removed from the cattle and the raw GPS data downloaded. The raw data was then processed through a spread sheet in Microsoft Excel®

which converted the raw data strings into meaningful columns of data, including time, date, latitude, longitude, satellites, and horizontal dilution of precision (HDOP).

Using Excel® and ArcGIS®, this data was then cleaned to remove any points outside the experiment period and incomplete or erroneous data. Incomplete data refers to data strings missing information. Erroneous data is positional information which exceeds the following distance thresholds; (i) more than 10m or (ii) a recorded location a large distance from previous and succeeding logs. The threshold for this filtering was based on calculating a speed from the distance between consecutive positions divided by the time interval between consecutive records. The threshold value used to reject data was speeds faster than 3 m/s.

Descriptive statistics of the individual tracking devices was produced, including the number of logs recorded of the expected position logs, satellites used to record fixes and average HDOP.

The cleaned dataset was imported to ArcGIS, and the ArcMap extension 'Hawth's Tools' (Beyer, 2004) was used to calculate the eastings and northings of the position logs. The diurnal activity was determined by averaging the distance travelled for each daylight hour over the experimental period. Movement metrics were also derived, including step length between consecutive positions. From step length, herd average distances travelled per day were calculated by summing all the distances between position logs for each animal on each day, then averaging these values for all tracked animals.

Average speed was determined by dividing the step length over the time between consecutive points. Based upon a speed-behaviour model developed by Putfarken *et al.* (2008), the animal's activity was determined. Each point was subsequently classified based on speed as either stationary (<0.02 m/s), grazing (≥0.02≤0.33 m/s) or travelling (>0.33 m/s). The mean proportion of time spent grazing by all six animals monitored was then calculated for each day of the deployment period by dividing the number of intervals between points classified in each behavioural category over the total number of intervals per day.

A livestock residence index (LRI) was calculated and mapped to determine how the livestock were utilising the paddocks. Here we define utilisation as grazing behaviour. A LRI unit for any given location is the proportion of time a tracked animal was located in that area of the paddock compared to the time spent in the paddock as a whole (M. Trotter, Lamb, Hinch, & Guppy, 2010). In order to calculate the LRI a 50 m X 50 m grid was first created for the paddock and the GPS location points accumulating in each cell defined by the grid were counted. The counts for each grid cell were divided by the total point count over the entire paddock and multiplied by 100 to obtain a percent occupancy for each cell. The LRI is given by:

$$LRI_x = \frac{\sum_x raw\ point\ count}{\sum_n raw\ point\ count} \times 100$$

Results and discussion

The six collars successfully deployed represented 4% of the total herd tracked. With the combination of cattle cohorts present this study, and the low proportion of livestock tracked, the results may not reflect the entire herd (Mitlöhner, Morrow-Tesch, Wilson, Dailey, & McGlone, 2001). Despite this limitation the data collected provides valuable insights into the challenges faced in using GPS tracking to monitor animal behaviour.

The GPS tracking collars is this study demonstrated a data capture rate of 99%; marginally higher than reported for other studies (Table 16) with the exception of the study by Ganskopp and Bohert (2006) which reported 100%. Similarly, the relatively high average number of satellites (7) for position recordings was a function of programming the GPS unit in "over-determination mode" (Trotter & Lamb 2008). The average HDOP of 2.0 for all position logs is considered very good (French, 1996).

The diurnal activity (Figure 12) followed the expected trend with the highest peaks around sunrise and sunset, and minor peaks in the middle of the day and night (Arnold & Dudzinski, 1978; Roath & Krueger, 1982; M. Trotter & Lamb, 2008; M. Trotter, D. Lamb, G. Hinch, *et al.*, 2010). As this traditional trend in daily activity was seen through GPS locational data of the cattle it supports the use of this remote monitoring for behavioural investigation.

Table 16 Average GPS position logging data for the six deployed collars, including the expected number of recorded positions, the average number of recorded positions, the percent of expected positions actually recorded, the average number of satellites used to record a position and the average HDOP of recorded positions.

Expected position logs	Average position logs recorded	Percent of expected logs (%)	Average satellites	Average HDOP
37,152	36,850	99	7	2

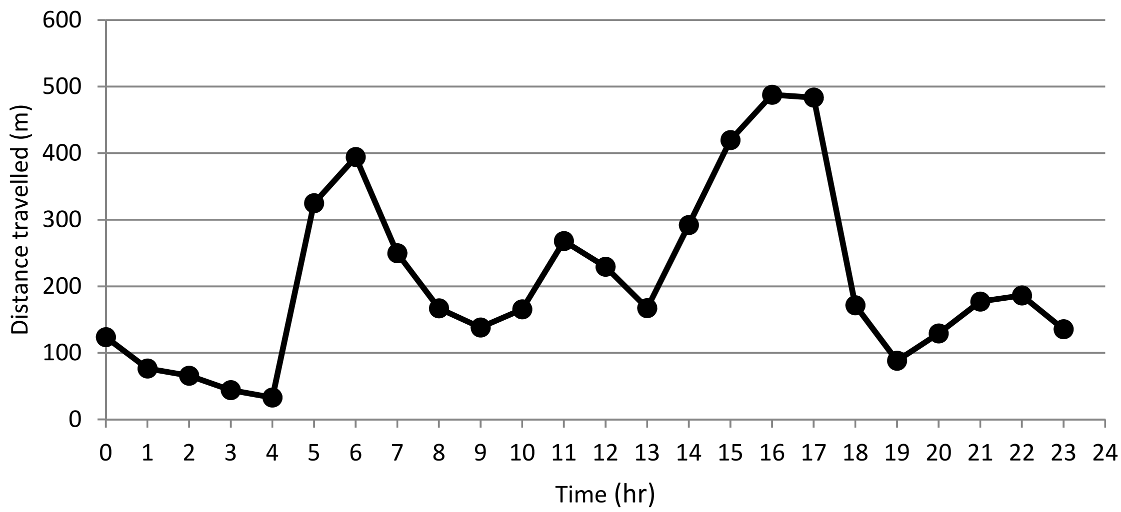


Figure 12 Diurnal activity of cattle, defined by the average distance travelled per day hour.

Table 0.17 Mean daily distance travelled and proportion of time spent grazing for each of the four periods of the study.

Period	Mean distance travelled (km)	Mean proportion daily grazing time (%)
1	5.9	36.3
2	5.7	36.7
3	5.2	37.2
4	4.4	36.2

Daily distance moved (Figure 13) and time spent grazing (Figure 14) are compared to daily temperature and rainfall for pre and post exclusion Period. Daily distance travelled was within the expected range; minimum herd average daily travel was 3.9 km and maximum herd average daily travel was 7.9 km with an average of 5.3 km/day). Examples of similar studies have found daily distances to be 5.2 km/day in a 20 ha paddock (D. Anderson & Kothmann, 1980) and 4.2 km/day in a 34 ha paddock (Hart, Bissio, Samuel, & Waggoner Jr, 1993).

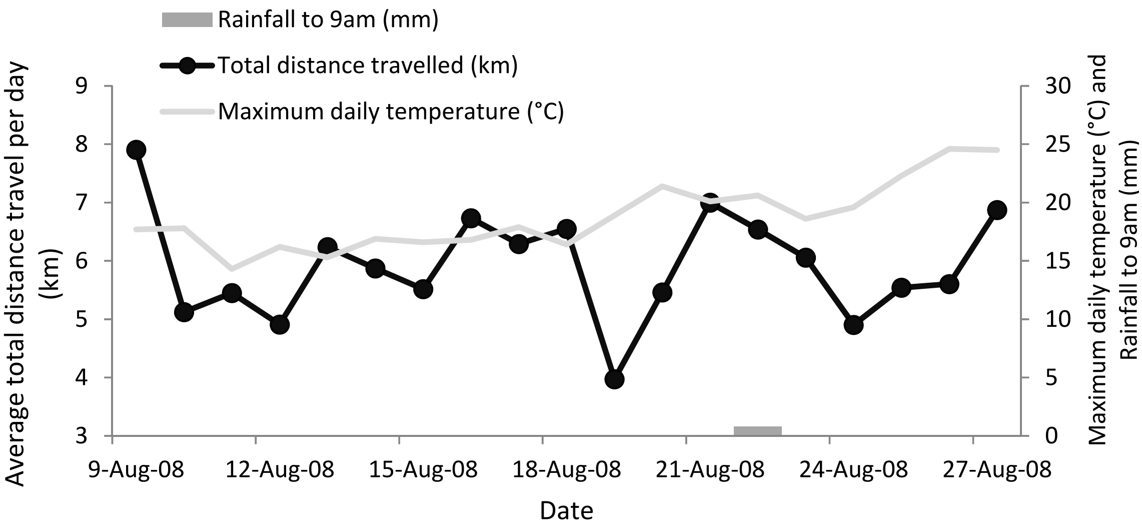
Literature suggests that with decreasing pasture availability, distance travelled would increase (Vallentine, 2001) and although we did see an overall reduction in pasture biomass in our trial field it may be that the animals were never 'nutritionally limited'. Daily distances travelled are known to change depending on climate factors such as temperature, wind and rain (D. Anderson & Kothmann, 1980), contrarily, no discernible relationship is observed. Perhaps the most significant change might be explained between the first two periods, and the second two periods where an extra water point was made available in the northern end of the paddock. This most likely contributed to a reduced average daily distance travelled between the two trial periods, as the cattle would have been closer to water when in the northern parts of the paddock, and therefore travelled lower distances for drinking.

As for distance travelled, daily grazing time was expected to increase over the study in line with diminishing pasture availability until biomass becomes so limiting that grazing time then begins to decline (EA Chacon, Stobbs, & Dale, 1978; Gibb, Huckle, Nuthall, & Rook, 1999). In contrast, there was little difference between the time spent grazing for Periods 1-4; means of 36.3, 36.7, 37.2 and 36.2 %, respectively), although there was a large amount of variation between days (Figure 14).

The daily temperatures during the study time frame did not appear to correspond with either distance moved or grazing time. Conversely, the largest rainfall events did appear to coincide with an increase in both distance moved and grazing time, although none of the rainfall events were large (<10mm) and additional peaks in activity on dry days renders these observations inconclusive.

Studies have demonstrated an inverse relationship between mean daily temperature and grazing time of cattle (Vallentine, 2001), and sheep (Thomas, Wilmot, & Masters, 2008). Comparatively, in this study the temperature recorded was only the daily maximum and minimum. It was difficult to isolate the effects of temperature from other variables which highlights the challenge of attempting to ascribe behavioural changes to individual variables. Without increased control and monitoring of variables including human interference, paddock changes (introduction of second water trough), pasture re-growth, and accuracy of biomass monitoring, GPS-derived parameters like grazing time cannot be specifically attributed to particular variables.

A)



B)

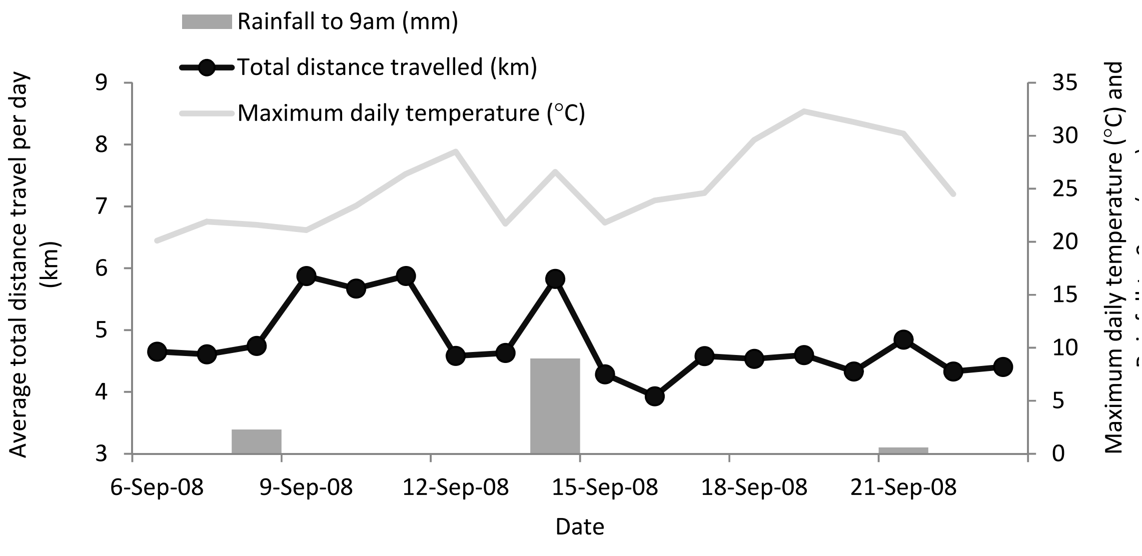
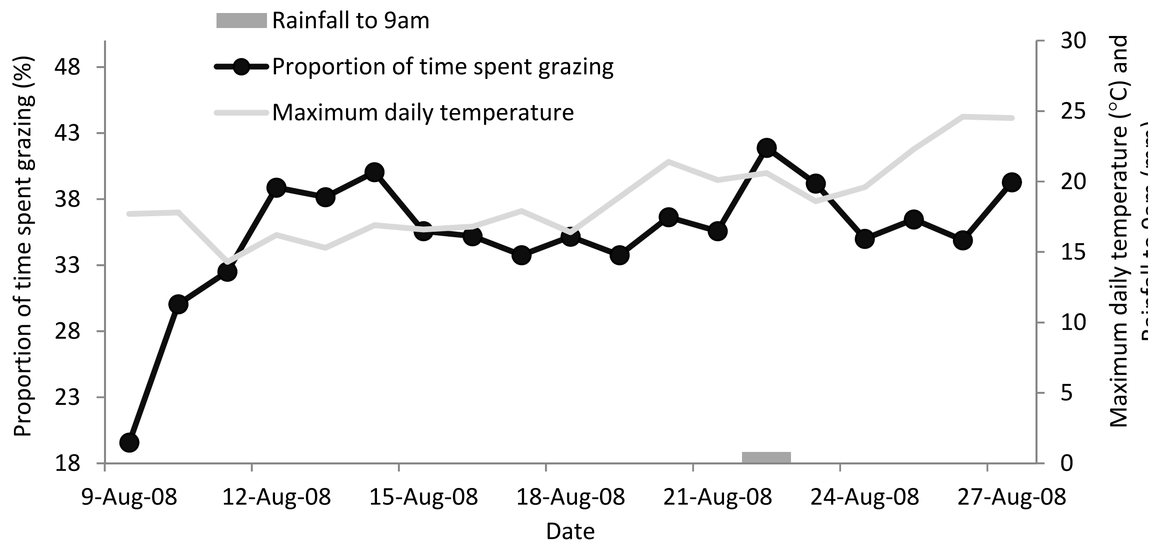


Figure 13 Total mean distance travelled by the cattle, rainfall and maximum daily temperature for A) exploration period, Period 1 and Period 2 and B) Period 3 and Period 4

A)



B)

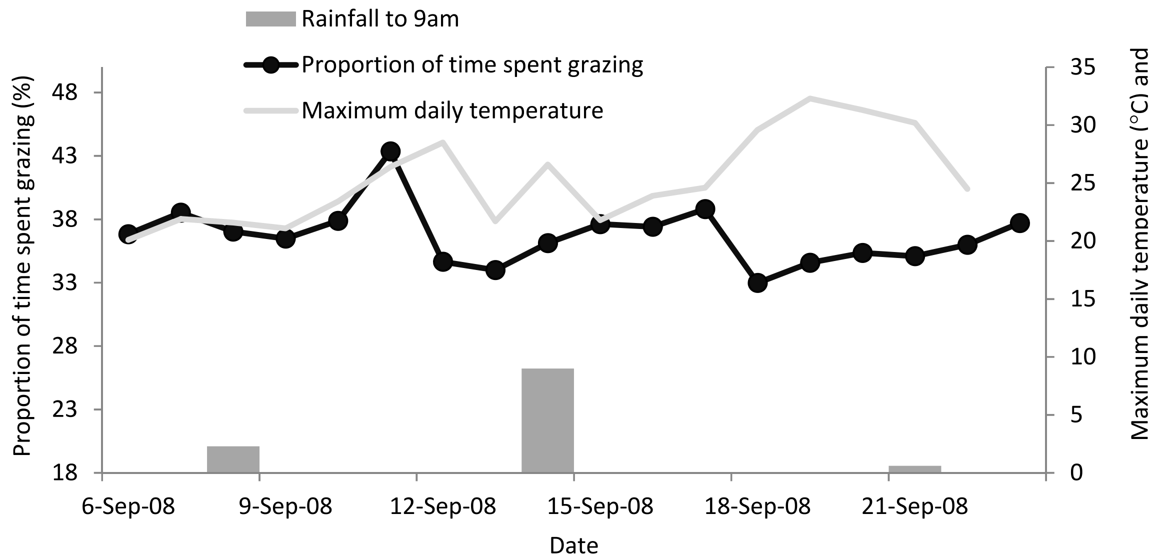


Figure 14 Percent time spent grazing, rainfall and maximum daily temperature for A) exploration period, Period 1 and Period 2 and B) Period 3 and Period 4

A potential alternative to simply monitoring animal movement and grazing time is examining the change in spatial landscape utilisation of livestock. During Period 1 (Figure 15), the south-east of the paddock experienced higher LRI values. The northern and western areas were the least utilised. In the LRI map for Period 2 (Figure 15), the south-east of the paddock again exhibited the highest LRI, and the north-west, the lowest. The differences in paddock utilisation between Periods 1 and 2 shows a small increase LRI. There is an increase in the number of paddock cells with an LRI larger than 0.25 by 14 grid cells, equating to 0.07 ha. This may represent an increase in the time spent in areas which provide a level of plant biomass that warrants visitation and are subsequently utilised by the animals in order to achieve adequate biomass intake.

The LRI map for Period 3 (Figure 15) highlights the paddock is approximately evenly visited. Most areas of lower LRI seen are along fence lines with some in the centre of the paddock. Differences between Periods 3 and 4 (Figure 15) are quite subtle, there does not appear to be an increase in the total paddock utilisation and in fact the cells with an LRI >0.25 increase marginally by only 6 cells, equating to 0.03 ha.

The LRI maps for Periods 3 and 4 demonstrate a significant increase in the spatial extent of and movement over the paddock as a whole, compared with Periods 1 and 2. However, as this followed the exclusion Period and rainfall it is difficult to determine the dominant influences affecting alterations in behaviour. Certainly, the decline in available forage would have contributed. Additionally, so too would the introduction of the second watering point (Bailey, VanWagoner, & Weinmeister, 2006). It is possible that, while overall green dry biomass available was low, the stocking density may have allowed for regrowth. The visitation across the whole paddock in Periods 3 and 4, compared to 1 and 2, may be attributed to cattle searching for new growth. Cattle are known to select fresh growth (Allred, Fuhlendorf, Engle, & Elmore, 2011), because of increased palatability and nutrition (Allred *et al.*, 2011).

Although there was no opportunity to collect validation data for behaviour in this preliminary study, the use of a speed based model to infer grazing does appear to have provided realistic results in terms of calculating the average time spent grazing. Excluding the exploratory phase, the animals were found to spend on average a minimum of 33 % and a maximum of 43 % of their time grazing. Although the proportion of time spent grazing was well below the 48 % reported by Putfarken *et al.* (2008), from which the speed based grazing behaviour model was derived, it was within the range reported in several other studies such as Stricklin *et al.* (1976) (35-38%) and Vallentine (2001) (29-50%). While the results appear realistic, the use of the Putfarken *et al. (2008)* speed model to determine behaviour is a genuine limitation of this study. The agroecosystem in which this speed based behavioural model was developed is quite different to that used in this study.

Figure 15 Livestock residence indexs (LRI) highlighting the areas (cells) utilised by cattle in Periods A) 1, B) 2, C) 3 and D) 4. Note the inclusion of the second water trough in C and D.

Table 18 Number of cells with an LRI of more than 0.25.

Period 1	Period 2	Period 3	Period 4
114	128	164	170

Conclusions

The GPS tracking devices deployed in this trial proved suitable for behavioural observations insofar as behavioural attributes including daily distance moved and grazing time were successfully extracted from GPS records over the study period. Paddock utilisation was also mapped using a livestock residence index. The results of this preliminary study suggests that there is opportunity to utilise the spatial monitoring tools in conjunction with an objective pasture monitoring tool such as the Crop Circle™ to investigate livestock and pasture interactions.

While this study was successful in testing the basic tools for livestock tracking and biomass monitoring, the simple behavioural components investigated suggest that biomass did not become limiting. In order to achieve the objective of investigating behaviour in relation to declining biomass, a response to limited feed must be elicited. The project aimed to investigate this further.

Part B - What are the key behavioural metrics that might be related to animal pasture interaction?

Introduction

The previous project found that simple measures of spatial and temporal behaviours of cattle grazing pasture can be extracted from GPS tracking devices. Specifically, it was found that distance travelled, grazing time and livestock residence could be quantified. The previous study did highlight the need for regular biomass monitoring, an increase in the proportion of animal's tracked, the need to minimize intervention to the livestock and paddock area, and the need to design a trial such that a decline of available biomass to a limiting amount is achieved.

The objective of this project were to identify the behavioral metrics that best relate to changes in available pasture biomass .

Materials and methods

Field Site and Experimental Events

This experiment was undertaken at University of New England's Douglas McMaster Research Station (150°36'0", 29°17'6" WGS84) as described in Section 2.2. Two flat, diagonally adjacent paddocks were used in this experiment: Paddock 1 (2.21 ha) and Paddock 2 (1.76 ha). Both paddocks comprised of vertisol soils of similar characteristics.

Pasture biomas

Paddocks were sown to forage oats (*sp. Avena Sativa var. Warrego*) (Figure 0.16). The timing of the experiment was so that grazing commenced when the plants were at the "booting" stage.

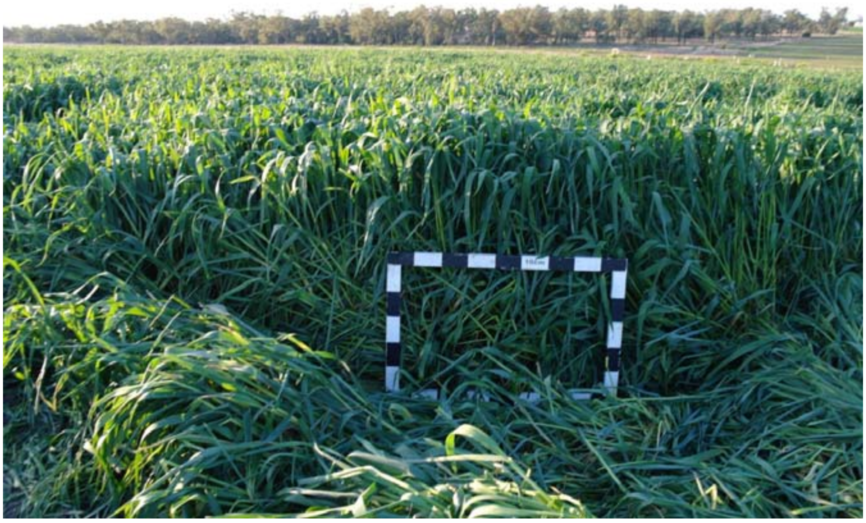


Figure 0.16 Paddock 1 on experiment day 1, containing forage oats variety "Warrego" approximately 9,393 DGLB (kg/ha). Each check (black and white) on the quadrat is 10 cm in length and 5 cm wide, giving a total external height of 60 cm and a width of 90 cm.

Forage biomass quantity was monitored using an active optical sensor (AOS), Crop Circle™ ACS-210 (Holland Scientific, Lincoln, NE, USA) as described in Section 2.2. This involved two processes; firstly calibration of the reflectance data collected by the AOS to the biomass determined by destructive sampling of several small Crop Circle™ sensed areas. This process was drawn from Zhao *et al.* (2007) and Trotter *et al.* (2010). Secondly, paddock transect reflectance data was collected with the AOS to inform whole paddock biomass.

Monitoring the Animal System

Paddocks were stocked with 50, Hereford, Angus and Hereford/Angus crossbred steers with a mean weight of 277kg (SD=21). The herd was randomly split into two mobs of 25 and were placed into the two experiment paddocks. Due to paddock size variation, Paddock 1 had a stocking rate of 11.3hd/ha and Paddock 2 14.2hd/ha.

Forty-four UNETrackerII collars (M. Trotter, D. Lamb, G. Hinch, *et al.*, 2010) were deployed randomly across the 50 steers, 22 animals in each mob were collared, which equates to 88%. The GPS devices were set to log in a multiple interval tracking (MIT) duty cycle, in which the GPS collects 4, 15 second apart logs every 15 minutes. Including short intervals improves the accuracy of the GPS. It was reported by Swain *et al.* (2008) that GPS accuracy improves as log interval decreases, below 1 minute.

The UNETrackerII collars were designed with the antenna facing skywards when on an animal. In order to keep the GPS at this position on the neck, a weight, heavier than the GPS device, was placed on the bottom of the collar. This was to improve the accuracy, precision and fix rate of the positions logged, by reducing interference from objects between the antenna and satellites, such as the ground, trees and other animals (Di Orio, Callas, & Schaefer, 2003).

Upon completion of the experiment, the collars were removed from the steers, and the raw GPS data downloaded. Using Excel® and ArcGIS®, Then the average distance moved per day and speed based behaviors (grazing, travelling, and stationary) were calculated.

To investigate the potential for social interaction to change in line with reducing feed a "socialisation metric" was developed. This was based on single interval tracking data and involved creating a new data set of only the first point from each MIT 15 minute cycle, creating a 15 minute log interval. The socialisation metric was derived by identifying the distances between animals during a grazing event each day. The daily peak grazing hour was determined by counting the number of grazing behaviour instances in each. The hour of the day which most often had the largest number of grazing incidences was 6-6:59am. To ensure only one location from each steer was included, a fixed 15 minute window within the peak hour was chosen, as each animal would only be represented once in this time frame. The fixed window was from 6:25:00am until 6:39:59am, chosen in particular as this period always represented all cattle i.e. there were no missing or excluded data points. Two different metrics were then calculated to express the dispersion of animals on a daily basis. The first was Minimum Convex Polygons (MCPs) and the second was distance between points providing intra-herd dispersion (IHD) values.

The proportion of paddock utilised, MCP areas, and IHD results were graphed against day and biomass. Polynomial trend lines were fitted to grazing, travelling and stationary time, proportion of paddock utilised, and values at inflection points were calculated. The inflection point values provided a single measure which could be compared between the two replicates.

Results

The measured biomass values (points) and the trend line created from the relationship between green leaf biomass and SAVI(0.75) reflectance values, is shown in **Error! Reference source not found.**. There is a progressive decrease in green leaf biomass throughout the experiment period.

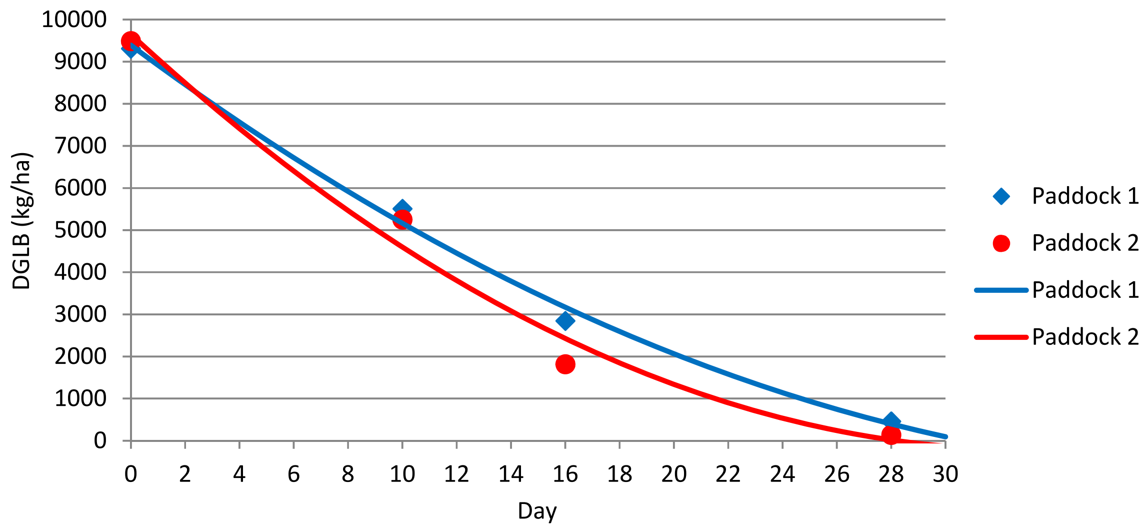


Figure 17 Measured (markers) and estimated (lines) GDLB (kg/ha) over the experiment period.

Biomass consistently decreased over the experiment period. Dry green leaf biomass decreased from 9,393 to 237 kg/ha (day 30) in Paddock 1, and from 9,646 to 378 kg/ha in Paddock 2 (day 25).

Figure 18 Cattle in paddock 1 on experiment day 1, containing forage oats. The estimated DGLB is 9393kg/ha.

Figure 19 Paddock 1 on experiment day 30, containing forage oats. The estimated DGLB is 237kg/ha.

Animal behavior

GNSS System Performance

A summary of the descriptive statistics of the GPS collars deployed is presented in Table 19, including the average per cent of location fixes received, satellites and HDOP of all of the location fixes. The focus of this research is the relationship between pasture availability and cattle at the herd level. Therefore, the herd is our experimental unit. For initial research, the more animals of the herd tracked, the better the understanding of the whole system. To ensure the pasture reached a limiting amount a high stocking rate was required. Due to resource limitations, there were not enough collars to be deployed on all cattle. As such, 88% of cattle had tracking collars. Further to this, GPS loss and malfunction meant that successful data capture occurred on 39 cattle (78%). When working with GPS, unfortunately missing data is not unusual (Frair *et al.*, 2004). Despite not being able to monitor all animals, we were able to capture herd behaviour as it relates to distance moved, grazing time, paddock utilisation and social interactions. The results of the two herds were comparable for the behaviours monitored; indicating tracked cattle numbers represented all animals in each experimental unit.

It is possible that an accurate picture of the herd may be gleaned without having to track all animals. Research around how many cattle represent the whole herd has been undertaken by Mattachini, Riva, Bisaglia, Pompe, and Provolo (2013). Unfortunately, this research studied the behaviour of dairy cows in a housed management system. Behaviour of housed dairy cows should not be used to assume the behaviour of grazing beef cattle. This is particularly important for this instance as we are focused on feed availability, a key difference between grazing and housed farming systems. Despite the conclusions that can be drawn from the research of Mattachini *et al.* (2013) are firstly, it may not be necessary to monitor all cattle in a herd (~40% in the example), and secondly there is a tried method to determine the proportion of herd monitoring required. This kind of investigation is outside the scope of this research, but has positive implications for the potential of GNSS as a commercial tool for pasture monitoring. As well as the influence on research, the number of animals tracked is also important when considering the reason for this research – improving commercial cattle production systems. Benefits of monitoring representative animals include lower expenditure to implement and maintain a system and reduced data storage and processing requirements.

Over both herds the proportion of expected position logs recorded was 96%. This is relatively successful and falls within the range reported by other studies (90-100%). The average number of satellites and HDOP meet the requirement of at least four satellites and a result of 1.3 is considered to be very good (French, 1996).

Table 19 Descriptive statistics of average herd GPS performance

Paddock	Count of all position fixes	% expected fixes*	Average of satellites	Average of HDOP
1	192653	96%	8.8	1.3
2	187169	97%	8.8	1.3
Total	379822	96%	8.8	1.3

* The expected number of fixes for paddock 1 was 11136 and for paddock 2 was 9216.

Distance Moved

The daily average distance moved in Paddock 1 (Figure 20), ranged from 2,500 m to 6,646 m with a mean of 4,311 m. In Paddock 2 distance moved ranged from 2,764 m to 6,103 m with a mean of 4,051 m.

On day 1 the cattle were active, both herds having a total distance of more than 5,000 m in the day and included the highest value recorded for this experiment of 6,646 m. The high distance is can be attributed to an exploratory phase of the cattle in a new environment (Vallentine, 2001). This indicates that the exploratory phase is not representative of 'normal' herd behaviour as a function of available biomass. Distance moved decreases on day 2, and from then there is a general increase in movement, before a general decrease towards the end of the experiment. This behavioural pattern met expectations that as biomass declined distance moved would increase until a point as cattle search for more feed until the energy of searching overcomes that provided by the feed REF. The peak for Paddock 1 at the end of experiment may be a socialisation affect due to the removal of the steers in Paddock 2. The increased travel time in Paddock 1 may be because cattle were unsettled after the neighbouring mob was relocated. While the herd from Paddock 2 were held in a paddock out of line of site, the Paddock 2 herd may have still sensed the other animals though sound and smell. These cattle were also originally in one herd and during this experiment, while separated; they were still in close proximity. As such, social contact may have been maintained throughout, despite the physical separation of a fence.

There were no clear trends apparent in the change of total distance moved as biomass declined in this experiment. From this, the next step was to investigate speed based behaviours during the experiment and how they changed in relation to declining biomass.

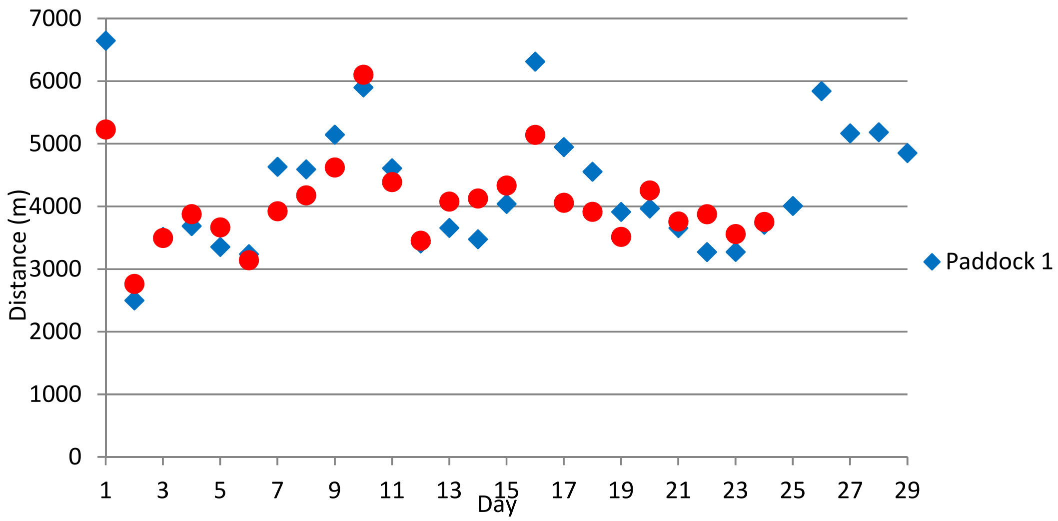


Figure 20 Average distance moved per day over the experiment period.

Behavioral modelling

Relevant speed based behaviours investigated were grazing, travelling and stationary movement. The proportion of time spent grazing was within the expected range of 20-50% (Vallentine, 2001) and was similar for both herds (Paddock 1 = 31-37% and Paddock 2 = 30-37%). As the experiment progressed grazing time increased each day to a maximum of 42% before declining to 32% at the end of the experiment, based on the inflection point of the fitted quadratic (Figure 21). This behaviour pattern has previously been described by Chacon and Stobbs (1976), where decline in grazing time in relation to decreased biomass availability was attributed to fatigue because of limiting energy gained from feed consumed. In their study, E Chacon and Stobbs (1976) aimed to determine whether low herbage intake on heavily grazed pasture was because of nutrient deficiency, bulk in the rumen or harvesting difficulty. Cattle grazed on setaria for 27 days, with decreasing available supplement, increasing the grazing intensity and reducing intake. Fistulated cattle were grazed and half had rumen contents removed and grazing time of these two groups were compared at 3 grazing intensities. The results showed at higher grazing intensity steers with removed rumen contents grazed less. Investigation of the rumen contents concluded that dry matter intake was limiting at high grazing intensity. In this experiment the grazing time pattern is the same for each herd. However, the timing (day) does not match because of the higher stocking rate in Paddock 2, resulting in less area available per animal and consequently a faster reduction in biomass and earlier behaviour response.

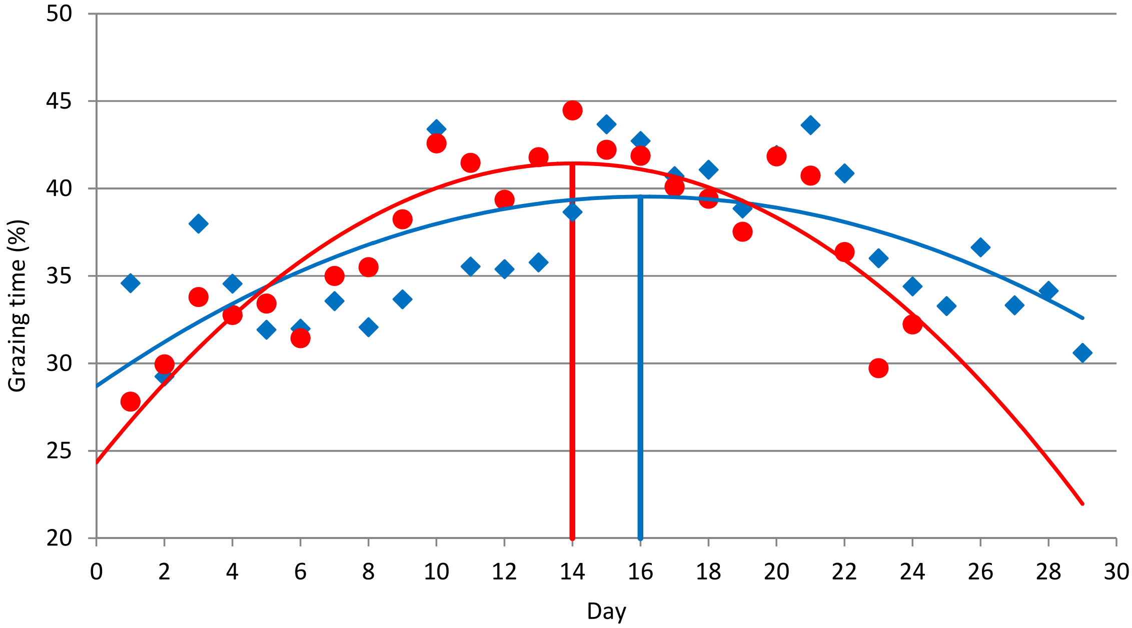


Figure 21 Average percentage of day spent grazing by the cattle. Quadratic curves are fitted to the data from day 6 with an r^2 of 0.62 for Paddock 1 and 0.77 for Paddock 2. The maximum grazing time in Paddock 1 occurred at day 17 and in Paddock 2 at day 15.

Travelling time per day was similar in both herds as seen in Figure 22. In Paddock 2 values were more consistent with all but two points falling between 2 and 4% of each day. Unlike, grazing time, travelling time each day was fairly consistent despite biomass reduction, with increases on day one and days with human interaction. The lack of effect on travelling due to biomass depletion observed in this experiment could be because of paddock size. In a very large rangeland paddock, livestock may travel further in search of food (Vallentine, 2001). In small paddocks the cattle can easily see or search for food without having to travel far. The days with high time spent travelling supports the exploration phase of the cattle, particularly when combined with the high distance moved. As distance travelled and daily time spent grazing are closely linked. As explored for distance travelled, it is likely that the removal of the Paddock 2 herd is thought to have affected time spent travelling of the Paddock 1 herd. This increase at the end of the time period has also had a strong effect on the quadratic fitted to this data. While it has already been explained that this quadratic is unsuitable, without the increase in travelling time at the end, the quadratic would have been more similar to that of Paddock 2 data.

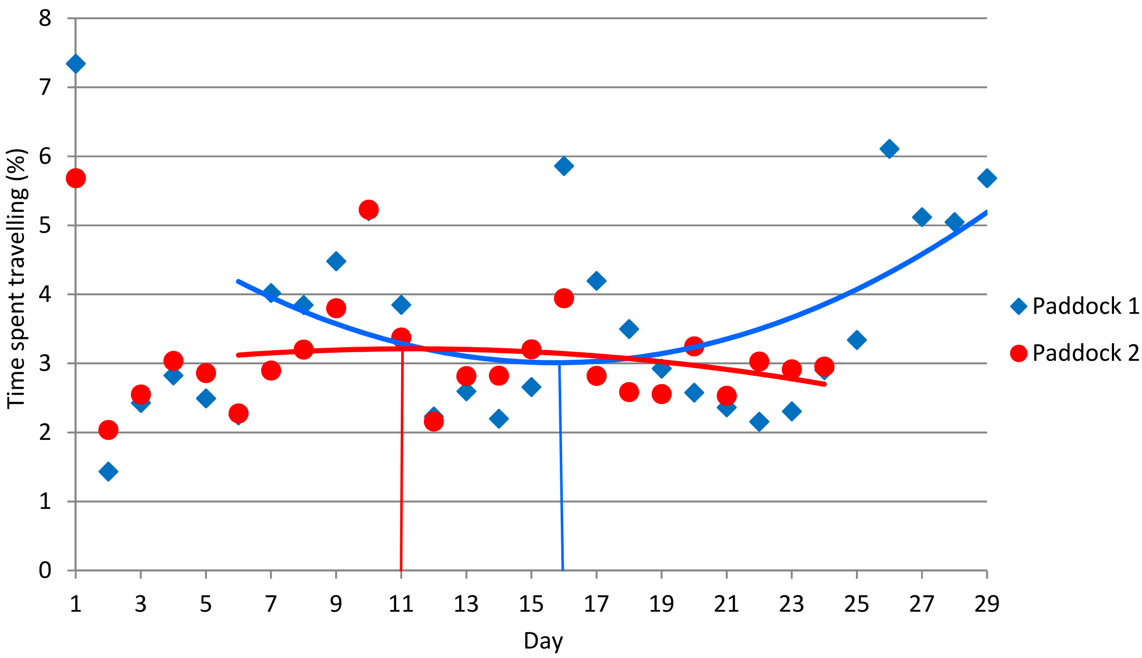


Figure 22 Average percentage of day spent travelling by the cattle. Quadratic curves are fitted to the data from day 6 with an r^2 of 0.23 for Paddock 1 and 0.05 for Paddock 2. The minimum moving time in Paddock 1 occurred at day 16 and the maximum moving time in Paddock 2 was at day 11.

Stationary behaviour, Figure 23, was similar in both herds and analogous to grazing behaviour. While stationary behaviour decreased and then increased over the experiment, grazing behaviour was the opposite. In paddock 2, peak grazing occurred on the same day as minimum stationary behaviour, and for Paddock 1 there was only one day difference. The Paddock 1 herd exhibited more stationary behaviour than Paddock 2, and in Paddock 2, this is replaced with higher grazing, rather than travelling behaviour. This result suggests that in small paddocks travelling behaviour is least affected by biomass availability, the animals sacrificing rest and/or rumination time for locating sufficient feed.

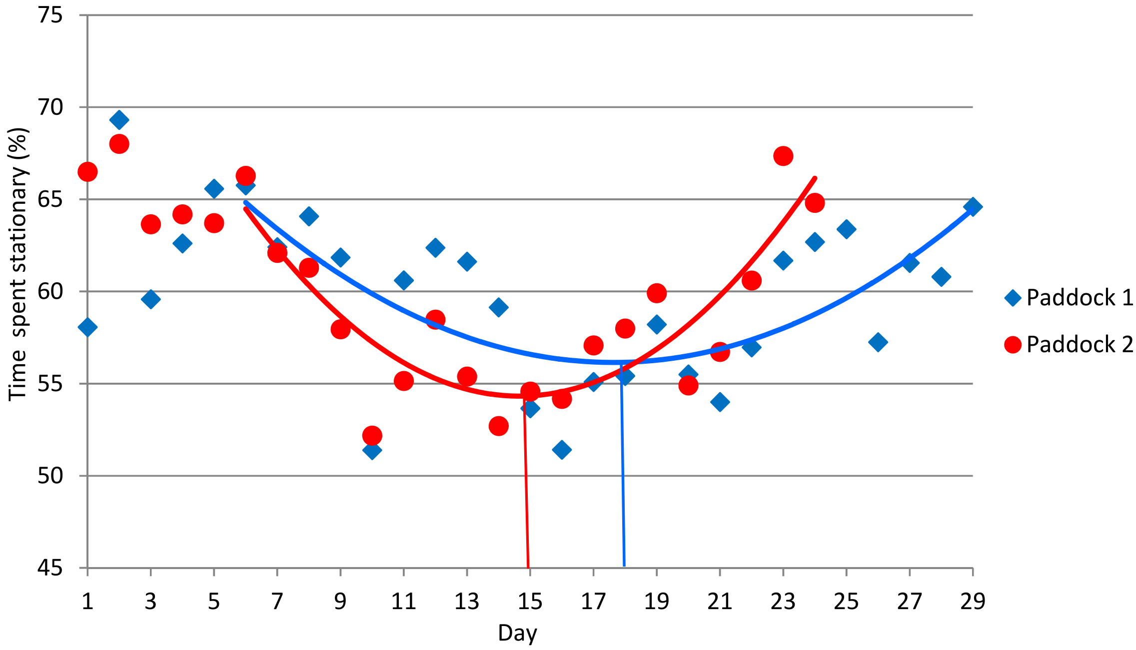


Figure 23 Average percentage of day spent stationary by the cattle. Quadratic curves are fitted to the data from day 6 with an r^2 of 0.44 for Paddock 1 and 0.72 for Paddock 2. The minimum stationary time in Paddock 1 occurred at day 18 and in Paddock 2 at day 15.

To investigate the general trends in behaviour in relation to biomass the behavioural data was graphed against this feature. While grazing time per day does not align between paddocks (Paddock 1 = Day 17, Paddock 2 = day 15), it does for DGLB, with the inflection point of grazing time occurring within 57 kg/ha of estimated DGLB, supporting that grazing time change is linked with available biomass (Figure 24). The quadratic fit was not appropriate for the entire dataset. However, noting the initial phase of behaviour perceived throughout this research the first 5 days of data were excluded. The pattern of behaviour after day 5, fitted to the quadratic (**Error! Reference source not found.**, Paddock 1 r^2 = 0.56; Paddock 2 r^2 = 0.75). It is also possible that a segmented quadratic may have been suitable, although, it would have complicated the purpose of fitting the quadratic: to simply compare the 2 herds. Previous investigations of grazing time and biomass availability depicts that behaviour increases, then decreases as biomass declines to a limiting amount. E Chacon and Stobbs (1976) found, with reduced intake, grazing time increased (P < 0.01) and declined after a peak. It is obvious that the travelling data and reduced biomass is not a quadratic relationship. It was included to compare with grazing and stationary behaviour. It highlights the stability of travelling behaviour over the experiment compared to grazing and stationary behaviour; highlighting that travelling time was not influenced by biomass in this experiment. The small paddock size restricted the expression of travelling behaviour.

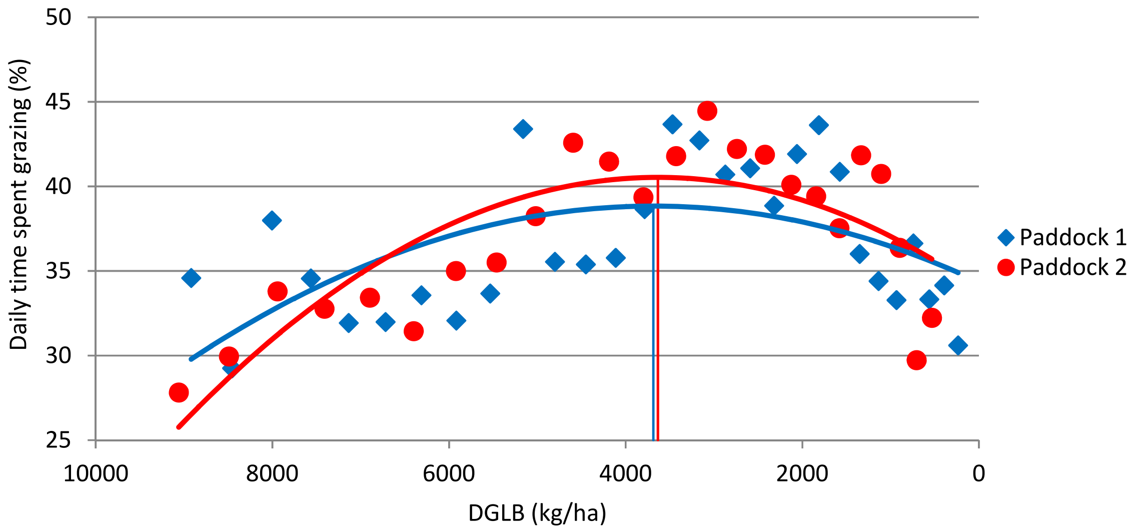


Figure 24 Average time spent grazing (% of day) as estimated DGLB declines. Quadratic curves are fitted to the data with an r^2 of 0.56 for Paddock 1 and 0.75 for Paddock 2. The maximum grazing time in Paddock 1 occurred at 3,248 DGLB (kg/ha) and in Paddock 2 at 3,305 DGLB (kg/ha).

As highlighted in the previous chapter, the use of a speed model for cattle behaviour under different conditions may not be accurate across all cattle. While it was intended, unfortunately validation of behaviour speeds was not possible for this experiment because of a limited view of cattle. The starting biomass in the paddocks was so high, cattle could not be easily seen, let alone individual animals and behaviours distinguished. This highlights the general potential for livestock sensors as they do not require a clear line of sight view of cattle. Had this experiment relied entirely on human or video collected observations it would have failed. While the speed model was unable to be validated in this experiment, as stated the results of the speed based behaviours are within expected ranges. A validation and development of a speed model will be presented in a later project.

Spatial landscape utilisation

Maps of LRI were created for each day of the trial for each herd. The daily cattle LRIs determined the proportion of each paddock utilised by the livestock per day Figure 25. The paddock proportion used for each herd against estimated DGLB is displayed in Figure 26. The maximum proportion as determined by the quadratic, of Paddock 1 was 65% at 3,001 DGLB (kg/ha) and for Paddock 2, 77% at 3,250 DGLB (kg/ha). The biomass difference between the two paddocks is 249 DGLB (kg/ha). This indicates that the proportion of paddock utilised is influenced by forage availability. The quadratic trend line fits the data very well with an r^2 value of 0.80 in paddock 1 and 0.78 in paddock 2. These results match cattle grazing time, exhibiting an initial increase in the proportion of the paddock utilised and grazing time, before declining. While the two herds exhibited similar paddock utilisation, the difference in proportion (i.e. Paddock 1 has a consistently lower proportion than in Paddock 2) is due to Paddock 2 having a higher stocking rate, thus there were more animals in a smaller space, as perceived with speed based behaviour. While maximum grazing time seemed to occur at a closer biomass than paddock proportions, the better fit of this data to a quadratic may mean that it is more useful for an online monitoring tool than grazing time. The difference of 249 kg of GDM is well within our biomass estimate and so, is considered close.

Decreasing nutrient availability of feed is known result in decreased cattle activity once nutrients are so low that the animals expend more than they can consume. Several behaviours indicate that this state of negative energy balance has been achieved (grazing time, stationary time and proportion of paddock utilised) and that has been attributed to amount of biomass available. It is possible the forage oats may have been limiting in nutrients, however an investigation of pasture quality was outside the scope of this research.

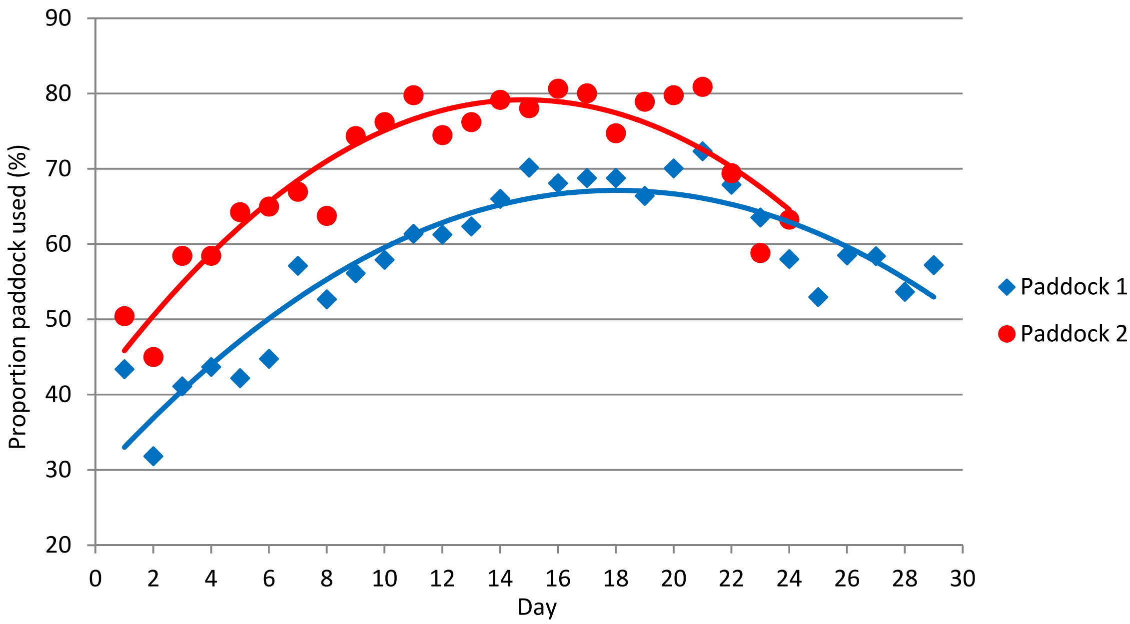


Figure 25 Daily proportion of Paddock 1 and Paddock 2 used by the cattle as calculated by LRIs. (r2 for Paddock 1 = 0.86 and r2 for Paddock 2 = 0.86)

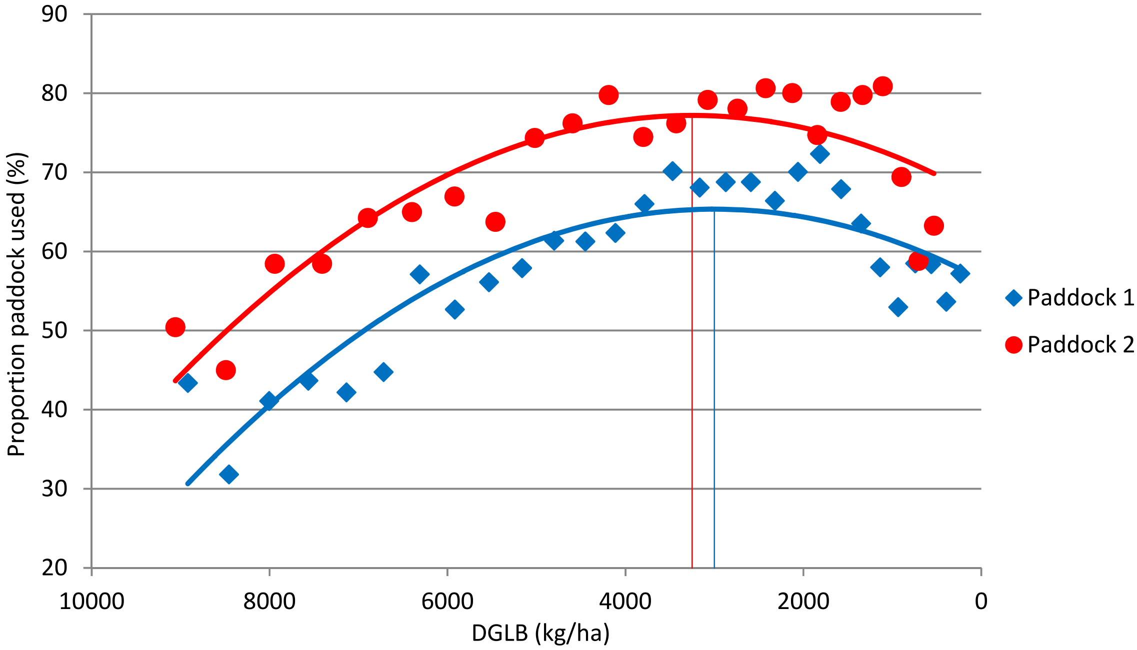


Figure 26 Proportion of Paddock 1 and Paddock 2 used by the cattle as calculated by LRIs and daily estimated DGLB (kg/ha). (r^2 for Paddock 1 = 0.80 and r^2 for Paddock 2 = 0.78)

Social Interaction modelling

Spatial distribution was investigated through whole herd dispersion (with MCPs) and within herd dispersion (with IHD). At the beginning of the experiment the animals appeared to be close together with little variation. As time progressed and biomass decreased, the distance between animals increased, however day to day variation was also larger. The results are supported by behavioural observations that livestock become more dispersed both between and within herds (Dudziński, Müller, Low, & Schuh, 1982; Vallentine, 2001). In a 170km^2 paddock cattle, monitored with 108 aerial surveys and nearest neighbour statistical analysis, were found to increase dispersion with decreasing biomass availability. Vallentine (Vallentine, 2001) reviewed seven articles which also established social dispersion of cattle increased when biomass declined. It is interesting that the small paddocks used in this experiment did not hinder this behaviour. The use of spatial and social aspects of cattle behaviour for biomass assessment is promising.

There appears to be 3 phases in MCP and IHD behavior. The initial phase was obvious in the speed based behaviours. Two possibilities of why there is an initial period with relatively stable behaviour are the high available and uniform biomass and/or the physical barrier of dense biomass. Initially high and uniform biomass was easily accessed from camp sites reducing the desired of cattle to graze over large areas at the beginning of the experiment. The forage was so dense the cattle also had some difficulty or simply preferred not to move through it to access other areas of the paddock. Additionally, the need for cattle within a herd to be within sight distance of each other would have prevented high dispersion when biomass was not limiting. The second phase occurs from around 6,313 kg/ha GDM to 2,061 in Paddock 1 and 6,400 to 1,336 in Paddock 2. This phase could be the response of cattle to an environment they are familiar with, is non-limiting for biomass and allows greater line of sight distance between cattle. Phase 3 occurred after biomass levels of 2,061 kg/ha GDM in Paddock 1 and 1,336 in Paddock 2. Based on the recommended grazing level of 1,500 kg/ha of GDM, the third phase occurs above this in Paddock 1 and below in Paddock 2. It is possible that the biomass was becoming limiting in both paddocks at this time.

The change in MCP area and IHD is very similar for individual herds and occurs at the same biomass. However, this biomass level is quite different to the biomass at inflection points for grazing time and the proportion of paddock utilised, at more than 6,000 DGLB (kg/ha). At this amount, the biomass was not limiting, suggesting that another factor is driving this change. Possibly, as previously suggested, the change from Phase 1 to Phase 2 could be linked with visibility of the cattle. The change between Phase 2 and 3 has occurred when biomass is thought to be at a limiting level (< 1,500 kg/ha GDM). It may be that these behaviours are affected by biomass, but the social behavioural response occurs at a lower amount than for speed based behaviour and paddock utilisation. This response would be triggered at a higher stress state of the animal.

The difference in MCPS was not possibly directly compared between mobs as there are different numbers of animals included in the area (Table 0.20). This presents an advantage of considering the IHD for a commercial monitoring system, as it is an average of the cattle included. As such IHD between herds was compared. There was little difference between IHD in any of the phases, though this could be due to small paddock size.

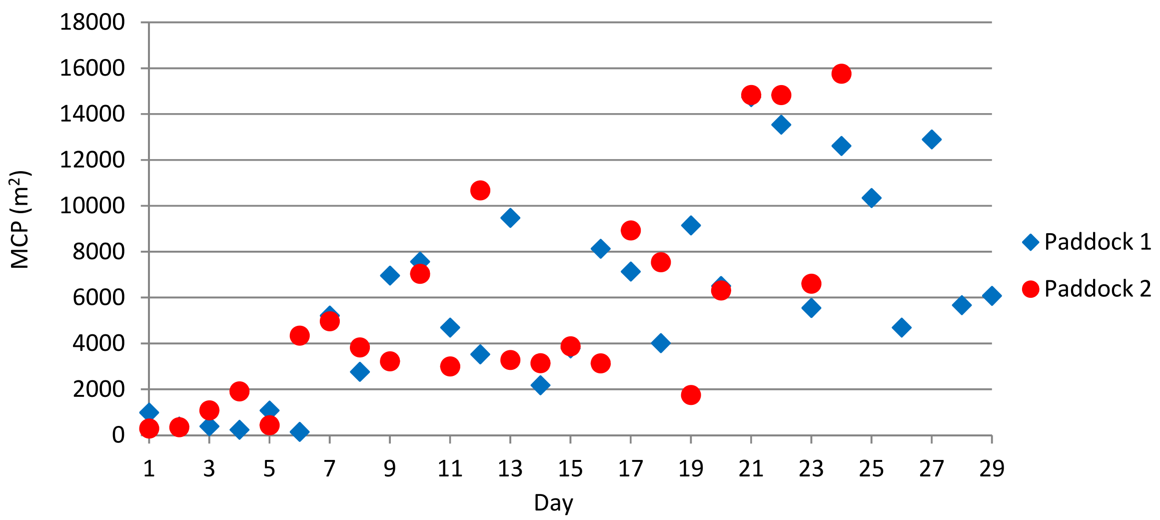


Figure 27 Daily MCP areas for each herd.

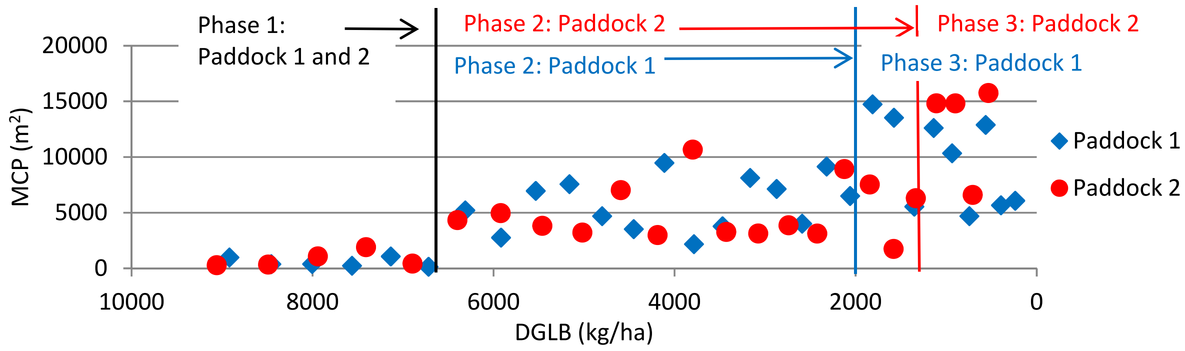


Figure 28 Daily MCP areas and estimated DGLB for Paddock 1 and Paddock 2. Three distinct phases for each herd have been identified with vertical lines. The point of interest is between Phase 1 and Phase 2 when MCPs suddenly increase after stability at 6,313 kg of biomass for Paddock 1 and at 6,401 kg of biomass for Paddock 2.

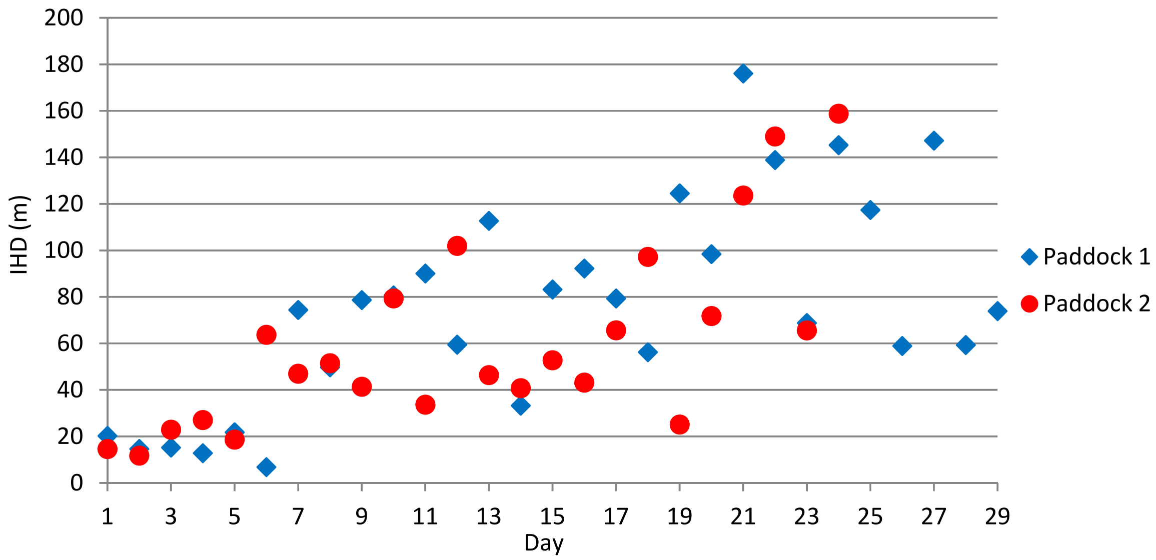


Figure 29 Daily average IHD for each point herd. Three distinct phases for each herd have been identified with vertical lines. The of interest is between Phase 1 and Phase 2 when dispersion suddenly increases after stability at day 7 for Paddock 1 and at day 6 for Paddock 2.

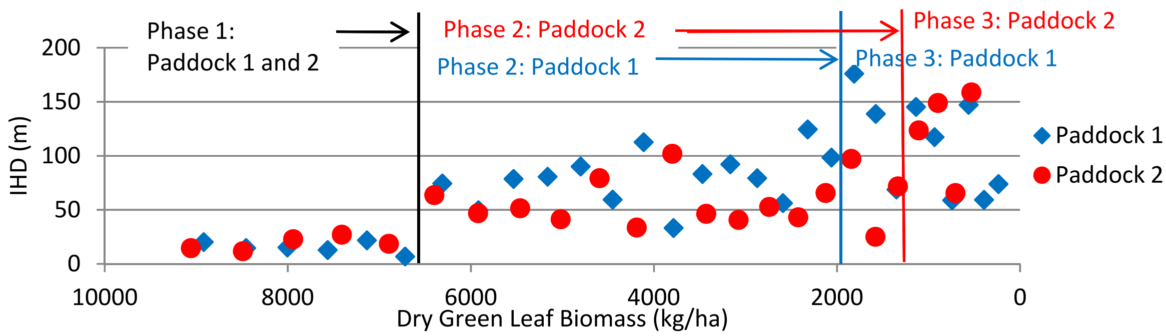


Figure 30 Daily IHD and estimated DGLB for Paddock 1 and Paddock 2. Three distinct phases for each herd have been identified with vertical lines. The point of interest is between Phase 1 and Phase 2 when MCPs suddenly increase after stability at 6,313 kg of biomass for Paddock 1 and at 6,401 kg of biomass for Paddock 2.

Table 0.20 Phase change values for Paddock 1 and Paddock 2 of MCP and IHD and the difference between paddocks of IHD.

	MCP (m^2)		IHD (m)		
Phase	Paddock 1	Paddock 2	Paddock 1	Paddock 2	Difference
1	538	817	15	19	4
2	5794	5004	80	58	22
3	9570	13008	110	124	14

Towards indicator metrics

The summary of key results, Table 21, highlights GPS observable behaviours which could be suitable for real-time GNSS indicators of pasture biomass availability. The key point of interest for grazing time and paddock proportion occurs at a similar biomass (3,001 to 3,305 kg/ha of DGLB). This suggests there is a key threshold biomass level inducing grazing behaviour changes i.e. in this environment around 3,000 kg/ha of DGLB.

Table 21 Summary of key results for Paddock 1 and Paddock 2, showing the corresponding dry green leaf biomass (kg/ha) with: the maximum daily grazing time; maximum proportion of paddock used; the point of interest for the MCPs; and the point of interest for IHD.

	Paddock 1 Behaviour value	Paddock 2 Behaviour value	Paddock1 DGLB (kg/ha)	Paddock 2 DGLB (kg/ha)	DGLB Difference (kg/ha)
Peak grazing time (%) from fitted quadratic	41	43	3248	3305	121
Maximum paddock proportion (%) from fitted quadratic	65	77	3001	3250	249
MCP (m^2) at change from phase 1 to phase 2	5216	4344	6313	6401	88
IHD (m) at change from phase 1 to phase 2	74.5	63.7	6313	6401	88

Conclusion

In this experiment, aspects of animal behaviour and biomass were successfully measured with technology. This has positive implications for using such technology in both research and commercial production systems. Additionally, the reduction of human variation (Brock & Owensby, 2000) and in-field error may be limited with the development of this technology.

Several specific behaviours were successfully monitored in relation to declining biomass. The results highlight that behaviour of cattle changes as available biomass decreases and livestock tracking can detect these behavioural changes. Specifically, the results have shown cattle change the way they utilise a paddock spatially and temporally as biomass declines. They also change how they interact with each other as feed declines. Most importantly, the results in this study show us that cattle behaviour can be detected and monitored with GNSS technology alone.

The major findings of the experiment, as related to the objectives, are that as biomass declines livestock behaviour changes and several key metric have been developed that might be used in a commercial livestock monitoring system:

1. Grazing time – as derived from a speed based model;
2. Spatial landscape utilisation – as derived from mapped positional data;
3. Social Interaction – as derived from either MCP or IHD analysis.

While it is unlikely that the actual values and thresholds developed in this study will be transferable to other situations and commercial tools these models will be. If commercial systems can be developed that provide the data (spatio-temporal) then these models could be implemented and the thresholds customized for the particular property on which it is deployed.

2. Can we determine key animal behaviours from spatio-temporal data?

The research presented in the previous two projects of this thesis successfully utilised the speed model developed by Putfarken *et al.* (2008). This was a clear limitation of our research and so we set out to develop our own speed model and validate the model developed by Putfarken *et al.* (2008).

Materials and methods

Field Site and Livestock

The field experiment was undertaken at the Precision Agriculture Research Group (PARG) Demonstration Site, University of New England, Armidale, New South Wales, Australia (30°28'49"S, 151°38'34"E). There were six adjacent paddocks each of 0.35ha, fenced with 3 strands of electric tape. The livestock in this field experiment were familiar with electric fences. Paddock maps and areas are displayed in **Error! Reference source not found.**.

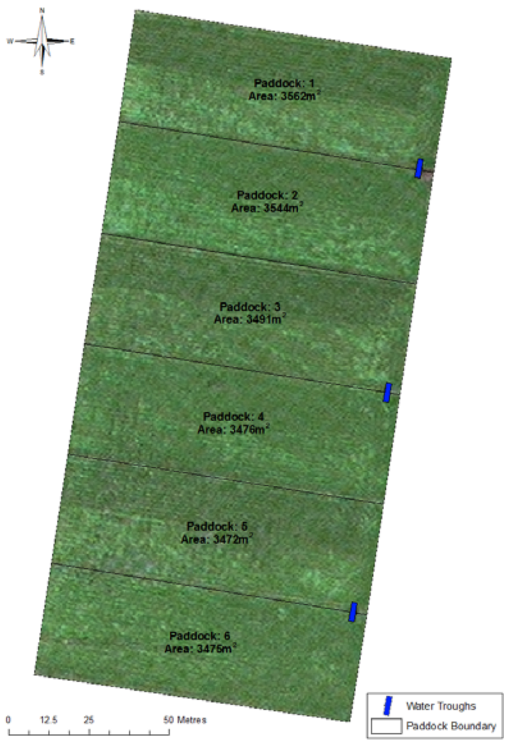


Figure 31 Map of the field site at the Precision Agriculture Research Group Demonstration Site, University of New England, Armidale, where GPS tracking collars were deployed on 18 steers. The allocated paddock numbers, areas and locations of water troughs are labelled.

Animals

The three mobs (six animals each) were randomly allocated to an initial paddock, with an empty paddock between each to reduce inter mob socialisation. A recent study involving GPS tracking of sheep in 3 mobs found there was bias towards shared fence lines (Barwick, 2011). Mobs were rotated so that the mob at the base of the hill was moved to the top, and the other 2 mobs moved to the adjacent paddock downhill. This was an attempt to remove possible slope and aspect effects between rotations. The GPS units deployed on the cattle were set to MIT of 5 records, spaced 15 seconds apart, every 15 minutes. GPS units were started at the same time, on the hour mark in an attempt to achieve synchronisation of position logs, as the devices could not be programmed to synchronise.

Livestock Observations

Cattle were visually observed every third day of the trial period. A vehicle was located approximately 50 m North East of paddocks providing the observer with a good view of the cattle in all paddocks. There was one main observer who undertook all observations from sun-up (approximately 5am) until 9am, 11am to 2pm and from 4pm until sundown (approximately 6pm). From 9-11am and 2-4pm, secondary observers recorded behaviour. These secondary observers were trained by the main observer to reduce human bias on the results.

Figure 32 A photo of the experiment taken from the observation point on an observation day (9/10/11), facing South-West. This picture shows some of the steers from each of the mobs in rotation 2, where Mob 1 is in Paddock 2 (foreground), Mob 2 is in Paddock 6 (background) and Mob 3 is in Paddock 4 (mid picture) during a camping event. Regrowth of the pasture utilised in rotation 1 (Paddocks 1, 3 and 5) can be seen between the rotation 2 utilised paddocks.

Individual Animal Scan Sampling

The behaviour observation method chosen was individual animal scan sampling in which one animal per mob was monitored throughout the experiment. The second steer from each of the mobs (12, 22 and 32), was marked with orange tail paint for identification. The behaviour of each of the focal (marked) animals was recorded every 15 minutes with the Apple iPod application WhatISee© (Heuser, 2009). This application had a spread sheet designed to record the time at which the focal cattle were exhibiting a particular behaviour state. Recordable behaviour states chosen were: "Standing", "Lying", "Grazing", "Walking" and "Other". For the purpose of data synchronisation with observed activity, one minute observations on steer 22 were also undertaken from 7:33am until 6pm on the 18th of September using WhatISee© (Heuser, 2009). This one minute data was filtered to remove any observations which were within 30 seconds of each other. This occurred on several occasions due to observer delay.

Statistical analysis

All statistical analysis was completed with the statistical software "R" version 2.15.0 (*R: A language and environment for statistical computing.*, 2012). Packages used include chron (James & Hornik, 2011), evd (Stephenson, 2002), lubridate (Grolemund & Wickham, 2011), ggplot2 (Wickham, 2009) and simpleboot (Peng, 2008).

As previously stated GPS data was recorded as a burst log every 15 minutes and the visual observations were undertaken every minute for steer 22 on the 18th of September. The one minute behavioural sampling data was used to compare with the 15 minute GPS data to ensure appropriate behaviours were aligned with spatial information.

Behaviour States

The visual observation dataset consists of behavioural observations on steers 22 (at one minute intervals), 12 and 32 (at 15 minute intervals) from 5:30am until 6:00pm on the 18/09/2011. From the one minute observations of steer 22, behavioural state change was determined and applied to the data set. The "Other" behaviour state records were removed from the analysis because of small sample sizes of less than 5% of observed activity states for each observed animal (n = 0, n = 29, n = 1 for steers 12, 22 and 32 respectively). "Walking" behavioural states were pooled with the "grazing" state, which is termed the "moving" state. Additionally, "Lying" and "standing" states were pooled to form the "stationary" state.

To determine the probability of a state change within a given time period, a mathematical method was developed. Using the visual observation data, a time referenced state vector was created for steers 12, 22 and 32:

$\mathbf{S}_{(i)} = [S_1, S_2, \ldots, S_t, \ldots, S_T]$,

where $\mathbf{S}_{(i)}$ is the state, i is the steer index, t is the observation index time and T is the final observation time.

Each of the state symbols, $\mathbf{S}_{(i)}$, represents one of the observed behaviour states denoted "M" for moving or "S" for stationary; observed at the 15 minute time period containing one GPS log cycle.

The time referenced state vectors, $\mathbf{S}_{(i)}$, for each steer in the herd was combined to give a herd-state, $\mathbf{H}$, matrix, which is defined as:

$$\mathbf{H} = \begin{bmatrix} \mathbf{S}_1 \\ \vdots \\ \mathbf{S}_\mathrm{N} \end{bmatrix}.$$

A binary indicator function, $\mathrm{I}(\mathbf{S}_\mathrm{i})$, was used to specify at what times a change of state occurred for the i^{th} animal (n = 3). If the state changed from the previous time, $t - 1$, the binary indicator was given the value 1, otherwise it was 0; for each time and each animal:

$$\mathrm{I}(\mathbf{S}_\mathrm{i}) = \begin{cases} 1, & \text{if } S_t \neq S_{[t:(t-1)]} \\ 0, & \text{otherwise} \end{cases}$$

for all the time indices excluding the first i.e. $t > 1$.

The indicator function was applied to all time-referenced state vectors $\boldsymbol{S}_i$ to create a state change matrix within the herd:

$$\mathbf{B} = \begin{bmatrix} \mathrm{I}_{\mathrm{S}_1} \\ \vdots \\ \mathrm{I}_{\mathrm{S}_\mathrm{N}} \end{bmatrix}.$$

Note: the number of columns in **B** will be one less than **H** because it describes the state changes between consecutive time steps.

From the rows of state change matrix **B**, time-lag indicator vectors $\mathbf{L}_k$ for select time-lags, k=(P_1, P_5, P_{10}, P_{15}, P_{30}, P_{60}), of matrix values were created for each animal. Entries within the $\mathbf{L}_k$ matrices were given by:

$$\mathbf{L}_{k(\mathrm{i})} = \sum_{t=1}^{\mathrm{T}} \left| B_{(i)[(t+1)k]} - B_{(i)[t_k]} = 1 \right|$$

In other words the entries in $\mathbf{L}_{k(\mathrm{i})}$ vector are formed for each animal by the sum of all possible combinations of state change indicators which are separated by time lag "k" formed by the sum of state indicators whose absolute difference is one for fixed lags. In the case where the fixed lag "k" was not available e.g. k = 5 minutes, the $\mathbf{L}_{k(\mathrm{i})}$ values are denoted unavailable as "NA" value.

For each of the animals, the probabilities, ($P_{k,i}$), of a state change occurring for the lag times, k, were calculated from the time lag indicator vectors $L_{k(i)}$. For the i^{th} animal, this probability is calculated as:

$$P_{k,i} = \frac{\sum_{\mathrm{i}=0}^{\mathrm{n}} \mathbf{L}_{\mathrm{k(i)}}}{\mathrm{T}_k}$$

for the time lag indicator vector $L_{k(i)}$with $T_k$entries.

The probabilities of each time lag (P_1, P_5, P_{10}, P_{15}, P_{30}, P_{60}) for steer 22 were assessed using a linear regression model to detect any change in probability magnitude with lag. This model had the form:

$$P_k = \beta_0 + \beta_1 \mathrm{k} + \varepsilon,$$

where $\varepsilon \sim N(0, \sigma^2)$ is the error or residual term which is assumed to obey a normal distribution, 'k' denotes the time lag between observations, P_k is the response referring to the probability of state change at time lag k, and β_0, β_1 are the regression coefficients (intercept and slope respectively).

A t-test was used to assess the slope coefficient for statistical significance. The intercept coefficient and its estimated uncertainty were also assessed to determine the base rate probability of state changes for lag times longer than one minute. The data from steer 22 was selected for the development of the regression model because it had the finest resolution of time periods, the probabilities for the other steers were calculated but had only three distinct lag values, (P_{15}, P_{30}, P_{60}), and therefore were not assessed using the regression model.

Animal speed

The distance and time between consecutive GPS logs can be used to calculate speed during this interval. Although five logs per GPS burst were taken, only the first four logs were averaged for this calculation. This is because in order to calculate the speed of a point, the position of the next point is required. For the last point in a burst series the next point is the first log of the consecutive burst, nearly 15 minutes later. The fifth log of each burst created the single point dataset. The longer a GPS has been "awake", and the smaller the interval between logs, the more accurate the position recorded will be (Swain, Bishop-Hurley, Wark, Butler, & Guo, 2008).

Speeds calculated from the GPS tracking were matched in R to visual observations based on time of log recording to within +/- 30 seconds. If speed was calculated to be greater than 0.5m/s for a stationary observation it was removed as erroneous as these are extreme speeds for inherent stationary GPS error.

Speed Threshold

The location data from focal animals (12, 22 and 32) contributed to the determined a threshold value of speed. Initially, a mathematical model was developed to estimate the speed at which an animal is deemed either "stationary" or "moving" from their GPS record.

Bootstrap samples of the speed records were used to estimate the mean speed for each state and to produce the order statistics used to fit the generalised extreme value distribution model (GEV). These "bootstrap" samples were formed by randomly sampling a single speed record for each steer in each state. The first of the bootstrap samples is denoted $B^{*(1)}$. This was repeated 999 times to form the sequence of bootstrap sample vectors:

$\mathbf{B}^* = (B^*_{(1)},\cdots, B^*_{(j)},\cdots, B^*_{(999)})$

The median speed was then calculated from the bootstrap samples in each case, $\tilde{v}^* = (\tilde{v}_1^*, \tilde{v}_2^*, \cdots, \tilde{v}_{999}^*)$, and the mean value of these bootstrap estimates of $\overline{\tilde{v}^*}_{stationary}$ and $\overline{\tilde{v}^*}_{moving}$ were calculated along with the 95% confidence intervals using the percentile methods (Davison & Hinkley, 1997).

For each of the steers and visual observation days the state (stationary or moving) histograms of speed records were examined. Based on the histograms, generalised extreme value (GEV) distributions were estimated (equation 1.9, Chapter 1, Smith (2003)) using the median values from the bootstrap samples:

$$f(\tilde{v}^*) = \exp\left(-\left(1 + \zeta\frac{x-\eta}{\psi}\right)_+^{-\frac{1}{\zeta}}\right)$$

where $\tilde{v}$ denotes median speed in m/s, η is the location parameter, $\psi > 0$ is the scale parameter, and ζ is the shape parameter. The maximum or zero selection function, ψ_+, is defined as:

$$\left(1+\zeta\frac{x-\eta}{\psi}\right)_{+} = \max\left(1+\zeta\frac{x-\eta}{\psi}, 0\right),$$

and ensures the exponent in the definition of the distribution is always greater than or equal to zero, thereby constraining the magnitude of the distribution to be between zero and one.

The speed threshold of the moving state change was determined with the GEV to estimate where the probability of a moving state change was greater than 0.5.

The GEV was also employed to estimate the speed thresholds of each individual steer. The thresholds estimated were only approximate in this case because the speed records were sampled from correlated records of each steer on the same day and are unlikely to be statistically independent.

Results

Behaviour States

The linear regression model for the probability of state change with time observation window was estimated to have the following parameters:

$\hat{\beta}_0 = 10.258859 \pm 1.654718, t = 6.200, p = 0.00344$

The results of the investigation of time lag for steer 22 supports the null hypothesis $H_0\colon \beta_1 = 0$ due to its estimate being not statistically significant:

$$\hat{\beta}_1 = 0.009478 \pm 0.058195, t = 0.163, p = 0.87852, df = 4$$

The probability of a state change for the given time intervals (1, 5, 10, 15, 30 and 60 minutes) are presented in Table 22. Probabilities were similar for all time intervals.

Table 22 Raw detected and probability of state changes after time elapsed for steer 22.

Timing (minutes)	Number of changes	Number of observations	Probability of state change	Standard deviation
1	64	519	12.33	0.002
5	8	94	8.51	1.00
10	5	47	10.64	2.00
15	4	32	12.50	3.00
30	1	16	6.25	6.30
60	1	8	12.50	13.00

Speed modelling

The distribution parameters were estimated for the GEV using the maximum likelihood routines in R package evd, as reported in Table 23.

Table 23 GEV parameter estimates for the distributions of the two states.

State	$\hat{\nu}$	$\hat{\psi}$	$\hat{\zeta}$
Moving	0.018040+/-0.0003202	0.009447+/-0.0002201	0.197526+/-0.0163109
Stationary	0.018519+/-0.0002178	0.006371+/-0.0001150	-0.186096+/- 0.0140786

Analysis of speed and behaviour observations resulted in histograms containing 'long-tails', which were 'right-skewed' (weighted toward smaller values), and had larger magnitudes at low probabilities, for example Figure 33.

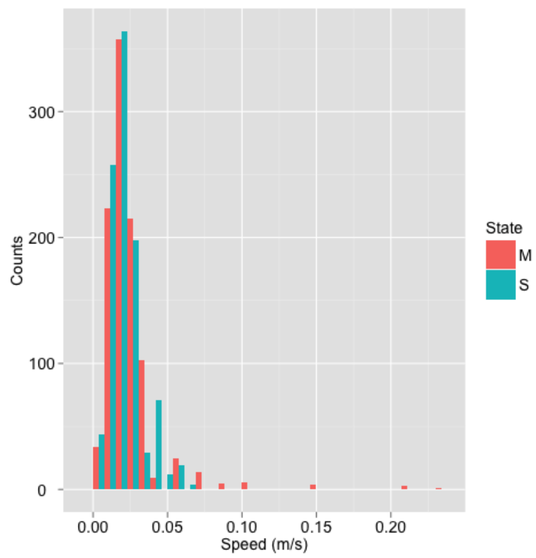


Figure 33 Histograms of GPS speeds for 'Stationary' and 'Moving' behaviours of steers 12, 22 and 32 on the 9-10-2011.

There were a total of 87,260,908 possible combinations from which 999 bootstrap samples were obtained which equates to 0.0011% of all possible combinations if each of the bootstrap samples is unique.

Speed Threshold

There is a difference in mean speeds of moving and stationary behaviour states as the confidence intervals do not overlap, presented in Table 24.

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Table 24 Key parameter estimates of mean speed (m/s) for the moving and stationary states for the herd.

State	95 % Confidence interval	
	Lower	Upper
Moving	0.0258	0.0301
Stationary	0.0204	0.0212

Since there is a difference between behavioural states, a speed threshold to determine the behavioural class of either moving of stationary was calculated, as displayed Table 25.

Table 25 Individual animal grazing thresholds for steers 12 and 32 on each of the behavioural observation days.

Steer	Date	Threshold (m/s)
12	15/09/11	0.0262
12	18/09/11	0.0240
12	21/09/11	0.0248
12	24/09/11	0.0260
12	30/09/11	0.0252
12	03/10/11	0.0253
12	06/10/11	0.0248
12	09/10/11	0.0258
12	12/10/11	0.0259
32	15/09/11	0.0257
32	18/09/11	0.0252
32	21/09/11	0.0260
32	24/09/11	0.0254
32	30/09/11	0.0245
32	03/10/11	0.0258
32	06/10/11	0.0253
32	09/10/11	0.0238

32	12/10/11	0.0238
	Average	**0.0252**
	SD	**0.0008**

There is a strong transition between probabilities, jumping from 0.024 m/s to 0.026 m/s (Figure 34). The speed threshold is when the probability of a behaviour occurring is 0.5, this equated to 0.025 m/s (3 dp). Thus, stationary behaviour relates to speeds less than 0.25m/s and moving behaviour to speeds equal to or larger than 0.25m/s.

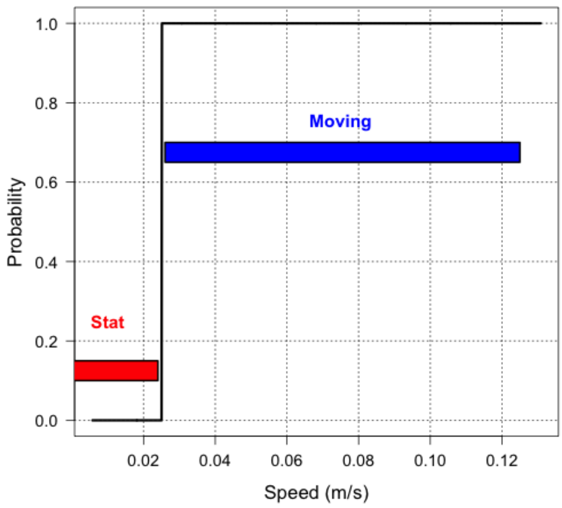


Figure 34 Probability of moving behaviour occurring at speeds (m/s) for steers 12, 22 and 32 on the 9-10-2011.

Putfarken (2008), Anderson (2012) and Guo (2009), all reported travelling behaviour in their research. Travelling behaviour was not exhibited in this experiment, and therefore speed could not be attributed to it. The grazing associated speeds reported in the literature are presented in Table 26 along with the moving result from this experiment.

Table 26 Comparison of results from research which developed activity speed models for cattle tracked with GPS devices.

Author	Experiment	Grazing speed (m/s)
Putfarken (2008)		0.220-0.330
Guo (2009)		<0.400
Anderson (2012)	1	0.060-0.550
	2	0.059-0.500
This experiment		≥0.025*

*moving speed

Discussion

Behaviour States

The investigation of state change probability for different time lags was non-significant. This indicates that the probability of a state change for steer 22 on the 18/9/2013 is constant irrespective of time lag. The intercept B_0=10.26 (sd = 1.65) (2 dp) indicates an approximately 10% probability of a change of state for each time lag. Similar fixed probabilities were found for steer 12, probability = 0.41 +/- 0.12 $(H_0: \beta_1 = 0, p = 0.61)$, and steer 32, probability 0.22 +/- 0.02$(H_0: \beta_1 = 0, p = 0.45)$. The practical implication of this result is that the number of state changes which occur overall in a 15 minute window should be the same as in a one minute window.

Across the whole herd, the probability of state change is likely to differ between animals but will remain constant for an individual animal. Therefore, increasing a time resolution by increasing the GPS sampling rate will not improve the number of successful state change detections. The use of a 15 minute GPS sampling interval has a similar proportion of missed behavioural changes to other intervals investigated and was both economical (battery-life) and practical (data processing) for this research. It should be noted that these results do not consider if a particular GPS sampling rate is favoured for particular state change detection, time of day or animal.

While not relevant for this research, there are several situations where the appropriate sampling period is dependent upon more than state changes. The first is if monitored behaviours are infrequent or short duration (Mitlöhner *et al.*, 2001). The second is if the total number of observations recorded is important. An increased number of observations reduce uncertainty in the estimates of the apparent rates. For this experiment, we can be confident that the speed threshold developed in the next section is not going to be GPS sampling period dependent.

Speed modelling

The skewed, long tailed histograms of speed, indicated that the statistical distributions were not like the usually assumed Gaussian distribution. Therefore a model other than the Gaussian was required to describe the distribution of speed values. Parametric models such as the GEV assume that each sample observation is statistically independent and identically distributed (Smith, 2003). The original speed samples of a single steer on one day is unlikely to meet this criterion. However, using bootstrap samples of the median values of speed (at random times within a single day) for three different steers is far more likely to meet the statistical independence criterion.

The large number of possible speed sample combinations of data for the bootstrap analysis, (87,260,908), indicates that it is unlikely that the records for the individual steers will be sampled with the same set of explanatory covariates such as time. It is therefore reasonable to assume statistical independence when the speed record bootstrap samples are not conditioned on other variables such as time of day or location relative to other animals.

Speed Threshold

There is an overlap of speeds to behaviour between- and within-animals. This is not unexpected as each individual animal is likely to move at slightly different speeds when undertaking activities and in response to daily influences such as feed availability (E.A. Laca, Distel, Griggs, &

Demment, 1994) and weather as seen in sheep (Powell, 1968) and people (Daamen & Hoogendoorn, 2003; Hoogendoorn & Daamen, 2005). GPS error will also contribute to individual speed as each device will have different error, potentially apparent in the speed results (Lachica & Aguilera, 2005; Putfarken *et al.*, 2008).

The lack of travelling behaviour exhibited by the cattle in this experiment could be due to small paddock area, with little distance required to reach camp areas, water or feed patches. Compared with paddock sizes used in other speed model development research, (Putfarken *et al.* (2008) = 180 ha; Anderson *et al.* (2012) = 433 ha; Guo *et al.* (2009) = 7 ha), at 0.35 ha, these paddocks are very small. As well as travelling, walking and grazing behaviour speeds were reported.

Although the threshold between stationary and moving was different to those previously reported, it is similar to that of Putfarken *et al.* (2008). This result supports the previous use of the speed model developed by Putfarken *et al.* (2008) in previous projects, which has a similar experimental situation. The larger difference to the models of Anderson *et al.* (2012) and Guo *et al.* (2009) is likely because of differing situations and the fix rate. The finer resolution of sampling will capture more distance as there is less time from point to point, thus leading to higher "speeds" at fine resolution. Cattle move in a tortuous nature, so the more points of a path captured, the further the distance recorded will be.

Conclusion

The development of a speed model based on GPS tracking and visual observations of cattle was investigated. This enhanced the accuracy of the behaviours derived from the GPS, thus improving our understanding of cattle behaviour and the relationship with available pasture.

The aim of this chapter was to develop a speed model specific to this experiment. The speeds associated with activity in this experiment are different to those reported in other research including Putfarken *et al.* (2008), Anderson *et al.* (2012), and Guo *et al.* (2009) and supports the hypothesis that speeds associated with behaviour in this experiment will be different to those previously reported in the literature.

So, different situations, cattle class and GPS log rates will results in different speeds associated with behaviour. Speeds may also change daily with environmental influences. The extent of the influence of within- and between-animal speed variations on speed-based behavioural analysis must be determined before commercial development. Speed can be a very useful for behavioural monitoring; although, as speed appears to be influenced by many factors, regular calibration may be required for use in industry.

Despite the possible limitations around technology at the moment in industry, the development of cattle and site specific speed models is feasible in research settings. The process developed here could be adapted to produce behavioural models for commercial tracking systems when they are made available.

3. Calibration of Active Optical Sensors for pasture biomass

Introduction

A recent MLA report (B.GSM.0004) concluded that the accurate and objective measurement of pasture biomass is a key requirement for producers seeking to increase grazing system productivity. Provision of accurate estimates of pasture biomass allows graziers to better meet the feed requirements of their livestock, directly increasing red meat production. Accurate, contemporaneous biomass measurements also enables producers to meet residual pasture targets resulting in improved sustainability, increased grazing utilisation and subsequent increases in pasture growth rates; all of which increase red meat production (MLA, 2004; (Westwood, 2008)).

There are several technologies currently available for real-time pasture biomass estimation, based on physical deflection by the sward (pasture height meters), contact leaf surface area (capacitance probe), occultation of readable scales or light sensors (pasture rulers, C-Dax sensor), or vertical height and texture (sonar, radar, LiDAR). However, most commercially-available tools have been targeted at the dairy industry with their monoculture pastures of spatially consistent phenology. These various plate meters, capacitance probes, the C-Dax pasture meter and the Sonar pasture reader all respond to total biomass (green and dead fraction), furthermore some are of limited use in red meat pastures because of their physical mode of deployment (C-Dax) and/or inability to delineate the green fraction (M. G. Trotter, D. W. Lamb, G. E. Donald, & D. A. Schneider, 2010). Moreover, existing commercial tools are expensive (e.g. C-dax pasture reader ~ $4,500, Automatic Pasture Reader ~$4,100).

Active Optical Sensors (AOS) are a relatively new class of sensor. These handheld devices direct a beam of light, usually comprising both red and near infrared wavelengths, onto the plant canopy and an on-board detector records the returning radiation and calculates the optical reflectance of the target canopy in those specific wavelengths. The key advantage of the technology over passive optical sensors (like radiometers and spectrometers) is that they contain their own light source and readings can be taken under any illumination conditions including at night. The combination of red and near infrared reflectance correlates to the photosynthetically active biomass (PAB) component of the canopy being scanned (the green fraction). To date these devices have been developed for use in the cropping industry, ostensibly for inferring crop nitrogen levels, however recent research has demonstrated the potential for applying the same technology to estimate the green fraction of pastures (Flynn, Dougherty, & Wendroth, 2008; M. G. Trotter et al., 2010; M. G. Trotter, Schneider, Lamb, Edwards, & McPhee, 2012). AOS measure the green fraction of the sward which is the key characteristic relating to animal productivity (MLA, 2004).

This project focussed on evaluating the potential for active optical sensors as a tool for measuring the green fraction of a pasture sward. The study was divided into three sub-projects:

1. Can active optical sensors be used provide a measure of pasture biomass?;
2. What is the potential for active optical sensors to provide biomass estimation in improved and native pastures across different seasonal conditions?; and

3. How accurate can an Active Optical Sensor theoretically be in predicting pasture biomass?

1. Can active optical sensors be used to provide a measure of pasture biomass?

Introduction

The first part of this study examines the use of an active plant canopy sensor to predict herbage biomass across seasons in a perennial pasture. Little work has been reported on the best indices for use when estimating pasture biomass from proximal active plant sensors and so several common indices were tested to determine which provided the best relationship to green biomass. The most commonly used indices with proximal active plant sensors are the Normalized Difference Vegetation Index (NDVI) and simple ration (SR) with known relationships to pigment content, leaf water stress and green biomass (Gong, Ruiliang, Biging, & Larrieu, 2003). These were tested along the other less commonly used indices to examine which provided the best relationship to green dry biomass. Those less commonly applied indices included: the Soil Adjusted Vegetation Index (SAVI) designed to minimise soil induced variations (Gong et al., 2003); the Non-Linear Vegetation Index (NLI) and modified Non-Linear Vegetation Index (MNLI); designed to take into account the non-linear relationships between surface factors (Gong et al., 2003); the and Modified Simple Ratio (MSR) also designed to take into account non-linear relationships to surface factors (Haboudane, Miller, Pattey, Zarco-Telada, & Strachan, 2004).

Materials and methods

Field Site

The study site was located on a commercial beef property situated approximately 30km east of Inverell in Northern New South Wales, 29o47’S 151o21’E, at an elevation of ~660m. Average yearly rainfall is 770mm (55 year average) of which about 65% falls between October and March. Topography consists of undulating hills with perennial pastures bordered by heavy scrub and perennial woody vegetation and has a predominately southern aspect. The study site was comprised of four 50 Ha paddocks and predominantly sown to tall fescue (*Festuca arundinace* var Fletcher). Crop circle scans and biomass cuts were taken at different locations within these paddocks across a 12 month period.

The commercial operator of the property aimed to keep green pasture biomass between 1000 and 3000 Kg/Ha using a four paddock rotational grazing system. Reduced seasonal rainfall resulted in lower than expected pasture production levels which saw green biomass levels fall below the targeted 1000Kg/Ha throughout the study period.

Sensor

The AOS sensor tested in this trial was the Crop Circle ACS-210 (Holland Scientific Inc, Lincoln Nebraska). The Crop Circle ACS-210 contains its own light source, an array of 15 modulated polychromatic light emitting diodes that simultaneously emit visible and near infra red light in defined wavelengths. In this case the Red ACS-210 model was used, emitting visible light in the 650nm range and near infra red light in the 880nm range. Two silicon photodiode arrays (400nm to 680nm for the visible and 800nm to 1100nm for the NIR light) measure the reflectance of the emitted light from the target vegetation. The Crop Circle ™ ACS-210 has an angular field of view of 32^{o} resulting in a projected beam width of approximately of approximately 0.57 x height of the sensor above the target. The crop circle can be set to record at up to 20 times per second and data is written to a removable SD card (Holland Scientific, 2008).

Previous experience with using the Crop Circle™ ACS-210 unit (T. F. Trotter, Frazier, Trotter, & Lamb, 2008) led to the development of specific biomass sampling technique, the aim of which was to match the area scanned with that harvested for biomass assessment. At each sample site, a line transect of 10 metres was marked out. The Crop Circle™ was then used to scan up and down this transect at a height of 90cm giving a projected beam width of 54cm. The Crop Circle™ was set to record at 5 times per second which at an average walking pace resulted in approximately 100 samples being collected per transect. These were averaged to give mean reflectance values for the visible and NIR reflectance for each sample.

After scanning, the transect was cut using a plot mower to a width of 43cm and a height of approximately 4cm. The samples were bagged and returned to the lab for analysis. A subsample of each bag was taken for sorting into green and dead biomass fractions to provide an estimate of percentage green for the entire transect sample. The samples were then dried at 40^{o}C for 48 hours and weighed. The sorted sub-samples were used to estimate the green fraction of the total biomass for each transect area which was converted to provide a value of green dry matter (GDM) per hectare for each sample site. A total of 156 samples were collected over the 12 month period of this trial. Of the 156 samples taken 21 samples were found to contain no green dry matter and were excluded from further analysis as these samples (GDM=0) could not be examined under the data transformations that were imposed in the statistical analysis.

Data analysis for all paddocks sampled

Reflectance data from the Crop Circle™ were used to create a number of indices to examine which would provide the best predictive relationship for green dry matter (Table 27). These indices along with the original individual reflectance bands were initially examined by regression to determine which indices offered the best relationships. Selected indices and bands were then chosen for further validation. The data set (n=135) was then randomly divided into two groups, the first (n=68) being used to create a predictive model and the second used as a validation data set (n=67) to test this model. The predicted and measured values were then correlated and a 1 as to 1 line was fitted to allow the RSME of each data set to be calculated.

Table 27 The individual reflectance bands and indices generated from them examined in this study

Index/Band	Short name	Formula	Reference
Near infra red band	NIR	NIR	
Visible red band	Red	Red	
Simple Ratio	SR	$SR = \frac{NIR}{Red}$	Jordon (1969)
Normalised Difference Vegetation Index	NDVI	$NDVI = \frac{NIR - Red}{NIR + Red}$	Rouse, Haas, Schell, and Deering (1973)
Soil Adjusted Vegetation Index	SAVI	$SAVI = \left(\frac{NIR - Red}{NIR + R + L}\right)(1 + L)$, L = 0.5	(Huete)((1988))
Non-Linear Vegetation Index	NLI	$NLI = \frac{NIR^2 - Red}{NIR^2 + Red}$	(Goel & Qi)((1994))
Modified Non-Linear Vegetation Index	MNLI	$MNLI = \frac{(NIR^2 - Red) * 1.5}{NIR^2 + Red + 0.5}$	(Gong et al.)((2003))
Modified Simple Ratio	MSR	$MSR = \frac{(NIR/Red) - 1}{(NIR/Red)^{1/2} + 1}$	(Chen)((1996))

Refining the modelling accuracy through identification of outliers

Following the publication of the results presented in Part A (M. G. Trotter *et al.*, 2010) further analysis was undertaken to explore this data set in more detail. During the original analysis of the data it became apparent that data from some of the areas sampled appeared to sit as outliers compared to the balance of sample points. These data point were identified and excluded from analysis. There were clearly identifiable reasons for the outliers being removed. Some of them were taken from areas of wet soil, stock camp areas and one particular area of a paddock which regularly appeared to provide a quite different phenotype of the pasture sward. The results for the SAVI and NDVI indices where analysed based on their strength of performance in part A. An additional model was also evaluated, the power function, $y=ax^k$ (where a and k are constants).

Results and discussion

Correlation of Crop Circle to pasture biomass across all sample sites

The Pearson coefficients for the NIR band and all indices demonstrate good correlation with GDM with the highest r^2 0.80 and the lowest 0.53 (Table 28). The best linear relationships were seen with the individual NIR band and the MNLI index. However, an examination of the data suggested that a non-linear relationship better represented the results. Fitting a curve to the Log transformation of GDM produced r^2 of up to 0.74 for the NLI. The best r^2 values were produced by square root transformation of GDM, the individual NIR band produced an r^2 of 0.78 and the MNLI the best r^2 of 0.80.

Table 28 Pearson coefficient for reflectance bands and indices with linear fit and log transformed and square root transformed

Reflectance band or index	r^2 Linear	r^2 Log normal transformation	r^2 Square root transformation
NIR	**0.74**	0.65	**0.78**
Red	0.20	0.17	0.22
SR	0.65	0.53	0.68
NDVI	0.61	**0.70**	**0.74**
SAVI (L=0.5)	0.66	**0.71**	**0.77**
NLI	0.58	**0.74**	0.73
MNLI (L=0.5)	**0.70**	**0.71**	**0.80**
MSR	0.67	0.61	0.73

Values in bold indicate those indices chosen for further validation.

To develop a predictive model for GDM Crop Circle™ reflectance, the best individual band and index correlations were used to guide model selection in the validation process (shown in bold in Table 28). Despite showing a reasonable initial r^2 the linear models produced for NIR and MNLI (Table 28) performed poorly (RSME 388kg and 420kg respectively - Table **29**) and clearly do not fit the data well (). All the indices using square root transformations of GDM examined tended to overestimate the GDM at higher biomass levels. Many of the Log transformed indices performed the best. The best predictive models was the Log transformed SAVI index.

Table 29 Indices of agreement between measured and predicted green dry matter values of the 68 randomly selected independent samples for the prediction models against line of slope=1 and intercept =0

Band/Index model type	Predictive equation derived from calibration samples (n=68)	RMSE of validation data set (n=67) kg GDM/Ha
Linear NIR	GDM = -1683 + 2433*NIR	388
Linear MNLI	GDM = -294 + 2590*MNLI	420
Log NDVI	Log(GDM) = 2.51 + 7.40*NDVI	341
Log SAVI	Log(GDM) = 2.87 + 6.06*SAVI	288
Log NLI	Log(GDM) = 3.90 + 4.81*NLI	295
Log MNLI	Log(GDM)) = 4.33 + 0.24*MNLI	358
Square root NIR	Sqrt(GDM) = -18.03 + 42.30*NIR	309

Square root NDVI	Sqrt(GDM) = -13.49 + 79.43*NDVI	400
Square root SAVI	Sqrt(GDM) = -10.04 + 65.71*SAVI	353
Square root MNLI	Sqrt(GDM) = 5.72 + 45.98*MNLI	318

Refining the modelling accuracy through identification of outliers

Closer evaluation of the data set revealed that several outlying data points where being integrated in the data set used for the analysis in Part A which was subsequently published as (M. G. Trotter *et al.*, 2010). An example is provided in Figure 35 which demonstrates how one set of cuts from a particular part of the paddock have been identified and removed as outliers. It is worth noting that a curve could still be fitted to this data however it would not be representative of the larger paddock area. The areas removed were commonly reported as being wet or damp and the variation from the balance of the field may have been caused by either changes in soil background reflectance (due to moisture) or a change in the phenology of the plant due to the different environment in which it was growing.

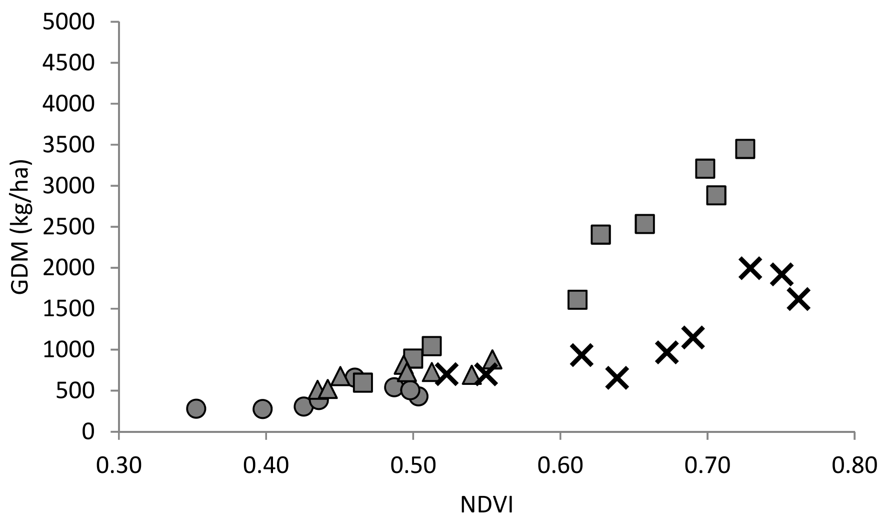


Figure 35 Correlation of crop circle NDVI and green dry biomass for one month (December) showing different locations across Newstead paddocks. The data represented by circles, triangle and squares was considered to be valid whilst the crosses represent outlier data which has been excluded for this analysis.

The removal of outlier points resulted in slightly higher Pearson correlations for both the NDVI and SAVI indices. This can be clearly seen in the increase in R-square for the power curves fitted for the original data set (Figure 36) and the cleaned data set (Figure 37) for the NDVI index and the original (Figure 38) and cleaned data sets (Figure 39) for the SAVI index.

The removal of outliers and application of the new power curve model resulted in a much improved error of prediction (Figure 40 and Figure 41) with the RMSE for NDVI being reported as 226kg/ha and SAVI as 216kg/ha (Table 30). This is a reasonable improvement over the RSME reported in the previous research (RMSE of NDVI = 341kg/ha and RMSE of SAVI = 288kg/ha) and compares favourably to all other pasture biomass assessment techniques.

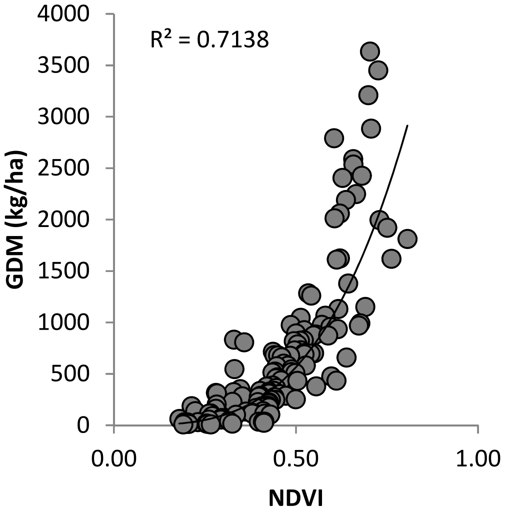


Figure 36 Correlation of NDVI and Green Dry Matter for original data set with power curve fitted

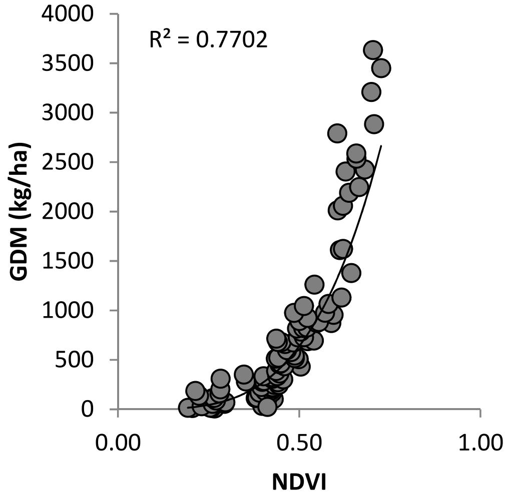


Figure 37 Correlation of NDVI and Green Dry Matter for cleaned data set with power curve fitted

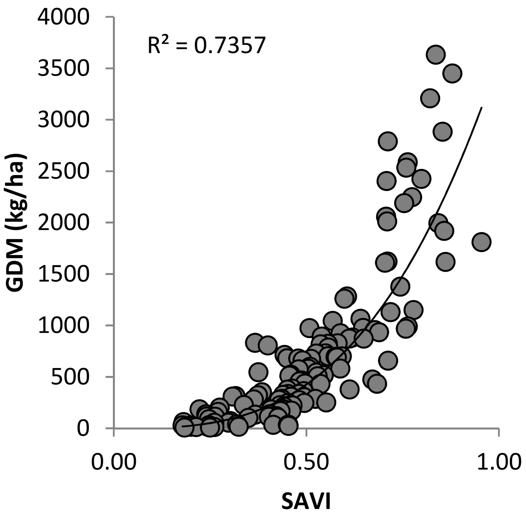


Figure 38 Correlation of SAVI (L=0.5) and Green Dry Matter for original data set with power curve fitted

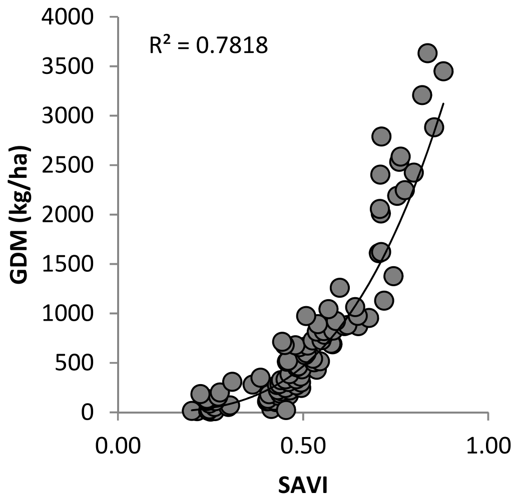
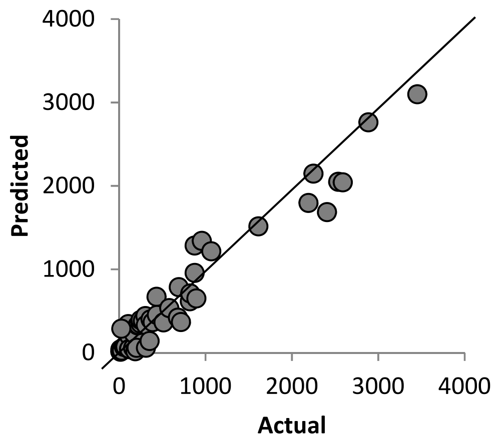


Figure 39 Correlation of SAVI (L=0.5) and Green Dry Matter for cleaned data set with power curve fitted



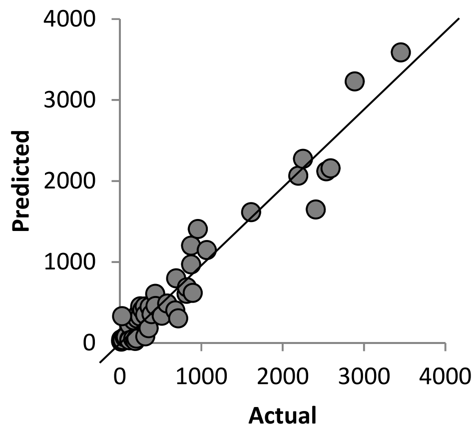


Figure 40 Correlation of predicted and observed green dry biomass for power curve NDVI

Figure 41 Correlation of predicted and observed green dry biomass for power curve SAVI

Table 30 Indices of agreement between measured and predicted green dry matter values of the 68 randomly selected independent samples for the prediction models against line of slope=1 and intercept =0

Band/Index model type	Predictive equation derived from calibration samples (n=49)	RMSE of validation data set (n=49) kg GDM/Ha
Log NDVI	Log(GDM) = 9.60*NDVI + 1.58	373
Log SAVI	Log(GDM) = 7.35*SAVI + 2.33	617
Square root NDVI	Sqrt(GDM) = 109.56*NDVI - 26.92	264
Square root SAVI	Sqrt(GDM) = 85.01*SAVI - 18.989	321
Power NDVI	**GDM = 11871*NDVI$^{4.19}$**	**226**
Power SAVI	**GDM = 5717.7* SAVI$^{3.60}$**	**216**

Conclusions

In the complete data set that included samples sites from across numerous fields and sites an RMSE of 288kg/ha was achieved. By identifying and removing outliers (particularly data taken from camp sites, tree and wet areas) we were able to improve this validated accuracy to 216kg/ha. This compares favourably with many of the ‘traditional’ non-destructive pasture measurement techniques discussed earlier. Investigations using rising plate meters have yielded errors as high as 447 kg/ha in perennial ryegrass and white clover pastures in New Zealand (Sanderson et al.

2001) and as low as 290 kg/ha for tall fescue pastures in the USA (Harmoney et al. 1997). Fulkerson and Slack (1993) reported standard errors of less than 200 kg/ha using a rising plate meter and less than 276 kg/ha using a capacitance probe in kikuyu and setaria pastures. Pasture rulers have reported errors as high as 500 kg/ha (Sanderson et al. 2001). This predictive model of SAVI for the Crop Circle also compares favourably with other studies using passive hyperspectral instruments and more complex spectral reduction processes. For example, Schut et al. (2005, 2006) reported errors of between 167 and 477 kg/ha. Hanna et al. (1999), using the NDVI and a filter-based radiometer, achieved an RSME of 262 kg/ha in New Zealand ryegrass pastures. Künnemeyer et al. (2001), using a multi-wavelength, active sensor, reported errors of 388 kg/ha of GDM in ryegrass pastures.

The benefits of understanding the quantity of pasture available to livestock have been well documented (Fulkerson et al. 2005). AOS have the potential to be developed into easily deployed tools for rapid pasture biomass assessment.

2. What is the potential for active optical sensors to provide biomass estimation in improved and native pastures across different seasonal conditions?

Introduction

One of the key issues identified in previous work was the potential limitations that variation in seasons might have on the calibration accuracy of Active Optical Sensors (AOS). This study examined the potential for AOS to provide estimates of green biomass in improved and native pastures across different seasonal conditions. Two sampling campaigns were undertaken across two pasture types (improved and native) in two different seasonal conditions (September and October 2011).

Methods

This study was undertaken in conjunction with a larger trial comparing the methane emissions from improved and native pastures. The improved pasture areas were located on creek flats and consisted of ryegrass, fescue, brome and white and subterranean clover. The native pastures were located on a hill adjacent to the flats and were dominated by native species such as redgrass, danthonia, poa tussock with some naturalised temperature species (e.g. brome and red clover). Two sampling campaigns were undertaken in September and October 2011 to collect biomass cuts and AOS scans. The September scan represented low growth seasonal conditions following winter before any spring rainfall. The October sampling represented a high growth season after rainfall and when temperatures had improved sufficiently to stimulate pasture growth rates. In reality it is unlikely that the biomass swards sampled would commonly occur (particularly the September sampling) on a commercial property as the total biomass was high (average biomass >4,000kg/ha). However this does offer significant insights into how an AOS sensor might function under these extreme conditions and seasonal variations.

The AOS used in this study was a Holland Scientific ACS210 which measures light reflectance in the 650nm (red) and 880nm (NIR) ranges. The median quadrat technique was used to select an area for harvest at pre-selected points across paddocks. The AOS was used at a height of 80cm and a single point scan taken within the quadrat. Both red and NIR reflectance values were recorded using the crop circle. After being scanned with the AOS the quadrat was cut to ground level bagged, dried and then sorted in green and dead fractions. Sample dry weights were converted into kilograms/hectare (kg/ha).

Data analysis was undertaken in Microsoft Excel with red and NIR reflectance values converted into the normalised difference vegetation index (NDVI = (NIR-Red)/(NIR+Red)) and these correlated with the green biomass fractions. Relationships (coefficients of determination) were assessed by fitting an exponential regression in Microsoft Excel.

Results and Discussion

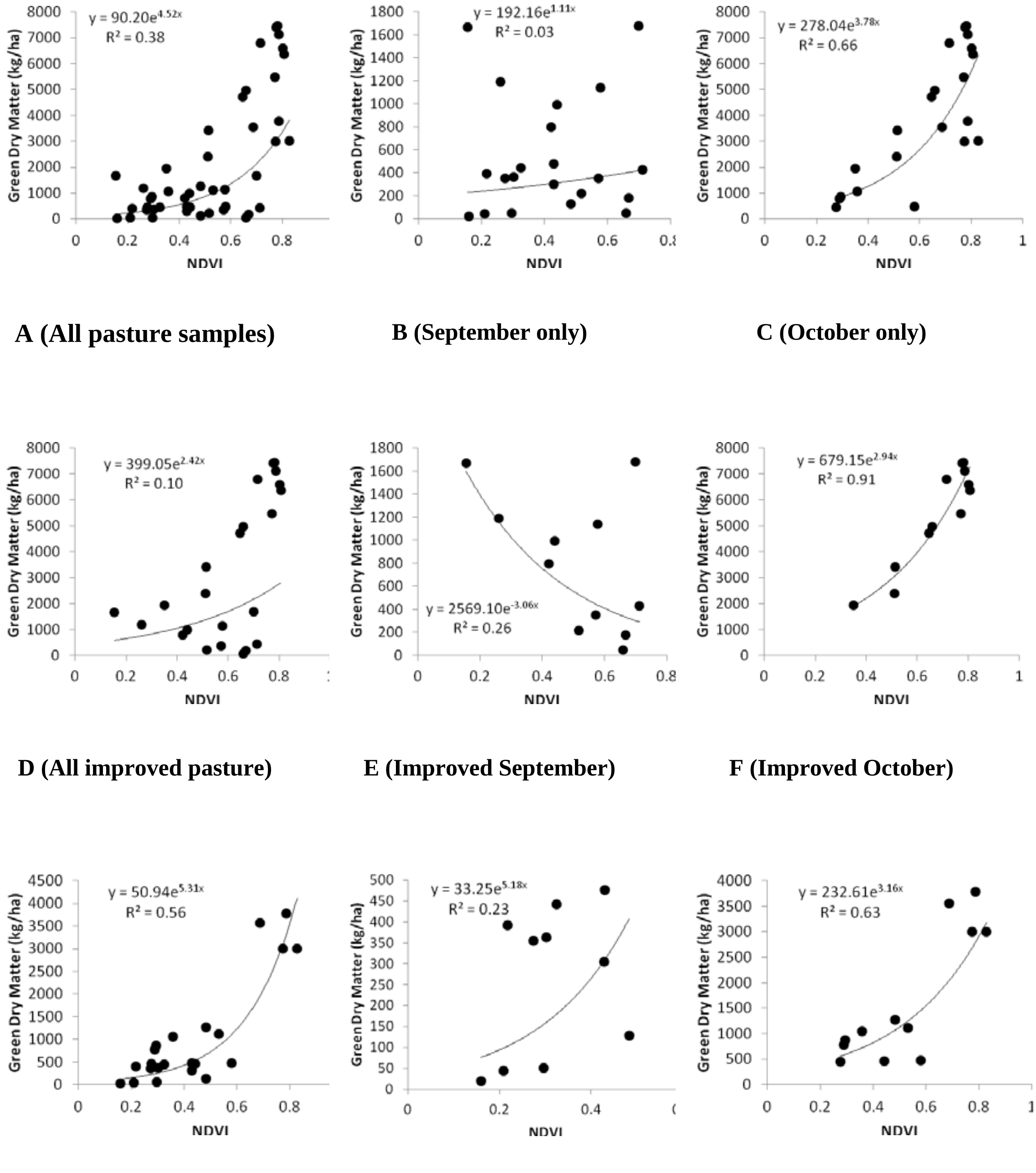
The biomass data collected from paddocks ranged from a maximum of 7451kg/ha to a minimum of 20 kg/ha of green dry matter (GDM). The average values recorded for each month and fraction of the pasture sward (

Table 31) reveal a large difference in the proportion of green and dead between the two months sampled. This is most noticeable on the improved pasture with average green fraction increasing from 15% of the sward in September to 83% in October. This shift in pasture composition had a dramatic effect on the correlation of the AOS to the green fraction of the sward.

Table 31 Average dry matter weights for pasture fractions from improved and native pastures over the two sampling periods, September and October 2011

		Dry matter (kg/ha)		
Pasture	Sample	Green	Dead	Total
Improved	September	791	4378	5169
	October	5387	1103	6490
Native	September	258	4987	5244
	October	1651	2754	4404

The combination of all the data (Figure 42 A) provided a reasonable correlation between NDVI and GDM. A similar non-linear response has been observed in other studies (Trotter *et al.*, 2010) however it is worth noting that range of values (up to ~7500kg/ha) far exceeds those previously reported. It is clear from the comparison of the results from September and October that the sensor performed better when a higher proportion of the sward was green (Figure 42 B and C). This trend is also clearly demonstrated in the improved pasture where the combined data (Figure 42 D) reveals a poor relationship. The lowest correlation was found between NDVI and GDM during September in the improved pasture (Figure 42 E) where an inverse relationship was found. This would have likely been caused by the large amount of dead material present obscuring the view of the sensor to any green material. This problem has been identified previously (Trotter *et al.*, 2010) and highlights the limitations of these sensor platforms. The highest correlation was found between the NDVI and GDM in the improved pasture in September (Figure 42 F), this was expected as the high proportion of GDM compared the senescent material has been reported to provide better relationships (Trotter *et al.*, 2008).



A (All pasture samples) **B (September only)** **C (October only)**

D (All improved pasture) **E (Improved September)** **F (Improved October)**

G (All native pasture) **H (Native September)** **I (Native October)**

Figure 42 Non-linear regression curves and correlation coefficients of the relationship between Green Dry Matter and NDVI across all pastures (A-C), improved pastures (D-F) and native pastures (G-I).

The relationship between NDVI and GDM was expected to be reasonable in the improved pasture (Flynn *et al.*, 2008), it was not expected to hold up for the native pasture for which this sensor has been suggested to perform poorly (Trotter *et al.*, 2008). Despite this, a reasonable correlation was reported between NDVI and GDM across both sample dates (Figure 42 G) and the sensor performed well in October (Figure 42 I) when the green fraction increased in the native pasture. Results in September (Figure 1H) were similar to that for the improved pasture although it should be noted that a positive correlation was found for the native pasture. This is likely to be due to the lower levels of overall biomass present in the native sward during the September sampling compared to the improved pasture. Whilst the AOS largely failed to perform accurately during the September sampling it does not discount the value of this sensor. The September pasture conditions with very high proportions of dry matter compared to green would not regularly be found on a commercial grazing property. It is also worth noting that most pasture management decisions made by producers are under conditions more like those represented by the October results. Testing under these extreme conditions (low percent green fraction) essentially provides an indicator of the limitations of this sensor. Whilst it is useful to understand these limitations the potential for AOS to provide good predictions of GDM under more normal production conditions remains. The performance on improved pasture during October demonstrates the potential accuracy of the sensor which compares favorably with other platforms being tested in more ideal pastures (Gourley and McGowen, 1991; Yule *et al.*, 2006). What is particularly encouraging is the ability of the AOS to provide a reasonable correlation with GDM in native pastures. Native pastures dominate Australian grazing production systems and more accurate biomass estimation techniques have been identified as a significant need by the industry.

Conclusion

The AOS was found to correlate poorly with the green fraction of the sward in September when senescent material dominated the sward (senescent=85%), particularly in the improved pastures. In contrast the AOS demonstrated good correlations with green dry matter in October when there was a higher proportion of green material in the sward (senescent=17%). The correlation was particularly sound for the improved pasture (r^2 0.91) and better than expected for the native pasture (r^2 0.63). This study demonstrates the potential for AOS to provide rapid estimates of biomass in both improved and native pastures and suggests that further research be undertaken to further quantify the value of these sensors

3. How accurate can an Active Optical Sensor theoretically be in predicting pasture biomass?

The research undertaken in previous sections outlined the potential for AOS as a pasture measurement tool. It also established that AOS could predict biomass within an accuracy of 216kg/ha (RMSE) in a typical pasture over a range of seasons. However several observations made throughout the data collection and analysis indicated that some of this error may be due to a mismatch of the sensor footprint and the actual sample cut. A further and obvious source of error was the slight differences in phenology that were present across the samples taken. The results of these initial trials raised questions about the actual accuracy of these sensors given a better match of sensor footprint to cut and when a consistent plant phenology was being assessed. This could be referred to as the "absolute theoretical accuracy" of the sensor excluding changes in background soil colour, calibration cut issues, sample handling protocols (particularly sorting of green and dead) and changes in plant phenology due to environment and season. If these sensors are to be of value to the industry they must at least be able to perform adequately under controlled conditions before consideration is given to making accommodations for the differences in seasons etc. The objective of this piece of research was to evaluate the absolute accuracy that might be achieved by an AOS under ideal conditions.

Materials and methods

Two separate trials were undertaken to evaluate the absolute accuracy of the AOS. The first trial used a forage oats crop and the second a tall fescue pasture. To determine the absolute accuracy of the AOS the sliding table platform was used to hold the Crop Circle ACS210 (Figure 43). The sensor platform was positioned over a sample site which was then progressively scanned and harvested from its maximum biomass down to a zero biomass. In this way a range of biomass values were generated with associated AOS reflectance values from a single sample site. This effectively isolated the variation in sample correlation due to variation in soil background reflectance.

The second trial was undertaken over a tall fescue pasture (Figure 44). In this case a ACS470 was used. In this trial the entire sample was meticulously sorted as opposed to subsampling which had been used in all previous trials involving pastures with a mix of green and dead. Whilst time consuming this was required to determine the absolute accuracy that could be achieved using an AOS.

Figure 43 Sliding table fitted with Crop Circle ACS210 in forage oats crop. This is the high biomass site (total > 7,000 kg/ha GDM).

Figure 44 The fescue pasture subjected to sampling, this is one of the moderate sites prior to sampling (biomass ~ 2,000 kg/ha GDM)

The forage oats was sampled twice, once at a relatively low biomass (oats site 1 >7,000 kg/ha GDM) and the other at a high biomass (oats site 2 ~ 4,000 kg/ha GDM). In both cases the plots were progressively harvested from the top down by trimming with electric shears.

The fescue was sampled twice at a moderate biomass level, once using the top down approach applied in the oats and a second time using a “checkerboard” plant removal approach. This was done at a moderate starting biomass level of approximately 2,000kg/ha of GDM. An additional sample site was harvested using the checkerboard approach with a starting biomass of over 4,500 kg/ha of GDM. The checkerboard approach involved progressively harvesting a predetermined area (approximately 10%) of the sample site between each scan and sample cut.

Linear regressions were fitted and coefficients of determination (R^2) calculated to each sample site. For each of the oats and a fescue sites data were pooled and a cross validation undertaken. Some data points were removed from the cross validation for reasons discussed in the results. Whilst it is recognised that the application of a cross validation process to this particular data is not necessarily relevant in the context of establishing the accuracy of a predictive model it does provide a point of comparison with the previously established calibrations.

Results and discussion

Forage oats

The correlation of the individual sample sites for the forage oats was excellent with the low biomass reporting and R^2 of 0.98 and the high an R^2 of 0.99 (Figure 45). One outlier point was excluded from the analysis of the high starting biomass. This was the first scan which was correlated with the total biomass for that site. This point (GDM = 7,410kg/ha) and the following point (7,029kg/ha) are working within the saturation zones of the NDVI for this sensor. It should also be noted that some change in canopy position was inevitable when progressively trimming the biomass down between scans and this may also have played a roll in the generation of the outlier point. The cross validation of the pooled data (Figure 46) gave an RMSE of 517 kg/ha of GDM over a mean of 3,386 kg/ha of GDM giving a COV of 15%.

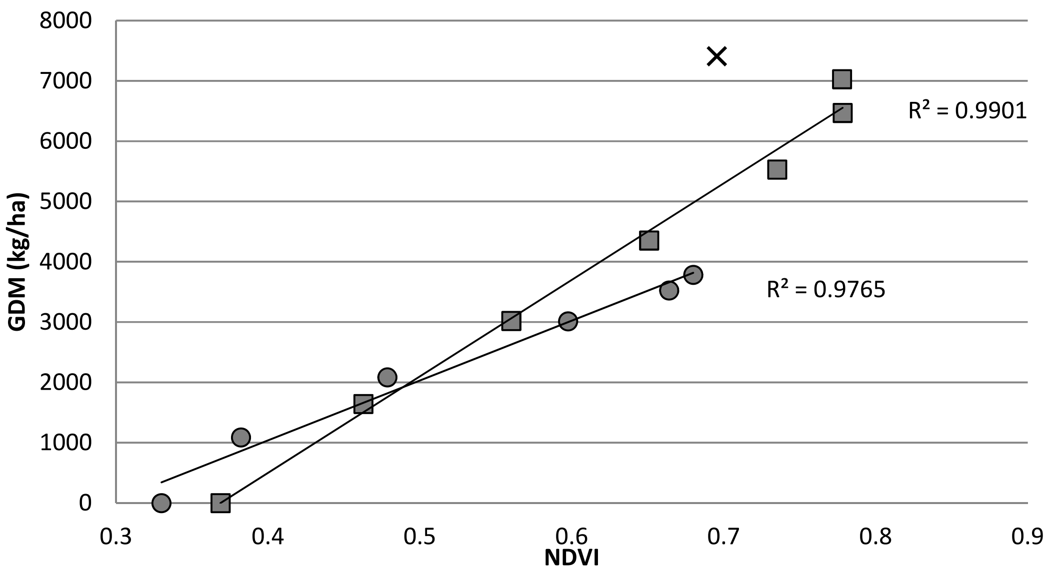


Figure 45 Correlation of NDVI with Green Dry Matter (GDM kg/ha) for two sample sites (high starting biomass = squares and low starting biomass = circles) which have been progressively scanned and harvested. The outlier (X) is the first scan of the high biomass (squares).

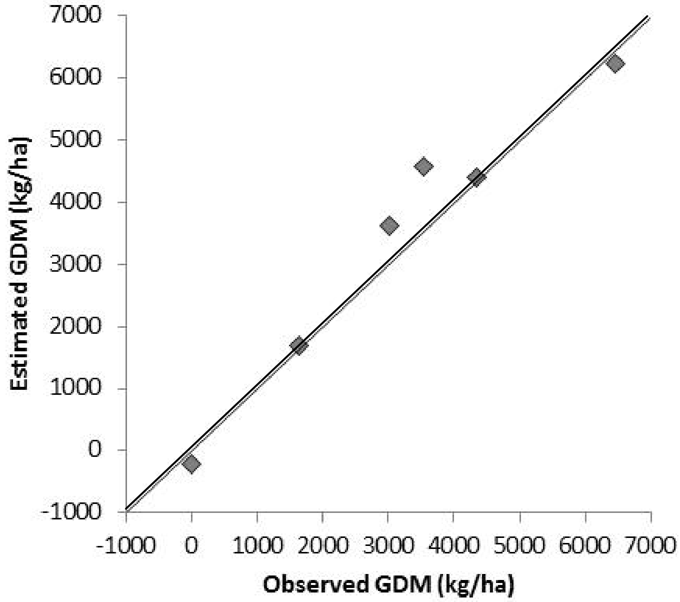


Figure 46 Observed and estimated GDM from a pooled cross validation of the both forage past sampling sites. RMSE = 517 GDM (kg/ha) on a mean of 3,386 GDM (kg/ha).

Fescue

The results of the different sampling techniques and the relationships between NDVI and biomass are presented in Figure 47. There is clearly very little difference between the calibration curves developed for all three sampling procedures and sites between the range of 0 to 2,000 kg/ha of GDM. The obvious variation occurs for the high biomass site where a different albeit still linear relationship appears to occur beyond 2,000 kg/ha GDM. In terms of the individual correlations both moderate level biomass samples (checkerboard and top-down trim) were remarkably similar and both reported R^2 >0.97.

The curve fitted to the high biomass checkerboard site is a 2nd order polynomial showing an R^2 of 0.99, however there appears to be a clear difference between the NDVI-biomass below and above 2,000 kg/ha GDM. Although NDVI saturation is likely to have played some part in this, it is more likely driven by a shift in sward structure as leaves adjacent to the holes left by the checkerboard removal process fall into the void and subsequently increases the effective leaf area index. This results in a reduced rate of change in the NDVI compared to the biomass. While it is an interesting artefact of the sampling protocols being tested further research is required to fully understand this relationship and its implications.

For the purposes of providing an indication of the absolute accuracy achievable using an AOS the moderate level biomass site data was pooled and a cross validation exercise undertaken (Figure 48). The results indicate that an RMSE of 132 kg/ha GDM over a mean of 949 kg/ha GDM. This equates to a COV of 14% which is similar to that achieved for the forage oats. As previously discussed there are a number of factors that have been isolated to enable this “absolute” accuracy to be calculated. Firstly the soil background has been maintained, secondly the green fraction of the sward was directly measured this differs from other studies where and estimate (based on a sub-sample) was used to calculate the GDM. The increased rigour of measuring rather than estimating the GDM is essential to determine the absolute accuracy and has likely removed a substantial component of the error associated with previous calibrations. Further research could be warranted to quantify the error caused by sub-sampling. Another factor which was intended to be kept consistent at each site was the phenology of the sward. In reality the local plant morphology would have changed as each cut was taken of the sward. This is most obvious in the high biomass fescue plot. Whilst this is clearly going to be a problem in the high biomass swards where the plant leaf canopy structure is prone to collapse the moderate biomass sites appear to be less prone. The evidence for this is found in the similarity of the top down trim and checkerboard sample sites. The different sampling processes applied to each site would have produced a different sward structure throughout the sampling process however they both responded in a very similar way. If any difference is evident it is a slightly sigmoidal relationship between the NDVI and biomass for the top down trim site which is not unexpected given the change in plant canopy structure from top to bottom.

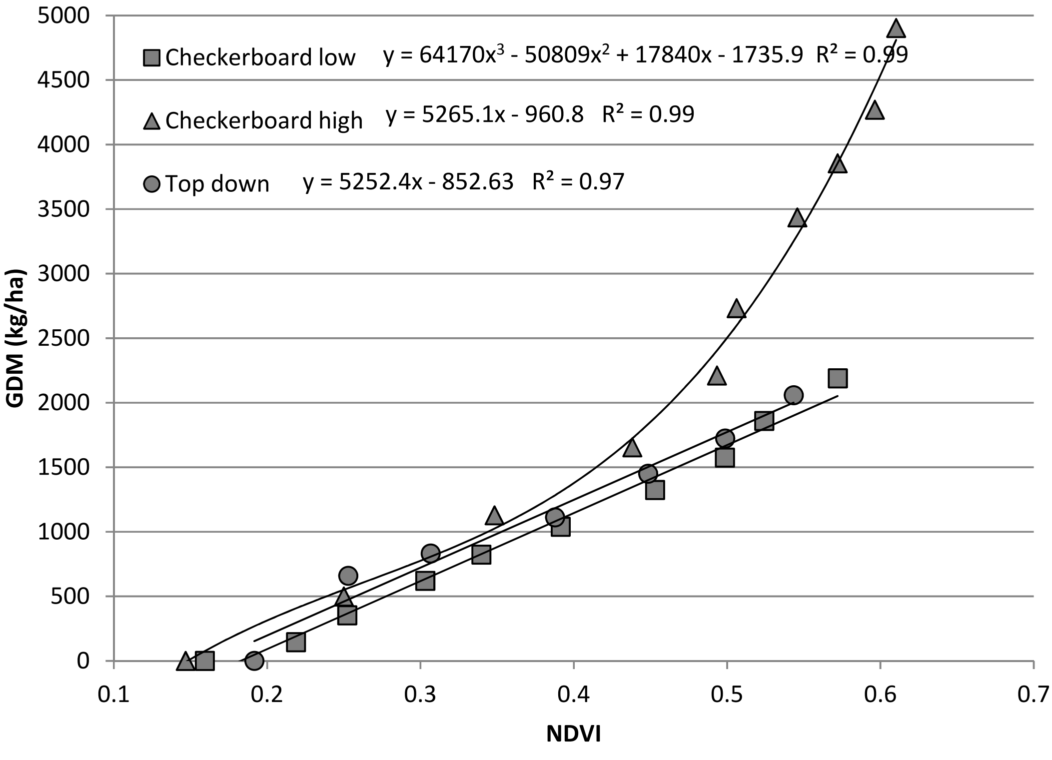


Figure 47 Correlation of NDVI with Green Dry Matter (GDM kg/ha) for three sample sites in a fescue pasture which have been progressively scanned and harvested.

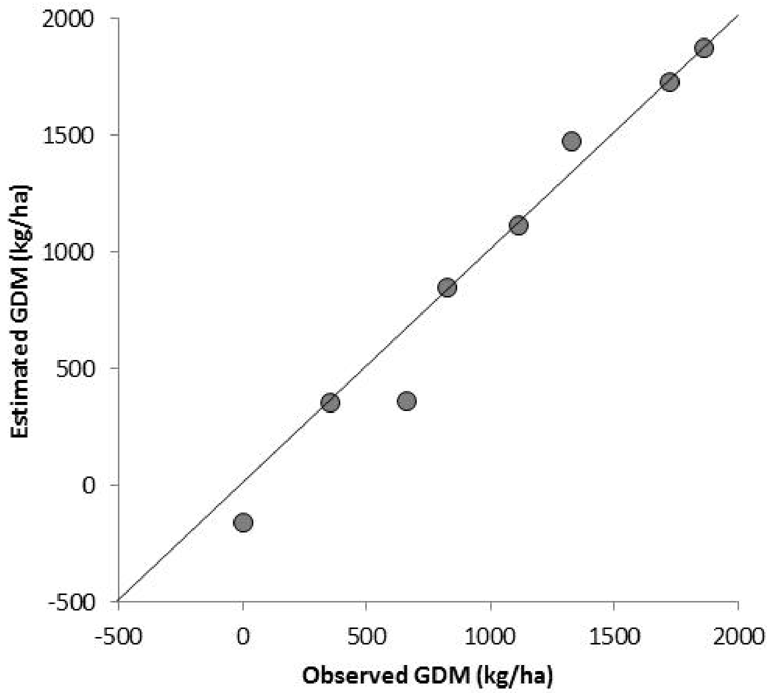


Figure 48 Observed and estimated (n=8) GDM from a pooled cross validation (n=9) of the moderate biomass sites (excluding the high biomass checkerboard site). RMSE = 132 GDM (kg/ha) on a mean of 949 GDM (kg/ha).

Conclusion

This exercise has demonstrated that there is a very strong relationship between an AOS sensor and green dry biomass under constrained conditions. For both oats forage and fescue pasture the relationship between NDVI and GDM was regularly found to be higher than an r-square of 0.95 and when considering the predictive capabilities of the models an accuracy of COV = 15% was achieved. While many of the factors that had previously caused error were controlled in this trial it is likely that some measurement error has occurred and that AOS are even more accurate than this. The challenge now remains to determine how repeatable these relationships are across different sites and different seasons where plant morphology can changed dramatically.

Recognition of CRCSI research

Special recognition of CRCSI researchers for innovation in precision livestock research

Dr Mark Trotter

In 2010 CRCSI researcher Dr Mark Trotter was awarded a travel scholarship by the AW Howard memorial trust to attend the combined 2010 Australian Society of Agronomy and New Zealand Grasslands Conference and follow on with a tour examining the latest precision agriculture technologies being developed in New Zealand. In 2011 Dr Mark Trotter was awarded a Science and Innovation Award for Young People in Agriculture, Fisheries and Forestry. This award recognised the work that Mark had undertaken in the field of spatially enabled livestock management and the award sponsor Meat and Livestock Australia provided funding to extend research initiated as part of the CRCSI Biomass Business PUE Activity.

Jessica Roberts – AW Howard Memorial Trust Research Fellowship – 2011

In 2011 Jessica Roberts was awarded an AW Howard Memorial Trust Research Fellowship to further her CRCRSI PhD project on spatially enabled livestock management as well as an AWI Travel Bursary to present the results of her CRCSI PhD at the joint Australian Agronomy and New Zealand Grassland Conference in Lincoln New Zealand.


26 ON-FARM

GPS as aid to rotational grazing

FAST FACTS

(a)

(b)

Figure 10: Article in AWI industry publication documenting Jessica Robert's AWI award. **Senator Joe Ludwig, Minister for Agriculture presenting Dr Mark Trotter with the Science and Innovation Award.**

Publications arising from this project

Journal articles

Trotter, M., Guppy, C., Haling, R., Edwards, C., & Trotter, T. (2014 in review). Spatial variability in pH and key soil nutrients: an opportunity to increase fertiliser and lime use efficiency in grazing systems. Crop and Pasture Science.

Dobos, R, Taylor, D, McCorkell, M, Schneider, D, & Hinch (2014 in review) Characterising the spatio-temporal activities of grazing Merino ewes before, during and after parturition from satellite tracking data. Animal Production Science.

Fogarty E, Manning J, Trotter M, Schneider D, Thompson J, Bush R and Cronin G (2014 in review) GNSS technology and its application for improved reproductive management in extensive sheep systems. Animal Production Science.

Dobos, Dickson & Trotter (2014 in review) Detection of lambing behaviour with the use of GNSS technology. Animal Production Science.

Manning J, Fogarty E, Trotter M, Schneider D, Thompson J, Bush R and Cronin G (2014 in review) A pilot investigation into the use of GNSS technology to quantify the behavioural responses of sheep during simulated dog predation events. Animal Production Science.

Falzon, G., Schneider, D., Trotter, M., Lamb, D.W., (2013). Correlating movement patterns of merino sheep to faecal egg counts using global positioning system tracking collars and functional data analysis. Small Ruminant Research (in press) 111, 171-174.

Trotter, M., (2013). PA Innovations in livestock, grazing systems and rangeland management to improve landscape productivity and sustainability. Agricultural Science 25, 27-31.

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Refereed conference proceedings

Trotter, M., Badgery, W., Barron, J., Guppy, C., Haling, R., Mitchell, D., Millar, G., (2013) Spatial variability of soil phosphorus in grazing systems. In: Michalk, D.L. (Ed.), 22nd International Grasslands Congress, Sydney.

McEntee, P., Belford, R., Mandel, R., Harper, J., Trotter, M., (2012). The integration and validation of precision management tools in mixed farming systems. 16th Australian Agronomy Conference. Australian Agronomy Society, Armidale, Australia.

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Trotter, M.G., Falzon, G., Dobos, R., Lamb, D., (2012b). Developing a Simple Accelerometer Based Grazing Sensor. Second Joint Conference of the New Zealand and Australian Societies of Animal Production, Lincoln, New Zealand.

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Trotter, M.G., (2010). Precision agriculture for pasture, rangeland and livestock systems. In: Dove, H., Culvenor, R. (Eds.), Food Security from Sustainable Agriculture15th Australian Agronomy Conference. Australian Society of Agronomy, Lincoln, New Zealand.

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