

# Final report

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## Data-driven system optimising the forage base for sustainable beef production

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## Abstract

This project was undertaken to address the challenge of optimising grazing management in Australian beef production systems by developing a scalable, data-driven model that integrates real-time animal performance data with environmental and pasture metrics. The goal was to understand paddock-level productivity in the Northwest region of NSW using animal liveweight gain as the primary indicator. The Paddock Performance Benchmark (PPB) tool was developed, using a combination of remotely collected liveweight data from in-field weigh stations (Optiweigh), CiboLabs biomass data (Total standing dry matter, TSDM), publicly available climate and soil datasets, and pasture quality indicators to describe how animal growth varies within and between farms.

The project acquired data from three commercial properties in North-West NSW under routine rotational grazing. Across farms large within-farm divergence in paddock ADG was observed, ranging from 0.44 to 1.03 kg/day across farms. These differences were influenced by forage composition, pasture quality, seasonal conditions and rainfall, aligning with the previous literature and the complexity of ground-based measurements for estimating productivity. The biomass of forage crops showed stronger correlations with animal performance than perennial pastures, likely due to variation in growth stage and feed quality at the time of measurement. This reinforces that biomass alone is insufficient to explain animal gain and that ADG can operate as a proxy for diet relevant intake.

A gross-margin template was created to link biological and economic performance, where paddock-level ADG is used as the measure of productivity. The PPB can be used as a workflow to enable producers to benchmark, diagnose and intervene with paddock-level grazing decisions, stocking strategies and feedbase selection to optimise farm productivity. Forecasting is positioned as long-term, conditional work requiring longer, region-specific datasets and improved remote proxies for diet-relevant quality and pasture utilisation.

This project established the data architecture to integrate datasets from remote platforms. This method using real time animal growth data to benchmark paddock productivity, could be incorporated into existing farm management platforms, supporting adoption through training and producer-led demonstration.

## **Executive summary**

### **Background**

This project addresses the challenge of optimising grazing management in Australian beef production systems, which operate across diverse landscapes and increasingly variable climates. The central question was how to use real-time, automated data to improve paddock-level decision-making for sustainable and profitable livestock production. The primary audience includes beef producers, advisors, and industry stakeholders seeking to enhance feedbase utilisation. A data-driven system to optimise forage utilisation and grazing management in Australian beef production was developed. The Paddock Performance Benchmark (PPB) integrates remotely collected data sets for real-time cattle liveweight (LW) data, satellite-derived biomass, and publicly available climate and soil data, with manual pasture quality information to benchmark paddock productivity.

The results can be used to inform grazing strategies, plant species selection, and future modelling tools to support sustainable beef production in the target region of North-West New South Wales (NW NSW) with potential extension across Australia.

### **Objectives**

- Develop a data-driven model (Paddock Performance Benchmark, PPB) linking cattle liveweight gain to pasture, soil, and climate data.
- Validate the model across multiple commercial farms and test its predictive capabilities.
- Evaluate integration of the model into existing platforms (e.g., CiboLabs, Optiweigh) to inform grazing decisions.
- Conduct extension activities to support adoption by producers.

Model development, validation, and extension activities have been achieved. Further work is required to develop a predictive model to forecast paddock productivity, and integration of the benchmarking tool into existing platforms and training materials. This is proposed as a future program building on the existing findings within this report.

### **Methodology**

Data were collected from growing weaner cattle on an initial eight (8), later refined to three (3), commercial farms located within the NW NSW region, spanning the Liverpool Plains Sub-bioregion of the Brigalow Belt South Bioregion and the Peel Sub-bioregion of the Nandewar Bioregion using Optiweigh (OW) in-field weighing systems and CiboLabs satellite biomass monitoring. Climate and soil data (Australian soil classification ASC) were sourced from national databases, including the Bureau of Meteorology (BOM) and the Sharing and Enabling Environmental Data (SEED) portal, respectively, while pasture quality indicators (crude protein, metabolisable energy) were manually sampled using quadrat-based harvesting of

above-ground herbage within selected paddocks, composited and analysed by a commercial laboratory (Feed Central). Ecological surveys conducted by a third-party service (Stringybark Ecological) provided insights into plant species composition of a subset of grazed paddocks on each farm. Monitoring plots (20 m × 20 m) were established on each farm to derive visual foliage cover estimates and quadrat-based ground cover assessments. Vegetation composition is presented as relative cover (%) by dominant species and functional group (grasses, forbs, high-threat exotics, litter and bare ground), alongside paddock-level species richness, providing descriptive indicators of variation in productivity that may inform future plant species selection. Statistical models were developed to estimate average daily gain (ADG) from Optiweigh data and assess the influence of environmental and feedbase variables. Finally, a gross margin analysis was developed to evaluate economic performance incorporating on-farm variables and ADG, and a template developed as a producer resource.

### **Key findings**

The project quantified substantial within-farm divergence in ADG between paddocks, ranging from 0.44 to 1.03 kg/day across farms. Relationships between biomass and ADG were system-dependent where forage crops showed strong positive associations, and perennial/native systems often showed weak or negative associations, reinforcing the role of feed quality and species composition in modifying these relationships. Where measured, pasture quality metrics crude protein (CP) and metabolisable energy (ME) varied greatly across paddocks and farms (CP 3.8- 26.1 % SD 0.9-0.82; ME 8.11-11.35 MJ ME/kg DM SD 0.4-0.82) and were positively associated with ADG on two farms, relating to the greater proportion of forage crops (oats, sorghum) across the sampling period. Soil classification using the ASC showed no detectable short-term effect at the study resolution. Ecological surveys highlighted that sown-species establishment, seasonal turnover, litter/bare ground and weed species help explain productivity differences between paddocks with similar biomass with further work required to integrate these features into the model. Additionally, gross margin analysis templates offered producers a tool to evaluate the economic impact of different forage systems using paddock level ADG, supporting strategic planning and investment decisions.

A fully specified predictive model (forecasting ADG) could not be finalised due to data gaps, seasonal disruptions and limited repeated grazing events; however, the data architecture, descriptive models and covariate effects required for forecasting and platform integration were established. Priorities include expanding longitudinal datasets, formalising multivariable models, progressing integration with commercial platforms, and delivering training to support adoption.

The project established the methods for combining data sources to deliver a method for benchmarking productivity of paddocks across a farm using remotely collected liveweight data to calculate paddock-level ADG across multiple grazing rotations and seasons. In the context of the project, ADG is used as a proxy for estimating the effect of factors known to affect animal productivity, including climate/season, soil and pasture biomass and quality, which are challenging to account for under commercial conditions. The PPB tool has the potential to inform producers on the impact of current grazing management practices on animal productivity within paddocks and identify opportunities for improvements such as plant

species selection and grazing management including stocking density and grazing duration that affect pasture utilisation and residual. The economic impact of these decisions can then be estimated using the gross margins tool incorporating paddock ADG and management factors to provide data-driven decision making at the farm level. This establishes the operational workflow of *identify* (paddocks by benchmarking), *diagnose* (variables which contribute to paddock performance) and *intervene* with appropriate management strategies.

### **Benefits to industry**

This project demonstrates the value of real-time, automated data in transforming grazing management and lays the groundwork for further work to enable on-farm adoption. Specifically, the project:

- Enables producers to benchmark paddocks based on animal performance which informs data-driven decision making on grazing duration, stocking density, and forage selection
- Provides a practical gross margin template that links biological performance to per-paddock financial outcomes.
- Establishes the data architecture and methods for automated extraction, geospatial alignment and benchmarking, creating a practical pathway to embed PPB outputs into existing platforms (e.g., Optiweigh, CiboLabs, AgriWebb) and extension programs.
- Supports MLA's strategic goals around digital innovation, climate resilience, and sustainable production.

### **Limitations and Recommendations for Future Research**

A key strength of the project is the collection of data from large, commercial farms representative of the regional production practices in NW NSW. Constraints across the project of climatic conditions, including a period of acute but intense drought conditions in 2023 affected continuity of data collection due to destocking and confinement feeding conditions. Because a single mobile Optiweigh unit followed one mob at a time on each farm, only a subset of paddocks could be monitored in any season, limiting long-term trend assessment. Irregular animal attendance at in-paddock weigh stations required statistical smoothing to estimate daily ADG, reducing the granularity of some growth curves. In addition, pasture biomass (satellite TSDM) and paddock-average quadrat-based samples for quality (CP and ME) do not adequately account for utilisation or selection, meaning these variables function as contextual diagnostics rather than stand-alone predictors.

Integrating multi-source datasets (Optiweigh, CiboLabs, BoM, SEED/ASC soils) required substantial geospatial and data-cleaning effort, particularly given the lack of validated remote pasture-quality proxies. Finally, variability in producer data-sharing practices and incomplete records of stocking density and exact days-in-paddock constrained formal utilisation estimates and further emphasised the need for an ADG-based benchmarking approach rather than predictive modelling.

Future work should focus on consolidating and scaling the PPB benchmarking and diagnostics workflow, with priority given to expanding datasets and improving the key inputs required to support robust, regionally relevant paddock benchmarking.

- Extend multi-year datasets across additional agro-climatic zones, forage systems and cattle classes to strengthen the transferability, robustness and adoption of the PPB framework.
- To improve utilisation and pasture-quality proxies remains a critical technical challenge: emerging approaches such as remote or automated sensing (e.g., drone-based imagery, faecal NIRS) may help approximate diet-relevant crude protein (CP) and metabolisable energy (ME), but require careful validation under commercial grazing conditions.
- Forecasting should be treated as a conditional, longer-term evaluation, limited to short-term look-ahead alerts anchored to on-farm ADG benchmarks and only feasible where region-specific datasets and validated proxies for utilisation and greenness exist.
- Expand economic and sustainability components of the framework, including gross-margin-based scenario testing and the potential integration of carbon and natural capital metrics where appropriate.
- Continued investment in data infrastructure and interoperability particularly through cloud-based platforms such as AgriWebb will be essential to ensure seamless integration of Optiweigh, CiboLabs, BOM and soil datasets.
- Establish demonstration sites to support scalable adoption with collaborative, producer-led innovation, using co-designed tools.

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# 1 Background

## 1.1 Introduction and research question

Australia's beef industry operates across a vast and ecologically diverse landscape, where producers face increasing challenges in matching livestock stocking rates to the carrying capacity of their forage base. This capacity is inherently dynamic, reflecting the complex interactions among climatic conditions, plant functional traits and soil properties that collectively regulate pasture growth and availability (Earl, 2014). Consequently, traditional grazing management tools, such as simulation models like GRASP, are often labour-intensive, require extensive manual data collection, and are limited in their ability to predict animal performance in real time (Stone et al., 2008). The core industry problem is the lack of a scalable, objective, and dynamic system that integrates real-time animal performance data with environmental and pasture metrics to guide grazing decisions. This project addresses that gap by asking: *how can automated, real-time data be used to determine paddock productivity and optimise grazing management?* This question is particularly relevant given the increasing need for sustainable intensification of livestock systems in response to climate change and resource constraints (Ash et al., 2012; Reeves et al., 2025; Ritchie, 2020).

This project builds on and extends previous work in several ways. While models like GRASP and APSIM have been used to simulate pasture growth and livestock performance (Keating et al., 2003; McKeon et al., 2010), they often require detailed site-specific calibration and are not easily scalable (Masoud et al., 2023). The study was conducted in Northwest NSW (**Figure 1**) a region characterised by variable, predominantly summer-dominant rainfall and recurrent drought (Hasan et al., 2024a; McKeon et al., 2009). In these grazing systems, pasture production is strongly rainfall-driven, with biomass (total standing dry matter, TSDM) typically increasing rapidly following rainfall and declining during extended dry periods (Ash et al., 2000). This creates strong seasonal and inter-annual variation in feed availability and animal growth potential, requiring adaptive grazing and stocking decisions (O'Reagain and Scanlan, 2013).

Recent advances in remote sensing and machine learning have enabled more dynamic and scalable approaches to forage monitoring, with satellite-derived biomass products providing spatially consistent estimates of total standing dry matter (TSDM), or biomass, to support feed budgeting (Shahi et al., 2025). Satellite-derived biomass products facilitate landscape-scale feedbase assessments by delivering spatially consistent estimates of forage availability (e.g., TSDM) across heterogeneous production environments (Ara et al., 2020; Azubuike et al., 2025; Gargiulo et al., 2020). Despite these advances, most existing systems remain focused on environmental indicators and rarely integrate animal-level performance data into decision-support (Hudson et al., 2021). Monitoring individual animal liveweight (LW) change can inform farm management about productivity (Imaz et al., 2020), linking feedbase dynamics with environmental variability and animal performance to support informed, data-driven management decisions. The Optiweigh (OW) in-field weigh station allows for the remote and near-real time measurement of individual cattle LW at regular intervals. Cattle voluntarily access the platform to access an attractant (loose lick or block). We have previously validated

the OW system for accuracy against yard weights, reporting a strong association between OW and static weigh (SW) weight (CCC = 0.97;  $P < 0.001$ ) (Hasan et al., 2024). This system has the potential to facilitate on-farm decision-making about the feedbase and grazing management to optimise forage utilisation, balancing target post-grazing residual pasture biomass with animal liveweight gain.

This project proposes a paddock performance benchmarking (PPB) model to address this gap by using remotely derived cattle average daily gain (ADG) as an indicator of paddock level productivity, under varying environmental, feed and management conditions, which are challenging to directly measure in detail and real-time. This approach enables benchmarking of paddock performance across a farm to provide data-driven decision support for producers. Satellite derived pasture biomass data (TSDM) provides an estimate of how much feed is available, while in field weigh stations (Optiweigh, OW) provide the observed performance used both for operational benchmarking using the PPB model, and as ground-truth for future development of forecasting models to predict ADG from input variables in the future.

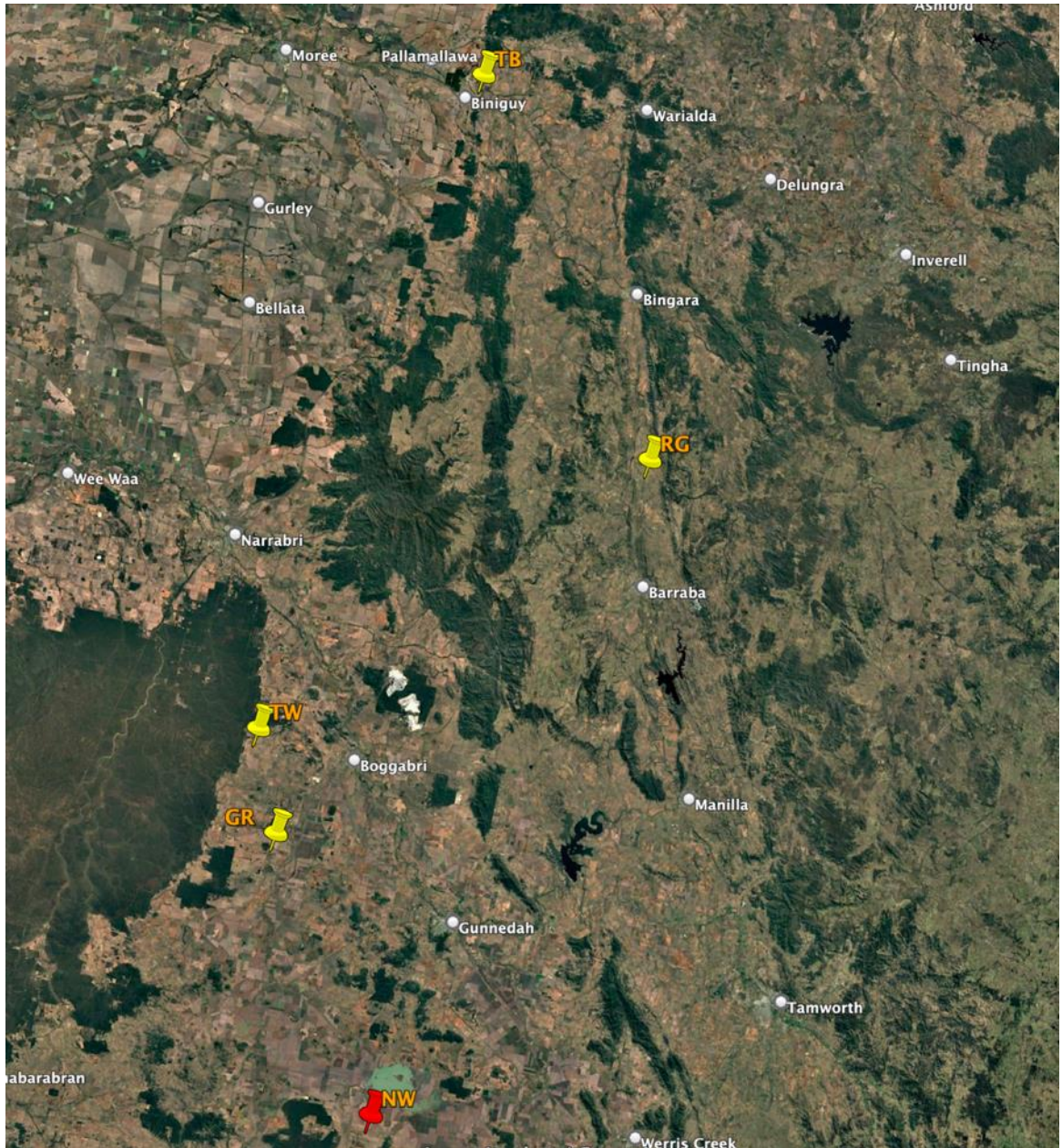
This aligns with global trends in precision livestock farming, where data-driven tools are increasingly used to enhance productivity and sustainability (Berckmans, 2017; Reeves et al., 2025; Romera et al., 2010). Moreover, the project contributes to the growing body of research on sustainable rotational grazing and its benefits for animal and pasture productivity and system resilience (García et al., 2024; Ritchie, 2020). Together, this project integrates routine and publicly available, holistic datasets to quantify paddock-level divergence in productivity and identify covariates associated with cattle growth, providing an evidence base for future forecasting and decision-support to strengthen climate resilience and long-term sustainability in extensive beef systems.

## 1.2 Target audience and impact

The primary audience for this research includes commercial beef producers, advisors, and industry stakeholders, particularly in regions like NW NSW (**Figure 1**). The research outcomes, specifically the development of the Paddock Performance Benchmark (PPB), are intended to provide producers with a tool that benchmarks paddock productivity using LW gain as the key indicator. By integrating near real-time cattle LW data (Optiweigh), satellite biomass data (CiboLabs), and environmental variables such as soil type and climate metrics, the model enables data-driven decisions on grazing duration, stocking density, and plant species selection. The relationship between Optiweigh derived ADG and satellite derived pasture biomass (TSDM) estimates, environmental covariates (temperature humidity index, rainfall and soil classification) was determined to understand how variables influence ADG within and between paddocks.

The development of a predictive model to forecast paddock level ADG based on these inputs would support how producers adapt their practices to changing climatic and market conditions. However this requires high resolution remote data sources which at the time of this project were not broadly available, validated tools. This approach is unique in its use of real-time animal performance data as the central metric for evaluating forage productivity, contrasting with traditional models that focus primarily on pasture biomass or digestibility

(García et al., 2024; Katoch, 2022). In this framework, satellite biomass and related indicators provide context on feed availability and help explain performance changes, rather than replacing the animal-based benchmark.



**Figure 1 Regional map showing the location of the three commercial partner farms used in the project. Farms were located in the North-West Local Land Services (NW LLS) management region of New South Wales, Australia, spanning the Liverpool Plains Sub-bioregion of the Brigalow Belt South Bioregion and the Peel Sub-bioregion of the Nandewar Bioregion. Sites have been de-identified and coded. Results for RG, TW and GR are included in this report.**

### 1.3 Applications of research outcomes

This project delivers a practical, scalable approach to paddock level benchmarking that producers and advisors can apply immediately, while laying the foundation for predictive decision- support- integrated into existing farm software. The results will be used to inform grazing strategies that improve pasture utilisation, reduce overgrazing, and enhance profitability, while also supporting broader goals of sustainability and climate resilience (Hudson et al., 2021; McKeon et al., 2009; Reeves et al., 2025).

Optiweigh-derived ADG can be used to benchmark paddock performance within a farm, across grazing rotations and seasons. This metric enables producers to identify paddocks with low productivity and make targeted practice changes that may include grazing duration, stocking density and pasture management or improvements based on measured animal performance rather than farm-level- averages. Historical paddock-level records will be retained to establish baseline performance ranges, enabling comparison with previous seasons and supporting trend-based management. The gross margin template can be used to link animal performance to per-paddock- financial outcomes, supporting transparent comparison of forage systems and targeted investment. For example, although some paddocks have a lower overall ADG, lower inputs for forage management may result in greater returns. Paddocks that consistently deliver a combination of greater ADG and gross returns can be used to inform changes across lower productivity paddocks, and underperforming paddocks can be prioritized for improvement through changes to e.g. stocking rate, grazing duration, or pasture improvements dependent on current management practices.

The project established the data architecture and geospatial methods for automated extraction, paddock alignment and benchmarking from Optiweigh, CiboLabs, climate (BoM) and soil (SEED) datasets, providing a clear pathway to embed PPB outputs in platforms such as Optiweigh, CiboLabs and AgriWebb and is a major pathway to adoption. The parent platform Pairtree should enable embedding PPB code into these platforms, where Optiweigh and CiboLabs are currently scaling integration with AgriWebb, as AgriWebb integrates paddock mapping, animal movements, and farm records in one platform and supports grazing planning. Furthermore, the project's emphasis on producer adoption, through field days and integration with existing platforms, ensures that the research is not only scientifically robust but also practically applicable.

## 2 Objectives

1. **Determine divergence in paddock productivity** based on cattle LW performance by developing a statistical model that integrates in-field weigh scale data (Optiweigh) with satellite pasture monitoring (CiboLabs), climate, pasture quality/quantity, and soil classification across 6–10 commercial farms in NW NSW.
2. **Validate and test the Paddock Performance Benchmark (PPB)** on trial sites over three years and on up to four additional validation/demonstration sites, including one University of Sydney farm.

3. Evaluate integration of historical and real-time PPB metrics with CiboLabs biomass estimates within the Australian Feedbase Monitor, and test their combined utility for informing grazing management decisions (e.g., grazing duration and stocking density), aiming to increase forage utilisation by at least 10%.
4. **Model the impact of varying input parameters** (e.g., location, LW, stocking density, forage base, and climate variables) to inform future expansion of the PPB across NSW and nationally, including under climate change and drought scenarios.
5. **Conduct 10 forums and 3 training workshops** with Northwest Local Land Services (NW LLS), including field days at the University of Sydney and partner sites, targeting 5,000 livestock producers in the region.

## 2.1 Assessment of Objective Achievement

Overall, the project successfully delivered a robust paddock-scale benchmarking framework, demonstrated meaningful divergence in paddock productivity, and integrated ecological, environmental and animal performance data into a coherent system. While the original ambition of delivering a fully predictive model was not achieved within the project timeframe, the analyses, infrastructure and findings provide a strong foundation for future forecasting, decision-support tools and commercial integration.

### 2.1.1 Objective 1: Determine divergence in paddock productivity

This objective was achieved. This project established Optiweigh units and CiboLabs pasture key subscriptions for collecting longitudinal remote cattle liveweight and pasture biomass data on three commercial partner sites (refined from an initial eight sites due to data quality and continuity constraints). A statistical model was developed to assess ADG across individual paddocks on five commercial farms using longitudinal LW data from OW systems. The model revealed significant variation in productivity between paddocks within the same farm, for example, paddock-level ADG for the farm GR typically ranged from 0.26 - 1.09 kg/day (inter-quartile range overall -1.26 to 2.85), highlighting the influence of forage type, pasture quality, and environmental conditions. Integration with satellite-derived pasture biomass (TSDM) confirmed that utilisation differed between paddocks and that biomass and ADG relationships varied markedly between forage crop systems and perennial or native pastures, supporting the need for a paddock-scale, animal-centred performance metric.

### 2.1.2 Objective 2: Validate and test the Paddock Performance Benchmark (PPB)

This objective has been substantially achieved. The model enabled the data collation and integration processes for benchmarking paddock productivity to support comparative analyses within farms. The PPB was developed, a paddock-scale benchmarking tool that uses OW-derived ADG as the primary indicator of performance, and evaluated the effect of satellite-derived pasture biomass (TSDM), climate and soil classification on ADG. Validation focused on descriptive and explanatory modelling rather than forecasting, with results demonstrating the utility of the PPB for identifying drivers of paddock-level variation in animal

performance. Full predictive validation was not completed within the project timeframe but has been scoped for future work.

### **2.1.3 Objective 3: Evaluate the integration of the PPB into CiboLabs/Australian Feedbase Monitor**

This objective was partially achieved. The project demonstrated the technical feasibility of extracting and integrating Optiweigh, CiboLabs, climate and soil data into a unified analytical framework. Methods for automated data extraction, geospatial alignment and paddock-level benchmarking were developed and tested. While full integration into commercial farm management platforms (e.g. CiboLabs dashboards or AgriWebb) was not achieved, scoping discussions with technology partners confirmed pathways for future integration. These discussions will inform continued development beyond the life of the project.

### **2.1.4 Objective 4 Model the impact of varying input parameters**

This objective was partially achieved. The effects of pasture biomass (TSDM), pasture quality (crude protein (CP) and metabolisable energy (ME), rainfall, temperature–humidity index (THI), soil classification, and plant species composition on ADG were evaluated. Feed quality (CP and ME) showed strong positive associations with ADG on two farms, while ecological surveys demonstrated that species dominance, establishment success and seasonal turnover provide important context for interpreting productivity differences between paddocks with similar biomass. Soil classification did not show a detectable short-term effect on ADG once farm-level variation was accounted for. The variables measured did not provide consistent prediction of animal productivity across seasons or time, suggesting the effect of animal influences such as species preference and pasture utilisation, which can be influenced by animal management factors such as grazing duration and stocking density which were not accounted for in the project. Together, these analyses identified key covariates for inclusion in future predictive modelling.

### **2.1.5 Objective 5 extension activities**

Objective 5 has been substantially achieved. Multiple field days, workshops, and producer forums have been conducted across the project's duration, with strong engagement and positive feedback. These activities have supported knowledge transfer and built awareness of the use of remote data collection systems, the PPB model and its applications. Further extension and training resources are recommended to support wider adoption as predictive and platform integrated tools are developed.

## **3 Methodology**

### **3.1 Data Collection**

Data collection commenced between April and December 2022 at project sites. Data sets from commencement through to June 2025 have been included in the analyses reported. It is important to note that an acute but significant period of drought affected data collection from March 2023 to January 2024 where partner sites had to destock or confinement feed cattle.

The project utilised a combination of automated in-field cattle weighing (Optiweigh), satellite-derived pasture biomass data (CiboLabs), soil classification (SEED database), and climate data (BOM). Data collection commenced with eight (8) commercial partner sites in NW NSW, including one University of Sydney farm. Five sites were then excluded due to data quality limitations to result in three (3) sites used for the final analysis.

There were multiple data systems used in this project, (1) Optiweigh LW recording, (2) CiboLabs pasture biomass data, (3) Geospatial data, and (4) other explanatory data including climate/ meteorological, soil and pasture quality. The focus was on the use of automatically collected datasets, rather than manually collected data. This required significant data processing techniques to enable a model that can extract data from publicly existing databases. This has been pivotal to developing a robust model forming the base of the research program.

Ultimately, paddock ADG (adjusted for other effects, such as seasonality) is used as a measure of paddock productivity. After fitting animal-specific growth curves, the ADG for each animal could be computed at any point of time over the growth trajectory, as described in Section 3.2.1. Ultimately, the overall average ADG for each monitored paddock (adjusted for other effects, such as seasonality) is derived and can be used as a measure of paddock productivity, as outlined in Section 3.2.2. Future work will focus on the further development of the model to forecast animal performance and inform grazing decisions such as grazing days for a paddock. The following sections outline the data management and statistical methodology used in the analyses.

#### **3.1.1 Cattle liveweight monitoring using Optiweigh in-field weigh stations**

The aim of the study was to collect data remotely from commercial operations to understand how OW data could be used to determine paddock productivity with limited access to producer data on cattle management. Each site was provided with an OW unit. Enrolment criteria required growing (weaner or yearling) cattle to be included in the study, and farms were required to use a rotational grazing system. All cattle on each of the three farms were 100% Angus, and comprised of steers, heifers or a mix of both. Mob sizes varied depending on farm management and sale of animals, with a minimum requirement of 50 in a mob based on enrolment in the study. At commencement, each farm was provided with one OW unit to be moved with the largest mob of weaner or yearling cattle as they rotationally grazed around each property. This logistical constraint limited simultaneous coverage and meant we

sampled a subset of paddocks per season at each site as detailed in Section 4.2. Granular detail of the animal numbers and stocking density for each rotation was unable to be provided by the property managers further limiting the management data that could be included in the study. In year three (2024), additional units were allocated (from the sites that were removed from the study) to three of remaining sites, allowing for multiple mobs and paddocks to be recorded concurrently.

Individual animal attendance to the in-field weigh stations is recorded through the RFID tag when an animal steps on the weigh plate. Weight, time, RFID, and date are exported as a comma-separated values (.csv) file, then collated into a data file and sent into the Cloud for viewing on the OW portal (<https://client.optiweigh.io/>). The OW data are recorded opportunistically at the OW weighing stations, so consequently, they are not recorded on a regular predetermined schedule. The goal of this analysis is to estimate the ADG at specific points of time, not necessarily on the days of weighing. For this, individual animal growth curves were developed, and from this the ADG computed as the slope of the growth curve at specific time points

#### *3.1.1.1 Summary of farms used in analysis*

We conducted a baseline survey of the farm managers to understand the farm systems and management practices upon commencement of the study, reported in Milestone 4.

**GR** is a large mixed cropping and grazing enterprise consisting of 13,000 ha across 19 mostly interconnected farms. GR has 2,000–2,500 Angus breeders. Management is flexible and season-driven rather than fixed-period rotations. Paddock choice and time-in-paddock respond to where rain has fallen and where feed is best. Marginal sandy paddocks have been re-planted to subtropical grasses and legumes and fertilised to maintain capacity. Supplementation is minimal (protein/calcium licks as required). For most of the study period one OW unit was used and towed between paddocks to follow a single priority mob at a time (typically where weight gain was being targeted). This necessarily means that, in any given season, only a subset of paddocks on the property could be monitored, with the monitored set changing as mobs rotated and seasonal conditions shifted. Data capture occurred under variable conditions (drought and high rainfall), and the timing of moves was based on visual feed assessment plus recent rainfall, so monitored paddocks in a given year could fall in different seasons (e.g., summer forage consisted of perennial grasses vs. winter forage crops, predominantly oats) depending on when the priority mob entered them.

**TW** consisted of an area of 1,440 ha with approximately 900 Angus breeders. The feedbase was comprised of native and improved pastures with mixed winter forages, predominantly oats, legumes and brassicas. TW operates rotational grazing with 30–40 ha paddocks and a practical rule of “ $\frac{1}{3}$  eaten,  $\frac{1}{3}$  trampled,  $\frac{1}{3}$  left”. Mobs typically move every couple of weeks. Every third year a paddock is rested to set seed (supporting winter legumes). Supplementation is used at seasonal nutrition gaps when required, and stocking rate was managed year-to-year to avoid over-grazing. For most of the study, one OW unit was deployed and moved with the mob through the rotation, so only one paddock at a time could be sampled, with two additional units added in 2024 where multiple paddocks could be captured sequentially across

the rotation. As a result, TW's monitoring sampled several paddocks over a year, but not all paddocks every season. Because the pasture base includes sub-tropical (summer) and mixed winter forages (perennial legumes and forage crops), the monitored paddocks in a given year spanned different seasons, reflecting when the priority mob occupied each paddock.

**RG** consisted of two farms comprising 1,400 ha with approximately 350–400 Angus breeders plus approximately 1,000 trade steers, seasonally dependent. The feedbase was comprised of native and improved perennial pastures (mix of cool climate Phalaris, cocksfoot and summer sub-tropicals). RG operates a flexible rotational system, where in summer, mobs are typically kept  $\leq 7$  days per paddock to maximise phase-1 pasture utilisation. Outside peak growth periods, movements rely more on visual assessment, to prevent over-grazing. Year-round dry-lick supplementation is used, and annual nitrogen is applied to improved pastures. As with other sites, one OW unit was initially deployed so one mob/paddock was monitored at a time over short windows, then the unit was re-deployed as rotations progressed, mobs were sold or animals matured. Consequently, only a limited number of paddocks could be monitored per season, and those paddocks could differ by season (e.g., warm-season vs cool-season allocations).

The exact number and dates of paddocks monitored per property were determined by the OW movement logs and paddock-allocation records (**Table 1**).

**Table 1 Summary of Optiweigh data recorded on the three observed partner farms. Details include the total animal numbers monitored on each farm and total number of paddocks and total area monitored.  $n$  = number.**

Farm	Start	End	No. of OW records	No. of animals	Total paddocks		Paddocks evaluated	
					n	Area (ha)	n	Area (ha)
<b>GR</b>	Dec-22	Jun-25	20,740	2,332	149	12,070	38	3,865
<b>RG</b>	Dec-22	Jun-25	18,977	1,295	33	1,073	18	764
<b>TW</b>	Apr-22	Jun-25	6,544	852	98	3,178	18	647

Currently, the data have been analysed separately for each farm. As animals sometimes go to an OW station several times on one day, the first stage was to calculate the average weight of an animal on a day and use these means for subsequent analyses when multiple visits occurred. Frequency of visits and a validation of the OW data against static weight data have been reported in a separate study (Hasan et al., 2024).

### 3.1.2 Pasture data collection

#### 3.1.2.1 Pasture biomass and quality assessment

A CiboLabs PastureKey subscription was established for each partner site, which provides access to biomass data at the paddock level with a resolution of 10 x 10m. Satellite recorded pasture biomass data from CiboLabs (<https://www.cibolabs.com.au/>) is exported as a .csv file,

providing weekly (rolling 5-day average) total standing dry matter (TSDM) in kg/ha for each paddock within the farm, recorded on a monthly basis. To visualise long- and short-term trends, such as drought and break-of-drought events, TSDM for each paddock was plotted over time (using ggplot2 in R).

Feedbase data were collected using the CiboLabs biomass collector mobile app (**Figure 2**). This includes visual assessments of pasture mass, photos of the pastures and paddocks. Above-ground pasture biomass was estimated using pooled whole-quadrat cuts to ground level (1 m<sup>2</sup>) at three sites per paddock, pre- and/or post-grazing, to provide a rapid, repeatable paddock-scale estimate of total standing dry matter (TSDM) for comparison with satellite TSDM. The protocol did not separate green vs. dead material, defoliation horizons or plant parts (leaf/stem), and therefore does not capture diet selection or vertical structure directly. This choice reflected the need for a time-efficient, cross-farm method to accompany routine satellite monitoring and to achieve sufficient replication across many paddocks and seasons. Laboratory assays (CP, ME, NDF, ADF) on pooled samples were used to partly address feed quality, but do not resolve animal selection effects.

For each site, 5 x 1 sqm cuts were collected at three sites within the paddock within 2 weeks pre and/or post grazing using the below methodology:

1. Three sites within paddock were selected based on variability in the feedbase (if any) or randomly representative of different topography or area within the paddock
2. For each site, 5 quadrat cuts were collected 10m apart in a straight line into one feed sample bag using a 1 sqm quadrat
3. Quadrats were randomly thrown onto an area for pasture cuts
4. Pasture was cut to ground level and placed in a paper sample bag for weighing. The 5 samples are pooled into one bag, and this was repeated at the 3 sites within each paddock
5. Samples were weighed for wet weight and then transported to the dehydrator, where they were dehydrated at 80°C for a minimum of 20h or until the dry weight is stable, to measure dry weight
6. DM Yield or Kg DM/ha in the paddock is calculated as = Weight of grass (kg) x DM% x 40,000
7. Dried pasture samples were sent to Feed Central (Toowoomba QLD) for analysis of CP, ME, NDF and ADF. A report was generated and data collated for the full observation period per paddock per farm.

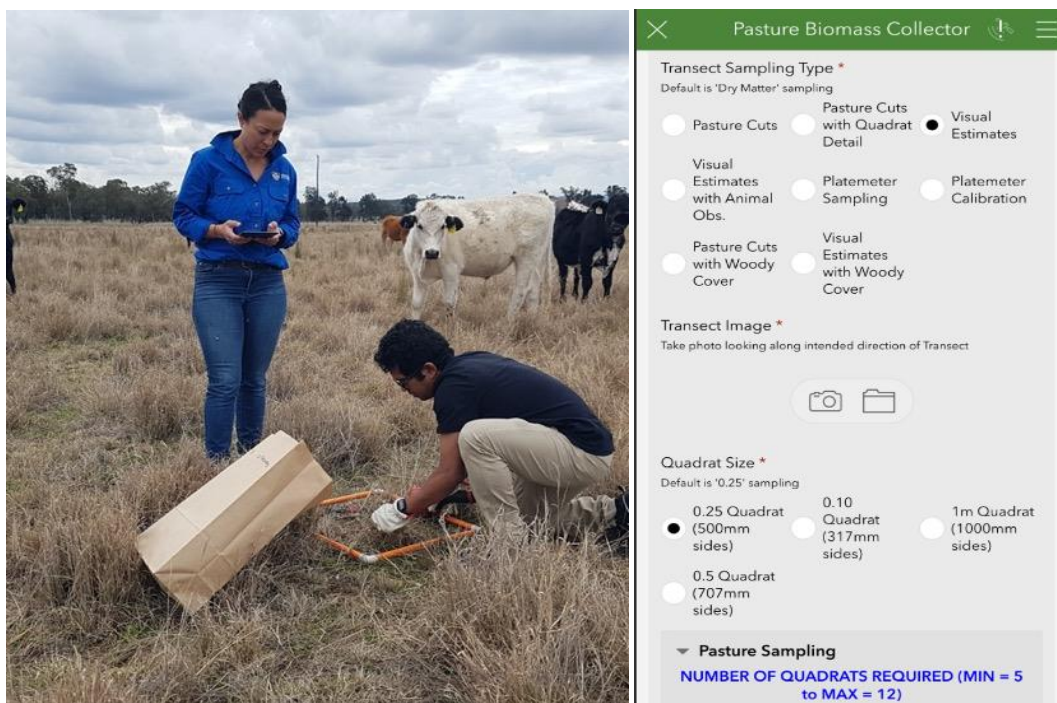
Whole-quadrat herbage cuts were dried, chopped and sent for analysis to a commercial laboratory (Feed Central Testing Lab, Toowoomba, QLD). Reported parameters (dry matter basis) included ADF, NDF, crude protein (CP), total digestible nutrients (TDN), digestible energy (DE) and metabolisable energy (ME). For the purpose of our analysis, we used the ME and CP values. Feed Central do not publish calculation formulas, because CP, DE, TDN and ME are standardised laboratory outputs. These equations are industry standards implemented across Australian feed-testing services, and the lab did not disclose a bespoke alternative. The

below specifications therefore state the operational formulae used to derive ME from the wet-chemistry panel (ADF, NDF, CP) (Future Beef).

CP is determined by wet-chemistry nitrogen analysis:  $CP (\%) = N (\%) \times 6.25$ . Consistent with common Australian forage-lab practice, we assumed energy was calculated from fibre fractions for the purpose of our report:

- Total digestible nutrients (TDN) is estimated from ADF:  $TDN (\%) = 88.9 - (0.79 \times ADF\%)$
- Digestible energy (DE) from TDN:  $DE (MJ/kg DM) = 0.151 \times TDN (\%)$
- Metabolisable energy (ME) from DE (ruminants):  $ME (MJ/kg DM) = 0.82 \times DE$

Data from the biomass collector app and the DM yield calculations were sent to the CiboLabs cloud for comparison to the satellite data as part of their ground truthing.



**Figure 2** Collection of pasture samples within paddocks using the CiboLabs biomass collector app.

### 3.1.2.2 Ecological sampling

Ecological sampling was conducted by Stringybark Ecological Pty Ltd. Baseline sampling was conducted across six of the initial partner sites, with the final survey conducted on three sites (GR, TW and RG). Pasture species composition and groundcover were assessed on each farm across 35 paddocks in total.

Using data provided by the research team and property managers, at least one paddock representing each available forage base category was selected for monitoring on each property, including introduced warm-season pastures, introduced cool-season pastures, unmodified (native-dominated) pastures (**Figure 3**). Within each selected paddock, a minimum of one 20 m × 20 m monitoring plot was established. In paddocks with substantial topographical variation, additional plots were established to account for slope position, with at least one plot placed on the upper slope and one on the lower slope.

Surveys were conducted during the warm season of 2024 across all properties, with cool-season resurveys in 2025 at GR, TW and RG to capture seasonal changes in species composition. Within each plot, all vascular plant species were identified and assigned a visual foliage cover estimate. Groundcover was assessed using quadrats to estimate bare ground and litter cover. Species were classified by growth form, origin (native or exotic), growth season, and life cycle, and high-threat weeds were identified using NSW Biodiversity Assessment Method criteria. Paddock-level metrics derived from these surveys included species richness and groundcover composition by functional group.

At each plot the following observations were recorded:

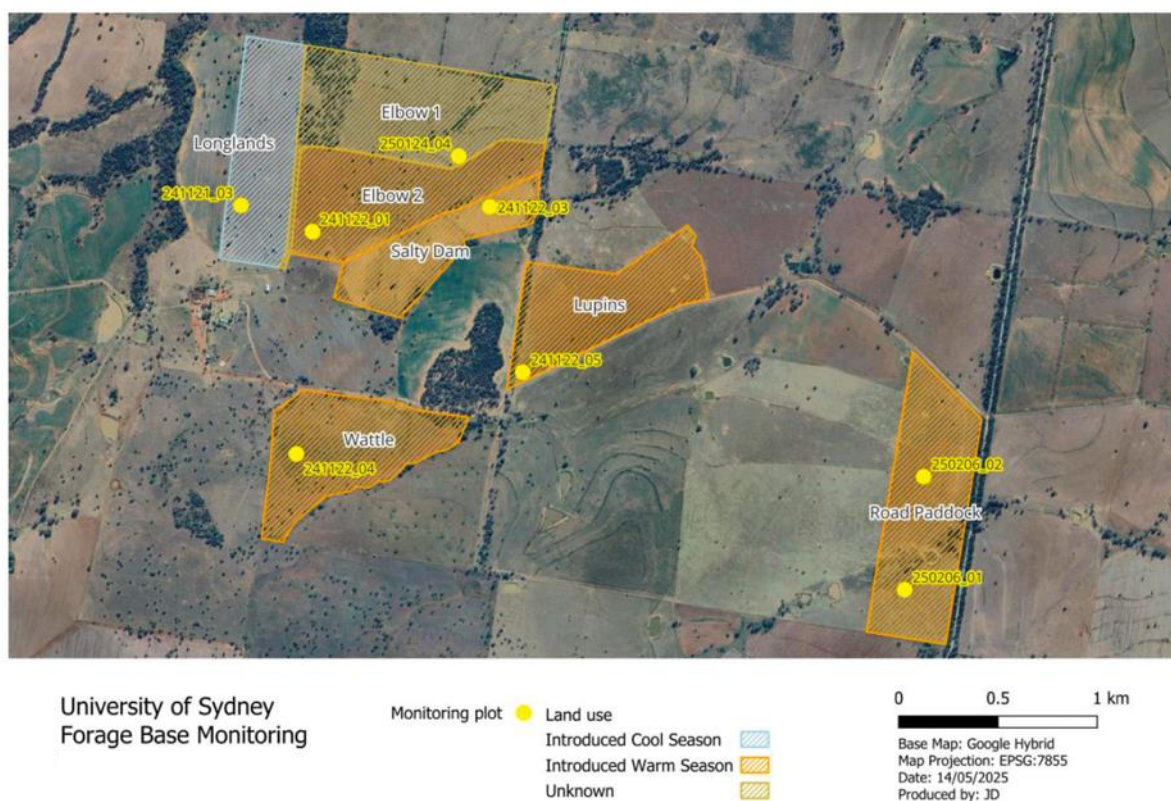
- Vascular plant inventory and cover. All species present were recorded with a visual foliage cover estimate at the plot scale. Species were classified by growth form, origin (native/exotic), dominant growth season (cool/warm) and life cycle (annual/perennial) following the survey protocol.
- Ground and litter cover. Ten 50 × 50 cm quadrats per plot were assessed to estimate bare ground and litter (% cover). Where multiple plots were present, plot-level estimates were averaged to the paddock.
- High-threat weeds (HTWs). Species listed as high-threat weeds under NSW guidance were identified and flagged for risk interpretation.

Survey observations were aggregated to paddock level to derive:

- Species richness (unique species per paddock across plots/season where resurveyed), and
- Groundcover composition (dominant species, grasses, forbs, “other” functional groups, HTWs, litter, bare ground) to support interpretation of feedbase function and condition.

Plot and paddock identifiers and GPS coordinates were reconciled with farm paddock boundaries to enable spatial linkage of ecological outputs with (i) Optiweigh in-paddock liveweight/ADG time series, (ii) CiboLabs paddock-level biomass (TSDM), and (iii) climate and soil datasets used elsewhere in the project. This allowed consistent paddock-scale integration across data streams for analysis and mapping.

Seasonal resurveys (TW, RG) were used to improve species detection and capture phenological change; however, ecological surveys are temporal snapshots and can be influenced by recent grazing or seasonal anomalies. Where grazing occurred near the time of survey, detectability of some perennials/forbs may have been reduced; interpretation in the results (Section 4.4) accounts for this constraint.



**Figure 3** Location of sampled paddocks and monitoring plots at TW, showing land use in each sampled paddock.

### 3.1.3 Geospatial data

Being mobile, the OW stations were frequently moved between paddocks. As the paddock movements were not consistently recorded, paddock allocations were determined by using the GPS coordinates generated by the OW station. This was facilitated by using kmz shape files depicting paddocks for each farm exported from Google Earth. The shape files showing paddock boundaries were extracted from the kmz file and imported into R and processed using the sf spatial analysis package in R. To determine which paddock an OW station was placed in, the pointsInPolygon function in the secr package in R was used. Farm maps showing paddock boundaries, overlaid with OW station positions were plotted using the sf package in R.

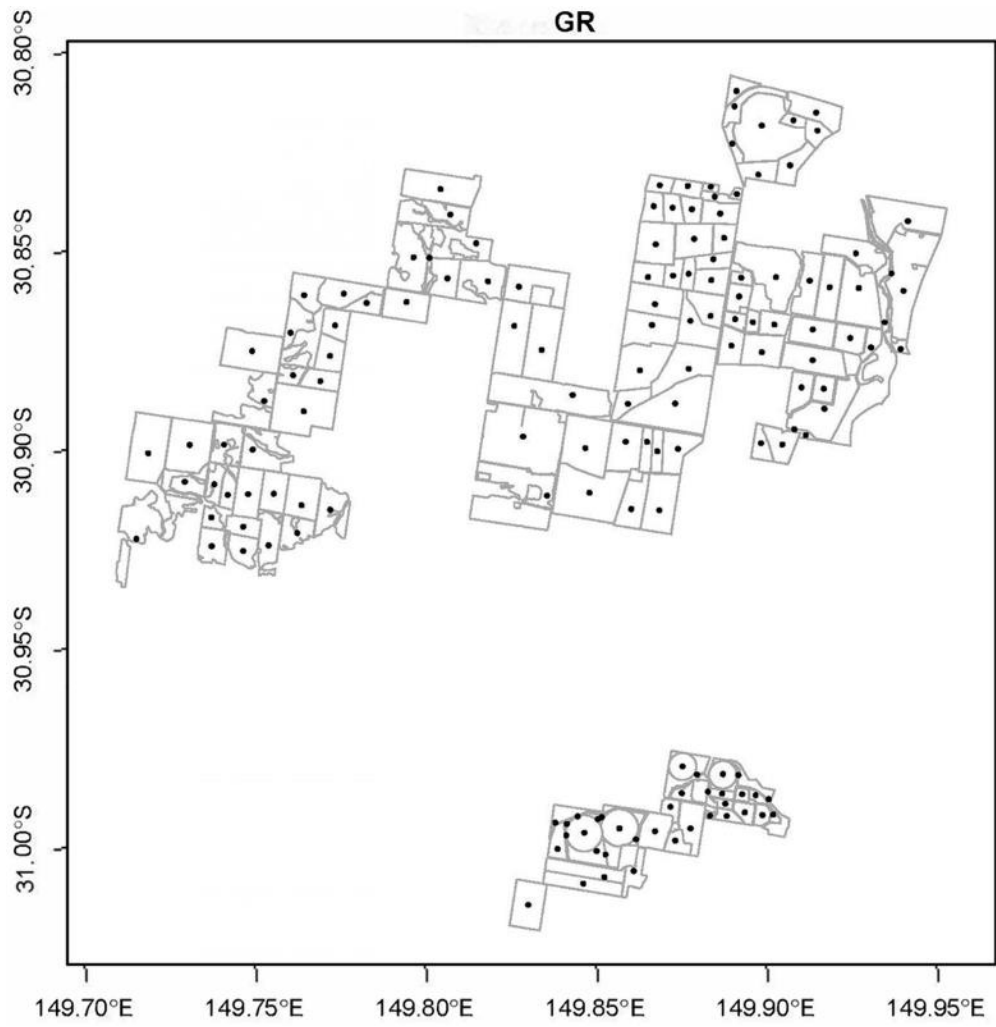
### 3.1.4 Climate Data

Weather stations were installed at each site to record climate data, including temperature, humidity, wind speed and rainfall, providing accurate on-farm measurements. To support the use of publicly available data sources, meteorological data were also obtained from the Australian Bureau of Meteorology (BOM) 3-hourly synoptic archive, with the nearest BOM station identified for each farm (GR, TW and RG). On-farm automatic weather-station (AWS) records (temperature, relative humidity and rainfall) were quality-checked and summarised to daily values, and corresponding daily BOM weather data were extracted for the same observation period. The temperature–humidity index (THI) was calculated using the Mader et al. (2006) equation, and the daily maximum THI ( $THI_{max}$ ) was derived from sub-daily THI values. Daily rainfall (mm/day) was also sourced from BOM and restricted to 1 July 2023–31 August 2025 to align with the animal growth (LW/ADG) datasets.

### 3.1.5 Soil Classification Data

Soil types across NSW were available from the Australian Soil Classification in the form of shape files (kmz) available from the Australian Soil Classification (ASC) soil type map of NSW (<https://www.seed.nsw.gov.au/>). Shape files were extracted as kmz files from the SEED database and imported into Google Earth for matching with the geospatial maps of the farms and paddocks (3.1.3). In addition to an overall state map, the soil types were overlaid on the paddock maps on three individual farms: GR, TW and RG. The paired data was imported into R for all mapping and analyses, with packages 'sf' and 'ggplot2' used for spatial mapping and visualising respectively.

To nominate the soil type for each paddock, the paddock centroid was first calculated, with an additional constraint that each centroid was restricted to lie within the paddock (**Figure 4**). The 'st\_point\_on\_surface' function of 'sf' was used for this. Next, the soil type at the paddock centroid was determined using the 'st\_nearest\_feature' function in 'sf'. It is acknowledged that there may be more than one soil type in a paddock, but the overall classification appears reliable. While the number of soil types on each farm varied, there was a limit in terms of those where ADG could be estimated due to allocated locations of the Optiweigh stations. Consequently, comparisons were made across three soil types, namely Chromosols, Sodosols and Vertosols. Farm-level soil maps and supporting outputs are provided in **Appendix 8.2** Soil classification .



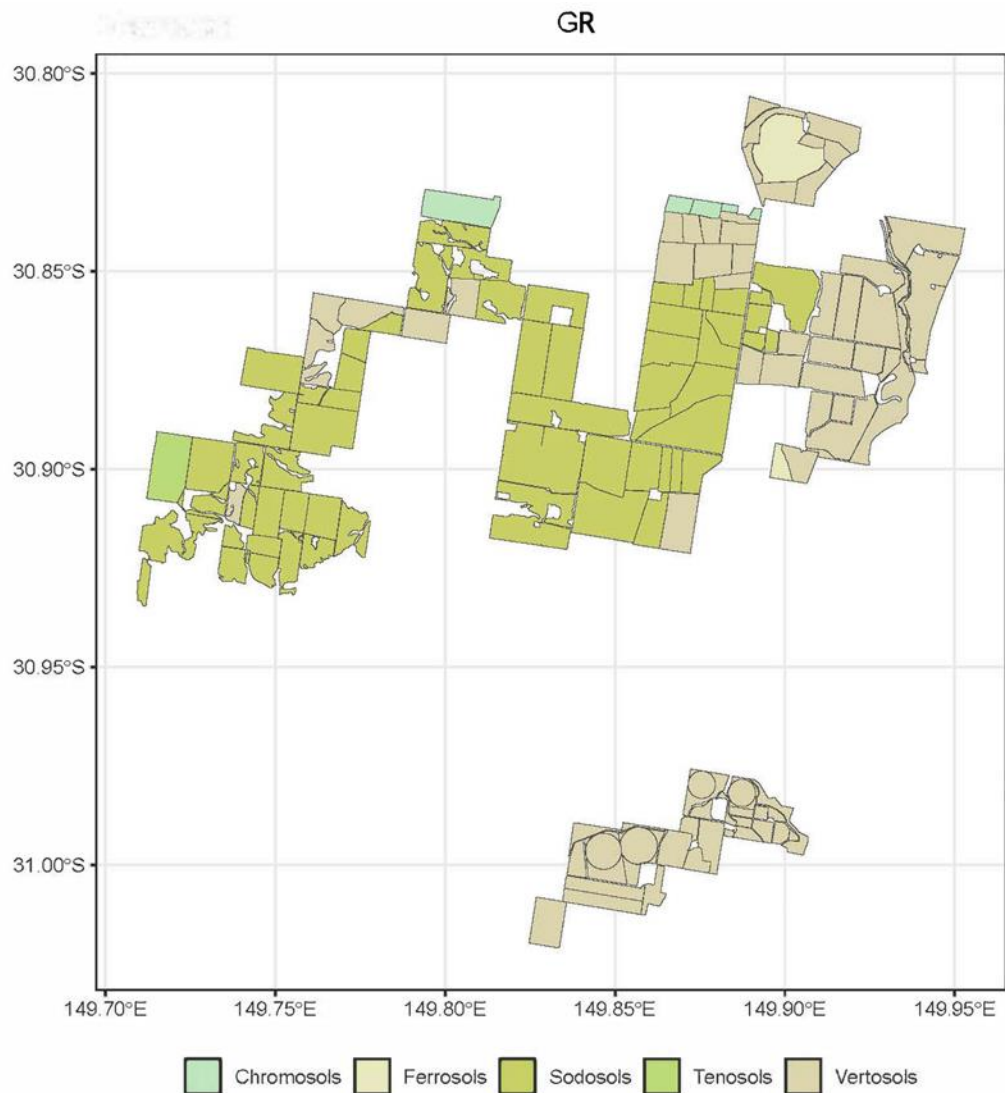


Figure 4 Example of paddock-level soil classification for GR: paddock polygons with centroid used for soil assignment (A) and paddocks coloured by soil class assigned from centroid location (B).

## 3.2 Modelling Techniques

### 3.2.1 Determining paddock productivity

The following statistical model was fitted to the cattle weight data; note that the incorporation of smoothing splines allows flexibility in the shapes of individual animal growth curves:

$$\text{Weight}_{it} = \beta_0 + (\beta_1 + b_{1i})t + \text{Animal}_i + s(t) + s_i(t) + \epsilon_{it}$$

where  $Weight_{it}$  is the LW (kg) of the animal  $i$  recorded on day  $t$ , with fixed effect parameters  $\beta_0$  (intercept) and  $\beta_1$  (overall linear LW gain);  $Animal_i$  is the random intercept effect for animal  $i$ ;  $b_{1i}$  is a random slope effect for the deviation of the linear trend of the animal,  $s(t)$  is an overall smoothing spline function of time  $t$ ;  $s_i(t)$  is the smoothing spline deviation for animal  $i$ , and  $\varepsilon_{it}$  is a random error. The model was fitted using ASReml-R (VSN International Ltd., England) via the `asreml` package in the R environment. It should be noted that for ASReml-R, all spline terms were fitted as random effects in the model. Residual diagnostic plots were obtained, records with a standardised residual in excess of 4 in absolute value were removed from the dataset, and the model was re-fitted.

Using the fitted model, individual cattle growth curves were generated, and model-based ADG (kg/day) was calculated from changes in predicted means between consecutive days. In certain situations, a 15-day floating mean centred on the day of smoothing was employed for final low-level smoothing of ADG due to the nature of ASReml-R predictions. The estimated ADG values of each animal at specific dates were obtained from these. Raw data growth curves, smoothed (model-based) growth curves and ADG curves for each animal were visualised using the `ggplot2` package in R.

### 3.2.2 Relationship between pasture biomass and average daily gain

The ADG (Optiweigh) data were merged with pasture biomass data (TSDM, kg/ha) extracted from CiboLabs Pasturekey for each paddock. The model used the TSDM value at the beginning of the grazing period for the paddock to align with any ADG values in the same period. Following this, in addition to plotting the association, the following linear mixed model was fitted:

$$ADG_{ijt} = \beta_0 + \beta_1 TSDM_{jt} + Paddock_j + Animal_{ij} + \varepsilon_{ijt}$$

where  $ADG_{ijt}$  is the growth rate of animal  $i$  in paddock  $j$  at time  $t$ ,  $TSDM_{jt}$  is the pasture content in paddock  $j$  and time  $t$  (fixed covariate effect),  $Paddock_j$  is the random effect of Paddock  $j$ ,  $Animal_{ij}$  is the random effect of Animal  $i$  while it is in Paddock  $j$ , and  $\varepsilon_{ijt}$  is a random error. Estimates of the random paddock effects were used to obtain average ADG for the paddock over the study period. The model was fitted using ASReml-R.

### 3.2.3 Effect of explanatory variables on cattle growth

#### 3.2.3.1 Effect of THI on cattle growth

Daily maximum temperature–humidity index ( $THI_{max}$ ) time series were derived from the selected BOM stations. The nearest BOM stations exhibiting the highest concordance with on-farm weather station data for daily  $THI_{max}$  were selected for subsequent analyses: station 55202 for GR (CCC THI 0.976), 54038 for TW (CCC THI 0.983), and 56018 for RG (CCC THI 0.920). Short gaps ( $\leq 3$  consecutive days) were linearly interpolated using the `imputeTS` package in R, with longer gaps retained as missing. The  $THI_{max}$  was decomposed into a long-term (smooth/background) component and short-term deviations using a linear mixed model fitted in ASReml, with centred calendar date as a fixed effect and station-specific non-linear

temporal variation represented by penalised splines (station as a random effect); fitted values and residuals were retained as the smooth and deviation components, respectively.

Optiweigh liveweight (LW) records were processed to a single daily mean LW per animal and decomposed into smooth growth trajectories and short-term deviations using linear mixed models in ASReml fitted separately by farm, where LW deviations were used as the response variable in subsequent analyses. THI and LW datasets were merged by date, and lagged predictors for THI<sub>max</sub> smooth and deviation components were generated for  $k = 0-28$  days by shifting each farm–station daily series.

Lag structure was screened within each farm using cross-correlation between LW deviations and lagged THI<sub>max</sub> deviations to inform selection of candidate lag terms for modelling. At selected lag(s), associations between LW deviations and lagged THI<sub>max</sub> deviations were modelled using (i) linear regression (lm) and (ii) generalised additive models (mgcv::gam) with thin-plate splines; models were optionally extended to include the lagged THI<sub>max</sub> smooth/background component. Marginal predictions were obtained using emmeans and visualised using ggplot2 and lattice/levelplot. Finally, candidate lag terms were evaluated in repeated-measures mixed models for LW deviations following Hasan et al., (2026).

### 3.2.3.2 Rainfall effects on ADG

Optiweigh-derived cattle liveweight (LW) records were analysed in ASReml-R. For each animal, a daily LW trajectory was fitted and average daily gain (ADG, kg/day) was calculated as the one-day difference in fitted LW. Daily rainfall (mm/day) was obtained from the Australian Bureau of Meteorology (BOM). Where on-farm rainfall data were incomplete, a representative BOM station was selected and validated against the on-farm record using concordance correlation coefficients (CCC): GR used station 55202 (33.9 km from the property centroid; CCC = 0.891), and TW used station 54038 (CCC = 0.789). Antecedent rainfall exposure was quantified as right-aligned rolling totals over 7, 14, 30, 60, and 90 days (computed with zoo::rollapply) and log-transformed to reduce skewness. Rolling rainfall metrics were merged to the ADG dataset by date. Associations between rainfall exposure and ADG were then tested using linear mixed models in ASReml-R with random intercepts for animal (EID) and paddock to account for repeated measures and clustering. Fixed effects were fitted additively (no interaction terms). Candidate rainfall windows were compared using AIC (with BIC as supporting evidence) under an identical model structure, and fitted effects were visualised (**Appendix Error! Reference source not found.**).

Additionally, a separate analysis of the impacts of climate on growth has been investigated using a national network of OW stations and BOM data (Hasan et al., 2026; Hasan et al., 2024a). To develop this model, we utilised data sets from a network of OW systems across Australia and paired this with climatic data from nearby BOM stations. Linear mixed models were used to analyse the ADG data and cattle response to climatic variables. This approach to climate-growth modelling will be integrated with the model.

### 3.2.3.3 *Soil classification*

Having classified the soil type of each paddock (3.1.5) the effect of this on average daily gain (ADG) was evaluated, using the overall ADG estimated for each specific paddock. A linear mixed model was fitted to the data across all three farms (GR, TW and RG) using the 'lme' function in the 'nlme' package with soil type as the fixed effect, and farm as the random effect, with allowance made for different variability in ADG between soil types.

### 3.2.3.4 *Pasture Quality and Plant Species*

Paddock-level feed quality reports were available for three farms (GR, TW and RG) and included crude protein (CP, %) and metabolisable energy (ME, MJ/kg dry matter), together with the sampling date and paddock identifier. Analysis was based on whole quadrat samples cut to ground level. Animal performance was derived from Optiweigh (OW) in-paddock weighing systems. Average daily gain (ADG, kg/day) was calculated either as daily ADG or over measurement intervals; for interval-based ADG, the midpoint of each interval was used as the reference date for data linkage.

Paddock names were standardised to ensure consistent identification between feed and ADG datasets. Feed quality was linked to ADG within paddock using a last-observation-before approach: for each ADG record, the most recent feed sample collected on or before the ADG reference date was assigned. To minimise temporal mismatch, matches were retained only when the gap between feed sampling and the ADG reference date was 14 days or less; unmatched records were excluded.

To avoid overweighting animals with repeated measurements, matched data were aggregated to a paddock unit by calculating mean ADG across animals. The number of distinct animals contributing to each paddock-unit mean was retained and used as an analytical weight. Associations between weighted mean ADG and feed quality were assessed using linear mixed models fitted in ASReml (v4.2). Separate models were fitted for CP and ME, with paddock included as a random intercept to quantify between-paddock variability, and the results were visualised.

Plant species monitored through the ecological surveys was limited to the sampled paddocks (3 per farm) across two surveys. Therefore, descriptive analysis based on productivity of sampled paddocks is provided for recommendations on plant species selection.

## 3.2.4 **Gross margins analysis**

A paddock-level gross margin (GM) analysis to translate biological performance into economic outcomes and support comparison of forage base options at commercial scale was developed. The analysis used the project's Optiweigh-derived ADG and paddock utilisation records together with property-supplied variable cost information to calculate GM per paddock. Results are reported for three partner farms (GR, TW, RG) and are anonymised.

Three of the partner farms (TW, RG and GR) were selected for the development of individual pasture (paddock) gross margins. Farm visits and producer surveys were performed by AgEcon and data collected on:

- Costs of cattle enterprise (to calculate the average daily management costs per head)
- Annual pasture management program (to understand the annual costs of the various pastures) including planting, fertiliser/ameliorants, weed control and operations, supplementary feed costs where applicable
- ADG by paddock (to understand the income by paddock)
- Price assumptions for liveweight based on current market value for stock class

Overhead and capital costs were not included in a gross margin analysis. Overhead costs include permanent labour, property rates, machinery depreciation or interest on purchases. Capital items include purchase costs of machinery and livestock.

A gross margin template was developed in excel that considered:

- Gross income = Paddock ADG (kg) x market price (/kg) x head of cattle x days in paddock
- Variable costs = Livestock enterprise costs (per head / per day) x head of cattle x days in paddock + forage base production costs (per ha) (including planting, fertilising, weed control etc) + supplementary + feed cost where applicable
- Gross margin = gross income – variable costs

The ADG data was supplied by the project, remaining input data was collected for the 2024 calendar year across the three farms (GR, TW, RG) using an in person, on farm survey approach. The data was applied to the gross margin template to provide a per hectare gross margin for each paddock, creating a useful tool for each farm to compare and explore forage base options and the productivity of each paddock.

### **3.2.5 Predictive Model development**

The current Paddock Performance Benchmark (PPB) tool provides the foundation for evaluating the potential of Optiweigh (OW) datasets to inform cattle productivity within and across paddocks on a farm, and benchmark productivity across seasons and time. Including the effects of variables (climate, feed quality and pasture biomass, soil) on ADG will help producers understand what factors drive variability and enable decision making around adjustments. This requires accounting for management and animal related factors such as pasture selection and grazing management (duration, stocking density). Variability of these factors makes prediction of productivity challenging without detailed ground-based measurements. The present analysis focused on describing and explaining variation in cattle growth, the PPB model builds directly on published work using the national OW network to quantify the effects of rainfall (Hasan et al., 2024a) and temperature–humidity index (THI) (Hasan et al., 2026) on cattle growth over time. Together, these studies demonstrate the capacity of OW data to capture biologically meaningful responses to environmental drivers and support their use within a broader predictive framework.

To progress from descriptive and explanatory analyses to forecasting, a multivariable modelling approach is proposed in which the primary prediction output is paddock productivity, expressed as paddock level ADG. This model will include factors considered in isolation in this report, including farm-level (weather data), paddock-level (pasture biomass, quality and soil type) animal-level (weight and growth history) and management practices (grazing density, grazing duration). These inputs would be combined within an expanded multivariable model that links drivers to outcomes, allowing the effects of environmental and biological variability on paddock performance to be quantified. Such a model would enable evaluation of alternative grazing strategies and support optimisation of paddock-level management under variable seasonal and climatic conditions but ultimately was out of scope given the constraints of the granularity of data and the acquisition methods available in this project.

### **3.3 Extension activities**

Local land services (LLS) extension activities have included field days and presentations at producer forums across the three years of the project, as reported in Milestones 2-5. The LLS hosted a final project field day in September 2025, featuring a workshop that demonstrated the PPB and tools developed, including the gross margins analysis. Final workshops will be conducted with the partner farms to present findings and provide training in using the modelling and gross margin tools developed in the project. Broader extension activities and dissemination of findings will continue in partnership with LLS NW following conclusion of the project.

### **3.4 Evaluation of Methodology**

The methodology employed in this project was designed to integrate automated, remotely collected data streams into a cohesive framework for benchmarking paddock-level productivity in commercial beef systems. A key strength of the approach was the use of in-paddock liveweight monitoring (Optiweigh) as the primary biological response variable, enabling direct quantification of cattle performance under real grazing conditions without the need for frequent manual handling. This animal-centred metric provided a robust and scalable basis for assessing paddock productivity and comparing performance across paddocks, farms and seasons.

The integration of satellite-derived pasture biomass (CiboLabs) with liveweight data allowed pasture availability to be assessed remotely at paddock scale across farms. The inclusion of pasture quality indicators (CP and ME), where available, and ecological survey data describing species composition improved interpretation of between-paddock differences in productivity. Whole-quadrat, cut-to-ground samples provide an efficient estimate of TSDM, but they do not account for diet selection or vertical distribution of green leaf, stems and senesced material. Consequently, they may over-represent non-selected fractions in mixed swards and under-represent the effective diet available to grazing cattle. We addressed this, in part, by (i) pairing ground cuts with satellite TSDM and paddock-level CP/ME assays, and (ii) analysing animal performance directly from in-paddock liveweight (ADG). Even so, the absence of green-fraction or horizon-specific biomass is a constraint and is acknowledged in the

interpretation of the biomass-ADG relationships in perennial/native systems. Interpretation also considers change in TSDM over the grazing period as a remote indicator of utilisation but recognise that quadrat-based CP or ME represents paddock-average quality rather than selected diet. Predictive forecasting is scoped for future work.

A further strength of the methodology was the integration of climate and soil datasets sourced from publicly available national databases. Rainfall and THI metrics were incorporated to determine climatic effects on cattle growth, while soil classification provided broader environmental context at paddock scale. The development of geospatial workflows to align Optiweigh station locations with paddock polygons, and to link biomass, climate and soil data to grazing events, was technically demanding but essential for achieving paddock-level inference.

The statistical modelling approach using spline-based growth curves and mixed-effects models accommodates for irregular weigh-station attendance, repeated measures, and clustering at animal and paddock levels. This method was adapted to the complexity of commercial datasets and allows for average daily gain (ADG) be estimated at any point in time.

Limitations of the methodology primarily reflect the realities of working in commercial production environments. Data gaps associated with drought, destocking and variable grazing rotations limited the number of repeated grazing events available for some paddocks, constraining formal predictive model development within the project timeframe. Irregular animal attendance at weigh stations introduced additional variability, although this was mitigated through statistical smoothing.

On properties with one OW unit, the unit was rotated with the mob into the paddock being grazed, establishing a clear entry–exit window for benchmarking. ADG for each grazing window was derived by converting opportunistic liveweight visits into daily weight curves and date-specific ADG using spline models. Because only one paddock can be monitored at a time, a sentinel set of key paddocks (4–6 per season, representing the property’s main forage systems) was monitored sequentially, enabling within-farm ADG benchmarking across seasons. For each window, satellite biomass data were used to compute change in pasture biomass, and rainfall/THI windows were aligned to provide diagnostic context for interpreting ADG. The data pipelines and PPB workflow developed in this project are designed for automatic execution within existing digital platforms, meaning paddock-window ADG, pasture biomass changes and climate context can be generated as a background process and accessed through systems such as Optiweigh, CiboLabs or AgriWebb.

Pasture quality and ground-based biomass data were manually collected and temporally sparse, in addition to previously mentioned limitations of quadrat-based measurements. This limits scalability for integration of pasture quality and grazing dynamics in future predictive models without the availability of validated remote monitoring systems.

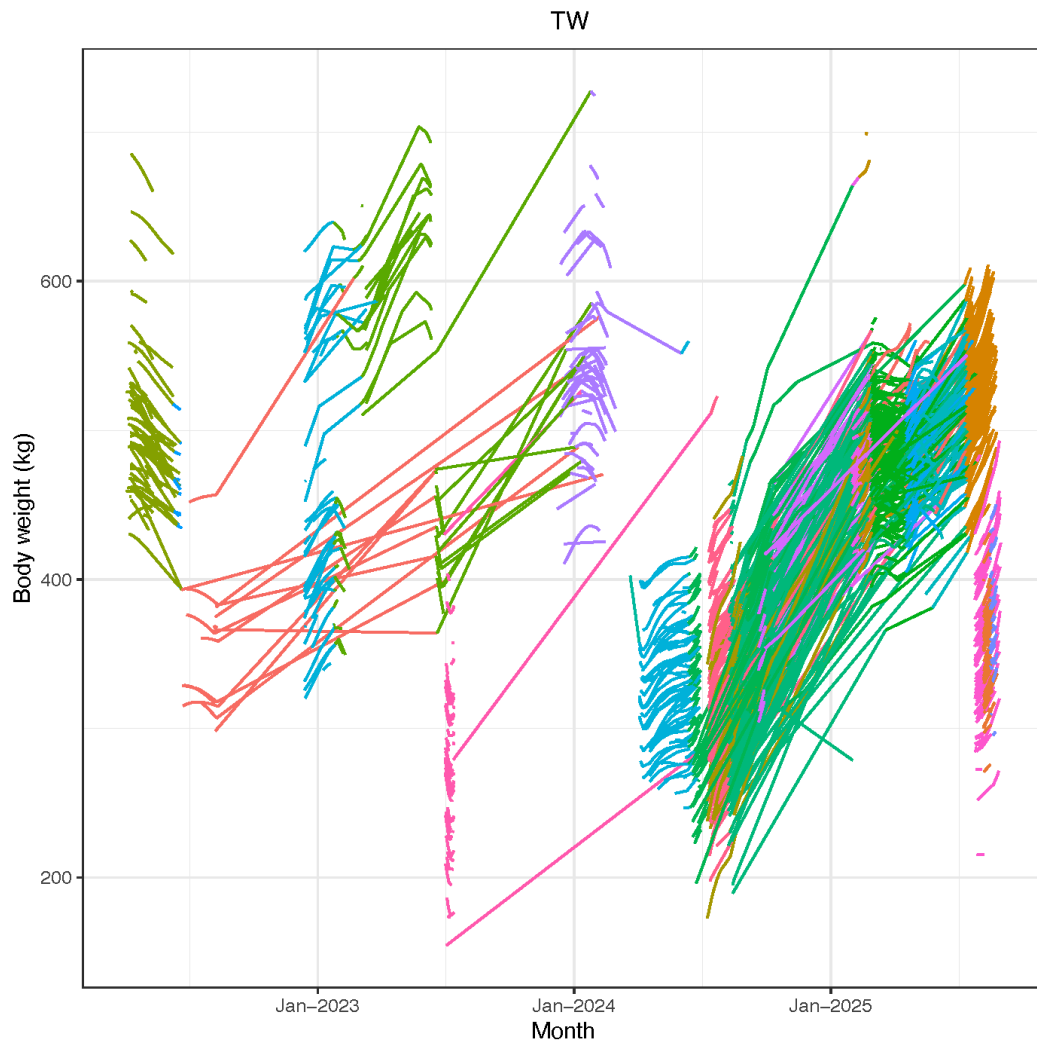
## 4 Results

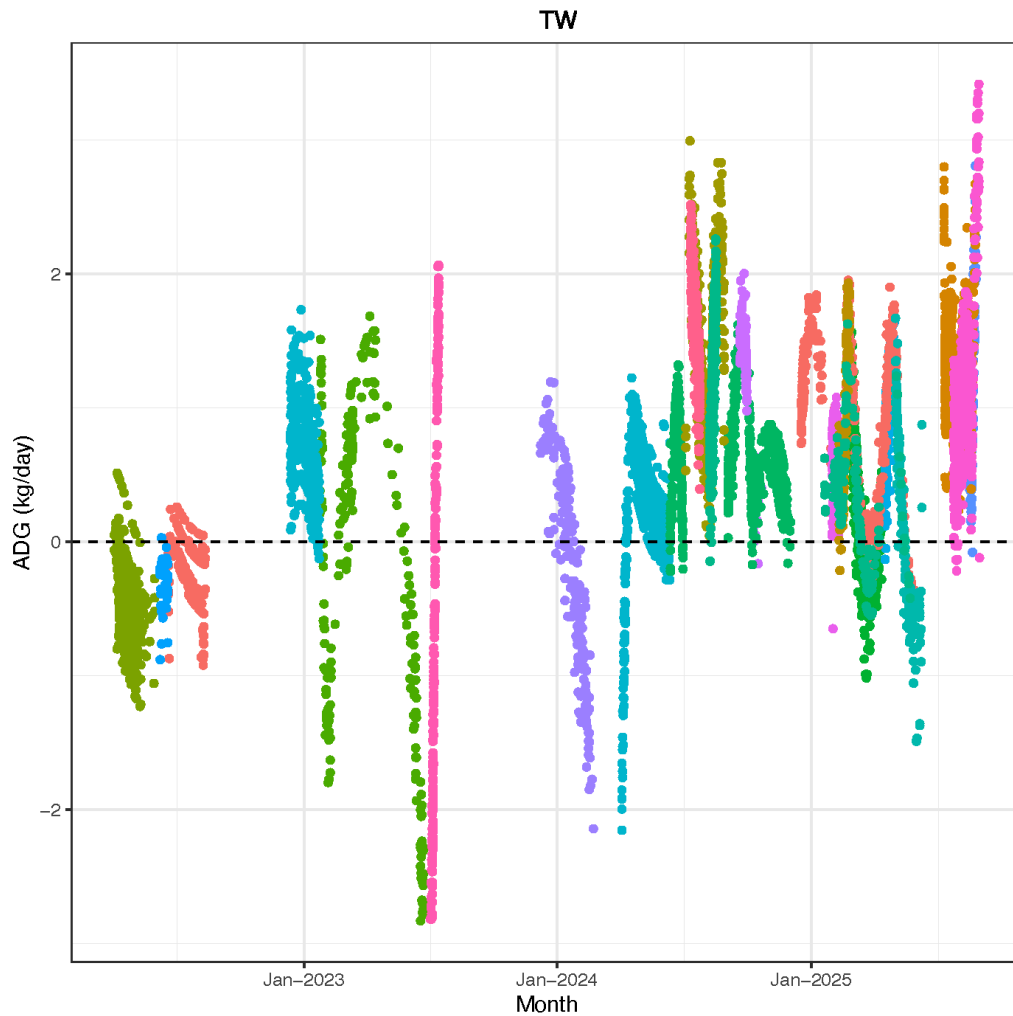
### 4.1 Descriptive model outputs

Detailed visual summaries of the final three project sites' data (GR, TW and RG) are provided in **Appendix 8.3**, where not provided in the body of the report.

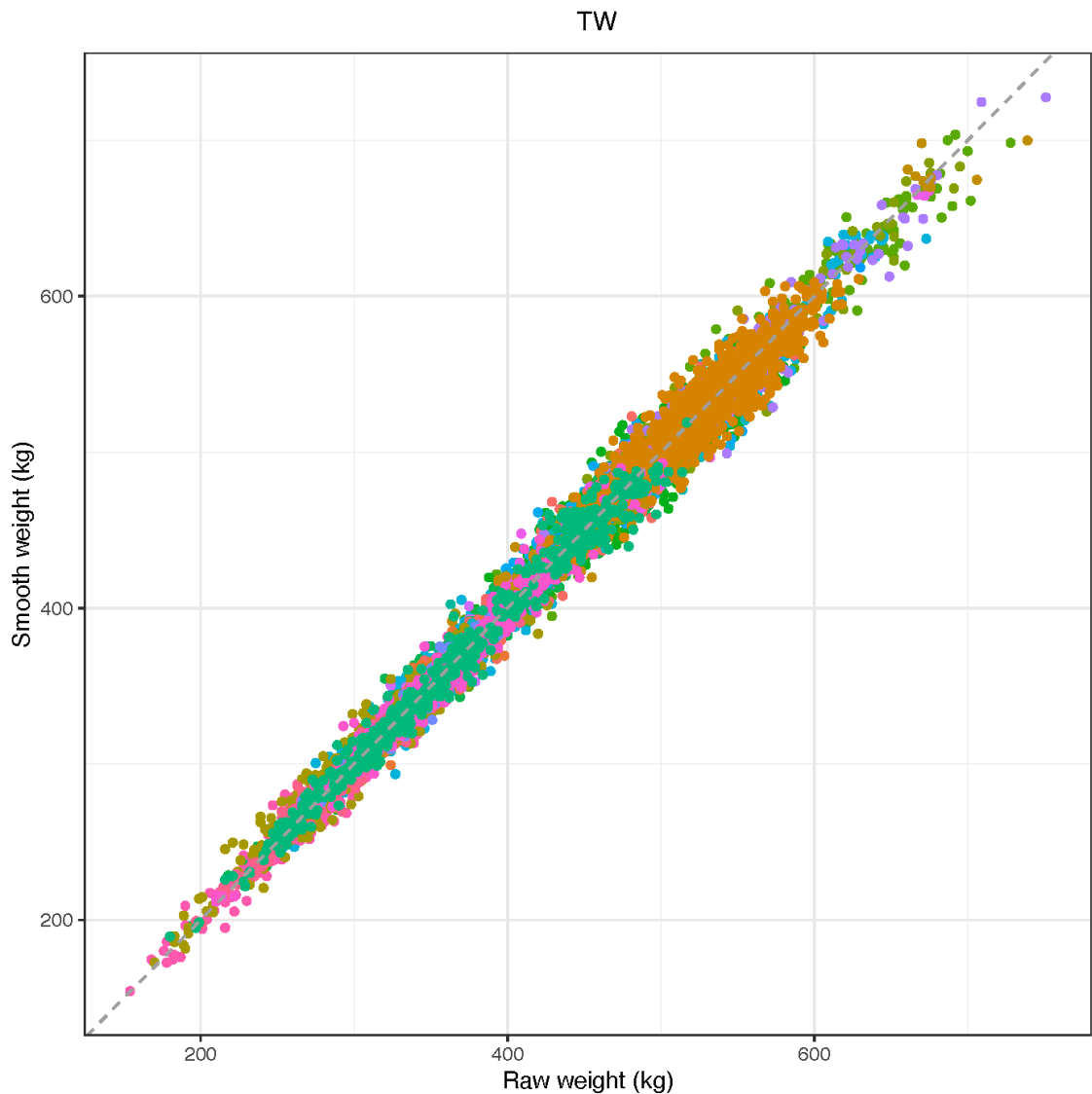
#### 4.1.1 Cattle liveweight monitoring using Optiweigh in-field weigh stations

To account for irregular attendance at OW stations and improve the reliability of growth estimates, individual animal LW data were smoothed using spline-based models. These models generated continuous growth curves from which ADG was calculated over time (**Appendix 8.3**). The smoothed outputs allowed for clearer visualisation of growth trends and identification of periods of accelerated or reduced performance. **Figure 5** illustrates the model-based LW and ADG trajectories for TW, highlighting the temporal variation in growth and the influence of paddock allocation and grazing events.





**Figure 5 Smoothed liveweight (top) and average daily gain (ADG) (bottom) plots for individual animals at TW. The model-based outputs reveal growth trends over time and enable comparison of performance across grazing periods and paddocks. Colours indicate when the observations commenced during a paddock placement, colour continues until next recorded weight of that animal. Where colours overlap, this indicates multiple OW units on the farm recording animals in different paddocks concurrently.**



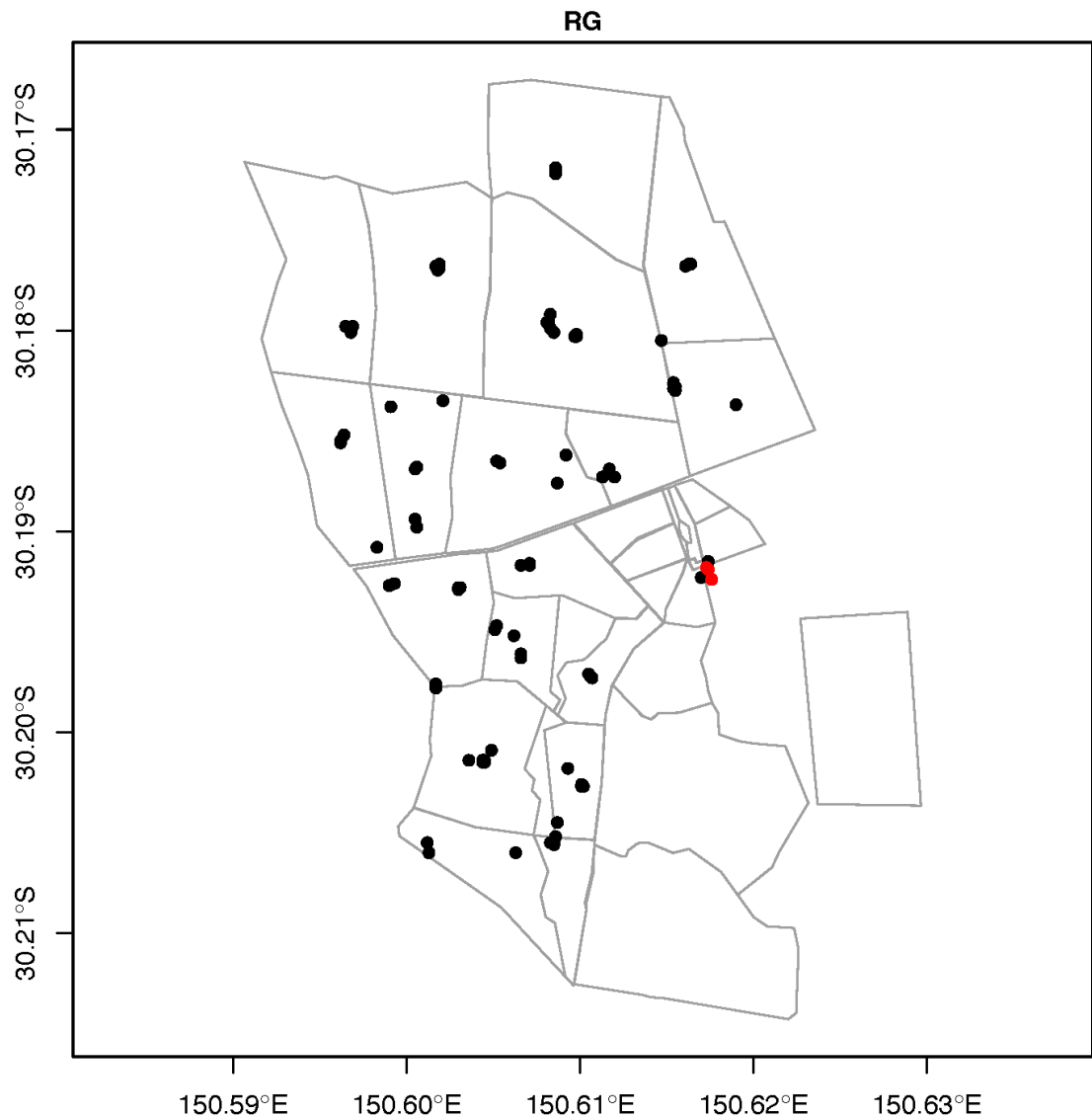
**Figure 6 Agreement between model-smoothed (predicted) and observed Optiweigh liveweights at TW (smoothed weights used to estimate days without unit attendance). Colours indicate paddocks.**

There was a very high agreement between the smoothed (model-based) weight and raw weight over time for each farm (**Figure 6**) demonstrating the accuracy of the smoothed data for estimation of ADG at points in time when animals did not attend the OW station.

#### **4.1.2 Geospatial data**

As part of the data integration process, OW station locations were geospatially mapped to ensure accurate alignment with paddock boundaries. GPS coordinates recorded by each unit were overlaid onto farm maps using spatial analysis tools, allowing for precise identification

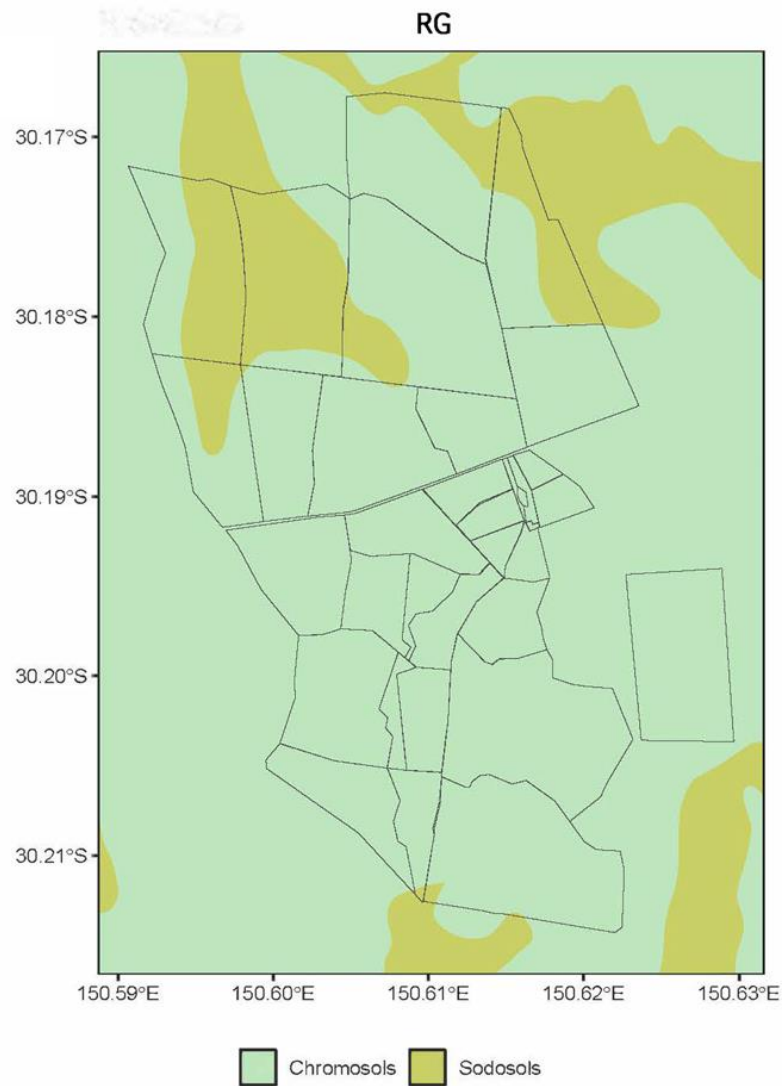
of the paddock in which each station was deployed. This mapping enabled the assignment of LW data to specific paddocks, which was critical for analysing paddock-level productivity. Error! Reference source not found. presents a sample farm map (RG) showing OW station placements, illustrating the spatial distribution of data collection points. Red points on the map are locations where the OW stations were unable to be matched to a paddock, due to close proximity to a fenceline with a neighbouring paddock or farm boundary. These data points were removed from further analysis to reduce error in the final analyses.

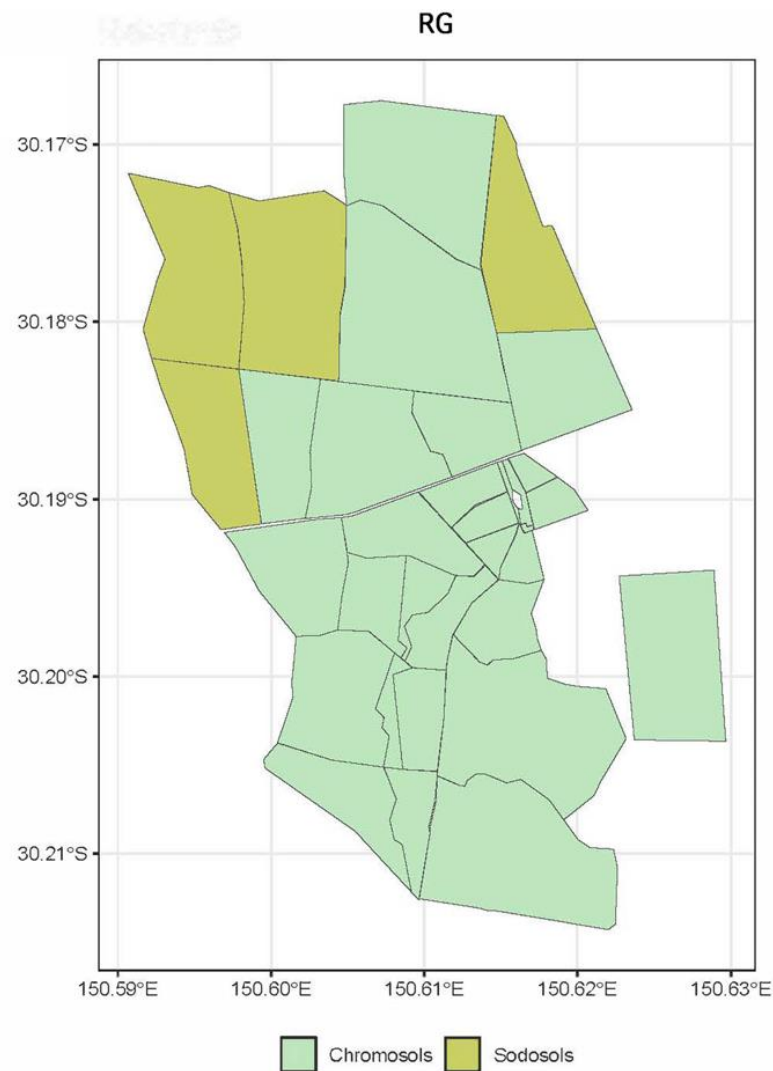


**Figure 7 Geospatial mapping of Optiweigh station placement across a partner farm. Dots show location of Optiweigh station, black is where the paddock was identified, red is where it was outside of any paddock polygon and therefore unable to be allocated.**

### 4.1.3 Soil classification

Soil classification data from the SEED database was digitised for visualisation. Individual paddock shape files were overlaid onto soil classification map to determine the dominant soil type for each paddock on the farm (**Figure 8**) which was an extensive process of code development. These can be viewed for each farm in **Appendix 8.2**.





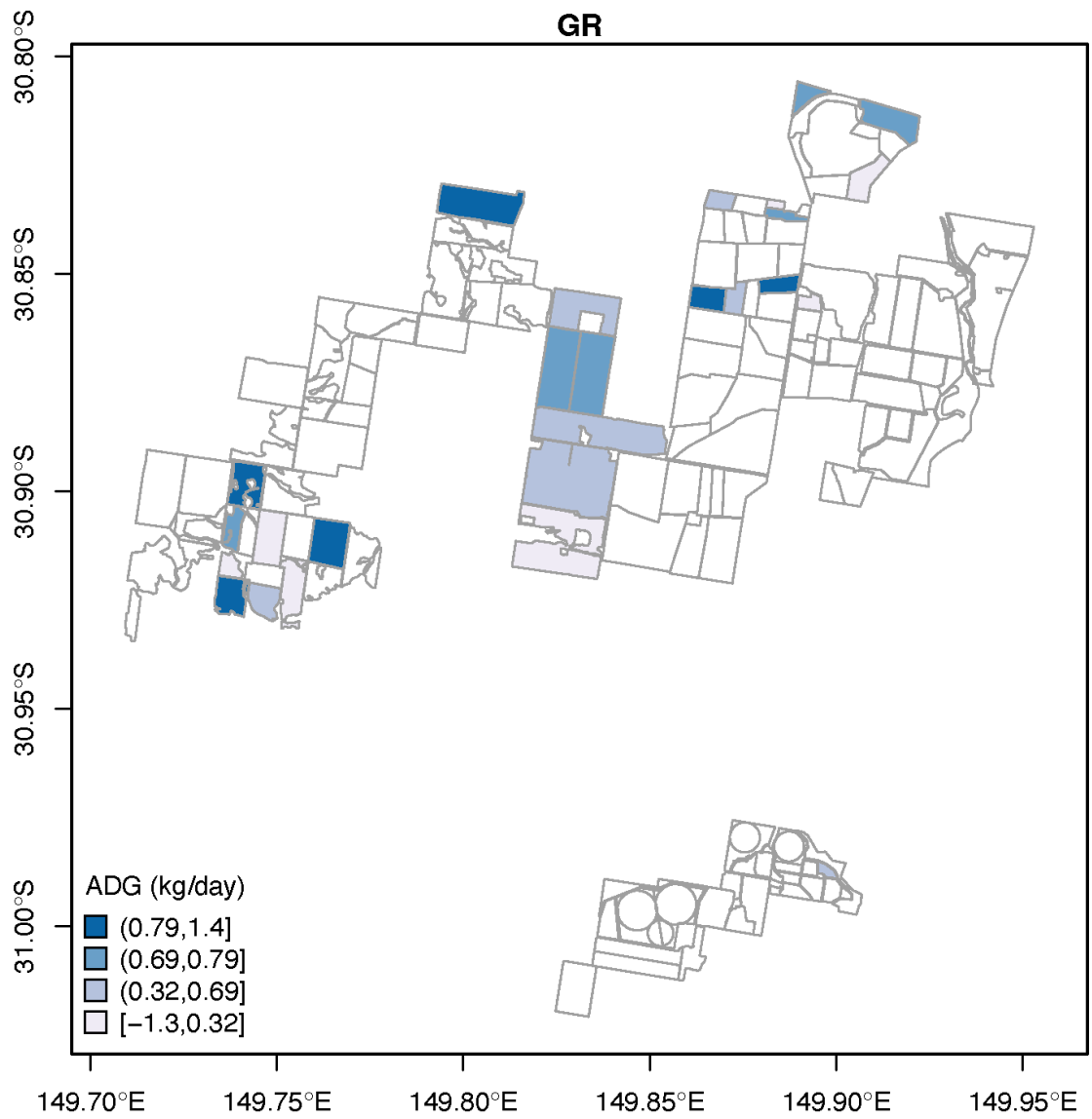
**Figure 8** The farm paddock shapefile was overlaid on the digitised soil map (top, A) to determine dominant soil type for each paddock on the farm (bottom, B). These figures demonstrate the process for farm RG.

## 4.2 Divergence in paddock productivity

Plots of ADG across time for each animal, per paddock on each farm have been produced (**Appendix 8.3**). There was significant variability in ADG observed between paddocks and farms (between 0.44 and 1.03 kg/day, **Table 2**), reflecting a high level of variation between paddocks likely due to feed type (forage vs. perennial improved or native pastures). This is further discussed in 4.4. Heat maps demonstrating the difference in ADG between paddocks (averaged across the observation period) have been produced for visualization (**Figure 9**).

**Table 2 Linear mixed model outputs for relationship between average daily gain (ADG) and total standing dry matter (TSDM), and between paddock variability in ADG for three of the partner sites. b\*\* Regression slope for the effect of TSDM on ADG (g/day); Standard deviation (SD) =**

Farm	Paddock variability				TSDM effect		
	Variance	SD (kg/day)	SE	P-value	b**	SE**	P-value
<b>GR</b>	0.314	0.56	0.094	< 0.0001	-0.19	0.023	< 0.0001
<b>RG</b>	0.197	0.44	0.068	< 0.0001	-0.182	0.017	< 0.0001
<b>TW</b>	1.053	1.03	0.411	< 0.0001	0.191	0.024	< 0.0001



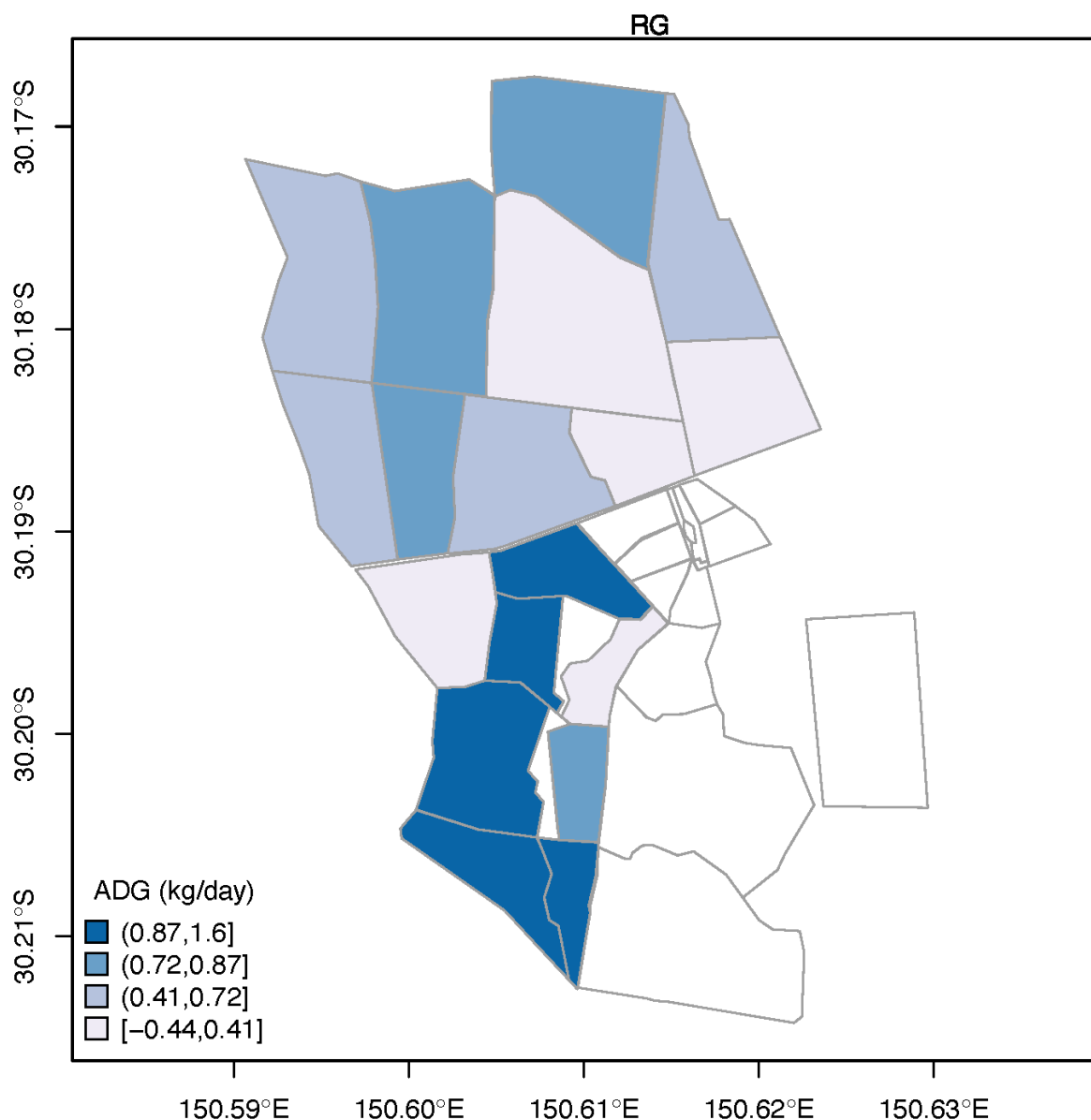


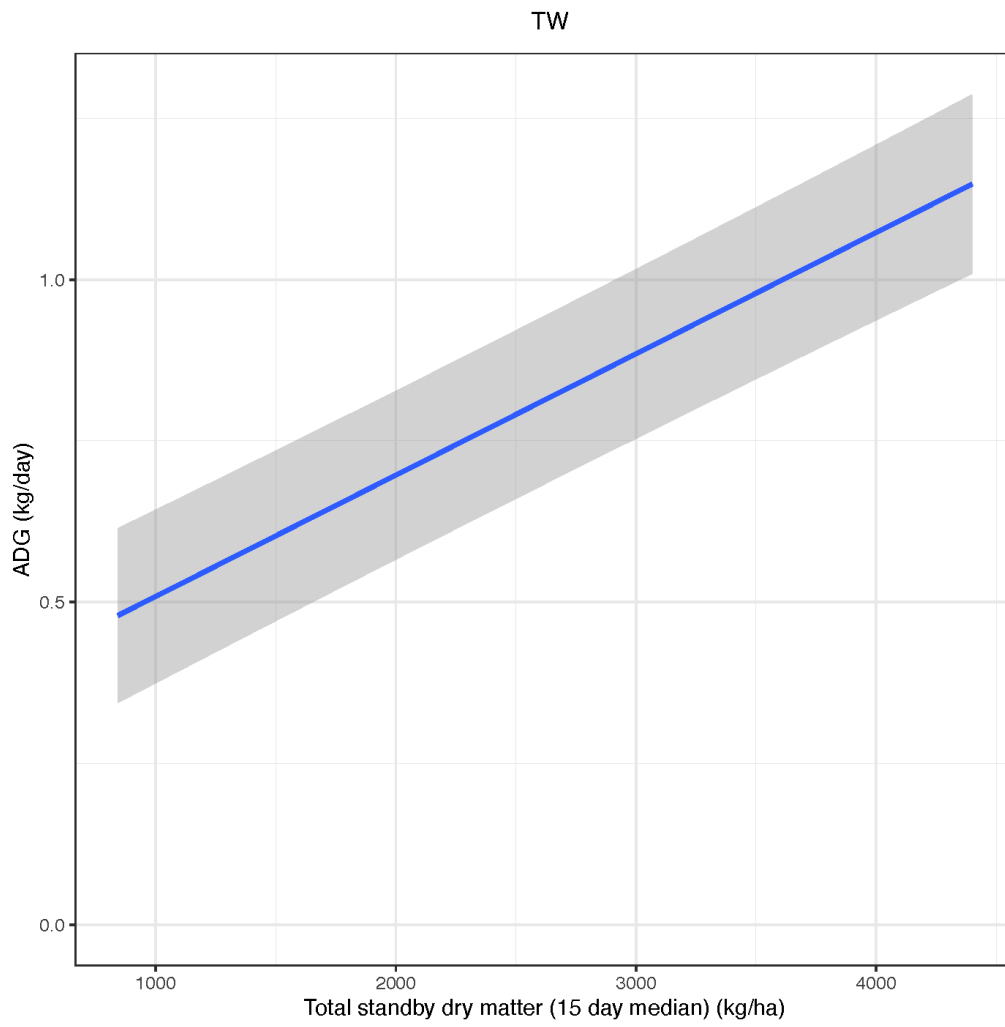
Figure 9 Heat maps of estimated paddock mean average daily gain (ADG) for GR (Top) and RG (Bottom) farms; colours represent four groupings of increasing ADG.

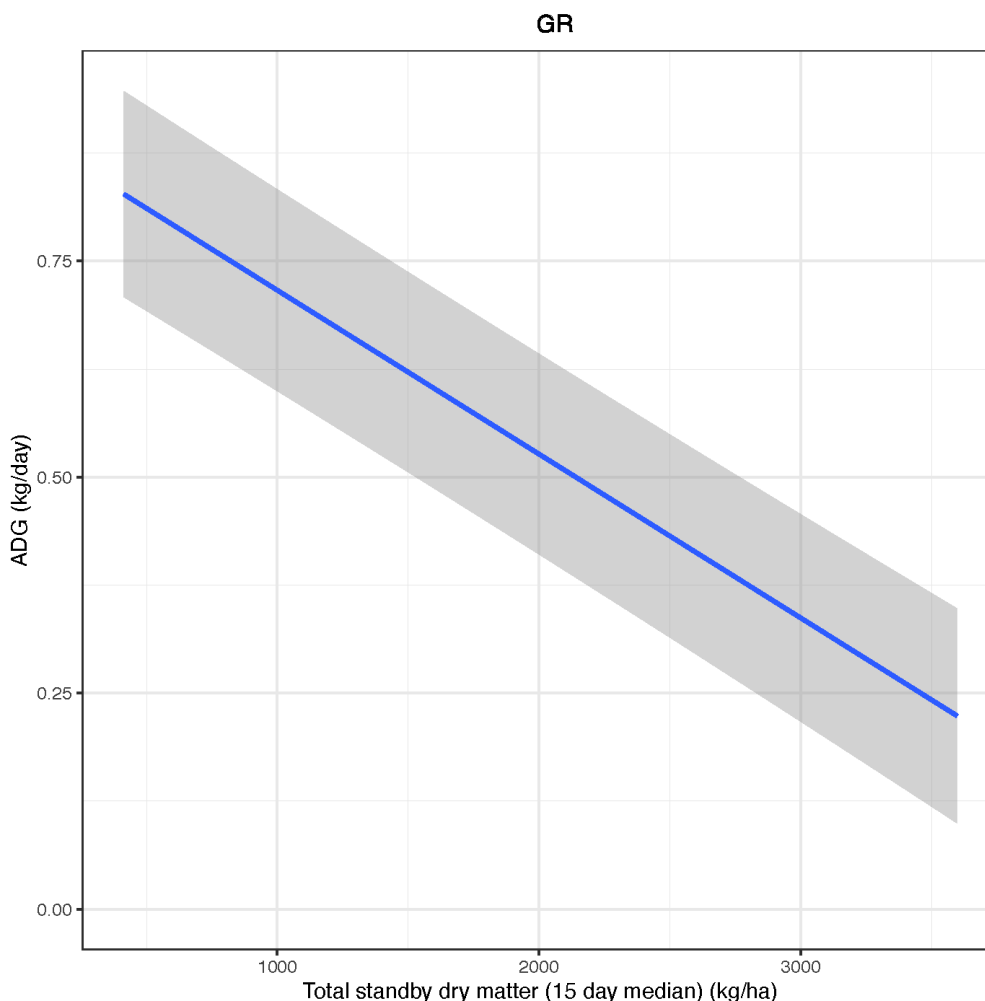
### 4.3 Relationship between pasture biomass and average daily gain

There was variability between farms in the relationship between ADG and pasture biomass (**Error! Reference source not found.**Table 2), confirming that biomass alone is not a reliable predictor of animal gain and that the relationship depends on feedbase type and grazing dynamics. This supports the use of ADG as a tool for inferring pasture quality when benchmarking paddock performance.

Overall, as expected, forage crops (e.g., oats) showed stronger correlations between biomass and ADG than perennial or mixed pastures. For some farms there was a significant positive relationship between pasture biomass and ADG, such as TW (**Error! Reference source not found.**). For TW, within the observed TSDM range of 842 to 4400 kg DM/ha, interquartile range (IQR) 1970-2454 kg DM/ha, a 1000 kg/ha increase in TSDM was associated with an increase in ADG of approximately 0.19 kg/day ( $P < 0.00001$ ; **Table 2**). In contrast, GR and RG showed a negative relationship between biomass and ADG (**Table 2; Figure 10**). For GR, within the observed TSDM range of 413 to 3599 kg DM/ha, (IQR 1375-2250 kg DM/ha), the regression slope indicated a decrease in ADG of approximately 0.19 kg/day for each 1000 kg/ha increase in TSDM ( $P < 0.00001$ ; **Table 2**). Similarly, for RG, within the observed TSDM range of approximately 1188 to 3250 kg DM/ha (IQR 1472-2159 kg DM/ha), the relationship between TSDM and ADG was also negative (slope -0.18 kg/day per 1000 kg DM/ha;  $P < 0.00001$ ; **Table 2**).

These differences can be explained by the predominant feedbase grazed by weaner cattle at the two farms and associated grazing dynamics. TW includes forage-based systems that may maintain higher forage quality as biomass increases. TW maintains a high level of feedbase productivity across the year, primarily due to the high investment in management of subtropical pastures during summer, and a combination of forage oats and perennial legumes during winter. In contrast, GR relies on perennial native pastures in addition to forage sorghum in summer and oats in winter. In some improved paddocks, sown cool-season species (e.g., lucerne, chicory) were present but not dominant at survey, and selected sites exhibited higher litter/bare-ground compared with unmodified paddocks, indicating establishment/condition differences and variable recovery potential. RG relies primarily on perennial native and improved perennial pastures. Native pasture is uniformly low in quality, during senescence, total herbage mass (biomass) may be high, but the lower green fraction is associated with lower nutritional content, which results in a negative relation between biomass and ADG (Ayres et al., 2001). In addition, grazing intensity and residual pasture biomass can also influence intake and performance, so utilisation can be as important as biomass. Pasture quality indicators and grazing intensity metrics have been evaluated in previous work (Azubuike et al., 2026), but were not measured in detail in this study. However, these results demonstrate that at an individual farm level, paddock level ADG can inform decisions on grazing management for optimal pasture utilisation dependent on the existing feedbase, and/or pasture species selection to improve productivity. A description of the relationship between plant species is provided in Section 4.4.



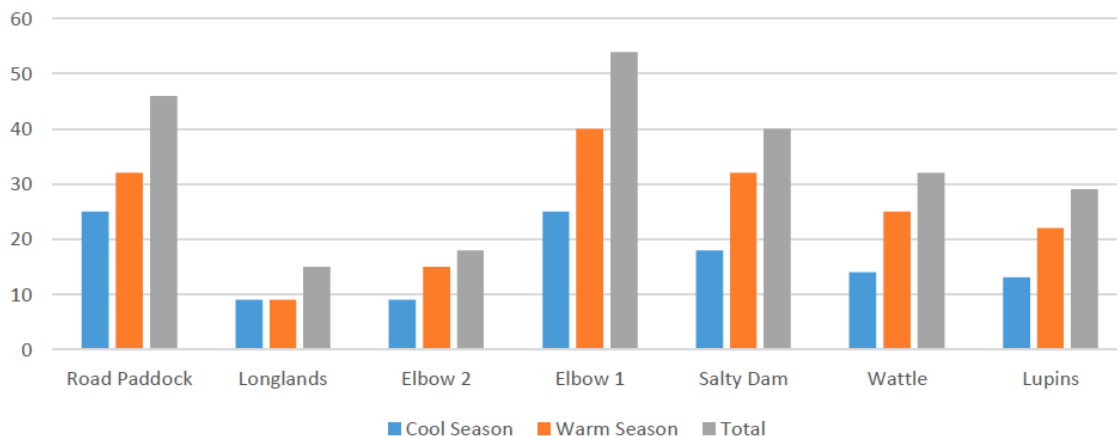


**Figure 10 Model-based average daily gain (ADG) versus total standing dry matter (TSDM) at the start of paddock allocation for two farm sites. The top panel shows TW and the bottom figure shows GR. Fitted linear relationships ( $\pm 95\%$  CI) indicate a positive association at TW and a negative association at GR**

#### 4.4 Ecological Sampling

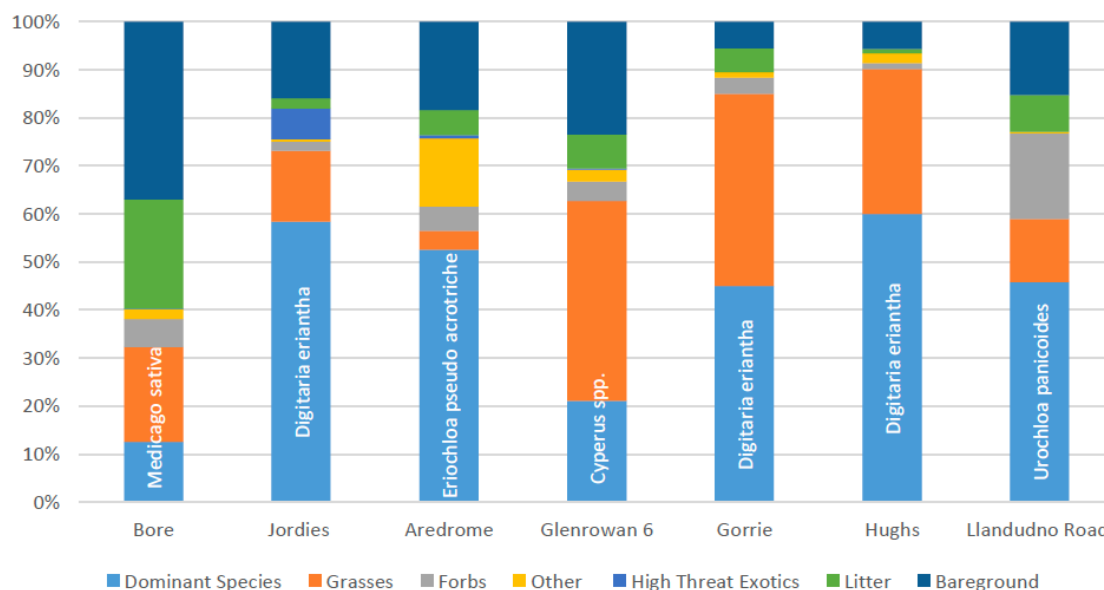
Ecological surveys revealed substantial variation in pasture species composition, groundcover and species richness both within and between farms (**Appendix 8.1**). Paddocks with well-established sown pastures were typically dominated by a small number of introduced species and exhibited lower species richness, whereas paddocks where sown species had failed to establish were often maintained by mixed native and exotic species with higher richness and greater seasonal variability. Multiple paddocks at TW (e.g., Elbow 2, Wattle, Lupins) remained Digit grass-dominant across seasons, while others (e.g., Road Paddock) showed dominance by non-sown species seasonally (Plains grass in summer; Burr medic in winter), evidencing

variable establishment success and strong seasonal contrasts. Species richness was highest in selected paddocks with mixed species (**Figure 11**).



**Figure 11 Plant species richness (total number of species present) by paddocks for cool and warm season surveys and the combined total for Farm TW.**

Seasonal shifts in dominant species were evident at TW (e.g., Longlands paddock transitioning from oats to Digit grass) and at RG (e.g., Black 1 paddock transitioning from digit grass to burr medic), indicating that feedbase condition and potential feed availability can change markedly across seasons. Several paddocks showed high proportions of litter or bare ground, indicating potential constraints on feed utilisation and recovery. For example, at GR the Bore paddock had a higher proportion of bare ground and litter, while an unmodified paddock (GR6) had higher vegetation cover with a lower combined bare ground and litter component (**Figure 12**). High threat weed species were recorded across multiple properties, posing risks to pasture productivity and ecological resilience, including African lovegrass (*Eragrostis curvula*), St John's wort (*Hypericum perforatum*) and *Opuntia* spp. Overall, the surveys demonstrated that pasture biomass alone does not adequately describe feedbase condition, and that species composition, establishment success and seasonal dynamics are important contributors to paddock level variation in performance. Further results are presented in **Appendix 8.1**.



**Figure 12 Ground cover composition by paddock on Farm GR, showing the relative proportions of dominant species, forbs, grasses, high threat exotics, litter, and bare ground recorded during warm season surveys.**

Surveys provide temporal snapshots and may be influenced by recent grazing (reduced detectability of some perennials/forbs) and the seasonal conditions preceding fieldwork. Dual-season resurveys (TW, RG, GR) improved detection of phenological change but do not replace continuous monitoring. Results should therefore be interpreted as paddock-level ecological context that complements animal performance data, rather than stand-alone measures of grazing value.

## 4.5 Effect of explanatory variables on ADG

The following analyses used automatically collected data, rather than on farm or manually sampled data. The availability of more data (Optiweigh and other systems) over time will facilitate more accurate and multi-variable models to be developed which will further explain the variable association between TSDM and ADG on farms and the development of a predictive model.

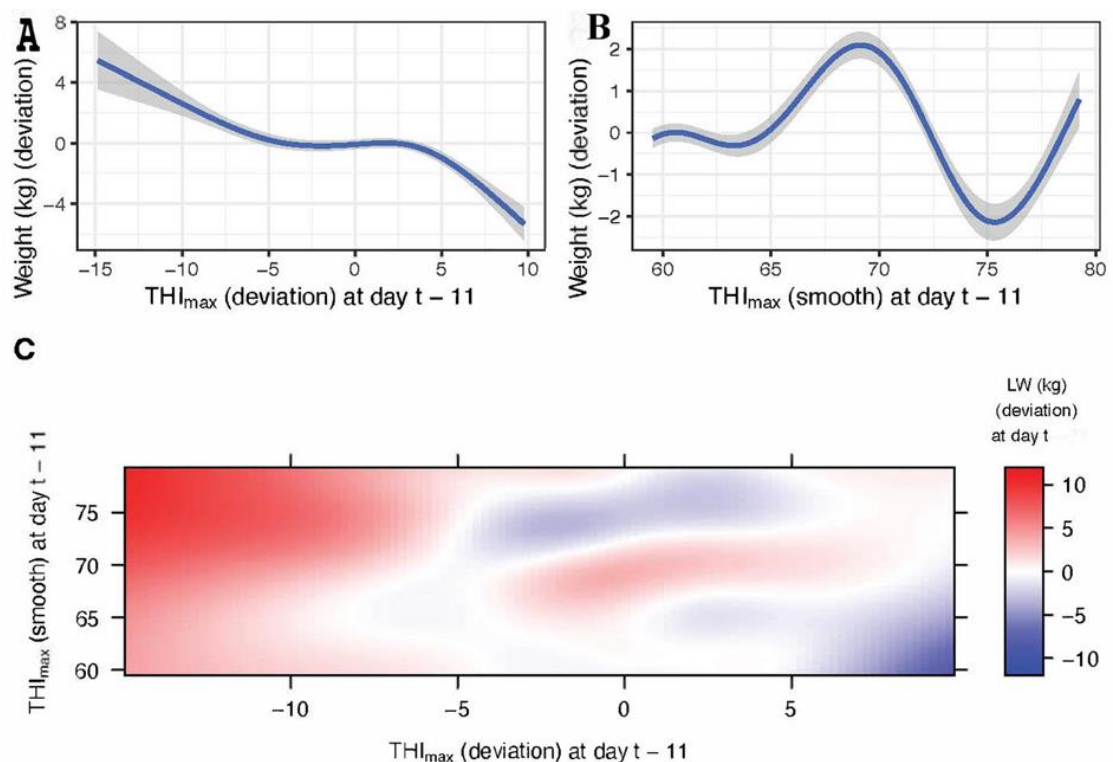
### 4.5.1 Effects of climate variables

#### 4.5.1.1 *THI effects on cattle growth*

Across farms, elevated daily maximum THI deviations (hotter-than-usual days relative to the smooth background) were followed by reductions in liveweight deviations, indicating a consistent short-term heat-stress (HS) signal in growth (**Figure 13**). The lag-screening step identified delayed peak responses occurring between 6 and 12 days after heat exposure

(GR:  $k = 12$ ; RG:  $k = 6$ ; TW:  $k = 11$ ), consistence with the established physiological sequence whereby acute heat load reduces feed intake and subsequently lower growth (Kim et al., 2021). Also, this delayed response aligns with the dynamic growth modelling framework described in Hasan et al. (2026).

In the corresponding linear models (Model 1), THI deviation at the selected lag was negatively associated with LW deviations in all farms ( $\beta \pm \text{SE}$ : GR  $-0.167 \pm 0.025$ , RG  $-0.150 \pm 0.025$ , TW  $-0.157 \pm 0.033$ ; all  $P < 0.001$ ), indicating that hotter-than-expected days were consistently followed by reduced growth relative to baseline conditions. Feedlot studies report that increasing heat load is associated with reduced feed intake and growth performance, with moderate stress commonly reported above THI 72-75 and severe stress conditions above THI 78-80 (Gaughan et al., 2010; Mader et al., 2006). These values mark the upper limit of the thermoneutral zone. In our study, THI exceeded these thresholds during episodic summer heat events, but most days were still within the border thermocomfort range. This supports acute heat impacts rather than long-term severe stress in extensive systems (Hasan et al., 2026).

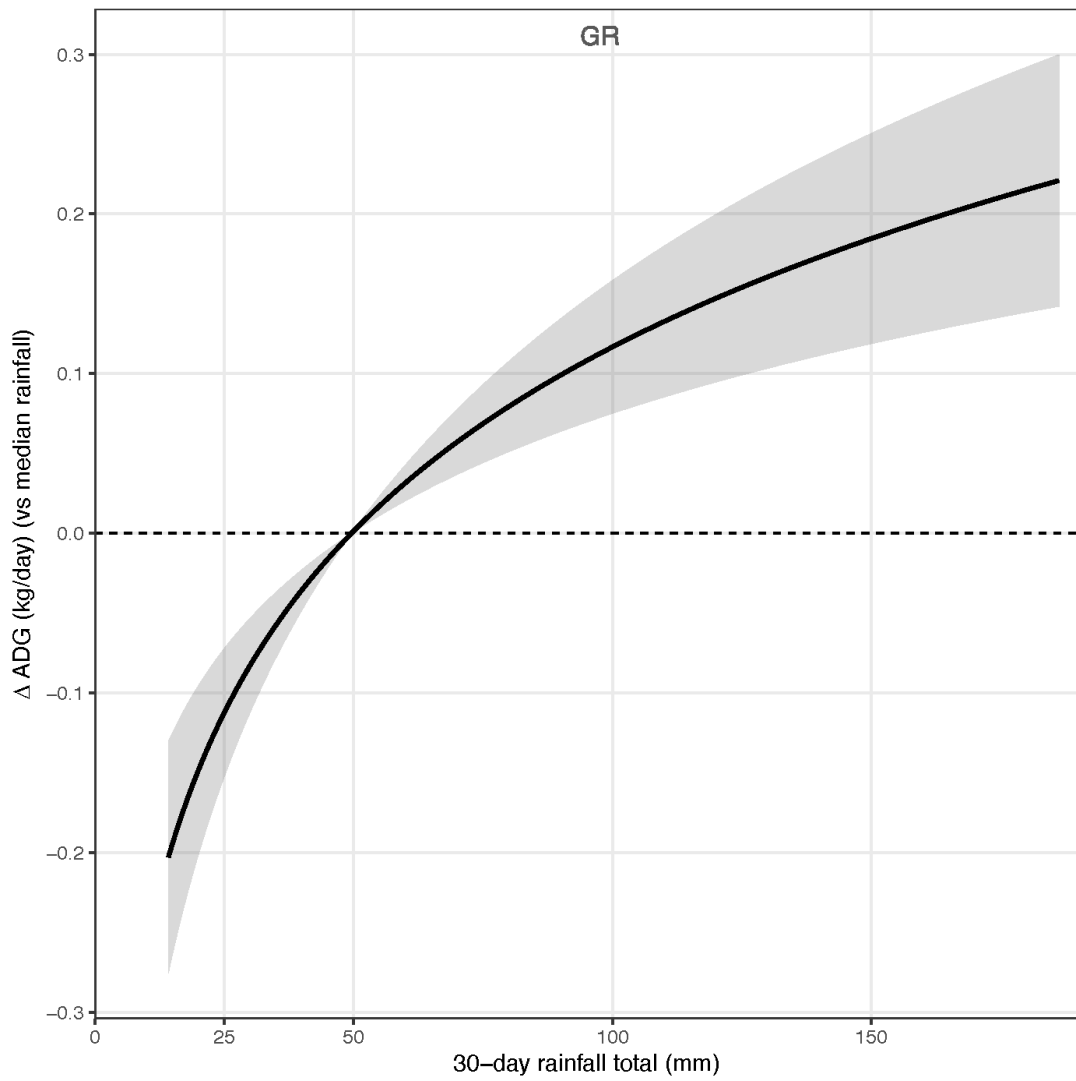


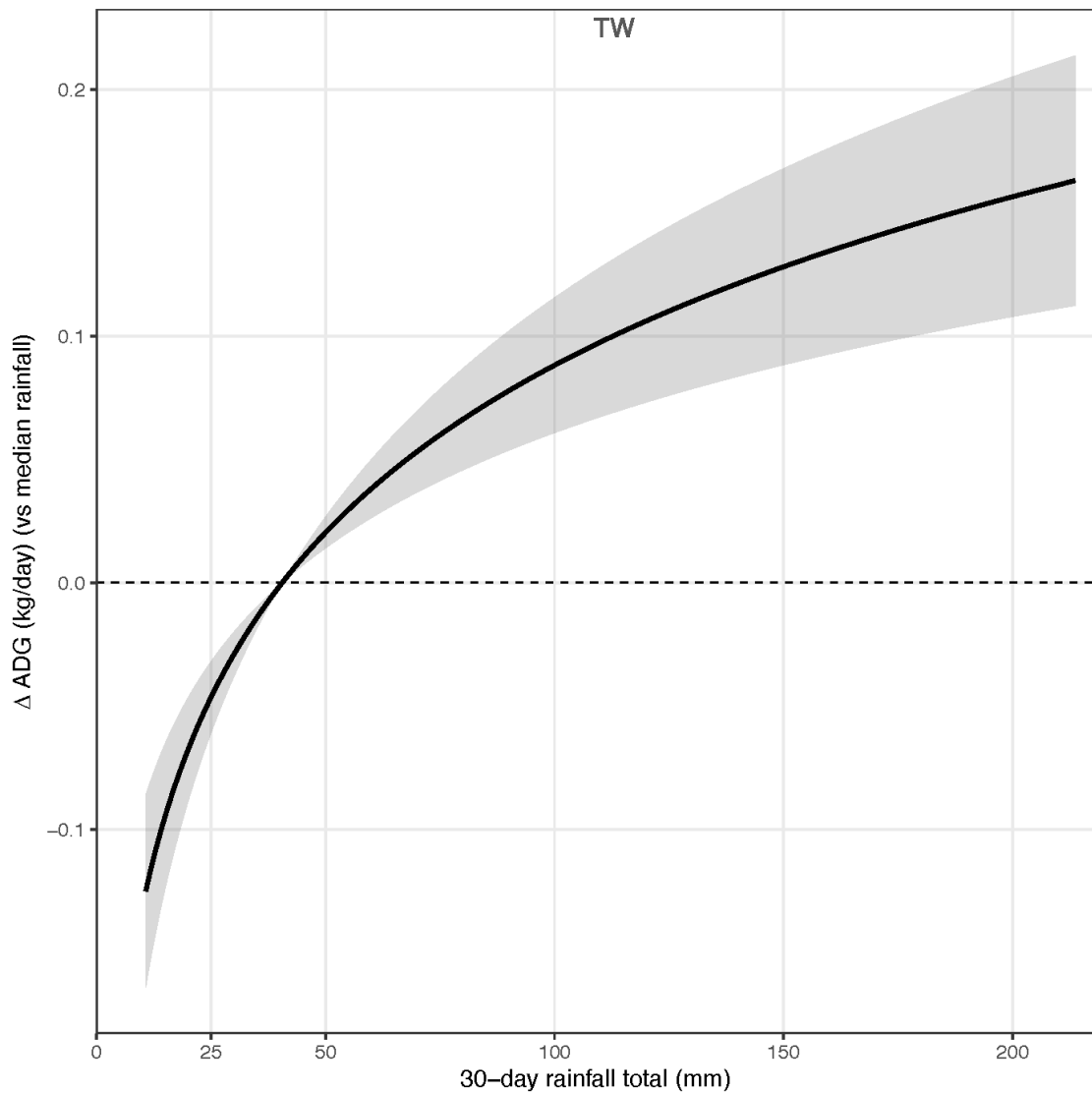
**Figure 13** Visualisations of fitted spline models for TW liveweight deviations. **A:** Effect of maximum THI deviations; **B:** Effect of smoothed maximum THI; **C:** Heatmap of the thin-plate spline model showing the interaction effect of maximum THI deviations and smoothed THI at day  $t-11$  on liveweight deviations at day  $t$ .

Nonlinear specifications supported the same overall direction of effect but indicated that the response was not strictly linear or proportional, with spline terms for THI deviations significant in each farm and providing improved fit relative to linear terms (Model 2; and Model 2 vs Model 1, all  $P < 0.001$ ), indicating that growth declined more sharply at higher heat levels. When the smooth/background THI component was added (Model 3), the background term was statistically evident for RG ( $\beta = 0.077 \pm 0.013$ ,  $P < 0.001$ ), suggesting a contribution of sustained warm conditions in humid environments. In contrast, GR and TW exhibited primarily deviation-driven effects ( $P = 0.309$  and  $0.134$ ), suggesting that short-term heat spikes were the dominant driver of growth variation. All model formulations and inference procedures followed our previously described framework (Hasan et al., 2026). The influence of THI on growth is embedded within a broader production, highlighting the importance of other on farm factors such as pasture quality and/or biomass, water availability, shade access, stocking density, and differences in animal class or management events which likely moderated animals' heat exposure and recovery capacity (Hasan et al., 2026). Together, these results indicate that growth responses to heat extensive systems are episodic and lagged, occurring when THI exceeds biologically relevant thresholds rather than across the full thermocomfort range.

#### 4.5.1.2 *Effects of rainfall on cattle growth*

Rainfall demonstrated clear yet farm specific influences on cattle growth, with cumulative moisture shaping short term average daily gain (ADG). Rolling cumulative rainfall showed window- and farm-specific associations with cattle growth (ADG) (Error! Reference source not found.). Over the 30-day window, rainfall was positively associated with ADG in both GR and TW, consistent with improved short-term feed availability and grazing conditions following recent rainfall (**Figure 14**). The plotted effect represents the predicted change in ADG relative to the site-specific median rainfall level. In contrast, the 60-day window revealed clear divergence between farms: GR showed a strong negative association, whereas TW remained positively associated, indicating that longer-duration wet accumulation can translate into different production outcomes depending on local conditions and constraints (e.g., soil–pasture responses, access, grazing efficiency, and management).





**Figure 14 Modelled relationship between 30-day cumulative rainfall (mm) and predicted change in average daily gain ( $\Delta$ ADG, kg/day) at GR (top) and TW (bottom), relative to the site-specific median rainfall. Shaded areas represent 95% confidence intervals.**

**Table 3 Association between rolling cumulative rainfall and average daily gain (ADG) for GR and TW (30 and 60-day windows). \*R30 and R60 represent total rainfall (mm) accumulated over the preceding 30 and 60 days,  $\beta$  is the estimated regression coefficient, SE is the standard error, Z is the Wald statistic.**

*Rain	GR			TW		
	$\beta \pm SE$	Z	P	$\beta \pm SE$	Z	P
<b>R30 days</b>	0.169 $\pm$ 0.031	5.49	<0.001	0.099 $\pm$ 0.016	6.30	<0.001
<b>R60 days</b>	-0.772 $\pm$ 0.065	-11.82	<0.001	0.134 $\pm$ 0.031	4.37	<0.001

The production response to rainfall is highly contextual. These findings emphasise the importance of integrating rainfall timing with paddock level conditions, pasture quality, and seasonal management to optimise cattle performance within a variable farm environment.

A separate study using national OW data demonstrated that rainfall significantly affects ADG, with varying lag effects across agro-climatic zones (Hasan et al., 2024a). Temperate zones showed year-round rainfall effects, while grassland and subtropical zones exhibited seasonal lag effects.

In future modelling frameworks, rainfall can therefore be incorporated as a multiscale predictor, with short-, medium-, and long lag rainfall variables used to characterise different components of paddock productivity. This would allow models to account for the fact that rainfall influences growth through immediate changes in the green leaf component of forage, delayed improvements in regrowth, and periods of reduced grazing efficiency during sustained wet conditions. Because rainfall patterns and their lag effects vary across agroclimatic zones, production systems, and soil types, incorporating rainfall as a flexible, rolling window variable will support more accurate, regionally responsive predictions of cattle growth and pasture performance across northern farms.

#### 4.5.2 Soil Classification

Across the three study farms, soil type showed no detectable effect on average daily gain (ADG) once farm-level variation was accounted for. There was no detectable effect of soil type on ADG ( $P = 0.50$ ). Mean ADG values were broadly similar across the three categories (

, **Appendix 8.2**) indicating overlap in performance across the soil classes evaluated.

These limited results likely reflect intra-paddock soil heterogeneity that is not fully captured by centroid-based classification, and the reality that soil type influences cattle growth indirectly, primarily through pasture species composition, water retention, and nutrient cycling. Soil type remains important for understanding long-term pasture potential, though alone is not a meaningful predictor of short-term cattle growth within the conditions and spatial resolution of this study.

**Table 4 Effect of Soil type on ADG across farms**

Soil type	ADG (kg/day)	
	Mean	SE
Chromosols	0.550	0.136
Sodosols	0.633	0.123
Vertosols	0.730	0.094
Overall	0.637	0.075

### 4.5.3 Pasture quality and plant species

#### 4.5.3.1 Pasture quality indicators

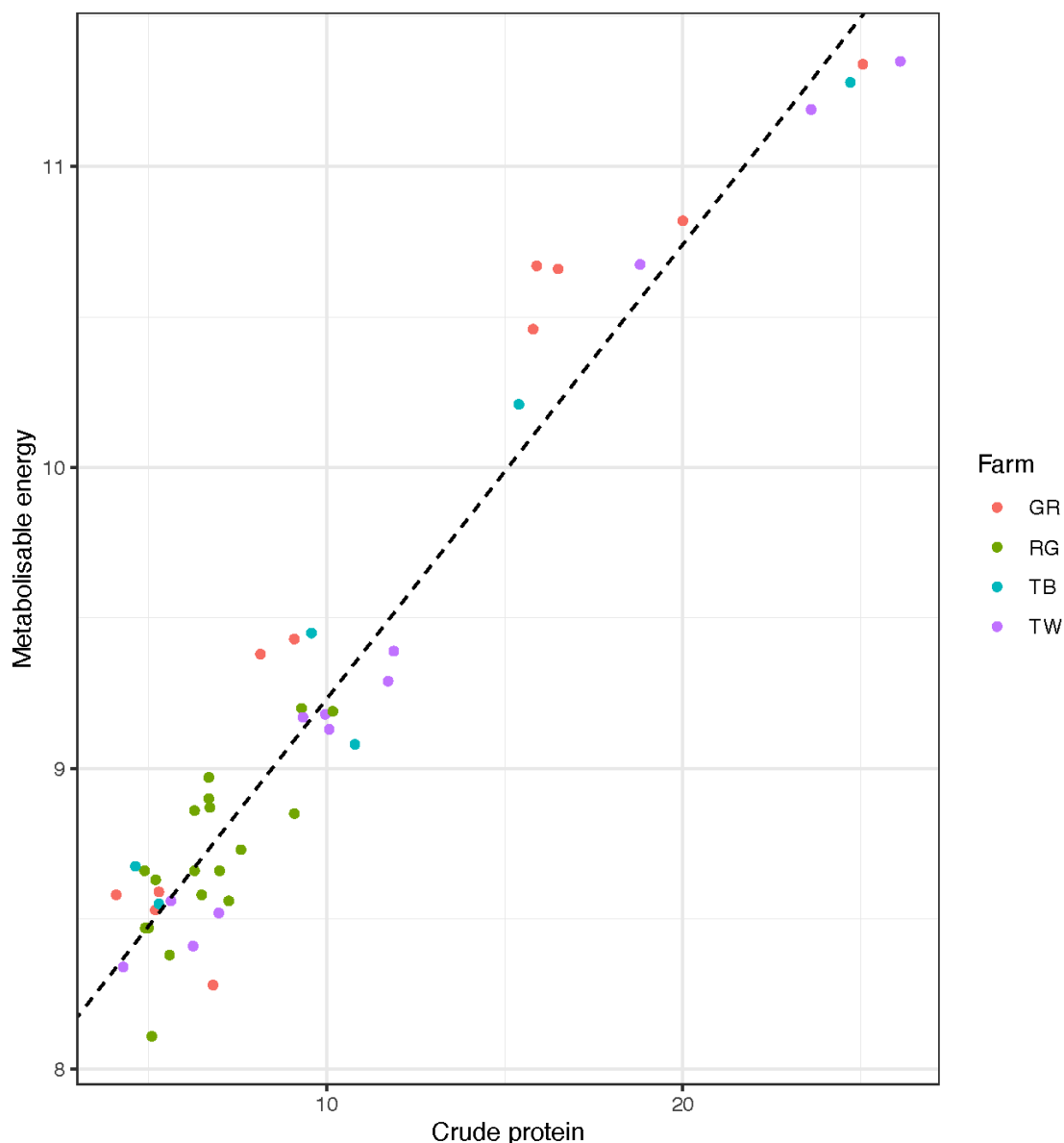
There was significant variation in the CP and ME of pasture samples across paddocks within each farm (**Table 5**). Higher CP and ME values reported for GR (CP 25%, ME 11.34 MJ/kg DM) and TW (CP 26.1%, ME 11.35 MJ/kg DM) were recorded during winter in paddocks where forage oats were the dominant species during the early growing period (April – May).

A detailed graphical summary of the pasture quality feed assessment and relationship with ADG across each farm is provided in **Appendix 8.5**.

**Table 5 Range and standard deviation of crude protein (CP, %) and metabolizable energy (ME, MJ/kg dry matter) for each farm across the three-year collection period. Number of paddocks sampled for each farm is also provided.**

Farm	CP range	ME range	Standard deviation	Number of paddocks sampled
GR	4.1-25.05	8.35 - 11.34	0.82	38
RG	4.9 - 17.7	8.11 - 9.94	0.40	58
TW	3.8- 26.1	8.33 -11.35	0.56	72

There was a highly linear association between CP and ME across farms, with an estimated regression line of Metabolizable energy =  $7.68 + 0.160 \times$  Crude protein,  $R^2 = 0.84$ ,  $P < 0.0001$  (**Figure 15**). Because ME was derived from chemically determined constituents (primarily ADF via TDN, with expected covariance with CP and NDF), a strong association between CP and ME is to be expected. In this dataset, CP correlated positively with ME, which likely reflects the shared chemical basis used to estimate ME, and the typical botanical/phenological pattern whereby higher CP coincides with lower fibre (ADF/NDF) and therefore higher digestibility and ME. It is therefore important to interpret the CP/ME relationship with caution and view it as partly algorithmic rather than an independent biological validation.



**Figure 15 Linear association between CP (%) and ME (MJ/kg dry matter) across farms using data collected between May 2023 and April 2024.  $R^2 = 0.84$ ,  $P < 0.0001$ . Slopes represent statistical associations over the observed ME range (8.3–11.3 MJ kg<sup>-1</sup> DM).**

Feed quality showed a consistent positive relationship with cattle growth at GR and RG, and both crude protein (CP, %) and metabolisable energy (ME, MJ/kg DM) were significant predictors of average daily gain (ADG) after accounting for paddock level clustering. At GR, higher CP and ME were strongly associated with increased ADG. Linear regressions were fitted at paddock-allocation level, with ADG specified as the response variable and either CP or ME as predictor variables. The general model was:

$$ADG_i = \alpha + \beta X_i + \varepsilon_i$$

where X represents CP or ME and  $\beta$  describes the fitted statistical relationship between pasture quality and ADG. At GR, ADG increased by 0.131 kg/head/day per 1% increase in CP (SE = 0.033,  $P < 0.001$ ) and by 1.08 kg/head/day per 1 MJ/kg DM increase in ME (SE = 0.271,  $P < 0.001$ ). RG showed a similar positive response, with ADG increasing by 0.114 kg/head/day per 1% increase in CP (SE = 0.029,  $P < 0.001$ ) and 0.852 kg/head/day per 1 MJ/kg DM increase in ME (SE = 0.323,  $P = 0.008$ ). In contrast, TW exhibited no detectable association between feed quality and ADG for either CP or ME (CP:  $P = 0.788$ ; ME:  $P = 0.830$ ), suggesting that other factors such as seasonal climatic fluctuations and feedbase composition may have impacted on ADG across the observation period. These farm level findings align with established nutrition frameworks in which both dietary protein and energy are important determinants of cattle performance. Results reinforce the qualitative finding that higher diet quality aligns with higher ADG, while the precise slope size is model-dependent and is constrained by physiological limits. The linear ME coefficient reflects a statistical association over the observed paddock-average ME range (8.3–11.3 MJ/kg DM) and may not translate to linear extrapolation beyond that range. In future model development CP and ME should be included as primary covariates, with their effects estimated alongside recent rainfall, THI and feedbase to reflect on farm context. Rainfall and THI would be derived from historical and near real-time climate datasets, TSDM from satellite biomass monitoring and pasture quality (e.g. CP, ME) from either periodic laboratory pasture sampling or predictive models calibrated to pasture composition and seasonal conditions.

These results highlight that feed quality is an important driver of cattle performance where animals can effectively access and utilise pasture, with realised effects on diet quality dependent on grazing utilisation and grazing intensity, but its influence varies between farms depending on local conditions, paddock functionality and interactions with other environmental factors. Accurate determination of paddock level quality indicators requires dedicated experimental assessment using detailed manual assessments to account for whole of paddock variability alongside animal grazing simulation. This approach was out of scope of the current project, further supporting the use of ADG to infer productivity across a paddock. Without robust technological advances to remotely and accurately determine pasture quality and utilisation, inclusion of these variables in modelling approaches is limited.

#### 4.5.3.2 *Influence of plant species composition on cattle growth*

The Stringybark surveys show that some paddocks sown to introduced species were not dominated by those sown grasses (e.g., TW Road Paddock), while others maintained strong sown species cover (e.g., TW Elbow 2, Wattle with Digit, **Figure 16**), alongside marked seasonal shifts in composition (warm vs. cool season resurveys at TW and RG), variable litter/bare ground, and occurrences of less preferable species or weeds (e.g., African lovegrass). These pasture structures help explain the modelling outcomes where CP and ME were strong, positive predictors of ADG at GR and RG, but not at TW. This is consistent with the ecological survey findings that several TW introduced species paddocks were functionally dominated by natives/annual forbs rather than the intended high-quality sown forage, and that composition changed across seasons. Where accessible green leaf and higher quality

species are present, CP and ME effects are evident on ADG, and where pasture composition or ground conditions limit intake, or mean quadrat samples, the relationship between CP or ME with ADG may not reflect the selected diet. This further reinforces limitations of quadrat-based sampling to determine whole of paddock feed quality. Comparative pasture species survey results for GR and RG are provided in **Appendix 8.1**.

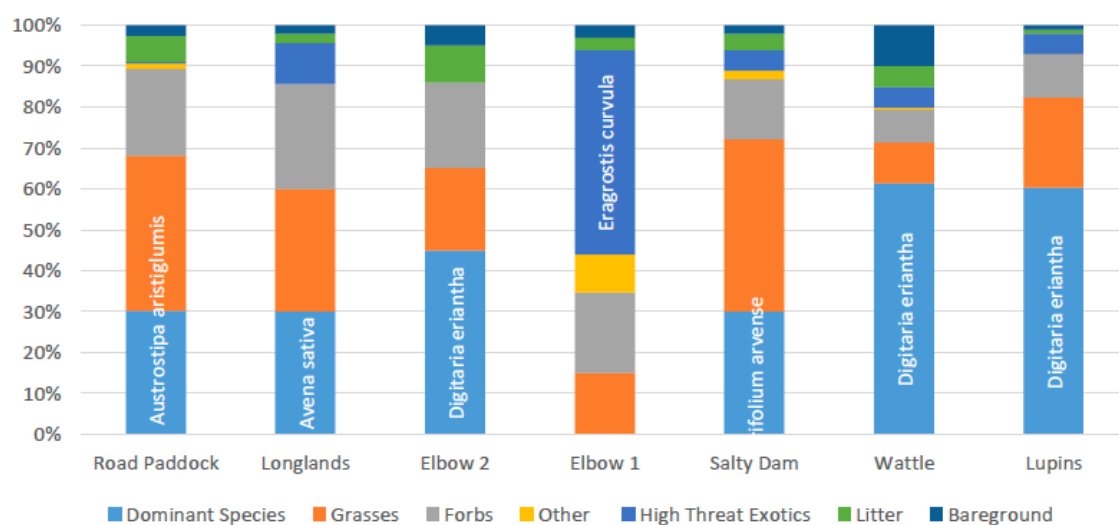
**Table 6 Summary of average daily gain (ADG) for paddocks sampled on three farms (GR, RG, TW) based on dominant species (% cover) and season. Average ADG (kg/day) is calculated for the nearest date that cattle grazed each paddock (Date ADG) relative to the date of survey.**

Farm	Paddock	Season of plant survey	Date of survey	Dominant species	Growth cycle	Native or Exotic	Growth period season	% Cover	Av. ADG (kg/day)	Date ADG
GR	Aerodrome	Summer 2025	Jan-25	Perennial cup grass	perennial	Native	warm	80	0.64	2024-02
	Jordies	Summer 2025	Jan-25	Digit grass	perennial	Introduced	warm	55	0.26	2024-03
	Llandudno Road	Summer 2025	Jan-25	Urochloa Grass/Lucerne	annual	Introduced	warm	30/30	1.07	2025-04
	Hinebury 4	Autumn 2024	May-24	Oats	annual	Introduced	cool	forage crop	1.54	2024-05
	180 acre	Winter 202	Jun-25	Oats	annual	Introduced	cool	forage crop	1.51	2024-06
RG	Airstrip	Late Spring 2024	Nov-24	Couch	perennial	Native		55	0.53	2025-01
	Back 1	Winter 2025	Jul-25	Medic	annual	Introduced	cool	60	1.28	2025-07
	Back 1	Late Spring 2024	Nov-24	Digit grass	perennial	Introduced	warm	40	1.16	2024-12
	Hamiltons Corner	Late Spring 2024	Nov-24	Phalaris / Digit grass	perennial	Introduced	cool/warm	65 / 24	1.43	2024-10
TW	Elbow 2	Late Spring 2024	Nov-24	Digit grass	perennial	Introduced	warm	45	1.06	2025-02
	Longlands	Winter 2025	Jul-25	Digit grass	perennial	Introduced	warm	80	0.20	2024-06
	Lupins	Winter 2025	Jul-25	Digit grass	perennial	Introduced	warm	20	0.89	2025-04
	Road paddock	Late Spring 2024	Nov-24	Plains Grass / Ryegrass	perennial / annual	Native / introduced	warm	60 / 35	0.73	2023-12
	Fuel Tank	Winter 2024	Aug-24	Oats	annual	Introduced	cool	forage crop	0.76	2024-09
	Tip paddock	Spring 2024	Oct-24	Oats	annual	Introduced	cool	forage crop	0.89	2024-10

Across the three properties (GR, RG, TW), the dominant-species align with the system-dependent patterns observed in the ADG analyses (Table 6). It is important to note that percentage cover does not account for biomass or ground cover but describes species representation in proportion to other surveyed species within the paddock. Due to only having two ecological sampling points, interpretation is limited to descriptive analysis.

For RG, the most productive paddock was “Hamilton’s Corner” (Table 6), which may be explained by dominant species and season of grazing, when the pasture had a high CP. The dominant species in this paddock were Phalaris (65%), a cool season perennial, and digit (24%) a subtropical perennial (Table 6; Appendix 8.1, Figure 21). This paddock was sampled for feed testing in late winter during the productive stage of Phalaris, with a CP value of 17.7% and again in April (CP 10.4%). Cattle grazed the paddock in late spring (Oct 2024) resulting in a paddock ADG of 1.43 (Table 6).

Where annual forage cereals (oats) or legume-rich phases (medic, lucerne) were dominant during the survey window, paddock-window ADG tended to be higher in corresponding grazing periods, consistent with greater accessible green leaf and ME/CP potential. In contrast, paddocks dominated by warm-season C4 perennials (e.g., Digit grass in paddocks at TW and RG) showed more variable animal performance, with ADG dependent on timing of the grazing period relative to the seasonal state of the species (active growth vs. senescence). This data demonstrates the importance of the dominant functional group and growth stage as determinants of diet quality and utilisation. Scheduling mobs onto the same paddock type in the most favourable window yields better ADG than grazing the identical paddock during a senescent phase.



**Figure 16 Ground cover composition by paddock, showing the relative proportions of dominant species, forbs, grasses, high threat exotics, litter, and bare ground for farm TW.**

Across farms, ecological surveys demonstrated that paddock-level variation in cattle growth and productivity was closely associated with differences in pasture species dominance, establishment success and seasonal turnover, rather than biomass alone. Paddocks with strong dominance of well-established sown species generally exhibited less variability, while paddocks with poor establishment of sown species were often maintained by mixed native and exotic communities that varied in feed quality and seasonal availability. These differences in species composition and phenology help explain the observed divergence in average daily gain (ADG) between paddocks with similar total standing dry matter, particularly in perennial

pasture systems where biomass was a weak predictor of animal performance. The presence of high-threat weeds, high litter loads or elevated bare ground further indicated constraints on feed utilisation and recovery potential that were not captured by biomass metrics alone. Integration of ecological indicators with liveweight data into a predictive model will provide a practical measure of paddock productivity, linking animal performance, stocking density and grazing duration. Together, these findings demonstrate that incorporating pasture composition and seasonal condition into the Paddock Performance Benchmark provides a more complete framework for interpreting paddock productivity and identifying management strategies such as plant species selection, resting or grazing intensity that can support improved performance and sustainability.

As this analysis is descriptive, the next step would be to formally incorporate ecological variables such as species dominance, groundcover, litter and high-threat weed presence into the PPB model as paddock-level covariates. This would allow testing of whether and how pasture composition moderates the effects of rainfall and feed quality on animal performance, rather than inferring these relationships qualitatively, and inform plant species selection and management.

## 4.6 Gross margins analysis

AgEcon developed a gross margin template to compare gross margin returns by paddock for varied forage bases on each farm. Examples from the gross margins template that will be provided to producers are shown in **Appendix 8.4**.

A gross margin by paddock, by month creates a clear picture of how individual paddocks and their forage base contribute to overall enterprise performance across the year. Data gaps and a small sample size mean that results should be considered as examples only and are certainly not representative. This analysis outlines the value of gross margin comparison and provides a template that can be used, to compare paddocks despite highly variable stocking rates, grazing duration, seasonal conditions and cost basis.

Rather than averaging results across the entire property, paddock-level analysis highlights the true variation in pasture productivity, livestock performance, and cost efficiency. This allows managers to identify which feed systems consistently generate strong gross margins and which areas underperform or carry disproportionate costs. It also supports more targeted decision-making around grazing allocation, pasture renovation, fertiliser investment, and stocking strategies. By linking animal performance directly to the feed base that produced it, per-paddock comparisons turn broad assumptions into measurable outcomes, enabling more confident planning and continuous improvement across the grazing system.

TW had the most complete data, however assumptions were required for the number of days cattle were in each paddock, and total numbers of cattle per paddock as these details were not accessed from the farm managers. The example results are synthesised to indicate how the results of the template can be interpreted. For TW a small number of paddocks consistently delivered strong returns relative to their size and input costs. These paddocks appear to be well aligned with their current management, offering reliable feed supply and

supporting efficient weight gain during key periods of the year. Their performance indicates the value of well-established perennial systems and timely utilisation. In contrast, several paddocks produced only modest returns, and in some cases the results were constrained by incomplete or inconsistent data. Tip Paddock and Alberts, for example, generated positive but comparatively low gross margins, suggesting that while they contribute to the overall feedbase, there may be opportunities to lift their productivity through targeted management. Seasonal patterns were also evident across the dataset. The early months of the year were characterised by low or negative returns, potentially reflecting the combined effects of heat stress, reduced pasture growth, and resulting lower ADG. Performance improved markedly from winter into early spring, with July through September emerging as the most profitable period. This seasonal contrast underscores the importance of aligning grazing pressure and feed allocation with expected pasture growth curves.

The findings from a monthly gross margin analysis could be used in the following ways for forage base management:

- **Identification of high-performing and underperforming paddocks:** High performing paddocks that deliver strong returns should remain a priority for careful management and ongoing investment. Paddocks with low or marginal GM/ha may require targeted interventions to improve pasture condition, utilisation, or seasonal fit.
- **Pasture performance:** Tracking the performance of pastures over time can highlight which forage bases consistently deliver strong returns, and pinpoint where investment in renovation, fertiliser, or altered stocking strategies will have the greatest impact. Over multiple seasons, this evidence-based approach builds a clearer understanding of pasture resilience, carrying capacity, and long-term profitability.
- **Seasonal variability:** Patterns in seasonal performance highlight that consideration needs to be given to the management of feed supply, stocking pressure, and pasture utilisation to ensure that both high-performing and vulnerable paddocks remain productive and financially resilient across changing seasonal conditions

## 4.7 Predictive model development

While the intention of this program was to develop a predictive model utilising multiple pieces of information simultaneously to assess paddock productivity, this ultimately was considered out of scope for this project. This was due to a combination of data limitations (as described in 6.1.1), and time to develop the analytical tools to complete each separate analysis. However, it is important to develop such a model in a future extension to this work.

## 4.8 Extension activities

Field days and workshops have been conducted with strong producer engagement. Integration of the model with platforms like CiboLabs, Optiweigh and AgriWebb is being explored for broader application. These have been comprehensively reported on in previous Milestone Reports.

Activities include at three field days on partner sites, and 5 project demonstration presentations held between August 2022 and October 2025. The LLS hosted a final project field day in September 2025, which included a workshop demonstrating the PPB and tools developed. The aim is to present the project findings to the partner farms and broader producer network at the conclusion of the project in May 2026.

LLS has not held MBFP and ProGraze programs in the past 18 months. The current PPB model can be included, and gross margins methods can be included in future training programs to demonstrate how paddock productivity can be benchmarked on farm and included in a whole farm economic analysis.

## 5 Conclusion

This project demonstrates that integrating near-real time animal performance with remote and public environmental datasets is a robust, scalable basis for paddock-level benchmarking in commercial beef systems. In practice, Optiweigh-derived ADG is used to identify high and low performing paddocks in near real time. Where ADG deviates from targets or expectations, we then use satellite derived biomass data (TSDM), climate, soil, and, where feasible, paddock-level feed quality and ecological data to explain drivers and target management changes. This paddock performance benchmarking tool can guide practical changes such as altered grazing duration, stocking density, paddock entry timing, and pasture renovation or species selection.

Across farms, we observed large within-farm divergence in paddock ADG and system-dependent pasture biomass and ADG relationships. Forage crops tended to show positive associations within observed ranges, whereas perennial or native systems often showed weak or negative associations. These results within a commercial context reinforce that biomass alone is not sufficient to predict performance and demonstrate the potential for ADG as a practical proxy for the quality of feed selected and consumed by cattle. Where sampled, CP and ME were positively associated with ADG on two of the three analysed farms, while ecological surveys clarified how plant species composition and seasonal turnover help explain productivity differences between paddocks with similar biomass. The gross-margin template translates ADG differences into economic terms, supporting prioritisation of interventions (e.g. rotate, rest or renovate paddocks). Together, these outcomes provide a practical, adoptable and sequential decision framework: benchmark, diagnose, intervene.

The project highlights the importance of longitudinal data collection and the value of automated systems in overcoming traditional barriers to grazing management. By leveraging technologies such as Optiweigh and CiboLabs, the model reduces reliance on manual data collection and enables near real-time decision-making.

In this project, the Paddock Performance Benchmark (PPB) is used to identify and diagnose paddock-level performance to inform management practices. A fully specified predictive model could not be developed within the project timeframe due to data constraints, reflecting challenges of working in commercial environments. This is outweighed by the value of using a diverse network of commercial partner sites reflecting a range of production environments typical of the NW of NSW. There is a need for more consistent and repeated grazing data to strengthen model validation. Access to continuous data sets across multiple seasons and years, will enable further training and testing of the benchmarking model to understand how practice change can be informed.

Ultimately, the project has established the data architecture, automated data acquisition pipelines and component analyses to embed paddock benchmarking in farm management software, contingent on continued industry investment into data infrastructure. Forecasting was out of scope for this project and is positioned as future work contingent on longer, region-specific datasets and improved remote proxies for diet-relevant quality and utilisation.

## 5.1 Key findings

**Data architecture.** Codes were developed to automatically extract and integrate multiple data sources, Optiweigh, CiboLabs, BOM, and SEED providing a framework for benchmarking paddock performance.

**Growth-curve modelling.** We developed and validated a workflow that transforms opportunistic, irregular Optiweigh records into continuous growth curves and date-specific ADG, then assigns those ADG values to paddock windows allowing stable comparison between paddocks and over time despite irregular station attendance.

**Geospatial data.** We developed and implemented workflows to allocate OW events to paddock polygons using GPS, spatial overlays and paddock boundary files, enabling consistent linkage of liveweight, biomass, climate and soils at the paddock scale across commercial farms.

**Significant variation in paddock productivity** was observed across farms and paddocks, highlighting the need for site-specific grazing strategies. Average daily gain varied not only between farms but also between paddocks within the same farm, influenced by forage type, grazing timing, and environmental conditions. This paddock-level benchmarking is a key outcome, enabling identification of paddocks for targeted intervention and management decisions.

**Biomass alone is not a reliable predictor of animal performance.** While satellite-derived total standing dry matter (TSDM) showed some correlation with ADG, particularly in forage crops, perennial pastures often exhibited weak or negative correlations due to senescence and reduced nutritional quality.

**Climate signal extraction with lags.** An analysis framework was established to quantify lagged effects of THI and rolling rainfall windows on growth, identifying short lag negative responses to heat and farm specific rainfall windows that affect ADG capabilities that will carry directly into forecasting.

**Pasture quality metrics (crude protein and metabolisable energy)** were strongly associated with ADG, however this effect was constrained by season and species composition. While both CP and ME relate positively to ADG within the observed paddock-average ranges, effect sizes are diagnostic rather than prescriptive. The linear slopes are local and biologically constrained, where diminishing returns may be evident at higher ME, however they are used to interpret deviations in ADG-based benchmarking rather than to predict absolute growth beyond the data's scope. This reinforces the importance of including feed quality indicators in productivity models, and the need for tools to remotely estimate these values.

**Ecological surveys** explained why similar-biomass paddocks can deliver different ADG, and identified plant composition and condition variables to include as paddock-level covariates in forecasting models

**Gross margin analysis** templates link paddock ADG to variable costs and prices, providing an economic analysis tool to benchmark current practice. This enables producers to compare forage systems and prioritise interventions economically.

## 5.2 Benefits to industry

The outcomes of this project offer substantial benefits to the red meat industry, particularly in enhancing the efficiency, profitability, and sustainability of beef production systems. The integration of real-time animal performance data with environmental and pasture metrics provides producers with a powerful decision-support tool that can transform grazing management practices.

### 5.2.1 Practical Applications derived from the project:

The Paddock Performance Benchmark (PPB) enables producers to make informed decisions about grazing duration, stocking density, and paddock rotation based on actual animal performance rather than visual estimates or manual assessments. We propose an operational workflow based on project outputs:

1. **Identify:** compute paddock-window ADG (and 3–7-day rolling ADG) using OW derived LW data and growth curve modelling. Deviations between paddocks can be identified using between paddock comparisons. Longer term evaluation of economic performance (gross margins template) may also be used here.
2. **Diagnose:** interpret deviations using explanatory variables (TSDM trends across the same entry-to-exit window, rainfall, THI deviations, soil, and where feasible feed quality and ecological context (species composition, pasture management)).
3. **Intervene:** adjust grazing duration, stocking density, entry timing, or rotate/rest/renovate that paddock.

**Recommended approach with one Optiweigh unit:** In practice, this benchmark - diagnose-intervene sequence can be automated within existing platforms. The data pipelines and PPB workflow developed in this project are designed for automatic execution within existing digital platforms. The PPB codebase aligns OW liveweight, CiboLabs biomass, climate and soil data in the background, allowing producers to view paddock-window ADG, deviation alerts and diagnostic layers within Optiweigh, CiboLabs or AgriWebb dashboards without additional data handling. Producers can use a single OW unit to benchmark paddock performance by rotating it through a sentinel group of key paddocks each season. Sentinel paddocks should be representative of the main forage systems on the property, routinely used by the target class of cattle, and management-relevant (e.g., improved or under renovation or frequently limiting performance such as native or unimproved perennials). For each paddock, entry and exit dates are recorded via data entry in the Optiweigh app as the unit moves with the mob. Paddock-window ADG can be calculated using the growth curve models developed in this project to benchmark performance. Over time, current paddock ADG can be compared to the paddock's historical range for the same season and other sentinel paddocks in the same rotation. Where deviations occur from targets or baselines, additional data layers (TSDM, Page 64 of 94

climate, farm level management or plant species information) can be used to diagnose likely causes and guide adjustments to grazing duration, stocking, entry timing or renovation/species selection. Repeating this cycle each season builds a robust within-farm paddock performance baseline to support targeted management.

**Feedbase Planning and Forage Selection:** By identifying the forage types and pasture qualities that correlate most strongly with animal growth, producers can strategically plan their feedbase to maximise productivity.

**Economic Decision-Making:** Gross margin analysis linked to paddock performance helps producers evaluate the cost-effectiveness of different forage systems, guiding investment in pasture improvement and grazing infrastructure.

**Integration with Existing Platforms:** The model's compatibility with systems like Optiweigh, CiboLabs, and AgriWebb supports seamless adoption and reduces the need for manual data entry, making it accessible to producers with varying levels of technical expertise. The project has delivered the data architecture, automated pipelines, and paddock-level ADG workflow (PPB) needed to embed the benchmarking system directly into existing commercial platforms. Integration conversations have already occurred with Optiweigh, CiboLabs and AgriWebb, and the PPB has been designed so that:

1. **Optiweigh** provides the liveweight data
2. **CiboLabs** provides TSDM and greenness context
3. **AgriWebb** provides the paddock map and animal-movement layer for seamless paddock attribution.

## 5.2.2 Benefits to the Wider Red Meat Industry

**Improved Productivity and Profitability:** By enabling more precise and responsive grazing management, the project supports increased LW gain per hectare and better utilisation of pasture resources.

**Sustainability and Climate Resilience:** Integrating animal performance with climate, soil and pasture data supports adaptive grazing decisions under variable seasonal conditions, promoting sustainable production and resilience to climatic events.

**Scalability and National Application:** The use of automated and remotely collected data makes the system scalable across diverse production environments, supporting broader industry adoption and benchmarking.

**Support for Extension and Training Programs:** The tools and insights developed through this project can be embedded into industry training programs, enhancing producer knowledge and accelerating adoption.

**Alignment with Industry Goals:** The project aligns with MLA's strategic priorities around data-driven decision-making, sustainable production, and digital innovation, contributing to long-term industry transformation.

## 6 Future research and recommendations

This project established a scalable, animal-centred framework for paddock-level benchmarking and linked it to practical economic interpretation. The next phase is to extend datasets across seasons and regions, automate key inputs (especially pasture quality), and deliver validated predictive and simulation tools embedded in existing farm software.

### 6.1 Key Challenges and Successes

#### 6.1.1 Key Challenges

**Data Gaps Due to Environmental and Operational Factors:** Across the observation period, climatic extremes including both drought conditions and flooding affected data continuity. In particular, drought conditions led to major destocking events in 2023 across multiple partner sites which interrupted data collection, reducing the continuity and completeness of some datasets. A single mobile Optiweigh unit followed one mob at a time for much of the study, so only a subset of paddocks was monitored per season. This limited the ability to model long-term trends in paddock productivity and animal performance.

**Inconsistent Animal Attendance at Weigh Stations:** Variability in how frequently cattle accessed the OW stations introduced gaps in LW data. While smoothing algorithms were applied, irregular attendance reduced the granularity of individual growth curves and complicated the estimation of ADG. This improved with longer periods of data collection.

**Limited Repeated Grazing Events:** Some paddocks were not grazed multiple times during the observation period, limiting the ability to assess seasonal variation and validate model predictions across different grazing cycles.

**Paddock level pasture biomass and quality estimations:** Satellite TSDM represents total biomass and bulk quadrat CP and ME are paddock-average samples. Neither directly capture the selected green layer or defoliation horizons, nor account for animal grazing behaviour and plant selection. These factors are included as variables affecting ADG and are limited as predictors of productivity.

**Integration of Heterogeneous Data Sources:** Combining data from multiple platforms (Optiweigh, CiboLabs, BOM, SEED) required significant effort in data cleaning, alignment, and geospatial mapping. Differences in data resolution and formats posed technical challenges for model development. Lack of remotely available sources of pasture quality data required manual collection, which should be addressed with technological advances.

**Producer Engagement and Data Sharing:** While producer interest was high, variability in digital literacy and data sharing practices across farms occasionally delayed data acquisition and limited the uniformity of implementation. Incomplete records of exact stocking densities and days-in-paddock constrained formal utilisation estimates for some events and precluded robust forecasting during the project timeframe.

### 6.1.2 Key Successes

The major outcome of this project is the use of automatically collected data in a typical farming system, rather than collecting data manually in an experimental farming system. This required the development of novel analytical procedures and data integration methods to address this complex feedbase system. Further, these tools would be applicable to many other complex agro-ecological systems under investigation. This could be achieved since most of the methods were developed using the free statistical software R rather than commercial software and can be passed along to bona-fide users.

This project delivers a practical, ADG-based paddock benchmarking (PPB) tool supported by automated data architecture that integrates Optiweigh liveweight, satellite biomass (TSDM), BoM climate and ASC soils at paddock scale. In practice, producers or consultants can now obtain paddock-window ADG during a monitored graze, identify high/low performing paddocks, and diagnose likely drivers for deviation to inform interventions and improve economic outcomes.

**Paddock performance benchmarking (PPB) and automated data pipelines:** We built and validated end-to-end pipelines to automatically extract Optiweigh, CiboLabs, BoM and soil data and attribute them to paddocks (using the GPS “point-in-polygon” technique), enabling near real-time benchmarking of paddock productivity using ADG as the key indicator.

**Livestock tracking within the property:** Cattle were regularly moved between paddocks in a farm, as were the Optiweigh units, although the locations were not routinely recorded by farm managers. However, the Optiweigh station routinely send GPS coordinates for each weighing. Consequently, an algorithm for extracting location using a ‘point in polygon’ technique with the paddock shape files was developed to identify the paddock that the Optiweigh station, and paddock location of cattle.

**Soil mapping: overlay on farms and assessment of paddock soil types** A soil map across NSW was obtained from the Australian Soil Classification (ASC) system in the form of a very detailed shape file; 17 soil types are recognised. An algorithm was developed in R, to enable soil information to be overlaid on the farm paddock maps. The soil type of each paddock could be assigned by identifying the soil type at the paddock centroid. The impact on soil type on ADG or pasture quality can then be assessed. This can be extrapolated to more detailed soil data sources in future.

**Integration of data sets:** The value of these datasets and analysis approaches is greatly increased when they are integrated. For example, this has allowed an evaluation of the effect of rainfall and THI across the country in terms of their effects on cattle growth across the various agro-ecological zones of Australia. At an individual farm level, it has allowed an investigation of the impact of pasture quality, soil type and other factors on ADG, and allowed ranking of paddocks by their ADG and visualisation of the variation of ADG using farm-specific maps.

**Multi-farm data sources:** The final models have been developed using data from three diverse commercial properties, demonstrating its adaptability and relevance to real-world production systems.

**Economic Insights Through Gross Margin Analysis:** The integration of productivity data with economic analysis provided clear evidence of the financial benefits and a tool for strategic forage planning.

**Strong Producer Engagement and Extension Activities:** Multiple field days, workshops, and producer forums were conducted, with positive feedback and strong interest in adopting the tools developed. This engagement has laid the foundation for future adoption and scaling.

**Foundation for Predictive Modelling and Decision Support:** The groundwork has been laid for the development of predictive tools that can simulate grazing scenarios, forecast paddock productivity and inform proactive management decisions, with potential for integration into platforms like CiboLabs, Optiweigh or AgriWebb.

## 6.2 Recommendations for Future R&D

**Consolidate the PPB benchmarking & diagnostics workflow** and broaden regional and system-Level Validation. Extend multi-year datasets across additional agro-climatic zones, forage systems and cattle classes to strengthen robustness, transferability and adoption.

**Improve utilisation and pasture quality proxies.** Emerging techniques for remote or automated monitoring (e.g. drones, faecal NIR) to approximate CP and ME have the potential to reducing manual sampling and improving timeliness and scalability for integration with the PPB framework. These techniques will require validation under commercial conditions and therefore represent future but not necessarily achievable research trajectories.

**Forecasting as a conditional evaluation:** Future forecasting should be limited to short-term look-ahead alerts anchored to on-farm ADG benchmarks, and only where region-specific data density and validated proxies (utilisation, greenness) exist.

**Enhance Economic and Sustainability Metrics:** Expand gross-margin analysis to include scenario comparisons (e.g., earlier exit vs longer graze; renovation vs rest) and explore optional sustainability metrics (carbon/natural-capital) where data are available, aligning with industry sustainability goals. The development of cost-benefit frameworks for different

grazing strategies, including regenerative practices and mixed-species pastures should be explored.

**Support Data Infrastructure and Interoperability:** The use of cloud-based platforms (e.g. AgriWebb) would enable seamless integration of data from Optiweigh, CiboLabs, BOM, and other sources. This would require standardisation of data formats and APIs to facilitate interoperability with farm management software and national or industry databases.

**Collaborative Research and Producer-Led Innovation:** Encourage partnerships between universities, tech providers, and producer groups to accelerate innovation and adoption. The co-design and testing of new tools would ensure relevance and usability.

**Develop Simulation Tools for Scenario Planning:** Add what-if modules (mob size, entry timing, paddock sequencing, forage choice under seasonal outlooks and extreme-event risk) to operationalise climate-resilient decisions alongside forecasts.

### 6.3 Recommendations for Practical Application

**Development of Decision Support Tools:** Automatic data syncing from OW units and CiboLabs is required to reduce manual data entry and improve real-time decision-making. The Paddock Performance Benchmark (PPB) and associated tools could be integrated into widely used farm management platforms (e.g. Optiweigh, CiboLabs, AgriWebb). These provide available user-friendly dashboards that visualise paddock performance, forecast productivity, and recommend grazing actions based on predictive modelling. Producers could then input basic paddock and livestock data and receive tailored recommendations on grazing duration, stocking density, and forage selection. Scenario planning features that simulate the impact of different management strategies (e.g., changing stocking rates, introducing forage crops, adjusting grazing timing) could also be included.

**Training and Capacity Building:** Deliver targeted training programs through Local Land Services (LLS), MLA, and producer groups to build capacity in using data-driven grazing tools. PPB tools and concepts could be incorporated into existing training programs such as ProGraze and More Beef from Pastures (MBfP). Online modules and video tutorials could be developed

**Demonstration and Adoption Sites:** Establish regional demonstration farms to showcase the practical use of the PPB model and LWD metric in real-world settings. Use these sites to generate case studies that highlight productivity gains, economic benefits, and improved sustainability outcomes. Involving early adopters in field days and producer forums can facilitate peer-to-peer learning.

**Industry Collaboration and Incentives:** Work with industry bodies to align PPB outputs with sustainability frameworks, such as carbon and natural capital accounting. Encouraging collaboration between tech providers, researchers, and producers will facilitate co-designed tools that are practical, scalable, and user-friendly.

## 6.4 Recommendations for Development and Adoption Activities: Establish Regional Demonstration Networks

**Set up long-term demonstration farms across key beef-producing regions** to showcase the practical application of the Paddock Performance Benchmark (PPB) and associated tools. Use these sites to generate case studies that highlight improvements in productivity, profitability, and sustainability. This should be supported by field days to facilitate engagement and build confidence in the system.

**Develop Producer-Focused Adoption Packages:** Provide setup guides, data-sync instructions, troubleshooting FAQs, and worksheet templates (LWD, gross margins) that align with common platform workflows. Include case studies from demonstration sites.

**Integrate with Industry Training and Advisory Programs:** The PPB model and associated tools could be embedded into existing MLA and LLS training programs such as ProGraze, MBfP, and EDGE Network workshops. Extension officers and private consultants would require training in the use of the model so they can support producers with implementation and interpretation.

**Digital Integration and Interoperability:** Work with software providers (e.g., AgriWebb, Optiweigh, CiboLabs) to integrate the PPB model into their platforms, ensuring user-friendly interfaces. This will require the development of APIs and data standards that support interoperability between data systems.

**Monitor Adoption and Impact:** Conduct follow-up surveys and interviews with participating producers to assess adoption rates, barriers, and benefits. Use this feedback to refine tools, training materials, and extension strategies. Report on adoption metrics and productivity outcomes to demonstrate return on investment and guide future funding.

## 7 References

- Ara, I. et al., 2020. Modelling seasonal pasture growth and botanical composition at the paddock scale with satellite imagery. *in silico Plants*, 3(1). DOI:10.1093/insilicoplants/diaa013
- Ash, A., O'Reagain, P., Mckee, G., Smith, M.S., 2000. Managing Climate Variability in Grazing Enterprises: A Case Study of Dalrymple Shire, North-Eastern Australia. In: Hammer, G.L., Nicholls, N., Mitchell, C. (Eds.), *Applications of Seasonal Climate Forecasting in Agricultural and Natural Ecosystems*. Springer Netherlands, Dordrecht, pp. 253-270. DOI:10.1007/978-94-015-9351-9\_16
- Ash, A., Thornton, P., Stokes, C.R.S., Togtohyn, C., 2012. Is Proactive Adaptation to Climate Change Necessary in Grazed Rangelands? *Rangeland Ecology & Management*, 65(6): 563-568. DOI:<https://doi.org/10.2111/REM-D-11-00191.1>
- Ayres, J.F. et al., 2001. Post-weaning growth of cattle in northern New South Wales. 1. Grazing value of temperate perennial pasture grazed by cattle. *Australian Journal of Experimental Agriculture*, 41(7): 959-969. DOI:<https://doi.org/10.1071/EA00096>
- Azubuiké, B.N., Chlingaryan, A., Correa-Luna, M., Clark, C.E.F., Garcia, S.C., 2025. Data Augmentation and Interpolation Improves Machine Learning-Based Pasture Biomass Estimation from Sentinel-2 Imagery. *Remote Sens.*, 17(23): 3787.
- Azubuiké, B.N., Chlingaryan, A., Correa-Luna, M., Clark, C.E.F., Garcia, S.C., 2026. Machine Learning for Grazing Event Detection and Pasture Utilisation Quantification from Sentinel-2 Data. *Smart Agricultural Technology*: 101954. DOI:10.1016/j.atech.2026.101954
- Berckmans, D., 2017. General introduction to precision livestock farming. *Animal Frontiers*, 7(1): 6-11. DOI:10.2527/af.2017.0102
- Earl, J., 2014. Grazing and pasture management. *Beef cattle production and trade*: 339.
- García, R., Jiménez, M., Aguilar, J., 2024. A multi-objective optimization model to maximize cattle weight-gain in rotational grazing. *International Journal of Information Technology*. DOI:10.1007/s41870-024-02226-w
- Gargiulo, J. et al., 2020. Spatial and Temporal Pasture Biomass Estimation Integrating Electronic Plate Meter, Planet CubeSats and Sentinel-2 Satellite Data. *Remote Sens.*, 12(19): 3222. DOI:10.3390/rs12193222
- Gaughan, J.B., Mader, T.L., Holt, S.M., Sullivan, M.L., Hahn, G.L., 2010. Assessing the heat tolerance of 17 beef cattle genotypes. *International Journal of Biometeorology*, 54(6): 617-627. DOI:10.1007/s00484-009-0233-4

Hasan, F.M. et al., 2026. Impact of heat stress on cattle systems: Responses of production metrics to thermal stress. *Computers and Electronics in Agriculture*, 240: 111143. DOI:10.1016/j.compag.2025.111143

Hasan, F.M. et al., 2024a. The impact of rainfall on beef cattle growth across diverse climate zones. *animal*: 101336. DOI:10.1016/j.animal.2024.101336

Hasan, F.M. et al., 2024. Monitoring cattle liveweight using a mobile, in-paddock weigh platform: Validation, attendance and utility. *Smart Agricultural Technology*, 9: 100639. DOI:10.1016/j.atech.2024.100639

Hudson, T.D., Reeves, M.C., Hall, S.A., Yorgey, G.G., Neibergs, J.S., 2021. Big landscapes meet big data: Informing grazing management in a variable and changing world. *Rangelands*, 43(1): 17-28. DOI:<https://doi.org/10.1016/j.rala.2020.10.006>

Imaz, J.A., Garcia, S., González, L.A., 2020. Using automated in-paddock weighing to evaluate the impact of intervals between liveweight measures on growth rate calculations in grazing beef cattle. *Computers and Electronics in Agriculture*, 178: 105729. DOI:<https://doi.org/10.1016/j.compag.2020.105729>

Katoch, R., 2022. *Forage Quality and Livestock Productivity, Techniques in Forage Quality Analysis*. Springer, pp. 7-10.

Keating, B.A. et al., 2003. An overview of APSIM, a model designed for farming systems simulation. *Eur. J. Agron.*, 18(3): 267-288. DOI:[https://doi.org/10.1016/S1161-0301\(02\)00108-9](https://doi.org/10.1016/S1161-0301(02)00108-9)

Kim, W.-S., Peng, D.-Q., Jo, Y.-H., Nejad, J.G., Lee, H.-G., 2021. Responses of beef calves to long-term heat stress exposure by evaluating growth performance, physiological, blood and behavioral parameters. *Journal of Thermal Biology*, 100: 103033. DOI:10.1016/j.jtherbio.2021.103033

Mader, T.L., Davis, M.S., Brown-Brandl, T., 2006. Environmental factors influencing heat stress in feedlot cattle. *J Anim Sci*, 84(3): 712-9. DOI:10.2527/2006.843712x

Masoud, M., Hsieh, J., Helmstedt, K., McGree, J., Corry, P., 2023. An integrated pasture biomass and beef cattle liveweight predictive model under weather forecast uncertainty: An application to Northern Australia. *Food and Energy Security*, 12(3): e453.

McKeon, G. et al., 2010. Improving grazing management using the GRASP Model. Final report on Project NBP, 338.

McKeon, G.M. et al., 2009. Climate change impacts on northern Australian rangeland livestock carrying capacity: a review of issues. *The Rangeland Journal*, 31(1): 1-29. DOI:10.1071/RJ08068

O'Reagain, P.J., Scanlan, J.C., 2013. Sustainable management for rangelands in a variable climate: evidence and insights from northern Australia. *Animal*, 7: 68-78. DOI:10.1017/S175173111100262X

Reeves, M.C. et al., 2025. Data-Driven Decision Support to Guide Sustainable Grazing Management. *Land*, 14(1): 140.

Ritchie, M.E., 2020. Grazing Management, Forage Production and Soil Carbon Dynamics. *Resources*, 9(4): 49. DOI:10.3390/resources9040049

Romera, A.J. et al., 2010. Use of a pasture growth model to estimate herbage mass at a paddock scale and assist management on dairy farms. *Computers and Electronics in Agriculture*, 74(1): 66-72. DOI:<https://doi.org/10.1016/j.compag.2010.06.006>

Shahi, T.B., Balasubramaniam, T., Sabir, K., Nayak, R., 2025. Pasture monitoring using remote sensing and machine learning: A review of methods and applications. *Remote Sensing Applications: Society and Environment*, 37: 101459. DOI:<https://doi.org/10.1016/j.rsase.2025.101459>

Stone, G., Fraser, G., O'Reagain, P., Timmers, P., Bushell, J., 2008. A new methodology for the calculation of pasture utilisation for grazing lands, *Proceedings of the Australian Rangeland Society Conference*. Charters Towers, Qld.(Queensland Department of Science, Information Technology, Innovation and the Arts: Brisbane) [www.longpaddock.qld.gov.au/about/publications/pdf/Stone\\_paper.pdf](http://www.longpaddock.qld.gov.au/about/publications/pdf/Stone_paper.pdf).

## 8 Appendix

### 8.1 Ecological sampling report summary findings

Stringybark Ecological was commissioned by the University of Sydney (USYD) to survey pasture species composition and groundcover across six mixed-enterprise farms on the Northwest Slopes and Plains of New South Wales. The project included properties located across the Brigalow Belt South and into the Nandewar Bioregions, areas characterised by significant agricultural activity and environmental variability. The aim of the project is to identify which species comprise the forage bases on these properties for the purpose of assessing their contribution to pasture productivity and ecological resilience.

#### Key findings include:

- Some paddocks sown with introduced cool or warm season pasture species had low ground cover of those species, indicating poor establishment and minimal contribution to the overall forage base.
- Species richness was generally lower in paddocks sown with introduced pastures, particularly where sown species were well-established and dominant. In the paddocks where sown species had low cover, species richness was comparable to or higher than in unmodified paddocks.
- Different species were detected at different times of year, with notable seasonal changes in cover. Conducting both warm and cool season surveys provided a more complete record of species present.
- Multiple high threat weed species were detected across the properties, including *Eragrostis curvula* (African Lovegrass), *Hypericum perforatum* (St. John's Wort) and *Opuntia* spp.

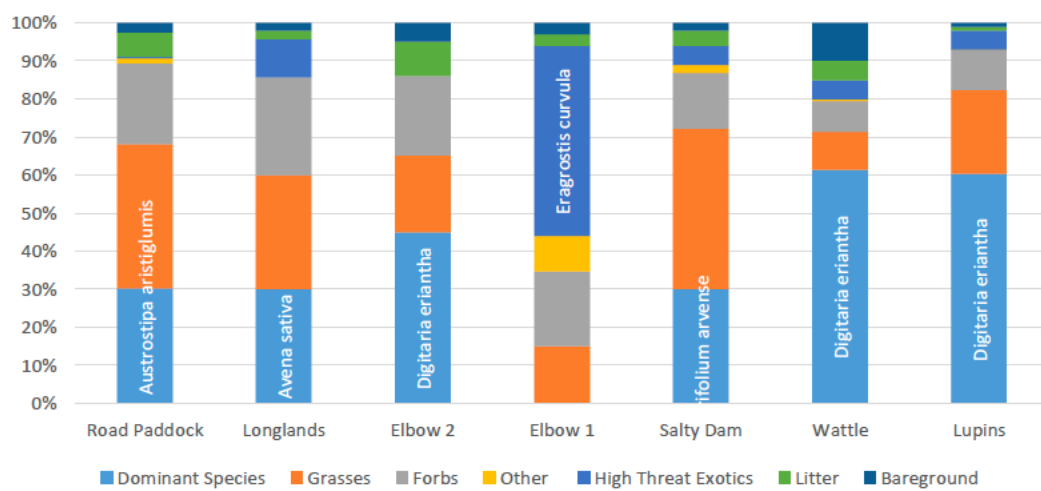
#### Limitations and recommendations:

- Some paddocks had been grazed prior to or during sampling, which compromised species identification and cover estimation. In particular, perennial species were difficult to detect or quantify during the season when they were not flowering or fruiting. Surveys would have been more accurate if scheduled prior to grazing events, when species are more intact and easily identified.
- The absence of detailed soil information for each paddock limited the ability to establish benchmarks for species richness and compare results between land-use types. Incorporating soil characterisation would allow for more meaningful interpretation of differences in species richness.
- The surveys represent a temporal snapshot of the forage base, influenced by the environmental conditions preceding sampling. The relatively average rainfall experienced across the study area in 2024 likely affected both species composition

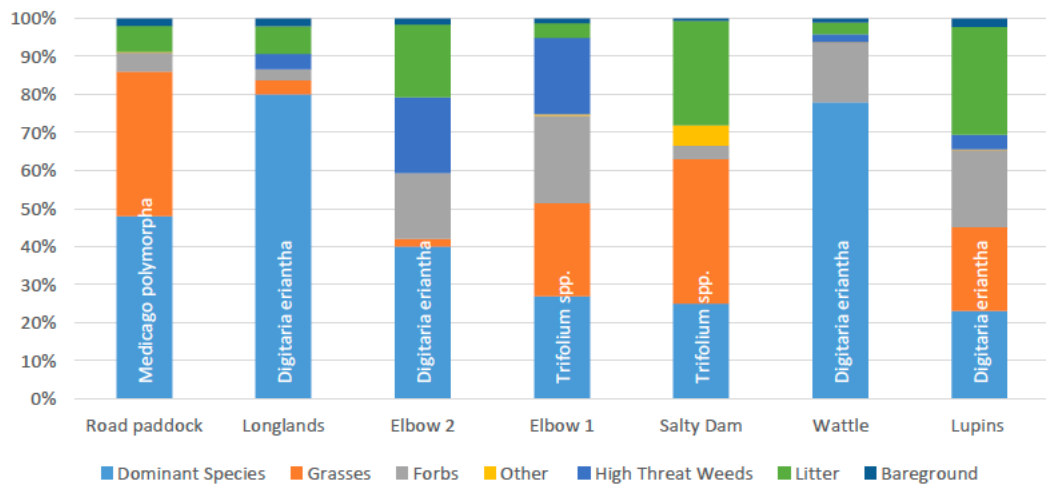
and groundcover, shaping the patterns observed in this dataset. To better understand how the species compositions change over time and their long-term contribution to pasture productivity and ecological resilience, monitoring should be extended over multiple years to capture variation under different environmental conditions (e.g. drought and above-average rainfall years).

### 8.1.1 TW results

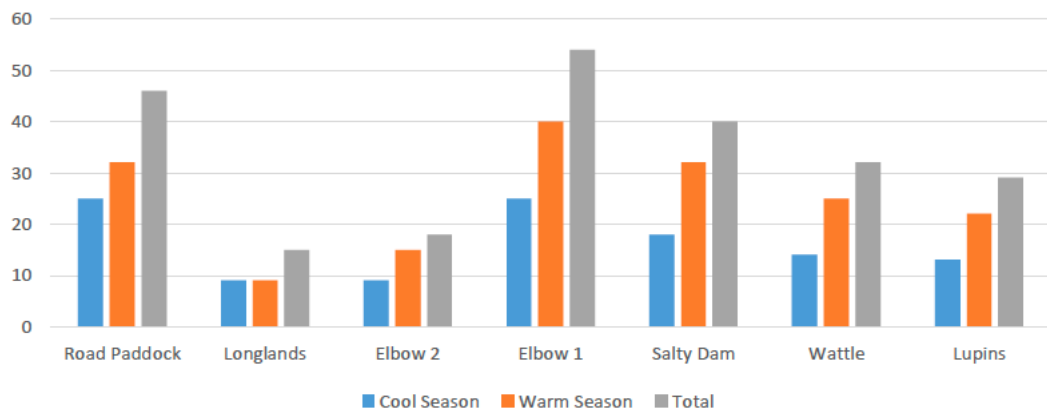
At TW, seven paddocks from two forage base types and one unknown were selected for sampling during the warm season of 2024 and the cool season of 2025.



**Figure 17** Ground cover composition by paddock at TW, showing the relative proportions of dominant species, forbs, grasses, high threat exotics, litter, and bare ground recorded during warm season surveys.



**Figure 18 Ground cover composition by paddock for TW, showing the relative proportions of dominant species, forbs, grasses, high threat exotics, litter, and bare ground recorded during cool season surveys**



**Figure 19 Plant species richness (total number of species present) by paddocks for TW for cool and warm season surveys and the combined total.**

### 8.1.2 Results RG

At RG, five paddocks from three forage base types were selected for sampling during the warm season of 2024 and the cool season of 2025.

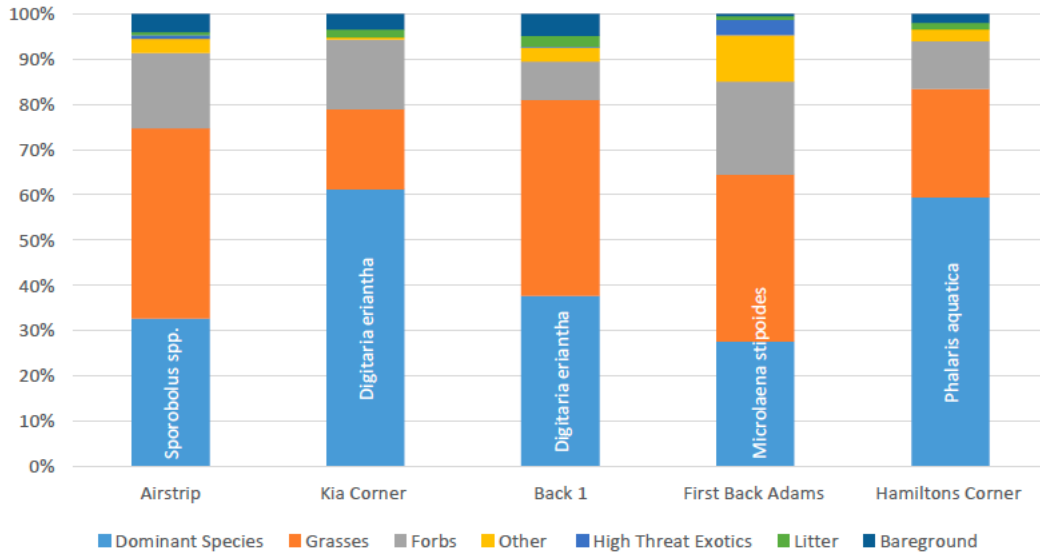


Figure 20 Ground cover composition by paddock for RG, showing the relative proportions of dominant species, forbs, grasses, high threat exotics, litter, and bare ground recorded during warm season surveys.

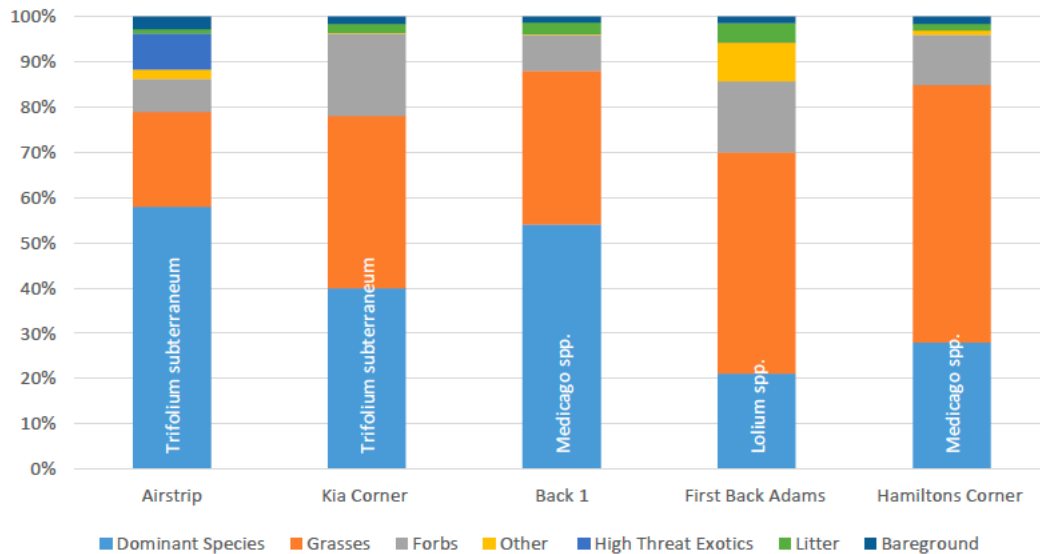


Figure 21 Ground cover composition by paddock for RG, showing the relative proportions of dominant species, forbs, grasses, high threat exotics, litter, and bare ground recorded during cool season surveys.

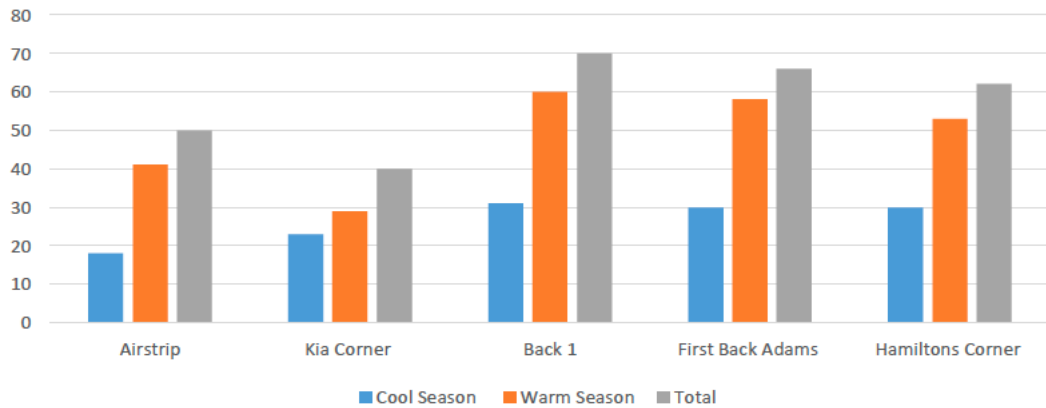


Figure 22 Plant species richness (total number of species present) by paddocks at RG for cool and warm season surveys and the combined total

### 8.1.3 Results GR

At GR, seven paddocks from three forage base types were selected for sampling.

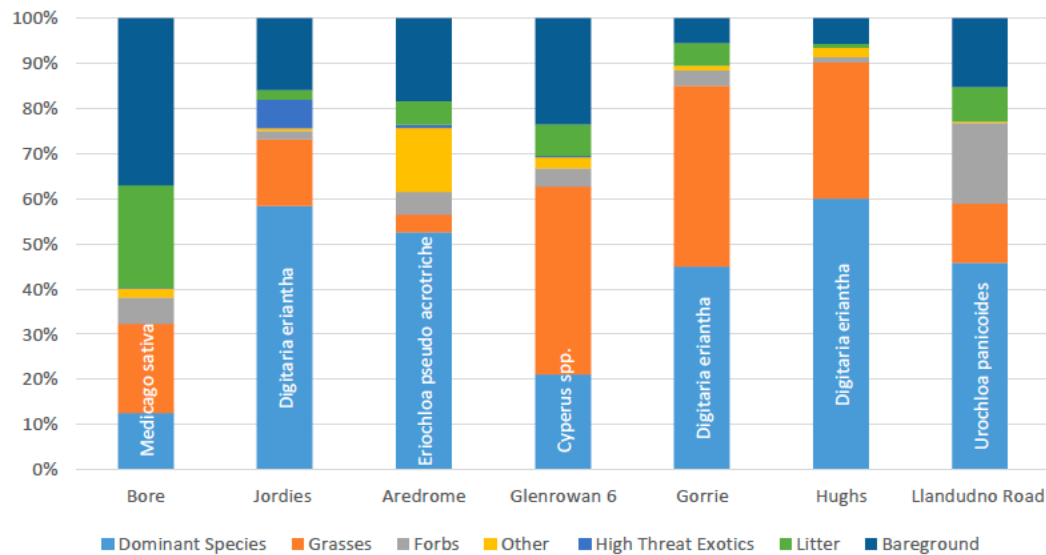
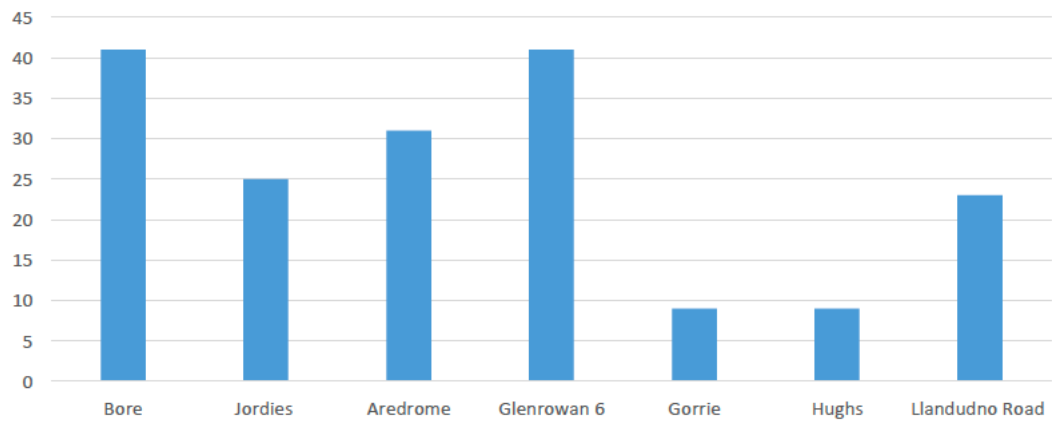
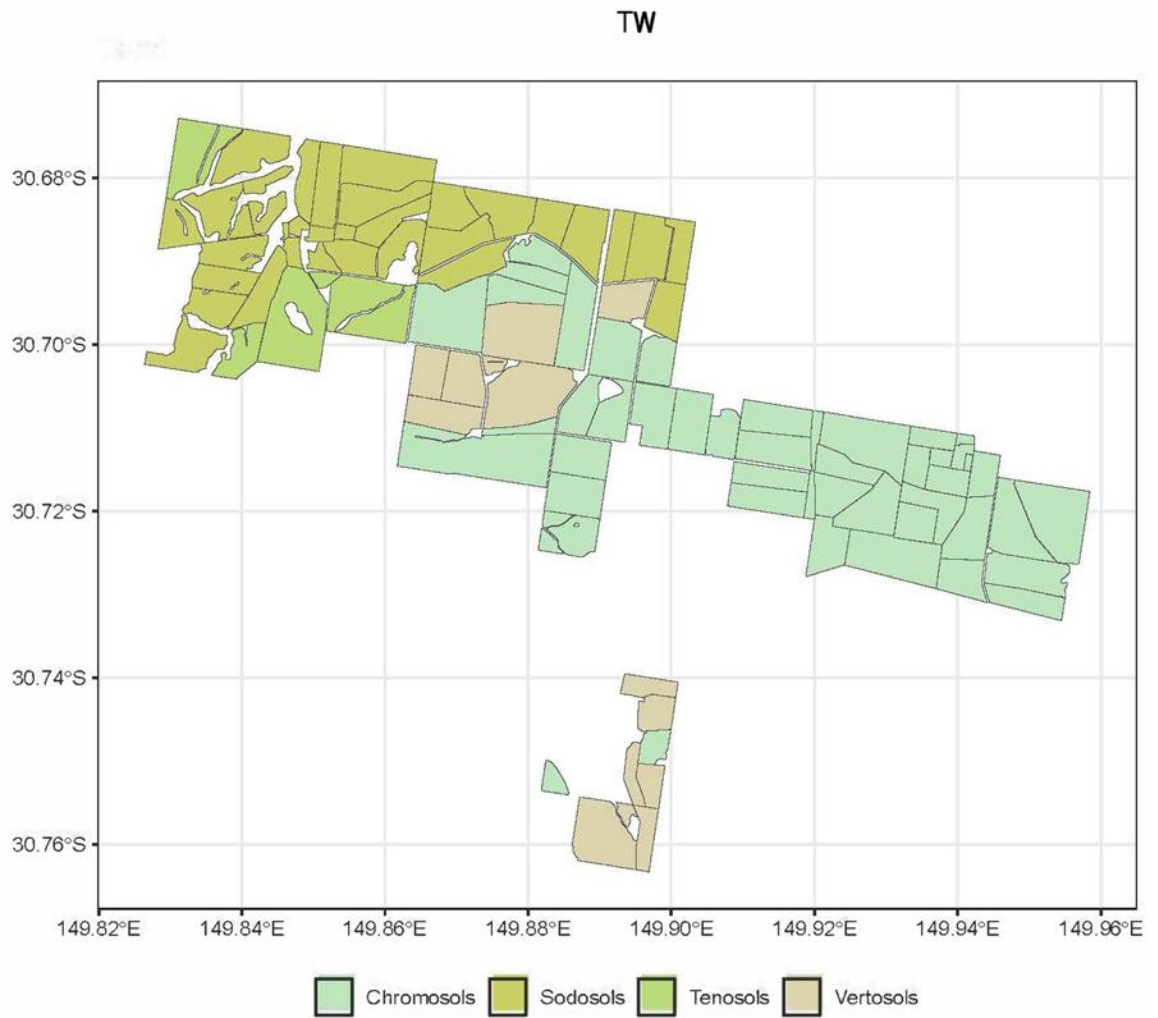


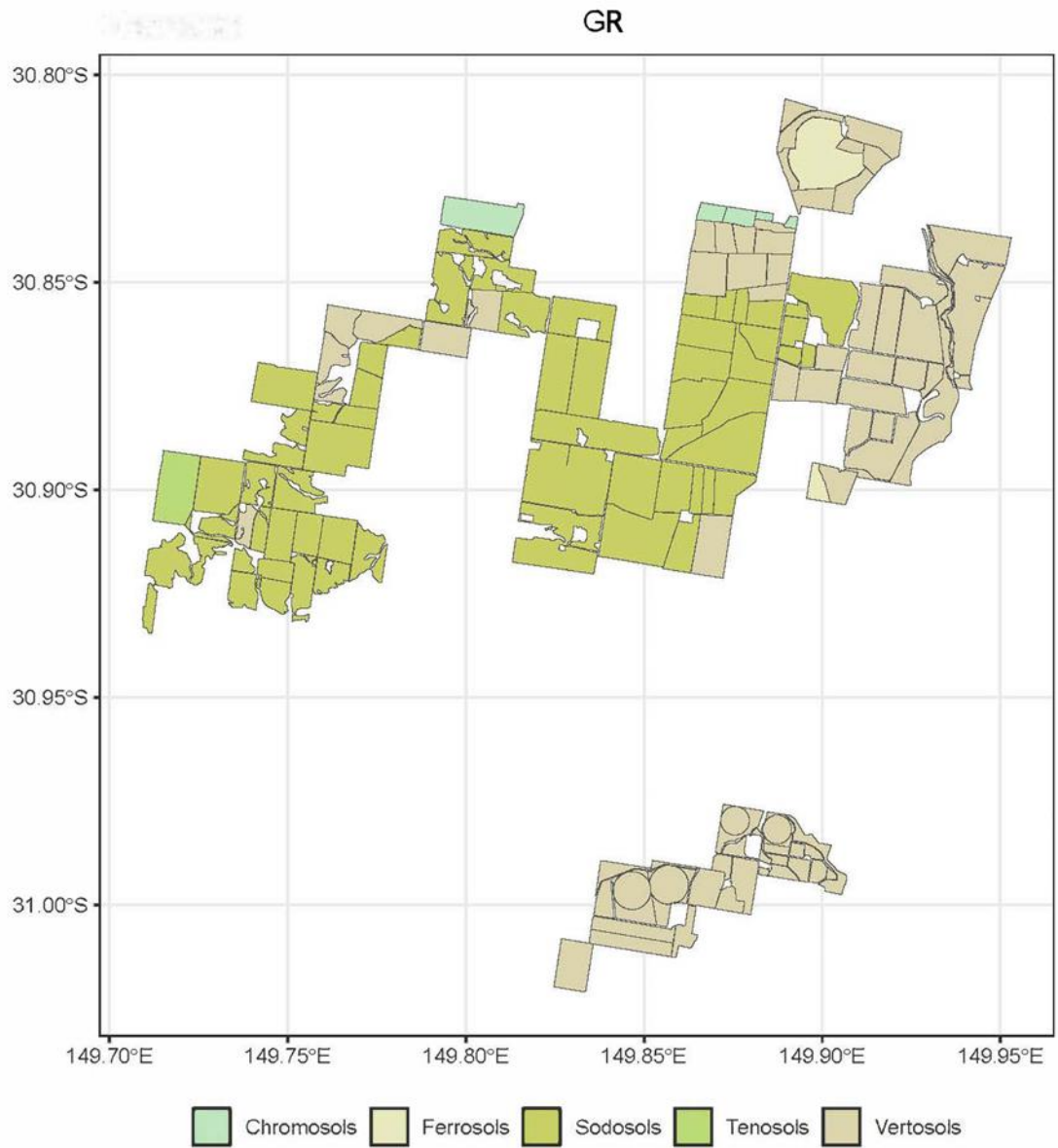
Figure 23 Ground cover composition by paddock at GR, showing the relative proportions of dominant species, forbs, grasses, high threat exotics, litter, and bare ground recorded during warm season surveys.

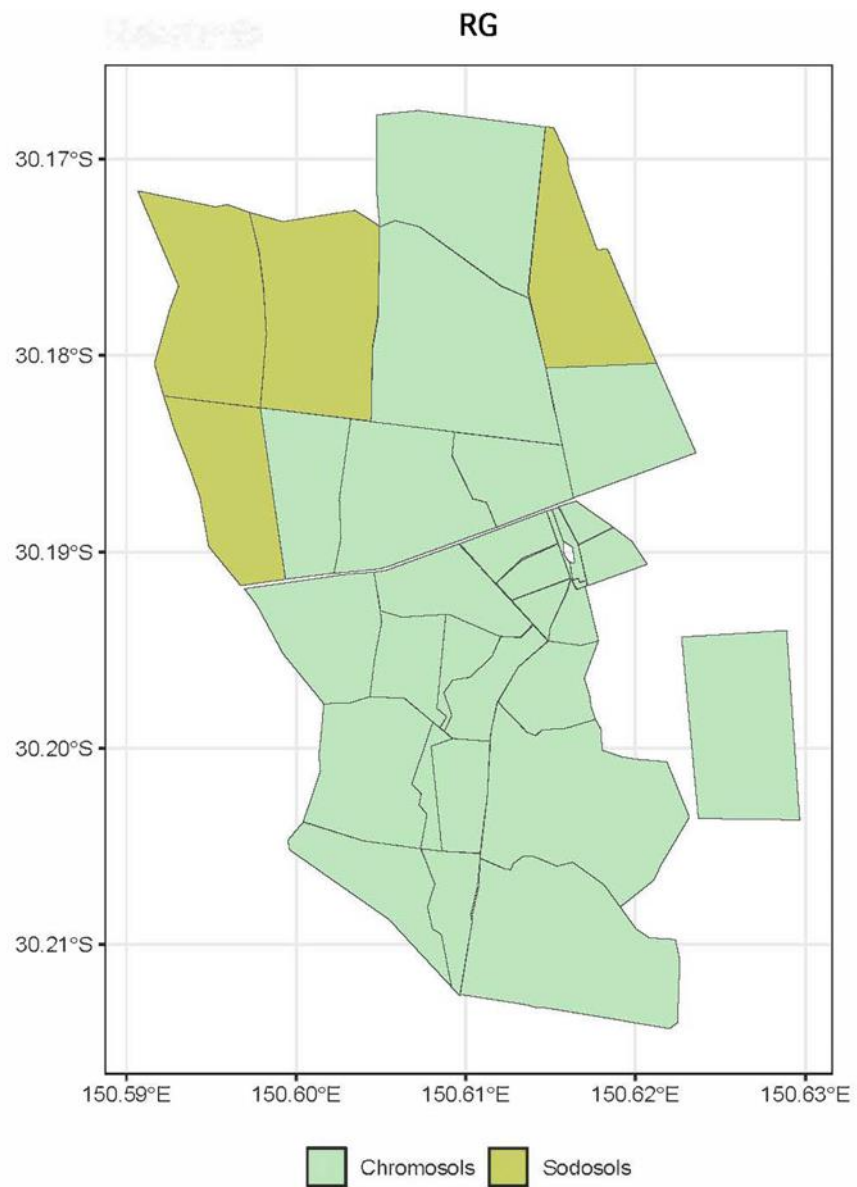


**Figure 24 Plant species richness (total number of species present) by paddocks for warm season surveys at GR**

## 8.2 Soil classification







**Figure 25 Paddock-level soil classification based on soil type assigned from paddock centroid location for TW, GR and RG (top to bottom)**

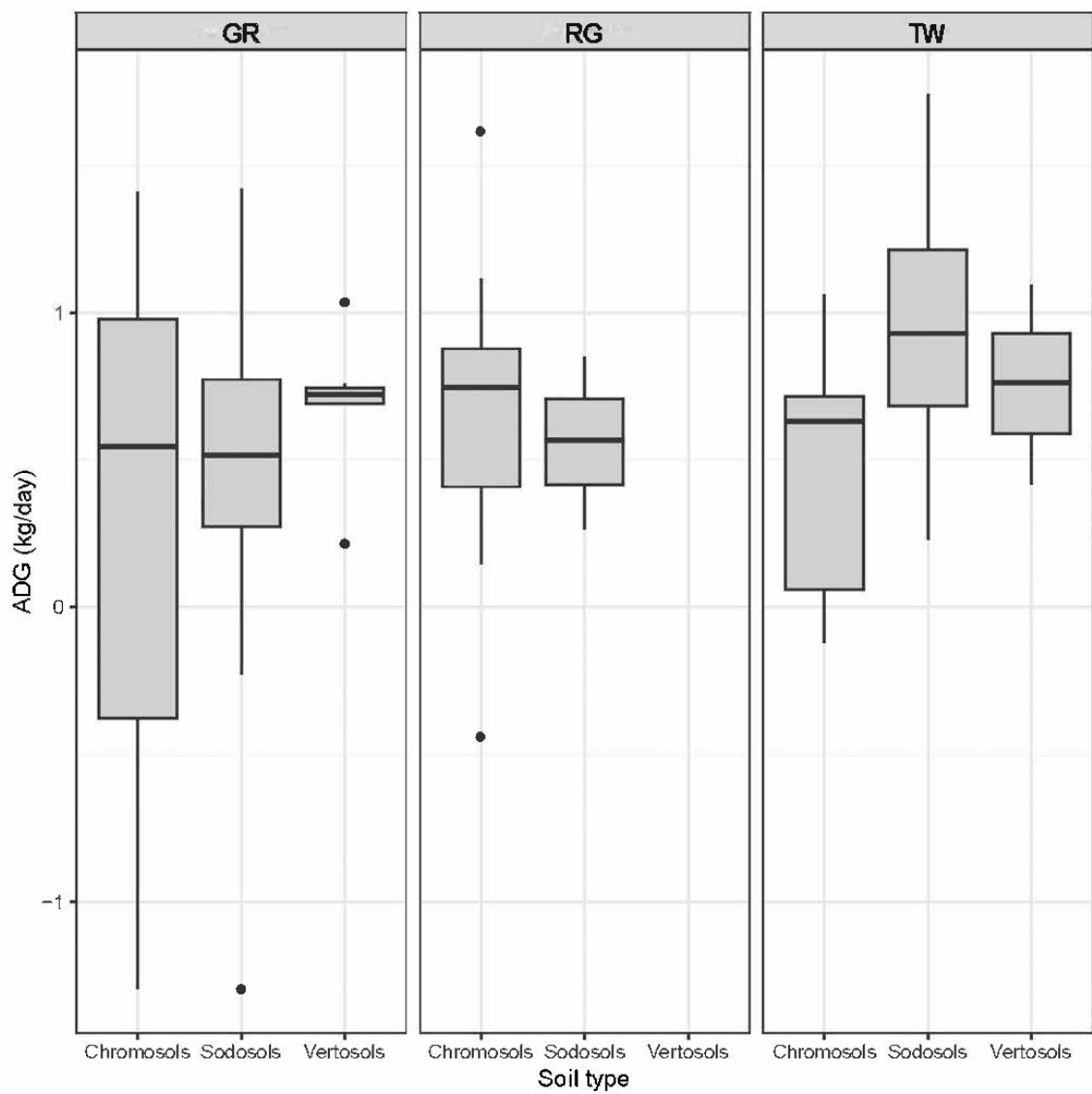
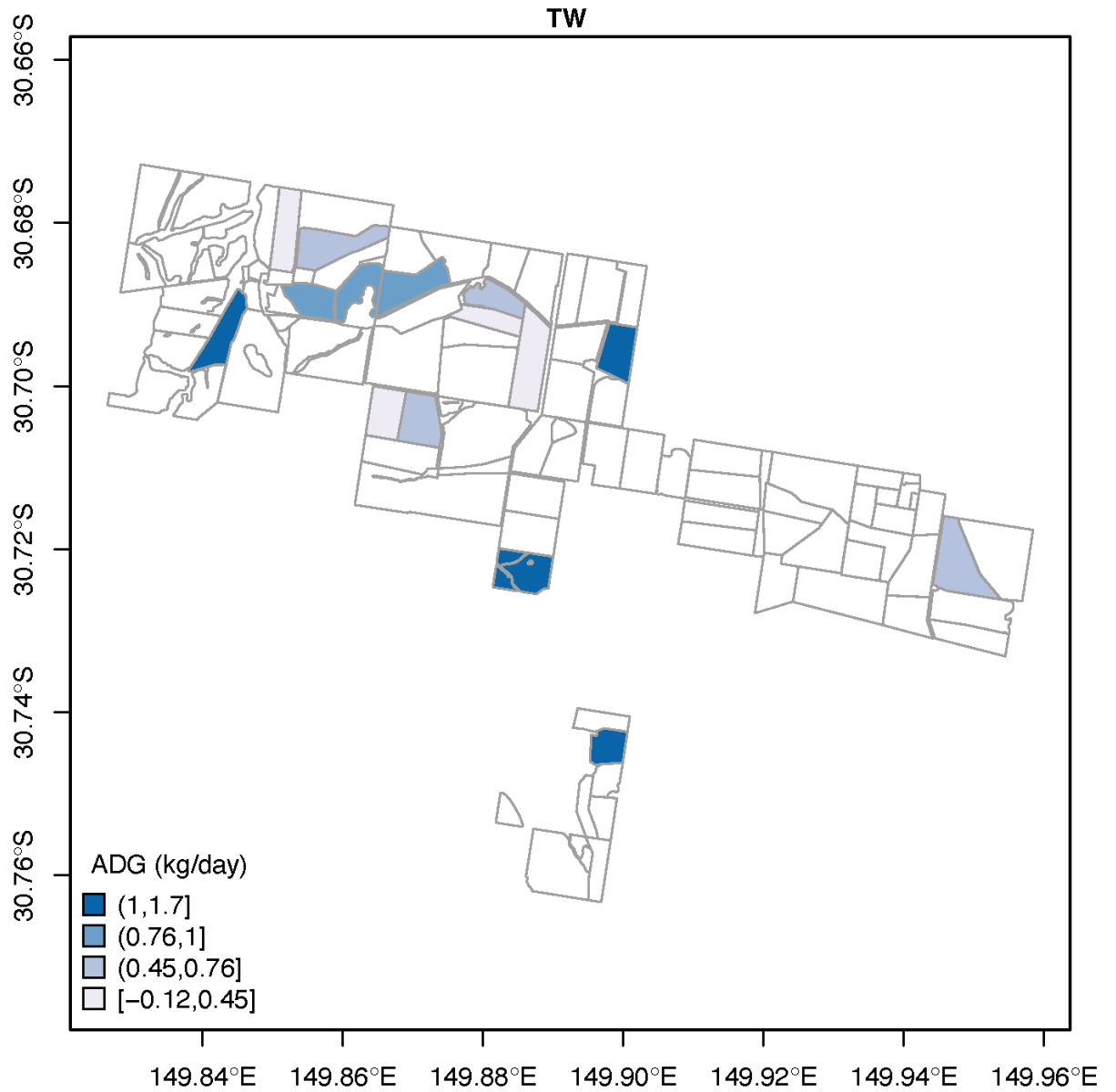
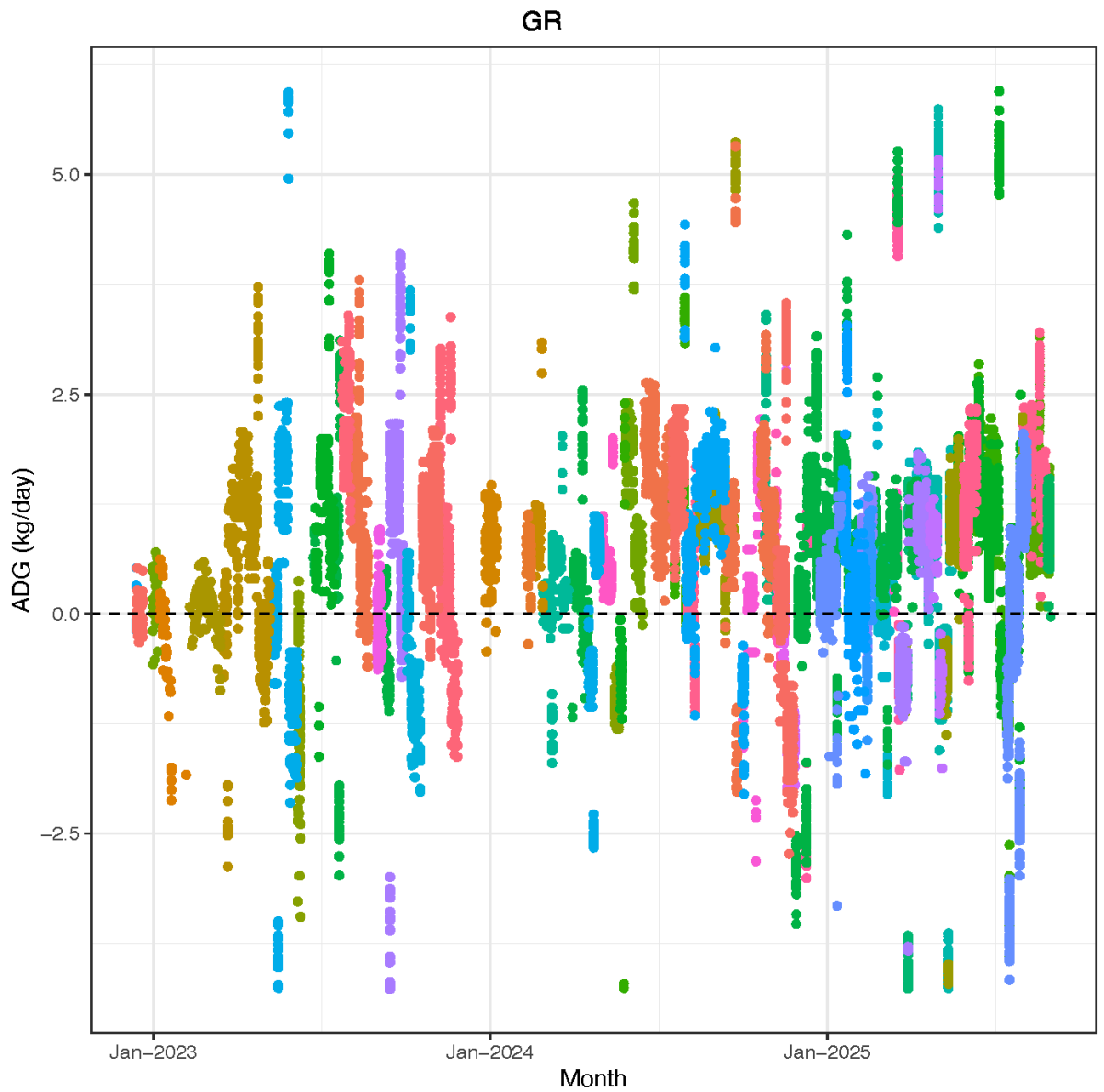


Figure 26 Average daily gain (ADG) by soil type across farms (GR, RG, TW)

### 8.3 Additional analysis outputs of ADG and TSDM data for farms



**Figure 27 Heat maps of estimated paddock mean average daily gain (ADG) for TW; colours represent four groupings of increasing ADG.**



**Figure 28 ADG (based on smooth weights) over time for GR, separate colour for each paddock.**

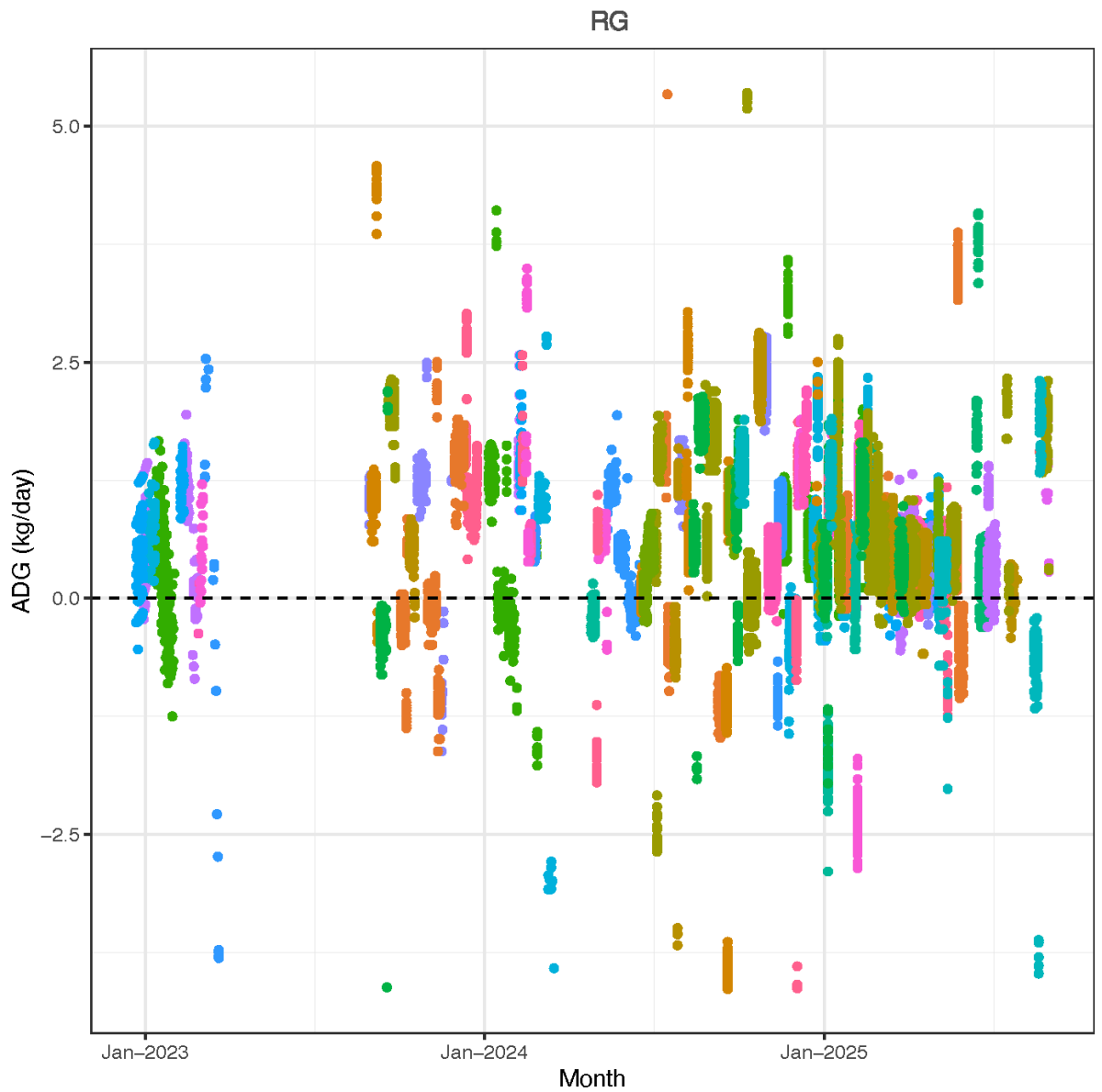
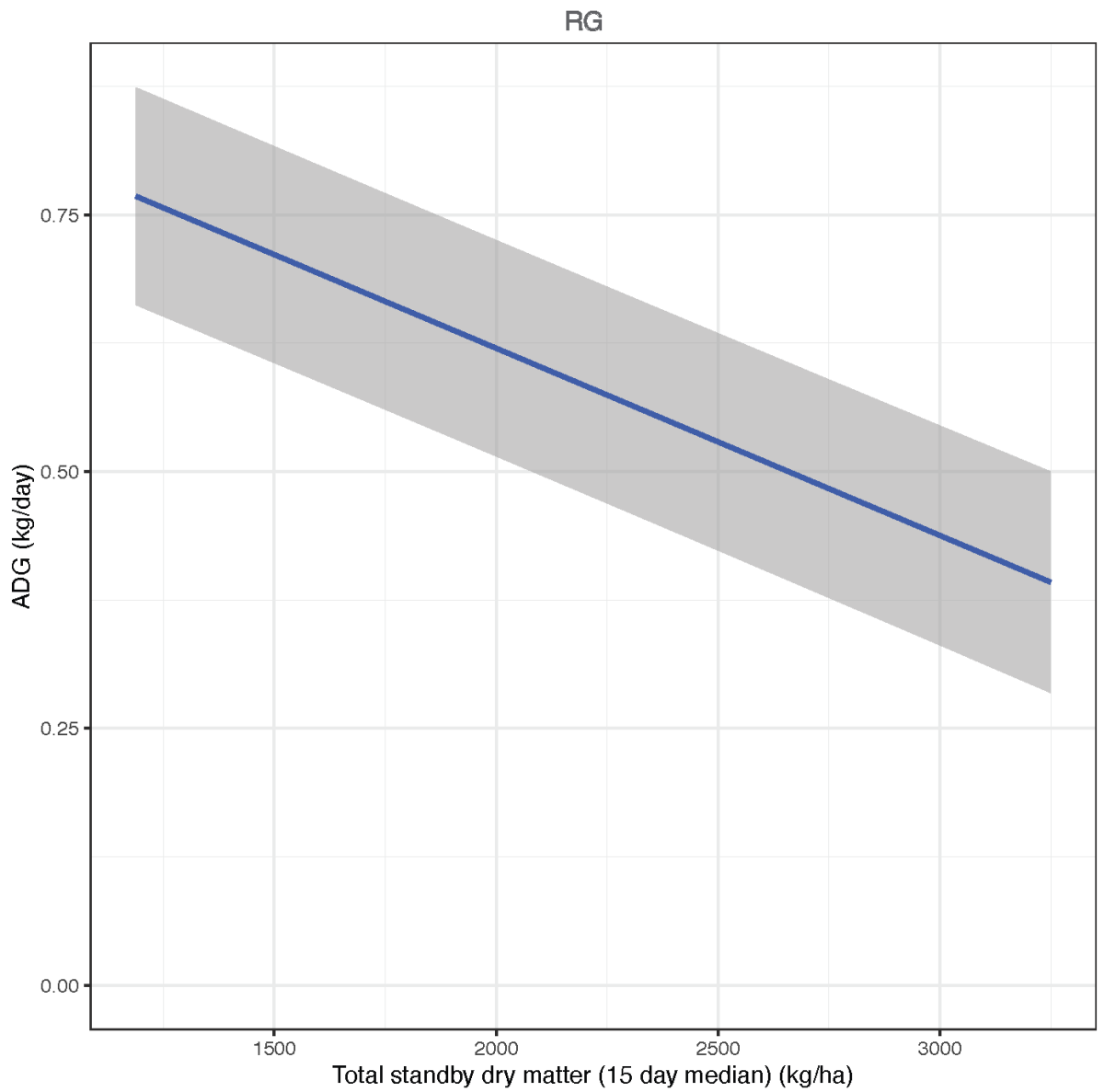


Figure 29 ADG (based on smooth weights) over time for GR, separate colour for each paddock.



**Figure 30 Model-based average daily gain (ADG) versus total standing dry matter (TSDM) at the start of paddock allocation for RG.**

#### **8.4 Gross margins analysis (AgEcon)**

An excel template was customised for each of the three farms to create a gross margin comparison tool and provided to the farm managers. This included a paddock comparison sheet, a sheet outlining the variable costs of livestock production and a sheet for each type of forage base, outlining the variable costs of that pasture. Examples of sheets are provided below (**Figures 31 and 32**). The spreadsheets were provided unlocked so they may be altered by the farm managers and used as a tool for their livestock management. **Figure 33** demonstrates visualisation of gross margins and costs which provide producers with a quick snapshot of where they can target improvements for returns.



Pastures Gross Margin Budget Overview									
Overview:	Straight Angus, herd = 15 bulls + 600 cows + 550 proginey 600 cows			Value	\$3.94 /kg	(Net of sales cost)			
Paddock name	Description	Size	Paddock costs (Total)	Livestock costs (Total)	Paddock income (Total)	Total paddock GM	GM \$/ha	Total Days in paddock	Ave kg/hd gain
Tip paddock	Forage - Mixed	27.5	\$ 10,682.38	\$ 1,502.57	\$ 17,833.30	\$ 5,648.36	\$ 205.39	31	22.63
Fuel tank	Forage crop - straight oats	25.0	\$ 9,711.25	\$ 5,234.75	\$ 48,844.13	\$ 33,898.13	\$ 1,355.93	108	61.98
Wynella House	Improved perienial pasture	21.0	\$ 1,232.00	\$ 484.70	\$ 5,887.10	\$ 4,170.40	\$ 198.59	10	7.47
Low road*	Improved perienial pasture	40.9	\$ 2,400.05	\$ 2,859.72	-\$ 23,814.28	-\$ 29,074.05	-\$ 710.68	59	-30.22
Windmill	Improved perienial pasture (digit etc)	30.5	\$ 1,789.33	\$ 630.11	\$ 16,979.33	\$ 14,559.89	\$ 477.37	13	21.55
Alberts	Perienial pasture	26.7	\$ 1,566.40	\$ 727.05	\$ 14,024.53	\$ 11,731.08	\$ 439.37	15	17.80
Longlands	Perienial pasture	35.6	\$ 2,088.53	\$ 3,344.42	\$ 12,556.32	\$ 7,123.36	\$ 200.09	69	15.93
Duckpond	Perienial pasture (mostly unimproved)	33.0	\$ 1,936.00	\$ 2,665.84	\$ 64,935.70	\$ 60,333.86	\$ 1,828.30	55	82.40
<b>TOTALS</b>									

Figure 32 example result summary from the excel template

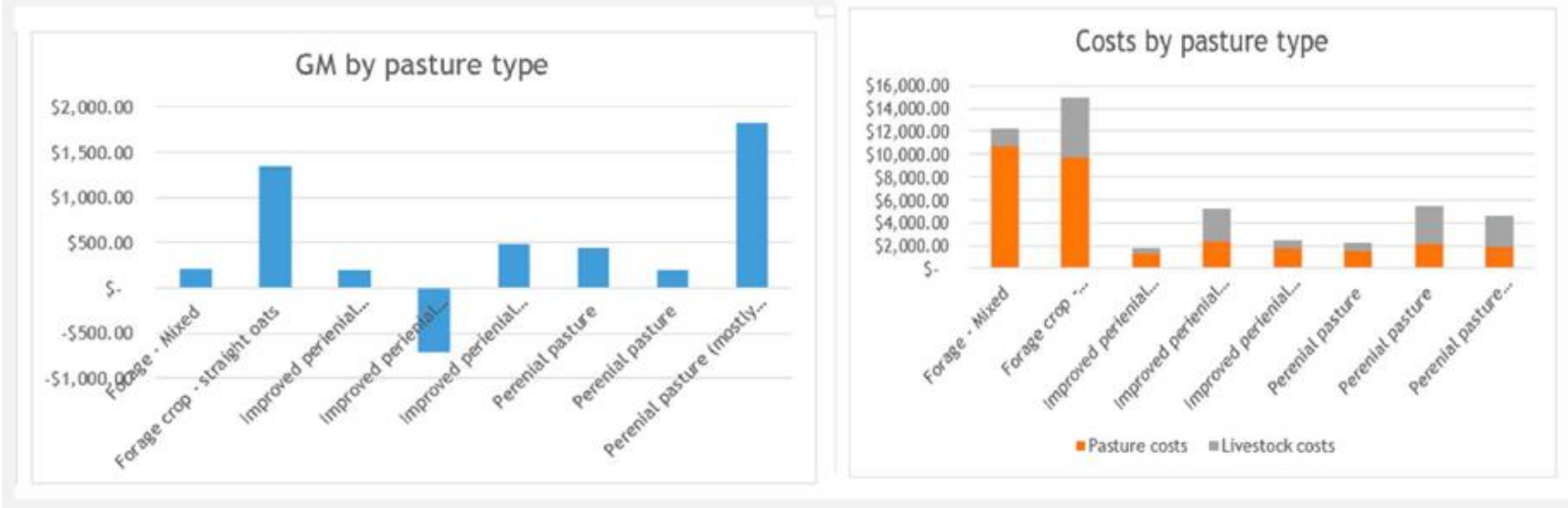


Figure 33 Example results graph

## 8.5 Pasture quality feed assessment

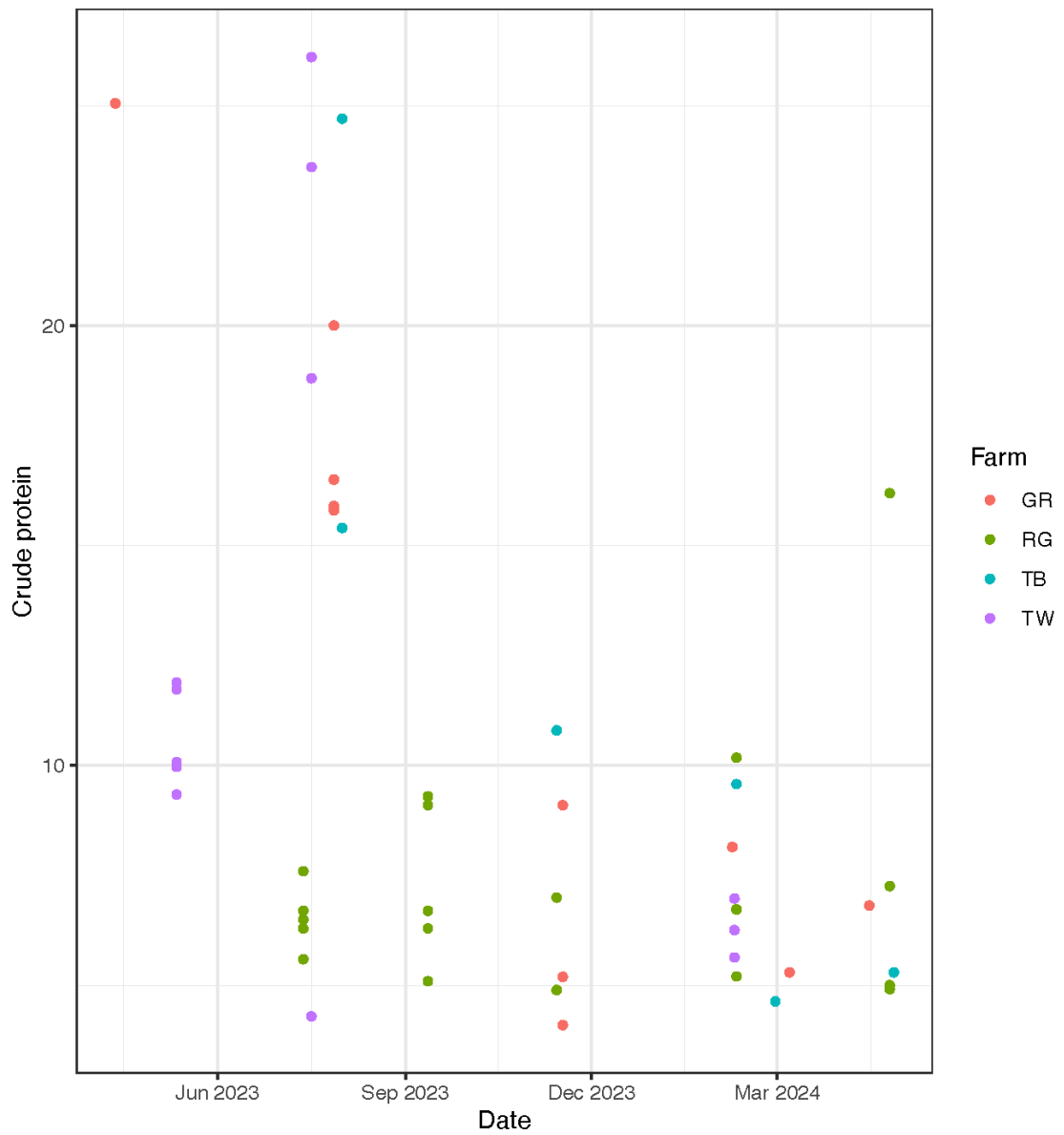


Figure 34 Plot of crude protein (%) on each recorded paddock (to Jan 2025) for each farm (GR, TW, RG).

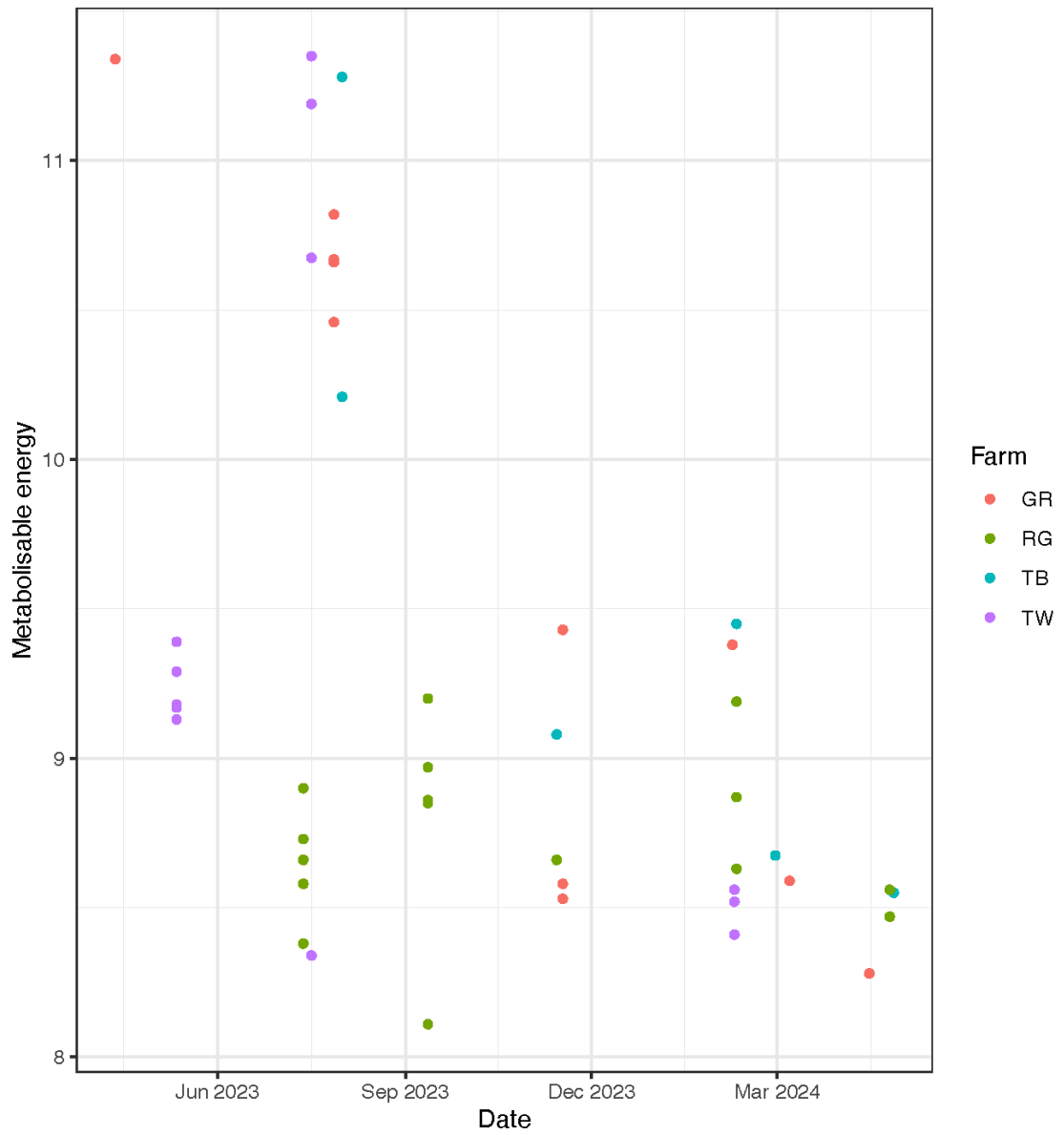


Figure 35 Plot of metabolisable energy (MJ/kg Dry Matter) on each recorded paddock

