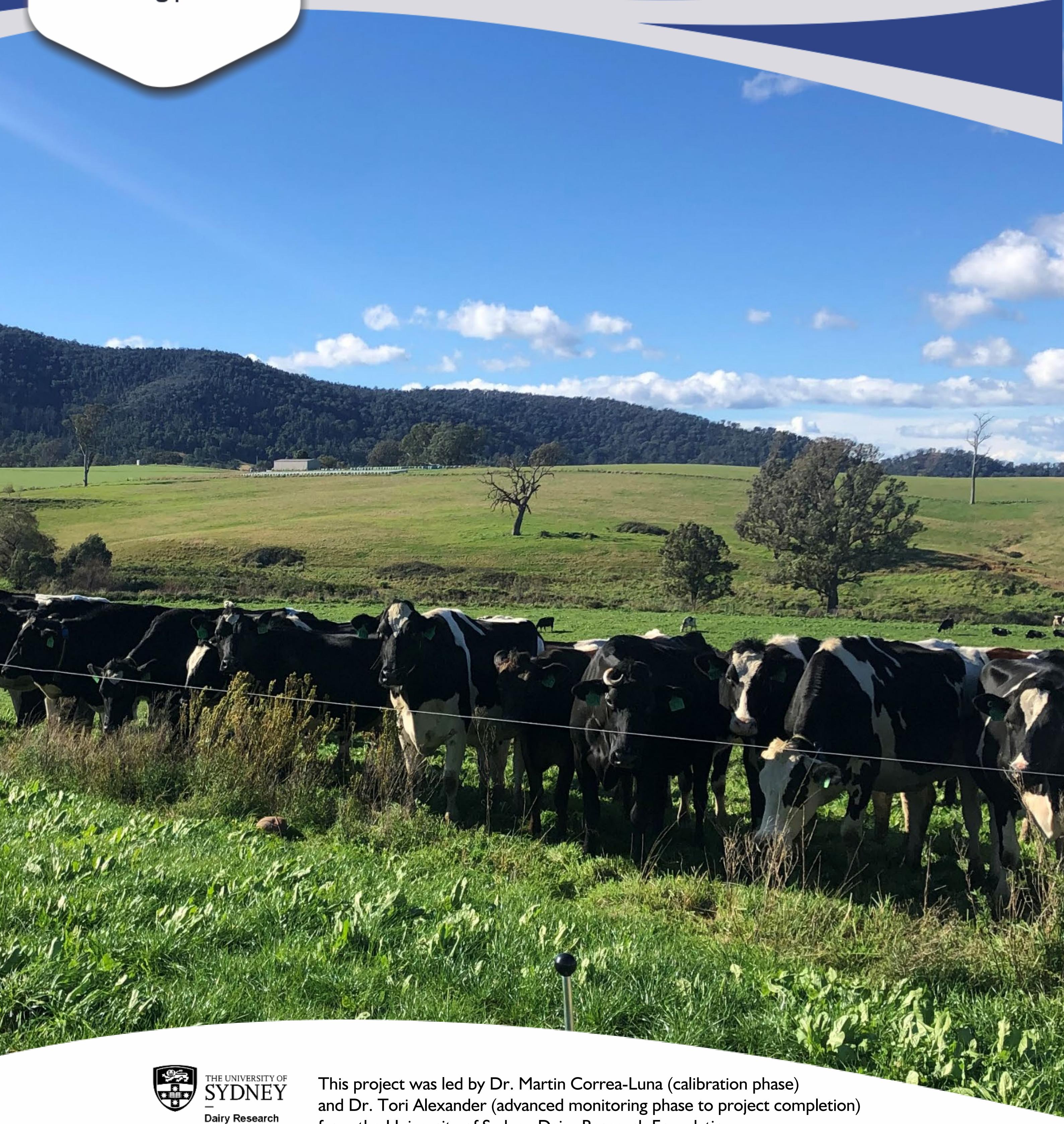
Final Report

P1a - Improving Kikuyu's productivity through remote sensing and data-based management



THE UNIVERSITY OF SYDNEY
Dairy Research Foundation

This project was led by Dr. Martin Correa-Luna (calibration phase) and Dr. Tori Alexander (advanced monitoring phase to project completion) from the University of Sydney Dairy Research Foundation

Dairy UP (Phase 1) was a $16 million, five-year industry driven project with a portfolio of 10 research, development and adoption projects collectively aiming to realise three primary objectives:

- Increase Productivity and Profitability by unlocking the potential of milk, the cow and water,
- De-risking the industry and
- Developing new markets.

A key part of Dairy UP was a coordinated network of partner farms across New South Wales (and beyond) providing valuable insights into real world application of new practices, including the challenges and benefits of new innovative technologies.

Dairy UP made a big contribution to dairy research and development rejuvenation, (attracting new researchers, PhD students and Industry investment).

Dairy UP was funded through the Australian and NSW Government's Bushfire Industry Package – Sector Development Grant (BIP-SDG) program, with cash co-contributions from Dairy Australia, The University of Sydney's Dairy Research Foundation, Local Land Services, Norco, Leppington Pastoral Co Ltd and Dairy NSW; and in kind contributions by all the above organisations plus NSW DPI (Biosecurity and Food Safety; Agriculture), Scibus, Australia Fresh Milk Holding Ltd, Dairy Connect and NSW Farmers.

This project was delivered jointly by University of Sydney's Dairy Research Foundation, Scibus, Department of Primary Industries and Regional development.

Proudly funded by

Delivery organisations

Additional program supporters, collaborations or partnerships

Charles Sturt University | DairyBio | DataGene | Eagle Direct | Entegra | Macquarie University | NSW EPA | smaXtec | UC Davis | University of Technology Sydney

Contents

1. Executive Summary

This report includes a synopsis of the P1a Dairy UP project "Improving Kikuyu's productivity through remote sensing and data-based management", offering a description of the sampling procedures and methodologies, key findings, implications and future considerations of the research, informed by results and farmer feedback.

The project's goal was to utilise a remote monitoring technology on NSW dairy farms to support pasture management through providing accurate and timely observations of pasture biomass, and to test and validate the reliability of the technology. Secondary to this, the project also conducted an exploration into further information that could be produced from the data generated by the remote monitoring technology which could aid decision making and provide a snapshot of pasture production and utilisation.

Farms participating in the project (n=16) were located across three distinct dairying regions of NSW, being the north coast, mid coast and south coast. Data were recorded over a two-year period, with farms being monitored by a commercially available remote monitoring satellite technology (RMST; Pasture.io) as well as on-ground monitoring with a calibrated rising plate meter (RPM). Other on-ground observations (e.g. farmer perception, farm management activities, pasture samples) were also made, with regular contact and dialogue between participating farmers and project officers.

The project confirmed the RMST could measure pasture biomass with comparable predictive precision to a calibrated RPM, although this level of accuracy was only achievable with fortnightly training of the RMST (involving measuring five representative paddocks with a RPM every fortnight; Correa-Luna, M., *et al*, 2024). The time required to measure the paddocks (approx. 1.5 h fortnightly) with a RPM was relatively low (particularly compared to the potential benefits), however is still perceived to be a barrier to adoption. A potential solution would be to develop an automated strategy to take on-ground pasture measurements for calibrating the technology, or alternately to improve the technology to a point where calibration is no longer required.

Through objectively monitoring pasture biomass using a RMST ("advanced monitoring"), the project identified that, on average, farms grew over 4 tonnes DM/ha more pasture than what they utilised through grazing-based activities (could also be perceived as "wastage"). Reducing this gap between pasture grown and pasture used through increasing pasture use would not only improve pasture utilisation but also have a potential large-scale positive impact in the business by more effectively utilising home-grown feed (pasture).

Further exploration of the data was able to quantify the relationship between pasture grown and pasture utilised. As expected, higher volumes of pasture grown were tied to higher pasture utilised. However, there was variation in pasture used between farms with the same or similar pasture grown. Some management factors were found to impact pasture utilisation (pasture use efficiency), being pre- and post-grazing biomass and grazing frequency (number of grazing events per year). Farm characteristics such as size and number of paddocks were not shown to be significant factors in pasture use.

Future research should focus on working with farmers, while monitoring their pasture through advanced monitoring techniques, to capture the steps/strategies and management decisions which lift pasture productivity and utilisation, the changes in management due to incorporating advanced monitoring techniques and the impacts on business performance (e.g. milk yield and, in turn, profitability).

Outside of the outcomes of the project, participating farmers received individualised reports outlining their farm's performance (including benchmarking with their region and all farms in the project) and were given the opportunity to provide feedback on their experience and value of the information generated. During data collection and following receipt of their individual farm report, farmers perceptions and confidence in the technology were observed. At the conclusion of the project, and after receiving their report, farmer confidence in the technology increased from 2.6 to 3.6, a rise of 38% (scored out of 5, with 1 being not confident and 5 being very confident). Commonly mentioned reasons why farmers felt information presented in the report was important included that it supported management decisions, offered reassurance and identified issues/areas of improvement.

Results illustrated how data from the trained RMST can aid in highlighting biomass and paddock variability, along with room for improvement in pasture production and utilisation. This work showed that satellite technology is a potential tool to assist farmers when making decisions related to pasture management, as it can not only monitor pasture in every paddock across the farm, but also provide information which can be used to quantify potential pasture losses, highlight inefficiencies and support decisions around productivity and profitability.

2. Project Overview

Item	Description
Project Title	Improving Kikuyu's productivity through remote sensing and data-based management
Funding Body	Dairy UP
Dairy UP Project	P1a
Project Duration	2022-2026
Lead Organisation	The University of Sydney
Project Lead	Dr. Martin Correa-Luna (calibration phase) Dr. Tori Alexander (advanced monitoring phase to project completion)
Research team	Prof. Sergio Garcia, Dr. Fernando Masia, Dr. Juan Gargiulo, Blessing Azubuike, Prof Cameron Clark, Peter Beale, Josh Hack, Chloe Wilson, Zac Geldof, Mikayla Woods, Kate Ireland
Key Collaborators	NSW Department of Primary Industries and Regional Development, NSW Local Land Services

3. Abbreviations

DM — Dry matter
GPS — Global positioning system
Ha — Hectare
Kg — kilogram
MAE — Mean absolute error
NSW — New South Wales
RPM — Rising plate meter
RMSE — Root-mean-square error
RMSPE — Root-mean-square prediction error
RMST — Remote Monitoring Satellite Technology
t — Tonne
TO — Technical Officer

4. Project Background and Rationale

Pasture productivity and utilisation across most pasture-based dairy farms in Australia has stagnated for some time and has long been seen as an area where improvements are possible but are currently unrealised. It is well understood that pasture management can be challenging and multifaceted, and losses contributing to differences between potential and realised pasture production and utilisation occur for a variety of reasons (Figure 1). These losses are not only in quantity (e.g. reduced production), but also in quality, and are often cumulative and difficult to quantify (hidden) (Garcia, S., *et al*, 2014).

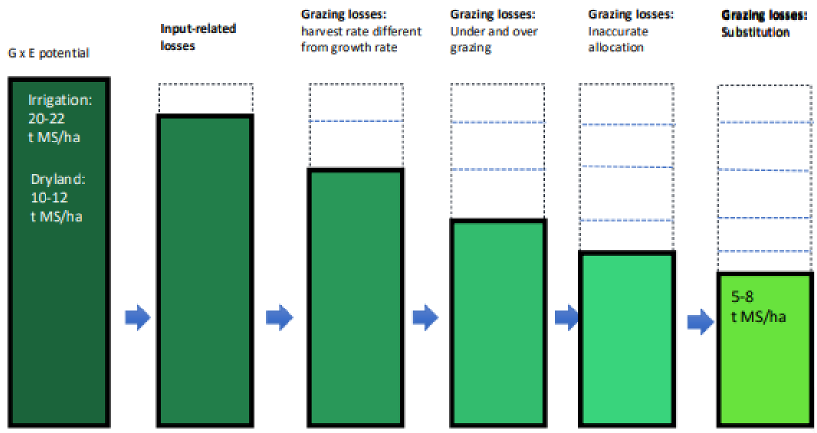


Figure 1: Illustration of some of the sources contributing to lost pasture productivity and utilisation, from research completed by the FutureDairy program (Farina et al., 2011).

Traditional monitoring (e.g. weekly pasture walks with a RPM) can help identify some of these losses but is not commonly performed on commercial dairy farms, with anecdotal evidence suggesting farmers may perceive objectively monitoring pastures as time consuming, may not be fully aware of the benefits or value of objectively monitoring, or may even lack trust in tools (Heins, B. J., *et al, 2023)*. Traditional methods of monitoring pasture are also limited somewhat in the level of detail they can provide when it comes to detecting and quantifying the full extent of hidden losses. However, technological advancements mean that farmers have access to tools that offer the option to monitor pasture remotely (via satellite, referred to here as an RMST).

This project set out to assess an RMST (the commercially available tool "Pasture.io") for suitability in monitoring pasture production in dairy systems. This tool (in its premium version) specifically uses satellites (Sentinel and Planet) for remote monitoring of pasture biomass and growth rates and integrates the use of cow-worn global positioning system (GPS) collars to automatically track grazing events and cow location on the farm.

The assumption was that utilising objective and reliable information captured by the RMST; farmers and operators could make informed decisions about their pasture management which are not influenced by subjective factors (e.g. estimates from eye assessments). It was also anticipated that using a RMST would encourage and support better communication between farmers and their farm advisors, staff, and researchers, and provide whole-of-farm pasture measurements at any given time. With progressive updates in system performance over time, problems can be identified and addressed, and outcomes improved.

5. Project Objectives

The primary goal of this project was to support NSW dairy farmers with their pasture management through testing an automated RMST which measures and estimates pasture growth and biomass. Current management practices and pasture biomass data were passively observed on the milking platform for all participating farms to assist in identifying excelling from underperforming paddocks and management settings and provide an independent assessment of the accuracy of the RMST being used. Once this had been achieved, the project then intended to actively work with the participating farmers to use the data and information produced by the RMST to make informed decisions to enhance pasture management. Unfortunately, the findings and outputs of the primary goal prohibited the project from embarking on its intention to actively work with farmers, as will be explained in this report. However, it is recommended that this work occur in the future.

A second objective of this project was to explore current pasture productivity and utilisation for the participating farms, as well as delving into the data obtained to better understand additional pasture management factors such as potential losses (grown vs grazed/harvested) and differences in pasture utilisation between paddocks under the same management.

To achieve the primary goal of the project, it was important to consider:

- Calibration of satellite data with field measurements – confirming how accurate the RMST was at measuring on-ground biomass, and then to determine how many field measurements are needed to calibrate the satellite to achieve accurate pasture cover and growth estimations.
- On-farm factors related to calculation of growth rates and pasture cover – requiring accuracy of the data flow – e.g. correct recording of when and where grazing events occurred (signalling pasture regrowth) or when farm operation occurred (e.g., mulching, spraying, sowing, fertiliser or missed fertiliser).
- Off-farm factors related to calculation of growth rates and pasture cover – requiring the software program to be adaptable and deal with missing data (e.g., missed readings from cloud cover, or irregular satellite flyovers).

6. Materials and Methods

Initial farm set up

The project monitored **pasture produced** (total amount of pasture grown, measured through objectively estimated weekly growth rate throughout the year) and **pasture utilised** (or harvested, being total pasture depletion from grazing events including direct grazing and cutting where it occurred) on 16 commercial dairy farms over a two-year period between July 2022 and June 2024. Data were collected remotely (from the RMST) and on ground with a Technical Officer (TO) taking measurements (RPM, pasture samples). Farmers were not directly engaged in the project activities, and data collection was largely passive in nature.

To capture representation across key dairying regions in NSW (including different climates), participating farms were located across 3 distinct geographical regions, being North Coast (n = 4), Mid Coast/Hunter (n = 7) and South Coast/Bega (n = 5) (Figure 2).

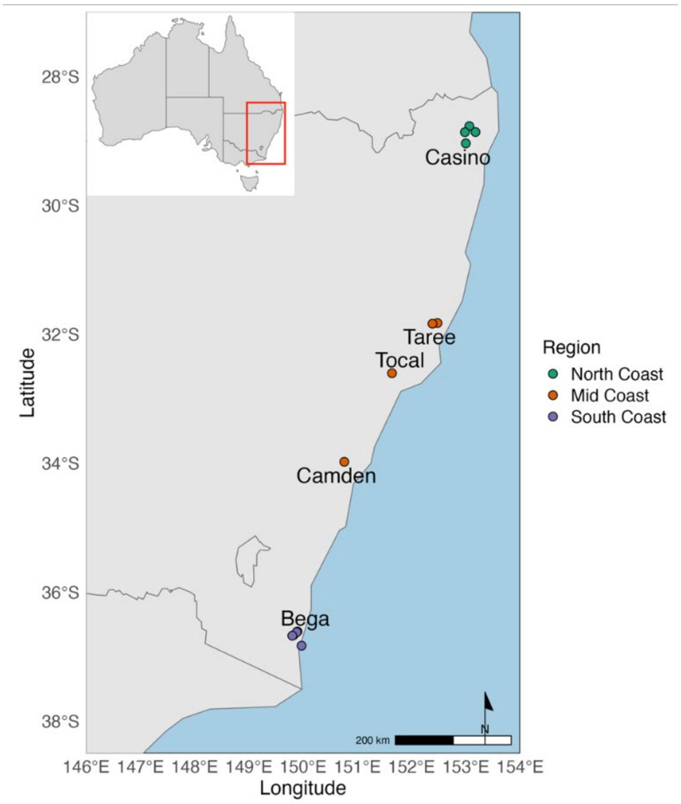


Figure 2. Location of the participating farms in New South Wales, Australia.

Farms were selected to participate in the project based on specific criteria, which included that they operate on an annual ryegrass–kikuyu grazing rotation. These systems typically involve grazing temperate C3-grass species such as annual ryegrass (*Lolium multiflorum L.*), which is generally sown in early autumn and grazed during winter and spring months, followed by grazing of the tropical perennial C4-grasses such as kikuyu (*Cenchrus clandestinum*) over the warmer months of the year (Garcia, S., *et al*, 2014).

Other criteria for participation in the project included:

- Willingness of the farmer/family to work with the project team; as well as the openness to try new things and/or work with the project constructively.
- Having sound cow performance data, including health, reproduction, and milk production data at the individual cow level.
- Having a continuous calving system with variable supplementary feed included throughout the year.
- Being located within reasonable distance from each other to facilitate travel and monitoring.
- Being reflective of typical dairy farm businesses (e.g. farm size).

Once a farm was formally recruited, the TO initiated the farm set up in the RMST. Set up included using a farm map to objectively determine paddock locations and sizes, which was then confirmed by the farmer. Table 1 includes a brief description of the initial farms included in the project. Out of all the farms, one utilized a robotic milking system and half of them had irrigation capability in at least some of their paddocks.

Table 1. Description of the participating farms in the project.

Farm	Area (ha)	Paddocks	Paddocks with irrigation capability	Milking system	Milking herd
North coast					
Farm 01	90.3	60	38	Conventional	175
Farm 02	130	35	-	Conventional	250
Farm 03	131.8	76	6	Automatic	210
Farm 04	105.6	43	-	Conventional	190
Mid coast					
Farm 05~	218.8	64	-	Conventional	388
Farm 16*	229.1	60	-	Conventional	440
Farm 06	174.8	46	46	Conventional	280
Farm 07	64.5	22	-	Conventional	200
Farm 08	134.1	27	-	Conventional	300
Farm 09	88.9	39	-	Conventional	105
Farm 15	83.4	39	-	Conventional	258
South coast					
Farm 10	260.4	53	8	Conventional	291
Farm 11	199.2	77	16	Conventional	160
Farm 12	152	48	35	Conventional	300
Farm 13	313	83	48	Conventional	580
Farm 14	149.4	45	14	Conventional	200

~This farm was sold and left the project after Year 1. *This farm replaced Farm 05 in March 2023.

Manual farm monitoring activities (on ground)

The procedural protocols for the project were meticulously formulated and deliberated upon with the project team at the project's inception. The following section includes the main considerations of the methodology.

Year 1 data collection procedure

Five paddocks per farm were monitored weekly by a TO during year 1, which ran from July 2022 until June 2023. The paddocks were selected based on the below criteria, enabling comparison across farms and regions and at the same time representing the baseline of a typical grazing platform for the dairy systems in the project. Selection criteria included:

- Pasture composition: ryegrass presence from autumn to late spring and thick and evenly distributed kikuyu presence during summer months.
- Proximity to the dairy: avoid paddocks too close to the dairy (greater risk of being night-paddocks or sacrificed paddocks).
- Being relatively flat.
- Had permanent fences.
- Sites convenient to road access to enable quick entry in and out of paddocks.

For each paddock, the TO measured and collected:

- Weekly pasture cover, using a calibrated RPM (Jenquip EC20 Electronic Pasture Meter, Fielding, New Zealand).
- Monthly quadrant cuts at 5cm height, with 9 samples taken from two of the five paddocks (18 samples total each month) to calibrate the RPM. The two paddocks were pre-selected and always the same.
- Visual assessment of pasture botanical composition.
- Weekly farm management data (e.g. fertilisation, irrigation, sowing and mulching).
- Regular checking of cow GPS collars for technical issues.

Cutting pasture to 5 cm height enabled samples to be dirt-free, desirable for water content determination and minimised the risk of collecting dried and dead biomass. Pasture cut samples were lab tested to measure metabolisable energy, crude protein, acid- and neutral-detergent fibre, and water-soluble carbohydrates content among other nutritional indicators. Pasture cuts were also used to calibrate the RPM.

Visual assessments of pasture botanical composition involved assessing photos along with the field notes taken on the date the paddock was monitored. A scoring system representing a percentage applied to each pasture type was implemented with the following classes: “annual ryegrass”, “kikuyu”, “white clover”, “other grasses”, “weeds” (predominantly broadleaf species), and “dead material” (of any species). This allowed a general characterisation of the pasture type (based on the main functional group of grasses) to be made throughout the duration of the project, with ryegrass-based pastures being any pasture with annual ryegrass and white clover presence higher than 70%. Similarly, when kikuyu and other grasses different from annual ryegrass were the main grasses present, pastures were categorized as being kikuyu-based.

Grazing records were automatically made (usually daily) using cow collars with integrating GPS trackers. These trackers generated a GPS point every three minutes, and data was automatically fed into the RMST. Each farm used 3 trackers across the milking herd, although the AMS farm used 5 trackers.

Year 2 data collection procedure

Results from Year 1 indicated that fortnightly data were the minimum required for satellite calibration (see below and Correa-Luna *et al*., 2024). Thus, commencing in July 2023, TO's began fortnightly visits to participating farms. During each visit, the following were measured with a calibrated RPM:

- Pasture cover from the same 5 paddocks as Year 1 (data used to calibrate the RMST) – same methodology as outlined for Year 1.
- Pasture cover from the paddock about to be grazed on the visit day (pre-grazing paddock). Pasture samples from this paddock (hand plucking at grazing height observed when visiting the farm) were also collected for quality analysis.
- Pasture cover of nearby grazed paddocks (post-grazing paddocks) were collected for quantification of grazing intensity, pasture allocation assessment, pasture use efficiency.

These visits provided an opportunity for the TO to engage with interested farmers, and to gather informal feedback from farmers on the functionality of the RMST. Insights into recent farm management practices, including cow feeding strategy and pasture allocation management, were also obtained.

Similarly to year 1, grazing events were monitored using GPS cow collars. In cases where GPS trackers failed to generate grazing records, TO's collected records from the dairy. These records were obtained by contacting farmers or accessing existing records and were manually entered into the RMST.

Remote farm monitoring activities

Weather data

Climatic data (daily rainfall, maximum and minimum air temperature, and global solar radiation) for each farm were obtained from the closest Australian Bureau of Meteorology Weather Station via the SILO service (www.longpaddock.qld.gov.au/silo/). This was important information to collect, as pasture growth is strongly linked with weather and climate factors.

RMST raw data

The RMST used works on algorithms originating from a series of machine learning models utilising neural networks developed from: (i) satellite optics and sensors; (ii) weather and atmospheric conditions; (iii) farm management activities (i.e., grazing records, fertilisation, pasture silage making); and (iv) pasture biomass measurements manually added by the user (which were strictly controlled for the purpose of this project). The remote sensing data originated from the PlanetScope CubeSats constellation (Planet Team, 2021) and the Copernicus Sentinel-2 mission (European Space Agency, 2022). While the PlanetScope CubeSats constellation provides multispectral data at 3–4m spatial resolution with a 30h global median average revisit interval, Copernicus Sentinel-2 images provide a lower spatial (10–60m) and temporal (five days) resolution imagery. By utilising a combination of the remote sensing data mentioned, the machine learning process generates algorithms for estimating pasture biomass and growth rate employing multiple bands (i.e., NDVI, EVI, ENDVI, SAVI) which are embedded within the satellite images.

Bulk raw data for all participating farms was accessed every two months. This data was mainly comprised of pasture biomass cover estimated by the RMST, grazing records generated with GPS trackers, and any farm management practices entered manually into the RMST by the farmer or the TO.

To facilitate smooth collaboration and data sharing between the research team and the operator of the RMST, a contractual partnership was established. This also ensured that reporting remained unbiased and transparent, without any conflicts of interest. Additionally, the research project had full access to the raw data produced by the RMST, enabling thorough analysis and evaluation. This collaboration reflects a dedication to scientific integrity and advancement in enhanced pasture management using remote sensing.

Evaluation metrics

The results of the manual monitoring were compared with predictions made by the RMST, which used high resolution satellite images to estimate pasture biomass. It could also incorporate local information (e.g. weather, soil and farm management data) which can be used to assist farmers in making informed pasture management decisions. The RMST had been developed and validated for perennial ryegrass pastures however NSW pastures are a mix of C3 (e.g. ryegrass) and C4 (e.g. kikuyu) grasses, and it was therefore important to compare the RMST pasture predictions with the on-ground manual measurements to independently evaluate the RMST for use in these types of pasture-based dairy systems (predominant in NSW, but common in many other dairying regions across Australia).

All evaluation undertaken included the root-mean-square error (RMSE) expressed in biomass (kg DM/ha) and in percentage of the observed pasture biomass. The RMSE was also decomposed by the three types of error: error in central tendency which is a measure of precision, error due the slope regression which refers to the accuracy, and error due to the disturbance which cannot be reduced. Given the contrasting range of conditions across farms in this study, the mean absolute error (MAE) was also reported (kg DM/ha and as a %) since it is less sensitive to potential outliers. For those comparisons with different numbers of observations, the RMSE to standard deviation of observed values (RSR) was also included.

7. Key Findings

Weather observations

Key observation: Weather patterns fluctuated throughout the project, and many farms experienced significant wet weather, or even flooding, throughout the project.

All three regions experienced an excessively wet autumn and spring in 2022 (start of Year 1), which continued into Year 2 (Table 2). These wet conditions (including flooding in some areas) were a significant challenge for farmers to manage and made quadrant cuts (to calibrate the RPM) difficult for TO's, resulting in some monitoring activities being impacted temporarily.

Table 2. Mean monthly rainfall (mm) during the project, separated into the three farm regions of New South Wales, Australia. Historical mean monthly rainfall produced from records starting on 01/01/1900.

Region	North coast		Mid coast		South coast	
	Monthly rainfall	Historic monthly rainfall	Monthly rainfall	Historic monthly rainfall	Monthly rainfall	Historic monthly rainfall
Year 1 (2022-2023)						
July	64	51	327	65	15	49
August	14	38	27	52	31	43
September	94	38	125	54	108	45
October	106	70	175	76	178	63
November	16	86	47	86	46	71
December	50	119	37	92	21	75
January	55	131	108	113	52	74
February	52	151	84	131	82	85
March	110	146	146	144	36	89
April	28	88	120	108	16	60
May	49	79	24	88	27	62
June	14	68	8	93	2	66
Total	652	1065	1228	1102	614	782
Year 2 (2023-2024)						
July	13	51	28	65	1	49
August	13	38	22	52	19	43
September	17	38	11	54	4	45
October	39	70	87	76	43	63
November	139	86	86	86	263	71
December	68	119	103	92	255	75
January	155	131	82	113	61	74
February	110	158	182	135	44	88
March	80	115	67	116	53	75
April	188	87	189	108	100	61
May	100	80	109	87	144	62
June	6	66	103	93	49	67
Total	928	1039	1069	1077	1036	773

Pasture quality and composition

Key results: There was noticeable variability in pre-grazing pasture biomass, particularly in the spring/summer months (in line with knowledge of the prolific growth of summer grasses). The months where biomass was most variable was also linked to the pasture quality falling (higher fibre, lower metabolisable energy and crude protein).

Pre-grazing pasture biomass and chemical composition averages per farm and per season are presented in Table 3. The missing data in autumn for the north coast is due to a delayed start for the TO in that region. The relatively lower biomass in autumn (compared to other seasons) is reflective of the general reduction in pasture availability at this time (summer pastures dying back while winter pastures are establishing), meaning farmers often need to open a paddock for grazing "early" (i.e. before it reaches a standard biomass target of around 3,000 kg DM/ha). Conversely, in spring and summer the winter pastures die back, and summer pastures emerge, with summer pastures commonly growing more prolifically and are often linked to higher pre-grazing biomass as farmers may not be able to graze paddocks quickly enough (can lead to paddocks being dropped from the grazing rotation). The higher biomass is almost always linked with a higher NDF content, as is seen in these results, due to a higher portion of stem and more mature/older leaf.

Table 3. Average pre-grazing pasture cover and chemical composition results reported during year 1.

Region	Farm	Autumn					Winter					Spring					Summer				
		Pasture cover	ME[1]	CP[2]	NDF[3]	ADF[4]	Pasture cover	ME[1]	CP[2]	NDF[3]	ADF[4]	Pasture cover	ME[1]	CP[2]	NDF[3]	ADF[4]	Pasture cover	ME[1]	CP[2]	NDF[3]	ADF[4]
North coast	Farm 01						2,655	12.6	20.2	41.07	20.10	3,436	11.3	20.9	46.47	23.38	3,384	9.6	20.9	55.41	26.30
	Farm 02						3,223	12.5	27.4	44.59	20.79	2,995	11.2	25.9	47.78	22.31	3,279	10.1	21.6	53.71	23.63
	Farm 03						2,359	12.1	29.4	46.80	20.16	2,863	11.5	27.1	47.44	19.98	2,665	10.2	22.8	51.70	22.56
	Farm 04						2,488	11.4	25.3	38.54	17.05	3,014	11.2	22.6	48.55	21.98	3,213	9.5	21.1	55.52	25.30
Mid coast	Farm 05	2,794	8.7	21.3	58.89	25.24	3,111	11.4	22.9	54.81	25.55	3,087	10.1	23.2	47.69	25.23	2,692	9.8	21.8	53.23	23.31
	Farm 06	3,108	9.6	26.3	48.60	19.61	3,143	12.9	29.3	39.03	20.29	3,073	10.6	25.0	46.58	26.99	3,477	8.5	18.4	63.21	29.56
	Farm 07	3,155	8.9	22.4	59.32	23.45	4,003	11.5	27.7	40.51	20.47	3,586	10.4	22.3	49.28	23.50	3,673	9.6	23.1	52.56	23.09
	Farm 08	2,666	8.5	22.8	58.46	23.81	3,239	12.1	29.2	44.01	22.51	3,207	10.5	25.4	50.46	23.85	3,140	9.8	25.8	51.55	22.11
	Farm 09	3,296	8.2	23.3	59.20	23.35	3,155	11.4	27.7	47.99	22.27	3,477	10.1	24.1	51.61	23.01	3,363	10.1	24.2	49.11	21.27
South coast	Farm 10	2,929	11.0	22.6	49.53	24.80	2,914	13.1	24.6	42.53	20.56	3,037	11.9	23.0	41.84	21.21	3,321	9.9	19.2	52.76	26.81
	Farm 11	2,517	11.4	23.0	46.53	22.83	2,711	12.5	27.6	52.04	26.31	2,838	11.5	23.3	46.58	23.09	3,967	9.5	22.1	53.40	25.49
	Farm 12	2,569	10.7	24.3	49.35	21.90	3,342	12.9	21.2	42.16	21.48	3,207	11.6	19.6	46.65	24.02	3,923	10.1	19.8	51.25	24.72
	Farm 13	2,602	10.5	24.2	46.67	22.87	2,812	12.6	25.5	45.16	23.24	3,238	11.6	22.6	46.30	23.67	3,088	10.2	20.6	51.03	25.25
	Farm 14	2,527	10.5	22.5	52.66	23.74	2,749	12.4	24.3	48.29	23.80	2,837	11.5	20.9	44.89	22.73	3,117	9.7	19.1	52.86	25.52

1Metabolizable energy content, MJ ME kg DM-1. 2Crude protein concentration, %. 3Neutral detergent fibre concentration, %. 4Acid detergent fibre concentration, %. Note, farms 15 and 16 are not included as they were not part of the project in year 1.

Figure 3 summarises average values for pre-grazing pasture quality collected during the first year of the project. The "whiskers" (vertical lines at each graph point) indicate the variability between samples (standard error) collected for that specific measurement, where the larger the whisker the higher the variability. There is variability in pre-grazing pasture cover (Figure 3a), which was also shown in the pre-grazing biomass values presented in Table 3. This variability indicates that the pre-grazing biomass target (3,000 kg DM/ha) wasn't being consistently met at the time of grazing and is an area for further investigation and potential improvement. Energy (Figure 3b) and crude protein (Figure 3c) both dropped over summer, occurring during the same period when pasture cover variability tended to be highest (Figure 3a). Fibre content (Figure 3d) also increased at this time. This aligns with our understanding that the higher the pasture biomass (particularly above 3,000 kg DM/ha), the lower the nutritive value and digestibility (i.e. the lower the quality).

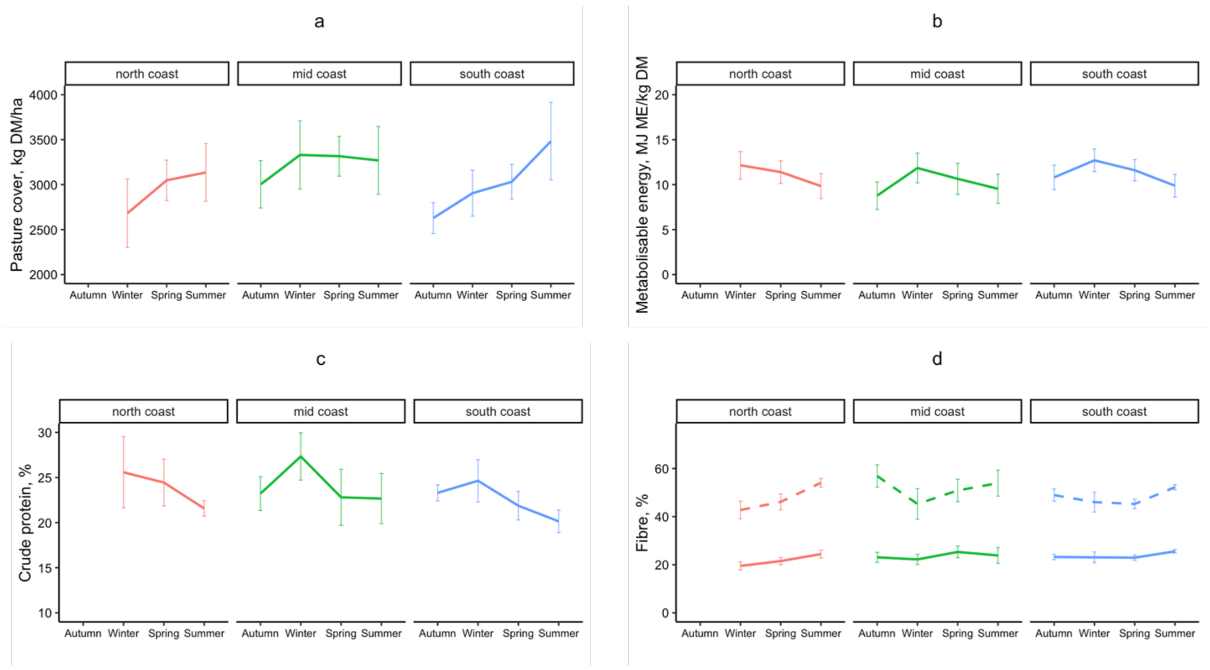


Figure 3. Mean pasture quality per season and region; a: pre-grazing pasture cover (kg DM ha-1), b: pasture energy content (MJ ME kg DM-1), c: crude protein concentration, d: neutral detergent fibre (solid line) and acid detergent fibre (dashed line).

As expected, pasture composition substantially changed during the year in all regions (Table 4). Annual ryegrass was the most predominant grass species in winter and spring, and kikuyu in summer. Autumn exhibited variability in the proportion of ryegrass and kikuyu present, with this being a period of transition where kikuyu starts to ease off and ryegrass becomes more prevalent. The further north (and typically the warmer the climate), the longer kikuyu persists, which is shown in the results with the north coast having the highest prevalence of kikuyu in Autumn out of the three farming regions. Other grasses noted included *Setaria sphacelata* var. *sericea*, *Paspalum dilatatum* Poir., and *Chloris gayana* in the North coast, and temperate grasses such as *Festuca arundinacea Schreb*., *Dactylis glomerata*, and perennial brome grasses in the South coast.

Table 4. Mean ± SD pasture composition content (%) throughout the year on farms located in three coastal dairy regions of New South Wales, Australia.

Region	Season	Annual ryegrass	Kikuyu	White clover	Other grasses	Weeds	Dead material*
North coast	Autumn	14.7 ± 0.01	70.0 ± 0.01	-	15.3 ± 0.01	-	-
	Winter	53.0 ± 28.1	15.3 ± 13.7	8.2 ± 6.2	17.3 ± 24.9	4.7 ± 10.1	1.6 ± 3.6
	Spring	50.9 ± 37.2	14.7 ± 23.2	7.1 ± 7.2	24.2 ± 26.1	2.9 ± 4.7	0.1 ± 0.7
	Summer	1.6 ± 6.0	61.5 ± 25.9	0.0 ± 0.0	33.6 ± 20.3	2.0 ± 4.1	1.3 ± 3.5
Mid coast	Autumn	38.5 ± 19.4	27.0 ± 18.9	7.8 ± 3.8	5.3 ± 5.7	8.0 ± 4.2	13.4 ± 7.4
	Winter	64.2 ± 22.7	20.0 ± 20.2	4.4 ± 5.3	3.3 ± 4.9	4.0 ± 4.9	4.1 ± 6.3
	Spring	55.3 ± 25.6	39.3 ± 22.3	1.3 ± 2.3	1.7 ± 4.3	0.0 ± 0.0	2.4 ± 6.1
	Summer	60.3 ± 21.5	34.5 ± 24.9	1.4 ± 2.2	1.9 ± 3.0	0.2 ± 0.7	1.7 ± 5.0
South coast	Autumn	13.7 ± 24.6	53.1 ± 32.0	1.2 ± 1.3	7.1 ± 11.1	6.1 ± 7.6	18.9 ± 19.9
	Winter	37.7 ± 24.5	26.6 ± 27.0	6.5 ± 6.5	4.7 ± 6.5	1.8 ± 2.2	22.7 ± 11.8
	Spring	72.8 ± 18.0	3.1 ± 3.7	10.0 ± 10.7	6.3 ± 6.1	3.4 ± 4.6	4.4 ± 4.9
	Summer	31.6 ± 31.9	43.6 ± 31.2	11.6 ± 12.8	3.8 ± 3.1	5.0 ± 2.1	4.4 ± 5.2

*Of any species.

Evaluation of the RMST

Calibrating the RPM

Key results: The RPM was calibrated with an acceptable error. The accuracy of the RPM remains well aligned when biomass is less than approx. 2,500-3,000 kg DM/ha but begins to fall once biomass exceeds this point (by 4,000 kg DM/ha, reliability is much lower).

A total of 2,261 quadrant cuts were taken during the first year of the project, and once outliers and unlikely observations were removed, 1,891 observations remained. These were used to create monthly linear regressions, along with compressed height measurements from the RPM, to calibrate the RPM in preparation for evaluation of the RMST. Details on the performance of the analysis are presented in Table 5. It is important to note that the residuals exhibited a normal distribution, and the MAE (a simple way to measure accuracy in the model, representing the average amount the model's predictions are off from the actual, true value) was 356kg DM/ha. The lower the MAE is, the better the predictions, and when looking at MAE%, <10% is considered excellent while 10-20% considered acceptable (in this case, the MAE% was 11.99%, making the results acceptable and close to excellent for the model).

Table 5. Overall, regional, and seasonal level evaluations of the performance of the monthly linear regression equations to calculate pasture biomass from compressed height using a rising plate meter in three coastal dairy regions of New South Wales, Australia.

Item	N	MAE, kg DM/ha	MAE, %	RMSE, kg DM/ha	ECT, %	ER, %	ED, %	RMSE, %	RSR
Overall	1,891	356	11.992	468.8	0.214	0.027	99.759	15.773	0.56
Region									
North coast	507	232	9.538	298	0.003	0.000	99.997	12.261	0.60
Mid coast	672	395	12.742	501	0.120	0.004	99.875	16.180	0.66
South coast	712	409	12.629	532	0.568	0.597	98.835	16.441	0.59
Season									
Autumn	297	407	12.691	497	0.628	0.000	99.372	15.499	0.60
Winter	518	332	12.520	432	6.539	3.014	90.447	16.296	0.72
Spring	586	347	11.830	473	1.072	1.707	97.221	16.117	0.58
Summer	490	363	11.288	484	0.001	0.001	99.998	15.037	0.52

n = number of observations. MAE = Mean-absolute error expressed in kg dry-matter (DM) per ha and as a proportion of mean observed pasture biomass (%). RMSE = Root-mean square error expressed in kg dry-matter (DM) per ha and as a proportion of mean observed pasture biomass (%). Equation error was decomposed into: ECT = error in central tendency (%), ER = error due the slope regression (%), and ED = error due to random disturbance (%). RSR = RMSE to standard deviation of observed values ratio.

In Figure 4, all calibration cuts and RPM pasture covers are presented along with the fitted calibration equation. Box plots (orange box and whiskers) illustrating the distribution of observations are also included. Confidence in the accuracy of the RMP measurements at lower biomass is high, as variability between measurements and the fitted calibration equation is small (i.e. dots are close to the equation line). However, as the biomass increases (e.g. >2,500-3,000 kg DM/ha), that variability increases and indicates that the accuracy falls, particularly once biomass exceeds around 4,000 kg DM/ha. Importantly, both the quadrat cuts and the corresponding biomass estimates obtained via the RMP display outliers at these higher biomasses and highlights the challenges and potential inaccuracies that are likely to occur at high biomass.

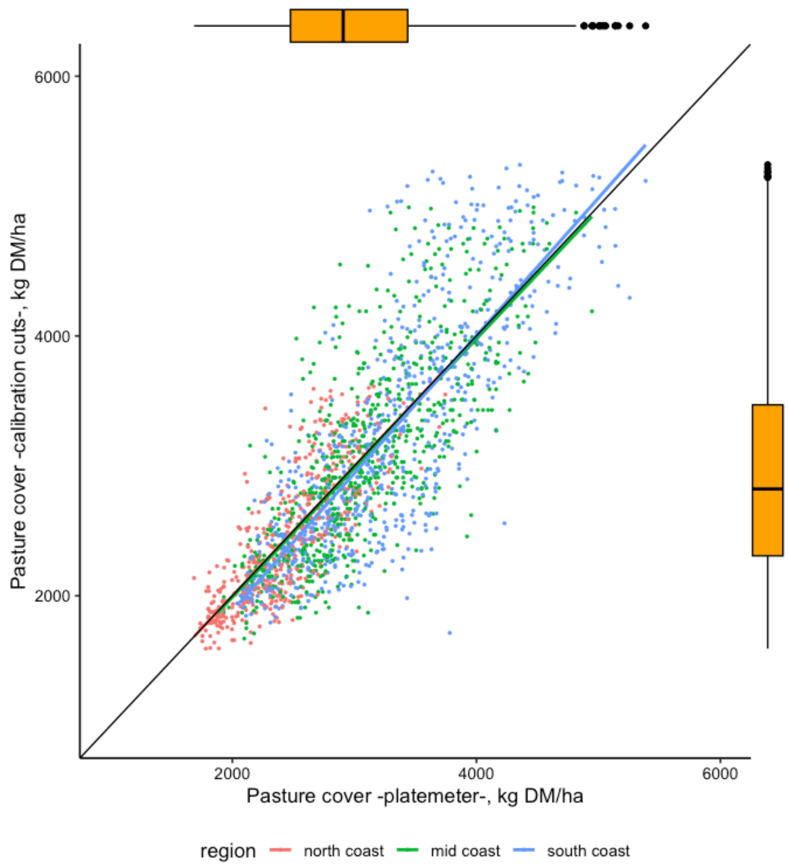


Figure 4. Fitted calibration equations (coloured lines) along with the distribution of fitted pasture cover estimates (RPM) and observed pasture cover (calibration cuts) (dots). Histograms (orange bars) show the distribution of observations for calibration cuts and RPM covers.

Evaluating the estimated pasture cover from the RMST in Year 1

Key result: The RMST was found to have an average MAE of 460 kg DM/ ha and appeared to lose predictive accuracy at both low and high pasture biomass levels. Therefore, its ability to accurately predict pasture biomass was initially perceived to be lower than that of the calibrated RPM (gold standard). Additional training of the RMST was necessary (Year 2).

Estimated pasture cover from the RMST (approximately 60,500 individual records) were evaluated against the mean pasture cover measured with the calibrated RPM (approximately 1,600 measurements, although only 612 measurements matched exactly with the date the RMST record was created – i.e. the TO farm visit was not always on the same day as a satellite flyover). This was done using the correlation coefficient (R), which describes the proportion of variance in the measured data (RPM) explained by the estimated data (RMST), with the root mean square prediction error (RMSPE) expressed as both kg DM ha/ha and as a percentage of the observed mean pasture cover. In addition, the mean absolute error (MAE) was also reported (expressed as kg DM ha/ha and in %) since it is less sensitive to potential outliers.

Initially (before training with the on-ground measurements from the RPM), the overall evaluation revealed a prediction error of approximately 20% (Table 6), which represents an MAE of approximately 460 kg DM/ ha on average (590 kg DM/ha of RMSPE). When running the evaluation by region, the mid coast region had a higher prediction error relative to other regions. For all results, the MAE was lower than the RMSPE and is likely due to the MAE being less sensitive to outliers.

Table 6. Goodness of fit of the pasture cover estimations at the paddock level for the RMST during year 1.

Item	n	MAE kg DM/ha	MAE %	RMSPE kg DM/ha	RMSPE %	mean predicted	mean observed
Overall	1350	458.3	17.1	590.2	22	2,471	2,680
By region							
North coast	309	403.8	17.5	510.6	22.2	2,413	2,302
Mid coast	381	527.8	18.5	650.8	22.9	2,454	2,846
South coast	553	417.7	15.2	557.2	20.3	2,551	2,744
By farm							
North coast							
Farm 01	79	468.4	19.2	556.9	22.9	2,257	2,434
Farm 02	84	263.8	10.7	326.8	13.3	2,396	2,459
Farm 03	92	439.5	21.7	555.3	27.4	2,418	2,029
Farm 04	54	466.3	20	588.9	25.3	2,658	2,332
Mid coast							
Farm 05	107	578.4	20.3	727.5	25.5	2,288	2,854
Farm 06	119	462.6	17.3	596.4	22.2	2,292	2,681
Farm 08	71	491.9	18.2	598.8	22.1	2,582	2,708
Farm 09	85	536.9	18.2	656.3	22.2	2,597	2,955
Farm 07	106	617.5	20.3	733.3	24.2	2,435	3,036
South coast							
Farm 10	113	447	16.2	671.4	24.3	2,416	2,767
Farm 11	128	403.2	14.5	501.7	18	2,782	2,787
Farm 12	101	431.6	14.5	609.3	20.5	2,596	2,968
Farm 13	105	394.3	15.3	471.1	18.3	2,473	2,573
Farm 14	106	413.7	15.8	511.7	19.5	2,451	2,622

Note: farms 15 and 16 are not presented here as they were not part of the project in Year 1.

The error obtained could be interpreted as a large error but does not necessarily mean that this remote monitoring system is unsuitable for pasture management. The RMST used in the project collects information from two separate satellite missions (Sentinel and Planet), local weather, and with farm management activities (i.e., grazing records, fertilisation, silage making), and uses the information to generate pasture cover and growth estimates. Regular input of on-farm activities will likely assist in refining the estimates from the RMST.

Figure 5 provides a visual analysis of the residuals obtained by subtracting estimated pasture biomass (RMST) from measured pasture biomass (RPM). The residuals displayed a normal distribution (Figure 5a), with a slight rise in values evident as pasture biomass surpassed the 3,000 kg DM/ha mark. Variation in residuals was fairly even when within "normal" pasture biomass range (approx. 2,000-3,000 kg DM/ha, Fariña, S., *et al, 2011*) but increased both below and above this biomass (Figure 5b and c). Lastly, the homoscedasticity test indicated notable variations between farms (Figure 5d), indicating imbalances in the data (i.e. each farm was different, and employed different management practices). This analysis offers an indication that the RMST likely overpredicts biomass at lower true ground biomass, while simultaneously underpredicting biomass at high biomass levels.

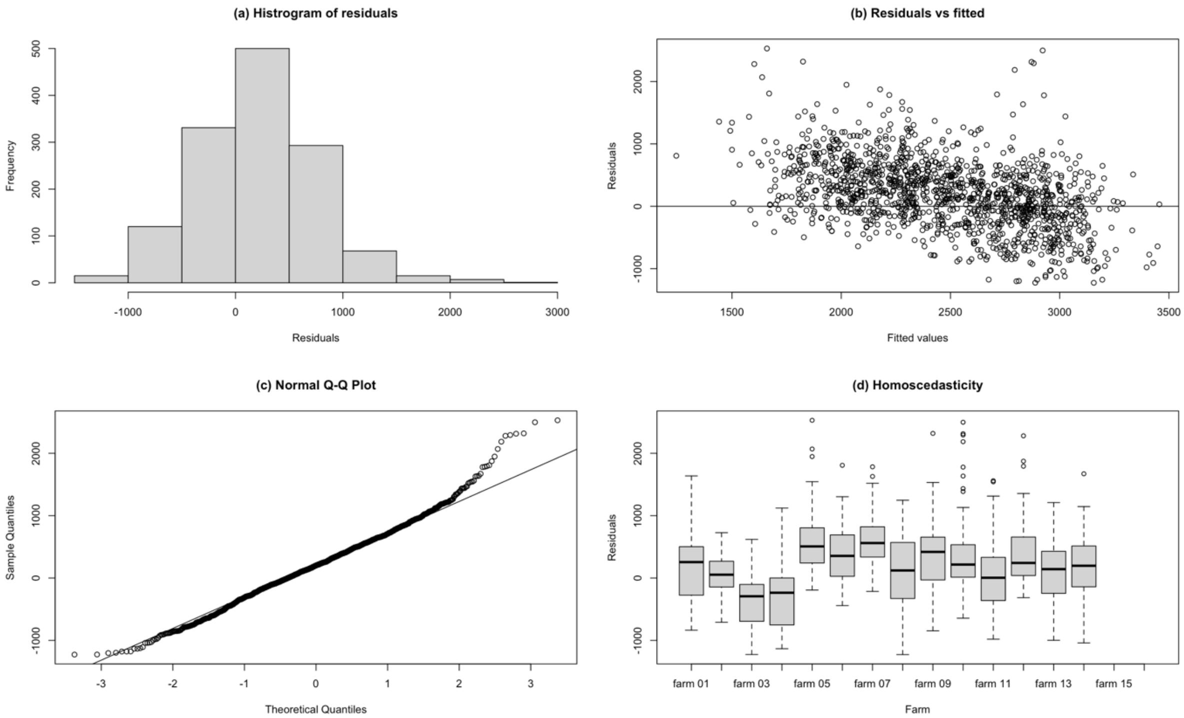


Figure 5. Analysis of residuals for the initial RMST evaluation with calibrated RMP data.

Training and re-evaluating the RMST in Year 2

Key result: training improved the accuracy of the RMST's pasture biomass estimates, where using 2 weeks per month training (from 5 paddocks per farm, or 10% of the grazing platform) significantly reduced the error (i.e. improved accuracy). The error continued to reduce when training increased further, but this change was not significant. Therefore, from a practical perspective, using 2 weeks a month of RPM data to train the RMST is likely to be the most effective approach (lowest level of input to achieve acceptable gain in accuracy).

The data collected in both years of the project were used to train and then re-evaluate the RMST after training to determine the impact and effectiveness of training on pasture biomass estimates and what level of training is needed to obtain the results.

Pasture biomass measurements recorded with a calibrated RPM were filtered to ensure the date of each RPM record matched the date of the RMST data for accurate comparisons. The RPM data was split into groups, called "training" (80% of the measurements) and "evaluation" (20% of the measurements). Training data was then sorted into four groups, being 1) 1 Week (1W; 25% of the data); 2) 2 Weeks (2W; 50% of the data); 3) 3 Weeks (3W; 75% of the data); and 4) 4 Weeks (4W; 100% of the data). These data groups were fed into the RMST sequentially, starting at W1, which enabled a clear assessment of the impact of increasing training frequency on RMST biomass estimates accuracy. The evaluation data was used to validate the RMST estimates across each of the 4 training groups.

For Year 1 data, there was minimal difference in MAE between the control error (evaluation data) and 1W (training data; Table 7), while 2W resulted in a significant drop in error – i.e. the accuracy of the RMST improved significantly at 2 weeks per month of training. Additional reductions in error were seen with further training (3W and 4W) but were not significantly different to 2W.

Table 7. Evaluation of pasture biomass performance of a machine learning algorithm decision support tool based on satellite imagery, weather, and farm management data after progressive model training intensities using calibrated rising plate meter data of 5 fixed paddocks per farm.*

Data	MAE kg DM/ha	MAE %	RMSE kg DM/ha	ECT %	ER %	ED %	RMSE %
Control	498a	19.1	602a	4.8	15.9	79.3	23.1
1W	518a	19.9	642a	0.8	28.0	71.2	24.6
2W	342b	13.1	431b	3.1	0.4	96.5	16.5
3W	298b	11.4	371b	3.6	0.9	95.5	14.2
4W	293b	11.2	362b	3.3	0.6	96.1	13.9

n = number of observations. MAE = Mean-absolute error expressed in kg dry-matter (DM) per ha and as a proportion of mean observed pasture biomass (%). RMSE = Root-mean square error expressed in kg dry-matter (DM) per ha and as a proportion of mean observed pasture biomass (%). Equation error was decomposed into: ECT = error in central tendency (%), ER = error due the slope regression (%), and ED = error due to random disturbance (%). Different superscripts in MAE and RMSE indicates statistical differences with respect to the mean differences at a p-value of < 0.05 according to the Tukey's HSD test. *Training intensities: Control (no training), 1W: training based on field data from week 1 of a given month, 2W: training based on field data from weeks 1 and 3 of a given month, 3W: training based on field data from weeks 1, 3, and 2 of a given month, 4W: training based on field data from 4 weeks of a given month.

When shown visually (Figure 6), the evaluation data (control – no training; Figure 6a) and 1W training data (Figure 6b) were poorly aligned with the RPM data. Like Table 8, they show high levels of error, but they also show that the RMST estimates were underpredicting pasture biomass compared to the mechanical measurements of the RPM. Figures 6c-6e show a strong alignment between the estimates of the RMST and the measurements of the RPM, again indicating improvement in accuracy of the estimates from the RMST.

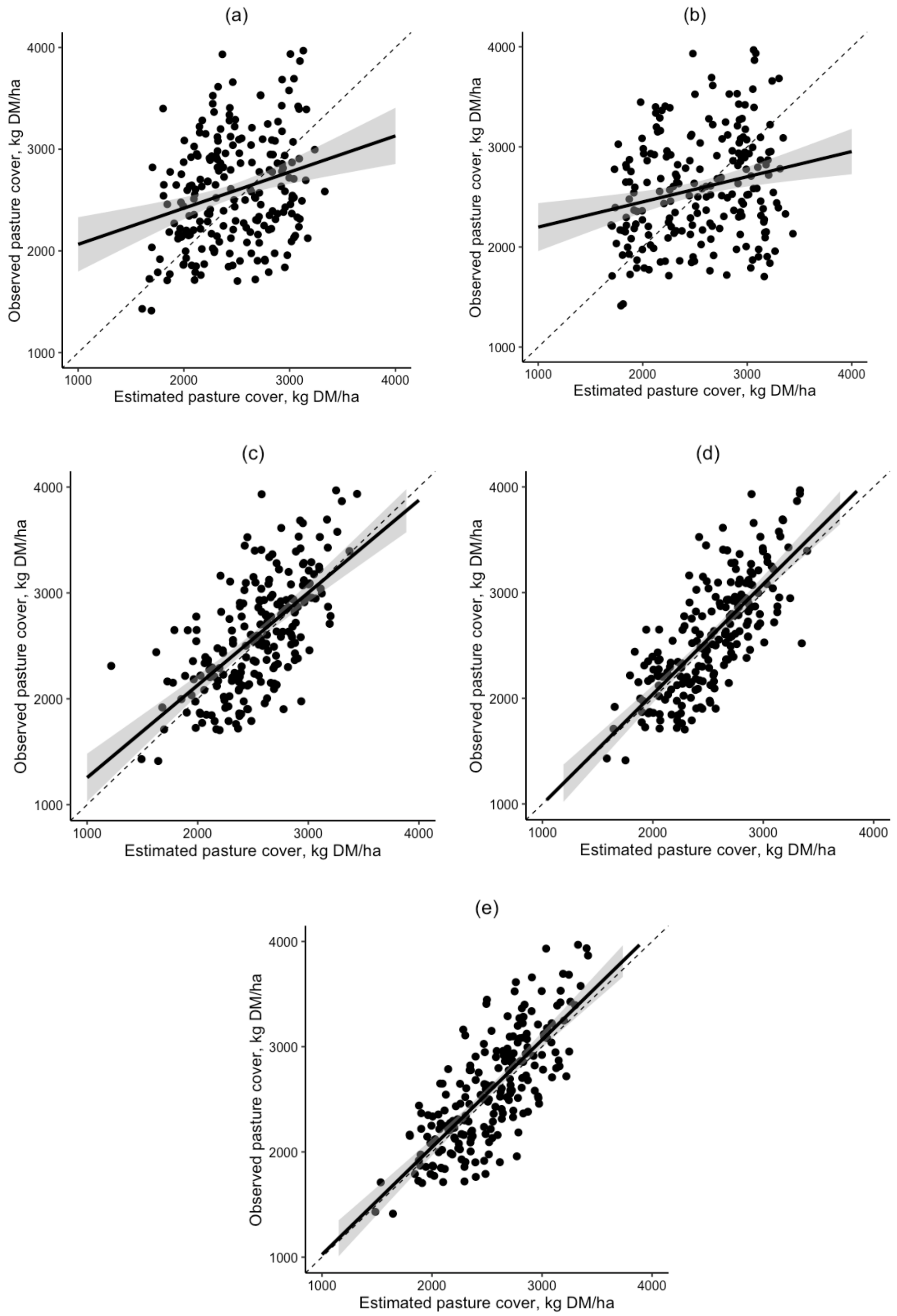


Figure 6. Scatter plots of observed (RPM) versus predicted (RMST) pasture biomass (in kg DM/ha) on four training intensities with calibrated RPM data using 5 fixed paddocks per farm: (a) control (no training), (b) 1W: RMST trained with RPM data of one week per month, (c) 2W: RMST trained with RPM data of two weeks per month, (d) 3W: RMST trained with RPM data of three weeks per month, and (e) 4W: RMST trained with RPM data of four weeks per month. Grey-shaded areas show the uncertainty in the relationship of observed vs estimated pasture biomass. Dashed line is the one-on-one line.

Even with training, the RMST had difficulty accurately estimating pasture biomass at higher volumes (Table 8), where the error at the highest biomass group (3,580 kg DM/ha) was much higher than at the lower two biomass groups. Like Table 7, training the RMST reduced the error (i.e. improved the accuracy).

Table 8. Evaluation of the accuracy of pasture biomass estimates from the RMST with RPM data at different pasture biomass volumes (tercile groups).

Item	Pasture biomass observed kg DM/ha				MAE	MAE	RMSE	ECT	ER	ED	RMSE
	N	Mean	Min	Max	kg DM/ha	%	kg DM/ha	%	%	%	%
First tercile	75	2,031	1,413	2,314							
Control					411a	20.2	509a	42.3	43.2	14.5	25.0
1W					521a	25.6	655a	36.0	54.3	9.7	32.3
2W					322ab	15.9	395ab	30.5	44.2	25.3	19.4
3W					261ab	12.9	307ab	30.9	30.6	38.5	15.1
4W					241b	11.9	303b	28.8	33.4	37.9	14.9
Second tercile	110	2,748	2,330	3,222							
Control					453a	16.5	531a	21.5	55.9	22.6	19.3
1W					430a	15.6	534a	8.3	69.4	22.3	19.4
2W					280ab	10.2	353ab	13.2	42.6	44.2	12.9
3W					250ab	9.1	311ab	10.5	36.3	53.2	11.3
4W					262ab	9.5	315ab	9.4	38.2	52.4	11.5
Third tercile	29	3,580	3,248	4,183							
Control					895a	25.0	967a	85.8	7.1	7.1	27.0
1W					848a	23.7	920a	84.8	8.1	7.1	25.7
2W					632b	17.6	702b	81.1	6.0	12.9	19.6
3W					577b	16.1	637b	82.1	4.4	13.5	17.8
4W					541b	15.1	597b	82.0	3.7	14.3	16.7

Different superscripts in MAE and RMSE indicate statistical differences with respect to the mean differences at a p-value of < 0.05 according to the Tukey's HSD test for each pasture biomass tercile separately. *Training intensities: Control (no training), 1W: training based on field data from week 1 of a given month, 2W: training based on field data from weeks 1 and 3 of a given month, 3W: training based on field data from weeks 1, 3, and 2 of a given month, 4W: training based on field data from 4 weeks of a given month.

Figure 7 also demonstrates the change in accuracy as biomass changes. Between 1,500 and 3,000 kg DM/ha, the MAE obtained was approx. 250 kg DM/ha with variation being quite low. Below 1,500 kg DM/ha, MAE doubled (500 kg DM/ha), while between 3,000 and 3,500 kg DM/ha the prediction error experienced a linear increase (MAE starting at 260 and reaching nearly 600 kg DM/ha). Beyond 3,500 kg DM/ha, MAE experienced a four-fold increase in the prediction error relative to the MAE obtained between 1,500 and 3,000 kg DM/ha. It is important to acknowledge that most of the training data used was within the 1,500 and 3,000 kg DM/ha range (potential to provide higher accuracy within this range, compared to the lower or upper ends). However, even if the RMST loses accuracy outside this range (as was the case in this project), pastures are intended to be maintained at a biomass between 1,500 and 3,000 kg DM/ha to avoid over- and under-grazing and maximise nutritional value in the pasture, and the results indicate the RMST is capable of predicting biomass in this range with an acceptable accuracy.

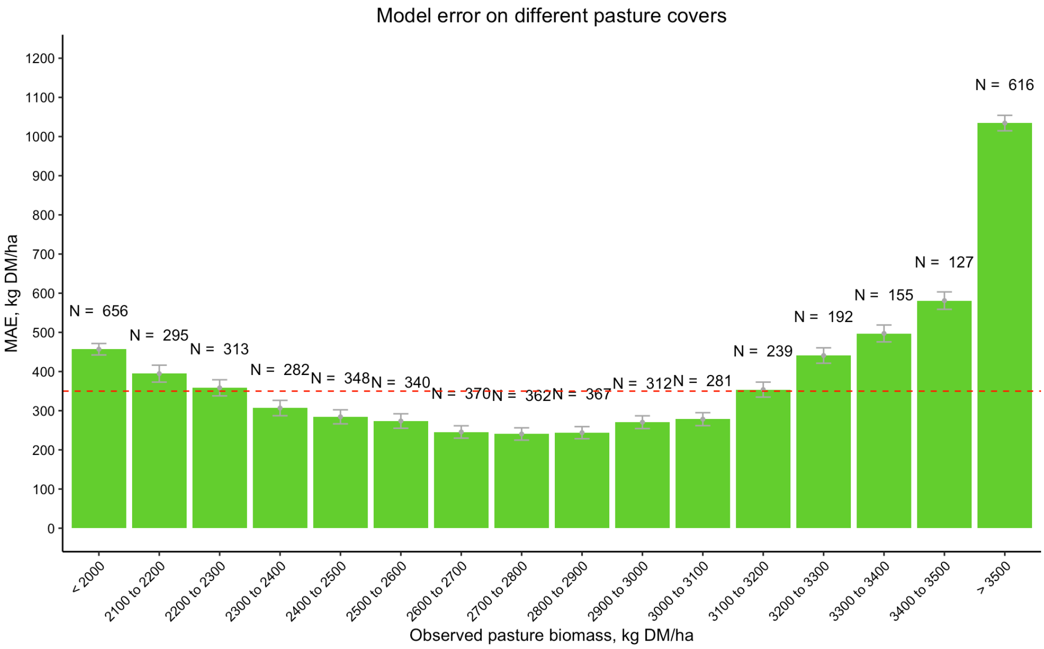


Figure 7. Mean-absolute error (in kg DM/ha) of the RMST at observed pasture biomass levels (RPM) after training is conducted. The dashed line is the average MAE.

RMST performance after training ends

The following result was not intended to be formally part of the project but was conducted and reported on out of interest. At the conclusion of Year 2, the RMST training (using the on-ground calibrated RPM data) ended. However, there was still data available from one participating farm which enabled a very rough assessment of the performance of the RMST without the fortnightly training. The results (Table 9) provide a very rough indication of what happens to the accuracy once training ends, but care must be taken when considering these results are they are from a single farm with an extremely small sized data set. The informal analysis indicated that MAE increases once training ends (i.e. the error increases, or conversely the accuracy reduces). The reduction of MAE in August 2025 is likely due to ryegrass being the predominant pasture species at that time, and (as mentioned at the start of this report) these types of technologies were created on ryegrass-based pastures, so it isn't surprising that performance is higher at this time.

Table 9. Informal evaluation of the accuracy of the RMST once training concluded.

Data	N	MAE kg DM/ha	MAE %	MAEse kg DM/ha	CCC	R	R2
Total	13	542.4	21	139.1	0.111	0.21	0.04
Dec 2024	4	481.3	20	217.5	0.269	0.77	0.59
Feb 2025	5	800.1	26	233.9	0.068	0.33	0.11
Aug 2025	4	281.5	13	162.9	0.297	0.47	0.22

n = number of observations. MAE = Mean-absolute error expressed in kg dry-matter (DM) per ha and as a proportion of mean observed pasture biomass (%). MAEse = standard error. CCC = concordance correlation coefficient. R = correlation coefficient. R2 = coefficient of determination. Note: data is from a single farm only.

Farm performance (pasture productivity and utilisation)

Key result: Average pasture utilisation as a percentage of pasture grown was 58.9%. The average difference between pasture grown and harvested was just over 4,500 kg DM/ha meaning that farms grew approx. 4.5 t DM/ha more than they utilised.

Growth rates were used to calculate pasture production throughout the year, while grazing records and biomass estimates enabled the calculation of pasture harvested. This in turn determined pasture utilisation (what proportion of grown pasture was harvested) and presented in Table 10. There were a range of results between farms, reflecting the intricate interplay of factors such as climate (particularly considering the unusually wet conditions experienced during the project period), soil composition, management strategies, and stocking rates. The far north coast exhibited the highest production and utilisation, while the mid and south coast regions were more similar. Production averaged 11,181kg DM/ha across all farms. The results indicated high consistency in pre-grazing biomass between farms (i.e. average pre-grazing biomass was close to target pre-grazing biomass, set at 3,000 kg DM/ha), which may indicate that farmers were opening paddocks for grazing when pasture was close to target. However, it is important to consider that the tools used (both the RPM and RMST) rapidly lose accuracy once biomass approaches and exceeds 3,000kg DM/ha, meaning pre-grazing biomass variation may be masked and should be interpreted with caution.

Table 10. Average yearly pasture production, pasture harvested and pasture management results for all farms and regions in the project (across both years of the project).

Unit	Pasture Production	Pasture disappearance	Pasture use efficiency (%)	Pre-grazing biomass	Post grazing biomass
Average overall	11,330	6,773	58.9	2,901	2,152
By region					
North coast	13,452	8,868	65.5	2,816	2,049
Mid coast	10,780	6,307	58.3	2,941	2,208
South coast	10,403	5,751	54.4	2,913	2,155
By farm					
North coast					
Farm 01	11,119	6,744	61.0	2,830	2,003
Farm 02	16,330	11,376	70.0	2,891	2,129
Farm 03	14,120	9,357	66.0	2,788	2,081
Farm 04	12,238	7,996	65.0	2,753	1,982
Mid coast					
Farm 05	10,772	6,175	57.0	2,896	2,244
Farm 16	10,861	6,842	63.0	2,966	2,165
Farm 06	9,612	3,838	40.0	2,883	2,285
Farm 07	11,599	7,093	61.0	3,010	2,299
Farm 08	11,735	7,699	66.0	3,002	2,215
Farm 09	12,082	6,687	55.0	2,835	2,163
Farm 15	8,798	5,816	66.0	2,992	2,083
South coast					
Farm 10	10,539	5,569	53.0	2,902	2,160
Farm 11	8,103	3,231	40.0	2,944	2,314
Farm 12	12,138	8,569	71.0	2,975	2,014
Farm 13	10,453	6,143	59.0	2,910	2,125
Farm 14	10,783	5,241	49.0	2,835	2,163

Presented as kg DM/ha for all measurements (unless specified)

Grazing events were tracked using manual records and GPS collars. Including grazing events in the yearly pasture growth patterns enabled a visual depiction of pasture management and highlights pre- and post-grazing biomass levels (Figure 8). This visual depiction assists in identifying where pasture management is excelling (e.g. paddocks or seasons where biomass targets were met) and where there is room for improvement (e.g. paddocks or seasons where biomass targets were not met).

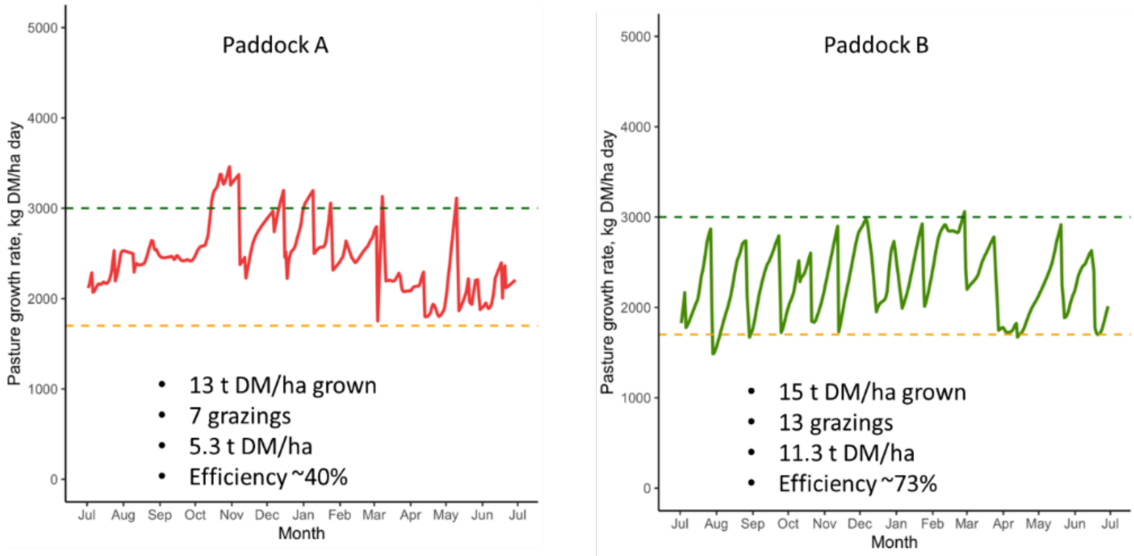


Figure 8. Example pasture management from two paddocks on the same farm (i.e. same management), showing the pasture biomass throughout the year, along with the pre- (green dotted line) and post-grazing (orange dotted line) biomass targets.

Relationship between pasture production and grazing performance

Key result: Pasture production strongly influenced total grazed, but differences between farms were mainly explained by pasture utilisation efficiency. Farms with higher pre-grazing pasture mass and lower post-grazing pasture level performed better, while farm size and paddock number had little effect.

To further understand differences between farms, the relationship between pasture production and total grazed was analysed (Figure 9). This analysis shows a strong and consistent pattern, where farms that produce more pasture generally harvested more pasture. The line on the figure represents the expected grazing outcome based on pasture production, indicating the average relationship observed across all farms.

While most farms follow this trend, there are clear differences in how closely individual farms align with the expected outcome. Some farms are positioned above the line, meaning they graze more pasture than expected for their level of production, while others fall below the line, indicating lower than expected utilisation. These differences highlight variation in grazing performance that cannot be explained by pasture production alone.

To better interpret these differences, farms were grouped based on both total grazed and their position relative to the expected line, which reflects how well pasture is being utilised. This allows separation of farms that achieve high grazing outcomes mainly through high production from those that achieve similar or better results through more effective use of pasture. The results suggest that grazing management plays a key role. In particular, farms that enter grazing with higher pasture mass and achieve lower post grazing residuals tend to perform better. In contrast, structural factors such as farm size or number of paddocks showed little influence on grazing performance.

Overall, the analysis reinforces that while pasture production sets the potential for grazing, differences between farms are largely driven by how effectively that pasture is utilised.

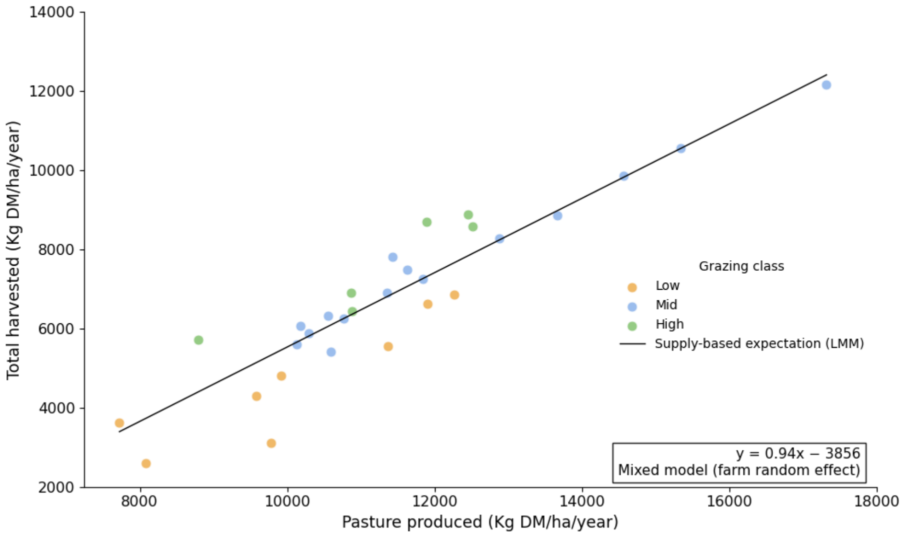


Figure 9. Relationship between pasture produced and total pasture harvested at the farm-year level. The line shows the expected level of harvesting based on pasture production.

Farmer perceptions and feedback

Key result: farmer confidence in the RMST increased by an average of 38% at the end of the project, and many indicated this type of technology has more than one purpose (i.e. more than just pasture monitoring).

Throughout the project, farmers were asked to indicate their confidence in the RMST (noting that confidence was contingent on both the RMST itself and the remote sensing approach, which can't be differentiated in the responses). Except for one farmer, farmers in the North Coast region generally improved their perception of the RMST. Similarly, nearly all farmers in the Mid Coast region reported an enhanced perception of the RMST. In contrast, farmers in the South Coast region reported a reduced perception, while Mid Coast farmers had mixed responses. Overall, confidence sat at 2.6/5 at this point.

At the conclusion of the project, farmers were sent individual farm reports which summarised their pasture production and utilisation. It also benchmarked their farm with those of their region, and the entire cohort of participating farms. After receiving their reports, farmers were given the opportunity to provide feedback on both the report and the project experience. Confidence in the RMST increased by 38% to 3.6/5 after farmers saw their individual report and the additional information the data could provide (outside what was available through the real-time RMST interface). Farmers also commonly indicated they would use the information from the RMST and presented in their report to assist with grazing and support reducing wastage, with more specific responses including:

- Assist with grazing (e.g. setting allocations, grazing more rigidly).
- Reduce wastage.
- Checking/confirming growth rates.
- Make decisions based on objective data (particularly useful in multi-manager set ups, and where managers/family members have different views on how to proceed).
- Can see peaks in growth/production and therefore support decision making and considerations into how to better use the excess pasture during those times.

Many farmers also found the RMST useful for other purposes, appreciating its capability as a comprehensive platform to document all farm activities. Notably, since pasture biomass is predominantly calculated from widely used remote sensing indexes such as NDVI and EVI, the RMST provided guidance to farmers in relative terms, allowing them to organise paddocks from highest to lowest biomass.

8. Outputs

The project produced several high-quality outputs, including:

- A Ph.D thesis (The Unrealised Potential of AI Solutions for Pasture-based Dairy Systems, Blessing Nnenna Azubuike).
- A high-quality pasture dataset spanning two years, collected using remote monitoring technology providing objectively measured pasture production, growth rates and pasture depletion data. Farm characteristics and grazing management information is also included. This is the first dataset of this nature compiled for NSW pasture-based farms that we are aware of.
- An informative, industry focused video outlining the key results of the project and application potential of those results on farm.
- Publication of research in multiple international journals, including Nature's Scientific Report (see list in Section 11).
- Conference presentations, industry reports and individualised participating farmer reports, disseminating findings to researchers, producers and industry audiences.

9. Applications and Impacts

The findings have direct implications for pasture-based dairy farms, not only in NSW but across Australia, and are particularly relevant for farms in regions that experience the C3-C4 winter-summer pastures, as previous work into remote pasture monitoring has focused largely on C3 pastures.

- **At the farm level**, the project demonstrated that the pasture monitoring technology tested could estimate pasture biomass with comparable accuracy as the RPM. To monitor the entire farm, the RMST required approx. 1.5h a fortnight of manual labour (to measure 5 paddocks with a RPM) for continuous training, a reduction in labour required for pasture monitoring using traditional methods. The technology was able to provide a clear and accurate estimate of pasture biomass (availability and depletion) in near-real time, and enabled visualisation of pasture performance and identification of well performing paddocks and paddocks that require additional attention to reduce inefficiency. This information could be used by farmers and advisors to support pasture management decisions and increase pasture use efficiency through increasing pasture production or increasing the amount of grown pasture which is consumed (e.g. more closely hitting pre- and post-grazing biomass targets).
- Being objective, this type of technology can help farm businesses maintain consistency in pasture management across different staff, aiding in stable pasture productivity and utilisation.
- **At the industry level**, the outcomes from this project offer a pathway forward for supporting increasing pasture utilisation, which has been identified as an important element of feedbase management. Farms in the project were found to grow, on average, 4.5 tonne DM/ha per year more pasture than they consumed through grazing, and "advanced monitoring" has huge potential to enable farmers to identify areas for improvement in their pasture management and work towards increasing pasture use efficiency (i.e. use more of what is grown).
- **At the technology level**, accuracy of tools needs to be factored into decision-making. Both tools (the RPM and RMST) were limited in their accuracy at very low (<1,500 kg DM/ha) and high (>3,000 kg DM/ha) biomass. However, pastures should be managed within that range to achieve best outcomes in terms of pasture nutrition and regrowth (reducing risk of under or over-grazing). The pasture species will still determine target biomass, along with the method of monitoring the pasture (e.g. type of tool).

10. Future Research Opportunities and Actions

- Work with farmers to implement objective monitoring practices on-farm and capture measurable gains in productivity, pasture use efficiency and profitability achieved through monitoring pasture (this project demonstrated that the average “gap” between pasture grown and pasture utilised was more than 4t DM/ha, meaning there are substantial gains to be made in pasture utilisation). Work should consider also aligning this information with milk production to ensure comprehensive monitoring of the entire farm system, aiding in discerning between suitable and poor strategic and tactical management decisions.
- One type of remote monitoring tool was evaluated in this project, although there are many more on the market. More work should be directed to better understanding the performance and reliability of other tools on the market so farmers can make informed decisions on how they may incorporate objective monitoring into their pasture management routines.
- Work with private consultants/agronomists to develop practical strategies for implementation of objective monitoring on dairy farms.

11. Project-wide Dissemination

The project has produced one PhD thesis, five peer-reviewed publications in high-impact international journals (Table 11).

Findings were also presented at multiple conferences and scientific events, including the American Dairy Science Association (ADSA) Annual Meeting in the USA, the Australasian Dairy Science Symposium (ADSS), and the Dairy Research Foundation Symposium (see Section 13 for details). These presentations collectively reached an estimated audience of thousands of people, spanning industry professionals, researchers, farmers and policymakers.

Beyond peer-reviewed and conference outputs, the project produced several other outputs. Of note was a video, highlighting the main findings and implications of the research as well as several project updates on the Dairy UP website and via the Dairy UP newsletter. Participating farmers were sent reports throughout the project, as well as a final report at the conclusion of the project detailing their farm's performance and providing benchmarking against other farms in the project. Farmers were also contacted and met with via phone call to discuss results and their perspective on the project, technology and farm data.

Table 11. Peer-reviewed publications.

Author	Title	Journal	Year Published
Correa-Luna, M. *et al*	Accounting for minimum data required to train a machine learning model to accurately monitor Australian dairy pastures using remote sensing	Nature, Scientific reports	2024
Azubuike, B.N., *et al*	Data Augmentation and Interpolation Improves Machine Learning-Based Pasture Biomass Estimation from Sentinel-2 Imagery	Remote sensing	2025
Azubuike, B.N., *et al*	Machine Learning for Grazing Event Detection and Pasture Utilisation Quantification from Sentinel-2 Data	Smart Agricultural Technology	2026
Azubuike, B.N., *et al*	Transfer learning and stacking ensembles for biomass estimation from smartphone imagery in pasture-based dairy systems	Journal of Agriculture and Food Research	2026
Azubuike, B.N., *et al*	AI in Pasture-Based Dairy Systems: Advances in Precision Feeding, Remote Sensing, and Grazing Management	Computer and Electronics in Agriculture	In review

12. Conclusions and Recommendations

The results of the evaluation and validation across a range of data collected on commercial dairy farms in NSW provided a rich dataset from which the following key messages, conclusions and recommendations can be taken.

- Clear and accurate estimates of pasture availability and depletion can be captured using remote monitoring technology (comparable to a calibrated RPM). This in turn can be used by farmers and farm advisors to make informed pasture management decisions, both predictively and retrospectively (i.e. predict future allocations/pasture availability, and review and address pasture management based on captured data such as pre- and post-grazing biomass).
- The RMST assessed had reduced accuracy initially. Following fortnightly training with calibrated RPM data (using 10% of the farms' grazing area), it produced pasture biomass estimates that were of comparable accuracy to the RPM (gold standard tool). This is encouraging as it indicates the RMST can be relied on, however still requires the approximately 1.5h a fortnight labour to generate the RPM data for training. This also does not guarantee that every technology on the market will perform the same way. It may be necessary to conduct additional research into understanding the performance of other commercially available products. Additionally, research into the performance of the RMST once training ends (i.e. had a period of training, which concludes) is recommended to better understand how training impacts performance if training is not planned to be continuous.
- Beyond approx. 2,800 kg DM/ha, pasture quality was seen to drop. This is in line with previous knowledge but sits slightly less than the standard 3,000 kg DM/ha target for pre-grazing biomass. For full results on pasture quality related to biomass, please see results from Project 1e "Understanding and predicting changes in nutritional value of Kikuyu" (https://dairyup.com.au/resource-library/). Importantly, the take home message here is that it is critical to graze (or harvest for silage) pasture before quality starts to drop and reinforced the key message of hitting pre-grazing biomass targets.
- Tools used in this project (both the RPM and the RMST) were limited in their accuracy at very low (<1,500 kg DM/ha) and high (>3,000 kg DM/ha) biomass. However, pastures should be managed within that range to achieve best outcomes in terms of pasture nutrition and regrowth (reducing risk of under or over-grazing), linking directly to the point above. The pasture species will still determine target biomass, along with the method of monitoring the pasture (e.g. type of tool).
- There is a need to work with farmers to implement objective monitoring practices on-farm and capture measurable gains in productivity, pasture use efficiency and profitability achieved through monitoring pasture (this project demonstrated that the average "gap" between pasture grown and pasture utilised was more than 4t DM/ha, meaning there are substantial gains to be made in pasture utilisation). Work should consider also aligning this information with milk production to ensure comprehensive monitoring of the entire farm system, aiding in discerning between suitable and poor strategic and tactical management decisions.
- Similarly, it is important to work with private consultants/agronomists to develop practical strategies for implementation of objective monitoring on dairy farms, recognising that farmers are likely to select technology that meets multiple farm and business needs, and so may not rely solely on accuracy when choosing a tool to support their pasture management.
- The concept of 'advanced monitoring' developed by this project can also help to improve management of C4 pasture for silage as well as help farmers to be more in control over the critical transition periods between C3 and C4 and vice versa. These will be assessed in Dairy UP2.

13. Annexes

Table 12. Conference presentations, abstracts, published material and other media engagements.

Authors	Title	Presentation Type	Conference/ Event	Location	Year	Audience
Dairy UP	Remote pasture monitoring P1a	Video		Online	2024	Industry/ farmer
Dairy UP	Improving pasture utilisation using satellite technologies	Case study		Online – Dairy UP	2024	Industry/ farmer
Sergio Garcia	The hidden losses of pasture utilisation	Written article	Magazine article	The Australian Farmer	2024	Industry/ farmer
Dairy UP	Mid-project insights: Remote pasture monitoring P1a	Project update		Online	2024	Industry/ farmer
Azubuike, B.N., *et al*	Machine learning increases the accuracy of satellite derived pasture cover estimation	Conference abstract	American Dairy Science Association	Louisville, KY, USA	2025	Scientific/industry
P1a team	Key results from Remote Pasture Monitoring Project (P1a)	Video		Online	**2025**	Industry/ farmer

14. References

Correa-Luna, M., Gargiulo, J., Beale, P. *et al.* Accounting for minimum data required to train a machine learning model to accurately monitor Australian dairy pastures using remote sensing. *Sci Rep* **14**, 16927 (2024). https://doi.org/10.1038/s41598-024-68094-3

Fariña, S., Garcia, S. C. & Fulkerson, W. J. A complementary forage system whole-farm study: forage utilisation and milk production. Anim. Prod. Sci. 51, 460–470 (2011). https://doi.org/10.1071/AN10242.

Garcia, S. C., Islam, M. R., Clark, C. E. F. & Martin, P. M. Kikuyu-based pasture for dairy production: A review. Crop Pasture Sci.65, 787–797. (2014) https://doi.org/10.1071/cp13414.

Heins, B. J., Pereira, G. M. & Sharpe, K. T. Precision technologies to improve dairy grazing systems. JDS Commun. 4, 308–315. (2023) https://doi.org/10.3168/jdsc.2022-0308.