Final report

Accelerating the Adoption of Satellite Assisted Forage Budgeting Across Northern Beef Businesses

Project code: P.PSH.1286

Prepared by: Dr Juan Pablo Guerschman, Dr Peter Scarth, Phil Tickle and Cibo Labs Pty Ltd

Date published: 24 May, 2023

PUBLISHED BY
Meat & Livestock Australia Limited
PO Box 1961
NORTH SYDNEY NSW 2059

This is an MLA Donor Company funded project.

Meat & Livestock Australia acknowledges the matching funds provided by the Australian Government to support the research and development detailed in this publication.

Contents

Abstract 4

Executive summary 6

1. Background 9

2. Objectives 10

3. Methodologies 12

3.1 Pasture Biomass Mapping Model Refinement 12

3.2 Palatable Biomass Mapping 14

3.3 Water Body Mapping 14

3.4 Landscape Response Unit Mapping 15

3.5 Land Type Mapping 16

3.6 Land Condition Mapping 17

3.7 Producer Surveys and Adoption 18

4. Results and Discussion 19

4.1 Pasture Biomass Mapping Model Refinement 19

4.2 Palatable Biomass Mapping 23

4.3 Water Body Mapping 25

4.4 Landscape Response Unit Mapping 28

4.5 Land Type Mapping 30

4.6 Land Condition Mapping 32

4.7 Producer Surveys and Adoption 37

5. Conclusions 40

5.1 Key findings 42

5.2 Benefits to industry 43

6. Future research and recommendations 43

7. References 44

8. Appendix 1 45

8.1 Queensland Land Type Classification. 45

Abstract

Market satisfaction is vulnerable to varying livestock availability in the supply chain. MLA's project review in this work area, B.ERM.0098 reported that profitable and environmentally sustainable beef industry is critical to continued productivity and allied socio-economic and cultural well-being in northern Australia. Cibo Labs was founded as a commercial entity in early 2018 to address the need for improved feedbase and land condition monitoring to support profitable and sustainable grazing management decisions. The Australian Agriculture Company (AACo's) has been a significant supporter of these developments in collaboration with Cibo Labs which now underpin many management decisions across the company.

The project aimed to achieve several ambitious objectives that would deliver significant benefits to both AACo and the broader industry. These included: refining the current pasture biomass and quality predictions; developing methods for mapping and monitoring surface water; the ability to automatically map land types; implementing and validating new methods for land condition prediction, and improved understanding of priorities and barriers to Agtech adoption. This project has successfully achieved these objectives.

The "living model" approach to the national biomass prediction service is now well established within operational systems and places Australia and Cibo Labs as a world-leader in this capability. With over 5100 field sites our pasture biomass predictions are achieving a Median Absolute Error of 235kg/ha for TSDM values <2000kg/ha. The Median Absolute Error (MAE) of the model increases when a larger range of TSDM observations is considered. Importantly, the model error matches the error in the field data as the TSDM increases. Initial research on predicting pasture palatability is showing very promising results, achieving a MAE of 279kg/ha.

The project has demonstrated the ability to use new sources of remote sensing data and methods to reliability map the presence and duration of surface water relevant to extensive grazing systems and ecosystem management. The Landscape Response Units (LRU) methodology was implemented for the entire nation (768 million ha) creating some 49 million individual mapped polygons describing long-term landscape spectral response. The LRU framework is a significant step forward that will underpin a range of developments associated with natural capital including sustainable grazing management, property development, carbon accounting and biodiversity assessments. The Landscape Response Units allowed us to extend the Qld Land Type mapping into the NT and northern WA at a higher resolution than the original mapping. We achieved an overall classification accuracy of 78.8%. The results indicate that the Qld Land Types map can be expanded to cover areas of Northern Australia in NT and WA by combining remotely sensed data and machine learning. This scoping study demonstrates that overall land condition can be successfully mapped using spatio-temporal information across the AACo estate, and across the Rangelands. Using the LRU's we were able to spatially predict ABCD Land Condition with a high degree of accuracy across AACo's northern properties. We achieved a mean absolute error (MAE) of 0.153. This means that, on average, the error in the Land Condition estimate was about the distance between one subclass, for example A to A-B. The overall accuracy calculated in this way was 80.4%. To be able to consistently map land condition at paddock scales for every extensive grazing property in Australia could be a game-changer for the industry. Having the capability to automatically estimate land condition, incorporate local knowledge from managers, and assess the impacts of land condition on stocking rate per paddock will allow producers to make more informed management and investment decisions on long-term carrying capacity, seasonal stock rates and grazing management, or infrastructure

investment decisions aimed at improving sustainable production capacity over time. This work is still in the early stages of development and our analyses have only focused on long-term land condition.

Executive summary

Market satisfaction is vulnerable to varying livestock availability in the supply chain. MLA's project review in this work area, B.ERM.0098 reported a profitable and environmentally sustainable beef industry is critical to continued productivity and allied socio-economic and cultural well-being in northern Australia.

Cibo Labs was founded as a commercial entity in early 2018 to address the need for improved feedbase and land condition monitoring to support profitable and sustainable grazing management decisions. Over the last 5 years there has been significant investment in data science, high performance computing; machine learning systems; targeted field data collection and most importantly strong engagement with producers to routinely deliver paddock level estimates of pasture biomass on a weekly basis to over 55 million ha. Fully automated high performance computing systems now deliver Sentinel-2, 10m resolution, 13 band imagery within 24 hours of acquisition. Machine learning (ML) algorithms and geospatial analysis based on data collected by producers, estimates total standing dry matter for each paddock every 5 days.

The Australian Agriculture Company (AACo's) has been a significant supporter of these developments in collaboration with Cibo Labs which now underpin many management decisions across the company. Using the Cibo Labs PastureKey service has transformed the forage budgeting and decision-making process for AACo. In 2022 property level forage budgets were completed over 2 months earlier than usual. This has provided a "whole of business" view to make informed early decisions on re-stocking and animal transfers and provided unprecedented transparency in decision making and communication from properties through to the Executive Board. It is also no doubt have major implications on cost savings, animal welfare, land condition and profit.

The project aimed to achieve several ambitious objectives that if successful, would deliver significant benefits to both AACo and the broader industry. These included:

- Refining and improving the precision of current pasture biomass and quality prediction in complex landscapes.
- Developing methods for mapping and monitoring surface water to support grazing management and infrastructure planning.
- Improving understanding of land type variability, its role in decisions on long-term carrying capacity and the ability to automatically map land types.
- Implementing and validating new methods for a Land Condition Model that demonstrate the potential to scale the proposed image segmentation methods across the extensive grazing zone.
- Improved understanding of priorities and barriers to Agtech adoption.

The project was implemented across several key themes which each included numerous work packages. These work packages included:

- Pasture biomass mapping refinement
- Palatable biomass (pasture quality) mapping
- Water body mapping
- Landscape response unit mapping

- Land type mapping
- Land condition mapping
- Producer surveys and adoption

The “living model” approach to the national biomass prediction service developed by Cibo Labs in collaboration with producers is now well established within operational systems and places Australia and Cibo Labs as a world-leader in this capability. The prediction framework recognises that our ability to reliability estimate pasture biomass is only as good as: the time-series satellite imagery; the data collected to train the models and our ability to adequately represent the pasture types and conditions important to grazing management decisions. Recent improvements in biomass field data collection during the exceptional growing season of 2022 and a recalibration of Cibo Labs’ biomass model has greatly improved the accuracy and precision, particularly in the SE of Australia.

Our advances in estimating pasture biomass from satellite and field data now put us in the position to advance pasture quality estimation. The work to date has identified significant potential to improve estimates of pasture quality. Significant investment is now required to coordinate the collection of standardised pasture quality information to build the next generation pasture quality model.

The Landscape Response Unit framework developed through this project has mapped Australia into 49 million landscape response units (polygons) that describe the landscapes spectral and land cover response dynamics over the last ~30 years. This work is a significant step forward that will underpin a range of developments associated with natural capital including sustainable grazing management, property development, carbon accounting and biodiversity assessments. The Landscape Response Units are already underpinning Cibo Labs initiatives related to land condition, land type mapping, landscape carbon estimation, biodiversity, and productivity assessments. There are significant opportunities for improvement which will require an investment of approximately $1M in computer processing to downscale from 100m to 10m resolution.

The Landscape Response Units allowed us to extend the Qld Land Type mapping into the NT and northern WA at a higher resolution than the original mapping. We are now in a position to develop consistent land type mapping nationally. This scoping study demonstrates that land condition can be successfully mapped using spatio-temporal information across the AACo estate, and across the Rangelands. To be able to consistently map land condition at paddock scales for every extensive grazing property in Australia could be a game-changer for the industry.

Several key recommendations have been identified to progress the capabilities developed to support a range of industry outcomes through direct benefits to individual producers:

- The unprecedented and highly variable seasonal weather and pasture conditions across Australia over the last 5 years has made the development of a robust pasture biomass prediction capability highly challenging. The focus now must be to work closely with individual producers to identify regions, pasture types and seasonal conditions were model performance needs to be improved and to coordinate data collection. This could be facilitated by the Northern and Southern Beef Research Councils and existing and proposed MLA Producer Demonstration Sites. The freely available Biomass Collector App provides a capability for nationally consistent data to be easily collected and fully utilised by the industry and research organisations.

- Significant investment is required to coordinate the collection of standardised pasture quality information to build the next generation pasture quality model.
- The Landscape Response Unit Framework should be downscaled from 100m resolution to 10m resolution, nationally. This would require an investment of $1M for data processing and additional project costs that could be shared across Agriculture Innovation Australia and Government partners.
- The ability to predict and map land condition is a game-changer. Significant site data exists across QLD, NT and WA. A coordinated data collation and analysis project should be initiated to provide the training data and capability for developing a northern and southern rangelands land condition prediction change monitoring capability.
- The Australian Feedbase Monitor and Environmental Credentials for Grassfed Beef platforms could be leveraged to provide secure and trusted access to this information in partnership with producers.
- Access to digital farm mapping is still a fundamental barrier to Agtech adoption across the industry. A national farm mapping service should be put in place to act as a single point of truth for the grazing industry.

1. Background

Market satisfaction is vulnerable to varying livestock availability in the supply chain. MLA's project review in this work area, B.ERM.0098 reported a profitable and environmentally sustainable beef industry is critical to continued productivity and allied socio-economic and cultural well-being in northern Australia.

This project addresses opportunities to improve feedbase and animal management, ensuring optimum seasonal feed supply, land condition and long-term sustainable production. Producers have readily adopted technology to increase herd productivity and counteract reduced labour availability; literacy surrounding management of natural resources has also increased, particularly with the principles and practice of Grazing Land Management from delivery programs such as the Grazing Best Management Practices Partnership in Queensland. Development of relevant technology, including timely, spatially extensive information on resource productivity and condition, can contribute to the efficiency and improved profitability of sustained livestock production in northern Australia.

Estimating safe carrying capacity and optimal seasonal stocking rates has been assisted by the capacity to model expected pasture growth following variable amounts of rainfall. Estimates have been derived from analysis of satellite data and on-ground knowledge of grazing impacts to support decisions on long-term carrying capacity and seasonally adjusted stocking rates. An integrated system of modelled and monitored pasture biomass, complemented by adequate ground-truth data, will provide land managers with improved information to better manage their animal production outcomes and natural resource base under continuing climate variability. Work has sporadically progressed to address the ability to accurately and consistently monitor pasture biomass across the diverse rangelands of northern Australia, both directly (i.e. field based) and remotely. This project progresses the recommendations from B.ERM.0098.

Cibo Labs was founded as a commercial entity in early 2018 to address the need for improved feedbase and land condition monitoring to support profitable and sustainable grazing management decisions. Over the last 5 years there has been significant investment in data science, high performance computing; machine learning systems; targeted field data collection and most importantly strong engagement with producers to routinely deliver paddock level estimates of pasture biomass on a weekly basis to over 55 million ha. Fully automated high performance computing systems now deliver Sentinel-2, 10m resolution, 13 band imagery within 24 hours of acquisition. Machine learning (ML) algorithms and geospatial analysis based on data collected by producers and Cibo Labs, estimates total standing dry matter for each paddock every 5 days. As of early 2023 approximately 5100 sites had been compiled, generating predictions of TSDM with a median absolute error of <300kg/ha across northern and southern pasture systems.

The continuing model development is also underpinning the Australian Feedbase Monitor (AFM) launched in partnership with MLA on November 30, 2022. The AFM is providing 1 hectare resolution, rolling monthly pasture biomass estimates which are updated every 5 days for every farm in Australia and can be accessed by MLA members for free. As of April 14, 2023, 1720 producers were using the service.

The Australian Agriculture Company (AACo) has been a significant supporter of these developments in collaboration with Cibo Labs, and which now underpin many management decisions across the company. Using the Cibo Labs PastureKey service has transformed the forage budgeting and decision-making process for AACo. In 2022 property level forage budgets were completed over 2 months earlier than usual. This has provided a "whole of business" view to make informed early decisions on re-stocking and animal transfers and provided unprecedented transparency in decision making and communication from properties through to the Executive Board. There is also no doubt that this will have major implications for cost savings, animal welfare, land condition and profitability.

2. Objectives

The project aimed to achieve several ambitious objectives that if successful, would deliver significant benefits to both AACo and the broader industry. These included:

1. *Refining and improving the precision of current biomass prediction in complex landscapes. This involves continued early, mid and late season data collection and extending to include denser woodland areas, lake and terminal drainage systems and key shrubland areas*.

ACHIEVED: The National Biomass Model was performing accurately in the northern tropical systems but, was under-predicting senesced high-biomass in the southern temperate pastures where vast areas had spring, summer and autumn growth accumulated across many under-stocked farms. The model presented in this report has incorporated around 2500 additional field biomass measurements, many of them in in SE Australia, during 2021 and 2022 which have significantly improved the performance of the biomass model in these regions.

2. *Developing and advancing predictions of palatable yield estimation aimed at improving feedbase management and nutrition in line with the priorities of the Northern Breeding Business (NB2) priorities.*

ACHIEVED: Two approaches were used to improve estimates of pasture quality associated with palatable dry matter and green dry matter across both the AACo estate and nationally:
a- We ran our previous calibration method on both the TSDM data, and then reran the calibration against palatable TSDM (PTSDM), calculated as PTSDM = TSDM x (1- unpalatable %). The results indicate that the prediction of palatable dry matter is at least as reliable as the prediction of total dry matter.
b- As a robust and simple measure of pasture quality we are calculating green standing dry matter (GSDM) as GTDM = TSDM x Green Fraction %.

3. *Mapping land condition for Brunette Downs, in addition to the persistency of natural waters to support understanding of seasonally variable pasture utilisation and planned infrastructure development*.

EXCEEDED: We mapped Land Condition across 10 AACo stations in the Victoria River, Barkly and Gulf regions (including Brunette Downs). The resulting Land Condition map had an accuracy of 80.4%. This information is already being used to support 2023 forage budgeting, stock rate decisions, infrastructure development, and the Rangelands Carbon Project.

4. *Improving understanding of land type variability, its role in decisions on long-term carrying capacity (re- planning infrastructure development, forage budgeting, nutrition need for supplements) via a proof-of-concept analysis using time series data that demonstrates the ability to generate "Landscape Response Units" (LRU) which effectively replicates the manual land type mapping in QLD*.

ACHIEVED: We developed the methodology to generate the Landscape Response Units (LRUs). The LRUs consist of segments (or polygons) which group together pixels that share similar values in their vegetation dynamics and landscape properties. Each segment retains the mean values of all the input layers used for their creation. The LRUs underpin several initiatives by Cibo Labs including the development of Land Condition and Land Type mapping and are also being used to stratify the landscape for soil carbon sampling as part of the Rangelands Carbon Project.

5. *Implementing and validating new methods for a Land Condition Model (LCM) at AACo's Anthony and Eva Downs stations in the Northern Territory that demonstrate the potential to scale the proposed image segmentation methods across the extensive grazing zone (area >2 M ha).*

EXCEEDED: We mapped Land Condition across 10 AACo stations (6.6M ha) in the Victoria River, Barkly and Gulf regions (including Brunette Downs). The resulting Land Condition map had an accuracy of 80.4%. This information is already being used to support 2023 forage budgeting, stock rate decisions, infrastructure development, and the Rangelands Carbon Project.

6. *Identifying and reporting land condition issues that have major impacts on long-term sustainability and production across target zones and utilise this for seasonal forage budgeting and decisions making on stocking rates and paddock spelling.*

ACHIEVED: We demonstrate how estimates of Total Standing Dry Biomass can be combined with maps of Land Condition to provide better assessments of carrying capacity and therefore improve decision making on stocking rates, grazing management decisions, and infrastructure development.

7. *In collaboration with Elder's project P.PSH.1117 (co-innovation and adoption pilot) develop a market survey questionnaire (10-12 questions) to inform producer benefit and commercialisation plans.*

EXCEEDED: Two market survey questionnaires were used to assess producer's knowledge of satellite-based forage monitoring. Additionally, the rate of usage and uptake of Cibo Labs' services following the launch of the Feedbase Monitoring System provides useful insights about the demand for this type of products with over 1800 producers using the AusTralian Feedbase Monitor in the first 5 months since launch.

A review of the outcomes of this project will form the basis of developing and refining the ongoing services for AACo and the broader northern industry. The project will also improve AACo and the northern industry's ability to measure and manage the pasture and land resource base, and lead to improved herd, feedbase and environmental management decisions through direct pathways to adoption.

3. Methodologies

The project was implemented across several key themes which each included numerous work packages. The remainder of the report is largely structured according to the themes addressed in the methodologies described below.

3.1 Pasture Biomass Mapping Model Refinement

Field samples of total standing dry matter (TSDM) across Australia were collected by Cibo Labs, clients and collaborators. This process is continuous and aims to capture the variability across species, growth stages and land types in the grazing regions (See Figure 1 and Figure 2). Coincident Sentinel-2 imagery (10 meter resolution) and the associated Landsat-derived persistent green fraction is used to train a three-layer, multilayer perceptron regression model generally using a 50% dropout, a maximum norm constraint, and a robust loss function to avoid over prediction.

50% of the field site data is randomly selected and used for training, with the remainder reserved for validation. This is common practice in model training and evaluation, particularly when using machine learning methods. The relative simplicity of this model, coupled with the availability of global imagery in cloud optimised formats, means that biomass estimates can be obtained in either batch mode over large areas in a high performing computing environment, or on demand as a cloud computing function. The typical latency between image capture and delivery is under 24 hours. This enables fast interrogation of individual paddocks from global scale imagery, either in the user's browser or through integrations with other farm management software, including detailed statistical summaries over space and time.

As of early 2023 Cibo Labs have compiled approximately 5100 pasture assessment sites for model calibration (See figures 1 and 2). Our Biomass Collector App is being used exclusively for all data collection. In the last two years the field data collection has duplicated in size and incorporated many observations in some land cover classes of particular relevance, such as Natural Surfaces [1], and woodlands.

The field data is collected by Cibo Labs staff, consultants and clients using the Biomass Collector App installed in a mobile phone or tablet. This app initially collects generic information about the transect such as the time and date, GPS reading and a photo. The user also enters qualitative information about the species composition, proportion of 3P species (these two are used in our assessment of Palatable Biomass mapping, see section 3.2), vegetation cover, dry matter content and average pasture height. Then the user has the option of collecting biomass data using pasture cuts, plate meter sampling or visual estimates. In the case of pasture cuts, the user proceeds to harvest biomass data, using quadrats separated by a regular interval. Cibo Labs recommends doing 10 paces between quadrats. The size of the quadrat is decided by the user choosing between 0.1, 0.25, 0.5 and 1 square meters. In each quadrat the user harvests all the standing biomass which is weighed with a portable scale. A small sample of ~100 grams is retained and dried in an oven to produce a more accurate measure of dry matter content. The number of quadrats in the transect is decided by the user, with a minimum of 5 and a maximum of 12. The estimate of Total Standing Dry Matter in the transect is finally calculated as the mean of all quadrats, after correcting by quadrat

[1] "Natural Surfaces" in the Geoscience Australia Landsat Land Cover 25m map is defined as: Comprised primarily of unconsolidated (often pervious, e.g. mudflats, saltpans) and/or consolidated (e.g. bare rock bare soil) materials. In Australia, the proportional area of natural surfaces is relatively low and primarily confined to the deserts and semi-arid areas, river channels (e.g. dry riverbeds) and the coastline (e.g. sand dunes, mudflats). Much of the interior of Australia is sparsely vegetated and can be dominated by herbaceous (annual or perennial) or woody lifeforms.

size and dry matter content. All data are managed through a secure, online database populated by the Biomass Collector App which provides offline ability to collect pasture site data. See Figure 3 below.

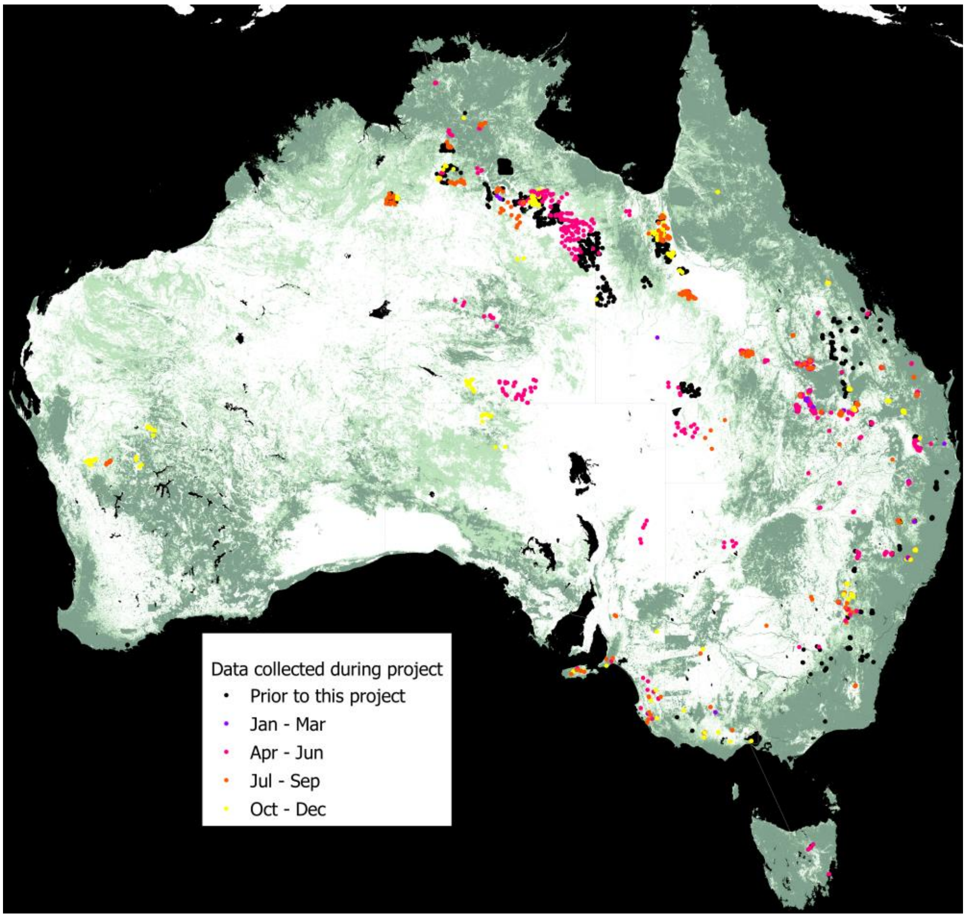

Figure 1. Distribution of pasture measurements per land cover type. New sites, in red, indicate those biomass measurements collected after Jan 2021. The Geoscience Australia Landsat Land Cover 25m map (Lucas et al 2019, Owers et al 2021) was used to identify the land cover classes for each field measurement site.

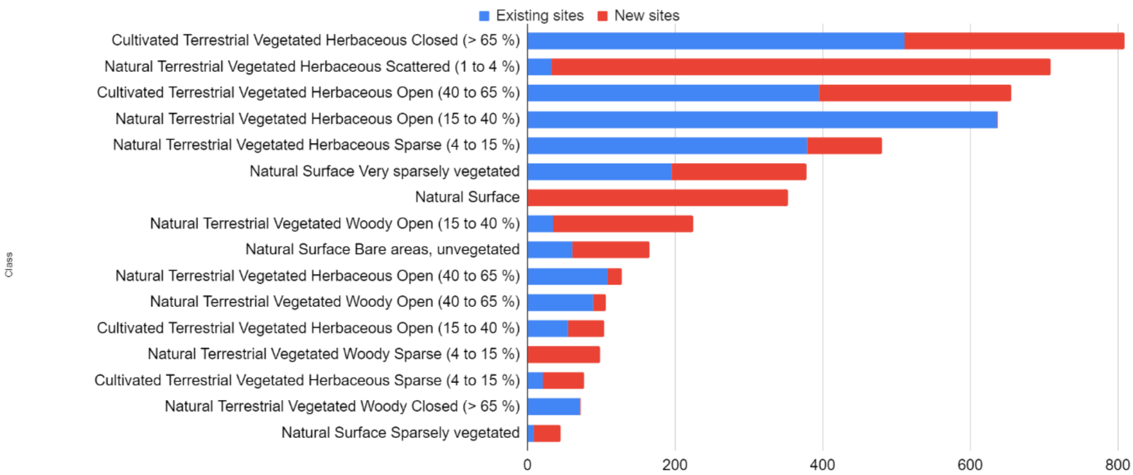

Figure 2. Frequency distribution of field sites across broad vegetation and land use classes.

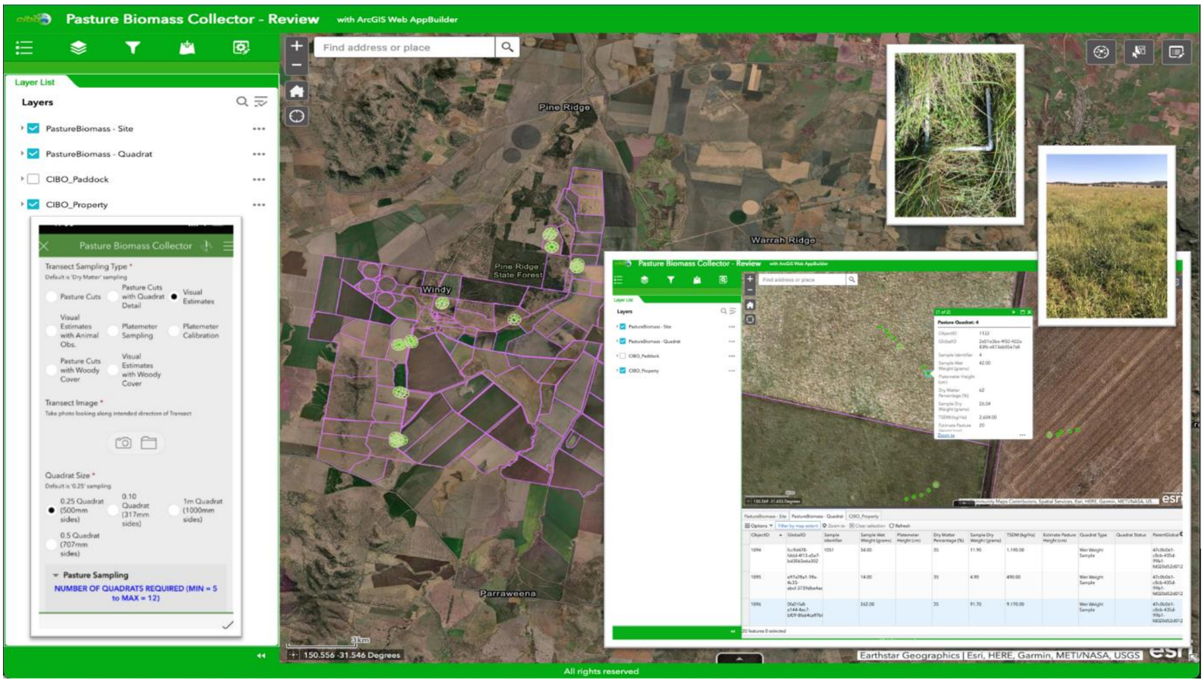

Figure 3. Pasture Biomass Collector App and dashboard for collecting and managing pasture data.

With a rapidly growing client base in southern Australia and improved seasonal conditions, in December 2021 Cibo Labs released a national pasture biomass model and commenced 5-day predictions of TSDM and Green Dry Matter (GDM). The new modelling framework is unique in that we have integrated both tropical and temperate pastures into a single prediction framework that does not require prior knowledge of the pasture type in each paddock. The result has been the ability to seamlessly predict biomass for any region in Australia and in areas of summer and winter growth (e.g Northern NSW) to reliability predict biomass in adjacent paddocks with temperate and tropical pastures at different growth stages.

3.2 Palatable Biomass Mapping

We used two approaches to improve estimates of pasture quality associated with palatable dry matter and green dry matter across both the AACo estate and nationally.

To test the prediction of a palatable dry matter model, we used an initial smaller dataset of 246 sites that were collected by AACo staff, rather than the full site database. These sites had quadrat cut estimates of total standing dry matter and visual estimates of unpalatable percent. Due to the limited number of sites, we were not able to apply our full machine learning model to the data. To test the hypothesis that palatable matter was able to be predicted we ran our previous calibration method on both the TSDM data, and then reran the calibration against palatable TSDM (PTSDM), calculated as PTSDM = TSDM x (1- unpalatable %).

As a robust and simple measure of pasture quality we are also now routinely calculating green total standing dry matter (GTSDM) as GSTDM = TSDM x Green Fraction %.

3.3 Water Body Mapping

We calculated the Normalised Difference Water Index (NDWI) on each Sentinel 2 image in the period 2017-2022. The NDWI is a widely used index that is highly sensitive to surface water. Typically, values greater than 0 are likely to be water, although this may vary depending on vegetation and soil conditions in the pixel. For this analysis we used a threshold of 0 to determine if a pixel was "wet" or "dry". We processed approximately 300,000 Sentinel 2 tiles where the solar zenith angle at the time of the overpass was greater than 45 degrees and the estimated tile cloud fraction was less than 50%. Both the European Space Agency's Sentinel Applications Platform (SNAP) cloud and cloud shadow mask and the Sentinel Hub cloudless mask were applied to minimise the effects of cloud contamination. From the stack of NDWI images we calculated temporal statistics including the 50^{th}, 75^{th} and 90^{th} percentiles of the 4-year stack of NDWI values. These will represent the NDWI values for different scenarios. For example, the 50^{th} percentile is the median NDWI value for the pixel and is useful for detecting those areas that are often wet. The 10^{th} percentile will detect near permanent water, and the 90^{th} percentile will detect areas that are wet very infrequently.

3.4 Landscape Response Unit Mapping

We produced the Landscape Response Units (LRUs) following the steps listed below. A schematic showing a summary of these steps is shown in Figure 4.

1. We generated a stack of raster layers including statistics from the time series of remotely-sensed vegetation and water, Digital Elevation Model-derived terrain, soil information, and interpolated climate data. The full list of input layers is provided in Table 1. All these layers were resampled to a common projection and grid of 20-meter resolution.
2. We ran a robust Principal Component Analysis over all input layers and retained the first 11 principal components, which account for 95% of the spatial variability. These were stretched from floating point to fill unsigned 16 bit space to improve segmentation performance.
3. Using the stretched 11 principal components to drive the initial *k* means clustering, we ran a segmentation following Shepherd et al (2019). The process was iterated several times changing the segmentation parameters outlined in table 2 and was visually assessed for performance in the northern rangelands. The final segmentation used a minimum segment size of and 2048 initial classes with a spectral distance percentile of 5% classes and four-connected growth.
4. As we added additional bands into the segmentation, it became clear we needed to reduce the segment minimum size as the segments were representing multiple attributes of the landscape such as land condition, land type and land management. By selecting a smaller minimum segment size, we were able to aggregate back up to larger segments depending on what attribute of the landscape we were predicting.
5. We calculated the mean, standard deviation, mode and count of values of the pixels in each segment and added those statistics to an attribute table.

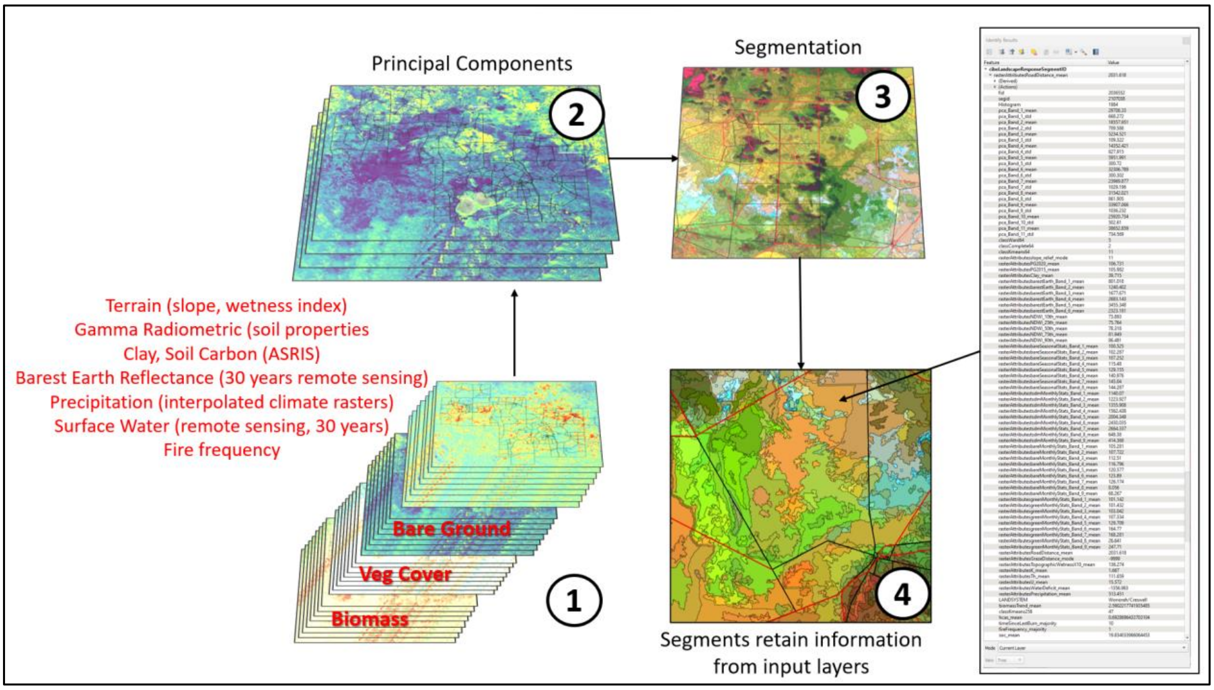

Figure 4. Landscape Response Unit (LRU) processing workflows and outputs.

Table 1. Input variables used to derive the Landscape Response Units.

Input	**source**	**type**
Total Standing Dry Matter	Sentinel 2, Cibo Labs	Monthly, 2017-2022, summary stats 8 bands
Bare ground %	Sentinel 2, Cibo Labs	Monthly, 2017-2022, summary stats 8 bands
Green Cover %	Sentinel 2, Cibo Labs	Monthly, 2017-2022, summary stats 8 bands
Water Dynamics	Sentinel 2 NDWI, Cibo Labs	Monthly, 2017-2022, summary stats 8 bands
Bare Ground Percentiles	Landsat, JRSRP	Seasonal 1988-2022 summary stats
Barest Earth	DES Barest Earth 1988 to 2018	Static, 6 bands
Slope	SRTM DEM	Static, 1 band
Clay content	TERN	Static, 1 band
Radiometric Map of Australia	TERN	Static, 3 bands
Topographic Wetness Index	TERN	Static, 3 bands

Table 2. Parameters and values used in the segmentation.

Segmentation Parameter	**Values Tested**
Minimum Segment Size (20m pixels)	1000, 500, 250, 200, 100, 50
Number of Initial Clusters	512, 1024, 2048
Spectral Distance Percentile	5,10,50
Connectivity	4,8

3.5 Land Type Mapping

For each Landscape Response Unit in Queensland, we obtained the mode (most abundant class) from the Queensland Land Type mapping. We then trained a Random Forest Classifier using the information retained in each Landscape Response Unit as features and the observed Qld Land Type as the target label. We obtained the optimum model parameters by running a five-fold cross validation, and then evaluated the model performance also running a five-fold cross validation. Cross-validation is a resampling method that uses different portions of the data to train and test a model on different iterations. It is a standard practice in machine learning applications which prevents the model from overfitting the training data.

The Qld Land Types Map has 250 classes distributed in 13 regions. One difficulty we faced is that there is no easy way to aggregate these classes into fewer of them, nor an alternative hierarchical classification system that can rank the degree of similarity between classes. For example, the classes MGD01 (Open Downs) and MGD02 (Ashy Downs) are very similar to each other and could be aggregated together for the purposes of our classification approach (See Appendix 1 (section 8)).

3.6 Land Condition Mapping

We used a dataset of field observations of Land Condition taken on the AACo properties between 2018 and 2022. The assessment of Land Condition follows the methodology developed by the Queensland government and uses the ABCD framework (Karfs et al 2009). Land Condition is always assessed considering the Land Type and incorporates in a single metric indicators of pasture composition, soil erosion, weeds and woody thickening. This poses a challenge to monitoring LC with remote sensing, as simple relationships between pasture biomass or vegetation cover cannot be directly established.

The data collected by AACo personnel included 3830 observations of Overall Land Condition in AACo properties in the Victoria River, Barkly Tablelands, Gulf and Channel country (Figure 5). Each Land Condition observation (coloured points in Figure 5) assess an area of approximately one hectare. In many instances two assessments are done at each side of a fence. Some of these observations also included specific Land Condition data for Soil, Pastures and Woody vegetation. For this analysis we used the Overall Land Condition only.

For each Land Condition observation, we extracted information from the corresponding Landscape Response Unit (see previous section). This included the mean and standard deviation of the 11 Principal Components, which summarises all the spatio-temporal data used for generating these LRU, i.e. average vegetation condition for the last 10-20 years. We pooled all the Land Condition observations together which include assessments made between 2018 and 2022. Therefore, we can consider the input data and the resulting outputs and maps as a summary for the average land condition between 2018 and 2022.

We converted the categorical Land Condition classes to an ordinal value using the conversion presented in Table 3. We then trained a Random Forest Regressor using the LRUs information as features and the observed Land Condition as the target value. We obtained the optimum model parameters by running a five-fold cross validation, and then evaluated the model performance also running a five-fold cross validation.

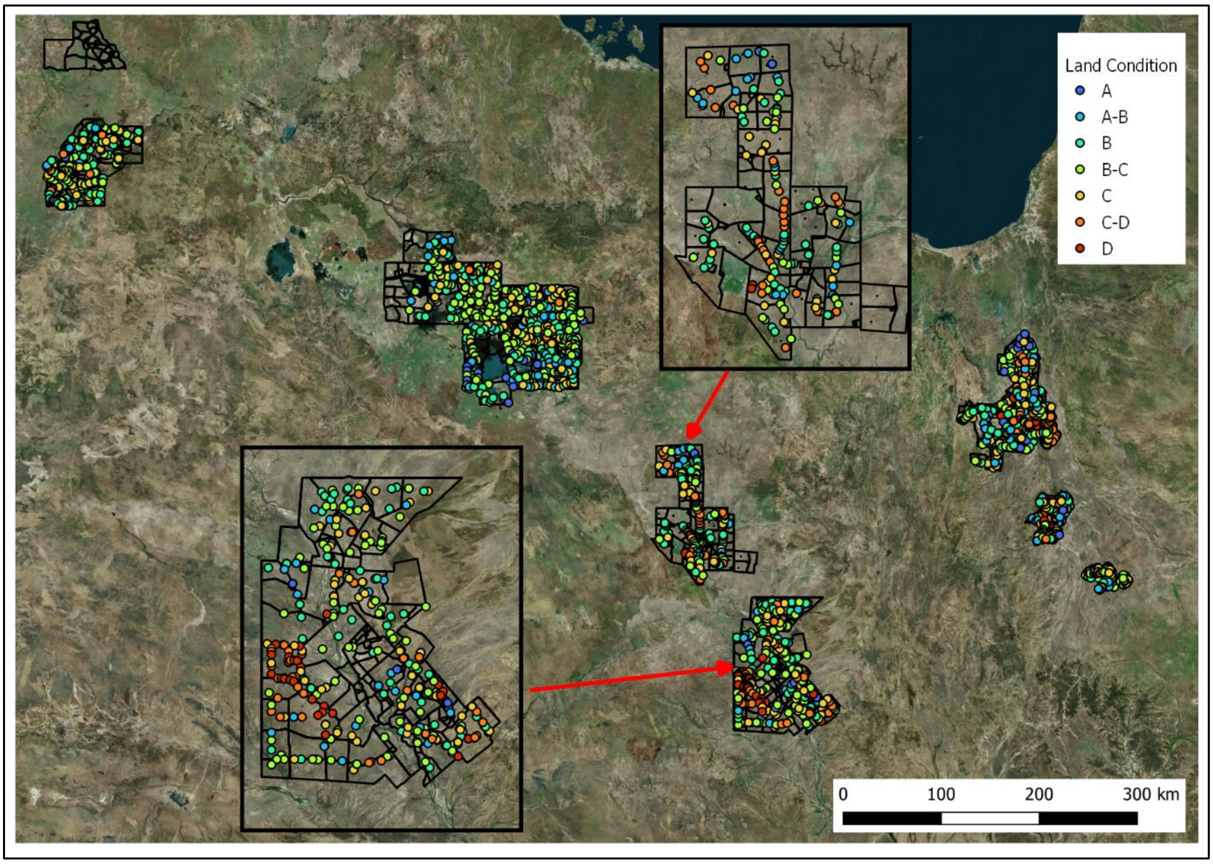

Figure 5. AACo properties with Land Condition site data.

Table 3. Land Condition classes including Categorical to Ordinal conversion of ABCD land condition class.

Land condition Class	Ordinal Value	Description (one or more of these condition)	Carrying capacity
A	1	no erosion, good coverage by 3P grasses, none or very early signs of woodland thickening	100%
A-B	0.833		
B	0.667	Minor erosion, increase in non 3P grasses, some thickening in woody plants	75%
B-C	0.5		
C	0.33	Obvious erosion, large quantities of non-3P grasses, General thickening in density of woody plants	50%
C-D	0.167		
D	0	Severe erosion or scalding, General lack of perennial grasses or forbs, Thickets of woody plants cover most of the area	20%

3.7 Producer Surveys and Adoption

Understanding current levels of technology adoption and management practices, barriers and benefits to adoption are critical to research and development, product development and commercialisation strategies. As a commercial business we need to be continually reviewing needs and opportunities to increase adoption and impact across the industry. While only a minor component of this project, several small activities were undertaken to better understand some of the barriers and opportunities, with a specific focus on the northern cattle industry and the Northern Breeder Business (NB2) initiative.

In collaboration with Elder's project P.PSH.1117 (co-innovation and adoption pilot) we developed a market survey questionnaire that was provided as an on-line survey at Beef Week 2021 through Elders. The survey questions and results can be found in Attachment 1.

In addition, Cibo Labs and Rayner Ag undertook a separate survey of 2100 Rayner Ag contacts.

4. Results and Discussion

4.1 Pasture Biomass Mapping Model Refinement

Figure 6 below provides a 10-fold cross validation of the Cibo Labs model using 14500 satellite observations that temporally match the 5100 field observations. Sites satellite imagery is retrieved when the imagery is cloud free and the overpass is within 10 days before and 5 days after the field observation. We assume minimal changes within this window, however rapid changes can occur dure to grazing events or when there is substantial growth occurring. However, these replicate samples across multiple image dates provide substantial resistance to atmospheric variability, improve model temporal stability and to boost the number of calibration sites with TSDM > 4000kg/ha to improve overall TSDM prediction performance. Each iteration used 60% of the data to develop the model, 30% of the data to provide internal validation, and 10% to test the model. Outliers can be due to poor model performance, rapid growth due to rain events close to the sampling, or pasture utilisation after the field sampling has taken place. It is important to note that the field data has an overall mean absolute percentage error (MAPE) of 40%. The lowest MAPE is from the pasture cuts, given by the variability pasture biomass from quadrat to quadrat within each site, however these are also highly variable with a MAPE of ~30%. This implies that our TSDM model estimates biomass with an uncertainty of a similar magnitude than the uncertainty of the field data.

The Median Absolute Error (MAE) of the model increases when a larger range of TSDM observations is considered. When TSDM values of up to 2000 kg/ha are considered, MAE is 235 kg/ha and the MAPE is 25.7%. Importantly, the model error matches the error in the field data. Figure 6 and Table 4 shows error metrics for various TSDM prediction levels.

Table 4. cross validation metrics for selected TSDM ranges.

TSDM range	Mean Error (kg/ha)	StDev Error (kg/ha)	RMSE (kg/ha)	MAE (kg/ha)	MAPE (%)
0 - 1000	287	543	618	184	90.5
1000 - 2000	35	563	564	235	25.7
2000 - 3000	268	735	783	453	24.0
3000 - 4000	618	892	1085	637	24.3
4000 - 6000	1218	1193	1705	1073	27.9
6000 - 10000	2404	1915	3074	2263	35.1

From Figure 6 we see that most field data collected for this project were from the late dry season but there was a spread of field sites across the entire year. No seasonal bias could be detected in the calibration, indicating that errors of this type were below the error already inherent in the field data.

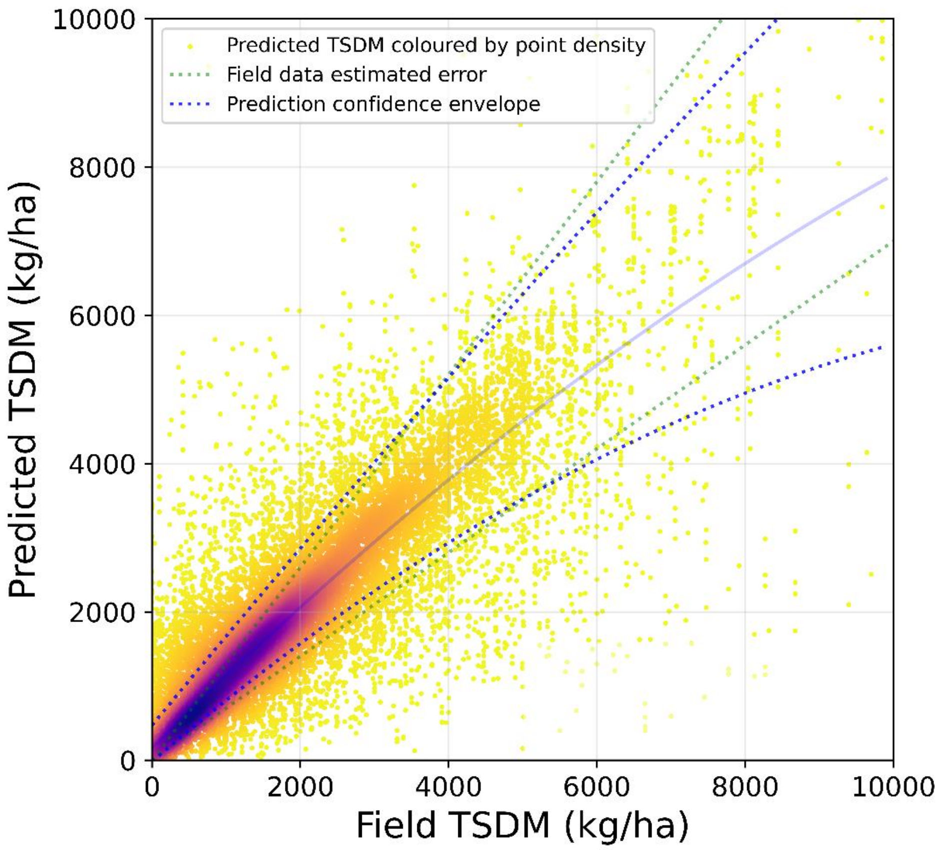

Figure 6. National pasture biomass model predictions compared to field sites using 10-fold cross validation. Points coloured by the density of nearby points highlighting areas with many points overlaying each other.

The scientific literature has numerous studies using remote sensing to estimate pasture biomass in small, localised regions. For example, *Chen et al* calibrated a model using Sentinel 2 imagery in Northern Tasmania and achieved a Median Average Error of 262 kg/ha. To the best of our knowledge, our data product is the first to have been calibrated and tested with more than 5000 observations, covering an entire continent, and being operationally available in near-real time.

Figure 7 below provides an example of the Cibo Labs PastureKey application interface for one of the AACo properties which is used by station managers, rangelands staff and the executive to make informed decisions.

- The Cibo Labs platform calculates the average TSDM for each land type and distance from water.
- Utilisation rates are applied differentially for each land type and distance from water to calculate a weighted available feed on offer (FOO) for each paddock. The proportion of palatable species depends on the land type. The proportion of palatable species consumed by livestock decreases with distance from water. A 100% percent utilisation is assumed within 3km of water, a 50% utilisation between 3 and 5 km and no utilisation further than 5 km.
- The weighted FOO predictions automatically populate a Forage Budgeting calculator based on animal class and AE rating to derive a recommended stock rate for the grazing period.
- The station manager and rangelands staff then adjust were necessary based on knowledge of pasture quality and land condition to set the final stocking rate for each paddock which are then automatically rolled up to the property level.

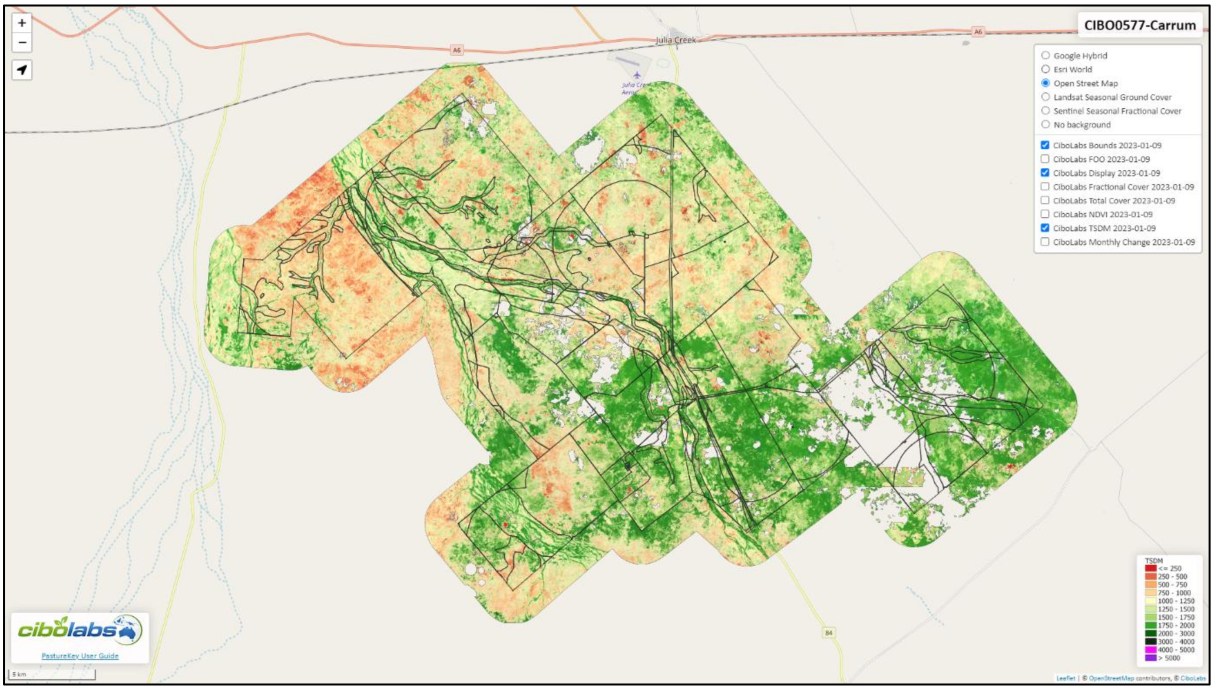

Figure 7. PastureKey interface of Carrum station showing the biomass predictions on Jan 9th 2023. The black lines are the combination of paddocks, distance from water and land type boundaries. Each zone has an independent prediction of feed on offer combining the TSDM estimation, the land type and the distance from water.

Using the Cibo Labs PastureKey service has transformed the forage budgeting and decision-making process for AACo. Property level forage budgets are now completed over 2 months earlier than usual. This has provided a “whole of business” view to make informed early decisions on re-stocking and animal transfers and provided unprecedented transparency in decision making and communication from properties through to the Executive Board. It will also no doubt have major implications on cost savings, animal welfare, land condition and profit.

AACo CEO Hugh Killen recently stated that *“the Cibo-AACo partnership had fundamentally changed the way AACo undertook forage budgeting and the way managers approached their grazing management decisions”. AACo Head of Environment and Sustainability Naomi Wilson also recently stated that the Cibo Labs PastureKey service “makes a range of grazing land management decisions easier, quicker, more accurate and cheaper than traditional methods*”.

South-Eastern Australia experienced unprecedented rainfall during the Spring, Summer and Autumn of 2021-22. Many areas of temperate improved pastures through central and southern NSW experienced very mild summer and autumn breaks with Fescue and Phalaris pastures often exceeding 8000kg/ha of total standing dry matter (TSDM). Generally low stock numbers resulted in a significant proportion of last summer growth still standing, with autumn growth covered by up to 5000kg/ha of dry-senesced pasture.

In early 2022 it has become apparent that while our National Biomass Model was performing accurately in the northern tropical systems, it was under-predicting senesced high-biomass temperate pastures in the south where vast areas had spring, summer and autumn growth accumulated across many under-stocked farms. The model presented here has incorporated around 1000 additional field biomass measurements in SE Australia during 2022 which has significantly improved the performance of the biomass model in these regions.

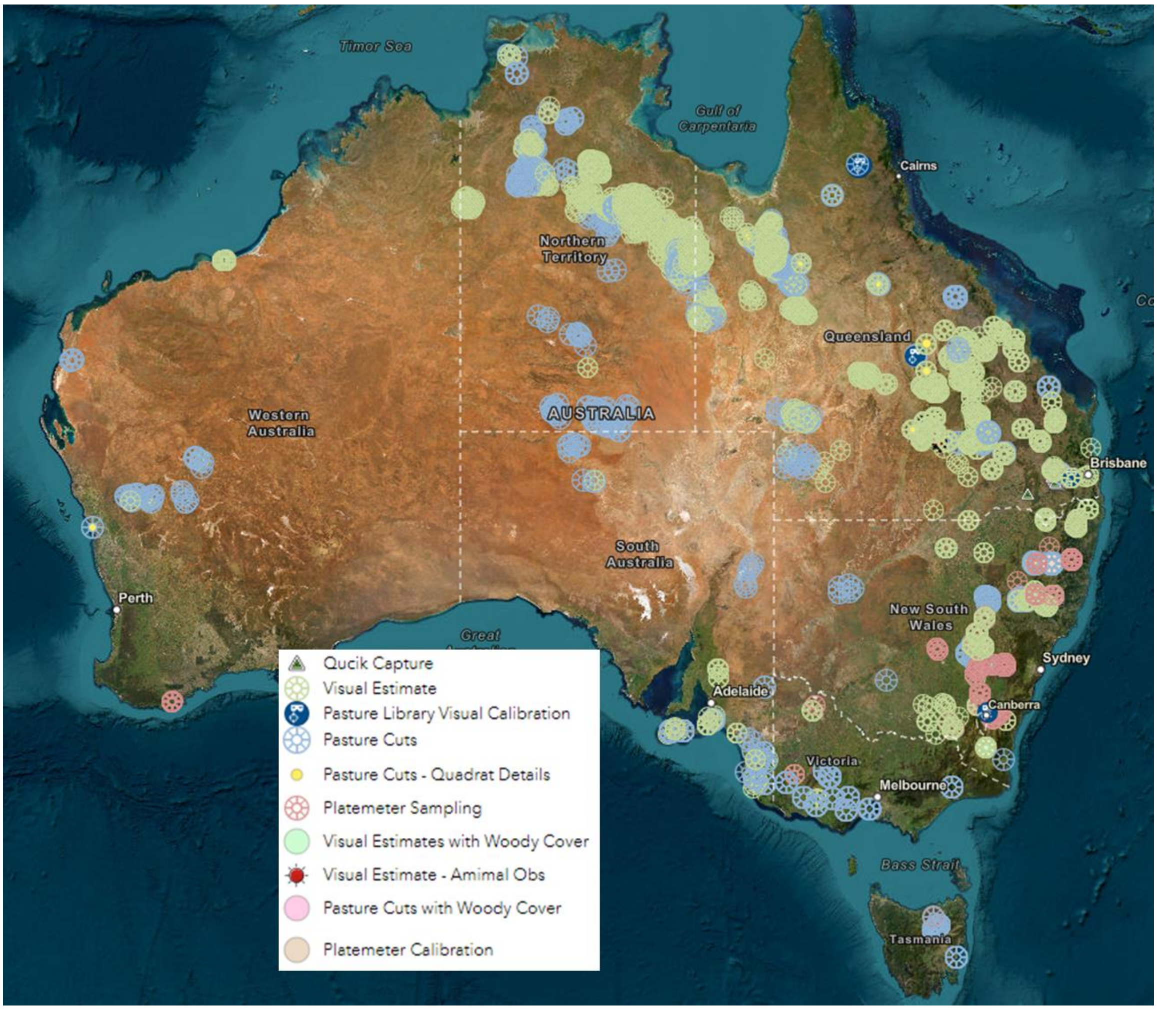

Figure 8 Pasture assessment site locations. Over 5100 sites have been compiled up to early 2023, with a focus on south eastern Australia during 2022

The integration of the northern and southern models into a seamless national biomass prediction model has been a significant success and to our knowledge the only commercial implementation of such a model anywhere in the world. Field data continues to be collected on an ad-hoc basis and planned basis, with particular emphasis in areas where our users detect under or over-estimation of biomass, compared to what they observe in the field. We will continue to improve our model as more field data becomes available. This has been the approach we took since the commencement of Cibo Labs' operations. We call this a "living model" approach.

The "living model" approach to the national biomass prediction service is now well established within operational systems. Our ability to reliably estimate pasture biomass is only as good as the data collected to train the models and our ability to adequately represent the pasture types and conditions important to grazing management decisions. This has been extremely challenging to achieve with highly variable seasonal weather and pasture conditions since development began in 2018.

The focus now must be to work closely with individual producers to identify regions, pasture types and seasonal conditions were model performance needs to be improved and to coordinate data collection. This could be facilitated by the Northern and Southern Beef Research Councils and existing and proposed MLA Producer Demonstration Sites. The freely available Biomass Collector

App provides a capability to nationally consistent data to be easily collected and fully utilised by the industry and research organisations.

4.2 Palatable Biomass Mapping

The results of this analysis are shown in Figure 9 below.

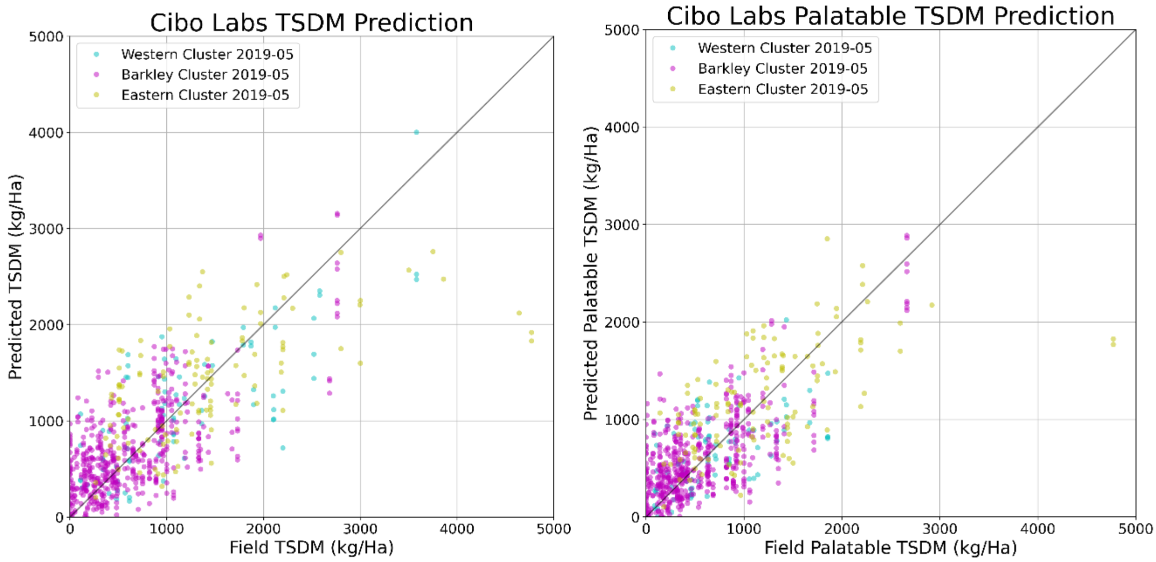

Figure 9. Left is Cibo Labs v1 TSDM prediction model run against 246 sites in 2019 showing a moderate predictive accuracy. Right is the same model form used to predict palatable matter which shows a similar accuracy to the TSDM model, with fewer outliers. Dot colour is related to the location of the field campaigns in northern Australia.

With the data available to this analysis, the prediction of palatable dry matter is at least as reliable as the prediction of total dry matter. In Table 5, the median absolute error and the root mean square error are reduced compared to the total standing dry matter. However, this is to be expected, as the palatable dry matter amounts are lower overall.

Table 5. Total TSDM and palatable TSDM predictive accuracy.

Measure	Total TSDM	Palatable TSDM
Median Absolute Error	299 kg/Ha	279 kg/Ha
Root Mean Square Error	545 kg/Ha	507 kg/Ha

Following the targeted data collection in high-biomass and senesced pastures in both southern and northern Australia over the last 12 months, we are confident that we will be able to build a palatable yield prediction layer over the current Cibo Labs machine learning framework which now leverages over 5100 sites nationally to enable consistent reporting nationally of this important measure.

To prepare for this data, as part of this project we have built a complete Extract-Transform-Load (ETL) process for our machine learning framework. This uses multiple database tables to capture and link field, spatial and image data in space and time. Once data is collected in the field, it is transferred to the ETL process, and all attributes are extracted and linked to the data. As part of this framework, Cibo Labs will shortly open source the pixel drilling process for those remote sensing scientists and developers who would wish to link their own field to image data.

The second approach was to provide an estimate of the green fraction of the dry matter. Many studies have reported a correlation between the greenness of forage and attributes such as nitrogen and phosphorous availability while other authors have reported a correlation between the ratio of green to dry forage and dietary crude protein and in vivo dry-matter digestibility (Pringle et al, 2021).

Here, we use $Green\ Mass = TSDM * \frac{Green\ Fraction}{Dry\ Fraction + Green\ Fraction}$ as an easy to use indicator to give an estimate of the green fraction of the dry matter. We have implemented this to run on every satellite overpass over the entire AACo estate. An example for Brunette Downs is shown in Figure 10.

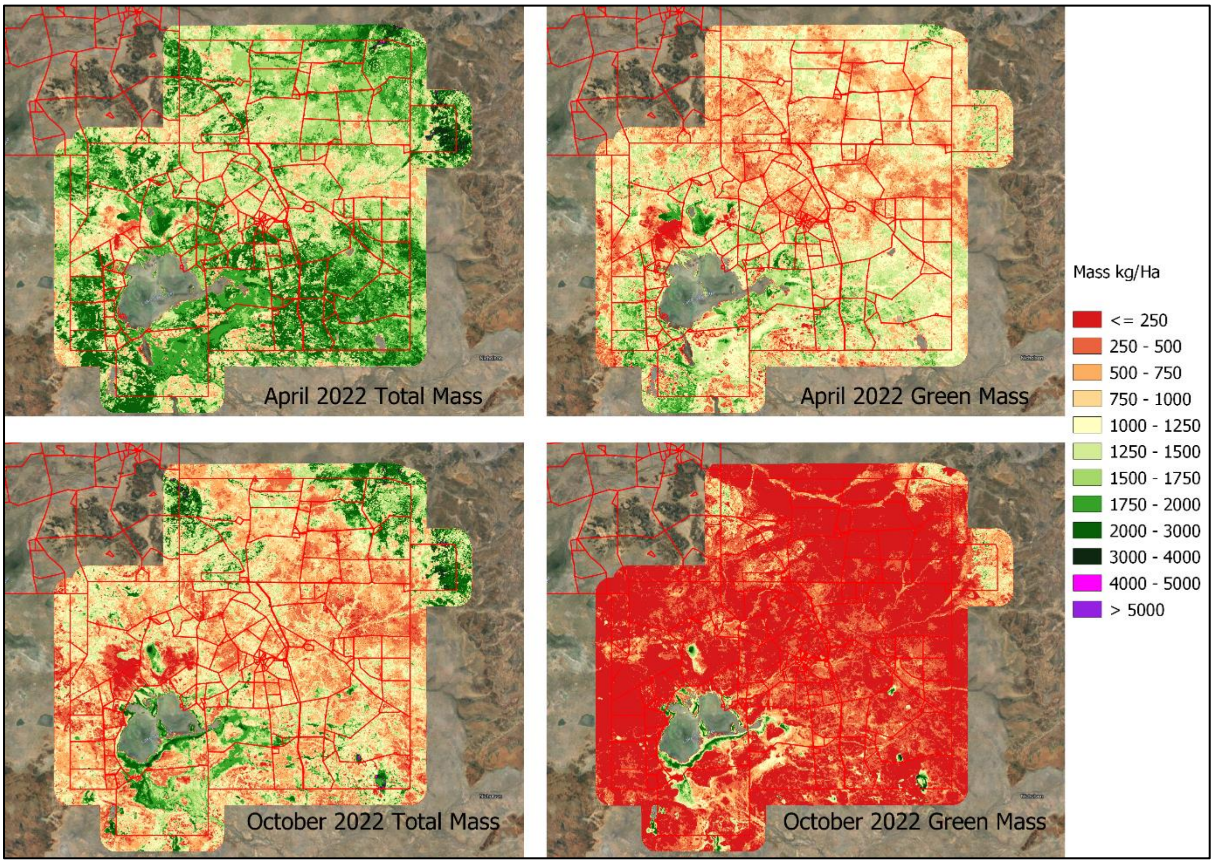

Figure 10. Brunette Downs TSDM and Green mass of TSDM at the start of season and end of season. In April the green mass represents the bulk of the palatable matter but as the season progresses, the forage hays off and the green mass drops to zero.

This process is now automatically applied to every mosaic produced for the Australian Feedbase Monitor launched on November 30, 2022, enabling producers to track the green mass throughout the year. Figure 11 shows an example from January 2023 just prior to the massive rain event.

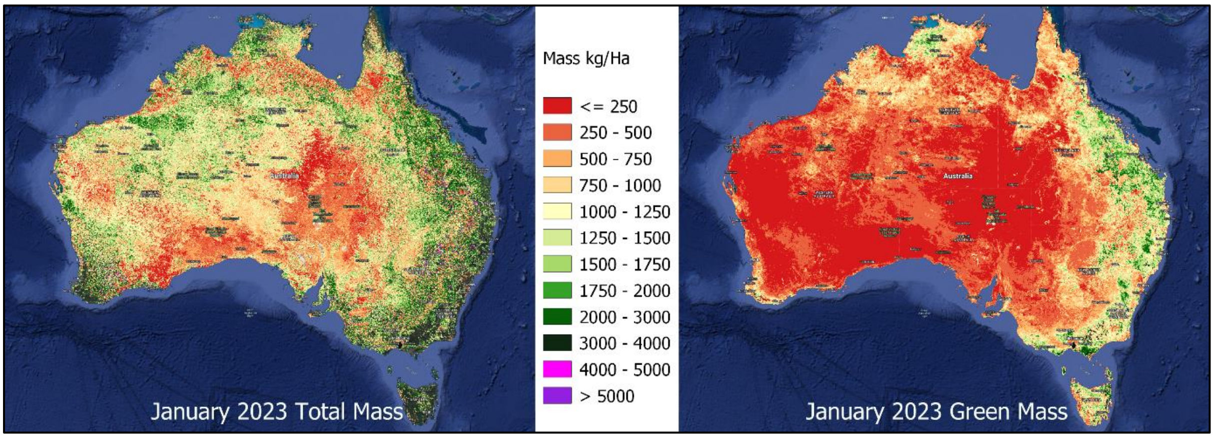

Figure 11. National TSDM imagery and Green mass produced operationally as part of the Australian Feedbase Monitor project.

This approach is consistent with Pringle et al (2021) that found strong correlations between the ratio of 'green grass' cover to 'dead (i.e. non-photosynthetic) grass' cover, derived from an archive of Landsat surface-reflectance imagery. Dietary crude protein was forecast with a median absolute error (MAE) of 0.86%; dry-matter digestibility was forecast with a MAE of 0.95%.

The work to date has identified significant potential to improve estimates of pasture quality. Significant investment is now required to coordinate the collection of standardised pasture quality information to build the next generation pasture quality model.

4.3 Water Body Mapping

The maps in Figure 12 and Figure 13 show a Red-Green-Blue combination of the 10th, 50th and 90th percentiles for the Normalised Difference Water Index (NDWI) respectively. In each case, the NDWI was converted to a binary water/no water classification using a value of 0 as a threshold. Theareas in red indicate permanent water, areas in green indicate frequent water (more than 50% of the time) and areas in blue show ephemeral water (10% of the time or less).

The Normalised Difference Water Index shows a strong correlation with the presence of water in the surface and can be used to detect standing water. The temporal metrics (percentiles) indicate how frequently water is detected.

Areas with permanent water (red in the figures below) are of importance to support livestock production as they indicate where drinking water is always available. These areas are also refuge for many animal species, particularly in the dry season, and therefore of high biodiversity relevance. It is important to emphasize that the smallest water body area that this method can detect is about the resolution of the imagery used, i.e. ~10 meters. Therefore, small water troughs cannot be detected, but large man-made dams or turkey nests can.

Areas with frequent water (green in the figures below) indicate where water is likely to be found early in the wet season but also likely to run out later in the season. Pasture type, condition and productivity are likely to be affected by these dynamics. Blue areas in the figures below is where water is found very infrequently during floods. Mapping these areas are important for emergency planning and animal welfare.

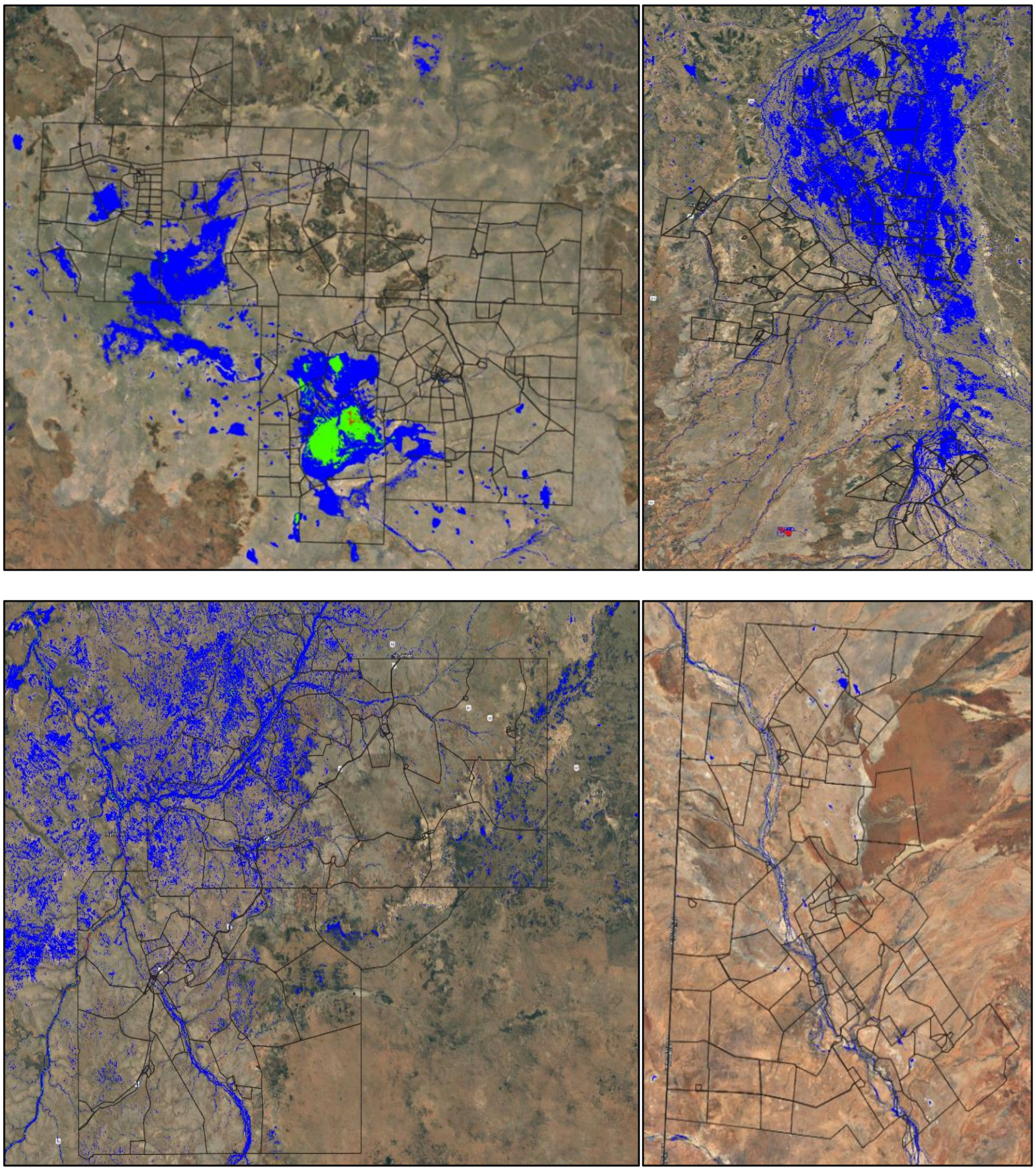

Figure 12: RGB composite of the NDWI showing permanent water (red) frequent water (green) and ephemeral water (blue). The maps correspond to the AACo properties in the Barkly Tablelands (top left), Victoria River (bottom left), Gulf (top right) and Headingly (bottom right)

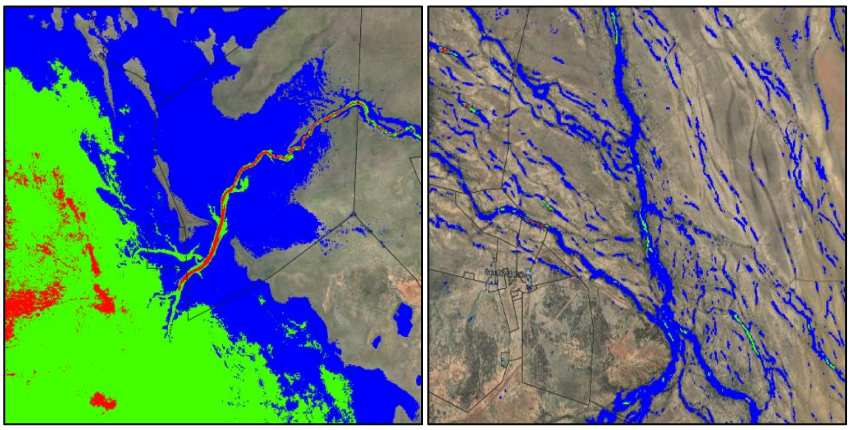

Figure 13: RGB composite of the NDWI showing permanent water (red) frequent water (green) and ephemeral water +(blue) showing the detail on the Lagoon system in Brunette Downs (left) and an area in Canobie station (right).

Soil and vegetation condition can modify the correlation between NDWI and water in the surface, making a single model based on NDWI that works in all environments difficult to establish. In other words, the same NDWI may indicate water in the surface in certain environments but not in others. The extensive blue and green areas in Montejini / Camfield illustrate this, where south-facing slopes tend to have high NDWI values and may be incorrectly labelled as water. This is also likely the case in the Northern part of the NT and Cape York, where the threshold chosen for the NDWI to indicate ephemeral water is possibly overestimating the areas that are flooded (Figure 14 below).

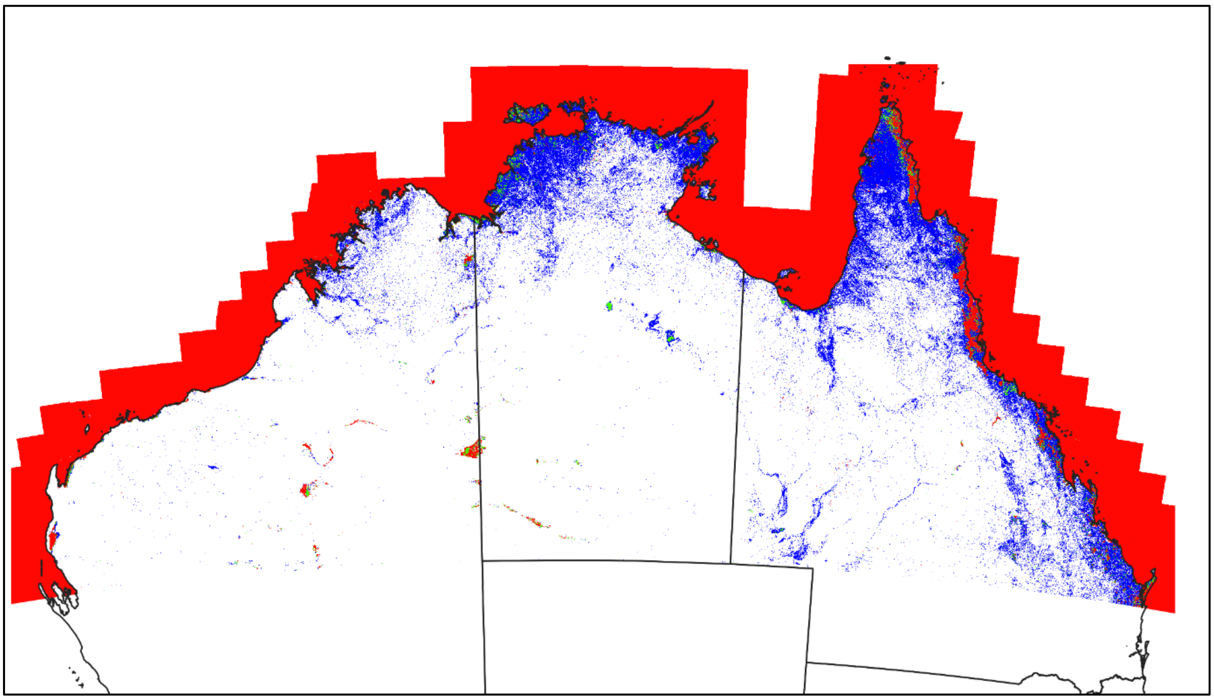

Figure 14. Northern Australia water persistency index.

We recommend taking the following steps to solve these classification issues and increase the confidence in the water layers produced:

- Develop the standing water recurrence maps further by tuning the NDWI percentiles maps locally through local manager knowledge. This could be done through crowd-sourcing information through a simple app.
- Test the use of the Fisher Water index, which has been tuned for Australian conditions and can improve on the NDWI, on Sentinel 2 data (Fisher et al 2016).
- Use the long-term statistics to map the locations of dams and waterbodies where water occurs for periods long enough to be useful for grazing animals.
- Attribute these waterbodies with counts of detected water on a seasonal basis to build a time series for each location.
- Determine optimum local/regional thresholds for classifying permanent and ephemeral waters.
- Classify the water areas in the presence of vegetation (such as along creek lines) using the relationship between persistent green and water indices.
- Expand to cover the entire Australian rangelands.

4.4 Landscape Response Unit Mapping

The Landscape Response Units methodology was applied nationally (Figure 15) creating ~49 million individual mapped polygons describing long-term landscape spectral response. This layer now underpins several initiatives by Cibo Labs and collaborators including the Land Condition and the Northern Land Types, which are described in the later part of this report.

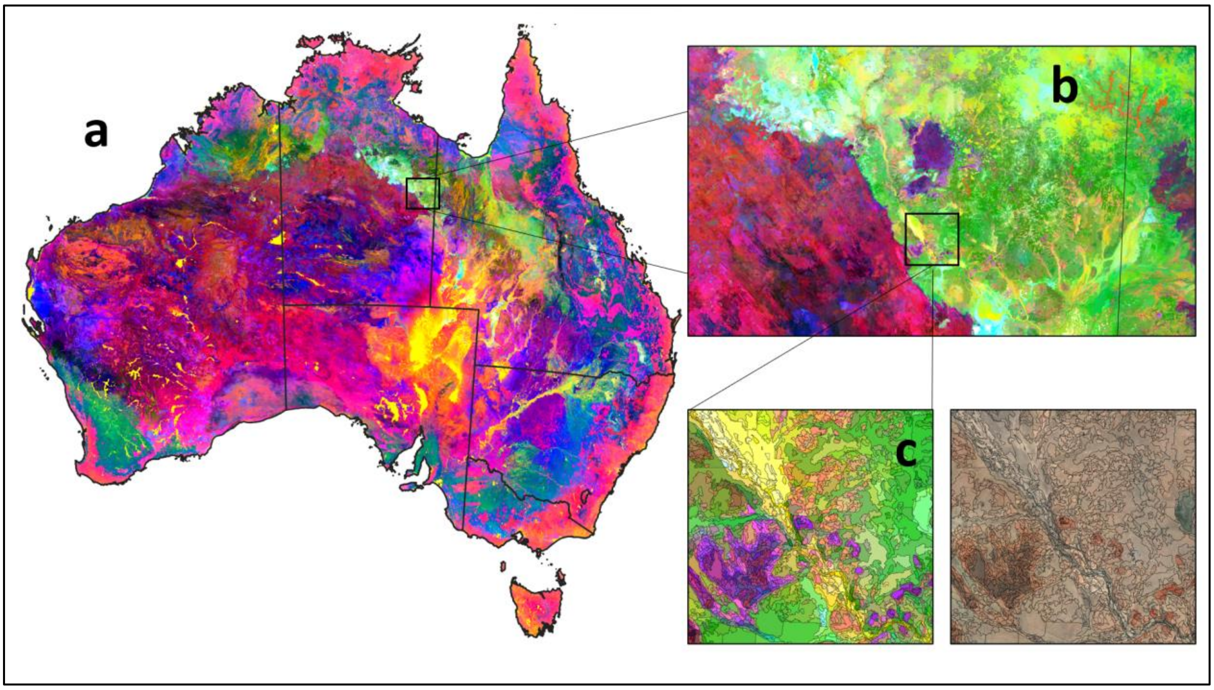

Figure 15. National Landscape Response Units (LRUs). Maps b and c show two levels of zoom. Inset c also includes a map with the Google Earth background.

Figure 16 compares the existing QLD Land Type mapping in white to the Landscape Response Unit segments in the black lines. It becomes evident that the LRU segments are around one order of magnitude smaller than the Qld Land Types and able to detect and resolve much finer features in the landscape, which respond to the environmental conditions, land management effects and their interactions.

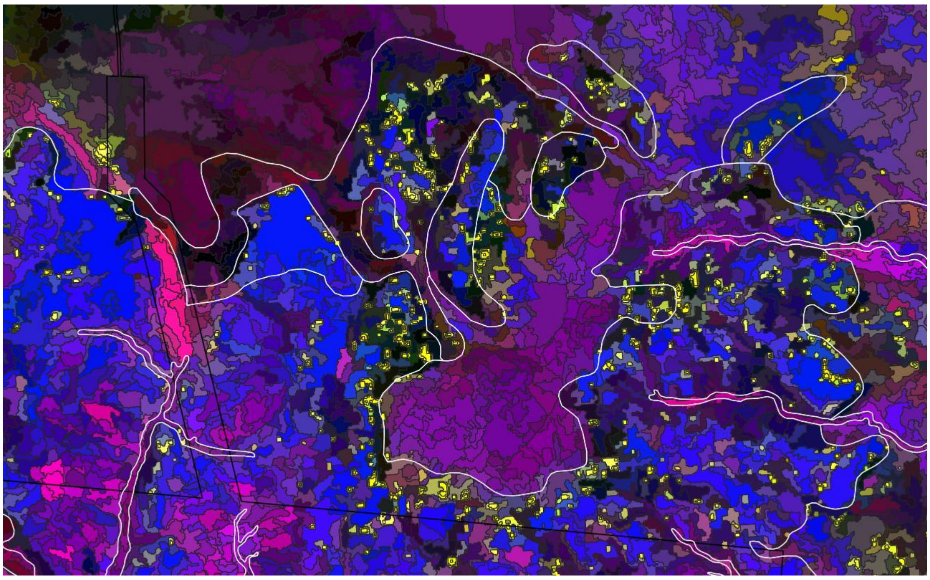

Figure 16. A comparison of the existing QLD Land Type mapping in white to the Landscape Response Unit segments in the black lines. The area is approximately 20km east-west.

The segmentation approach is an important first step in reducing the data volume in a way that captures variability at multiple scales. It enables the use of significantly more complex modelling approaches and links naturally to both process based and machine learning models of landscape state, function, and change.

The $6.5M Rangelands Carbon project managed by the Food Agility CRC is also already using the LRUs in the AACo estate. The LRUs have been used for clustering the landscape and are guiding the field sampling protocol including the location of soil and vegetation sampling. The LRUs layer has been shared with the project partners who are using the input rasters and segments as covariates for spatialising the soil carbon results from the first two field campaign measurements in 2022.

There are however several limitations to the current approach that we believe can be improved. As the LRU's were targeted to capture vegetation and geological variability for the AACo project, they may be sub optimal for higher resolution landscape mapping tasks, despite the reduction in segment size. The average segment size for Australia is approximately 15ha. We would recommend removing the radiometric layers and running the time series sentinel 2 statistics at the native resolution rather than at 100m resolution to enable finer scale mapping of surface features. This is computationally expensive and would require 100x more compute and cost than the current 100m model so for national mapping would cost more than $1M in compute. Given the investment currently committed on the national soil carbon initiatives, this is a relatively modest cost for a national dataset that could underpin numerous national and farm-scale programs. In the short term the method can also be applied on a per-farm basis to reduce costs.

The segment statistics currently do not contain the complete set of spatial statistics optimised for land condition assessment, noting that we used the 11 Principal Component statistics for the Land Condition prediction in this project. At the time of the project, the tools to build these efficiently had not been developed. However, these tools are now available and would add an additional $20k to compute for Queensland and the Northern Territory using JRSRP Sentinel 2 seasonal bare ground. To compute these nationally would require running the fractional cover model over every Sentinel image and then building the statistical layers used for the spatial statistics. We estimate that a two year window is required for reliable minimum bare ground estimation, and this would entail processing 200,000 Sentinel 2 tiles at a cost of around $0.4 each followed by temporal compositing, so for each era a minimum of $100k in computer time would be required.

Due to the increase in compute ability by Cibo Labs and their partners, it would be possible to compute the segments at a smaller minimum size, of the order of 50 to 100 pixels. This would still significantly reduce data volumes and radiometric “noise”. If this were to be undertaken, we would suggest storing the raster attributes in a linked spatial database rather than an attribute table.

4.5 Land Type Mapping

The Landscape Response Units allowed us to extend the Qld Land Type mapping into the NT and northern WA at a higher resolution than the original mapping, well beyond the original plan to do it into two AACo properties. The overall balanced accuracy calculated through the 5-fold cross validation was 78.8%. This number, however, does not take into account the similarity between classes, i.e. any class wrongly labelled is considered within the 11.2% misclassification regardless of how similar or different it is to the correct label. The resulting map is shown in Figure 17. A detailed view of the resulting map with only the dominant Land Type classes in the AACo properties in the Barkly region is shown in Figure 18.

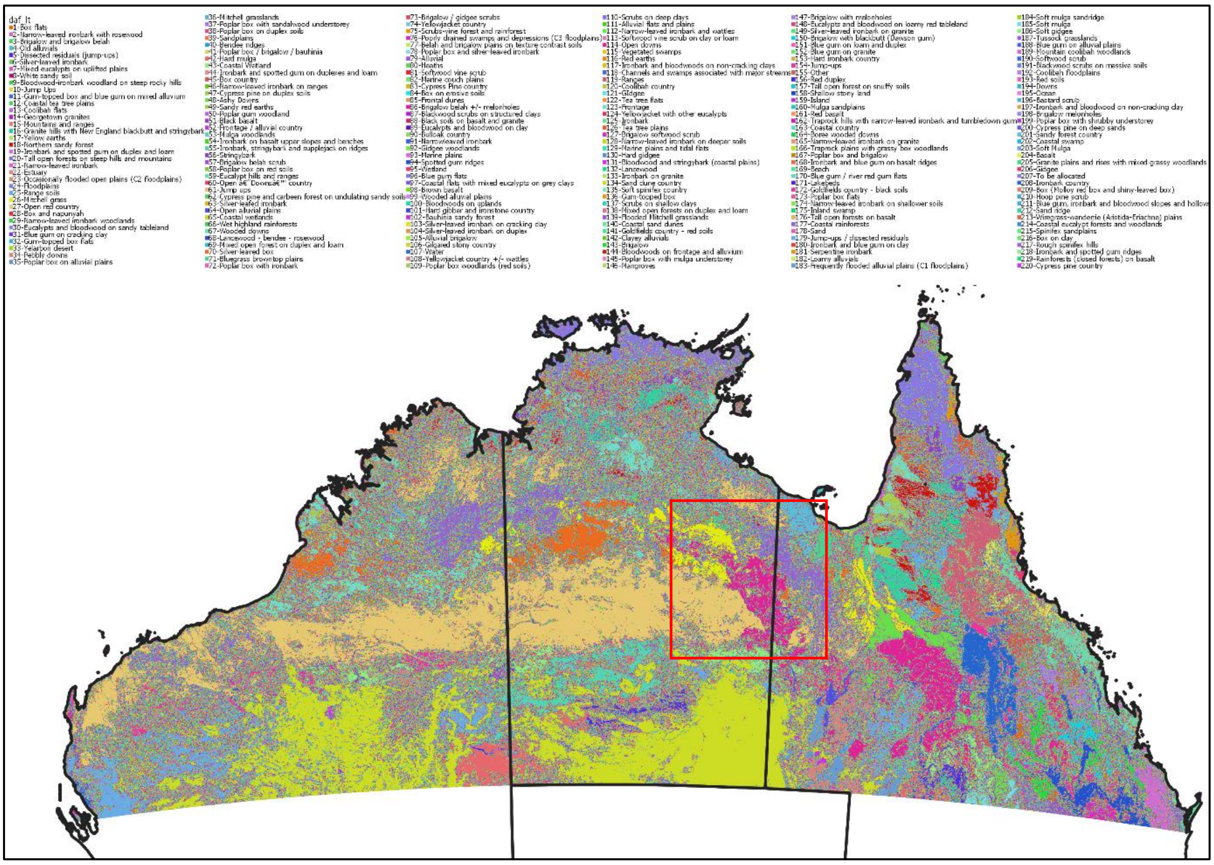

Figure 17. Northern Land Types v1.0. The rectangle in red shows the location of the detailed map in the figure below.

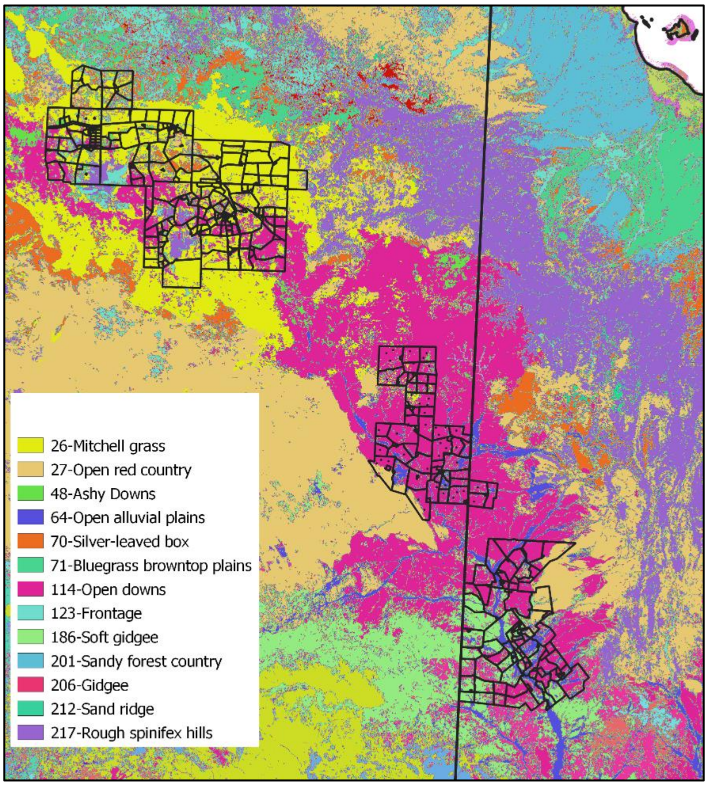

Figure 18. Northern Land Types v1.0 for an area straddling the NT/QLD border. Black lines are paddock boundaries?

The results presented indicate that the Qld Land Types map can be expanded to cover areas of Northern Australia in NT and WA by combining remotely sensed data and machine learning. This scoping work has not included a thorough and detailed on-ground assessment of the accuracy of the resulting maps, although feedback from AACo staff has been very positive, and the classification accuracies are clearly strong. We can summarise the main observations as follows:

- There is overall strong agreement with the expected land types.
- Where land types in the NT or WA do not have an equivalent textural label applied to a grouping of regional ecosystems in Qld, the methodology and resulting map we produced will fail to correctly label such land types. This is a limitation of the use of a locally based and variable land type nomenclature where a given label can apply to multiple ecosystem types depending on the region, or conversely the same ecosystem may be labelled differently between regions.
- Even though the Qld Land Types map is very comprehensive and detailed, we still found issues that prevent taking full advantage of it. In particular, the difficulty in grouping together land type classes based on objective similarity metrics.

Based on these results we recommend the following next steps:

- Develop a minimum set of grassland response descriptors that capture the variation in response (to grazing and growth), persistence and fragility and where possible map these to local land type terminology.
- Improve the Northern Land Types v1.0 map combining one of more of the following:
    - Take full advantage of the existing land types maps in the NT and WA and use them in combination with the Qld Land Types.
    - Generate a clustering (non-supervised classification) of the Landscape Response Units and name the resulting clusters into "meaningful" labels using the land type

maps of Qld, WA and NT taken together. This needs to first, reconcile those classes that represent the same land type but have different labels in different mappings, and then repeat the approach taken here.

4.6 Land Condition Mapping

Using the LRU's, we were able to spatially predict Land Condition with a high degree of accuracy across AACo's northern properties.

The Mean Absolute Error of the Random Forest Regressor was 0.153. This means that, on average, the error in the Land Condition estimate was about the distance between one subclass, for example A to A-B (Figure *19*, left). The resulting Land Condition estimation is a continuous number ranging from 0 (class D) to 1 (class A). We converted this value back to an ordinal classification and calculated the overall accuracy as the number of cases when the resulting classification was in the same class as the field observation or up to one subclass different (Figure *19*, right). The overall accuracy calculated in this way was 80.4% (2741 out of 3411).

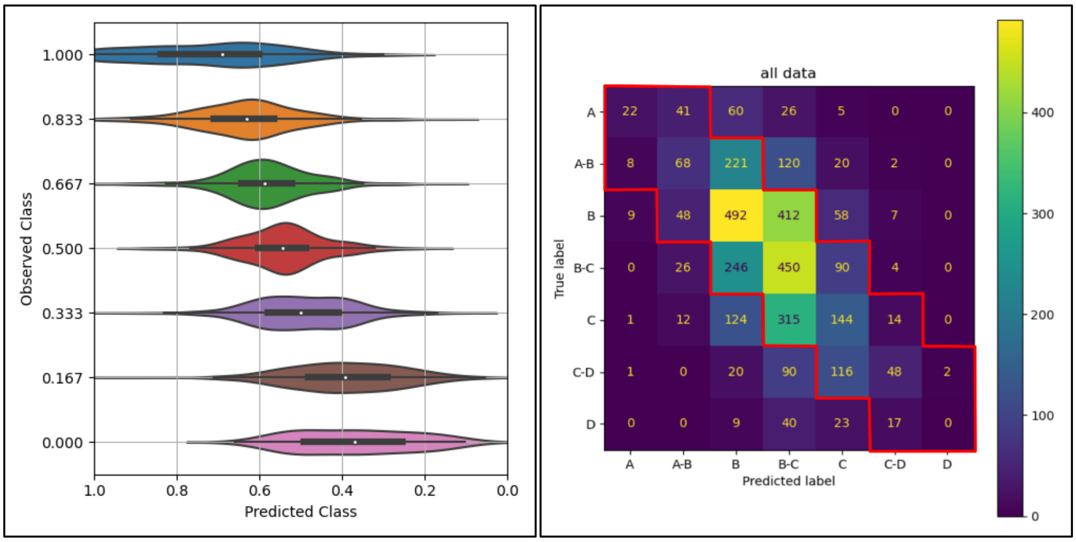

Figure 19. Results of the 5-fold validation matrix showing agreement between Observed and Predicted Land Condition) from the Random Forest Regression with the classes converted to ordinal values which range from 1 (class A) to 0 (class D) (left). The results are shown as violin plot indicating the probability density of the data (in colour) and the 25, 50 and 75 quantiles in the black box. The Mean Absolute Error was 0.153. The contingency matrix on the right shows the same result as the boxplots with the resulting classes re-classified to the ABCD scheme. The red lines indicate the cases that were considered as correct in the accuracy calculation. The colors indicate the number of sites in each combination, also shown as number in the cell. The accuracy was 80.4%.

There are few studies available which tried to estimate Land Condition in the ABCD framework. Using data from the Fitzroy and Burdekin catchment in Qld, Beutel et al (2021) explored the relationship between satellite-derived vegetation cover and on-ground measured Land Condition, including using benchmark areas. They reported moderate success, with Land Condition correctly classified at >60% of A and D condition sites, but Land Condition in B and C sites poorly predicted. Scarth et al (2020) used the same data as Beutel et al (2021) but with an approach similar to the one we tried here. Even though Scarth et al (2020) did not explicitly state the overall accuracy of the resulting classification, their figure 11 suggests a similar degree of accuracy to the one we found here.

The Land Condition classifier was applied to all the Landscape Response Units for AACo northern properties and the results are shown in Figure 20, and a more detailed view of this map in Wondoola is shown in Figure 21.

This scoping study demonstrates that Overall Land Condition can be successfully mapped using the spatio-temporal information, collected in the Landscape Response Units segments in the AACo estate, and across the Northern Rangelands.

Graziers use the land condition information to assess the carrying capacity in their paddocks. AACo currently modifies the estimates of carrying capacity by a scaling factor that depends on Land Type and Land Condition, to obtain carrying capacity in each farm or paddock. The assessment of Land Condition is currently performed in a very subjective manner. The work presented here can be adopted as a more objective and quantitative way to do such analyses. For example, by combining the Queensland Land Type map with the draft Land Condition presented here (see Figure 20 and Figure 21), we have quantified the area in each land condition in each paddock, also discriminated by Land Type (Table 6 and 7).

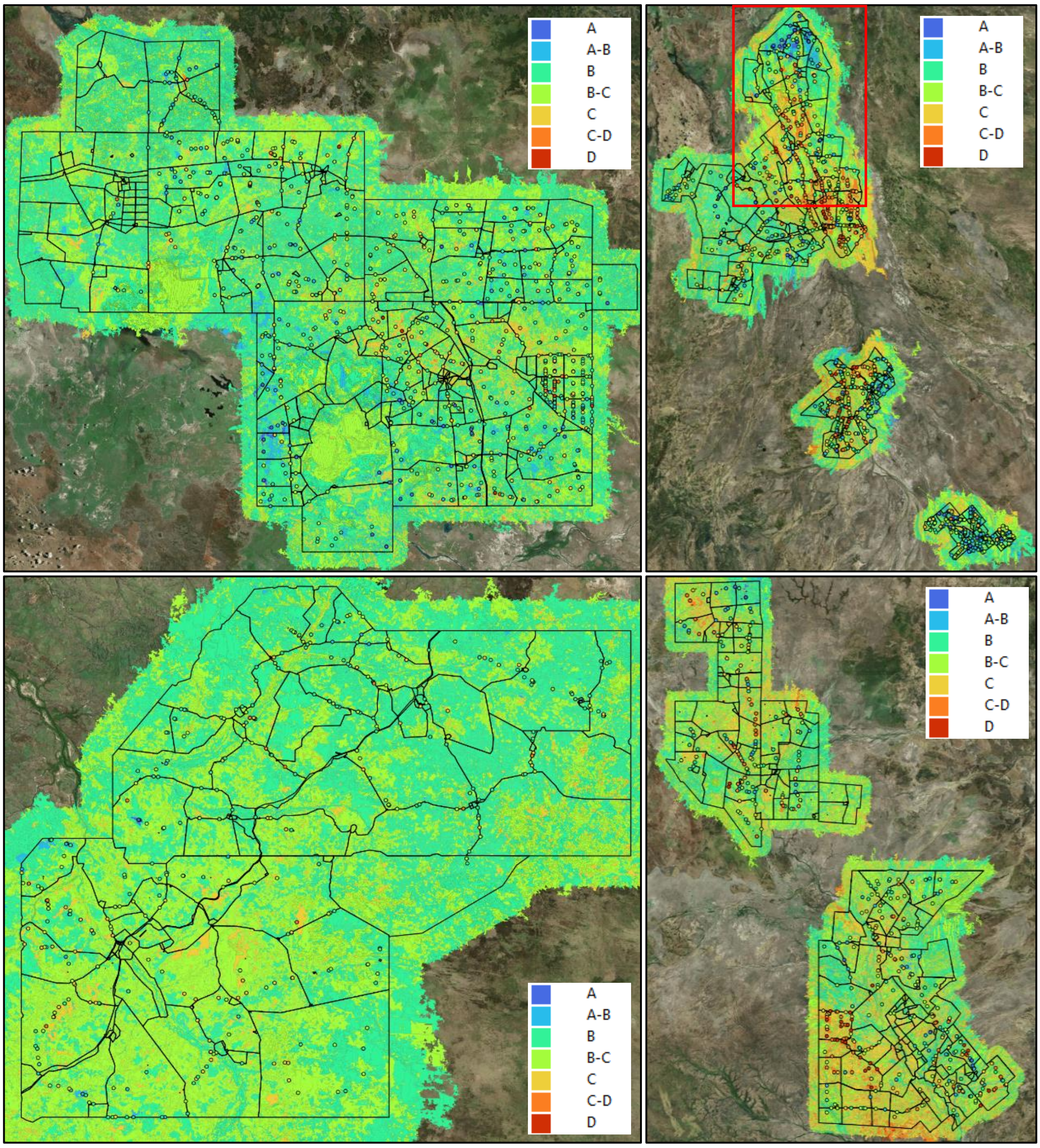

Figure 20: Predicted Land Condition in the AACo properties (Random Forest Regressor variant). The points show the field observations. The red rectangle in the top right indicates the area shown in Figure 21: .

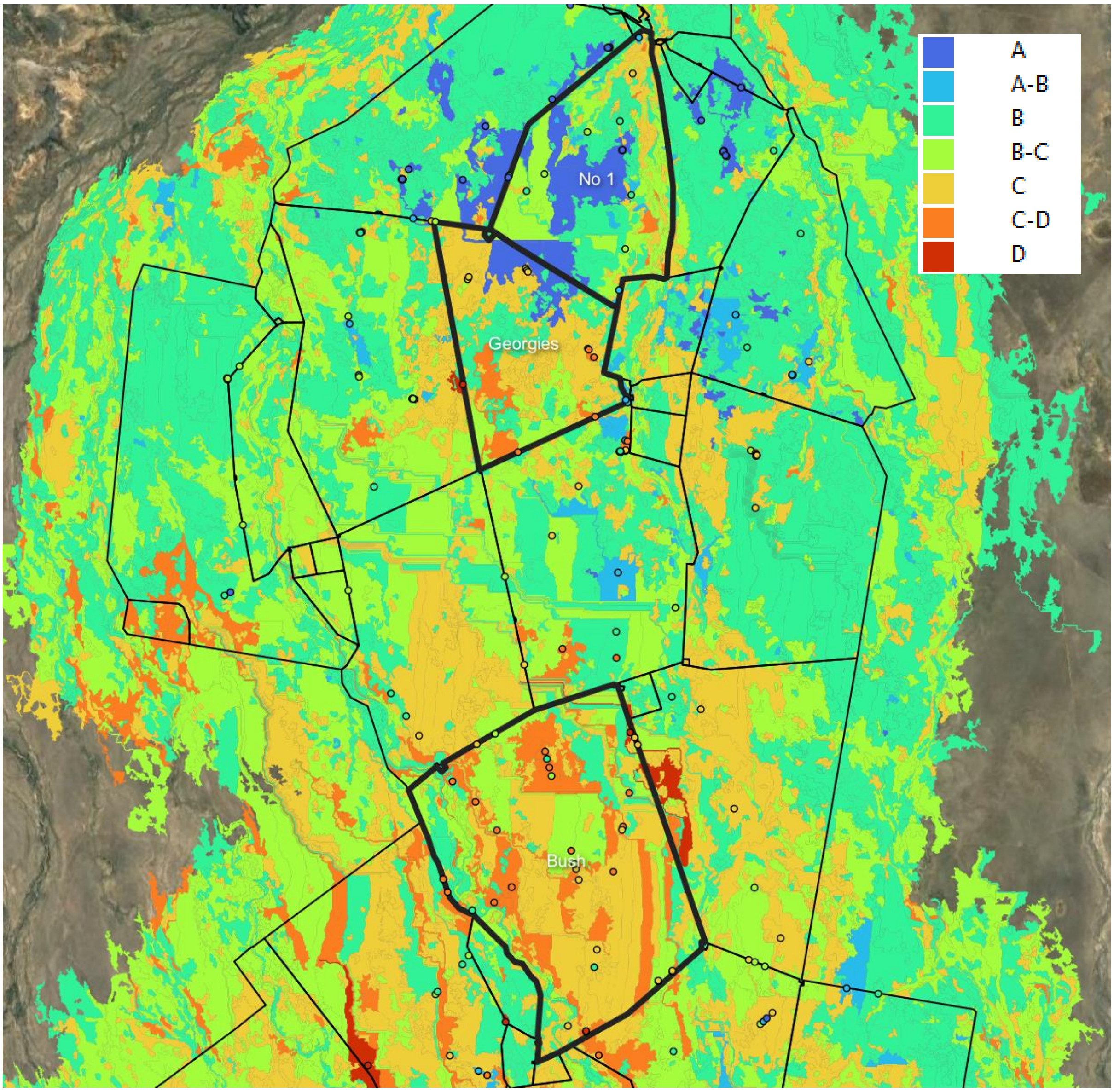

Figure 21: Close up map showing the Land Condition in the floodplains of Canobie-Wondoola. Dotted lines show Land Types from the Queensland government mapping. Statistics for the three paddocks with thicker borders are shown in Table 4.

Table 6 summarises the area in each Land Condition class and Land Type in the three paddocks in Wondoola Station highlighted in Figure 21. The numbers show the area in ha in each paddock and Land Type class.

Table 6. Area in each Land Condition class per Land Type in three paddocks in Wondoola Station. The numbers show percentages of the total area in each paddock and Land Type class.

Paddock	Land Type	A	A-B	B	B-C	C	C-D	D	Total	Total [%]
Bush	Bluegrass browntop plains	0	0	74	18	2	7	0	**102**	0%
	Frontage	0	0	1981	246	223	385	0	**2834**	14%
	Mitchell grass	0	0	1449	3806	6547	5627	0	**17429**	85%
	Wetland	0	0	19	0	1	1	0	**22**	0%
	TOTAL [ha]	**0**	**0**	**3523**	**4070**	**6773**	**6021**	**0**	**20386**	100%
	Total [%]	0%	0%	17%	20%	33%	30%	0%	100%	
Georgies	Mitchell grass	922	44	1608	1940	4060	767	0	**9342**	100%
	TOTAL [ha]	**922**	**44**	**1608**	**1940**	**4060**	**767**	**0**	**9342**	100%
	Total [%]	10%	0%	17%	21%	43%	8%	0%	100%	
No 1	Bluegrass browntop plains	0	3	272	92	216	0	0	**583**	6%
	Frontage	0	17	737	317	564	18	0	**1652**	16%
	Mitchell grass	1632	244	1870	3441	613	76	0	**7875**	78%
	Wetland	0	0	23	2	16	0	0	**41**	0%
	TOTAL [ha]	**1632**	**264**	**2902**	**3851**	**1409**	**93**	**0**	**10152**	100%
	Total [%]	16%	3%	29%	38%	14%	1%	0%	100%	

The ability to reliably predict land condition per paddock and within paddocks has significant implications for decision making around seasonal stocking rates, long term carrying capacity and establishing plans for improving land condition over time. Guidelines available from the Future Beef Program https://futurebeef.com.au/resources/land-condition/) suggest B, C and D condition land is likely to be at 75%, 45% and 20% of long term carrying capacity respectively. Table 5 illustrates the calculation of carrying capacity for each land type and land condition in Wondoola. The available dry matter is converted to animal equivalents assuming a consumption of 9 kg/day, or 3,285 kg/year. For example, one hectare of Mitchell Grass in A condition in Wondoola will produce 2400 kg/ha/year, with an assumed utilisation rate of 22%. That gives an estimated carrying capacity of 0.16 AE per ha, or 6.2 ha/AE.

Table 7 Calculation of carrying capacity in Wondoola

LAND SYSTEM	A	A-B	B	B-C	C	C-D	D	UTILISATION RATE
	100%	88%	75%	60%	45%	33%	20%	
Bluegrass browntop plains	3080	2695	2310	1848	1386	1001	616	0.2
Frontage	2700	2363	2025	1620	1215	878	540	0.2
Mitchell grass	2400	2100	1800	1440	1080	780	480	0.22
Wetland	800	700	600	480	360	260	160	0.15

Combining the areas in each land type and land condition (Table 6) with the estimated long-term production and utilisation rate of each land type and land condition (Table 7), we have calculated the carrying capacity of the three paddocks as shown in Table 8. The effect of the differences in Land Condition can be clearly seen. The paddocks "No 1" is the one in best condition and has a carrying capacity 40% higher than "Bush".

Table 8 Carrying capacity in three paddocks in Wondoola.

Paddock	utilisable feed [kg/ha/year]	Carrying capacity [AE/ha]	Carrying capacity [ha/ AE]	Area [ha]	Carrying capacity [AE]
Bush	262	0.084	11.8	20386	1628
Georgies	306	0.099	10.2	9342	869
No 1	368	0.119	8.4	10152	1138

If Land Condition can be improved these paddocks could increase their carrying capacity. We have simulated the changes in carrying capacity if the areas in condition B-C and C could be improved to B (Table 9). We assume the areas in condition C-D and D cannot be restored and were left unchanged. The paddocks "No 1" and "Georgies" which are in the worst condition, could increase their carrying capacity 28% and 26% respectively.

Table 9. Carrying capacity in three paddocks in Wondoola if Land Condition was improved. We assumed that areas in condition B-C and C are improved to condition B. Areas in C-D and D condition were not changed.

Paddock	utilisable feed [kg/ha/year]	Carrying capacity [AE/ha]	Carrying capacity [ha/ AE]	Area [ha]	Carrying capacity [AE]	% increase in carrying capacity
Bush	331	0.101	9.9	20386	2053	26%
Georgies	391	0.119	8.4	9342	1112	28%
No 1	421	0.128	7.8	10152	1301	14%

Having the capability to automatically estimate the impacts of land condition per paddock and to incorporate local knowledge from managers will allow producers to make more informed management and investment decisions on long-term carrying capacity, seasonal stock rates and grazing management or infrastructure investment decisions aimed at improving sustainable production capacity over time.

A limitation of the analysis presented here is that it only includes variables that represent long-term land condition. In this study we have not assessed changes in land condition over time in relation to management, seasonal conditions or disasters such as the impact of floods in 2019 on the examples presented. We recommend expanding the development to improve the performance of the classifier by adding input layers that can capture changes in Land Condition over time, including:

- Dynamic Cover Reference method of Bastin et al (2012).
- Spatial variance measures within segments to capture landscape leakiness measures and vegetation clumping.

Many of the observations taken by AACo and used in this analysis also include Pasture Condition and Soil condition (taken separately). Pasture Condition is defined by the proportion of 3P grasses, the density of tussocks and the abundance of weeds. Soil Condition is assessed as how many signs of soil erosion are present in the site. The Overall Land Condition results from combining the condition of soil and pasture and generally reflects the worst of those two. We have only used the aggregated Overall Land condition in our analysis. We therefore recommend expanding the analysis to test whether mapping pasture condition and soil condition separately is feasible.

4.7 Producer Surveys and Adoption

There were 41 respondents to the survey conducted during BeefWeek2021 by Elders.

In summary:

- 95% said they could improve their feedbase management.
- In the last 10 years there were an average of 13 occasions when producers had to make unplanned decisions to reduce stock numbers.
- 76% used visual inspections and previous experience to match stocking rates to carrying capacity and only 2% did pasture sampling. None of the respondents had used satellite imagery.
- Only 41% had a digital farm map.
- 98% used visual inspection to monitor land condition, with only 7% using permanent monitoring sites and 2% using satellite imagery.
- 85% said they would be interested in using satellite imagery to monitor their feedbase and land condition.
- 80% said they would be interesting in training to use satellite imagery to help manage their feedbase.
- 80% said they would be interested in completing a comprehensive farm plan and carrying capacity assessment.

The follow up survey with Rayner Ag focused more on grazing management and decision making. The survey was distributed to approximately 2100 producers, with 380 responses. They were asked about the method of assessing pastures; frequency of assessment and the number of unplanned changes to stock numbers, sales and supplementary feeding.

In summary.

- 84% of the producers undertook regular pasture assessments.
- 40% of producers assessed their pastures on a weekly basis.
- 75% of producers relied on visual assessments and previous experience.
- In the past 5 years 29% of producers had to make significant unplanned decisions at least twice.
- 63% of producers forced into this position had to make unplanned sales.
- 48% of producers said they had lost money on sales as a result.

Importantly, given the nature of the surveys, we are likely evaluating significantly different cohorts of producers. The BeefWeek2021 survey was likely dominated by northern producers and relatively unbiased in terms of adoption levels. The Rayner Ag survey was to a mailing list of producers largely from southern grazing systems, and likely to be more progressive producers given they were on a grazing consultant mailing list.

These small surveys have again reenforced numerous key challenges in relation to awareness, adoption and quantifying the benefits of adopting technologies. These include:

- Most producers are still reliant of subjective visual estimation of their feedbase.
- Balancing information associated with feed supply, feed demand and management or commercial decisions is inherently complex, often leading to forced or unplanned decisions that often lose money as a result.
- Most producers are interested on more objective and repeatable methods for assessing their feed supply and land condition.
- Very few producers have used satellite or other digital technologies to assess their pastures.
- After several decades of numerous State and Commonwealth funding associated with farm planning only the minority of farms have a current digital farm map suited to the adoption of digital farm management systems.

However, we are able to provide a broader picture of the current levels of adoption of our technologies.

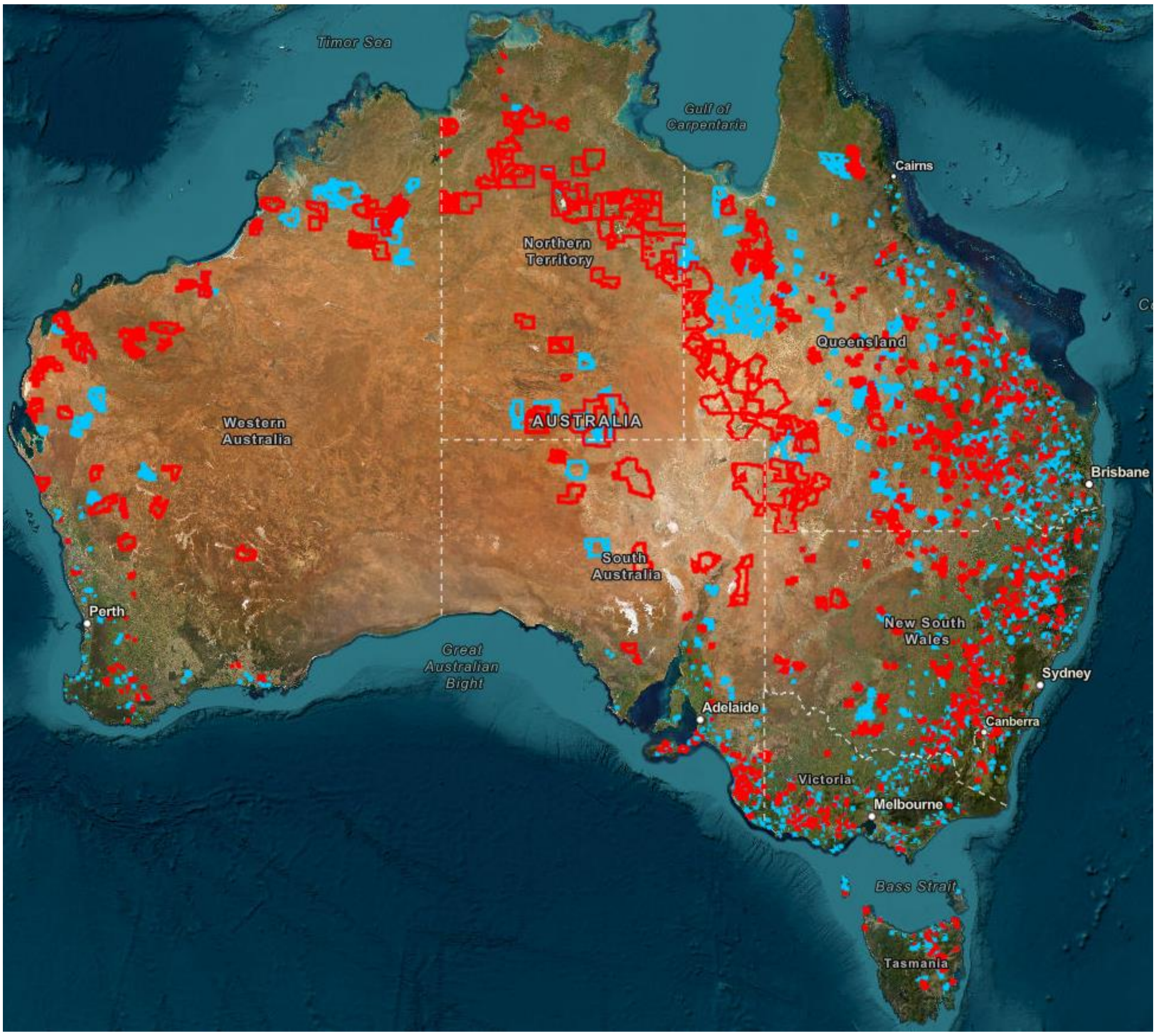

Figure 22. Map showing the locations of properties registered on the Australian Feedbase Monitor launched November 30 (in BLUE) and existing Cibo Labs PastureKey subscriptions (in RED) as of May 24 2023.

Figure 22 above (in blue) confirms a very even distribution across Australia's major grazing regions of the Australian Feedbase Monitor (AFM) users (in blue), and PastureKey users (in red). Following the launch on November 30, 2022, as of May 24, 2023 there were 1835 registered AFM users, covering more than 20 million ha. Current Cibo Labs PastureKey subscriptions are servicing over 60 million ha per week at paddock scale, compared to the AFM which provides farm-scale information.

The Australian Feedbase Monitor application interface for a property near Goondiwindi QLD (in Figure 23 below) shows the spatial variability of pasture biomass (kg/ha) and the graph shows monthly comparisons back to March 2017. In this example the property level pasture biomass is averaging around 3000 kg/ha which is more than double the 2017-2020 summers. Figure 24 shows the same property using the 10m resolution paddock-level PastureKey service.

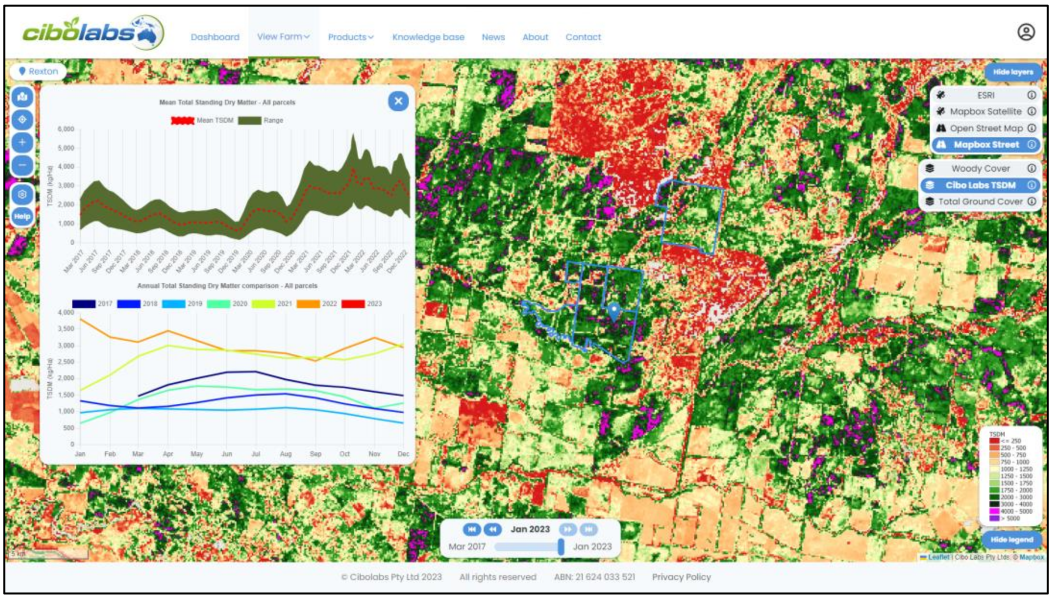

Figure 23. The Australian Feedbase Monitor application interface for a property near Goondiwindi QLD. The map shows the spatial variability of pasture biomass (kg/ha) and the graph shows monthly comparisons back to March 2017. 80m resolution, rolling monthly estimates of pasture biomass updated weekly at land parcel and farm-scale.

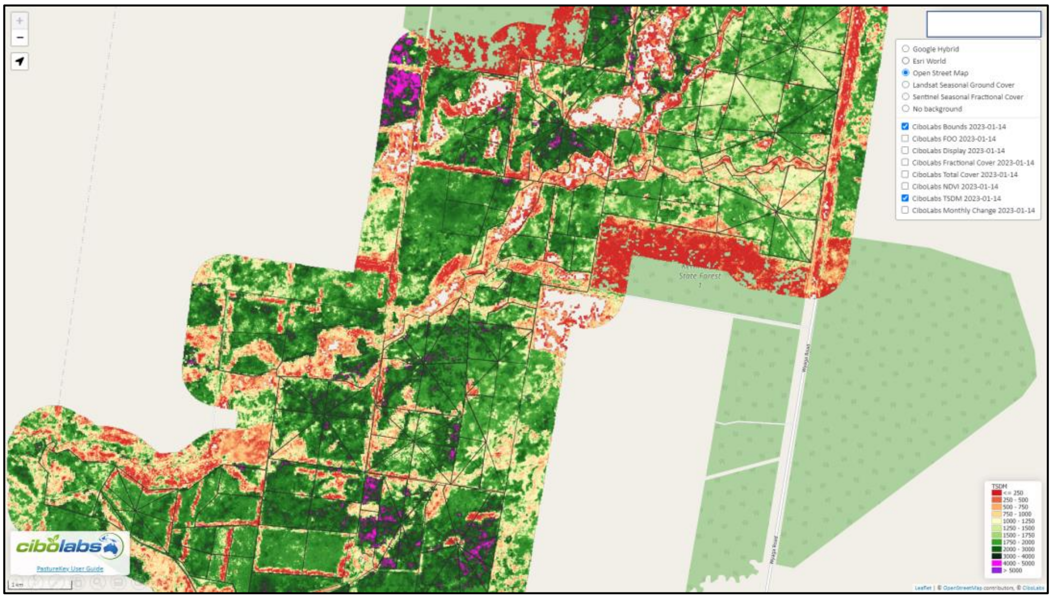

Figure 24. PastureKey application interface for the same property as Figure 24. 10m resolution, 5 daily, paddock level estimates of biomass.

5. Conclusions

The “living model” approach to the national biomass prediction service is now well established within operational systems and places Australia and Cibo Labs as a world-leader in this capability. To the best of our knowledge there is no similar operational service anywhere else in the world.

Work is continuing to revise and improve the national biomass prediction service. A revised model described here was released in early 2023 to support our weekly paddock-level PastureKey service and the Australian Feedbase Monitor. Later in 2023 we plan to move to a fully adaptive model which is continually tuned to local conditions as data is collected.

Our ability to reliably estimate pasture biomass is only as good as: the time-series satellite imagery; the data collected to train the models and our ability to adequately represent the pasture types and conditions important to grazing management decisions. This has been extremely challenging to achieve with highly variable seasonal weather and pasture conditions since development began in 2018. The focus now must be to work closely with individual producers to identify regions, pasture types and seasonal conditions were model performance needs to be improved and to coordinate data collection. This could be facilitated by the Northern and Southern Beef Research Councils and existing and proposed MLA Producer Demonstration Sites. The freely available Biomass Collector App provides a capability to nationally consistent data to be easily collected and fully utilised by the industry and research organisations.

The work to date has also identified significant potential to improve estimates of pasture quality. Significant investment is now required to coordinate the collection of standardised pasture quality information to build the next generation pasture quality model.

The project has demonstrated the ability to use new sources of remote sensing data and methods to reliability map the presence and duration of surface water relevant to extensive grazing systems and ecosystem management. Further work is required to test alternative methods such as the Fisher Water Index (FWI) and to locally tune these indices and thresholds required to accurately map permanent and ephemeral water. This could be done through crowd-sourcing information through a simple app to expand the data to cover the entire Australian Rangelands.

The Landscape Response Units (LRU) methodology was implemented for the entire nation (768 million ha) creating some 49 million individual mapped polygons describing long-term landscape spectral response. The LRU framework is a significant step forward that will underpin a range of developments associated with natural capital including sustainable grazing management, property development, carbon accounting and biodiversity assessments. The image segmentation approach is an important first step in reducing the data volume in a way that captures variability at multiple scales. It enables the use of significantly more complex modelling approaches and links naturally to both process based and machine learning models of landscape state, function, and change. The Landscape Response Units are already underpinning Cibo Labs initiatives related to land condition, land type mapping, landscape carbon estimation, biodiversity, and productivity assessments.

There are, however, several limitations to the current approach that we believe can be improved to increase the spatial resolution from 100m resolution to 10m native Sentinel-2 solution to enable finer scale mapping of surface features. This would require a 100x increase in computing resources and around $1M to process nationally or could be done on-demand per farm to reduce up-front costs. Given the investment currently committed on the national soil carbon initiatives, this is a relatively modest cost for a national dataset that could underpin numerous national and farm-scale programs.

The Landscape Response Units allowed us to extend the Qld Land Type mapping into the NT and northern WA at a higher resolution than the original mapping. We achieved an overall classification accuracy of 78.8%. The results indicate that the Qld Land Types map can be expanded to cover areas of Northern Australia in NT and WA by combining remotely sensed data and machine learning. Based on the excellent results to date we recommend the following next steps:

- Developing a minimum set of grassland response descriptors that capture the variation in response (to grazing and growth), persistence and fragility and where possible map these to local land type terminology.
- Improve the Northern Land Types v1.0 map combining one of more of the following:
    - Take full advantage of the existing land types maps in the NT and WA and use them in combination with the Qld Land Types
    - Generate a clustering (non-supervised classification) of the Landscape Response Units and name the resulting clusters into “meaningful” labels using the land type maps of Qld, WA and NT taken together.

This scoping study demonstrates that Overall Land Condition can be successfully mapped using spatio-temporal information across the AACo estate, and across the Rangelands.

Using the LRU’s we were able to spatially predict ABCD Land Condition with a high degree of accuracy across AACo’s northern properties. Our field data provided by AACo used a 7-class classification (A, A-B, B, B-C, C, C-D, D). By converting this to an ordinal scale from 1(A) to 0(D) we achieved a mean absolute error (MAE) 0.153. This means that, on average, the error in the Land Condition estimate was about the distance between one subclass, for example A to A-B. The overall accuracy calculated in this way was 80.4%.

To be able to consistently map land condition at paddock scales for every extensive grazing property in Australia could be a game-changer for the industry. Having the capability to automatically estimate land condition, incorporate local knowledge from managers, and assess the impacts of land condition on stocking rate per paddock will allow producers to make more informed management and investment decisions on long-term carrying capacity, seasonal stock rates and grazing management, or infrastructure investment decisions aimed at improving sustainable production capacity over time.

This work is still in the early stages of development and our analyses have only focused on long-term land condition. We have not assessed changes in land condition over shorter timeframes associated with specific grazing management, seasonal conditions, or disasters such as floods.

We recommend expanding the land condition prediction methods to improve the performance of the classifier by adding input layers that can capture changes in Land Condition over time, including: Dynamic Cover Reference method of Bastin et al (2012); Spatial variance measures within segments to capture landscape leakiness measures and vegetation clumping.

Adoption of “AgTech” across the grazing industry is still in its very early stages, but we’re believe very rapid and high-impact progress is being made. This project again reinforced key challenges in relation to awareness, adoption and quantifying the benefits of adopting technologies. These include:

- Most producers are still reliant of subjective visual estimation of their feedbase.

- Balancing information associated with feed supply, feed demand and management or commercial decisions is inherently complex, often leading to forced or unplanned decisions that often lose money as a result.
- Most producers are interested on more objective and repeatable methods for assessing their feed supply and land condition.
- Very few producers have used satellite or other digital technologies to assess their pastures.
- After several decades of numerous State and Commonwealth funding associated with farm planning only the minority of farms have a current digital farm map suited to the adoption of digital farm management systems.

Our weekly PastureKey service is currently supporting paddock level forage budgeting on over 55 million hectares. Following the launch of the Australian Feedbase Monitor on November 30, 2023 in the first 7 weeks (including the Christmas-New Year break) 1155 producers have registered onto the AFM platform covering nearly 20 million ha. There were 367 users in QLD and NT alone covering 14.8 million ha. As of April 14, 2023 there were 1720 AFM users.

5.1 Key findings

The Australian Agriculture Company (AACo) has been a significant supporter of these developments in collaboration with Cibo Labs which now underpin many management decisions across the company. Using the Cibo Labs PastureKey service has transformed the forage budgeting and decision-making process for AACo. In 2022 property level forage budgets were completed over 2 months earlier than usual. This has provided a "whole of business" view to make informed early decisions on re-stocking and animal transfers and provided unprecedented transparency in decision making and communication from properties through to the Executive Board. It is also no doubt have major implications on cost savings, animal welfare, land condition and profit.

- The "living model" approach to the national biomass prediction service is now well established within operational systems and places Australia and Cibo Labs as a world-leader in this capability.
- Our ability to reliability estimate pasture biomass is only as good as: the time-series satellite imagery; the data collected to train the models and our ability to adequately represent the pasture types and conditions important to grazing management decisions. This has been extremely challenging to achieve with highly variable seasonal weather and pasture conditions since development began in 2018.
- The work to date has identified significant potential to improve estimates of pasture quality. Significant investment is now required to coordinate the collection of standardised pasture quality information to build the next generation pasture quality model.
- The Landscape Response Unit framework is a significant step forward that will underpin a range of developments associated with natural capital including sustainable grazing management, property development, carbon accounting and biodiversity assessments.
- The Landscape Response Units are already underpinning Cibo Labs initiatives related to land condition, land type mapping, landscape carbon estimation, biodiversity, and productivity assessments. There are significant opportunities for improvement which will require an investment of approximately $1M in computer processing to downscale from 100m to 10m resolution.

- The Landscape Response Units allowed us to extend the Qld Land Type mapping into the NT and northern WA at a higher resolution than the original mapping. We are now in a position to develop consistent land type mapping nationally.
- This scoping study demonstrates that Overall Land Condition can be successfully mapped using spatio-temporal information across the AACo estate, and across the Rangelands.
- To be able to consistently map land condition at paddock scales for every extensive grazing property in Australia could be a game-changer for the industry.
- After several decades of numerous State and Commonwealth funding associated with farm planning only the minority of farms have a current digital farm map suited to the adoption of digital farm management systems.

5.2 Benefits to industry

The broader industry outcomes of the project include (but are not limited to):

- Increasing transparency and accountability in pasture and land condition management and improve visibility up the management chain on the status of the production asset base.
- Improve capacity to manage seasonal risk.
- Increased accuracy and precision in pasture measurement and management.
- Better herd production outcomes through optimizing pasture utilization and nutrition.
- Improved risk mitigation for long-term carrying capacity development.
- Improved paddock to nation reporting

6. Future research and recommendations

- The unprecedented and highly variable seasonal weather and pasture conditions across Australia over the last 5 years has made the development of a robust pasture biomass prediction capability highly challenging. The focus now must be to work closely with individual producers to identify regions, pasture types and seasonal conditions were model performance needs to be improved and to coordinate data collection. This could be facilitated by the Northern and Southern Beef Research Councils and existing and proposed MLA Producer Demonstration Sites. The freely available Biomass Collector App provides a capability to nationally consistent data to be easily collected and fully utilised by the industry and research organisations.
- Significant investment is required to coordinate the collection of standardised pasture quality information to build the next generation pasture quality model.
- The Landscape Response Unit Framework should be downscaled from 100m resolution to 10m resolution, nationally. This would require an investment of $1M for data processing, additional project costs that could be shared across Agriculture Innovation Australia and Government partners.
- The ability to predict and map land condition is a game-changer. Significant site data exists across QLD, NT and WA. A coordinated data collation and analysis project should be initiated to provide the training data and capability for the developing a northern and southern rangelands land condition prediction change monitoring capability.
- The Australian Feedbase Monitor and Environmental Credentials for Grassfed Beef platforms could be leveraged to provide secure and trusted access to this information in partnership with producers.

- Access to digital farm mapping is still a fundamental barrier to Agtech adoption across the industry. A national farm mapping service should be put in place to act as a single point of truth for the grazing industry.

7. References

Bastin, G., Scarth, P., Chewings, V., Sparrow, A., Denham, R., Schmidt, M., O'Reagain, P., Shepherd, R., & Abbott, B. (2012). Separating grazing and rainfall effects at regional scale using remote sensing imagery: A dynamic reference-cover method. Remote Sensing of Environment, 121(0), 443–457. doi:10.1016/j.rse.2012.02.021

Beutel, T. S., Shepherd, R., Karfs, R. A., Abbott, B. N., Eyre, T., Hall, T. J., & Barbi, E. (2021). Is ground cover a useful indicator of grazing land condition? *The Rangeland Journal*, *43*(1), 55–64. https://doi.org/10.1071/RJ21018

Chen, Y., Guerschman, J., Shendryk, Y., Henry, D., & Harrison, M. T. (2021). Estimating Pasture Biomass Using Sentinel-2 Imagery and Machine Learning. *Remote Sensing 2021, Vol. 13, Page 603*, *13*(4), 603. https://doi.org/10.3390/RS13040603

Fisher, A., Flood, N., & Danaher, T. (2016). Comparing Landsat water index methods for automated water classification in eastern Australia. *Remote Sensing of Environment*, *175*, 167–182. https://doi.org/10.1016/J.RSE.2015.12.055

Karfs, R. A., Abbott, B. N., Scarth, P. F., & Wallace, J. F. (2009). Land condition monitoring information for reef catchments: a new era. *The Rangeland Journal*, *31*(1), 69. doi:10.1071/RJ08060

Lucas, R., Mueller, N., Siggins, A., Owers, C., Clewley, D., Bunting, P., Kooymans, C., Tissott, B., Lewis, B., Lymburner, L., & Metternicht, G. (2019). Land Cover Mapping using Digital Earth Australia. *Data 2019, Vol. 4, Page 143*, *4*(4), 143. https://doi.org/10.3390/DATA4040143

Owers, C. J., Lucas, R. M., Clewley, D., Planque, C., Punalekar, S., Tissott, B., Chua, S. M. T., Bunting, P., Mueller, N., & Metternicht, G. (2021). Living Earth: Implementing national standardised land cover classification systems for Earth Observation in support of sustainable development. *Big Earth Data*, *5*(3), 368–390. https://doi.org/10.1080/20964471.2021.1948179

Pringle, M.J., O'Reagain, P,J., Stone, G.S., Carter, J.O., Orton, T.G., Bushell, J.J. (2021) Using remote sensing to forecast forage quality for cattle in the dry savannas of northeast Australia. Ecological Indicators, 133 (0), doi.org/10.1016/j.ecolind.2021.108426

Scarth, P., Trevithick, R. & Tindall, D. 2020. RP105G – Monitoring ground cover patchiness and land condition in the grazing lands of the Great Barrier Reef catchments. Brisbane: Department of Environment and Science, Queensland Government.

Shepherd, J. D., Bunting, P., & Dymond, J. R. (2019). Operational Large-Scale Segmentation of Imagery Based on Iterative Elimination. *Remote Sensing 2019, Vol. 11, Page 658*, *11*(6), 658. doi:10.3390/RS11060658

8. Appendix 1

8.1 Queensland Land Type Classification.