

Pasture biomass mapping in hill country using remote sensing and geospatial tools

Duy TRAN^{1*}, Alec MACKAY¹, Mike DODD¹, Rachel COLE¹ and Emma NOAKES¹

¹BSI - AgResearch Group - Bioeconomy Science Institute, Grasslands Research Centre, Tennent Drive, 11 Dairy Farm Road, Turitea 4442, Palmerston North, New Zealand

*Corresponding author: Duy.Tran@agresearch.co.nz

Abstract

Measuring pasture biomass in hill country is challenging. Our objective was to demonstrate how the fine-scale spatial pattern of pasture biomass in a highly heterogeneous grassland landscape can be quantified using multispectral remote sensing and spatial machine learning. Images derived from the Sentinel 2 satellite and topographical indices (e.g., slope, aspect), were used as predictor variables. These variables could all be captured remotely, meaning minimum requirement for 'manual' data provision by the land manager. Pasture biomass samples were collected from 43 pre-selected spatially balanced sites across the long-term phosphorus (P) and sheep grazing experiments located on AgResearch Ballantrae Research Station to train and validate the prediction model. The spatial pasture biomass model achieved a moderate prediction performance ($R^2 \sim 0.6$, Root mean squared error = 581 kg dry matter/ha). This is a significant achievement, comparable to others, despite addressing the most diverse grassland landscapes at a finer scale. Our study provides insight into the pattern of pasture biomass in heterogeneous landscapes, showing that biomass can be highly variable within a slope class, an aspect, or single paddock. Integrating remote sensing with spatial machine learning can improve pasture biomass estimates and advance our ability to routinely update pasture cover in feed budgets for diverse landscapes.

Keywords: feed budgets, machine learning, pasture biomass, Sentinel 2, spatial mapping

Introduction

Precision pasture management is critical for pasture-based farm systems as it links directly to pasture utilisation, a key driver of profitability. The spatial pattern and distribution of pasture biomass is essential underlying information for pasture management and feed budgeting. Too often it is not collected. Nowhere is this truer and more challenging than in hill country. Under current practices, assessment of the farms pasture biomass is often based on samples from a few select paddocks (Gard et al. 2024). The next generation of sensors and models provide the opportunity for a more complete picture of the pattern of pasture covers across

the farm, especially across topographically complex farmed landscapes.

Integrating multispectral remote sensing data such as Sentinel 2 with machine learning (ML) has recently been successfully used as an alternative option for high-resolution biomass mapping in grassland landscapes (Chen et al. 2021; De Rosa et al. 2021; Zwick et al. 2024). In New Zealand, remote sensing and/or ML for mapping pasture biomass is a proven technology, with several commercial remote pasture measuring platform products focused on providing average pasture biomass estimates at paddock scale for lowland dairy areas (i.e., LIC SPACE, Aimer Farming). As is often the case, topographically complex farmed landscapes (e.g. the c. 4 M ha of hill country remain challenging). Pastue.io, an overseas company has recently offered pasture biomass data at the paddock level for both dairy and sheep and beef farms. Data provided at the paddock level while useful in feed budgeting is limited in developing the grazing plan particularly in hill country.

Despite its increasing potential, pasture biomass mapping using remote sensing still faces several technical and commercial challenges that inhibit widespread adoption of this approach at scale (Nicola et al. 2025). A key challenge is the limited model transferability at fine scale due to the combination of variations including topography, soil, vegetation composition, through to land management practices (Smith et al. 2023). New Zealand is an ideal example of this challenge, due to its diverse pastoral landscapes, ranging from flat and rolling lowlands to topographically complex hill and steep hill land and associated farming systems.

In developing a biomass prediction model that can account for the influence of topography, it is important that the underlying ground-truth data for training and validation is collected at the locations and scale required to capture the features of the landscape that align with fine-scale heterogeneity that contributes to differences in pasture biomass patterns. This includes requiring the use of a sampling technique that ensures sample locations are well-distributed and proportionally represented across different landscape features (e.g., slopes, aspects). Critically in our view, it also requires actual measure of pasture biomass, rather than the use

of data derived from other measurement tools that come with existing calibration error terms (e.g., Rising Plate Meter).

The Normalized Difference Vegetation Index (NDVI) has been used as a key remote sensing input to calculate pasture biomass (Donald et al. 2010; Smith et al. 2011; Fern et al. 2018), however, using NDVI alone is limited due to its sensitivity to combined effect of landscape features and pasture conditions (Mutanga & Skidmore 2004). Other spectral indices such as the Enhanced Vegetation Index (EVI) and the Soil-Adjusted Vegetation Index (SAVI) may have better capability than NDVI in capturing the complexity of landscapes and vegetation characteristics (Lourenço et al. 2021). Therefore, using multiple spectral variables, instead of relying solely on NDVI, is suggested as a solution to provide a better pasture biomass prediction accuracy.

A recent study highlighted the effect of underlying features, such as climate and topography, especially in highly heterogeneous areas, on the pasture biomass prediction accuracy using remote sensing (Nicola et al. 2025). This is because remote sensing primarily offers correlational insights rather than establishing direct causal relationships. In NZ hill country grassland, topographical variables such as slope, aspect, and topographical position can affect the pattern and distribution of pasture biomass through their impacts on soil moisture, nutrient availability, exposure to sunlight, and the grazing pattern (i.e., uneven grazing due to animal movement behaviour) (Zhang et al. 2006). In addition, pasture biomass may be influenced by management practices, such as fertiliser application, which significantly affects pasture growth.

Our objective was to demonstrate how the fine-scale spatial pattern of pasture biomass in a highly heterogeneous grassland landscape can be quantified using a combination of multispectral remote sensing, topography, fertiliser and sheep grazing management practices, and advanced geospatial techniques.

Materials and Methods

Data and study site

We used the long-term P fertiliser and sheep grazing experiment located on the AgResearch Ballantrae Hill Country Research Station situated near Woodville, in the Hawke's Bay region of the southern North Island of New Zealand (Figure 1).

A total of 43 pasture biomass samples were collected across the long-term experiment to train and validate the machine learning models (Figure 1). The location of each of site was identified using spatial balanced sampling, an advanced statistical method of Theobald et al. (2007), developed from the approach of Stevens and Olsen (2004). Spatially balanced points, i.e., sample

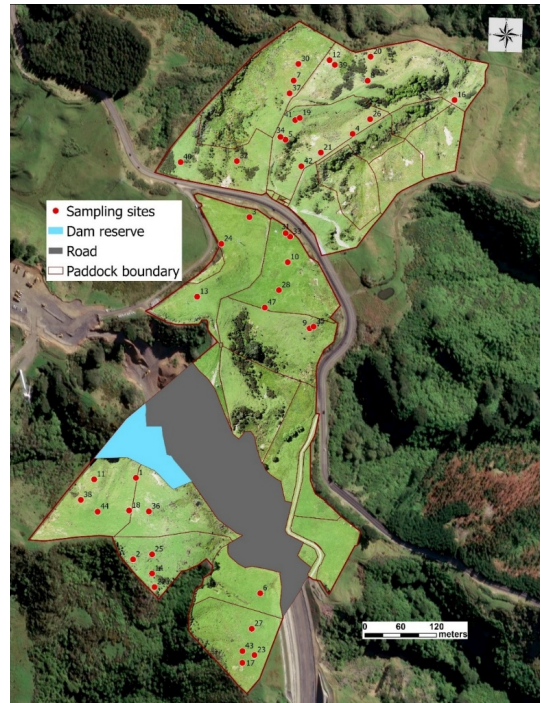


Figure 1 The study area and located on the 43 pre-selected spatial balanced pasture sampling sites

sites for measuring pasture biomass in the studied landscapes, were created based on the following steps:

- Using the Reverse Randomized Quadrant-Recursive Raster algorithm (Theobald et al., 2007) to map 2D space into a 1D space.
- Using unequal inclusion probabilities (IP) to handle variations in sampling intensity.
- Standardising IP (ranging from 0 to 1) to specify the probability that a location (raster cell) will be selected relative to other locations.
- Ensuring IP incorporate four key strata: slopes, aspects, terrain roughness, and P fertiliser management histories. Distribution of samples was described in Table 1.
- Weighting the IP layers using proportion of each stratum and their categories to total land area.
- Excluding areas close to trees, water bodies, farm tracks, and fence lines to ensure the sample reflects the typical and general conditions of the pasture were excluded.

Pasture sampling and processing

Sampling locations identified from the spatial balance sampling method were visualised on a map. A week before the sampling date, we visited these sites in the field, measured the slope and aspect to confirm the alignment with samples profile derived from the model,

Table 1 Distribution of pasture samples across six slope classes, seven aspect classes, and three farmlets with different fertiliser and sheep grazing management systems. The LFLF farmlet has received 125 kg superphosphate ha⁻¹ year⁻¹ since 1980, the HFHF has received 375 kg single superphosphate ha⁻¹ year⁻¹ since 1980 and LFNF has received no P fertiliser inputs since 1980.

	Area (ha)	%	N ^o of samples	%
Slope (°)				
0-8	1.1	5.0	3	7.0
8-15	2.8	13.2	8	18.6
15-20	2.2	10.4	6	14.0
20-25	2.5	11.5	2	4.7
25-35	6.0	27.8	19	44.2
>35	6.9	32.0	5	11.6
Aspect				
East	3.7	17.3	10	23.3
North	4.6	21.3	12	27.9
Northeast	4.2	19.7	8	18.6
Northwest	2.7	12.4	2	4.7
South	1.8	8.6	3	7.0
Southeast	2.5	11.9	3	7.0
Southwest	0.8	3.7	3	7.0
West	1.1	5.0	2	4.7
P fertiliser and sheep grazing management history				
HFHF	6.6	30.7	15	34.9
LFLF	5.7	26.5	8	18.6
LFNF	9.2	42.8	20	46.5

and marked each sample's location with a stake. A 1m² quadrat was placed in the centre of each pasture sampling site and the herbage was cut to ground level using an electric shearing handpiece. The coordinates of sample sites were recorded using a Trimble DA2 GNSS system. Due to the GPS device's 60 cm accuracy limitation, some sample locations positioned inaccurately. To correct this, the sampling points were overlaid on a high-resolution drone image (~1.5 cm) allowing us to see the stakes and cut area clearly, and adjusted to ensure these points were centred within the 1m² cut area.

Pasture samples did not require washing to remove soil or earthworm casts as conditions were dry when pastures were cut. In the laboratory, a fresh weight was obtained from the whole sample and then a subsample was oven-dried at 60°C for 72 hours to determine dry weight. The subsample was ground to 1 mm particle size to be sent for analysis of nutritive quality. A second pasture sample was used to obtain the grass, legume, and dead matter contents. Pasture biomass measured from the 43 field sites, were highly variable, with the minimum, maximum, and mean biomass of 237, 4731, and 1965 kg DM/ha, respectively (Figure 2).

Pasture biomass predictors

This study utilised remote sensing, topography, and management variables for mapping the biomass. Twenty-five surface reflectance spectral variables derived from Sentinel 2 (spatial resolution of 10 m), including single spectral bands, band-ratios, and vegetation indices, were downloaded from Climate Engine (<https://www.climateengine.org/>). Sentinel 2 data captured on January 10th 2025 were selected as this acquisition date was relatively close to the Jan 13th when

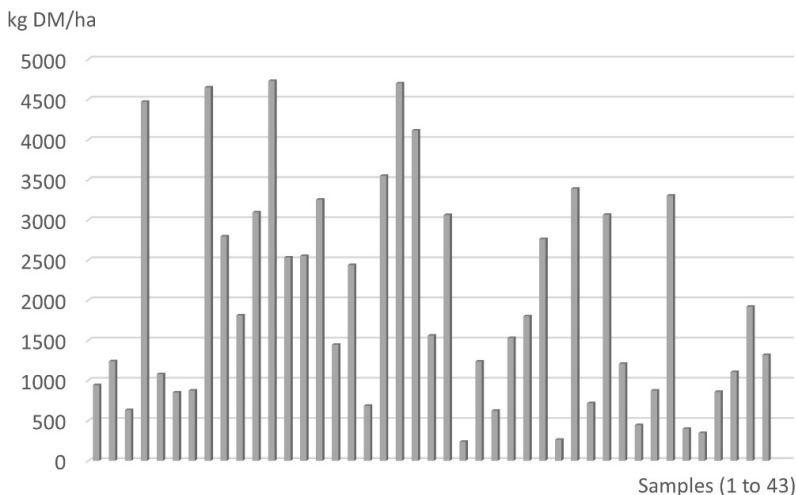


Figure 2 Pasture biomass (kg DM/ha) at the 43 field sites

the pasture was sampled, to ensure the two datasets were aligned. A detailed description of multispectral indices is available online (<https://custom-scripts.sentinel-hub.com/custom-scripts/sentinel-2/indexdb/>).

Six topographical variables (elevation, slope, aspect, topographic wetness, topographic roughness, topographic position), calculated from LiDAR DEM using ArcGIS Pro (version 3.4), were used as explanatory variables for supporting the pasture biomass prediction. Topographic wetness index (TWI) indicates how local topography affects runoff flow and accumulation, highlighting areas with high runoff potential and low slopes with large upslope contributions. Topographic roughness index (TRI) measures the variability in elevation within an area, indicating how rough or uneven the terrain is. The topographic position index (TPI) was used to classify topographic features such as a hilltop, valley bottom, exposed ridge, flat plain, based on the difference between the elevation of a location to the average elevation of its surrounding area. For more detailed information see Tran et al. (2024).

Management variable was superphosphate fertiliser inputs and sheep grazing histories across the three farmlets, including a low P fertiliser (LFLF), which has received 125 kg superphosphate ha⁻¹ year⁻¹ since 1980), a high P fertiliser (HFHF), which has received 375 kg single superphosphate ha⁻¹ year⁻¹ since 1980 and has received no P fertilizer input since 1980 (Bilotto et al. 2022).

Spatial machine learning

Geospatial-based machine learning incorporates spatial location in the computation of data-driven algorithms and techniques. In this study, the “Random Forest” algorithm was used to model the spatially explicit pasture biomass. This is an ensemble learning technique, operating by constructing a multitude of decision trees during the training phase and combining their outputs to improve the overall accuracy and stability of the model (Breiman et al. 2017). For the biomass prediction, the model averages the outputs of all decision trees to produce a continuous value. The method introduces randomness by following two steps: selecting random subsets of features at each split in the trees and training each tree on a bootstrap sample of the data (random sampling with replacement). This randomness helps reduce overfitting, making Random Forest robust to noise and outliers, while its ability to handle large datasets and complex feature interactions makes it widely applicable across various domains. The field measures were divided into a training set (80% of sites) and validation set (20% of sites). The coefficient of determination (R^2) and root mean squared error (RMSE) were used as model performance assessment indicators. We set the “number of runs for

validation” up to 100 to perform multiple iterations. The model iteratively partitioned the data into training and validation sets multiple times, each iteration utilising a unique random seed, trained and validated the model for each partition, and computed the average of performance metrics (e.g., R^2 , RMSE) across all iterations. This provides more robust performance metrics and reduce the impact of random variation in the data split to ensure the reliability of the validation metrics and model performance.

Results

Diagnostics of the prediction model

The performance of the model to predict pasture biomass and the contribution of the top explanatory variables to this prediction are listed in Table 2. The training fitted well with the field data ($R^2 = 0.93$ and RMSE = 462 kg DM/ha). The validation showed a moderate prediction performance ($R^2 = 0.59$ and RMSE = 581 kg DM/ha). The mean biomass estimated by the spatial pasture model (i.e., calculating for all locations) was 2312 kg DM/ha, 17% higher than the mean of the 43 field measurements (1965 kg DM/ha). Regarding the contribution of explanatory variables to biomass prediction, the band ratios of Red/Blue, Green/Red, and Modified Soil-Adjusted Vegetation Index (MSAVI) were found to be the top three remote sensing variables. The key topographical variables for predicting biomass were elevation, topographic roughness, and aspect.

Spatially explicit pasture biomass pattern

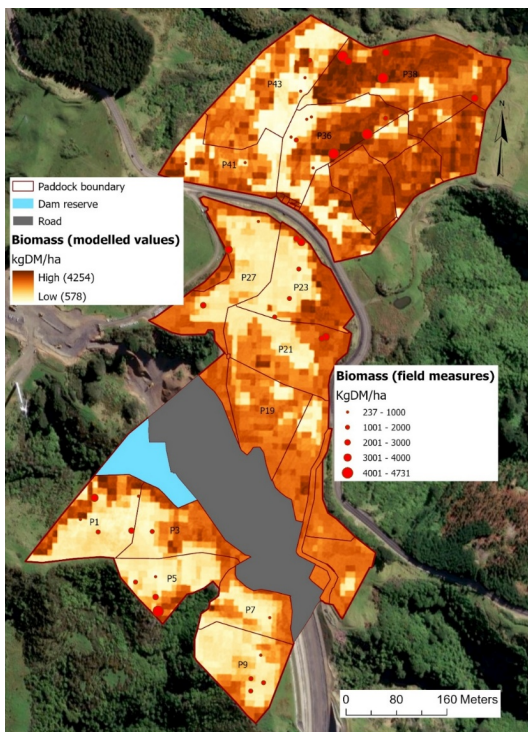
The pasture biomass distribution map in the study area generated from the model aligns well with the field measurements (Figure 2). The highest biomass (>4000 kg DM/ha) was seen in the north-end and central northern paddock of the study area. Northeast and southeast paddocks also had high biomass value. The lowest biomass (<1000 kg DM/ha) was seen in hill-top/ridge areas in the north of the farm. The flat and rolling land areas of the central paddocks presented relatively low biomass (1000-2000 kg DM/ha). Low pasture cover was also observed in all paddocks in the south of the study area.

The information derived from the map in Figure 3 reveals that biomass levels between 2000 and 3000 kg DM/ha occupied approximately 40% total area. Biomass from 1000 to 2000 kg DM/ha and from 3000 to 4000 kg DM/ha, accounting for 36% and 22%, respectively. Areas having these levels of biomass were found across most slope classes and aspects. Only small area has biomass less than 1000 kg DM/ha. The highest biomass (>4000 kg DM/ha) was observed in steep land (>25°) and north-facing aspect areas.

The pattern of pasture biomass within a single paddock (P23) within the study area is demonstrated

Table 2 Model performance (a) and top training variables contributing to the biomass prediction (b)

(a) Model performance		
<i>Indicator</i>	<i>Training</i>	<i>Validation</i>
R-Squared (R ²)	0.93	0.59
Root Mean Square Error (RMSE)	462.8	581.2
p-value	0.00	0.03
Standard Error	0.04	0.18
(b) Top variable importance		
<i>Variable</i>	<i>Importance</i>	<i>%</i>
Red/Blue band ratio	7643361	12
Green/Red band ratio	6933923	11
Modified Soil-adjusted Vegetation Index (MSAVI)	5769921	9
Enhanced Vegetation Index (EVI)	5010195	8
Soil adjusted vegetation Index (SAVI)	3955819	6
Advanced Vegetation Index (AVI)	3935862	6
Difference Vegetation Index (DVI)	3867217	6
Digital Elevation Model (DEM)	2449166	4
Fluorescence Correction Vegetation Index (FCVI)	2279768	3
Near Infrared (NIR)	2257850	3
Terrain Ruggedness Index (TRI)	2134435	3
Normalised Difference Water Index (Vegetation water) (NDWI)	2066907	3
Aspect	2062309	3
Normalised Difference Vegetation Index (Water) (NDWI1)	1725064	3



in Figure 4. Despite located on a rolling landscape (i.e., mean slope ~16°), this paddock had five levels of biomass with the lowest class (below 1000 kg DM/ha) distributed in the west and highest class (above 3000 kg DM/ha) presented in the east is not to different from the variation across the whole study area. Very high-resolution drone images (cell size <5cm²) captured in three locations show a clear difference in pasture conditions associated with three levels of biomass.

Discussion

Results from this study demonstrate that advanced technologies, including high-resolution multispectral remote sensing data and spatial machine learning, can provide detailed pasture cover in a highly heterogeneous grassland landscape. This finding extends recent overseas studies that show the feasibility of combining remote sensing and machine learning for pasture cover mapping in relatively homogeneous landscapes (Otgonbayar et al. 2019; Chen et al. 2021; Amarsaikhan et al. 2023; Ogungbuyi et al. 2024).

Figure 3 Pasture biomass distribution predicted by the spatial pasture model on January 13th 2025 in the study area

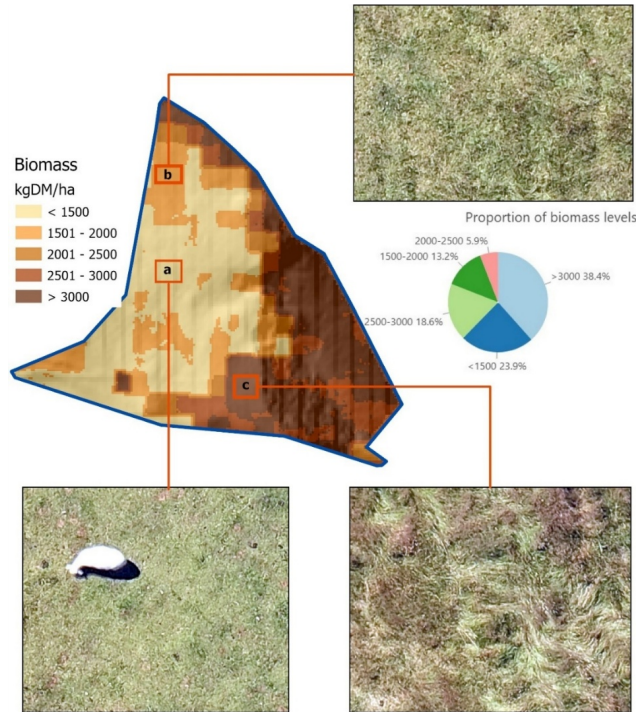


Figure 4 Spatial distribution and variation in pasture biomass within paddock (paddock 23), along with drone images from three locations demonstrating different pasture biomass levels: (a) below 1500 kg DM/ha, (b) 1500-2000 kg DM/ha, and (c) over 3000 kg DM/ha.

Potential of ML and remote sensing in modelling pasture biomass

This study is one of the first attempts to explore the potential of remote sensing and advanced machine learning in mapping pasture biomass in a hill country farm in NZ, hence providing valuable references for modelling practices. Choosing an appropriate pasture sampling strategy is important to acquire good training data for the machine learning model. The spatial balanced sampling method is highly advantage in heterogeneous landscapes, given that the method ensures a more even distribution of samples across the landscapes. This provides the representative samples required to capture the full range of heterogeneity within the landscape and therefore, better reflect spatial patterns and variability of biomass across the farm.

Using multiple spectral indices instead of relying on a single remote sensing variable, combining with topographical variables, is important to increase the opportunity to explain the variation of biomass across landscapes. The minimal contribution of NDVI in the prediction model may be due to the presence of some very high pasture biomass measurements in the study area. The tendency of NDVI to saturate at high vegetation cover reduces its ability to differentiate between levels of high pasture biomass within an area

(Mutanga & Skidmore 2004). In this case, the band ratios (i.e., Red/Blue and Green/Red) and spectral indices like MSAVI was seen to perform well in biomass prediction, due to better capturing variations in chlorophyll content and the capability to account for background disturbance from soil and bare ground (Ritchie et al. 2010; Thinley et al. 2024). This study demonstrated the benefit of including topographical factors in the pasture biomass prediction, although their contribution to the overall accuracy of the model (3-4%) was less than that of remote sensing indices (6-12%). Utilizing multiple spectral indices and topographical variables provides better capability in capturing the complexity of landscapes and vegetation characteristics.

The findings of this study provide a 'complete spatial' picture of the distribution of pasture biomass, one which is not possible with the current approaches providing an estimate of biomass in 'representative areas' (i.e. selected paddocks). Other non-spatial approaches (e.g., process-based models) may provide information on potential biomass produced based on slope, soil, and aspect, but are not capable of capturing the impact topography has on pasture utilisation by the animals resulting residuals.

An integrated approach combining remote sensing

and machine learning to model the spatially explicit biomass at a very high spatial resolution provides a more complete picture of the pattern and change in biomass across every location of the farm. Spatial information on pasture biomass illustrated in this study goes far beyond the average information provided at paddock scale by existing commercial services. Similarly, spatially explicit pasture biomass data could not be achieved by common methods (i.e., sward stick, rising plate meter, probe or eye estimation) used in NZ hill country. Having this information is valuable for farmers/land managers to help them in feed budgeting and informing the grazing plan, by identifying areas of poor pasture utilisation for specific treatment. It also enables maximising the operational efficiency of emerging grazing technologies like virtual fencing by optimising grazing cell design and precise stock allocation.

Uncertainties, limitations and future directions

This study used field samples and remote sensing data collected on a single date in summer to develop the model, and therefore we must interpret the results with caution. The contribution of leading variables (including remote sensing and topography) to biomass prediction may change across season. For example, the effects of aspect and band ratio of Red/Blue may not be the same in spring or winter when moisture is high and when the contrast between dry and green pasture is low. In the future, using a time-series approach once data is available, is suggested to fill this limitation.

With moderate prediction accuracy ($R^2 \sim 0.6$), we must recognise the possibility of inaccuracies in biomass prediction in some areas due to limited sample size. Considering that the pattern of pasture biomass in hill country landscapes is highly complex, a small number of samples (i.e., 43) may not be good enough to effectively capture this complexity. The model performing better in the training data than the test data indicates that some underlying generalisable patterns were not captured. Future work should look at mitigation options such as increasing sample size and optimising the model's parameters to improve the pasture biomass prediction performance.

Despite the advantage of using satellite-based remote sensing in mapping biomass, the implementation of this approach relies on high-quality, cloud-free multispectral remote sensing data at a frequency of weeks and months, rather than year (Reinermann et al. 2020). This is a major limitation to areas with commonly high cloud cover, such as New Zealand Aotearoa. Given that the satellite imagery was acquired 3 days before the site cut sampling was performed, a time-lag between two datasets may affect the prediction accuracy. Sentinel 2 with a spatial resolution of $10 \times 10 \text{m}^2$ is not sufficient

to effectively model the variation of pasture biomass in hill country. It is essential to test the performance of using higher resolution remote sensing data (e.g., drones and commercial images at sub-metre resolution). An integration of Sentinel 2 with other multispectral data (e.g., Landsat, CubeSat) and radar and drone images could provide a solution. For instance, using advanced geostatistical techniques such as data fusion can improve both the spatial and temporal resolution of Sentinel 2 data (Ogungbuyi et al. 2024).

Collecting pasture samples to initially train and validate the prediction spatial pasture model will come at a cost. Applying standardised validation protocols and sampling strategies such as utilising data collected using the rising plate meter would limit the costs involved collecting field samples. It is important that future work tests the capability of the approach to map pasture biomass more frequently (e.g., weekly or seasonal) to provide more detail information for management practices.

Conclusions

Advanced remote sensing, GIS, machine learning, and spatial statistical methods can facilitate the mapping of pasture biomass in heterogenous landscapes. This provides critical information which can be used in feed budgeting and critically in the subsequent grazing plan. These tools can effectively map the spatially explicit pattern of pasture biomass and show variations between and within paddocks. Pasture biomass is influenced by various factors, including topographical characteristics, grazing behaviour and fertiliser management histories, in addition to previous grazing practices. Information derived using these advanced techniques could allow farmers to gain a better understanding of the distribution of pasture biomass across their farm and make more effective use of emerging technologies that have the potential to fundamental change current grazing management practices.

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REFERENCES

- Amarsaikhan E, Erdenebaatar N, Amarsaikhan D, Otgonbayar M, Bayaraa B. 2023. Estimation and mapping of pasture biomass in Mongolia using machine learning methods. *Geocarto International* 38: 2195824. <https://doi.org/10.1080/10106049.2023.2195824>

- Bilotto F, Vibart R, Mackay A, Costall D, Harrison MT. 2022. Towards an integrated phosphorus, carbon and nitrogen cycling model for topographically diverse grasslands. *Nutrient Cycling in Agroecosystems* 124: 153-172. <https://doi.org/10.1007/s10705-022-10231-3>
- Breiman L, Friedman J, Olshen RA, Stone CJ. 2017. *Classification and regression trees*: Chapman and Hall/CRC. New York, United State.
- Chen Y, Guerschman J, Shendryk Y, Henry D, Harrison MT. 2021. Estimating pasture biomass using sentinel-2 imagery and machine learning. *Remote Sensing* 13: 603. <https://doi.org/10.3390/rs1304060>
- De Rosa D, Basso B, Fasiolo M, Friedl J, Fulkerson B, Grace PR, Rowlings DW. 2021. Predicting pasture biomass using a statistical model and machine learning algorithm implemented with remotely sensed imagery. *Computers and Electronics in Agriculture* 180: 105880. <https://doi.org/10.1016/j.compag.2020.105880>
- Donald G, Gherardi S, Edirisinghe A, Gittins S, Henry D, Mata G. 2010. Using MODIS imagery, climate and soil data to estimate pasture growth rates on farms in the south-west of Western Australia. *Animal Production Science* 50: 611-615. <https://doi.org/10.1071/AN09152>
- Fern RR, Foxley EA, Bruno A, Morrison ML. 2018. Suitability of NDVI and OSAVI as estimators of green biomass and coverage in a semi-arid rangeland. *Ecological Indicators* 94: 16-21. <https://doi.org/10.1016/j.ecolind.2018.06.029>
- Gard S, Neal M, Minnee E. 2024. Pasture performance tools: current and future state. *Journal of New Zealand Grasslands* 86: 273-279. <https://doi.org/10.33584/jnzg.2024.86.3688>
- Lourenço P, Godinho S, Sousa A, Gonçalves AC. 2021. Estimating tree aboveground biomass using multispectral satellite-based data in Mediterranean agroforestry system using random forest algorithm. *Remote Sensing Applications: Society and Environment* 23: 100560. <https://doi.org/10.1016/j.rsase.2021.100560>
- Mutanga O, Skidmore AK. 2004. Narrow band vegetation indices overcome the saturation problem in biomass estimation. *International journal of remote sensing* 25: 3999-4014. <https://doi.org/10.1080/01431160310001654923>
- Nicola F, Miguel R-CJ, Intrigliolo DS, Giuseppe T, Sabina F. 2025. Remote Sensing for Pasture Biomass Quantity and Quality Assessment: Challenges and Future Prospects. *Smart Agricultural Technology* 12: 101057. <https://doi.org/10.1016/j.atech.2025.101057>
- Ogungbuyi MG, Guerschman J, Fischer AM, Crabbe RA, Ara I, Mohammed C, Scarth P, Tickle P, Whitehead J, Harrison MT. 2024. Improvement of pasture biomass modelling using high-resolution satellite imagery and machine learning. *Journal of Environmental Management* 356: 120564. <https://doi.org/10.1016/j.jenvman.2024.120564>
- Otgonbayar M, Atzberger C, Chambers J, Damdinsuren A. 2019. Mapping pasture biomass in Mongolia using partial least squares, random forest regression and Landsat 8 imagery. *International Journal of Remote Sensing* 40: 3204-3226. <https://doi.org/10.1080/01431161.2018.1541110>
- Reinermann S, Asam S, Kuenzer C. 2020. Remote sensing of grassland production and management—A review. *Remote Sensing* 12: 1949. <https://doi.org/10.3390/rs12121949>
- Ritchie G, Sullivan D, Vencill W, Bednarz C, Hook J. 2010. Sensitivities of normalized difference vegetation index and a green/red ratio index to cotton ground cover fraction. *Crop science* 50: 1000-1010. <https://doi.org/10.2135/cropsci2009.04.0203>
- Smith HD, Dubeux JC, Zare A, Wilson CH. 2023. Assessing transferability of remote sensing pasture estimates using multiple machine learning algorithms and evaluation structures. *Remote Sensing* 15: 2940. <https://doi.org/10.3390/rs15112940>
- Smith RC, Adams M, Gittins S, Gherardi S, Wood D, Maier S, Stovold R, Donald G, Khohkar S, Allen A. 2011. Near real-time Feed On Offer (FOO) from MODIS for early season grazing management of Mediterranean annual pastures. *International Journal of Remote Sensing* 32: 4445-4460. <https://doi.org/10.1080/01431161.2010.487078>
- Stevens Jr DL, Olsen AR. 2004. Spatially balanced sampling of natural resources. *Journal of the American statistical Association* 99: 262-278. <https://doi.org/10.1198/016214504000000250>
- Theobald DM, Stevens DL, White D, Urquhart NS, Olsen AR, Norman JB. 2007. Using GIS to generate spatially balanced random survey designs for natural resource applications. *Environmental Management* 40: <https://doi.org/10.1007/s00267-005-0199-x>
- Thinley J, Pickering C, Ndehedehe C. 2024. Using vegetation and chlorophyll indices to model above ground biomass over time in an urban arboretum in subtropical queensland. *Remote Sensing Applications: Society and Environment* 34: 101202. <https://doi.org/10.1016/j.rsase.2024.101202>
- Tran DX, Dominati E, Lowry J, Mackay A, Vibart R, Pearson D, Devantier B, Noakes E. 2024. Effects of spatial data resolution on the modelling and mapping of soil organic carbon content in hill country grassland landscapes. *Soil Use and Management* 40: e12966. <https://doi.org/10.1111/sum.12966>
- Zhang B, Valentine I, Kemp P, Lambert G. 2006. Predictive modelling of hill-pasture productivity:

integration of a decision tree and a geographical information system. *Agricultural Systems* 87: 1-17. <https://doi.org/10.1016/j.agsy.2004.10.003>
Zwick M, Cardoso JA, Gutiérrez-Zapata DM, Cerón-Muñoz M, Gutiérrez JF, Raab C, Jonsson N, Escobar M, Roberts K, Barrett B. 2024. Pixels to pasture:

Using machine learning and multispectral remote sensing to predict biomass and nutrient quality in tropical grasslands. *Remote Sensing Applications: Society and Environment* 36: 101282. <https://doi.org/10.1016/j.rsase.2024.101282>