



## Remote sensing and machine learning for monitoring carbon stocks to support sustainable grazing management

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### Abstract

Grasslands offer a sustainable and cost-effective resource for livestock feed while supporting carbon sequestration, thereby mitigating climate change. However, current remote sensing methods for grassland monitoring have not adequately addressed adaptive grazing management at the fine scales required for intensive grazing systems. Grazing trials conducted under La Niña conditions, with recovery periods of 3, 6, 9, 12, and 15 months, aimed to advance regenerative grazing techniques in small plots (<1 hectare). Sentinel-2 imagery combined with random forest outperformed XGBoost in estimating biomass, achieving better regression statistics ( $R^2 = 0.56$ , RMSE = 1,532 kg DM/ha vs.  $R^2 = 0.48$ , RMSE = 1,726 kg DM/ha). The model effectively captured carbon stock variability across recovery periods, with the 3-month recovery exceeding 2,000 kg C/ha. This proof-of-concept study underscores the potential of high-resolution remote sensing to enhance precision agricultural management and promote climate-resilient farming practices

### Introduction

Pasture biomass, a major natural carbon sink, plays a critical role in global carbon sequestration and mitigating greenhouse gas emissions (GHG) to meet Paris Agreement targets (Harrison et al., 2016). While remote sensing and machine learning have advanced sustainable grazing management, most studies focus on regional scales, limiting their applicability at field scales (Ali et al., 2016; Ogungbuyi et al., 2023a). Regenerative grazing practices, such as short, intensive grazing periods and multi-paddock systems, promote soil health by enhancing microbial activity and organic matter incorporation (Ogungbuyi et al., 2023b). However, field biomass measurement and soil organic carbon (SOC) assessment remain capital-intensive and labourious (Mondal et al., 2017).

This study is proposing Sentinel-2 imagery, with its high spatiotemporal resolution, and machine learning to estimate carbon stocks at the field scale. Destructive sampling, combined with carbon conversion factors and root-to-shoot ratios recommended by the IPCC, provides a direct means to quantify carbon stocks (Cienciala et al., 2006; Penman et al., 2003). Previous studies show that machine learning models, such as random forest and XGBoost, effectively handle smaller datasets and manage model complexity, enabling accurate biomass estimates (Morais et al., 2021). The main objective of study is to assess pasture biomass and carbon stock variability across paddock treatments under regenerative grazing systems.

## Methods

The study was conducted in Triabunna, southeastern Tasmania (S 42° 30, E 147° 59), with annual rainfall of 648 mm and temperatures ranging from 7°C to 17°C. Fertile soils and a mix of sown and native pastures support intensive rotational grazing, aided by reliable winter rainfall.

Six 0.25-ha plots—Vault 1 (V1), Vault 2 (V2), Vault 3 (V3), Vault 4 (V4), Vault 5 (V5)—and a 10-ha Vault Control (VC) plot were stocked at a rate of 2000 DSE/ha for one day. This corresponds to a stocking density of 8000 DSE/ha for the 0.25-ha plots (see Ogungbuyi et al., 2024 for details). The treatment plots were subjected to high stocking density with varying spelling and recovery periods, except for the Vault Control, which had no specific recovery period. The recovery periods were as follows: 12 months (V1), 9 months (V2), 6 months (V3), 3 months (V4), and 15 months (V5).

Aboveground biomass was destructively sampled from December 2021 to November 2022 using a battery-operated shearing handpiece in 50 x 50 m quadrats, with the average of five readings computed per paddock to minimise sampling error. Cloud-free Sentinel-2 Level 2 surface reflectance images (n=56) were downloaded from Digital Earth Australia for dates matching the biomass sampling period. Ten spectral bands (b2–b8A, b11, b12) were used to extract reflectance values after removing cloudy pixels with a detection algorithm.

A random forest model was trained using the ten spectral bands and 56 biomass samples, split into 75% training and 25% test sets. To prevent overfitting, model parameters included 50 trees, limited tree depth, and default maximum features per split. Training accuracy was assessed using out-of-bag (OOB) error estimates, and performance was evaluated with R<sup>2</sup>, RMSE, and MAE. Similarly, an XGBoost model was trained with the same dataset and features. Hyperparameters included a learning rate of 0.05, maximum tree depth of 4, and subsample/column sampling rates of 0.8, with boosting rounds optimized using early stopping. Model performance was evaluated with R<sup>2</sup>, RMSE, and MAE.

Aboveground carbon (AGC) and belowground carbon (BGC) were derived from field biomass and Sentinel-2 random forest (S2-RF) estimates using Equations (1) and (2):

$$\text{Carbon} = \text{Biomass} \times \text{Carbon conversion factor} \quad (1)$$

$$\text{BGB} = \text{AGB} \times \text{root-to-shoot ratio} \quad (2)$$

We used a carbon conversion factor of 0.47 and a root-to-shoot ratio of 0.3. Total carbon stock was calculated using Equation (3)

$$\text{Carbon stock} = \text{AGC} + \text{BGC} \quad (3)$$

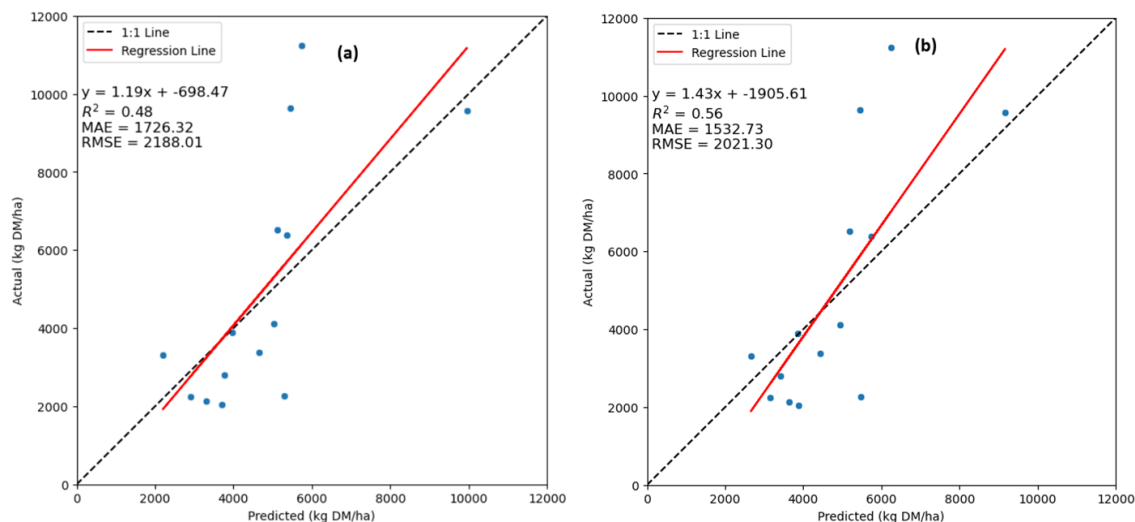
Seasonal carbon stock variability for treatment plots was analysed using standard error of the mean. Due to the lack of SOC field data for validation, we examined NDMI, derived from Sentinel-2 as Equation (4)

$$\text{NDMI} = \frac{\text{NIR} - \text{SWIR}}{\text{NIR} + \text{SWIR}} \quad (4)$$

## Results

### *Modelling pasture biomass with XGBoost and random forest*

The random forest model outperformed the XGBoost model with better regression statistics (R<sup>2</sup> = 0.56, RMSE = 1,532 kg DM/ha, and MAE = 2,021 kg DM/ha) compared to XGBoost (R<sup>2</sup> = 0.48, RMSE = 1,726 kg DM/ha, and MAE = 2,188 kg DM/ha), demonstrating its suitability for handling complex environmental datasets, such as high biomass volumes resulting from seasonal accumulation (Figure 1).



**Figure 1.** Comparison of Sentinel-2 estimated biomass using (a) the XGBoost model and (b) the random forest model against the actual biomass.

### ***Carbon stock variability in the Vault Plots***

The Vault plots exhibited seasonal variability in carbon stock, with Vault 4 (the three-month spelling plot) showing strong alignment between field-measured and Sentinel-2-derived carbon estimates, particularly exceeding 2,000 kg C/ha in seasonal trends (Figure 2). Additionally, the Vault 4 plot recorded the highest soil moisture index (Figure 3).

### **Discussion**

This study highlights the capability of Sentinel-2 imagery combined with a random forest model to accurately estimate pasture biomass at the field scale, even with a limited dataset. Unlike earlier studies, this approach effectively handles high biomass volumes accumulated seasonally without saturation (Ali et al., 2016; Ogungbuyi et al., 2023a), leveraging ten spectral bands to account for environmental conditions. The random forest model outperformed XGBoost, demonstrating superior adaptability to complex data.

Vault 4, with its three-month spelling and recovery period, exhibited the highest carbon stock, benefiting from La Niña-induced rainfall and improved productivity. This aligns with prior research (Ogungbuyi et al., 2024), which found that short-term spelling under intense grazing enhances litter formation and carbon sequestration through trampling effects. Additionally, the Sentinel-2-derived soil moisture index validated this result, showing Vault 4's highest soil moisture concentration (Figure 3).

The use of a carbon conversion factor consistent with Tasmanian soil properties (50% SOC as noted by (Brady et al., 2008; Cotching, 2018) strengthens the study's methodology. This innovative approach provides a proof of concept for deriving carbon stock in the absence of direct soil sampling, offering a valuable tool for future research.

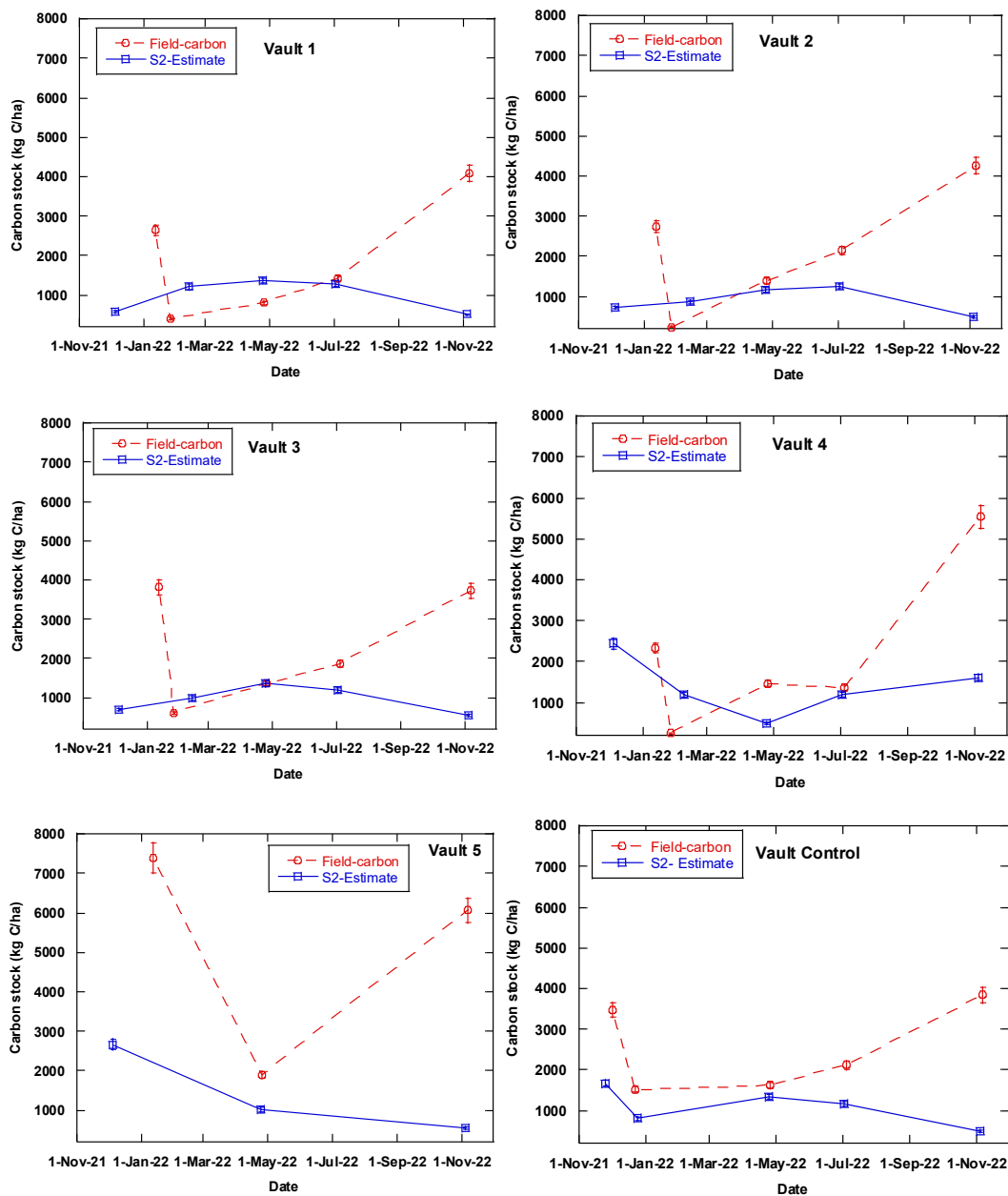
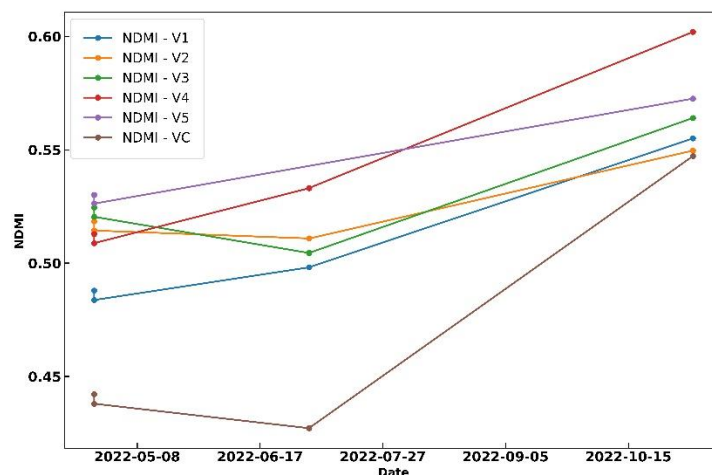


Figure 2. Seasonal variability of carbon stock in the Vault Plots.



**Figure 3.** Seasonal soil moisture index derived from Sentinel-2 data.

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