Remote Sensing Based Crop Monitoring

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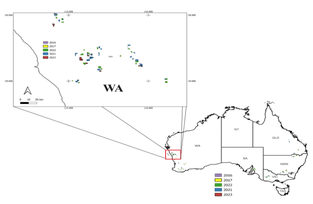
AAGI Analytics for the Australian Grains Industry

Abstract

This project aims to use remote sensing data to predict wheat grain yield using a five-year dataset covering Australia and grain protein content as a key quality indicator using a seven-year dataset from northern New South Wales (NSW). It also integrates optical and radar satellite observations to improve crop monitoring under cloudy conditions.

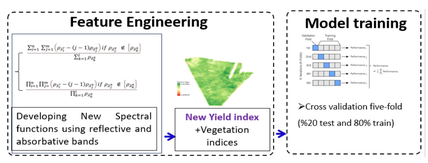
A Wheat Yield Model at National Scale

❑Prediction of wheat yield at the peak of greenness at field scale using Sentinel_2 and stress index across Australia

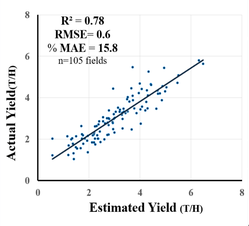


✓Input data (Satellite data, Observed field data for five historical seasons and simulated stress index from weather station)

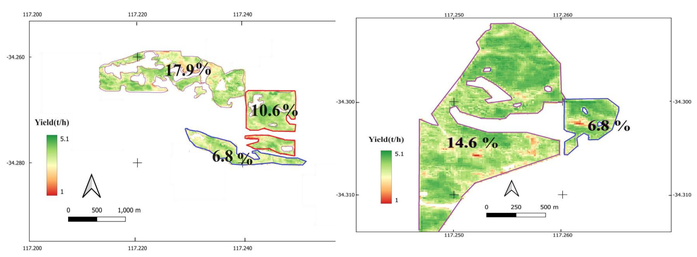
❑ML methods were applied using vegetation indices, stress index and a developed yield index



❑ Yield map with spatial variation and aggregated field yield levels



Actual Yield	Estimated Yield	Area (Ha)	%Error
4.4	4.7	77	6.8
4.1	4.2	158	2.4
4.7	4.2	109	10.6
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3.0	3.2	113	6.8
Mean			10.2



(Example: West of Australia in 2023)

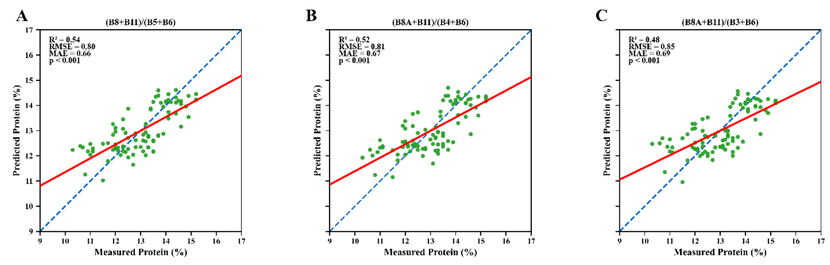
B Protein Model

❑Prediction of protein around the peak of greenness at field scale using Sentinel_2

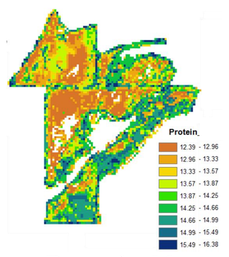
✓Input data (Satellite data, Observed field data and simulated PTQ from weather station)



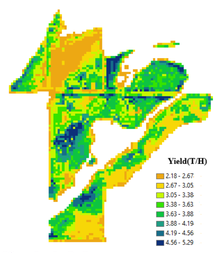
❑ Protein indices



❑Protein map (%) with spatial variation at field levels



Protein Map



Yield Map

C Cloudy Condition

❑Clouds often block tracking vegetation using optical indices such as NDVI. This project aimed to developing a geometric-weighted method that fills NDVI gaps during cloudy periods

❑Suggested Geometric Method for a specific cloudy day

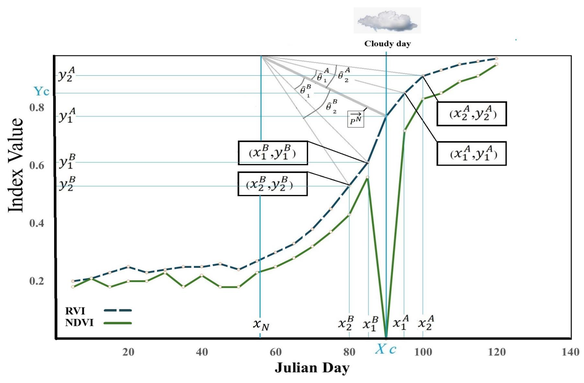
$$\vec{P}^N = \left(\frac{-\frac{dy}{dx}}{\sqrt{\left(\frac{dy}{dx}\right)^2 + 1}}, \frac{1}{\sqrt{\left(\frac{dy}{dx}\right)^2 + 1}} \right) \qquad \vec{V}_i = (x_i - x_N, y_i - 1)$$

$\vec{P}^N$: Normalized Vector — $\vec{V}_i$: reference vector

$$\hat{\theta}_i = \cos^{-1}\left(\frac{\vec{V}_i \cdot \vec{P}^N}{\|\vec{V}_i\| \cdot \|\vec{P}^N\|} \right) \qquad w_{\hat{\theta}_i} = \frac{\frac{1}{\hat{\theta}_i}}{\sum_{i=1}^{z} \frac{1}{\hat{\theta}_i}}$$

The angle $\hat{\theta}_i$ between $\vec{V}_i$ and $\vec{P}^N$ — $w_{\hat{\theta}}$ as weight for z angles of P^Z matrix

$$\text{Reconstructed_NDVI} = \sum_{i=1}^{z} w_{\hat{\theta}_i} \times NDVI_i$$



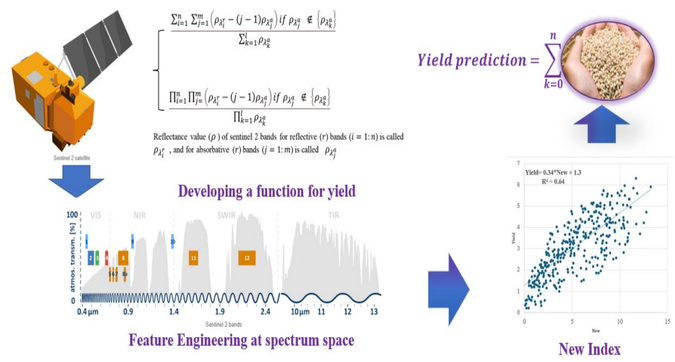
Consecutive Cloudy Days	5	10	15	20	25
RMSE (Proposed)	0.02	0.03	0.04	0.04	0.04
RMSE (Average NDVI)	0.04	0.04	0.06	0.06	0.08
% Increase in Accuracy	50	25	33	33	50

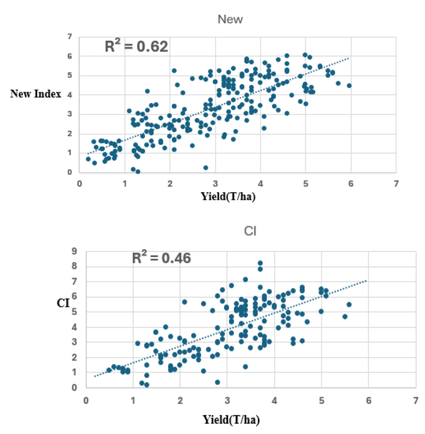
The proposed method showed a significant reduction in error (25%to 50%), offering a reliable solution for long-term vegetation monitoring under persistent cloud cover in comparison with average method

Feature Engineering as a key part of the project

❑Using the potential of remote sensing data for specific applications

✓ Advanced feature generation can further enhance the value of remote sensing data by extracting more information from the available spectral bands.





Comparison of Traditional and New Indices

Conclusion and Future Work

✓ Remote sensing data have shown strong potential for mapping wheat yield and grain protein content across Australia.

✓ integrating optical and radar observations improves crop monitoring, particularly under cloudy conditions,

✓ weather data and machine learning methods complement and strengthen remote sensing–based models

❑ Early season yield prediction using historical, remote sensing Including optic and radar and whether station data

❑Exploring the potential of new radar sensors for phenology mapping

Outputs and Publications

❑ Pipeline of wheat yield and protein
Input: field boundary and weather station data
Output: Yield and protein map at pixel scale and field scale

❑ **Publications:**

1- Potgieter, A. B., Brider, J., Ashourloo, D., Schepen, A., Zhao, Y., Jiang, R., Chapman, S., Zhang, M., Wu, B., Russell, K., & Hammer, G. L. (2026). CropVision: A multiscale EO–AI–climate-biophysical modelling framework for predicting crop performance in Australian wheat and sorghum systems. *in silico Plants, 8*(2), diag018.
2- Ashourloo, D., Brader, J., Zhao, Y., Jiang, R., Zhang, M., Chapman, S., Hammer, G., & Potgieter, A. B. (2026). Machine learning approaches for wheat yield prediction integrating biophysical modeling and remote sensing: Effects of sample size, dimensionality, and transferability. *Smart Agricultural Technology, 13*, 101936.
3- Ashourloo, D., Devoto, F., Jiang, R., Zhao, Y., & Potgieter, A. (2025). A novel geometric method for reconstruction of NDVI during cloudy period using Sentinel-1 & Sentinel-2. In *IGARSS 2025—2025 IEEE International Geoscience and Remote Sensing Symposium* (pp. 3633–3636). IEEE
4- Ashourloo et al. Developing a new mathematical function for wheat yield prediction using Sentinel 2 imagery . *Manuscript in preparation*.
5- Ashourloo et al. Developing a new framework for wheat protein prediction around peak greenness using Sentinel-2 imagery. *Manuscript in preparation.*

GRDC Grains Research & Development Corporation | Adelaide University | Curtin University | The University of Queensland Australia

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