Adaptive AI for Climate Resilience

This Food Agility CRC project identified a robust and repeatable framework so AI models can be used to understand the implications of climate change and related risks on agricultural crop outcomes.

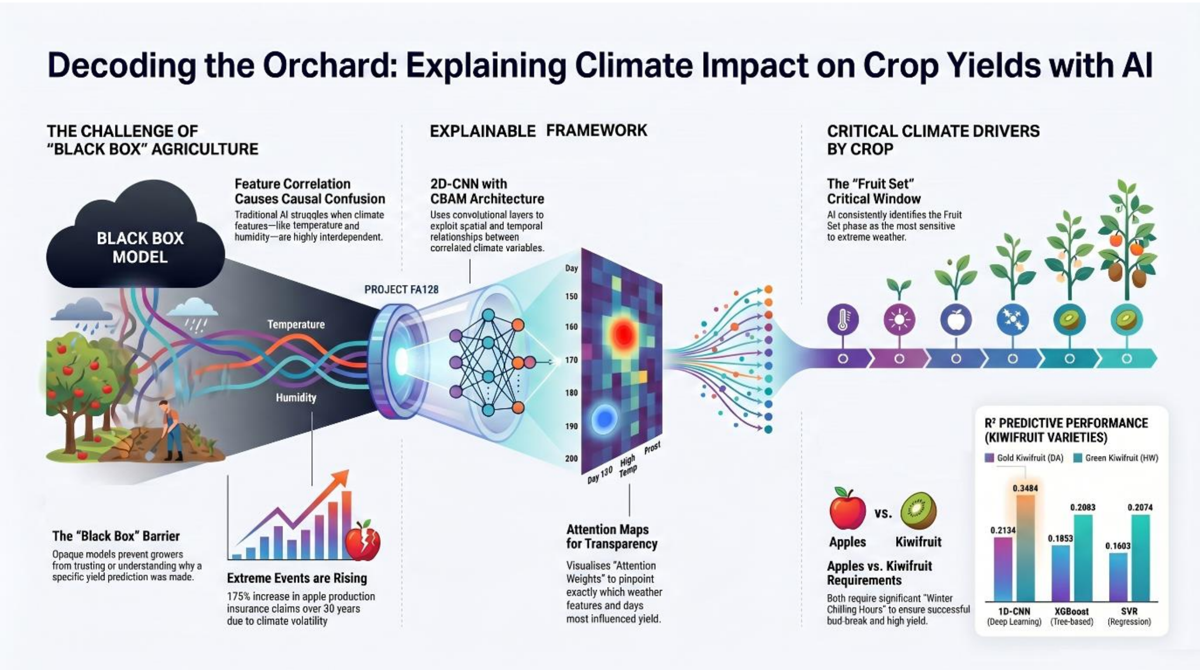
By Dr Victor Chu, Dr Boyuan (Bryan) Zheng, A/Prof Zhidong Li, Nino Eclarin, Dr Evan Webster, Ashley Rootsey

foodagility UTS YAMAHA AGRICULTURE

PROJECT SUMMARY REPORT

Project Overview

The FA128 Yield Explainability & Climate Adaptiveness project focused on improving the understanding of how climate variability and extreme weather events influence crop yields through the application of artificial intelligence (AI) and explainable AI (XAI) methods. The project analysed real-world datasets across multiple horticultural industries, including apples in the United States, grapes in Australia, and kiwifruit in New Zealand. The work aimed to support more informed decision-making by making model outputs more transparent and interpretable for industry stakeholders.



Project Objectives

1. To improve the transparency and interpretability of AI-based yield prediction models
2. To identify key climate drivers that influence crop productivity
3. To support climate adaptation and risk management strategies within horticulture systems

Project Approach

The project combined both research and applied analysis to investigate climate–yield relationships. A systematic literature review was undertaken to assess the current use of explainable AI in agriculture. This was followed by the integration of multiple datasets, including climate observations and yield data across different regions and crops. Machine learning models, such as gradient boosting methods and convolutional neural networks, were applied to predict yield outcomes. Various explainability techniques were then tested, including SHAP, LIME, Integrated Gradients, and attention-based approaches. In addition, new models incorporating explainability features were developed to better handle complex and correlated climate variables.

Key Findings

- Climate variables such as temperature, rainfall, humidity, and extreme events have a significant impact on crop yields, with effects varying depending on the timing within the growing season
- The growth stage of the crop is critical, as the same climate condition can have different impacts depending on when it occurs
- Traditional explainability methods can struggle when dealing with highly correlated climate variables, limiting their reliability when used in isolation
- Convolutional neural network models incorporating attention mechanisms provided more stable predictions and improved interpretability
- Using multiple explainability techniques in combination produces more reliable insights than relying on a single method
- Extreme weather events, including heatwaves and frost, play a major role in yield variability, although their impacts can be difficult to isolate at the farm level
- Large-scale climate drivers such as El Niño and La Niña influence yield outcomes, but their effects are region-specific and complex

Challenges

The project identified several challenges related to both data and modelling. Strong correlations between climate variables made it difficult to clearly attribute impacts to individual factors. There were also limitations in the availability and quality of data describing extreme weather events and their severity. In addition, aligning weather station data with farm-level production outcomes proved challenging, which affected the precision of some analyses.

Project Outcomes and Impacts

The project delivered a practical and replicable framework for modelling and interpreting the relationship between climate and yield. It demonstrated the value of combining AI with explainability techniques to support better decision-making in horticulture. The findings provide a foundation for the development of decision-support tools that can help industry stakeholders manage climate risk and improve resilience. The project also strengthened collaboration between research organisations and industry partners, ensuring that the outcomes are relevant and applicable in real-world contexts.

Future Opportunities

There is an opportunity to further enhance the modelling framework by improving methods for detecting and quantifying extreme weather events. In particular, moving toward biologically aligned modelling by using Growing Degree Days (GDD) as a temporal unit should better match the natural growth rhythms of crops compared to standard calendar dates. Incorporating farm management practices and operational data into the models would also strengthen their predictive capability. Expanding the approach to additional crops and regions could increase its applicability across the agricultural sector. Finally, integrating these insights into user-friendly decision-support tools, such as to provide early warnings and practical mitigation guidance, would enable broader industry adoption and impact.

For a detailed overview of the project, methodology and results, please download the full final report from the Food Agility website.