# Pathways towards trustworthy, transparent and transferable machine learning for agricultural modelling

***Lily-belle Sweet, Helmholtz Centre for Environmental Research***

Recent advances in artificial intelligence have demonstrated excellent performance across scientific tasks such as numerical weather prediction and protein-structure prediction. Agricultural science is also adopting these tools: machine learning techniques are increasingly used to build data-driven crop models, calibrate existing process-based models and generate, process or gap-fill environmental input datasets. Interpretable machine learning approaches are also being used to analyse the biophysical relationships influencing crop yields.

However, the use of machine learning for agricultural research applications has exposed several methodological limitations. Models have a tendency to overfit to their training data in ways that are difficult to detect, often performing well on familiar conditions but failing when applied to new regions or years. Commonly-used model interpretation methods have been found to return ambiguous or contradictory results. Additionally, the inductive bias of some model architectures makes them potentially inappropriate for some use-cases; for example, random forests are fundamentally unable to extrapolate beyond the training data distribution, limiting their suitability for tasks such as projecting agricultural outcomes under future climate scenarios.

For robust, trustworthy and impactful use of machine learning in agricultural research, we need to understand the extent to which the limitations of current methods impact domain-specific modelling tasks, and how this is influenced by data quality or availability, the use of different methodologies, model architectures, or other factors. This requires community effort to share knowledge, to create and maintain benchmark datasets, evaluation strategies and metrics that meaningfully reflect the complexities of agricultural modelling tasks and stakeholder needs. By testing and comparing the performance of different approaches on these benchmarks, researchers can develop improved methods for specific applications, and can build trust, where warranted, in the utility of these tools.

This talk will share insights from the AgMIP Machine Learning community (AgML) since its launch in 2023, highlighting lessons emerging from a recent benchmark challenge focused on predicting climate change impacts on agricultural yields, and outline pathways for more robust and trustworthy use of machine learning for agricultural modelling.