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APSIM crop model innovations for breeding and deep learning

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Abstract: The principles of crop models were well established between the 1960s and through the 1980s. By the time APSRU and APSIM were established in the 1990s (Keating et al 2003), there was increased interest in developing cropping system models in which the focus could be the soil and its management in concert with the climate of any location. Crop science was incorporated into the APSIM models so that they became a 'library' of crop processes that could be examined in the context of plant breeding. More recently crop models have been used to generate 'synthetic datasets' which may be scaled out by applying deep learning techniques in diverse applications from yield estimation to satellite remote sensing, some of which we outline below.

Keywords: *Crop models, machine learning, deep learning*

1. CROP TEMPLATE DESIGNS FOR PLANT BREEDING

Crop models continued to develop with Wang et al (2002) outlining the concept of a 'crop template' with generalised processes for crop growth and development and APSIM research teams updating this concept over several iterations (Hammer et al 2010; Holzworth et al 2014). The 'crop template' has been further developed and upgraded to the plant modelling framework (Brown et al, 2014) in APSIM Next Generation.

From the latter part of the 1990s, plant breeding became a research interest for APSIM. It began with concepts such as characterization of environment types (Chapman et al 2000 and multiple papers and crops since) for interpretation of plant breeding trials. Through the 2000s, APSIM and other crop models were interfaced with quantitative genetics models (Chapman et al 2002) with these approaches now termed CGM-WGP (Crop Growth Model – Whole Genome Prediction) strategies, i.e. enabling incorporation of 'physiological trait effects' into modern genomic prediction-based breeding programs (Cooper et al 2021).

In parallel with applications in plant breeding, there was greater focus on improving APSIM for multiple plant traits with direct linkage with gene effects. This required 'sub-models' with detailed algorithms, e.g. in wheat, to model flowering time dynamics (Zheng et al 2010) and in sorghum for heat tolerance in grain set and tillering effects on canopy dynamics (Hammer et al 2014; Hammer et al 2023). A substantial effort has been implementation of a photosynthesis model to capture key biochemical pathways interactions with canopy structure, leaf nitrogen and transpiration. This demonstrated the relative value (or not) of genetic modification of photosynthesis biochemistry when effects are scaled up to canopy biomass and crop yield (Wu et al 2019).

2. SYNTHETIC DATASETS AND DEEP LEARNING APPLICATIONS

In cropping system and decision support research, cropping system models have often been used to create massive synthetic databases of crop management interventions (e.g. WhopperCropper, Nelson et al 2002) and to provide 'real-time' simulations of in-crop decision making (e.g. YieldProphet Hochman et al 2009). The research in plant breeding has further motivated the use of APSIM to create 'synthetic datasets' and initiated various research efforts to improve statistical methodologies used in 'real-world datasets'; for example Bustos-Korts et al. (2019) demonstrated how synthetic datasets could be used for evaluation of alternative phenotyping strategies. There are now multiple papers attempting to build direct emulations of APSIM using machine-learning methods, e.g. to scale out the biological model insights to large spatial extents (e.g.vXiao et al 2022). A further extension of applications has been to link APSIM to radiative transfer models in order to be able to represent the spectral reflectance of plant canopies in synthetic datasets (Chen et al 2022). Deep learning methods are used to invert these models so that traits like LAI and biomass can be directly estimated from spectral data collected by satellites or other spectral sensors carried by drones for example.

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