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Conference Abstract

On the design of AI-driven decision support tools in agriculture: what is possible, practical, and useful for land managers and farmers and what is not?

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Abstract

Advances in the computational sciences and AI have been critical in simulating the projected impacts of climate change in agriculture together with quantifying mitigation strategies to reduce agriculture's influence on climate change. The role of computation in bringing understanding to agroecosystem change from the farm to national scales is pervasive, being central for remote and ground IoT sensing, big data analysis, process simulation, data assimilation, the capture of error and uncertainty, sensor network design and interactive visualization of high dimensional outputs. Component farm processes for soils, plants, livestock, biodiversity, and water and gaseous emissions are multi-scale and casual with complex space-time connections. Respective component datasets, measured or sensed optimally and adaptively in space and time, are needed to dynamically inform model simulations for past, present, and future states.

This can be couched within a scale-aware, farm decision support tool (DSTs - say, via a digital model, shadow, or twin), where its virtual-world forecasts can inform both on-farm decisions and, via extension to networked farm DSTs, farming policy. Given an accurate capture of uncertainty, the risk associated with farm management decisions can be quantified facilitating planning for sustainable farming in the long-term, coupled with

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(short-term) early warning signals for diminishing system resilience to increasing threats of abiotic, biotic, and other stresses.

However, while such AI-driven technologies in agriculture often appear good on paper, what is actually viable in practice? (Rose et al. 2016) noted the existence of 395 agricultural DSTs and recommended 15 of them for their effective design and delivery. Suffice to say, not all of the 395 DSTs are still available, nine years on. Further, the reviewed DSTs were not all sofware-based (on- or off-line) but included those that were paper-based. A question then arises, does AI implicitly change what is possible, practical, and useful for land managers, farmers and their advisors? Or do the same inherent limitations of DSTs remain? In turn, how does this translate to effective government agricultural policy? This paper seeks to elucidate on such questions through a consideration of the following:

- What advantages might an AI-driven DST (AI-DST) have when compared to one using older technologies?
- What data does the farmer need to collect and manage to support the AI-DST? What are the minimum data requirements and at what cost? Does the AI-DST provide functionality for cost benefit analyses for the on-going relevance of the data collected? How do the AI-DST outputs reflect data quality, error, and sparseness? Does the scale of on-farm measurements match the scale of the sampled process and subsequent scales of decision making? Is data capture timely enough with tolerable latency?
- For an AI-DST scenario evaluation – are the interplays between different management and climate scenarios fully described and caveated for practical use?
- How can the farmer be empowered with their intrinsic expert knowledge of their farm or their farming philosophy within the AI-DST? Is an AI-DST only ever complementary? What about an AI-DST with human in the loop AI? What training and support are required for AI-DST use?
- How does the farmer know if decisions informed by the AI-DST are beneficial - especially in the long run? Has the weather just been coincidently beneficial?
- Does the AI-DST capture the interplay between farm profitability and government payments or incentives. How does this interplay vary over time, different geographies, and for different farm practices?
- How should a farmer proceed with conflicting advice when using multiple AI-DSTs with different objectives. For example, priority decisions from an AI-DST for soil health may conflict with those from an AI-DST for field margin biodiversity. Is there a ‘one-size-fits’ all AI-DST? Is this AI-DST desirable?
- What are the options for retraining / revising / updating a given AI-DST’s model framework and software given ever changing challenges of climate change; for example, are extremes (drought, floods) or extreme changes (i.e. winter one day, summer the next) in the weather the greater problem? Is the AI-DST typically on board with or resilient to the Zeitgeist (e.g., a 'world without livestock' debate).

Does the AI-DST allow for alignment with digital innovations, in say soil sensing, robotics?

- Does the AI-DST adequately capture and explain concepts of decision risk? Are the AI-DST's output (and input) visualisations relevant and appropriate, in this respect?
- Given not all farms, farmers and their advisors are made equal – how does the AI-DST cater for this? How does the AI-DST capture the inherently diverse nature of farming? Are AI-DST informed decisions to be made by a farm owner, farm tenant or farm manager? Does the AI-DST cater for a given farm's route to market and when and where are these routes optimal?
- How does the AI-DST capture, and adapt to, unintended consequences of the decisions made? Similarly, how does the AI-DST respond to unforeseen external influences, such as international conflict, widespead drought?
- Are AI-DST-based decisions effective across multiple scales – benefitting individual farms and networked farms alike? Does the AI-DST promote use within farmer networks, community of practise and farmer cooperation? For example, AI-DSTs informed by shared data resources amongst farms within the same catchment.
- How do on-farm decisions influence the food supply chain – from farm to fork? Does the AI-DST provide this broader picture functionality? For example, does the AI-DST provide options, not only for farm productivity and farm emissions but also those concerned with externalities such as energy use, transportational costs, societal effects and more?
- What can be learnt and transferred from AI-DSTs and non-AI DSTs in other domains?

Where appropriate, some of the above questions are illustrated using the unique and open datasets of four instrumented research farms at Rothamsted Research's North Wyke Farm Platform (NWFP) in south west UK. The NWFP was established in 2010 to facilitate system-scale research (Takahashi et al. 2018), where to date over 400 *in-situ* sensors have been deployed and over 100 million measurements have been captured. Currently, the NWFP consists of two grassland (cattle and sheep), one arable and one indoor cattle farm.

Keywords

On-farm decision making, Farmer behaviour, Long-term experiment, Digital Models/ Shadows/Twins

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Conflicts of interest

The authors have declared that no competing interests exist.

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