

the theory of graphical causal models, the analysis transparently puts forward its assumptions and explicitly incorporates domain knowledge in it. Combined with accurate and performant systems, such analyses can benefit the reliability and adoption of digital agriculture as well as farmers' trust. The provision of information on the actual impact expected from a recommendation system may also enable a cost-benefit analysis on behalf of the farmer, by simply comparing the digital tool cost to the expected yield gain. Even though the analysis is transparent, it is as good as the causal assumptions it makes and the DAG it develops. Our graph is consistent with agri-environmental knowledge on cotton, however there is always a possibility that bias exists, either due to a missed confounder or due to a missed interaction between observed variables. The robustness checks we performed were all successful; noting that when we add strong unobserved confounding, the UCC test estimates become volatile - an expected behavior to a certain degree. Given the homogeneous management practices among farmers in our data, we remark that external validity of estimates is low, as results cannot be expected to generalize to other farms that might follow different routines. Nevertheless, it is not uncommon for farmers to follow similar practices in other regions or even entire countries. While the transfer of effect estimates warrants caution, the same does not hold for the proposed framework itself. Given relevant data and knowledge, a graph-based empirical evaluation of an agricultural recommendation system can normally proceed. If consensus among estimation methods in terms of ATE significance is reached, the tool is deemed beneficial; otherwise, more work is required. All in all, this system equips farmers with a provably valuable tool based on cotton knowledge and weather forecasts. It contributes to a successful growing season and lowers the likelihood of farmers resorting to expensive actions, e.g., replanting a field. For the growing season of 2022, the recommendation system was deployed at national scale and extended to two other crops (maize, sunflower). These new pilot applications will allow us to practically test the external validity of our results across different seasons, crops and locations. Moreover, given the developed causal graph  $G$ , the crop growth ( $CG$ ) variable that is sufficiently captured through its NDVI proxy, mediates the effect of  $T$  on  $Y$ . The front-door criterion (?) might thus provide an alternative identification method for the ATE, and we plan on exploring it in collaboration with domain experts. Finally, the more growing seasons the recommendation system has seen, the more data are obtained. Going beyond ATE estimation by learning Conditional ATEs and using causal machine learning methods for providing personalized effect estimates is another next step. Due to the rich and well-established domain knowledge, we finally believe that the potential of causal reasoning in agriculture extends far beyond effect identification. Fitting Structural Causal Models and performing counterfactual inference can enable a greater understanding of the farm system and supercharge decision support tools.

Most generally, the essential condition that allowed us to utilize causal inference for empirically evaluating an agricultural recommendation system is the ample, long-

established domain knowledge that exists. Decision support systems are being used on multiple fields (?) such as medical decision making (?) or forest and fire management (??). The aforementioned fields possess accumulated domain knowledge on the interactions a good system exploits; the same way we possess information on environmental conditions related to cotton planting. We thus expect graphical approaches to be valuable for the empirical evaluation of decision support systems of diverse domains.

## Conclusion

In this study, we design, implement, and test a digital agriculture recommendation system for the optimal sowing of cotton. Using the collected data and leveraging domain knowledge, we evaluate the impact of system recommendations on yield. To do so, we utilize and propose causal inference as an ideal tool for empirically evaluating decision support systems. This idea can be upscaled to other digital agriculture tools as well as to different fields with well-established domain knowledge. This paradigm is in principle different to decision support systems that frequently use black-box algorithms to predict variables of interest, but are oblivious to the evaluation of their own impact. In that sense, this work comes to the defence of the farmer, by introducing an AI framework for elaborating on the assumptions, reliability, and impact of a system before discussing service fees.

## Acknowledgements

We thank the Agriculture Cooperative of Orchomenos for the collaboration and data provision, and Corteva Hellas for their support. This work was supported by the EU H2020 Research and Innovation program through the eshape project (grant agreement No. 820852). It was also supported by the MICROSERVICES project (2019-2020 BiodivERsA joint call / BiodivClim ERA-Net COFUND programme, and with GSRI, Greece - No. T12ERA5-00075).

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