Received: 23 January 2020 | Accepted: 27 January 2020 | Published online: 24 April 2020

DOI: 10.1002/csc2.20116

Crop Science

PREDICTIVE AGRICULTURE SPECIAL ISSUE

Crop science: A foundation for advancing predictive agriculture

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This special issue in *Crop Science* provides a diverse cross section of views from prior and current efforts to enable prediction in agriculture. The contributions discuss and demonstrate how current advances in phenomics, genomics, and artificial intelligence are being combined to explore new modeling paradigms and prediction frameworks to advance crop science and improve decision making in agriculture. The synthesis of these views can motivate a transdisciplinary dialogue to define predictive agriculture as a discipline and guide future research efforts for the integration of data-driven and science-based methodologies. Collectively, these methods can provide the needed foundation for design in agricultural and food systems (National Academies of Sciences, Engineering, and Medicine, 2019).

Why focus on prediction in agriculture? In general, whenever it is possible, taking steps to avoid problems is preferable to solving the problems once they exist. There are many issues in agriculture where avoiding problems –e.g., through agricultural systems design, breeding, or developing adequate crop management solutions- is a far preferable approach than solving problems once they have occurred. In the last half century there were substantial efforts to encode concepts in crop and soil science, genetics and breeding, and agronomy in the form of quantitative models. Integrating these models and their associated scientific knowledge with socio-economic models enables ex-ante and strategic foresight studies to evaluate research investments, technologies, and interventions in agricultural systems (Kruseman et al., 2020). Significant developments in crop sciences have enabled application of models in agriculture within the CGIAR (formerly Consultative Group for International Agricultural Research) system (Kruseman et al., 2020; Ramirez-Villegas et al., 2020), other public institutions (Hammer et al., 2020; Jones et al., 2017; Sinclair, Soltani, Marrou, Ghanem, & Vadez, 2020), and industry (Cooper et al., 2014; Cooper et al., 2020). Outcomes from these long-term research efforts have contributed to many aspects of the target agricultural systems (e.g., small holder agriculture) and agricultural research, leading to improvements in the sustainability and productivity of diverse production systems. The complexities associated with encoding biological mechanisms for the simulation of credible genotype responses to management and environmental variation (Hammer et al., 2020; Hammer, Messina, Wu, & Cooper, 2019; Messina et al., 2019), acquiring the right and accurate information to exercise prediction models (Archontoulis et al., 2020; Kruseman et al., 2020; Ramirez-Villegas et al., 2020) and the need for transdisciplinary research to connect biological with socio-economic models (Cooper et al., 2020; Kruseman et al., 2020) remain significant barriers to adoption of prediction methods. While it is being advocated that using simple mechanistic models for prediction (Messina et al., 2018; Sinclair et al., 2020) and modern frameworks for collaboration and data exchange (Ramirez-Villegas et al., 2020) can accelerate realizing societal value facilitated by prediction technologies, achieving the right balance between parsimony and biological reality adequate to enable the intended application remains elusive and a fertile area of future research (Hammer et al., 2019).

To accelerate the development of prediction methods for agriculture, there are many opportunities to learn from other disciplines such as economics and climatology that have a long history of applying them in research and decision-making. In this special issue, Casadebaig, Debaeke, and Wallach (2020) explore the opportunity to leverage concepts from meteorology and climatology, known as post-processing, to improve prediction skill to levels adequate for target applications. Washburn, Burch, and Valdez Franco (2020) review methods for integrating statistical prediction with mechanistic biological models as a means to accelerate genetic gain in plant breeding. Recent advances in information technologies, statistical learning algorithms, and the availability of large datasets for analysis motivated studies to replace science-based models with data-driven models to enable prediction and classification in breeding (Ersoz, Martin, & Stapleton, 2020; Washburn et al., 2020) and agronomy (Schwalbert et al., 2020). While these studies have produced useful solutions in agriculture, it is opportune to ask how this encapsulated knowledge will contribute to advancing plant science, and in turn to improving the robustness of prediction methodologies (Mitchell, 2019).

The mathematical framework applied by Ersoz et al. (2020) to demonstrate prediction methodologies illustrates the possibility of advancing understanding of the genetic and phenotypic architecture of integrated traits (e.g., kernel numbers). In turn, this knowledge can help inform efforts to improve prediction based on advanced genomic prediction approaches (Amadeu et al., 2020; Ferrão, Marinho, Muñoz, & Resende Jr, 2020). Although progress has been made towards incorporating environmental features to model genotype-by-environment (GxE) interactions (Ferrão et al., 2020; Ramirez-Villegas et al., 2020) the ability to predict with accuracy new genotype-by-environment-by-management (GxExM) combinations that are outside the domain used to train the genomic prediction models remains to be demonstrated. Approaches that integrate concepts of prediction established in economics, climatology, and crop science can expand the inference space. For example, Hammer et al. (2020) proposes a generalizable design methodology based on (a) use of scientific understanding of how sorghum responds to variation in E and M conditioned to G, and (b) consideration of economic and decision-making theory. By structuring the design method on scientific principles and considering risk, uncertainty, and stochasticity in inputs, the method proposed by Hammer et al. (2020) helps overcome, at least in part, the limitations of data-driven approaches to prediction of adaptation of crops to future climates and environments for which there are no data available today for model training purposes. This knowledge-based methodology illustrates how encoding scientific knowledge enabled broader consideration of opportunities to explore GxExM solutions to the significant problem of adapting to climate change.

Predicting performance of biocomplex systems such as crops is challenging due to the emergence of consequential phenotypes, and rugged and evolving performance landscapes (Hammer et al., 2006; Messina, Podlich, Dong, Samples, & Cooper, 2011) that can set biophysical, computational, and complexity limits on the predictability of the system (Cooper et al., 2020). However, using suitable crop models (Archontoulis et al., 2020; Hammer et al., 2020) it is feasible to predict important, fundamental properties of the performance landscapes (Cooper et al., 2020; Messina et al., 2019). In combination with statistical learning methods, this enables applications to advance predictive breeding (Bogard et al., 2020; Washburn et al., 2020), predictive breeding and agronomy (Cooper et al., 2020; Messina et al., 2018), forecasting (Archontoulis et al., 2020), and crop design (Cooper et al., 2020; Hammer et al., 2020) for a wide range of agricultural production systems. These principles have the potential to move the problem from that of attempting to independently predict genetic (breeding) and management (agronomy) solutions to poorly defined GxExM problem spaces, to that of predicting integrated genetic-management (GxM) solutions for the challenges inherent in both current and future target populations of environments (TPEs) of agricultural systems. Thus, the foundations of predictive agriculture explored in this special issue have the potential to help us evolve our teaching curricula, research programs and methods, and extension approaches from interdisciplinary to transdisciplinary efforts seeking novel GxM solutions for the immediate TPE challenges we face today, balanced with an assessment of how our research strategies and trajectories will prepare us to adapt to the future TPEs. Thus, we propose that effective transdisciplinary efforts that adopt a (GxM)xE focus, enabled through predictive agriculture, can move us from our current paradigm of describing the problems of GxExM interactions from individual discipline domains to predicting testable (GxM) technology solutions for more clearly defined TPE targets of agricultural systems. Hence, we move from a descriptive GxExM experimental paradigm to a predictive (GxM)xE research solution paradigm with greater options to manage the complexities of agricultural systems.

Plant science in general, and crop science in particular, underpins technological developments that are instrumental to improving the life of the world's poor and society in general. Crop growth models are cognitive constructs that synthesize our current scientific understanding of plant growth and development. Reviews presented in this special issue show how these models can be instruments of translational plant biology (Bogard et al., 2020; Cooper et al., 2020; Hammer et al., 2020; Ramirez-Villegas et al., 2020; Washburn et al., 2020). When combined with breeding, field, farm and socio-economic models, they can help breeders, agronomists, farmers and policymakers utilize foundational concepts in crop science to improve realized genetic gain and the sustainability of agroecosystems (Kruseman et al., 2020). The body of scientific contributions to this special issue in *Crop Science* suggests that integrating science-based and data-driven approaches could be a productive path towards enabling (GxM)xE prediction in agriculture at scale. Perhaps an initial concept of predictive agriculture is of a transdisciplinary domain that enables quantitative forecasting, emergent engineering, and crop design for agriculture, grounded in disciplinary principles from statistical learning, plant biology, breeding, agronomy, and socioeconomics.

ACKNOWLEDGEMENTS

We thank Natalia de Leon and Marilyn Warburton for their support and motivating discussions that help shape and bring to completion this special issue on predictive agriculture.

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How to cite this article: Messina CD, Cooper M, Reynolds M, Hammer GL. Crop science: A foundation for advancing predictive agriculture. *Crop Science*. 2020;60: 544–546. https://doi.org/10.1002/csc2.20116