



Data science in agriculture

Part I: Introduction

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Editor's note: This article is Part I of a two-part series. See next month's article for the second half focusing on "Applications and Future Prospects."

Globally, food production needs to be increased between 60 and 110% by 2050 to feed the growing population through intensification and/or expansion of agriculture (Pradhan et al., [2015](#); Kamilaris et al., [2017](#)). Data science has improved the capability of researchers and farmers with surveying, classifying, deciphering, and circulating data. Data is then used to inform scientific actions that increase productivity while reducing the impacts on the environment (Zaks & Kucharik, [2011](#)). Data science integrates sensors, information systems, enhanced machinery, and information management to

understand environmental variables and enhance production of crops and animals without needlessly wasting resources. Data science is the backbone of precision agriculture where the main goals of precision technologies are to: (1) advance the way growers use resources such as water and fertilizer to optimize profits while increasing sustainability, (2) decrease the adverse effects of agricultural practices on the environment, and (3) strive for better work environments, both socially and physically.

Information-driven management of agricultural operations began in the mid-1980s with an initial focus on maximizing fertilizer use efficiency based on the variation in soil conditions within a field. This increased the understanding of variation in both above- and belowground conditions and how it affects crop productivity (Gebbers & Adamchuk, 2010). Certain technologies can even be used for forecast modeling, allowing farmers to prepare for weather extremes and take the proper precautions to prevent crop damage (Zaks & Kucharik, 2011). One important aspect of data science is that it allows growers to take either a predictive or reactive approach to management. The predictive approach uses soil, topography, and past crop performance data to prescribe inputs across a variable landscape. The reactive approach utilizes sensors to gather data on crop health at a given time, so growers can make decisions on crop requirements and inputs. This has been shown to be effective for timing of nitrogen applications and improving water management strategies (Coble et al., 2018).

Agriculture has entered an era of big data: large datasets that feature five “V’s”, i.e., “volume” (size of the data), “velocity” (measuring the flow of the data), “variety” (multiple sources and lack of structure), “veracity” (accuracy and credibility of the data), and “valorization” (ability to generate knowledge and innovation) (Kamilaris et al., 2017; Coble et al., 2018). However, big data analysis does not necessarily need to satisfy all five features (Rodriguez et al., 2017). With growing knowledge on big data analytics, evolution of computing infrastructures such as cloud

computing/supercomputing, artificial intelligence (AI), internet of things (IoT), sensor innovations, robotic platforms, and programmable agricultural machines, data science has become popular in almost all arenas of food production systems. Next month, we will discuss some of the applications and advancements of data science in agriculture and its future prospects.

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