Basic Concepts and Technologies of Smart Agriculture

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Smart agriculture (SA) entails the exploitation of data to optimize agricultural systems. The distinction from precision agriculture may seem minor, but is crucial, as it defines the next revolution within agricultural and digital industries. The focus of SA is on data exploitation; this requires access to data, data analysis, and the application of the results over multiple (ideally, all) farm or ranch operations.

digital agriculture artificial intelligence internet of things (IoT) machine learning

1. Introduction

The modernization of agriculture and the adoption of various technologies in production practices have resulted in new concepts in agriculture, including precision agriculture, digital agriculture, and smart agriculture. While in some of the literature these terms are used interchangeably, there are differences in the details, which become important when defining “Smart Agriculture”.

For example, the International Society of Precision Agriculture organization defines “Precision Agriculture as “… a management strategy that gathers, processes and analyzes temporal, spatial and individual data and combines it with other information to support management decisions according to estimated variability for improved resource use efficiency, productivity, quality, profitability and sustainability of agricultural production”. In brief, SA is the application of connectivity (e.g., IoT) to traditional agriculture, where the use of sensors and software is used to collect data to optimize agricultural production decisions through mobile platforms, such that traditional agriculture becomes “smarter”. In a broad sense, smart agriculture also includes agricultural e-commerce, food traceability and anti-counterfeiting, agricultural leisure tourism, agricultural information services, and other aspects.

Precision agriculture, as important component of smart agriculture, is a method of farm management where the input needs of individual crops, fields, and livestock are optimized through data gathering, observation, and analysis. Big data and advanced analytics, as well as robotics, imagery, sensors, and weather forecasts enable precision agriculture to be an extremely effective agricultural management strategy [1]. For example, by assessing the conditions and needs of individual crops, fields, and livestock, precision agriculture can increase the quantity and quality of agricultural output while reducing inputs of water, energy, fertilizer, pesticides, supplements, etc., in order to save costs and reduce the environmental impact [2].

Smart agriculture (SA) entails the exploitation of data to optimize agricultural systems. The distinction from precision agriculture may seem minor, but is crucial, as it defines the next revolution within agricultural and digital industries. The focus of SA is on data exploitation; this requires access to data, data analysis, and the application of the results over multiple (ideally, all) farm or ranch operations. On-farm and on-ranch decisions are made using smart, mobile devices to access data on conditions, climate, input use, and labor, and more in real time, allowing the producer to subsequently make informed decisions based on validated data. SA implies a system of connectivity (e.g., Internet of Things, edge devices, low-power wide area network (LPWAN), 5G, etc.), where "things" are connected in a network of communication. The data (i.e., the information) are processed in farm management software (i.e., apps and online platforms) in a timely manner and relayed back to the producer to make informed decisions [3].

The International Organization for Standardization (ISO) defines SA as the "combination of network connectivity, widespread sensor placement, and sophisticated data analysis techniques [which] now enables 'smart farming' due to large amounts of data generated by IoT devices" [4]. For the purposes of this report and in an effort to standardize the concept of SA, the following definition will be used: SA uses Internet of Things (IoT) technology; various sensors are placed on equipment, livestock, or in the field to relay data to a platform (i.e., cloud-based; that is, using WLAN, edge devices, or to the cloud directly) allowing the creation of an information system for users (e.g., including farmers, agro-supply professionals, consultants, researchers).

2. Related Terminology, Concepts, and Technology

Beyond the technical jargon of SA, there are additional related technologies and social concepts that support the idea of SA which are worth mentioning.

Agriculture 4.0 is a term used by the World Government Summit (2018) [5]; as an analogy to Industry 4.0 [6]. It refers to the integrated internal and external networking of farming operations as a result of the emergence of smart technology in agriculture [7]. The trend is towards automation, intelligence, and data exchange in agriculture. Agriculture 4.0 aims to disrupt the current food and agriculture regime and sustainably improve production capacity by using new techniques and technologies in production (e.g., hydroponics, algae feedstock, bioplastics, desert agriculture, seawater farming). The intent is to use novel technologies to improve food access, and change the current food supply chain (e.g., vertical/urban farming, genetic modification, 3D printing), and to incorporate cross-industry technologies and applications (e.g., UAVs, IoT, data analytics, PA, nanotechnology, blockchain, AI/ML, food sharing, and crowd farming) (World Government Summit, 2018) [8].

Based on the definition of Agriculture 4.0, the concept of "SA" generally resides within the third category: incorporating cross-industry technologies and applications; these inter-related technologies will be briefly defined in the following section [9].

Geographic Information Systems (GIS) are included within Agriculture 4.0, and are characterized by making significant use of global positioning system (GPS) technology. The latter allows plots to be mapped for increased precision during technical operations. For example, mapping the nitrogen requirements of a plot allows the inputs to be tailored not just at plot-level but for different zones within it identified by satellite. In addition, GIS systems can provide a framework for the deeper analysis of a broader scope of inputs, including weather patterns, topological features, and watershed models [10].

3. Big Data Analytics, Artificial Intelligence, and Machine Learning

In short, the application of Internet of Things technology to traditional agriculture, the use of sensors and software to control agricultural production through mobile platforms or computer platforms, so that traditional agriculture is more ‘wisdom’. In addition to accurate perception, control, and decision management, in a broad sense, smart agriculture also includes agricultural e-commerce, food traceability anti-counterfeiting, agricultural leisure tourism, agricultural information services and other aspects.

The anticipated value of artificial intelligence and machine learning (AI) for Digital Agriculture is not different to that for general systems biology, materials science, drug design, or knowledge-based design in the transformation of genotype to phenotype.

Overall, the value of AI methods lies in those arising from the translation of theoretical advances to application tools that accelerate the creation of predictive models (e.g., with existing tools like Google’s Tensorflow, Facebook’s PyTorch). These application frameworks are designed to accelerate the creation of predictive models by transforming application data (e.g., labelled data instances like genomic samples from crop phenotypes).

It is important to note that the application of AI is possible in all areas of scientific research; overall, the idea is to capture and compress existing scientific knowledge into models that accelerate the prediction of new hypotheses (e.g., new molecules with potential impact as drugs) and to discover new hypotheses that human scientists would not consider because of knowledge bias. As noted above with respect to the three categories of Smart Agriculture, Precision Agriculture, and Digital Agriculture, each one can take advantage of a variety of AI methods to create decision support based on captured data, including soil data, genomic and phenomics data, drone-created crop profiles, and all manner of animal management (e.g., beef, swine, fowl) [11].

To note the scope of the applications of AI to these general areas, the development of Alphafold and Foldit [12] have accelerated the identification of plausible protein folds and helped identify previously unconsidered folding hypotheses. Similarly, within the metaphor of genomics for materials [13], specific applications of current AI tools have been used to identify preferred material alloys for solar materials [14]. The same advantage arises in the identification of appropriately active small molecules in so-called “in silico” drug design [15][16].

While application domain scientists may not make these observations, the frameworks for applying AI to Digital Agriculture are identical, in the overall data science framework, to those used in protein folding, materials science, and drug design. One framework that can support this position comes from the general development of

“Phenomics,” arising from a 2011 workshop sponsored by the USA Department of Agriculture, and the USA National Science Foundation (NIFA, 2011). The overall framework is captured in this quote:

“Recent advances in DNA sequencing and phenotyping technologies, in concert with analysis of large datasets have spawned ‘phenomics’, the use of large-scale approaches to study how genetic instructions from a single gene or the whole genome translate into the full set of phenotypic traits of an organism”.

This framework provides the basis for the general study of all transformations from genome to phenome, in both animal and plant models, and creates a foundation for the crop science aspects of Digital Agriculture anticipated in this research. At the next level of scientific granularity, AI has already been applied to understand the causality between bovine genomics and phenomics properties, and it can be similarly applied to crop genomics [15][17]. In this regard, the promise of crop phenomics within Digital Agriculture lies within the increasing sophistication of predictive data models that approximate the causal connections between genome and phenome.

4. Synopsis of Data Driven Methods

Overall, the deployment of analytic methods to Smart Agriculture is rapidly changing, since progress in so many fields (e.g., sensing, robotics, flight-based data capture) is happening at the intersection of data collection and the basic biological science of animal and crop genomics [18][19].

Just across these two aspects of scientific endeavors, the emerging tools for analytics based on machine learning have been used in both the consolidation and prediction of crop models and in the analysis of the path from genome to phenome [20][21].

The researchers will continue to see many new technologies linked together; this means that, increasingly, waste will be minimized, productivity will be maximized, and the impact on the environment will shrink. Success in these aspects will depend on setting standards and metrics to ensure that the progress is captured and made in a desirable direction and that technologies (current and future) will continue to drive productivity and sustainability [22].

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