Introduction

Precision Agriculture: Modelling

Evert, Frits K.; Cammarano, Davide; Kempenaar, Corné

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Introduction

Frits K. van Evert, Davide Cammarano, and Corné Kempenaar

1 Rationale

Modern agriculture is in many ways a success story. The number of people in the world has increased markedly during the last 200 years, and it is projected to reach about 9.8 billion by 2050 (Fig. 1a), while the productivity of many crops from the beginning of the Green Revolution has kept up until now (Fig. 1b). As a result of these two opposing trends, the prevalence of undernourishment is at a historic low and still decreasing (Fig. 1). Of course it remains to be seen if these trends can continue in the face of more frequent exceptional climate events (IPCC, 2021), the coronavirus pandemic and breakout of war.

The increases in productivity have been possible because of a number of contributing factors ranging from technical to socioeconomic. From a technical point of view, plant breeding, better crop rotation and fertilization, mechanization of most field operations and crop protection against pests and diseases have helped to increase yields (Aggarwal et al., 2019). From a socioeconomic point of view, many governments also started to support agricultural research, as well as education for farmers and extension services, to ensure that the knowledge produced by research can be used in practice. There were also many systemic changes, such as

F. K. van Evert (✉) · C. Kempenaar
Agrosystems Research, Wageningen University & Research, Wageningen, The Netherlands
e-mail: frits.vanevert@wur.nl

D. Cammarano
Department of Agroecology, iClimate, Centre for Circular Bioeconomy (CBIO), Aarhus University, Tjele, Denmark

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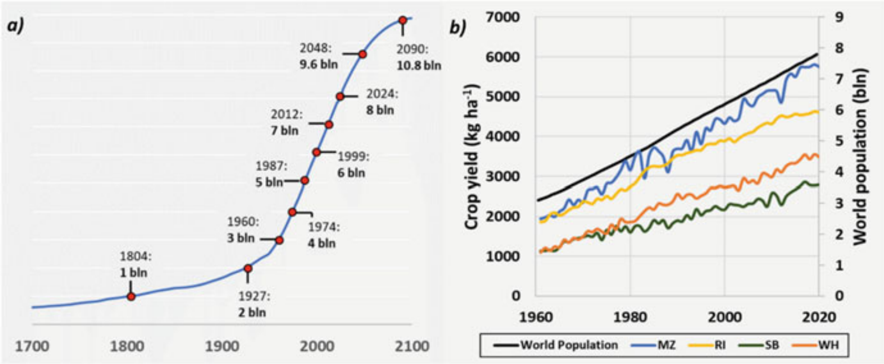

Fig. 1 Patterns of (**a**) population growth from 1700 to a projected growth in 2100. The blue line shows the continuous patterns, while the red dots report the world's population at given points in time. The data from 1700 to 2100 were from (https://ourworldindata.org/grapher/population?time=1500), while the world's population from 2010 to 2100 were downloaded from https://ourworldindata.org/future-population-growth; (**b**) crop unit yield of maize (MZ, blue line), rice (RI, yellow line), soybean (SB, dark green line), wheat (WH, orange line) and the world's population growth (black line) from 1960 to 2020. The data on crop yields were obtained from https://www.fao.org/faostat/en/#data, while the world's population data were from https://ourworldindata.org/grapher/population?time=1500..latest

subsidies on fertilizers, the establishment of cooperative banks, the development of road networks and the opening of borders as in the European Union.

Even when several technological innovations helped to increase yield, it may be possible to attribute yield increases to specific factors (Fig. 2). However, in most cases, socioeconomic and technical factors interact to determine yield, together with decision-making (e.g. farmers' decisions on when to plant and how much fertilizer to apply). However, as the wheat yield trend in Australia shows (Fig. 2), recent climate extremes can still cause deviation from a long-term trend no matter what the level of technology. This is something to consider in future planning because it is likely that climate extremes will be more frequent and affect yield (IPCC, 2021).

At the same time, modern agricultural practices are having a large negative impact on the environment. The use of large amounts of fertilizers has led to problems with nitrate leaching to groundwater, phosphates causing eutrophication of surface water and a rise in greenhouse gas emission (during production of fertilizers as well as during crop production) from the whole farming sector. For some specific issues (e.g. nitrate in groundwater), the European Union (EU) has regulated the amount of organic and inorganic nitrogen farmers can apply in specific areas deemed nitrate vulnerable zones (NVZs) to limit the environmental impacts of fertilization (EU, 1991).

In addition, crop protection agents affect more than just the pests and diseases that are targeted. Chemical crop protection agents can also affect nontarget insects, birds and mammals, as can herbicides used to control weeds (Voltz et al., 2022).

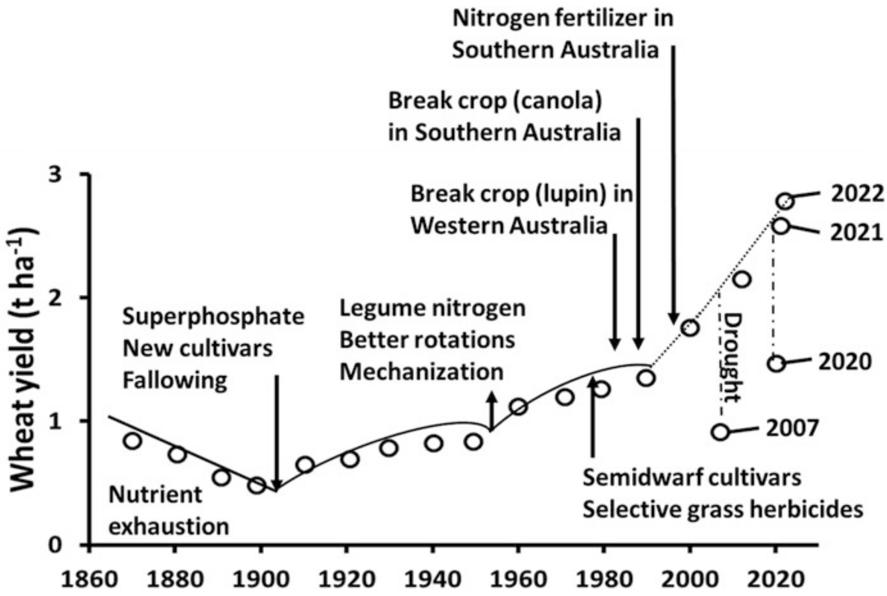

Fig. 2 A modified Australian wheat yield patterns from 1860 to 2022 from Angus (2001). The data from 1860 to 2000 were extracted from Angus (2001), while those from 2000 to 2022 were obtained from ABARES (2022)

The common practice of having rotations with only a few different crops grown in large fields is an important contributing factor to a reduction in biodiversity.

Finally, the use of heavy machinery leads to loss of soil structure and increased soil compaction (Hamza & Anderson, 2005). Among other things, this means that the soil has difficulty absorbing rainwater which in turn may lead to surface runoff and erosion.

All the above factors could be exacerbated by the predicted changes in climate patterns and extremes. Therefore, for agriculture to be economically profitable and minimize environmental effects, it must become more sustainable. Digital agriculture is one of the novel scientific fields that may help to make agriculture more sustainable. Precision agriculture (PA) is a branch of this which could benefit from the insight gained from such new discipline. Precision agriculture is one of the technologies (among breeding, agronomy and so on) that can help to make agriculture more sustainable from an economic and environmental point of view. And accounting for dynamic interactions between soil-plant-atmosphere-crop management with crop growth models can support decision-making in precision agriculture. Figure 3 shows how the links between deterministic crop growth models, machine learning and other technologies in PA can help sustain the upward trend of technology.

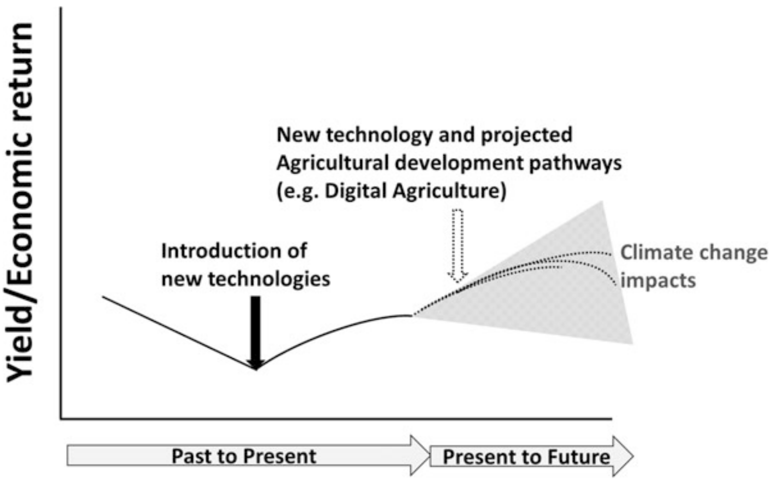

Fig. 3 A theoretical diagram that draws from the work of Angus (2001) in which the value of introducing new technologies can be reduced by projected changes in the climate

2 Crop Modelling

A model is a simplified representation of a part of reality. Models are used to understand and manage our surroundings and can take many different forms. For example, it is a model if one expresses in poetic language the fact that including a legume crop in the rotation leads to higher yields.[1] Another example of a model is a linear (or curvilinear) regression relationship between the amount of manure applied and crop yield. A model can also take into account time, for example, when a curve is used to relate crop nitrogen uptake to the number of days since emergence (Steltenpool & van Erp, 1995).

In this book we concern ourselves primarily with complex dynamic models. These models describe discrete event systems, continuous state systems (differential equations) and hybrid continuous state and discrete event systems. A foundational theory of dynamic systems and models is available (Zeigler, 1976; Zeigler et al., 2000).

Crop simulation models, or crop growth models, are a formal representation of mathematical algorithms that describe the interaction of crops with the environment (Jones et al., 2003; Van Ittersum et al., 2003). Crop models are dynamic models (time is a factor) and usually simulate daily (or hourly, depending on the models) interactions between the soil, plant, weather and crop management. They are constructed with many subroutines that simulate specific processes (e.g. crop phenology, soil organic carbon and so on) that are then interrelated. Therefore, crop growth models comprise a mix of simple empirical and mechanistic subroutines.

[1] The Georgics, by Virgil. For example, https://gutenberg.org/ebooks/232

Table 1 The main category of input data needed for running a crop simulation model

Input	Common input among crop models
Weather	Solar radiation, maximum and minimum temperature, rainfall
Soil	Clay, silt, sand; organic carbon, nitrogen
Management	Planting date, density and depth; fertilizer (or irrigation) application date and amount; fertilizer type (usually for nitrogen only)
Boundary conditions (or initial conditions)	Value of soil water and nitrogen at the start of the simulation (usually prior to sowing)

They require a certain number of inputs to be able to run as highlighted in Table 1; although the number of those inputs depends on the complexity of the crop model. Furthermore, when inputs are not available, they are usually estimated. Kersebaum et al. (2015) classified the amount of detail needed in terms of input data and for model calibration.

Nevertheless, crop models have been used in different branches of research to extrapolate experimental agronomic information beyond field experimentation and to test and assess climate impacts and changes (Asseng et al., 2015, 2019; Rötter et al., 2016). In recent years crop models have been included in frameworks and support systems that also include economics and human behaviour (Cammarano et al., 2020).

Crop modelling is not new; it started in the 1960s in the Netherlands under De Wit (Van Ittersum et al., 2003) as a mathematical relationship was developed between biomass growth and solar radiation. Since then, the number of modelling schools and modelling approaches has grown until we have now reached a point of having multiple models for simulating the same crops. For example, there are about 30 wheat crop models, 19 for maize and 13 for rice (www.agmip.org).

The key processes simulated in those models are development, growth, yield, nutrient and water uptake. For each of these processes, external environmental factors control the main processes. Phenological development, which simulates the passage through different stage of the plant's life, like flowering or maturity, is generally controlled by air temperature and day length, and crop growth by solar radiation and temperature. The external factors for nutrient and water supply are rainfall, irrigation, temperature and nutrient supply.

The majority of crop models utilize De Wit's (Van Ittersum et al., 2003) concept to simulate crop growth. First, in a potential production situation, crop growth is limited only by light, temperature and the crop's genetics. Water-limited production takes place when in addition to the above, growth is limited at least part of the time by the availability of water; nitrogen-limited production takes place when growth is limited by the availability of nitrogen. In order to simulate water- and nitrogen-limited production, rainfall, irrigation, nutrient supply and soil conditions need to be known.

Another advantage of the use of crop models is that they can extrapolate the interactions between plant-soil-agronomy through time. In this instance, crop growth simulations with historical long-term weather data should not be interpreted as trying to simulate a particular year; rather, this kind of simulation can help to increase our understanding of the crop's sensitivity to different weather patterns in a given area (e.g. what is the probability of crop failure because of heat stress).

Despite being considered 'point-based' models, crop models have been applied at different spatial scales. For instance, at the global level, they have been used to quantify the effects of climate change on crop production (Elliott et al., 2015; Jägermeyr et al., 2021) and the values of adaptation (Asseng et al., 2019). At the regional level, they have been coupled with economic modelling to predict how climate change affects rates of poverty (Cammarano et al., 2020). Other applications are their use in gene-based modelling and to design crop ideotypes for better crop adaptation to the future climate (Bustos-Korts et al., 2019; Zheng et al., 2012).

3 Precision Agriculture

It could be argued that the earliest farmers already engaged in precision agriculture. If you are farming for subsistence on a small piece of land, and the work is done by hand, then by definition, you are working with a great level of precision, for example, removing weeds close to the crop plants and applying fertilizer where it counts the most. This precision was lost with the advent of mechanization, when manufactured fertilizer and crop protection agents were applied uniformly over large areas.

Modern precision agriculture was initially developed, from a theoretical point of view, in the early 1980s with the aim of understanding factors that lead to spatial variation in crop growth within a field and how to manage it. However, PA was not very popular until technologies such as global navigation satellite systems (GNSS), remote sensing and better agricultural equipment (e.g. variable-rate application, yield monitors) became widely available after 2000. Despite an increase in popularity, the adoption among farmers is still not widespread (Lowenberg-DeBoer & Erickson, 2019).

There have been many definitions of precision agriculture, but the International Society of Precision Agriculture (ISPAG, www.ispag.org) recently defined it as:

> Precision Agriculture is 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.

Nowadays precision agriculture, pushed by new data analytical tools and better high-resolution images, is generating a lot of data which are often used in models in a 'black box' situation. It is not that straightforward to assume that a given drone/satellite image represents nutritional stress without understanding what is happing at the soil-plant interface and how weather affects this relationship (Colaço & Bramley, 2018; Colaço et al., 2021).

4 Use of Models in Precision Agriculture

In precision agriculture the goal of models has been to understand and explain the spatial variation of crop growth or yield (as mapped by drones, satellites, yield monitoring) and to help address the management decisions related to the site-specific input application (Basso et al., 2001). A variety of modelling approaches has been used in precision agriculture. Of particular interest are regression models, simple dynamic models, crop growth models, digital twins and machine learning.

4.1 Regression Models

The models that were first used in precision agriculture were not crop growth models, but much more simple decision rules that related a measurement on the crop or the soil to a specific action. They are still used successfully for developing functional relationships between agronomic input and yield. Several manufacturers market a sensor that measures crop reflectance in two or more wavebands and use this approach to derive an immediate rate for a side dressing of nitrogen. Such a system can be delivered in a single package, it bypasses the need for a data infrastructure, and it addresses an important problem, namely, the over-use of nitrogen fertilizers.

Nitrogen uptake and plant reflectance values are affected by factors other than soil nitrogen supply (Colaço & Bramley, 2018); therefore normalization procedures like well-fertilized reference strips, non-N-fertilized strips, and relative yield are usually used to gain understanding. In addition, over the years, researchers have developed relationships between sensor readings and nitrogen rates to determine the optimal amount of nitrogen. This was done by developing a variety of indicators like the NSI (nitrogen sufficiency index) and INSEY (in-season estimated yield) or the relationship between chlorophyll meter readings, grain yield and chlorophyll index as reviewed by Samborski et al. (2009).

A major limitation of the use of such algorithms, however, is that they can be highly site- and year-specific and it could be difficult to extrapolate them to other genotypes, soils and environments. Ransom et al. (2019) evaluated statistical and machine learning (ML) algorithms for including soil and weather information to improve N recommendation tools for maize.

Puntel et al. (2019) identified static and dynamic variables that affect the algorithms for the economic optimal rate of nitrogen and found that some static variables (e.g. soil depth) and some dynamic ones (e.g. number of days with precipitation >20 mm, residue amount, soil nitrate at planting and heat stress around silking) helped in improving such algorithms.

Over the years, however, successful commercial products were developed using this type of approach (Samborski et al., 2009; Tremblay et al., 2011). An example of a successful application of such models using a combination of remote sensing and nitrogen response is with the passive or active remote sensors and algorithms developed for linking crop N response to the normalized difference vegetation index (NDVI) (Butchee et al., 2011; Holland et al., 2004, 2012; Scharf et al., 2011).

The Yara N-Sensor provides a real-time variable rate of N for different crops (e.g. wheat (*Triticum aestivum* L.), oilseed (*Brassica napus* L.), barley (*Hordeum vulgare* L.) and maize (*Zea mays* L.)) given the crop-specific algorithms developed. The advantage of the system is that the prediction of N uptake in real time enables a correction for N on the go. However, this system does not provide absolute recommendations but focused on applying more fertilizer where the crop does not grow well (Jasper et al., 2009; Reusch, 2003).

Another agronomic practice that has been optimized through the use of models is herbicide application. Pre-emergence herbicides are applied to the soil between sowing and emergence of the crop to kill weeds in the topsoil layer. The amount of herbicide needed to control the weeds depends on the clay and organic matter contents of the soil. These soil properties can be estimated with measurements of apparent electric conductivity of the soil. Thus, the rate of soil herbicide application can be derived from an instantaneous measurement of the soil (Kempenaar et al., 2014) in the same way that a measurement of crop reflectance can be used to determine a rate of nitrogen application. The above technology when used for variable-rate application of herbicide for potato haulm killing (PHK) results in a reduction of herbicide use of up to 50% compared to a uniform rate application (Kempenaar et al., 2004, 2008, 2017).

Several approaches have been proposed for irrigation, and those that fit the scope of this chapter are the thermal-based algorithms for scheduling irrigation based on canopy temperature, such as the crop water stress index (CWSI) (Jackson et al., 1981, 1988) and the time-temperature threshold (TTT) (Wanjura et al., 1992, 1995). The latter index was used to set up automatic irrigation on cotton and to automate the amount of irrigation for soybean (O'Shaughnessy & Evett, 2010; Peters & Evett, 2008).

A good overview of the differences between statistical and process-based crop models is discussed in Lobell and Asseng (2017).

4.2 *Simple Dynamic Models*

A dynamic model takes time into account, and in its simplest form, with thermal time as one of the independent variables, has been successful in recommending the rate of N for side dressing in potatoes (Booij et al., 2017; Van Evert et al., 2012). Soil nitrogen supply in the Netherlands varies widely from year to year and from field to field. Therefore, the standard practice of applying the recommended amount of N around planting frequently results in either an over- or undersupply of N. A recommendation system was developed where some N is applied at planting, and then around 1 July, a simple dynamic model is used to determine how much N the crop would have taken up in the absence of N limitation. The ideal amount of N is then compared with the actual amount of N measured by canopy reflectance; the difference between the two numbers is applied as side dress N. This system maintains yield and reduces N on average by 15% (van Evert et al., 2012; Kempenaar et al., 2017).

4.3 Crop Growth Models

An important limitation of the N side dress system for potatoes mentioned above is that it does not consider nitrate leaching, mineralization of organic matter and other processes that influence the availability of N in the soil. For example, after several weeks with limited rain, the side dress system will recommend a large rate of N for side dressing even though crop growth is limited by lack of water and not nitrogen. This is where crop growth models become useful.

One of the advantages of running a crop model in precision agriculture is that they take into account the effect of climate variation at each point in space as highlighted in the scientific literature (Basso et al., 2021; Batchelor et al., 2002; Cammarano et al., 2021; Maestrini & Basso, 2018; Martinez-Feria & Basso, 2020; Paz et al., 1999; Puntel et al., 2018; Thorp et al., 2008). Basso et al. (2001) demonstrated how to minimize the technical costs for running a crop model in the precision agriculture context.

Early efforts to use complex dynamic models in PA include EPIPRE (Zadoks, 1981), GOSSYM/COMAX (McKinion et al., 1989) and Tipstar (Jansen, 2008; Jansen et al., 2003). Those early efforts were difficult to implement because of the limited processing power of early computers which meant that it required hours or even days of runtime to obtain a result. The practical application of these models was also limited by obstacles related to acquisition, storage and distribution of the relevant crop, soil and farm management data needed to run the models.

Batchelor and Paz (1997) and Paz et al. (1998, 1999) then used two crop models to evaluate how the spatial variation of soil moisture affects crop yield. Thorp et al. (2008) developed a prototype of a decision-support tool based on a crop growth model to use in precision agriculture. Their aim was to let a crop growth model simulate a homogeneous unit of land to improve understanding of the effect of spatiotemporal variation on crop growth and development and to adopt better site-specific management. The research was based on the concept of defining homogeneous management zones, a common theme in PA which has been subjected to extensive scientific work (Nawar et al., 2017). Basso et al. (2001) integrated the information from remote sensing with a crop growth model to identify management zones and have an improved understanding of the causes leading to the variation in yield. An improved approach was adopted by Cammarano et al. (2021) using a farmer's field and demonstrated that the use of crop models can help to identify the cause of spatial variation in yield but also to quantify the effects of soil and weather on crop quality.

McNunn et al. (2019) used a crop growth model to predict site-specific subfield optimum seeding density and N rates based on publicly available data sources. They also used the modelled outputs to estimate the environmental footprint in terms of N leaching and greenhouse gas emissions. This example shows how a crop growth model can aid the estimation of economically optimal rates of N by also taking into account the dynamic interactions of the N cycling and how it affects the environment. Nowadays the advances in computing technologies and digital data of soil and weather have simplified the use of crop models (from simpler crop models to more mechanistic ones). For example, a global simulation study on the effect of climate change on wheat and maize production made in the early 1990s (Rosenzweig & Parry, 1994) produced an overall message that is comparable to current research (Elliott et al., 2015; Jägermeyr et al., 2021; Müller et al., 2019). Given that the same crop models were run, the main technical differences between the two studies were the speed and computational capability and the availability of input with a finer spatial resolution of the crop models (see the global figures of the two studies). Therefore, simple 'apps' and technological progress (computers and data) have led to an interest in full-fledged crop models as showcased in Part III of this book.

4.4 Digital Twins

Recently there has been interest in using crop growth models as a digital twin. A digital twin (DT) is a model of a physical object with emphasis on (1) the connection between the real-world object and its virtual counterpart and (2) the use of real-time data from sensors to keep the model synchronized (Grieves, 2014). DTs are widely used in engineering and the concept has recently started to receive attention in agriculture (Pylianidis et al., 2021; Van Evert et al., 2021).

While DT is not a new research field, the integration of crop growth models in DT is still in development. There are only a few examples on how crop growth models can benefit from DT. The integration of sensor information to help to improve model simulations is being developed for field crops as well as for livestock (Van Evert et al., 2021).

4.5 Machine Learning

Another expanding research field is machine learning (ML) applied to PA. Machine learning is a field of computer science comprising algorithms that give the computer the ability to learn without explicit programming (Samuel, 1959). To simplify the ML approach, the steps can be divided into three parts: (I) input data, (II) building the model and (III) generalization (which is like a crop model evaluation, e.g. testing the model with dataset not used for training the model).

Ransom et al. (2019) used an ML algorithm to improve a simple regression model for optimizing N fertilization. But ML algorithms are also suited to analysing the output from real-time sensors, such as the data from soil moisture and weather sensors. Machine learning has potential for estimating soil properties as reported in an extensive review by Nasirahmadi and Hensel (2022) and other research where maps of the apparent electrical conductivity of bulk soil were used together with some targeted soil samples to estimate soil properties spatially. However, if the interest is, for example, the conservation of soil organic carbon, ML might fail to predict the dynamic changes of organic carbon and how soil type, weather and human management affect it. In this case, a dynamic soil carbon model would be more suited than ML because it takes into account explicitly the effect of microbial activities and the role of different fractions of soil organic carbon.

Crop yield estimation is another field that has been extensively studied in which ML has been applied (Nasirahmadi & Hensel, 2022). Although there is potential in this area for ML, yield prediction using remote sensing and simple regression has also produced satisfactory results (Bean et al., 2018; Puntel et al., 2019; Raun et al., 2005). An issue with yield prediction is that ML models, once tested and trained in a given environment/crop/soil/year, cannot be applied easily in other contexts (or other years) because they are highly site-specific. The main limitation, in this case, is not ML per se but the agronomic understanding as to why yield prediction is needed. It has often been reported that the integration of ML and remote sensing improves yield, quality and agronomic management. However, in most cases yield prediction is done too late when farmers cannot do anything to correct eventual problems. It is important that scientists using ML for yield prediction should be aware of the agronomic implications of their applications.

On pest-disease and weed recognition, ML has shown considerable potential in applicability with images from digital cameras and the application of convolutional neural networks (CNNs) (Alibabaei et al., 2022). A high accuracy (about 99%) has been reported with respect to manual procedures that might make future applications of ML in weed-disease detection profitable. But it has also been reported that the accuracy depends strongly on the quality of training datasets and that overtraining the ML models could also hamper the approach (Alibabaei et al., 2022; Nasirahmadi & Hensel, 2022).

Machine learning applied to irrigation has been shown to improve the optimization of irrigation water while minimizing the use of resources (e.g. water and electricity). In particular, the increased number of sensors deployed in the field has made ML algorithms robust, but this is also their main limitation in applicability because of the associated costs for the farmers.

5 Chapters of the Book

The book contains three parts. Part I gives a broad overview of precision agriculture, modelling and issues related to the use of models in agricultural practice. Part II explores the state-of-the-art modelling for precision agriculture. Part III contains a series of short chapters that each describe a commercial, model-based service that is currently available to farmers.

In Part I, Kersebaum and Wallor (chapter "Process-Based Modelling of Soil–Crop Interactions for Site-Specific Decision Support in Crop Management") discuss the use of process-based models for soil-crop interactions and how those modelling approaches can help to describe the spatiotemporal dynamics of soil-crop-atmosphere relationships. Knowledge about within-field spatial variation of temporally stable soil properties can be used to make timely and spatially adapted management decisions. In chapter "Models in Crop Protection" Fedele, Bove and Rossi describe different modelling approaches for crop protection, focusing on process-based approaches. It is interesting to note that the crop growth modelling community is working closely with the crop protection community to include these approaches in the crop growth models (Bregaglio et al., 2021; Donatelli et al., 2017). The chapter also discusses how the plant disease models can be used to improve decision-making in integrated pest management because they can be used to analyse complex relationships among factors and improve tactical decision-making and strategic management. Chapter "Development and Adoption of Model-Based Practices in Precision Agriculture" (Akaka, Gallego, Georgantzis, Rhan and Tisserand) discusses adoptions and limitations of model-based practices in PA. In particular, the authors explore those issues from a scientific point of view and a sociocultural point of view. They introduce the concept of 'co-creation' and conclude that this is important: users need to be involved from the start. Scientifically we are able to create very sophisticated models, but their adoption is somewhat lagging behind. A model for application in PA should also take into account stakeholders' needs and address their relevant questions.

Part II starts with the chapter "Process-Based Models and Simulation of Nitrogen Dynamics" (Cammarano, Miguez and Puntel), which gives an overview of the modelling approaches used to simulate soil and plant nitrogen. The chapter is a non-exhaustive description of nitrogen modelling (which are often subroutines to more complex crop models), but it gives the reader an idea of the complexity of process-based crop growth models. The authors describe two case studies in which crop growth models are used in a spatial context to optimize nitrogen management through an improved understanding of the soil-plant-weather-agronomy interactions. The chapter by Heinen (chapter "Modelling Soil Water Dynamics") describes the theory and application of different water modelling approaches. The author describes the main theory of water movement and how those models can be used to predict current and projected changes in soil water content. The chapter also consider how to model the spatial variation of soil processes and properties. In chapter "Data Fusion in a Data-Rich Era", Castrignanò and Belmonte introduced the topic of data fusion in precision agriculture. They highlight how geostatistical models can be useful in data fusion for PA applications. The authors discuss the implications of spatial and/or temporal autocorrelation and the effect of different supports on agricultural operations. Keiji, Kozan and De Wit (chapter "Data Assimilation of Remote Sensing Data into a Crop Growth Model") follow with a discussion on the assimilation of remote sensing data into a crop growth model. The chapter gives an overview and history of data assimilation between remote sensing and crop growth models. Then it points out the potential and limitations of such an approach and how current technologies might facilitate such integration.

Part III comprises a series of chapters describing model-based solutions available for farmers from commercial companies. Each chapter is organized in a structured way in which the contributors introduce their solution and give a brief generic overview of the technology, application, benefits and any additional information. In this section, we have contributions from Adapt-N ® (Yara International) which demonstrates how their process-based solution is developed into a commercial tool for optimizing N fertilization. Granular Agronomy's software also deals with the spatial optimization of N fertilization in which a crop growth model is used to estimate N requirements. The Xarvio ® Digital Farming Solutions illustrates how their crop model is integrated in their digital farming platform and also describes a case study on how to integrate model output into agronomic decision-making. The Kubota Corporation discussed their Kubota Smart Agri System used for precision farming and autonomous unmanned agricultural machinery with a working example on a rice transplanter with automatic steering, a combine harvester with an automatic operating assistance function and a fully autonomous tractor. The TSC Research and Innovation described the AgSkyNet platform used to provide growers with information during crop growing and post-harvest. They discuss case studies of solutions for integrated pest assessment, crop growth simulation to estimate yield and to assess the severity of effects of stubble burning and pesticide residue detection. The Dacom Farm Intelligence highlights their information system and how it is used to connect data and models and how that information is processed to make informed decisions on crop protection, crop growth, irrigation and precision agriculture decisions. Finally, **farm**maps, a platform made for precision agriculture, comprises multiple models (for potato, soil water dynamics, late blight infection and nematode management) and can be used to identify field and within-field agronomic management solutions. The user interface of **farm**maps is explicitly designed with farmers in mind in order to facilitate uptake of the platform.

6 Current State of Modelling for Precision Agriculture and Work Needed

Please recall that PA is *…a management strategy that gathers…and analyzes…data…to support management decisions*. This simple statement can break down in several places. In many cases there is a lack of sensors for some applications of precision agriculture. For example, it is currently not possible to measure potato tuber size and weight in the field in the same way that aboveground biomass can be measured. It may also be the case that a suitable actuator (such as a precision planter, spreader or sprayer) is not available. For example, few farmers today own a sprayer with section control. In this book we focus on the transformation of data into agronomic advice that can be relayed to an actuator. In the market this step is often left unspecified. You can see this in the many soil and crop sensors that are marketed today for more sustainable nutrient use or crop protection, but that lack models for making agronomic advice and an application rate prescription map. They leave this decision to the expertise of the user or their advisor. This hampers the adoption of precision agriculture. Successful applications of precision agriculture consist of three parts: data, decisions and actuators. A chain is only as strong as its weakest link.

It is starting to be recognized that successful application of precision agriculture requires that knowledge on PA technology and decision-support models are combined in order to develop and align the three components of a precision agriculture application. In the Netherlands, this is done, e.g. on the National Field Lab Precision Agriculture (www.proeftuinprecisielandbouw.nl) and Farm of the Future (www.farmofthefuture.nl). These are partnerships that are supported by the national government and which involve farmers, companies and scientists. All relevant parties are brought together to integrate technologies and know-how into fully functional applications. This approach is also applied in international projects in Brazil (Soybean Brazil NL[2]) and Japan (TTADDA[3]). Precision agriculture is all about cooperation and integration.

6.1 Data

Access to data is a major obstacle for the application of model-based technologies in precision agriculture. Both technical and socioeconomic obstacles exist.

From a technical point of view, it can be noted that a large number of farm management information systems (FMIS) is on the market, including systems offered by the major tractor companies. However, there is no easy way to transfer data from one FMIS to another or combine data from two FMIS. Some of the major manufacturers offer application programmer's interfaces (APIs) built around the data model of their system, but the difficult task of translating from the source data model to the target data model is left to the user. A generic approach is taken by AgGateway, a non-profit consortium with more than 100 members, whose Agricultural Data Application Programming Toolkit (ADAPT)[4] proposes a unified data model which can exchange data between any two FMIS. The Open Ag Data

[2] https://www.wur.nl/nl/Onderzoek-Resultaten/Onderzoeksprojecten-LNV/Expertisegebieden/kennisonline/Smart-technology-for-soybean-production.htm

[3] https://www.wur.nl/nl/onderzoek-resultaten/onderzoeksprojecten-lnv/expertisegebieden/kennisonline/transition-to-a-data-driven-agriculturen-ttadda-for-a-new-dutch-japanese-potato-circular-value-chain-.htm

[4] https://adaptframework.org/

Alliance[5] and DKE agrirouter[6] are similar efforts. Several vocabularies and data standards have been available for many years (Agro-XML,[7] EDI-Teelt++[8]), but they have not gained widespread acceptance.

Interoperability of equipment is another technical barrier frequently encountered by farmers (Van Evert et al., 2018). Connections between machines typically use the ISO 11783 (ISOBUS)[9] standard which defines the communication between agricultural machinery and also the data transfer between these machines and farm software applications. Unfortunately, the standard leaves room for interpretation so that in practice many incompatibilities arise when farmers buy equipment from different manufacturers. Competition between commercial providers precludes in many cases the formation of successful networks.

Social and legal issues related to agricultural data include data ownership, exchange, control and security (Kritikos, 2017). Farmers are often hesitant to share data because of social and legal challenges stemming from the wide range of actors involved in the farm data chain and the fragmented and uneven character of the data ecosystem. While it is clear that farmers' personal data is protected by current personal data regulations,[10] the ownership of equipment-generated data raises concerns among farmers and other agricultural stakeholders. Most companies state that farmers own the data they produce, but when they are aggregated with other farmers' data companies will consider the aggregated data their property. For example, measuring yield with a drone or a combine harvester yields data that are not personal (and therefore not protected), but may nevertheless give an indication of farm income (which is protected, personal data). Farmers may also waive data ownership rights by signing service agreements that they have not read (Rasmussen, 2016) or which are imposed on them unfairly because they are the weaker party.[11]

Data security in agriculture and privacy implications resulting from a security breach are a major concern for the digitization process of agriculture. The large number of devices and connections used in precision agriculture renders the complete system vulnerable, and the users of such systems should be aware of these and obtain protection.

Data-based decision tools can bring benefits to farming, but ethical questions must be asked about the consequences of changes in power relations between farmers and the other stakeholders that may follow the introduction of modelling in precision agriculture. Mepham's ethical matrix (Mepham, 2005) has been

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[5] https://openag.io/

[6] https://my-agrirouter.com/en/

[7] www.agroxml.de

[8] https://www.agroconnect.nl/

[9] https://www.isobus.net/isobus/

[10] The Data Protection Directive (95/46/EC). From 25/05/18: The General Data Protection Regulation (GDPR) (Regulation (EU) 2016/679).

[11] Bertolo, S. Building a European Data economy. EIP-AGRI Workshop. Bratislava, 4–5 April 2017.

proposed as a tool to examine ethical questions (well-being, autonomy and fairness) in agriculture and biomedical practice. An ethical issue is that in some cases data are provided by citizens (farmers), yet the information primarily benefits the commercial actors. Another ethical issue is that individual farmers may not be able to make the investments that are necessary to reap the benefits of data-based tools. The organisation of farmers around data cooperatives that collect and sell data can be a solution for ensuring smallholder farmers also benefit from the data economy.

Finally, farmers may be willing to exchange their data if they see the benefit and understand the risks (Van Evert et al., 2018). To this end, a consortium of agricultural associations has developed the EU Code of Conduct on agricultural data sharing.[12]

6.2 Models

Combining models and data provide useful information for farmers. The benefits of digital twin technology will only be realized if a sensible combination of model calibration, model initialization and data assimilation is used. If that is done, it will enable high-quality fertilizer recommendations and in a broader sense better agronomic management. The main limitation is not the data analysis or the computational capability, but rather a critical and improved understanding of what we need and can obtain from the model. Farmers have specific agronomic needs and any technology (remote sensing, modelling, etc.) needs to be adapted to answer those questions. The third section of this book shows clearly that it is possible to use crop growth models in precision agriculture, but in the basic and applied research field, it seems that this issue is less developed.

There is often a diffidence towards crop models (e.g. arguments used against them are that they are too hard to use or they require too many data) which is sometimes due to users' limited knowledge of the agricultural system (soil-plant-atmosphere or agronomy per se) rather than the limitation of the models.

Another practical issue to solve in the near future is the frequency of data that are needed to drive/parameterize/calibrate a crop model during data assimilation. Nowadays it is possible to obtain very detailed data at high spatial and temporal resolutions from drones and satellites. However, does a crop model need all those data? Can the same accuracy be obtained with less data? This is not a trivial question because it might affect the willingness of farmers to adopt new technologies.

Finally, despite the models used (crop growth models or ML), it is important to translate the data into agronomic decisions. It is possible that models and modelling approaches used to estimate yield or grain quality are applied too late during the growing season, which makes the utility of those simulations less relevant because it might be too late to correct for any deficiency. Identifying the right time is therefore

[12] https://www.cema-agri.org/images/publications/brochures/EU_Code_of_conduct_on_agricultural_data_sharing_by_contractual_agreement_2020_ENGLISH.pdf

important. In addition to that, applied research should focus on involving farmers and agronomists in the design of the experimental approach because they are the ones working on those issues on a daily basis.

6.3 Actuation

Actuation is not the biggest bottleneck, even though many farmers do not own precision application equipment. But, the next generation of machines, the new generations of farmers cultivating the land and better data analytics linking sensors and machinery will enable further actuation of digitalization.

In some contexts, for example, in developing countries, actuation is occurring at a fast pace (MaMo, 2019). Rather than the modelling per se, it is the actuation of digital and precision agriculture that is happening because in most cases the farmers are young and open to new technologies and therefore their main entry point is digital agriculture (e.g. smart phone usage in agricultural management).

7 Conclusion

Crop growth models have great potential to be of benefit in precision agriculture. A combination of models and data from sensors (i.e. DT) can generate information to support farmers' management decisions. When a suitable crop growth model is not available or does not offer the required functionality, statistical techniques like ML can be used instead.

The greatest bottleneck is represented by data availability, usage and quality. Farmers are weary to invest in collecting the real-time (or near real-time) data needed to run simulations as long as the transformation of these data into agronomic decision is uncertain. Acceptance of models by farmers and other practitioners is also a bottleneck in many cases. Lack of trust in models and feeling overwhelmed by complexity play a role. This points to the need for better connections between researchers, extension workers, farmers and advisors to leverage the benefits of data and modelling.

Further Reading *Models*: the Agricultural Model Intercomparison and Improvement Project (https://agmip.org/) contains information and papers about crop modeling activities at different scales and for different purposes. Some specific websites such as https://www.apsim.info/, https://dssat.net/, and https://www.wur.nl/en/Research-Results/Research-Institutes/Environmental-Research/Facilities-Tools/Software-models-and-databases/WOFOST.htm contain information about specific crop growth models.

Precision agriculture: The International Society of Precision Agriculture's webpage (https://ispag.org/) contains links to scientific publications from the scientific Journal Precision Agriculture and additional material.

Conflict of Interest The authors declare that there are no conflicts of interest.

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