

Vision Article

Opportunities for control engineering in arable precision agriculture[☆]A.T.J.R. Cobbenhagen^{*}, D.J. Antunes, M.J.G. van de Molengraft, W.P.M.H. Heemels

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ABSTRACT

In this paper, we present an overview of several challenges in arable farming that are well suited for research by the control engineering society. We discuss the global needs that these challenges are related to as well as the relation of these challenges to future applications of arable farming. For each of these opportunities we provide several concrete and detailed research questions. Particular attention is paid to the management of resources and sensors in farms. The objective of writing this paper is to further entice control engineers into the domains of agronomy and agricultural technology.

1. Introduction

1.1. Global challenges

The global population is expected to grow by approximately one third between 2009 and 2050, which is an increase of approximately 2.3 billion people (FAO, 2009). In order to sustain this growth, the food production has to increase as well. Combined with the trend of urbanisation (UN, 2018), it becomes increasingly more important to produce more food using the available farmland.

The current resource-intensive farming paradigms have shown not to be scalable due to their enormous environmental impacts such as deforestation, water scarcity, and green house gas emissions (FAO, 2017). As such, it is an imperative challenge to increase the crop yield per available area, whilst significantly reducing the usage of resources such as water, pesticides, and herbicides in order to minimise the environmental impact and increase the sustainability of the food production chain.

Due to its global scale, developing and developed countries alike will face the challenges of revolutionising the paradigms of agriculture. In 2015, 17 global sustainability goals for 2030 were identified in *The General Assembly of the United Nations* (2015). Agriculture plays a prominent role in many of these goals. The clearest presence of agriculture is in *Goal 2*: “End hunger, achieve food security and improved nutrition and promote sustainable agriculture” (*The General Assembly of the United Nations*, 2015, p. 14). However, the importance of agriculture can also be seen in Goals 6, 12, 13, 14, and 15 (sustainable management of water, sustainable consumption and production patterns, combat climate change, sustainable use of oceans, and protection of ecosystems, respectively).

1.2. Goal and scope

In the present paper we will discuss the challenges within arable farming to which the control engineering society could contribute significantly. In particular, the main focus of this paper is automated decision making in arable farming. This includes management of resources such as water, herbicides and pesticides, as well as the management of sensors. In this work we will highlight several of such challenges with the goal of (further) enticing control engineers to this important and societally relevant line of research.

It is noteworthy to mention that there is a vast amount of literature on control of crops in greenhouses (as well as greenhouse horticulture). Greenhouses are evidently more ‘controlled’ environments and ‘less harsh’ than fields of crops, which has led to control methods that are not directly applicable to arable farming. On the actuation side, greenhouses are able to control humidity, carbon dioxide levels, temperature, and irradiation. Irrigation can sometimes occur on an individual crop level. Also the placement of sensors is more ubiquitous. This has led to much interesting research and many successful instances of control applications, see, e.g., Van Straten and Van Henten (2010), Van Straten et al. (2010). Anyone interested in control for arable farming is advised to study the applied control technologies in greenhouses as well.

Additionally, much research has been carried out on the topic of machinery and robotics for arable farming, which is of interest as well. However, in the present work the focus is on management and allocation of machinery and robots. Methods of sensing, manipulation, path planning, and motion control of such robots are left outside the scope of this work (for a review, see, e.g., Bechar and Vigneault (2016)).

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1.3. Outline of the paper

The remainder of this paper is structured as follows. In Section 2 we provide a definition of *Precision Agriculture* (PA) and how it is related to the global challenges mentioned above. In Section 3 we present our main recommendations for research directions for the control scientists and engineers interested in PA. Several advanced applications of these research directions are presented in Section 4. Practical recommendations and considerations for doing research in these directions are presented in Section 5 and we end with conclusions in Section 6.

2. Precision agriculture objectives

There are numerous definitions of Precision Agriculture (PA) (see, e.g., Jawad et al. (2017), McBratney et al. (2005), Pierce and Nowak (1999)). In the present paper, we consider PA to be *the type of agriculture that aims to maximise the number of (correct) decisions per unit area of land per unit time with associated net benefit* (following McBratney et al. (2005)). Led by the global challenges mentioned in Section 1.1, we define the global goal of PA for the purpose of the present paper to be:

To help farmers across the world to increase the production of high-nutritious foods at minimal environmental impact through the use of technologies, in order to sustain the food demand of humanity.

The technologies mentioned in the global goal above include advanced machinery, data-gathering and processing infrastructure, and automated decision making schemes. In the present work we will mostly focus on the data-gathering and automated decision making, as these are closest to the control community. However, these are evidently strongly related to the machinery. There are many different kinds of machines and robots for arable farming on both the sensing and actuation side (Bechar & Vigneault, 2016; Hajjaj & Sahari, 2016), such as automated harvesting robots (Bac et al., 2014; Zhao et al., 2016), *unmanned aerial vehicles* (UAVs) for remote sensing (Lottes et al., 2017; Mulla, 2013; Zhang & Kovacs, 2012), and machines/robots for application of resources such as fertiliser, pesticides, and water (Bechar & Vigneault, 2016). Closely related to the robots are the advanced machines that farmers operate. Both agricultural robots and machines are an integral part of farm-wide automated crop growth management.

In the remainder of this section we will elaborate further on several aspects of the PA goal, including minimal resource usage and environmental impact (Section 2.1), and availability of technology (Section 2.2).

2.1. Minimal resource usage and environmental impact

The four main resources used in arable farming are water, fertiliser, pesticides, and fuel for machinery. In the remainder of this section we will discuss these in more detail.

2.1.1. Water

Currently, there are several countries facing a freshwater crisis. Studies show that many more cities and countries across the planet will face a freshwater crisis if water is kept being used at the current rate (FAO, 2011). Of all the water withdrawn for human use, 70% is used for irrigation (FAO, 2011). This is mainly due to the vast scale at which crops are produced. For example, in order to produce a kilogram of rice, over 1600 litres of freshwater is needed and one kilogram of potatoes needs approximately 287 litres of freshwater (Mekonnen & Hoekstra, 2010a). Livestock has an even worse ‘efficiency’ in terms of produced mass and nutritious value relative to the water needed (Mekonnen & Hoekstra, 2010b). This is partly due to the fact that animals are higher in the foodchain and thus require a large amount of crops, which in turn require a lot of water. Hence,

reducing the water usage in arable farming could have a huge impact on the availability of freshwater throughout the world.

The importance of smart irrigation systems is explicitly stated in FAO (2011, p. 8): “Most future growth in crop production in developing countries is likely to come from intensification, with irrigation playing an increasingly strategic role through improved water services, water-use efficiency improvements, yield growth and higher cropping intensities”.

2.1.2. Fertilisers

The main components of fertilisers are nitrogen (N), phosphorus (P), and potassium (K) (often abbreviated as NPK). Remaining nutrients include calcium, magnesium, and sulphur (Kiiski et al., 2016). Insufficient application of nitrogen, the primary component of fertiliser, can result in low crop yields and insufficient food production, whereas an excess can lead to serious environmental harm (Hasler et al., 2015; Stevens, 2019). These negative effects include increased greenhouse gas emissions, poor air quality and water pollution (Stevens, 2019). It is predicted in Springmann et al. (2018) that in the absence of technological changes and mitigation measures, the environmental effects of excessive use of nitrogen and potassium in agriculture will increase between 2010 and 2050 by 50% to 90% and reach dangerous levels. In most countries there are strict regulations as to how much nitrogen, phosphorus and potassium can be applied.

Timing of fertilisation is delicate. If fertiliser is applied too late then the crop will have a reduced growth. On the other hand, if it is applied too early, then the nutrients may be lost in the soil. This makes it an interesting case study for control engineering, especially in the case where there are many (sub)fields requiring large-scale control and optimisation, see, e.g., Cobbenhagen et al. (2018).

2.1.3. Pesticides

The objective of using pesticides is to protect crops from pathogens and parasites. Pesticides are, by definition, toxic and bio-active substances (Imfeld & Vuilleumier, 2012). As a result, the use of pesticides can affect the health of the crops, soil, and humans (Carpay et al., 2000; Imfeld & Vuilleumier, 2012; Maroni et al., 1999).

Limiting the usage of pesticides is not only desired due to its negative side effects, it is also a cost saver for the farmer. Hence, the careful application of pesticides is an interesting topic for research in control engineering. It could be interesting to see what the optimal policy is under risk constraints. In Section 4.1 we will focus on intercropping, a technique that has the potential to reduce or even eliminate the use of pesticides.

2.1.4. Fuel

One of the resources that should not be forgotten is the fuel used by the farming machinery. In fact, the logistics within the entire foodchain ‘from farm to plate’ is an interesting topic of research, but is not considered here (refer to, e.g., Wakeland et al. (2012)). In terms of local usage of farming machinery, the minimisation of fuel results in obvious reductions in greenhouse gas emissions and less expenses for the farmer (see, e.g., Dalgaard et al. (2001) for a study on the impact of fossil fuel use).

2.2. Availability of technology

Farming is a business. Income is generated by the sale of high quantity and high quality foods and the expenses are mainly governed by resource usage and labour. Advanced PA technologies can potentially have high starting costs. One might argue that these start-up costs may hold back the implementation of the technologies at smaller farms. However, investing in PA technologies becomes a necessity if smaller farms want to compete with larger farms that have more capital and invest in these technologies.

It is thus of importance to keep in mind how advanced technologies can be used in less technologically developed areas or by smaller farms. When discussing new technologies in farming it is easy to forget that it is worthwhile to investigate ‘lower-tech’ solutions. For example, it can be argued that with an increase in advanced *decision support systems* (DSS), that there is also a demand for DSS that require limited computation power and sensing capabilities. The latter system helps farmers that do not have access to state-of-the-art sensors to make better informed decisions. Instead of allocation of automatic sensors such as UAVs, such a DSS would advise the farmer where and what to measure (even visual/manual inspection) such that the DSS obtains better information on the current state of the field and hence can make better decisions. Due to the reduction in costs of GPS devices and wireless technologies, it is possible to create ‘lower-tech’ solutions for information gathering in PA, see, e.g., [Maia et al. \(2017\)](#), [Wachowiak et al. \(2017\)](#) for examples.

3. Model-based crop growth management

3.1. Why model-based crop growth management?

A fundamental question in PA is what the level of ‘precision’ should be. Consider two extreme scenarios, the first of which is where an entire field is treated homogeneously, the second scenario is where each plant in the field is individually monitored and controlled. Evidently, the first scenario is suboptimal: there are variations over the field and not all crops and soils in a field have the same properties nor do the crops have to ‘behave’ the same. However, it is a cheap/easy option in terms of monitoring and caring. The second scenario may produce more crops as each plant is treated individually and therefore its needs can be exactly met. The downside of this scenario is that it is rather difficult and expensive to monitor each plant individually and (currently) the costs of this approach are larger than the potential profits. It is evident that these two extreme scenarios are suboptimal. This raises the question where the optimal level of precision is between these extremes, that is, the level at which the costs of managing and monitoring are balanced with the profits due to the level of attention given to each crop.

The trend in developments in PA is clearly towards operating at a higher resolution, which can, for instance, be seen from the developments in and usages of sensors and actuators ([Reyns et al., 2002](#)). However, we hypothesise that, *in order to push for an increased resolution in PA, we require a scalable ‘software approach’ in order to go beyond the hardware limitations of sensors and actuators.* This hypothesis is the main motivation for the importance of doing *model-based crop growth management*. The main idea of which is to create a ‘digital twin’ of the crops (i.e., crops are monitored by monitoring a simulation model of the crop growth), which uses sensor inputs of the crop or nearby crops in order to predict the state of the crop. Additionally, this model of the crop is used to compute the best actions for the crop (e.g., amount of irrigation or fertiliser). The addition of a model-based crop growth management to the sensors and actuators increases the resolution of PA.

The hypothesis above is central to this paper and due to the importance of a model-based control approach, several interesting and important opportunities for the systems and control community in PA can be identified. In the remainder of this section we elaborate on three important research directions for the interested control engineer: crop growth models for control, model-based control of crop growth, and estimation of state variables of crops and fields. These subjects all contribute to the purpose of *farm-wide on-line automated decision making and/or providing decision support to the farmer.*

We refer to the seminal work [McBratney et al. \(2005\)](#) in which general research lines of PA have been identified. These research lines form the starting point of our work; we will specify and detail them for the systems and control engineering community and expand upon them.

3.2. Crop growth modelling for control

There exists a plethora of models that predict the growth of crops. See, e.g., [Brisson et al. \(2003\)](#), [de Wit et al. \(2019\)](#), [Shibu et al. \(2010\)](#), [Steduto et al. \(2009\)](#), and [Bouman et al. \(1996\)](#) and the references therein. Most of them are well-validated and proved to be able to predict the crop growth. These models have traditionally been created by biologists, ecologists, and agronomists. However, these models typically do not lend them to be directly used by ‘standard techniques’ from control engineering in order to design controllers or state estimators ([Carson et al., 2006](#)). In many research areas within control engineering, it is assumed that the dynamical model of the system to be controlled is given by a proper mathematical description, for instance, in terms of a set of differential or difference equations. These can be linear or non-linear, and they may include partial derivatives. The aforementioned crop growth models generally are not in such a form. They are mostly in the form of executable simulation models, consisting of many lines of code. Although many models do have differential and difference equations at their core, much of the reasonable performance in prediction comes from added relations. Such relations take the form of, e.g., ‘if-else-statements’ and look-up tables for empirical data.

In order to bridge the gap between these crop growth models and the control engineering domain, we identify the following directions of research:

- (1) Adaptation of control methods such that the existing crop growth simulation models can be used directly.
- (2) Creation of novel crop growth models that rely on the domain knowledge of the experts, but with the intent to have both appropriate prediction accuracy and a mathematical description of reasonable complexity that lends itself to be used in ‘conventional’ control engineering methods.
- (3) Identification of models based on data and related data-driven control methods.

The difference between direction (3) and the other two is that (3) allows for the use of black-box models. In this work we focus on the first two of these directions. The interested reader is referred to, e.g., [Beza et al. \(2017\)](#) for a recent review on using data in modelling the yield gap. It should be mentioned that it may be interesting to explore the use of *reinforcement learning* if only simulation models are available (see, e.g., [Bu and Wang \(2019\)](#), [Jiang et al. \(2018\)](#), [Sun et al. \(2017\)](#) for recent examples). However, such control policies have the downside that they lose much ‘explainability’ of the optimal actions, which is important for practical implementation. This will be further discussed in Sections 3.3 and 5.2. Note that data-driven methods combined with expert domain knowledge (i.e., grey-box modelling) have high potential. This allows data to be used in modelling, while maintaining a high level of explainability and generality.

Aside from the fact that it may be interesting to employ the models in control engineering methods, there are additional benefits in creating models as described in (2). Firstly, by explicitly stating the workings of such models they become more accessible to the users. It allows for scientists to share and improve them and apply them to different locations, crops and weather patterns. Furthermore such models allow governmental agencies, non-governmental organisations (NGO) and companies to create their own decision support systems.

3.3. Difficulties in crop growth modelling

In many situations, control engineers are designing controllers for a system that they can redesign. For instance, in electro-mechanical devices, one may be able to change the mechanical or electrical design in order to obtain a system that is ‘easier’ to model and control (e.g., reducing the extent of non-linear dynamics by more expensive or better designed hardware). In arable farming, we are dealing with a biological system where such modifications are difficult. Moving

crops from arable lands into greenhouses is the primary example of how one might control part of the dynamics. For instance, farmlands located on an uneven terrain may see a movement of soil water due to gravity. When crops are placed in a greenhouse, they are most of the time placed in containers with soil, which can be set level and hence reducing (or even eliminating) such effects. In mechanical systems, a first approximation of the dynamics can often be done by an application of Newton's second law of motion and constitutive relations such as Hooke's law. It is then relatively easy to obtain a simple, yet descriptive, dynamical model. Further predictive performance is then obtained by adding more relations and including non-linear effects. The same can be said of electrical systems and thus also electro-mechanical systems. The basis of modelling crop growth for arable farming is 'storage' (integrator) of sugars, water, and biomass. Hence, it often exhibits first-order behaviour. The difference with the electro-mechanical situation discussed above is that most of the predictive performance of the crop growth models comes from the 'non-linear inputs'. These non-linear inputs in crop growth modelling are not as well-known and often require a high degree of non-linearity and many (unknown) parameters. Recently, a successful instance of this approach was shown in [Pelak et al. \(2017\)](#), where a crop growth model with four first-order non-linear differential equations (the states are canopy cover, relative soil moisture, total nitrogen content in the soil, and the crop biomass) was demonstrated.

The typical time scale for performing actions in farming is minutes to hours, whereas the time scale of crop growth dynamics is typically in the order of days. On top of that, the objective of decision making is often related to a terminal reward as harvesting is done at the end of the growing season, which has a duration of multiple months. In greenhouse management, the short-term decision making (temperature, ventilation, etc.) is often made by a closed-loop decision making system, whereas the long-term decisions are made by the farmer/grower ([Van Straten et al., 2000](#)). Increasingly more novel research is done towards extending the short-term decision making over increasingly longer time scales. This raises the question of how these facts can be leveraged to improve arable farming.

Any practically useful crop growth model should be able to handle the different circumstances between farms. For example, a crop growth model should be able to take into account the local soil parameters, and climate and weather patterns. Not for the purpose of creating a 'crop growth model for all', rather due to the fact that designing a model for every farm and crop cultivar separately is not a sustainable option. It is therefore of interest that crop growth models for control can be calibrated with relative ease and have parameters that are 'explainable' to the user (i.e., no black-box parameters that require 'tweaking'). Another reason why it is important to have explainable parameters in crop growth models is that models are continuously adapted due to the effects of climate change ([Asseng et al., 2015](#)) and responses at the farm-level to climate change are required ([Reidsma et al., 2010](#)). Hence, in order to be able to adapt models even slightly, a high degree of 'explainability' is needed.

3.4. Model-based control

Model-based control in PA is concerned with computing the optimal allocation of resources such as water, fertiliser, and pesticides, to fields using models to predict the future crop growth. The objective by which the 'best' actions are judged is a combination of financial profit, risk aversion, and environmental impact. The current state-of-the-art for many arable farmers that make use of such models, is to run (Monte Carlo) simulations where the actions and weather patterns are varied. Based on the outcomes of these simulations, a reasonable set of actions is selected. See, e.g., [Bergez et al. \(2010\)](#) for an example application.

In recent years, there have been several endeavours into optimal control methods that explicitly use crop growth models in order to compute the 'optimal' amount of water to irrigate crops, see, e.g., [Cobbenhagen et al. \(2018\)](#), [Kalboussi et al. \(2019\)](#) and for a model predictive

control setting, see, e.g., [Lozoya et al. \(2014\)](#), [Saleem et al. \(2013\)](#), [Schoonen et al. \(2019\)](#). For illustrative purposes, we have included an example of the latter in the [Appendix](#), which is based on previous work ([Schoonen et al., 2019](#)) by some of the authors of the present paper. On a larger scale, the control of irrigation networks between farms has been extensively studied in, e.g., [Cantoni et al. \(2007\)](#), [Mareels et al. \(2005\)](#), [Negenborn et al. \(2009\)](#). However, due to the large scale of irrigation networks, these controllers do not make use of crop growth models.

The primary research directions we identify in model-based control for farm management are:

- (1) The design of control methods to be used with (existing) crop growth models.
- (2) The incorporation of the allocation of water, fertiliser, and pesticides into a single framework.
- (3) The scalability of control methods to large-scale systems.
- (4) How to deal with or exploit the time-scale separation between the crop/field dynamics and control actions (see [Section 3.3](#)) in control schemes.

Related to these practical primary research directions, we identify several questions that may find a partial answer to the directions mentioned above. Firstly, the model-based approach may give answers to the question of which level of granularity in both time and space is optimal. The scalability of the control methods, item (3) in the list above, is especially important if the granularity is high. Secondly, it may increase our understanding of the interplay between when to fertilise and when to irrigate. There is much biological and ecological theory on how these factors influence each other and it is thus of interest to investigate what an optimal control approach would provide as the optimal pattern of applying fertiliser and irrigation.

3.5. State estimation and digital twins

The use of sensors in arable farming has drastically increased over the past decades ([Reyns et al., 2002](#)) as well as research into vision-based sensing ([Chen et al., 2002](#)). These systems can measure a wide variety of properties of the crop and soil such as leaf area, soil water content, and soil conductivity. Not all of these measurements are properties that would typically be a state in a dynamical crop growth model. It is the use of empirical correlations that are employed in order to estimate the status of the crop using the measurements. For instance, using hyperspectral imagery of the crops, one can compute the NDVI (normalised difference vegetation index) from which approximations of the 'leaf area index' and nitrogen content in the leaves can be obtained (see, e.g., [Carlson and Ripley \(1997\)](#)). State observers could be used in conjunction with on-line parameter updates, which enables the creation of 'digital twins' of the crops and fields. This provides better insights into what is happening on the fields and the importance of digital twins was stated in our central hypothesis in [Section 3.1](#).

The first research direction we identify from a control-theoretical perspective is to analyse which measurements lead to observability (or detectability) of the states of the crops and soils. Using the crop growth models for control it could be possible to design observers. See, e.g., [Bono Rossello et al. \(2019\)](#) for a recent example of using a simple water/soil model in order to design observers to monitor the soil water content.

Secondly, the design of state observers could lead to an increase in understanding of where one wishes to sense. For instance, farmers that have several UAVs would like to know when and where they should fly them to collect measurements. At first glance, there are many possibilities: to the field with highest uncertainty of crop states, to the 'best' fields that have the highest (potential) yield, the 'worst' fields, and more. All these possibilities have their benefits and downsides, but the question remains which is the best in the grander scheme of farm management. Combined with a controller design, it may be possible to device the optimal policy of allocation of sensing agents such as UAVs.

3.6. Reduced-order crop models

Reduced order crop growth models are especially useful in the crop growth management of large-scale farms. Consider the case where a farmland is divided into hundreds or thousands of subfields. Using reduced order crop growth models may then help to significantly reduce the computation time, while still performing well in such a large-scale setting.

If one were to obtain a crop growth model that lends itself to be used to design controller and state estimators, a natural question would then be whether the closed-loop system is of minimal order.¹ If the controller and sensors can achieve the same input–output behaviour with fewer states, then the system model is not minimal. Even if the model is minimal, it may be interesting to analyse which of the states are the most ‘important’ in the model and subsequently obtain a reduced order model.

Such an approach has the potential to objectively *quantify* the relative importance of sensors and resource inputs to the overall crop management. This would provide an interesting new perspective on the role of decisions and measurements in PA.

4. Advanced applications

Building upon the essentials of model-based control and estimation in arable farming as discussed in Section 3.4, we present three advanced applications in this section. These applications are intercropping, multi-agent systems, and vertical farming.

4.1. Intercropping: Enabling natural symbiosis

When discussing arable farming, chances are that large swathes of land with a single crop come to mind. Naturally, crops would not grow as such large mono-cultures. There is a natural symbiosis between crops, other plants, bacteria, and animals that enable an exchange of protection and nutrition. *Intercropping* is the practice of cultivating different crops in close proximity with the intentional purpose to benefit from a natural symbiosis. Intercropping is one of the core applications within the science of agroecology (Wojtkowski, 2019).

Initially, humankind’s first attempt at farming had different types of crops close together. As human societies grew larger, managing of such multi-crop fields became too difficult in order to satisfy the increasing demand of food as settlements grew in population. The difficulty in managing intercropped fields arises due to the fact that if many crops grow close to one another, it is more difficult to seed, monitor and harvest. Humanity therefore shifted towards monoculture farming over time as it was more efficient due to the available specialised tools and animal labour (later machine power). Yet, intercropping is still widely used by farmers with small lands in the tropics (Boudreau, 2013), but it currently is not manageable for large-scale farms.

There are several advantages to intercropping. Firstly, by placing different types of crops close to one another, crops may benefit from natural protection from diseases (Boudreau, 2013). This reduces the need of pesticides and herbicides. Secondly, intercropping stimulates an increase in biodiversity in the soil and of insects. This can lead to an increase of nutrients for the crops and a healthier soil. Thirdly, the density of crops in a field can be higher in intercropping, which may lead to a higher yield. An example is placing a crop with deep roots near a crop with a shallow root system.

Systematic research on intercropping started many years ago, see, e.g., the seminal work by Vandermeer (1989). However, it has even recently been argued that there still is a need of a systematic theory behind agroecology and intercropping (Wojtkowski, 2019). The interplay

¹ Here we use the terminology for linear state–space systems for didactic purposes. Extensions to other types of systems are implied.

between crops, soils, and pests is delicate and not straightforward. For instance, intercropping in itself does not reduce pest damage (Smith & McSorley, 2000, p. 154). It is evident that control theory and especially game theory may provide interesting new insights into the dynamics of intercropping (Wojtkowski, 2019, p. 187). Yet, surprisingly little research has been done within these domains (to the best of our knowledge). An exception can be found in the domain of statistics (Federer, 1999; Lupatini et al., 2014). It is a great and highly relevant challenge for the domain of systems and control engineering to develop such theories for agroecology.

The second challenge is of a more applied nature. Due to the fact that intercropped fields do not necessarily follow the ‘row orientation’ that conventional mono-cropped fields have, a new kind of machinery is required to seed, monitor, maintain, and harvest. We identify the computation of optimal patterns for such new machinery as the second challenge for control engineering within agroecology. It should be mentioned that there are forms of intercropping that follow the traditional ‘row orientation’, which is known as ‘strip cropping’ (Francis et al., 1986; Mousavi & Eskandari, 2011). In strip cropping, each row has the same type of crop, but adjacent rows may have different crops. A recent meta-analysis (Yu et al., 2015) has shown that intercropping can, on average, result in a 22% increase of crops relative to mono-cropping. Fig. 1 illustrates the differences between the various configurations of crop orientations.

There is an even more advanced form of intercropping, namely *agroforestry* (Sanchez, 1995; Torralba et al., 2016). It takes ecology ‘into a third dimension’ and it is the science of cultivation crops in combination with trees. As in ecology, the aim is to improve productivity of the farm through symbiosis of the crops and trees. Evidently, this can increase the complexity of decision making and hence it is of interest to study it from the systems and control perspective.

4.2. Soil compaction and the disturbance of the top soil: Multi-agent systems and remote sensing

By driving large machines over the soil, the biotope of the top-soil is heavily disturbed and compacted, which can have negative impacts on the soil health and the crop yield (Lipiec & Hatano, 2003). In order to manipulate the crop by the least amount and minimally disturb the biotope of the top-soil, the trend to make use of both lighter and smaller tractors, and remote sensing is evident. Application of nutrients and other resources is therefore challenging.

Smaller resource-delivering vehicles (both ground or aerial) evidently have a smaller capacity. As discussed earlier, by careful monitoring one can reduce the amount of resources that need to be delivered to the crops. However, there are still considerable amounts that need to be delivered. In order to lessen the disturbance of the top soil, there are desires and trends to reduce the mass (or size) of a resource delivering agent by orders of magnitudes 10 to 100, whereas the decrease in resource delivered by advanced optimisation schemes will most likely be in the order of 1.2 to 2. This implies that many resource delivering agents are required in order to fulfil the resource demands for crop production. This warrants a careful deployment and allocation of agents. Hence, it is necessary to develop multi-agent optimisation tools. An example of a multi-agent resource allocation scheme for irrigation can be found in Schoonen et al. (2019).

4.3. Vertical farming

In 2018, approximately 55% of the world population resided in urban areas. That number is expected to increase to 69% by 2050 (UN, 2018). With this global increase of urbanisation, there is a rising demand for locally grown food. *Vertical farming* is a way to incorporate farming into cities. It is called ‘vertical’ due to the fact that such farms take form of high-rise buildings where produce is grown on each floor (Benke & Tomkins, 2017; Garg, 2014). It has been shown

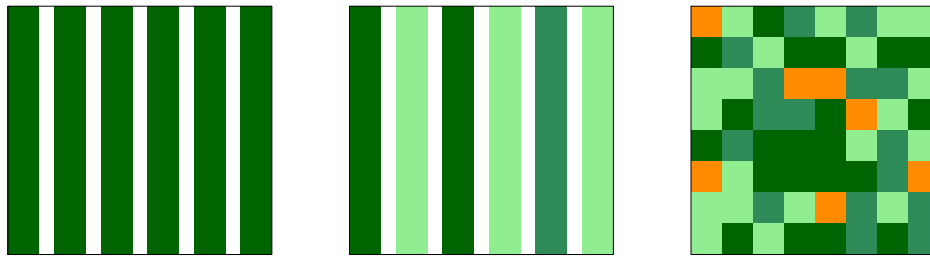


Fig. 1. Sketch of differences in configuration of crops on arable land: traditional monocropping (left), stripcropping (middle), and full intercropping (right). The different colours represent different crops.

that it has the potential to be an economically viable way to produce food with a small environmental footprint and area demand (Banerjee & Adenaeyer, 2014; Benke & Tomkins, 2017; Kalantari et al., 2018). Currently there are successfully operating vertical farms around the world, see, e.g., Benke and Tomkins (2017), Kalantari et al. (2018) for an overview. The most successfully grown crops in vertical farming today are leafy greens (Sarkar & Majumder, 2015).

Part of the reason of the low environmental footprint is that vertical farming requires less water than traditional farming as there is less evaporation and water can be recycled more easily. Many of the vertical farming operation make use of hydroponics, where the crops are placed in nutrient-enriched water rather than soil. This eliminates the need for fertiliser and pesticides (Benke & Tomkins, 2017). Since the farmlands are stacked upon each other in vertical farming, not every floor can obtain sunlight as well as in an ordinary greenhouse. Such artificial lighting comes at an increase in investment costs and energy costs which should, of course, be taken into account.

Vertical farming poses challenges for many disciplines of engineering. The challenge we identify for system and control engineering is the automated management of crops in vertical farming. Just as in traditional greenhouses, the environment is closed, which allows for better monitoring and control of the crops. One might argue that this is no longer arable farming and it is more related to growing crops in greenhouses. The reason why we include vertical farming in the present paper is that there is a need for arable crops to be grown within the vertical farming environment. Hence, when designing models, controllers, or estimators for arable farming, it is of interest to consider how these would work in vertical farming in order to increase the number of crops that can be grown in such environments.

5. Practical considerations

So far in this work we have discussed the challenges and opportunities for control engineering within arable farming. In this section we will provide several considerations and recommendations to take into account when tackling the challenges discussed throughout this work.

5.1. Domain knowledge

The most important consideration is the involvement of domain experts. As mentioned in Section 3.3, crop growth modelling is an inter-disciplinary activity where researchers from disciplines such as agronomy, biology, and ecology have done a tremendous amount of work in order to better understand crop growth. Whether designing a crop growth model for control or adapting an existing crop growth model to be used in control, the domain knowledge is extensive and must be consulted.

5.2. User adoption

In any case of practical controller design, one must take the user into consideration. This is definitely very much the case in arable farming. The control actions are, in general, performed by the farmer as the primary user. As mentioned, it may be the case in the future that robots perform farm management with the human out of the control loop, but this is currently not the case and will not be for the near future. With automated decision making with humans in the loop, the computed decisions and state estimations must be explainable to a reasonable degree. The most prominent reason is that if the computed decisions are not reasonable at first glance, then the user may not execute them at all. Notice for instance, that the terminology within PA for automated decision making algorithms is ‘decision support system’ (DSS): the farmer still makes the ultimate decision and is only advised by the DSS.

We refer to Van Straten et al. (2000) for a survey done among suppliers of control systems for greenhouses as well as users of the control systems (i.e., farmers) on the requirements of control systems for proper adoption. One of the questions that was often asked by the farmers in this survey was whether the prediction models can be trusted (Van Straten et al., 2000, p. 233). It is thus of key importance that the crop growth models to be used in any control scheme should have an explainable behaviour.

5.3. Degree of available equipment

Many novel robots, machinery, and sensors come to market every year. It is tempting to design automated decision making systems that use such hardware as there is obviously a market for such systems. As mentioned in Section 2.2, it is also of importance to design advanced decision making schemes that do not rely on such machinery. In the design of control methods for arable farming, one must thus take in mind which types of machinery and how much computing power will be available to the farmer.

6. Conclusion

In this work we identified several research directions for control engineering research within the domain of precision agriculture (PA) for arable farming with the purpose of attracting control engineers and researchers to the highly relevant and interesting application domain.

We presented an overview of the challenges that humanity faces and how PA can help to tackle these challenges. For research in the short term, we highlighted optimal control of resources through model-based control of crops, and estimation of crop and soil states as the main directions of research. We gave specific research questions on these topics and how they can lead to answering fundamental questions in farming operations. Using model-based crop growth management as a central notion, it was shown that deployment of ‘digital twins’ of crops and soils can help increase the precision of decision-making in agriculture and thus increase the quality and quantity of the food while taking into account environmental and financial aspects. Beyond

control of resources, estimation, and control-relevant crop-modelling, relevant research directions for control engineering in advanced applications such as intercropping, multi-agent systems, and vertical farming were stated in detail. These are research directions for the long term.

Many fundamental challenges in PA for arable farming can be researched from the perspective of control engineering and it offers the systems and control community an interesting and important research area.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Appendix. An example of model-based control using existing crop growth models

For illustrative purposes, we include an example of a control scheme that utilises some structure of several crop growth models in a model predictive control setting. In this example we consider a single field that is operated by a single irrigation agent. This example is a simple set-up of the more general setting as discussed in previous work by some of the authors of the present paper (Schoonen et al., 2019), which considers multiple (sub)fields and multiple irrigation agents. The model of the crop growth dynamics is here assumed to be a simulation model.

Consider the set-up of a single arable field where the crops and soil are homogeneous over the space. Let T denote the length of the growing season and we consider growth and actuation to occur on a daily basis, to this end we label time t from the set $\mathcal{T} := \{1, 2, \dots, T\}$. Let x_t be the state vector of crops on day $t \in \mathcal{T}$, where the states include, for instance, the biomass of the crop organs and the leaf area, and let u_t denote the amount of water that is irrigated on day $t \in \mathcal{T}$. Let π be a vector that represents the relative weighting of the crop states to each other and the amount of irrigation. The simple objective we consider here is to maximise the crop yield at harvesting, whilst minimising the amount of irrigation (the cost of irrigation is normalised to 1). In a mathematical formulation, we consider the maximisation of

$$J = \pi^\top x_T - \sum_{t=1}^{T-1} u_t, \quad (\text{A.1})$$

with $u_t, t \in \mathcal{T}$, as the optimisation variables. The discrete-time dynamics of the crop are assumed to be

$$x_{t+1} = x_t + G_t,$$

for $t \in \mathcal{T}$, where G_t is the crop growth, which depends on the crop states, soil water content, weather influences and irrigation. Hence, we can rewrite (A.1) as

$$J = \pi^\top x_1 + \sum_{t=1}^{T-1} (\pi^\top G_t - u_t). \quad (\text{A.2})$$

We resort to maximising J using a model predictive control (MPC) scheme.

A popular method to model crop growth is by introducing a hierarchy in growth and production factors (Van Ittersum et al., 2003): growth-defining factors, growth-limiting factors, and growth-reducing factors. The growth-defining factors determine the maximum possible growth and are dependent on crop-specific parameters and weather influences such as temperature and solar irradiation. The growth-limiting factors are due to shortage or excess of water and nutrients such as nitrogen. The growth-reducing factors are due to, e.g., weeds and pests.

A common way to model the growth reducing factor due to water shortage is the following. Let $\theta_t \in [0, 1]$ denote the growth-reducing factor due to water shortage on day t and let w_t denote the soil water content. Furthermore, let w_p be the wilting point such that if the soil

water level w_t is below w_p , there is no growth possible ($\theta_t = 0$). Let cr_t denote the *critical water level*, which is dependent on both the state of the crop and weather influences. For $w_t \geq cr_t$, it is assumed that there is no reduction in growth due to water shortage ($\theta_t = 1$). Between w_p and cr_t , θ_t increases linearly, see also Fig. A.2. Versions of such models for growth-reduction due to water shortage can be found in, among others, LINTUL2/3 (Shibu et al., 2010), WOFOST (de Wit et al., 2019), STICS (Brisson et al., 2003), AquaCrop (Steduto et al., 2009) and a derivation thereof in Pelak et al. (2017).

For illustrative purposes, let us assume that there are no other growth-limiting factors and there are no growth-reducing factors. Under this assumption, the crop growth G_t at time $t \in \mathcal{T}$ can be modelled as

$$G_t = \theta_t G_t^*, \quad (\text{A.3})$$

where G_t^* is the maximum potential growth (due to growth-defining factors). As an illustrative example of a G_t^* , let us consider the crop growth model LINTUL2/3 (Shibu et al., 2010). In this model, the optimal growth is given by $G_t^* = \frac{1}{2} \lambda i_t (1 - e^{-\kappa L_t})$, where λ is the light-use efficiency in g MJ^{-1} , i_t is the total daily solar irradiation in MJ, κ is an attenuation coefficient and L_t is the *leaf area index* (LAI) at time $t \in \mathcal{T}$.

From (A.3), one might be inclined to assume that the crop growth has been separated into a part that is dependent on the soil water level (θ_t) and one that is dependent on the crop states (G_t^*), but there is an interplay between the soil water level and the crop growth. In the example with the LINTUL2/3 model mentioned above, it is clear that this occurs through the LAI (L_t), which is typically a state in most crop growth models. However, when doing MPC with a (relatively small) finite horizon of several days up to two weeks, many crop states do not vary much or their variation can be approximated. This allows the MPC to compute the optimal amount of irrigation needed for crop growth through θ_t , and the crop growth model can provide a reasonable approximation for G_t^* .

The last item we need to take into account is that the objective function J considers a ‘terminal cost’ as we require the crop state at the end of the season. It was shown in Schoonen et al. (2019) that a reasonable approximation is that the reduction of crop growth outside of the prediction horizon is equal to average reduction of crop growth within the prediction horizon. To this end, we perform two additional simulations, one where the growth is optimal from the current day to the end of the season, and one where there is almost complete stop of growth. Linear interpolation between the results of these two simulation by using the average crop growth reduction within the prediction horizon, yields an approximation for x_T .

In this way, we have limited the number of simulations to be done compared to a crop growth management system that uses Monte Carlo simulations, as it is only required to know (an approximation of) G_t within the prediction horizon and an approximation of the yield at time of harvest. Furthermore, we are now able to use the amount of irrigation as an optimisation variable, rather than discretising it as is done in the Monte Carlo setting. This is especially important in the setting where we do not wish to irrigate a single field, but multiple (sub)fields (more than 100 or 1000) using a limited number of irrigation machinery. We refer to the original work (Schoonen et al., 2019) for more information on the control in this setting.

This example only considered a single field, a single resource (water), and a single delivery agent. Farming considers many more (sub)fields, resources, and deliver agents. This introduces non-trivial constraints on the allocation that should be taken into account (see Schoonen et al. (2019)). Beyond such extensions, it is also of importance to consider the advanced applications as discussed in Section 4. It is evident that there are huge challenges for modelling, model-based management, large-scale control and optimisation, and estimation.

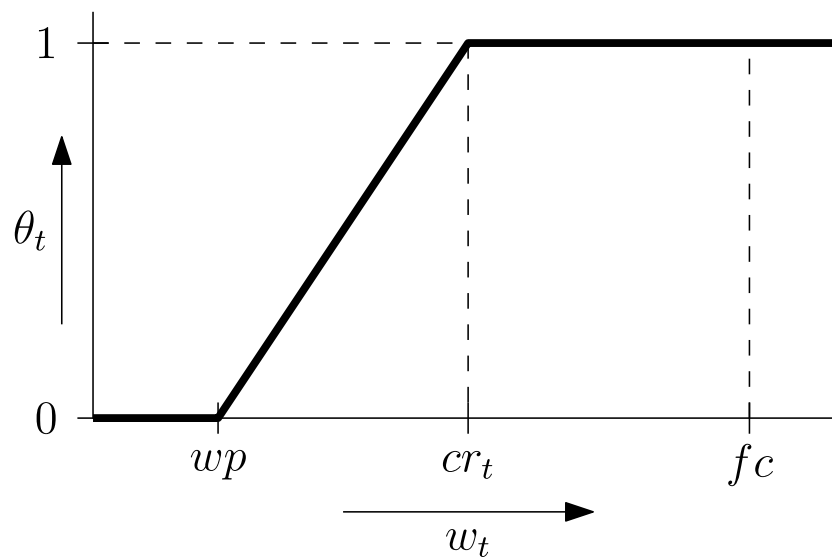


Fig. A.2. Dependency of growth-reduction factor θ_t on the soil water content w_t for a day t , where cr_t is the critical water level, w_p is the wilting point and fc is the field capacity.

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