Grand challenges for the 21st century: what crop models can and can't (yet) do

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Abstract

Crop production is at the core of a 'perfect storm' encompassing the grand challenges of achieving food and nutrition security for all, in the face of climate change, while avoiding further conversion of natural habitats for agriculture and loss of biodiversity. Here, we explore current trends in crop modelling related to these grand challenges by reflecting on research presented at the Second International Crop Modelling Symposium (iCropM2020). A keyword search in the book of abstracts of the symposium revealed a strong focus on 'climate change', 'adaptation' and 'impact assessment' and much less on 'food security' or 'policy'. Most research focused on field-level investigations and far fewer on farm(ing) systems levels – the levels at which management decisions are made by farmers. Experimentation is key to development and testing of crop models, yet the term 'simulation' outweighed by far the terms 'experiments' and 'trials', and few contributions dealt with model improvement. Cereals are intensively researched, whereas roots, tubers and tropical perennials are under-researched. Little attention is paid to nutrient limitations apart from nitrogen or to pests and diseases. The aforementioned aspects represent opportunities for future research where crop models can help in devising hypotheses and driving new experimentation. We must also ensure that crop models are fit for their intended purposes, especially if they are to provide advice to policymakers. The latter, together with cross-scale and interdisciplinary efforts with direct engagement of stakeholders are needed to address the grand challenges faced by food and agricultural systems in the next century.

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Introduction

Mankind is facing what could be termed a 'perfect storm': the grand challenges of achieving food and nutrition security for all in the face of climate change, while avoiding further land use change for agriculture coupled with loss of biodiversity and other ecosystem services. This is perhaps the most challenging perfect storm ever faced, in which crop production plays a central role. Therefore, what is the role of crop models and crop modelling in addressing the grand challenges?

Crop modelling has played a major role in the development of our basic understanding and underlying processes that have revealed the extent of the challenges faced. For example, crop models have been used to quantify the magnitude of crop yield gaps (van Ittersum *et al.*, 2016; Schils *et al.*, 2018), the gaps between food demand and availability (Keating *et al.*, 2014), and the land area needed to feed the population now and in the future (Gerten *et al.*, 2020), coupled with the potential need for expansion of agriculture into natural habitats if yield gaps are not closed (Stehfest *et al.*, 2019). Crop models have also proved indispensable in evaluating and selecting the most promising options for adaptation to climate change across the globe (Knox *et al.*, 2012; Rosenzweig *et al.*, 2014; Webber *et al.*, 2015). Yet, large knowledge gaps remain. Although approaches to simulate limitations of water and nitrogen availability on crop growth are well-established (e.g. Shibu *et al.*, 2010), much less attention has been placed on phosphorus or potassium limitations or on yield reduction due to pests and diseases (Donatelli *et al.*, 2017; Rötter *et al.*, 2018). Moreover, crop model development and application focused largely on the major cereal crops and much less on root and tuber crops or tropical perennials (Rosenzweig *et al.*, 2014; Beza *et al.*, 2017).

Crop models come in many forms and are designed for different purposes, ranging from understanding of physiological processes (Yin *et al.*, 2003; Chenu *et al.*, 2009) to the simulation of crop behaviour in the field (Jones *et al.*, 2003; Keating *et al.*, 2003; Steduto *et al.*, 2009). Crop models have also been deployed in the field of agronomy to inform operational decisions on water and nutrient management, to identify optimal sowing dates and to explore the feasibility of new cropping systems (e.g. Asseng *et al.*, 2014; Silva *et al.*, 2017b). There has been significant progress linking crop models with quantitative genetics (Yin *et al.*, 2003; Chenu *et al.*, 2009), with major genetic loci (Messina *et al.*, 2006; White *et al.*, 2008) or with remote sensing (Huang *et al.*, 2019), and in expanding the capabilities of the models to simulate

product quality (Nuttall *et al.*, 2017) and the impact of extreme weather events on crop growth (Rötter *et al.*, 2018), to name a few.

It is widely recognized that building 'model monsters' capturing all possible processes and integration levels is undesirable, if not impossible, as it tends to amplify errors and uncertainties. Yet, unravelling the grand challenges requires an understanding of constraints, synergies and trade-offs in crop production at different levels (van Ittersum *et al.*, 2003). Analyses of agricultural systems require attention to the crop, the cropping system, the farm system (including livestock), to farming systems (Giller *et al.*, 2006) and to regional scales (van Ittersum *et al.*, 2003). We are increasingly asked to think within a broader 'food systems' framework (Brouwer *et al.*, 2020), and considerable thought has gone into understanding how different integration levels can be linked (Ewert *et al.*, 2011; Passioura, 2020).

This paper does not intend to provide an exhaustive review of crop models and their strengths and pitfalls – for this, the reader is referred to the compendium on crop modelling of Boote (2019) and to the special issue on 'Next Generation Models' (Antle *et al.*, 2017). Our aim is to reflect on how crop modelling can contribute to address the grand challenges for the agricultural sector in the next century. To do this, we draw upon earlier experiences with crop modelling in Wageningen University and upon a keyword search in the book of abstracts of the 'Second International Crop Modelling Symposium' (iCropM2020) held on 3–5 February 2020 in Montpellier, France. The iCropM2020 is a central international scientific symposium for crop modellers although we acknowledge we miss important research in related fields by restricting our analysis largely to this conference. For this reason, we also highlight examples of research which we consider illustrative of problems and potential areas where future research should be focused.

Detailed information on the keywords search is presented in Table S1. The keyword search covered the whole book of abstracts of the 'Second International Crop Modelling Symposium' including abstracts, titles, acknowledgments, references and affiliations. If more than one keyword was found in an abstract, these were recorded as separate hits. We recognize the limitations of the approach taken, such as the occurrence of false positives which should be borne in mind when interpreting Fig. 1 and Table 1. Nonetheless, we consider the findings to be indicative of current research activities.

Grand challenges for the 21st century

Grand challenges for the next decades were framed in the Sustainable Development Goals (SDGs) of the United Nations (United Nations, 2015). In light of the SDGs, the agricultural sector is asked to contribute to ending hunger, achieving food security and improved nutrition through sustainable agriculture (SDG 2) while protecting, restoring and promoting sustainable use of terrestrial ecosystems and halting biodiversity loss (SDG 15) and, at the same time, taking action to combat climate change (SDG 13). Diverging paradigms regarding what to produce where, and how, is a fourth grand challenge for the agricultural research community in the years ahead.

Ensuring food and nutrition security for all

Analysis of 'food wedges' indicates that even if food losses are avoided and food demand is reduced through changing diets, at least 46% of future food demand in 2050 must come from increased food production (Keating *et al.*, 2014). The demand for food in the future will, no doubt, vary across regions, depending on projected population growth rates and improvements in economic well-being. For instance, the population of Africa is expected to grow exponentially until the end of the century whereas the population in Asia is expected to plateau in 2050 and decline thereafter (United Nations, 2019).

Satisfying the additional production needed to meet future food demand requires an understanding of the gap between the potential or water-limited yield and the actual farm yield currently achieved (van Ittersum *et al.*, 2013). The potential (Y_p) and water-limited yields (Y_w) are ceilings that indicate the maximum yields that can be achieved under irrigated and rainfed conditions, respectively. Mapping these yield ceilings for the main crops and growing regions provides, in effect, a planetary boundary for the maximum amount of food that can be produced. There is increasing evidence that crop yields of smallholders in Africa reach only ca. 20% of Y_w or less (Tittonell and Giller, 2013) while in Europe and North America actual yields approach 80% of Y_p or Y_w (Silva, 2017; Schils *et al.*, 2018; see also www.yieldgap.org). The causes of these yield gaps differ per region with the lack of inputs being a key determinant for smallholders in Africa (Sanchez, 2002; Silva *et al.*, 2019) and the timeliness and spatial distribution of the inputs applied being more important in Europe (Silva *et al.*, 2017a).

Product quality, health and nutrition are also gaining increasing attention in the analysis of food systems (Brouwer *et al.*, 2020). This is important to broaden the food security debate beyond staple (cereal) crops only and to assess the role of nutritional diversity as a key component of agricultural systems. It also helps to contextualize health and nutrition with other macroeconomic transformations such as rising incomes and a growing middle class.

Avoiding land use change and biodiversity loss

Closing yield gaps is essential to prevent future food demand being simply met through expansion of existing farmland (Foley *et al.*, 2011). Farmland expansion is undesirable given the associated biodiversity loss (Zabel *et al.*, 2019) and greenhouse gas emissions (van Loon *et al.*, 2019). In fact, the area of farmland under staple crops at the global level has expanded at the rate of 12.6 Mha/year during the period 2002–14, rates of change never seen before in human history (Cassman and Grassini, 2020). More than half of the increase in farmland is attributed to increased areas of rice, maize, wheat and soybean replacing natural ecosystems in Africa, South America and Asia.

Area expansion has indeed been the key pathway to increase production of staple crops in Africa, while in Europe and Asia increases in cereal production occurred through yield gap closure (data not shown). Despite the large land resources considered to be suitable for agriculture in Africa (Chamberlin *et al.*, 2014), it is important to spare land for nature and avoid greenhouse gas emissions associated with land clearing. This is particularly true, given that most biodiversity is found outside of protected areas in production landscapes managed by people, where agricultural expansion represents a serious threat (Baudron and Giller, 2014). Land sparing and land sharing are both realistic options to increase agricultural production while minimizing negative consequences for biodiversity, but the preferred pathway largely depends on local circumstances.
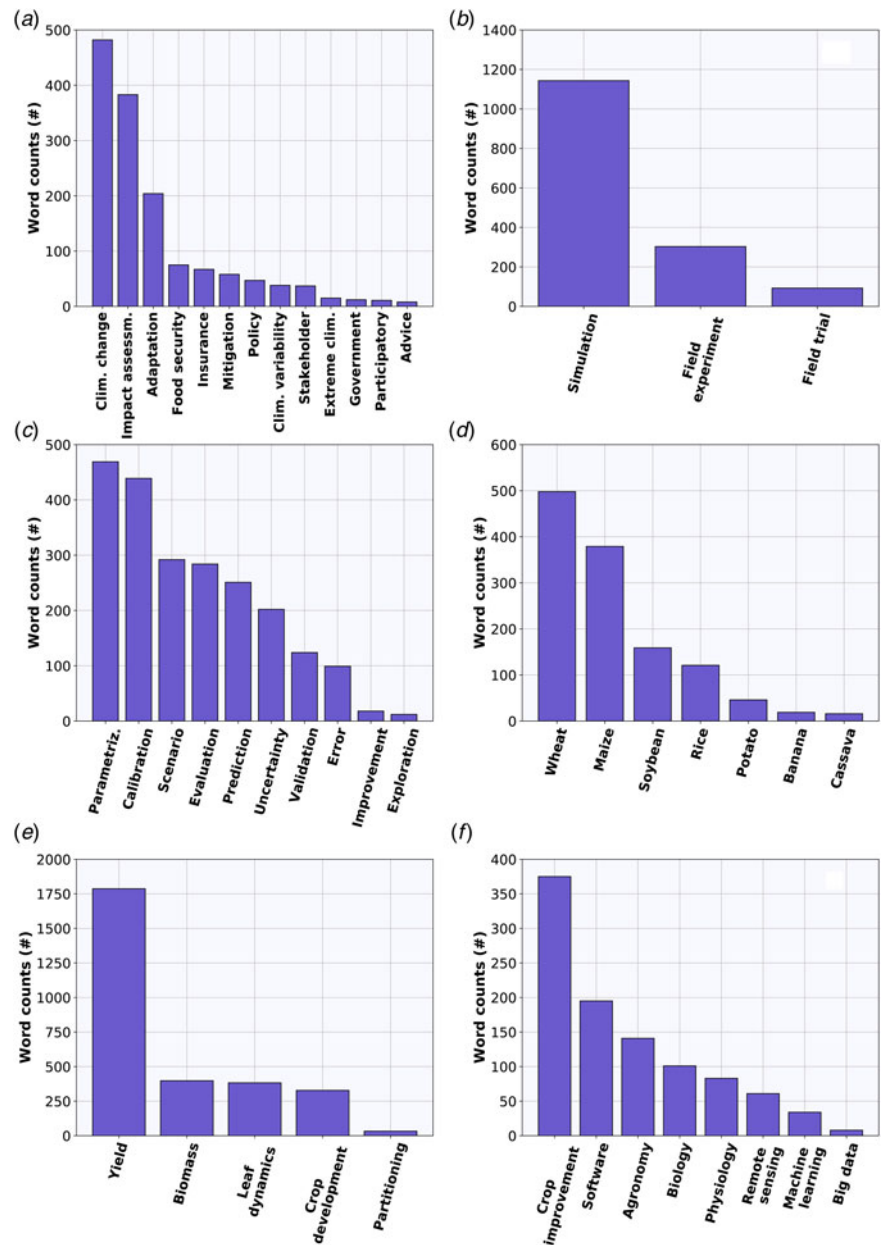
Fig. 1. Summary results of the keyword search in the book of abstracts of the iCropM2020: (*a*) research topics, (*b*) simulation and experimentation, (*c*) model applications, (*d*) focus crops, (*e*) crop traits studied and (*f*) core disciplines. Further information about the keyword search is provided in Table S1.

Climate change adaptation and mitigation

Climate change is expected to put global food supply on a razor's edge due to its negative impact on crop yields (Rosenzweig *et al.*, 2014) coupled with a future reduction in the area of land suitable for farming in the tropics (Ramankutty *et al.*, 2002). The steady increase of CO_2 and other greenhouse gases in the atmosphere over the last few decades is the main driver of the temperature rise and changing rainfall patterns and of the associated increases in climate variability and frequency of extreme weather events. Crop models have been widely used for climate change impact assessments and most evidence indicates rising temperatures are expected to negatively affect future cereal yields (Bassu *et al.*, 2014; Asseng *et al.*, 2015; Li *et al.*, 2015) and that this can be offset by a CO_2 'fertilization effect' to a certain extent (Long *et al.*, 2006).

Experimental field research through the 'FACE' experiments (e.g. Long *et al.*, 2006) has been of critical importance to understand the physiological responses of crops to changing temperatures and CO_2 concentrations. Given that experiments cannot reproduce the impacts of future climates with confidence, crop models are a key tool to understand and explore potential impacts of climate change on food production. To be credible tools, crop models must be based on solid physiological understanding of how crops respond to environmental signals – knowledge that can only be gained through detailed experimentation.

The keywords 'climate change', 'adaptation' and 'impact assessment' occurred 482, 383 and 204 times in the book of abstracts of the iCropM2020 (Fig. 1*a*). The aforementioned numbers were considerably larger than those for food security (*n* = 75), insurance (*n* = 67), climate variability (*n* = 38) or policy (*n* = 47). The data do indeed confirm the large number of crop model applications dealing with climate change adaptation and show an imbalance with other topics which would also benefit from the insights provided by crop models. Examples of the latter include exploratory studies mapping the suitability of a given

Table 1. Overview of growth factors that crop models can and cannot account for when simulating crop yields and hierarchical levels at which crop models have been applied

	Can/can't do	Frequency	Selected examples and references
Defining factors			
Radiation	✓✓✓	84	Proximal sensors to determine RUE (Chapman *et al.*, 2020)
Temperature	✓✓✓	284	Temperature effects at leaf-layer scale (Albasha *et al.*, 2020)
	✓✓	446	Soybean suitability in Europe (Nendel *et al.*, 2020)
Sowing	✓✓✓	172	Yield variability in a Mediterranean environment (Bassu *et al.*, 2020)
Total		986	
Limiting factors			
Water	✓✓	1226	Irrigation requirements of olive orchards (Lopez-Bernal *et al.*, 2020)
Nutrients (largely N)	✓	406	Multi-model comparison in Africa (Falconnier *et al.*, 2020)
Total		1632	
Reducing factors			
Pests	×	77	Population dynamics in maize models (Rasche and Taylor, 2020)
Diseases	×	63	Diseases in wheat models (Bregaglio *et al.*, 2020)
Weeds	×	90	Diversification and crop-weed canopies (Colbach *et al.*, 2020)
Total		230	
Hierarchical levels			
Field scale	✓✓✓	405	WOFOST calibration for Dutch potato cultivars (ten Den *et al.*, 2020)
Farm scale	×	314	Farm productivity and resilience in Malawi (Ngwira *et al.*, 2020)
Cropping system	✓✓	276	Rotations and climate change in Germany (Kersebaum *et al.*, 2020)
Farming system	×	18	No study was found dealing specifically with farming systems.
Food system	×	10	No study was found dealing specifically with food systems.

'Frequency' refers the number of keywords counted in the book of abstracts of the iCropM2020. References refer to abstracts included in the book of abstracts of the iCropM2020 and were selected for illustrative purposes. Peer-reviewed articles are cited for the contributions already published. ✓✓✓ = very well; ✓✓ = fairly well; ✓ = well; × = not very well.

region to introduce new crops (Nendel *et al.*, 2020) or resource-use efficiency assessments at regional scale (Silva *et al.*, 2020). We also note that most crop model applications currently target cropping systems ($n = 276$) at the field scale ($n = 405$; Table 1), with findings being often directly extrapolated to the regional level. Extrapolations from field to region are simple and attractive but they do not account for explanatory factors at the farm level, the most important decision-making level. To overcome this limitation, spatially-explicit crop models have been incorporated with farming systems modelling to evaluate trade-offs in management options while considering heterogeneity of farming systems (Capalbo *et al.*, 2017; Antle *et al.*, 2018; Descheemaeker *et al.*, 2020).

Current agricultural systems need to adapt and contribute to mitigate future climate change, and farmers are the people making key management decisions that drive that process. As such, it is critical to contextualize adaptation and mitigation options at a 'systems level' and within the broader livelihoods of farmers (e.g. Descheemaeker *et al.*, 2020). Our keyword search indicated a relatively high frequency of words associated with the term 'farm scale' ($n = 314$), but we note that more than two-thirds of these records refer to words such as 'farmer(s)' or 'farming' (data not shown), while the term 'farming system' received considerably less attention ($n = 18$, Table 1). Case studies in the Netherlands and Zimbabwe clearly indicate the need for farm and farming system level analysis (Descheemaeker *et al.*, 2020). The findings indicate that large farms are more likely to benefit from climate-smart agriculture technologies than small farms, and price variability or poor soil fertility are as important as climate change in explaining future farm performance (Descheemaeker *et al.*, 2020).

Diverging paradigms for the future of agriculture

The fourth grand challenge for agricultural scientists is to arrive at a consensus on what should be produced where, and how (Foran *et al.*, 2014). Different paradigms have been proposed to address these issues, all with their pros and cons (Wezel *et al.*, 2014). We are confronted by a plethora of approaches and definitions – ecological intensification, sustainable intensification, agroecology, agroecological intensification, organic agriculture, conservation agriculture, circular agriculture, regenerative agriculture – each with its own protagonists and flag-bearers. 'Alternative' approaches are often juxtaposed against an undefined 'conventional' or industrial agriculture claiming the high ground. We argue that although this polarization may help in scoring political points it helps little in addressing the problems facing humanity – dogma has no place in agronomy nor science at large (Giller *et al.*, 2017).

Diverging paradigms remain a contentious point and put considerable pressure on the prioritization of the research agenda needed to address the grand challenges introduced earlier, for which there is a general consensus. A solid, prioritized research agenda for the agricultural sector is needed to ensure that scarce

research funds are used effectively and to avoid that humanity is pushed towards short-term solutions in the medium- and long-term that may prove unsustainable.

What crop models can and can't (yet) do

Crop models to generate and test hypotheses

Approaches to crop modelling build upon three fundamental concepts: system, model and simulation (de Wit, 1993). A 'system' is defined as a limited part of reality that contains interrelated elements, and the totality of the relations within a system is known as 'system structure'. A 'model' is a simplified representation of a system, and both models and systems have a structure. Explanatory models are of particular interest as they build upon different levels of organization and knowledge. Explanatory models may be defined as dynamic or static, depending on whether or not they represent systems that change with time. Simulation models are a genre of dynamic models which consider changes in states and rates over time, whereas optimization models or statistical models are examples of static models. Finally, 'simulation' refers to the building of mathematical models and the study of model behaviour in reference to that of the system it represents.

Models can only be used to solve practical problems once they have been tested for their usefulness and once their errors and uncertainties have been quantified. Disagreements between model outputs and reality are to be expected as the conceptualization of the studied system and the development of a model to represent it involves simplifications and assumptions (de Wit, 1993). Such disagreements and model failures are the starting point for model improvement. Models are essentially complex hypotheses, and model testing and improvement involves the identification of the explanatory processes in the model responsible for an unacceptable representation of reality, and their modification. Experiments with both the model and the system are crucial in this regard as a means to generate new information that can be used to test and improve elements of the model. Model development and improvement are thus a continuous cycle of simulation and experimentation as new questions and hypotheses are generated and tested (see Rötter et al., 2018, for an example on weather extremes).

'No simulation without experimentation' is a mantra often attributed to C.T. de Wit. This proposition lacks a formal reference, but it is known to have been used by C.T. de Wit with 'characteristic conviction' (van Keulen, 2008). An extended version was later reformulated by Leffelaar (1987) as 'no simulation without experimentation' and 'no experimentation without simulation'. Rötter et al. (2018) recast the proposition as 'no modelling without experimentation and no experimentation without modelling'; yet 'simulation' is a much broader concept than 'modelling' alone (de Wit, 1993). During the iCropM2020, the propositions 'if you don't understand it you can't model it, if you don't model it you can't understand it' (Hammer, 2020) and 'we learn most when the models don't work' (Giller, 2020) were also proposed to highlight the role of crop models to generate and test hypotheses (Loomis et al., 1979).

C.T. de Wit's proposition remains highly relevant for the agricultural research community to remind us that simulation is as important as experimentation and that these two should go hand-in-hand at the core of a research cycle. Yet, this appears not to be reflected in the book of abstracts of the iCropM2020 (Figs 1b and 1c). Firstly, the number of records with the keyword 'simulation' (n = 1143) far outweighs those with 'field trials' (n = 93) or 'field experiments' (n = 303, Fig. 1b). Secondly, the number of records with terms like 'model parametrization' (n = 469) or 'model calibration' (n = 439) also far outweigh those with 'model evaluation' (n = 284), 'model validation' (n = 124) or 'model improvement' (n = 18, Fig. 1c). Thirdly, 'model prediction' (n = 251) is more common than 'model exploration' (n = 12, Fig. 1c). Field studies are expensive, laborious and unable to test multiple genotype × environment × management interactions (G × E × M), which crop models can do in a very cost-effective way. Yet, despite the aforementioned limitations, experiments provide the bedrock on which models are developed and remain crucial to re-calibrate models or test model improvements.

'Forgotten' crops, growth factors and traits

Many crop models have been developed specifically for cereal crops and most modelling exercises devoted their attention to cereal crops. This is justified given the large area share of cereals and their importance as a staple food in most regions. The iCropM2020 was no exception (Fig. 1d). Crops such as 'wheat' (n = 498), 'maize' (n = 379) and 'rice' (n = 121) featured much more prominently than 'potato' (n = 46), 'banana' (n = 19) or 'cassava' (n = 16, Fig. 1d). Highland banana, root and tuber crops are important staples for smallholders in Africa (Tittonell and Giller, 2013) which should not be neglected in food security assessments. This remains challenging because the crop models available for root and tuber crops lack proper field testing (Raymundo et al., 2014).

Tropical perennials such as coffee and cocoa are important cash crops that also have received remarkably little attention when compared with recent advances in experimentation and modelling of the major cereals (Rozendaal et al., 2020). Predicted impacts of climate change on future suitability regions for production of coffee (Ovalle-Rivera et al., 2015) and cocoa (Schroth et al., 2016) were initially based on agroecological characterization of current production areas and superimposing these on maps of projected future climates. Such approaches are highly relevant in the absence of robust crop models, and in the case of both crops indicated major geographic shifts, and reductions in land suitability due to climate change. Indeed, major reductions in yields of Arabica coffee have already been observed in East Africa due to rising minimum temperatures resulting from climate heating (Craparo et al., 2015). Development of a coffee crop model allows the interacting effects of drought, rising temperatures and CO_2 fertilization to be taken into account (Rahn et al., 2018), which should give greater confidence in projections of climate change impacts. Recent experiments in Brazil indicate that yield-enhancing effects of CO_2 fertilization may dampen and compensate for the negative impacts of rising temperatures and drought on coffee yield (DaMatta et al., 2019). Current research in Wageningen University is focusing on improving an existing cocoa simulation model (Zuidema et al., 2005) for use in climate change research.

The threats of climate change on future yields and production areas of coffee and cocoa are very real and of commercial interest to producers, traders and processors of these commodities. Such companies also have considerable experience and observations on which research can build, and which seem to defy our current physiological understanding of these crops. Research under controlled conditions suggests that the flowers of Arabica coffee are sterile at temperatures above 33°C (Drinnan and Menzel, 1995), yet it is currently grown with irrigation in Bahia, Brazil, producing

excellent yields in areas where maximum temperatures exceed 35°C during flowering, with peaks observed up to 39°C (Piet van Asten, personal communication, 2020). Similarly, cocoa produces very high yields (ca. 2 kg/tree/year)[1] with irrigation in Andhra Pradesh, southern India, where temperatures often exceed 46°C and sometimes even reach 50°C (Nicholas Cryer, personal communication, 2020). These are conditions where, based on current physiological understanding of coffee and cocoa, we would predict the crops should not be grown. Such observations in farmers' fields provide a perfect basis for collaboration between public institutions and the private sector to extend our knowledge of the climate responses of these crops. Such cooperation, if properly established to ensure open sharing of data and results, will be key to understanding options for adaptation to climate change.

Concepts of production ecology are useful to identify the relative contribution of growth-defining, -limiting and -reducing factors to actual yields (van Ittersum and Rabbinge, 1997). Growth-defining factors are essential to simulate the potential yield and their effects on crop production are captured well in crop models. The importance of defining factors was also reflected in the iCropM2020 as indicated by the number of records for 'radiation' ($n = 84$), 'temperature' ($n = 284$), 'variety' ($n = 446$) and 'sowing' ($n = 172$, Table 1). Growth-limiting factors are required to simulate attainable yields and crop models can simulate the effects of water and nitrogen limitation on crop production fairly well. Limiting factors received by far the most attention in the contributions to the iCropM2020, with terms associated with 'water' and 'nutrients' recorded 1226 and 406 times in the book of abstracts, respectively (Table 1). Growth-defining and -limiting factors (especially water) are the focus of most climate change impact assessments (Fig. 1a). By contrast, most crop models are unable to handle growth-reducing factors, the pests, diseases and weeds that are responsible for the gap between attainable and actual yields (Donatelli *et al.*, 2017). This was also noticeable in the iCropM2020 with relatively few records for terms such as 'pests' ($n = 77$), 'diseases' ($n = 63$) and 'weeds' ($n = 90$, Table 1). Regarding the traits investigated, by far the most focus goes to crop yield ($n = 1787$) followed by aboveground-biomass ($n = 398$), leaf dynamics ($n = 383$) and crop phenology ($n = 328$, Fig. 1e). Partitioning coefficients received almost no attention ($n = 33$) despite requiring re-calibration for recent varieties (e.g. ten Den *et al.*, 2020).

The capacity of crop models to simulate improved management practices increases with their capacity to simulate the effects of growth-limiting and -reducing factors on crop growth (cf. Tittonell and Giller, 2013). Although most crop models are able to simulate water- and nitrogen-limited yields under different management practices (e.g. amount, time and efficiency of application), little progress has been made in simulating phosphorus and potassium limitations and the interactions between these factors. An exception is found for cassava in West Africa, an example where simulation and experimentation were combined. The amounts of nitrogen, phosphorus and potassium required to achieve the potential yield of cassava (32 t DM/ha) were calculated using the QUEFTS model (Ezui, 2017). These nutrient requirements were used to design field experiments that were in turn used to parametrize, evaluate and improve the performance of

the crop model LINTUL in simulating cassava yields (Adiele *et al.*, 2021). When balanced nutrient requirements were provided, yields of 35 t DM/ha were achieved, the largest yields ever recorded in West Africa to the best of our knowledge. Indeed, the yield response to potassium was still linear at 300 kg K/ha suggesting that potential yields of cassava have been underestimated (Adiele *et al.*, 2020). Despite these efforts, interactions between potassium and water stress remain poorly understood. This is a clear example of model improvement where simulation was combined with experimentation and vice-versa with an application to a crop often neglected in food security assessments.

Hierarchical levels and farm(ing) systems research

Agricultural systems involve a large number of components and interactions among these components. It is thus useful to partition agricultural systems into nested levels to better understand their complexity (Ewert *et al.*, 2011). For such an analysis, it is assumed that each nested level shares the same time and spatial dimension so that components in a given level are nested into the components above them. Interactions between the different system components occur between hierarchical levels (e.g. between field and farm or farm and region) and between components in each level (e.g. multiple fields within a farm). Navigating through the different hierarchical levels requires updating space and time dimensions and involves different degrees of complexity.

Another key feature of agricultural systems is the importance of biophysical and socio-economic dimensions (van Ittersum *et al.*, 2008). In the case of a farm, the biophysical dimension plays a role at the field level where water and nutrients are used for production and may leak to the environment while the socio-economic dimension controls the decision-making process on how resources are allocated across the farm (i.e. crop and farm management). The latter includes strategic, tactical or operational decisions (de Koeijer *et al.*, 2003), which are subjected to farmers' objectives and resource constraints due to limited availability of land, labour and capital. Up-scaling between different nested levels requires information transfers within each dimension and between different dimensions (Ewert *et al.*, 2011). For instance, up-scaling from the field to the regional level requires up-scaling the biophysical processes dealing with crop growth at the field level and the socio-economic aspects controlling the decision-making process at the farm level. Missing the latter is not advisable as it implies missing the context where farmers operate.

Crop models are the engines most commonly used to up-scale biophysical processes in agricultural systems and thus provide the building blocks for integrated assessments at multiple scales. This was true in earlier *ex-ante* policy assessments at the farm and regional levels in Europe where crop models were embedded within the multi-layered and multi-dimensional approaches described above (van Ittersum *et al.*, 2008). The same applies to earlier efforts on modelling the effects of farmer decision-making under resource constraints in sub-Saharan Africa (van Wijk *et al.*, 2009), where a summary crop model was deployed to simulate attainable yields (Tittonell *et al.*, 2010). More recently, crop models have been combined with breeding and experimentation to explore whole-farm benefits of an early sowing system with slower-developing wheat cultivars in Australia (Hunt *et al.*, 2019). Rather than simply assuming the full yield benefits of the adapted crop management could be implemented across the whole area of wheat production, as it is often done, the authors took into account the time of sowing required across the huge

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[1]Cocoa in Andhra Pradesh, southern India, is grown intercropped with coconut, so yields are difficult to express accurately on a kg/ha basis, but probably represent somewhere between 1700 and 2000 kg/ha/year. For comparison, average yields in the major cocoa producing countries of West Africa are below 500 kg/ha/year.

Fig. 2. Risk assessment framework for quality assurance of models in Wageningen University and Research (cf. de Bie, 2019). Risk is calculated as the product of the probability of occurrence of a problem, and the impact of the occurrence of a problem. Unknown probability is ranked as high risk. Types of use are shown as guidance for the potential impact of a problem occurring. The reader is referred to the main text for a full explanation of this figure.

farms which cover several thousand hectares. By including these operational limitations, the overall yield advantage across the farm could be calculated, taking yield advantage of early-sown slow-developing cultivars and the larger area of fast-maturing cultivars sown in a timely fashion. These adaptation strategies increased wheat yields by 0.54 t/ha, equivalent to 7.1 Mt annually, at national scale and are the result of a close collaboration between farmers, breeders, field agronomists and crop modellers over more than a decade of research: 'An example of 'systems agronomy' at its best' (Giller and Ewert, 2019).

The philosophy underlying the use of crop models to understand farm level problems, as illustrated in the three examples above for contrasting farm(ing) systems, is not present in most climate change impact assessments presented in the iCropM2020 (Table 1 and Fig. 1c). Can crop models help us understand the farm level implications of adapting to, and contributing to mitigate, the negative impacts climate change? And how can these models be contextualized in concrete farm(ing) systems applications?

Core disciplines and emerging technologies

Most crop model applications are within the realm of agronomy and crop improvement, followed by plant biology and physiology (Fig. 1f). These were indeed the disciplines within which models were developed and have proven to be useful research tools (Jones et al., 2017). Combining crop models with technologies such as remote sensing, machine learning and opportunities of big data for model parametrization were also reported during the iCropM2020 (Fig. 1f). Such applications often require new types of models or the re-packaging of old models in new programming languages that facilitate their integration with new types, and large amounts, of data (e.g. de Wit et al., 2019). Emerging technologies will contribute to increase the efficiency and accuracy of crop models in the future to design sustainable agricultural systems at farm and landscape scales (Basso and Antle, 2020).

New sources and large amounts of data are becoming available for crop modelling, allowing for the application of crop models at greater spatial and temporal resolutions. For example, combining spatial data from remote-sensing imagery with crop models allows for better estimates of crop yield, water use and N uptake across large scales (Huang et al., 2019), which can be helpful for

planning logistics and analysing markets of crops across large farms or regions. Machine learning has already proved helpful to calibrate crop models for specific genotypes based on large amounts of phenotyping data (Chapman et al., 2020). At another, finer scale, detailed models of plant components dealing with, for example, root morphology in relation to nutrient uptake and of leaves to gas exchange and photosynthesis can play a major role in understanding plant plasticity in relation to environmental changes. The same is true for functional-structural plant models (Vos et al., 2009) which further allow studying resource competition between crops or devising management options for operations that manipulate plant structure such as pruning (Tosto et al., 2020). Crop modelling is also now being used in CGIAR research programmes to inform and accelerate breeding programmes (Ramirez-Villegas et al., 2020) and to analyse socio-economic factors to improve policy recommendations (Kruseman et al., 2020).

Policy advice and the credibility of science

Quality assurance of (crop) models is important to minimize the risks of public disputes about data and model quality, particularly when studies are designed to provide policy advice or steer public opinion. Model (and data) quality is key to the credibility of both the research done and the advice provided and serves as an entry point for discussion on model saliency and legitimacy. Credibility refers to the scientific logic of the model and the soundness of the used knowledge (*is the thing done right?*), saliency to the societal and political relevance of the use of the model (*is this the right thing to do?*) and legitimacy to the fair representation of the views, values and concerns of stakeholders in the model used (*is there a right to do this?*; van Voorn et al., 2016).

Within Wageningen University and Research, models are used in all manner of ways, often specifically to provide policy support under contract from the Dutch government. This has led to the development of an internal system of model quality control that assesses potential risks involved when advice is provided (de Bie, 2019). For each model a risk assessment is made based on the probability whether a problem might arise and the potential impact if a problem actually does arise (Fig. 2). Most academic research is situated at the left side of Fig. 2, focused on exploratory research which is published in peer-reviewed papers. Research

conducted specifically to support decisions on thorny and contentious issues, that require regulation, is situated at the top right-hand side of the figure, where incorrect policy advice can have strong impacts on society (Fig. 2). Outputs generated specifically for policy advice are thus subjected to close scrutiny and detailed review before being released to policy makers. To qualify for such policy support purposes, researchers must provide the code and detailed documentation of the model, perform sensitivity analysis to study model behaviour, be open about the capabilities of the model and about what has been tested (or not) and provide guidance on how model outputs can be interpreted. Only then can the model be used for policy advice, as these steps should ensure the credibility, saliency and legitimacy of the model.

Even with such safeguards in place, problems still arise from time to time. In 2020, the Dutch economy ground to a halt because of a court case that ruled the government was not taking sufficient steps to control atmospheric nitrogen deposition, which was causing loss of biodiversity in nature. This led to thousands of farmers disrupting traffic and protesting in the centre of the capital city, cessation of building projects throughout the country and changes in the maximum speed allowed on the motorways. It also led to detailed scrutiny and critique of the models used to calculate nitrogen deposition (Hordijk *et al.*, 2020). As part of the scientific debate behind this issue it became clear that the models were robust enough for use at national or regional scale, but too uncertain at the finer scale needed to assess local interventions (de Vries, 2020; Hordijk *et al.*, 2020). This stoked considerable controversy as to how to design the correct policy and interventions to reduce nitrogen deposition.

Climate change rightly deserves a central focus of research and policy efforts as it is undoubtedly one of the grand challenges facing humanity. Yet, current climate change impact assessments with crop models involve large uncertainties arising from different modelling approaches (Bassu *et al.*, 2014; Asseng *et al.*, 2015), physiological responses of crops to environmental conditions (Allen *et al.*, 2020), calibration protocols (Seidel *et al.*, 2018) or input data (Nissan *et al.*, 2019). Indeed, modelling the effects of weather extremes on crop growth, and their interaction with future climate change, is challenging (Rötter *et al.*, 2018), and crop models are ill-equipped to simulate such events. Moreover, the climate change projections widely used in climate change impact assessments suffer from errors in capturing local conditions, have problems downscaling global estimates to finer resolutions and are characterized by deep uncertainty, which renders them unfit for decision-making at the local level (Nissan *et al.*, 2019). Of particular concern is that studies of climate change impacts on crop production often focus on longer time scales (several decades). At such time-scales, climate projections are highly uncertain and management options may indeed be maladaptive in the short term. For example, East Africa is predicted to get wetter in the long term, but drier for the coming decade for which immediate action is required to reduce the risk of crop failure (Nissan *et al.*, 2019).

Referring to Fig. 2, although researchers are often working on exploratory research (i.e. the left side of the figure), there is always a temptation to suggest what this could mean for policy. This means results are often picked up in the news and by politicians and used for other purposes (i.e. the right side of the figure), although the models and their outcomes have not been subjected to the scrutiny that would normally be expected for policy support processes. Nissan *et al.* (2019) recommended that, before making claims of the relevance of research for policy, whether for adaptation or mitigation of climate change, modellers should engage in participatory research with stakeholders focusing on the time scales relevant for their decisions, recast long-term decisions or shorter time frames or stress the system under hypothetical weather scenarios to identify high sensitivities to small changes in weather. Such an approach would imply embedding climate change impact assessments with crop models within the multi-layered and multi-dimensional approach characteristic of earlier integrated assessments (van Ittersum *et al.*, 2008), certainly when the goal is to derive policy implications or to propose adaptation and mitigation options for farmers.

Crop models will also have a major role in defining how much food can be produced on the planet currently and under future climate change. To do so, however, models need to be improved for simulating the effects of other growth-limiting and -reducing factors on crop growth (cf. Table 1) and expanded to cover other important staples such as root and tuber crops and highland banana (Fig. 1*d*). Moreover, food production assessments cannot rely on global gridded crop models as these are not rigorous in their account of crop physiological processes and agronomic management (van Ittersum *et al.*, 2013). For this reason, bottom-up protocols are employed in the Global Yield Gap Atlas (www.yieldgap.org) to map yield ceiling and yield gaps at regional scale. Yet, it still remains important to contextualize such assessments at regional scale within broader farm and farming systems aspects. Only then one can grasp the scope to increase yields and resource-use efficiencies in relation to the management decisions and farmers' personal objectives (Silva, 2017).

We hope the examples highlighted above will serve to remind crop modellers that model simulations need to be embedded within a well-described context. The latter includes thorough experimentation in case of model improvement, quality assurance of the models used given the purpose of the simulations and participatory work with stakeholders when exploring options to adapt to and mitigate future climate change. More than ever, rigorous and high quality research, which documents its limits and uncertainties, is needed to inform policy and society at large and avoid the misuse of scientific evidence by different stakeholders.

Conclusion

Grand challenges for the 21st century include ensuring food and nutrition for all while avoiding land use change and biodiversity loss and adapting to and mitigating the negative impacts of climate change. Diverging paradigms regarding what to produce where and how is another important feature of this perfect storm. Crop models are a core tool to explore plausible futures for food security and climate change adaptation and to deepen our understanding on how crops respond to abiotic and biotic stresses. Despite their proven usefulness, it is also evident that current crop models need improvement and that a continuous research cycle of simulations and experimentation is needed. Future research should prioritize the development of crop models for crops other than cereals (e.g. root and tuber crops and tropical perennials) and to expand current capabilities of crop models (i.e. simulation of potential, water-limited and nitrogen-limited yields) to simulate limitations of phosphorus and potassium and yield reductions due to pests and diseases. Moreover, attention should also be paid to simulate processes at cropping systems level and to contextualize model applications within broader farm(ing) systems and food systems aspects.

To ensure that crop models fulfil their promise to support policy and decision making, the research cycle of simulation and experimentation must be broadened. Close collaboration among different disciplines is required with active participation of the private sector and policy makers and due attention to ensure model quality is fit for purpose. Only then will crop modelling be able to contribute fully to addressing the grand challenges faced in our food and agricultural systems.

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