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1 Introduction

Climate change has become a major concern, especially for agriculture (Wiebe et al., 2019). The IPCC Sixth Assessment Report (AR6) projects that global surface temperature will continue to increase until 2100 by +1.0°C to +1.8°C under the very low greenhouse gases (GHG) emissions scenario (SSP1-1.9) and up to +3.3°C to +5.7°C under the very high GHG emissions scenario (SSP5-8.5), compared with 1850–1900 (Porter et al., 2014; IPCC, 2021). As global

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temperature rises, the rainfall regime will be significantly altered. Precipitation is likely to become more variable across regions, with an increase in high latitudes and a decrease in parts of the subtropics. Changes in atmospheric circulation and wind speed are also expected (Zeng et al., 2019; Abell et al., 2021). Beyond the changes in mean variables, the intensity, frequency and severity of extreme weather events such as heavy precipitation, flooding, drought and heatwaves are likely to become amplified (IPCC, 2021), but these events are generally difficult to predict (Sillmann et al., 2017).

Although there is uncertainty with regard to the nature, timing and extent of climate change impact, there is a general consensus that the combined effects of increasing temperatures, changing precipitation patterns and elevated carbon dioxide (CO_2) concentrations will affect agricultural and livestock production (Escarcha et al., 2018; Makowski et al., 2020), and that the effects of extreme climate events are likely to exceed those estimated from changes in mean variables (Tubiello et al., 2007). On a biophysical level, increased temperatures accelerate plant growth and development, leading to shifts in plant phenology and growing periods (Gong et al., 2021). Rising temperatures also increase soil evaporation (Abtew and Melesse, 2013), diminish soil moisture (Grillakis, 2019) and increase the water requirement of plants. Changing climatic conditions may also affect the geographical distribution of crops and crop pests (i.e. insects, pathogens and weeds) and outbreak severity (Lamichhane et al., 2015), and facilitate the spread of animal diseases and pests from low to mid-latitudes (Tubiello et al., 2007). The occurrence of climate shocks, such as heat or water stress during critical stages of plant development, could have deleterious effects on yields (Zampieri et al., 2020). A meta-analysis estimated that without implementing adaptation measures, future climate trends and variability are likely to result in higher crop yield variability and aggregated yield losses for the most commonly grown cereals (rice, wheat and maize) (Challinor et al., 2009). It may also impair crop quality, e.g. reduced grain protein and mineral nutrient concentrations and altered lipid composition (DaMatta et al., 2010). Climate change may also be a threat for livestock production because of its impacts on feed crop and forage quantity and quality, animal growth and milk production, animal reproduction, health and mortality (Thornton et al., 2009; Nardone et al., 2010; Rojas-Downing et al., 2017a). Beyond the impact on plant and animal physiology and food quality, climate change may also alter land suitability for crop production (Ramirez-Cabral et al., 2017; Paola, 2018) and changes in hydrological cycles may drive an increased risk of soil erosion (Borrelli et al., 2020).

Climate change is also likely to have socio-economic impacts at farm, local and global levels. Changes in crop productivity could affect farmers' income and threaten food security (Schmidhuber and Tubiello, 2007). In

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addition, adverse weather shocks can result in an increase in food prices and price volatility (Hertel, 2010; Nelson et al., 2014), which could affect farmers' income and their cropping decisions, and disrupt food supply and the global agricultural market (Porfirio et al., 2018). Studies have also shown that extreme climate events such as drought can alter farmers' risk preferences regarding climate change (Bozzola and Finger, 2021), which may lead to investments in low-risk, low-return activities (Dercon and Christiaensen, 2011).

Climate-smart agriculture (CSA) is promoted as an approach to transform and reorient agricultural development to address the impacts of climate change (Lipper et al., 2014). CSA is defined by the FAO as a set of actions that (FAO, 2010):

1 sustainably increases agricultural productivity;
2 builds resilience to climate change from the farm to national levels (adaptation); and
3 reduces or removes GHG emissions (mitigation) while enhancing the achievement of national food security and development goals.

Mitigation encompasses crop and livestock management strategies, increases soil and biomass carbon storage (e.g. by introducing cover crops and developing pasture-based systems) and reduces energy and fertiliser nitrogen (N) use (e.g. reduced tillage or using legumes; better housing and manure management in livestock systems). Adaptation strategies range from small adjustments to the redesign of entire systems (Willaume et al., 2014) that aim to reduce the vulnerability of agricultural systems to climate change, i.e. 'the degree to which a system is susceptible to, and unable to cope with, adverse effects of climate change', which is a function of exposure, sensitivity and adaptive capacity (IPCC, 2022).

For livestock systems, adaptation measures include modifying periods and frequencies of grazing, stocking rates, timing of reproduction, using more heat-tolerant livestock breeds (Rojas-Downing et al., 2017b) and increasing animal and grassland diversity (Martin and Magne, 2015). Adaptation strategies in cropping systems encompass the selection of species and varieties that are better adapted to extreme climate events and resistant to pests and diseases, the use of climate forecasting, adjustment of fertiliser rates, amount and timing of irrigation, the location and timing of cropping activities, diversification of cropping systems (e.g. more diverse rotations) and the use of new technologies and practices that improve water use efficiency, maintain soil moisture and prevent water erosion (e.g. through Conservation Agriculture) (Tubiello et al., 2007; Debaeke et al., 2017).

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2 Understanding models and their application to problems such as climate change

Models are partisan and simplified representations of reality (Bouleau, 1999). By partisan, we mean that the model is the result of choices made by the modeller for a given purpose and hypothesis. These are *a priori* choices about the representation of the processes to be described, the state variables chosen and the form of the equations describing the behaviour of these variables. By simplified, we mean that a model is a representation or an abstraction of a piece of reality which does not represent the overall complexity of the systems studied and the many ways elements in the system function and interact.

Since the infancy of modelling (Whisler et al., 1986; Sinclair and Seligman, 1996), when models were mainly a way to gather knowledge and test assumptions, the use of models has become more widespread. Models make it possible (Van Ittersum and Donatelli, 2003):

1. to represent and order new knowledge not yet acquired (conceptual operating models);
2. to synthesise knowledge (acquired through experimentation or bibliographical research);
3. to predict the evolution of systems under untested conditions (virtual experiments, forecasting);
4. to challenge different knowledge (points of view) and identify new ideas for reflection and research; and
5. to provide a tool for understanding and negotiating trade-offs as well as for capacity-building.

Use of the possibilities offered by the models thus depends on the purpose of the model: knowledge (scientific world) or innovation (transfer in the socio-economic world). Other aspects related to modelling work that have also changed significantly include:

1. new sources of data to build models (e.g. remote sensing, field sensors, high-throughput phenotyping in platforms, etc.) and (in some cases) a huge flow of data obtained at high speed or on a large scale (crowdsourcing);
2. evolution of software engineering, including the development of coupling solutions, interoperability and modelling framework;
3. new ways of using models (from on-lab modelling to participatory modelling, ensemble modelling, surrogate models, etc.); and
4. improvement of computer performance, development of cloud computing and the evolution of programming languages.

When discussing modelling in this chapter, we do not include only classical differential or difference equation types of model. All types of modelling (statistical models, process-based models, data-driven models, Bayesian model, finite-state and Petri network models, agent-based models and so on) share similar basic issues such as a necessary level of simplification and abstraction.

The impact of climate change on agricultural systems, as for other processes, requires specific understanding, hypotheses and types of knowledge. Models are well designed to reach such goals. The use of simulation models to explore the impact of climate change and assess the effects of mitigation and adaptation strategies has grown over time, and a review for two crop system models (APSIM and DSSAT) showed that climate change has become one of the largest fields of application (Keating and Thorburn, 2018). However, when dealing with climate change, certain modelling aspects need to be considered:

1 New processes and an extended range of environmental factors have to be integrated as current knowledge is not sufficient to deal with the expected climatic impacts on living organisms and agricultural production.
2 A transition phase is an important element as the adaptation to climate change is a long, dynamic process compared with the annual cycle of farming systems and related incremental decisions. Simulated indicators, showing the evolution of the states of the farming systems, have to be developed.
3 Adaptation of farming systems requires multi-criteria assessment and a focus on some processes that require new models.
4 Mitigation of farming practices to reduce climate change is an important feature that needs modelling, as well as the synergies and trade-offs involved in adaptation strategies.
5 The climate in coming years is still uncertain regarding e.g. the spatial and temporal distribution of rainfall or extreme events. Therefore, stochastic modelling needs to be taken into account.
6 In the case of adaptation and mitigation, the needs of decision-makers are crucial. Specific modelling of decision-making processes and adaptive behaviour modelling are therefore necessary.
7 New types of simulations for different scenarios (to reflect the needs of different stakeholders, institutions and policymakers) require innovative approaches to simulation.

This chapter has the following structure. In the first section, we describe an 'ideal' conceptual model to consider every aspect of the effects of climate change on agriculture. We will highlight the operational challenges of such an approach considering the general climate change issues we described earlier. In the following sections, we describe advances in modelling relating to climate change and agricultural production. These sections are based on real modelling exercises and show current advances in integrating different models assessing the impact of climate change on agriculture. In the final section, we highlight missing elements and provide some guidance to moving towards a more complete toolbox for modelling impacts, adaptation and mitigation of agricultural systems facing climate change.

In the following sections, we will use the terms 'system' and 'sub-system' to describe the conceptual entities of the modelled entity (systemic approach), and module and sub-module for the implemented model. The resulting model is, therefore, composed of modules and sub-modules. Simulation is used when a model is run.

3 The 'ideal model' to assess the impact of climate change on agriculture

The agricultural system is composed of a central sub-system, the farm, which interacts with its local environment but is also dependent on more global factors. In theory, to comprehensively model the impact of climate change on agriculture, all these components and their interactions should be represented in a conceptual framework. On each scale (farm, local and global), biophysical and socio-economical sub-systems should be identified (Fig. 1).

At the farm level, biophysical systems are numerous and complex. Plants, animals and soil behaviour can be modelled at different scales (plant to field, animal to herd). They can be modelled within the cropping system or livestock system separately or combined (fodder/manure system). Management is also an important part of this farm system and is driven by the socio-economical sub-system of the farm, i.e. the farmer and resources (financial, workforce, land, equipment etc.). This can be represented by fixed values (i.e. amount of fertiliser, date of sowing, grazing periods, feed ration) or decision rules (i.e. irrigation strategy, crop and variety choice, breeding strategy for animals). Farmer's decisions occur at several levels in time (i.e. planning and investment, strategy and tactical responses) and in space (i.e. field level, crop planning on the farm, animal stocking rate). Each component of these systems can be described in detail or in outline.

The farm is an open system interacting with biophysical and socio-economical sub-systems that can also be affected by climate change. Farms are nested in a landscape and within a hydrological system. These three sub-systems affect, and are impacted by, surrounding biodiversity, either wanted (e.g. pollinators) or unwanted (pests and diseases). The surrounding socio-economical environment of the farms should also be considered in an

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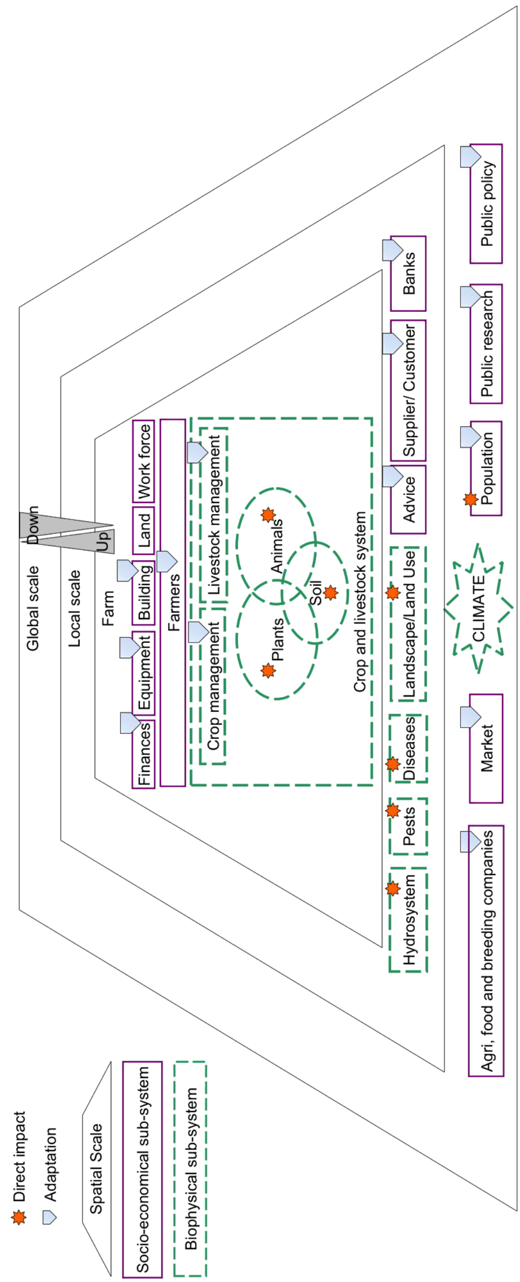

Figure 1 'Ideal' conceptual model to deal with climate changes. All sub-systems and their interactions should be represented.

'ideal model', including interaction with advisors, support from banks and relationships with suppliers/consumers, taking into account their organisation and dynamics. The farm is also influenced by more global phenomena such as market dynamics and regulation, population growth and food security, public policies and subsidies and advances in research. Breeding companies influence farms by disseminating cultivars better adapted to new environments, while agro-food chain companies also provide inputs to the system. Climate change also operates at a global scale. This complex environment represents a system in nested scales with different levels of organisation to model, raising the issue of upscaling and downscaling. Modelling on such a large spatial scale also implies representing a large temporal scale since both are linked (Ewert et al., 2011).

The impact of climate change on agriculture will mainly modify the biophysical sub-systems at various scales (field level, landscape level, etc.). These effects should be modelled whatever the climatic event (temperature rising, drought, flooding, storm, increased carbon dioxide, etc.). The 'ideal model' should also be able to combine the effects of adaptation and mitigation measures designed and applied by all socio-economical actors at the various scales. Time is also a crucial component, since some effects may be cumulative over time or transitory.

Ideally, this model should be parsimonious, i.e. it should be as simple as possible in design and computing power required, simple to understand and easy to handle and use. It should be easy to calibrate ; be robust in a wide range of soil, climate and agronomic conditions ; and require little data to initialise new simulations. The calculation time should also be minimised to allow multi-simulation over large ranges of situations or spatial areas.

To build such a model is quite challenging, as it is like a 'labyrinthine system'. However, this representation could be used as a toolbox in which one can select the necessary sub-systems to consider in order to address a specific question. Depending on the objective, it is not necessary to model all sub-systems with the same level of detail.

We have described the different components and organisation levels of the agricultural system with a focus on the farm. Numerous interactions exist between the system components and the environment, which have not been accounted for in this approach. Besides climate change, many biophysical and socio-economic dynamics influence farms leading to emerging properties and unexpected behaviour of the whole system. The complexity of this system has generally to be simplified for modelling purposes.

The impact of climate change is often quantified by simulating variables of interest (e.g. crop production, GHG fluxes, etc.) under climate projections at regional or national levels considering near- or far-future climatic scenarios by way of statistical or process-based models applied to croplands or grasslands

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(Challinor et al., 2009; Lobell and Burke, 2010; Rosenzweig et al., 2014). In finer resolution approaches, management (sowing date, crop species, variety, grazing period, stocking rate, irrigation, etc.) is used as input data for site-specific or gridded approaches (White et al., 2011; Lehmann et al., 2013). Less frequently, models also include the decision process, the cropping plan or the farm structure, which allow evaluation of incremental or systemic adaptations to climate change in terms of production, management and land use (Holman et al., 2019). All these approaches simulate the effect of climate change on crop production but at different levels, with differing resolutions and based on various sources of information.

It is often not necessary to represent every part of the system to assess the impact of climate change on a specific part of the agricultural system (such as crop yield, nitrate leaching or calf production, for instance) or to evaluate the impact of adaptation measures. Only some sub-systems are needed to make this assessment depending on the specific objectives of the study or the scenarios to be tested. The level of detail in each sub-system varies and depends on the objectives and accuracy requirements in the simulation, from a very simplified to a more refined representation. The end use of the model is an important element to consider when designing such models to keep them useful (Prost et al., 2012).

Building a model on a large spatial and temporal scale by integrating all the different levels of organisation is extremely challenging. It raises issues regarding lack of knowledge of all the different processes (and quite often interactions between entities), of having data of sufficient accuracy and on a sufficient scale to calibrate, evaluate and run the model, all of which could compromise the accuracy of the results. Nevertheless, some attempts have been made to integrate several to almost every dimension(s) of the agricultural system. The various modelling choices have different advantages and limits that will be detailed in the following sections.

4 Implementing the 'ideal model': current approaches

Implementing the 'ideal model' is a dual challenge given:

1 the integration of a large number of scientific disciplines; and
2 technical implementation requirements.

Nevertheless, there have been several examples developed over the last few decades. The majority have been initiated because stakeholders need an estimation of the impact of climate change on agriculture using multi-criteria assessment. They also need information to build new public policies (e.g. the EU Green Deal for a more climate-smart European agriculture) and devise adaptation and mitigation solutions.

The SEAMLESS-IF modelling framework (Van Ittersum et al., 2008) is a good example of the implementation of such an 'ideal model'. It is the result of exchanges between the scientific community of agronomic and economist modellers and the European Commission. The SEAMLESS-IF framework is based on the concept of Integrated Assessment and Modelling (IAM) (Parson, 1995; Harris, 2002; Parker et al., 2002). Operational IAM is part of the systems analysis paradigm which is seen as a way to model the biophysical, economic, social and institutional aspects of a system in an integrated and balanced way.

Other models include AROPAj (Barberis et al., 2021) and GlobAgri-WRR (Le Mouël et al., 2016) used in different European studies. GlobAgri-WRR is a global accounting and biophysical model that is designed to quantify GHG emissions and land-use demands related to agricultural production for specified levels of diets, population, non-food uses, food loss and waste and production systems (techniques, crop yields) in every country of the world. It incorporates several biophysical models (e.g. a global livestock industry model, a European Commission Joint Research Centre [JRC] land-use model, a nitrogen emissions model, etc.) but does not consider economic feedback effects. GlobAgri-WRR has primarily been used to estimate how changes in demand or production (from climate change impacts or new production methods) might impact land-use demands and GHG emissions (Searchinger et al., 2019). Such frameworks also make the links between micro-level (field-farm-small region) and macro-level (market or sector).

More recently, 'user-friendly' tools have been developed, such as the Integrated Assessment Platform (IMPRESSION) (https://climate-adapt.eea.europa.eu/metadata/tools/climsave-integrated-assessment-ia-platform). This tool offers a web interface, directly usable by European stakeholders, to explore the complex multi-sectoral issues surrounding impact, vulnerability and adaptation to climate and socio-economic change across Europe.

At the regional or watershed scale, some models have been developed following the philosophy of the 'ideal model', such as the MAELIA platform (Catarino et al., 2021) or MOSAICA model (Chopin et al., 2015). The MAELIA platform enables the assessment of the environmental, economic and social impacts of combined changes in agricultural activities (e.g. recycling of biomass), natural resource management strategies (e.g. water) and global drivers (e.g. dynamics of land cover and climate change). It aims to design sustainable strategies for water resource management within a watershed in the uncertain context of global change. The MOSAICA model aims to understand the effects of policy changes on cropping systems at the regional scale and their contribution to the sustainable development of regions. It explicitly incorporates information at field, farm, sub-regional and regional scales to provide cropping system mosaics by way of regional optimisation of the sum of the individual farmer's options under field, farm and territory biophysical and socio-economic constraints.

It is important that integration is achieved without favouring one aspect of the system over another, since biases are often observed in integrated assessments towards economic, biophysical or environmental issues (Van Ittersum et al., 2008). Britz et al. (2014) distinguish several approaches in a context of design of public policies: bio-economic farm models (BEFMs), multi-agent models, life cycle analysis and agri-environmental impact simulation. For example, BEFMs have been widely used and are a specific form of model that aims to optimise resource management decisions by the farmer, in relation to inputs and outputs. Used for public policy issues, they integrate different scales and are linked to a partial equilibrium model, e.g. CAPRI-FT (Britz and Witzke, 2014), IFM-CAP (Louhichi et al., 2017), FARMDYN (Britz et al., 2014) and FSSIM (Kanellopoulos et al., 2014). Even if these models are operational and have been used in different projects, they are still based on basic assumptions and simplifications (e.g. an inflexible representation template of farm processes, a limited number of farms not necessarily representative of all the farms in the territory, etc.), which may be a limitation to their use in a climate change context.

5 From ideal to pragmatic modelling of climate change: coupling sub-models

Modellers have to adopt a systemic approach but limit the complexity of the system representation by selecting the relevant spatial and temporal granularity or the appropriate interactions, depending on the issue they want to address. Over the last decade, we have observed a trend in promoting this approach to develop pragmatic modelling approaches to climate change analysis (Gouttenoire et al., 2011; van Oosterzee et al., 2014; Ewert et al., 2015; Ghahramani and Bowran, 2018; Naulleau et al., 2022). This pragmatism often leads to selecting and linking specific existing models. The subsequent model is therefore the result of coupling:

1. Sub-modules coming from other models (recycling existing knowledge);
2. New sub-modules developed as required by a project (new knowledge); and
3. specific interfaces for the engineering aspects of coupling and management of inputs and outputs.

Coupling refers to communication and interchange of information between sub-modules. As noted by Siad et al. (2019), the way the sub-modules are coupled varies greatly, depending on the expected outcomes but also on the possible computational techniques.

We have distinguished a gradient in the levels of coupling (Fig. 2). The first case concerns where models are chained: the principle of modelling

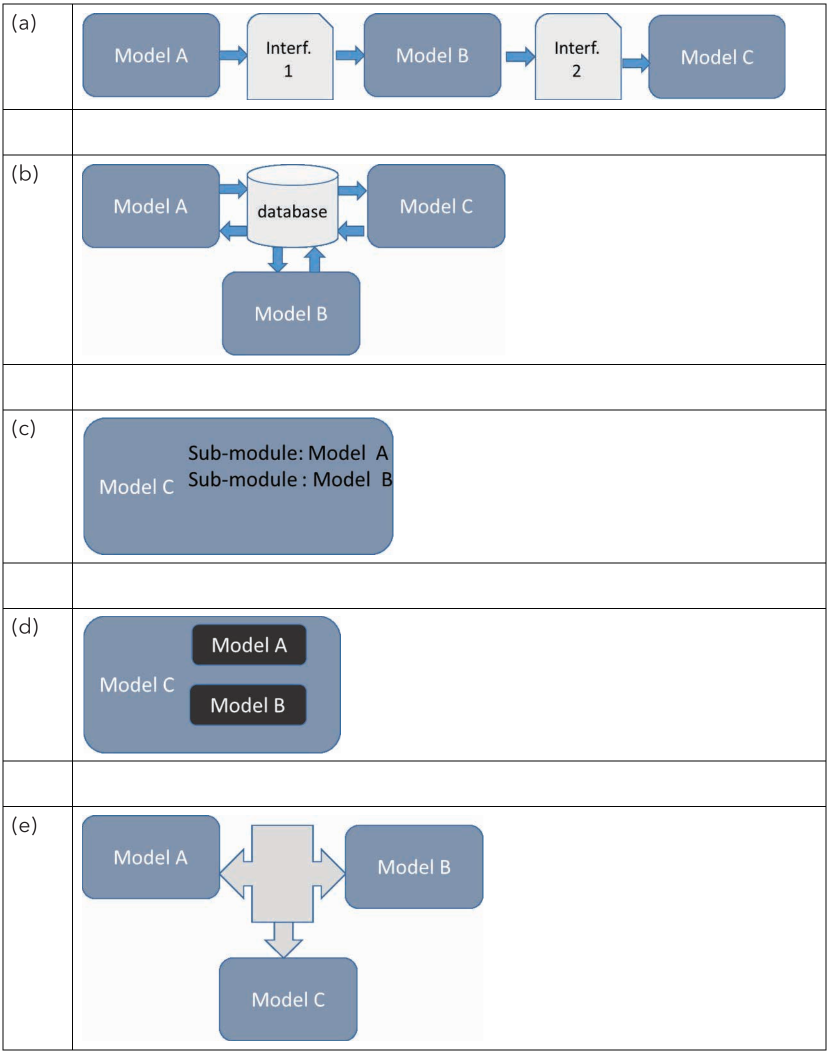

Figure 2 The main five ways to couple models and modules: (a) modelling chain, (b) weak coupling, (c) sub-model integrated as a sub-module, (d) code integration, and (e) model coupling served by the modelling framework engine.

chains or workflow. In this case, there is no real coupling as each model is fully independent. The second case concerns so-called weak coupling where the models will exchange information through files or a shared database. The third case consists of completely integrating models so that the included model becomes a simple module or sub-module. The fourth case consists of integrating different modules within the same model, at the level of the computer code. This case also includes models developed from scratch and fully rewriting codes. The result is a coherent whole from a computer science point of view and generally allows easier representation of interactions, in particular, feedback type between the various components of the model. Finally, the fifth case consists of developing the model in a framework, with coupling ensured by the coupler engine of the platform.

The sub-models to combine can be selected using different approaches. For instance, the decision can be driven by scientific considerations (e.g. relevant processes included in the sub-model), operational constraints (e.g. software simulation performance) or a participatory modelling approach (Voinov and Gaddis, 2008). In the latter case, scientists and key actors in designing adaptation and mitigation strategies work together to build the model. Together they select the sub-models by introducing biodiversity into biogeochemistry models, for instance as Van Oijen et al. (2020a), and scenarios to test in order to address climate change issues (Rodriguez et al., 2014; Cradock-Henry et al., 2020; Van Oijen et al., 2020b; Naulleau et al., 2022). Today, a large variety of coupled models arise from completeness of the modelled processes, method of coupling used or IT solutions. As the 'ideal model' emphasises the importance of representing the farm level, we include some examples where the farm model is designed by coupling sub-models: Robert et al. (2016); Lieffering et al. (2016); Fitzgerald et al. (2009); and Kalaugher et al. (2017). Later we discuss techniques commonly used to represent farmer behaviour.

6 Integrating new knowledge and facilitating interoperability

Coupling technically facilitates the development of new models by combining existing ones, but it is often not enough. New issues related to climate change assessment, adaptation and mitigation necessitate the improvement of models through the integration of advanced knowledge and processes. For example, over the last few decades, the cropland and grassland modelling community has been organised into two international knowledge hubs:

1. The Agricultural Model Intercomparison and Improvement Project (AgMIP; www.agmip.org); and
2. The Modelling Agriculture with Climate Change for Food Security project (MACSUR; www.macsur.eu).

These networks have been important arenas of the exchange of knowledge for the agricultural modelling community and have contributed significantly to the improvement of farming systems models, both in their design and in their computational implementation (Thorburn et al., 2018). To account for the impact of climate change on plant development, crop modellers have been obliged to revisit current crop models. This exercise was chiefly initiated by crop model intercomparison exercises for major crops, which showed important differences between models (Fig. 3). This was mainly explained by the fact that climate change (e.g. elevation of the CO_2 rate, temperature increase), by exploring unexperimented conditions, requires significant modifications in the representation of some biophysical processes currently implemented in most crop growth models (e.g. effect of priming and microbial diversity in ecosystem functioning as presented in Perveen et al. (2014)). It soon became clear that this work was easier when the original model had been built in a modular way, with a module associated with each process. If modelling frameworks such as APSIM (Holzworth et al., 2018), BioMA (Donatelli et al., 2010), DSSAT (Hoogenboom et al., 2019), OpenAlea (Pradal et al., 2015), RECORD (Bergez et al., 2013) and Simplace (Gaiser et al., 2013) helped to produce models with a good level of

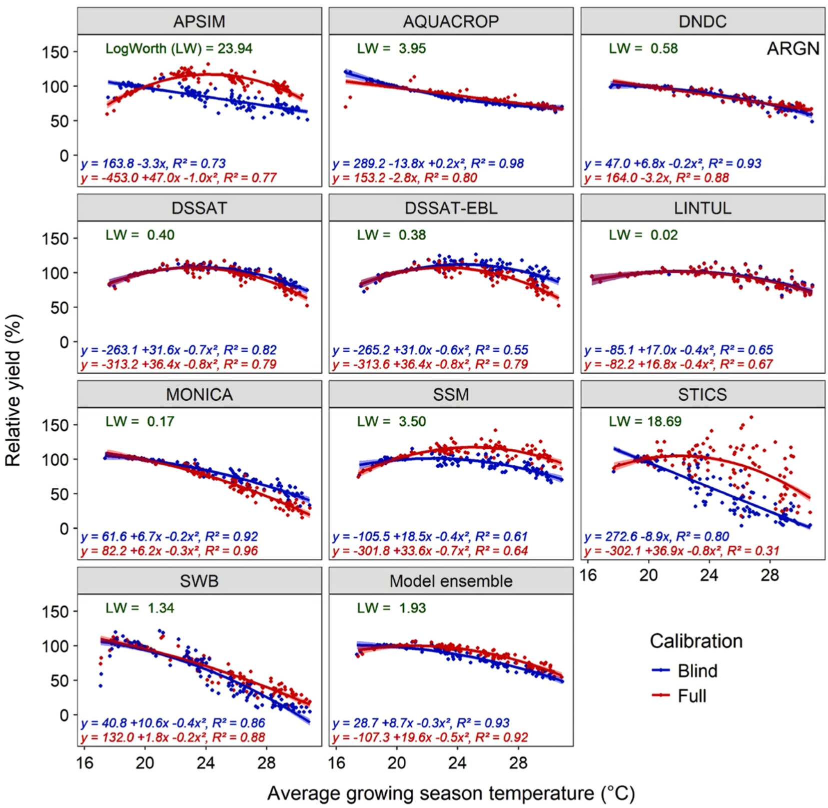

Figure 3 The use of different crop models to test the impact of climate change on soya relative yield. Instead of developing a new model, the AgMIP approach provides new knowledge on comparing different existing well-known models. From Kothari et al. (2022).

modularity, this was rarely the case for models with legacy code. Modularity has long been a recommended practice in the crop modelling community (Reynolds and Acock, 1997; Jones et al., 2001).

Most models today have developed a modular approach (Brown et al., 2018), which facilitates their readability, their evolution by adding new modules and their sharing with the modeller community.

In addition, to facilitate model sharing, these communities have worked for the implementation of semantic interoperability. The interoperability is also essential because simulation results are, and will remain, uncertain despite all the progress on the models themselves. This is reinforced by the fact that, in order to assess the impact of climate change or to explore possible adaptation pathways, it is necessary to consider uncertainties in future climate predictions. One way to reduce uncertainty is to cross-reference information sources and this relies, in particular, on semantic interoperability. In connection with AgMIP, researchers have worked on the definition of standards to facilitate the interoperability of modules of models and data. Interoperability corresponds to one of the FAIR principles (Wilkinson et al., 2016), now extensively promoted in the agrifood community (Top et al., 2022), and uses the International Consortium for Agricultural Systems Applications (ICASA) vocabulary (White et al., 2013). Recently, a module specification standard and a metalanguage Crop2ML (Midingoyi et al., 2021) were proposed as a standard to express module equations.

Beyond the AgMIP community, we also observe the development of ontologies and their use in modelling work. They help in sharing data used as model inputs for model calibration and documentation. The agronomic community has developed many controlled vocabularies and ontologies such as AGROV OC (Subirats-Coll et al., 2022) from FAO or AGROPORTAL (Jonquet et al., 2018). Some ontologies are very specific, such as OntoHydroAgro, which is dedicated to the impact of climatic changes and agricultural activities on water resources (Bonacin et al., 2016). To facilitate the access to cross-referenced sources, it is also necessary to have open and collaborative software systems enabling the sharing of large-scale, multifaceted data and models (e.g. knowledge hub). Interoperability also relies on progress in software engineering with the development of virtualisation which allows model simulation whatever the computer environment. This involves, for example, distributing virtual images, using software engineering tools (e.g. docker) (Anderson, 2015).

7 Integrating adaptation management practices into models

These improvements, although necessary, do not consider changes in management practices that will result from global change. In particular, during a working session of the MACSUR knowledge hub (Kipling et al., 2019), modellers emphasised the importance of integrating biophysical/economy/management interactions into models when working on adaptation to, or mitigation of, climate change. This triple interaction involves a wide range of actors such as farmers and government decision-makers, each of them with a different perspective on what they want from models. This included different spatial scales, from the agricultural plot, the farm up to country or region. Models must consider operational, tactical and strategic decision-making processes.

However, these models require other approaches than those classically used to build biophysical models, with the latter based on mathematical formulae such as differential equations. An alternative approach e.g. has been to use decision rules to represent management aspects of cropland/grassland. For each crop practice, a set of rules is defined which, during the simulation, will allow triggering of a decision (e.g. sowing, harvesting, irrigation, fertilisation, grazing) according to the model state variable (e.g. available biomass, leaf area index, soil moisture, air temperature) or even by calculating, for example, the rate of nitrogen fertiliser or the optimal animal stocking rate (Aubry et al., 1998; Bergez et al., 2006; Vuichard et al., 2007; Martin-Clouaire and Rellier, 2011; Dury et al., 2012; Chabrier et al., 2015). Using this approach in modelling work related to climate change is particularly important since climate change makes the use of fixed calendar dates for particular agronomic practices based on the current context obsolete. For example, in one model intercomparison study (Constantin et al., 2019), sowing dates were adapted using decision rules to accommodate climatic variability and trends (Fig. 4).

For tactical decisions at the plot or farm level, there are fewer examples than for operational decisions. Nevertheless, we can refer to a number of works related to crop rotation or crop planning (Robert et al., 2018; Hajimirzajan, 2021; Pahmeyer, 2021). In these studies, the crop model is coupled to an economic model built to optimise an objective function (such as profit) under different constraints (e.g. water availability). Aghajanzadeh-Darzi et al. (2017) coupled PaSim to AROPAj in order to estimate the economic effect of climate change on grassland. Others have developed applications for optimisation of fertilisation, such as in Ramos-Castillo et al. (2021). In the case of approaches at a broader (e.g. territorial) scale accounting for interactions between different actors, multi-agent formalism is often used (Burli et al., 2021). Multi-agent-based models are used when assessing the impact of policymakers' decisions on climate change mitigation policies (Huber et al., 2018).

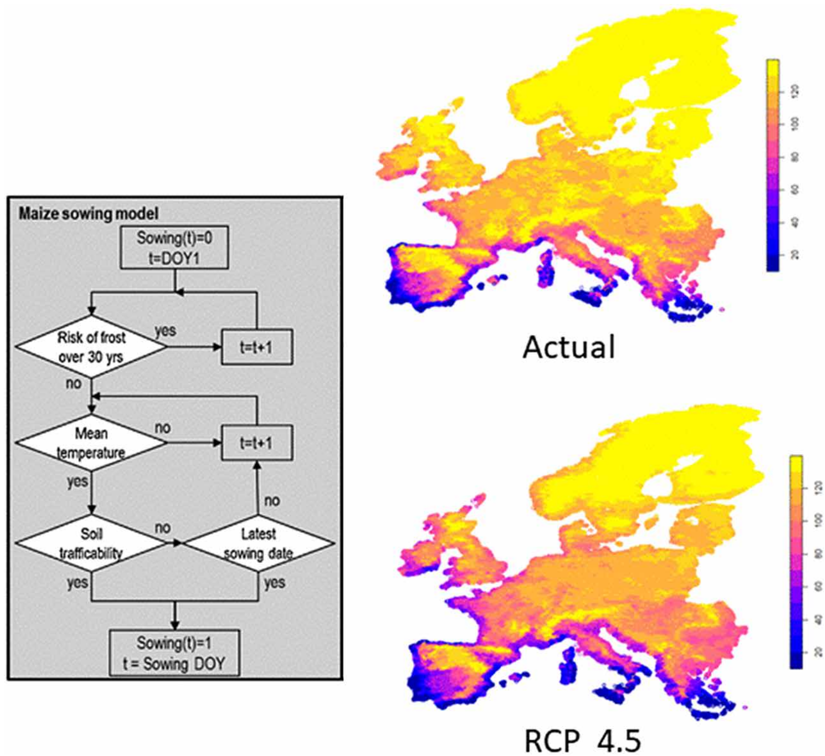

Figure 4 Modelling decision-making is important when considering climate change. In Constantin et al. (2019), a simple maize sowing decision model was created to analyse the impact of the sowing dates.

8 Incorporating inter- and intra-species diversity into models

The consideration of more global processes can overlook more local processes which, if not taken into account, could distort simulations. For example, there is now evidence that climate change impacts species diversity and that this diversity is also a major way to mitigate the effects of climate change (Van Oijen et al., 2018). More and more modelling work is taking into account this inter-specific diversity (Li et al., 2011; Movedi et al., 2019). It is important to take account of genetics in models because designing new varieties able to deal with abiotic and biotic stresses is a way to adapt to climatic extremes and variability (Martre et al., 2015). White and Hoogenboom (2003) have described five ways of considering genetics in models:

1. No reference to species, making the model generic;
2. The model is species-specific without references to genotypes;

3 Genetic differences are represented by cultivar-specific parameters of the model;
4 Genetic differences are represented by specific alleles and gene action is represented through linear effects on model parameters; and
5 Genetic differences are represented by genotypes, with gene action explicitly simulated.

Until recently, most crop models have only integrated cultivar-specific parameters and based calibration on field experiments, in order to compare several varieties and determine those that are best adapted to a given climate change scenario (e.g. Zhang et al. (2022) for rice cultivars in China; Tao et al. (2017) for barley; Gérardeaux et al. (2018) for cotton, etc.). Extending the inclusion of genetics in models is a promising approach for breeders facing climate change. It implies integrating more ecophysiology into the crop or animal model, and making the link to quantitative trait loci (QTL) and genes (Hammer et al., 2002). More recently, models have been customised in order to simulate response to climate change depending on genes/QTL. Martre et al. (2017) have provided an overview of progress in this area. Guitton et al. (2018) worked on sorghum to develop a photosensitive ideotype adapted to climate change using a crop and a combination of QTL, and Wallach et al. (2016) have predicted the flowering time of beans.

9 From white to black box models: hybrid approaches and gridded simulations

The multiplicity of processes involved at heterogeneous scales has tended to make models more complex in their implementation and use more resources (e.g. more input required, more computing power and time needed). In recent years, statistical models have emerged from the expansion of machine learning techniques (Liakos et al., 2018). They are constructed by relating historical variables (e.g. yield) which are then simulated with other variables such as climate, soil or management and then applied in a context of future climate. While the use of statistical models beyond observed conditions raises the issue of uncertainty associated with the results (Lischeid et al., 2022), they are useful in high-resolution simulations over a large area. They require less data than mechanistic models and decrease the computational load.

A hybrid approach using mechanistic models and a metamodel emulating the mechanistic model is one method to address the issue of climate change impact, adaptation and mitigation on a large scale. Successful examples of this hybrid approach include choosing a cultivar to adapt to climate change (Zhang et al., 2022; Tao et al., 2017; de los Campos et al., 2020) simulating soil organic carbon (SOC) (Luo et al., 2019), crop yield prediction and mapping (Corrales

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et al., 2022; Guilpart et al., 2022) and climate impact assessment (Blanc, 2017). This hybrid approach can also be used successfully in optimisation processes used to mimic farmer tactical decision-making (Nguyen et al., 2019). Modellers have often used a linear regression method to build the surrogate model. Advanced statistical methods can be used to improve performance (e.g. learning methods such as random decision forests).

However, the use of statistical models is not always appropriate because they are generally built on historical data, limiting their ability to predict the future. Statistical models built from simulated data also require adding and updating the knowledge base whenever the model is modified. One approach is the use of gridded simulations. This involves a map divided into cells. In Launay et al. (2021) e.g. cells are the intersection of climate and soil data which are heterogeneous in terms of surface. It is then necessary, for each of these cells, to run one or more instances of the model with its own inputs based on soil, climate, management, etc. Gridded simulations require increasingly large computing resources. This can range from a high-performance workstation to a cluster (e.g. where information needs to be provided in real time, such as for water flows in a watershed) or a computing grid (independent simulations between cells, with their own resources on each node). Moreover, these gridded simulations require specific databases at the territory scale. There are numerous sources for these databases and there is ongoing work to develop them, e.g. soil data at 10 km^2 resolution (Han et al., 2019), irrigation mapping (Zajac et al., 2022), testing (e.g. light radiation data) (Araghi et al., 2022) and climate forcing data (Ruane et al., 2021).

Specific platforms have been developed to supervise these gridded simulations. These platforms are responsible for formatting the data for the model, distributing model operations over the available resources and then aggregating the outputs in an easily manipulated format (i.e. NetCDF). These platforms can be model-specific: Jang et al. (2019) for EPIC, Eza et al. (2015) for PaSim or multi-model, Shelia et al. (2019) for DSSAT, APSIM and SARRA-H and Kim et al. (2020) for ORYZA2000.

10 Ensemble modelling

Given the multiplicity of models and easy access to computational resources needed to run simulations, many studies have compared model outputs with each other and shown that even similar models differ in predictions relating to climate change (Sándor et al., 2016) and in sensitivity to different types of climatic hazards. In some fields of research, it is well known that models, due to their structure, can produce highly variable outputs. Pearson et al. (2006) e.g. showed that the prediction of species range distribution can vary, for a specific species, from -92% to +322% depending on the model used.

The multi-model ensemble (MME) technique is used to reduce prediction errors and has been described in detail by Wallach et al. (2016). It consists of aggregating the independent predictions of the MME to define a global prediction and an associated degree of uncertainty. Several models can be included in this MME. In addition, several sets of parameters and input data sets can be used for the same model.

Numerous studies have shown the efficiency of such a process, such as Martre et al. (2015) who concluded that the result of such an MME (by using mean or median) is better than that of its best model. Similarly, recent work (Ehrhardt et al., 2018; Sándor et al., 2020) has shown the reduction of uncertainties by using the MME median for the simulation of yield and carbon–nitrogen (C–N) cycles in field crops and grasslands. This reduction in uncertainty is also found for the calculation of soil C by Farina et al. (2021). Sándor et al. (2018) show that this approach can be used to test the impact of grassland management (reduced animal stocking and N input) on GHG emissions. These types of projections can be greatly improved in terms of accuracy and robustness, as shown by Araujo and New (2007). This can also be seen in Ruane et al. (2021) who evaluated 14 models and 11 climate data sets.

11 Conclusion and future trends

As we have seen, there are many differing features that models can (should) integrate, as well as different uses of models within agricultural systems in relation to climate change (mitigation, adaptation and impact). Figure 5 provides an overview of the required properties of the models using a structured list based on the 5W1H approach:

1. What is the target for the stakeholder?
2. Why do we want to model?
3. What about the climatic change dimension?
4. What about the sustainability dimensions?
5. What biophysical processes are involved?
6. What decision-making processes are needed?
7. What geographical scale needs to be considered?
8. What timescale should be used?
9. How to model?
10. How to use the model?
11. Any view on the simulation output analysis?

All these questions have to be answered before modelling can begin. In Fig. 5, we have highlighted some of the different examples discussed in this chapter. However, not all the cases mentioned in the figure have been discussed. We

Target/ stakeholdersMM	Researcher M A N G	Farmer	Advisors N	Branch organisation G	decision-makers M A N G		
Why ?	Understand A	Produce Knowledge A G	Warn /alert/ educate M N	Investigate/forecast M N G	Anticipate/ react	Conceive M N	
What about CC ?	Impact A G	Mitigation M	Adaptation N	Opportunities M	Risks M A N	Resilience	
What about sustainability ?	Agronomical M A N	Environment M A N G	Biodiversity M	Economical M A?N G	Social M G		
What biophysical processes ?	Physiology A N	Genotype Environment Interaction A	Hydrology M N	Soil M A N	Abiotic M A N	Biotic M A(?)	Farming practices M N G
What decision making processes ?	Operational (ex: Agricultural practices) M N	Tactical Ex: Crop rotation, location M N	Strategical ex: Ressources sharing investiment M N	Stakeholders interaction M			
Spatial scale	Field/animal M A N	Crop and/or livestock system M N	Gridded A	Farm M N	Local N	Regional M A	Global G
Time scale	Short (2030) M N	Middle (2050 - 2060) A G	Long term (2100)	Historic M A N			
How to model ?	Reuse/ Benchmark M A	Add CC specific features in current models A	Model chaining / weak coupling	Models integration/ strong coupling M N	Development from scratch	Participatory modeling	
How to use ?	Ensemble modeling simulation A	Participatory simulation M	Scenario test M A N G	Optimization	Support decision tools M	Surrogate simulation	

Figure 5 Specific properties of agricultural models dedicated to climate change. Letters are related to examples given in this chapter: M, MAELIA; A, AgMIP; N, Namaste; G, GlobAgri.

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have not e.g. discussed the development of a direct farmer decision-system support tool to deal with climate change. Mitigation is also a large source of uncertainty regarding modelling. The 'what if?' and 'how to?' queries require a specific modelling approach that is currently lacking in the literature. The feedback loops between climate change and different sub-systems have not really been considered. To date, mitigation actions have not impacted the climate and therefore modified the properties of the modelled systems. A larger list of such feedback loops could be created, but this is not the topic of this chapter.

Figure 5 highlights a range of new challenges in relation to climate change when discussing modelling. Some of these are listed below:

1 Adaptation and learning processes in a long-term series simulation. If one wants to simulate a long-term series, and especially when dealing with climate change, which is quite a lengthy process, models should take into account adaptation and learning processes. Farmers often change their practices depending on conditions (climate, economic, pest pressure, etc.). Ecological processes also change depending on environmental pressure. Progress has been poor with regard to integrating such changes into a model.
2 Feedback effects due to mitigation. A large body of research is available on mitigation options (reducing GHG, increasing C storage, etc.) at different scales (plot, farm, territory, nation and even globally). Several EU projects are concerned with this (see for example ClieNFarms, https://www.inrae.fr/sites/default/files/pdf/ClieNFarms_PR.pdf). One of the big challenges when mitigation is modelled is to integrate feedback effects. Depending on differing levels of some variables, different processes can be triggered or not, but this dynamic modelling is far from simple.
3 Systemic and holistic approach. As explained throughout this chapter, a larger systemic and holistic approach to integrate climate change and effects on farming systems is required, which needs a more interdisciplinary approach. 'Interdisciplinary' is a buzz word in current research but is complicated to achieve in practice.
4 New end users involved. As explained earlier, modelling is the process of creating a model in order to simulate a specific scenario. When dealing with climate change, some new end users and types of simulation may be required. As explained in the discussion of the ideal model, policymakers e.g. are a key group who need models to simulate climate change processes. Integrating the modelling process and education of users on the use of models may also be a challenge.

Other chapters of this book will give more information on the different models to tackle some specific questions (Fig. 6), and will cover a large range of

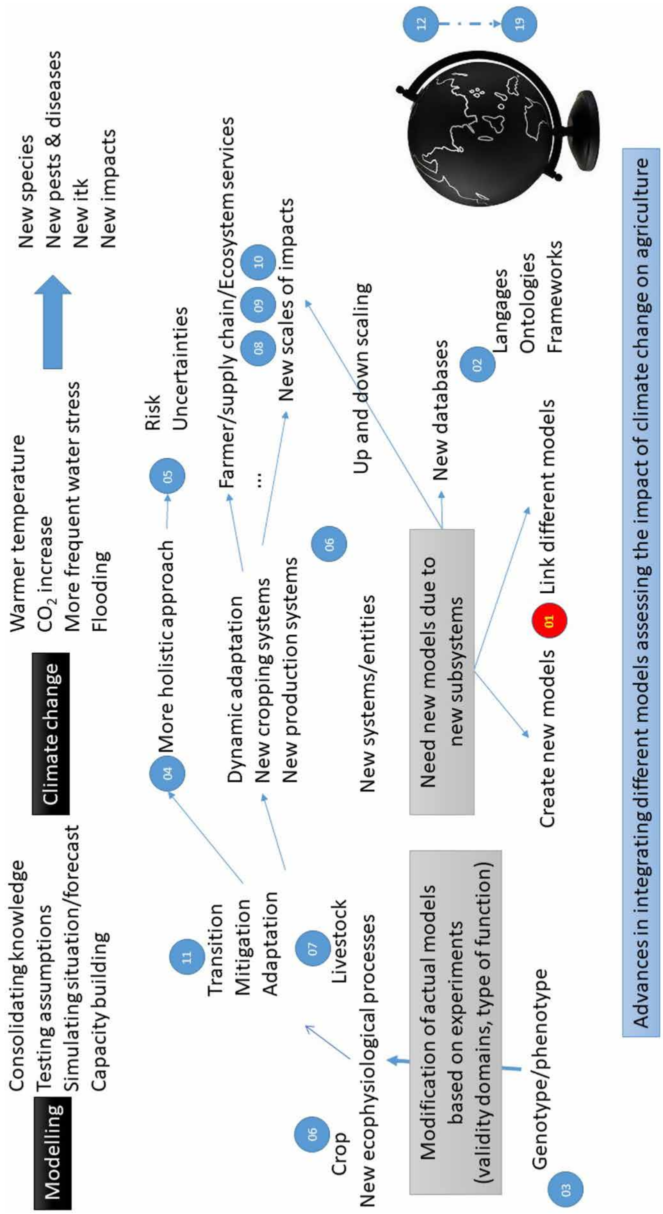

Figure 6 The general positioning of this chapter in the general layout of the book. Circled numbers refer to the chapter number.

applications from gene to region, from biophysical processes to decision-making aspects, from north to south. This introductory chapter sets the scene and provides a broad overview of the impressive advances in modelling over the last few decades to tackle climate change issues impacting agricultural systems.

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