Innovations in Sustainable Agriculture
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Spatializing Crop Models for Sustainable Agriculture

Fabrizio Ginaldi, Sofia Bajocco, Simone Bregaglio, and Giovanni Cappelli

Abstract Crop models mathematically represent dynamic point-scale interactions between plant, weather, soil and management practices. They have been increasingly applied large scale (i.e. from farm-level to regional and global applications) to understand and quantify the trade-off between productivity, management and the sustainability of cropping systems, in terms of responsible use of resources (e.g. water and nitrogen) and of adaptation to or mitigation of climate change impacts. This contribution reviews the most recent information about spatializing crop models and provides a comprehensive overview of major assumptions and criticalities related to this methodological approach. The first paragraph focuses on the definition of crop models, presenting their historical evolution and main fields of application. A bibliometric analysis was carried out on 1017 scientific papers published between 1990 and 2018 in order to identify the most frequent scientific topics concerning the adoption of crop simulation modelling for sustainable agriculture. The second section describes the main sources of uncertainty in spatializing crop models, addressing two main aspects. Firstly, basic assumptions and validity domains of processes/phenomena represented may still not be valid when applied in a different spatial resolution. Secondly, reference input data needed to characterize the cropping system under study, to run models and test their performance at large scale can often be scarce and/or uncertain due to aggregation/disaggregation issues. The third section defines the minimum amount of data about environment (i.e. site, weather, soil), management (e.g. sowing and harvest date, cultivars and crop operations adopted) and crop type, needed to operate crop models at a given location under current/future climate scenarios. Necessary methodological indications for building a multi-layer georeferenced database facilitating coupling with biophysical models are also provided. Ways of integrating proxy variables (e.g. obtained from

F. Ginaldi  ·  S. Bregaglio  ·  G. Cappelli
Research Centre for Agriculture and Environment, Council for Agricultural Research and Economics, Bologna, Italy
e-mail: fabrizio.ginaldi@crea.gov.it

S. Bajocco
Research Centre for Agriculture and Environment, Council for Agricultural Research and Economics, Roma, Italy

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pedo-transfer functions and remote sensing data) and crop models have been reported. The last section presents two case studies dealing with the spatialized application of crop models to promote the sustainability of agriculture. A European case study is centred on the definition of farmer adaptation strategies to alleviate climate change impacts, while a regional case study evaluates the efficiency of water management and water footprint of tomato cultivation in Southern Italy.

**Keywords**  Biophysical models · Crop model uncertainty · Cropping system sustainability · Model data requirement · Remote sensing assimilation · Spatially-explicit modelling · Spatial-temporal scale

1 **Crop Simulation Models in a Nutshell**

The main challenge of global agriculture is the need to enhance crop productivity to guarantee food security (Ray et al. 2013), whilst at the same time achieving cropping system sustainability (Ramankutti et al. 2018). Crop simulation modelling is being widely used to support this objective because of its ability to quantify the complex, non-linear and mutual interactions between the crop genotype, farmer management and pedo-environmental conditions, thus permitting evaluation of the environmental and economic performance of an agricultural system (Li et al. 2015). The main requirement of a crop simulation model is the capability to reproduce the functioning of the target cropping system – intended here as the nexus of land, atmosphere, and human processes (Malek et al. 2017) – in order to provide a simplified representation of its behaviour and reactions to variations of farmer management and pedo-climatic conditions. Our dissertation focuses on dynamic crop simulation models (Jones et al. 2017a, b), which are software applications embedding algorithms, which are meant to reproduce the functioning of the different domains of the agricultural systems, with model outputs as the values of state variables over time (e.g., soil water content, leaf area index, aboveground biomass). This branch of science was born in the era of the Cold War and space exploration, when new technologies in computer science and knowledge about system analysis were initially employed to analyse and reproduce the interactions of components in complex systems (Sinclair and Seligman 1996). The first crop models provided a simple estimation of crop productivity as a function of light interception and photosynthesis, through the adoption of empirical relationships considering the basic biochemical and biophysical mechanisms converting solar energy into plant biomass (Loomis and Williams 1963; de Wit 1965; Duncan et al. 1967). The complexity of crop models suddenly increased over the following decades, thanks to a better description of carbon assimilation which considers the effect of stomatal conductance in regulating leaf gas exchange (e.g., Cowan 1978), and the description of plant phenology and its influence on the partitioning of assimilates among plant organs. The addition of these various components led to a number of models of
daunting complexity, such as GOSSYM (Whisler et al. 1986), CERES (Ritchie and Otter 1984), and SOYGRO (Wilkerson et al. 1983). In more recent years, the focus of crop modelling has shifted from the assessment of crop productivity to the integrated analysis of the system, in order to tackle new challenges such as the mitigation of greenhouse gas emissions, the enhancement of ecosystem services and environmental performance of agricultural systems, loss reduction associated to pest and disease, improvement of the qualitative aspects of crop production, design of improved ideotypes, and the adaptation and mitigation of climate change impact. Examples of dynamic models for cropping systems are those in the DSSAT suite of models (Jones et al. 2003), and APSIM (Keating et al. 2003), CropSyst (Stöckle et al. 2003), and EPIC (Williams et al. 1983, 1989).

A bibliometric analysis of the adoption of crop simulation modelling for sustainable agriculture, from 1990 to 2018 (1017 documents), groups the most frequent scientific topics into three clusters: (i) water resource and its corresponding domain (i.e. irrigation, water balance, precipitation, etc.); (ii) climate change, economic benefit and food security, both at field and global scale; (iii) bioenergy, biomass production, soil organic carbon and greenhouse gases (Fig. 1). Crop models are

![Density mapping of the terms most used in the crop modelling research for sustainable agriculture (1990–2018). Clustering is determined by topic co-occurrence. The larger the halo, the higher the frequency of the topic. Analysis performed with VOSViewer (http://www.vosviewer.com)](http://www.vosviewer.com)
increasingly applied on a large scale, from farm-level applications to regional and global studies, to investigate the influence of global trends such as market dynamics and climate change, on crop productivity (Porwollik et al. 2017). Yield gap analyses with crop models have been performed on different spatial and temporal scales in the context of food security, land use and climate change research (Mueller et al. 2012; Challinor et al. 2014; Asseng et al. 2015). Topics associated with crop model projections have been widely discussed, including those attributed to climate forcing data (Rosenzweig et al. 2014), model structure and parameterization (Rötter et al. 2012), and the effectiveness of CO$_2$ fertilization (Deryng et al. 2016). Research projects and analyses focused on four main staple food crops: wheat (*Triticum aestivum* L.), rice (*Oryza sativa* L.), maize (*Zea mays* L.), and soybean (*Glycine max* (L.) Merr.). These crops had been listed in the Global Gridded Crop Model Intercomparison (GGCMI) project as Priority 1 crops; they represent key agricultural goods given the global harvest area they cover, production quantities, trade levels, and contribution to human diet (Porwollik et al. 2017).

Nowadays, a large number of crop models are available but little emphasis has been placed on their improvement. As a result, great untapped potential in model development still remains, and filling this gap would contribute to tackling emerging issues in food security, policy assessment, farmer advice, and human health and nutrition (Holzworth et al. 2015).

2 Sources of Uncertainty in Spatializing Crop Models

Spatializing a crop model means applying it over a geographical area that is larger than the one for which it was originally designed (i.e. a homogeneous area within the field), characterized by a higher variability of pedo-climatic and management conditions both in space and time (Faivre et al. 2004; Challinor et al. 2018). Therefore, as basic concepts, hypotheses and validity domains of crop models are usually derived on the plot scale, this upscaling implies various sources of uncertainty (Hansen and Jones 2000; Faivre et al. 2004). In the past, spatial heterogeneity has often been neglected in favour of the analysis of temporal processes and behavioural rules (Wallentin 2017), mainly due to the complex and multi-dimensional form of spatial data (Porwollik et al. 2017). The large amount of freely available spatial data and the increasing capability of managing high computational demand has renewed the attention of the scientific community towards the integration of simulation modelling and spatial databases in order to improve current model resources (Grimm and Railsback 2005; Wallentin 2017). Taking geospatial context into account is indeed crucial for disentangling how individual-based processes can be modelled from the crop level to the cropping system, and to regional and global scales (Manson and O’Sullivan 2006). Goodchild (2001) defined four criteria for a model to be spatially explicit: (i) it has to depict the location of its inputs; (ii) its design has to involve concepts like spatial configuration and neighbourhood; (iii) the outputs vary if the model is run in different locations, and; (iv) the spatial structure of model input and output is different (Wallentin 2017). Spatializing crop mod-
els requires making assumptions concerning the selection of the crop model(s) to be applied, the handling of the input data, and the design of the simulation experiments (Donatelli et al. 2012). The resulting decisions set the limits of applicability of the analysis results, and should be considered *a priori*, to avoid introducing conceptual errors.

Once the aim of the study (i.e. what exactly the model should do) and the conditions of applications (e.g. spatial and temporal scale, data availability) are defined, the next step of a simulation study is the choice of model (Donatelli and Confalonieri 2011). The recommended criteria when selecting the crop model are (i) structure (modelling approaches, equations and parameter values); (ii) time step; (iii) feasibility for use in spatially-explicit applications, and; (iv) data handling capacity.

A crop model is a simplified representation of the real system; the suitability for a specific study is subject to its ability to simulate the processes that drive the aspects of cropping systems which are the target for analysis. The relationships coded in the model equations have some level of empiricism, but that empiricism has to be enclosed into one or more levels below the level of the prediction (Acock and Acock 1991) as highlighted in the scheme of the organizational levels in a cropping system (Fig. 2).

The choice of an appropriate time step in dynamic simulations depends on the processes being simulated and its temporal resolution must be short enough to allow capturing variations of the system (e.g. if a crop can wilt irreversibly in a week, a monthly time step cannot be used, Donatelli and Confalonieri 2011). In crop- and cropping-system models the time step is frequently 1 day (i.e. all processes are simulated every day), or 1 h or even less.

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**Fig. 2** Level of prediction and level of empiricism in process-based models. (Redrawn from Acock and Acock 1991)
A crop model can be run, independently or dependently from one simulation unit (SU) to another. In the first case, no interactions among SUs exist. Such an assumption is plausible for coarse spatial resolutions, e.g. $25 \times 25$ km or lower, in which each SU includes and represents a multitude of fields, which markedly differ in soil, nutrient, climatic, and management conditions, and whose inflows and outflows cannot be determined and quantified at simulation runtime. The consideration of local- and regional-scale heterogeneities requires an explicit simulation of the flows within the area, and the spatial interactions between SUs. This can be obtained by interfacing the crop model with a spatial one, which accounts for simulation unit interactions (e.g. a hydrological model handling lateral water flows, a farm system model accounting for constraints due to work organisation).

Besides model structure, the quality of input data (i.e. weather, soil) is one of the major sources of uncertainty in predictions (Confalonieri et al. 2016) as input variables are the main driver of crop model simulations (Grassini et al. 2015).

First of all, analysis of the input data requirement demands definition of the appropriate scale of investigation. In such a context, it is important to distinguish between the two components of scale – resolution and extent – which both significantly influence model outcomes (Wallentin 2017). While the resolution affects the detail of the information modelled, the extent defines the size of the target area: the same input data collected at different resolutions within the same area could provide markedly different model outputs (Wu 2004).

Moreover, there is often a trade-off between data quality and spatial coverage; the quality of measured data is profoundly uneven across global agricultural regions (Donatelli et al. 2012; Grassini et al. 2015; Mourtzinis et al. 2017). Here is a brief overview of the principal issues concerning specific input data:

### 2.1 Weather Data

Weather conditions are roughly uniform at field scale, therefore, crop simulations performed at this and/or finer level can rely on data collected at weather stations placed in close proximity. Specific issues connected to the unavailability of these data (i.e. poor quality standard, presence of missing values or absence of key variables) can be solved using estimation methods (Donatelli et al. 2004), though this introduces a further source of uncertainty (Rivington et al. 2006). Large-scale crop model applications (from regional to continental scale) require an up-scaling of the climatic data, via site-specific interpolation of weather data on a regular grid (e.g. ECMWF ERA-Interim, Dee et al. 2011), with increasing uncertainty depending on data quality and spatial coverage (Hansen and Jones 2000; Ewert et al. 2011; Van Wart et al. 2013). Also, comprehensive climate change impact assessments targeting land use change and food security need to consider climate projections from contrasting Global Circulation Models (GCM), if they are to take into account plausible realizations. Various GCMs exist and provide different projections, depending mainly on the level of detail in the representations of the global climatic system.
Moreover, while the spatial resolution of GCMs (generally hundreds of kilometres in latitude and longitude) is sufficient to simulate the average global climate, their output is often unsuitable when the scale of interest is refined. For instance, while a GCM may estimate monthly precipitation correctly, the daily precipitation may be spread across the month in a very unrealistic way (raining a little every day for example). Such distortions of daily weather variability can seriously bias crop model simulations (Semenov and Porter 1995; Mearns et al. 1996; Hansen and Jones 2000; Baron et al. 2005; van Bussel et al. 2011).

At higher resolution, several factors complicate climate modelling, including local topography, vegetation cover, land use, the presence of atmospheric aerosols and other pollutants. In order to refine the spatial and temporal resolution of GCMs to obtain inputs suitable for crop modelling at a local and regional scale, three different strategies can be pursued: (i) statistical downscaling of GCMs outputs; (ii) the coupling of GCMs with weather generators (WGs) or with; (iii) Regional Climate Models (RCMs). The first method makes use of empirical relationships between fine and coarse scale data, derived from observational data. The main concern is the assumption that current relationships in climatic data will remain unchanged in future scenarios. The second methodology involves perturbing site-specific calibrated parameter sets of the WG by the use of GCM-driven information, such as the mean changes in temperature and precipitation for a given future time slice, under a particular emission scenario. The principal drawback of this approach is that the spatial consistency of generated weather is often unpreserved. Finally, while the spatial resolution of the climate simulations is improved when coupling GCMs with RCMs (in the order of 50 km or less, Christensen and Christensen 2007), the simulation process is slow, computationally expensive, and the temporal distortion of precipitation and (to a lesser extent) temperature are still present in the generated weather series. As is well known, such series need to be bias-corrected (e.g. Christensen et al. 2008) prior to being used for feeding hydrological and crop models otherwise they may lead to unrealistic results (Teutschbein and Seibert 2010). Bias correction in turn requires ground-based observations, and may be limited by their unavailability, poor quality or heterogeneity (Challinor et al. 2003). Furthermore, as pointed out by Duveiller et al. (2015), so-obtained GCM-RCM weather projections are still inadequate for crop simulation and need to be further processed: global solar radiation and wind speed may still have unrealistic distributions when compared to observed data, whereas specific input variables needed for running crop models are still not present in available databases (e.g., evapotranspiration).

### 2.2 Soil Data

Running crop models with high resolution soil data (e.g., texture, depth, slope) could enable performing more accurate and detailed spatial simulations, albeit requiring large computational and time costs. Water-limited crop model simulations
are indeed sensitive to soil parameters derived from soil texture and soil depth, as they determine the basic hydraulic characteristics. However, since the coverage of soil profiles and the quality of information available in public databases is not often uniform over large-scale simulation areas, the predominant soil profile within each SU is often used as a proxy, even though this approximation could lead to a marked underestimation of output variability. In fact, soil-type-related yield variability could outweigh the simulated inter-annual variability in yield due to weather under specific management conditions (i.e. unfertilized cropping systems, Folberth et al. 2016). This concept does not apply when performing crop model applications within a frame of precision agriculture, where the variability in pedological features must be explicitly considered to support the application of spatially variable rates of fertilizers, irrigation water, or chemical treatments within a single field (Sadler et al. 2016).

2.3 Production System

In crop model simulations at large spatial scales, the production systems are often abstracted at “crop” level, ignoring the local farm typologies and cropping system structures. Rather than using crop growth models, it is more appropriate to tackle the issue by modelling cropping systems. When aimed at being used as supporting tools to design adaptation strategies for farmers, these studies must explicitly consider the impact of alternative management strategies. Indeed, farmers are able to timely respond to environmental changes modifying management practices. Basic practices which can be simulated by most of the current crop models are the choice of the variety, which is coded in the model mainly with respect to the crop cycle length, the shifting of the sowing dates based on weather conditions, and the implementation of alternative irrigation and fertilization plans. The capability of handling crop rotations, even if representing a more complex task, is nowadays necessary for a crop model. Crop modelling studies must test different management scenarios in order to anticipate future trends in crop productivity as affected by farmer management in order to identify possible solutions to better adapt to climatic changes.

2.4 Model Calibration

The calibration of the parameters of a crop model is often based on the adjustment of their values within their biophysical ranges, in order to improve the model’s performance in reproducing field experimental data. This activity is supported by literature, which makes available reference values of the main parameters used by many crop models in different trials over large areas. Such parameter sets need to be refined through interaction with local experts and stakeholders when spatial simulations are carried out, in order to improve the information on the actual cropping
systems simulated as opposed to the idealized crop types. However, the results of spatialized simulations are able primarily to identify main trends and to capture extensive regional signals, and need to be interpreted with caution since they are sensitive to the specific model settings.

3 Data Requirements for Spatializing Crop Models

Spatializing crop models requires information on the heterogeneity of pedo-climatic conditions and management practices within the simulated geographic region; such data need a level of detail that is consistent with model requirements (e.g. model time step versus weather data resolution) and the study’s objectives (Donatelli and Confalonieri 2011). While in temperate and flat areas soil can represent the main source of yield variability (regardless of scale; Hoffmann et al. 2016), thermal and pluviometric patterns drive crop production in rainfed agriculture or in morphologically complex hillside areas, where land slope and aspect are substantial in determining yield levels and fruit quality (e.g. vineyards; Esteves and Manso Orgaz 2001).

Basic layers of information for spatialized crop modelling studies are mainly related to pedo-environmental conditions and management practices (Hunt and Boote 1998; Kasampalis et al. 2018). The minimum dataset of information (MD) for running crop models depends on the simulated production level (i.e. potential (P) vs water (WL)/nitrogen (NL)/disease (DL) limited) (Table 1).

The potential level represents the productivity of a crop grown under non-limiting conditions for water, nutrients, weeds and pest/diseases pressure, under prevailing environmental conditions. It is determined by incoming solar radiation, air temperature, atmospheric CO$_2$, and by genetic traits that modulate e.g., the length of the growing season and light interception (canopy structure) (van Ittersum et al. 2013). In water/nutrient depleted production systems, additional data are necessary in order to set soil conditions (i.e. water and nitrogen content) at model initialization (Müller et al. 2017).

It is to be noticed that, as the simulation scale increases, performing a detailed model calibration/validation with field measurements or gridded datasets becomes more difficult. This is because spatially distributed information related to main phenological variables and growth dynamics (leaf area index, aboveground biomass) is rare (Faivre et al. 2004; Müller et al. 2017). In this context, gridded yields or official sub-regional/national statistics should be approached with extreme caution since such data can include disturbing factors that are yet to be considered by the model or are of unknown origin e.g. technological/time trend, nitrogen shortage/surplus, hailstorms events (Donatelli and Confalonieri 2011).

It is our aim to obtain a representative set of data in areas with significantly different pedo-climatic and management conditions (Coucheney et al. 2015), whilst integrating available experimental data with literature information (e.g. modelling experiments performed in the same or similar environments).
Model application in climate change impact assessment requires additional data concerning future climate projections (i.e. GCM-RCM based realizations – e.g. CMIP – https://www.wcrp-climate.org/wgcm-cmip, CORDEX – http://www.cordex.org/, projects), atmospheric CO₂ concentration and adaptation strategies (e.g. adoption of improved varieties and/or more efficient irrigation systems, chemical applications) (Donatelli et al. 2015; Challinor et al. 2018).

From an operational point of view, most existing simulation studies rely on the outputs of crop models coupled with databases containing MDs in the areas of interest (Fig. 3). To this end, the study area (e.g. a region, an agrozone, a producing district, a watershed, etc.) is divided into a finite number of smaller areas called simulation units (SUs), characterised by homogeneous pedo-climatic conditions.

<table>
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<th>Table 1 Minimum amount of input data for operating crop growth models (Hunt and Boote 1998), according to the production level of interest</th>
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<td>Residue (organic fertilizer) applications (material, depth of incorporation, amount and nutrient concentrations)</td>
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<tr>
<td>Chemical (e.g., pesticide) applications (material, amount)</td>
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<td>Harvest schedule</td>
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P potential, WL water-limited, NL nitrogen-limited, DL disease-limited
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and/or cropping/farming systems (Faivre et al. 2004). Then, MDs are georeferenced in a multi-layer and spatially explicit database and univocally assigned to each SU depending on spatial attributes (e.g. geographic coordinates of centroids), via the use of GIS-based software applications.

Environmental information often relies on data of different resolutions which need therefore to be aggregated/disaggregated before being used via dedicated procedures (e.g. based on weighted average, interpolation, selection of the most representative unit/class of data within the SU) (Faivre et al. 2004; Hoffmann et al. 2016). If unavailable, information can be replaced by proxy variables, as those obtained by pedo-transfer functions (as in the case of hydrological properties computed from soil texture; Donatelli and Confalonieri 2011) or by the use of remote sensing data (Faivre et al. 2004; Kasampalis et al. 2018).

Information related to crop management is highly variable and discontinuous in space and can change from year to year according to farm, consortium, regional, national or supranational decisions (Faivre et al. 2004). Thus, the spatial characterization of such data is rare and the available information does not permit characterization of the system in a detailed way (Müller et al. 2017). The tools available to fill these gaps are literature search, expert opinion or remote sensing data. During the execution of the crop model, management practices can then be implemented through automatic rules triggering the occurrence of agricultural operations based on management decisions (e.g. scheduled events for sowing and irrigation) and/or some states of the system (e.g. irrigation starts when available soil water in the root zone is lower than a critical threshold) (Donatelli et al. 2016).

Remote sensing collects spatial information regularly, with wide coverage and low cost, and therefore has been an advantageous tool for the detection of natural and agricultural resources over the last decades (Kasampalis et al. 2018). Several ways of integrating remote sensing data and crop models have been suggested.
(Delécolle et al. 1992; Dorigo et al. 2007; Liang 2004), including calibration (i.e. model parameters or initial states are adjusted to obtain an optimal agreement between the simulated and the RS-observed state variables), forcing (i.e. a state variable in the model is replaced by using the observed RS data), and updating method (i.e. model state variables are continuously updated whenever a RS observation is available), as shown in Fig. 4.

Leaf area index (LAI), fractional cover (fCOVER), fraction of photosynthetically active radiation absorbed by the canopy (fAPAR), and plant chlorophyll concentration are among the most relevant canopy state variables which are commonly assimilated in crop simulation models. Remote sensing can also provide plant phenological information (Xin et al. 2002; Karnieli 2003; Dorigo et al. 2007; Bajocco et al. 2019); regular provision of the phenological crop status will markedly improve the spatial outputs of agroecosystem models (Delecolle et al. 1992; Jin et al. 2018).

Remote sensing data are available at multiple spatial scales, from sub-meter (e.g. for precision farming applications), to more than a kilometre (e.g. for regional applications), and at variable temporal resolution, from daily to twice weekly coverage. The choice of the scale and temporal resolution depends on the questions to be answered (Jones et al. 2017a). Newer satellite sensors have been launched to obtain higher spatial and temporal resolution (such as Sentinel-2, Landsat-8, RapidEye, WorldView-2, etc.). The so-called big data revolution is the framework in which the collaboration between remote sensing data and crop models can find new challenges and solutions (Kasampalis et al., 2018).

**Fig. 4** Schematic representation of different methods for the assimilation of remotely sensed state variables in agroecosystem models: (a) calibration, (b) forcing, and (c) updating (Dorigo et al. 2007)
4 Application Examples of Crop Model Use in Sustainable Agriculture

This section presents two case studies which deal with the spatialized application of crop models to promote the sustainability of agriculture. The main themes of these case studies cover two out of the three clusters mapped in Fig. 1, i.e. climate change impact and the use of water resources. The common goal of these studies is the assessment of the sustainability of cropping systems under contrasting future climate scenarios; they differ both in resolution and extent of the spatial scale, the latter ranging from continental (Europe, Donatelli et al. 2015) to regional (Apulia, Italy, Ventrella et al. 2017). The European case study focused on the definition of farmer adaptation strategies to counteract climate change impacts, whereas the regional case study evaluates the efficiency of water management and water footprint of tomato cultivation in Southern Italy.

4.1 European Scale

The long-term sustainability of agroecosystems and associated livelihoods is unattainable without actively reacting to global climatic and socio-economic changes with feasible and effective adaptation strategies. Climate change adaptation is an adjustment in natural or human systems in response to real or expected climatic stimuli or their effects, which moderate harm or exploit beneficial opportunities (IPCC 2001). Potential adaptation policies include the improvement of technology and management practices, agro-environmental climate payments, the design of more sustainable farming systems, Common Agriculture Policy payments for agricultural practices that are beneficial to the climate and the environment (“greening” measures), the introduction of new crop varieties, land use related policies, etc.

In 2015, Donatelli et al. provided an impact assessment of climate change scenarios on agriculture over the EU27 Member States, focusing on three (20-year) time horizons centred on 2000 (baseline), 2020 and 2030. The Authors simulated water-limited yields for three priority crops (wheat, rapeseed and sunflower) and tested some technical adaptation options which could offset climate change impacts. The CropSyst model (Stöckle et al. 2003) was coupled with a georeferenced database including information on (i) land use, (ii) crop distribution, (iii) soil properties, (iv) farming practices (i.e. sowing and harvest dates) and (v) current/climate change scenarios for two contrasting realizations of the same IPCC emission scenario (A1B). Spatially-distributed simulations were executed at 25 × 25 km resolution considering crop responses to different atmospheric CO₂ concentrations, and future yield projections were evaluated as a percentage change compared to the baseline.

Results primarily showed that different realizations of the same emission scenario led to large variations in crop performances in the same time slice. Without adaptation, simulated wheat yield variations in 2030 strictly reflected the spatial
pattern of rainfall changes across Europe (Fig. 5a): indeed, projected declines in the amount of rainfall generally resulted in yield reductions and vice versa. Further reasons for the increase in yields in Southern Europe were the CO$_2$ fertilization effect and the shortening of the crop cycle that may have reduced the occurrence of water stress in summer. Simple adaptation techniques such as changes in sowing dates and varieties (in terms of duration of the crop cycle) were effective in alleviating the adverse effects of climate change in most areas (Fig. 5b). In general terms, the best yield was realized by delaying the wheat planting date by 10 days, and using a variety with a longer growth cycle (Fig. 5c; results did not account for a possible greater pressure of plant diseases, for instance wheat rusts).

Figure 5 illustrates large spatial variability in the performance of wheat systems. It enables identifying critical spots for focusing breeding and policy-making efforts, and it highlights opportunities for European wheat agriculture in future time horizons. It should be noted that taking into account the effect of future technological changes and economic consequences (e.g. costs of alternate technologies or levels of fertilizer application in response to changes in prices) would tend to further reduce adverse impacts of climate change. One aspect that requires additional investigation is the impact of extreme events which may lead to crop failure, even in the context of possibly improved weather patterns.
4.2 Regional Scale

Italy is the sixth major tomato producer and supplier of tomato processing worldwide. About a fifth of the national harvested area and productions are concentrated in the Capitanata plain, an area of about 4000 km$^2$ in the northern part of the Apulia region (Southern Italy). The cultivation of tomatoes in this area plays a key socio-economic role, although the achievement of high quality products is largely driven by the intensive use of chemicals (i.e. fertilizer/pesticides) and irrigation (300–800 mm), with great impact on local natural resources. The major constraint to crop growth is water stress, due to the prevalent semi-arid climate, characterized by precipitation between 25 and 110 mm and temperature peaks over 40 °C in summer. Significant action is thus needed to support tomato growers to enhance production levels while saving irrigation water. Ventrella et al. (2017) applied the DSSAT-CROPGRO model to simulate the growth of industrial tomato and to quantify the green (GW; crop evapotranspiration deriving from rain stored in the soil) and the blue water (BW; crop evapotranspiration deriving from irrigation), the blue water requirement (BWR; ratio between yield and BW) and the water footprint (WFP), under both rainfed and fully-irrigated conditions. Spatially distributed simulations covered the whole tomato area and a period of 30 years for baseline and future climate realizations (IPCC AR4 SRES A2 and A5 scenarios), based on average temperature raises of 2 and 5 °C respectively.

Future scenarios affected all indicators significantly, especially in the drier areas where high thermal and rainfall anomalies are foreseen. In general, the largest increase in BW consumption and BWR were simulated in the northern and south-eastern part of the Capitanata, where available soil water content is already a limiting factor for the crop (Fig. 6). Compared to the baseline, simulated BW under the A5 scenario showed an average increase of about 30%, while yield reductions fluctuated at about −20%. As a consequence, the BWR and WFP are projected to rise steeply to 40 and >65%, respectively. Results confirm that for a global temperature

![Fig. 6](image-url) Distribution maps of blue water (BW) and blue water requirement (BWR) in terms of low (LV), medium (MV) and high (HV) values calculated on the basis of corresponding first and third quartiles (Ventrella et al. 2017)
change of 5 °C potential adaptation measures may not be sufficient to counterbalance the projected negative impact on crop performance in terms of yield and WFP.

These findings could be important to support planning policies for effective allocation of scarce water resources, by concentrating them where water use efficiency is highest (i.e. highest BWR and lowest WFP). Nevertheless, future improvement of WFP simulation under climate change can be obtained by considering the CO₂ effect on stomatal conductance and therefore on crop transpiration.

5 Conclusions

This chapter primarily defines the main research topics involving the application of crop models for promoting sustainable agriculture in the last three decades: water resource management, global climate change and carbon cycle.

Then, focus moved to spatializing crop models with particular attention on defining model data requirements and describing underlying methodological concerns and constraints. In spatial modelling the choice of scale together with input data retrieval and harmonization are two of the most crucial issues to be tackled.

Since spatial simulation output is scale-dependent, the choice of the appropriate scale of analysis is fundamental. Selection of the scale of the system being modelled depends on the goal and the final beneficiary. For example, if the objective refers to the best management practices to adopt, or how to make the land more profitable, the target system should be on a field scale. At farm and larger scales, the goal is understanding how weather, soil, socio-economic factors and crop management practices affect crops and how simulation tools can easily and effectively support policymakers.

The spatialization of crop models needs to link different scales: for example, the scale on which the processes are described by the model, the scale on which input data or information (model parameters and input variables) are be available, or the scale on which output results are expected or sought. In turn, there is also a wide range of variability in input data quality and coverage. Data reconstruction (applied to missing values, to estimate key variables, to replace poor quality data) as well as cross-scale data harmonization are crucial processes in spatial modelling since they introduce uncertainty in predictions.

Furthermore, as the simulation scale increases, performing a detailed model calibration/validation becomes more difficult because spatially distributed information related to main phenological variables and growth dynamics (leaf area index, aboveground biomass) is rare.

In this context, increasing use of “big data” and smart sensors for agriculture is leading to closing information gaps and provides opportunities for multiple sources of information, including remotely sensed data, to be combined into one predictive system. Remote sensing data can be used to calibrate, force and update state variables of the simulation model in runtime. We claim that with the assimilation of model state variables (e.g. leaf area index dynamic over crop cycle, soil water
content evolution) via smart sensors, their simulation processes in crop models may be no longer necessary. This practice can be adopted in high-resolution in-season simulation studies, provided that output accuracy is preserved.

The final unaddressed issue concerning spatial modelling is a technical one, and regards whether or not current crop/cropping system models are adequate to implement the concepts of spatially explicit simulation modelling discussed so far. The challenge lies in the integration of two complementary toolsets: agent-based models and Geographic Information Systems (GIS). Spatial simulation workflows often make use of GIS in the preparation of spatial input data and in outcome visualization, whereas the model is used to handle spatially-distributed dynamic simulation of biophysical processes.

References


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