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How can plant modelling be a leverage for cropping system improvement by integrating plant physiology and smart horticulture?

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Abstract

The main objective of the workshop "How can plant modelling be a leverage for cropping system improvement by integrating plant physiology and smart horticulture?", developed within the frame of IHC2022, was to promote a discussion on the utility of plant modelling in the management of horticultural crops. A better understanding of the physiological response of crops to interaction with environmental factors (temperature, light, CO_2, water and nutrients) and crop management (soil, irrigation, phytosanitary treatments) would allow to improve crop growth and production (fruit quality and/or yield), thereby saving resources that are becoming ever scarcer. Modelling is becoming more and more important for horticulture in the broadest sense, both to help advancing innovation and for a better understanding of the functioning of existing systems. This workshop was a great opportunity to create a platform for exchange between researchers working in different areas such as process-based models (PBM), Functional–structural plant models (FSPM) and greenhouse climate models (GCM). Interaction of different models is necessary to analyze the spatial and temporal distribution of crop production. This workshop aimed to establish interactions between the different areas of modeling to obtain decision support tools for plant production in smart horticulture. A panel consisting of four researchers (two invited senior researchers, and the animators of the workshop) promoted an open discussion with the participants, on their views and experiences about the integration of plant physiology and smart horticulture. The workshop allowed an interdisciplinary discussion between scientists to identify the potential roles and new research directions of plant modelling. In this paper some points of common interest for all scientists working with crop models are presented based on the results of the discussion in the workshop and in published papers.

Keywords: processed-based modelling, functional-structural plant modelling, plant ecophysiology, greenhouse climate, decision-support tool, model evaluation, simulation

CONTEXT

The workshop (W5) took place on the evening of the 15th of August 2022, during the XXXI International Horticultural Congress (IHC2022) in Angers, France, and was attended by about 100 colleagues, with very diverse backgrounds, professional or academic experience, and age distribution: crop modelling, plant ecophysiology and physiology, consultancy in horticulture, functional-structural plant modelling, computational fluid dynamics, etc. It was held in a very informal way, minimizing frontal presentations by the animators, while allowing a maximum of participation by the public. However, the authors would like to point out here that the current article still mostly reflects their personal views and opinions as they did not record or systematically note down all contributions made by the attendees of the workshop.

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Should we have gotten it wrong in some or all respects, then we invite colleagues to come forward with critical remarks by email.

This workshop was organized in advance of the International Symposium on Models for Plant Growth, Environments, Farm Management in Orchards and Protected Cultivation (HorchiModel 2023) that was held in Almería (Spain) from June 26th to 28th 2023.

CROPPING SYSTEMS

Modelling in and for agronomy, or "crop modelling" as it is better known, has been a fairly straightforward endeavor, initiated by personalities such as Cornelis Teunis de Wit (de Wit, 1965) or Aristid Lindenmayer (Lindenmayer, 1968), the latter founding the branch of structural models. Crop modelling consists of establishing a series of mathematical algorithms that quantitatively represent the growth and production of crops in interaction with their environment. Crop models mainly allow to simulate the dynamics of plant development or phenology (anthsis, maturity, pod set, seed set, tuber initiation), the growth and biomass accumulation (aboveground biomass, leaves, stems, pods, seeds or grain yield, tubers, roots, harvest index), its ability for photosynthesis and transpiration (CO_2 and water uptake), nutrient uptake (mostly nitrogen) and stresses (water or nutrition deficit, low or high temperature stress) (Asseng et al., 2015). In general, crop models are designed considering four main components: plant growth, carbon capture, water requirement and fertilizer absorption. Plant development or phenology regulates the timing and duration of basic growing process, providing the framework within absorption of carbon, water and nutrient happen (Craufurd et al., 2013).

When applied to horticulture, crop modelling has to deal with the huge diversity of horticultural crops and the equally enormous diversity of cropping systems that go along with them. The great diversity of horticultural cropping systems can be characterized in a variety of ways, for instance according to the location (greenhouse or field), within the greenhouse according to the type (closed, semi-closed, with full climate control, and optional lighting), or most importantly according to the type of crop produced (small fruit, vegetables, ornamentals, with cut and potted produce). Among the specialized cropping systems, we can name the traditional or professional orchard, the market garden, or the garden-orchard, the latter being an intercropping system combining fruit trees with various vegetable or cereals. Urban horticultural systems (pot- or container based on roof terraces, indoor vertical farming, etc.) are the latest innovations, which bring the fresh produce even closer to the city-dwelling consumer.

Given the great diversity in horticultural production systems and the wide range of production objectives, it is appropriate to ask whether these systems should all be modelled, and if so, at which resolution: should one create one model for each variety, for each system, for each production basin, for each product…? A partial reply to this difficult question is, of course, that this has all been done already, for a wide range of species and varieties, for greenhouse and field crops, more or less successfully, but then, is this high number of models justified, and can these models be generalized or certain of them reused for other crops?

CURRENT CHALLENGES

The workflow from experimentation to modelling and decision-support is all too often still going in one direction, and modellers are too little involved in the early stages of experimental design, with negative repercussions on data quality for parameterisation. Data acquisition techniques are evolving rapidly, with high-throughput phenotyping devices becoming increasingly available. The challenge here is to organize the workflow as to avoid data redundancy or lack of usability. Coupling model design with data acquisition and analysis at an early stage in the project, with mutual sharing of the responsibility for success or failure, sounds trivial but is the way to go forward.

Several questions were raised in the workshop that were discussed by all the participants. Below we have tried to present the results of published works that can help us answer these questions.

What measurements are necessary for crop models validations?

The objective of crop model evaluation is to know how well model predictions are relevant with measures collected in real-world situations (Pasquel et al., 2022). Evaluation can include only qualitative information about the quality of the model to represent a crop system or quantitative measure of quality (Wallach, 2019). Model evaluation should begin at the start of model development by identifying the objectives, their range of application, the output variables of interest, and the acceptable level of error (Wallach, 2019). Once a crop model has been developed, it is necessary to carry out a sensitivity and uncertainty analysis and an estimation of the parameters (calibration).

In order to apply crop models correctly, it is essential to perform uncertainty assessments of their predictions (Wallach et al., 2016). The uncertainty information can be used to analyze the effect of the number of field trials on model accuracy (Nissanka et al., 2015). Crop models includes uncertainty from input variables (due to error of measurement), from parameters whose values cannot be directly measured and need been estimated (their accuracy depends on the estimation technique and quality of experimental data set) and from model equations (Wallach, 2019). It is very important that the same scientist can participate in all the processes to have knowledge of the different sources of error.

Three different approaches have been used in traditional studies for crop model evaluation and improvement (Roux et al., 2014; Wallach et al., 2016; Pasquel et al., 2022): validation, uncertainty propagations studies, multi-model ensembles and calibration.

1. Validation.

The first method for crop model evaluation, typically described as validation, consists of making estimates on a crop already developed and comparing them with the experimentally measured values, calculating statistically the error. In this method, the observed discrepancy between past observations and simulations are taken as a measure of uncertainty for future predictions (Wallach et al., 2016).

A first method to analyze the uncertainty of crop model predictions is to evaluate error of prediction comparing simulated values with experimental data observed to calculate an statistical criterion of error, mainly mean squared error (MSE) (Palosuo et al.,2011) or root mean square error (RMSE) (Jégo et al., 2013). This evaluation of the uncertainty based in comparisons of prediction of the model with experimental data includes all sources of error in the observed values, in parameters, in input variables or in model equations (Roux et al., 2014). A second method of analysis method consists of evaluating the mean squared error averaged over the distributions of model structure, inputs and parameters. Model uncertainty is estimated using hindcasts, and a model variance term estimated from a simulation experiment (Wallach et al., 2016).

2. Uncertainty propagations studies.

The second approach to crop model evaluation tries to analyze how the uncertainty in the model inputs, due to high spatial or temporal variability, or in the values of the parameters, that are only approximations of reality, can propagate through the crop model resulting in an uncertainty in predictions (Confalonieri et al., 2006; Roux et al., 2014; Wallach et al., 2016). In many cases, simple sensitivity analysis are carried out that are limited to identify the inputs and parameters of the model that generate greater uncertainty in the final predictions (Confalonieri et al., 2006; Post et al., 2008; Iizumi et al., 2009).

Error propagation analyses allow to determine the effect on predicted values when input parameters or variables vary on a temporal or spatial scale, and estimate uncertainty for long-term (Post et al., 2008) or large-scale predictions (Iizumi et al., 2009). Typically, sensitivity studies or uncertainty analysis focus on only one of the possible sources of error, such as input variables, model parameters or the mathematical equations used. These works usually provide more detailed information than the complete evaluations of the models (analyzing all the components) and also allow to observe the effect of hypothetical (conditions that have never been experienced before) values of the input variables or parameters (Roux et al., 2014). The influence of the uncertainty in the observations used for calibration in the model predictions are not consider by most of modellers (Confalonieri et al., 2016).

3. Multi-model ensembles.

A third method of models evaluation is based on multi-model ensembles (MMEs) whereby several crop models, developed by different teams, are used simultaneously to estimate the same variables from an identical set of input data (Wolf et al., 1996; Confalonieri et al., 2006; Palosuo et al., 2011; Wallach et al., 2016). The variability between different crop models is used to measure the prediction inaccuracy produced by uncertainty associated to model structures (Palosuo et al., 2011), that is a major source of error in predictions for mechanistic crop models (Wallach et al., 2016).

MMEs studies in crop simulations usually have find that using indicators, such as the ensemble mean (e-mean) and ensemble median (e-median) of simulated data improves the estimates made with the best available single crop model (Wallach et al., 2018). In general, the prediction error decreases with the number of crop models used (Wallach et al., 2018), although the improvement is reduced beyond 10 models (Martre et al., 2015). Improvements of the individual model through re-parameterization and/or incorporating or modifying equations can reduce the number of models needed in the MMEs (Maiorano et al., 2017).

4. Calibration.

Calibration consists of estimating the parameters of the models to allow that model predictions fit the experimental data as well as possible. In many cases the parameters that characterize the crops are obtained from the literature assuming their validity in large regions, without subjecting them to an adequate calibration process (Angulo et al., 2013). Calibration constitutes one of the main stages in the development of models of crop systems since it has an important impact on the results of the simulations (Wallach et al., 2020).

Crop models can be calibrated in different way, using the average values observed of parameters, taking it directly from other models, or adjusting several parameters simultaneously to minimize the difference between simulated and measured values (Jégo et al., 2013). When the objective of the models is to make point predictions, it is acceptable to perform a frequent analysis using the minimum root mean square error (RMSE) between simulated and observed data as criteria to determine crop model parameters (Angulo et al., 2013; Wallach et al., 2020). In this case, crop model parameters can be estimated using any standard statistical software package providing the best-fit parameters and uncertainty information about those parameters (Nissanka et al., 2015).

Different strategies can be used to calibrate crop models using only specific parameters of phenological development for a region that can be directly adjusted according to the average observed dates (Jégo et al., 2013), including a correction factor for yield estimations (Jagtap and Jones, 2002) or calibrating some selected growth parameters (Angulo et al., 2103).

How can existing crop models help growers with horticultural systems management?

Mechanistic or process-based crop models (as opposed to empirical or statistical) can be used to evaluate physiological characteristics to understand the interactions of different genotype with the environment where plants growth and with agronomic practices (Messina et al., 2009). Crop models are a powerful tool to evaluate genetics and breeding strategies, to simulate growth and yield, to assessment the impact of environment in plants and finally to crop management (Craufurd et al., 2013; Wallach et al., 2016). Thus, the use of crop models has allowed the development of decision support system capable of presenting farmers with various management alternatives to improve the use of resources such as irrigation water (Rinaldi and He, 2014) and nutrients (Gallardo et al., 2021).

In order to analyze the interactions of crops with the surrounding environment, it is necessary to consider the whole soil-plant-atmosphere as a continuous system. In this sense, models have been developed that consider in a global system the interactions between crop growth and environmental factors, combining phenology models, root growth models, soil water balance models and irrigation decision models (Steduto et al., 2012; Zhang and Feng, 2010). In the same way, transient computational fluid dynamic (CFD) models including a sub-model that consider the water transport in the substrate-plant-atmosphere continuum, and crop interactions with the greenhouse environment can been used to improved water and climate systems management (Ali et al., 2019).

Crop modeling can also help manage horticultural greenhouses through digital twins that not only represent the actual states of objects like plants and greenhouses but can also analyze historical states and simulate future behavior as crop growth or expected yields (Ariesen-Verschuur et al., 2022).

What is the level of extrapolation of current crop models to large commercial farms?

Despite of the large availability of crop models, most of them have been limited to studies located in specific locations and climatic conditions, without analyzing the variability of production in large commercial farms or at the regional level (Jagtap and Jones, 2002). The main difficulty for extend the use of crop simulation models to commercial farms is a significant discrepancy between spatial and temporal scales of available data and input requirements (Jagtap and Jones, 2002). Recently some crop models are being used to simulate the climate change impact on crop production at regional scales (Angulo et al., 2013).

The integration into a large-scale dynamic model of the strengths of conventional crop models to represent crop growth processes (phenological development, carbon allocation, yield formation, biological nitrogen fixation processes) and the management practices (tillage, cover cropping and genetic improvements) can provide robust and consistent guidance to growers, development agents and policy makers (You et al., 2022).

How can crop models help to predict the effect of climate change on plants development and production?

Plants can implement several strategies of defense to mitigate the effects of climatic parameters variability produced by the climate change, by varying phenological trends, changing physiology, increasing carbon sequestration and metabolites synthesis (Medda et al., 2022). Due to the complexity of horticultural systems and the complex processes involved in climate change, crop models are an essential tool to understand the impact of climate change on crops and for the development of new adaptation strategies (Asseng et al., 2015). Crop models can help to estimate the capacity of plants to adapt to the direct and indirect consequences of climate change influencing agricultural sustainability (Anderson and Song, 2020).

In recent years, process-based crop models have been widely used to analyze the effects of climate change on crop production (Palosuo et al., 2011; Rosenzweig et al., 2013; Angulo et al., 2013; Peng et al., 2020; Jägermeyr et al., 2021). However, most of studies focused in crop models only consider main aspect of climate change such as rainfall, atmospheric CO_2 and temperature (Wolf et al., 1996; Jägermeyr et al., 2021) but do not consider the effect of climate change impact on evaporative demand, vapor pressure deficit and wind, that could improve the simulations of the crop system responses (Asseng et al., 2015).

Uncertainties linked to crop model estimations, and arising from potential greenhouse gas emission scenarios and climate model projections make crop production estimates highly uncertain (Jägermeyr et al., 2021). The AgMIP is a major international effort to link the climate, crop, and economic modelling communities with cutting-edge information technology to produce improved crop and economic models and the next generation of climate impact projections for the agricultural sector (Rosenzweig et al., 2013).

FUTURE DIRECTIONS

The first aspect necessary to improve future works on crop modelling is to obtain more comprehensive and high-quality data, with a finer spatial and temporal resolution, allowing application of improved strategies for crop model calibration (Angulo et al., 2103). A second aspect to which it is necessary to pay more attention in the future, is the development of conceptual and mathematical frameworks where the different sources of uncertainty affecting model predictions could be analyzed in an integrated way (Confalonieri et al., 2016). Another challenge is the parameterization of the phenology of new crop varieties and cultivars that are continuously being introduced in horticultural systems (Nissanka et al., 2015). That can help determine in each region, which are the most suitable species and varieties to adapt to the new climatic conditions generated by the climate change. Finally, it is necessary to develop studies that relate the different methods of analysis of the crop models (comparison with hindcasts, propagation of input or parameter uncertainty and variability in multi-model ensembles) to identify an overall criterion of uncertainty and estimate the separate contributions from different sources of error (Wallach et al., 2016).

One thing is certain: Horticulture will face massive challenges in the future – and it will master them, as it has done in the past. However, to do so, ever more integrated and powerful decision-support tools are necessary, and models can play a decisive role in this. New generations of models will be developed by new generations of scientists, scientists who will be, from the start of their career, much more interdisciplinary. Sharing models (even unready ones) on platforms like GitLab or GitHub, making code snippets accessible and executable using tools like Jupyter notebooks, will enhance model use and development and render models more applied and applicable. This is in no contradiction with the continued practice of using proprietary models in horticultural consultancy, for the creation of expert reports, or for policy makers.

Literature cited

Ali, H.B., Bournet, P.E., Cannavo, P., and Chantoiseau, E. (2019). Using CFD to improve the irrigation strategy for growing ornamental plants inside a greenhouse. Biosyst. Eng. *186*, 130–145 https://doi.org/10.1016/j.biosystemseng.2019.06.021.

Anderson, J., and Song, B.H. (2020). Plant adaptation to climate change - where are we? J. Syst. Evol. *58* (*5*), 533–545 https://doi.org/10.1111/jse.12649. PubMed

Angulo, C., Rötter, R., Lock, R., Enders, A., Fronzek, S., and Ewert, F. (2013). Implication of crop model calibration strategies for assessing regional impacts of climate change in Europe. Agric. For. Meteorol. *170*, 32–46 https://doi.org/10.1016/j.agrformet.2012.11.017.

Ariesen-Verschuur, N., Verdouw, C., and Tekinerdogan, B. (2022). Digital twins in greenhouse horticulture: a review. Informatics and Electronics in Agriculture. *199*, 107183 https://doi.org/10.1016/j.compag.2022.107183.

Asseng, S., Zhu, Y., Wang, E., and Zhang, W. (2015). Crop modeling for climate change impact and adaptation. In Crops Physiology, Chapter 20, V.O. Sadras, and D.F. Calderini, eds. (D.F.: Academic Press), p.505–546. 10.1016/B978-0-12-417104-6.00020-0

Confalonieri, R., Acutis, M., Bellocchi, G., Cerrani, I., Tarantola, S., Donatelli, M., Genovese, G. (2006). Exploratory Sensitivity Analysis of CropSyst, WARM and WOFOST: a Case-Study with Rice Biomass Simulations. Italian Journal of Agrometeorology. *11* (3) 17–25. JRC35589.

Confalonieri, R., Bregaglio, S., and Acutis, M. (2016). Quantifying uncertainty in crop model predictions due to the uncertainty in the observations used for calibration. Ecol. Modell. *328*, 72–77 https://doi.org/10.1016/j.ecolmodel.2016.02.013.

Craufurd, P.Q., Vadez, V., Jagadish, S.V., Vara Prasad, P.V., and Zaman-Allah, M. (2013). Crop science experiments designed to inform crop modeling. Agric. For. Meteorol. *170*, 8–18 https://doi.org/10.1016/j.agrformet.2011.09.003.

de Wit, C.T. (1965). Photosynthesis of Leaf Canopies. Agricultural Research Report No. 663 (Wageningen: PUDOC).

Gallardo, M., Cuartero, J., Andújar de la Torre, L., Padilla, F.M., Luz Segura, M., and Thompson, R.B. (2021). Modelling nitrogen, phosphorus, potassium, calcium and magnesium uptake, and uptake concentration, of greenhouse tomato with the VegSyst model. Sci. Hortic. (Amsterdam) *279*, 109862 https://doi.org/10.1016/j.scienta.2020.109862.

Iizumi, T., Yokozawa, M., and Nishimori, M. (2009). Parameter estimation and uncertainty analysis of a large-scale crop model for paddy rice: application of a Bayesian approach. Agric. For. Meteorol. *149* (*2*), 333–348 https://doi.org/10.1016/j.agrformet.2008.08.015.

Jägermeyr, J., Müller, C., Ruane, A.C., Elliott, J., Balkovic, J., Castillo, O., Faye, B., Foster, I., Folberth, C., Franke, J.A., et al. (2021). Climate impacts on global agriculture emerge earlier in new generation of climate and crop models. Nat. Food *2* (*11*), 873–885 https://doi.org/10.1038/s43016-021-00400-y. PubMed

Jagtap, S.S., and Jones, J.W. (2002). Adaptation and evaluation of the CROPGRO-soybean model to predict regional yield and production. Agr. Ecosyst. Enrivon. *93* (*1–3*), 73–85 https://doi.org/10.1016/S0167-8809(01)00358-9.

Jégo, G., Bélanger, G., Tremblay, G.F., Jing, Q., and Baron, V.S. (2013). Calibration and performance evaluation of the STICS crop model for simulating timothy growth and nutritive value. Field Crops Res. *151*, 65–77 https://doi.org/10.1016/j.fcr.2013.07.003.

Lindenmayer, A. (1968). Mathematical models for cellular interactions in development. II. Simple and branching filaments with two-sided inputs. J. Theor. Biol. *18* (*3*), 300–315 https://doi.org/10.1016/0022-5193(68)90080-5. PubMed

Maiorano, A., Martre, P., Asseng, S., Ewert, F., Müller, C., Rötter, R.P., Ruane, A.C., Semenov, M.A., Wallach, D., Wang, E., et al. (2017). Crop model improvement reduces the uncertainty of the response to temperature of multi-model ensembles. Field Crops Res. *202*, 5–20 https://doi.org/10.1016/j.fcr.2016.05.001.

Martre, P., Wallach, D., Asseng, S., Ewert, F., Jones, J.W., Rötter, R.P., Boote, K.J., Ruane, A.C., Thorburn, P.J., Cammarano, D., et al. (2015). Multimodel ensembles of wheat growth: many models are better than one. Glob. Change Biol. *21* (*2*), 911–925 https://doi.org/10.1111/gcb.12768. PubMed

Medda, S., Fadda, A., and Mulas, M. (2022). Influence of Climate Change on metabolism and biological characteristics in perennial woody fruit crops in the Mediterranean environment. Horticulturae *8* (*4*), 273 https://doi.org/10.3390/horticulturae8040273.

Messina, C.D., Hammer, G.L., Dong, G., Podlich, D., and Cooper, M. (2009). Modelling crop improvement in a G×E×M framework via gene-trait-phenotype relationships. In Crop Physiology, V. Sadras, and D. Calderini, eds. (The Netherlands: Academic Press), p.235–265.

Nissanka, S.P., Karunaratne, A.S., Perera, R., Weerakoon, W.M.W., Thorburn, P.J., and Wallach, D. (2015). Calibration of the phenology sub-model of APSIM-Oryza: going beyond goodness of fit. Environ. Model. Softw. *70*, 128–137 https://doi.org/10.1016/j.envsoft.2015.04.007.

Palosuo, T., Kersebaum, K.C., Angulo, C., Hlavinka, P., Moriondo, M., Olesen, J.E., Patil, R.H., Ruget, F., Rumbaur, C., Takáč, J., et al. (2011). Simulation of winter wheat yield and its variability in different climates of Europe: a comparison of eight crop growth models. Eur. J. Agron. *35* (*3*), 103–114 https://doi.org/10.1016/j.eja.2011.05.001.

Pasquel, D., Roux, S., Richetti, J., Cammarano, D., Tisseyre, B., and Taylor, J.A. (2022). A review of methods to evaluate crop model performance at multiple and changing spatial scales. Precis. Agric. *23* (*4*), 1489–1513 https://doi.org/10.1007/s11119-022-09885-4.

Peng, B., Guan, K., Tang, J., Ainsworth, E.A., Asseng, S., Bernacchi, C.J., Cooper, M., Delucia, E.H., Elliott, J.W., Ewert, F., et al. (2020). Towards a multiscale crop modelling framework for climate change adaptation assessment. Nat. Plants *6* (*4*), 338–348 https://doi.org/10.1038/s41477-020-0625-3. PubMed

Post, J., Hattermann, F.F., Krysanova, V., and Suckow, F. (2008). Parameter and input data uncertainty estimation for the assessment of long-term soil organic carbon dynamics. Environ. Model. Softw. *23* (*2*), 125–138 https://doi.org/10.1016/j.envsoft.2007.05.010.

Rinaldi, M., and He, Z. (2014). Chapter Six - Decision Support Systems to Manage Irrigation in Agriculture. Ed: D.L. Sparks. Advances in Agronomy, Academic Press. *123*, 229–279.

Rosenzweig, C., Jones, J.W., Hatfield, J.L., Ruane, A.C., Boote, K.J., Thorburn, P., Antle, J.M., Nelson, G.C., Porter, C., Janssen, S., et al. (2013). The agricultural model intercomparison and improvement Project (AgMIP): protocols and pilot studies. Agric. For. Meteorol. *170*, 166–182 https://doi.org/10.1016/j.agrformet.2012.09.011.

Roux, S., Brun, F., and Wallach, D. (2014). Combining input uncertainty and residual error in crop model predictions: a case study on vineyards. Eur. J. Agron. *52*, 191–197 https://doi.org/10.1016/j.eja.2013.09.008.

Steduto, P., Raes, D., Hsiao, T.C., and Fereres, E. (2012). AquaCrop: concepts, rationale and operation. In: Steduto, P., Hsiao, T.C., Ferere,s E., Raes, D. (Eds.). Crop Yield Response to Water. FAO irrigation and drainage paper no. 66. FAO, Rome, p.17–49.

Wallach, D. (2019). Model Evaluation. In Working with dynamic crop models, 3rd edn, D. Wallach, D. Makowski, J.W. Jones, and F. Brun, eds. (Amsterdam, the Netherlands: Academic Press).

Wallach, D., Thorburn, P., Asseng, S., Challinor, A.J., Ewert, F., Jones, J.W., Rotter, R., and Ruane, A. (2016). Estimating model prediction error: should you treat predictions as fixed or random? Environ. Model. Softw. *84*, 529–539 https://doi.org/10.1016/j.envsoft.2016.07.010.

Wallach, D., Martre, P., Liu, B., Asseng, S., Ewert, F., Thorburn, P.J., van Ittersum, M., Aggarwal, P.K., Ahmed, M., Basso, B., et al. (2018). Multimodel ensembles improve predictions of crop-environment-management interactions. Glob. Change Biol. *24* (*11*), 5072–5083 https://doi.org/10.1111/gcb.14411. PubMed

Wallach, D., Palosuo, T., Thorburn, P., Hochman, Z., Gourdain, E., Andrianasolo, F., Asseng, S., Basso, B., Buis, S., Crout, N., et al. (2020). The chaos in calibrating crop models. bioRxiv. 2020.09.12.294744.

Wolf, J., Evans, L.G., Semenov, M.A., Ecker, H., and Iglesias, A. (1996). Comparison of wheat simulation models under climate change. I. Model calibration and sensitivity analyses. Clim. Res. *7* (*3*), 253–270 https://doi.org/10.3354/cr007253.

You, Y., Tian, H., Pan, S., Shi, H., Bian, Z., Gurgel, A., Huang, Y., Kicklighter, D., Liang, X.-Z., Lu, C., et al. (2022). Incorporating dynamic crop growth processes and management practices into a terrestrial biosphere model for simulating crop production in the United States: toward a unified modeling framework. Agric. For. Meteorol. *325*, 109144 https://doi.org/10.1016/j.agrformet.2022.109144.

Zhang, Y., and Feng, L. (2010). CropIrri: A Decision Support System for Crop Irrigation Management. In Computer and Computing Technologies in Agriculture III. CCTA 2009. IFIP Advances in Information and Communication Technology, Vol. 317, D. Li, and C. Zhao, eds. (Berlin, Heidelberg: Springer).