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ESTIMATION OF MAIZE YIELDS IN THE BARAGAN PLAIN (ROMANIA) - A SPATIALLY EXPLICIT APPLICATION OF A CROP GROWTH MODEL

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Abstract

Crop growth models are useful tools for in-depth analyses on agricultural productivity and resource (land and water) use under various environmental and management conditions, rendering solution-oriented information for end-users. The paper showcases a spatially explicit application of a crop growth model for simulating the cultivation of a commonly used maize cultivar in the Baragan Plain, South-East Romania. We have parameterized the EPIC⁺ model (Williams et al., 1989; Kamali et al., 2018) with geographical, agricultural practices and experimental-based crop inputs, and have designed two scenarios for crop parameter calibration and improved nutrient and irrigation application, respectively. These methodological and conceptional steps enabled model performance assessment and maize yields estimation in the study area. With adjustments of sensitive crop parameters and agricultural practices in the model setup, crop growth is particularly constrained by stress factors (e.g. nutrient stress), and potentially by model structure parameters, which also need to be calibrated. It was achieved a good agreement between areal averaged estimated yields and reported yields, suggesting that the model is suitable for further regional investigations and for supporting decisions on agricultural resources management.

Key words*: agricultural modeling, plant stress, model parametrization, EPIC⁺, SE Romania.*

INTRODUCTION

Crop growth simulation models are increasingly used for assessing a wide range of environmental problems, such as soil and water resources quality and availability, climate change impacts on crop production or soil carbon sequestration. They basically allow for designing virtual experiments to study, in a systematic and integrated way, the complex and interdependent biophysical effects of atmosphere and soil processes on crop growth and formation (Minoli et al., 2019). Coupled with a geographic information system, crop growth models have been applied particularly at regional and global-scale levels to estimate present and future crop yields, agricultural water productivity, nitrogen losses, crop vulnerability to drought, etc. under various environmental conditions and agricultural practices (Liu at al., 2007; Liu, 2009; Folberth, et al., 2012, 2016; Mauser et al., 2009; Liu et al., 2016). Termed as global gridded crop models (Rosenzweig et al., 2014) given the geospatial character of the utilized datasets, they provide evidence-based information, comprehensive overviews and comparisons among regions, being useful tools in decision making processes concerning, for instance, nature-based solutions for climate mitigation and adaptation (Balkovic et al., 2018), land and water management in agriculture (Flach et al., 2020), or sustainable agricultural productivity (Mauser et al., 2015).

The current challenging trajectories of both societal development and consumption, and climate change put a stress on water resources use. It becomes clear that sustainable management of agricultural water resources is a priority supported by deep understanding of the processes at the interface of atmosphere-soil-plant system and by evidence-based estimates of yield production and water consumption. In Romania, such investigations are particularly useful considering the new development strategies in agriculture, according to which the irrigated area is planned to increase from 0.5 million ha to almost 2 million hectares by 2020, in an ambitious objective which aims to boost agricultural activities and production, contributing also to climate change adaptation and rural communities' resilience (MADR, 2016).

In this context, the aim of this paper is to test the application and performance of a crop growth model for a pilot area in the Romanian Plain in order to analyse the effect of increasing irrigation capacities on crop production and to exemplify the utility and relevance of crop models in studies on agricultural resource management. To this end, we applied an extended version of the EPIC (Environmental Productivity Integrated Climate) crop growth model (Williams et al., 1989) which is equipped with a module for automatic calibration and parameter uncertainty assessment (Kamali et al., 2018).

The pilot area chosen for this study is the Baragan Plain, a representative agricultural region located in SE Romania (Figure 1). The area is a geographical unit of the Romanian Plain characterised by relatively homogeneous features in terms of relief, climate and soil type coverage. Generally, the soils are nutrient rich soils of the Chernozems types with good water retention capacity, while the climate is temperate-continental with increasing dry spells which intensify the already existing conditions of regional drought.

Figure 1. Cropland in the Baragan Plain, SE Romania; geospatial dataset: Dogaru & Kucsicsa, 2015

MATERIALS AND METHODS

Brief information on the crop model

EPIC$^+$ is a gridded crop model that has been created by Kamali et al., 2018 as a Python-based spatial framework for the application and calibration of the field-scale, bio-physical EPIC (Environmental Productivity Integrated Climate) model. EPIC was developed by Williams et al., 1989 and constantly improved to accurately simulate process-based interactions at the interface of soil-crop-atmosphere system under various environments (Gassman et al., 2005; Izauralde et al., 2006).

In EPIC, potential crop growth is calculated daily based on intercepted photosynthetically active radiation and conversion of CO_2 to biomass (Stockle et al., 1992; Williams et al., 1989). The model simulates plant growth, yield and soil dynamics on a daily time step using a set of empirically based algorithms and climate, soil types and properties and crop management input data (Williams et al., 1989). EPIC first estimates potential plant growth and then reduces it according to the limitation due to the most dominant stresses (i.e. N and P deficit, water, temperature, aeration, salinity) by a factor between 0 and 1.

Yield is estimated using an actual harvest index (HI), which is calculated by the model within the range of a defined potential HI and a minimum HI depending on water stress. Potential evapotranspiration (ET) is calculated using the Hargreaves method (Hargreaves and Samani, 1985) and actual ET according to Ritchie (1972).

The EPIC$^+$ model runs EPIC in each grid cell at a user defined resolution (Kamali et al., 2018) and implements the newest version of it, (i.e. EPICv.0810). It is coupled with the SUFI-2 automatic calibration module of SWAT (Soil and Water Assessment Tool) model, accounting for parameter uncertainty from all sources (e.g., inputs, crop parameters, and model structure) (Abbaspour, 2015). Uncertainties are expressed by distributions associated to crop growth and model structure parameters. Latin hypercube method is applied to sample the parameters, while the output uncertainty is quantified as the 95% prediction uncertainty band (95PPU) calculated at the 2.5% and 97.5% levels of the cumulative distribution function of the output variables (Abbaspour, et al., 2007). Detailed information on EPIC$^+$ application and model automatic calibration is found in Kamali et al. (2018).

Model set up

Input datasets

EPIC model operates with both detailed process-based parameters of atmosphere - soil - plant interactions and comprehensive input datasets on: 1) location (longitude, latitude, elevation and slope), 2) climate, 3) soil types and properties, 4) land use, 5) cropland management such as irrigation and fertilization application, and 6) crop specific parameters. In this study all geospatial datasets were rasterized where applicable and harmonized at 1 km resolution grid cell.

DEM data were obtained from the 3 arc-seconds (approx. 90m resolution) digital elevation model of the NASA Shuttle Radar Topographic Mission provided by CGIAR-CSI GeoPortal (Consortium for Spatial Information, 2018). Terrain slopes were subsequently derived from the DEM raster based on the maximum change in the elevations between each cell and its eight neighbours.

ROCADA gridded climatic data was downloaded from PANGAEA data portal to assimilate in the crop model the daily parameters including: min. temperature, max. temperature, precipitation, and solar radiation. This dataset is based on daily observations recorded at all meteorological stations in Romania covering 1961-2013 time interval (Birsan & Dumitrescu, 2014).

The geospatial dataset of harvested area for maize was created on a 30´´x30´´ latitude-longitude grid (~ 1km) by combining locality-level reported data on land use and crop-specific harvested area from the National Institute of Statistics with CORINE Land Cover 2006 (CLC) raster data provided by European Environmental Agency (EEA, 2016). Once we re-classified the CLC maps for cropland, pasture and non-cropland areas, we calculated the proportion of cropland in each 1km grid cell (Dogaru & Kucsicsa, 2015) by applying the methodology developed by Ramankkuty, et al. (2008) for creating global geospatial datasets of cropland distribution on the basis of high-resolution satellite derived land cover data, calibrated against agricultural census data. Further on we followed the steps proposed by Monfreda, et al. (2008) to first determine the ratio of the crop area to the total cropland in each locality and then to multiply it with the proportion of cropland in each 1km grid cell for the associated locality of that grid cell. The result ultimately represents the proportion of the specific crop in each grid cell. Since the crop-specific harvested area from the National Institute of Statistics at locality level is available until 2003, the final dataset of maize harvested area was averaged around the year 2002, being though in a relatively close time scale correspondence with the CLC 2006 dataset used in this study.

Soil types and their physical-chemical characteristics were provided by the National Research and Development Institute for Soil Science, Agrochemistry and Environment – ICPA Bucharest, Romania. The following soil parameters were used to create the soil files used in EPIC: depth, percentage of silt and sand, bulk density, pH, organic carbon content, fraction of calcium carbonate, cationic exchange capacity, electrical conductivity, mobile N and mobile P. The files of soil properties were linked with the digital Soil Map of Romania existing at the scale of 1:200 000.

Fertilizer application rates for N and P on cultivated areas treated with fertilizer were obtained from the National Institute of Statistics. These data are reported as annual amounts of applied fertilizer per ha at county level, without specifying the crop for which it is applied. Given a number of socioeconomic reasons, farmers opted for rather low fertilizer inputs, at least during the last decades (Popescu, 2013). For instance, during the 2000s the average rate of N fertilization was of 85 kg / ha in Călărași county and of 82 kg / ha in Ialomița county, respectively. Here, we used a multiannual mean of N and P allocation for cultivated areas, for the entire simulation period. In spite of its coarseness, we consider that the usage of fertilizer aggregated data is a practical compromise.

The spatial dataset representing the area equipped for irrigation resulted from digitizing a publicly available map of irrigation infrastructure issued in the framework of the Irrigation Strategy in Romania (MADR, 2011). Yearly irrigated areas in each county were downloaded from the online data portal of the National Institute of Statistics (http://statistici.insse.ro:8077/tempo-online/).

To account for the areal effect of irrigation in the simulation outcomes, the irrigated and rain fed yields were weighted in each grid cell as follows:

- the irrigated and rain-fed areas were simulated separately in each grid cell
- then, the weighted yield was calculated on a grid cell basis for each year (eq. 1):

$$Y_W^{j,c} = Y_I^{j,c} \times A_{Ip}^{j} + Y_R^{j,c} \times \left(1 - A_{Ip}^{j}\right) \quad \text{(eq. 1)},$$

where $Y_W^{j,c}$ [t ha^{-1}] is the average (weighted) yield in the grid cell *c* in the county *j*, $Y_I^{j,c}$ [t ha^{-1}] is the yield on irrigated cropland in the grid cell *c* in the county *j*, A_{Ip}^{j} [.] is the percentage of irrigated area in the county *j* applied for each irrigated grid cell found in the county *j*, and $Y_R^{j,c}$ [t ha^{-1}] is the yield on rain-fed cropland in the grid cell *c* in the county *j*.

Potential heat units for F376 maize cultivar

Phenologic development of the crop depends on the number of heat units (or growing degrees days) from planting to maturity. The heat units (HU) are calculated for each day (k) according to a certain base temperature, which is crop-specific and above which the plant starts to grow, min. temperature and max. temperature in that day (eq. 2). We run the EPIC model for a maize cultivar with medium duration until maturity (i.e. F376) which is widely cultivated in the southern part of the country, including the Bărăgan Plain. To have a general, representative value of the potential heat units (PHU) for the F376 maize cultivar we used the planting and maturity dates of this cultivar obtained in the amelioration experimental fields at INCDA Fundulea during 2007-2013, and the ROCADA climatic variables in several random locations throughout the study area. Consequently, the PHU was determined as an average of the accumulated HU from planting to maturity during 2007–2013 and throughout the considered locations.

$$HU_k = \frac{T_{max,k} + T_{min,k}}{2} - T_b \quad \text{eq. (2)}$$

Crop management, simulation run-time and evaluation of model performance

Maize was assumed to be planted after fertilizer application, top-layer plowing and field preparation. In EPIC harvest is programmed to occur at 115% of the calculated PHU fraction (i.e. the default assumption), taking into account the post-maturity drying of the crop on the field. Additionally, we considered no residual biomass removal after harvest as in many places farmers incorparate it into the soil for maintaining or increasing its quality. Automatic N and P fertilizer and irrigation options were set up in the model. They are based on the plant threshold factors (e.g. if N stress exceeded 20% on a giving day, N is added up to the maximum amount of N fertilizer application rate specified here by the county-level multiannual average during the simulation period).

According to the availability of the time series of input data, especially in what regards climate and management opperations (i.e. fertilization and irrigation), the simulation period was 1997-2013.

The simulated yields were automatically calibrated against the county-level reported yields for the same period of time, using the SUFI-2 module (Kamali et al., 2018). The coefficient of determination (R^2) and the standardized root mean square error (RSR) are the two statistics that evaluated the comparison between the reported and the simulated yields (i.e. model efficiency). R^2 expresses the linear correspondence between the two variables, with 1 being the optimal result, while RSR measures the difference between the reported and the simulated yields and takes values from 0 to ∞, where 0 is the best value. During the calibration process new ranges or values of crop / model parameters are calculated in a user-defined number of iterations, forming the parameters sensitivities. These are determined on a basis of a multiple regression system where the parameters are regressed against the objective function which is considered the RSR value. Basically the sensitivities express the changes in the objective function resulting from changes in each parameter while all other parameters are changing. In this we chose study 5 influential parameters (i.e. PHU, plant density, N and P fertilization rates and irrigation volume applied) over 3 iterations to perform the sensitivity analysis and calibrate the model for the entire study area (Table 2). Besides, to have a better sense on model robustness, we performed model calibration and validation on rain-fed yields at a finer spatial scale, specifically in 4 localities in the study area for which reported data were available (Figure 3). For this latter approach we took into account the same influential parameters, but ran 10 to 50 iterations to minimize parameter interaction and then fixed the parameters to their best values (i.e. the best simulation resulting from the values that produced the smallest objective function). However, studies highlight a larger range of both model and crop parameters that are sensitive and worth being calibrated in order to obtain reliable results (Liu, 2009; Gaiser et al., 2010, Folberth et al., 2012). Given the large computational time needed for simulation (calibration), we opted here to test the model for a pilot area in order to showcase its relevance for further analyses which in most cases require adequate infrastructure as well as collaborative research frameworks for implementation.

Scenario design

To highlight the EPIC$^+$ model applicability in regional studies on cropping systems productivity, we envisaged two cases of crop management conditions which are consistent with the new development plans in the irrigation sector in Romania, specifically the rehabilitation of the primary irrigation infrastructure with the purpose of increasing the irrigated area (MADR, 2016). These cases are:

- default parameters with no irrigation increased capacities (default simulations),
- calibrated crop parameters with no increased irrigation capacities (baseline scenario). In this case the fertilization rates were as described above, while of irrigation water supply was set at 1000 mm per year per maize cultivated area, being in line with many reported values by farms in the agricultural areas where irrigation was available.
- increased irrigation capacities and improved fertilization rates (improved crop management scenario). Here, the irrigated area was enhanced according to MADR, 2016 irrigation plans, while the levels of fertilization were increased to lower plant growth nutrient limitations at values of 200 kg / ha. We assumed sufficient irrigation water supply in grid cells that are equipped for irrigation.

RESULTS AND DISCUSSIONS

The comparison between maize yield estimates resulted from simulations run with model default parameters and the reported yields shows promising results for conducting this study. Aggregating the simulated yields at county level we obtained a good agreement between the observed and the estimated yields (Figure 2).

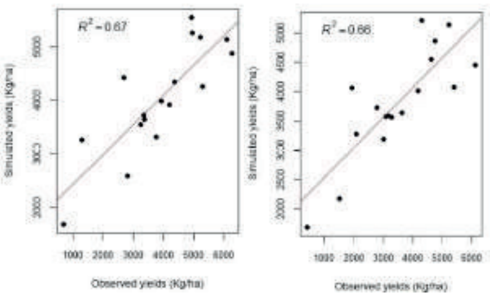

Figure 2. Reported yields and estimated yields simulated by default runs for the reference period (1997 – 2013) for Călărași County (left) and Ialomița County (right). Each point in the graph represents a year and the model fit is expressed through r squared adjusted (R^2)

However, the model overestimates the simulated yields in the years recognized as drought years of the first decade of the 21st century (Mateescu et al., 2013) (Table 1).

Moreover, aggregated measures can mask the variability in both time and space of yield trends, increasing the uncertainty level in the model outcomes and indicating the necessity for calibration and uncertainty measuring.

Table 1. Annual average of observed yields (Y_{obs}) and simulated yields with model default parameters (Y_{sim_d})

Year	Calarasi County			Ialomita County		
	Y_{obs} kg ha^{-1}	Y_{sim_d} kg ha^{-1}	Y_{dif} %	Y_{obs} kg ha^{-1}	Y_{sim_d} kg ha^{-1}	Y_{dif} %
1997	5218	5182	-0.7	5216	5140	-1.5
1998	3379	3645	7.9	3084	3575	15.9
1999	4373	4338	-0.8	4182	4020	-3.9
2000	1307	3259	149.3	2078	3280	57.8
2001	2818	2593	-8.0	1514	2177	43.8
2002	2698	4424	64.0	1930	4065	110.6
2003	3349	3721	11.1	2783	3727	33.9
2004	6111	5142	-15.9	4742	4866	2.6
2005	4941	5540	12.1	4288	5211	21.5
2006	4189	3924	-6.3	3619	3645	0.7
2007	696	1682	141.6	425	1683	295.9
2008	3763	3321	-11.7	2991	3185	6.5
2009	3923	3980	1.4	3152	3590	13.9
2010	4957	5263	6.2	4623	4550	-1.6
2011	5290	4264	-19.4	5382	4075	-24.3
2012	3258	3547	8.9	3265	3561	9.1
2013	6274	4879	-22.2	6113	4452	-27.2

In the process of calibration we adjusted the following crop parameters: PHU, plant density, N and P fertilization rates and irrigation volume applied. This led to an increase of the R2 of the county-base time series yields from 0.67 to 0.70 for Calarasi County and from 0.66 to 0.69 for Ialomita County, respectively.

Nevertheless, we could not identify a distinct pattern of reduction of the difference between the estimated yields and the reported yields in the drought years, suggesting that the model is very much sensitive to water stress conditions and that thorough investigations on model behaviour in water limited environments are highly recommended. Moreover, the sensitivity analysis indicates that the estimated yields are considerably constrained by nutrient stress factors, especially by N fertilization, temperature, as shown by increased PHU values, and water supply (Table 2).

Table 2. Sensitivity analysis on several influential parameters of crop growth and yield development

Crop growth influential parameters	Initial parameters (first iteration)	Adjusted parameters (three number of runs)	Parameter variation unit (from initial value)
PHU (accumulated number of heat units)	1640	2017	+0.23
Plant density (plants / m^2)	5	4	-0.23
Applied irrigation volume (mm / year)	1000	1200	+0.29
Nitrogen application amount (mean annual amount in kg / ha)	85 / 82#	101 /104#	+0.23
Phosphorous application amount (mean annual amount in kg / ha)	63 / 57#	63 / 57#	–

#The values represent the multiannual mean of N and P application rates on maize cultivation areas in Călărași and, Ialomița county, respectively.

The spatial distribution of the estimated yields under the calibrated crop growth parameters (i.e. baseline scenario) highlights the strong effects of drought conditions on crop production (Figure 4), showing, for instance, that yields in 2007 were below 2 t / ha in many parts of the study area.

Parameter adjustment at locality level further underpins the need to perform the calibration process on both crop and model structure parameters. In this respect, we considered 4 localities in the study area where we knew from our field work experience that irrigation had not been applied particularly since agricultural privatization reforms have been enforced (Figure 3).

Hence, all cropland in the calibration at locality level analysis was treated as rain-fed in order to reduce any possible bias by additional water supply given irrigation application.

Previous studies found that simulated maize yield was sensitive to several input and model parameters, such as: planting date, PHU, HI (harvest index, i.e. the ratio of grain to total crop biomass under ideal growing conditions), WSYF (the lower limit of HI due to water stress), PARM03 (the fraction of maturity when water stress starts reducing the harvest index) and PARM42 (indicator that affects runoff and thus soil water and evapotranspiration) (Liu, 2009; Wang et al., 2012; Folberth et al., 2012).

Figure 3. Selected sites for validation (LAU level) in the Bărăgan Plain

Therefore, our approach for calibration at locality level consisted in a systematic calibration implemented in a step-wise manner on management input data (fertilization and planting density), crop phenology and cultivar properties (PHU, planting date, HI and WSYF) and model parameters (PARM03 and PARM42).

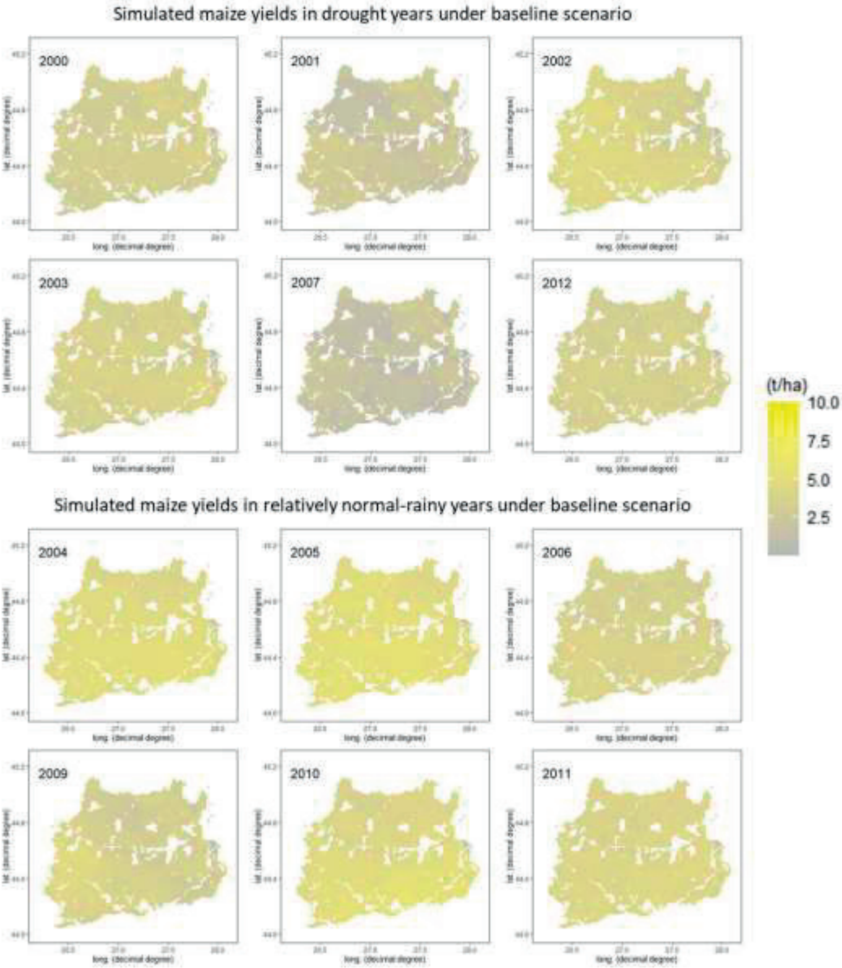

Figure 4. Simulated maize yields in the Bărăgan Plain during the drought and relatively normal or rainy years of the 2000-2013 interval, based on model parameterization for actual crop management conditions (baseline scenario)

The results showed a realistic improvement in model performance statistics, especially in the case of Budesti and Stelnica localities, with considerable decrease in the percentage of bias (PBIAS) between simulated and observed yields in all 4 cases during the calibration process (Figure 5). Enforcing parameter calibration first on 50 (first step), then on 25 (second step) and lastly on 10 (third step) simulation iterations, it clearly led to a reduction in the differences between the simulated and reported yields by producing smaller objective functions and improving model performance statistics (e.g. adjusted R^2 reached in the end values between 72% and 96%) (Figure 5).

The improved crop management scenario shows, as expected, that higher nutrient and water application rates resulted in consistently higher simulated crop yields (Figure 6). The averaged crop yield values for drought and relatively normal-rainy years reach to 4 t / ha and 7 t / ha, respectively, while highest maize yields are closer to 10 t / ha. Moreover, minimizing water stress through increased irrigation it reduces the yield variation throughout the study area, especially in area equipped for irrigation (i.e. the coefficient of variation is much lower for the yields estimated during the normal-rainy years, 0.2, as compared to those estimated during drought years, 0.6).

The results obtained in this scenario support future analyses for examining which crops and agricultural areas could benefit more from improved fertilization levels and additional blue water (irrigation water), as well as where blue water would account more of a larger share of the total water demand. Such approaches are relevant for analyses regards water use efficiencies in the context of drought intensification and water demand increases in all economic sectors.

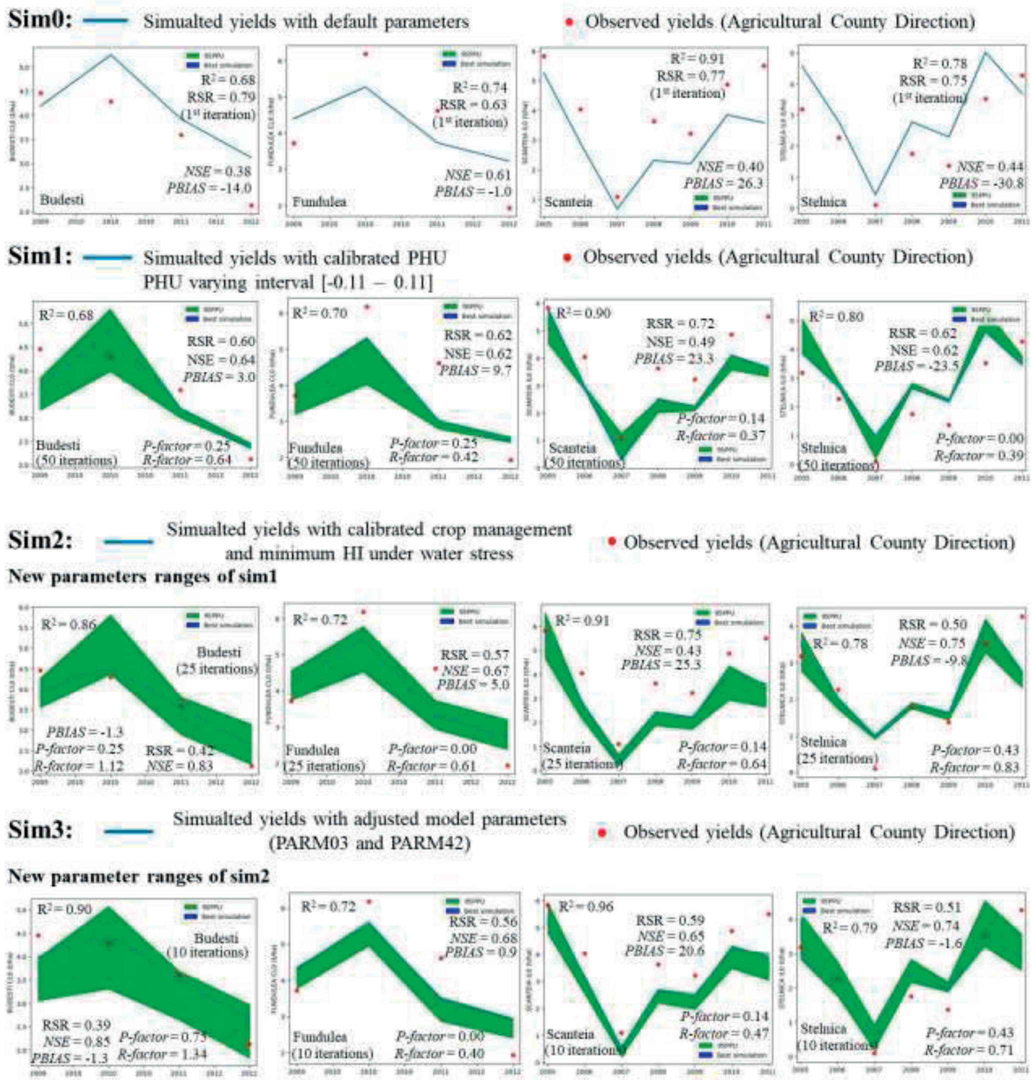

Figure 5. Comparison between the reported yields and the simulated yields expressed by the 95PPU prediction uncertainty band and the best simulation obtained after a number of iterations evaluated through RSR criteria in four localities in the Bărăgan Plain. Two statistics, i.e. r-factor and p-factor, show the goodness-of-fit and the model uncertainty. Top row displays the yields simulated with the first model iteration, while the bottom row shows the calibrated model results. The model performance was evaluated in each case by several statistical criteria, like Nash-Sutcliffe efficiency (NSE), R^2 (coefficient of determination) and percent bias (PBIAS). The reported yields used in this calibration exercise were available for 2009-2012 / 2005-2011 periods.

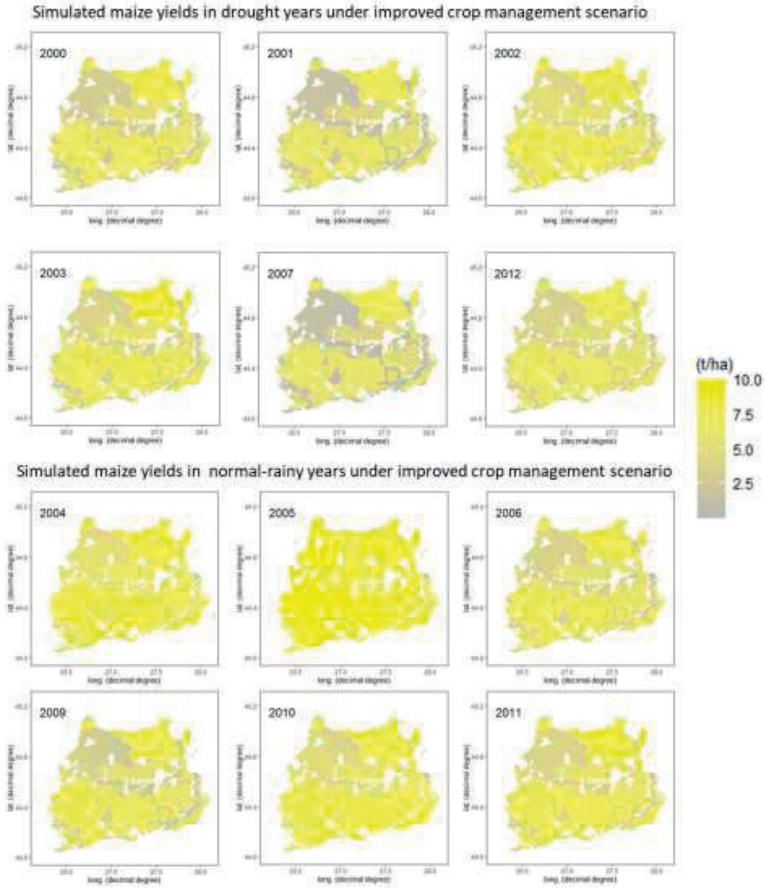

Figure 6. Simulated maize yields in the Bărăgan Plain during the drought and relatively normal or rainy years of the 2000-2013 interval, based on model parameterization for improved crop management conditions (improved crop management scenario)

CONCLUSIONS

EPIC^{+} proved to be a promising tool for calibration of the EPIC model and thus for future assessments on various topics ranging from agricultural resources use in various environments to soil quality and impacts on agricultural production. Similarly, the model can be used at different spatial and time scales and offers the possibility to implement different crop management strategies. However, the model reliability greatly depends of fine scale input data as well as on long-term available yield records for validation (Wang, et al., 2012; Abbaspour, 2015; Kamali et al., 2018).

The sensitivity analysis on crop model parameters shows that PHU largely influences maize yields, suggesting a plus 23% change in the parameter´s space for model optimization process. This is particularly true because PHU sets the time scale (expressed in temperature rather than days), within which short PHU values give rapid early growth but less time to convert energy to biomass, thus highlighting the weather variables´ importance for crop yield (Liu, 2009). However, future studies could benefit from better estimation of PHU values using optimal crop calendars, more homogeneous units of simulation and longer climatic data ranges (Folberth et al., 2012; Flach et al., 2020). In this way it is possible to reduce the sources of uncertainty, especially in what regards model parameterization and to achieve higher consistency between PHU values and crop planting / harvesting dates.

In the calibration process, it was shown that with the adjustments of sensitive crop parameters and agricultural practices in the model setup, crop growth is, in many parts, mainly constrained by nutrient, temperature and water stress factors. Nevertheless, sensitivity analyses on parameters that influence, for instance, harvest index under water stress conditions or soil water are necessary. It is also recommended to consider soil input parameters into model calibration and validation procedures, given the influence of soil physical and chemical properties, especially through their water and nutrient storage capacities, on crop yield model simulations (Folberth et al., 2016).
Moreover, whenever detailed information is available, particularly in terms of observed data on yields and other crop growth parameters (e.g. actual evapotranspiration), automatic calibration procedures offer possibilities to simultaneously adjust EPIC input parameters on cropland management, phenology, yield and cultivar properties, as well as on model influential parameters for the respective cropping system. In this study we used SUFI2 module of EPIC$^+$ (Kamali et al., 2018) to perform a systematic calibration of EPIC crop model at locality level, choosing four localities as exemplary showcases. The results were expressed by objective function, uncertainty quantification and model performance criteria. Automatic calibration procedures applied at locality level led to considerable reduction of biases between the simulated and reported yields by producing smaller objective functions and improving model accuracy.
The application of the model requires suitable infrastructure given the large computational time needed for simulation runs and calibration, as well as collaborative research frameworks for its implementation.

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