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Climate sensitivity analysis of maize yield on the basis of precision crop production

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Abstract.
In this paper by prediction we have defined maize yield in precision plant production technologies according to five different climate change scenarios (Ensembles Project) until 2100 and in one scenario until 2075 using DSSAT v. 4.5.0. CERES-Maize decision support model. Sensitivity analyses were carried out. The novelty of the method presented here is that precision, variable rate technologies from relatively small areas (in our case 2500 m^2) enable a large amount of data to be collected and conclusions to be extended to larger areas. We have concluded for the soil chemical parameters that according to the summarized ranking indexes the order is P_2O_5, clay content, Ca, NO_2-NO_3-N. Concerning yield, in the model predicting most critical changes 5.22 mm precipitation compensates for 1ppm CO_2 increase, or 1 degree temperature maximum increase compensates for 2.18 degrees temperature minimum increase or 18.56 ppm CO_2 increase is compensated for by 1 degree temperature minimum increase.

Keywords. *maize yield (Ceres-Maize), climate change and impacts, sensitivity analysis, site-specific data collection*

Introduction

This article is the continuation of the article entitled “Climate change and sustainable precision crop production with regard to maize (*Zea mays L.*)” (Kovács et al., 2014). Maize yield in precision plant production technologies according to five different climate change scenarios (Ensembles Project) until 2100 and in one scenario until 2075 using DSSAT v. 4.5.0. CERES-Maize decision support model was defined. The applied climate change models were: DMI-ARPEGE, KNMI-ECHAM5, SMHI-BCM, ETZH-HadCM3Q, MPI-ECHAM5, C4I-HadCM3. Referring to the methods published in the above mentioned article yield was predicted and sensitivity analysis was carried out for soil and climate parameters.

Recently several articles have been published in connection with evaluating the effect of climate change and soil properties on agricultural production with sensitivity analysis, using the results provided by decision support models, such as DSSAT, CERES-Maize (Bert et al., 2007; Ruane et al., 2013a; Ruane et al., 2013b). Bert et al., 2007 concluded that higher soil nitrogen content at sowing and soil water storage capacity increase maize yield.

Ruane et al., (2013a and 2013b) in the AgMIP (The Agricultural Model Intercomparison and Improvement Project) with their sensitivity analysis have determined the rate of climate change by the following parameters: minimum and maximum temperature, precipitation and carbon dioxide concentration. The investigations clearly indicated that in the case of increasing temperatures a decrease in yield can be expected. At the same time precipitation change can lead to positive or negative sensitivity. CO_2 changes have a positive effect on plant production in the analysis, however the authors also mention that this depends on emissions and the applied climate models.

The basis of the creation of agricultural regions is the farm level, within the farm the field level and the management zones (Fischer et al., 2006, Kovács et al., 2014; Ruane et al., 2013a). Based on the modelling and calculations we can state that precision crop production technologies can moderate the effect of climate change on plant production (Fischer et al., 2006, Kovács et al, 2014).

Material and methods

The research area is a 15.3 ha research farm (47^{o}54'20.16" N, 17^{o}15'08.57" W; University of West Hungary, Faculty of Agricultural and Food Sciences) which is divided into 66 treatment units (each unit is ~0.25 ha). The determination of the size of the treatment units is described by Mesterházi (2003) and Mike-Hegedűs (2006). In this project 11 treatment units were investigated. In the selected treatment units, soil physical parameters showed certain variability.

Eight different meteorological parameters were used for yield predictions: daily maximum and minimum temperatures, wind speed, amount of precipitation, relative humidity, potential evaporation, duration of sunshine and surface radiation. The global climate models (GCMs) DMI-ARPEGE, KNMI-ECHAM5, ETZH-HadCM3Q, MPI-ECHAM5, C4I-HadCM3 and SMHI-BCM have daily parameters in a 25 km^2 resolution (Table 1.). Each global climate model includes the A1B carbon dioxide model, which predicts a moderate CO_2 increase until 2100.

Table 1. Basic characteristics of the regional climate models.

Model	Country	Institute	Spatial and temporal distribution (2000-2100 in data packages of ten years duration)
DMI-ARPEGE	Denmark	Danish Meteorological Institute	174*190*3652
KNMI-ECHAM5	Netherlands	The Royal Netherlands Meteorological Institute	170*190*3652
ETZH-HadCM3Q	Switzerland	Swiss Institute for Technology	170*190*3600
MPI-ECHAM5	Germany	Max-Planck-Institute for Meteorology	170*190*3652
SMHI-BCM	Sweden	Swedish Meteorological and Hydrologic Institute	170*190*3652
C4I-HadCM3	Ireland	Community Climate Changes Consortium for Ireland	190*190*3600

The DSSAT v. 4.5.0. CERES-Maize model (Hoogenboom et al., 2003; Hoogenboom et al., 2010; Nyéki et al., 2013; Tian et al., 2012) inputs contain soil, experiment, management and phenological phase’s database and daily meteorological data, as well. This biophysical crop model requires at least four meteorological parameters (daily minimum and maximum temperature, daily rainfall and daily solar radiation).
The measured soil and other input parameters are included in Table 2. It should be noted that the nitrogen fertilizer level was 60kg N/ha, potassium and phosphorous levels were 30-30 kg/ha. Given the above the previous crop of the baseline year (2013) was soybean. As energy balance calculations and experiments showed that 100 kg/ha N fertilizer is the optimum level for maize production we have calculated with 40 kg/ ha N residuum after soybean.

Table 2. Site, technology and soil input parameters for Ceres-Maize model.

Parameters	**Soil type**			**Parameters**	
	loam	sandy loam	silt loam	Technology	Phenological
pH KCl*	7.58	7.48	7.51	Planting date, method, depth	
CaCO3 %*	18.20	16.98	17.73	Harvest date	
P2O5 mg/kg*	223.67	220.50	245.50	Cultivar (hyrid)	
K2O mg/kg*	294.67	314.50	387.25	Fertilizer application and material (N*, P, K)	
Ca cmol/kg*	58.03	61.70	59.40	Irrigation	
NO2-NO3-N mg/kg*	9.32	9.57	10.15	Plant Population	
water content cm^3/cm^3*	0.14	0.12	0.13	Previous crop (root weight, nodule weight, residue)	
SO4 mg/kg*	27.67	34.23	32.45	Field position, slope	
bulk density cm^3/cm^3*	1.60	1.42	1.48	Fertilizer methods, depth	
saturation *	1.99	3.16	2.54	Tillage implement	
pH in water*	7.60	7.50	7.58	P1juvenile phase	
organic carbon %*	1.70	1.60	1.73	P2 photoperiod sensitivity	
clay content %*	15.6	12.3	8.3	P5 grain filling duration	
silt content %*	38.8	30.8	66.3	G2 potential kernel number	
Cation exchange capacity, soil layer L				G5 potential kernel weight	
Soil type, colour					
Thickness of soil layer					
Bare soil albedo					
Maximum temperatures,					
minimum temperatures,					
wind speed,					
amount of precipitation,					
relative humidity,					
potential evaporation,					
sunshine duration					
surface radiation					
CO2 level					

Sensitivity analysis

This sensitivity modelling (Saltelli et al., 2008; Pannell, 1997) framework was described by Newlands et al. 2012 in Biome-BioGeoChemical Cycles with carbon-water-nitrogen and energy balance models, focusing on forest and agricultural production. Hidy et al., 2012 used Biome-BGC model for simulation of phenology, soil processes in C3 and C4 grasslands. The aim of yield prediction is to identify the effect on yield caused by climate, soil and other parameter changes. In this study we have investigated the effects of climate scenarios together with soil physical and chemical parameter changes. Fifteen soil physical and chemical parameters were taken into consideration (marked with an asterisk in Table 2.) and seventy-five different soil parameter groups were generated from them. Sensitivity analysis is a statistical approach. The presented results are based on variance (scattering) and calculated two indices: main effects (first-order) sensitivity index and total effect index. Sensitivity tests were run for all six climatic models which provided daily data. The evaluations were carried out for the two extreme value scenarios mentioned earlier. Sensitivity tests ranked CO_2 concentrations, minimum and maximum temperature and precipitation change for agricultural response.

Based on the available data basis we can reconstruct the calculation method for the indices. According to Newlands et al. (2012), for this even where well-chosen input parameters are available, the modelling has to run several thousand times in order to have consistent calculated indices. However, the calculation of the effective indices can only guarantee a good estimate of the relevance and ranking, if the input parameter vectors have a given distribution and are constructed as Sobol sequences (Sobol, 1993), which have the low-discrepancy sequence property.

To this end, where we have “s” input parameters, “s” points have to be defined in an “s” dimension unit hypercube in accordance with certain rules, while the input parameter vectors can be formed (one point – one vector) (Czitrom, 1999). This also means that for the sensitivity analysis – in contrast to the earlier one – the executing has to be done by input parameters defined by the constructing rule of the Sobol sequence in the above mentioned numbers. The evaluations were carried out for the two earlier mentioned scenarios resulting in extreme values: ETZH-HadCM3Q and SMHI-BCM.

The climate parameter effect express what changes are realized in the yield, for instance in the case of one unit change in the input parameter CO_2. This is calculated based on five designated years (2013, 2025, 2050, 2075, 2100) using the modelled yield by linear regression as the basis. In a given climate scenario this parameter was constant independent of the investigated area, therefore we have concluded that during the simulation the climate parameter changes induce linear changes in yield (within an investigated area the non-climatic parameters i.e. soil parameters such as Ca or clay fraction were constants in time, therefore these caused the constant members of the linear prediction.

Scattering can be calculated for each input parameter (such as CO_2) which expresses the variability of the parameter in time. The normal effect of the parameter is expressed by the multiplication of the climate parameter by the (time horizon) scattering of the parameter – in practice this describes how an average change in the parameter affects the value of the yield.

In the parameter-sensitivity analysis evaluation, new simulations have to be carried out with the defined parameter combinations in order to be able to execute the sensitivity tests. After the simulations have been carried out we could define the sensitivity indices ($i=1..15$) for all S_i (main effect) and S_{Ti} (total effect) parameters in the five investigated years for the calculated yield. In the course of indexing the parameters this can be interpreted as S_3 (main effect) and S_{T3} (total effect) indices belong to soil organic matter content. The sensitivity result table contains $5_{year}*15_{parameter}*6_{yield}*2_{effectindex}$ ~ 870 data as C4I-HadCM3 scenario provides data only until 2075.

Results and discussion

According to the sensitivity analysis the parameters exercising the main effect on the maize yield were P_2O_5, clay content, NO_2-NO_3-N. According to total effect indexes the most important parameter was clay content, in second place P_2O_5 and in third place NO_2-NO_3-N.

Averaging the effect indexes show the average effect of the given parameter (weight, importance), whilst scattering indicates the expected accuracy of the average value. The scattering of the data was similar to the average data, highlighting the uncertainty of the data and questioning the applicability of the average; therefore the conclusions about the ranking of the sensitivity effect indexes had to be supported in a different way as well.

The above described parameters were in summarized ranking, therefore the order of the indexes was: P_2O_5, Ca, Na, NO_2-NO_3-N. The NO_2-NO_3-N parameters have a huge effect on the ETZH-HadCM3Q predicted models but have no effect on the other models. Based on the summarized ranking indexes the order repeated itself: P_2O_5, clay content, Na, NO_2-NO_3-N.

According to the results provided by all the simulations for maize yield the most negative climate model is ETZH-HadCM3Q, and the least negative is SMHI-BCM (Table 3.).

Based on the sensitivity analysis, climate scenarios can be differentiated even if very small scattering (consistent database) appears. The highest negative effect in the basic simulation was given by ETZH-HadCM3Q model (effect: -0,08286, scattering: 1,45551E-17), the least was given by SMHI-BCM (effect: - 0.00621, scattering: 9,09697E-19). Based on the sensitivity analysis carried out by the 75 generated parameter input simulations the highest negative effect was produced by ETZH-HadCM3Q model (effect: -0,05753, scattering: 0,026174-17), the least effect was provided by SMHI-BCM (effect: - 0,02903, scattering: 0,025786).

Table 3. Base and total simulations results

	Base simulations		Total simulations	
Scenario	**Effect**	**Scattering**	**Effect**	**Scattering**
ETZH-HadCM3Q	-0,08286	1,45551E-17	-0,05753	0,026174
MPI-ECHAM5	-0,0449	1,45551E-17	-0,04602	0,02369
DMI-ARPEGE	-0,02783	3,63879E-18	-0,03712	0,025707
KNMI-ECHAM5	-0,01648	3,63879E-18	-0,03018	0,024808
C4I-HadCM3	-0,02412	3,10317E-18	-0,03895	0,039073
SMHI-BCM	-0,00621	9,09697E-19	-0,02903	0,025786

In the climate effect evaluation we have considered the designated years effect of the four parameters on maize yield. This means a ranking based on the effectiveness of the scenarios. During the investigation four-dimension linear regression was applied. Table 4 shows the coefficients connected to climate parameters that are (given identical scenarios) the same for each treatment unit, which means that the areal parameters of each treatment unit were constant in the yield function, changes in the designated year being caused only by climatic parameters. Rising CO_2 and temperature in nearly all cases caused a decrease in the yield, and rising precipitation always increases yield. A rise in minimum temperature generally also increases maize yield.

Table 4. Climate parameters ranking with sensitivity analysis - Normalized effect index with scattering.

Climate model	**Climate parameters effect**				
	CO2 ppm	**precipitation**	**maximum temperature**	**minimum temperature**	**constant-change**
MPI-ECHAM5	-0,018960243	0,001574	-2,47269	0,596704	1,778
ETZH-HadCM3Q	-0,036826056	0,007045	1,491355	0,68335	1,778
SMHI-BCM	-0,001529906	0,000442	-0,36137	0,435233	1,778
KNMI-ECHAM5	-0,006911322	0,00787	-0,5114	-0,28296	1,778
DMI-ARPEGE	0,00539868	0,011239	-1,44363	2,161368	1,778
C4I-HadCM3	0	0,011076	-1,99137	1,718008	1,778
C4I-HadCM3	-0,0108	0	1,532759	-0,73706	1,778

Conclusions

Based on the results of the sensitivity tests the ranking of the indexes are: P_2O_5, clay content, Ca, NO_2-NO_3-N. According to the results provided by all the simulation carried out in the sensitivity tests the most negative effect on maize yield is ETZH-HadCM3Q, the least negative is SMHI-BCM climate model. Based on the calculations carried out by climate parameters ranking with sensitivity analysis (Normalized effect index with scattering) the coefficients in the case of SMHI-BCM model: 3.46 mm increase of precipitation balances 1 ppm CO_2 increase, or 1 degree temperature maximum increase is balanced by 0.83 degree temperature minimum increase, or 284.48 ppm CO_2 increase is balanced by 1 degree temperature increase. These balances are calculated for the predicted yield. The coefficients in case of ETZH-HadCM3Q model: 5.22 mm increase of precipitation compensates for 1 ppm CO_2 increase, or 1 degree temperature maximum increase is compensated for by 2.18 degree temperature minimum increase, or 18.56 ppm CO_2 increase is compensated for by 1 degree temperature increase. These compensation factors are also calculated for the predicted yield.

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