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Response of maize yield under changing climate and production conditions in Vietnam

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Abstract. This study concerns rainfed maize (Zea mays. L) grown in two different (winter and spring) growing seasons under current and future climate conditions in north-east of Vietnam. The yield response of rainfed maize was investigated by applying the DSSAT CERES-Maize crop model and two climate scenarios according to Representative Concentration Pathways (RCPs), RCP 4.5 and RCP 8.5. The results show that maize responds with a wide range of yield-levels due to the different climatic and production conditions. On average, under RCP 8.5 climate scenario, annual maize yield (including both winter and spring maize yields) increases by 1.1% while under RCP 4.5 the increase is 3.6%. The annual balanced maize yield increase under both RCPs is based, however, on significant changes in the simulated winter and spring maize yields, respectively. Winter maize yield was simulated to rise up to 33.3% and 31.9% under RCP 4.5 and RCP 8.5, respectively. In contrast, simulated spring maize yield decreases under both RCP 4.5 and RCP 8.5 by 30.3% and 33.9%, respectively. From those findings, it can be concluded that rainfed maize yields under future changing climatic conditions maybe positively affected in winter growing season while it will be reduced in the spring growing season, mainly due to increasing drought stress. Therefore, irrigation will be crucial key for spring maize production in the future to mitigate the effects of changing climate on crop water availability.

Keywords. Maize production, crop model, DSSAT, CERES-Maize, climate scenario, drought, adaptation, Vietnam

INTRODUCTION

An increase in the frequency and intensity of drought events is considered a consequence of climate change impact in many regions of the world (Baldock et al., 2000; Powell and Reinhard, 2015; Steffen et al., 2015). In the north of Vietnam, the decrease in precipitation by 5 to 10% throughout the year (IMHEN, 2011) has recently been considered as the main reason for increasing drought events, causing negative effects on crop production such as for grain maize (Thi-Minh-Ha et al., 2011).

Maize originated in South America (Mangelsdorf, 1947) and the highlands of Mexico (Tenaillon and Charcosset, 2011; Mickleburgh and Pagán-Jiménez, 2012). Maize is the third largest crop after wheat and rice globally and is cultivated around the world under a wide range of climatic conditions, from the temperate to tropical zones (Hardacre and Turnbull, 1986). However, changing climate conditions, such as increasing droughts, could become limiting factor that negatively influence maize growth.

Concerning water requirement, maize shows a wide range of responses in different production and climatic regions, depending on factors such as potential evapotranspiration and cultivar specific characteristics (e.g. phenological development). For example, over a province in the north of Iran, the total water requirement for maize cultivation, derived from satellite and meteorological data, ranges from 345 to 384 mm (Kamali and Nazari, 2018)there's a need for further investigation on various crops to identify the optimum water requirements to avoid water wasting in regions that are already facing water shortage. The focus of this work is to determine water requirement maize farming Mazandaran Province in Northern Iran, located on the southern side of the Caspian Sea, using Landsat satellite data. In order to use SEBAL algorithm, the images were atmospheric calibrated. Evapotranspiration maps with RMSE values equals to 0.73, 1.38 and 0.74 mm/day were produced and compared to Reference Book (RB while it is approximately 423 mm in a region of Ethiopia (Araya et al., 2015) and gets much higher in another region near the river basin in Northwest China with 618 mm (Zhao et al., 2010) six methods for estimating ETc have been applied to maize field in the middle Heihe River basin, China. The ETc was estimated by the soil water balance and Bowen ratio-energy balance methods while the Priestley–Taylor, Penman, Penman–Monteith and Hargreaves methods were used for estimating the reference evapotranspiration (ET0. These differences in water requirement for maize indicate that the response of maize not only depends on local weather conditions but also on genetics and other factors, such as crop management, prevailing soil and topographic conditions.

To identify and analyze climate change or weather impacts on crop growth dynamics, crop yields and effects of different crop management options, process-oriented crop models are widely used (e.g. Devkota et al., 2013; Ebrahimi et al., 2016; Eitzinger et al., 2013a, Jones et al., 2003).

As a decision support system of several crop-specific simulation models, the DSSAT (Decision Support System for Agrotechnology Transfer) shell (MacCarthy et al., 2017) has been used for more than 30 years worldwide for various purposes (e.g. Kadiyala et al., 2015). In most studies, DSSAT has been approved that it is a useful tool for crop simulation (Soler et al., 2011). DSSAT crop models′ performance and sensitivity analysis were carried out for the most important crops in many studies (Eitzinger et al., 2013b; Kisekka et al., 2017)However, calibration and validation do not cover all cultivars, weather conditions as well as soil conditions all over the world. The DSSAT crop model for maize used in our study, CERES-Maize, has been used in other studies to simulate grain yield, maximize the maize yield, and help to avoid yield losses (Iyanda et al., 2014; Jing et al. 2017; MacCarthy et al., 2017). However, DSSAT models have some limitations, for example Ngwiraet al. (2014) proved that it performed well for no-till and crop residue impacts but poor for crop rotation effects.

Being the first crop simulation study on the impact of climate change on maize production in the central north of Vietnam, we first tested the performance of CERES-Maize model for simulating seasonal maize growth under local conditions. We then applied the model to simulate maize yields for 100 years from 2001-2100 under two climate change scenarios (CCSs) of RCP 4.5 and RCP 8.5, respectively, in order to determine the response of maize yields to climate change conditions in Thai Nguyen province, a mountainous region in the north of Vietnam.

MATERIAL AND METHODS

To run process-based crop models for a specific location, a set of minimum data is required (MacCarthy et al., 2017). These include daily meteorological data (from Thai Nguyen center for Hydro-Meteorological Forecasting), soil data (from Thai Nguyen Department of Environment and Resources), field experiment data (from field experiment by Nguyen(2008)) and crop management data (from The Department of Agriculture and Rural Development, Thai Nguyen).

Material

The meteorological data were obtained from two local weather stations covering together 55 years from 1961 to 2015, namely Dinh Hoa station and Thai Nguyen station. They both record daily maximum temperature, minimum temperature, solar radiation, rainfall, and relative air humidity. The observed daily weather data from Dinh Hoa weather station was only available for 30 years from 1961-1990 while the daily data from Thai Nguyen weather station were recorded for 25 years from 1990-2015. However, the monthly weather data from Thai Nguyen weather station was available for 35 years from 1980-2015, providing an overlapping period from 1980-1990 of both weather stations to support the observed trend of climate change in Thai Nguyen province.

Soil properties involving soil textures, pH (acidic water-based solution), OM (organic matter), total N (total nitrogen), CEC (Cation exchange capacity) were examined by additional soil profilesfrom maize fields to ensure the accuracy of crop simulation. Three main soil types were chosen to simulate maize yields based on the main local soil types namely Ferralsols, Acrisols and Fluvisols (Tab. 1). Generally, Ferralsols and Acrisols are the two main soil types in Thai Nguyen province, with Ferralsols occupying approximately 75% of the total land area (TNDNRE, 2015). However, according to the FAO soil classification, local soil properties in some regions may fit to Acrisol classification. In addition, Ferralsols and Acrisols, Fluvisols and Gleysols are commonly found near the river banks and are strongly affected by flooding in the rainy season in the case of a poor water-drainage system; however, they only occupy tiny proportions.

Field experimental data, used for crop model calibration of 3 selected maize cultivars, were collected from a report published in Thai Nguyen scientific journal in 2008. In the field experiment, three maize cultivars (SX2010, SX5012, and LVN 47) were grown in spring and winter season in 2007/2008 under irrigated condition and optimized fertilizer application (Nguyen, 2008) (Tab. 2). Each field was planted by different maize hybrid cultivars in the area of 1 ha. The field experiment provided statistical significant data (P-value < 0.05) for five main genetic plant coefficients for cop model calibration for each cultivar, including total number of leaves per stem (LAIH), beginning peg stage (days after sowing) (R2AT), day of physiological maturity (harvest day) (MDAPs), leaf area index (LAIXS) and grain yields (HWAMS), (Nguyen, 2008).

For model validation de-trended reported annual yields from regional yield statistics of recent past 15 years were used, to meet recommended validation setups (e.g. Grassini et al., 2017). For this baseline period of 2000-2014, additional information on current crop management practices (common planting date, fertilizer dose and application schedule, irrigation system, irrigation schedule, pest management) was collected by the author, provided by 10 local agricultural experts from the Department of Agriculture and Rural Development, Thai Nguyen.

Tab. 1. Soil properties of examined soil profiles in the study region (Thai Nguyen province, Vietnam).

Profile	Depth (bottom) (cm)	Texture (%)		pH (KCl)	OM (%)	Total N (%)	CEC (cmol/kg)	Drained		Bulk density g/cm^3
		< 0.002	0.02-0.002					Lower limit	Upper limit	
Profile A – Dong Hy	0-20	15.1	49.8	5.2	1.49	0.05	11.5	0.064	0.143	1.2
GleyicAcrisol	20-90	23.7	9.8	4.2	0.44	0.04	5.7	0.052	0.078	1.56
	90-120	23.7	9.1	4.3	0.37	0.03	4.3	0.051	0.075	1.58
Profile B - Vo Nhai	0-20	15.2	33.3	4.5	0.6	0.03	11.5	0.065	0.132	1.42
Calcic-Acric-Ferralsols	20-80	16.5	30.1	4.2	0.3	0.01	5.7	0.07	0.135	1.48
	80-120	16.9	30.9	4.4	0.1	0.01	4.3	0.057	0.11	1.51
Profile D - Phu Binh	0-20	18.2	33.5	6.0	1.7	0.06	18.1	0.147	0.283	1.29
Fluvisols	20-60	20.1	32.9	5.5	0.3	0.03	11.1	0.121	0.226	1.47
	60-120	17.8	35.1	5.0	0.1	0.01	9.4	0.106	0.209	1.48

(OM: Total organic matter; CEC: Cation exchange capacity).

Tab. 2. Calibration results of the DSSAT model forthespring maize season.

Genotype Crop indices	SX2010		SX5012		LVN47	
	Observed	Simulated	Observed	Simulated	Observed	Simulated
Planting date (DOY)	Spring	53	Spring	53	Spring	53
Silking(Beginning Peg stage) (*)	77	70	75	62	77	70
Physiological maturity (Harvest) (*)	117	105	121	99	125	105
Leaf index, at harvest	3.6	5.72	3.9	5.59	4.0	5.98
Number of leaves per stem	20.2	15.62	20.2	14.18	20.1	15.29
Yield (kg/ha)	5720	5993	6350	6144	5990	6202

(*) (days after planting).

Climate change scenarios

Two climate scenarios from the Representative Concentration Pathways (RCP), RCP 4.5 and RCP 8.5 were used in this study. They are stabilized to limit radiative forcing at 4.5 and 8.5 W m^{-2}, respectively. Both of them were created by Danish Meteorology Institute and derived from CORDEX (coordinated Regional Climate Downscaling Experiment https://esg-dn1.nsc.liu.se/search/cordex/). The scenarios were based on the driving GCM (global circulation model), namely ICHEC-EC-EARTH and the RCM (regional climate model) DMI-HIRHAM5.

Methods

Crop simulation

In this study, spring (from February to early May) and winter (from October to early January) maize yields were simulated by the crop model CERES-Maize.

The simulation was implemented by setting the different sowing time of winter and spring maize and the share of three soil types within the case study region (Tab.1). The crop management was the same in all simulations, except for irrigation. Irrigation in the simulation was applied only for model calibration and validation, to reflect support irrigation practice. Every single estimated annual maize yield is calculated as an average of two simulated seasonal maize yields in the year. Annual yields were calculated in order to validate the model performance between simulated and reported annual maize yield. The maize yields were available only at annual basis for Thai Nguyen province for 15 years (TNDNRE, 2015).

Crop model calibration and validation

To ensure and enhance the accuracy of simulation results, model parameter estimation is a critical aspect of crop modeling because simulation results heavily dependent on parameter values, particularly crop (growth) parameters. The calibration of this study was based on the above described maize experiment in winter and spring 2008.

Based on the cultivars related calibration settings, validation of simulated grain maize yields was carried out using regional yield statistic reports of Thai Nguyen province of annual maize yield during the period of 15 years from 2000-2014 (TNDNRE, 2015). The three main regional soils (Tab.1), historical weather data and common crop management practice was used as input data to simulate the seasonal grain maize yields.

Finally, model performance analysis was carried out by two statistical methods as follows:

The Normalized Rood Square Error (NRMSE) was used to evaluate the performance of CERES Maize model using the simulated and observed maize yield as follows:

$$\mathrm{RMSE} = \sqrt{\frac{1}{\mathrm{n}}\sum_{\mathrm{i}=1}^{\mathrm{n}} (o_i\text{-}s_i)^2} \tag{1}$$

$$\mathrm{NRMSE} = \frac{RMSE}{\bar{O}} \times 100 \tag{2}$$

where RMSE: root mean square error, NRMSE: normalized root mean square error, n: number of simulated years, s_i: simulated maize yield in year I, o_i: observed maize yield in year I, : the mean of observed maize yield

NRMSE gives a relative measure (%) of the difference between simulated and observed data. The smaller the value of RMSE, the better the model performance, while a minimum of zero implies the perfect model fit. The simulation is considered excellent with a NRMSE less than 10%, good if the normalized RMSE is greater than 10% and less than 20%, fair if the NRMSE is greater than 20% and less than 30%, poor if the NRMSE is greater than 30% (Bannayan and Hoogenboom, 2009).

The second indicator used for estimating model performance was the Index of Agreement (d):

$$d=1-\frac{\sum_{i}^{n}(O_i-S_i)^2}{\sum_{i}^{n}(|S_i-\overline{O}|+|O_i-\overline{O}|)^2} \tag{3}$$

Where d: index of agreement, O_i: Observed yield in year i, S_i: Simulated yield in year I, : the mean of observed maize yield.The Index of Agreement (d) developed by Willmott (1981) is a standardized measure of the degree of model prediction error and varies between 0 and 1. A value of 1 indicates a perfect match, and 0 indicates no agreement at all (Willmott, 1981). Besides, the index of agreement can detect additive and proportional differences in the observed and simulated means and variances; however, it is overly sensitive to extreme values due to the squared differences (Legates and McCabe, 1999).

De-trending observed yields

Technological improvements that lead to more effective crop production techniques over time, e.g. during the validation period (2000-2014) add a yield impacting factor. These trends are normally not simulated in multi-year crop model application such as in our study. Therefore, to obtain a reliable comparison (for model validation) between multi-year regional yield reports and simulated yields, the observed yield trends caused by improved production technology were removed by de-trending the yield time series. The year to year residuals from the smoothed time series of observed maize yields were calculated by a 6-year running mean, as shown in equation (4):

$$y=\frac{x-\overline{x}}{\overline{x}}\times 100(\%) \tag{4}$$

Where y is the residuals, x is the actual value, and represents the smoothed 6- year running means.

RESULTS

Climate change in Thai Nguyen province

Local weather in Thai Nguyen province, Vietnam, revealed an increase in temperature and a reduction in precipitation (Fig. 1) within the observed period (1990-2015).

Similarly, an increasing trend of temperature and a decreasing trend of precipitation conditions in the local area was figured out by the data from projected period (2001-2100) under two climate change scenarios (i.e. RCP 4.5 and RCP 8.5. The average annual temperature increases from 24.4 °C (1990-2015) to 25.9 °C (2001-2100) under RCP 4.5 and 26.5 °C (2001-2100) under RCP 8.5. In contrast, a substantial reduction in precipitation by approximately 67.4% and 47.7% under RCP 4.5 and RCP 8.5 was determined in comparison with the average precipitation during the observed period from 1990-2015. Further, the decreasing trend of precipitation seems logical by the increase in annual and monthly percentage of dry days (Fig. 2). The total number of dry days was projected to increase, especially under RCP 4.5 by 72.3%, followed by RCP 8.5 with the value of number dry days is 71.2%.

The performance of CERES-Maize model

The result of the calibrated CERES-Maize model with three regional representative cultivars was very good for simulating the grain yields in the spring season, 2008. The percentage similarity between the observed grain yield and simulated grain yield was approximately 98% for all three maize varieties. Crop development was simulated acceptable, where e.g. for silking the deviation was 7 days (2 cultivars) and 13 days for the third cultivar (SX5012). A restriction for that comparison was that the sowing date from the experiment was not reported and, therefore, was set according to expert assessment. However, the observed leaf area indices were lower than the simulated ones, whereas the observed numbers of leaves per stem were higher than the simulated ones (Tab.2). These results show that there was still a misbalance between observed and simulated leaf areas (overestimation by the model) and the number of leaves (underestimation by the model) probably due to a deviation of mean leaf size and specific leaf weight to reality. Unfortunately, there were no further experimental data available for clarification.

Similar to the results for spring maize, for winter maize the CERES-Maize model showed a good agreement between observed and simulated grain yields. The percentage of similarity, however, ranged only from 78 to 88% for the three varieties. Crop development was slightly better simulated than for spring maize, where e.g. for silking the deviation was 5-6 days (2 cultivars) and again 13 days for the third cultivar (SX5012). Nevertheless, the accuracy of the crop model was again low

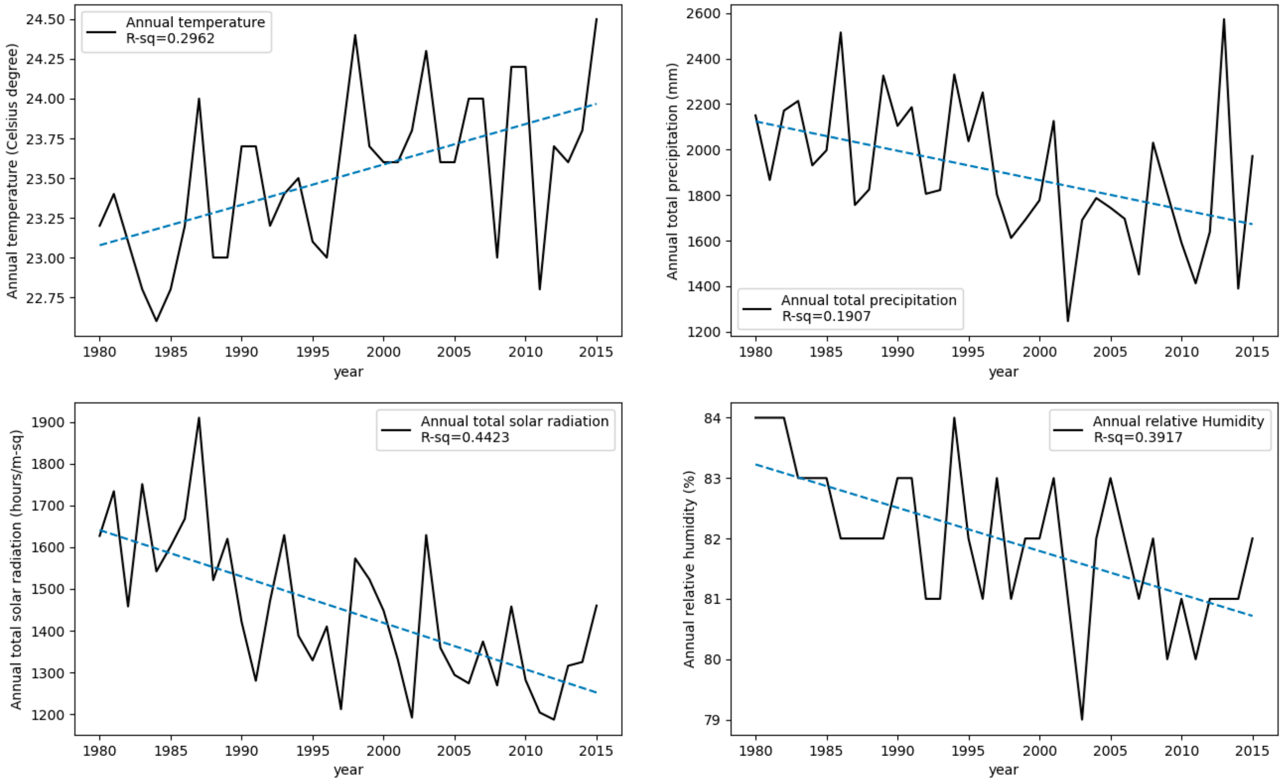


Fig. 1. Annual temperature and precipitation data from 1980-2014 in Thai Nguyen, Vietnam (R-sq termed R square).

in terms of leaf indices, in specific by a significant overestimation of the leaf area index (Tab.3).

Based on these calibration results, we conclude that the CERES-Maize model was moderately good calibrated and acceptable for simulating maize grain yields in the region of interest with three representative cultivars. The genetic parameters for these maize cultivars are presented in Table 4.

CERES-Maize model validation under fixed irrigation

Due to a lack of suitable field experimental data, model validation was carried out on regional statistical grain maize yield reports (e.g. Grassini et al., 2015) of annual production, where no deviation between spring and winter maize is available. As in agricultural practice, maize is normally irrigated on demand, we validated CERES-Maize for irrigated simulation.

In general, moderately good performance of the CERES-Maize model was achieved with a NRMSE value for the annual maize yields of 10.3%. As the simulated yield level between spring and winter maize differs in most of the years, the comparison between the mean simulated seasonal and mean annual reported yields shows a larger NRMSE value of 18.9% (spring maize) and 19.4% (winter maize) (Fig. 3).

Analysis of the performance of CERES-Maize by Index of Agreement (d) showed a moderate match between observed (statistical) annual maize yields and simulated annual maize yields with the (d) value of 0.77 (Fig.3).

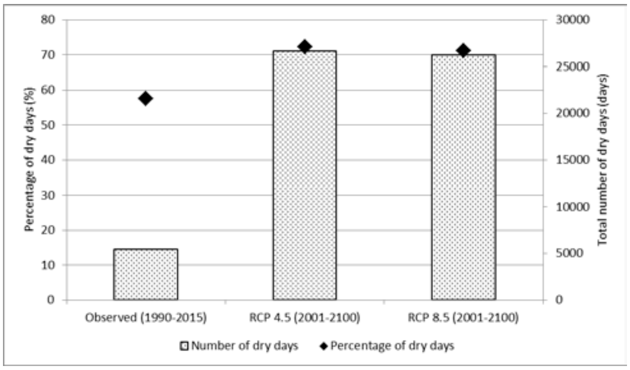


Fig. 2. Number of dry days from observed period (1990-2015) and projected period from 2001-2100 under RCP 4.5 and RCP 8.5.

Tab. 3. Calibration results of the DSSAT model for thewinter maize season.

Genotype / Crop indices	SX2010		SX5012		LVN47	
	Observed	Simulated	Observed	Simulated	Observed	Simulated
Planting date (DOY)	Winter	265	Winter	265	Winter	265
Silking(Beginning Peg stage) (*)	66	60	67	54	68	63
Physiological maturity (Harvest) (*)	120	133	123	122	123	136
Leaf index	2.9	5.66	2.4	5.68	2.9	5.76
Number of leaves per stem	19.6	15.49	19.9	16.22	19.5	16.07
Yield (kg/ha)	6440	7816	7370	8271	5660	8072

(*) (days after Planting date).

Concerning the technical improvement, the results reveal that the performance of CERES-Maize grain yield simulation between de-trended observed yields and simulated yields is better than the performance of the model between the real observed yields and simulated yields, shown by an increase of d-index from 0.77 to 0.86 and a decrease of the value of NRMSE from 10.3% to 7.3%. It was assumed that the detrended results are removed from climate-related influences such as new technologies in crop management or better cultivars.

Rainfed winter and spring maize yields under the selected climate scenarios

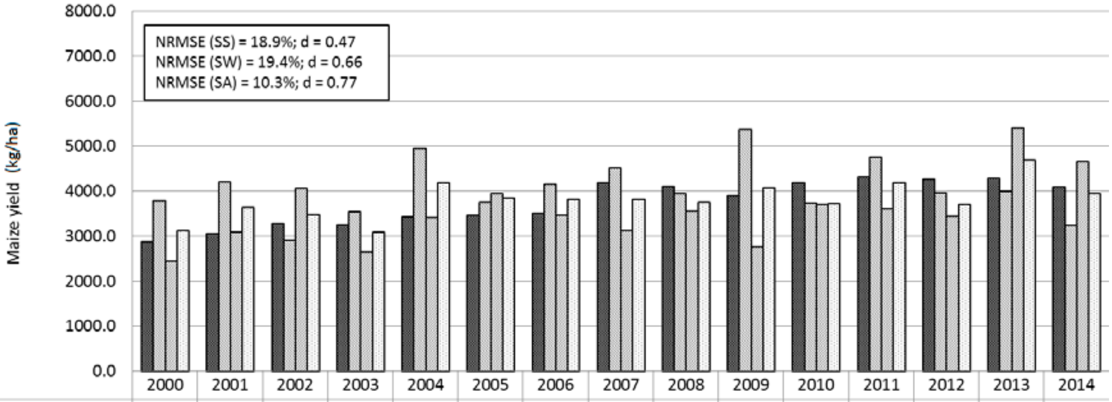
The simulated annual rainfed maize yields were mostly highest in the second 30-year period from 2035-2065, followed by the first 30-year period from 2001-2030. The lowest maize yields were received in the period 2070 – 2100. Besides, the average maize yields under both RCPs are quite similar. Under the RCP 4.5 scenario, the mean annual maize yield, the mean spring maize yield, and the mean winter maize yield are about 3957 kg/ha, 2483 kg/ha, and 5411 kg/ha, respectively, where under RCP 8.5 they are about 3854 kg/ha, 2353 kg/ha, and 5355 kg/ha, respectively (v. 4a-d).

In comparison with observed annual maize yields in the historical period (2000-2014), under the RCP 4.5 scenario, the mean annual rainfed maize yields over the 100 year period 2001-2100 increase by +3.6%, contributed by the increase in winter maize yields by +33.3% and a reduction of spring maize yields by 30.3%.

Under the RCP 8.5 scenario, the simulated spring maize also decreased in comparison with observed spring maize yield, and especially dramatic from 2070-2100 with a decline of 50.1% (w. 5). The simulated win-

Tab. 4. Calibrated crop coefficients for Thai Nguyen, Vietnam.

COEFF	Definitions	SX2010	SX5012	LVN47
P1	- Thermal time from seedling emergence to the end of the juvenile phase (expressed in degree days above a base temperature of 8 °C) during which the plant is not response to change in photoperiod.	140.4	121.0	125.0
P2	– Extent to which development (express as days) is delayed for each hour increase in photoperiod above the longest photoperiod at which development proceeds at a maximum rate (which is considered to be 12.5 h).	0.3	0.0	0.0
P5	- Thermal time from silking to physiological maturity (expressed in degree days above a base temperature of 8 °C).	685.0	685.0	685.0
G2	- Maximum possible number of kernels per plant.	907.9	907.9	907.9
G3	- Kernel filling rate during the linear grain filling stage and under optimum conditions (mg/day).	6.6	10.0	10.00
PHINT	– Phyllochron interval; the interval in thermal time (degree days) between successive leaf tip appearances.	44.92	38.9	38.9



	2000	2001	2002	2003	2004	2005	2006	2007	2008	2009	2010	2011	2012	2013	2014
■ Observed annual yield	2880.0	3060.0	3280.0	3260.0	3430.0	3470.0	3520.0	4200.0	4110.0	3910.0	4200.0	4320.0	4270.0	4290.0	4090.0
▨ Simulated yield in spring (SS)	3794.2	4209.2	2913.2	3539.9	4956.9	3756.0	4165.6	4522.4	3953.7	5372.7	3745.2	4762.9	3961.6	3993.8	3233.8
▩ Simulated yield in winter (SW)	2440.8	3094.1	4060.8	2652.8	3419.9	3955.7	3473.3	3123.9	3568.5	2775.3	3713.8	3611.8	3443.7	5410.6	4669.2
□ Simulated average annual yield (SA)	3117.5	3651.6	3487.0	3096.3	4188.4	3855.8	3819.4	3823.2	3761.1	4074.0	3729.5	4187.4	3702.7	4702.2	3951.5

Year

Fig. 3. Yield validation of spring and winter season maize 2000-2014 against statistically reported maize yields.

ter maize yield increased only by +18.2%, leading to a lower increase in annual maize yield compared to RCP 4.5 during the period 2001-2100 by +1.1% compared the observed yields 2000-2014.

DISCUSSION

To identify the impacts of climate parameters for maize yield potentials and trends in Vietnam under climate scenarios we focused on the simulation of rainfed maize only, although this does not fully represent current irrigation practice of occasional support irrigation.

The difference between spring and winter maize yields

On average, the simulated winter maize yields are significantly higher than spring yields. In reality, winter maize in northern Vietnam is sown after the end of the rainy season, where soils have still high water content. During winter maize growing season, precipitation is continuously decreasing, and effective solar radiation (data not shown) increases, forming ideal conditions for yield formation. The spring maize, sown in February, with low soil water contents often suffers drought stress during vegetative period, limiting its yield potential, so the spring maize yield stays lower on average than the yield of spring maize under current climate.

Climate change impacts on maize production in Vietnam and adaptation recommendations

Overall, under the two climate change scenarios in this study, RCP 4.5 and RCP 8.5, climate conditions are projected to be more extreme than in the past with higher temperature and lower seasonal precipitation. Both is expected to negatively impact maize production by a) shorter growing periods for annual crops due to higher temperatures and b) more drought stress conditions due to a higher number of dry days and higher evapotranspiration rates (forced again by higher temperatures).

Related to Thai Nguyen province, especially the spring maize season will suffer by increasing drought under future climate scenarios, while the winter growing season, despite increasing number of dry days, still remains with higher soil water content combined with increasing effective solar radiation. The study showed that annual rainfed maize yields in the 21st century will be slightly higher under two climate scenarios (RCP 4.5 and RCP 8.5) as in the reference period of 2000-2014, and only in the far future (period 2071-2100) would be generally lower than in the past, especially for spring season maize from 2070 to 2100 and under unchanged production technology. Although winter maize yield increase strongly, it could just outbalance the strong decreases in spring maize yields concerning annual yields under both applied climate scenarios. Other impacts on maize production, not considered in our simulation study, additionally can occur (e.g. reduced fertility, increased pest and disease challenges etc.). The influence of high temperature will become even more

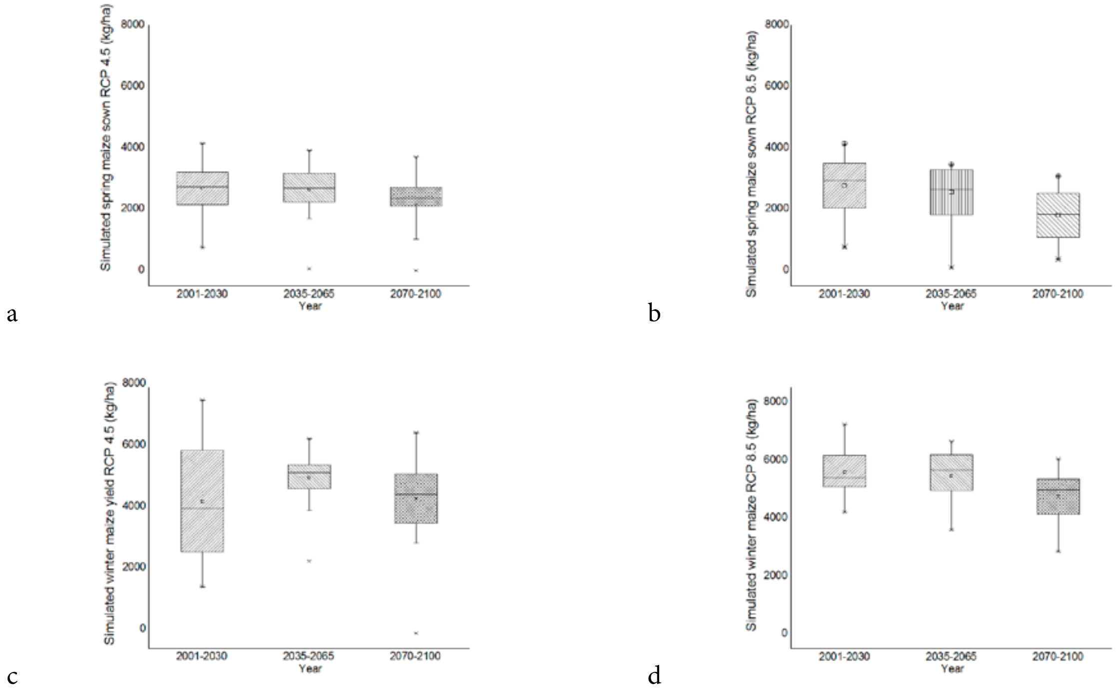


Fig. 4a-d. Simulated rainfed spring and winter season maize yields under the two different scenarios RCP 4.5 and RCP 8.5 for Thai Nguyen province, Vietnam. Boxes present 50% of all cases, including a horizontal line at the median and a dot at the mean.

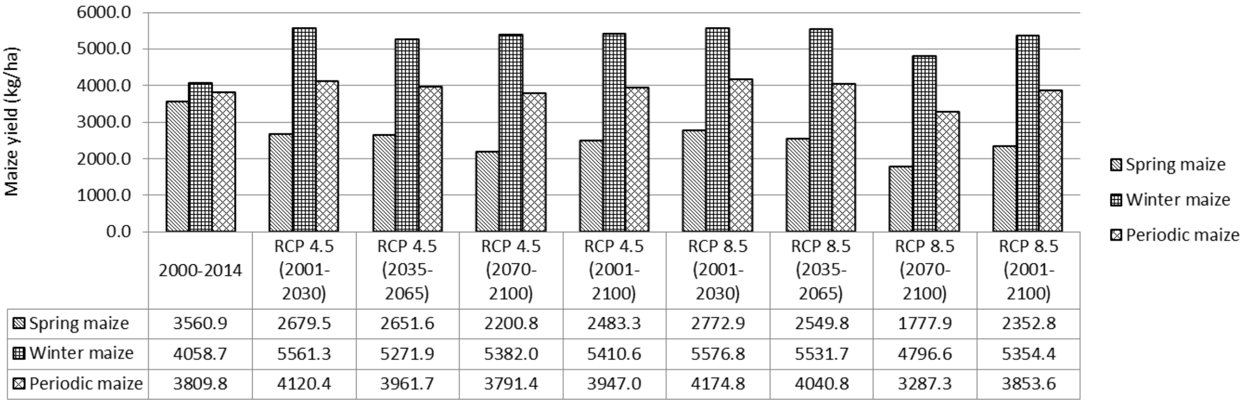
extreme when it accompanies with water deficiency and drought stress. For example, in central Vietnam, maize yield decreased in dry seasons, driving farmers to change land use systems into other crops such as peanut, cassava or green bean (Uy et al., 2015).

Irrigation is considered globally as a crucial factor to mitigate the influence of drought stress on maize growth (van der Velde et al., 2010). Irrigation will become more important under the climate change perspective, especially in South Asia (Döll, 2002). Due to the typical characteristics of topography and hydrologic conditions of our study region Thai Nguyen, Vietnam, the irrigation system may expose to some difficulties in terms of water delivery in the dry season. Therefore, simultaneously building up an irrigation system, a system of dam or water storage in the local area might be a solution to store water in the rainy season and deliver water in the dry season.

In conjunction with irrigation, a shift in planting date also has positive influence in reducing drought stress impacts on maize production. Abraha & Gårn (2016) reported that flexible planting and rainwater harvesting have a substantial potential for reducing the negative impacts of climate change, and possibly even increasing outputs. In Southern Mali, earlier planting date of maize in combination with recommended fertilizer rates and late-maturing varieties for medium farms were projected to decrease the impact of warming by 2.9 to 3.3 °C. Under controlled conditions, simulated maize grain yield even increased by 51-57% under current farmer fertilizer practices (Akinseye et al., 2017). Based on the local climate conditions (dry in early spring and late winter season), the planting date, therefore, may shift to be later in the spring season and sooner in the winter season to avoid the most extreme dry periods in early spring and late winter.

Limitations of the study

The uncertainties of our study can firstly be related to the availability of empirical data for crop model calibration and validation, however, fulfilling basic recommendations for crop model applications in data-poor countries (e.g. Grassini et al., 2015). Model validation was hampered by missing recorded seasonal maize yields that were not available in the local reports. Moreover, the recorded yields could have some mistakes that caused by the reporting local farmers and the local agriculture department. Another reason for deviations could be a difference in crop management between reality and



	2000-2014	RCP 4.5 (2001-2030)	RCP 4.5 (2035-2065)	RCP 4.5 (2070-2100)	RCP 4.5 (2001-2100)	RCP 8.5 (2001-2030)	RCP 8.5 (2035-2065)	RCP 8.5 (2070-2100)	RCP 8.5 (2001-2100)
▧ Spring maize	3560.9	2679.5	2651.6	2200.8	2483.3	2772.9	2549.8	1777.9	2352.8
⊞ Winter maize	4058.7	5561.3	5271.9	5382.0	5410.6	5576.8	5531.7	4796.6	5354.4
⊠ Periodic maize	3809.8	4120.4	3961.7	3791.4	3947.0	4174.8	4040.8	3287.3	3853.6

Fig. 5. Comparison of historical maize and simulated climate scenario periods rainfed maize yields.

simulation, for example, a different irrigation scheme between the simulation and reality in winter and spring seasons. In addition, the applied crop model may not be robust in simulating grain yield under extreme weather conditions, such as soil erosion occurring in the midland of the mountainous area or flooding which occurs in the fields located near the rivers. Further, the fact that we did not account for the potential CO2-fertilizing effect (although limited for maize, but with complex and still uncertain environmental vs cultivar interactions (Adishesa et al., 2017) as well as crop rotation effects in the simulation (Ngwira et al., 2014), contribute to uncertainties in the results. In the study region, maize is usually cultivated with other crops in a flexible rotation to obtain the highest productivity. Additionally, the real maize yields and long term yield trends are also influenced by various elements that were not considered in the CERES-Maize model runs, such as occasional support irrigation, impacts of diseases and pests, future changes in production methods and technologies (fertilization, irrigation or new hybrid varieties or cultivars better adapted to drought conditions). All these effects are, however, ongoing in our case study region, which is still strongly developing towards more effective production.

CONCLUSIONS

Being the first crop simulation study on the impact of climate change on maize production in the central north of Vietnam, our study revealed important ongoing and potential future climatic changes of the two regional applied maize growing seasons, the spring and winter growing seasons. Main conclusions include especially an increasing rainfed yield difference between the two growing seasons with important implications for increasing irrigation demand, especially for the spring season.

Although the CERES-Maize model applied in our study, showed good performance in estimating maize production under current conditions, several uncertainties remain, calling also for further research and data needs. First of all, there is still a gap on suitable, qualitative regional data bases for climate change impact studies, especially on experimental crop related data sets for model calibration and validation. This includes cultivar specific responses to various stresses such as drought, heat and nutrient based stresses and its combinations. Although the assimilation response to further increasing atmospheric CO2-concentrations are considered as limited for C4 crops such as maize, uncertainties remain in relation to cultivar vs. environmental effects. More studies with complementary model approaches and ensemble simulations, based on improved and extended regional data bases of agricultural systems and ecosystems are needed to reduce potential uncertainties in future assessments.

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