



Simulating impacts of El Niño and climate change on corn yield in Isabela, Philippines

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Abstract

Advancing climate change and increasing frequency of El Niño events will impact corn growth and development in Isabela Province. This study assessed the potential impact of El Niño and climate change on yellow corn (*Zea mays* L.). The Aquacrop model was calibrated and validated with acceptable accuracy using destructive sampling in four farms in Isabela Province. Yields from past El Niño events were simulated and analyzed. Future yields were simulated using MarkSim daily weather generator. The MarkSim-generated weather files showed good agreement with observed temperatures in our study site but poor agreement with rainfall. The projected increases in temperatures were within the ranges predicted by the Intergovernmental Panel on Climate Change. Projected rainfall patterns showed wet months becoming wetter and dry months becoming drier. Crop simulations showed 7% to 13% reductions in growing cycles and 17% to 41% reductions in mean yields. Reductions in mean yields were due to the larger influence of water stress on dry yields. The 11% to 13% reductions in wet yields were due to effects of rising temperatures than CO₂ fertilization impacts. The expansion of dry months will reduce length of growing seasons and shorten available growing windows for rainfed farms. Changing planting dates and improving irrigation access can help mitigate heat and water stress from climate change.

Keywords: AquaCrop · yellow corn · Isabela · El Niño · climate change · crop model

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Introduction

El Niño and La Niña represent opposite extremes in a complex naturally occurring climate cycle known as the El Niño Southern Oscillation (ENSO)—when the surface air and water temperature in the equatorial Pacific varies from the norm. In the Philippines, El Niño is associated with high temperatures and severe dry spells. It is normally followed by La Niña, which is characterized by heavy rains, severe typhoons, and flooding.

The impact of climate change and variability to food supplies has taken center stage in world food policy and research (Lobell et al., 2008; Ray et al., 2015; Wheeler & Braun, 2013; Osborne & Wheeler, 2013; Porter & Semenov, 2005). Climate model studies are beginning to understand linkages between sea surface warming associated with climate change and increasing frequency of ENSO events (Cai et al., 2014; Li et al., 2013; Cai et al., 2015). The rising frequency of ENSO events in the Philippines will have devastating effects, especially in agriculture (Lizumi et al., 2014; Battisti & Naylor, 2009) where the poorer sectors of society depend.

The severity of these impacts will depend on emission pathways taken in the future. The Intergovernmental Panel on Climate Change (IPCC) introduced Regional Concentration Pathways (RCPs) to standardize projections by modelers of future emissions. RCP2.6 is an emission pathway that leads to very low greenhouse concentration levels that peaks to 490 ppm by 2050 and declines by 2100. RCP8.5 uses a very high baseline emission scenario with greenhouse concentration rising to 1,370 ppm by 2100. Assumptions about driving forces vary with respect to population, economy, land use, primary energy sources, energy intensity, climate policy, and the role of technologies (Van Vuuren, 2011).

Crop models are inexpensive tools that help us understand climate effects on plant growth and development. Crop models developed so far rely on physical concepts of soil, plant water, and climate interactions (Challinor et al., 2009). When coupled with weather generators that are downscalable to represent local weather, crop models can simulate responses of locally grown crops to a range of environmental conditions including climate change scenarios.

Modeling the impacts of climate change on food-producing regions in the Philippines provides better understanding of the range of threats as well as adaptation options available to farmers. As the country's top yellow corn (*Zea mays* L.) and second rice producer, Isabela Province is an important grain producer that supplies the requirements of other provinces including Metro Manila (Reyes et al., 2009; Isabela Provincial Profile, 2016). In 2015, the province produced 1.12 M metric tons contributing 15% to national corn production of 7.5 M metric tons (Bureau of Agricultural Statistics, 2016). While Isabela province is a major grain producer, it is also vulnerable to flooding and dry spells. During the 2010 ENSO event, drought and flooding accounted for PhP2.26 B and

PhP70 M, respectively in damages to the agricultural sector in a single year, according to records from the Provincial Agriculture Office.

Using crop models, we hypothesized reductions in corn growth and development and changes to growing seasons in Isabela. The objectives of this study were to: 1) calibrate and validate the AquaCrop Model for rainfed hybrid corn in selected field sites in Isabela, 2) evaluate the Global Circulation Models (GCMs) and MarkSim weather generator and compare modeled weather with observed data from a local weather station, and 3) assess the potential impact of El Niño and climate change on the growth, development, and yield of rainfed hybrid corn in Isabela.

Materials and Methods

Study Areas

The study areas comprised three rainfed farms located in Barangays (Brgy.) Cabisera 10, Villa Imelda, and Sindon Bayabo, located in the Abuan watershed east of Ilagan City at the foothills of the Northern Sierra Madre Natural Park of Isabela Province. A fourth plot was located in the floodplain inside the experimental station of the Cagayan Valley Research Center (CVRC) of the Department of Agriculture in Brgy. San Felipe, Ilagan City (Figure 1). The farmers in this province rely on small-scale rainfed farming, which is mostly non-mechanized and involves little use of external inputs. Corn farms in this province are located in three agro-ecological zones: flood plain, rolling, and hilly (Reyes et al., 2009). Crop yields differ across agro-ecological zones in Isabela reflecting variations in soil, topography, irrigation, drainage, rainfall, and other climatic factors (Gerpacio & Pingali, 2007).

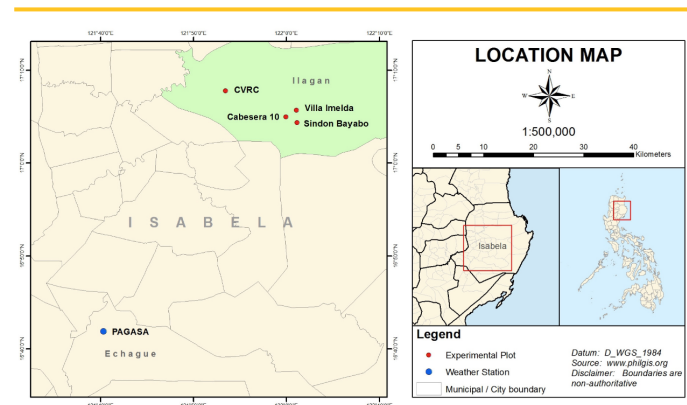


Figure 1. Location map of Villa Imelda, Sindon Bayabo, Cabisera 10 and CVRC farm plots; and PAGASA agrometeorological station in Echague, Isabela.

Agro-meteorological weather stations are located in Villa Imelda and CVRC (Figure 1). Historical weather data were observed at Philippine Atmospheric Geophysical and Astronomical Services Administration (PAGASA) Echague Station.

AquaCrop Model

AquaCrop is a low-input crop water productivity model developed by the Food and Agriculture Organization (FAO) (downloadable at <http://www.fao.org/nr/water/AquaCrop.htm>). It is designed to balance simplicity, accuracy, and robustness, and is suited to address conditions where water is a limiting factor in crop production. It also includes features for carrying out future climate scenario analyses (Steduto et al., 2009; Raes et al., 2009). The AquaCrop model has been parameterized and validated for simulating yield response to water (Hsiao et al., 2009; Heng et al., 2009), therefore making it suitable for rainfed farms. It uses a relatively small number of input variables requiring simple methods for their collection (Vanuytrecht et al., 2011; Abedinpour et al., 2012). Todorovic et al. (2009) recommended AquaCrop under limited input information and water supply conditions.

AquaCrop was used in simulating impacts of climate change on crops in different locations (Hunink & Droogers, 2010; Deb et al., 2014; Masanganise et al., 2012). The model was updated following empirical studies on crop responses to elevated CO₂ conditions (Vanuytrecht & Raes, 2011).

Creating Input Files

AquaCrop requires input files for daily maximum and minimum temperature, rainfall, and evapotranspiration (ET_o). Daily weather data was collected from an automated agro-meteorological weather station located next to the plot in Brgy. Villa Imelda. Solar radiation was recorded from a sunshine recorder and a pyranometer sensor installed at a multi-parameter agro-meteorology station located next to the field plot in CVRC, Brgy. San Felipe, Ilagan City, about 13 km west from the Villa Imelda station. Daily solar radiation was converted to reference ET_o based on FAO Penman–Monteith method as described in Allen et al. (1996).

Soil File

Soil sampling was carried out and brought to Bureau of Soils and Water Management (BSWM) laboratory for analysis. The soils were described as loam, clay, silty clay loam, and sandy clay loam for plots located in Brgys. Cabisera 10, Villa Imelda, Sindon Bayabo, and San Felipe (CVRC), respectively. Soil analyses showed low natural fertility for all farms and high soil acidity with pH values ranging from 4.5 to 5.6. For modeling purposes, field capacity values were set at 16% based on soil moisture sensor readings. Pedo-transfer values for clay loam were set to 8% for permanent wilting point (θ_{WP}), 800 mm/day for saturated hydraulic conductivity (K_{sat}), and 38% (θ_{SAT}) for volumetric water content at saturation.

Irrigation and Field Management

The plots were planted to Dekalb 9132 which is the dominant cultivar planted by farmers. Plant spacing was 6.6 plants/m² based on recommended plant spacing for all sites. Nitrogen

applications adhered to the 120 kg-N/hectare requirement for all plots. All the farms except for CVRC plot were rainfed. Irrigation was applied thrice on the CVRC plot at 32, 47, and 68 days after planting (DAP) at field capacity, during the 2014 dry season. Phenological events (days to emergence, days to flowering, days to senescence, and days to physical maturity) were recorded when 50% of the plants have reached the development stage.

Field Data

Destructive sampling consisted of collecting ten plant samples every ten days from date of sowing until date of harvest in all plots. A 5 m x 8 m sampling area was delineated in the middle of each plot. Farm data consisted of weighed fresh and dry above-ground biomass, and leaf area index (LAI) collected every ten days. Fresh weights of plant specimens were taken using a digital scale balancer. Plant specimens were oven-dried for 48 hours at 70°C and again weighed for above ground dry biomass (i.e., without the roots). The kernels were dried and weighed separately at harvest. The Harvest Index (HI) was computed as dry weight ratio of kernel to above ground biomass.

LAI was converted into Canopy Cover (CC) using the conversion formula in Hsiao et al. (2009).

$$CC = 1.005[1 - \exp(-0.60 LAI)]^{1.2} \quad (1)$$

The average dry weight per plant is multiplied by plant density to arrive at dry biomass per hectare (kg/ha). The user enters dry biomass in kg/ha, canopy cover, and days after sowing.

Model Calibration and Validation

The model was calibrated to generate a set of parameters that can be applied to all three agro-zones as represented by the four plots. The model was calibrated using observed values from the field sampling of the 2014 dry season as input. The crops were grown under optimal conditions, i.e., non-limiting water and nutrients, no pests and diseases. The same conditions are assumed when validating the model and in simulating crop responses to future scenarios. Controlling these variables as well as other sources of yield variability (e.g., soil, slope) was necessary to isolate climate effects on yields.

The number of days to emergence, flowering, start of senescence, and physical maturity were recorded based on farmers' observation and shape of graph depicting percent canopy cover. After entering the DAP for each phenological event, the model was run for each plot to predict biomass, canopy cover and yields through the HI. The default HI value of 0.48 was used.

Validation was done using weather values during the 2014 wet season and by employing the same sampling methods used in the calibration. For model calibration and validation, the predicted versus the observed values for canopy cover, biomass, and phenology were compared and model performance was evaluated using Normalized Root Mean Square Error (nRMSE) (Loague & Green, 1991). Values of nRMSE close to zero

indicate small differences between simulated and observed mean; thus indicating little systematic deviation or bias in the entire data set and expressing precision and reliability of the simulation for observed estimation points. The performance of the model is excellent when nRMSE is less than 10%, good if it is greater than 10% and less than 20%, fair if it is greater than 20% and less than 30%, and poor if it is greater than 30% (Nyang'au et al., 2014). The equation is expressed as:

$$nRMSE = \sqrt{\frac{\sum_{i=1}^n (Si - Oi)^2}{n}} \cdot \frac{100}{\bar{O}} \quad (2)$$

where S_i and O_i are the simulated and observed (measured) values of samples taken along the season (e.g., biomass and CC), n is the number of observations, and $\bar{O}$ is the mean value of O_i .

Simulating Impacts of El Niño

The validated model was used in simulating El Niño effects on yields. Historical daily records from 1987 to 2014 were obtained from the PAGASA station based in Echague, Isabela, which is 58 km southwest to the study area. The dataset was not continuous and daily weather values were available for 19 years, i.e., 1986 to 1989, 1996 to 2001 and 2006 to 2014. AquaCrop was ran over available years assuming planting dates of May 15 and November 15 representing wet and dry seasons, respectively. The El Niño events with corresponding categories set by the Climate Prediction Center (CPC, 2015) included the following: 1987 to 1988 (strong), 1997 to 1998 (very strong), and 2009 to 2010 (strong). The percentage yield anomalies were derived and plotted by planting date. Years with significant yield reductions were analyzed with respect to the timing and distribution of rainfall.

Simulating Potential Impacts of Climate Change

A feature of AquaCrop is the ability to simulate yields normalized to higher temperatures and CO_2 concentrations. MarkSim was used to produce downscaled daily weather values for the study site. The 16 GCMs of MarkSim were evaluated to see how close they predict weather in Villa Imelda station in 2014 using nRMSE scores. The monthly values for temperature and rainfall generated for each GCM were compared with observed monthly values obtained from the Villa Imelda Station for the year 2014. Model skill was evaluated using nRMSE scores.

CSIRO-Mk3.6 (Commonwealth Scientific and Industrial Research Organization) model (Gordon et al., 2002) was selected to generate daily weather files for RCP 2.6 (best case) and RCP 8.5 (worst case) scenarios for both medium-term (2030 to 2055) and long-term (2075 to 2095). The number of hot days (daily maximum temperature $\geq 35^\circ C$), extremely hot days (daily maximum temperature $\geq 40^\circ C$), days with heavy rains (daily rainfall ≥ 100 mm) and annual maximum consecutive days without rains (daily precipitation (P) < 0.1 mm) were counted for both scenarios.

Inter-annual and monthly rainfall variability was measured using coefficient of variation (cv). The equation is expressed as:

$$cv = \sigma / \mu \quad (3)$$

where σ is the standard deviation and μ is the mean.

Time series crop simulations were performed over the medium-term (2030-2055) and long-term (2075-2095) assuming planting dates of May 15 and November 15, representing wet and dry season yields, respectively. Changes in growing periods, plant water demand, wet yields, and dry yields under climate change were noted. Impacts of mitigation measures on yields were simulated.

Results and Discussion

The Climatological Normals for PAGASA Echague Station over the period of 1987 to 2003 is presented in Figure 2. The temperature ranges are $23.7^\circ C$ to $33.9^\circ C$ and $20.1^\circ C$ to $27.3^\circ C$ for the wet and dry seasons, respectively. The corn growing season in Isabela is characterized by warm wet season with temperatures averaging $28.8^\circ C$ from May to September followed by dry cooler season with temperatures dropping to $23.7^\circ C$ from October to March. The average minimum and maximum temperatures for the wet season are $23.7^\circ C$ and $33.9^\circ C$, respectively. During the dry season, the average minimum and maximum temperatures are $20.1^\circ C$ and $27.3^\circ C$, respectively. Cumulative rainfall for the wet season is 891.0 mm and 614.8 mm for the dry season.

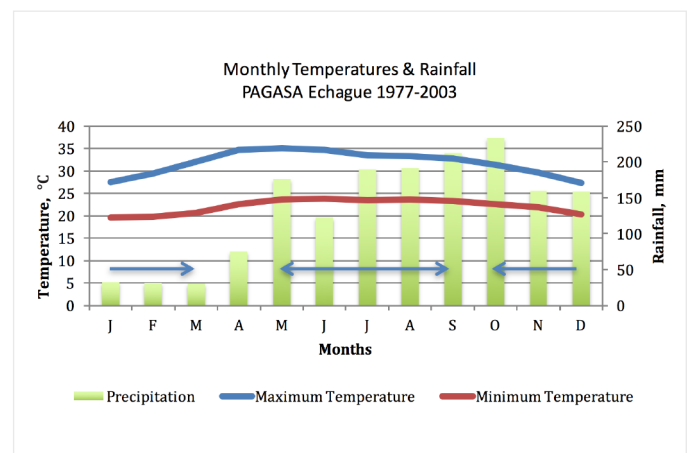


Figure 2. Cropping calendar showing dry cropping season (October to March) and wet cropping season (May to September).

The weather profile during the dry and wet cropping season of 2013 to 2014, as read from the Villa Imelda Station, is shown in Figure 3. The average maximum and minimum temperatures for the dry season (Figure 3a) were $28.1^\circ C$ and $21.5^\circ C$, respectively, with mean of $24.8^\circ C$. The cumulative rainfall was 967 mm, most of which fell in November and December. The average maximum and minimum temperatures for the wet

season (Figure 3b) were 32.6 °C and 23.2 °C, respectively, with mean of 27.9 °C. The cumulative rainfall was 1,040 mm, which was evenly spread from July to November. The dry season was cooler and relatively drier with more sunshine hours. The wet season was warmer, wetter and cloudy.

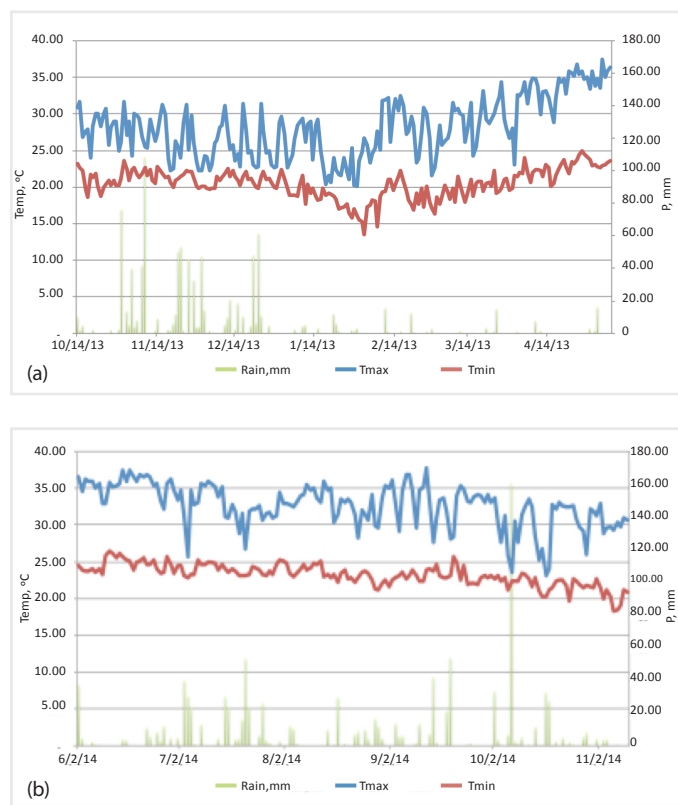


Figure 3. (a) Dry season weather file used in crop model calibration (14 Oct 2013 to 15 May 2014) and (b) Wet season weather file used in model validation (2 Jun to 10 Nov 2014). (Weather file source: Villa Imelda Station).

Model Calibration and Validation

Calibration was done to fit the model to actual conditions over the 2013 to 2014 dry season. The growing period or days to physical maturity was set to 125 days, equivalent to 1,883 growing degree-days. The thermal time from sowing date to emergence, flowering, start of senescence, and maturity were set at 39, 907, 1,503, and 1,883 growing degree-days, respectively. The observed dry biomass clustered at 16 tons/ha at 125 DAP for the four farms. The water productivity (WP*) normalized for ETo and CO₂ was 33.7 gm/m². The temperature above which pollination starts to fail was set at 40 °C. The minimum temperature required for optimal biomass production was 12 °C-day. The reference HI was set at 0.48. The difference between predicted and observed values for biomass and canopy cover was minimized by adjusting soil fertility loss to 38%.

The calibration data set consists of field samples for phenological events, canopy cover, dry biomass, and HI collected over the 2013 to 2014 dry season. The model performance in predicting phenological events (i.e., days to

emergence, flowering, senescence, and physical maturity) was excellent to good based on nRMSE scores. Model performance in simulating canopy cover was good to fair. The model performance in simulating corn biomass production was excellent to good. The observed HI was 0.46, 0.48, 0.52, and 0.51 for Sindon Bayabo, Cabisera 10, Villa Imelda, and CVRC, respectively, with mean HI = 0.49.

Validation results showed acceptable accuracy for AquaCrop. The validation data set consisted of field samples for phenology, canopy cover, dry biomass, and HI collected over the 2014 wet season. The model performance in predicting phenological events was excellent to good. The model performance in simulating canopy cover had a mix of good, fair, and poor nRMSE scores. The model performance in predicting biomass was good for all sites. The observed HI values were 0.48, 0.53, 0.54, and 0.42 for Sindon Bayabo, Cabisera 10, Villa Imelda, and CVRC, respectively, with mean HI = 0.49.

Simulating Impacts from El Niño

Figure 4 shows the time series AquaCrop simulations for years 1986 to 1989, 1996 to 2001, and 2006 to 2014 assuming May 15 (wet) and November 15 (dry) planting dates. High yield reductions of 70% and 68% were simulated for the dry cropping seasons of 2010 and 1998, respectively. Smaller reductions of 19% and 18% were simulated for the dry season of 1987 and 2014. Yield reductions of 19% were simulated for the 2007 wet season.

Figure 5 shows rainfall anomaly for years 1987, 1998, 2010, and 2014. The onset of below normal rains from December to March coincided with El Niño episodes for 1987, 1988 and 2010. Yield losses of 68% to 70% were simulated for 1988 and 2010 when December rainfall fell by more than 100 mm. The onset of drought in December inhibited canopy growth and yield production affecting final yield.

Validating MarkSim

MarkSim-generated weather values from 16 GCMs were evaluated with those from Villa Imelda station for the year 2014 using nRMSE scores. The model performance in predicting average monthly maximum and minimum temperatures was excellent with nRMSE scores ranging from 7% to 8% and 5% to 8%, respectively. However, MarkSim performance in predicting monthly precipitation was poor with nRMSE ranging from 93% to 140%. The good fit for temperature indicates higher confidence that long-term projected temperatures are reliable and can be applied to the study area. However, the poor fit for rainfall indicates low confidence in the projections by MarkSim. Of the 16 GCMs, the CSIRO-Mk3-6 GCM was selected in projecting temperatures and rainfall by 2050s and 2090s.

Change in Temperature

The projected change in monthly temperatures is presented in Figure 6. By 2050, projected increases in average annual

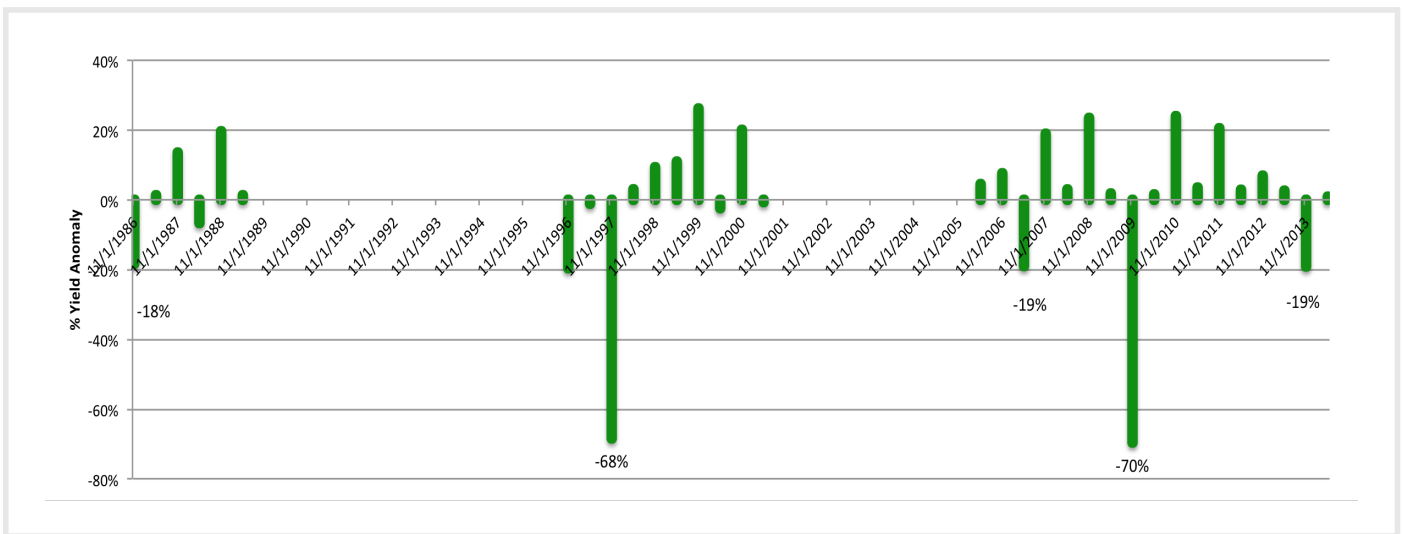


Figure 4. Simulated % yield anomalies by planting dates assuming May 15 (wet season) and November 15 (dry season) planting dates for the period 1987-2014 (selected years). (Daily weather source: PAGASA Echague Station)

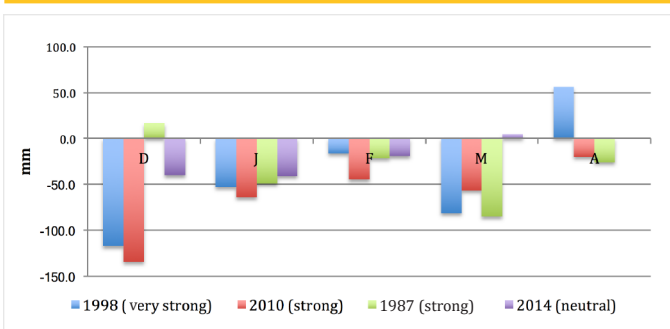


Figure 5. Dry season rainfall anomaly for various El Niño years (1987, 1998, 2010) and 2014 (normal year). (Source: PAGASA Echague Station)

temperature were $+1.38^{\circ}\text{C}$ and $+1.74^{\circ}\text{C}$ for best case and worst case, respectively. Beyond mid-century, the projections start to diverge dramatically. By 2090, the best case scenario shows temperature stabilizing at $+1.96^{\circ}\text{C}$, while the worst case scenario showed an increase of $+4.08^{\circ}\text{C}$.

Table 1 presents the change in temperatures under climate change. The baseline showed CO_2 concentrations of 369 ppm and mean temperatures of 26.9°C for Isabela. The climate scenarios showed increase in CO_2 concentrations ranging from 450 ppm (best case) to 630 ppm (worst case) by 2050 and from 450 ppm (best case) to 1,100 ppm (worst case) by 2090.

By 2050, mean temperatures will increase by $+1.38^{\circ}\text{C}$ from 26.9°C to 28.3°C and by $+1.74^{\circ}\text{C}$ to 28.6°C under best case and worst case scenarios, respectively. By 2090, their tracks will diverge dramatically. The best case scenario showed CO_2 concentrations stabilizing at 440 ppm with lower mean temperature increase of $+1.96^{\circ}\text{C}$, whereas the worst scenario showed mean temperature increase of $+4.08^{\circ}\text{C}$. These projected

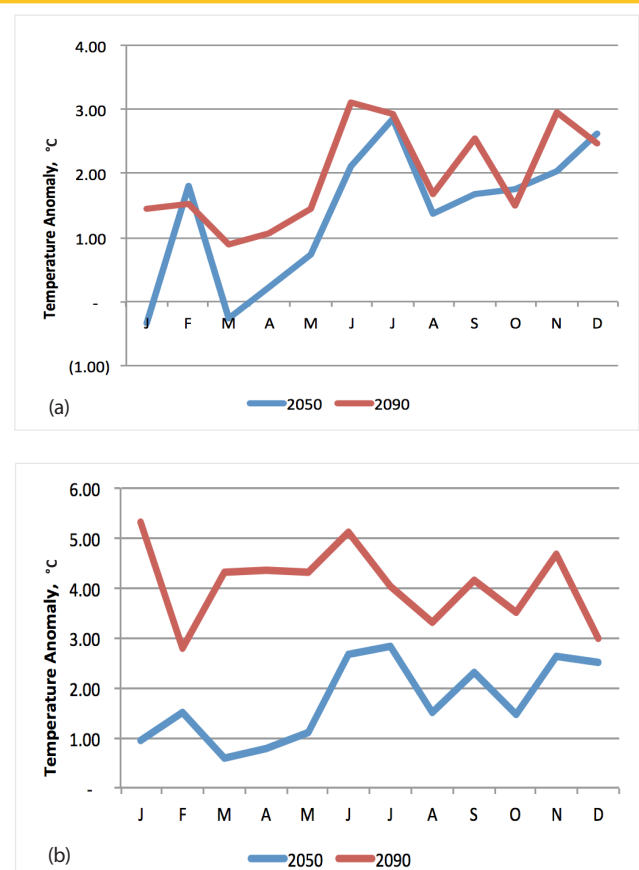


Figure 6. Monthly temperature anomalies under (a) best case RCP2.6 and (b) worse case RCP8.5 scenarios.

increases were well within the range of CO_2 and temperature increases predicted in the 5th Assessment Report of the Intergovernmental Panel on Climate Change (IPCC, 2014).

Table 1. Change in temperature under climate change

Baseline, 1987-2014, n=19	369 ppm CO ₂ , 26.9 °C	
Tmax, °C		31.8
Tmin, °C		22.0
No. days with Tmax≥35 per year		60
No days with Tmax≥40 per year		0.25
Months with days Tmax≥40		Apr, May, Jun
Annual ETo, mm		1,368
	Best Case, RCP2.6	Worst Case, RCP8.5
Medium-term, 2030-55, n = 25	450 ppm CO ₂ , 28.3 °C	630 ppm CO ₂ , 28.6 °C
Tmax, °C	32.9	33.3
Tmin, °C	23.7	24.0
No. days with Tmax≥35 per year	108	123
No days with Tmax≥40 per year	6	8
Months with days Tmax≥40	Apr–Oct	Mar–Oct
Annual ETo, mm	1,583	1,593
Long-term, 2075-94, n=20	450 ppm CO ₂ , 28.9 °C	1100 ppm CO ₂ , 31.0 °C
Tmax, °C	33.5	35.7
Tmin, °C	24.2	26.3
No. days with Tmax≥35 per year	134	218
No. days with Tmax≥40 per year	12	41
Months with days Tmax≥40	Apr–Oct	Jan, Mar–Sep
Annual ETo, mm	1,621	1,740

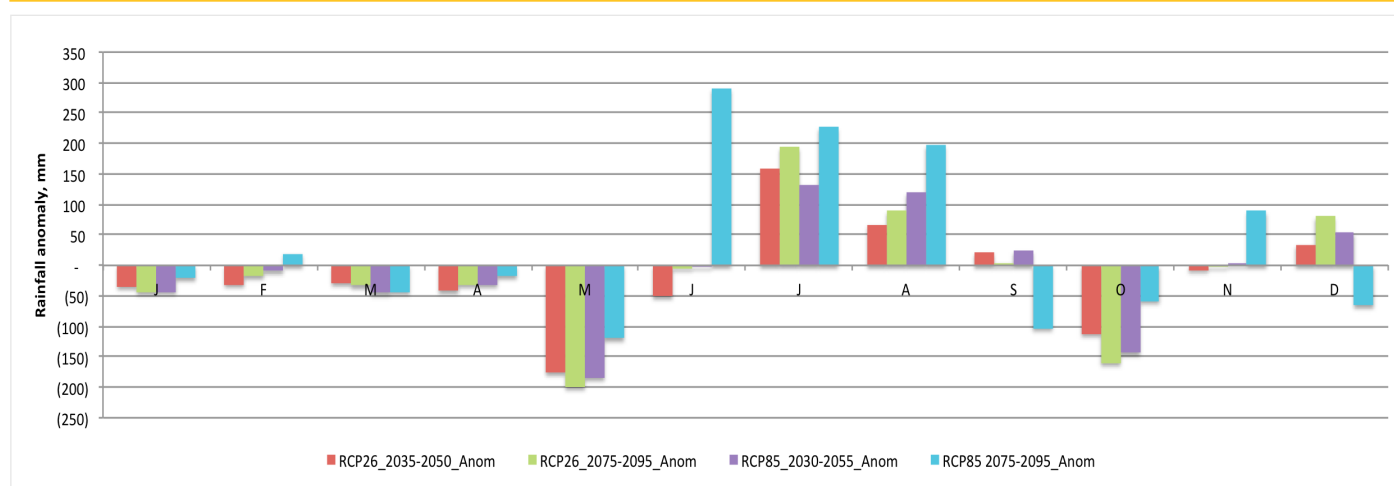
Annual ETo will increase from 1,368 mm to 1,621 mm to 1,740 mm in the long term. The number of extremely hot days will increase from 0.25 days a year to 6 to 8 days a year by 2050 and to 12 to 41 days a year by 2090. Months with extremely hot days will expand from April-June to March-October.

Change in Rainfall

The rainfall distribution under climate change showed a pattern of wet months getting wetter and dry months getting

drier (Figure 7). This indicates higher risk of dry spells during summer and flooding during rainy season. A decrease in rainfall in May will delay the start of the growing season to June, while decreases in January to April rainfall may advance the end of the growing season to December.

Table 2 shows the change in mean and variability in rainfall for the medium-term and long-term. The baseline conditions showed mean rainfall of 2,097 mm, with an inter-annual variability of $cv = 0.19$ over 19 years for the baseline period 1987 to 2014. The inter-annual variation in projected rainfall

**Figure 7.** Projected monthly rainfall anomalies for medium-term (2050s) and long-term (2090s) under climate change

is low with *cv* of 0.04 in the medium-term and 0.02 to 0.05 for the long-term. The variability of projected December rainfall is also low dropping from 0.74 to 0.04 to 0.49 in the long-term.

The annual average maximum consecutive number of dry days was 18 days for the baseline period, mostly occurring in the summer months from January to March. The highest number of days without rain was 34, 30, and 28 days in the months of February 2010, January 1998, and March 1987, respectively, coinciding with El Niño.

The annual average maximum consecutive number of dry days will jump from 18 days to 27 days by 2050, mostly projected in November or October. This contradicted current experience where maximum dry days usually occurred during January to April.

The low variability of projected intra-annual and inter-annual rainfall and the occurrences of extreme events in months outside the current experience in Isabela Province suggests possible failure of the MarkSim weather generator to incorporate the effects of past El Niño and other extreme weather events. This confirms the observation by Jones and Thornton (2000) where MarkSim failed to simulate ENSO effects in Peru and Ecuador, and findings of Mavromatis

and Hansen (2001) where MarkSim showed tendency to overpredict mean monthly rainfall totals, while under representing inter-annual variability of monthly precipitation totals when compared to historical datasets.

Simulating Potential Impacts on Corn

Table 3 presents the results of crop simulations for time slices 2030 to 2055 and 2075 to 2095 for both RCP 2.6 and RCP 8.5 scenarios with reference to the baseline (1987 to 2014). Comparisons were made with respect to growing days, plant transpiration demand (Tx), wet yields, and dry yields.

Simulations show growing days (days to maturity) will be reduced by 7 to 9 days (7% to 8%) by 2050 and by 8 to 15 days (7% to 13%) by 2090. These reductions correspond to 3% to 5% decrease in growing periods per degree rise for all scenarios. By 2050, mean yields will decline from 34% to 41%. By 2090, yields under best case scenario will drop 41% to 4.31 tons/ha, while yields will drop by only 17% under the worst case scenario. Yield reductions ranged from 21% to 25% per °C rise, larger than results from earlier studies (Makadho, 1996; Lobell & Field, 2007; Bassu et al., 2014) and from local studies (Lansigan & Salvacion, 2007). The better yield performance under the long-term worst case scenario was attributed to

Table 2. Change in rainfall under climate change

Baseline, 1987-2014		
Mean Annual P, mm		2,097
cv (across years)		0.19
cv (across months)		0.41 - 0.86
December rainfall, cv		0.74
Ave. no. of maximum consecutive days (P<0.1mm)		18
No. of days with P>100 mm		1-3 times/yr, May, Oct, Nov
	Best Case, RCP2.6	Worst Case, RCP8.5
2050s		
Mean Annual P, mm	1,897	1,974
cv (across years)	0.04	0.04
cv (across months)	0.08-0.62	0.10-0.85
December rainfall, cv	0.18	0.13
Ave. maximum no. of consecutive dry days (P<0.1mm)	27	27
No of days with P>100 mm	1-2 times/yr, Nov-Dec	1-2 times/yr, Nov-Dec
2090s		
Mean Annual P, mm	1,972	2,493
cv (across years)	0.02	0.05
cv (across months)	0.08 - 0.47	3.93-0.02
December rainfall, cv	0.08	0.49
Ave. no. of maximum consecutive dry days (P<0.1mm)	27	24
No. of days with P>100 mm	1-2 times/yr, Nov-Dec	1-2 times/yr, Nov

Table 3. Impacts of climate change on maize yields and adaptation options.

Baseline (1987-2014)				
Growing days, d				110
Tx, mm				125
Wet yield, tons/ha				6.78
Dry yield, tons/ha				7.711
Mean yield, tons/ha				7.25
	Best Case, RCP2.6		Worst Case, RCP8.5	
2050s	% change		% change	
Growing days, d	103	-7%	101	-8%
Tx, mm	183	46%	175	40%
Wet yield, tons/ha	6.06	-11%	5.96	-12%
Dry yield, tons/ha	3.47	-55%	2.64	-66%
Mean yield, tons/ha	4.77	-34%	4.30	-41%
% mean yield loss/deg		-25%		-23%
Oct 15 planting date, yield	6.94	-10%	6.24	-19%
With irrigation, yield	7.60	-1%	7.27	-6%
2090s	% change		% change	
Growing days, d	102	-7%	95	-13%
Tx, mm	181	45%	177	42%
Wet yield, tons/ha	6.05	-11%	5.89	-13%
Dry yield, tons/ha	2.57	-67%	6.18	-20%
Mean yield, tons/ha	4.31	-41%	6.04	-17%
% mean yield loss/deg		-21%		-4%
Oct 15 planting date, yield	6.94	-10%	6.23	-19%
With irrigation, yield	7.44	-4%	6.89	-11%

favorable rainfall that supplied 94% of plant water requirements during the dry season.

Findings showed that the larger reductions in mean yields were influenced more by dry yields where the impacts of water scarcity were larger compared to counterbalancing impacts of rising temperatures and CO₂ levels. By 2050, mean dry yields of 7.7 tons/ha were predicted to drop between 55% to 66% for both scenarios. By 2090, yields dropped to 67% and 20% under best case and worst case, respectively.

Plant demand for water will increase 40% to 46% in all scenarios. Decreasing rainfall during dry months showed only 76% to 81% of the plant water requirement will be met by rainfall. Advancing planting dates to mid-October may reduce yield losses of 55% to 66% to only 10% to 19% by 2050. Vulnerability to water stresses from advancing dry seasons can also be mitigated by access to irrigation.

Wet yields showed losses ranging from 11% to 13% for all scenarios, smaller than those of the dry season. The counterbalancing effects of elevated CO₂ concentrations and temperatures can be inferred from reductions in wet

yields, where rainy weather control for the effects from water stress. The effects of reduced life cycles on final yield nullified the effects from CO₂ fertilization in both medium and long-term scenarios. The limited response of C4 crops to CO₂ fertilization is due to their lower carbon sink potential. Findings agreed with earlier studies that showed zero or negligible net effects, and validated the limited carbon sink potential of C4 crops (Ainsworth & Rogers, 2007; Long et al., 2006; Zvereva & Koslov, 2006; Hatfield et al., 2011).

Simulating Impacts on Length of Growing Seasons

The length of the growing season (LGS) or growing period as defined by FAO is the period in days during the year when soil moisture is sufficient for plant growth or when rainfall exceeds half the potential ETo rates (FAO, 1978). The calculation of the growing period is based on a simple water balance model, comparing water availability with crop water demand (precipitation with ETo), using monthly values.

The baseline LGS is 11 months, which lasts from April to February the following year. This can accommodate two croppings of 120-day hybrid corn a year. By 2050, the LGS is

reduced from 11 months to 9 months (May to January) under best case scenario and further reduced to 8 months (May to December) under the worst case scenario. By 2090, the LGS will be 9 months (May to January) under both scenarios.

Conclusion

The scenarios projected a future of shorter growing seasons, advancing dry months, hotter days and higher rainfall under climate change. Simulations showed reduced corn yields for all scenarios.

Advancing planting dates is a low-cost strategy to addressing El Niño. Low cost small-scale impounding systems can help farmers cope with advancing dry weather and supply increasing plant water requirements. Research on short-duration, drought, and heat-tolerant crops is imperative.

Simulation for other crops in other crop growing provinces will also help build knowledge on spatial impacts of climate change. Because it uses fewer and readily observable input variables, models like AquaCrop are better suited to practitioners and novice users. Its widespread use will accelerate the research growth in the country.

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