



Simulating Impacts of ENSO and Climate Change on Sugarcane Production in Negros Occidental Province, Philippines

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Abstract

The Philippines is a major exporter of sugarcane, ranking 9th in global production. By 2024, the government aims to increase the country's sugar productivity by 27% (from 60 t/ha to 75 t/ha) by consolidating rainfed farms and investing in irrigation. Although it is generally known that climate change affects crop production and food security, there is little understanding of how climate change and El Niño-Southern Oscillation (ENSO) events will impact production targets and future irrigation requirements. Crop models are cost-effective tools that can help policy makers and food planners to adapt to the changing weather and rising CO₂ emissions; however, the methods used in crop modeling need to give robust, reproducible, and transparent estimates before they are used with confidence by food authorities. This study simulated the crop responses of sugar-growing farms in Negros Occidental, Philippines to ENSO events and mid-century climate using the AquaCrop model. The point model was extrapolated and converted into provincial scale to help agricultural planners in their decision making. The upscaled model was validated using yield data from 2005 to 2017. The climate change projections show that cane yield would increase from 5% to 30% by 2050 due to wetter summers. Rainfall from December to March explains 82% of the variability in the simulated annual yields, indicating higher irrigation returns. This study demonstrated the utility of crop models and upscaling methods, which can guide future climate change assessments at larger scales.

Keywords: AquaCrop · sugarcane · Negros · ENSO · climate change · irrigation

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Introduction

Sugar is a major export crop of the Philippines. Globally, the country ranks 9th in sugarcane production, 8th in terms of area planted, and 37th in yield, which averages 74 tons per hectare (t/ha) (Zhao & Li, 2015). The industry directly employs 630,000 workers and five million workers indirectly (Development Bank of the Philippines [DBP], 2015). The annual production is highly variable (coefficient of variation [cv] = 11.94 t/ha), and growth is relatively flat, averaging 0.25 t/ha per year (Food and Agriculture Organization [FAO], 2013). About 79% of the country's sugar production in 2017 came from Negros province (Philippine Statistics Authority [PSA], 2018).

Large modern farms in the Philippines operate more efficiently, generating yields up to 100 t/ha. Smallholder farms (areas with ≤ 5 ha), on the other hand, comprise 80% of the total number of farm holdings in the country. Most smallholder farms are rainfed, with average yields of 60 t/ha. Espino (2017) cited that the 83 sample farmers from Negros Occidental had shown yields of 80.6 t/ha and 62.5 t/ha for irrigated and rainfed farms, respectively.

The Sugar Industry Development Act of 2015 (Republic Act [RA] No. 10659) aims to increase rainfed farmers' yield by 27% (from the current 60 t/ha to 76 t/ha) by 2024 through consolidating small farms and investing in irrigation. However, the impacts of climate change (e.g., changing rainfall patterns, higher temperatures, and future crop responses) pose a challenge toward this goal. Accordingly, the Philippine government has pushed the issue of climate change impacts and variability on food supplies and irrigation infrastructure to the center of the country's food policy and research. Disruptions in these systems due to climate change and El Niño-Southern Oscillation (ENSO) events can trigger shortages and significant economic losses. Unfortunately, most irrigation infrastructures in the country are designed without considering the impacts of climate change.

Crop models are inexpensive tools that help researchers to understand how climate can affect plant growth and development. So far, the crop models that have been developed have relied on the physical concepts of soil, plant water, and climate interactions. Crop models can simulate the responses of locally grown crops to a range of environmental conditions, including climate change, particularly when these models are combined with weather generators that are downscalable to represent local weather.

Developing models to show the impacts of climate change on food-producing regions in the Philippines can help researchers to better understand the range of threats and the corresponding adaptation options available to farmers. Methods used in crop modeling need to give robust, reproducible, and transparent estimates before

food authorities can use them with confidence. However, researchers are not able to maximize the use of crop models when doing regional assessments because the data collection procedure for such assessments is expensive and time consuming. To the best of our knowledge, no large-scale impact assessments of the sugarcane grown in the Philippines have been made using crop models.

In this study, we developed an approach for modeling sugarcane production at a provincial scale using less rigorous data sources while still satisfying the minimum data requirements for calibrating and validating the model. Negros Occidental was chosen as the sample province because agricultural surveys are regularly conducted in this province. Moreover, official records are updated regularly and are accessible through the PSA website. Such advantages would allow future researchers to further refine the model and validate official figures, or vice-versa. Crop models would also complement existing survey methods and facilitate the decision making of the provincial agricultural office and the Sugar Regulatory Administration as they prepare their development plans for the sector.

This study aims to demonstrate how a crop model can be used to assess the present and mid-century impacts of ENSO and climate change on sugarcane growth and productivity in Negros Occidental province, Philippines. Likewise, the research aims to recommend the optimal irrigation strategies for sugar production in order to address the foreseen impacts of climate change.

Related Studies

The existing physiological studies involving chamber experiments provide information regarding the effects of high temperature, elevated CO₂, and drought stress on cane plant processes (de Souza et al., 2008; Inman-Bamber, 1994; Singels et al., 2000). These studies have demonstrated that sugarcane productivity increased due to higher photosynthetic rates and improved water-use efficiency, which resulted from higher CO₂ concentrations. Likewise, the results have helped researchers to identify the parameters that can be used in crop models in order to simulate plant responses to increasing CO₂ levels (Singels et al., 2000).

A number of climate change modeling studies generally agree on the positive effects of the future climate on cane yields (yield increase of about 4%–29%). Singels, Jones, Marin, Ruane, and Thorburn (2013) projected 4%, 9%, and 20% increases in cane yields in Australia, Brazil, and South Africa, respectively. Other studies reported increases of 15%–29% in Brazil by 2050 (Marin et al., 2013); 15–25 t/ha increases in South Africa by 2055 (Schulz & Kunz, 2010); 16% increase with CO₂ effects (compared with the +5% without CO₂ effects) in Swaziland by 2050 (Knox, Rodriguez, Nixon, & Mkhwanazari, 2010); 7%–15% increases in irrigated

cane yields by 2100 in South Africa (Jones, Singels, & Ruane, 2013); and 5%–6% increases with CO₂ effects by 2050 in Australia (Sexton, Everingham, Inman, & Stokes, 2014). On the other hand, other studies have shown negative effects. Singh and El Maayar (1998) reported 20%–40% reduction in cane yield in Trinidad and Tobago, whereas Cheero-Nayamuth, and Nayamuth (2001) cited 32%–57% decreases in Mauritius. These studies, however, did not consider the effects of CO₂ on photosynthesis and transpiration (Singels et al., 2013).

Other studies reported mixed results. In Australia, Biggs, Thorburn, Crimp, Masters, and Attard et al. (2013) reported that climate change has a “weak” effect when yield increases and a “strong” effect when yield decreases. The variations in the modeling results may be due to the differing general circulation models (GCMs) used in the climate projections and to the varying crop model responses to the effects of elevated CO₂ (Biggs et al., 2013; Vanuytrecht & Raes, 2011; Vanuytrecht, Raes, & Willems et al., 2011).

Meanwhile, several studies point to the beneficial effects of elevated CO₂ conditions on the increased photosynthesis and reduced stomatal conductance, which improve starch accumulation and water-use efficiency (Ainsworth & Roger, 2007; Vu & Allen, 2009a, 2009b; de Souza et al., 2008). Nevertheless, most models agree on the significant impacts of water variability on soil moisture, especially in rainfed farms.

Crop models are upscaled from field to regional scale because food authorities need science-based and data driven evidence to support their decision making. Point-based crop models that are originally developed, calibrated, and tested for field scale applications are increasingly used for larger areas and longer time periods (Marin & Carvalho, 2012; Cheero-Nayamuth & Nayamuth, 2001). Upscaling methods, ranging from the simplest method (using a single point) to more sophisticated nested models, have already been classified (van Oijen et al., 2009; Ewert et al., 2011).

However, upscaling creates uncertainty in the model’s output due to limitations in data quality, availability, and aggregation approaches, thereby constraining their use in regional studies (Hansen & Jones, 2000).

Coarse-weather, soil, and cropping system data are used for climate assessments that rely on crop yield simulations because finer spatial high-quality data are absent. Thus, pragmatic shortcuts are required to achieve full terrestrial coverage (Grassini et al., 2015). These shortcuts are rarely evaluated to reproduce yield data using high-quality and measured data, such as those obtained from government statistical records. Without validation, yield estimates using coarse-scale data sources can seriously distort results, thereby decreasing their usefulness to inform regional or national policies for agriculture. Protocols to overcome data limitations

have been developed as part of global yield gap studies (van Wart 2012, van Bussel 2015, & Grassini, 2015). Accordingly, these protocols are applied in this study for climate change assessments.

Materials and Methods

Study Area Description

Negros Occidental is a province in the Philippines located in the Negros Island region. It is known as the “sugar bowl of the Philippines”, producing more than half of the nation’s sugar output. The landscape consists of alluvial plains and hilly and mountainous areas. A mountain range lines the eastern part of the province that forms the basis of the border shared with another province, Negros Oriental.

The climatological records from the La Granja station of the Philippine Atmospheric, Geophysical, and Astronomical Services Administration (PAGASA) show that the average minimum and maximum temperatures in Negros Occidental from 1987 to 2003 are 22.1 °C and 32.8 °C, respectively. The rainy season starts in May to December, whereas the dry season starts from January to April. Annual rainfall is 2,642 millimeters (mm), with cv = 0.15. Rainfall records show an increasing trend of 11 mm per year during the period 1975–2016.

Point models refer to a plant’s response to a combination of cultivar, climate, soil, and farm management interactions. Accordingly, we developed a point model to represent the farms in the Araal–Najalin–Marayo watershed. This watershed is a 19,535-hectare-wide sugar-growing region surrounding the La Granja-PAGASA station in La Carlota City and supplies the La-Carlota sugar central milling district (Figure 1).

Upscaling Method

The choice of upscaling methods would depend on the desired changes in the extent, coverage, or resolution of the crop area being studied. The simplest method is the point extrapolation method, which has been used in earlier studies that assessed the impacts of climate change on crops (Rosenweig & Party, 1994). We chose this method as it demands less data, has low computing time, and has high reusability, i.e., low required knowledge to reuse the method (Ewert 2011). Using the point extrapolation method, we extrapolated and then converted the Araal–Najalin–Marayo watershed point model into provincial scale in accordance with the published guidelines (Grassini et al., 2015; van Wart, Kersebaum, Peng, Milner, & Cassman, 2013; van Bussel et al., 2015). Accordingly, the guidelines for upscaling recommend the following:

1. Selecting homogeneous locations with minimum coverage of about 40%–50% of the total harvested

area in order to account for the largest proportion of total production for a chosen scale (e.g., province or country);

2. Choosing weather stations with sufficient geospatial coverage and data quality; and
3. Identifying the dominant soil type and averaging farmer practices in each location where yield is simulated (van Wart et al., 2013; van Bussel, 2015).

In this study, we selected the sugar-growing areas in Negros Occidental based on the expansive homogeneous topography of its lowland cane-growing areas. In place of crop maps, we used the land area of the province as proxy for harvestable area. The land area within a buffer zone of 50 kilometers (km) of fixed radius around the La Granja PAGASA station represents 40% of the total area of the province (Figure 1).

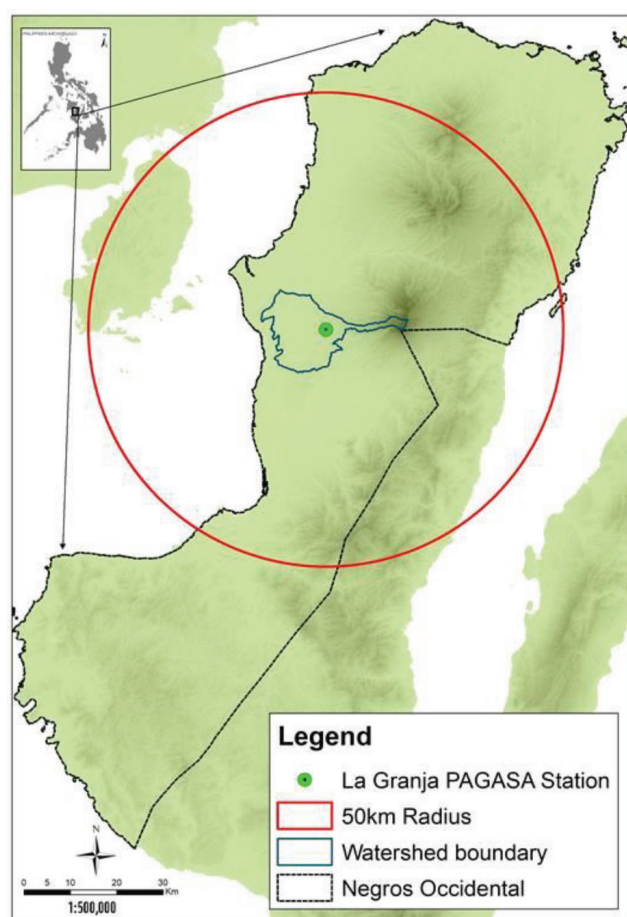


Figure 1. Map of the La Granja PAGASA Station

AquaCrop Model

We used the AquaCrop model¹ to simulate the growth and development of sugarcane crops under typical management practices in La Carlota City, Negros Occidental province. The year 2010 was used as the current baseline and year 2050 as the future climate scenario. The model simulated the impacts of elevated CO₂ concentration and higher temperature on photosynthesis, transpiration, and phenology.

AquaCrop requires input files for the daily maximum and minimum temperature, rainfall, and evapotranspiration (ET_o). The baseline for rainfall consists of a 41-year time series of historical monthly rainfall (1975–2016) and 12-year daily rainfall records (2004–2016), which were collected from the La Granja-PAGASA station. Since the daily temperature records from La Granja station were not available, the 23-year daily record of Iloilo City (which is 56 km away from La Carlota City) from 1987 to 2010² was used.

AquaCrop sets CO₂ concentrations at 388 parts per million (ppm) to represent the 2010 baseline. The mean monthly solar radiation, which can be obtained from climatological normals, was converted into ET_o using the ET_o calculator.³ The ET_o calculator follows the Penman–Monteith method described in the study of Allen, Pereira, Raes, and Smith (1998).

Model Calibration and Validation

Crop models that cover large spatial areas require high-quality input data to account for the variations within a given agronomic landscape. These high-quality data are not available for most parts of the Philippines. Thus, we collected the data for calibration from different sources, including the PAGASA weather records, farmer interviews, PSA website, independent reports, and installed pre-calibrated model parameters. Farmers were interviewed to collect data on the planting dates, growing period to maturity, and cultivar types. Based on the soil sampling reports of Evangelista (2017), the soil type at the study site is predominantly clay loam.

¹ This can be downloaded at <http://www.fao.org/nr/water/AquaCrop.htm>.

² The data are available and can be downloaded from the National Oceanic Atmospheric Administration website (<https://www.ncdc.noaa.gov/cdo-web/datasets/GHCND/locations/FIPS:RP/detail>).

³ This can be downloaded from the FAO website.

The Aquacrop model was calibrated by setting the yield⁴ values for rainfed farms to 60 t/ha and irrigated rainfed farms to 80 t/ha; both values are based on the yield estimates of Espino (2017). The ratio of rainfed to irrigated farms by harvest area was assumed to be 80:20, which corresponds to the proportion of smallholder (< 5 ha) to large farms (≥ 5 ha). The composite yield from both areas was calculated using their weighted contribution by harvest area.

Clay loam is the dominant soil texture in the study area, with field capacity and wilting points set at 16% and 8% by volume, respectively. The modeling error was minimized by adjusting soil fertility loss to 20%. AquaCrop does not model nutrient fluxes but uses a biomass loss adjustment factor to account for nutritional effects from nutrient-deficient treatments (Hsiao, Heng, Steduto, Rojas-Lara, & Fereres, 2009). Based on the information gathered from the farmers' interviews, the planting month was set to May as this is the period when rainfed small-scale farmers wait for the onset of rains. The initial condition assumes that soil moisture is at field capacity. The coefficients for growing degree days, water use productivity, and ETo crop factors were derived from pre-calibrated default values that comes with AquaCrop for sugarcane (de Souza et al., 2008; Singels, Jones, & den Berg, 2008).

The model was validated using the PSA reports on fresh cane biomass production from 2005 to 2016 for Negros Occidental (PSA, 2018). The model skill and the simulated versus the observed values were evaluated using the normalized root mean square error and r^2 scores.

Normalized Root Mean Square Error

Normalized root mean square error (nRMSE) values that are close to zero mean that the differences between the simulated and observed yields are small. This further indicates that there is little systematic deviation or bias in the entire data set, and that the data set expresses precision and reliability of the simulation for observed estimation points. The performance of the model is *excellent* when the 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, Mati, Kalamwa, Wanjogu, & Kiplagat, 2014). The equation is expressed as

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

where:

- Si = number of simulated yields from the point model represented by farms in the Araal–Najalin–Marayo watershed,
- Oi = number of observed (measured) yields taken from the PSA provincial yield data for the years 2005–2016,
- n = number of observations, and
- $\bar{O}$ = mean value of Oi .

Coefficient of Determination

The coefficient of determination (r^2) is the regression sum of squares divided by the total sum of squares (SST). It is expressed as

$$r^2 = 1 - \frac{\sum_i (yi - fi)^2}{\sum_i (yi - \bar{y})^2}$$

where:

- y_i = observed data point,
- f_i = regression value, and
- $\bar{y}$ = mean of the data points.

The coefficient of determination (r^2) measures the goodness-of-fit of a model or how well the regression line approximates the real data points. An r^2 score close to 1 indicates a good fit of the model to the data.

Coefficient of Variation

Interannual and monthly rainfall variabilities were measured using cv , which can be expressed as

$$cv = \sigma / \mu$$

where σ is standard deviation and μ is the mean.

Irrigation Water Use Efficiency

The irrigation water use efficiency (IWUE, t/ha per 100 mm) can be expressed as the fresh cane biomass produced ($Y_{irr} - Y_{rain}$, t/ha) per unit of irrigation water applied (W_{irr} , 100 mm):

$$IWUE = \frac{Y_{irr} - Y_{rain}}{W_{irr}}$$

Simulating the Impacts of ENSO

We simulated the interannual cane yields from 1975 to 2016 while assuming that May is the planting month. The annual anomalies (departure from average values) were analyzed and correlated with the ENSO episodes for 1988, 1993, 1998, 2003, 2010, and 2015. Intra-annual yields were simulated and averaged by planting month. Monthly yield anomalies were analyzed with respect to monthly rainfall intensity falling during the course of the

⁴ In this paper, "yield" refers to fresh stalk biomass or cane biomass.

growing season.

The rainfall intensity uses the PAGASA categories for *above normal* (>1.2), *near normal* ($0.81-1.2$), *below normal* ($0.41-0.8$), and *way below normal* (<0.4). Rainfall intensity scores of 4, 3, 2, and 1 were assigned to each rainfall category in descending order. The scores were averaged for the four-month period from December to March to arrive at the rainfall intensity index for the period. The higher the index, the higher the rainfall intensity for the four-month period. The indices were then correlated to the annual percentage yield anomalies for the study period.

Future Climate Projections

Multi-model ensembles, when compared to single GCMs, can draw on the strengths of different GCMs and provide better estimates of the range of uncertainty behind the climate projections. Accordingly, 16 GCMs derived from the *5th Assessment Report of the Intergovernmental Panel on Climate Change* were evaluated in terms of how close they can predict the observed monthly values for the 2010 baseline period. Four of the best-fitting GCMs were selected based on the lowest nRMSE and highest r^2 scores for temperatures and rainfall. The selected GCMs were then used to project future climate and crop productivity. The simulations were limited to the mid-century as uncertainties increase when projecting beyond 2050.

In each of the GCM selected, the MarkSim weather generator produced ten-year replicates of daily weather files for five time slices, i.e., 2010 (control), 2030 (short-term), and 2050 (medium-term) for both representative concentration pathways (RCP) 2.6 (best case) and RCP 8.5 (worst case) scenarios.

The projected values were corrected for bias from the raw GCM outputs using the “delta method” (Graham, Andreasson, & Carlsson, 2007; Weiland, van Beek, Kwadijk, & Bierkens, 2010; Wilby et al., 2004; Tabor & Williams, 2010). The “delta method” uses the differences between baseline and projection periods for temperature and rainfall, as shown in Equations [1] and [2], respectively.

$$x_{cor} = x_o + \mu_p - \mu_b \quad [1]$$

$$x_{cor} = x_o + \mu_p / \mu_b \quad [2]$$

where:

x_{cor} = bias-corrected data in the baseline period;

$x_{0,i}$ (1, 2, ..., 25) = observed data in the baseline period;

b, p , and, o = simulated data in the baseline period, projection period, and observed data, respectively;

μ_p / μ_b = change factor for precipitation; and

$\mu_p - \mu_b$ = change factor for temperature.

The change factors were then plotted using box plots in order to quantify the uncertainty generated by the ensemble. The median change factors were applied to the historical baseline by adding the delta values to the observed temperature and by multiplying the ratio changes by the observed precipitation and ETo.

Simulating Potential Impacts of Climate Change

The bias-corrected weather files were read into the AquaCrop simulations. The yield by planting month was simulated for each month for both the baseline and projection periods. This required 960 runs ($40 \text{ years} \times 12 \text{ months} \times 2 \text{ time periods}$). In each time period, the box and whiskers were plotted to each planting month for biomass, growth cycle day, net irrigation requirement, transpiration, and water productivity (WPET).

The impact of CO₂ fertilization on cane crop was investigated for the 2050 projection period by running AquaCrop. The first scenario involves increased CO₂ from 388 ppm to 468 ppm, whereas the second scenario maintains CO₂ levels at 388 ppm (*No CO₂ scenario*). The *No CO₂* scenario simulates the impacts of increased CO₂ on yield and also the effect on yield if the CO₂ fertilization effect does not occur. Subsequently, the significance of the difference between the ensemble medians of projected periods and the baseline period was tested using students' t-test, with the threshold set at $p < 0.05$.

Results and Discussion

GCM Fitting and Bias Correction

We selected 4 GCMs out of the 16 GCMs available in MarkSim based on the model's ability to project climate scenarios for the 2010 baseline period. Accordingly, all GCMs had nRMSE scores for the monthly maximum and minimum temperatures ranging from 0.04 to 0.06 (excellent). Meanwhile, the nRMSE scores for predicting the monthly rainfall for the baseline period varied widely, ranging from 0.25 to 0.67 (poor). The r^2 score of the predicting median monthly rainfall values range from a high 0.86 to a low 0.19. The top four GCMs selected based on the highest to lowest r^2 scores are BCC-CSM1_M, CSIRO-Mk3-6-0, GISS E2-H, and GFDL-ESM2G (see Table 1).

Climate Projection

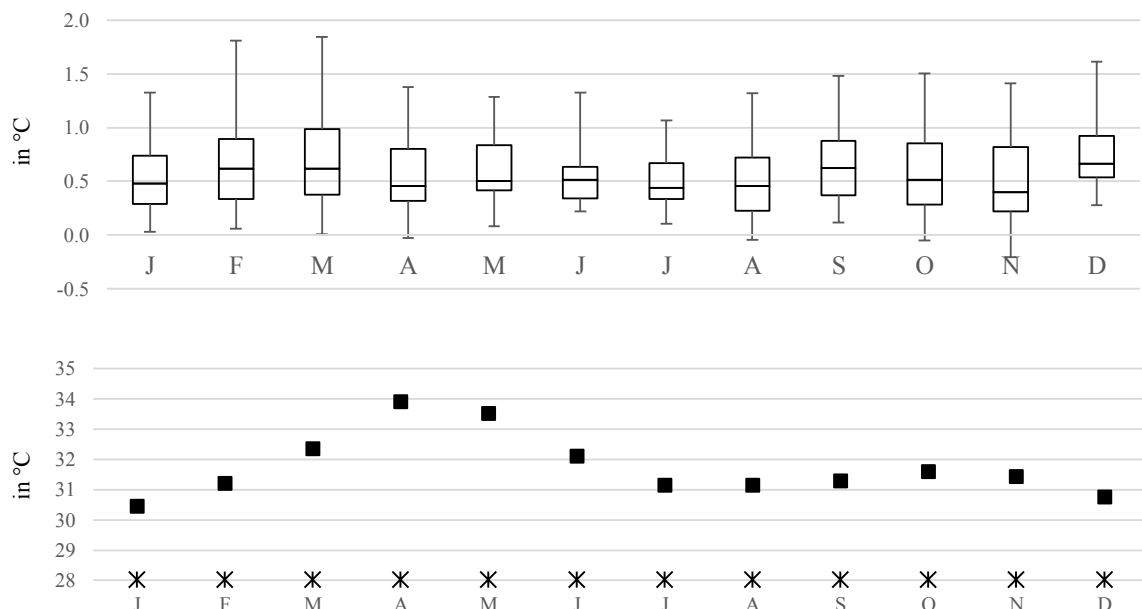
All four models agree on the projected temperature increases, with an average increase of 0.75 °C by 2050. Likewise, all of the values are significant at $p < 0.05$. The highest temperature increases are projected in February and May, whereas the lowest are in November, December, and January (not shown). The standard

deviation (σ) of the daily maximum and minimum temperatures are 1.6 °C and 1.1 °C, respectively, based on the daily temperature records of the PAGASA Iloilo station (1987–2010). The projected increase of 0.75 °C is close to the upper limit (0.8 °C) of the historical daily maximum temperatures.

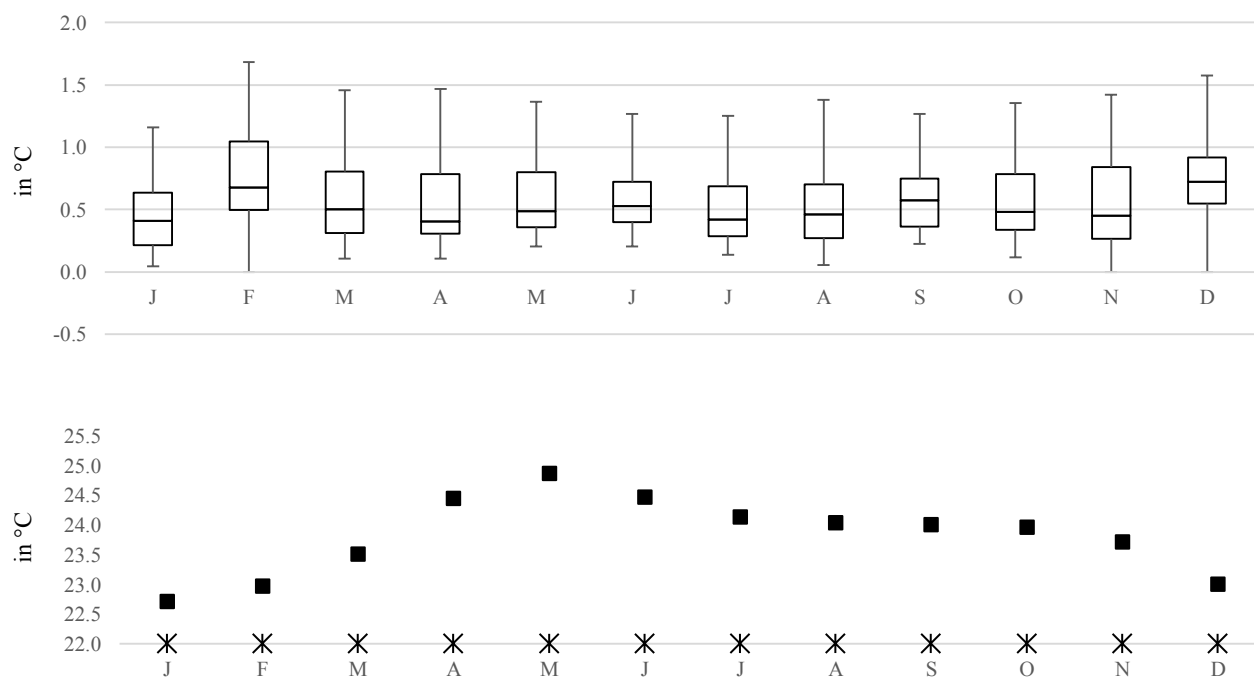
There is no apparent agreement on the change in rainfall in the GCM projections. The boxplots of the monthly precipitation change factors show wider variations from January to March ranging from 0.5 to 3.2. This result is consistent with the wide rainfall variability experienced during these months. The median monthly values for these months range from 1.2 to 1.4, which implies wetter summers. Little change is projected for the rest of the year. The estimated changes in March and May are significant at $p < 0.05$. Figures 2(a) to 2(c) show the multi-model box plots of projected changes in maximum and minimum temperatures and rainfall.

Table 1. GCMs selected for this study

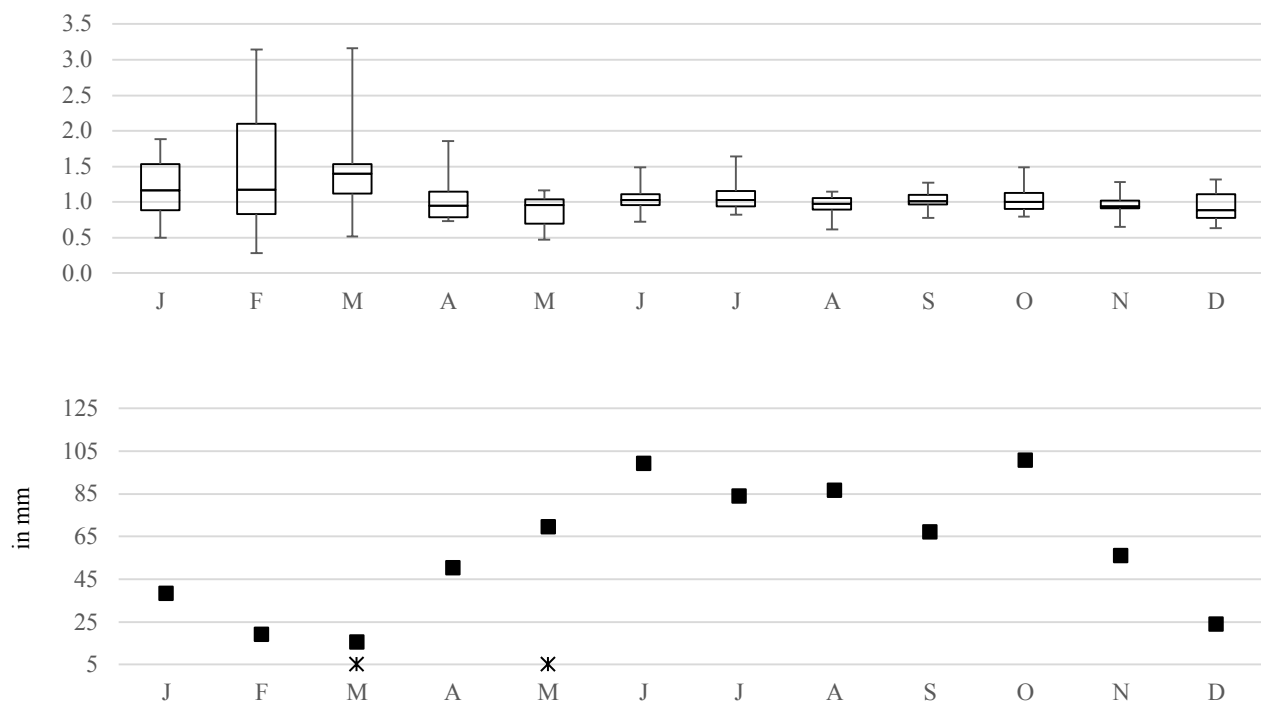
Model	Institution	Resolution, Lat° × Long°	Reference
BCC-CSM1_M	Beijing Climate Center China Meteorological Administration	2.8125 × 2.8125	Wu (2012)
CSIRO-Mk3-6-0	Commonwealth Scientific and Industrial Research Organization Queensland Climate Change Centre of Excellence	1.875 × 1.875	Collier et al. (2011)
GISS-E2-H	NASA Goddard Institute for Space Studies	2.0 × 2.5	Schmidt et al. (2006)
GFDL-ESM2G	Geophysical Fluid Dynamics Laboratory	2.0 × 2.5	Dunne et al. (2012)



(a) Upper: Box plots of monthly change factors for maximum temperature by 2050. Lower: Monthly average maximum temperatures, PAGASA-La Granja station, 1975–2003. Box plot represents 25th, 50th, and 75th percentile values. Whiskers represent maxima and minima.



(b) Upper: Box plots of monthly change factors for minimum temperature by 2050. Lower: Monthly average minimum temperatures, PAGASA-La Granja station, 1975–2003.



(c) Box plots of monthly change factors for rainfall by 2050. Lower: Monthly average rainfall, PAGASA-La Granja station, 1975–2003.

Figure 2. Multi-model box plots of projected changes in maximum and minimum temperatures and rainfall.

Notes. Figures with * refer to values that are significant at $p = 0.05$, one-tailed t-test.

Evaluating PAGASA Climate Forecasts by 2050

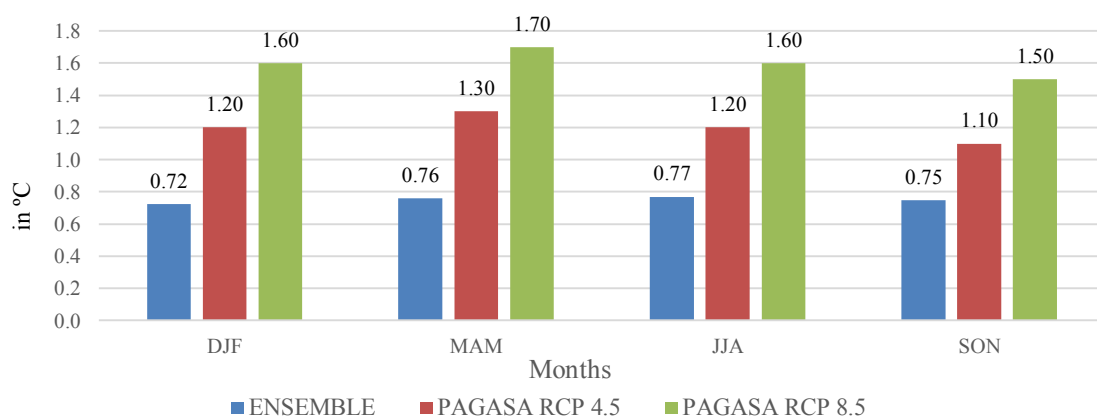
The PAGASA forecasts of 1.2–1.5 °C temperature increases in Negros Occidental by 2050 are twice higher than the model ensemble findings of 0.75 °C increase [Figure 3(a)]. Although the ensemble projections are lower, its values are closer to the national trajectory of 0.1 °C per decade or 0.4 °C by 2050 (PAGASA, 2018). The PAGASA annual rainfall forecasts by 2050 are 10% higher than the present baseline, albeit they still fall within one standard deviation of historical variability. The simulations show no significant trends in future annual rainfall (not shown).

There is also no agreement with regard to seasonal rainfall. The median ensemble forecasts for rainfall agree on the direction in only one of the four PAGASA quarterly scenarios [Figure 3(b)]. In the rainy months of June to November 2050, the PAGASA forecasts range

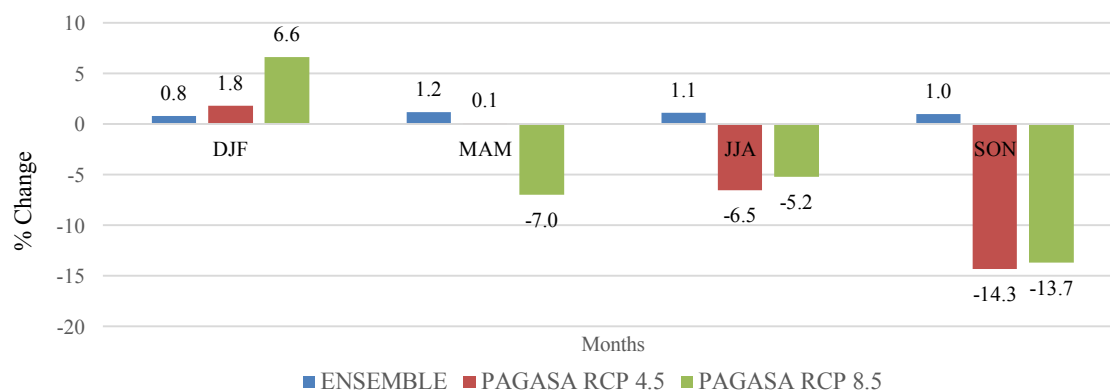
from –5.2% to –14.3%, which means that there would be lesser rains during these months. In the months of March to May, findings show small increases, whereas the PAGASA projections show decreases of –7.0% (worst case scenario) to 0.1% (no change). Lastly, the study shows a small increase (0.8%–1.2%) from the baseline in the months of December to February, as compared with the PAGASA data at 2%–6% increases.

There was good agreement between the simulated and observed yields after calibrating the crop parameters against the independent data (see Table 2).

The validation data consist of 12-year production data (2005–2016), which were downloaded from the PSA (2018) website for Negros Occidental province. The statistical indices (nRMSE = 0.07, excellent) support the good performance of the model.



(a) Temperature mean forecasts against the PAGASA forecasts, 2050, Negros Occidental



(b) Rainfall forecasts against the PAGASA forecasts, 2050, Negros Occidental

Figure 3. Projected increase in mean temperatures and rainfall by 2050.

Note. DJF = December, January, February. MAM = March, April, May. JJA = June, July, August. SON = September, October, November

Table 2. Parameters entered into AquaCrop

Parameter	Value
Attainable yield (fresh biomass, nonlimiting water and fertilizer)	80 t/ha
Actual yield, rainfed farm (assuming May planting)	60 t/ha
Plants per hectare	133,000
Ratio of rainfed to irrigated land areas	80:20
Soil texture	Clay loam
Field capacity (% volume)	16%
Saturation point (% volume)	36%
Permanent wilting point (% volume)	8%
Soil fertility loss	20%
Water productivity	30 g/sqm
Growth stage	
DAP to recovered transplant	10 days; 148 GDD
DAP to 95% maximum canopy cover	71 days; 1,257 GDD
DAP to maximum root depth	67 days; 1,188 GDD
DAP to start of early senescence	337 days; 6,039 GDD
DAP to harvest	371 days; 6,631 GDD
Corresponding FAO stages	
Initial stage	32 days
Canopy development	39 days
Mid-season stage	266 days
Late season stage	34 days

Note. DAP = days after planting. GDD = growing degree days (in °C)

Except in 2008 when the model overpredicted the yield values, the predicted values for the rest of the years fall within one standard deviation (11.9 t/ha) of the PSA data (Figure 4).

The production anomalies from the PSA data and the crop simulations were plotted on a scatter plot. The regression line, fitted to the points, showed fair to good correlation, with $r^2 = 0.68$ (see Figure 5). The AquaCrop model, as proxy for rainfall, explains 68% of the variation in Negros Occidental cane production. This is considered good, seeing that provincial statistics account for many other factors aside from rainfall, e.g., varying farmer practices, effects of pest infestations, and damages from flooding.

ENSO Impacts

El Niño and La Niña events represent opposite extremes in a complex, naturally occurring climate cycle known as the ENSO. This condition occurs when the surface air and water temperature in the equatorial Pacific deviate from the normal temperature. In the Philippines, El Niño is associated with high temperatures and severe dry spells. El Niño may be preceded or followed by La Niña, which is characterized by heavy rains, severe typhoons, and flooding.

Table 3 presents the monthly rainfall records of the PAGASA from 1975 to 2016, categorized by rainfall intensity class. *Below normal* (in yellow) and *way below normal rainfall* (in red) records most often fall from January to April, but may extend earlier to December and November. Severe El Niño events occurred in 1988, 1998, 2010, and 2015. Conversely, La Niña occurred in 1989, 1999, 2008, and 2011.

The interannual cane production of Negros Occidental from 1975 to 2015 was simulated using the AquaCrop model. Figure 6 shows the simulated percentage yield anomaly by planting year or the departures from the 45-tons-per-hectare average within the study period. The highest yield losses, ranging from 15% to 17%, were simulated for the El Niño years 1991–1992, 1997–1998, 2002–2003, and 2009–2010. The higher positive yield anomaly of 32%–34% coincided with those of the La Niña years, i.e., 1998, 1999, 2007, 2010, and 2011.

El Niño tends to have greater effect on rainfall during the summer months than during the rainy season. The regression analysis shows that the rainfall intensity index scores from December to March have positive relationship ($r^2 = 0.81$) with the simulated yield anomalies (Figure 7).

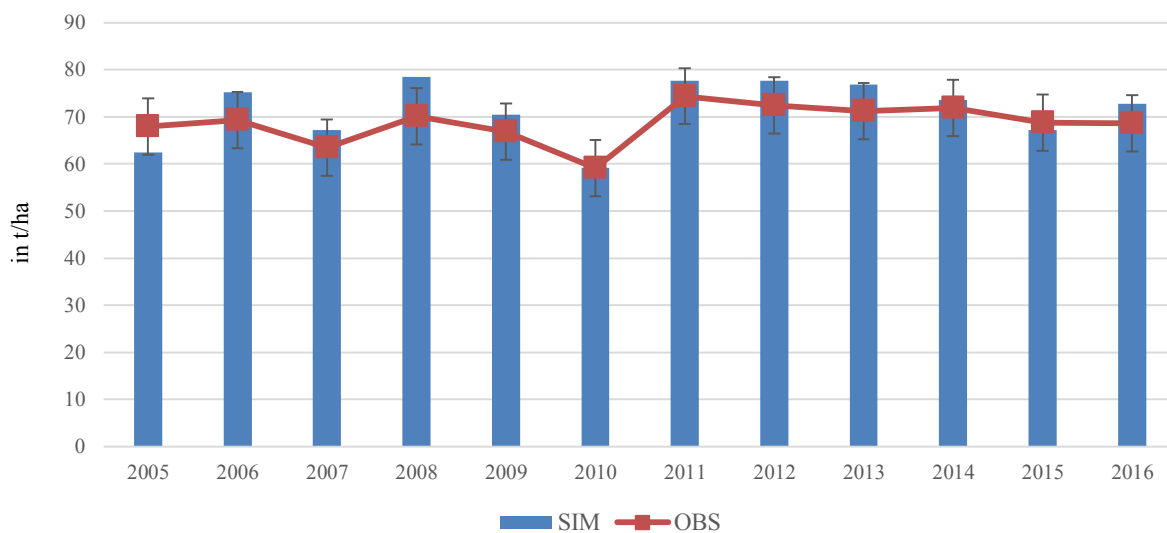


Figure 4. Simulated and observed yield data, 2005–2016

Note. Error bars are one standard deviation (11.9 t/ha) from the annual historical yields.

Source of basic data. PSA (2018)

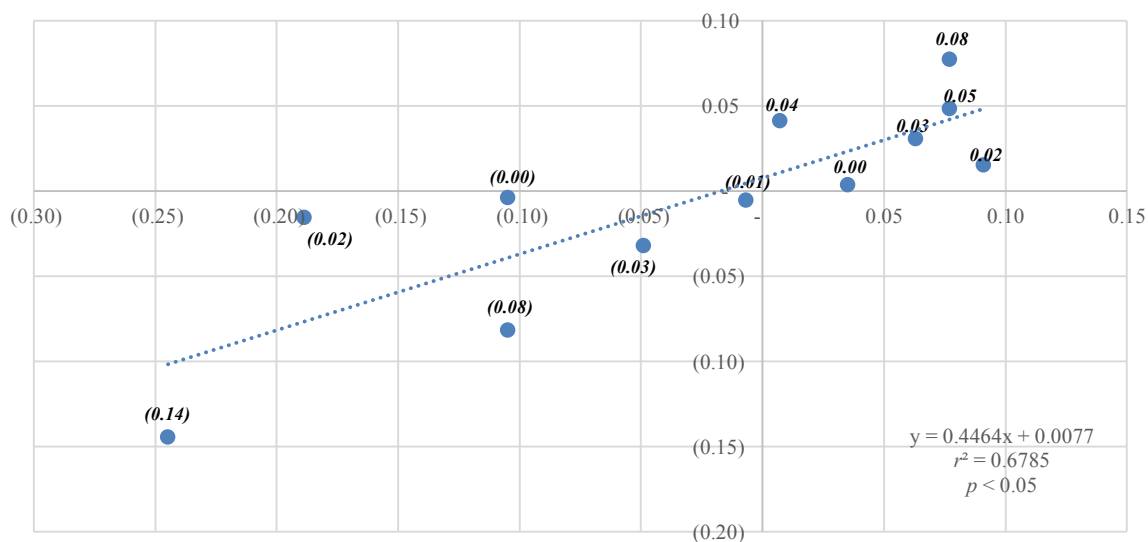


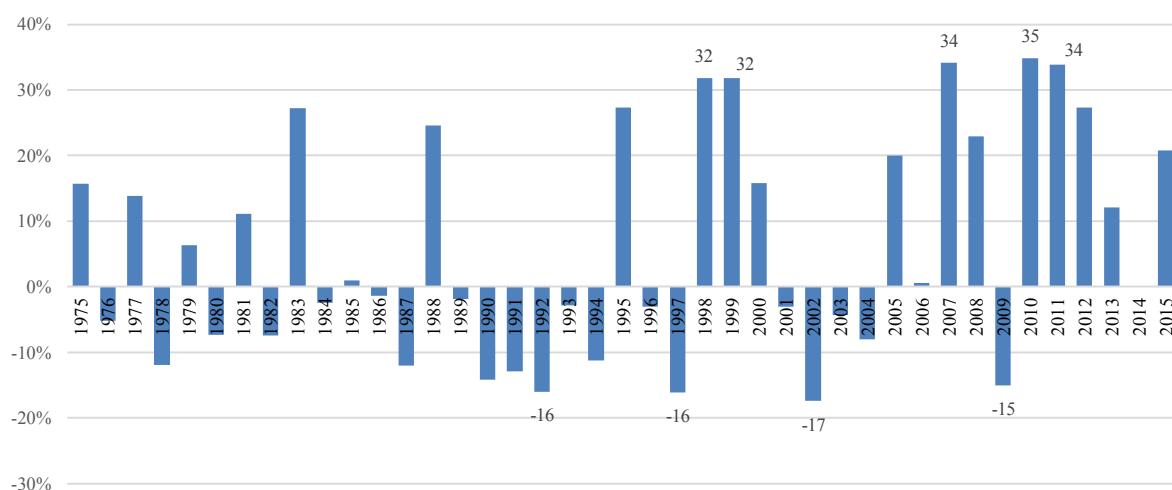
Figure 5. Observed and simulated % yield anomaly, 2005–2016

Note. $r^2 = 0.68$, $p < 0.05$

Source of basic data. PSA (2018)

Table 3. Monthly rainfall records of the PAGASA, 1975–2016, by rainfall intensity class

YEAR	JAN	FEB	MAR	APR	MAY	JUN	JUL	AUG	SEP	OCT	NOV	DEC
1975						101%	122%	105%	60%	94%	41%	149%
1976	88%	118%	123%	131%	262%	72%	64%	116%	134%	71%	99%	124%
1977	35%	108%	21%	9%	29%	94%	173%	106%	119%	64%	76%	1%
1978	323%	65%	6%	164%	49%	71%	36%	101%	80%	127%	68%	60%
1979	23%	49%	37%	109%	90%	109%	160%	108%	80%	135%	26%	51%
1980	119%	37%	329%	16%	20%	195%	74%	91%	100%	74%	128%	62%
1981	90%	16%	29%	130%	98%	74%	28%	99%	90%	133%	78%	53%
1982	44%	55%	238%	85%	108%	166%	107%	110%	57%	67%	42%	60%
1983	102%	2%	0%	0%	41%	45%	95%	52%	76%	66%	127%	114%
1984	330%	201%	105%	223%	118%	157%	55%	111%	117%	82%	101%	70%
1985	122%	47%	42%	184%	116%	56%	62%	57%	105%	117%	73%	68%
1986	243%	8%	18%	60%	67%	102%	90%	114%	92%	104%	106%	128%
1987		57%	4%	21%	116%		133%	78%	208%	47%	77%	44%
1988	30%	9%	27%	86%	65%	79%	49%	41%	87%	236%	316%	40%
1989	180%	154%	229%	55%	128%	143%	75%	76%	49%	46%	40%	66%
1990	150%	3%	16%	6%	85%	88%	74%	124%	65%	66%	295%	17%
1991	28%	81%	76%	91%	44%	91%	89%	136%	59%	126%	199%	45%
1992	14%	3%	10%	25%	59%	152%	95%	68%	88%	97%	82%	16%
1993	8%	111%	26%	38%	31%	55%	86%	128%	45%	120%	72%	271%
1994	86%	18%	20%	455%	160%	121%	122%	98%	68%	41%	14%	94%
1995	26%	63%	128%	9%	70%	60%	100%	91%	158%	140%	104%	109%
1996	263%	229%	65%	116%	82%	61%	98%	35%	156%	122%	163%	52%
1997	44%	170%	15%	82%	94%	60%	100%		62%	45%	67%	10%
1998	1%	0%	0%	0%	101%	107%	69%	49%	98%	103%	153%	133%
1999	168%	145%	383%	312%	96%	119%	110%	93%	85%	100%	111%	146%
2000	25%	595%	269%	132%	115%	117%	96%	138%	73%	151%	187%	323%
2001	92%	117%	176%	36%	118%	119%	82%	163%	20%	142%	219%	188%
2002	16%	46%	135%	36%	82%	74%	150%	146%	90%	80%	28%	27%
2003	33%	24%	42%	35%	167%	44%	141%	76%	106%	146%		
2004	22%	49%	80%	58%	87%	127%	81%	202%	81%	125%	117%	62%
2005	11%	15%	22%	55%	129%	96%	104%	82%	93%	75%	39%	108%
2006	104%	105%	184%	12%	158%	129%	109%	170%	73%	88%	82%	199%
2007	93%	15%	33%	48%	59%	86%	124%	90%	216%	98%	105%	67%
2008	175%	491%	340%	168%	166%	138%	114%	53%	131%	98%	47%	150%
2009			0%	282%	121%	95%	312%	70%	155%	107%	54%	
2010	39%	0%	8%	15%	53%	78%	103%	78%	141%	153%	153%	144%
2011	287%	188%	206%	213%	156%	103%	83%	104%	129%	92%	84%	204%
2012	46%	202%	324%	113%	132%	112%	136%	57%	81%	66%	65%	99%
2013	34%	146%	161%	116%	146%	128%	93%	99%	161%	59%	0%	139%
2014	260%	14%	64%	135%	113%	63%	125%	91%	91%	90%	116%	244%
2015	48%	18%	4%	107%	73%	114%	0%	157%	142%	57%	26%	23%
2016	99%	226%	102%	132%	97%	102%	83%	139%	77%	147%	123%	133%

**Figure 6.** Simulated % yield anomaly, by planting year, 1975–2015, Negros Occidental

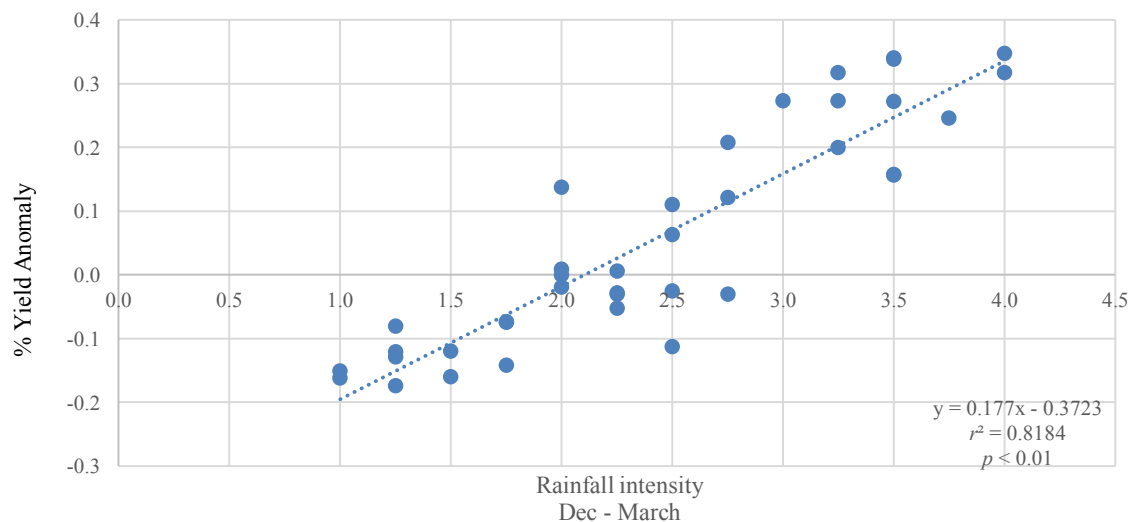


Figure 7. Correlation of dry months' rainfall to annual yield, 1975–2016, Negros Occidental

Note. $r^2 = 0.81$, $p < 0.01$

Below normal or *way below normal* rains during these months, such as those during the El Niño years, reduced average yield by 15%. On the other hand, above average rains, such as those during La Niña, increased yield by 20%. The high r^2 score shows that the December to March composite rainfall index is a good predictor of annual yield anomaly. This also indicates the positive effects of irrigation applied during these dry months.

Shifting Planting Dates

This section examines how shifting the planting month would affect yield. The model assumes that soil moisture is at field capacity, which means that initial irrigation is accessible even in the dry months. Figure 8 shows the box plots of yield by planting month from 1975 to 2016. The results show that the optimal planting months were from February to May when yield ranges from 60–70 t/ha.

Figure 8 shows that the planting season of February to May have higher yields due to the ability of the crop to draw on excess rainfall, and this is accordingly used to supply crop transpiration demand during the vegetative stage and throughout the course of the yield-forming months. At the onset of the dry period in the early part of the year, plants begin to mature and their water requirements begin to drop. Water stress at this time can benefit the crop as it induces the plant to increase sucrose content before harvest (Zhao & Li, 2015).

Most of the crop's water requirements are supplied by rainfall; thus, the net irrigation requirement was lower during these planting months (March to May). Beyond June, late planting reduces yield to 40 t/ha and below. This is due to water stress during the summer months (February to April) when the plant is in the middle of the growing season. The plant's net irrigation requirement consequently rises at this time.

Net Irrigation Requirements

Irrigation plays an important role during dry spell events. Figure 9 shows the estimated monthly average net irrigation requirement from 1975 to 2016, which ranges from 150 mm to 350 mm. With irrigation, crop transpiration increased by 97% or from 531 mm to 1,044 mm during the period 1975–2016. About 30% (288 mm) of the water transpired by the plants came from irrigation, whereas 70% were supplied by rainfall (not shown).

Figure 10 presents the simulated interannual net irrigation requirement from 1975 to 2015. The data show that the planting years with high net water requirements (up to 500 mm) are 1991, 1992, 1997, 2002, and 2009. Each of these years coincides with El Niño episodes that happened in the year succeeding them. During a major dry spell, irrigation can supply up to 50% (or 500 mm) of the plant water requirements. The least water requirements (less than 100 mm) were simulated during the La Niña years (e.g., 1998, 1999, 2007, 2010, and 2011) (not shown).

The IWUE measures the yield returns from irrigation. The higher the IWUE, the higher the returns from irrigation would be. The results show that IWUE ranges from a low 1.5 t/ha to a high 24 t/ha per 100 mm of water applied, depending on the planting month (Figure 11). IWUE rises starting March and then peaks in January.

IWUE increases during those planting months when the growth cycles mostly depend on summer irrigation for plant survival. For example, January planting will require more irrigation and is therefore less efficient than the March planting.

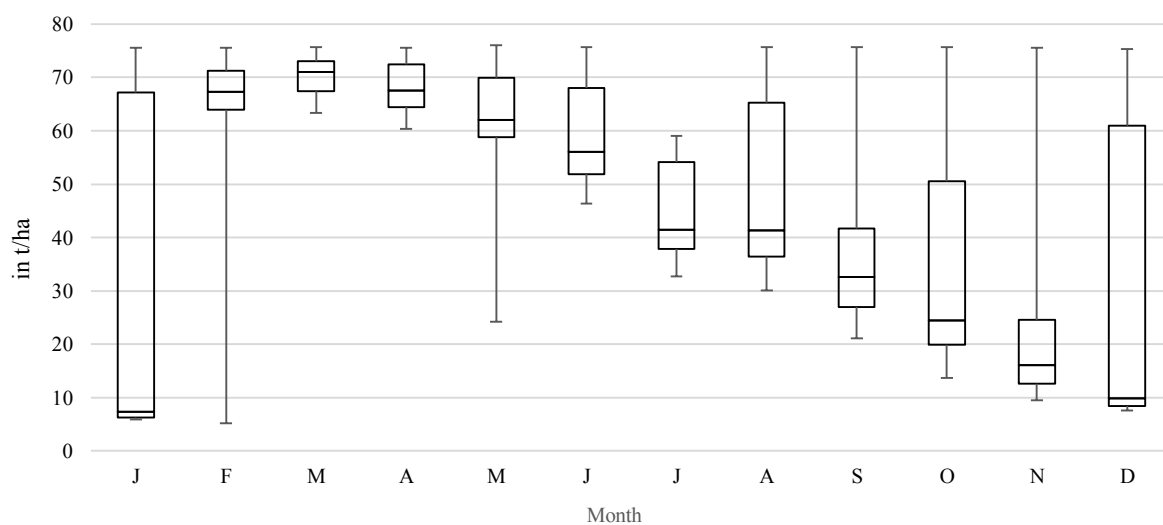


Figure 8. Yield box plot, by planting month, 1975–2016

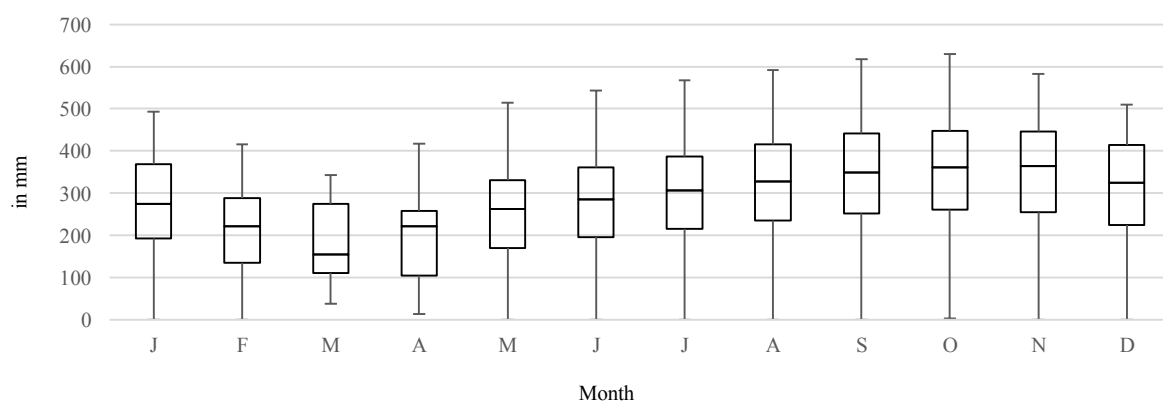


Figure 9. Estimated annual net irrigation requirements, by planting year, 1975–2016, May planting

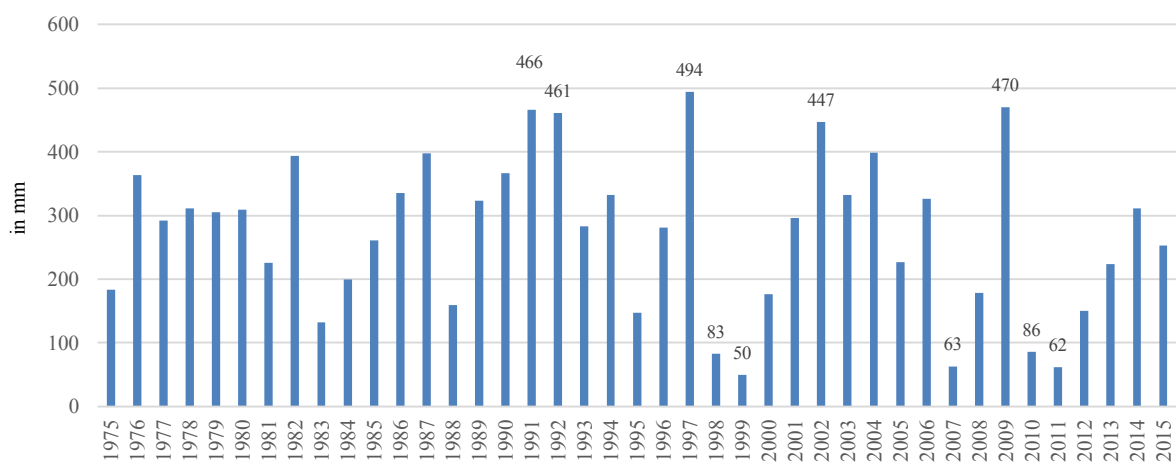


Figure 10. Simulated annual net irrigation requirement, by planting month, 1975–2016

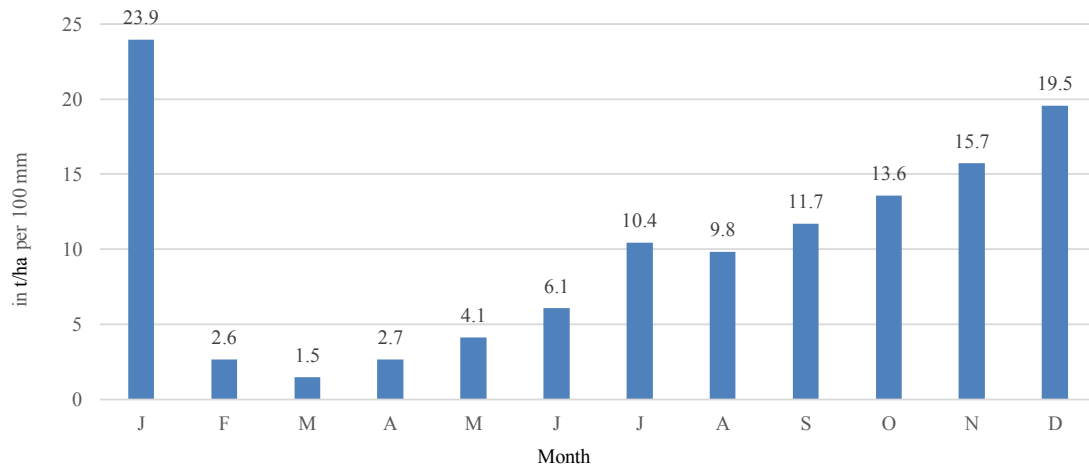


Figure 11. Simulated irrigation water use efficiency, by planting month, 1975–2016

Future Production

Table 3 summarizes the results of the crop yield simulations for the baseline and 2050 projection periods of both *with and without CO₂ effects*. Planting during the dry months implies access to supplemental irrigation.

In summary,

- Yield would increase during wetter summer months by 2050 for all planting months, with values ranging from 5% to 30%. Yield would increase in March, April, May, June, and July planting dates at $p < 0.05$ (not shown).
- Yields from May and March planting are expected to increase by 9% and 8%, respectively, by 2050.
- Temperature effects would reduce the length of the growing season by 10% (36 days). *With no CO₂ effects*, the reduction would be almost the same (11%).
- CO₂ fertilization would increase WPET by 7%. Without CO₂ effects, WPET would decrease by 3%.
- Transpiration would decrease by 3% by 2050 as WPET increases. The effect of *No CO₂ scenario* on transpiration by 2050 is insignificant (–1%).
- Net irrigation requirement under climate change would decrease by 8% (assuming May planting), albeit it would be negligible (–1%) under the *No CO₂ scenario*.
- Year-round irrigation would increase yields of rainfed farms by 17% or from 62.9 t/ha to 73.8 t/ha (assuming May planting).

Wetter summers explain the increased yields of rainfed farms under climate change. The elevated CO₂ effects on photosynthesis and transpiration show a 7% improvement in the overall WPET. Net irrigation requirements under climate change would decrease by 8%, assuming a May planting month, with 4% average reduction for all months.

Cane yields would increase under climate change due to the expected increase in the interception of radiation. This interception of radiation, in turn, results from the accelerated canopy development due to higher temperatures, wetter summers, and higher CO₂ fertilization effects on photosynthesis. As canopies develop faster, the soil loses less moisture from evaporation; thus, the plant absorbs more moisture (Allen, Pereira, Raes, & Smith, 1998).

The *No CO₂ scenario* show small (from –1% to –2%) decreases in biomass despite large decreases (–11% or 38 days) in the growth cycle. These reductions are due to the higher temperatures, albeit the reduction is not high enough to affect biomass during the yield-forming months. Water productivity shows an opposite effect, diminishing from 7% to 3%.

Shifting the planting dates from May to March would increase yield by 13%. CO₂ fertilization effects would add 8% or an overall 21% improvement. This assumes that farmers can access irrigation when the planting month shifts to March. Full irrigation for March planters is not recommended due to marginal benefits, as indicated by the low IWUE.

Table 4. Summary results of crop yield simulations under climate change with and without CO₂ fertilization effect

Output	Baseline (388 ppm)	Future 2050 (468 ppm)	% Change	No CO ₂ Effects 2050 (388 ppm)	% Change
Average annual Tmax, °C	31.74	32.50	2*		
Average annual Tmin, °C	23.80	24.60	3*		
Average annual rainfall, mm	2,642.30	2,563.00	-3		
Average annual ETo, mm	1,531.00	1,561.60	2		
Fresh stalk mass, t/ha (rainfed, May planting)	62.90	68.80	9*	62.90	0
Fresh stalk mass, t/ha (rainfed, March planting)	71.00	76.30	8*	69.40	-2
Fresh stalk mass, t/ha (irrigated, May planting)	73.80	79.50	8	72.90	-1
Growing cycle, days	360.00	324.00	-10	322.00	-11
Net irrigation requirement, mm (May planting)	263.00	243.00	-8	260.00	-1
Net irrigation requirement, mm (all months)	288.00	277.00	-4	291.00	1
Transpiration, mm (irrigated, May planting)	1,020.00	992.00	-3	1,029.00	1
WPET, kg/m ³	2.20	2.34	7	2.11	-3

Notes: * refers to values that are significant at $p = 0.05$. ETo = evapotranspiration. Tmin = minimum temperature. Tmax = maximum temperature. WPET = water productivity

Conclusions

Changes in climatic conditions have and will continue to directly or indirectly affect sugarcane production. The most significant challenges to sugarcane production are the more frequent and intense occurrence of extreme weather events, especially during ENSO events. The 40-year-old rainfall records presented in this study have captured past weather extremes, thereby improving the understanding of the impacts of ENSO and extreme events on cane yield.

The trends in cane productivity predicted in this study under elevated temperatures and CO₂ levels are consistent with the earlier studies reviewed in this article. This study found that cane yield would increase by 5%–30% by 2050, which is consistent with the 4%–29% yield increase reported in the past studies. The 8% yield increase for rainfed farms are higher than the 5%–6% yield increase reported by Sexton, Everingham, Berber, and Stokes (2014) in Australia.

The results are also close to the 10% increase reported by Marin et al. (2013) in Brazil, which has similar climatic conditions as the rainfed farms in the Philippines, where rainfall is also high (Stokes 2016). The predicted improvements, however, may be overstated because the effects of the changed climate on other factors, such as pests and diseases, were not considered in this study. The mid-century climate projections that were generated differ from the PAGASA forecasts. The projected temperature increases of 0.75 °C in this study are lower than that of the PAGASA. Its effect on yield would not be high enough to reduce cane yields substantially. The median change in rainfall shows wetter summers, and this value also differs from the PAGASA forecast. Projecting rainfall during the months of December to March is particularly critical as it affects 68% of yield variability.

Many of the models simulated in this study do not agree on the rainfall projections, which indicate that rainfall is difficult to model. This study recommends using multi-scenario probabilistic models and expanding ensemble simulations such that other GCMs and regional climate models can be included. This approach can overcome the limitations posed by the single GCMs that the PAGASA uses in projecting future climate scenarios. Deploying crop models for large spatial scales has been constrained by data collection, which can be costly and time consuming. This study has demonstrated, even without rigorous primary field data, that minimum data requirements can also be used to extrapolate modeling results from field to provincial scale, provided that the minimum conditions are met. This approach is recommended for crops grown in provincial landscapes with relatively homogeneous topography such as flood plains, valleys, and lowlands, which account for majority of production.

A protocol for regional assessments, adapted from the recommendations of van Wart (2013), can include the following:

1. Select and rank the most productive provinces for the crop under study. Start with homogeneous landscapes found in the major islands of Luzon, Mindanao, and the larger islands comprising the Visayas region.
2. Within the highest-ranked province, select the reference weather station. Check historical weather data for length and quality. Sum the crop area within a 100-kilometer-radius buffer zone from the reference weather station. Check if 40% of harvest area is covered. If 40% is not reached, then add the next ranking reference weather stations that do not overlap with those buffer areas already included. Repeat the procedure until 40% of the harvested area is covered.
3. Specify current average sowing date, maturity date, plant density, and dominant soil type for the homogeneous landscape. These should be representative of what farmers use in the target location and cropping system.
4. Apply the weighing procedure for yield estimates based on the area of rainfed vis-a-vis irrigated farms.
5. Choose the appropriate crop model that has been validated for the crop under study.

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