Modelling the impact of climate change on maize yield in Victoria Nile Sub-basin, Uganda

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Abstract

Agriculture is the backbone of Uganda's economy, with about 24.9% contribution to the gross domestic product (GDP) as per the Uganda National Household Survey 2016/17. Agricultural productivity (yield per hectare) is still low due to the high dependence on rain-fed subsistence farming. Climate change is expected to further reduce the yield per hectare. Therefore, this study aims to evaluate the potential impact of climate change on maize yield in the Victoria Nile Sub-basin using the AquaCrop model. It further assesses the possible adaptation measures to climate change. The Hadley Centre Global Environmental Model version 2–Earth System (HadGEM2-ES) data downloaded from the Coordinated Regional Downscaling Experiment (CORDEX) was used to simulate maize yield in the near future (2021–2040), mid future (2041–2070) and late future (2071–2099). Results show that maize yield is likely to reduce by as high as 1–10%, 2–42% and 1–39% in the near, mid and late futures, respectively, depending on the agro-ecological zone. This decline in maize yield can have a significant impact on regional food security as well as socio-economic well-being since maize is a staple crop. The study also shows that improving soil fertility has no significant impact on maize yield under climate change. However, a combined application of supplementary irrigation and shifting the planting dates is a promising strategy to maintain food security and socio-economic development. This study presents important findings and adaptation strategies that policymakers and other stakeholders such as farmers can implement to abate the effects of climate change on crop production.

Keywords AquaCrop · Food security · Climate change adaptation · Crop modelling · Maize yield

Introduction

The Victoria Nile Sub-basin (VNSB) is one of the ten (10) sub-basins in the Nile River Basin, where agriculture is the main economic activity. Even though there is abundant water resource, food insecurity is still a big challenge in

most sub-Saharan African communities due to the rapid population growth rate and endemic poverty within communities (Oestigaard 2012). The population is expected to increase by 20% in the year 2050 (Ministry of Water and Environment 2015), yet the increased population has a direct correlation with increased food demand (Thuo and Schütte 2011). According to Egeru et al. (2014), the cropping patterns have potentially changed mainly due to a shift in the onset of rainfall by a month in some parts of Uganda. Even though commercial farming for lucrative export is on the rise globally, most Ugandan farmers are still growing on a small scale and subsistence basis. Furthermore, more than 95% of the crop production in the country is under rain-fed farming (Sridharan et al. 2019; Babel and Turyatunga 2014). This high reliance on rainfall for the farming of staple crops threatens the national food security, as the rainfall pattern is most times unpredictable (Siderius et al. 2016). The rainfall pattern throughout the growing season is the major driving factor for the rain-fed crop productivity of an area (Huang et al. 2015). The pattern of rainfall of an area informs the

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agronomical practices such as setting the planting date, available water for crops and on-farm runoff management which are key in crop production (Lotfie et al. 2018).

Maize (*Zea mays L*) is a staple crop in most African communities; climate change's impact on its yield has been widely studied. Most literature predicts a decline in rain-fed maize yield in sub-Saharan Africa (SSA) under climate change (Adhikari et al. 2015; Villegas and Thornton 2015; Roudier et al. 2011). Among East African countries, Uganda is the most vulnerable to the decline in crop yield since most of its staple crops are rain-fed. Although maize can be produced at an average annual rainfall of as low as 200 mm, water stress at certain growth stages significantly affects its growth and overall yield. According to Song et al. (2019), severe water stress during the seedling stage has a higher effect on the growth and development of maize than during the jointing, heading and grain-filling stages. Therefore, rainfall distribution across the growing season of maize is an important factor. Maize growth is affected not only by rainfall (water) stress but also by temperature. Meerburg et al. (2009) reported that maize yield increases with an increase in temperature up to 29°C, followed by a severe reduction as the temperature increases further. However, according to Hatfield and Prueger (2015), the optimum growing temperature for maize is 25°C. Lobell et al. (2011) noted a 1% reduction in maize yield for every 1°C beyond 30°C per day even under optimal rain-fed conditions. Furthermore, results by Raza et al. (2019) showed that maize yield declined by as high as 10% for every 1°C above the optimum. On the other hand, Runge (1968) found that temperatures as high as 37.8°C can be beneficial to maize yield, provided that soil moisture is adequate. These findings suggest that at a high temperature, not only temperature stress but also moisture stress are the restrictive factors for maize yield. Under climate change, rainfall alone may not meet the crop water requirement due to its poor distribution and potential variations. Therefore, climate adaptation measures such as irrigation and shifting the planting dates may be necessary. Saddique et al. (2020) analysed the adaptation strategies for maize production in Guanzhong Plain, China, using five crop models. Results indicate a decline in maize yield of up to 33% in the 2070s using the current adaptation measures and an increase of up to 31% after the combined application of irrigation and planting date adaptation. Using the CERES-Maize, Msowoya and Madani (2016) predicted a 14% reduction in maize yield in the mid-century and a 33% reduction by the end of the century for the South African country, Malawi. By the years 2030 and 2050, it is predicted that maize yield will increase by between 11.7–17.7% and 9.3–17.0% in Kenya and Rwanda, while a decline of between 1.5–13.0% and 1.3–15.6% is predicted for Tanzania and Uganda, respectively (FAO 2016). Yield gains in Kenya and Rwanda are attributed to beneficial temperature increase as it

approaches the optimum temperature in tropical highlands. However, yield losses in Tanzania and Uganda will be as a result of growing season temperature increasing beyond the optimum temperatures. Waithaka et al. (2013) and MWE (2015) provided a detailed report of crop yield variations under different climatic scenarios for districts in Uganda. However, the authors did not evaluate main staple crops such as maize, which pose a higher food security risk than cash crops like coffee and tea.

Maize is one of the major staple crops contributing over 11% of the caloric intake of households in the VNSB and Uganda at large (MAAIF 2019). Since maize is predominantly rain-fed and produced on a subsistence basis, there is a lot of uncertainty about the performance of maize under different climatic scenarios. It is against these uncertainties that the authors seek to understand what the maize yield will be under different climate change scenarios. Should a decline in maize be predicted in the future, what should the stakeholders (policymakers and farmers) do to realise national food security? Therefore, this study aims to:

- 1) evaluate maize yield in the Victoria Nile basin under different climate change scenarios using a bio-physical crop model, AquaCrop,
- 2) compare future seasonal yield under the different climate change scenarios, and
- 3) evaluate possible climate change adaptation measures to improve maize yield.

Methodology

Study area

The study was carried out in the Victoria Nile sub-basin (VNSB), one of the ten sub-basins in the Nile River Basin that supplies water to 11 riparian countries, as shown in Figs. 1, 2, Tables 1, 2. About 96% of VNSB is situated in Uganda, while the remaining 4% is in Kenya. This region is termed as the food corridor for Uganda, with 32% of Uganda's arable land (NBI 2018). The average annual rainfall of the sub-basin is nearly 1300 mm, and the average annual potential evapotranspiration is 1544 mm. The agricultural practice in the sub-basin is mainly subsistence and rain-fed. The study area has two definite growing seasons that are March to May and August to December.

Climate data collection and analysis

Observed data

In this study, observed data recorded at nine (9) weather stations that are well distributed in the VNSB is used. This

Fig. 1 The location of VNSB among the ten Nile River sub-basins (NBI 2018)

data was provided by the Uganda National Meteorological Office, Kampala. The stations are spread across the study area, and the spatial resolution of inter-station spacing is approximately 25 km². 0 and 0 show the geophysical location and information of the stations employed in this

study. The daily time series dataset observed at the stations was recorded from 1975 to 2018 with different recording periods of each station. Thus, to harmonise the recording period of the station with the simulation data from the GCM, a dataset observed from 1986 to 2016 is employed

Fig. 2 Geographical location of the stations **Table 1** Information of the stations used

No.	Name	Latitude	Longitude	Altitude
1	Jinja	0.45	33.18	1173
2	Namulonge	0.53	32.61	1148
3	Soroti	1.71	33.61	1123
4	Lira	2.25	32.9	1085
5	Mbale	1.1	34.15	1340
6	Mpanga	0.2	32.3	1250
7	Masindi	1.68	31.71	1147
8	Kampala	0.31	32.61	1140
9	Entebbe-Airport	0.05	32.45	1155

Table 2 Period classification

Period	Classification
2021–2040	Near future
2041–2070	Mid future
2071–2099	Far Future

in this study. The datasets obtained included daily rainfall (mm), minimum and maximum daily temperature (°C), average relative humidity (%), wind speed (km/h)

and direction, solar radiation and sunshine hours. To validate the data obtained, average monthly data curves were developed and compared with those found on the World Bank's Climate Change Knowledge Portal (<https://climateknowledgeportal.worldbank.org>). It was found out that the average monthly data curves developed had similar and identical trends with those provided on the climate change knowledge portal with very insignificant differences in the data values.

Trend analysis

Air temperature has a good influence on evapotranspiration, thus crop water requirement. Under rain-fed farming, rainfall is the only source of water for crops. It is therefore important to understand the pattern and overall variations in these climate variables. Trend analysis of air temperature and rainfall data is used to assess the state of the climate of an area and estimate its past variation. During trend analysis, the non-parametric Mann–Kendall test was carried out to detect whether there is a significant pattern change in the precipitation and temperature data (Adnan and Atkinson 2011). This test was adopted because, unlike other tests, the data does not have to be normally distributed. In addition, the test has very low sensitivity to sudden peaks resulting from non-uniform time series (Panda 2019). It includes any non-detected data by assigning them a common value that is smaller than the smallest measured value in the dataset (Mubiru et al. 2018). Data values are evaluated as an ordered time series, and each data value is compared to all subsequent data values. Initially, the Mann–Kendall statistic, S , is presumed to be zero (0), meaning that there is no trend. S is increased by one (1) if the data value formerly sampled is less than a data value from a later period. Furthermore, S is reduced by one (1) if the data value from the former period is bigger than a data value from a later period. According to this test, the null hypothesis (H_0) assumes that there is no trend ($S = 0$), and this is tested against the alternative hypothesis (H_1), which assumes that there is a trend ($S \neq 0$). Given that signifies n data points where at a time j , the data point is the Mann–Kendall statistic (S) can be expressed as (Egeru et al. 2019)

$$S = \sum_{i=1}^{n-1} \sum_{j=k+1}^n \text{sgn}(x_j - x_i) \quad (1)$$

where n is the time series length; x_j and x_i are the data values for the times (years) j and i . A negative value of S designates a downward trend, while a positive one indicates an upward trend. The existence of a statistically significant trend is analysed with the p -value. The null hypothesis (H_0) would be accepted in a two-sided test when the p -value is critical at a 0.05 significance level. In this study, a significance level of 0.05 is applied.

Trend magnitude is analysed with the non-parametric Sen's slope approach (Tan et al. 2015). The test was performed using XLSTAT 2017 software. Sen's slope is positive if the trend is increasing and is negative when the trend in the time series is decreasing.

Climate projection data

The global circulation models (GCMs) are used to determine historical and future climate change scenarios. There

are differences in predictions by GCMs since they are run by different research centres using different methods. Therefore, GCMs are appropriately and properly selected using the following criteria: availability, resolution, independent weight, historical forecast skill, reproducing seasonal and annual variability, consensus with other projections, reproducing extremes and vintage (Ghazal et al. 2019).

The Hadley Centre Global Environmental Model version 2–Earth System (HadGEM2-ES) with a spatial resolution of about $50 \text{ km} \times 50 \text{ km}$ was selected for this study because it has been widely used (Hardiman et al. 2017; Collins et al. 2008). This simulation data was obtained from the Coordinated Regional Downscaling Experiment (CORDEX) project and downloaded from <https://esgf-index1.ceda.ac.uk/cordex-ceda/>. For purposes of this study, the reference period of the model is from 1971 to 2005, and the future scenario is from 2021 to 2099. Two representative concentration pathways of the GCM were obtained that is low-medium (RCP4.5) and high (RCP8.5). The data was obtained in a Network Common Data Form (NetCDF) format and was further processed in R software into an Excel file that can easily be analysed. The simulated data was a daily time series dataset for different climate variables, including precipitation ($\text{Kg/m}^2/\text{s}$), maximum and minimum temperature (K).

The GCM output is characterised by a coarse spatial resolution. For local climate change's impact assessment studies, this resolution is a big challenge when applied directly since its output results in large uncertainty, significant errors and biases (Eden et al. 2012). Therefore, during change impact assessment, climate data should be downscaled to obtain a finer local-scale resolution. Dynamic downscaling, statistical and weather generators are some of the most common techniques employed to downscale GCMs into local-scale data. To test scenarios for many decades, statistical techniques of downscaling were used for they require less computational effort because they only require the existence of the predictor and predictands relationship (Eden et al. 2012). Consequently, in this study, the quantile mapping (QM) method implemented in Matlab software version R2015a was used as in Equation (1–3) for rainfall data. The results from Matlab software were compared with those from the available qmap package in R software. QM method has been widely employed because it corrects biases considering high-order moments (Heo et al. 2019). In addition, the method is designed to preserve the long-term changes in the quantiles predicted by climate change models.

Using a transfer function, the QM constructs cumulative distribution functions (CDFs) of the GCM and observed data and, in turn, corrects the GCM data. The CDF of the corrected data is made to match that of the observed data set. Mathematically, QM is constructed using (Ayugi et al. 2020)

$$y = F_{obs}^{-1}(F_{GCM}(x)) \quad (2)$$

where y is the corrected value of precipitation, x is the value of the precipitation to be corrected, F_{obs}^{-1} is the inverse CDF of the observed data, and $F_{GCM}(x)$ is the CDF of the used GCM.

The QM method assumes that the distribution of simulated or estimated data preserves the distribution of any observed data. In QM, simulated data corresponding to a given probability is replaced by an observed quantile corresponding to the same probability. The probability distribution models of observed and simulated data are essential for QM. Hence, selecting an appropriate probability distribution model is critical for successfully implementing the QM method. Gamma distribution (GAM) which is widely used for the probability distribution of precipitation (Yue et al. 2010) was selected for this study. GAM was selected because of its generality and simplicity.

For the distribution mapping for temperature, the procedure described by Akumaga et al. (2018) was done where CDFs were constructed for both the observed and the GCM-simulated climate data for all days within a certain month. Then, the value of the GCM-simulated temperature of day d within month m was searched on the empirical CDF of the GCM simulations together with its corresponding cumulative probability. Thereafter, the value of the temperature of the same cumulative probability was located on the empirical CDF of observations. Finally, this value was used as the corrected value for the GCM. This procedure was also performed in MATLAB software.

Downscaled local climate scenarios simulated by the GCM were made for three time periods as classified in 0.

Crop data

The ten-year (2005–2014) experimental data for maize was obtained from the National Agricultural Research Organization (NARO). This crop data included the location, sowing period, yield, crop growth stages, irrigation water applied, harvest period, organic and inorganic nitrogen fertilisation quantity, tillage and other management practices. This data was required in the development of the AquaCrop model.

Modelling the impact of climate change on maize productivity

To account for spatial variability in conditions affecting maize yield, the case study area was first divided into agro-ecological zones (Fig. 3) based on the climatic characteristics, landform, soil and land cover. The purpose of zoning was to separate areas with similar but not identical sets of potentials and constraints for crop development. The particular parameters used in the definition focused attention

on the climatic and edaphic requirements for maize crops and on the management system under which maize is grown.

Dominant soil types within each agro-ecologic zone were selected from the developed study area soil map as in Fig. 3. The soil map was developed in Q-GIS software by overlaying and clipping the study area shapefile into the FAO digital world soil map version 3.6. The soils are generally Petric Plinthosols and Acric Ferralsols. The dominant soil texture was interpreted as clay loam, silty clay and clay using the soil unit information table provided with the map (FAO 2016). The soil map was later validated using secondary data obtained from experiments conducted by the districts' agricultural office. Soil characteristics of the obtained secondary data included soil texture, pH, organic matter percentage, soil profile and electrical conductivity. This facilitated the development of soil files used in AquaCrop for the simulation of maize yield in each agro-ecological zone.

AquaCrop is a crop growth simulation model developed by FAO that was used to simulate the potential maize yield under different climate change scenarios. AquaCrop describes the interactions between the plant, water and soil. This was developed by FAO to assess the effect of environment and management on crop production to address food security. In the model design, simplicity, accuracy and robustness were highly considered and optimally balanced. A comprehensive description of the AquaCrop model is reported in Steduto et al. (2009). AquaCrop calculates crop yields using the harvest index, which is defined as the yield fraction in biomass.

$$Y = f_{HI} \times HI_0 \times B \quad (3)$$

where Y is the yield (dry mass) (gm^{-2}), f_{HI} is the quantity and timing of stress, HI_0 is the reference harvest index (%), and B is the biomass above the ground (gm^{-2}). An important equation termed as 'AquaCrop growth engine' is used to estimate biomass.

$$B = K_{sb} \times WP^* \times \sum \frac{Tr}{ET_0} \quad (4)$$

where K_{sb} is the coefficient of air temperature stress (unit less), WP^* is the water productivity (g/m^2), Tr is the transpiration value of the crop (mm/day), and ET_0 is the reference evapotranspiration (mm/day).

The main inputs for AquaCrop are the daily minimum and maximum temperature, rainfall, crop evapotranspiration and CO_2 concentration. The crop evapotranspiration data was calculated using the CROPWAT model, while the CO_2 concentration was selected from the AquaCrop model database. The model was selected for this study due to its robustness and relative ease of application and less data requirement (Foster et al. 2017). In addition, it is recognised with the capability to simulate the growth of many crops

Fig. 3 Agro-ecological zones within the VNSB

from a uniform structure and a common set of parameters. AquaCrop model was calibrated and validated using field experimental data and recorded yield for a period from 2005 to 2014 (Fig. 4).

Model calibration and validation

AquaCrop model calibration involved modification of non-conservative parameters in the model interface such as crops, soil and management parameters. The parameters that were adjusted during calibration included planting density, reference harvest index, length of the growth cycle, maximum rooting depth and soil parameters. The model was validated using Mbale districts' ten (10) years (2005–2014) historical maize yield records (Ikuchi et al. 2016). Data for the 2005 growing seasons was used for calibration, while data for 2010–2014 was used for validation.

Statistical parameters such as mean absolute error (MAE), predictor error (Pe), root mean square error (RMSE), coefficient of determination (R^2) and model efficiency (E) were used. The model performance is good when values of E and R^2 are closer to one (1) and when Pe, RMSE and MAE are nearer to zero (0). The model efficiency used in this study was Nash–Sutcliffe efficiency coefficient (E) calculated using Eq. (5):

$$E = 1 - \frac{\sum_{t=1}^T (Q_0^t - Q_m^t)^2}{\sum_{t=1}^T (Q_0^t - \bar{Q}_0)^2} \quad (5)$$

where Q_0 is the observed data, Q_m is the simulated data, Q_t is the value at the moment t , and $\bar{Q}_0$ is the average of the observed data. The value of E ranges from $-\infty$ to 1. When E is close to 1, it means that the simulation result is reliable;

irrigation systems for future maize production. It further details the future irrigation management practices. Therefore, supplementary irrigation was simulated with additional amounts of 10 mm, 20 mm and 30 mm using sprinkler irrigation as per the NIMP. Each irrigation depth was applied five times at 10 days interval. Irrigation was simulated to start 15 days before the sensitive crop stage like flowering.

To obtain the optimum planting date, planting was moved (backward and forward) 5 times at a weekly interval for both seasons.

To assess the impact of soil fertility on the maize yield under climate change, the soil fertility stress was reduced to 5% at intervals of 5. Likewise, the percentage of surface mulch and soil bunds was varied. Fertiliser application levels could not be directly considered for the simulation because AquaCrop does not explicitly consider nutrient cycles or balances and does not well simulate yield under water stress (Akumaga et al. 2017).

Results and discussion

Climate variability

Variability analysis of meteorological parameters is of great importance for researchers and policymakers in decision

making, as rainfall and temperature play a dominant role in deciding the use of water availability in the areas. In the first instance, monthly rainfall variations have been shown in Fig. 5. The variation between months of observed rainfall is significant, with a significant difference between the wettest (April) and driest month (July). This reflects a climate with well-defined seasons. An increase in rainfall is noted in the month of September, whereas a decline occurs from November to February. Evidently, water scarcity rises during the dry months since water demand rises during this period. More so, the temperature data indicates high temperatures during the dry months which may translate into high evapotranspiration rates (ET).

When comparing with the observed data, both the historical and the future GCM simulations generally underestimated the precipitation. The model data exhibit underestimation between January to September and overestimation during October and November. Similar observations were made by Ayugi et al. (2020) and Olaka et al. (2019). On developing the CDF for the daily data sets for observed and simulated data as in Fig. 6, the GCM was still underestimating the rainfall. This prompted the need to bias correct the data before applying it in the climate change's impact assessment study. QM was employed in this study to correct rainfall data. Figure 7 shows QM results comparing the CDFs of the simulated data before and after correction. In

Fig. 5 Monthly average rainfall variation

Fig. 6 CDF of the GCM simulation data before correction

Fig. 7 CDF of the GCM simulation after correction

addition, results show that QM does bias correct not only the simulation data but also the absolute or relative changes in quantiles are conserved at the same time Fig. 8.

Trend analysis results

The historical period (1986–2016) indicates an average annual rainfall of 1488 mm. The year 2013 was observed to have received the maximum total annual rainfall of 1861

mm, whereas the minimum rainfall of 1039 mm occurred in the year 2004. Statistical parameters such as the median, mean, variance, standard deviation (SD), coefficient of variation (CV), kurtosis and skewness were tested for both annual and monthly rainfall and presented in Table 3. Results indicate very large CV values for the months of June, July and February and small CV values for April, May and October. These small CV values indicate that there is uniform rainfall variation in these months (Nsugba et al. 2014). In addition to a very large CV value, June also shows the highest skewness of 2.4 Table 4.

During the Mann–Kendall test, Sen's slope estimator is used to determine the trend of the rainfall data (31 years) for each month starting from January to December, as in 0. For the seven months of January, June, August, September, October, November and December, there is an upward trend (positive Sen's slope), while a downward trend is shown for five months of February, March, April, May and July (negative Sen's slope). The rejection of the null hypothesis in September, October and December indicates that there is a significant trend in these months. No statistically significant trends are found for the rest of the months, given their acceptance of the null hypothesis. This is true even though both negative and positive trends are shown for different months for the entire period (1986–2016). Mann–Kendall test and Sen's slope also show that there is a positive trend in annual rainfall. The null hypothesis was rejected for the annual rainfall trend (value = 0.032) at a 5% significance level. The rainfall is changing at a rate of about 11.26 mm/year. Comparing this rate with the average annual change of 201.4 mm, it is not significant. This agrees with the results of Kikoyo and Nobert (2016) that showed no significant trend in the rainfall data for the past 5 decades. From the climate projection data, annual rainfall reductions of 16.2% and 11.8% are projected for RCP4.5 and RCP8.5 climate change scenarios, respectively. However, for both scenarios, an increase in rainfall is projected for the August to December growing season, whereas a reduction in rainfall is expected for the March to May season.

On plotting the linear trend line for the rainfall data (31 years), the following results in 0 were obtained. There is a general increasing trend of the seasonal rainfall in the studied region for the base period (1986–2016), where the linear regression equation is showing a positive slope value ($a = 10.59$) and the R^2 value comes about 0.1576. R^2 which is a coefficient of determination indicates a 15.8% variability in the annual rainfall.

The observed temperature data were analysed for the period of 1986–2016 and represented as in Fig. 9. The data show that the temperatures are low during March, April, May and October and are high during months from June, July, August and January. Statistical parameters were

Fig. 8 Trend line corresponding to rainfall data (1986–2016) **Table 3** Statistical summary of annual and monthly rainfall

	Minimum	Maximum	Median	Mean	Variance	SD	CV	Skewness
Jan	1.70	206.30	76.00	93.27	3109	55.76	0.60	0.46
Feb	9.40	204.80	60.70	68.98	1894	43.52	0.63	1.08
Mar	44.70	314.40	148.20	157.77	4060	63.72	0.40	0.50
Apr	80.50	344.20	215.00	216.81	5370	73.28	0.34	0.02
May	72.40	276.70	165.90	168.15	1920	43.82	0.26	0.12
Jun	19.70	376.20	72.60	97.75	6289	79.30	0.81	2.40
Jul	0.00	156.50	48.90	49.22	1260	35.49	0.72	0.71
Aug	0.00	123.70	71.30	71.58	830	28.81	0.40	−0.18
Sep	33.80	320.50	104.60	114.80	3602	60.02	0.52	1.38
Oct	19.70	255.10	143.00	153.53	3051	55.24	0.36	0.14
Nov	37.40	335.50	153.40	157.32	5059	71.13	0.45	0.77
Dec	16.20	323.30	117.70	138.92	6860	82.83	0.60	0.66
Annual	86.59	159.02	123.42	124.01	396	19.89	0.16	−0.19

evaluated for minimum and maximum temperature and presented in Tables 5 and 6, respectively.

Mann–Kendall test was also carried out for temperature; results of which are shown in Tables 7 and 8. The results for maximum annual temperature showed a significant increasing trend (Sen's slope = 0.062), while the minimum annual temperature trend showed no significant trend (Sen's slope = 0.001). From the future climate projection data, annual temperature increments by 1.38°C under RCP4.5 and 2.32°C under RCP8.5 are projected for the future up to 2099 compared with the historical period (1986–2016). This correlates with the report of the IPCC published in 2007 that indicated that, generally, the East African region is getting warmer with a varying degree of warming.

In general, results of the Mann–Kendall test for monthly temperature and total monthly rainfall indicate both significant and non-significant trends. It may be non-significant in some cases and significant in other cases. This is in line with Chombo et al. (2020), who, in a study of the regions around lake Kyoga, found both positive and negative trends, some significant and others non-significant in different subzones. About 90% of these subzones studied are situated within the VNSB that is being considered in this study.

Table 4 Mann–Kendall test results of annual and monthly rainfall at $p = 0.05$ significance level

	Mann–Kendall	p -value	Sen's slope value	Interpretation
Jan	81	0.18	1.27	H_0 accepted
Feb	−75	0.21	−1.02	H_0 accepted
Mar	−1	1.00	−0.03	H_0 accepted
Apr	−27	0.66	−0.71	H_0 accepted
May	−77	0.20	−1.46	H_0 accepted
Jun	29	0.63	0.59	H_0 accepted
Jul	−43	0.47	−0.55	H_0 accepted
Aug	93	0.12	0.77	H_0 accepted
Sep	131	0.03	0.03	H_0 rejected
Oct	125	0.03	1.75	H_0 rejected
Nov	47	0.44	0.98	H_0 accepted
Dec	59	0.33	1.89	H_0 accepted
Annual	127	0.032	11.26	H_0 rejected

The impact of climate change on maize yield

A bio-physical crop simulation model, AquaCrop, was used to simulate maize yield under different RCP4.5 and RCP8.5 climatic scenarios.

Model calibration and validation

The model was calibrated using experimental data obtained from NARO and validated using Mbale district's 10 years (2005–2014) yield data. Table 9 shows a comparison of

simulated yields and the actual yields. In the beginning, yields as high as 5.34 t/ha were realised. After adjusting the parameters, yield results of 1.43 t/ha and 2.62 t/ha were obtained for years 2008 and 2012 which closely correlated with the actual yields of 1.46 t/ha and 2.57 t/ha, respectively.

During validation, Nash–Sutcliffe efficiency coefficient (E) and the R^2 were calculated as 0.91 and 0.92, respectively, from a simple regression plot of simulated yield against recorded yield (Fig. 10). Consequently, the errors (RMSE ≈ 0.09 , Pe = 1.089% and MAE ≈ 0) were calculated. Thus, it was concluded that the model's performance is reliable and suitable for the simulation of yield.

Model sensitivity analysis

The inputs used in this analysis for the AquaCrop model were days to maturity, soil fertility, soil type, soil depth and harvest index. The percentage change in inputs was arbitrarily selected and depended on the limits of the parameters, their model sensitivity and convergence rate. The interval of variation of the inputs was chosen from -25% to $+25\%$ of its median value. According to the relative influence on the simulated yield, the sensitivity of the parameters was classified into three (3) categories (high, moderate and low). Table 10 shows the results of the sensitivity analysis. The sensitivity coefficient was evaluated according to Eq. (6). Results indicate that soil fertility level is the most sensitive parameter, whereas the days to maturity is the least. It is worth noting that the simulated maize yield is highly impacted if the days to maturity are underestimated by a

Fig. 9 Trendline for maximum and minimum temperature

Table 5 Statistical summary of minimum temperature (1986–2016)

	Minimum	Maximum	Median	Mean	SD	CV	Skewness
Jan	14.250	19.350	16.930	16.949	1.192	0.070	−0.155
Feb	14.580	18.560	16.280	16.444	0.953	0.058	0.228
Mar	14.970	18.820	17.320	17.055	0.849	0.050	−0.363
Apr	15.430	19.150	17.060	17.330	0.972	0.056	0.205
May	12.560	19.030	16.480	16.446	1.864	0.113	−0.390
Jun	12.300	20.330	15.890	16.018	1.798	0.112	0.025
Jul	13.660	20.260	16.940	17.144	1.547	0.090	−0.318
Aug	16.150	19.550	17.910	17.890	0.846	0.047	−0.191
Sep	16.540	18.830	17.920	17.847	0.683	0.038	−0.254
Oct	16.020	18.630	17.660	17.535	0.574	0.033	−0.432
Nov	14.720	19.030	17.130	17.115	0.806	0.047	−0.433
Dec	15.110	18.830	16.760	16.961	0.941	0.055	−0.035

Table 6 Statistical summary of maximum temperature (1986–2016)

Months	Minimum	Maximum	Median	Mean	SD	CV	Skewness
Jan	25.630	33.650	29.930	29.764	1.947	0.065	−0.007
Feb	24.580	31.760	28.690	28.200	1.755	0.062	−0.210
Mar	26.870	34.820	30.850	30.879	2.252	0.073	0.066
Apr	26.200	36.530	32.620	32.218	2.661	0.083	−0.346
May	26.100	30.130	28.230	28.430	0.961	0.034	−0.344
Jun	23.480	32.780	28.910	29.021	1.889	0.065	−0.433
Jul	23.100	33.960	29.110	29.185	2.430	0.083	−0.645
Aug	26.340	38.010	33.500	32.906	2.978	0.091	−0.346
Sep	27.060	36.650	32.580	32.184	2.723	0.085	−0.234
Oct	26.850	35.600	32.390	31.873	1.933	0.061	−0.397
Nov	25.620	33.900	32.070	31.262	2.158	0.069	−1.063
Dec	24.200	32.070	29.260	29.123	2.152	0.074	−0.434

Table 7 Mann–Kendall test results for minimum temperature at $p = 0.05$ significance level

	Mann Kendall	p -value	Sen's slope value	Interpretation
Jan	−129	0.029	−0.051	H_0 rejected
Feb	193	0.001	0.065	H_0 rejected
Mar	−66	0.268	−0.014	H_0 accepted
Apr	41	0.496	0.017	H_0 accepted
May	−176	0.003	−0.126	H_0 rejected
Jun	78	0.190	0.058	H_0 accepted
Jul	245	0.000	0.115	H_0 rejected
Aug	78	0.190	0.027	H_0 accepted
Sep	−125	0.035	−0.031	H_0 rejected
Oct	3	0.973	0.000	H_0 accepted
Nov	−109	0.066	−0.024	H_0 rejected
Dec	−59	0.324	−0.023	H_0 accepted
Annual	9	0.893	0.001	H_0 accepted

Table 8 Mann–Kendall test results for maximum temperature at $p = 0.05$ significance level

	Mann–Kendall	p -value	Sen's slope value	Interpretation
Jan	39	0.518	0.024	H_0 accepted
Feb	28	0.646	0.012	H_0 accepted
Mar	85	0.155	0.083	H_0 accepted
Apr	200	0.001	0.200	H_0 rejected
May	9	0.892	0.004	H_0 accepted
Jun	−37	0.541	−0.023	H_0 accepted
Jul	−13	0.838	−0.006	H_0 accepted
Aug	23	0.708	0.056	H_0 accepted
Sep	273	0.000	0.239	H_0 rejected
Oct	86	0.148	0.071	H_0 accepted
Nov	252	0.000	0.149	H_0 rejected
Dec	143	0.016	0.121	H_0 rejected
Annual	165	0.005	0.062	H_0 rejected

Table 9 Parameters and results for model calibration for maize crop

Parameter	2008	2012
Reference harvest index	25	25
Rooting depth	Medium	Medium
Plant density (plants/ha)	44000	44,000
Planting date	15th August	15th August
Days to maturity	125	125
Soil type and depth (m)	Clay/loam (1.69)	Clay/loam (1.69)
Simulated yield (t/ha)	1.43	2.62
Actual yield (t/ha)	1.47	2.50

substantial value. However, the impact is minimal if the days to maturity are overestimated.

Future maize yields under climate change

Table 11 presents the results of the percentage change in maize yield under climate change in the different agro-climatic zones. Maize yield is highly affected for the warm-sub-humid zone, whose warming is faster and receives little rainfall, while climate change will have a positive impact on the cool-humid zone. The reduction in yield will still be experienced in warm-sub-humid areas whether the rains received are low or high. For the August to December season under RCP4.5, there will be a reduction in maize yield of 5.2%, 10.3% and 3.2% for the near, mid and far futures, respectively, compared to the mean yields attained from 1986 to 2016. A reduction in maize yield will still be experienced under RCP8.5. Results show that there will be a 1.8%, 5.4% and 3.1% reduction for the near, mid and far futures under the RCP8.5. However, the reduction under RCP8.5

is lower than that under RCP4.5. This can be attributed to the slightly high rainfall expected for RCP8.5 compared to RCP4.5. Although the percentage reduction looks small, *p*-values indicate that they are significant. This implies that these small reductions can heavily injure the food security of the community. Furthermore, results indicate an average reduction of as high as 36.7% and 22.7% for RCP4.5 and RCP8.5, respectively, during the March to May growing season. Similar results were obtained by Msowoya and Madani (2016) in a study that used the CERES-Maize model to evaluate the climate change impacts and adaptation measures on maize cultivation in Uganda. For the cool-humid areas whose warming is low and receives high rainfall, results show an increase in maize yield by 3.5%, 5.4% and 2.8% for near, mid and far futures under RCP4.5 during August to December growing season. In addition, there is an increase of 2.6%, 6.1% and 3.1%, respectively, for the August to December season under RCP8.5. Although there is also an increase in the maize yield for both RCP4.5 and RCP 8.5 for the March to May growing season, this increase is less compared to the percentage increase in the August to December season. The difference can be attributed to the expected reduction in rainfall for the March to May Season for all the scenarios.

Table 10 Sensitivity coefficient of AquaCrop model for maize crop

Input parameter	$S_C (+25\%)$	$S_C (-25\%)$	Sensitivity level
Days to maturity	0.04	0.07	Low
Reference harvest index	0.63	0.92	Moderate
Soil fertility	0.44	1.39	High
Planting density	0.07	0.29	Moderate

Fig. 10 Comparison of recorded and predicted maize grain yield for years 2005–2014

Table 11 Projected percentage change in seasonal maize yield for the near, mid and far futures under two climate change scenarios (RCP4.5 and RCP8.5) and corresponding *P*-values

Zones	Near	Pn	Mid	Pm	Far	Pf	Scenario	Season
Warm-humid	−10.3	0.020	−8.9	0.042	−13.8	0.057	RCP4.5	M-M
	−6.5	0.047	−12.3	0.041	−8.5	0.011	RCP8.5	
	−2.3	0.050	−3.9	0.116	−2.8	0.164	RCP4.5	A-D
	−1.1	0.144	−3.8	0.076	−1.9	0.315	RCP8.5	
Warm-sub-humid	−28.9	0.009	−42.1	0.005	−39.0	0.016	RCP4.5	M-M
	−18.2	0.012	−26.2	0.041	−23.7	0.014	RCP8.5	
	−5.2	0.048	−10.3	0.033	−3.2	0.091	RCP4.5	A-D
	−1.8	0.058	−5.4	0.051	−3.1	0.073	RCP8.5	
Cool-humid	0.8	0.570	1.1	0.228	1.3	0.992	RCP4.5	M-M
	0.4	0.515	1.2	0.588	0.9	0.497	RCP8.5	
	3.5	0.188	5.4	0.079	2.8	0.189	RCP4.5	A-D
	2.6	0.304	6.1	0.151	3.1	0.527	RCP8.5	
Cool-sub-humid	−5.2	0.049	−6.8	0.252	−14.3	0.050	RCP4.5	M-M
	−1.7	0.143	−2.3	0.951	−3.4	0.053	RCP8.5	
	1.4	0.484	0.8	0.068	0.6	0.104	RCP4.5	A-D
	0.2	0.457	0.7	0.138	0.2	0.983	RCP8.5	

According to the crop modelling results, maize yield is projected to generally decline under climate change. The percentage decline in maize yield for the near, mid and far future compared to the base period of 1986–2016 ranges from 1 to 10%, 2 to 42% and 1 to 39%, respectively. Adhikari et al. (2015), in a study of eight sub-Saharan Africa countries, projected that by the end of the 21st century, grain crop yields such as maize will reduce by up to 45% which is in agreement with results obtained in this study. The reduction in maize can be attributed to the expected increase in temperature beyond the optimum. According to the *t*-test results, the *p*-values indicate that even small percentage reductions are statistically significant and small increases are non-significant. This is in line with the expectation that after a long period of time, yield is expected to increase so much compared to the base period.

Maize is a staple crop that is highly relied on for nutritional and socio-economic values; this mild-predicted decline soon may be very consequential to the regional socio-economic well-being and food security. More so, it is predicted to be statistically significant as most *P*-values are less than 0.05. This is since most farmers in the region completely rely on rainfall for farming (Daly et al. 2016). Uganda may run into food insecurity and famine situations as maize yield declines and the prices hikes (Anthony et al. 2019). The situation will further be exacerbated by the rapid population growth, as it may double by 2050 at the current growth rate of 3% a year, putting additional pressure on the declining food production. This calls for rapid response by embracing climate change adaptation measures during field management.

The negative (−) sign indicates a reduction in the yield. M-M indicates the March to May growing season, while

A-D denotes the August to December season. Pn, Pm and Pf are *P*-values for near, mid and far futures, respectively

Assessment of climate adaptation measures

Supplementary irrigation

Maize yield was simulated for supplementary irrigation in incremental amounts of 10 mm, 20 mm and 30 mm using sprinkler irrigation. Each irrigation level was applied five times at 10 days interval. Table 12 shows the results of the percentage change in maize yield due to supplementary irrigation. For the cool zones under all scenarios, the optimum amount of supplementary irrigation is about 100 mm (20 per application) and 50 mm (10 mm per application) for the May to March and August to December seasons, respectively. However, for the warm-sub-humid zone, the optimum amount of irrigation was 150 mm (30 mm per irrigation) during the March to May season. Results indicate that with supplementary irrigation, maize yield is improved compared to without. For the warm-sub-humid zone, yield is simulated to reduce by 28.9%, 42.1% and 39.0% for the near, mid and far futures, respectively, under RCP4.5 during the March to May season. After applying supplementary irrigation, yield reduces by only 10.9%, 15.1% and 9.3%, respectively, under the same scenario. This implies an improvement in maize yield during the March to May season. However, there is no significant change in yield during the August to December season. This indicates that the rainfall could be sufficient to meet the crop water requirement. The reduced yield in the August to December season for some zones could be attributed to other factors other than insufficient water. Temperature increase in the future could

Table 12 Percentage change in seasonal maize yield under supplementary irrigation and corresponding *P*-values

Zones	Near	Pn	Mid	Pm	Far	Pf	Scenario	Season
Warm-humid	−3.4	0.051	−2.1	0.633	−3.6	0.297	RCP4.5	M-M
	−1.5	0.086	−3.2	0.567	−2.5	0.254	RCP8.5	
	−2.2	0.015	−3.7	0.083	−2.9	0.557	RCP4.5	A-D
	−0.9	0.607	−3.5	0.212	−2.0	0.035	RCP8.5	
Warm-sub-humid	−10.9	0.002	−15.1	0.044	−9.3	0.044	RCP4.5	M-M
	−5.3	0.055	−6.7	0.256	−5.5	0.026	RCP8.5	
	−2.4	0.051	−1.9	0.793	−3.1	0.051	RCP4.5	A-D
	−1.0	0.051	−3.4	0.992	−3.0	0.013	RCP8.5	
Cool-humid	3.6	0.030	4.5	0.970	4.9	0.034	RCP4.5	M-M
	2.5	0.076	3.7	0.137	2.8	0.024	RCP8.5	
	3.9	0.039	4.8	0.131	2.9	0.046	RCP4.5	A-D
	5.1	0.065	5.7	0.152	3.6	0.022	RCP8.5	
Cool-sub-humid	2.2	0.253	1.1	0.876	0.92	0.053	RCP4.5	M-M
	2.2	0.285	1.5	0.471	2.1	0.990	RCP8.5	
	3.0	0.832	1.3	0.576	1.5	0.412	RCP4.5	A-D
	1.2	0.947	1.9	0.764	3.2	0.123	RCP8.5	

be one of the factors. It is also noted that yield improvement is higher under RCP4.5 compared to RCP8.5. Furthermore, in some zones, supplementary irrigation leads to increased yield, although a reduction is still noted in most zones. This implies that supplementary irrigation alone without other management measures may not solve the food insecurity issue in the region. Similar observations were noted by Durodola and Mourad (2020) in a study to simulate crop water requirements for maize crops under different climate scenarios. They further noted that irrigation infrastructure and equipment would require a financial investment that, to some extent, make maize production economically inviable for smallholder farmers.

The negative (−) sign indicates a reduction in the yield. M-M indicates the March to May growing season, while A-D denotes the August to December season. Pn, Pm and Pf are *P*-values for near, mid and far futures, respectively

Shifting planting date

To determine the optimum planting dates, maize yield simulations were performed at one week's intervals 5 times backward and forward from 5th March for the March to May season and 15th August for the August to December season under all climatic scenarios. Under all climate scenarios, results indicate maximum yields when the planting date is shifted on average by 14 days backward from 5th March for the March to May season. Therefore, planting maize for this season should be between 16th and 23rd February to attain maximum yield. To some extent, this agrees with some farmers' practices in the last 5 years. For the August to December season, maximum yields are obtained by shifting the planting date forward on average by 7 days. This implies

that planting should be between the 20th and 25th of August. Planting maize on the 21st of February under RCP4.5 results in only 0.9%, 1.8% and 1.2% increase in yield for near, mid and far futures for the warm-sub-humid zones. Consequently, planting on 22nd August under RCP4.5 resulted in a 1.9%, 3.2% and 2.1% increase in yield for the near, mid and far futures, respectively, for the warm-sub-humid zone. Under RCP8.5, maize yield for the warm-sub-humid zone increases by 1.2%, 1.3%, 2.3% and 3.4%, 2.8%, 3.3% for the March to May and August to December seasons, respectively. In all the warm agro-ecological zones under all climate scenarios, an increase in maize yield is noted. Shifting the planting date significantly mitigates the impact of climate change on maize yield. Shifting planting dates has been recommended by several studies as a successful adaptation measure to climate change (Waongo 2015; Baum 2019). However, carrying out site-specific studies for specific crops has been emphasised to identify by how many days the date should be shifted, either forward or backward. In the case of the VNSB, the improvement in yield is noted, but it may not be sufficient to meet the food demand of the regional population that has continuously increased. Therefore, this mitigation measure alone is not sustainable.

Soil fertility improvement and other field surface practices

Results indicate that there is no significant impact on the maize yield in all climate scenarios and agro-ecological zones when soil fertility is improved beyond its current state and field surface practices such as mulches and soil bunds are applied soil fertility. This can be attributed to the increased organic content of the soil in the study area. However, it must be noted that this organic content (soil

fertility) will decline with the continued cultivation of the soil over time. Therefore, fertiliser application will be very vital in improving maize yield in the future, especially under climate change. This finding is in line with the findings of Rehmani et al. (2018) in a climate change's impact study on maize production in Uganda's cattle corridor. These findings suggest that even if the soil is fertile, but other factors such as temperature and water stress are still available, the yield will not improve.

Combined application of supplementary irrigation and shifting of planting dates

Maize yields under supplementary irrigation were simulated when planting dates are set at 21st February and 22nd August for March to May and August to December seasons, respectively, under all climatic scenarios. Results indicate that there is a significant improvement in the maize yield for all agro-ecological zones and climate change scenarios. The yield increase ranges from 9.8 to 19.4% for March to May season and 8.7 to 21.5% for the August to December season under RCP4.5. Moreover, the maize yield ranges from 11.3 to 15.8% and from 11.4 to 22.8% for the March to May and August to December seasons, respectively, under the RCP8.5 climate scenario. Changing the planting date does not only improve the yield but also reduces the crop irrigation water requirement and the subsequent pumping energy demand. This implies that for the Victoria Nile sub-basin to meet its food requirement under climate change by significantly improving maize yield, a combined application of supplementary irrigation with shifting the planting dates will be necessary. It is therefore recommended that policymakers should develop a food security plan for the VNSB communities considering climate change. This may include having an irrigation plan for up to the year 2100, diversifying crop production and capacity building for the local food producers (Table 13).

Conclusion and recommendations

The primary objective of this study was to assess the impact of climate change on maize yield, taking the case of the Victoria Nile Sub-basin. The 31 years (1986–2016) observed climate data set showed that VNSB has received abundant rainfall, but its seasonal variability and distribution was critical to sustain crop productivity. HadGEM2-ES Global Circulation Model was selected to simulate the historical (1971–2005) and future (2021–2099) rainfall and temperature data under two representative pathways (4.5 and 8.5). The projected climate data indicate a slight increase in rainfall during the August to December growing season. The average temperature is simulated to increase as time goes

Table 13 Percentage change in yield under combined supplementary irrigation and shifting the planting dates

Zones	Near	Mid	Far	Scenario	Season
Warm-humid	16.4	13.3	17.7	RCP4.5	M-M
	14.0	15.1	14.8	RCP8.5	
	19.2	20.7	18.2	RCP4.5	A-D
	20.1	19.9	21.3	RCP8.5	
Warm-sub-humid	12.8	17.6	19.4	RCP4.5	M-M
	15.8	14.9	15.2	RCP8.5	
	17.7	21.5	20.8	RCP4.5	A-D
	19.6	22.8	21.3	RCP8.5	
Cool-humid	9.8	11.3	13.4	RCP4.5	M-M
	12.2	13.6	15.0	RCP8.5	
	12.5	14.2	13.9	RCP4.5	A-D
	11.4	13.9	16.2	RCP8.5	
Cool-sub-humid	11.5	10.3	9.9	RCP4.5	M-M
	13.2	11.8	11.3	RCP8.5	
	8.7	10.6	11.8	RCP4.5	A-D
	12.4	15.6	14.2	RCP8.5	

on. The increase in temperature is greater under the RCP8.5 climate scenario than the RCP4.5. Results indicate that there is a significant reduction in maize yield of as high as 42% during the March to May season. The reduction in maize yield is greater in the mid future (2041–2070) as compared to the near and far futures for both seasons. The reduction in maize yield in the future is due to increased crop water requirement that is not met by the rainfall and high temperature expected in the future.

To overcome the adverse effects of climate change on food security, the Government of Uganda, together with the farmers in the Victoria Nile Sub-basin, should concentrate more on climate change adaptation measures. Based on the results of this study, shifting planting date backwards by an averagely of 14 days from 5th March and forward by an averagely of 7 days from 15th August is highly recommended to improve yield. Farmers should also adopt supplementary irrigation technologies to meet the crop water deficit expected in most future scenarios. Farmers can also leverage rainwater harvesting technologies to supply water for supplementary irrigation (Durodola and Mourad 2020). A combined application of both supplementary irrigation and shifting of the planting dates has shown a significant improvement in maize yield, hence food supply and socio-economic development. Supplementary irrigation reduces the pumping energy consumption and associated costs that would be incurred under full irrigation, yet yield is optimised. Furthermore, climate-resilient varieties or adapted to take advantage of a longer growing season for increased yield are highly encouraged. However, this must follow site-specific studies recommending these maize varieties.

Change in diets and crop diversification could be another option for food security. The crop water requirement for some food crops like cassava and sweet potatoes is less than that of maize. Furthermore, they are more climate change resilient and with less fertiliser requirement. In addition to climate adaptation measures, other measures such as proper post-handling management can also be of crucial importance while abating food insecurity and shortage (Bwambale et al. 2020). The National Agricultural Research Organisation (NARO) has developed a few local maize varieties that are being grown in Uganda. However, there is limited data on crop genetic coefficients for most of these varieties. Therefore, future research works are needed to determine the genetic coefficients of these varieties and evaluating their resilience to climate change.

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Data availability All the used data are included in the manuscript

Declarations

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Consent for publication We give our consent for the publication of all related materials to be published in the above journal and article.

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