**Article:**

Feukam Nzudie, HL, Zhao, X, Tillotson, MR orcid.org/0000-0002-3362-021X et al. (2 more authors) (2020) Modelling and forecasting roots & tubers losses and resulting water losses in sub-Saharan Africa considering climate variables. Physics and Chemistry of the Earth, Parts A/B/C, 120. 102952. ISSN 1474-7065

https://doi.org/10.1016/j.pce.2020.102952

# Modelling and forecasting Roots & Tubers losses and resulting water losses in sub-Saharan Africa considering climate variables

**Harold L. Feukam Nzudie[a], Xu Zhao[b*], Martin R. Tillotson[c], Fei Zhang[d], Yiping Li[a*]**

[a]Key Laboratory of Integrated Regulation and Resource Development on Shallow Lakes, Ministry of Education, College of Environment, Hohai University, Nanjing 210098, China
[b] Institute of Blue and Green Development, Shandong University, Weihai, 264209, China
[c]water@leeds, School of Civil Engineering, University of Leeds, Leeds LS2 9JT, United Kingdom
[d]Jiangsu Provincial Department of Agriculture and Rural Afairs
*Corresponding author. Email: xuzhao@sdu.edu.cn, liyiping@hhu.edu.cn

**Abstract**

The implications of climate change coupled with anthropogenic activity on water resources have caused great concern, particularly in areas vulnerable to water stress such as sub-Saharan Africa. We focused on the future magnitude of food loss (FL) in African regions, using an ARIMAX model to fit and forecast roots & tubers (R&T) losses of five major crops cultivated in Africa regions, including cassava, potato, sweet potato, yam, and “other” roots & tubers. The forecast was done up to 2025 under the influence of five exogenous variables, namely, gross domestic product, harvested area, precipitation, temperature, and food production. In addition, the future crop water requirement (CWR) of production under climatic variables, and the associated water loss embodied in FL were quantified by means of CROPWAT 8.0. Our findings showed that in 2025 the magnitude of FL is expected to increase by 19.06%, 104.78%, and 27.72% at 2013 levels for East Africa, Middle, and West Africa, respectively. Under future climate the CWR of the selected crops is expected to be higher in West Africa (1790.24 $m^3$/tonne), than in East (989.03 $m^3$/tonne), and Middle Africa (903.64 $m^3$/tonne). The future water loss embodied in FL is expected to be 114.37, 112.80, and 12.06 $m^3$/cap/yr for the West, Middle, and East Africa regions, respectively. Our results show that measures aimed at preventing FL will also alleviate pressure on available water resources.

Keywords: climate change; crop water requirement; food loss; forecasting; Africa

## 1. Introduction

The implications of climate change on the environment and anthropogenic activities is profound. It may be linked to agricultural practices, crop production, water resources, and so on (Bocchiola et al., 2013; Kusangaya et al., 2014; Mimikou et al., 2000; Shrestha et al., 2017; Stancalie et al., 2010; Tingem et al., 2008). Agricultural production is vulnerable to climate change, particularly in low income countries including in sub-Saharan African (SSAn) regions

(Maddison et al., 2007; Muller et al., 2011). The low resilience of African agricultural practices to climate change is likely to generate greater food loss (FL) impacting on food security (Muller et al., 2011).

FL can be considered as the decrease in edible food mass throughout the part of the supply chain that specifically leads to edible food for human consumption (Gustavsson et al., 2011). FL is more related to the production, postharvest, and processing stages of the food supply chain (Kummu et al.,2012). FL is historically a major concern in Africa (Feukam Nzudie et al., 2020). The continent has a high prevalence of undernourished people, estimated at 20.4 % of its population in 2017 (FAO, 2018). Preventing FL becomes even more difficult when coupling this with the impacts of climate change. For example, in most SSAn regions, FL in fresh vegetables has a tendency to increase due to hot climates (Gustavsson et al., 2011). Furthermore, weather conditions more generally impact on FL (Huang et al., 2017; Kaminski and Christiaensen, 2014). A crop which requires a warm dry climate to attain a specific dryness can be spoilt when exposed to a humid climate (Abass et al., 2014). Climate may also promote the development and spread of pests and plant diseases on/off-farm which indirectly act on FL (Manjula et al., 2009). Other than climate, there are also other factors which can influence FL. The economic situation of a nation may also impact on FL (Aulakh and Regmi, 2013; Gustavsson et al., 2011). For example, less developed (lower income) countries are more likely to generate FL due to lower levels of technological advancement, such as crop storage and transport facilities, and food processing. Other factors affecting FL include the magnitude of food production and the harvested area. This may be explained by the fact that a relatively high production (in the case where demand is lower) is likely to lead to loss of some of the excess food (The Economist Intelligence Unit, 2014). Since FL can be expressed per unit of harvested area, the latter is also an important influencing factor. Overall, FL is being driven and aggravated by the aforementioned factors in SSAn regions.

FL impacts on food security, economic prosperity, and natural resources such as water (Rezaei and Liu, 2017). Numerous studies have been conducted into the impacts of FL on water resources. Ridoutt et al. (2010) found that mango loss was responsible for 16.6 GL of blue water consumption in Australia. Kummu et al. (2012) used a process analysis to find that FL was responsible for 24% of total water resources globally, which translated into 27 $m^3$/cap/yr. Liu et al. (2013) found that total water embodied in FL in China was equivalent to $13.5 \times 10^4$ GL in 2010. By means of process analysis, le Roux et al. (2018) found that 4 GL/yr water was lost from the Steenkoppies Aquifer in South Africa due to FL in vegetables. However, these studies stop short of considering the implications of climate change on FL and associated water resource. Furthermore, FL reduction in the long term could potentially alleviate pressure on water resource. As such, and to inform integrated water management and planning practices, quantitative assessment of the implications of climate change on FL and associated water resources is required.

Roots & tubers (R&T) play an important role in feeding the world and tackling food insecurity (Scott, 2000). In SSAn regions ca. 20 % of food energy consumption is derived from R&T (Scott et al., 2000). However, large amounts of R&T is lost before reaching final consumption. Most R&T FL occurs post-harvest than at other stages of the food supply chain in many SSAn countries (Gustavsson et al., 2011). Aforementioned, FL induces water loss which is in turn linked to the crop water consumption. As known the water consumption in growth stage is highly depend on the crop itself. As an example, taking potato as a crop belonging to R&T, its water consumption is about 500-700 mm/growing period (FAO, 1986). While the range of water consumption for other crops is from 300 to 2500 mm/growing period for bean and sugarcane respectively (FAO, 1986). Although potato has a relatively lower water consumption during its growing stage compared to the previous range, the point is how significant a large consumption of R&T could impact on total water consumption. In this study, we use an ARIMAX model to forecast the magnitude of R&T associated FL in East, Middle, and West SSAn. The major R&T crops cultivated in SSAn are classified as cassava, potatoes, sweet potatoes, yams, and "other R&T". Our forecast has been undertaken to 2025, considering five independent variables, namely, Gross domestic product (GDP), harvested area (Har), precipitation (Pre), temperature (Temp), and production (Pro). The ARIMAX model was selected since it can integrate both a dependent or response variable (in this case FL) and several independent or exogenous variables (Anggraeni et al., 2017). In addition, we investigate the implications of future climate change on crop water requirement (CWR) in order to assess the water embodied in the expected FL. Note, that due to insufficient data in other African regions, only East, Middle, and West Africa were considered.

## 2. Methodology

Fig.1 presents a framework describing the relationship between climate change, FL, and water resource as developed for the current study. The first step was to investigate the potential implications of climate and exogenous variables on human activity by means of the ARIMAX model, forecast until 2025. The second step was to quantify future CWR of production under climatic variables, and the third step was to investigate the implications of climate and human activity through the quantification of expected water embodied in FL.

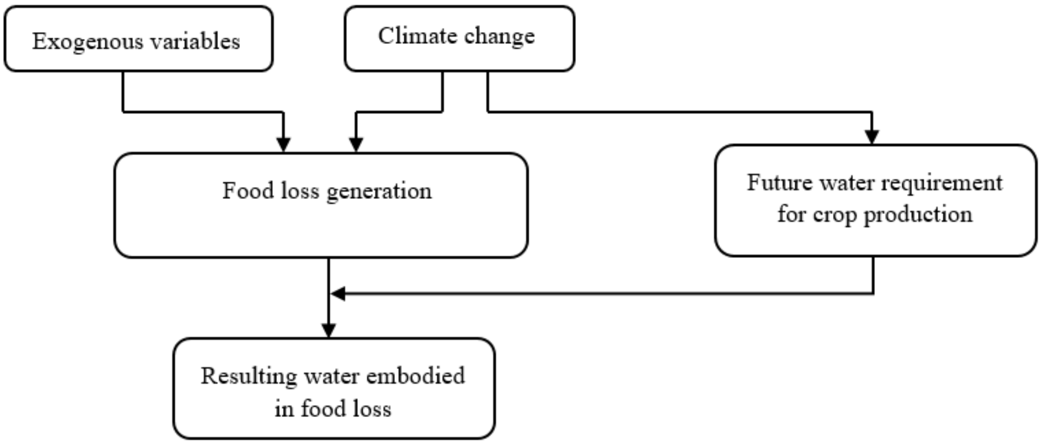



**Fig.1.** Interlinkage amongst climate food loss, and water resources.

## 2.1. ARIMAX model

The schematic shown in Fig. 2 illustrates the relationship between the three embedded ARMA/ARIMA models to the more complex ARIMAX model. It can be seen that this modelling approach integrates two major components, namely, autoregressive (Ar) and moving average (Ma). Considering time-series input variables including a dependent or response variable Y, and one or several independent or exogenous variables in X, ARIMAX becomes ARIMA if X does not exist, and ARIMA becomes ARMA if the dependent variable or the variable of interest (Y) is already stationary at level. ARIMAX therefore gives a closer interpretation of real phenomena. The outputs of the three different models can also be seen in Fig. 2.

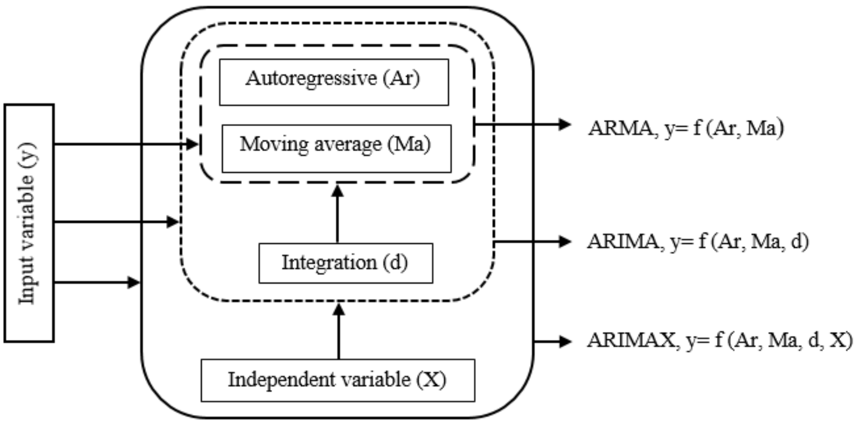



**Fig. 2.** Conceptual approach of ARIMAX modelling.

Note that the different steps used to perform the ARIMA modelling via a Box-Jenkins' method has been widely reported elsewhere (Rathod et al., 2017; Udom and Phumchusri, 2014), hence only a brief description is provided here. The general form of an ARIMA (p, d, q) model is given as follows:

$$\Omega(\mathrm{L})(1-\mathrm{L})^{\mathrm{d}}\mathrm{y}_{\mathrm{t}} = c + \Phi(\mathrm{L})e_t \tag{1}$$

Where Ω and Φ represent the autoregressive and moving average components respectively. L is the lag operator that links a current variable to its pass value, $e_t$ is the error term, c is a constant, d is the order of integration, and y is the variable of interest. Since ARIMAX is considered as a general form of ARIMA (Sutthichaimethee and Ariyasajjakorn, 2017), it is written as ARIMAX (p, d, q), however the independent variables in use should be indicated. Let us consider a case where the order of integration d=1 and including an independent variable X. ARIMAX yields the following equation (Hamjah, 2014):

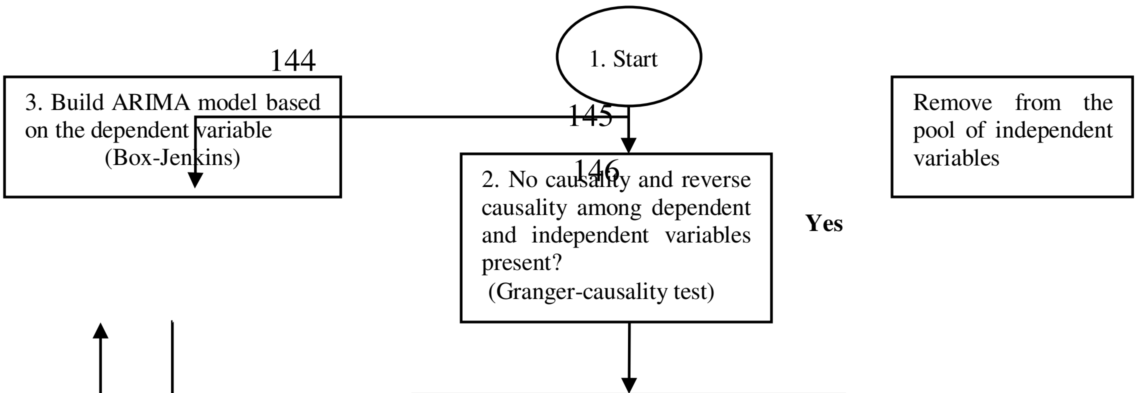
$$y_t = \beta_1 y_{t-1} + \beta_2 y_{t-2} + \ldots + \beta_{\mathrm{p}} y_{t-p} + e_t - \varphi_1 e_{t-1} - \varphi_2 e_{t-2} - \ldots \varphi_{\mathrm{q}} e_{t-q} + \alpha_1 X_{t1} + \alpha_2 X_{t2} + \ldots + \alpha_{\mathrm{n}} X_{tn} \tag{2}$$

Where α is the coefficient of the independent variables, β and φ are the coefficients of the autoregressive and moving average parts respectively. A more general form of ARIMAX, where the independent variable X includes real time-series processes, is given as follows (Anggraeni et al., 2017):

$$\left(1-\mathrm{L}\right)^{\mathrm{d}} \Psi_{\mathrm{p}}\left(\mathrm{L}\right) y_{\mathrm{t}} = \Gamma_{\mathrm{q}}\left(\mathrm{L}\right)\mathrm{e}_{\mathrm{t}} + \sum_{i=1}^{m} a_i x_{i,t} \tag{3}$$

Where Ψ and Γ are functions of the lag operator and represent the autoregressive and moving average parts respectively, a coefficient of the independent variable X.

The different steps used in performing ARIMAX are shown in Fig. 3. Note that the use of the Granger-causality test was to identify causal relationship amongst variables, in other words it was to test whether values of an independent variable could be helpful in predicting one of the dependent variables (Foresti, 2006). This was used in a probabilistic sense, whereas a cross-correlation analysis helped to identify lags at which a correlation may exist between dependent and independent variables. This led us to choose an appropriate lag order of the independent variable. Step 2 did not necessarily need time series to be stationary, since we used the well-known Toda-Yamamoto procedure (Alimi and Ofonyelu, 2013) to perform the Granger-causality test hence it could be performed at an earlier stage of the modelling process. Step 3 used the Box-Jenkins method to build an ARIMA model which was used in the development of the ARIMAX model.



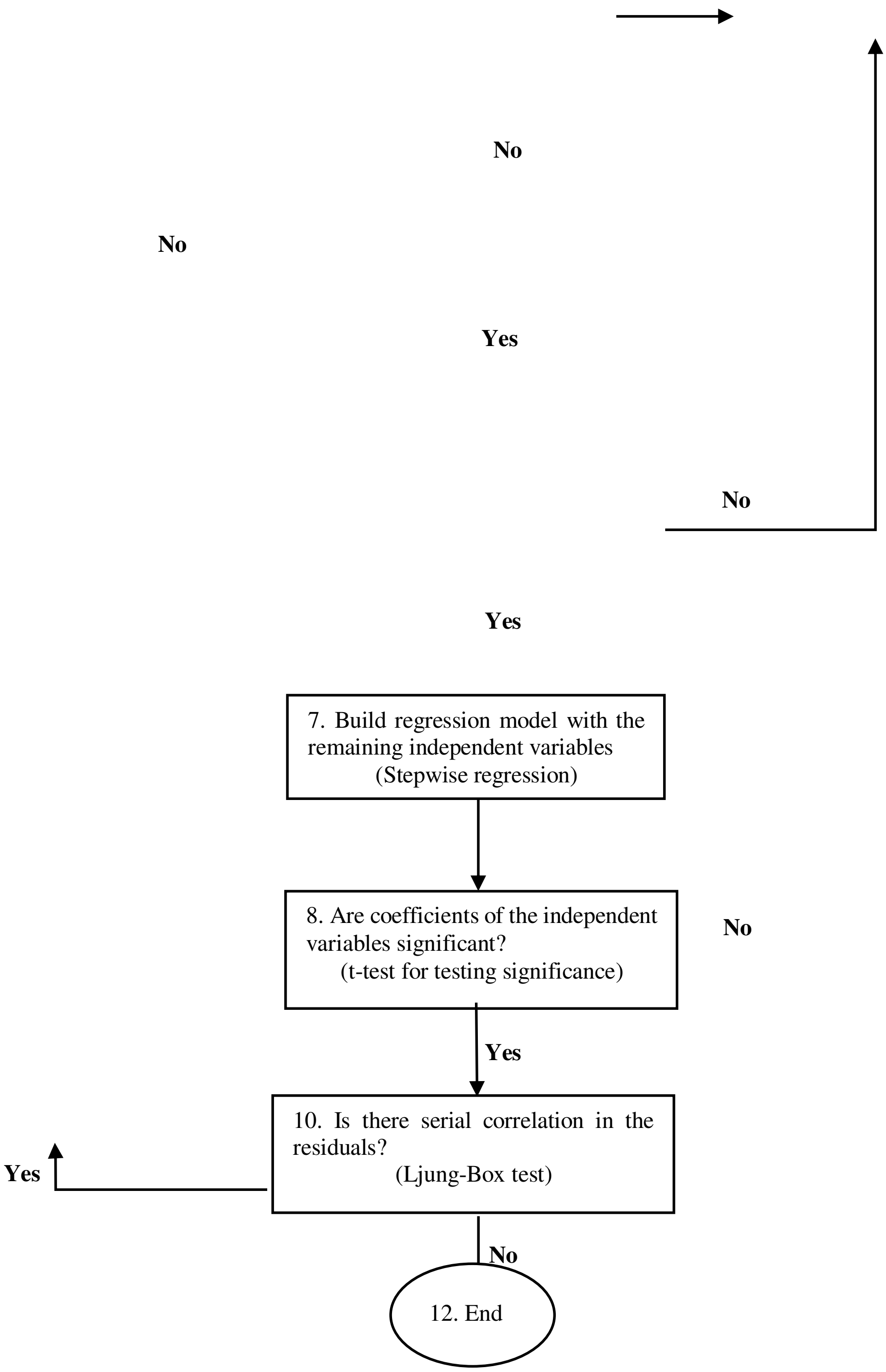



**Fig. 3.** Flowchart of the different steps used to develop the ARIMAX model.

It should be noted that the development of our models was based on “additive lag”. This indicates that only relevant lags were included in the model. This was different from the “order lag” method which considers all lags until a significant lag, let’s say, p is identified (Andrews et al., 2013). The choice of “additive lag” was based on its easier interpretability of resulting models (Stige et al., 2007). Additionally, the introduction of the selected independent variables during model development followed a “stepwise regression”. Each independent variable was introduced successively to the model, and only a variable with significance was kept whilst the insignificant one was discarded from the pool (Andrews et al., 2013).

## 2.2. CROPWAT description

CROPWAT v8.0 is a software platform integrating a large number of equations developed by scientists under the Food and Agriculture Organization (FAO) (Stancalie et al., 2010). It is used to calculate reference crop evapotranspiration (ETo), crop evapotranspiration (ET), and irrigation crop water requirement (IWR). CROPWAT may be used to schedule field irrigation and crop management. CROPWAT requires various input data classified into weather variables, crop parameters, soil properties, and scheduling criteria (Stancalie et al., 2010).

## 2.3. Crop water requirement

The CWR for production calculated in this study was based on the crop water footprint (WF) calculation (Zhao et al., 2017). Here, we briefly present the basic equations used for calculating WF for crop production since the latter has been thoroughly described in the literature (see, for example, Aldaya et al. (2012)). The CWR of production is derived from crop evapotranspiration as follows:

$$WF_{crop} = 10 \times {}^{ET_{crop}}/_{Y} \tag{4}$$

with

$$ET_{crop} = K_c \times ET_0$$

Where $Y$ is the crop yield per unit of area, $ET_o$ *is* the reference evapotranspiration calculated using weather variables, and $K_c$ is the crop coefficient. $WF_{crop}$ and $ET_{crop}$ reflect the WF and the crop evapotranspiration respectively. Note that we used the method provided by the U.S. Department of Agriculture (USDA) to calculate effective rainfall (Ewaid et al., 2019). We used cocoyam as the reference to calculate the CWR of other R&T since it is the major crop for this group (Ngopya, 2002). More specifically, equation (4) was used to estimate future CWR in 2025. The equation requires as inputs crop data, Kc, crop yield, and future climatic data in 2025, i.e. maximum and minimum temperature (°C), precipitation (monthly), relative humidity (%), sunshine duration (h), and wind speed (m/s). Water loss embodied into future FL was then estimated by multiplying the projected magnitude of FL with the future CWR for production (calculated in this study). This was completed for each African region.

We defined a hypothetical scenario, identified as S1, which was the magnitude of water loss embodied in FL in 2025 considering an unchanged CWR at 2013 level (the one provided in Mekonnen and Hoekstra (2011)). The development of scenario S1 was to investigate how future crop production using historic CWR may potentially affect the future amount of water embodied in FL in 2025.

### 2.4. Data

This study used yearly time series data of FL as a dependent variable, and five independent variables including two climatic variables (Pre and Temp), two food production variables (Har and Pro), and one economic variable (GDP). Most climatic data providers present data in a monthly or daily basis. Since we needed our data to be on an annual basis (for case of forecasting FL), climatic data was averaged, extracted and then aggregated on a regional scale using R software and ArcGIS 10.3.1. A descriptive summary of the different data used in this study is given in Table 1. Note that the current study includes 32 nations in SSAn, with 10 being in East Africa, 7 in Middle Africa, and 15 in West Africa (Fig. 5). The exclusion of other African nations was due to data limitations. For simplicity, the 32 countries were aggregated as East, Middle, and West regions, respectively.

The GDP time series data for some countries included in this study do not cover the entire study period. An estimation was therefore required to obtain regional data wherever a given country presented lack of data in a specific year. To estimate the GDP of a region, a weighted approach based on population was used as follows. Considering three countries X, Y, and Z within the same region (Middle Africa, for example) and with GDP denoted $G_X$, $G_Y$, and $G_Z$, respectively, hence $g_X$, $g_Y$, and $g_Z$ was their per capita GDP. The average GDP per capita (g) of that region is therefore derived from the following equation:

$$g = \frac{G_X + G_Y + G_Z}{p_X + p_Y + p_Z} \tag{5}$$

Where p is the population of country X, Y or Z. Including the GDP per capita of each country in equation 5 yields:

$$g = \frac{p_X}{p_X + p_Y + p_Z} g_X + \frac{p_Y}{p_X + p_Y + p_Z} g_Y + \frac{p_Z}{p_X + p_Y + p_Z} g_Z \tag{6}$$

Note that wherever we encountered missing values in GDP per capita data, the population of the country concerned was not included in equation (6). It is also worth noting that since data related to the independent variables used to forecast FL were not available for the forecast horizon (year 2025), part of those data were forecasted using the ARIMA model (equation 1). This was termed “unconditional forecast” which is different from “conditional forecast”. In the latter, future values of the independent variable were assumed to be known or set to a target value (Chatfield, 2000).

**Table 1**
Summary of different data used.

| Variables | Description | Sources |
|---|---|---|
| Food loss, temperature, precipitation, harvest area, food production | These were used for the model development in order to forecast the magnitude of food loss up to 2025. The relevant data were observed between 1961 and 2013. The selected period was due to data availability. | CRU, 2017; FAO, 2019a |
| Temperature, precipitation, relative humidity, sun hours, *Kc*, and wind speed | This second set of data was predicted climatic data in 2025 (except *Kc* which depends on crop type). They were used to quantify future water requirement for crop production. Moreover, future climatic data used here was simulated and derived from global climate models (GCMs), namely, BCM2.0_PICTL, CGHR_PICTL, HADGEM_SRA1B, NCPCM_COMMIT, and MOHC_HADGEM2. | Allen et al., 1998; IPCC, 2020 |
| Crop yield | This data was used to calculate water requirement. The data for crop yield was the latest available (2018) at the time of the study. We assumed that its value in 2018 would likely stay constant in 2025. | FAO, 2019b |
| Population | This was used to evaluate food loss and water embodied food loss on a per capita basis. | United Nations, 2019 |

## 3. Results and discussion

### 3.1. Model development

The results of the Granger-causality test between the dependent variable and the independent variables are summarized in Table 2. Considering East Africa, all five independent variables showed no Granger causality with the dependent variable (see the Conclusion column for the East Africa case); their p-values were all greater than 0.1 (10% considered for this study). This infers that the relevant independent variables cannot be used to improve or give much information in model development for forecasting FL. For the Middle Africa case, there was no Granger causality between FL and Temp (p-value >0.1), while there was a reverse Granger causality between FL and Pro (p-value <0.1 in both directions). This latter scheme indicates that both FL and Pro could be used to forecast one another. According to the theory of using causality to forecast, reverse causality should be avoided, hence, only GDP and Pre was used in forecasting FL. Similar reasoning can be made for West Africa; Har and Temp have passed the test for Granger causality. Therefore, GDP, Pre, and Pro were removed from the pool of independent variables to be considered in the development of the forecast model.

**Table 2**
Granger-causality test (Wald test).

| Variables | East Africa | | | Middle Africa | | | West Africa | | |
|---|---|---|---|---|---|---|---|---|---|
| Schemes | Chi-square (x2) | P(> X2) | Conclusion | Chi-square (x2) | P(> X2) | Conclusion | Chi-square (x2) | P(> X2) | Conclusion |

| | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|
| GDP –FL | 2.1 | 0.35 | No | 29.8 | <0.005 | GDP granger cause FL. The inverse is false. | 3.3 | 0.19 | No |
| FL- GDP | 1.5 | 0.48 | | 4.3 | 0.37 | | 3.2 | 0.2 | |
| Har-FL | 1.1 | 0.3 | No | 9.1 | 0.028 | Both variables granger cause each other. | 3.078 | 0.014 | Har Granger cause FL. The inverse is false. |
| FL- Har | 0.02 | 0.89 | | 20.8 | <0.005 | | 1.873 | 0.109 | |
| Pre-FL | 0.00065 | 0.98 | No | 4.9 | 0.087 | Pre granger cause FL at 10%. The inverse is false. | 0.52 | 0.47 | No |
| FL-Pre | 0.021 | 0.89 | | 1.8 | 0.41 | | 0.15 | 0.7 | |
| Temp-FL | 4.8 | 0.19 | No | 0.11 | 0.95 | No | 16.4 | 0.002 | Temp Granger cause FL. The inverse is false. |
| FL-Temp | 1.9 | 0.6 | | 0.25 | 0.88 | | 5.1 | 0.27 | |
| Pro-FL | 0.11 | 0.74 | No | 37.3 | <0.005 | Both variables granger cause each other. | 4.0 | 0.26 | FL Granger cause Pro. The inverse is false. |
| FL-Pro | 0.13 | 0.72 | | 19.4 | <0.005 | | 10.8 | 0.013 | |

"No" stands for no Granger-causality relationship between the relevant variables. GDP= gross domestic product, Har=harvested area, Pre= precipitation, Temp= temperature, Pro = food production.

As mentioned previously, building the ARIMAX model involved building ARIMA on the dependent variable. ARIMA (0,1,0), ARIMA (1, 2, 2), and ARIMA (1, 2, 1) were found to be the best models which fitted respectively the East, Middle, and West African FL (dependent variable) data. The remaining independent variables (the ones which have passed the Granger-causality and cross-correlation analysis tests) were progressively introduced in each ARIMA model. The results of the models that best fitted the observed FL data associated to the exogenous variables are summarized in Table 3.

**Table 3**
ARIMAX models for the three studied African regions.

| **Model** | | | | | **AIC** | **BIC** | **Exo. variables** | | |
|---|---|---|---|---|---|---|---|---|---|
| | | | | | | | lags | Coef. | Pr(>\|t\|) |
| East | ARIMA (0.1.0) | terms | Coef. | Std. E | | | — | — | — |
| | | | 73770.56 | 68992.22 | 1515.78 | 1519.68 | | | |
| Middle | ARIMAX (1, 2, 2) with GDP | Ar1 | 0.1249 | 0.189 | 1287.69 | 1298.79 | lag (3) | 1278.14 | 6.26e-06 *** |
| | | Ma1 | -1.7214 | 0.114 | | | lag | -1448.0 | 2.34e-07 *** |
| | | Ma2 | 0.99 | 0.117 | | | | | |
| West | ARIMAX(1,2,1) with Har | Ar1 | -0.5366 | 0.1386 | 1455.211 | 1464.77 | Har(lag 0) | 0.807 | 3.32e-09 *** |
| | | Ma1 | -0.6883 | 0.1433 | | | Har(lag1) | -0.334 | 0.0045** |

Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1. Std. E= standard error, Coef. = coefficient estimation.

The forecasting models developed here for both Middle and West Africa (since all the exogenous variables did not satisfy conditions to be used for the East Africa case) were based on the additive lags approach and stepwise regression. This means that only significant lags were considered and added up in the relevant models (Andrews et al., 2013). Moreover, the future magnitude of FL was linked to that of the independent variables. We used what is called "unconditional forecast" since the forecasted values of FL required independent variables to be forecasted (due to the lack of future values) (Chatfield, 2000).

## 3.2. Forecasted food loss

Fig. 4 shows how the modeled values fit the data and forecasted results of FL for East, Middle, and West Africa. The total FL across all three African regions is expected to equal 47.42 million tonnes in 2025, of which 61.54%, 26.79%, and 11.66% will be in West, Middle, and East Africa respectively. In 2025, FL in East Africa is expected to be 5.54 million tonnes, corresponding to an increase of 19.06 % at the 2013 level. FL in Middle Africa is expected to increase and reach about 12.70 million tonnes by 2025. This corresponds to an increase of 6.5 million tonnes of FL, accounting for 104.78% of that in 2013. Considering West Africa, FL is expected to reach 29.18 million tonnes in 2025, corresponding to an increase of 6.33 million tonnes and accounting for 27.72% of that in 2013. Overall, while FL in Middle Africa is expected to double, in West Africa it is expected to increase by less than 1/3 of that of 2013.

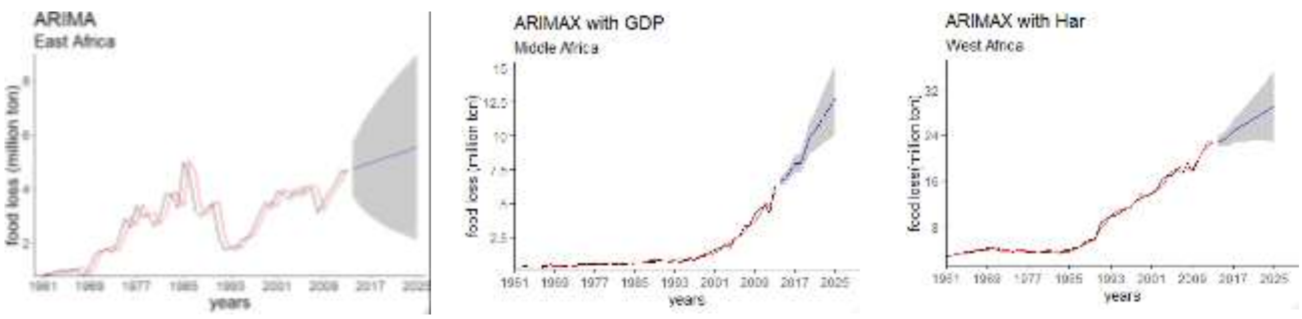



**Fig. 4**. Forecasted values of food loss (FL) for the East, Middle, and West Africa. Black line= observed values (data), red line = fitted values (model), blue line= forecasted values of FL, and shaded area is the confidence interval at 95 %.

The spatial distribution of FL across the three African regions (Fig. 5) reveals that per capita FL is expected to be relatively lower in East Africa, corresponding to 0.012 tonne/cap/yr compared to West Africa (0.064 tonne/cap/yr.) and Middle Africa (0.125 tonne/cap/yr.). The lower amount of FL per capita in East Africa is probably due to its expected larger population compared to that of Middle Africa (almost three times) hence its associated lower magnitude of forecasted FL (Fig.4). Even though West Africa's population is expected to be in the same range as that of East Africa (less than 0.7 % difference), the per capita FL in West Africa will be higher because of its larger magnitude of FL (Fig.4). The per capita FL in Middle Africa is expected to be nearly twice that of West Africa despite its lower expected magnitude of FL. This is attributed to Middle Africa's population being forecast be the lower than that of West Africa (approximately 348.78% of Middle Africa's population). A further explanation could be the relatively greater reliance R&T make to diet in Middle Africa countries, assuming that consumption patterns of R&T remain unchanged in 2025. This finding is underlined by the lowest per capita income expected in Middle Africa in 2025 compared to those of East and West Africa (Cilliers et al., 2011); Kenyon et al. (2006) indicated that low per capita income in SSAn leads to increased demand for R&T. For example, R&T provides a substantial proportion of daily food calories in the Middle Africa nation of Central African Republic (expected lower incomes per capita in 2025), compared to Nigeria in West Africa even though the latter is the bigger producer (Ngopya, 2002). Furthermore, R&T in Middle Africa is generally consumed in different forms involving several food processing steps (derived R&T products such as "gari", flour, dried chips to name but a few) rather than in raw form. These multiple transformations of cassava are sources of FL, hence, including more R&T into one's diet is likely to generate more FL. Meanwhile, the relatively lower per capita FL expected in East and West Africa might be attributed to higher expected incomes per capita in 2025 (Cilliers et al., 2011). This is likely to lead to broadening of diet involving food types other than R&T. Since East and West Africa have important livestock sectors (Chauvin et al., 2012), the introduction of meat into one's diet in those regions would probably help reduce per capita FL in R&T. Additionally, East and West Africa are expected to be less urbanised (46.6% and 58 % of their total population, respectively) than Middle Africa (63.6 % of the total population) by 2025 (Hope, 1998). This may explain the lower per capita FL in both East and West Africa. As shown by Scott et al. (2000), urbanisation in SSAn leads to the development of local markets and greater consumption of R&T; urban dwellers in Africa tend to consider R&T as cheap starchy food and consume more of it, including derived processed products. Consequently, greater R&T consumption will lead to more FL. Note that urbanization is well-known to be an increase in the number of people living in towns and cities. It is mainly due to the movement of people from rural to urban areas. Indeed, urbanization induces better employment, new income opportunities, and may increase the well-being of urban people. However, a rapid and unplanned urbanization particularly in areas with less job opportunities, not appropriate economic policies could lead to poverty (The Open University, 2016). Furthermore, urbanization induced-poverty can be intensified if the migration is driven by factors such as war and natural disaster. In this case, sudden high rise of urban people may lead to increase the gap between job availability and labor. Generally, large amount of the migrants from rural to urban areas are unskilled and may be unable to find adequate job and consequently would make more social pressure on cities where they live. This can explain that Middle Africa has higher urbanization rate and lower per capita income simultaneously.

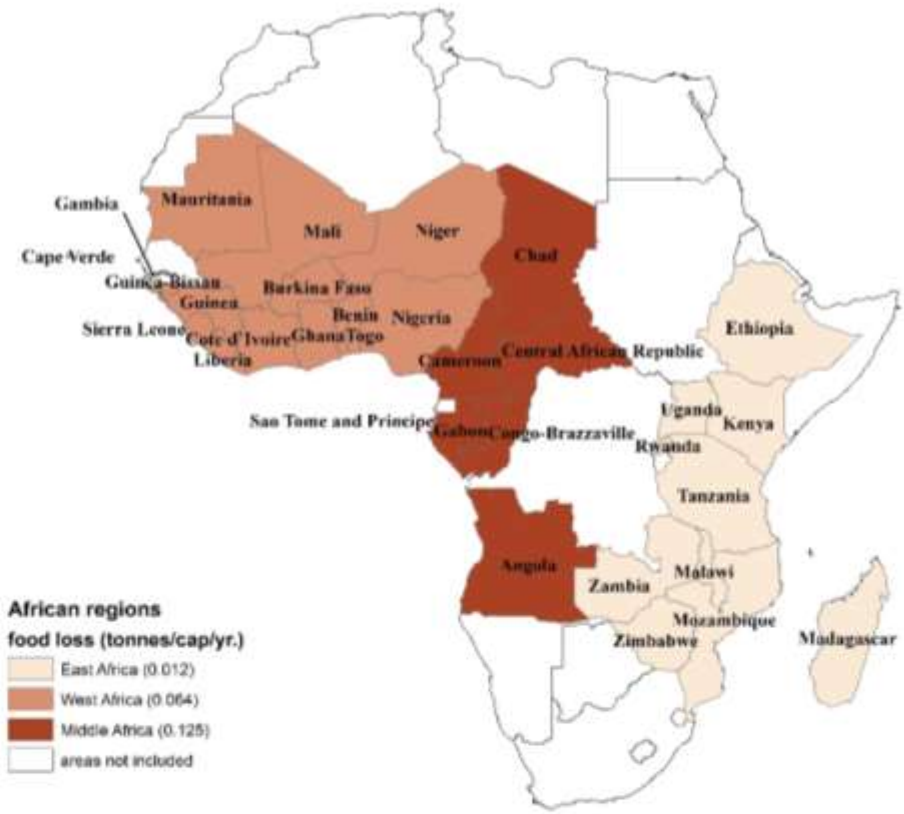



**Fig. 5**. Spatial distribution of FL in African regions in 2025. Note that blank nations were not included due to lack of data.

### 3.3. Future water requirement to produce R&T crops

Table 4 presents the projected CWR required to produce the selected R&T crops in different African regions in 2025. Our results show that in 2025, yam is expected to require less water (577.14 $m^3$/tonne) than other crops in East Africa. This finding is despite the longer growing period (over 252 days) of this tuber. The lowest water requirement for yam is expected to be in East Africa compared to that in Middle and West Africa, and may be attributed to the relatively higher yam yields in East Africa. This amounts to nearly double that of the Middle and West Africa regions (assuming yield is unchanged between 2018 and 2025) (FAO, 2019b). In Middle and West Africa cassava is forecast to be the least water consuming crop, with water requirements equal to 640.59 $m^3$/tonne and 835.55 $m^3$/tonne, respectively. This may also be attributed to the higher cassava yields in the relevant regions.

Interestingly, all studied R&T crops (excepting cassava) are forecast to require more water in West Africa than in Middle and East Africa. The reason for this may be due to the warmer climate expected in West Africa. Indeed, parts of West Africa extending from central Nigeria and crossing almost all West African territories to Senegal (far West Africa) are classed as tropical zone (Adams et al., 1996). This zone is characterized by a relatively long dry season marked by high temperatures as well as diffuse tree covering (Adams et al., 1996). This effect likely to reduce tree derived humidity and shading, leading to greater exposure of crops to sunshine and greater evapotranspiration from crops (an increase in CWR). This finding is in line with studies by Möller and Assouline (2006) and Sharma et al. (2015), which found that crops cultivated under shade have a tendency to require less water. Whilst shade is capable of reducing ambient temperature (Dussadee et al., 2018), it is well-known that high ambient temperatures raise crop evapotranspiration (Haseeb, 2017). Other climatic factors explaining the higher forecast CWR for R&T production in West Africa are the lower humidity and higher wind speeds expected in 2025. These latter variables are known to influence CWR (Brouwer and Heibloem, 1986).

The highest water consuming crop across all African regions is expected to be "other" R&T. This may be a function of crop characteristics, since these R&T tend to have the largest leaf surface area (spatial distribution of leaves can significantly increase transpiration) compared to that of the other crops. The projected highest CWR is expected to be in West Africa, amounting to 2609.31 $m^3$/tonne. Overall, on an average basis, crops cultivated in Middle Africa are forecast to require less water than those in East and West Africa. This is attributed to an expected favourable climate condition in Middle Africa characterized by lower wind speeds and higher humidity. Moreover, "other" R&T has the lowest yield amongst the other crops, as well as a long growing period extending throughout the year. It should be noted that the CWR calculated for R&T production herein is defined as the theoretical water consumption required by crops to grow under ideal conditions. However, the actual CWR would likely be lower influenced by variables such as soil water stress (Allen et al., 1998). In general, the selected crops would have different water requirements due to differences in altitude and associated weather conditions in the relevant regions.

The CWR is a spatial and temporal variable, implying that within the same region a given crop is likely to have different water requirements for its growing period. The current values of CWR for production in Table 4 are forecast to be higher than the globally averaged figures provided in Mekonnen and Hoekstra (2011) (for example, the world average water requirement for cassava is 550m$^3$/tonne, whereas in the current study it ranges between 640.59 and 867.07 m$^3$/tonne; Table 4). This may be due to the effects of climate change in Africa, which is forecast to become relatively hotter and, in terms of range, to the uneven distribution of landscape and altitudes across a vast continent (Doorenbos and Pruitt, 1992). Overall, the amount of CWR presented in Table 4 are averages over the entire African region and reflect the different values of CWR for production that might occur in each geographical unit (country level) within each relevant region.

**Table 4**
Projected water requirements of different R&T crops in 2025 (m$^3$/tonne).

| Crop | East Africa | Middle Africa | West Africa | Global average |
|---|---|---|---|---|
| cassava | 867.04 | 640.59 | 835.55 | 550 |
| potato | 595.63 | 785.78 | 1448.19 | 224 |
| sweet potato | 732.74 | 885.90 | 2603.85 | 329 |
| "other" roots & tubers | 2172.58 | 1252.39 | 2609.31 | 388 |
| yam | 577.14 | 953.52 | 1454.32 | 341 |
| total average | 989.03 | 903.64 | 1790.24 | 364.5 |

Note the R&T crops are defined as in FAO. Hence, "other" R&T presented here includes cocoyam as the principle crop.

### 3.4. Projected water loss associated with future food loss

The results showing the impact of future FL generation on water resource are depicted in Fig. 6. The total water loss embodied in FL across all regions is expected to be 69.19×10$^9$ m$^3$ in 2025, of which 75.49%, 16.59%, and 7.9% will be in West, Middle, and East Africa respectively. As can be seen, West Africa is expected to lose significantly more water to FL, amounting to 52.24×10$^9$ m$^3$ (Fig. 6- a). This finding may be attributed to the forecasted large magnitude of FL, combined with future climate-induced drastic weather variables manifest in evapotranspiration. As corroborated in previous study by Liu and Yang (2010), West Africa has a relatively higher magnitude of consumptive water for crop production compared to Middle and East Africa. Indeed, FL is associated to production (The Economist Intelligence Unit, 2014). The highest production of R&T in West Africa (compared to other regions) combined with its consumptive water would likely lead to more water loss. While water loss embodied in FL is projected to be lower in Middle Africa (11.48×10$^9$ m$^3$) and in East Africa (5.74×10$^9$ m$^3$). In general, forecast water loss in West Africa represents approximately four and nine times that of Middle and East Africa respectively. However, looking at projected per capita water loss embodied in FL in Middle Africa (112.80 m$^3$) and West Africa (114.37 m$^3$) (Fig. 6- b), there is only a slight difference of 1.56 m$^3$/cap/yr. The higher per capita water loss forecast in Middle Africa compared to East Africa (12.06 m$^3$/cap/yr) can be attributed to the lower population expected to be partaking in FL generation in 2025 in the former. In contrast, East Africa is expected to have the lowest water loss per capita because of its larger forecast population, nearly in the range of that of West Africa. There is no doubt that FL implicitly leads to loss of water resources. Considering the renewable water resources in 2017 in each region (FAO, 2020), the expected water embodied in FL would represent 60%, 5.63%, and 4.96% of the total average renewable water resources in West, East, and Middle Africa, respectively. This large share of water loss in West Africa (60%) may be due to the lower water endowment in the region (compared to East and Middle Africa) associated to large production of R&T inducing FL (agriculture is well-known to be the most water consuming activity (Döll, 2009). Indeed, R&T is the major crop type cultivated in West Africa leading the region as the second largest producer of R&T in the world. Note that even if the share of water loss embodied in FL is expected to be relatively lower in East Africa (5.63%) than that of West Africa, particular attention should be paid in East Africa since the latter presents physical water scarcity in some parts (Ethiopia, Uganda, Rwanda) (AQUASTAT, 2020). Furthermore, assuming the expected amount of water embodied in FL as blue water equivalent (we make this assumption because green water has less opportunities in use than blue), it could be used to produce about 29.18 $\times 10^6$, $12.7\times 10^6$, and 5.8 $\times 10^6$ tonnes of R&T (considering the total average in each region, Table 4) in West, Middle, and East Africa respectively. This would help to feed approximately 35.03, 15.25, and 6.97 million people per year in West, Middle, and East Africa, respectively (considering the minimum daily energy requirement for a healthy life to 2100kcal/cap/day as defined by the World Health Organization (WHO) (Kummu et al.,2012), resulting in improving food security in the relevant African regions. These show the need to address FL as well as water mitigation strategies.

Fig.7 shows the differences amongst estimated water loss embodied in FL in 2025, scenario S1, and water embodied in FL at 2013 levels. The total water loss embodied in FL for all studied regions amounts to $11.43\text{x}10^9$ $m^3$in 2013. The expected increase in water loss between 2013 and 2025 in West Africa was found to be the largest (558.79% increase based on 2013 levels), followed by that of Middle Africa (498.78% increase), and East Africa (246.46% increase). Considering scenario S1, i.e. the CWR for production in 2025 remains unchanged from 2013 levels equal to those provided in Mekonnen and Hoekstra (2011), the total water loss embodied in FL across all regions is $15.93\text{x}10^9$ $m^3$of which 63.56%, 24.64%, and 11. 8% is expected to be in West, Middle, and East Africa respectively. The increase in water loss embodied in FL according to scenario S1 is higher in Middle Africa, i.e. 104.78%, while in

West and East Africa it is 27.72% and 19.05% respectively. If scenario S1 is realised, the change between the projected water embodied in FL (estimated in this study) and the water loss obtained from scenario S1 will lead to a reduction in water loss amounting to $42.1 \times 10^9$ $m^3$ and representing 531.07 % of the total water loss at 2013 levels in West Africa. While, in Middle and East Africa, that change would lead to reductions amounting to $7.55 \times 10^9$ $m^3$ (394% at 2013 levels) and $3.59 \times 10^9$ $m^3$ (227.40 % at 2013 levels) respectively. Overall, the achievement of scenario S1 would be useful in reducing the pressure on water resources. This is shown by the previous results of water loss reduction in different African regions (Fig. 7). The justification of these water reductions lies on the fact that the CWR used in scenario S1 is relatively lower compared to the one estimated in this study. Consequently, considering the same magnitude of FL in 2025, scenario S1 will lead to significant water loss reduction compared to the estimated water loss in this study.

We do acknowledge that the achievement of scenario S1 would be difficult across all three studied African regions. This is in great part connected to the high interdependence of CWR for production and the dynamics of anthropogenic climate change; the latter being greatly influenced by socioeconomic factors. Attention should be paid to reducing future CWR for production and FL, as well as to release pressure on water resources. As such, measures which may be taken to reduce future total water needed in crop production, at least to some extent, are (a) development and use of high yielding varieties of R&T characterised by shorter growing periods, and which are more resistant to drought; (b) the integration of water-saving technologies, including deep ploughing into standard agricultural practice; and (c) a shift in production towards less water consuming R&T such as cassava in Middle and West Africa and yam in East Africa. However, we recognise this may lead to other issues such as loss of culinary habits and financial losses to farmers (derived from the reduction of crop less produced). Care should therefore be taken when implementing such approaches. Reducing FL may also be encouraged through development of local food markets, upgrading food storage and transport facilities, and promoting food reduction habits amongst consumers.

### 3.5. Limitations

This study contains some limitations linked to both data and model development. We used FL data from FAO, which raises the concern of its completeness, collection and accuracy to adequately describe the real situation (Corrado et al., 2019; Xue et al., 2017). In developing our models, the use of the notion of causality can make one consider it as "the generator/cause of FL" in literal terms, however, it should be perceived as what comes before FL (Hacker and

Hatemi-J, 2006). Hence, causality in this context may involve other intermediate variables which were assumed to be captured by the independent variables considered in this study. Additionally, combining two models may generate more errors (associated to each model) than using one. Developing our models has implicitly involved one "sub-model" (the one linked to the forecast of the independent variable). The combined effect of one model with its sub-model might lead to a bias in the forecast values of FL. Furthermore, the forecasted values of FL are expected only if those of the independent variables are "true". Hence, using "conditional forecast" (the one using observed/defined values of the independent variable in the future) may reduce the bias issue.

The CWR for production calculated during our study was done assuming that crop yield in 2025 would be the same as in 2018, being the latest set of available data. We recognise this assumption is unlikely to be the case since crop yield will change in the future, influenced by factors such as climate, demand, agricultural policies to name but a few (Tingem et al., 2008). Such crop yield variations would likely increase/decrease the amounts of CWR presented in this study. This assumption was made based on the example of one African country, Cameroon, where it was indicated that crop yield is likely to decrease or remain more or less unchanged in to the future (Abia et al., 2016). We do however believe that the resulting CWR for production reflects the maximum future water which will be used for crop growth in the relevant African regions.

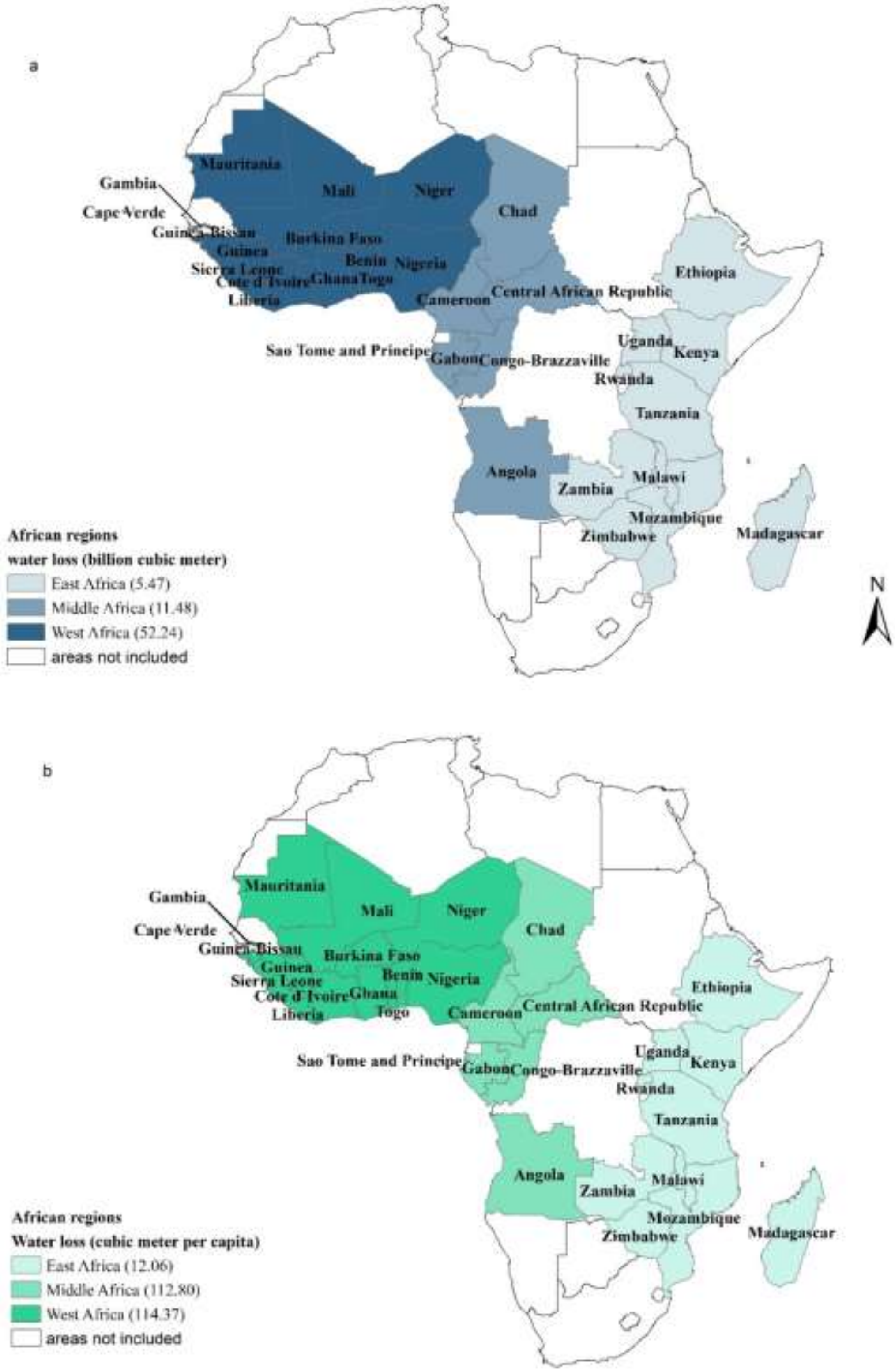



**Fig. 6.** Mapping projected water loss embodied in FL in 2025 in African regions: (a) total water loss embodied in food loss (FL) per African region, and (b), total water loss embodied in FL per capita per year. Note that blank areas were not investigated due to insufficient data.

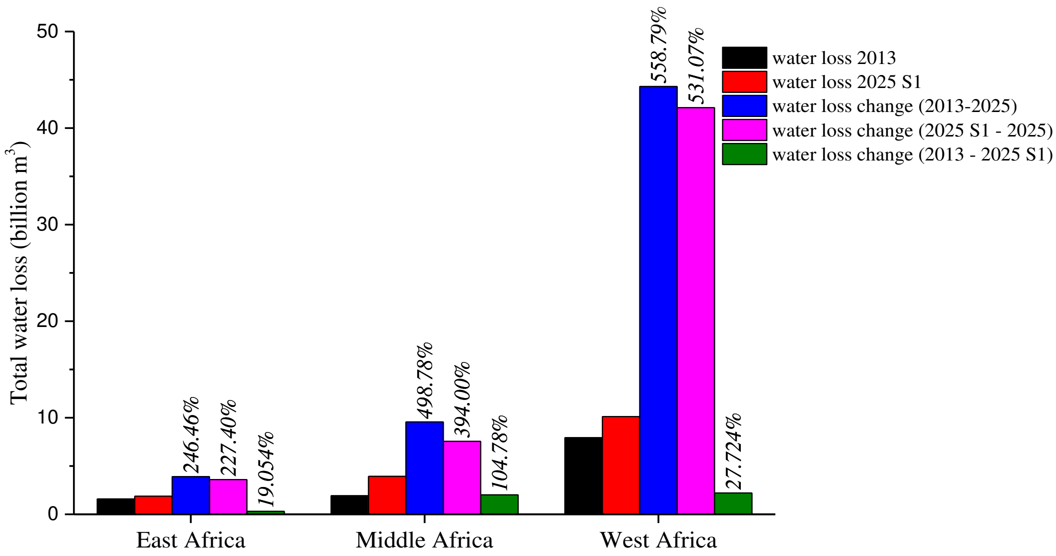



Fig. 7. Scenario analysis of projected water embodied in food loss (FL) in East, Middle, and West Africa at 2013 level. Note that 2013 and 2025 S1 utilised crop water requirement (CWR) data provided in Mekonnen and Hoekstra (2011), while 2025 used CWR estimated in the present study.

## 4. Conclusions

Climate change variables such as temperature (Temp), precipitation (Pre), and wind speed can potentially affect food loss (FL) and associated water resource loss. Here, we used five exogenous variables including two climatic variables (Pre and Temp), two food production variables (harvest area and food production), and one economic variable (gross domestic product, GDP) to forecast the magnitude of R&T losses for cassava, potato, sweet potato, yams, and "other" roots & tubers. By means of the ARIMAX model forecasting up to 2025 for East, Middle, and West Africa was completed. Due to data limitations it was not possible to model for all SSAn regions. Additionally, future climatic variables including wind speed, relative humidity, and sunshine hours were used to quantify the future water embodied in FL. Our findings reveal the projected magnitudes of FL in 2025 amount to 29.18, 12.7, and 5.53 million tonnes in West, Middle, and East Africa respectively. These correspond to a FL increase, amounting to 104.78%, 27.72%, and 19.06% of total FL in 2013 in Middle, West, and East Africa respectively. In addition, the effect of climate change is expected to increase R&T water requirements in different ways in each African region. Water requirements are expected to be higher in West Africa (1790.24 m$^3$/tonne) than in East Africa (989.03 m$^3$/tonne) and Middle Africa (903.64 m$^3$/tonne). Furthermore, the future magnitude of FL associated to climate change will lead to water embodied in FL amounting to 114.36 $m^3$/cap/yr for West Africa, 112.80 $m^3$/cap/yr for Middle Africa, and 12.06 $m^3$/cap/yr for East Africa.

Since the present study was based on regional averages and aggregated values of climatic variables (temperature, precipitation, relative humidity etc.) to investigate crop water requirement (CWR) for production at a regional level, one might further investigate future CWR at the country level in order to capture differences which may occur from one country to another. In addition, future crop yield relating to a target year should be considered in evaluating future CWR, and soil water stress may also be integrated to obtain the actual CWR. A final point worth consideration when investigating future CWR for production, is the differentiation between blue, green and grey water. This would help address the issue of water scarcity (blue water), the magnitude of future irrigation that would be required (blue and green water), and the level of water pollution (grey water). This information would help define agricultural policy for sustainable agriculture throughout Africa.

**Declaration of conflicting interests:** none.

**Acknowledgements**

This work was supported by the National Natural Science Foundation of China (No. 72074136; 72033005; 72022009). The authors are grateful to Albert Ling Sheng Chang for his valuable assistance.

**References**

Abass, A. B., Ndunguru, G., Mamiro, P., Alenkhe, B., Mlingi, N., Bekunda, M., 2014. Post-harvest food losses in a maize-based farming system of semi-arid savannah area of Tanzania. J. Stored Prod. Res. 57, 49-57.

Abia, W.A., Shum, C.E., Fomboh, R.N., Ntungwe, E.N., Ageh, M.T., 2016. Agriculture in Cameroon: Proposed Strategies to Sustain Productivity. International Journal for Research in Agricultural Research 2, 13.

Adams, W.M., Goudie, A., Orme, A.R., 1996. The physical geography of Africa. Oxford University Press.

Aldaya, M.M., Chapagain, A.K., Hoekstra, A.Y., Mekonnen, M.M., 2012. The water footprint assessment manual: Setting the global standard, Routledge.

Alimi, S.R., Ofonyelu, C.C., 2013. Toda-Yamamoto causality test between money market interest rate and expected inflation: the Fisher hypothesis revisited. Eur. Sci. 9.

Allen, R.G., Pereira, L.S., Raes, D., Smith, M., 1998. FAO Irrigation and drainage paper No. 56. Rome: Food Agriculture Organization of the United Nations 56, e156.

Andrews, B.H., Dean, M.D., Swain, R., Cole, C., 2013. Building ARIMA and ARIMAX models for predicting long-term disability benefit application rates in the public/private sectors. Society of Actuaries, 1-54.

Anggraeni, W., Pusparinda, N., Riksakomara, E., Samopa, F., Pujiadi, 2017. The Performance of ARIMAX Method in Forecasting Number of Tuberculosis Patients in Malang Regency, Indonesia. Int. J. Appl. Eng. Res. 12, 6806-6813.

AQUASTAT, 2020. Distribution of physical water scarcity by major hydrological basin (Global). https://data.apps.fao.org/aquamaps/(accessed October 2020).

Aulakh, J., Regmi, A.J., 2013. Post-harvest food losses estimation-development of consistent methodology. 4-9.

Bocchiola, D., Nana, E., Soncini, A., 2013. Impact of climate change scenarios on crop yield and water footprint of maize in the Po valley of Italy. Agric. Water Manag. 116, 50-61.

Brouwer, C., Heibloem, M., 1986. Irrigation Water Management: Irrigation Water Needs.

Chatfield, C., 2000. Time-series forecasting. Chapman and Hall/CRC.

Chauvin, N.D., Mulangu, F., Porto, G., 2012. Food production and consumption trends in sub-Saharan Africa: Prospects for the transformation of the agricultural sector. UNDP Regional Bureau for Africa: New York, USA.

Cilliers, J., Hughes, B., Moyer, J., 2011. African Futures 2050-the next forty years. Institute for security studies monographs 2011, 102.

CRU, 2017. CRUTS v3.24.01 Data Variables. https://crudata.uea.ac.uk/cru/data/hrg/cru_ts_3.24.01/ (accessed 12 April 2019)

Corrado, S., Caldeira, C., Eriksson, M., Hanssen, O.J., Hauser, H.E., van Holsteijn, F., Liu, G., Ostergren, K., Parry, A., Secondi, L., Stenmarck, A., Sala, S., 2019. Food waste accounting methodologies: Challenges, opportunities, and further advancements. Glob. Food Sec. 20, 93-100.

Döll, P., 2009. Vulnerability to the impact of climate change on renewable groundwater resources: a global-scale assessment. Environ. Res. Lett. 4.

Doorenbos, J., Pruitt, W.O., 1992. Calculation of crop water requirements. FAO irrigation drainage paper, 1-65.

Dussadee, N., Ramaraj, R., Sutassanamarlee, N., 2018. Effect of Plant Shading and Water Consumption on Heat Reduction of Ambient Air. Chiang Mai J. Sci. 45, 188-197.

Ewaid, S.H., Abed, S.A., Al-Ansari, N., 2019. Crop Water Requirements and Irrigation Schedules for Some Major Crops in Southern Iraq. Water 11,756.

FAO, 1986. Irrigation Water Management: Irrigation Water Needs

FAO, 2018. The State of Food Security and Nutrition in the World 2018. Building climate resilience for food security and nutrition, Rome.

FAO, 2019a. Food balance sheets - Food losses. http://www.fao.org/faostat/en/#data/FBS/ (accessed 12 June 2019).

FAO, 2019b. FAOSTAT- Crops production. http://www.fao.org/faostat/en/#data/QC/ (accessed October 2019).

FAO, 2020. AQUASTAT. http://www.fao.org/nr/water/aquastat/data/query/index.html?lang=en (accessed 12 October 2020).

Feukam Nzudie, H.L., Zhao, X., Liu, G., Tillotson, M.R., Hou, S., Li, Y., 2020. Driving force analysis for food loss changes in Cameroon. J. Clean. Prod., 123892.

Foresti, P., 2006. Testing for Granger causality between stock prices and economic growth.

Gustavsson, J., Cederberg, C., Sonesson, U., Van Otterdijk, R., Meybeck, A., 2011. Global food losses and food waste. FAO, Rome.

Hacker, R.S., Hatemi-J, A.J., 2006. Tests for causality between integrated variables using asymptotic and bootstrap distributions. Theory Appl. 38, 1489-1500.

Hamjah, M.A., 2014. Temperature and Rainfall Effects on Spice Crops Production and Forecasting the Production in Bangladesh: An Application of Box-Jenkins ARIMAX Model. Journal Mathematical Theory Modeling 5, 45-59.

Haseeb, J., 2017. Factors Affecting Crop Water Requirements. Water Resources Engineering. https://www.aboutcivil.org/factors-affecting-crop-water-requirement.html/ (accessed 1 February 2017).

Hope, K.R., 1998. Urbanization and urban growth in Africa. J. Asian Afr. Stud. 33, 345-358.

Huang, T., Li, B., Shen, D., Cao, J., Mao, B., 2017. Analysis of the grain loss in harvest based on logistic regression. Procedia Comput. Sci. 122, 698–705.

IPCC, 2020. Data Distribution Centre. http://www.ipcc-data.org/sim/gcm_monthly/SRES_AR4/index.html/ (accessed 2 February 2020).

Kaminski, J., Christiaensen, L., 2014. Post-harvest loss in sub-Saharan Africa—what do farmers say? Glob. Food Sec. 3, 149-158.

Kenyon, L., Anandajayasekeram, P., Ochieng, C., Ave, C., Uk, K., 2006. A synthesis/lesson-learning study of the research carried out on root and tuber crops commissioned through the DFID RNRRS research programmes between 1995 and 2005. DFID, United Kingdom.

Kummu, M., de Moel, H., Porkka, M., Siebert, S., Varis, O., Ward, P.J., 2012. Lost food, wasted resources: global food supply chain losses and their impacts on freshwater, cropland, and fertiliser use. Sci. Total Environ. 438, 477-489.

Kusangaya, S., Warburton, M.L., Archer van Garderen, E., Jewitt, G.P.W., 2014. Impacts of climate change on water resources in southern Africa: A review. Phys. Chem. Earth., Parts A/B/C 67, 47-54.

Le Roux, B., van der Laan, M., Vahrmeijer, T., Annandale, J., Bristow, K., 2018. Water Footprints of Vegetable Crop Wastage along the Supply Chain in Gauteng, South Africa. Water 10, 539.

Liu, J., Lundqvist, J., Weinberg, J., Gustafsson, J., 2013. Food losses and waste in China and their implication for water and land. Environ. Sci. Technol. 47, 10137-10144.

Maddison, D., Manley, M., Kurukulasuriya, P., 2007. The impact of climate change on African agriculture: A Ricardian approach. The World Bank.

Liu, J., Yang, H., 2010. Spatially explicit assessment of global consumptive water uses in cropland: Green and blue water. J. Hydrol. 384, 187-197.

Manjula, K., Hell, K., Fandohan, P., Abass, A., Bandyopadhyay, R., 2009. Aflatoxin and fumonisin contamination of cassava products and maize grain from markets in Tanzania and republic of the Congo. Toxin Rev. 28, 63-69.

Mekonnen, M.M., Hoekstra, A.Y., 2011. The green, blue and grey water footprint of crops and derived crop products. Hydrol. Earth Syst. Sc. 15, 1577-1600.

Mimikou, M.A., Baltas, E., Varanou, E., Pantazis, K., 2000. Regional impacts of climate change on water resources quantity and quality indicators. J. Hydrol. 234, 95-109.

Möller, M., Assouline, S., 2006. Effects of a shading screen on microclimate and crop water requirements. Irrig. Sci. 25, 171-181.

Muller, C., Cramer, W., Hare, W.L., Lotze-Campen, H., 2011. Climate change risks for African agriculture. PNAS USA 108, 4313-4315.

Ngopya, F., 2002. Importance of root crops in Africa. FAO.

Rathod, S., Singh, K.N., Arya, P., Ray, M., Mukherjee, A., Sinha, K., Kumar, P., Shekhawat, R.S., 2017. Forecasting maize yield using ARIMA-Genetic Algorithm approach. Outlook Agr. 46, 265-271.

Ravallion, M., Chen, S., Sangraula, P., 2007. New Evidence on the Urbanization of Global Poverty. Popul Dev Rev 33, 667-701.

Rezaei, M., Liu, B., 2017. Food loss and waste in the food supply chain. Tech. Rep., Nut Fruit, FAO.

Ridoutt, B.G., Juliano, P., Sanguansri, P., Sellahewa, J., 2010. The water footprint of food waste: case study of fresh mango in Australia. J. Clean. Prod. 18, 1714-1721.

Scott, G.J., 2000. Roots and tubers in the global food system: A vision statement to the year 2020. Iita.

Scott, G.J., Rosegrant, M.W., Ringler, C., 2000. Roots and Tubers for the 21st Century Trends, Projections, and Policy Options (Vol. 31). Intl. Food Policy Res. Inst.

Sharma, P., Kothari, M., Lakhawat, S.S., 2015. Water requirement on drip irrigated tomatoes grown under shade net house. Engineering and Technology in India 6, 12-18.

Shrestha, S., Chapagain, R., Babel, M.S., 2017. Quantifying the impact of climate change on crop yield and water footprint of rice in the Nam Oon Irrigation Project, Thailand. Sci. Total Environ. 599, 689-699

Stancalie, G., Marica, A., Toulios, L., 2010. Using earth observation data and CROPWAT model to estimate the actual crop evapotranspiration. Phys. Chem. Earth., Parts A/B/C 35, 25-30.

Stige, L.C., Chan, K.-S., Zhang, Z., Frank, D., Stenseth, N.C., 2007. Thousand-year-long Chinese time series reveals climatic forcing of decadal locust dynamics. PNAS 104, 16188-16193.

Sutthichaimethee, P., Ariyasajjakorn, D., 2017. Forecasting Energy Consumption in Short-Term and Long-Term Period by Using ARIMAX Model in the Construction and Materials Sector in Thailand. J. Ecol. Eng. 18, 52-59.

The Economist Intelligence Unit, 2014. Food loss and its intersection with food security.

The Open University, 2016. Urbanisation: Trends, Causes and Effects. https://www.open.edu/openlearncreate/mod/oucontent/view.php?id=79940&printable=1/ (accessed 12 October 2020)

Tingem, M., Rivington, M., Bellocchi, G., Azam-Ali, S., Colls, J., 2008. Effects of climate change on crop production in Cameroon. Clim. Res. 36, 65-77.

Udom, P., Phumchusri, N., 2014. A comparison study between time series model and ARIMA model for sales forecasting of distributor in plastic industry. IOSR-JEN. 4, 32-38.

United Nations, 2019. Total population.

http://data.un.org/Data.aspx?q=population&d=PopDiv&f=variableID%3a12/(accessed 17 June 2019).

Xue, L., Liu, G., Parfitt, J., Liu, X., Van Herpen, E., Stenmarck, A., O'Connor, C., Ostergren, K., Cheng, S., 2017. Missing Food, Missing Data? A Critical Review of Global Food Losses and Food Waste Data. Environ. Sci. Technol. 51, 6618-6633.

Zhao, X., Tillotson, M.R., Liu, Y.W., Guo, W., Yang, A.H., Li, Y.F., 2017. Index decomposition analysis of urban crop water footprint. Ecol. Model. 348, 25-32.