African Journal of Rural Development, Vol. 5 (2):April-June 2020: pp. 69-86. ISSN 2415-2838

Resource use efficiency among maize producers around East African wetlands: An agricultural land-use management systems perspective

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ABSTRACT

An efficient food production system bridges the gap between sustainable food production and wetland conservation. Often maize is grown under three agricultural land-use management systems, namely, upland-rainfed, upland-irrigated, and wetland-only. This study assessed technical efficiency among 300 randomly selected maize producing households at Ewaso Narok and Namulonge wetlands in Kenya and Uganda, respectively. Data analysis utilized a one-step stochastic frontier analysis using FRONTIER 4.1c software. The study revealed that the upland-irrigated system was associated with the highest efficiency. Land, seeds, manure, basal fertilizers, pesticides, and labor were among the major determinants of maize yield. Age, group membership, gender, farming experience, distance to the extension service provider, and upland-rainfed system were the significant determinants of inefficiency. The study concluded that government policies should consider different wetland regimes and encourage maize farmers to grow maize under the upland-irrigated system using subsidized alternative sources of water to reduce pressure on wetland resources.

Key words: Agricultural land-use management systems, Kenya, maize production, technical efficiency, Stochastic Frontier Analysis

RÉSUMÉ

Un système efficace de production alimentaire comble le fossé entre la production alimentaire durable et la conservation des zones humides. La culture du maïs est souvent sujette à trois systèmes de gestion de l'utilisation des terres agricoles, à savoir, régime pluvial sur terres fermes, irrigation sur terres fermes et les bas-fonds. La présente étude a évalué l'efficacité technique de 300 ménages producteurs de maïs échantillonnés au hasard dans les zones humides d'Ewaso Narok au Kenya et de Namulonge en Ouganda. Le modèle d'analyse de frontière stochastique à une étape a été utilisé dans logiciel FRONTIER 4.1c pour traiter les données. L'étude a révélé que le système irrigué des terres émergées avait la plus grande efficacité. La terre, les semences, le fumier, les engrais de base, les pesticides et la main-d'œuvre étaient les principaux déterminants du rendement du maïs. L'âge, l'appartenance aux groupes, le genre, l'expérience agricole, la distance par rapport au bureaux des services de vulgarisation et le régime pluvial étaient les déterminants significatifs de l'inefficacité. L'étude a conclu que les politiques gouvernementales devraient envisager la mise en œuvre de différents régimes dans les bas-fonds et encourager les producteurs de maïs à utiliser le système irrigué sur terres fermes, en utilisant des sources d'eau alternatives subventionnées pour réduire la pression sur les ressources des zones humides.

Mots clés : Systèmes de gestion de l'utilisation des terres agricoles, Kenya, production de maïs, efficacité technique, analyse des frontières stochastiques

Cite as: Kamau, P.N., Willy, D.K. and Ngare L.W. 2020. Resource use efficiency among maize producers around East African wetlands: An agricultural land-use management systems perspective. *African Journal of Rural Development* 5 (2): 69-86.

Received: 27 July 2019
Accepted: 14 May 2020
Published: 30 June 2020

INTRODUCTION

East Africa faces low agricultural productivity and food insecurity (FAO, IFAD, & WFP., 2015). Moreover, low agricultural production accounts for poverty among many of the rural inhabitants given that the agricultural sector employs nearly 75%, and 66% of the Kenyans and Ugandans, respectively (MoAAIF, 2011; IFAD, 2014). Agriculture also supports approximately 30% and 21% of Gross Domestic Product (GDP) in Kenya and Uganda, respectively. Besides the national efforts, some international bodies such as the Food and Agriculture Organization (FAO) and International Fund for Agricultural Development (IFAD) are providing support towards the improvement of agricultural productivity in the region (FAO, IFAD and WFP, 2015).

There is still widespread low productivity of maize, which is the major staple food crop in East Africa despite different national and international interventions (Macauley, 2015). In Kenya, the Kenya Seed Company (KSC) and Kenya Agricultural and Livestock Research Organization (KALRO) among other organizations have introduced high yielding varieties such as KS-DH13, KS-H6217 and KH 600-23A (Kang'ethe, 2011). Productivity, still remains low with an average yield of 1.8 t ha^{-1} against a potential yield of over 6 t ha^{-1} (Schroeder *et al.,* 2013; One Acre Fund , 2015). In Uganda, the National Crops Resources Research Institute (NaCCRI) has also released high-yielding, drought-tolerant, and pests and diseases resistant maize varieties such as Longe 10 and Longe 11. However, yields stagnate at 1.5 t ha^{-1} against a possible yield of 7 t ha^{-1} (Okoboi *et al.,* 2012).

One of the farmers' practices of increasing crop production is the opening out of agricultural lands in productive fragile ecosystems such as wetlands (Turyahabwe *et al.,* 2013). As such, crop production in wetlands is under different agricultural land-use management systems (ALUMSs) namely upland-rainfed, upland-irrigated, and wetland-only. The upland-irrigated and wetland-only systems assist farmers in managing risks associated with agricultural production under unpredictable climatic conditions. Agricultural production under the upland-rainfed system has no direct anthropogenic impact on the wetland ecosystem because farmers depend on rain for water. The effect is only felt due to unsustainable intensifications where agrochemicals may leach out to the wetland ecosystem, thus degrading water and soil. The upland-irrigated may involve the use of wetland water in irrigation of crops, especially in commercial farming (Kyalo and Heckelei, 2018). The wetland-only system involves the creation and maintenance of canals in the wetlands to create arable farms from the marshes. The system directly interferes with the natural processes, such as hydrology and soil formations, that take place in wetlands (Turyahabwe *et al.,* 2013).

Unregulated farming practices such as overuse of agrochemicals (especially pesticides and inorganic fertilizers) and uncontrolled traditional irrigation has caused a deterioration in wetlands' health (Baldock *et al.,* 2000). The negative effects of such practices on wetlands include water regime changes, groundwater reduction, habitat loss, and vegetation loss (Raburu *et al.,* 2012). Through regulating the intensification in agriculture and controlling the use of wetland water, the wetlands will retain their natural capacity to hold water supply (FAO, 2008). The unregulated use of inputs that exacerbates degradation of wetlands resources can be addressed through more efficient production practices (Pretty and Bharucha, 2014).

Wetlands play several critical ecosystem functions such as ecosystem conservation, among others (Wood *et al.,* 2013; IWMI, 2014). Notably, agriculture is the most significant menace to wetlands as farmers have widely and permanently transformed wetlands to enhance agricultural productivity. One approach of mitigating the negative impact of agriculture around East African wetlands is through encouraging practices that minimize the externalities from farming activities while producing food efficiently. Also, given that farmers engage in crop production under different agricultural land-use systems, there is a need to identify the system that is associated with the optimal resource use, thus the highest technical efficiency (TE) to ensure appropriate resource usage and allocation.

Technical efficiency can be defined as the ability of an individual farm to convert resources (inputs) into maximum products (outputs) based on the inputs mix (Toma *et al.,* 2015; Kansiime *et al.,* 2018). It presents the performance of the transformation process of inputs into outputs. It also depicts the optimality of a production process due to a reduction in wastage of inputs. Efficiency can either be output-oriented or inputs-oriented. The output-oriented technical efficiency (TE) allows farmers to achieve maximum output using the available quantities of inputs while the input-oriented technical efficiency allows farmers to achieve a given output using minimal quantities of inputs at a given technology (Hong *et al.,* 2019). Normally, due to scarcity of resources, many farmers attempt to achieve the output-oriented efficiency. For a farm to be termed as technically efficient, it has to produce output at the best level or the frontier, implying no inputs wastage. Typically, the expected production frontier is rarely realized due to random factors such as pests, diseases, and climate vagaries. The measurement of technical efficiency helps farmers to identify the target factors that need to be addressed to achieve maximum output through the separation of managerial weaknesses from inefficiency.

Efficient production is essential as it minimizes the wetland degradation due to expansion of arable lands into marshes and unsustainable intensification as farmers attempt to increase their crop yields (Pretty and Bharucha, 2014). Food production in East African wetlands must be technically efficient to thwart further anthropogenic damages. Efficient production will ensure a reduction of unsustainable agricultural intensification from improper inputs use that may exacerbate soil degradation (Willy *et al.,* 2019). With high technical efficiency in resource use, wetlands will support food security as well as the provision of the other critical ecosystem services.

Several studies have highlighted the threat of anthropogenic degradation to wetlands (Schuyt, 2005; Halima *et al.,* 2009; McCartney *et al.,* 2010; Turyahabwe *et al*., 2013; Gardner *et al.,* 2015). The process is hastened by pressures associated with population density growth, urbanization, and changes in weather patterns (FAO and IWMI, 2017). Besides all these dynamics, wetlands are still facing pressure from multiple competing uses and this requires efficient production to sustain their capacity (Kyalo and Heckelei, 2018). However, there is dearth of scientific studies on technical efficiency among maize farmers around the East African wetlands considering the different agricultural land-use management systems under which farmers engage in crop production. This is despite the contribution of wetlands to food security while degradation continues to threaten their existence. Further, determining the efficiency levels in each system can guide policy to develop targeted strategies on how to improve efficiency in wetland farming since blanket approaches may not bear the targeted fruits. We, therefore, carried out cross-sectional research on two wetlands in East Africa to assist in understanding the agricultural intensifications and efficiency under different systems in the wetland zones. The research questions that guided the study were; What are the determinants of maize yield among the inputs used in East African wetlands?; Which agricultural land use management system (ALUMS) is associated with the highest productive efficiency and would be best suited for sustainable wetland conservation?; and What are the socio-demographic, economic and institutional factors that influence the technical efficiency in maize production?

MATERIALS AND METHODS

The study area. The current research was done in two wetlands located in Kenya and Uganda. They represent two types of wetlands namely highland floodplains and inland valley bottoms. The Ewaso Narok highland floodplain in Kenya is located along the Eng'are Narok River, within Laikipia County (Thenya, 2001). The wetland starts at the Rumuruti-Nanyuki road and stretches about 17 km up to the veterinary out span close to the Ol'Maisor ranch. The area experiences a semi-arid climate. Mean annual rainfall received ranges between 400 mm and 840 mm (Mwita, 2013). Long rains in the area are experienced from March to May and short rains fall between October and November. There have been increasing incidences of cultivation of maize, tomatoes, and beans due to human population increase (Thenya *et al.,* 2011). The Namulonge wetland is at Kyaddondo County in the Wakiso district of Uganda. The inland valleys are located at the site of NACRRI and extend to areas near Lake Kyoga, Lake Victoria, Jinja and Kampala around the Ugandan equator (Leemhuis *et al.,* 2016). The area is characterized by broad valleys, which have swamps and several flat-topped hills. Besides, the wetland experiences a sub-humid climate and receives a mean annual rainfall of 1170 mm. Mean temperature ranges between 15^0C to 30^0C (Nsubuga *et al.,* 2011). Major crops grown are maize, sweet potatoes, beans, cassava, and bananas.

Data and sampling procedures. Within each target wetland, a sampling frame was generated, which comprised of the households who were engaged in maize farming within and around the wetland. The sample size was determined using the formula by Kothari (2004). The primary data used for the current research were acquired over a cross-sectional survey from 300 randomly selected maize-farming households located near the target wetlands. Each wetland had 150 maize-farming households randomly selected. Maize farming households were purposively selected since maize is a staple crop that almost all farmers around East African wetlands engage in its production (Alibu *et al.,* 2019; Ondiek *et al.,* 2020).

In Ewaso Narok, a two-stage sampling process was used because the wetland was well defined. First, administrative officers and knowledgeable villagers assisted in listing all the villages located around the wetlands. Secondly, in order to ensure a reasonable representation of households across the entire wetland, all villages adjacent to the wetland were selected. A sampling frame was then developed from the sampled villages and each village, proportional to its size, contributed to the drawing of a random sample of households. In Namulonge, a three-stage sampling procedure was used because the wetlands were not well defined. First, a map of all the wetlands at Namulonge was obtained from the Wakiso district environmental officer. The map assisted in listing all the four major wetlands and later a random sample of wetlands was drawn. The selected wetlands were accessed and a list of villages around each of the wetlands developed with the help of the village elders. Then, the sampling process of the households that were to be included in the survey followed.

Data were later captured in a pretested semi-structured interview schedule.

Analytical framework

Measurement of technical efficiency. Two main approaches are used in the measurement of technical efficiency namely stochastic frontier analysis (SFA) (Aigner *et al.,* 1977) and data envelopment analysis (DEA) (Charnes *et al.,* 1978). The former is a parametric approach while the latter is a deterministic method that assumes all deviations from maximum production output are attributed to farmer's inefficiency. The data envelopment analysis approach can incorporate multiple inputs and outputs. However, it suffers serious limitations due to computational complexities and sensitivity to outliers. Also, due to the failure of data envelopment analysis to account for measurement errors, the mean technical efficiency is normally overestimated. As such, the current study used the stochastic frontier analysis model. The stochastic frontier analysis model separates the error term into inefficiency effects and random variations due to statistical noise and therefore, unlike the envelopment analysis, it allows for hypotheses testing regarding the production structure and the level of inefficiency (Coelli *et al.,* 2005).

Diagnostic tests . To determine if the traditional average response function, which is the ordinary least squares (OLS) was adequate over the stochastic frontier analysis model, a null hypothesis (H_0: γ=0) implying that the inefficiencies (U_i) are not stochastic was tested. If the null is true, SFA reduces to a conventional function due to a lack of inefficiency effects. The test uses lambda (λ), given by the generalized likelihood-ratio statistic in equation 1 (Battese and Broca, 1997), i.e.,

$$\lambda = -2[\ln\{L(H_0)\} - \ln\{L(H_1)\}] \qquad (1)$$

Where L (H_0) and {L (H_1) denote the null and alternative hypotheses respectively. If the null hypothesis (H0: γ=0) is not rejected, λ assumes a mixed χ^2 distribution. Consequently, a stochastic frontier analysis may not be the best analytical method since the error term assumes both inefficiency effects (U_i) and random effects (V_i). As such, the traditional average response function remains necessary as opposed to stochastic frontier analysis and the contrary is true.

Stochastic frontier analysis (SFA). The most common model specifications of stochastic frontier analysis are Cobb-Douglas (CD) and translog. The specification tests of multicollinearity and heteroscedasticity were performed on both models. First, the test for multicollinearity in the data was done using the variance inflation factor (VIF) in which $VIF_i = 1/1 - R_i^2$, where R_i^2 represents an R^2 in an artificial OLS that treats i^th^ explanatory variable as a "dependent" variable (Otieno *et al.,* 2012). As a rule of thumb, a VIF value greater than 10 reveals the presence of multicollinearity in the data (Gujarati, 2004). Secondly, Breusch-Pagan / Cook-Weisberg tests for heteroscedasticity were done where the null hypothesis was the assumption of homoscedasticity in data, $Var\varepsilon = E[\varepsilon - E(\varepsilon)] = \delta^2$. The translog model was disqualified due to high multicollinearity.

The stochastic frontier analysis model of the Cobb-Douglas function by Battese and Coelli (1995) is given as

$$Y_i = exp(x_{mi,}\beta_{i,} + \varepsilon_i) \qquad (2)$$

where i=1,2,...,m and $\varepsilon_i = V_i - U_i$, Y_i represents the i^{th} farm yield, x_i is the inputs vector for the i^{th} farm and β_i are the unknown parameters. The notation ε_i represents the error term composed of random error (V_i) that denotes the environmental influence, which has zero mean and variance N(0; σ_U^2). The term V_i is associated with measurement errors and factors which a farmer does not have control over. The term U_i is the other component of ε_i and it is a random non-negative ($U_i \geq 0$) half-normally distributed N(0; σ_U^2) variable that hinders a certain farm from achieving maximum output because it is associated with farm factors.

Two types of stochastic frontier analysis approaches exist, namely one-step and two-step estimation. One-step SFA estimation by Huang and Liu (1994) produces unbiased coefficients of inefficiency determinants compared to a two-step approach by Pitt and Lee (1981). Huang and Liu (1994) assumes U_i as truncated-normally distributed and combines production function with the inefficiency model. However, the efficiency estimates under such assumption reflect gross efficiency that is not totally adjusted for the influence of exogenous variables (Frohloff, 2007). It is under the half-normal distribution assumption of U_i where the analysis can obtain net efficiency by including the exogenous variables in the production function (Coelli *et al.,* 1999). The two-step approach suffers from a contradiction of the assumption of the distribution of the inefficiency term (U_i) in both stages. In the first step, the model estimates the stochastic frontier based on an assumption of half-normal distribution. In the second step, the inefficiency effects assume truncated-normal distribution to allow an estimation of the influence of exogeneous variables on (U_i) in a Tobit model. The inconsistency in the inefficiency distribution assumptions results to biased estimated in the second stage. Also, the first step assumes that inefficiency effects (U_i) have an independent and identical distribution (iid) but then regress the exogenous variables against the inefficiency indices.

The current study utilized a one-step estimation where U_i assumes a half-normal distribution and depends on exogenous factors Z_i where ($Z_i=Z_{1i},\ldots,Z_{mi}$). The inefficiency effects model is presented as

$$U_i = Z_i\delta + W_i \qquad (3)$$

where Z_i represents all possible factors that influence the i^th^ farm TE, δ represents the parameters to be estimated, and W_i represents the residual efficiency presented as the random error. The truncation of U_i is at zero with a constant variance $\sigma^U{}_2$ and mode $Z_i\delta$ changing over the farms. A log-likelihood function that assumes U_i and V_i being independently distributed of each other is presented by

$$lnY_i|\beta,\lambda,\sigma^2) = mln\frac{\sqrt{2}}{\sqrt{\Pi}} + mln\sigma^{-1} + \sum_{i=1}^{m}\ln[1 - F(\varepsilon_i\lambda\sigma^{-1})] - \frac{1}{2\sigma^2}\sum_{i=1}^{m}\varepsilon_i^2 \qquad (4)$$

where the term ε_i can be obtained by Y_i-$x_i\beta$ while F represents the distribution assumption, which is the conditional distribution function (cdf). The maximum likelihood estimation of equation (4) gives the values of parameters β,λ,σ. The TE of the i^{th} farm is thus expressed by the ratio of the observed production output (Y_i) to the highest predicted output (frontier output) (Y_i^*) (Furesi *et al.,* 2013). It is expressed in equation 5.

$$TE_i = \frac{Y_i}{Y_i^*} = \frac{Exp\ (\beta_0 + \sum_m \beta_m\ lnx_{mi} + V_i - U_i)}{Exp\ (\beta_0 + \sum_m \beta_m\ lnx_{mi} + V_i)} = Exp(-U_i) \qquad (5)$$

Technical inefficiency is then 1-TE_i and TE prediction requires that U_i should be estimated.

Equation 6 shows the estimation of the conditional expected value of U_i that best predicts U_i given ε_i.

$$E(U|\varepsilon) = \sigma_*\left[\frac{f(\varepsilon\lambda/\sigma)}{1 - F(\varepsilon\lambda/\sigma)} - \left(\frac{\varepsilon\lambda}{\sigma}\right)\right] \qquad (6)$$

From equation 6 $\lambda=\sigma_U/\sigma_V$, $\varepsilon\lambda = -U_*/\sigma_*$, and f is the normal density function (Jondrow *et al.,* 1982). The notations σ_* and U_* are unobservable thus they are replaced by their respective estimates giving technical efficiency as

$$TE_i = E[(exp(-U_i|\varepsilon_i] = \left\{\frac{1 - \Phi[\sigma_* - (U_i^*/\sigma_*)]}{1 - \Phi(-U_i^*/\sigma_*)}\right\} exp\left(-U_i^* + \frac{1}{2}\sigma_*{}^2\right) \qquad (7)$$

where Φ represents the cumulative density function (Battese and Coelli, 1988).

Model specification. The stochastic frontier analysis model of the production function in equation 2 per ALUMS was specified as

$$ln\,Y_i = \beta_0 + \sum_{m=1}^{8}\beta_m lnX_{mi} + v_i - u_i \qquad (8)$$

where ln = natural logarithm, β_0 β_{mi} = parameters to be estimated, $i=i^{th}$ farm, $m = m^{th}$ input, Y_i = farm yield, X_1= farm size (ha), X_2= family and hired labor (Man-days ha^{-1}), X_3= seed (Kg ha^{-1}), X_4=basal fertilizer (Kg ha-1), X_5=topdressing fertilizer (Kg ha^{-1}), X_6=manure (Kg ha^{-1}), X_7=pesticides (litre ha-1), X_8=herbicides (litre ha^{-1}), u_i = inefficiency component of the error term, and v_i represents the random error term.

The one-step stochastic frontier analysis inefficiency model of equation 3 specification for the two wetlands was given by

$$U_i = \delta_0 + \sum_{m=1}^{13} \delta_m Z_{mi} + W \qquad (9)$$

where U_i represents technical inefficiency, δ_m=unknown parameters, Z_1=gender (1= Female), Z_2=age (years), Z_3=education (years), Z_4=household size (number of persons), Z_5=farming experience (years), Z_6=extension access (Km to provider), Z_7 =credit access (1=Yes), Z_8 =group membership (1=Yes), Z_9=annual off-farm income (EURO), Z_{10}=market access (Km to product market), Z_{11}=ALUMS1 (upland-rainfed), Z_{12}= ALUMS2 (upland-irrigated), Z_{13} = ALUMS3. To avoid the problem of the dummy variable trap (Gujarati, 2004), the third ALUMS3 (wetland only) was dropped and became the benchmark variable in the model. ALUMSs were used to capture the variations in inefficiency among maize farmers within different management systems in the East African wetlands. The inefficiency model was analyzed for the two wetlands since most of the socioeconomic factors significantly varied depending on the wetland's country of location and not across ALUMSs.

RESULTS AND DISCUSSION

Descriptive statistics. Table 1 shows the descriptive statistics for some farmer and farm-specific characteristics. The mean age of maize farmers in Ewaso Narok and Namulonge were approximately 50 and 49 years, respectively. Maize farmers in Namulonge had acquired approximately eight years of formal schooling, which was significantly higher ($p<0.01$) than the six years that their Kenyan counterparts had acquired. The household size in Ewaso Narok was about five persons while in Namulonge, it was about six persons. Maize farming experience in Ewaso Narok was about 15 years,

Table 1. Descriptive statistics for some farmer and farm-specific characteristics

Variables	Pooled (N=300) Mean (SD)	Ewaso Narok (N=150) Mean (SD)	Namulonge (N=150) Mean (SD)	t-Value
Age (Years)	49.86 (13.24)	50.03 (13.96)	49.69 (12.5)	-0.222
Education (Years)	7.08 (5.03)	6.13 (5.06)	8.04 (4.82)	3.351***
Household size (Continuous number)	5.6 (2.42)	5.39 (2.33)	5.81 (2.5)	1.531***
Farming experience (Years)	11.93 (12.84)	15.23 (13.37)	8.61 (11.42)	-4.589***
Distance to Market (km)	4.86 (7.03)	6.95 (8.5)	2.78 (4.22)	-5.366***
Distance to extension agent (km)	8.5 (6.99)	7.34 (6.86)	9.65 (6.69)	2.889***
Total farm size (Ha)	2.54 (2.45)	2.44 (2.37)	2.64 (2.55)	0.671
Maize land (Ha)	0.59 (0.78)	0.75 (0.98)	0.41 (0.87)	-3.907***
Off-farm income (EURO)	1045.12 (3056.12)	752.72 (1039.50)	1337.52 (4182.08)	1.662*
	Percent	Percent	Percent	Chi^2 (χ^2)
Gender (1=Female)	32.3	38.7	26	5.500**
Group membership (1=Yes)	47.7	48	47.3	0.13
Credit access (1=Yes)	11	13.3	8.7	1.668

Notes: The figures in the parentheses are the standard deviations
*** $p<0.01$, ** $p<0.05$, * $p<0.1$
Source: Survey data, 2017

which was significantly higher ($p<0.01$) than nine years that the Namulonge counterparts had accumulated. Maize plots were approximately 0.75 and 0.41 hectares in Ewaso Narok and Namulonge, respectively. Ewaso Narok wetland maize producers received an off-farm income of about EUR 752.72, which was significantly lower ($p<0.01$) than EUR 1337.52 that their Namulonge wetland counterparts received.

Women maize producers in Ewaso Narok were about 39% in number, which was significantly higher than 26% in Namulonge. About 48% and 47% of maize producers in Ewaso Narok and Namulonge belonged to farmer groups. Credit was accessed by about 13% and 9% of maize producers in Ewaso Narok and Namulonge, respectively.

Figure 1 shows that about 45% and 95% of maize producers in Ewaso Narok and Namulonge respectively were under the upland-rainfed system. Those who produced under the wetland-only system in Ewaso Narok were about 39%. About 16% of maize farmers in Ewaso Narok engaged in maize production under the upland-irrigated system. The system is mainly utilized by farmers who majorly engage in commercial farming due to the costs that may be involved in the irrigation facilities acquisition and maintenance (Kyalo and Heckelei, 2018).

Table 2 shows that farmers under the upland-rainfed system had maize plots averaging at 0.7 ha, which was significantly higher ($p<0.01$) than 0.3 and 0.4 ha under the upland-irrigated and wetland-only systems respectively. Maize seeds planting rate across the three systems averaged at approximately 18 kg ha^{-1}. The rate was, however, lower than 25 kg ha^{-1} that Association for Strengthening Agricultural Research in Eastern and Central Africa recommends (Asea *et al.,* 2014). Both basal and topdressing fertilizers had the least usage under the upland-rainfed system. This may be attributed to the production risks that are associated with the system. As such maize producers may not invest so much on yield-enhancing inputs under this system compared to the other systems.

The number of person-days used under the

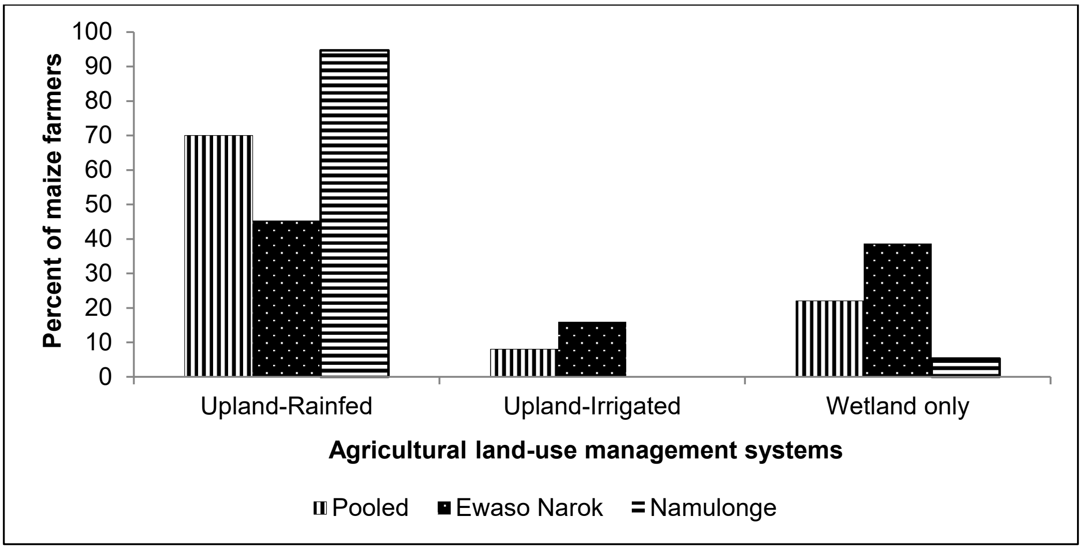

Figure 1. Agricultural land-use management systems under which farmers do their farming

wetland-only system for all maize production activities, ranging from land preparation to post-harvest handling, was the highest, averaging at about 60 person-days per hectare, which was significantly higher ($p<0.1$) than the rates under the other two systems. Weeds grow rapidly under the wetland-only systems, unlike the other two systems. Farmers are also required to make and maintain canals under the wetland-only system. Extensive weeding and canalization may contribute to higher labor demand under the wetland-only system compared to the other systems (Department of Ecology - State of Washington, 2010; Verhoeven and Setter, 2010).

Manure had the highest usage under the upland-irrigated system. Farmers under the upland-rainfed used significantly more pesticides and herbicides than farmers under the other two systems. Agricultural intensification in the upland plots has the potential to exacerbate the degradation of wetland ecosystems due to pesticide residues, leachates, and sediments, especially during heavy rains. Large maize plots under the upland-rainfed system may require increased use of agrochemicals for a more effective remedy compared to manual scouting of pests and diseases. The yield was highest under the upland-irrigated system while the least was under the upland-rainfed system and the difference was statistically significant.

Stochastic frontier analysis under different agricultural land use management system in East African wetlands

Model diagnostic test results. By estimating equation (1), the calculated statistics (χ^2 = 15.148) was greater than the critical value ($\chi^2(1)$ = 2.706) thus rejecting (H_0: γ=0). SFA was thus the appropriate model for the analysis of TE. The χ^2 tests follow the critical values in Kodde and Palm (1986). The results of multicollinearity and heteroscedasticity tests for both one-step translog and Cobb-Douglas (CD) stochastic frontier models in the entire sample are presented in Table 3.

Table 2. Inputs use and yield among maize farmers under different agricultural land use management system in East African wetlands

Variables	Pooled (N=300)	Upland-rainfed (N=210)	Upland-irrigated (N=24)	Wetland-(N=66) only	F-Stat
Area under maize	0.59 (0.78)	0.67 (0.87)	0.31 (0.23)	0.43 (0.4)	4.031**
Seeds (kg ha^{-1})	18.57 (11.33)	18.23 (11.47)	22.11 (12.23)	18.35 (10.51)	1.277
Basal fertilizer					
(kg ha^{-1})	65.15(73.61)	63.07 (74.62)	65.45 (68.77)	71.68 (72.71)	0.343
Topdressing fertilizer	47.15 (68.41)	43.89 (66.94)	56.48 (52.58)	54.16 (77.61)	0.808
(kg ha^{-1})					
Labor	55.31 (40.49)	55.90 (40.63)	38.05 (31.78)	59.67 (41.77)	2.615*
(Person-days ha^{-1})	2283.21 (2656.29)	2257.08 (2815.36)	2521.9 (2260.51)	2279.56(2267.1)	0.106
Manure (kg ha^{-1})					
Pesticides	5.33 (4.86)	6.02 (4.88)	4.0 (3.93)	3.63 (4.64)	7.341***
(Litres ha^{-1})					
Herbicides	4.41 (3.73)	4.97 (3.81)	3.1 (2.95)	3.09 (3.31)	8.370***
(Litres ha^{-1})					
Yield (kg ha^{-1})	853.09 (1016.59)	700.08(742.15)	1373.18 (1412.28)	1186.73 (1425.96)	8.984***

Notes: The figures in the parentheses are the standard deviations

*** $p<0.01$, ** $p<0.05$, * $p<0.1$

Source: Survey data, 2017

Table 3. Tests of multicollinearity and heteroscedasticity in the one-step translog and Cobb-Douglas specifications

Model	Specification violation	Test type	Test results	Conclusion
Translog	Multicollinearity	Mean VIF	65.15	High multicollinearity
	Heteroscedasticity	Breusch-Pagan / Cook-Weisberg	2.67	Homoscedastic
Cobb-Douglas	Multicollinearity	Mean VIF	1.38	No multicollinearity
	Heteroscedasticity	Breusch-Pagan / Cook-Weisberg	3.30	Homoscedastic

In the CD function, individual and mean VIF values were all less than 10. The translog model exhibited high levels of individual and mean VIFs with the mean value being 65.15. As a rule of thumb, a VIF value greater than 10 reveals the presence of multicollinearity in the data (Gujarati, 2004). The χ^2 values from the Breusch-Pagan / Cook-Weisberg tests in both models were insignificant ($p>0.05$).

Table 4 shows that the maximum likelihood estimation of the overall model had a log-likelihood value of -436.592 and the Wald Chi^2 was 59.21, which was strongly significant ($p<0.01$) attesting the robustness of the model and indicating the collective ability of the explanatory variables in explaining the variations in maize yield. Lambda had a value of 2.29 which indicates that the inefficiency term (μ) overshadows the random error term (v).

Inefficiencies in the model were confirmed by the value of γ, which implies that 84% of the variations in maize yield emanated from technical inefficiency. The value of γ also assists in rejecting the null hypothesis (H_0: $\gamma=0$) that presumes lack of inefficiencies in the stochastic production frontier model, which reduces it to OLS. The Likelihood-ratio test proved the presence of technical inefficiency in maize production in East African wetlands because its value (15.15) was significantly different from zero ($p<0.01$).

Maize plot size under the wetland-only system strongly and negatively influenced maize yield ($p<0.01$). Ng'ombe and Kalinda (2015) also found that land significantly influenced maize yield negatively but the findings contradict those of Kibirige (2014). This is an indication of the overuse of wetlands due to unsustainable land expansion leading to dwindling land quantity and quality. This may contribute to the inadequate provision of other critical wetland services (Gardner *et al.,* 2015). Under the upland-rainfed system, the influence was significantly positive ($p<0.05$) implying that there is room to expand maize production under this system.

There were positive significant influences from seeds ($p<0.01$), basal fertilizers ($p<0.05$), topdressing fertilizers ($p<0.1$), pesticides ($p<0.01$), and labor ($p<0.1$) on maize yield under the upland-rainfed system. The seed rate in maize production was low compared to 25 kg ha^{-1}, which is the recommended rate (Asea *et al.,* 2014). The positive coefficient of basal and topdressing fertilizers showed a possibility of underuse that might have reduced the possibility of maximizing maize yield. Pesticides' strong influence on maize yield implies that pest invasion in this regard could significantly compromise maize productivity if farmers did not apply the pesticides within the wetlands. Manure was a strong positive determinant of yield ($p<0.01$) under the wetland only system implying that it is capable of contributing to wetland soil conservation. Marenya *et al*. (2017) pointed out that manure increased crop yield and soil conservation. In the current study, manure use may be crucial for wetland sustainability. Manure may ensure the availability of Nitrogen for the successive crop. Labor positively and significantly influenced yield under the upland-rainfed ($p<0.1$) and upland-irrigated ($p<0.01$) systems indicating underuse of labor, which compromises yield maximization. Finally, topdressing fertilizers ($p<0.01$) and pesticides ($p<0.05$) were overused at the wetland-only system, which implies danger to the aquatic life (Pimentel, 2009; Van Grinsven *et al.*, 2012).

Individual efficiency indices were obtained using FRONTIER 4.1c software. It revealed that upland-irrigated had significantly higher efficiency ($p<0.01$) at a 52% level compared to the other systems [$F_{(2,297)}=6.781$, $p=0.001$]. Upland-rainfed had the lowest efficiency that averaged at 41%. The upland-irrigated is thus associated with the highest efficiency, which translates into higher productivity. In most cases, farmers under the upland-irrigated system utilize water from the wetland to irrigate the crops. This exerts pressure on wetlands, which are expected to provide other ecosystem services. Agricultural production under the upland-irrigated system can help in the reduction of pressure in the wetlands if other subsidized alternative sources of water are made available, such as from water harvesting through the establishment of dams.

Table 4. Stochastic frontier analysis maximum likelihood estimation results of the Cobb-Douglas function

	Pooled		Upland-rainfed		Upland-irrigated		Wetland only	
Variable	Coefficient	Std. Error	Coefficient	Std. Error	Coefficient	Std. Error	Coefficient	Std. Error
Land (ha)	-0.032	0.085	0.255**	0.102	-0.065	0.190	-0.393***	0.100
Seed (kg ha^{-1})	0.314***	0.094	0.339***	0.113	-0.210	0.43	0.096	0.223
Basal fertilizer (kg ha^{-1})	0.145**	0.059	0.189**	0.068	0.025	0.02	0.463***	0.016
Topdressing fertilizer (kg ha^{-1})	0.021	0.053	0.113*	0.057	0.010	0.018	-0.263***	0.006
Labor (person-days ha^{-1})	0.117	0.074	0.152*	0.087	0.541***	0.042	-0.038	0.129
Manure (kg ha^{-1})	0.103*	0.054	-0.035	0.063	0.236	0.247	0.350***	0.045
Pesticide (litre ha^{-1})	0.072*	0.043	0.218***	0.052	-0.009	0.04	-0.137**	0.055
Herbicide (litre ha^{-1})	-0.034	0.045	0.043	0.063	0.166**	0.068	0.073***	0.008
_cons	4.636***	0.523	4.867***	0.617	4.451***	1.182	3.762***	0.280
sigma_v (σ_v)	0.623***		0.543***		1.41e-07		5.97e-08	
sigma_u (σ_μ)	1.427***		1.429**		1.415		1.397***	
lambda (λ)	2.288		2.631		1.01e+07		2.34e+07	
gamma (γ)	0.840		0.873		0.99		0.99	
LR test of $\sigma_\mu=0$: $Chibar^2(01)$	15.15		15.30		14.57		19.64	
Prob>=$chibar^2$	0.000		0.000		0.000		0.000	
Log likelihood	-436.592		-294.933		-25.758		-69.976	
Wald $chi^2(8)$	59.21		55.26		94.73		3.58e+09	
Prob>Chi^2	0.000		0.000		0.000		0.0000	
Mean TE	0.43		0.41		0.52		0.48	

Notes: *** p<0.01, ** p<0.05, * p<0.1

Gamma (γ), the variance ratio is derived from $\{\sigma_\mu^2/(\sigma_\mu^2+\sigma_\mu^2)\}$ or $\{\sigma_\mu^2/\sigma^2\}$.

Source: Survey data, 2017

Table 5. Inefficiency model maximum likelihood estimation results

	Pooled		Ewaso Narok		Namulonge	
Variable	Coeff.	Std. Error	Coeff.	Std. Error	Coeff.	Std. Error
Dependent variable (U_i)						
Age (Years)	-0.035***	0.014	-0.042**	0.019	-0.041	0.034
Household size (number of persons)	-0.109*	0.065	-0.055	0.092	-0.058	0.133
Education (Years)	-0.131***	0.038	-0.212***	0.063	-0.056	0.077
Farming experience (Years)	-0.036**	0.017	-0.043**	0.021	-0.062	0.041
Distance to the market (km)	0.048***	0.016	-0.001	0.026	0.185***	0.054
Off-farm income (EUR/year)	-0.00001	0.00007	-0.0003	0.0003	-0.00004	0.0001
Gender (1=Female)	0.389	0.317	0.496	0.465	0.472	0.656
Group membership (1=Yes)	-0.387	0.286	-0.261**	0.431	-0.035	0.603
Credit access (1=Yes)	0.552	0.513	-0.120	0.479	1.468	1.041
Distance to extension service provider (km)	0.071***	0.022	0.079***	0.030	0.136**	0.067
Upland-rainfed	0.845*	0.455	0.593	0.588	2.896	1.826
Upland-irrigated	0.282	0.700	1.204	0.753	-	-
_cons	1.743**	0.867	2.569**	1.307	-3.493	2.977

Notes titles *** p<0.01, ** p<0.05, * p<0.1
Source: Survey data, 2017

Determinants of technical inefficiency among maize farmers. Table 5 presents the determinants of technical inefficiency among maize producers in East African wetlands. Age, household size, education, farming experience, distance to the market, group membership, distance to the nearest extension service provider, and upland-rainfed system were the significant determinants of inefficiency.

Age reduced technical inefficiency in the Namulonge wetlands (p<0.01) and Ewaso Narok (p<0.05) by 3.5% and 4.2%, respectively. This implies that in general, younger maize farmers in the wetlands were less efficient compared to their older counterparts. As farmers advance in age, they gain more skills and can make crucial farming decisions in terms of efficient inputs use (Dessale, 2019; Mengui *et al*., 2019). The physical capability combined with accumulated skills and knowledge gives older farmers the advantage of accepting new technologies over their younger counterparts. Also, around the wetlands, an additional household member from 6 to 7 persons in a household significantly reduced inefficiency (p<0.1) by 10.9%. It implies that a bigger household increases efficiency, probably due to the availability of inexpensive labor that is easily allocated to different crop production activities (Ayinde *et al*., 2015).

Formal education had a negative influence on inefficiency in the East African wetlands at large (p<0.01) and in particular at Ewaso Narok (p<0.05). Less-educated farmers are therefore inefficient as they may have little ability to utilize the available agricultural information and technologies (Ahmed *et al*., 2013; Thabethe and Mungatana, 2014; Dessale, 2019). Also, an additional year spent on maize production gave farmers around the East African wetlands an opportunity to significantly increase their technical efficiency by 3.6% - 4.3%, ($p<0.05$). Oumarou and Huiqiu (2016) explained that farmers who have planted a certain crop for a long time can predict accurately when to plant, the appropriate cropping materials, and the types and amounts of inputs to use in production. They are also knowledgeable about various wetland conservation activities.

The maize farmers who belonged to organized groups in Ewaso Narok had 26.1% higher efficiency than their counterparts did ($p<0.05$). Ahmed and Melesse (2018) found that membership to a group such as cooperatives was a positive determinant of participation in off-farm activities that in turn influenced efficiency positively. Wetland maize farmers who belong to farmer groups or associations can access input credits, agricultural training, and linkage to product markets, among other benefits. This improves their productivity due to the proper and efficient allocation of resources. Group membership may increase farmers' chances of engaging in collective action regarding wetland conservation activities. With regards to extension access, an additional kilometre between maize-farming households and extension services providers in the general East African wetlands (from 9 to 10 km), Ewaso Narok (from 7 to 8 km), and Namulonge (from 10 to 11 Km) significantly increased inefficiency by 7.1%, 7.9%, and 13.6% respectively for ($p<0.01$). This is especially so when maize farms are located in remote areas where feeder roads are impassable and thus it becomes difficult for the extension officers to make frequent visits to farmers. Maize farmers' inefficiency under the upland-rainfed system was likely to be more than that of maize farmers under the wetland-only by 84.5% ($p<0.1$). This showed that there was a possibility of improvement of efficiency in resource utilization (such as fertilizers and improved seeds) if maize farmers produced under the upland-irrigated system. This is because the maize crop would be secure from agricultural risks regarding flooding and water scarcity during the wet and dry seasons, respectively (Kyalo and Heckelei, 2018). The system appeared as the best risk management strategy that has the potential to save wetland resources while increasing maize production output.

CONCLUSIONS AND POLICY IMPLICATIONS

Maize plots size under the wetland-only system were highly overused ($p<0.01$). Expansion of agricultural land within and around the wetland means overuse of the land resource and failure to conserve the fragile environment as a result of inefficient food production. As such, the extension agencies should assist farmers to sustainably intensify maize production by utilizing the other significant determinants of maize yield other than land expansion, i.e., use the efficient system, which is the upland-irrigated system. Such practices may include the underused topdressing and basal fertilizers. The upland-irrigated system would provide a balance between food production and environmental sustainability. In addition to the wetland degradation due to extensive land expansion, the unregulated use of agrochemicals such as pesticides and fertilizers also harm aquatic life within the wetlands. Sustainable intensification should, therefore, be the focal point if farmers have to produce their crops within and around wetlands. The finsings also indicate that farmers with formal education and belonged to organized groups had a higher chance of increasing the efficiency of production in the wetlands. Thus, emphasis be put on farmer training.

Implications for policy and practice. Upland-irrigated system was associated with the highest technical efficiency; thus, the governments and farmer associations should support maize farmers to produce under this system especially with subsidized alternative sources of water such as government-owned dams. Since the unpredictable weather vagaries and lack of alternative sources of water for upland plots have triggered the need to utilize wetland water and land, the respective governments can establish dams around the wetlands while leaving the fragile ecosystems intact. This would reduce pressure on wetland for resources and help in wetland conservation for future food production. Formal education is also needed to increase farmers' technical efficiency. Further, policy implementers should organize programs that encourage maize farmers to utilize farmer groups to maximize their efficiency. Since inefficiency reduced with increased age, youth empowerment programs should target young maize producers to ensure that they increase their efficiency like in the case of their older counterparts.

The study did have limitations. For instance, the study used cross-sectional data to propose policy interventions. Also, despite maize being the staple for most African countries, the population as well rely on livestock for food security. This study recommends a panel survey efficiency in wetlands with consideration to livestock production systems namely, extensive, intensive, and semi-intensive. Such a study would provide a more holistic policy intervention as far as wetlands conservation and food production balance is concerned.

ACKNOWLEDGEMENT

The authors appreciate the financial support for this research from the German Federal Ministry of Education and Research (BMBF) and the Federal Ministry for Economic Cooperation and Development (BMZ) through the GlobE wetlands in East Africa project.

STATEMENT OF NO-CONFLICT OF INTEREST

The authors declare that there is no conflict of interest in this paper.

REFERENCES

Ahmed, B., Haji, J. and Geta, E. 2013. Analysis of farm households' technical efficiency in production of smallholder farmers: the case of Girawa district, Ethiopia. *American-Eurasian Journal of Agricultural and Environmental Sciences* 13 (12): 1615–1621. https://doi.org/10.5829/idosi.aejaes.2013.13.12.12310

Ahmed, M. H. and Melesse, K. A. 2018. Impact of off-farm activities on technical efficiency: evidence from maize producers of eastern Ethiopia. *Agricultural and Food Economics* 6 (1): 6-15. https://doi.org/10.1186/s40100-018-0098-0

Aigner, D., Lovell, C. A. K. and Schmidt, P. 1977. Formulation and estimation of stochastic frontier production models. *Journal of Econometrics* 6 (6): 21–37.

Alibu, S., Neuhoff, D., Senthilkumar, K., Becker, M. and Köpke, U. 2019. Potential of cultivating dry season maize along a hydrological gradient of an inland valley in Uganda. *Agronomy* 9 (10): 1–12. https://doi.org/10.3390/agronomy9100606

Asea, G., Serumaga, J., Mduruma, Z., Kimenye, L. and Odeke, M. 2014. Quality protein maize production and post-harvest handling handbook for East and Central Africa. Association for Strengthening Agricultural Research in Eastern and Central Africa (ASARECA), Entebbe, Uganda.

Ayinde, I. A., Aminu, R. O. and Ibrahim, S. B. 2015. Technical efficiency of maize production in Ogun State , Nigeria. *Journal of Development and Agricultural Economics* 7 (2): 55–60. https://doi.org/10.5897/JDAE2014.0579

Baldock, D., Caraveli, H., Dwyer, J., Einschütz, S., Peteresen, J. E., Sumpsi-Vinas, J. and Varela-Ortega, C. 2000. The environmental impacts of irrigation in the European Union. In: Studies and Reports on Agriculture . European Commission (Vol. 5210). Retrieved from http://ec.europa.eu/environment/agriculture/pdf/irrigation_xs.pdf%5Cnhttp://

ec.europa.eu/environment/agriculture/studies.htm

Battese, G. E. and Broca, S. S. 1997. Functional forms of Stochastic frontier production functions and models for technical inefficiency effects: A comparative study for wheat farmers in Pakistan. *Journal of Productivity Analysis* 8 (4): 395–414. https://doi.org/10.1023/A:1007736025686

Battese, G. E. and Coelli, T. J. 1988. Prediction of firm-level technical efficiencies with a generalized frontier production function and panel data. *Journal of Econometrics* 38 (3): 387–399. https://doi.org/10.1016/0304-4076(88)90053-X

Battese, G. E. and Coelli, T. J. 1995. A model for technical inefficiency effects in a stochastic frontier production function for panel data. *Empirical Economics* 20 (2): 325–332. https://doi.org/10.1007/BF01205442

Charnes, A., Cooper, W. W. and Rhodes, E. 1978. Measuring the efficiency of decision making units. E*uropean Journal of Operational Research* 2 (6): 429–444. https://doi.org/10.1016/0377-2217(78)90138-8

Coelli, T.J., Rao, D.S.P., O'Donnell, C.J. and Battese, G.E. 2005. An introduction to efficiency and productivity analysis. Springer Science and Business Media. 348pp.

Coelli, T., Perelman, S. and Romano, E. 1999. Accounting for environmental influences in Stochastic Frontier Models: With application to international airlines. *Journal of Productivity Analysis* 11 (3): 251–273. https://doi.org/10.1023/A:1007794121363

Department of Ecology - State of Washington. 2010. Focus on Irrigation-Influenced Wetlands. In: Shorelands and Environmental Assistance Program.

Dessale, M. 2019. Analysis of technical efficiency of small holder wheat - growing farmers of Jamma district, Ethiopia. *Agriculture and Food Security* 8 (1): 1–8. https://doi.org/10.1186/s40066-018-0250-9

FAO, IFAD and WFP. 2015. The state of food insecurity in the world 2015. Meeting the 2015 international hunger targets: taking stock of uneven progress. Rome, FAO.

Food and Agriculture Organisation (FAO). 2008. Scoping agriculture-wetland interactions: towards a sustainable multiple-response strategy. FAO Water Report 33, Food and Agriculture Organization of the United Nations, Rome, Italy.

Food and Agriculture Organisation (FAO). and IWMI. 2017. Water pollution from agriculture: a global review. A report by the Food and Agriculture Organization (FAO) of the United Nations and the International Water Management Institute (IWMI).

Frohloff, A. 2007. Cost and technical efficiency of German hospitals – A Stochastic Frontier Analysis. Rheinisch-Westfälisches Institut für Wirtschaftsforschung (RWI), Essen.

Furesi, R., Madau, F. A. and Pulina, P. 2013. Technical efficiency in the sheep dairy industry: an application on the Sardinian (Italy) sector. *Agricultural and Food Economics* 1 (1): 1–11. https://doi.org/10.1186/2193-7532-1-4

Gardner, R. C., Barchiesi, S., Beltrame, C., Finlayson, C. M., Galewski, T., Harrison, I. and Walpole, M. 2015. State of the world's wetlands and their services to people: A compilation of recent analyses. https://doi.org/10.2139/ssrn.2589447

Gujarati, D. 2004. Basic Econometrics. 4th ed. New York: McGraw-Hill Companies.

Halima, K. Hassan and Munishi, K. P. 2009. Contribution of wetlands to household income and food security in the nyumba ya mungu wetland system, Nothern Tanzania. *Tanzania Journal of Forestry and Nature Conservation* 79 (2): 99-108.

Hong, Y., Heerink, N., Zhao, M. and van der Werf, W. 2019. Intercropping contributes to a higher technical efficiency in smallholder farming: Evidence from a case study in Gaotai County, China. *Agricultural Systems* 173: 317–324. https://doi.org/10.1016/j.agsy.2019.03.007

Huang, C. J. and Liu, J. T. 1994. Estimation of a non-neutral stochastic frontier production function. *Journal of Productivity Analysis*

5 (2): 171–180. https://doi.org/10.1007/BF01073853

IFPRI. 2003. IFPRI Strategy Towards Food and Nutrition Security. International Food Policy Research Centre: Washington, DC: International Food Institute.

International Fund for Agricultural Development. 2014. Investing in rural people in the United Republic of Tanzania. A report for Building a poverty- free world by IFAD, Rome, Italy, 2014.

International Water Management Institute. 2014. Wetlands and people. Colombo, Sri Lanka: International Water Management Institute (IWMI). 32pp. doi: 10.5337/2014.202 /.

Jondrow, J., Knox Lovell, C. A., Materov, I. S. and Schmidt, P. 1982. On the estimation of technical inefficiency in the stochastic frontier production function model. *Journal of Econometrics* 19 (2–3): 233–238. https://doi.org/10.1016/0304-4076(82)90004-5

Kang'ethe, E. 2011. Situation analysis: improving food safety in the maize value chain in Kenya. Report prepared for FAO.

Kansiime, M. K., van Asten, P. and Sneyers, K. 2018. Farm diversity and resource use efficiency: Targeting agricultural policy interventions in East Africa farming systems. *NJAS - Wageningen Journal of Lif*e Sciences 85:32–41. https://doi.org/10.1016/j.njas.2017.12.001

Kibirige, D. 2014. Estimation of technical efficiency among smallholder maize farmers in Uganda: A case study of Masindi District of Uganda. *International Journal of Economics, Commerce and Management* 2 (5):1-15.

Kodde, D. A. and Palm, F. C. 1986. Wald criteria for jointly testing equality and inequality restrictions. *Econometrica* 54 (5): 1243–1248.

Kothari, C. R. 2004. Research methodology: methods and techniques. New Delhi: New Age International (P) Limited.

Kyalo, W. D. and Heckelei, T. 2018. Assessment of agricultural intensification and determinants of the relative choice of land management systems in East African wetlands. *African Journal of Rural Development* 3 (3): 821–830.

Leemhuis, C., Amler, E., Diekkrüger, B., Gabiri, G. and Näschen, K. 2016. East African wetland-catchment data base for sustainable wetland management. *Proceedings of the International Association of Hydrological Sciences* 374:123–128. https://doi.org/10.5194/piahs-374-123-2016

Macauley, H. 2015. Cereal crops: Rice, maize, millet, sorghum, sheat. Cereal crops report prepared for United Nations presented on 21-23 October 2015 at Dakar, Senegal.

Marenya, P. P., Kassie, M., Jaleta, M., Rahut, D. B. and Erenstein, O. 2017. Predicting minimum tillage adoption among smallholder farmers using micro-level and policy variables. *Agricultural and Food Economics* 5 (1): 1–22. https://doi.org/10.1186/s40100-017-0081-1

McCartney, M., Rebelo, L.-M., Sellamuttu, S. S. and Sanjiv de Silva. 2010. Wetlands, agriculture and poverty reduction. Colombo, Sri Lanka: International Water Management Institute. 39pp. (IWMI Research Report 137). doi: 10.5337/2010.230 /.

Mengui, K. C., Oh, S. and Lee, S. H. 2019. The technical efficiency of smallholder irish potato producers in Santa subdivision , Cameroon. *Agriculture* 9 (256): 1–13.

Ministry of Agriculture, Animal Industry and Fisheries. 2011. Statistical Abstract. A statistical abstract by Agricultural Planning Department of Ministry of Agriculture, Animal Industry and Fisheries, Uganda.

Mwita, E. J. 2013. Geophysics and remote sensing land cover and land use dynamics of semi arid wetlands : A case of Rumuruti (Kenya) and Malinda (Tanzania). *J Geophys Remote Sensing* S1:001:1-9. https://doi.org/10.4172/2169-0049.S1-001

Ng'ombe, J. and Kalinda, T. 2015. A Stochastic Frontier analysis of technical tfficiency of maize production under minimum tillage in Zambia. *Sustainable Agriculture Research* 4 (2): 31–46. https://doi.org/http://dx.doi.org/10.5539/sar.v4n2p31

Nsubuga, F. N. W., Olwoch, J. M. and Rautenbach, C. J. de W. 2011. Climatic trends at Namulonge in Uganda: 1947-2009. *Journal of Geography and Geology* 3 (1):119-131. Online. https://doi.org/10.5539/jgg.v3n1p119

Okoboi, G., Muwanga, J. and Mwebaze, T. 2012. Use of improved inputs and its effect on maize yield and profit in Uganda. *African Journal of Food, Agriculture, Nutrition and Development* 12 (7): 6931–6944.

Ondiek, R. A., Vuolo, F., Kipkemboi, J., Kitaka, N., Lautsch, E., Hein, T. and Schmid, E. 2020. Socio-economic determinants of land use/cover change in wetlands in East Africa: A case study analysis of the Anyiko wetland, Kenya. *Frontiers in Environmental Science* 7: 1-16. https://doi.org/10.3389/fenvs.2019.00207

One Acre Fund. 2015. Optimizing maize variety adoption and performance. 2015 Trial Report.

Otieno, D. J., Hubbard, L. and Ruto, E. 2012. Determinants of technical efficiency in beef cattle production in Kenya. International Association of Agricultural Economists (IAAE) Triennial Conference 1–25. https://doi.org/10.5897/JDAE2013.0525

Oumarou, B. and Huiqiu, Z. 2016. Technical efficiency of rice farming in south-western Niger : A Stochastic Frontier Approach. *Journal of Economics and Sustainable Development* 7 (24): 58–65.

Pimentel, D. 2009. Environmental and economic costs of the application of pesticides primarily in the United States. In: Integrated Pest Management: Innovation-Development Process. 89pp. https://doi.org/10.1007/978-1-4020-8992-3 Library

Pitt, M. M. and Lee, L. F. 1981. The measurement and sources of technical inefficiency in the Indonesian weaving industry. *Journal of Development Economics* 9 (1): 43–64. https://doi.org/10.1016/0304-3878(81)90004-3

Pretty, J. and Bharucha, Z. P. 2014. Sustainable intensification in agricultural systems. (1911): 1571–1596. https://doi.org/10.1093/aob/mcu205

Raburu, P. O., Okeyo-Owuor, J. B. and Kwena, F. 2012. Community Based Approach to the Management of Nyando Wetland, Lake Victoria Basin, Kenya. First Edit. Mcpowl Media Ltd, Kenya.

Schroeder, C., Onyango K'Oloo, T., Ranabhat, N. B., Jick, N. A., Parzies, H. K. and Gemenet, D. C. 2013. Potentials of hybrid maize varieties for smallholder farmers in Kenya: a review based on SWOT analysis. *African Journal of Food, Agriculture, Nutrition and Development* 13 (2): 7562–7586.

Schuyt, K. D. 2005. Economic consequences of wetland degradation for local populations in Africa. *Ecological Economics* 53:177–190.https://doi.org/10.1016/j.ecolecon.2004.08.003

Thabethe, L. and Mungatana, E. 2014. Estimation of technical, economic and allocative efficiencies in sugarcane production in South Africa : A case of Mpumalanga Growers. *Journal of Economics and Sustainable Development* 5 (16): 86–96.

Thenya, T. 2001. Challenges of conservation of dryland shallow waters, Ewaso Narok Swamp, Laikipia District, Kenya. *Hydrobiologia* 458: 107–119. https://doi.org/10.1023/A:1013196500456

Thenya, T., Kahiu, N., Karanja, F., Ojwang', D., Ouko, C., Wambugu, G. and Njuguna, E. 2011. Assessment of ecological status and socio-economic dynamics of upper Ewaso Ng ' iro Basin wetlands. Draft report on Dynamic of Upper Ewaso Ng'iro Basin Wetlands. CETRAD.

Toma, E., Dobre, C., Dona, I. and Cofas, E. 2015. DEA applicability in assessment of agriculture efficiency on areas with similar geographically patterns. *Agriculture and Agricultural Science Procedia* 6: 704–711. https://doi.org/10.1016/j.aaspro.2015.08.127

Turyahabwe, N., Kakuru, W., Tweheyo, M. and Tumusiime, D. M. 2013. Contribution of wetland resources to household food security in Uganda. *Agriculture and Food Security* 2 (5): 1–12.

Van Grinsven, H. J. M., Ten Berge, H. F. M., Dalgaard, T., Fraters, B., Durand, P., Hart, A. and Willems, W. J. 2012. Management, regulation and environmental impacts of nitrogen fertilization in northwestern Europe under the Nitrates Directive: A benchmark study. *Biogeosciences* 9 (12): 5143–5160. https://doi.org/10.5194/bg-9-5143-2012

Verhoeven, J. T. A. and Setter, T. L. 2010. Agricultural use of wetlands: Opportunities and limitations. *Annals of Botany* 105 (1):155–163.https://doi.org/10.1093/aob/mcp172

Willy, D. K., Muyanga, M. and Jayne, T. 2019. Can economic and environmental benefits associated with agricultural intensification be sustained at high population densities ? A farm level empirical analysis. *Land Use Policy* 81:100–110. https://doi.org/10.1016/j.landusepol.2018.10.046

Wood, A., Dixon, A. and Mccartney, M. 2013. Wetland management and sustainable livelihoods in Africa. pp. 1-42. In: Wood, A., Dixon, A., McCartney, M.P. (Eds.). New York, USA: Routledge.