RISK INCLUSION IN FORECASTING AND ECONOMIC FEASIBILITY ANALYSES OF STAPLE FOOD CEREALS IN TANZANIA: THE CASE OF MAIZE, SORGHUM AND RICE

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EXTENDED ABSTRACT

Maize (*Zea mays L.*), rice (*Oryza sativa*), and sorghum (*Sorghum bicolor* L. Moench) are major staple food crops to the most population in Tanzania. The three crops provide the primary source of livelihood for the majority of rural farming households. Of the three crops, maize is the most important, accounting for about 20% of the total agricultural GDP, followed by rice. Sorghum plays an important role in fighting hunger and food insecurity in central Tanzania, particularly in Dodoma and Singida regions. Unfortunately, like any other crops, some uncertainty exists about the future productivity and profitability of these important food crops. Such uncertainty hinders the implementation of different agricultural policies, plans and strategies set to achieve an agriculture revolution, hence impacting the decision of investment in agricultural technologies. The inadequacy of accurate and timely information on productivity and profitability of crops have a tremendous impact on farmers' decisions, as well as on policy and planning. Hence, a complete model to help in forecasting and economic analyses of crucial crop sub-sectors while including their stochastic nature is essential. In this regard, stochastic risk analysis models were developed and demonstrated to analyse risk and uncertainty in forecasting and economic analyses of major cereal crops in Tanzania. Most of the available models in economic analyses and forecasting yields, prices, and net returns of agricultural systems are deterministic. These models ignore the inherent risk of random variables and provide only a point estimate for the key output variables (KOVs) instead of values with probability distributions. Therefore, this study was conducted to address three specific objectives. The first objective was to develop and demonstrate a stochastic simulation model for analysing the future viability of main cereals crops in semi-arid and sub-humid areas of Tanzania. For this reason, a Maize-Sorghum-Rice Simulation Model (MASORISIM) was developed to simultaneously forecast yields, prices, and probable net

returns for maize, sorghum, and rice as probability distributions. It utilizes deviations from historical yields and prices (2008 – 2018) to forecast random variables for seven years from 2019 – 2025. Since the analysis involved yields and prices of three crops, a multivariate probability distribution was built in the model to incorporate correlations of the variables and control their heteroscedasticity. The forecasting results on crop yield show an increasing trend for maize and rice with a marginal increase for sorghum in the Dodoma region by 2025. Likewise, the yield for rice is expected to rise in Morogoro with a slight increase for maize and a decreasing trend for sorghum during the same period. Meanwhile, the prices for the three crops all are projected to increase in the two regions. The results on economic feasibility using NPV values revealed a high probability of success for all crops in both regions except maize in Morogoro. The results for maize in Morogoro presented a 2.93% probability of negative NPV. Of the three crops, maize indicated the highest relative risk associated with NPV for both regions and was relatively higher in Morogoro (55.1%) than in Dodoma (34.2%). Although the results on production indicate increasing trends for the crops, the increase is relatively small, particularly in Morogoro, which is one of the food basket regions in the country. The second specific objective of the study was to develop and illustrate a bio-economic simulation model for analysing the economic feasibility of improved management practices on maize production in the Wami Basin of Tanzania. The bio-economic simulation model is an integrated decision support system (IDSS) developed to link data from two biophysical models, namely APSIM and DSSAT and econometric model (Simetar) for comprehensive decision-making. Under this objective, the economic feasibility of two farm management practices was analysed. These practices included the application of 40 kg N/ha and adjustment of plant population at a rate of 33 000 plants/ha from the current rate of 18 000 to 20 000 plants/ha. The simulated yield from the two crop models was then entered into the bio-economic IDSS model along with output prices, and cost for each option to simulate the probable economic net returns to farmers. The APSIM and DSSAT crop models were used in this study because the two models are capable of simulating yield as a function of the soil-plant-atmosphere conditions with and without the proposed farm management practices. However, crop models normally simulate yields and cannot simulate other variables like prices and costs of management alternatives to inform economic decisions. The bio-economic simulation model, therefore, was built to bridge the gap. The results on the economic viability show that the application of 40 kg N/ha was more profitable than the plant population of 33 000 plants/ha having a zero probability of negative returns. Both APSIM and DSSAT models suggest that when plant population is adjusted from current average of 20,000 plants/ha to 33 000 plants/ha, there is 16% and 27% probability of negative returns in semi-arid part, with a 14% and a 30% probability in sub-humid area. However, the net return for farms supplemented with the two management options (40 kg N/ha and the 33 000 plants/ha) has a slight difference from the farms with additional of 40 kg N/ha alone. However, the results suggest that the application of either fertilizer alone reduces the risks associated with the annual mean returns. The increase in plant population at a rate of 33 000 plants/ha without application of 40 kg N/ha has a high probability of economic failure. The third specific objective was to demonstrate user-friendly Monte Carlo simulation procedures to simulate the economic viability of different rice farming system in Tanzania. Production data for three seasons were used to demonstrate how panel survey data can be made stochastic to include risk available in the data. In this analysis, the rice farming systems entailing traditional and improved practices were compared by considering the risk associated with each system, and the best farming system was identified. The systems were categorized based on the type of seeds used (local or improved), application of fertilizers, and application of the systems of rice intensification (SRI) practices (partially or fully). The results of the economic analysis show a high probability of success for rice farmers using all the recommended SRI principles. Moreover, rice farms that partially applied the SRI principles did not realize better returns compared to their counterpart farmers that fully adopt the SRI package. Rice farms that applied fertilizers plus improved seeds were also better-off compared to rice farms under traditional practices. The study revealed that farmers who use SRI partially and fully had 2% and zero probabilities of negative annual net cash income (NCI), respectively. Meanwhile, farmers using fertilizers and improved varieties had a 21% probability of negative NCI. The farmers using improved and local rice varieties had 60% and 66% probabilities of negative returns, respectively. With high dependence on rain-fed farming, production of main cereal crops is likely to face a high degree of risk and uncertainty threatening incomes, livelihoods, and food availability to poor households. However, there is a high chance that such households will be better-off if improved technologies like the application of recommended fertilizers and SRI are properly applied. Nonetheless, the adjustment in plant population has demonstrated a slightly impact on both yield and economic returns, particularly under rain-fed production system. With evidence from crop models like APSIM and DSSAT, bio-economic integrated studies are, however, needed to explore the potential of more crop management practices and technologies for better decision-making. This study forms a basis for more studies that include risks and uncertainty to improved decision marking for farmers, government, and stakeholders in the agricultural sector. The methodology used in this study can be expanded to include more zones and other non-cereals crops and livestock farming systems.

DECLARATION

I, Ibrahim Lwaho Kadigi, do hereby declare to the Senate of Sokoine University of Agriculture that this thesis is my own original work done within the period of registration and that it has neither been submitted nor being concurrently submitted in any other institution.

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This dissertation is dedicated to my beloved Late grandmother Juliana Ibrahim Kadigi, my mother Enia Lwaho, and to my grandparents Lucas Ibrahim Kadigi and Willickister Mbuke Nkuba for their heartfelt love, care, and constant encouragement.

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LIST OF ABBREVIATIONS AND ACRONYMS

AASS	Annual Agricultural Sample Surveys
ASDP	Agricultural Sector Development Plan
AU	Africa Union
CAADP	Comprehensive African Agriculture Development Programme
CDF	Cumulative Distribution Functions
CV	Coefficient of Variation
DAE Ltd	Dan and Associates Enterprises Limited
DAICO	District Agricultural, Irrigation, and Cooperative Officer
DDS	Department of Development Studies
FAO	Food and Agriculture Organization of the United Nations
FGDs	Focus Group Discussions
FYDP	Five Year Development Plan
GDP	Gross Domestic Product Government
IFAD	International Fund for Agricultural Development
KENFAP	Kenya National Federation of Agricultural Producers
KOV	Key Output Variable
MAPE	Mean Absolute Percent Error
MCS	Monte Carlo Simulation
MoA	Ministry of Agriculture
MT	Metric Tons

MVE	Multivariate Empirical
NBS	National Bureau of Statistics
NEPAD	New Partnership for Africa’s Development
NFSD	National Food Security Division
NMB	National Microfinance Bank
NPV	Net Present Value
NSGRP	National Strategy for Growth and Reduction of Poverty
OCGS	Office of the Chief Government Statistician
PDF	Probability Distribution Functions
PRSP	Poverty Reduction Strategy Paper
SAEBS	School of Agricultural Economics and Business Studies
SAGCOT	Southern Agriculture Growth Corridor of Tanzania
SD	Standard Deviation
SSA	Sub-Saharan Africa
SUA	Sokoine University of Agriculture
TAFSIP	Tanzania Food Security Investment Plan
TDV	Tanzania Development Vision
TZS	Tanzanian Shillings
UNDP	United Nations Development Programme
URT	United Republic of Tanzania
USD	United States Dollar

CHAPTER ONE

1.0 GENERAL INTRODUCTION

1.1 Background Information

Maize (*Zea mays L.*), rice (*Oryza sativa*), and sorghum (*Sorghum bicolor L. Moench*) are major staple food crops to the most population in Tanzania. The three crops provide the primary source of livelihood for 80% of the population (URT, 2014; Kahimba *et al.*, 2015). Maize alone accounts for about 72% of total cereal production, followed by rice/paddy 23%, sorghum 5%, and 1% for the remain cereals (URT, 2014). Despite their importance in the economy, the full potential of these cereals to create food security in Tanzania is only marginally due to low performance. For example, the existing land productivity of maize is below 2.0 MT against the productivity potential of 6 -7.5 MT per hectare. Also, the productivity potential for paddy is as high as 6-8 MT, while the average actual productivity is below 3.0 MT per hectare (URT, 2013). In Tanzania, more than $\frac{3}{4}$ of rice is produced under lowland rain-fed system. However, apart from overdependence on rain-fed agriculture, other constraints leading to the lower performance of these crops include the inadequate application of agricultural technologies, unreliable markets, and climate change and variability (URT, 2013; Kahimba *et al.,* 2015).

Maliondo *et al.* (2012) claimed that despite their importance, the main cereals in Tanzania are sensitive to extreme climatic variables. Hence, if the sector is adversely affected by any climatic shock, their productivity would be at risk leading to food insecurity for a large number of people (Kahimba *et al.,* 2015). Crop modelling studies including Ehrhart and Twena (2006), Munishi *et al.* (2010), Jack (2010), Rowhani *et al.* (2011), and Arndt *et al.* (2012) to mention a few, concluded that future yields of the most critical food crop yields like maize, sorghum, and rice might significantly decline, mainly due to projected changes in temperature and rainfall. Besides, prices of cereal crops are in Tanzania change seasonally. They tend to drop during the harvesting period, especially when there is bumper harvest and increase during the shortage, which increases further the risk for farmers.

The government of Tanzania has formulated several policies and plans in response to the low performance within the agricultural sector. These initiatives include the National Agricultural Policy (URT, 2013); Agriculture Climate Resilience Plan (URT, 2014), the Agricultural Sector Development Programme Phase II (URT, 2016), and the Tanzania Agriculture and Food Security Investment Plan (URT, 2011) to mention a few. These initiatives are connected to the Comprehensive African Agriculture Development Programme (CAADP), the African Union initiative for restoring agricultural development in Africa through the New Partnership for Africa's Development (NEPAD) (URT, 2013). However, there is still a concern about the achievements of set goals under these initiatives, especially for ensuring household food security, improved agricultural productivity, profitability, and alleviation of rural poverty (Leyaro *et al.*, 2014; Mourice *et al.*, 2015).

1.2 Problem Statement and Justification

Forecasting and feasibility analyses of agricultural production and prices are critical for farmers, government, and agribusiness industries (Kantanantha, 2007; Meena and Singh, 2013). Because of the unique position of food production on food security, governments have become both principal suppliers and central users of agricultural forecasts (Allen, 1994). Governments need internal projections of yields and prices to execute policies that provide technical and market support for the agricultural sector (Kantanantha, 2007;

Kahimba *et al.*, 2015). Lack of accurate and timely information on crop yield and price forecasts may have partly been responsible for not attaining most of the goals initiated by many governments, particularly in developing countries (Meena and Singh, 2013; Mourice *et al.*, 2015).

Farmers, policymakers, and commodity traders, therefore, need reliable and up-to-date information on expected yields and prices for their decision making (Allen, 1994; Richardson *et al.*, 2008). Likewise, Kantanantha (2007) argued that accurate and timely crop yield and price forecasts on national to community scales are increasingly becoming important in both developing and developed countries. In Tanzania, information on crop yields and prices has become an essential component for the Ministry of Agriculture, particularly the National Food Security Division (NFSD). The NFSD has a responsibility to ensure food availability at all levels and at all times. Hence, it has to carry out the overall monitoring and forecasting of food production based on crop performance in the country and early warning systems for food security.

However, it is difficult to make the right forecasting and feasibility analyses because the analysts have to take into account uncertainties in yields and prices influenced by factors such as weather, demand, supply as well as resource limitations (Richardson *et al.*, 2000; Kantanantha, 2007). These factors are out of control of the farmer or a decision-maker and pose difficulties in making the right forecasting and feasibility analyses. These difficulties challenge the involved parties, particularly governments, in determining a solution that will help producers reach their goals (Maliondo *et al.*, 2012; FAO, 2008). In dynamic modelling, the best way to analyse the uncertainty nature of yields and prices is to allow the model to incorporate the stochastic behaviour of the variables by mimicking the historical situation (Richardson *et al.,* 2000; 2007; Lien *et al.,* 2007; Rezende and Richardson, 2015).

As yield and price have a tremendous impact on the farmers' final returns, there is, a need to take into account the uncertainty of these factors to enhance decision making and planning (Kantanantha, 2007). In other words, forecasting and feasibility analyses that include the uncertainty nature of agricultural production are essential for planning and decision making. However, the current models used in forecasting and viability analyses are commonly deterministic and have limited ability to include the dynamic behaviour of random variables such as yields and prices (Richardson *et al.,* 2000; Maliondo *et al.,* 2012; Kahimba *et al.,* 2015). Stochastic models produce outcomes that incorporate the uncertainty of random variables, but they have not been developed to a level of usefulness in forecasting and feasibility analyses (Allen, 1994; Richardson *et al.,* 2000; 2007; 2008; Basso *et al.,* 2013).

Hence, some uncertainty remains about the feasibility of the agriculture sector in Tanzania, particularly the main cereal sub-sectors during the coming years. Such uncertainty is affecting the implementation of different policies and plans set to address the low productivity of main food crops in the country and also the decision on new investments in the farm sector. For example, one of the ASDP II objectives is to improve agricultural productivity and profitability driven by improved research, extension, input access and mechanization (URT, 2016). Achieving this objective may need a thorough analysis of the risk and uncertainty associate with agricultural production. A complete integrated model which requires minimum data is unavoidable, and this study paves a way to related studies.

1.3 Objectives

1.3.1 Overall objective

The overall objective of this study was to develop, validate and demonstrate stochastic simulation procedures that include risk and uncertainty in forecasting and feasibility analyses of maize, sorghum, and rice sub-sector in Tanzania. The study's specific objectives are presented below.

1.3.2 Specific objectives

i. To develop a stochastic simulation model for analysing the future viability of main cereal crops in semi-arid and sub-humid areas of Tanzania;
ii. To develop a bio-economic simulation model for estimating the benefits of recommended farm management practices on productivity and profitability of maize production in the study area and;
iii. To demonstrate Monte Carlo simulation procedures for analysing the economic feasibility of different rice farming systems is the study area.

1.4 Research Questions

This study is governed by four core research questions as follows:

i) What are the probable profits of major cereal crops in the study area for the next seven years from 2019 through 2025?
ii) What are the benefits of recommended farm management practices on productivity and profitability of maize production in the study area?
iii) What is the economic viability of rice farming systems in the study area?

Question one evaluates the economic viability of three cereal crops (maize, sorghum and rice) for the next seven years from 2019 through 2025. The question first forecasts the probable yields and prices (stochastic variables) of the three crops using historical data. The forecasted yields and prices are later combined with production costs, interest rates and inflation rates which are also random variables to calculate the stochastic in annual net returns and the net present value of the three crops. Question two evaluates the benefits of recommended management practices on maize production in the study area. Question three addresses the economic feasibility of rice farming systems in the study area and identify the best one.

1.5 Conceptual Framework of the Study

This study follows the Monte Carlo Simulation (MCS) framework. The MCS performs risk analysis by building models of possible results by substituting a range of values (a probability distribution) for any factor that has inherent uncertainty (Palisade, 2020; Richardson *et al.,* 2008). MSC calculates results over and over, each time by using a different set of random values from the probability functions (Palisade, 2020). Depending upon the number of uncertainties and the ranges specified for them, an MCS could involve thousands or tens of thousands of recalculations before it is complete. The analysis under MCS produces distributions of possible outcome values (Richardson *et al.,* 2008). Through these probability distributions, a variable can have different probabilities of different outcomes occurring.

Unlike deterministic modelling, probability distributions are a much more realistic way of describing risk and uncertainty in random variables in forecasting and economic analyses. Figure 1.1 shows a diagram flow chart of the typical Monte Carlo simulation procedures followed in this study. The figure demonstrates how different data sets can be made stochastic to include inherent risk. The amber arrows show that historical or time-series data can be assembled and entered in the Monte Carlo simulation engine to generate a stochastic risk analysis/forecasting model. The blue arrows show how cross-sectional or panel survey can be made stochastic for scenario analysis. Likewise, the green arrows illustrate how data from biophysical models like APSIM and DSSAT can be linked with

Monte Carlo simulation models to create an integrated decision support system for better decision making.

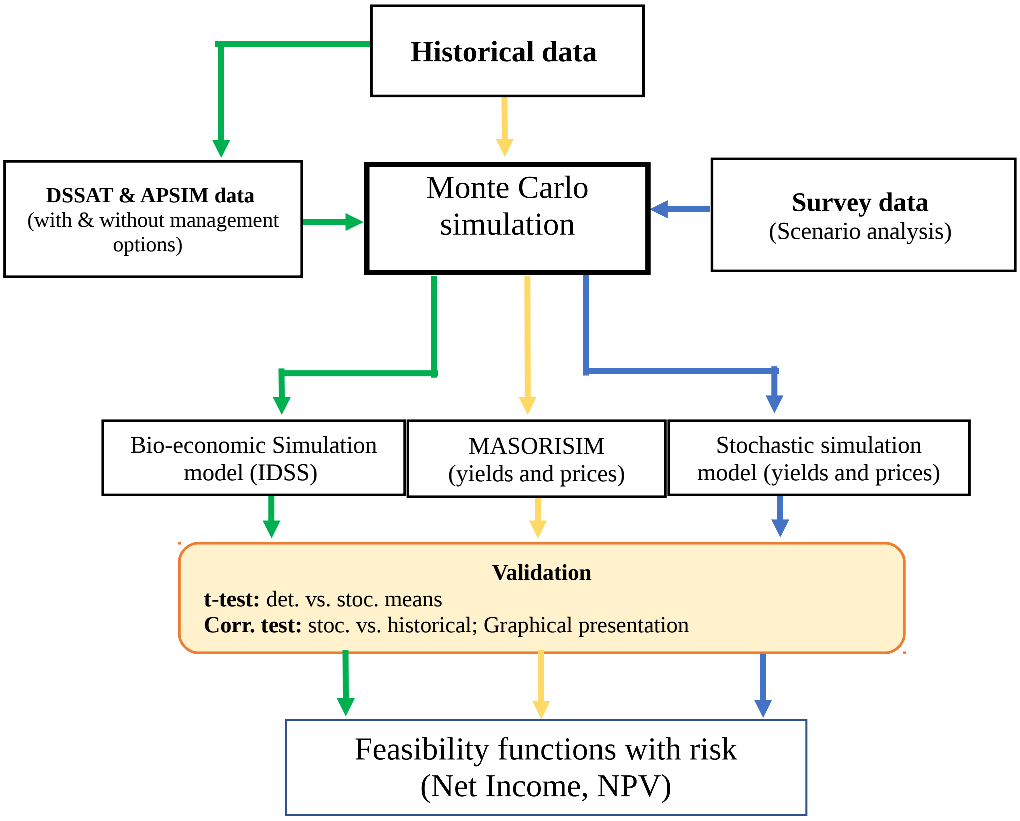

Figure 1.1: The Schematic process of Monte Carlo simulation model
Source: Configured by the author

1.6 Organisation of the Thesis

This dissertation is organized in the form of publishable manuscripts according to the format of Sokoine University of Agriculture (SUA). The whole thesis is divided into six chapters. Chapter one covers the background of the study, problem statement and justification, objectives, research questions and conceptual framework of the study. Chapter two presents the literature review and analytical framework. It provides an overview of risk analysis, theoretical overview of deterministic and stochastic risk analysis models and the analytical framework of this study. The three specific objectives are presented by three Manuscripts, in Chapter Three, Chapter Four and Chapter Five, respectively. The overall conclusions and recommendations are presented in Chapter Six.

References

Allen, P. G. (1994). Economic forecasting in agriculture. *International Journal of Forecasting*, *10*(1), 81-135.

Arndt, C., Farmer, W., Strzepek, K. and Thurlow, J. (2012). Climate Change, Agriculture, and Food Security in Tanzania. *Review of Development Economics* 16(3): 378-393.

Basso, B., Cammarano, D. and Carfagna, E. (2013). Review of crop yield forecasting methods and early warning systems. In *Proceedings of the first meeting of the scientific advisory committee of the global strategy to improve agricultural and rural statistics, FAO Headquarters, Rome, Italy* (pp. 18-19).

Ehrhart, C. and Twena, M. (2006). Climate change and poverty in Tanzania: Realities and responses. *Background report for the CARE International poverty-climate change initiative, CARE, Tanzania*. [http://www.taccire.suanet.ac.tz:8080/xmlui/bitstream/handle/123456789/472/Climate%20change%20and%20poverty %202006.pdf?sequence=1] site visited on 07/11/2018.

FAO (2008). Climate change and food security: a framework document. *FAO Inter-Departmental Working Group on Climate Change*. [http://re.indiaenvironmentportal.org.in/files/climate-foodsecurity.pdf] site visited on 17/05/2016.

Jack, C. (2010). Climate Projections for the United Republic of Tanzania. *Climate Systems Analysis Group, University of Cape Town*.

Kahimba, F. C., Sife, A. S., Maliondo, S. M. S., Mpeta, E. J. and Olson, J. (2015). Climate change and food security in Tanzania: Analysis of current knowledge and research gaps. *Tanzania Journal of Agricultural Sciences* 14(1).

Kantanantha, N. (2007). Crop decision planning under yield and price uncertainties Dissertation for Award Degree of Doctorate at Georgia Institute of Technology. 157pp.

Leyaro, V., Morrissey, O., and Boulay, B. (2014). Food crop production in Tanzania: Evidence from the 2008/09 National Panel Survey.

Lien G., Hardaker J. B. and Flaten O. (2007), “Risk and economic sustainability of crop farming systems" Agricultural Systems, volume 94, issue 2:541-552. DOI: 10.1016/j.agsy.2007.01.006

Maliondo, S.M.S., Mpeta, E.J. and Olson, J. (2012). Climate change and food security in Tanzania: an analysis of current knowledge and research gaps and recommendations for a research agenda. *iAGRI Reference Background Paper*.

Meena, M. and Singh, P.K. (2013). Crop Yield Forecasting Using Neural Networks. In; *International Conference on Swarm, Evolutionary, and Memetic Computing* Springer, Cham. pp. 319-331.

Mourice, S.K., Tumbo, S.D., Nyambilila, A. and Rweyemamu, C.L. (2015). Modeling potential rain-fed maize productivity and yield gaps in the Wami River sub-basin, Tanzania. *Acta Agriculturae Scandinavica, Section B—Soil and Plant Science 65*(2): 132-140.

Munishi, P. K. T., Shirima, D., Jackson, H. and Kilungu, H. (2010) February. Analysis of climate change and its impacts on productive sectors, particularly agriculture in Tanzania. In; *Workshop on Prospects for Agricultural Growth in a Changing World, Government of Tanzania and World Bank, Dar es Salaam, Tanzania.* Vol. 2010.

Palisade (2020). Advanced Risk Analysis for Microsoft Excel. https://www.palisade.com/risk/risk_analysis.asp

Rezende, M.L. and Richardson, J.W. (2015). Economic feasibility of sugar and ethanol production in Brazil under alternative future prices outlook. *Agricultural Systems* 138: 77-87.

Richardson, J. W., Herbst, B. K., Outlaw, J. L., and Gill, R. C. (2007). Including risk in economic feasibility analyses: the case of ethanol production in Texas. *Journal of Agribusiness*, *25*(345-2016-15144), 115-132.

Richardson, J. W., Klose, S. L. and Gray, A. W. (2000). An applied procedure for estimating and simulating multivariate empirical (MVE) probability distributions in farm-level risk assessment and policy analysis. *Journal of Agricultural and Applied Economics* 32(2): 299-315.

Richardson, J.W., Schumann, K.D. and Feldman, P.A. (2008). Simetar: Simulation & Econometrics to Analyse Risk. *Agricultural and Food Policy Center, Department of Agricultural Economics, Texas A&M University, College Station, TX*.

Rowhani, P., Lobell, D.B., Linderman, M. and Ramankutty, N. (2011). Climate Variability and Crop Production in Tanzania. *Agricultural and Forest Meteorology* 151: 449–460.

URT – The United Republic of Tanzania. (2011). Tanzania Agriculture and Food Security Investment Plan (TAFSIP). [https://www.grain.org/attachments/ 2688/download] site visited on 18/02/2017.

URT – United Republic of Tanzania. (2013). National Agricultural Policy: Ministry of Agriculture Food Security and Cooperatives. Dar es Salaam. [http://www.tzdpg.or.tz/fileadmin/documents/dpg_internal/dpg_working_groups_clusters/cluster_1/agriculture/2._Ag_policies_and_strategies/National_ag_policies/1._2013_National_Agricultural_Policy_-_Finalfebruari_2013.pdf] site visited on 12/10/2018.

URT – United Republic of Tanzania. (2014). Ministry of Agriculture, Food Security and Cooperatives: Agriculture Climate Resilience Plan 2014-2019. [http://extwprlegs1.fao.org/docs/pdf/tan152483.pdf] site visited on 22/01/2016.

URT – United Republic of Tanzania. (2016). Agricultural Sector Development Programme Phase Two (ASDP II). [http://www.tzdpg.or.tz/fileadmin/documents/external/national_development_frameworks/ASDP2_Final_Document_20_May._2016__after_edit__1_.pdf] site visited on 12/10/2018.

CHAPTER TWO

2.0 LITERATURE REVIEW AND ANALYTICAL FRAMEWORK

2.1 Overview of Risk Analysis

Risk is typically defined as an adverse event, such as losing money on a venture or losing yield in agricultural production, which results in a negative return to the farmer (Palisade, 2020). The process of risk analysis uncovers not only the adverse outcomes but also the positive potentials (Hardaker *et al.,* 2004; Richardson *et al*., 2008; Palisade, 2020). By exploring the full space of possible outcomes for a given situation like agricultural production, a good risk analysis can both identify pitfalls and uncover new opportunities (Palisade, 2020). Risk analysis can be undertaken qualitatively or quantitatively. Palisade (2020) also highlights that assessing risk qualitatively involves a situation by instinct or “gut feel” and is characterized by statements like, “that seems too risky” or “we’ll probably get a good return on this.”

On the other hand, qualitative risk analysis which is the focus of this study attempts to assign numeric values to risks, either by using empirical data or by quantifying qualitative assessments (Richardson *et al*., 2008; Palisade, 2020). Quantitative risk analysis can be performed mainly in two different ways. The very dominant one way is by using single-point estimates which is deterministic in nature and stochastic risk analysis. Risk analysis is, therefore, part of every decision we make. We are always faced with ambiguity, uncertainty and variability (Palisade, 2020). Risk analysis is a systematic use of available information to determine how often specified events may occur and the magnitude of their consequences (Richardson *et al*., 2008; Palisade, 2020). Likewise, agricultural production in Tanzania is faced by these challenges leading to low performance of the sector. Even though we have unprecedented access to information, we can’t accurately predict the future. Sub-section 2.2 and 2.3 elaborates the quantitative risk analysis using deterministic and stochastic approaches correspondingly.

2.2 Theoretical Overview of Deterministic Risk Analysis Models

Deterministic risk analysis involves assigning values for discrete scenarios to see what the outcome might be in each (Hardaker *et al.,* 2004; Richardson *et al.,* 2008; Palisade, 2020). For instance, in financial modelling, an analyst commonly examines three different outcomes which are worst case, best case and most likely case.

i) *Worst case scenario* – this occurs when all costs are the highest possible value, and sales revenues are the lowest of possible projections. The outcome in this scenario is losing money.

ii) *Best case scenario* – this occurs when all costs are the lowest possible value, and sales revenues are the highest of possible projections. The outcome in this scenario is making a lot of money.

iii) *Most likely scenario* – the values under this scenario are chosen in the middle for costs and revenue, and the outcome shows making a moderate amount of money.

Deterministic risk analysis models are the most traditional statistical tools or methods used in many yield and price economic forecasting and risk analyses (Lobell *et al.,* 2013; Basso *et al.,* 2013). Deterministic models ignore risk and provide only a point estimate for key output variables (KOVs) instead of values with probability distributions that presents the possibilities of success and failure (Pouliquen, 1970; Reutlinger, 1970; Hardaker *et al.,* 2004). The deterministic models include regression analysis and process-based models. Regression models are the most widely used method in forecasting yields, prices, and many variables. The predictive power of these models is usually selected based on the values of R-squares and other model performance criteria (Jha and Sinha, 2013; Choudhury and Jones, 2014). The distribution of the error-term (ê), which carries the risk component in deterministic models, is always not well explained (Richardson *et al.*, 2006; 2008; Basso *et al.*, 2013).

The most commonly used deterministic regression model is the Box-Jenkins ARMA (autoregressive moving average) which has been used in yield forecasting by many scholars, including Najeeb *et al.* (2005), Badmus and Ariyo (2011), Gerretsadikan and Sharma (2011); Suleman and Sarpong (2012). Other models include Simple Exponential Smoothing, Double Exponential Smoothing, and Damped-Trend Linear Exponential Smoothing (Boken, 2000; Pal *et al.*, 2007; Choudhury and Jones, 2014). The advantage of a statistical model is that the calculations are easy, less time is required to run the model, and the data requirements are limited. The limitation of these models is that they have limited power to estimate the distribution of the risk component of the model (Richardson *et al.*, 2008; Basso *et al.*, 2013).

Process-based models are deterministic simulation tools used in crop yield forecasting. These models are complex, and they go beyond regression analysis to include data for the agroecosystem such as soil, temperature, water, and solar radiation (Hadar and Russell, 1969; Russell and Gardingen, 1997; Hoogenboom, 2000 and Basso *et al.*, 2013). Unlike deterministic statistical models, process-based models are built to consider the continuum soil-plant-atmosphere and corresponding daily changes on the daily accumulation of biomass and nitrogen (Asseng *et al.*, 2013 and Basso *et al.*, 2013). Examples of these models include the Agricultural Production Systems Simulator (APSIM), the System Approach to Land Use Sustainability (SALUS), and the DSSAT [www.dssat.net]. Although process-based models are claimed to be the most appropriate tools for yield forecasting, they are based on agronomic perspectives excluding the entailing economic variables like price and costs, which are vital for estimating farm returns on investments.

There are several challenges with deterministic models. These challenges include consideration of only discrete outcomes and ignoring hundreds or thousands of others. They give equal weight to each outcome, and no attempt is made to assess the likelihood of each outcome. These models also ignore the interdependence between inputs, the impact of different inputs related to other outcome and other nuances. However, despite its drawbacks and inaccuracies, many analysts and organizations operate using this type of analysis.

2.3 Theoretical Overview of Stochastic Risk Analysis Models

Stochastic risk analyses or models are techniques that allow analysts to account for risk in quantitative analysis and decision making (Hardaker *et al.,* 2004; Palisade, 2020). These techniques are used in such widely disparate fields as finance, project management, energy, engineering, insurance, oil and gas, transportation research and development, environment and agriculture (Richardson *et al.,* 2000; 2007; 2008; Palisade, 2020). Stochastic risk analysis uses a computerized mathematical technique called Monte Carlo simulation to furnish the decision-maker with a range of possible outcomes and the probabilities they will occur for any choice of action (Palisade, 2020). In Monte Carlo simulation, uncertain inputs in a model are represented using ranges of possible values known as probability distributions. By using probability distributions, variables can have different probabilities of a different outcome occurring. Probability distributions are a much more realistic way of describing uncertainty in variables of a risk analysis (Richardson *et al.,* 2000).

Monte Carlo simulation was first used by scientists working on the atom bomb; the technique was named for Monte Carlo, the Monaco resort town renowned for its casinos (Palisade, 2020). Since its introduction in World War II, Monte Carlo simulation has been used to model a variety of physical and conceptual systems. Standard probability distributions include normal, lognormal, uniform, triangular, PERT, and discrete.

i) *Normal distribution or "bell curve"* – the analyst defines the mean or expected value and a standard deviation to describe the mean. Values in the middle near the mean are most likely to occur. The normal distribution is symmetric.

ii) *Lognormal distribution* – values are positively skewed and non-symmetric like a normal distribution. It is used to represent values that don't go below zero but have unlimited positive potential.

iii) *Unform distribution* – all values have an equal chance of occurring, and the user defines the minimum and maximum.

iv) *Triangular distribution* – the analyst under this distribution defines the minimum, most likely, and maximum values. Values around the most likely are more likely to occur.

v) *PERT distribution* – the analyst defines the minimum, most likely, and maximum value, just like triangular distribution. Values around the most likely are more likely to occur. However, values between the most likely and extremes are more likely to occur than the triangular, but the extremes are not as emphasized.

vi) *Discrete distribution* – the analyst defines specific values that may arise and the likelihood of each.

Stochastic models are tools used to estimate probability distributions of possible outcomes by giving a chance for random variation in one or more inputs/values over time (Richardson *et al.,* 2008). The random variation is usually based on variabilities observed in historical information for a selected period using standard time-series techniques (Richardson *et al.,* 2000; 2006). Stochastic models are also called Monte Carlo simulation models, used as a quantitative analysis tool to understand and quantify risk and uncertainty of the analysed KOVs (Basso *et al.*, 2013). These models are also used in feasibility analyses of proposed management options to provide a range of outcomes embedded with risk and uncertainty. They produce more reliable results for decision-makers and policy advisers in a probabilistic way (Richardson *et al.*, 2007; Basso *et al.*, 2013). In other words, these models simulate a thousand samples for the risky variables to estimate the probable outcomes for KOVs. The simulated sample of values for each KOV constitutes an estimate of the variable's probability distribution, which can be used to make decisions in a risky environment (Richardson *et al.*, 2000; 2007).

Monte Carlo simulation provides several advantages over deterministic, or "single-point estimate" analysis:

- *Probabilistic results* – the model produce results that show not only what could happen, but how likely each outcome is.
- *Graphical results* – because of the data the model generates, it's easy to create graphs of different outcomes and their chances of occurrence. This is important for communicating findings to other stakeholders.
- *Sensitivity analysis* – with just a few cases, the deterministic analysis makes it difficult to see which variables impact the outcome the most. In Monte Carlo simulation, it's easy to see which inputs had the most significant effect on bottom-line results.
- *Scenario analysis* – in deterministic models, it isn't easy to model different combinations of values for different inputs to see the effects of truly different scenarios. Using Monte Carlo simulation, analysts can see exactly which inputs had which values together when certain or specific outcomes occurred. This is invaluable for pursuing further analysis.
- *Correlation of inputs* – in Monte Carlo simulation, it's possible to model interdependent relationships between input variables. It's important to accurately represent how, in reality, when some factors go up, others go up or down accordingly.

Stochastic simulation models, therefore, have, for a long time, played a role in economics – whether it is pure economic theory particularly policy-oriented, macro-and micro-economics, or what has progressively come to be called empirical or experimental economics (Nyangito, 1992; Velupillai and Zambelli, 2015). Stochastic models which are developed following the Monte Carlo simulation protocols involve simulating uncertain economic systems that are a function of risk variables, for the express purpose of making better decisions (Richardson *et al.,* 2008). Although stochastic models have a great potential to analyse risk in agriculture, there is currently little research work employing this technique.

2.4 Analytical Framework of the Study

In stochastic models, the risk is assumed to mimic historical risk, so past variability is used to estimate parameters for the probability distributions of random variables in a model (Nyangito, 1992; Richardson *et al.,* 2000; Hardaker *et al.*, 2004). In cross-section analyses or experimental studies, the variability of the observed/experimental data (deviations from the mean) is used to estimate the probability distributions of the uncertain variable (Richardson *et al.,* 2008). Probability distributions are estimated a large number of times to formulate probabilistic projections for the risky variables. The interaction of the risk variables with other variables in the system allows the analyst to project under risk on how the decision would likely perform under alternative management strategies (Bizimana and Richardson, 2019). In this way, stochastic simulation models can provide decision-makers with useful information about the probable outcomes of alternative management decisions under risk (Richardson *et al.,* 2008).

Hence, the development of a stochastic model generally starts with developing a deterministic model and then converting it to be stochastic by making some of the exogenous variables stochastic (Richardson *et al.,* 2007; Rezende and Richardson, 2015; Bizimana and Richardson, 2019). For instance, the forecast for a stochastic variable such as maize yield (*Y)* can be represented as:

$$\tilde{Y} = \hat{Y} + \tilde{e} \quad \text{...} \quad (2.1)$$

where $\hat{Y}$ is the deterministic component and $\tilde{e}$ is the stochastic component.

On the one hand, the variable in the equation is then forecasted by simulating values from a probability distribution. On the other hand, in a traditional environment (deterministic feasibility studies), use the $\hat{Y}$ values as the forecast, and ignore the $\tilde{e}$ by assuming a zero risk. Monte Carlo simulation feasibility studies estimate parameters for the $\tilde{e}$ distributions based on historical or observed data and simulate a large number of iterations to generate a probabilistic forecast or feasibility analysis $\tilde{Y}$.

Since the study has three specific objectives, three Monte Carlo simulation models were developed, validated and used for analysis. The following are typical steps used in developing the models:

i) Probability distributions for all risk variables were defined, parameterized, simulated.
ii) The simulated values were validated to ensure that the random variables are simulated correctly and demonstrate the appropriate properties of the parent or historical distribution.
iii) Stochastic values sampled from the probability distributions make the entire analysis stochastic.
iv) The completed stochastic models were simulated for 500 iterations using the Latin Hypercube Simulation technique. The Latin Hypercube sampling procedure

segments the distribution into N (500) intervals and makes sure that at least one value is randomly selected from each interval.

v) The results of the 500 samples were used to estimate the empirical probability distributions of the KOVs, which include annual net returns and net present values.

vi) The results are provided in the form of probabilities and probabilistic forecasts for the KOVs.

Monte Carlo simulation in probabilistic forecasting (specific objective one)

In addressing the first specific objective, a Monte Carlo simulation model, namely "MASORISIM" was developed based on the steps outlined by Richardson *et al.,* (2008). The MASORISIM which stands for **ma**ize-**so**rghum-**ri**ce **si**mulation **m**odel was designed to simulate risk ($\tilde{e}$) in the forecasting of yields, prices, and net returns for maize, sorghum, and rice crops. The first task performed by the MASORISIM was to show how variability in historical data (time series) for yields and prices of cereals (maize, sorghum and rice crops) can be used to forecast the possible future outlook. Past variability in yields and prices of agricultural sectors can be used to predict the future. The same procedures for analysing the future based on historical trends have been used by many scholars including Richardson *et al.* (2000; 2007; 2008), Outlaw *et al.* (2007), Palma *et al.* (2011), Rezende and Richardson *et al.* (2015).

The MASORISIM was not only developed to include the randomness (stochastic nature) of yields and prices of cereal crops but also to address the three critical problems in farm-level simulation modelling. These challenges include:

i) Non-normally distributed random yields and prices of cereal crops

ii) Correlation of yields and prices within and across enterprises (maize, sorghum and rice sub-sectors)

iii) Heteroscedasticity of random variables (prices and yields) over time

The procedure for MASORISIM model is well elaborated in Manuscript one in Chapter Three of this thesis.

Monte Carlo simulation in integrated decision support systems (specific objective two)

The Monte Carlo simulation procedures were also used to develop a bio-economic model which is an integrated decision support system (IDSS) used to estimate the distribution of economic returns of rice farming systems for better decision making. The bio-economic simulation is a cutting-edge integrated risk assessment approach emphasized by global agriculture modelling communities (Rosenzweig *et al.*, 2015). The model was named bio-economic simulation because it links data from biophysical (process-based) and econometric models to simulate the targeted key output variables.

The bio-economic simulation model changes all the random variables such as yields, prices, production cost, interest rates, and discount rates into stochastic. The best way to capture risks and uncertainties in stochastic modelling is to include the variability of random variables into the model (Richardson *et al.*, 2000; 2007). It shows how data from different sources are converted into a stochastic form. Data from two crop models, namely APSIM and DSSAT, were used in the model. First, the models simulated the impact of nitrogen fertilizers, and improved plant population on maize yield and the simulated yields from the two process-based models were then entered into the bio-economic simulation model for economic analysis. The typical procedures for bio-economic simulation are well elaborated in Manuscript two in Chapter Four of this thesis.

Monte Carlo simulation on scenario analysis (specific objective three)

The third specific objective was to demonstrate how the Monte Carlo simulation protocols can be programmed to evaluate the economic viability of different rice farming system in

Tanzania. In this dissertation, production data for three were used to demonstrate how panel survey data can still be made stochastic to include risk available in the data. In this analysis, the rice farming systems entailing traditional and improved practices were compared by considering the risk associated with each system, and the best farming system was identified. The farming systems were categorized based on the type of seeds used (local or improved), application of fertilizers, and application of the systems of rice intensification (SRI) practices (partially or fully). The detailed analytical procedures are well explained in manuscript three in Chapter Five of the dissertation.

Reference

Asseng, S., Ewert, F., Rosenzweig, C., Jones, J.W., Hatfield, J.L., Ruane, A.C., Boote, K.J., Thorburn, P.J., Rotter, R.P., Cammarano, D., Brisson, N., Basso, B., Martre, P., Aggarwal, P.K., Angulo, C., Bertuzzi, P., Biernath, C., Challinor, A.J., Doltra, J., Gayler, S., Goldberg, R., Grant, R., Heng, L., Hooker, J., Hunt, L.A., *et al*., (2013). Uncertainty in simulating wheat yields under climate change. Nature Climate Change DOI: 10.1038/nclimate1916.

Badmus, M. A. and Ariyo, O. S. (2011) ‘Forecasting Cultivated Areas and Production of Maize in Nigeria Using ARIMA model,’ *Asian Journal of Agricultural Sciences 3*(3), 171- 176.

Basso, B., Cammarano, D. and Carfagna, E. (2013). Review of crop yield forecasting methods and early warning systems. In *Proceedings of the first meeting of the scientific advisory committee of the global strategy to improve agricultural and rural statistics, FAO Headquarters, Rome, Italy* (pp. 18-19).

Bizimana, J. C. and Richardson, J. W. (2019). Agricultural technology assessment for smallholder farms: An analysis using a farm simulation model (FARMSIM). *Computers and electronics in agriculture*, *156*, 406-425.

Boken, V.K. (2000). Forecasting spring wheat yield using time series analysis: a case study for the Canadian Prairies, *Agronomy Journal*, *92*(6), 1047-1053.

Choudhury, A. and Jones, J. (2014). Crop yield prediction using time series models. Journal of Economics and Economic Education Research, 15(3), 53.

Gerretsadikan, A and Sharma, M.K. (2011) ‘Modeling and forecasting of rainfall data of mekele for Tigray region (Ethiopia),’ *Statistics and Applications 9*(1-2), 31-53.

Hadar, J. and Russell, W.R. (1969). Rules for ordering uncertain prospects. *The American Economic Review* 59(1): 25-34.

Hardaker, J. B., Huirne, R. B. M., Anderson, J. R. and Lien. G. (2004). *Coping With Risk in Agriculture*. Wallingford, Oxfordshire, UK: CABI Publishing.

Hoogenboom, G. (2000) ‘Contribution of agrometeorology to the simulation of crop production and its applications, *Agricultural and Forest Meteorology,* 103(1-2), 137–157.

Jha, G. K., and Sinha, K. (2013). Agricultural price forecasting using neural network model: An innovative information delivery system. *Agricultural Economics Research Review*, *26*(347-2016-17087), 229-239.

Lobell, D. (2013). The use of satellite data for crop yield gap analysis. Field Crop Res. 143, 56–64.

Najeeb, I., Khuda, B., Asif, M., and Abid, S.A. (2005). Use of ARIMA Model for Forecasting Wheat Area and Production in Pakistan. *Journal of Agricultural and Social Sciences* 1(2), 120- 122.

Nyangito, H.O. (1992). *Economic evaluation of alternative livestock disease control methods in Kenya.* Dissertation for Award Degree of Doctorate at University of Tennessee. 263pp.

Outlaw, J.L., Ribeira, L.A., Richardson, J.W., da Silva, J., Bryant, H., Klose, S.L. (2007). Economics of sugar-based ethanol production and related policy issues. *J. Agric. Appl. Econ. 39* (2), 357–363.

Pal, S., Ramasubramanian, V. and Mehta, S.C. (2007). Statistical models for forecasting milk production in India. *Journal of Indian Society of Agricultural Statistics* 61(2), 80–83.

Palisade (2020). Advanced Risk Analysis for Microsoft Excel. https://www.palisade.com/risk/risk_analysis.asp

Palma, M.A., Richardson, J.W., Roberson, B.E., Ribeira, L.A., Outlaw, J., and Munster, C. (2011). Economic feasibility of a mobile fast pyrolysis system for sustainable bio-crude oil production. *Int. Food Agribus. Manag. Rev. 14* (3), 01–16.

Pouliquen, L. Y. (1970). Risk analysis in project appraisal. *World Bank Staff Occasional Papers* (11), International Bank for Reconstruction and Development, The John Hopkins University Press.

Reutlinger, S. (1970). Techniques for project appraisal under uncertainty. *World Bank Staff Occasional Papers* (10), International Bank for Reconstruction and Development, The John Hopkins University Press.

Rezende, M.L., and Richardson, J.W. (2015). Economic feasibility of sugar and ethanol production in Brazil under alternative future prices outlook. *Agricultural Systems*, *138*, pp.77-87.

Richardson, J. W., Schumann, K. and Feldman, P. (2006). Simetar: Simulation for excel to analyse risk. *Department of Agricultural Economics, Texas A&M University*.

Richardson, J.W., Herbst, B.K., Outlaw, J.L., and Gill II, R.C. (2007). Including risk in economic feasibility analyses: The case of ethanol production in Texas. *Journal of Agribusiness* 25(2): 115–132

Richardson, J.W., Klose, S.L., and Gray, A.W. (2000). An applied procedure for estimating and simulating multivariate empirical (MVE) probability distributions in farm-level risk assessment and policy analysis. *Journal of Agricultural and Applied Economics*, *32*(2), pp.299-315.

Richardson, J.W., Schumann, K., and Feldman, P. (2008). Simulation and econometrics to analyse risk. *Simetar, Inc.: College Station, TX*.

Rosenzweig, C., Jones, J., Antle, J. and Hatfield, J. (2015). Protocols for AgMIP Regional Integrated Assessments, version 6.0. [http://www.agmip.org/wp-content/uploads/2015/09/AgMIP-RIA-Protocols-V6sm.pdf] site visited on 30/06/2017.

Russell, G. and Gardingen, P.R. (1997). Problems with using models to predict regional crop production. *Scaling up: from cell to landscape, Cambridge University Press, Cambridge*. pp. 273–294.

Suleman, N. and Sarpong, S. (2012). Forecasting Milled Rice Production in Ghana Using Box-Jenkins Approach. *International Journal of Agricultural Management and Development*, 2(2), 79-84.

Velupillai, K. V., and Zambelli, S. (2015). Simulation, computation and dynamics in economics. *Journal of Economic Methodology*, *22*(1), 1-27.

CHAPTER THREE

3.0 MANUSCRIPT ONE

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Forecasting yields, prices and net returns for main cereal crops in Tanzania as probability distributions: A multivariate empirical (MVE) approach

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3.1 Abstract

Maize (*Zea mays L.*), sorghum (*Sorghum bicolor* L. Moench), and rice (Oryza sativa) are essential staple crops to the livelihoods of many Tanzanians. But the future productivity of these crops is highly uncertain due to many factors including overdependence on a rain-fed production system, poor agricultural practices, and climate change and variability. Despite the multiple risks and constraints, it is vital to highlight the pathways of cereal production in the country. Understanding the trends of cereal production helps to inform policymakers, so they can make better decisions to improve the viability of the sector and its potential to increase food production and income for the majority population. A Monte Carlo simulation model was developed to evaluate the economic performance of main cereal sub-sectors in semi-arid and sub-humid agro-ecological zones in Tanzania. A multivariate probability distribution model was embedded in the model to simulate many variables. Historical data for eleven years from 2008 to 2018 of yields and price data for maize, sorghum, and rice were used in the model to simulate and forecast yields and prices in Dodoma and Morogoro regions of Tanzania for seven years, from 2019 to 2025. Dodoma and Morogoro regions represent semi-arid and sub-humid agro-ecological zones, respectively. The simulated yields and prices were used with total costs and total area harvested for each crop to calculate the probable net present value (NPV). The results on crop yield show an increasing trend for maize and rice with a marginal increase for sorghum in the Dodoma region by 2025. Likewise, the yield for rice is expected to rise in Morogoro with a slight rise for maize and a decreasing trend for sorghum. Meanwhile, the prices for all three crops are projected to increase in both regions in the future timescale. Generally, results on economic feasibility in terms of NPV revealed a high probability of success for all the crops in both regions except maize in Morogoro. The results for maize in Morogoro presented a 2.93% probability of negative NPV. Of the three crops, maize indicated the highest relative risk associated with NPV for both regions and is relatively higher in Morogoro (55.1%) than Dodoma (34.2%). This study helps to understand better the outlook of the main cereal crop sub-sectors in two agro-ecological zones of Tanzania over the next seven years up to 2025. Although the results on production indicate increasing trends for cereal crops in the study areas, the increase is relatively small, particularly in Morogoro, which is one of the national food basket regions. With high dependence on rain-fed agriculture, the production of main cereals in Tanzania is likely to face a high degree of risk and uncertainty that will affect livelihoods, incomes, and food availability to the poor households.

Keywords: Cereal crops, MVE probability distribution, MASORISIM, stochastic simulation, Semi-arid, Sub-humid, Simetar

3.2 Introduction

Maize (*Zea mays L.*), sorghum (*Sorghum bicolor* L. Moench), and rice (*Oryza sativa*) are major staple food crops in Sub Saharan Africa (SSA) consumed by people with varying food preferences and socio-economic backgrounds (Waithaka *et al.,* 2013). The three staple crops are grown in diverse agro-ecological zones and farming systems and account for the largest share of calories and protein consumed in SSA (Macauley and Ramadjita, 2015). However, recent productivity trends and current performance of food crops in SSA are progressively less able to meet the needs of its rapidly increasing population (Wilson and Lewis, 2015). The low productivity of these crops in SSA is attributed to many constraints including high dependence on rain-fed agriculture, drought, floods, pest and diseases, and inadequate application of improved seed and fertilizers leading to food insecurity in rural areas (Ziervogel *et al.,* 2006; Cooper *et al.,* 2008; Ziervogel and Ericksen, 2010; URT, 2013a; 2013b; Kahimba *et al*., 2015; Wilson and Lewis, 2015).

As the population of SSA is likely to grow to around 1.7 billion by 2050, demand for food to feed the people also increases (Waithaka *et al.,* 2013). In the African Union (AU), recommitments have been made to transform agricultural productivity in Africa by focusing on vulnerable social groups. One of the examples is the Comprehensive Africa Agriculture Development Programme (CAADP) under the 2014 Malabo Declaration on Accelerated Agricultural Growth and Transformation for Shared Prosperity and Improved Livelihoods (AU, 2014). Addressing the low performance of agriculture in SSA has, therefore, become a focal point towards attaining an agriculture revolution. For instance, under the third commitment of the Malabo Declaration, African leaders agreed to end hunger in Africa by 2025 by at least doubling current agricultural productivity levels (AU, 2014).

The same commitment is embraced in the Tanzania National Agriculture Policy, which is an instrument for facilitating the attainment of Tanzania Development Vision 2025 (TDV-2025). Its objective, among others, is to have modernized agriculture for increased agricultural productivity and profitability by 2025 (URT, 2013a). Additionally, the rationale of the current Agricultural Sector Development Strategy Phase II (ASDP-II) (2015/2016–2014/2025) is to operationalize the transformation of the agricultural sector from low productivity into a semi-industrialized, modernized, highly productive, commercial and more resilient to climate change and variability (URT, 2016a).

Nevertheless, some uncertainty remains about the future productivity and profitability of staple food crops in Tanzania. These uncertainties hinder the implementation of different agricultural policies, plans and strategies for achieving an agriculture revolution in the country, hence impacting decisions of investment in agrarian technologies (Ingram *et al.*, 2008; Thornton *et al.,* 2011; Yao *et al.,* 2011; Msongaleli *et al.*, 2017). Moreover, Lack of timely and accurate information on future yields and prices trends of important crops affect the food security, import and export plans, crop insurance policy and government aid to farmers at national, regional, village and household levels (Kantanantha, 2007; URT, 2014; Kahimba *et al.*, 2015). In general, there is limited information in terms of understanding future yields and prices of major food crops in Tanzania. This information is essential to ensuring food availability and household income predominantly for the most impoverished population. Therefore, it emphasizes the need for location-specific research to estimate the feasibility of producing staple crops in Tanzania while considering the stochastic nature of agricultural production increases the level of understanding in the agricultural sector.

The present study applies a multivariate empirical (MVE) probability distribution model to forecast yields and prices of maize, sorghum, and rice in Dodoma and Morogoro regions of Tanzania. A stochastic simulation model was first developed, with an MVE probability distribution built-in to capture correlations among the variables. The forecasting analysis performed for seven years through 2025. Dodoma and Morogoro represent the semi-arid and sub-humid agro-ecological zones, respectively. The forecasted values were combined with production costs, harvested area (ha), and quantities of inputs used in production to estimate the probable net present value (NPV) of each crop for seven years. The MVE distribution model has been used in many studies, including Richardson *et al.* (2000, 2006; 2007; 2008), Hardaker *et al.* (2004) and Rezende and Richardson (2015). A seven-year horizon (2019–2025) in this study is in line with the Tanzanian National Agricultural Policy, TDV-2025, ASDP-II, and CAADP. These policy documents have a common goal of modernizing agriculture in Tanzania to a highly productive and profitable sector by 2025. Therefore, this study provides a roadmap of cereal production from 2019 to 2025, and the findings will help the government, especially the National Food Security Division (NFSD) and regional officials to develop better plans for future production, storage, marketing, and in ASDP II result measurement framework.

The scope of this study provides a computational framework nested in the MASORISIM model for quantifying the possible variability on yield and price of staple crops and the probable economic implications at the agro-ecological zone or regional level. Nonetheless, given the ability of a MASORISIM to simulate multiple correlated random variables concurrently, this study demonstrates a base for similar studies to be conducted, including those on non-cereal food and cash crops, possibly covering the entire country.

3.3 Materials and Methods

3.3.1 Description of the study area

The study area encompassed two agro-ecological zones: (i) the semi-arid zone represented by the Dodoma region; and (ii) the sub-humid represented by Morogoro Region (Figure 3.1). Dodoma Region is in the central part of Tanzania mainland and lies between GPS coordinates of 6° 9′ 40.2624″ S and 35° 44′ 43.5336″ E. Much of the region is a plateau rising gradually from some 830m in Bahi swamps to 2000m above sea level in the highlands North of Kondoa (URT, 2012a).

A semi-arid climate characterizes the region, receiving <800mm of rainfall with the mean number of rain days between 10 and 20 per annum. Dodoma is one of the regions dominated by a long dry season lasting from late April to early December and a short single wet season during the remaining months (Schechambo *et al.*, 1999; Kempf, 2007; Yanda *et al.*, 2015). The temperature in the region varies according to altitude, but generally, the average maximum and minimum for October to December are 31°C and 18°C, respectively. The average rainfall for Dodoma Region is low (570mm on average) and unpredictable in frequency, and the amount. To some extent, the rain is higher in Mpwapwa and Kondoa Districts (URT, 2012a).

Based on the 2012 population and housing census, there were about 2.1 million inhabitants in the Dodoma Region, with an average annual increase of 2.1% (URT, 2013b). Major food crops grown in the Dodoma Region are sorghum, maize, paddy (rice), beans, bulrush millet, groundnuts, and finger millet with sunflower and sesame being the main cash crops. Dodoma is one of the regions with numerous livestock, including cattle, goats, sheep, poultry, and pigs. The region also grows maize is particularly in Kondoa, and Kongwa Districts, followed by Chamwino and Mpwapwa Districts, while rice is highly produced in the Bahi District. Sorghum is a dominant crop in Dodoma is positively grown in Chamwino, Kondoa, Bahi, and Mpwapwa Districts.

The Morogoro Region is in the Mid-Eastern part of Tanzania Mainland. It lies between the GPS coordinates of 6° 49′ 49.3428” S, and 37° 40′ 14.1204″ E. Morogoro is among the largest regions in Tanzania having a total area of about 73 000 km2 much of which have good potential for agriculture. Morogoro region is characterized by a sub-humid climate with an average temperature of 24°C, having a minimum of 18°C in the highland areas, and a maximum of 30°C in the lowland areas (URT, 2012b). The average rainfall for Morogoro Region is between 500mm in lowland areas and 2 200 mm in the mountainous zones. The region had about 2.2 million inhabitants, with an average annual increase of 2.5% (URT, 2013b). Major food crops grown in the Morogoro Region are maize, rice, sorghum, bulrush millets, and beans, whereas the main cash crops include sugarcane, rice, cotton, sisal, and tobacco. Livestock keeping is also an important activity in the region. Maize is predominantly grown in Gairo, Kilosa, and Mvomero Districts, while Ulanga District and Morogoro Municipal Council are the least maize producer in the region.

Morogoro District Council Rural (MDCR) produces the highest volume of sorghum in the region, followed by Kilosa, Gairo, and Mvomero Districts. Kilombero District leads in rice production, followed by Ulanga and Kilosa Districts. For the last ten year (2008 - 2018), the hectares harvested maize was estimated at 183 142 and 438 945, followed by rice between 111 821 and 189 226. Sorghum is grown under the smallest area estimated at 10 679 and 24 743 ha. Meanwhile, the harvested areas in Dodoma follows between 141 870 – 253 551 ha for maize, 198 183- 324 920 ha for sorghum, and 7 933 – 11 570 ha for rice. (URT, 2012a; 2012b; 2016b; 2017). Morogoro has been named one of the national food basket regions together with Mbeya, Ruvuma and Iringa Regions. Morogoro is leading in rice production by >12% of the total rice produced in the country and the 8th region in maize production (Cochrane and Souza, 2015). Dodoma region is vital in sorghum production, accounting to over 31% of the total area and about 24% of sorghum produced in the country (Cochrane and Souza, 2015; URT, 2017). Food prices are slightly higher in Dodoma and other deficit regions than the Morogoro Region.

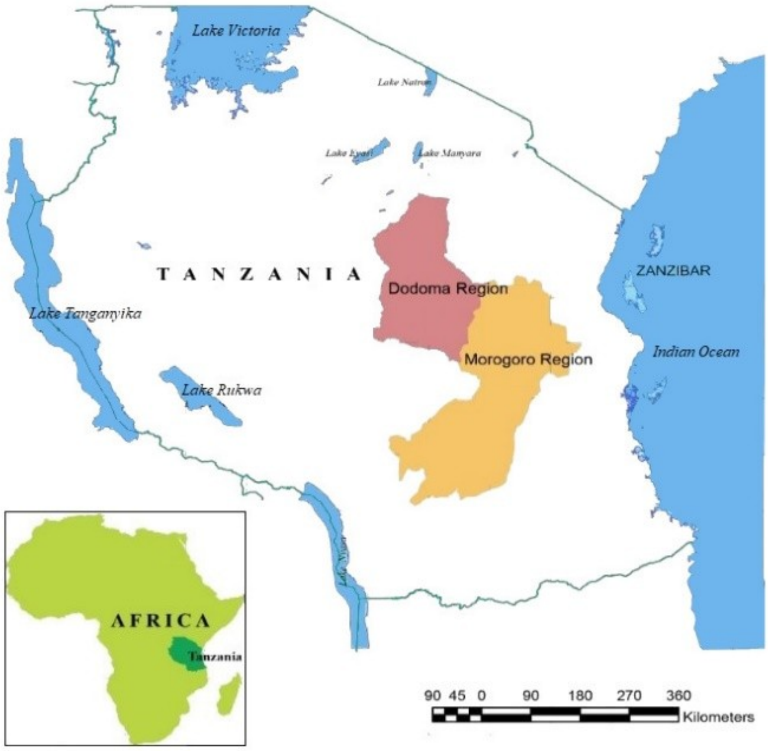

Figure 3.1: The study area

3.3.2 Data

This study uses data from many different sources, including a series of focus group discussions (FGDs) with representatives from the National Bureau of Statistics (NBS), and Ministry of Agriculture (MoA) particularly the National Food Security Division (NFS) and the Agricultural Marketing Section (AMS). Other sources are household surveys under Trans-SEC, and Scale-n projects conducted in both Dodoma and Morogoro Regions supplemented with grey literature from government agricultural documents. Trends on yield and total area harvested (ha) for each crop were obtained from the NFS and AMS. The missing data were acquired and compiled from the Regional Agricultural Offices in Dodoma and Morogoro Regions where crop yields per district are collected annually and kept in paper-based files. Similarly, the cost of production per unit area for each crop was obtained from different sources Such as literature review and FGDs where farmers and experts on maize, sorghum, and rice supply chains were involved. The data also were supplemented by household surveys conducted under Scale-N and Trans-SEC projects and through reviewing Regional Agricultural Reports (URT, 2012a; URT, 2012b). The costs of production (TZS/ha) comprise of: land preparation, seeds, planting, weeding, fertilizer and pesticide application, harvesting, and postharvest handling. Appendix 3.1 summarizes the production costs used in this study.

Annual price data for cereals were obtained from the regional agricultural marketing departments, where daily prices of all crops are collected and archived or published. Table 3.1 presents the historical mean yields (in t/ha) and prices (in TZS/t) for all crops per region. For convenience, the variables were abbreviated for the Dodoma Region as follows MzY_1=maize yield, SoY_1=sorghum yield, RcY_1=rice yield; MzP_1=maize price, SoP_1=sorghum price, and RcP_1=rice price and variables for Morogoro were subscripted by a number two.

Table 3.1: Historical mean yields and prices per crop per region

Year	Yields for Dodoma			Prices Dodoma (x 100,000)			Yields for Morogoro			Prices Morogoro (x 100,000)		
	MzY_1	**SoY_1**	**RcY_1**	**MzP_1**	**SoP_1**	**RcP_1**	**MzY_2**	**SoY_2**	**RcY_2**	**MzP_2**	**SoP_2**	**RcP_2**
	t/ha	***t/ha***	***t/ha***	***TZS***	***TZS***	***TZS***	***t/ha***	***t/ha***	***t/ha***	***TZS***	***TZS***	***TZS***
2008	0.60	0.70	0.80	3.487	2.804	10.210	1.30	1.30	1.30	3.551	3.929	9.220
2009	0.30	0.60	0.80	4.111	3.633	11.685	0.90	0.90	1.00	4.173	4.918	10.932
2010	0.63	1.20	1.23	3.904	3.634	11.950	1.33	1.14	1.75	3.748	6.072	10.201
2011	0.90	0.90	1.10	4.196	4.177	14.103	1.60	1.10	1.40	4.094	5.997	11.376
2012	0.50	1.00	0.60	5.748	4.956	19.263	0.80	0.80	1.30	5.202	6.992	16.253
2013	0.60	1.10	0.70	6.969	7.088	16.956	0.80	1.00	1.20	6.033	9.054	13.305
2014	1.00	0.90	2.00	5.125	5.049	13.563	0.84	0.80	2.14	4.243	8.253	11.726
2015	0.85	0.94	1.90	5.560	5.450	17.252	0.99	0.77	2.02	5.338	8.153	16.074
2016	1.10	0.80	1.70	6.809	7.264	16.771	1.20	1.10	2.10	6.944	11.954	16.962
2017	0.90	0.50	1.04	8.042	9.235	18.631	1.50	0.98	1.89	7.590	12.032	16.942
2018	1.10	1.07	1.80	4.959	5.140	17.792	1.53	1.21	2.6	4.357	10.289	17.218

Source of Data: MoA (NFSD and AMS)

Table 3.2 provides additional data and assumptions used in the model. The data include: (i) the approximated area growing maize, sorghum, and rice for each region compiled from NSCA, AASS, NBS, FGDs and regional agricultural offices (RAO); (ii) average production cost for each crop enterprise collected from FGDs, and scale-n project and (iii) inflation rate and the discount rate were obtained from NBS website, Bank of Tanzania (BOT) and the trading economics website [www.tradingeconomics.com]. The site provides a collection of economic indicators, including actual values, historical data charts, time-series, and long-term forecasts. An inflation rate ranging from 3.5 – 16% was assumed for projected production costs. A discount rate of 7 – 16% was assumed in the discounting process of future returns. The historical inflation and discount rates used in this study were collected from the NBS website (Table 3.3). Since inflation and discount rates are random variables, their stochastic behaviour were also included in the MASORISIM model.

Table 3.2: Additional data used the model

Variable	**Units**	**Agro-ecological zones**	
		Dodoma	**Morogoro**
Area under maize (harvested area)	ha	141 870 – 253 551	183 142 – 438 945
Area under sorghum (harvested area)	ha	198 183 – 324 920	10 679 – 24 743
Area under rice (harvested area)	ha	7 933 – 11 570	111 821 – 189 226
Average production cost for maize	TZS/ha	473 000	561 000
Minimum production cost for maize	TZS/ha	355 000	430 000
Maximum production cost for maize	TZS/ha	597 000	676 000
Average production cost for sorghum	TZS/ha	378 000	375 000
Minimum production cost for sorghum	TZS/ha	328 000	324 000
Maximum production cost for sorghum	TZS/ha	439 000	428 000
Average production cost for rice	TZS/ha	745 000	760 000
Minimum production cost for rice	TZS/ha	450 000	500 000
Maximum production cost for rice	TZS/ha	960 000	980 000
Inflation rate for production cost	%	3.50 – 16.00	3.50 – 16.00
Discount rate for NPV	%	7.00 – 16.00	7.00 – 16.00

Notes: Source of data include FGDs, NBS, MoA, (details of costs are in Appendix 3.1).

Table 3.3: Average consumer prices inflation rate and per annum discount rate from 2008 to 2018

	2008	2009	2010	2011	2012	2013	2014	2015	2016	2017	2018
Inflation rate	10.3	12.3	7.2	12.7	16.0	7.9	6.1	5.6	5.2	5.3	3.5
Discount rate	15.99	3.70	7.58	12.00	12.00	16.00	16.00	16.00	16.00	9.00	7.00

Source: NBS

3.3.3 Stochastic simulation procedures

The MASORISIM model was developed and used in this study. MASORISIM is a Monte Carlo simulation model used in this study to forecast yields, prices and net returns of **ma**ize, **so**rghum and **ri**ce cereals for the next 7-years. The MASORISIM model was programmed in Microsoft Excel using the Simetar© add-in, following a procedure by Richardson *et al.* (2000; 2008). Since the study comprises yields and prices three crops and two agro-ecological zones, the multivariate empirical (MVE) distribution was used in the model to account for the correlation among the stochastic variables according to Richardson *et al*. (2000). The MVE distribution was applied because the yields and prices of maize, sorghum, and rice are correlated and non-normally distributed.

Additionally, the production of cereal crops in Tanzania, as well as the rest of SSA, is affected by weather leading to the high variability of yields and prices. Given this inconsistency, imposing the MVE distribution in the MASORISIM to capture the heteroskedasticity variability is important (Richardson *et al.,* 2008). Eleven years (2008–2018) of historical yield data for maize, sorghum, and rice were used alongside 11-years of local prices to develop the MASORISIM model for the three crop sub-sectors at the agro-ecological level. The model was simulated for a period of seven years from 2019 up to 2025 using stochastic yields and prices from the historical trend to forecast the distribution of the probable yields and prices. The simulated variables were combined with the total area harvested to simulate total revenue for each crop. Next, the inflated production cost was deducted to calculate the stochastic annual net cash income and the net present value (NPV) per crop per agro-ecological zone. The key benefit of the MASORISIM model is that it produces both the deterministic and stochastic results for better decision making.

The MASORISIM model is a step-wise process that considers changing traditional trend forecasts to stochastic simulations of random variables. Since historical data were used, the de-trending of the random variables (yields and prices) was the first step to estimate the deterministic component of yields and prices. De-trending of historical data helps to remove possible systematic risk inherent in the random variables. The next steps involved the calculation of the stochastic parts and finally combining the deterministic and the stochastic elements to simulate random values for stochastic modelling.

Steps for simulation procedures are summarized as follows:

Step 1: Estimation of deterministic components

The yields and prices are de-trended as the yield and price data are from historical data. Alternative functional forms (linear, quadratic, and cubic) were tested to remove systemic risk, and the polynomial function of degree three (a cubic regression) was selected based on the R-Square (R^2). The deterministic component of the probability distribution from the trend regression for two equations is expressed without an error term ($\hat{e}_{t,\,ij}$), as shown in Equation (1) and (2).

$$\hat{Y}_{t,ij} = \hat{a} + \hat{b}T_{t,ij} \tag{3.1}$$

$$\hat{P}_{t,ij} = \hat{a} + \hat{b}T_{t,ij} \tag{3.2}$$

where:

$\hat{\alpha}$ = intercept;

$\hat{b}$ = slope;

T= time (Year);

i = crops (maize, sorghum, and rice);

j = regions (Dodoma and Morogoro);

$\hat{Y}$ = average yield for crop i in the year t;

$\hat{P}$ = price for crop i in the year t;

Step 2: Estimation of stochastic components

The unexplained variability about the deterministic component or $\hat{e}_{t,ij}$ (Equations 3.1 and 3.2) is the stochastic component for each variable (i) for each year (t). The residuals from the cubic regression forecasts constitute the $\hat{e}_{t,ij}$ and are divided by their respective trend forecasted values for each year to calculate the fractional deviates denoted by $F\hat{e}_{t,ij}$, and sorting of the fractional residuals denoted by $S_{t,ij}$ expressed as follows:

For yield:

$$\hat{Y}_{t,ij} = \hat{\alpha} + \hat{b}T_{t,ij} + \hat{e}_{t,ij} \tag{3.3}$$

$$\hat{e}_{t,ijY} = Y_{t,ij} - \hat{Y}_{t,ij} \tag{3.4}$$

$$F\hat{e}_{t,ijY} = \hat{e}_{t,ijY} / \hat{Y}_{t,ij} \tag{3.5}$$

$$S_{t,ijY} = Sorted\ (F\hat{e}_{t,ijY})$$

(3.6)

For price:

$$\hat{P}_{t,ij} = \hat{\alpha} + \hat{b}T_{t,ij} + \hat{e}_{t,ij} \tag{3.7}$$

$$\hat{e}_{t,ijP} = P_{t,ij} - \hat{P}_{t,ij} \tag{3.8}$$

$$F\hat{e}_{t,ijP} = \hat{e}_{t,ijP} / \hat{P}_{t,ij} \tag{3.9}$$

$$S_{t,ijP} = Sorted\ (F\hat{e}_{t,ijP})$$

(3.10)

where:

Y and *P* represent the deterministic component of the Equation (3) and (7).

Step 3: Setting the Pseudo minimum (**Pmin$_{\hat{e}}$*****) and maximum (*****Pmax$_{\hat{e}}$*****)**

The (Pminê) and (Pmaxê) provide the endpoints for the distribution, calculated by multiplying the minimum and maximum residuals by 1.0001.

Step 4: Estimation of the correlated uniform standard deviates (CUSD's)

Estimating the CUSD's is a crucial step in the stochastic simulation as it appropriately correlates the random variables to retain the observed stochastic dependency between variables. The Simetar add-in for Excel generates a correlated uniform standard deviate (CUSD) by calculating the square root of the correlation matrix and multiplying it by a vector of independent standard normal deviates. It then converts the resulting correlated standard normal deviates to CUSDs using the inverse transform of a standard normal distribution (Richardson *et al.*, 2008). The resulting vector of simulated CUSDs is used to simulate random prices and yields that are appropriately correlated. The CUSDs are used to avoid either over or under-stating the variance and mean for cash receipts if price and yield are correlated, and the correlation ignored (Richardson *et al.*, 2000; 2008). Stochastic prices and yields for maize, sorghum, and rice for each agro-ecological zone are simulated for seven years using a correlation matrix method. This method ensures that the regions are simulated using local prices and yields. Since we have three cereal crops, and three price sets, the correlation matrix is a 6×6 dimension for each zone for each agro-ecological zone. Given six random variables and seven years, the model simulated 42 correlated yields and prices per zone using the unsorted deviations from cubic regression. Additional details for steps 1, 2, 3, and 4 are in Appendix 3.2.

Step 5: Generation of random variables

Step 5 involves a combination of the deterministic forecasts and the stochastic parameters to calculate the random values for a stochastic model. The analysis applies the CUSD to the inverse transform of the empirical distribution defined by the S_i and $F(S_i)$ using the EMP functions demonstrated in Equations 3.11 and 3.12. The two equations are simulated for 500 iterations using the Latin Hypercube procedure to simulate the random yields and prices for seven years. The Latin Hypercube sampling procedure segments the uniform distribution into N (500) intervals and makes sure that at least one value is randomly selected from each interval. In other words, it ensures that all areas of the probability distributions are considered in the simulation (Richardson *et al.*, 2008).

$$\tilde{Y}_{t,ij} = \hat{Y}_{t,ij} * (1 + EMP(S_{t,ij}, F(S_{t,ij}), CUSD_{t,ij}))$$

(3.11)

$$\tilde{P}_{t,ij} = \hat{P}_{t,ij} * (1 + EMP(S_{t,ij}, F(S_{t,ij}), CUSD_{t,ij}))$$

(3.12)

Where:

tilde (~) represents a stochastic variable; *EMP()* is the Simetar function which simulates an empirical distribution defined by $S_{t,ij}$, and $F(S_{t,ij})$ using the inverse transform method. $F(S_{t,ij})$ is the frequency distribution for the fractional deviates from the trend ($S_{t,ij}$), and CUSD defined above.

Step 6: Model simulation and evaluation

This step consists of checking the completeness and accuracy of the simulated values. The Student's-*t*-test determines if the correlation coefficients for two matrices (historical and simulated) are statistically equal at the indicated confidence level. For example, in Appendix 3.3, the simulated correlation coefficients were statistically equal to the historical correlation coefficients on a critical value of 2.94 at the confidence level of 99.6%. It also checks if the mean of each simulated and historical variables is statistically equal at a given confidence level (Richardson *et al.*, 2000; 2008). Hence, the calculated t-test statistics are all less than the critical value of 2.25, so we fail to reject the null hypothesis that the simulated mean of price and yield is statistically equal to the historical mean at the 95.0% confidence level. Additional details describing the evaluation tests are provided in Appendix 3.3.

Step 7: Simulation of key output values (KOVs)

After the evaluation of random variables used in the model, the final step consists of formulating a stochastic simulation model in order to simulate the KOVs as illustrated in Equations 3.13 to 3.17.

$$\tilde{\mu}_{ij} = a_{ij} * \tilde{Y}_{ij} \tag{3.13}$$

$$\tilde{c}_{ij} = \sum_{\theta} \left(a_{t,ij} * \tilde{k}_{t,ij\theta} * (1 + \tilde{r}_{t,\theta}) \right) \tag{3.14}$$

$$\tilde{C}_{ij} = \tilde{c}_{ij} + FC_{ij} \tag{3.15}$$

$$\tilde{V}_{ij} = \tilde{P}_{ij} * \tilde{\mu}_{ij} \tag{3.16}$$

$$\tilde{\pi}_{ij} = \tilde{V}_{ij} - \tilde{C}_{ij} \tag{3.17}$$

Where:

Tilde (~) indicates a stochastic variable;

$\tilde{Y}_{ij}$ = stochastic yield from Equation (3.11)

i = the three crops maize, sorghum, and rice;

j = regions (Dodoma and Morogoro);

$\mu_{t,ij}$ = production for crop i for region j in year t;

$a_{t,ij}$ = land area devoted to crop i, for region j (in hectares) in year t;

$k_{t,ij\theta}$ = variable cash cost per ha for every input (θ) applied to crop i,

θ = inputs like land preparation, seeds, fertilizers, weeding, herbicides, transport, labor, storage and marketing cost*;*

$\tilde{r}_{t,\theta}$ = stochastic annual inflation rate in the price per unit of input θ for year t, simulated by a Simetar function "=UNIFORM(MIN, MAX)", where MIN=3.0, and MAX=5.32;

$c_{t,ij}$ = total variable costs for each crop i in year t,

$FC_{t,ij}$ = fixed cost, (the FC for was set equal to zero as the crops mainly cultivated at small-scale level with limited machinery loans, land loans, property taxes, and insurance).

$\tilde{C}_{t,ij}$ = total production cost for each crop i, for each region j in year t;

$\tilde{V}_{t,ij}$ = total receipts or gross revenue for each crop i, per region in year t;

$\tilde{P}_{t,ij}$ = stochastic price from Equation (3.12)

$\tilde{\pi}_{ij}$ = Net return for each crop *i,* region j.

Stochastic inflation rates for variable inputs were simulated using a uniform distribution function denoted by U(Min, Max). The uniform function is used in Simetar to return a random number between the specified minimum and maximum, where each number between the range has an equal probability of being observed. Simetar simulates it with the=UNIFORM (min, max) function. The historical values for each cost were used to parameterize the U(Min, Max) distribution for variable costs per hectare. Likewise, the inflation rate of values between 3.5 and 16.0% was simulated as=UNIFORM(3.5, 16.0) to generate a range of random numbers between 3.0 and 5.32%. The generated random numbers were used to inflate the current total cost over the 7th forecasting horizon. Similarly, the area of production per each crop is stochastic and is simulated using a uniform distribution. For example, the total harvested area (in ha) under maize in the Dodoma region was estimated between the range of 141 870 – 253 551 (Table 3.2); therefore, a uniform function was simulated as=UNIFORM(141 870, 253 551) to generate the area between the two boundaries inclusively.

The net present value (NPV) for each crop for seven years was calculated using the stochastic net crop returns. An annual discount rate of 7.0 – 16.0% was used for calculating the present value of net crop returns across seven years. For the two agro-ecological regions, the NPV for each crop was calculated as follows:

$$N\tilde{P}V_{ij} = \sum_{t=1}^{T} \left(\frac{\tilde{\pi}_{t,ij)}}{(1+\tilde{R})^{t}} \right) \quad (3.18)$$

where:

$\tilde{R}$ = stochastic discount rate simulated by a Simetar function “=UNIFORM(MIN, MAX)”, where MIN=7.0%, and MAX=9.0%.

t = number of periods (1, 2, 3, …7 years)

Cumulative distribution functions (CDFs) and the probability density functions (PDFs) were used to verify the simulated variables for the KOVs. Fan graphs were developed to show how the relative variability of a stochastic variable changes over time from the year 2019 through 2025.

3.3.4 Probability of target values

Richardson and Mapp (1976) defined the probability of economic success as the chance of NPV being greater than zero. Therefore, when the NPV is positive, the business earns a higher rate of return than the discount rate. In this study, the probability of NPV being negative for each crop was estimated, i.e., the probability of failure.

3.4 Results and Discussion

The first step performed by the MASORISIM model is the simulation of yields and prices of the main cereals for seven years from 2019 to 2025 using the Multivariate empirical distribution (step 1–5) followed by an evaluation stage (step 6) before the simulation of key output variables (step 7). The strength of the MASORISIM was not only on its ability to account for non-normally distributed random variables and historical correlations, but also its capability to handle the heteroscedasticity of random variables in two regions and to produce results that are consistent with historical data based on the statistical tests in Appendix 3.3.

3.4.1 Crop yields

Results of maize yield are presented in Table 3.3, which summarizes the statistics for maize yield (t/ha), and displays the distribution of yield in the 1st and 7th year for the two regions. The mean, standard deviation (STDV), coefficient of variation (CV), and minimum and maximum statistics are presented for each year. The CVs measure the relative risk/variability associated with yield. The mean represents the deterministic component of the model while, the minimum and maximum represent the stochastic component. The relative variability of the average maize yield for each year in Dodoma and Morogoro regions corresponds to a range of 23.5–24.2% and 24.1–24.8%, respectively. In Dodoma, the annual mean yield for maize is projected to have an increase of about 0.362 t/ha with an increase in minimum and maximum yield of 0.208 t/ha and 0.509 t/ha by 2025, respectively. In Morogoro, the mean, minimum and maximum yield for maize is expected to increase by 0.154 t/ha, 0.075 t/ha and 0.155 t/ha, respectively. Figure 3.2 and Figure 3.3 show the difference between the deterministic forecast vs. stochastic forecast.

Table 3.4: Summary statistics of deterministic and stochastic forecasted maize yield (t/ha) from 2019 to 2025

	2019	2020	2021	2022	2023	2024	2025
Dodoma region							
Mean	1.142	1.201	1.258	1.325	1.383	1.447	1.504
SD	0.27	0.29	0.30	0.32	0.33	0.34	0.36
CV	23.64	23.91	24.09	23.91	24.19	23.53	24.02
Min	0.646	0.681	0.715	0.750	0.785	0.819	0.854
Max	1.575	1.659	1.744	1.828	1.913	1.997	2.081
Morogoro region							
Mean	1.283	1.290	1.309	1.323	1.343	1.365	1.384
SD	0.31	0.32	0.32	0.33	0.32	0.34	0.34
CV	24.16	24.58	24.13	24.77	24.05	24.73	24.27
Min	0.875	0.887	0.900	0.912	0.925	0.937	0.950
Max	1.806	1.832	1.858	1.884	1.910	1.935	1.961

Note: SD = Standard deviation; CV = Coefficient of variation; mean = deterministic forecastic; Mini&Max = stochastic forecasts

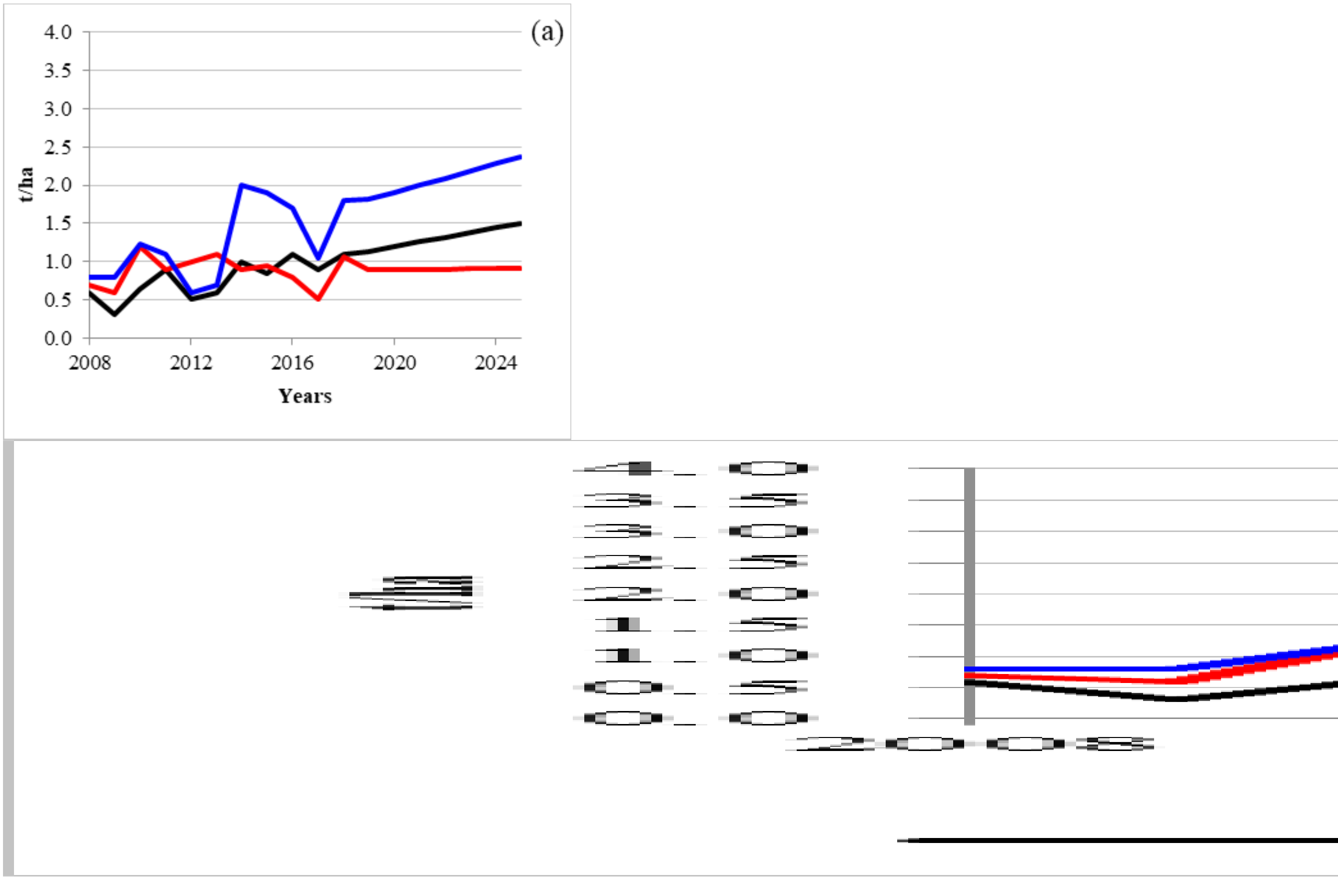

Figure 3.2: Deterministic forecasts (a) vs. stochastic forecasts (b) for maize, sorghum and rice yield in Dodoma

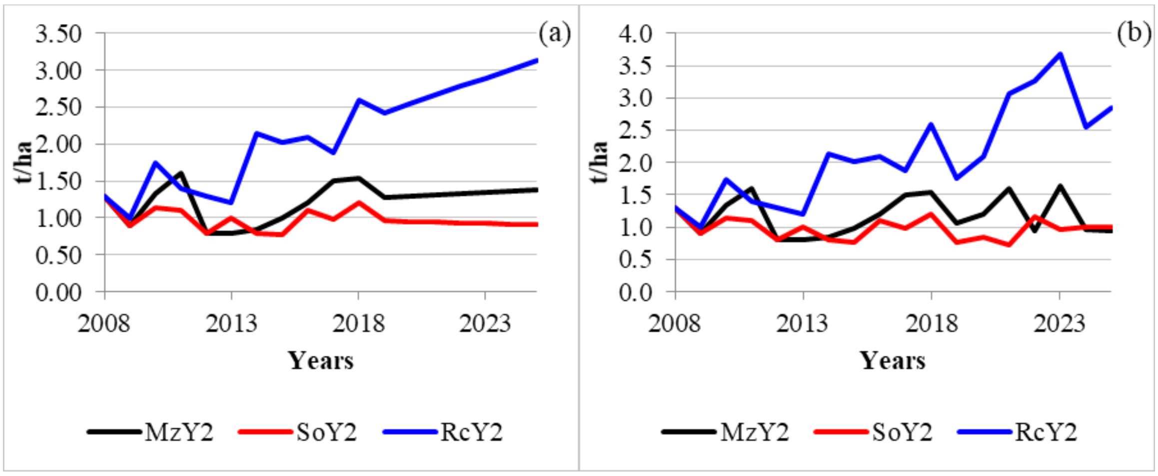

Figure 3.3: Deterministic forecasts (a) vs. stochastic forecasts (b) for maize, sorghum and rice yield in Morogoro

Figure 3.4 presents the probability distribution functions (PDF) for total maize production in tons for the year 2019 and 2025. The mean for each function is represented by a vertical bar at the centre, while vertical bars at the left and right sides represent the confidence intervals at the alpha level equal to 5%. In Dodoma, the production distribution for the year 2025 is illustrated in Figure 3.4-a. The average, minimum, and maximum total production of maize in 2025 is likely to be 297 402 tons, 124 768 tons, and 512 829 tons, respectively, which is relatively higher compared to 224 776 tons, 92 262 tons and 395 460 tons in 2019 correspondingly. In Morogoro, the PDF chart for maize production in the year 2025 in terms of average (430 182 tons), minimum (175 061 tons), and maximum (844 996 tons) in Figure 3.4-b contrasts with 2019 data with average (399 306 tons), minimum (160 988 tons) and maximum (792 859 tons). This difference implies that, for the next 7-years, the total production of maize is likely to increase in both regions, but the increase is relatively small in Morogoro as compared to Dodoma.

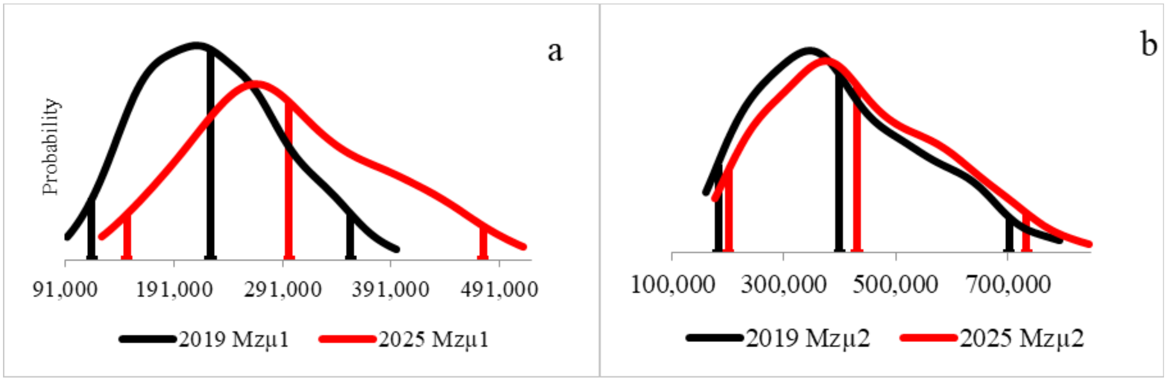

Figure 3.4: PDF approximations of total maize production (in 1000 tons) for the year 2019 and 2025: a=Dodoma region and b=Morogoro region; Mzμ$_1$= production (MT) of maize in Dodoma; Mzμ$_2$= production (MT) of maize in Morogoro.

Rising maize production in the semi-arid area is consistent with Kilembe *et al.* (2013), who highlighted that by 2050, maize yield in the semi-arid part of Dodoma would experience an increase of >25% due to climate change and variability. As for sub-humid areas, the relatively lower increase in maize production could be due to many factors, including rising maximum and minimum temperatures, increasing variability of rainfall, and increasing frequency and severity of extreme events (Kahimba *et al.*, 2015). Additionally, the lower increase in maize yield could be associated with low adoption of the conservation agriculture technologies in the country. These technologies provide a viable means of strengthening resilience in agro-ecosystem and livelihoods if they are properly applied (URT, 2014).

Table 3.4 presents results on sorghum yield for the two regions. Dodoma region forecasts show a slight annual increase in sorghum yield. For example, the average yield in Dodoma is would experience a very small increase of about 0.008 t/ha by 2025. Likewise, the minimum and maximum yield would slightly increase to 0.007 t/ha and 0.016 t/ha, respectively. Sorghum yield in Morogoro is likely to decrease between 0.910 t/ha and 0.961 t/ha on average with the minimum and maximum yield between 0.742 t/ha and 0.702t/ha and 1.196 to 1.132 t/ha respectively. The relative risk associated with the mean yield is higher in Dodoma (21.80–23.78%) than in Morogoro (16.25–16.62%). -0.051 t/ha, -0.04 t/ha and -0.064

Table 3.5: Summary statistics of deterministic and stochastic forecasted sorghum yield (t/ha) from 2019 to 2025

	2019	2020	2021	2022	2023	2024	2025
Dodoma region							
Mean	0.898	0.896	0.901	0.902	0.904	0.910	0.906
SD	0.20	0.21	0.21	0.21	0.21	0.21	0.21
CV	21.80	23.00	22.98	23.22	23.78	22.69	22.86
Min	0.502	0.503	0.504	0.506	0.507	0.508	0.509
Max	1.225	1.227	1.230	1.233	1.236	1.238	1.241
Morogoro region							
Mean	0.961	0.950	0.943	0.933	0.924	0.913	0.910
SD	0.16	0.16	0.15	0.15	0.15	0.15	0.15
CV	16.53	16.41	16.25	16.41	16.55	16.42	16.62
Min	0.742	0.735	0.729	0.722	0.716	0.709	0.702
Max	1.196	1.185	1.175	1.164	1.154	1.143	1.132

Note: SD = Standard deviation; CV = Coefficient of variation; mean = deterministic forecastic; Min&Max = stochastic forecasts

Figure 3.5 depicts total sorghum production distribution for the years 2019 and 2025. Dodoma's production PDF for the year 2025 lies very close to the distribution in the year 2019 (Figure 3.5-a), while, Morogoro has a production PDF for the year 2025, which lies slightly to the left of a PDF in 2019. The left shift of a PDF implies a small decrease in total sorghum production in the sub-humid region and a very small increase in production for the semi-arid region. The results are in agreement with observations by Msongaleli *et al.* (2015), where more than twenty Global Circulation Models (GCMs) and two crop models (DSSAT and APSIM) were used to assess future production of sorghum in central Tanzania. They reported that sorghum yield is likely to increase in central Tanzania between 5.4% and 6.9% in the near-term (2010–2040).

However, the study didn't develop much about the production of sorghum in sub-humid areas. Elsewhere in Africa, sorghum production is projected to increase in semi-arid regions by a range of 19 to 72% across Eastern and Southern Africa (Turner and Rao, 2013; Zinyengere *et al.*, 2014). The increase in sorghum yields reported by different scholars under different climate change scenarios may be attributed to increases in temperatures and the slight changes in projected rainfall, which appear to create conducive conditions for sorghum growth, being more tolerant to heat and water stress (Msongaleli *et al.*, 2015).

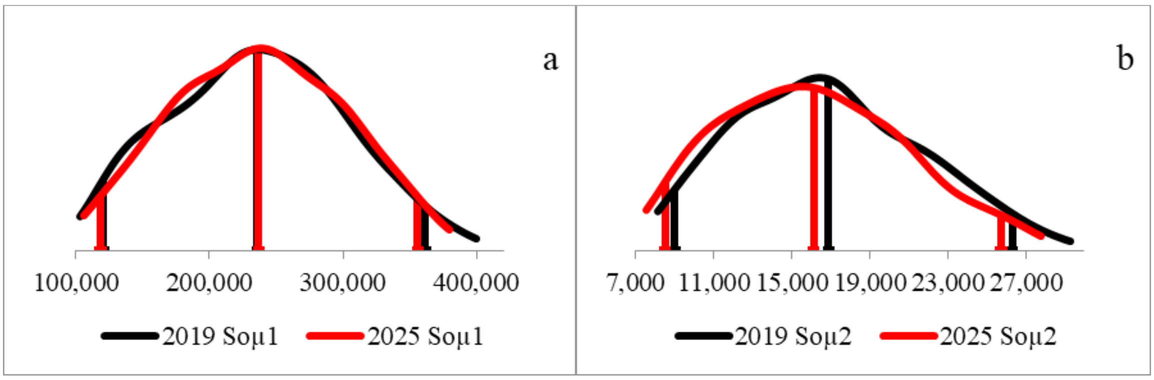

Figure 3.5: PDF approximations of total sorghum production (in 1000 tons) for the year 2019 and 2025: a=Dodoma region and b=Morogoro region; Soμ$_1$= production (MT) of sorghum in Dodoma; Soμ$_2$= production (MT) of sorghum in Morogoro.

The results on rice yield are presented in Table 3.5. Rice yield is likely to increase for all regions by 2025. An increase in mean yield of about 0.583 t/ha was projected in Dodoma with a minimum increase of 0.296 t/ha and a maximum yield of about 0.846 t/ha for year 2019 and 2025. Similarly, the mean yield of rice in Morogoro is would expect an increase of 1.132t/ha for the year 2025. The maximum yield would be an increase of about 0.938 t/ha by 2025.

Table 3.6: Summary statistics of deterministic and stochastic forecasted rice yield (t/ha) for seven years

	2019	2020	2021	2022	2023	2024	2025
Dodoma region							
Mean	1.806	1.902	1.997	2.093	2.205	2.284	2.389
SD	0.54	0.57	0.59	0.62	0.64	0.68	0.72
CV	29.78	29.82	29.73	29.71	28.98	29.65	30.15
Min	0.945	0.994	1.044	1.093	1.142	1.191	1.241
Max	2.706	2.847	2.988	3.129	3.270	3.411	3.553
Morogoro region							
Mean	2.421	2.543	2.662	2.787	2.899	3.033	3.142
SD	0.42	0.45	0.47	0.50	0.50	0.55	0.55
CV	17.32	17.56	17.52	17.97	17.32	18.12	17.49
Min	1.708	1.793	1.877	1.962	2.047	2.131	2.216
Max	3.151	3.307	3.464	3.620	3.776	3.932	4.089

Note: SD = Standard deviation; CV = Coefficient of variation; mean = deterministic forecastic; Mini&Max = stochastic forecasts

The PDFs in Figure 3.6 portrays the total production of rice (tons) in the two regions. The PDF for the year 2025 in Morogoro lies more to the right of the year 2019, indicating a significant increase of rice production in both regions (Figure 3.6-b). In Dodoma, the distribution of total rice production for 2025 is expected to be 9 270 tons, 22 303 tons, and 39 696 tons for the minimum, average, and maximum, respectively (Figure 3.6-a). Rice production in Morogoro is forecasted to range between 250 852 tons, 473 958 tons, and 755 308 tons for minimum, average, and maximum values, respectively. This implies a substantial increase in rice production, predominantly in the sub-humid region. However, the rising in rice production in semi-arid areas is consistent with Lamboll *et al.* (2001). They argue that an increasing trend in low rice-producing areas like Dodoma may have been influenced by many factors, including the rice irrigation projects funded mainly by the International Fund for Agricultural Development (IFAD). As rice has become a substantial cash and food crop, farmers have increased their productivity by adopting technologies such as the application of improved seeds and system of rice intensification (SRI) in addition to having favourable markets and timely payments. Furthermore, since rainfall is unfavourable to semi-arid areas, farmers have learned to collect runoff water and divert it into bunded fields or paddies to facilitate the storage of water for rice growing. This also prevents erosion, which may occur when the runoff catchment area becomes too big.

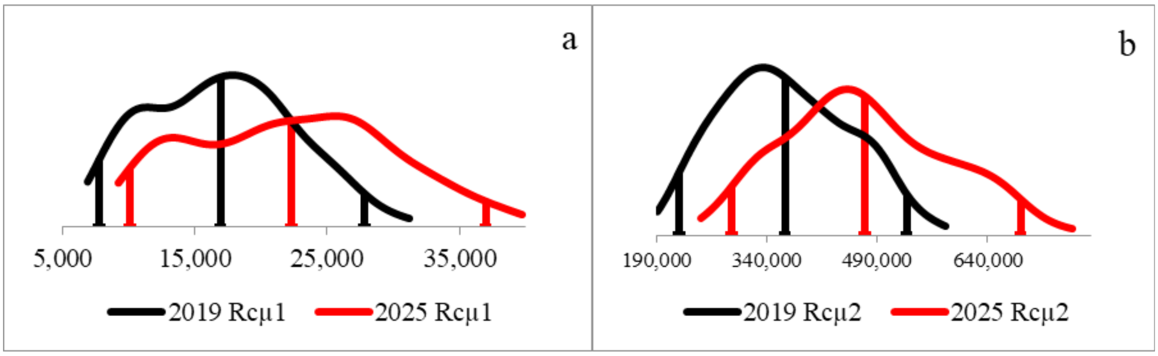

Figure 3.6: PDF approximations of rice production (in 1 000 tons) for the year 2019 and 2025: a=Dodoma region and b=Morogoro region; Rcμ$_1$= production (MT) of rice in Dodoma; Rcμ$_2$= production (MT) of rice in Morogoro.

3.4.2 Cereal prices

Figure 3.7 and Figure 3.8 show the difference between deterministic and stochastic forecasting for prices of cereals in Dodoma and Morogoro, respectively. The MASORISIM model was able to capture the stochastic nature of the prices for the three crops. Table 3.6 summarizes the deterministic mean prices and stochastic prices (minimum and maximum). The results show that prices for all three crops for each region are likely to increase throughout the forecasting horizon. By 2025 a higher price of maize is forecasted in Dodoma compared to Morogoro. The deterministic results show an increasing average price from TZS 0.719 to 0.903 million/t and TZS 0.659 to 0.816 million/t for the two regions, respectively, over the next seven years. However, the stochastic results show a possibility that the price may go up to TZS 1.2 million/t and 1.0 million/t in Dodoma and Morogoro by 2025, respectively.

The minimum and maximum prices for Dodoma are forecasted at TZS 0.518–0.651 million/t and TZS 0.938–1.178 million/t, respectively. The minimum maize price for Morogoro is expected to range between TZS 0.454–0.562 million/t with maximum values ranging between TZS 0.825 to 1.021 million/t. The higher price of maize in Dodoma could be influenced by many factors, including the increasing population in the region. The growing population in Dodoma is likely to be associated with the total shift of the administrative activities of the Tanzanian government from the Dar es Salaam city, accelerating to a higher demand for food.

Table 3.6 also shows probabilities of the price being above the deterministic mean over the forecasted period. For example, for the next seven years, maize price has a 39.0% to 42.3% and a 43.9% to 47.6% probability that it will be above the deterministic mean in Dodoma and Morogoro, respectively. These probabilities represent the risk and uncertainties which are always ignored when deterministic forecasting is used.

Table 3.7: Summary statistics of deterministic vs. stochastic price (in 1 000 TZS) for Seven Years

	2019	2020	2021	2022	2023	2024	2025
Maize price/t in Dodoma							
Mean	718.43	749.58	781.06	812.84	840.97	872.46	904.15
SD	117.08	121.52	126.40	133.22	139.21	143.52	143.64
CV	16.30	16.21	16.18	16.39	16.55	16.45	15.89
Min	518.10	540.27	562.43	584.60	606.77	628.93	651.10
Max	937.66	977.78	1 017.90	1 058.02	1 098.14	1 138.26	1 178.37
Prob(>Mean)	39.0%	41.0%	42.2%	39.3%	42.3%	39.0%	39.9%
Maize price/t in Morogoro							
Mean	660.42	685.51	711.61	737.34	762.92	790.41	816.83
SD	111.62	115.66	119.82	126.29	130.59	133.93	136.25
CV	16.90	16.87	16.84	17.13	17.12	16.94	16.68
Min	453.67	471.69	489.70	507.71	525.72	543.74	561.75
Max	824.52	857.25	889.99	922.73	955.47	988.21	1 020.94
Prob(>Mean)	47.1%	47.6%	43.9%	46.0%	46.5%	44.2%	45.7%
Sorghum price/t in Dodoma							
Mean	787.77	832.12	872.22	916.86	960.61	1 001.30	1 046.13
SD	144.12	151.15	154.73	167.01	173.91	181.34	185.12
CV	18.29	18.16	17.74	18.22	18.10	18.11	17.70
Min	543.77	573.53	603.30	633.06	662.82	692.59	722.35
Max	1 055.39	1 113.15	1 170.92	1 228.68	1 286.45	1 344.22	1 401.98
Prob(>Mean)	44.4%	43.3%	41.8%	42.5%	43.7%	43.3%	42.1%
Sorghum price/t Morogoro							
Mean	1 249.56	1 325.69	1 401.12	1 478.05	1 552.82	1 628.53	1 703.26
SD	122.07	130.22	136.97	144.73	151.76	159.44	167.83
CV	9.77	9.82	9.78	9.79	9.77	9.79	9.85
Min	1 076.22	1 141.45	1 206.68	1 271.91	1 337.14	1 402.37	1 467.60
Max	1 461.13	1 549.69	1 638.24	1 726.80	1 815.36	1 903.92	1 992.48
Prob(>Mean)	40.4%	40.5%	40.6%	39.3%	42.0%	39.1%	39.8%
Rice price/t in Dodoma							
Mean	1 966.96	2 040.32	2 113.62	2 186.94	2 260.14	2 333.55	2 406.97
SD	239.69	248.76	257.57	266.52	275.24	284.38	293.36
CV	12.19	12.19	12.19	12.19	12.18	12.19	12.19
Min	1 667.00	1 729.14	1 791.29	1 853.43	1 915.58	1 977.72	2 039.86
Max	2 606.56	2 703.73	2 800.90	2 898.07	2 995.24	3 092.41	3 189.58
Prob(>Mean)	43.4%	44.4%	44.9%	41.5%	44.9%	45.0%	43.0%
Rice price Morogoro							
Mean	1 851.32	1 932.35	2 013.39	2 094.50	2 175.37	2 256.49	2 337.61
SD	192.79	201.21	209.64	218.18	226.37	234.96	243.43
CV	10.41	10.41	10.41	10.42	10.41	10.41	10.41
Min	1 501.11	1 566.82	1 632.54	1 698.25	1 763.96	1 829.68	1 895.39
Max	2 343.51	2 446.10	2 548.70	2 651.29	2 753.88	2 856.47	2 959.06

Prob(>Mean)	40.3%	41.9%	41.4%	41.6%	43.8%	41.2%	40.1%

Note: SD = Standard deviation; CV = Coefficient of variation; mean = deterministic forecastic; Mini&Max = stochastic forecasts; Prob(>Mean) = probability of price greater than the deterministic average.

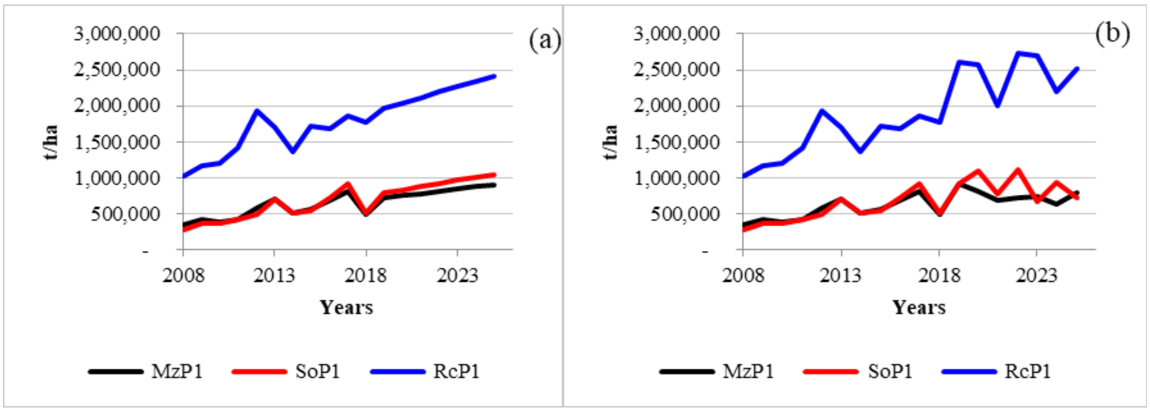

Figure 3.7: Deterministic forecasts (a) vs. stochastic forecasts (b) for maize, sorghum and rice prices in Dodoma.

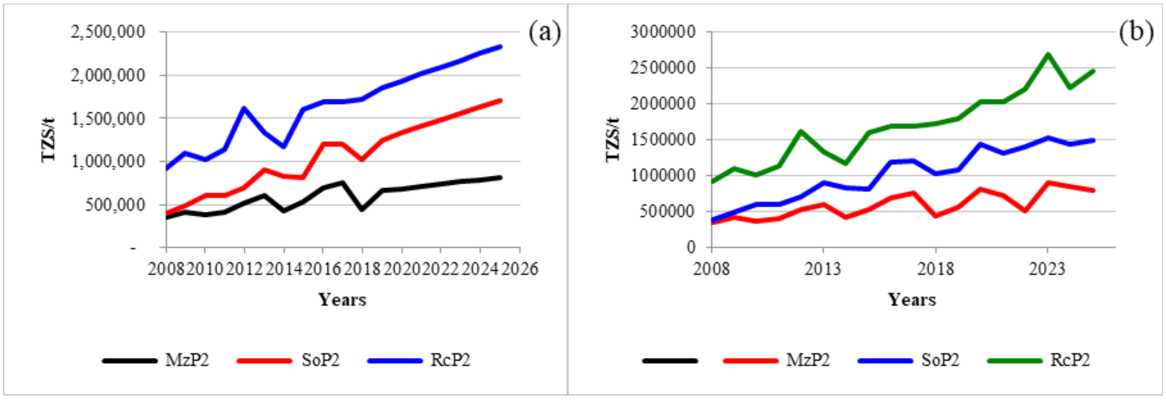

Figure 3.8: Deterministic forecasts (a) vs. stochastic forecasts (b) for maize, sorghum and rice prices in Morogoro.

On the other hand, the price for sorghum is generally higher in Morogoro than Dodoma. The forecasting results show that the deterministic average price in Morogoro would increase up to TZS 1.704 million/t with a minimum of TZS 1.468 million/t and the maximum of TZS 1.992 million/t by 2025. This increase approximately represents a 36% increase from the price in 2019. Dodoma would experience an average of TZS 1.044 million/t with a minimum of TZS 0.722 million/t. The maximum price would go up to TZS 1.402 million/t by 2025, correspondingly to a 33% increase from the 2019 price. The relative variability of sorghum price is twice as high in Dodoma (18.05%) than Morogoro

(9.70%). Sorghum price in Dodoma has a 41.8% to 44.4% probability of being above the deterministic mean, with a 39.1% to 40.6% probability in Morogoro.

The higher sorghum price in Morogoro could be due to low sorghum production in the region compared to Dodoma. The high price could also be influenced by rising demand for sorghum for use in different products. The increasing demand for sorghum can be due to efforts regarding the nutritional and health benefits campaign conducted my research agents including the Sokoine University of Agriculture has been one of the organizations (Nkuba, 2009; Noel, 2015; Kinabo *et al.*, 2016; Mahenge, 2018).

Of all the three crops, the price for rice was the highest, with a slight difference between the two regions as presented in Table 3.6. The deterministic average price reflects an increasing trend of TZS 1.967 to 2.409 million/t in Dodoma and from TZS 1.854 to 2.337 million/t in Morogoro. The maximum price in the regions is projected to range between TZS 2.607 to 3.190 million/t and TZS 2.344 to 2.959 million/t for Dodoma and Morogoro, respectively. The stochastic prices are also presented fan graphs in Appendix 3.4, and reveal how the relative variability of stochastic crop prices changes from 2019 to 2025. Except for sorghum price in Morogoro, rice price shows a lower relative variability of the average price in comparison with other crops. Generally, the findings on price forecasts are consistent with observations by Von Braun (2008). He reported that important cereals in most developing countries would experience a price increase of up to 30% by 2020.

3.4.3 Profitability of cereals

Table 3.7 summarizes the statistics for total annual net returns per crop per region. The mean represents the deterministic component of the model and the annual stochastic part is represented by the minimum and maximum values. A probability of negative annual net return for maize is high in Morogoro (3.1 – 15.0%) compared to Dodoma (0.4 – 2.2%). These changes suggest that even with the higher risk particularly for maize in Morogoro, there will likely be a slight improvement in the net returns for all the crops in the two regions, for the next seven years. Other crops have a zero probability of negative net return.

Table 3.8: Deterministic and stochastic annual net return for each crop for each region from 2019 to 2025

	2019	2020	2021	2022	2023	2024	2025
Annual net returns for maize in Dodoma (x 1 000 000 000)							
Mean	54.21	68.21	80.22	92.19	104.07	117.00	132.79
STDV	35.22	40.48	45.84	50.25	55.70	60.52	65.58
CV	64.97	59.35	57.15	54.51	53.52	51.73	49.38
Min	-28.80	-29.13	-10.54	-13.00	-20.53	-10.24	-2.37
Max	198.16	209.72	257.43	291.51	302.92	349.69	447.88
P(<0)	2.22%	1.36%	0.36%	0.81%	0.81%	0.35%	0.42%
Annual net returns for maize in Morogoro (x 1 000 000 000)							
Mean	63.89	78.88	92.11	105.23	116.23	131.07	142.68
STDV	63.30	70.99	75.31	81.67	88.78	91.24	95.53
CV	99.07	90.00	81.76	77.61	76.38	69.61	66.95
Min	-122.04	-133.04	-107.40	-116.81	-134.20	-149.32	-50.42
Max	268.58	373.21	378.76	384.49	476.50	482.21	572.15
P(<0)	15.02%	8.70%	7.30%	7.20%	7.58%	4.87%	3.06%
Annual net returns for sorghum in Dodoma (x 1 000 000 000)							
Mean	83.82	101.29	110.88	123.04	131.46	144.24	153.47
STDV	41.55	49.86	52.46	55.78	57.31	64.95	65.31
CV	49.57	49.22	47.31	45.34	43.59	45.03	42.55
Min	4.38	13.00	7.05	8.52	22.38	24.40	27.06
Max	228.82	265.56	299.77	355.29	344.76	389.77	373.86
P(<0)	-	-	-	-	-	-	-
Annual net returns for sorghum in Morogoro (x 1 000 000 000)							
Mean	13.04	15.22	16.49	17.56	18.63	19.80	20.89
STDV	4.10	4.95	5.38	5.63	6.03	6.56	6.80
CV	31.45	32.51	32.64	32.08	32.36	33.12	32.56
Min	5.24	6.68	5.67	6.50	7.22	8.25	7.52
Max	29.29	34.65	37.36	36.45	39.19	43.59	49.97
P(<0)	-	-	-	-	-	-	-
Annual net returns for rice in Dodoma (x 1 000 000 000)							
Mean	18.59	22.17	24.96	27.43	29.71	33.15	36.15
STDV	7.90	9.09	10.29	11.01	11.36	13.43	14.41
CV	42.46	41.03	41.23	40.13	38.26	40.50	39.86
Min	5.59	4.97	7.57	8.61	9.38	9.93	11.51
Max	58.62	54.18	60.17	78.29	71.65	82.71	110.01
P(<0)	-	-	-	-	-	-	-
Annual net returns for rice in Morogoro (x 1 000 000 000)							
Mean	342.03	421.68	473.63	529.47	591.26	651.98	713.80
STDV	119.87	145.90	157.14	166.59	192.37	211.87	217.51
CV	35.05	34.60	33.18	31.46	32.54	32.50	30.47
Min	50.19	33.66	66.25	148.73	150.08	156.70	251.82
Max	949.15	1009.11	1086.33	1106.58	1407.74	1455.93	1559.89
P(<0)	-	-	-	-	-	-	-

Note: SD = Standard deviation; CV = Coefficient of variation; mean = deterministic forecasts; Min&Max = stochastic forecasts; Prob(<0) = probability of Annual Net Return being negative.

Results for the maize crop in Dodoma demonstrate an increase in the mean yearly income from TZS 54.2 billion in the first year to TZS 132.8 in the 7th year, meanwhile, the stochastic results show a negative minimum net return oscillating between TZS -2.4 to -29.1 billion for next seven years. The maximum annual net returns would range between TZS 447.9 to 198.2 billion for the next seven years. In the Morogoro region, the analysis forecasts a varying annual average return between TZS 63.9 to 142.7 billion with negative minimum returns oscillating between TZS – 50.4 and -149.3 billion. The maximum values vary between TZS 268.6 to 572.1 billion across the seven years. The relative risk associated with annual income for maize in terms of CV is higher in Morogoro (changing between 69.6 to 99.1%) than Dodoma (changing between 49.4 to 65.0%).

Likewise, the rice crop forecasts an increasing annual net return for both regions, although the crop has a higher risk associated with the mean return, especially in the Dodoma region. The CVs for annual rice net returns are higher in Dodoma, varying between 38.3 – 42.5% with a zero probability of negative returns. Meanwhile, in Morogoro, the CV values range between 30.5% - 35.1%. The two regions have a zero probability of negative net returns throughout the forecasting period. Furthermore, sorghum has positive minimum values for net returns throughout the forecasting period for the two regions. Regardless of the high variability of the mean annual return (31.5 – 32.6%), the mean, minimum, and maximum yearly return values for sorghum expected to vary in the Dodoma region between TZS 83.4 to 153.5 billion, TZS 4.4 to 27.1 billion and TZS 228.8 to 389.8 billion respectively.

In Morogoro, the study projects an increase for sorghum annual net return. The deterministic average return is expected to increase between TZS 13.0 to 20.9; meanwhile, the stochastic return shows that minimum and maximum values would fluctuate between TZS 5.2 to 8.3 billion and TZS 29.3 to 350.0 billion, respectively. The CVs for annual sorghum returns are lower in Morogoro (31.5%) than Dodoma (42.5 - 49.6%).

Table 3.8 presents the NPV distribution results for each crop for each region for seven years. The relative variability of the mean NPV for maize is higher in Morogoro (55.1%) than in Dodoma (34.2%). The CV values for sorghum and rice are almost the same for the two regions. The three crops have positive means for NPV values, with the minimum value being negative only for maize in Morogoro (TZS -547.7 billion). This implies that maize has a higher relative variability (risk) for NPV among the three crops in Morogoro than the Dodoma region. The high variability in NPV for maize may be influenced by the relatively low prices offered to maize, especially when production is higher.

Table 3.9: Summary statistics for deterministic and stochastic NPV (billions TZS)

	Dodoma region			Morogoro region		
	Maize	**Sorghum**	**Rice**	**Maize**	**Sorghum**	**Rice**
		(x 1 000 000 000)			*(x 1 000 000 000)*	
Mean	648.70	848.20	192.16	730.10	121.63	3,723.86
STDV	221.67	218.08	42.95	402.54	30.62	862.15
CV	34.17	25.71	22.35	55.14	25.17	23.15
Minimum	49.23	320.88	98.76	-547.66	58.56	1,484.51
Maximum	1,409.36	1583.53	367.90	2,049.46	211.85	6,133.68
P(<0)	–	–	–	2.93%	–	–

Note: SD = Standard deviation; CV = Coefficient of variation; mean = deterministic forecasts; Min&Max = stochastic forecasts; p(<0) = probability of NPV being negative.

Figure 3.9 presents the CDF charts for NPV of all three crops for the two regions in which Figure 3.9-a and Figure 3.9-b represents the distribution of NPV for crops in the Dodoma region and the Morogoro region, respectively. Sorghum is the highest income generator in Dodoma region, followed closely by maize with rice being the least (Figure 3.9-a). In contrast, rice in Morogoro is the highest income generator of the main cereals in the region (Figure 3.9-b). Morogoro has a 2.93% probability of negative NPV for maize with a zero probability for other crops in the two regions. In general, the distribution functions indicate that there is a considerable risk or variability for the three crops, and the risk is higher for maize in the Morogoro region. The study reveals that the three crops have a high chance of contributing to the farmers' economic success. However, there is need for the researchers and experts to identify appropriate technologies that will help to reduce the risks and variability associated with productivity and profitability of the sub-sectors.

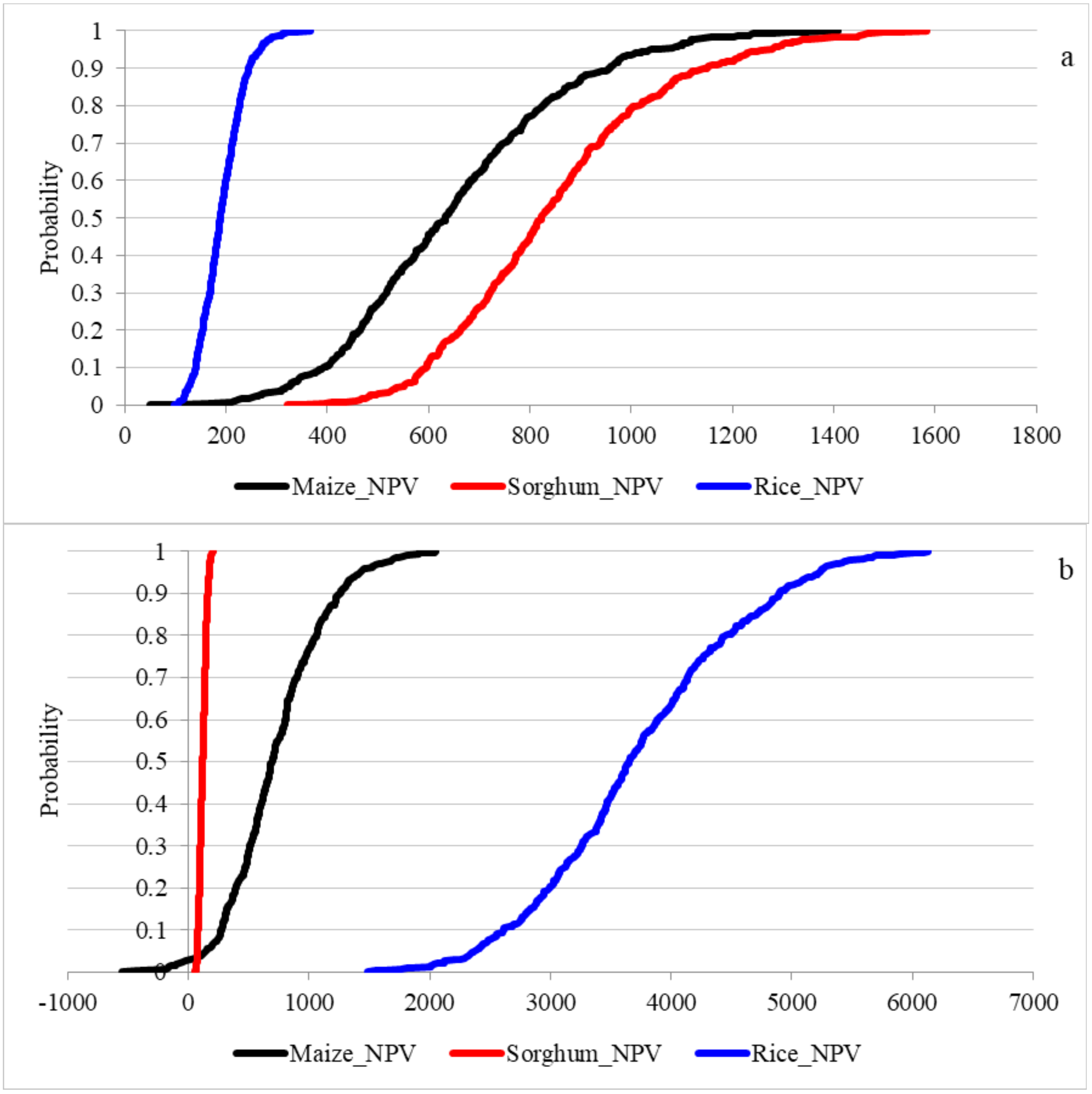

Figure 3.9: CDF of NPV for all three crops in the Dodoma region (a) and Morogoro region (b) for the seven years from 2019 to 2025.

3.5 Conclusions

The purpose of this paper was to apply a stochastic model to simulate and forecast stochastic yields, prices, and net returns of three food staples in Tanzania from 2019 to 2025. The paper describes the practical steps in using a MASORISIM stochastic simulation approach deliver forecasts that include risks and uncertainties for main food crops Tanzania. The study was conducted using 11-years of historical data for maize, sorghum, and rice crops in Dodoma and Morogoro regions of Tanzania. The variables were simulated for seven years using stochastic variables to estimate the distribution of the future yields, prices, and net returns per crop by region. The MASORISIM model was run for 500 iterations using the Latin Hypercube sampling procedure, and the simulated statistics and correlation matrix were compared to the historical input values. The comparison was made for validation purposes to ensure that the random variables are simulated correctly and to demonstrate the appropriate properties of the parent distribution. The validation statistics showed that the stochastic procedure to simulate the means and historical correlations were met.

This study enabled the prediction of the major cereal crops over the next seven years, in terms of grain yield and economic success. The results on yields for all three crops show a slight increasing trend, and the prices are likely to increase for both regions. Moreover, the results showed a high probability of success for all three crops regardless of the small probability of negative net returns for maize and rice. Despite the probability of success for crops, there is a need to increase investment in relation to farm management practices. If no alternative risk management strategies are available, the productivity of the main cereal crops in Tanzania will continue to experience a high degree of risk and variability.

The data used in this study is based on aggregates at regional levels, focusing on semi-arid and sub-humid agro-ecological zones. This may generally lead to a downward bias in the estimation of yields and incomes regarding districts and villages specialized in crop production. With the availability of farm-level panel data sets, further analyses should also be directed at community, village, or site-specific levels to estimate risks faced by farmers.

The methodology used in this study can be modified to simultaneously simulate an array of random variables using a multivariate empirical distribution. Further studies should also consider non-cereal and cash crops like pulses, cassava, banana, potatoes, coffee, cotton, sisal, and sugarcane, which are essential crops in generating domestic and foreign income in the country. One of the most hindering factors in achieving different agricultural development strategies in Tanzania is the lack of an appropriate model to provide a roadmap of what would happen in the year ahead and beyond. Therefore, this study paves a way to a complete stochastic simulation model that comprises the country's essential crops. It provides accurate information to policymakers, particularly the national food security division, which is responsible for ensuring food availability in the country.

Furthermore, this study utilized historical yields and prices for cereal crops in the regions analysed. It was assumed that the relative variability of yield would be the same in the future as it has been in the past and that the differences in yields within 11years represent the effects of weather variability. Further integrated assessments that integrate climatic conditions like precipitation, maximum and minimum temperatures are still needed to provide accurate forecasts beyond a seven-year period. Finally, this study adds a good theoretical reference on the stochastic risk analysis particularly on the application of Monte Carlo simulation.

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References

AU – African Union (2014). Malabo Declaration on Accelerated Agricultural Growth and Transformation for Shared Prosperity and Improved Livelihoods Doc. Assembly/Au/2 (Xxiii). In: http://archives.au.int/bitstream/handle/123456789/277/ Assembly%20AU %20Decl%201%20(XXIII)%20_F.pdf?sequence=2, (Accessed November 07, 2018).

Cochrane, N. and D'Souza, A. (2015). Measuring Access to Food in Tanzania: A Food Basket Approach (No. 1476–2016-121041). In: https://ageconsearch.umn.edu/record/198784/files/eib135.pdf, (Accessed October 2018).

Cooper, P.J.M., Dimes, J., Rao, K.P.C., Shapiro, B., Shiferaw, B. and Twomlow, S. (2008). Coping better with current climatic variability in the rain-fed farming systems of sub-Saharan Africa: an essential first step in adapting to future climate change? *Agric. Ecosyst. Environ. 126* (1–2), 24–35.

Hardaker, J.B., Richardson, J.W., Lien, G. and Schumann, K.D. (2004). Stochastic efficiency analysis with risk aversion bounds: a simplified approach. *Aust. J. Agric. Resour. Econ. 48* (2), 253–270.

Ingram, J.S.I., Gregory, Izac, P.J. and A.M. (2008). The role of agronomic research in climate change and food security policy. *Agriculture Ecosystems and Environment* 126, 1–12.

Kahimba, F.C., Sife, A.S., Maliondo, S.M.S., Mpeta, E.J. and Olson, J. (2015). Climate change and food security in Tanzania: analysis of current knowledge and research gaps. Tanzania Journal of Agricultural Sciences 14 (1), 21–33.

Kantanantha, N. (2007). Crop Decision Planning under Yield and Price Uncertainties (Doctoral dissertation). Georgia Institute of Technology https://smartech.gatech.edu/bitstream/handle/1853/24676/kantanantha_nantachai_200708_phd.pdf?sequence=1&isAllowed=y, (Accessed April 2018).

Kempf, M. (2007). Jatropha Production in Semi-Arid Areas of Tanzania. A Feasibility Study. Rural Livelihood Development Company, Dodoma.

Kilembe, C., Thomas, T.S., Waithaka, M., Kyotalimye, M. and Tumbo, S. (2013). Tanzania. In: Waithaka, M., Nelson, G.C., Thomas, T.S., Kyotalimye, M. (Eds.), East African Agriculture and Climate Change: A Comprehensive Analysis. IFPRI, Washington, DC, pp. 313–343.

Kinabo, J., Mamiro, P., Dawkins, N., Bundala, N., Mwanri, A., Majili, Z., Jumbe, T., Kulwa, K., Mamiro, D., Amuri, N. and Ngowi, M. (2016). Food intake and dietary diversity of farming households in the Morogoro region, Tanzania. *Afr. J. Food Agric. Nutr. Dev. 16* (4), 11295–11309.

Lamboll, R., Hella, J., Riches, C., Mbwaga, A.M. and Ley, G. (2001). Integrated Management of Striga Species on Cereal Crops in Tanzania: Preliminary Study of Farmer Perceptions of Soil Resources in Central, Lake and Eastern Zones. Project R7564. Crop Protection Programme, Department for International Development, UK.

Macauley, H. and Ramadjita, T. (2015). Cereal Crops: Rice, Maize, Millet, Sorghum, Wheat. vol. 36, Feeding Africa, (Accessed October 15, 2018) https://www.afdb.org/fileadmin/uploads/afdb/Documents/Events/DakAgri2015/Cereal_Crops-_Rice_Maize_Millet_Sorghum_Wheat.pdf.

Mahenge, A.B. (2018). Nutritional, Physical and Sensory Quality of Extruded Instant White Sorghum-Pigeon Peas Gruel Flour (Doctoral dissertation). Sokoine University of Agriculture.

Msongaleli, B.M., Rwehumbiza, F., Tumbo, S.D. and Kihupi, N. (2015). Impacts of climate variability and change on rainfed sorghum and maize: implications for food security policy in Tanzania. *J. Agric. Sci. 7* (5), 124–142. https://doi.org/10.5539/jas.v7n5p124.

Msongaleli, B.M., Tumbo, S.D., Kihupi, N.I. and Rwehumbiza, F.B. (2017). Performance of Sorghum Varieties under Variable Rainfall in Central Tanzania, (International scholarly research notices, 2017).

Nkuba, M.D.E. (2009). Factors Influencing Nutrition and Food Insecurity in Kiroka Village. The doctoral dissertation Sokoine University of Agriculture.

Noel, N.F. (2015). Projection of Sorghum Production Response through Multiple Uses Promotion Strategies in Selected Districts of Tanzania (Doctoral dissertation). The Sokoine University of Agriculture.

Rezende, M.L. and Richardson, J.W. (2015). Economic feasibility of sugar and ethanol production in Brazil under alternative future prices outlook. *Agric. Syst.* 138, 77–87.

Richardson, J.W., Klose, S.L. and Gray, A.W. (2000). An applied procedure for estimating and simulating multivariate empirical (MVE) probability distributions in farm-level risk assessment and policy analysis. *J. Agric. Appl. Econ. 32* (2), 299–315.

Richardson, J.W., Schumann, K. and Feldman, P. (2006). Simetar: Simulation for Excel to Analyse Risk. Department of Agricultural Economics, Texas A&M University.

Richardson, J.W., Herbst, B.K., Outlaw, J.L., Gill, R.C., 2007. Including risk in economic feasibility analyses: the case of ethanol production in Texas. *Journal of Agribusiness 25* (345–2016-15144), 115.

Richardson, J.W., Schumann, K.D. and Feldman, P.A. (2008). Simetar: Simulation & Econometrics to Analyse Risk. Agricultural and Food Policy Center, Department of Agricultural Economics, Texas A&M University, College Station, TX.

Schechambo, F., Sosoveli, H. and Kisanga, D. (1999). Rethinking Natural Resource Degradation in Semi-Arid Sub-Saharan Africa: The Case of Semi-Arid Tanzania. Overseas Development Institute, Dar Es Salaam, Tanzania.

Thornton, P.K., Jones, P.G., Ericksen, P.J. and Challinor, A.J. (2011). Agriculture and food systems in sub- Saharan Africa in a 4 °C + world. Philos. Trans. R. Soc. 369, 117–136.

Turner, N.C. and Rao, K.P.C. (2013). Simulation analysis of factors affecting sorghum yield at selected sites in eastern and southern Africa, with emphasis on increasing temperatures. *Agric. Syst.* 121, 53–62.

URT (2012a). National Sample Census of Agriculture 2007/2008: Volume Va: Regional Report: Dodoma Region. In: https://www.nbs.go.tz/nbstz/index.php/english/statistics-by-subject/agriculture-statistics/269-the-regionalreport-s-for-2007-2008-agriculture-sample-census, Accessed 4 January 2018.

URT (2012b). National Sample Census of Agriculture 2007/2008: Volume Ve: Regional Report: Morogoro Region. In:

https://www.nbs.go.tz/nbstz/index.php/english/statistics-by-subject/agriculture-statistics/269-the-regionalreport-s-for-2007-2008-agriculture-sample-census, Accessed 4 January 2018.

URT (2013a). National Agricultural Policy: Ministry of Agriculture Food Security and Cooperatives. Dar Es Salaam.In:http://www.tzdpg.or.tz/fileadmin/documents/dpg_internal/dpg_working_groups_clusters/cluster_1/agriculture/2._Ag_policies_and_strategies/National_ag_policies/1._2013_National_Agricultural_Policy_-_FinalFebruari_2013.pdf, (Accessed October 12, 2018).

URT (2013b). 2012 Population and Housing Census: Population Distribution by Administrative Areas. In: http://www.tzdpg.or.tz/fileadmin/documents/dpg_internal/dpg_working_groups_clusters/cluster_2/water/WSDP/Background_information/2012_Census_General_Report.pdf, (Accessed January 04, 2018).

URT (2014). Ministry of Agriculture, Food Security and Cooperatives: Agriculture Climate Resilience Plan 2014–2019. In: http://extwprlegs1.fao.org/docs/pdf/tan152483.pdf, Accessed 1 June 2016.

URT (2016a). Agricultural Sector Development Programme Phase Two (ASDP II). In: http://www.tzdpg.or.tz/fileadmin/documents/external/national_development_frameworks/ASDP2_Final_Document_20_May._2016__after_edit__1_.pdf, (Accessed October 12, 2018).

URT (2016b). 2014/15 Annual Agricultural Sample Survey Report. In: https://www.nbs.go.tz/nbstz/index.php/english/statistics-by-subject/agriculture-statistics/774-2014-15-annual-agricultural-sample-survey-report, (Accessed May 22, 2018).

URT (2017). 2016/17 Annual Agricultural Sample SurveyReport. In: https://www.nbs.go.tz/nbs/takwimu/Agriculture/2016-17_AASS%20Report%20_Final.pdf, (Accessed October 22, 2018).

Von Braun, J. (2008). Food and Financial Crises: Implications for Agriculture and the Poor. vol. 20, *Intl Food Policy Res Inst*.

Waithaka, M., Nelson, G.C., Thomas, T.S. and Kyotalimye, M. (Eds.) (2013). East African Agriculture and Climate Change: A Comprehensive Analysis. *Intl Food Policy Res Inst.*

Wilson, R.T. and Lewis, J. (2015). The Maize Value Chain in Tanzania. In: https://saiia.org.za/wp-content/uploads/2016/06/008-Tanzania_maize.pdf, (Accessed June 12, 2019).

Yanda, P., Maganga, F., Liwenga, E., Kateka, A., Henku, A., Mabhuye, E., Malik, N., Bavo, C. and Schubert, C. (2015). Tanzania: Country Situation Assessment. PRISE Working Paper. In: http://prise.odi.org/wp-content/uploads/2015/12/Low_Res_Tanzania-Country_Situation_Assessment.pdf.

Yao, F., Qin, P., Zhang, J., Lin, E., and Boken, V. (2011). Uncertainties in assessing the effect of climate change on agriculture using model simulation and uncertainty processing methods. *Chin. Sc. Bull.*, *56*(8), 729-737.

Ziervogel, G., and Ericksen, P. J. (2010). Adapting to climate change to sustain food security. *Wiley Interdisciplinary Reviews: Climate Change*, *1*(4), 525-540.

Ziervogel, G., Nyong, A., Osman, B., Conde, C., Cortés, S., and Downing, T. (2006). Climate variability and change: Implications for household food security. *Assessment of Impacts and Adaptations to Climate Change (AIACC): Washington, DC, USA*.

Zinyengere, N., Crespo, O., Hachigonta, S., and Tadross, M. (2014). Local impacts of climate change and agronomic practices on dryland crops in Southern Africa. *Agriculture, ecosystems & environment*, *197*, 1-10.

APPENDICES

Appendix 3.1: Production cost distribution per crop per region

Since the three crops are usually cultivated at the local level, typically, low technology is used. Of all crops, rice is the costliest in production occupying 48 to 50% of the total costs, followed by maize (28 - 30%); the remaining proportion is for sorghum. Farmers do not have the same costs of production for each crop per unit area, some farmers use minimal costs, and some use higher costs depending on their income and wiliness to apply the needed inputs. Because the expenses are expressed in terms of minimum and maximum, Uniform Distribution Function U(Min, Max) was used to simulate the distribution of each cost category used. Simetar provides a platform to simulate a uniform distribution using the command=UNIFORM(min, max). For example, land preparation for maize per ha in Dodoma has a range of TZS 50 000 to 80 000. In Simetar this range was simulated as=UNIFORM(50 000, 80 000) to get random costs between the two costs and avoid using an average of the two costs. Likewise, fertilizer cost between 0 and 100 was simulated as=UNIFORM(0,100). Table 3.1.1 presents a range of expenses used for inputs and labour, the simulated total costs and the proportion of each input and labour cost used in the model. Production costs were generally high in Morogoro than Dodoma for maize and rice. The production cost for sorghum almost the same for all the two regions (Figure 3.1.1).

Table 3.10 Production costs used for inputs and labour for each crop

Input and labour cost	Dodoma			Morogoro		
	Maize	Sorghum	Rice	Maize	Sorghum	Rice
	TZS/ha (x 1 000)			*TZS/ha (x 1 000)*		
Land preparation	50 – 80	50 – 80	80 – 200	60 – 100	45 – 90	80 – 250
Seeds	45 – 100	30 – 60	130 – 285	80 – 110	45 – 60	150 – 300
Planting	30 – 60	15 – 40	150 – 400	30 – 60	20 – 30	200 – 400
Weeding	80 – 120	110 – 140	300 – 540	60 – 190	80 – 120	350 – 600
Bird scaring	0	0	120 – 200	0	0	120 – 200
Fertilizers	0 – 100	0	0	50 – 100	0 – 50	0
Pesticides	0 – 60	0	0	12 – 60	0 – 24	0
Harvesting	30 – 80	50 – 90	100 – 380	20 – 60	60 – 90	120 – 350
Postharvest handling	40 – 70	30 – 60	50 – 200	50 – 80	50 – 60	80 – 250
Simulated total cost using =UNIFORM() Command						
	TZS/ha	*TZS/ha*	*TZS/ha*	*TZS/ha*	*TZS/ha*	*TZS/ha*
Mean	472.50	377.50	1567.48	561.00	375.00	1,725.01
SD	44.15	22.53	145.93	47.11	19.65	140.09
CV	9.34	5.97	9.31	8.40	5.24	8.12
Minimum	355.16	327.56	1,212.13	429.66	323.97	1,310.34
Maximum	596.53	439.49	2,017.61	676.49	427.64	2,123.92
Percentage of input and labour cost per ha per crop						
	Percent	*Percent*	*Percent*	*Percent*	*Percent*	*Percent*
Land preparation	12.5	17.6	7.0	14.3	22.5	5.8
Seeds	16.1	14.5	13.0	16.9	14.1	15.8
Planting	8.0	9.9	21.7	8.0	7.7	19.0
Weeding	21.3	30.4	27.7	22.3	24.5	23.3
Bird scaring	0.0	0.0	8.8	0.0	0.0	10.7
Fertilizers	13.1	0.0	0.0	13.4	0.0	0.0
Pesticides	6.3	0.0	0.0	6.4	0.0	0.0
Harvesting	10.3	16.7	13.3	7.1	16.1	17.3
Postharvest handling	9.1	10.9	8.6	11.6	15.2	8.0
Total	*100.0*	*100.0*	*100.0*	*100.0*	*100.0*	*100.0*

Notes: SD = standard deviation; CV = coefficient of variation; Cost in Tanzanian Shilling (TZS).

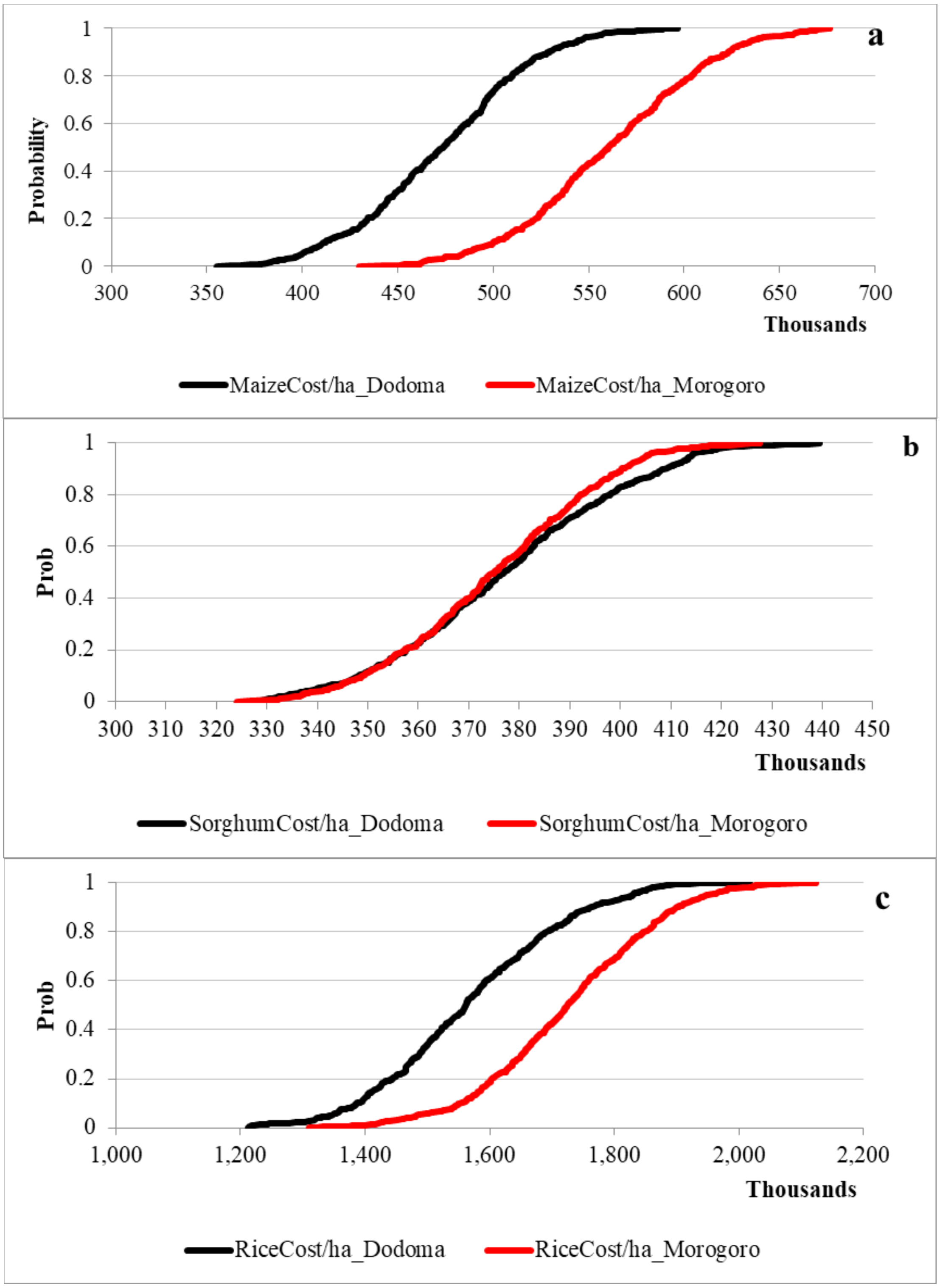


Figure 3.10: CDF of per ha production costs: ***a = cost for maize; b = cost of for sorghum; and c = cost for rice***

Appendix 3.2: Steps for estimating the parameters for an MVE distribution

The steps expressed in Section 2.3 are presented in Table 3.2.1. The residuals/deviates of prices and yields from cubic regression were used in the model to develop the stochastic component of the MVE.

Table 3.11: Steps for estimating the parameters for an MVE distribution

Obs.	Yields for Dodoma (t/ha)			Price for Dodoma			Yields for Morogoro (t/ha)			Prices Morogoro		
	MzY_1	SoY_1	RcY_1	MzP_1	SoP_1	RcP_1	MzY_2	SoY_2	RcY_2	MzP_2	SoP_2	RcP_2
Unsorted deviations from polynomial function (from Eqs. (4) and Eqs. (8))												
1	0.133	-0.172	0.029	-32717	-34375	-140835	0.227	0.248	0.200	-16403	-24388	-38196
2	-0.228	-0.274	-0.065	-1184	5260	-66733	-0.191	-0.143	-0.220	19610	-1425	51962
3	0.046	0.324	0.268	-52643	-37892	-113588	0.222	0.108	0.405	-49079	38120	-102231
4	0.250	0.022	0.046	-54335	-26898	28272	0.473	0.074	-0.060	-40730	-45311	-65742
5	-0.210	0.120	-0.548	70054	7753	470858	-0.346	-0.217	-0.280	43916	-21649	340878
6	-0.171	0.218	-0.543	161385	177600	166709	-0.364	-0.009	-0.500	100831	108625	-35002
7	0.168	0.016	0.663	-53872	-69550	-245994	-0.338	-0.201	0.322	-104358	-47392	-274043
8	-0.042	0.052	0.470	-41203	-72751	49524	-0.208	-0.224	0.084	-21121	-133224	79688
9	0.146	-0.088	0.174	52912	65318	-72043	-0.018	0.116	0.041	113331	171002	87413
10	-0.115	-0.390	-0.580	145348	219133	40546	0.264	0.006	-0.294	151773	102923	4368
11	0.024	0.176	0.086	-193744	-233598	-116716	0.279	0.240	0.301	-197769	-147282	-49095
Unsorted deviations from polynomial function as a percent of predicted (Eqs. (5) and Eqs. (9)												
1	0.285	-0.198	0.038	-0.086	-0.109	-0.121	0.212	0.236	0.182	-0.044	-0.058	-0.040
2	-0.432	-0.314	-0.076	-0.003	0.015	-0.054	-0.175	-0.137	-0.180	0.049	-0.003	0.050
3	0.077	0.369	0.280	-0.119	-0.094	-0.087	0.201	0.105	0.303	-0.116	0.067	-0.091
4	0.386	0.024	0.044	-0.115	-0.060	0.020	0.419	0.072	-0.041	-0.090	-0.070	-0.055
5	-0.296	0.136	-0.478	0.139	0.016	0.324	-0.302	-0.214	-0.177	0.092	-0.030	0.265
6	-0.222	0.246	-0.437	0.301	0.334	0.109	-0.313	-0.009	-0.294	0.201	0.136	-0.026
7	0.202	0.018	0.496	-0.095	-0.121	-0.154	-0.286	-0.200	0.177	-0.197	-0.054	-0.189
8	-0.047	0.059	0.328	-0.069	-0.118	0.030	-0.173	-0.226	0.043	-0.038	-0.140	0.052
9	0.153	-0.100	0.114	0.084	0.099	-0.041	-0.015	0.118	0.020	0.195	0.167	0.054
10	-0.113	-0.438	-0.358	0.221	0.311	0.022	0.213	0.007	-0.135	0.250	0.094	0.003
11	0.022	0.197	0.050	-0.281	-0.312	-0.062	0.222	0.248	0.131	-0.312	-0.125	-0.028
Sorted deviations from polynomial function as a percent of predicted step 2 [Eqs. (6) and Eqs. (10) and Step 3 (Pmin$_{\hat{e}}$, Pmax$_{\hat{e}}$)]												
F(x)	MzY_1	SoY_1	RcY_1	MzP_1	SoP_1	RcP_1	MzY_2	SoY_2	RcY_2	MzP_2	SoP_2	RcP_2
0	-0.432	-0.439	-0.478	-0.281	-0.312	-0.154	-0.313	-0.226	-0.294	-0.312	-0.140	-0.189
0.045	-0.432	-0.438	-0.478	-0.281	-0.312	-0.154	-0.313	-0.226	-0.294	-0.312	-0.140	-0.189
0.136	-0.296	-0.314	-0.437	-0.119	-0.121	-0.121	-0.302	-0.214	-0.180	-0.197	-0.125	-0.091
0.227	-0.222	-0.198	-0.358	-0.115	-0.118	-0.087	-0.286	-0.200	-0.177	-0.116	-0.070	-0.055
0.318	-0.113	-0.100	-0.076	-0.095	-0.109	-0.062	-0.175	-0.137	-0.135	-0.090	-0.058	-0.040
0.409	-0.047	0.018	0.038	-0.086	-0.094	-0.054	-0.173	-0.009	-0.041	-0.044	-0.054	-0.028
0.500	0.022	0.024	0.044	-0.069	-0.060	-0.041	-0.015	0.007	0.020	-0.038	-0.030	-0.026
0.591	0.077	0.059	0.050	-0.003	0.015	0.020	0.201	0.072	0.043	0.049	-0.003	0.003
0.682	0.153	0.136	0.114	0.084	0.016	0.022	0.212	0.105	0.131	0.092	0.067	0.050
0.773	0.202	0.197	0.280	0.139	0.099	0.030	0.213	0.118	0.177	0.195	0.094	0.052
0.864	0.285	0.246	0.328	0.221	0.311	0.109	0.222	0.236	0.182	0.201	0.136	0.054
0.955	0.386	0.369	0.496	0.301	0.334	0.324	0.419	0.248	0.303	0.250	0.167	0.265
1	0.386	0.369	0.496	0.301	0.334	0.324	0.419	0.248	0.303	0.250	0.167	0.265
Correlation matrix estimated using the residuals from polynomial function (Step 4)												
	MzY_1	SoY_1	RcY_1	MzP_1	SoP_1	RcP_1	MzY_2	SoY_2	RcY_2	MzP_2	SoP_2	RcP_2
	1	0.09	0.64	-0.50	-0.37	-0.60	0.53	0.46	0.66	-0.40	-0.12	-0.57
MzY_1		1	0.20	-0.31	-0.40	0.16	-0.14	0.05	0.29	-0.45	-0.24	-0.08
SoY_1			1	-0.69	-0.65	-0.71	0.03	-0.04	0.82	-0.62	-0.43	-0.54
MzP_1				1	0.96	0.53	-0.38	-0.30	-0.81	0.94	0.77	0.36
SoP_1					1	0.36	-0.18	-0.16	-0.75	0.94	0.83	0.19
RcP_1						1	-0.35	-0.41	-0.70	0.45	0.10	0.82
MzY_2							1	0.76	0.34	-0.22	-0.08	-0.25
SoY_2								1	0.34	-0.19	0.13	-0.27
RcY_2									1	-0.74	-0.44	-0.51
MzP_2										1	0.82	0.44
SoP_2											1	0.09
RcP_2												1
Deterministic forecasts $\hat{Y}_{t,ij} = \hat{a} + \hat{b}T_{t,ij}$ and $\hat{P}_{t,ij} = \hat{a} + \hat{b}T_{t,ij}$ forecasts without risk (error term)												
	MzY_1	SoY_1	RcY_1	MzP_1	SoP_1	RcP_1	MzY_2	SoY_2	RcY_2	MzP_2	SoP_2	RcP_2
12	1.137	0.894	1.809	720,520	790,919	1,969,380	1.273	0.958	2.419	659,637	1,252,099	1,851,977
13	1.198	0.896	1.903	751,348	834,209	2,042,797	1.291	0.950	2.539	685,828	1,327,989	1,933,051
14	1.259	0.898	1.997	782,176	877,499	2,116,214	1.309	0.941	2.659	712,019	1,403,879	2,014,124
15	1.319	0.900	2.092	813,003	920,789	2,189,631	1.327	0.933	2.779	738,210	1,479,770	2,095,197
16	1.380	0.902	2.186	843,831	964,079	2,263,048	1.345	0.924	2.899	764,401	1,555,660	2,176,271
17	1.441	0.904	2.281	874,659	1,007,369	2,336,464	1.364	0.916	3.019	790,593	1,631,550	2,257,344
18	1.502	0.906	2.375	905,487	1,050,660	2,409,881	1.382	0.907	3.139	816,784	1,707,441	2,338,417

Appendix 3.3: Model simulation and evaluation

This appendix provides the evaluation tests used to check for completeness, accuracy and forecasting ability for the MASORISIM model. The evaluation of the model indicates that the MVE procedures appropriately correlated the random variables as none of the Student-*t* statistics in Table 3.3.1 are greater than the critical value of 2.94. The *t*-Tests of the means for the random variables in the year 2019 indicated that the simulated means are statistically equal to their deterministic means at the 95% level. The test statistics (test values) are less than the critical value of 2.25 for the random variables, and the *p*-values are >0.1 at the alpha equal to 5% (*p*>.05) then failed to reject the null hypothesis that the means are equal. The remaining seven years have similar results, hence based on the evaluation tests, the simulated yields and prices can reliably be used for future decision-making, particularly national and household food production trends over time. The null and alternative hypotheses for the Student's-t test are as follows:

$$\text{Ho:}\ \hat{Y}_{ij} = Y_{ij}$$
$$\text{HA:}\ \hat{Y}_{ij} \neq Y_{ij}$$

$$\text{Ho:}\ \hat{P}_{ij} = P_{ij}$$
$$\text{HA:}\ \hat{P}_{ij} \neq P_{ij}$$

$$\text{Ho:}\ \rho_{\hat{Y}\hat{P},ij} = \rho_{YP,ij}$$
$$\text{HA:}\ \rho_{\hat{Y}\hat{P},ij} \neq \rho_{YP,ij}$$

where: $\hat{Y}_{ij}$ and $\hat{P}_{ij}$ is the simulated mean yield and price for crop *i*, for region j, respectively; Y_{ij} P_{ij} is the mean from historical yield and price for crop *i*; for region *j*, respectively; $\hat{\rho}_{\hat{Y}\hat{P},ij}$ is the individual correlation coefficient between the simulated variables for *i* and *j* and $\rho_{YP,ij}$ is the historical correlation coefficient between variables *i* and *j* used to simulate the multivariate distribution.

Table 3.12: Statistical evaluation test to determine the MVE procedures

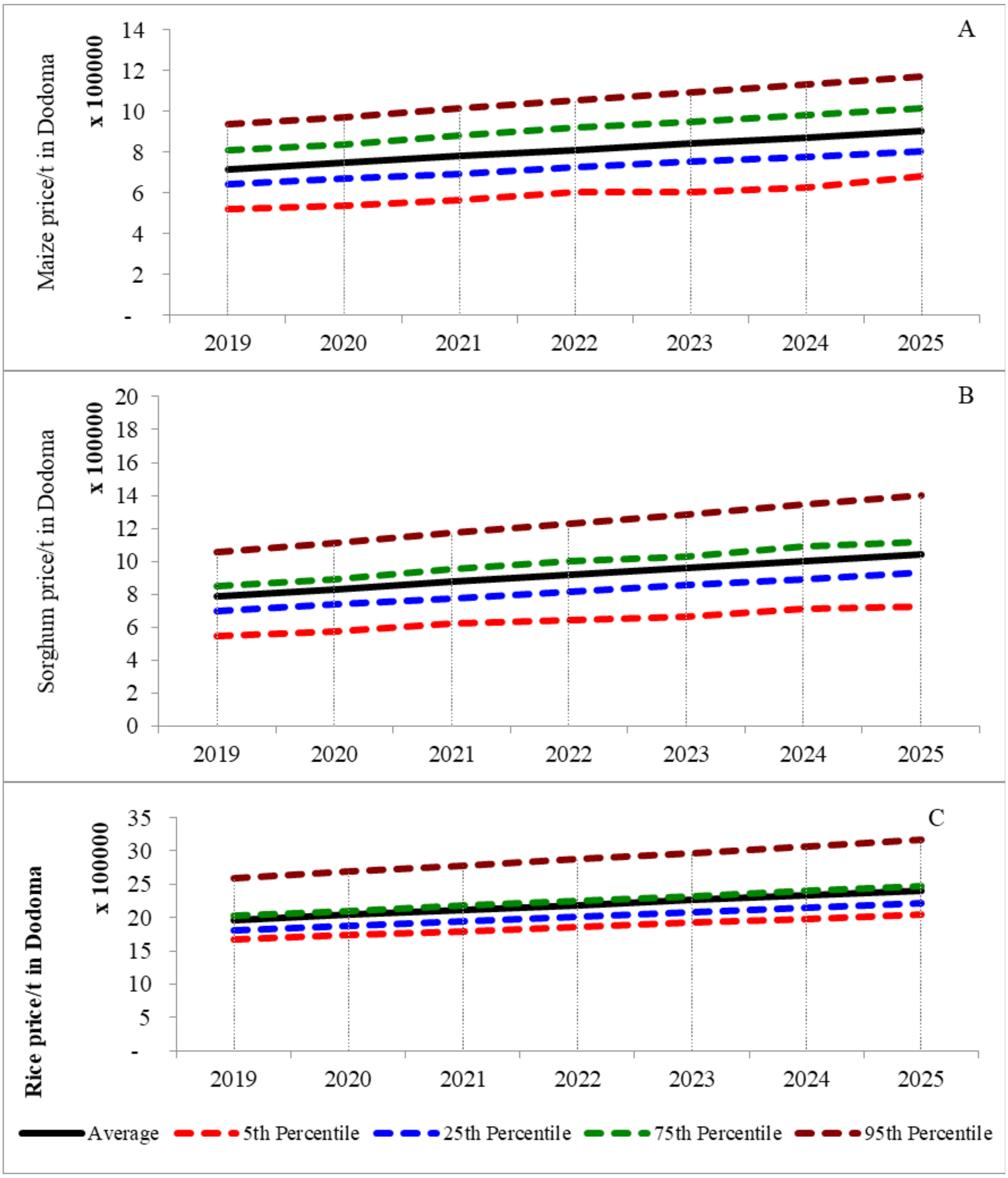
a) Test Correlation Coefficient		
Confidence Level	99.6586%	
Critical Value	2.94	

	Dodoma region						Morogoro region				
	SoY1	RcY1	MzP1	SoP1	RcP1		SoY2	RcY2	MzP2	SoP2	RcP2
MzY1	1.07	0.81	0.53	0.12	1.00	MzY2	1.78	0.63	0.38	2.34	2.06
SoY1		1.94	0.37	1.00	1.08	SoY2		0.90	0.07	1.44	1.29
RcY1			0.13	0.67	1.73	RcY2			0.59	1.30	1.08
MzP1				1.44	0.29	MzP2				1.26	0.08
SoP1					0.08	SoP2					0.63

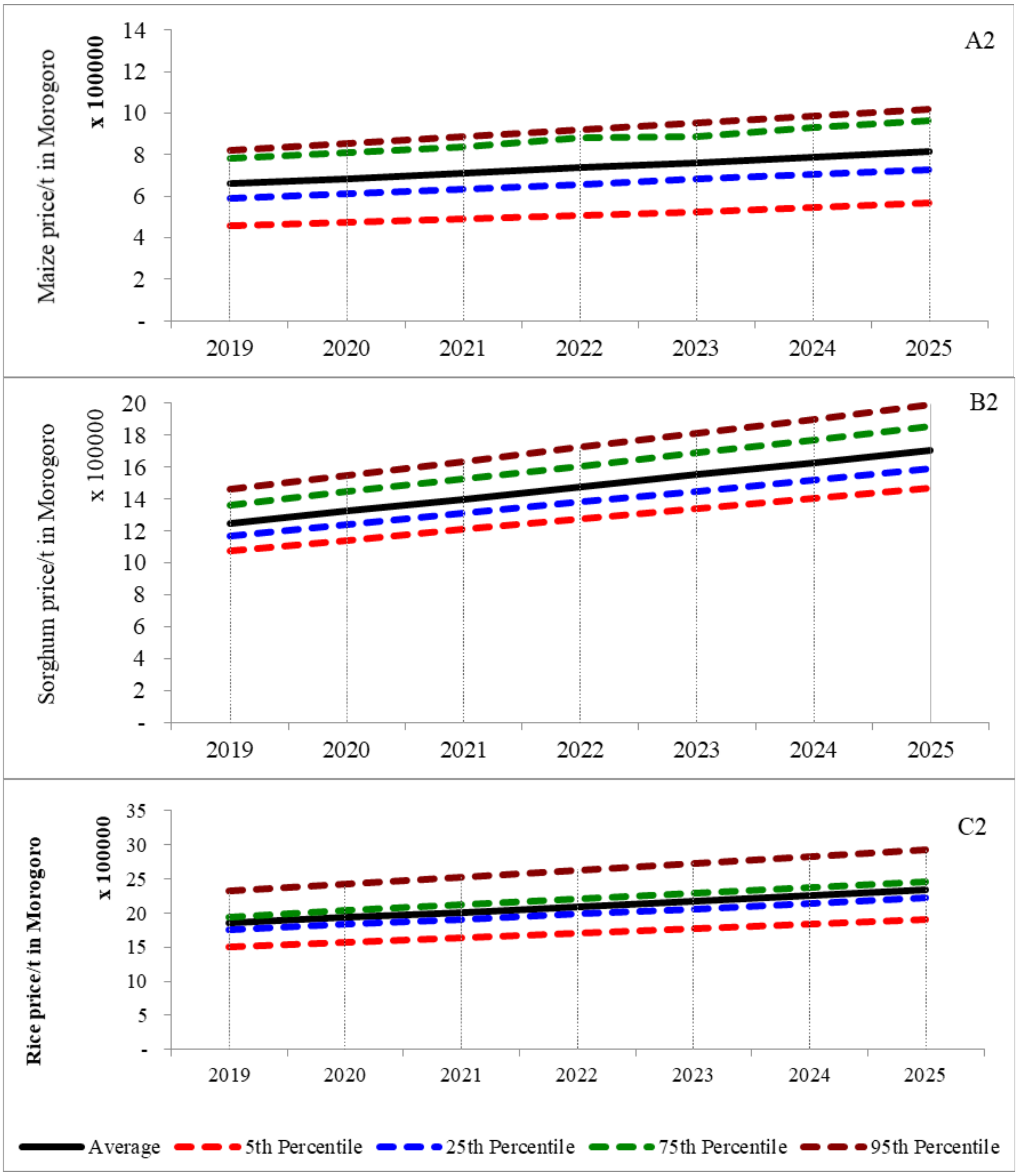
b) Test Parameters (Test for simulated vs deterministic means)

Confidence Level		95.0000%	Critical Value	2.25
Simulated vs. deterministic maize mean yield for 2019 in Dodoma				
	Given Value	Test Value	P-Value	
t-Test	1.137	0.17	0.86	*Fail to Reject the Ho that the Mean is Equal to 1.137*
Simulated vs. deterministic sorghum mean yield for 2019 in Dodoma				
	Given Value	Test Value	P-Value	
t-Test	0.894	0.24	0.81	*Fail to Reject the Ho that the Mean is Equal to 0.894*
Simulated vs. deterministic rice mean yield for 2019 in Dodoma				
	Given Value	Test Value	P-Value	
t-Test	1.809	0.16	0.87	*Fail to Reject the Ho that the Mean is Equal to 1.809*
Simulated vs. deterministic maize mean price for 2019 in Dodoma				
	Given Value	Test Value	P-Value	
t-Test	720,520	-0.44	0.66	*Fail to Reject the Ho that the Mean is Equal to 720,520*
Simulated vs. deterministic sorghum mean price 2019 in Dodoma				
	Given Value	Test Value	P-Value	
t-Test	790,919	-0.93	0.35	*Fail to Reject the Ho that the Mean is Equal to 790,919*
Simulated vs. deterministic rice mean price for 2019 in Dodoma				
	Given Value	Test Value	P-Value	
t-Test	1,969,380	-0.40	0.69	*Fail to Reject the Ho that the Mean is Equal to 1,969,380*
Simulated vs. deterministic maize mean yield for 2019 in Morogoro				
	Given Value	Test Value	P-Value	
t-Test	1.273	0.40	0.69	*Fail to Reject the Ho that the Mean is Equal to 1.273*
Simulated vs. deterministic sorghum mean yield for 2019 in Morogoro				
	Given Value	Test Value	P-Value	
t-Test	0.958	-0.24	0.81	*Fail to Reject the Ho that the Mean is Equal to 0.958*
Simulated vs. deterministic rice mean yield for 2019 in Morogoro				
	Given Value	Test Value	P-Value	
t-Test	2.419	0.18	0.86	*Fail to Reject the Ho that the Mean is Equal to 2.419*
Simulated vs. deterministic maize mean price for 2019 in Morogoro				
	Given Value	Test Value	P-Value	
t-Test	659,637	-0.41	0.68	*Fail to Reject the Ho that the Mean is Equal to 659,637*
Simulated vs. deterministic sorghum mean price for 2019 in Morogoro				
	Given Value	Test Value	P-Value	
t-Test	1,252,099	-0.59	0.56	*Fail to Reject the Ho that the Mean is Equal to 1,252,099*
Simulated vs. deterministic rice mean price for 2019 in Morogoro				
	Given Value	Test Value	P-Value	
t-Test	1,851,977	-0.42	0.68	*Fail to Reject the Ho that the Mean is Equal to 1,851,977*

Appendix 3.4: Fan graphs showing the relative variability of stochastic prices (in TZS) over the seven years from 2019 to 2025



Fan graph showing how the relative variability of stochastic prices (in TZS) change over the seven years from 2019 to 2025 in Dodoma. A = maize, B = sorghum, and C = rice.



Fan graph showing how the relative variability of stochastic prices (in TZS) change over the seven years from 2019 to 2025 in Morogoro. A = maize, B = sorghum, and C = rice.

CHAPTER FOUR

4.0 MANUSCRIPT TWO

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The effect of nitrogen-fertilizer and optimal plant population on the profitability of maize plots in the Wami River sub-basin, Tanzania: A bio-economic simulation approach

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4.1 Abstract

Maize (*Zea mays L.*) is the essential staple in sub-Saharan Africa (SSA) and Tanzania in particular; the crop accounts for over 30% of the food production, 20% of the agricultural gross domestic product (GDP) and over 75% of the cereal consumption. Maize is grown under a higher risk of failure due to the over-dependence rain-fed farming system resulting in low income and food insecurity among maize-based farmers. However, many practices, including conservation agriculture, soil and water conservation, resilient crop varieties, and soil fertility management, are suggested to increase cereal productivity in Tanzania. Improving planting density and the use of fertilizers are the immediate options recommended by Tanzania's government. In this paper, we evaluate the economic feasibility of the improved planting density (optimized plant population) and N-fertilizer crop management practices on maize net returns in semi-arid and sub-humid agro-ecological zones in the Wami River sub-Basin, Tanzania. We introduce a bio-economic simulation model using Monte Carlo simulation procedures to evaluate the economic viability of risky crop management practices so that the decision-maker can make better management decisions. The study utilizes maize yield data sets from two biophysical cropping system models, namely the APSIM and DSSAT. A total of 83 plots for the semi-arid and 85 plots for the sub-humid agro-ecological zones consisted of this analysis. The crop management practices under study comprise the application of 40 kg N-fertilizer/ha and plant population of 3.3 plants/m^2. The study finds that the use of improved plant population had the lowest annual net return with fertilizer application fetching the highest return. The two crop models demonstrated a zero probability of negative net returns for farms using fertilizer rates of 40 kg N/ha except for DSSAT, which observed a small probability (0.4%) in the sub-humid area. The optimized plant population presented 16.4% to 26.6% probability of negatives net returns for semi-arid and 14.6% to 30.2% probability of negative net returns for sub-humid zones. The results suggest that the application of fertilizer practices reduces the risks associated with the mean returns, but increasing the plant population has a high probability of economic failure, particularly in the sub-humid zone. Maize sub-sector in Tanzania is projected to continue experiencing a significant decrease in yields and net returns. Still, there is a high chance that it will be better-off if proper alternatives are employed. Similar studies are needed to explore the potential of interventions highlighted in the ACRP for better decision-making.

Keywords: Bio-economic Simulation, APSIM, DSSAT, N-fertilizer; 33 000 plants/ha, Risk, Maize

4.2 Introduction

Maize (*Zea mays L.*) is a major staple food crop in sub-Saharan Africa (SSA) grown in diverse agro-ecological zones and farming systems. The crop is predominantly consumed by people with varying food preferences and socioeconomic backgrounds. Maize accounts for almost half of the calories and protein consumed in eastern and southern Africa (Macauley and Ramadjita, 2015). In Tanzania, maize accounts for around 30% of overall food production, over 75% of cereal consumption and between 20 and 30% of the total agricultural gross domestic product (GDP) with 70% of the population eat maize as their staple food (URT, 2014; Wilson and Lewis, 2015). Tanzania is the dominant producer for maize in eastern and central Africa (Waithaka *et al.,* 2013).

However, like many other cereal sub-sectors in Tanzania, the maize sub-sector is grown under a higher risk of failure due to high dependence on a rain-fed farming system and low ability to adapt to climatic variability (URT, 2014). Mostly, the maize sub-sector is sensitive to even a small change in temperature and precipitation in Tanzania and SSA in general (Waithaka *et al.,* 2013; URT, 2014; Kahimba *et al.,* 2015). Hence, given the importance of maize in SSA where the vast majority of the world's poor people are located, exploring agronomic and management practices that will help the sector progress has recently attracted attention from several governments (Waithaka *et al.,* 2013; Kahimba *et al.,* 2015; Msongaleli *et al.,* 2015; Richardson and Bizimana, 2017).

To address the challenges hindering agricultural production in Tanzania, the government has introduced policies, strategies, and guidelines to stimulate the sector. These include the Tanzania National Adaptation Program of Action (NAPA) formulated in 2007 (URT, 2007), Climate-Smart Agricultural Guideline (URT, 2017), and Agriculture Climate Resilience Plan (ACRP) 2014–2019 (URT, 2014). Others are National Agricultural Policy

(URT, 2013) and the Agricultural Sector Development Programme phase two (ASDP-II), to mention a few (URT, 2016). These policies and strategies listed several potential agronomic and technology practices that would help integrate resilience in agricultural policy decisions, influence the planning process, and implement investment on the ground. The ACRP pinpointed several intervention practices that sustainably increases productivity, resilience, and enhances the achievement of national food security and reduces poverty. These practices include conservation agriculture (e.g., crop rotation, contour cropping), soil and water conservation (mulching, terracing), resilient crop varieties (drought/heat-tolerant varieties, pest & disease-resistant varieties), cropland management (cover crop, reduced tillage), soil fertility management (fertilizers, mulching) and agro-forestry (crop tree planting, tree nurseries).

Of all the practices identified by the ACRP 2014–2019, improving planting density and the use of fertilizers were the immediate options recommended because of their expected ease in realizing yield benefits, particularly in high rainfall areas or seasons (URT, 2007; URT, 2014; Msongaleli *et al.*, 2015). The interventions are proposed to be implemented either at the country level or in the selected agro-ecological zones like the alluvial plains, northern highlands, plateau, semi-arid lands, south-western highlands, southern highlands, and western highlands. Although the government suggested several options to be implemented in different agro-ecological zones, their economic feasibility should be known to the majority so they can make better decisions. Lack of enough information on the proposed alternative management practices' economic viability may hinder the adoption and proper use of the technologies. Feder *et al.* (1985) argued that adoption at the individual farmers' level is defined as the degree of use of new technology in the long-run equilibrium when the farmer has full information about the new technology and it’s potential. Based on Feder's argument, the most critical problem on the adoption of a technology/intervention is the one related to the information asymmetric.

On the other hand, detailed assessment studies that link data from biophysical and economic models are required to provide relevant information on the possible benefits of the proposed agronomic practices for better decision-making (Thompson *et al.,* 2010; White *et al.,* 2011; Kahimba *et al.,* 2015; Rosenzweig *et al.,* 2015). The use of multiple models in assessment studies has shown to enhance the quantification of uncertainties and reliabilities as different models differ in structure and parameterization (Rötter *et al.,* 2011; Msongaleli *et al.,* 2015). With this regard, the Agricultural Model Inter-comparison and Improvement Project (AgMIP) highlights procedures to utilize multiple models (Rosenzweig *et al.,* 2015). The AgMIP realizes the importance of integrating biophysical and socioeconomic models to improve decision making in agricultural production systems.

The objective of the present work is to demonstrate the benefits of using Monte Carlo simulation techniques to examine the economic viability of two risky alternatives, namely N-fertilizer application and plant population adjustment. The study develops a practical framework that links data from biophysical process-based models to build a Monte Carlo bio-economic simulation model, used to estimate the distribution of economic returns for alternative management strategies.

Two biophysical models, namely the Agricultural Production Systems sIMulator (APSIM) and Decision Support System for Agro-technology Transfer (DSSAT) cropping systems models, were used to develop a bio-economic simulation model. The two biophysical models are recommended for integrated assessment in SSA to improve decision-making for farm managers and policy-makers (Rosenzweig *et al.,* 2015). A bio-economic simulation model using a Monte Carlo simulation procedure was developed to link the baseline and alternative data from the two biophysical models. A Monte Carlo simulation approach to assess the economic feasibility of management practices in the agricultural sector has been used by Richardson *et al.* (2008), Palma *et al.* (2011), Rezende and Richardson (2015), Richardson and Bizimana (2017) and more recently by Bizimana and Richardson (2019).

4.3 Theoretical Background of the Bio-economic Modelling

Bio-economic theory in agriculture combines the biological and economic aspects of agricultural systems to explain yields as a function of soil-plant-atmosphere dynamics under described management over time (Antle and Capalbo, 2001; Jones *et al.,* 2001; 2003; Basso *et al.,* 2013). The bio-economic theory was pioneered in the 1950s by Gordon (1954) and Schaefer's (1954) to assess risk and uncertainties in fishing industries, and it gained momentum to be included in other agricultural research late in 1990s to 2000s (Just and Antle 1990; Kaiser *et al.,* 1993; Antle *et al.,* 1994; 1998; 1999; 2001; Kruseman *et al.,* 1995; Prato *et al.,* 1996; Segerson and Dixon, 1998; Antle and Stoorvogel, 2000; Antle and Capalbo, 2001). For example, Prato *et al*. (1996) used a bio-economic approach to link economic models with environmental-process models; Adams *et al.* (1999) employed an aggregate model with representative farms for U.S. regions to study the impacts of climate change on the U.S. agriculture. Kruseman *et al.* (1995) developed and demonstrated a bio-economic modelling approach that integrated biophysical information with linear programming models.

Bi-economic models allow discrete choices among technologies, and they represent production technology explicitly, so they can be linked to biophysical-process models of agricultural production (crop or livestock) to enhance decision making (Antle and Capalbo, 2001). Segerson and Dixon (1998) utilized econometric methods to estimate neoclassical production, cost and profit functions. Bio-economic models can, therefore, used to estimate and simulate site-specific data and can be used to represent notable variability in both biophysical conditions (soil-yield-atmosphere) and economic behaviour (prices, costs, inflation rates) (Antle and Capalbo, 2001). On the other hand, bio-economic models can explicitly represent the impacts of biophysical conditions on the productivity and profitability of an agricultural system within the study area.

Most empirical economic production models do not incorporate biophysical data and information about growth processes (Kaufmann and Snell, 1997; Antle and Capalbo, 2001). Leaving site-specific soil and climate variables out of a production function may lead to biased and inconsistent parameter estimates. Bio-economic modelling has, for a long time, been advocated as an essential tool in risk assessments for determining suitable management options that produce high returns. This is because the models combine the unobservable dynamics or characteristics that influence final output or net returns like soil and climatic conditions (Clark, 1985, 1990; Hannesson, 1993; Seijo *et al.,* 1998; Antle and Capalbo, 2001; Anderson and Seijo, 2009). Since bioeconomic modelling can incorporate some elements of human decision making, it is a tool that is most effective form modelling risk in agricultural production (Larkin *et al.,* 2011).

The integrated risk assessment paradigm for agricultural production systems is a stepwise process. For example, the economic data are inputs into economic models, and soil and climatic conditions data are input into the crop-processed models that calculate site-specific productivity (Antle and Capalbo, 2001). The outputs of crop models (crop yield) are inputs into economic models. If the biophysical and economic data are statistically representative of the population analysed, and economic decision-makers outcomes can be statistically used to assess the economic viability of the farming system or alternative management analysed.

Even with these ready-made conceptual frameworks on bio-economic modelling, there are limited studies in Tanzania that applied the model. The contribution of this study to the board of knowledge is to demonstrate how the biophysical models can be integrated with econometric models to improve decision making. The study illustrates the procedure for integrating data from biophysical models into stochastic economic models to examine the economic viability of N-fertilizer application and plant population adjustment. The study develops a practical framework that links maize yield (with and without) alternatives management practices to estimate the distribution of economic returns in a probabilistic method. The producers used in this analysis to estimate the net returns for agricultural management options in probability distributions have been used by Palma *et al.* (2011), Rezende and Richardson, (2015), Richardson and Bizimana (2017) and more recently by Bizimana and Richardson (2019).

4.4 Materials and Methods

This study is part of modelling activities under AgMIP protocols (Rosenzweig *et al.*, 2015) conducted from 2015 to 2017 with improved computing tools for enhanced regional integrated assessment studies in developing countries, including SSA (see Version 6 of the AgMIP handbook of methods and procedures at www.agmip.org). The AgMIP protocols recommend implementing two crop models (DSSAT and ASPIM) and at least one socioeconomic model.

4.4.1 Study area

The maize plots used in the present study are located in the Wami River sub-Basin of Tanzania. The Wami River sub-Basin lies between 5°–7°S and 36°–39°E, where it extends from the semi-arid in Dodoma region to the humid inland swamps in Morogoro region, to the Saadani village at the coast of Indian Ocean (Figure 4.1). It covers an area of approximately 43 000 km^2, with altitude ranging from 0m at the coast to 2260m in Ukaguru Mountains.

Wami River sub-Basin is characterized by crop production, livestock keeping with numerous off-farm activities. The study area is dominated by smallholder farms, growing an array of crops including maize, sorghum, rice, legumes, cassava, groundnuts, millet, and beans. Maize is the staple food crop in the study area. The area's onset of rainfall usually occurs in mid-September. The rainy season extends until April in the sub-humid part and early-mid December to April in a semi-arid region. The availability of weather stations in the study area (Kongwa, Dodoma airport, Malali, Wami prison, and Morogoro) provide useful weather data needed by the two crop models (Figure 4.1).

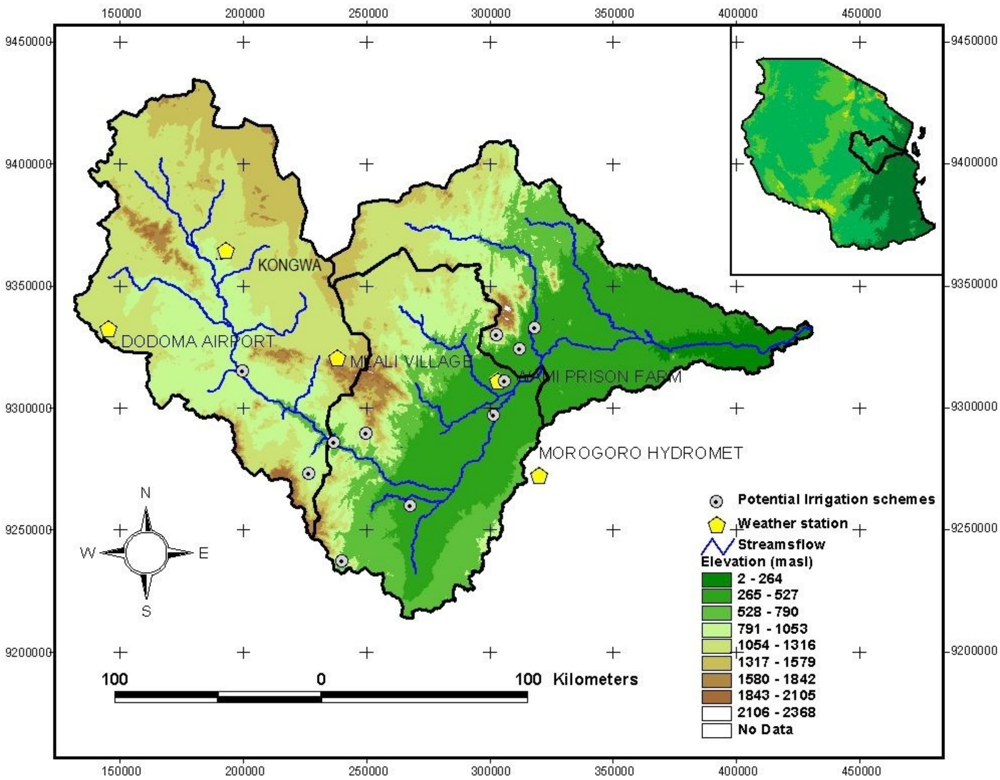

Figure 4.1: Wami-sub basin, Tanzania

4.4.2 Source of the data and modelling framework

This study followed is a Monte Carlo simulation approach to develop a bio-economic simulation model. The developed model was used to simulate the key output variables (KOVs), including revenues (yield x price) and net cash returns, using yield and price risk associated with different management practices. The model uses maize yield data (with and without management practices) obtained from work done by Tumbo *et al.* (2020) in which two biophysical (process-based) crop models were used. The two models were the Agricultural Production Systems sIMulator(APSIM) and the Decision Support System for Agrotechnology Transfer (DSSAT). These models employed maize production data from the second wave of the Tanzania National Panel Survey (TNPS) (NBS, 2012).

A total of 168 maize plots within the Wami River sub-Basin were sorted (83 plots for the semi-arid part and 85 plots for the sub-humid part). The TNPS also provided data on production costs, the area planted, and all inputs used for maize production. The average area for maize plots size was 1.26 ha and 1.76 ha for semi-arid and sub-humid, respectively. Table 4.1 displays the distribution of the area planted to maize used in this study. However, the information on maize prices was obtained from regional agricultural offices (marketing unit) within the basin to have all the information required to model the key output variables (KOVs). The bio-economic model incorporated the risk of maize production in the Wami River sub- Basin by using probability distributions to simulate random values for yields, prices, and costs.

Table 4.1: Distribution of maize plots (ha) per agro-ecological zone in Wami River sub-Basin

Zone	**Average**	**Minimum**	**Maximum**	**Total area**
Semi-arid	1.26	0.5	2.8	97.4
Sub-humid	1.76	0.8	3.80	158.3

Source: TNPS

Figure 4.2 presents a diagram of the bio-economic model. The diagram shows that the simulated yield from the two biophysical models was first validated (Validation 1) by comparing the simulated yield probability distribution functions (PDFs) to the biophysical baseline observed yield distributions (Appendix 4.1). With the similarities in the PDFs, the yield data from the two process-based models were used to develop a Monte Carlo bio-economic model, as explained in the sub-sections 2.4 to 2.7. Before applying a Monte Carlo bio-economic the data were validated again (Validation 2) to ensure that the rando ulated nstrate the appropriate properties of the two section 2.5). The second validation, the last activity in the model was to estimate the KOVs, discuss them, and conclude. The bio-economic simulatio oped us www.simetar.com] in Microsoft Excel ools developed by Richardson *et al.* (2000; 2008).

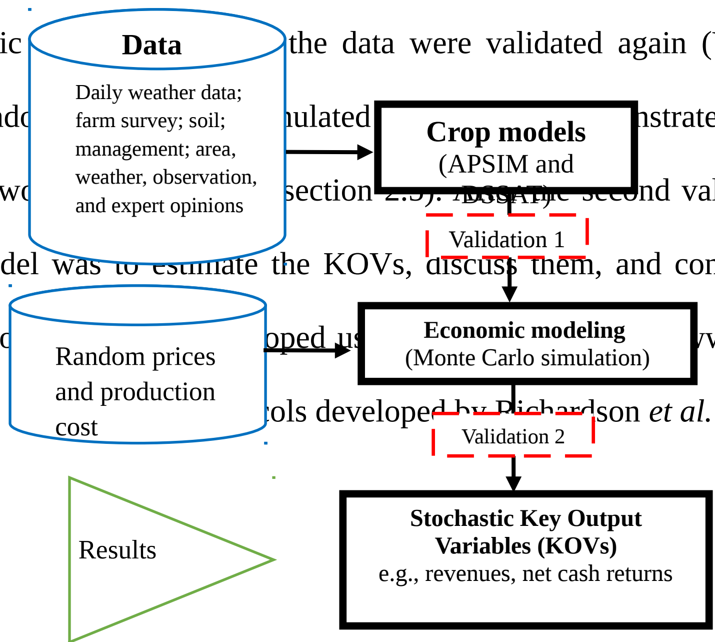

Figure 4.2: Bio-economic simulation model

4.4.3 Overview of APSIM and DSSAT cropping system models

APSIM is a modelling environment software tool that enables sub-models to be linked to simulate agricultural systems. APSIM uses various tools and component modules to dynamically simulate cropping systems in the semi-arid tropics (McCown *et al.*, 1996; Wolday and Hruy, 2015). The model simulates the mechanistic growth of crops, soil processes, and a range of options considering the cropping system perspective (McCown *et al.,* 1996). APSIM was designed as a farming systems simulator to combine accurate yield estimation in response to management with the prediction of the long-term consequences for alternative farming practices (Keating *et al.,* 2003). Required inputs for APSIM include weather, soil, crop data, and management options (Ahmed and Hassan, 20211).

DSSAT is a software application program that comprises crop simulation models for over 42 crops as well as tools to facilitate effective use of the models (Hoogenboom *et al.*, 2019a; 2019b). The crop simulation models simulate growth, development, and yield as a function of the soil-plant-atmosphere dynamics under specified management practices over time (Jones *et al.*, 2003). DSSAT includes database management programs for soil, weather, crop management, and experimental data, utilities, and application programs. DSSAT and APSIM crop models allow users to simulate options for alternative crop management scenarios to assess yield risks (Ahmed and Hassan, 2011).

In this study, APSIM and DSSAT provided the processed maize yield with-and without the recommended management practices. Different biophysical parameters like soil type, management practices (cultivars, planting dates, fertilizer application, and plant population) and climate/weather available within the basin were included in the model (Tumbo *et al.*, 2020). Increasing soil fertility and planting density adjustment were two alternative practices considered. For each farm, a 40 Kg N/ha was applied for soil fertility and 33 000 plants/ha (3.3 plants/m^2) and simulated by APSIM and DSSAT cropping systems, as detailed by Tumbo *et al.* (2020).

4.4.4 Overview of the proposed interventions

Increasing soil fertility through fertilizer application and improving planting density were two interventions considered in this study. The two options are highlighted in the ACRP 2014 – 2019 as the immediate interventions for improving maize and other cereals productivity. Historically, Tanzania has had a low level of fertilizer application, among the lowest in the world. In 2010, this averaged only about 9 kg/ha/year, and it reached 12.6 kg/ha/year in 2016 as a result of the input subsidy (Wilson and Lewis 2015; World Bank 2020). Although the current data shows an increasing trend for fertilizer consumption per unit area, there is a possibility of dropping because of the COVID-19 impacts on fertilizer prices, as many of the fertilizers are imported. Maize production consumes over 56% of all the fertilizers used. According to IFDC (2012), the Wami-Ruvu basin is within regions where the proportion of farmers using fertilizers is below 5%. A current study by Tumbo *et al.* (2020), highlighted that the percentage of farms using inorganic fertilizers in Wami Sub-basin is very low, ranging between 3% to 13%. The small fertilizer application is because over 80% of the maize producers are dominated by smallholder farmers who sometimes minimize their production cost by choosing not to use the recommended fertilizers (Wilson and Lewis 2015).

Most of the farms in the study did not use fertilizers. Therefore, DSSAT and APSIM crop models were used to identify the optimum fertilizer rate and the planting density suitable for the Wami River sub-Basin under current climate and current farm management practices. The procedures for the selection of fertilizer rates and plant populations are well documented by Rao *et al.* (2015) and Tumbo *et al.* (2015; 2020). The fertilizer rate of 40 kg N/ha was therefore selected for use within the Wami River sub-Basin. The increased plant population to 33 000 plant/ha (3.3 plants/m^2) was chosen which is a significant increase from the current rates of 18 000 – 22 000 plants/ha (20 000 plants/ha on average).

4.4.5 Bio-economic simulation framework

The development of the bio-economic simulation model involved five stages. The first stage was to validate the original or observed data from the survey and baseline data from the two biophysical, process-based crop models. The details of the baseline data have been reported by Tumbo *et al.* (2020). The output from the two models was used to develop a bio-economic simulation model. Four scenarios under study are summarized below:

- ***BASELINE:*** current agricultural farming system;
- ***ALT.1:*** baseline plus fertilizer application of 40 kg N/ha for all the plots.
- ***ALT.2:*** baseline plus plant population of 33 000 plants/ha (3.3 plants/m^2).
- ***ALT.3:*** baseline plus (*ALT.1* + *ALT.2*).

The above-described scenarios make a total of 16 simulations for the bio-economic model. That is 1 scenario for two models for two agro-ecological zones (*BASELINE* = 2x2; *ALT.1*

= 2x2; *ALT.2* = 2x2 and *ALT.3* = 2x2). Since we have multiple scenarios, the multivariate empirical (MVE) distribution described by Richardson *et al.* (2000) was used to account for all 16 scenarios. MVE distributions are defined by the fractional deviations from the mean ($S_{ij\omega}$) and cumulative probabilities ($F(S_{ij\omega})$) where *i* indicates maize yield for each scenario, for crop model *j* per zone *ω* to estimate the probability distributions. We programmed the economic model in Microsoft Excel using the Simetar add-in, following a detailed Monte Carlo simulation modelling procedure described by Richardson *et al.* (2000).

4.4.6 Stochastic yields

To simulate the stochastic component of the model for analysing risky alternatives, a vector of uniform standard deviates (USDs) was computed first. USD is a probability distribution included in Simetar to produce a uniform standard deviate on the 0-1 scale and is simulated with a function =UNIFORM(). It simulates several random variables for all probability distributions via the inverse transformation method of generating random variables (Richardson *et al.*, 2008). The resulting vector is used to simulate random yields for each scenario analysed for all cropping system models.

$$\tilde{Y}_{ij\omega} = \bar{Y}_{ij\omega} * (1 + MVEMP(S_{ij\omega}, F(S_{ij\omega}), CUSD_{ij\omega})) \quad (4.1)$$

Where $\tilde{Y}_{ij\omega}$ = random mean yield/ha,

i = scenarios (*BASELINE*, *ALT.1*, *ALT.2 AND ALT.3*),

j = crop model (APSIM and DSSAT),

ω = agro-ecological zones (semi-arid and sub-humid)

$S_{ij\omega}$ = sorted deviations from mean (percentage deviations from the mean)

$F(S_{ij\omega})$ = the frequency distribution for the fractional deviates from the mean

MVEMP = Simetar function used to simulate an MVE defined by $S_{ij\omega}$ and $F(S_{ij\omega})$ and the correlation matrix for the random deviates indicated as CUSDs

Each scenario in Equation (4.1) was simulated for 500 iterations to provide an adequate sample of the yields to simulate economic KOVs to estimate their probability distributions and relative variability. The simulated yields were validated to check for model completeness, accuracy, and simulation ability. PDF charts for bio-economic simulated vs. process-based data for all the agro-ecological zones data were developed for this purpose. A detailed procedure for how the results of bio-economic simulation results were validated is provided in Appendix 4.2. Due to limited space, only the validation PDFs for semi-arid areas are presented in the Appendix, but the procedures of the bio-economic simulation model to simulate the process-based data sets were met for all the agro-ecological zones.

4.4.7 Stochastic price and revenue

Maize price within the basin was simulated using a GRKS distribution. The GRKS distribution was developed by Gray, Richardson, Klose, and Schumann to simulate subjective probability distributions based on minimum, mid-point, and maximum input data (Richardson *et al.*, 2008). Simetar simulates it with the =GRKS(min, mid-point, max) function. The output from GRKS is a stochastic price denoted in this study by ($\tilde{\boldsymbol{P}}_{\omega}$). The stochastic prices were combined with the yield for each scenario in Equation (4.1) to simulate the stochastic receipts ($\tilde{\boldsymbol{R}}_{ij\omega}$). Table 4.2 provides the distribution of maize prices used to parameterize the GRKS distribution in Equation (4.2). The equation for the stochastic revenue for each scenario was given by Equation (4.3).

$$\tilde{P}_{\omega} = GRKS(Minimum_{p\omega}, Average_{p\omega}, Maximum_{p\omega})$$

(4.2)

$$\widetilde{R}_{ij\omega} = \widetilde{Y}_{ij\omega} * \widetilde{P}_{\omega}$$

(4.3)

Where:

$Minimum_{p\omega}$ = minimum price (TZS/t) for agro-ecological zone ω,

Maximum = maximum price (TZS/t) for agro-ecological zone ω,

Average = average price (TZS/t) for agro-ecological zone ω,

$\widetilde{R}_{ij\omega}$ = stochastic revenue for scenario *i*, crop model *j*, for agro-ecological zone ω

Table 4.2: Annual prices distribution for maize grains in the Wami Basin

	Semi-arid (TZS/t)	Sub-humid (TZS/t)
Minimum	445 556	356 725
Average	555 830	542 100
Maximum	666 811	694 082

Source: Focus group discussions, and Regional Agricultural Office in Dodoma and Morogoro

4.4.8 Production cost and net returns

The production cost for the baseline scenario is composed of field preparation costs, planting costs, farm management costs, harvesting, and transportation. Appendix 4.3 summarizes the production cost incurred. The cost of the proposed interventions was also included in the model. This involved addition of fertilizer and increased seeding rates, both of which imply increases in production cost. Thus, the total variable cost of production is expected to increase (Rao *et al.*, 2015). We calculated the additional cost for the farmer to purchase the 40 kg of nitrogen fertilizer and the additional cost of buying extra kilograms of maize seeds to make a required of ≥ 33 000 plants/ha. With consideration of expert opinions, it was argued that the current average plant population in the Wami River sub-Basin is between 18 000 and 22 000 plants/ha (20 000 plants/ha on average), which is equivalent to 18 – 22 kg/ha. Therefore, 7 – 10 kg is needed to make the plant population per ha ≥ 33 000.

With this regard, it was agreed that the cost of 40 kg N ranges from TZS 55 000 to TZS 65 000 (TZS 60 000 on average), including transport and labour charges. One kilogram of maize seeds ranges from TZS 4 000 to TZS 6 000, hence farmers are likely to incur an additional cost of between TZS 28 000 to TZS 60 000 to purchase extra seeds. Again, the GRKS distribution was used to simulate the stochastic production cost ($\tilde{C}_{ij}$) for the baseline and alternatives. It was also observed that the distribution of production cost per ha for the baseline scenario was the same for sub-humid and semi-arid areas in the basin with the same distribution for the risky alternatives (Table 4.3). The costs for each scenario in Table 3 were, therefore, simulated in Simetar using the function in Equation (4.4). Net returns for each scenario in Equation (4.5) were calculated as the total receipt minus total cost.

$$\tilde{C}_{ij\omega} = GRKS(Min_{ij\omega}, Average_{ij\omega}, Max_{ij\omega}) \tag{4.4}$$

$$\tilde{\pi}_{ij\omega} = \tilde{R}_{ij\omega} - \tilde{C}_{ij\omega} \tag{4.5}$$

Where:

Min = minimum production cost (TZS/ha) value for the distribution,
Max = maximum production costs (TZS/ha) value for the distribution
Average = average production cost (TZS/ha) value for the distribution
$\tilde{C}_{ij\omega}$ = stochastic production cost for scenario *i*, crop model *j*, for agro-ecological zone ω
$\tilde{R}_{ij\omega}$ = stochastic revenue for scenario *i*, crop model *j*, for agro-ecological zone ω
$\tilde{\pi}_{ij\omega}$ = stochastic net revenue for scenario *i*, crop model *j*, for agro-ecological zone ω

Table 4.3: Distribution of costs for the baseline and the alternative scenario within the Wami sub-basin (TZS/ha)

	Baseline	**Alt.1**	**Alt.2**	**Alt.3**
Minimum	155 000	215 000	200 000	260 000
Average	210 000	270 000	254 000	314 000
Maximum	360 000	420 000	404 000	464 000

Source: TNPS

The bio-economic simulation model results were presented using tables as well as the Cumulative Distribution Functions (CDF) and the Probability Distribution Functions

(PDF). The PDF and the CDF were drawn to estimate the distribution of economic returns for scenarios so decision-makers can make better decisions. The results of the model were also presented using the Stoplight Chart. The Stoplight Chart is a function in Simetar used to develop ranking probabilities. It summarizes the probabilities that the KOV(i.e., net returns) for scenarios/alternatives will be less than the lower target and the probability the KOV will exceed a maximum target (Richardson *et al.* 2008; Bizimana and Richardson 2019; Kadigi *et al.* 2020). We set the minimum net returns target to be TZS 0 and the maximum target to be the average maize returns per ha, which is around TZS 500 000. The Stoplight chart estimated the probabilities of net profits falling below zero (being negative), exceeding TZS 500 000, and the probabilities of falling between the two targets.

4.5 Results and Discussion

4.5.1 Relative risks for baseline and alternative scenarios on maize yield in the **Wami River sub-basin**

The first thing performed by this study is the evaluation of the relative variability about the mean yield for each risk alternative analysed. Yield data from the two process-based crop models (APSIM and DSSAT) were simulated using a Monte Carlo simulation procedure for 500 iterations to capture the relative risks associated with maize yield for each scenario (Table 4.4). The table provides the mean, standard deviation (SD), coefficient of variation (CV), minimum and maximum statistics for each alternative. The CV measures the relative risk associated with the mean yield per scenario for each agro-ecological zone in the basin. Both APSIM and DSSAT reported the highest CVs for the *BASELINE* scenario and *ALT.2* with relatively small CVs for *ALT.1* and *ALT.3* in both agro-ecological zones. *BASELINE* in semi-arid has a CV equal to 63.9% and 74.2% for APSIM and DSSAT; and in the sub-humid region, the *BASELINE* has a CV equal to 65.9% and 57.9% for the two models, respectively. Of all the scenarios, *ALT.2* had CV values closer to *the BASELINE* for both APSIM and DSSAT models. *ALT.1* and *ALT.3* have the smallest CVs of between 18.4% and 29.1% for APSIM and 20.5% and 33.7% for DSSAT. The simulation results indicate that the *BASELINE* and *ALT.2* have the highest relative risk.

Table 4.4: Summary statistics for the stochastic distribution of maize yield of the bio-economic simulation model

	APSIM				DSSAT			
	Baseline	***Alt.1***	***Alt.2***	***Alt.3***	***Baseline***	***Alt.1***	***Alt.2***	***Alt.3***
	t/ha	t/ha	t/ha	t/ha	t/ha	t/ha	t/ha	t/ha
	Semi-arid agro-ecological zone of the basin							
Mean	0.823	2.161	0.898	2.263	0.813	2.540	0.837	2.668
SD	0.526	0.435	0.529	0.416	0.603	0.532	0.639	0.548
CV	63.89	20.13	58.86	18.39	74.15	20.95	76.34	20.53
Min	0.122	1.384	0.100	1.611	0.197	1.566	0.221	1.607
Max	3.357	3.915	3.357	3.738	2.917	3.964	3.016	3.817
	Sub-humid agro-ecological zone of the basin							
Mean	0.841	2.380	0.889	2.439	0.698	2.302	0.689	2.292
SD	0.554	0.693	0.524	0.519	0.404	0.761	0.387	0.771
CV	65.93	29.14	59.00	21.29	57.88	33.05	56.10	33.66
Min	0.286	1.584	0.451	1.667	0.346	0.634	0.361	0.580
Max	3.568	5.612	3.595	5.086	3.719	4.638	3.612	4.182

The *BASELINE* and *ALT.2* scenarios had the smallest mean, minimum, and maximum maize yields with *ALT.1* and *ALT.3,* having the highest values for each crop model for all the zones. The bio-economic simulation model for the two zones suggests that 40 kg N/ha would lead to an average increase of 2.16 – 2.54 t/ha in the semi-arid and 2.30 – 2.38 in the sub-humid. The minimum yield would lie between 1.38 – 1.57 t/ha and 0.63 – 1.58 t/ha for semi-arid and sum-humid. The results also suggest that the addition of 3.3 plants/square meter would have no significant impact on maize yield.

The yield distributions for all scenarios in the semi-arid and sub-humid agro-ecological zones of the Wami River sub-Basin are also presented in Figure 4.3. The two models for both zones suggest that maize yield PDFs for *ALT.1* and *ALT.3* lie to the right of the PDFs for the *BASELINE* and *ALT.2* scenarios. The *ALT.2* yield PDF is not different from the

BASELINE for the two models. Likewise, *ALT.1* and *ALT.3* yield PDFs are only slightly different, except for DSSAT in the sub-humid area.

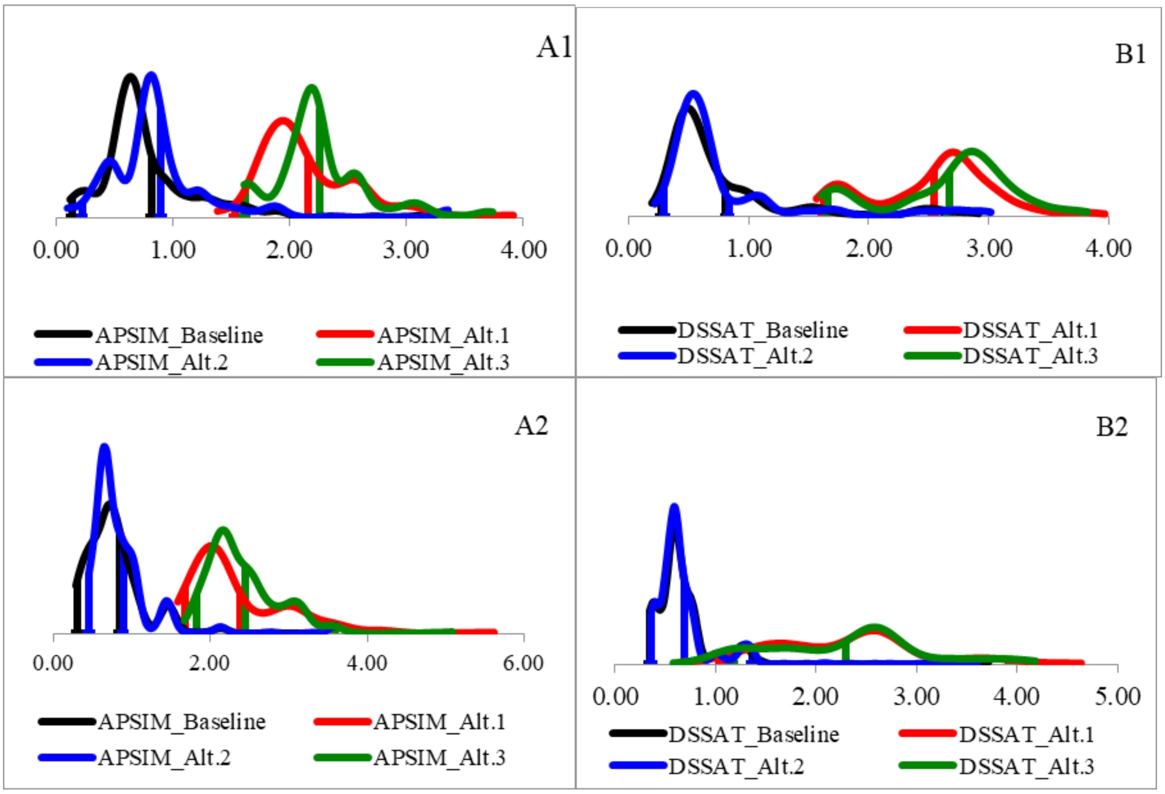

Figure 4.3: PDF of annual maize yields for baseline and alternative scenarios in semi-arid (A1 & B1) and sub-humid (A2 & B2) part of the Wami basin

4.5.2 Effect of alternative scenarios on maize net return

The effect of alternatives in semi-arid agro-ecological zone

Table 4.5 shows the summary statistics of the effect of alternative scenarios on maize net returns per ha in the semi-arid area of the Wami River sub-Basin. The results on annual net income per ha for *BASELINE* in the semi-arid agro-ecological zone under both APSIM and DSSAT have a mean net return of TZS 226 000 and TZS 221 000 with a negative minimum value of TZS –316 000 and TZS –209 000 respectively.

Table 4.5: Summary statistics of annual maize net return (TZS hundred thousand) in semi-arid

	APSIM				DSSAT			
	BASELIN	*ALT.1*	*ALT.2*	*ALT.3*	*BASELIN*	*ALT.1*	*ALT.2*	*ALT.3*

	E				*E*			
	TZS/ha	TZS/ha	TZS/ha	TZS/ha	TZS/ha	TZS/ha	TZS/ha	TZS/ha
Mean	226	912	226	925	221	1,125	195	1,148
SD	288	274	301	273	337	336	373	338
CV	127.2	30.1	133.2	29.5	152.1	29.9	191.1	29.4
Min	-316	327	-336	296	-209	355	-243	278
Max	1,632	1,960	2,010	1,954	1,499	2,044	1,657	2,170
Prob(π<0)	13.9%	-	16.4%	-	16.6%	-	26.6%	-

The probability of negative net returns (Prob(π<0)) is higher for *ALT.2* and *BASELINE* scenarios because net returns were not enough to pay for the added seed. The maximum value is TZS 1 632 000 for APSIM and TZS 1 499 000 for DSSAT. *ALT.2* has slightly different from the *BASELINE* in terms of mean, minimum, and maximum annual net returns (Table 4.6). *ALT.1* and *ALT1.3* have greater net returns than the *BASELINE* with a mean of more than TZS 900 000 and TZS 1 000 000 for APSIM and DSSAT. The minimum net return for *ALT.1* and *ALT.3* is TZS 327 000 and TZS 296 000, with the maximum values of TZS 1 960 000 and TZS 1 954 000 for APSIM respectively. DSSAT has a minimum of about TZS 355 000 and TZS 278 000, with the maximum amount of over TZS 2 000 000 for *ALT.1* and *ALT.3*. The relative risk associated with the annual average net return is higher for the *BASELINE* (127.2% for APSIM and 152.1% for DSSAT) and *ALT.2* (133.2% for APSIM and 191.1% for DSSAT). The relative variability about the mean is less than 31% for *ALT.1* and *ALT.3* for both DSSAT and APSIM.

Figure 4.4 represents the CDF for annual net returns in the semi-arid part of the basin for all the scenarios and models. The solid lines of the CDF are for APSIM, and the square dotted lines are for DSSAT. *BASELINE* and *ALT.2* scenarios display negative values with non-negative values for *ALT.1* and *ALT.*3. *ALT.1* and *ALT.3* scenarios lie to the right of the *BASELINE* and *ALT.2* with a minor difference for the two scenarios, which indicates that the increased fertilizer scenarios produce higher net returns with less risk at each net return level. DSSAT is slightly more to the right for *ALT.1* and *ALT.3*, but the maximum and minimum values fall in the same range as APSIM. The baseline scenarios for both APSIM and DSSAT show a 13.9% and 16.6% probability of negative returns. The two models also suggest that *ALT.2* has 16.4% and 26.6% probability of negative net returns and a zero probability for *ALT.1* and *ALT.3*.

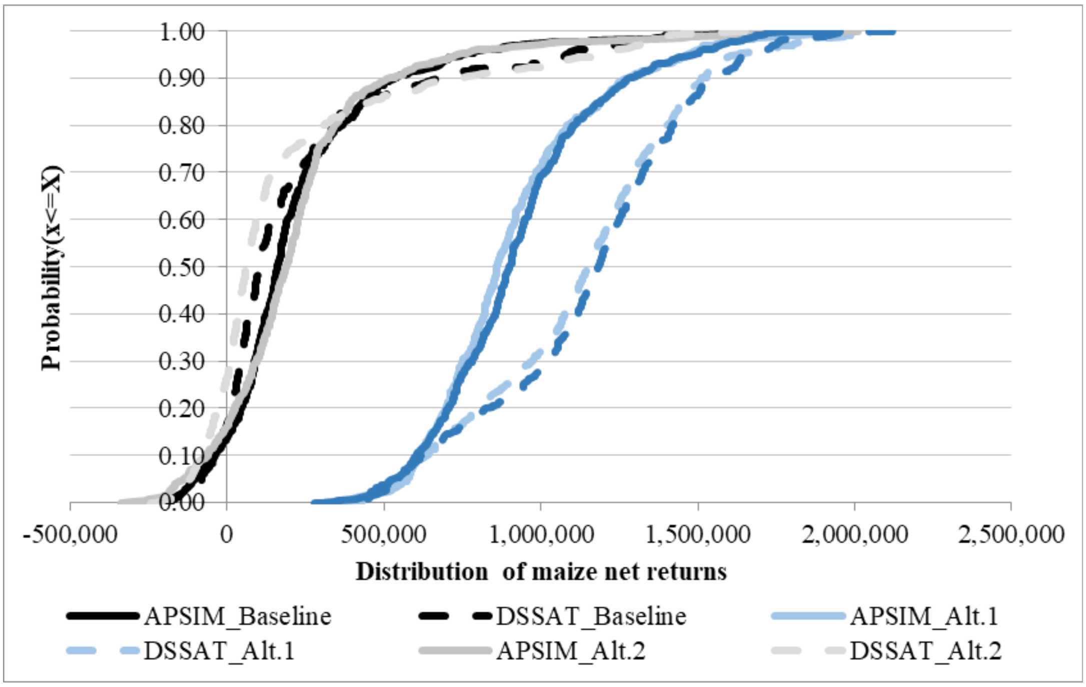

Figure 4.4: CDF of annual net return in semi-arid as for APSIM and DSSAT cropping models

Table 4.6: Summary statistics of annual maize net return (in TZS/ha) of the bio-economic simulation model

	APSIM				DSSAT			
	Baseline	***Alt.1***	***Alt.2***	***Alt.3***	***Baseline***	***Alt.1***	***Alt.2***	***Alt.3***
	TZS/ha	TZS/ha	TZS/ha	TZS/ha	TZS/ha	TZS/ha	TZS/ha	TZS/ha
	Semi-arid (values are in thousands)							
Mean	226	912	226	925	221	1,125	195	1,148
SD	288	274	301	273	337	336	373	338
CV	127.2	30.1	133.2	29.5	152.1	29.9	191.1	29.4
Min	-316	327	-336	296	-209	355	-243	278
Max	1 632	1 960	2,010	1 954	1 499	2 044	1,657	2,170
	Sub-humid (values are in thousands)							
Mean	225	984	201	972	144	938	95	894
SD	330	429	284	344	239	449	218	469
CV	147.0	43.6	141.1	35.4	165.7	47.8	229.9	52.4
Min	-234	124	-243	288	-183	-58	-233	-85
Max	2 173	3 098	2 071	2 723	2 706	3 013	1 794	2 432

Figure 4.5 is the Stoplight chart presenting the probabilities of the net return falling below zero and probabilities of being more significant than the maximum target (TZS 500 000)

for the farms in the semi-arid. The BASELINE scenarios for the APSIM and DSSAT models show a 14% and a 17% probability of negative annual net returns, respectively. The likelihood of BASELINE net return exceeding the maximum target of TZS 500 000 were 11% and 14%, with the probability of falling between the two targets being 75% and 70% for the two models. Both *ALT.1* and *ALT.3* have zero probability of net returns being negative and over 96% probability of exceeding the upper target for the two models. APSIM and DSSAT show that *ALT.2* has 16% and 27% probability of net return being negative with the probability of exceeding the upper target net returns equalling the *BASELINE.*

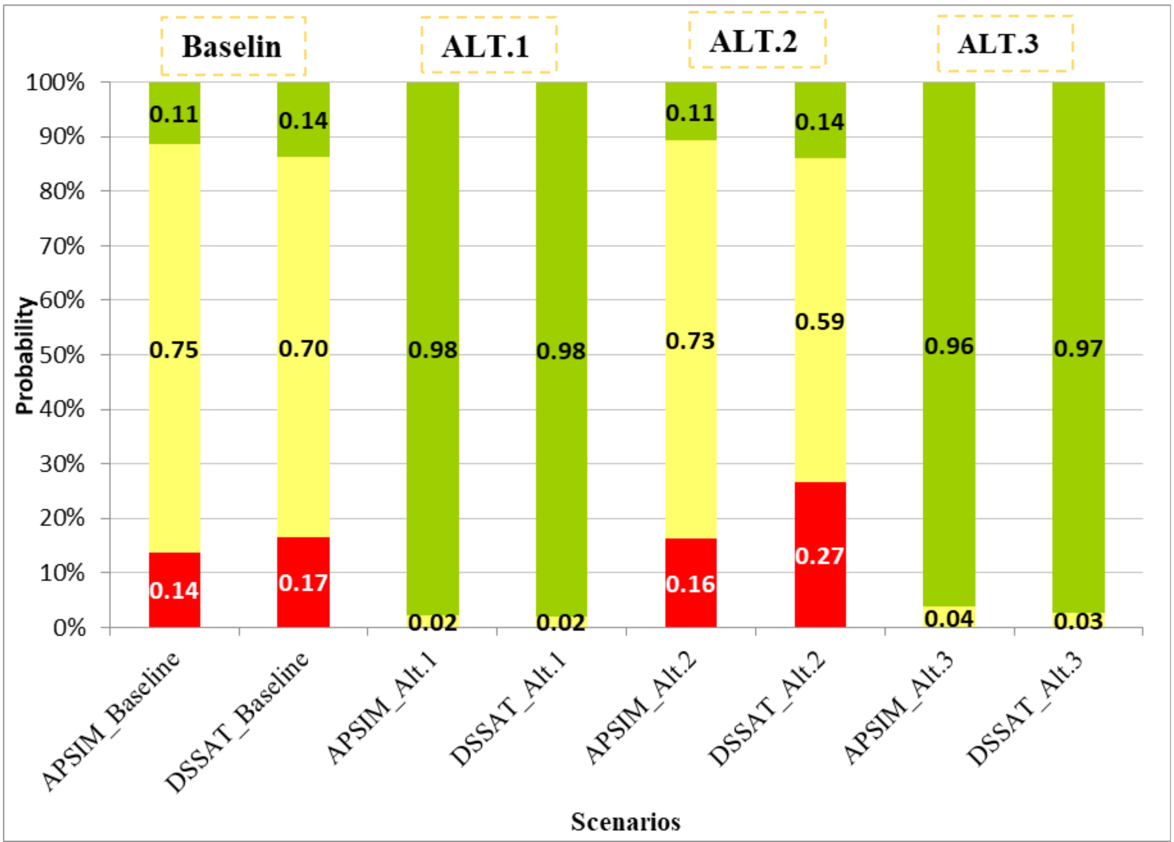

Figure 4.5: Stoplight chart for probabilities of the annual net return being less the 0 and greater than TZS 500 000 thousand in the semi-arid part of the Wami River sub-Basin

The effect of alternatives in sub-humid agro-ecological zone

Table 4.7 presents the summary statistics for the effects of alternative scenarios on maize net returns in the sub-humid area. Likewise, APSIM results in a sub-humid agro-ecological zone of the basin report negative minimum net profits for the *BASELINE* and *ALT.2* scenarios (Table 4.7). DSSAT also reports negative minimum returns for all the scenarios, with the risk being high for the *BASELINE* and *ALT.2*. The *ALT.1* and *ALT.3* scenarios have mean annual net returns of more than TZS 900 000 per ha for both APSIM and DSSAT. The CVs for *ALT.1* and *ALT.3* are relatively small compared to *BASELINE* and *ALT.2*. Although DSSAT demonstrated a negative return for all scenarios in the sub-humid area, the probability is less than 1.0% for *ALT.1* and *ALT.3* compared to *BASELINE* and *ALT.*2 with 20.2% and 30.2% respectively.

Table 4.7: Summary statistics of annual maize net return (TZS hundred thousand) in semi-arid

	APSIM				DSSAT			
	BASELINE	***ALT.1***	***ALT.2***	***ALT.3***	***BASELINE***	***ALT.1***	***ALT.2***	***ALT.3***
	TZS/ha	TZS/ha	TZS/ha	TZS/ha	TZS/ha	TZS/ha	TZS/ha	TZS/ha
Mean	225	984	201	972	144	938	95	894
SD	330	429	284	344	239	449	218	469
CV	147.0	43.6	141.1	35.4	165.7	47.8	229.9	52.4
Min	-234	124	-243	288	-183	-58	-233	-85
Max	2,173	3,098	2,071	2,723	2,706	3,013	1,794	2,432
Prob(π<0)	18.6%	-	14.6%	-	20.2%	0.4%	30.2%	0.7%

Figure 4.6 shows the CDF for annual net returns in the sub-humid area of the basin for all the scenarios both models. The *BASELINE* and *ALT.2* CDFs lie entirely to the left of *ALT.1* and *ALT.3*, implying that the two scenarios have a high probability of failure compared to *ALT.1* and *ALT.3* and that at each level of income the later scenarios have less risk. DSSAT demonstrated a 30% likelihood of negative returns for investing in *ALT.2* with about 15% probability for APSIM. Also, the result shows that *ALT.1* and *ALT.3* have a zero chance of negative returns for APSIM with 0.4% and 0.7% probability of negative returns for DSSAT.

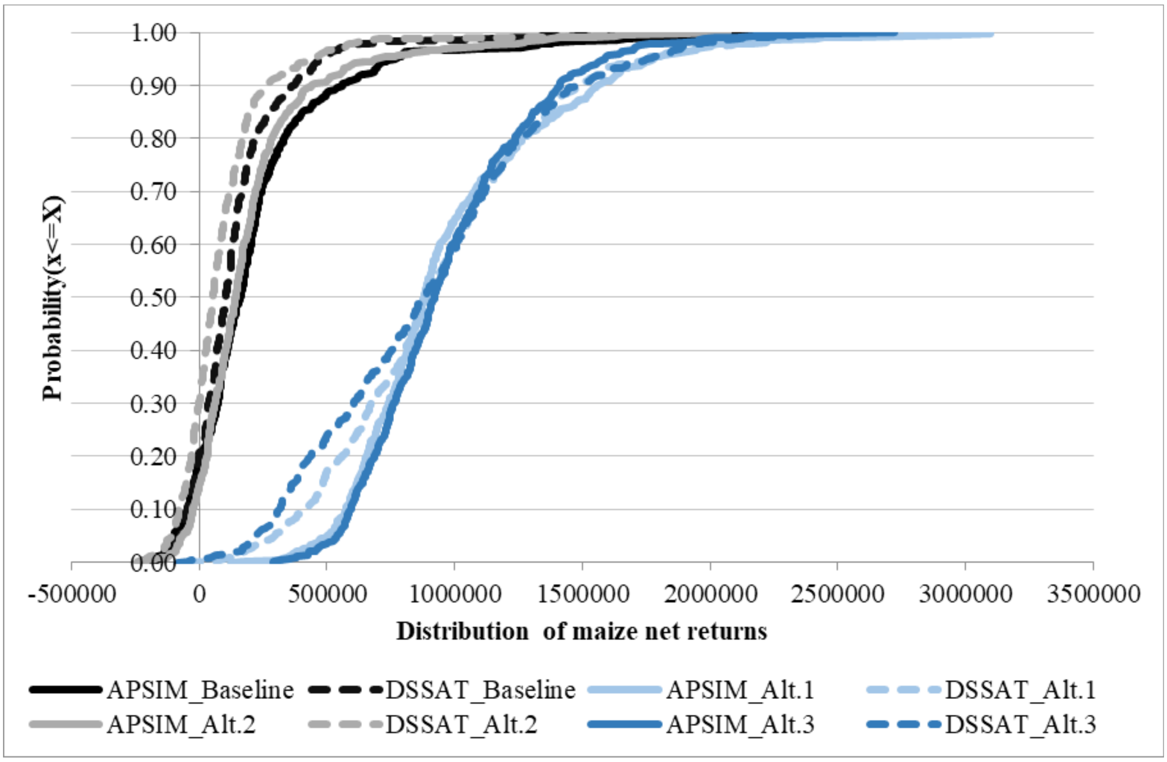

Figure 4.6: CDF of annual net return in sub-humid as for APSIM and DSSAT cropping models

Figure 4.7 is a Stoplight chart presenting the probability of annual net returns being below, above or between TZS 0 and TZS 500 000 in the sub-humid area. The *BASELINE* under the bio-economic simulation model for both APSIM and DSSAT has 18% and 20% probability of negative net returns. The ALT.1 and ALT.3 have zero probability of negative annual net returns for the two crop models. APSIM and DSSAT results indicate a 14% and 30% probability of negative returns for *ALT.2*. *ALT.1* and *ALT.3* have the highest probability of net return, exceeding the upper target of TZS 500 000. For example, results from APSIM show 95% and 96% probabilities that the net returns would exceed the upper target, while DSSAT presents 83% and 76% probabilities for *ALT.1* and *ALT.3*. Of all the scenarios in the sub-humid basin, *ALT.2* has the smallest probability of net revenue being above the upper target for the two models.

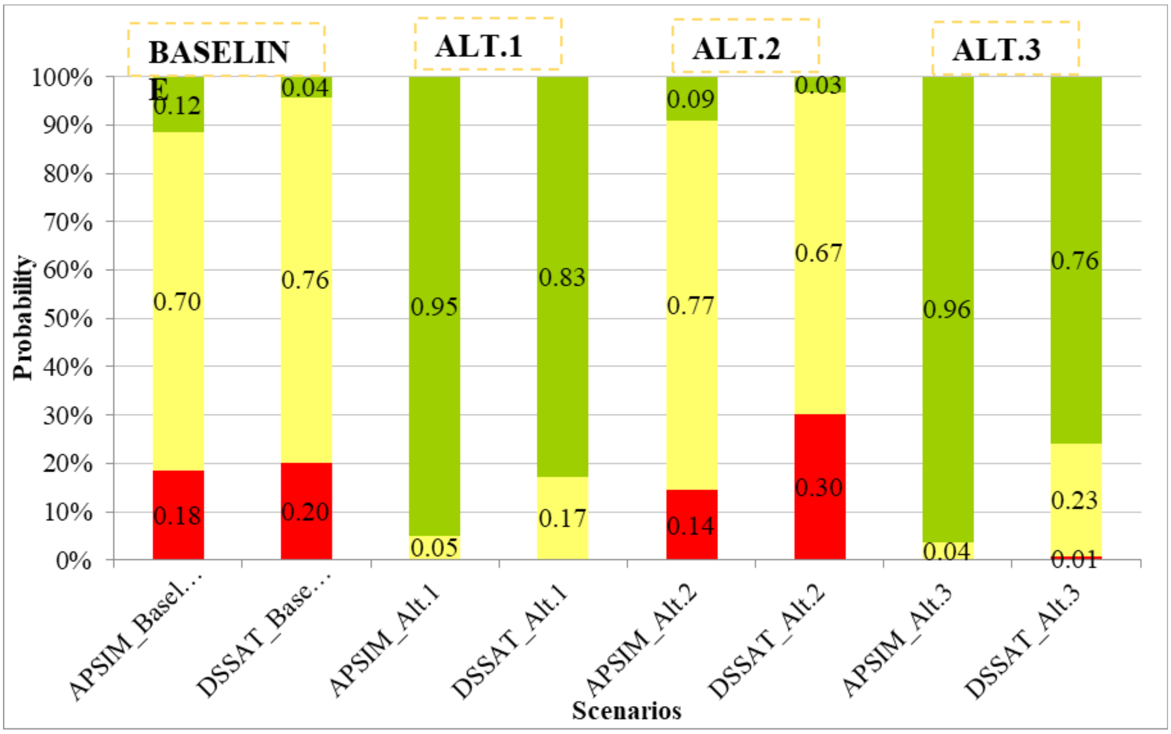

Figure 4.7: Stoplight chart for probabilities of the annual net return being less than 0 and greater than TZS 500 000 thousand in sub-humid part of the Wami River sub-Basin.

The net income distributions of the alternatives in the semi-arid and sub-humid areas are also presented as PDFs in Figure 4.8. The PDFs suggest that the net income distributions for *ALT.1* and *ALT.3* are more favourable than the *BASELINE* and *ALT.2* because they are further to the right. The PDFs for APSIM and DSSAT show that *BASELINE* and *ALT.2* have negative net returns lies to the left of the other PDFs. This difference implies that the relative variability of average net return is more likely to be lower for *ALT.1* and *ALT.3* than *BASELINE* and *ALT.2* as demonstrated by the APSIM and DSSAT crop models.

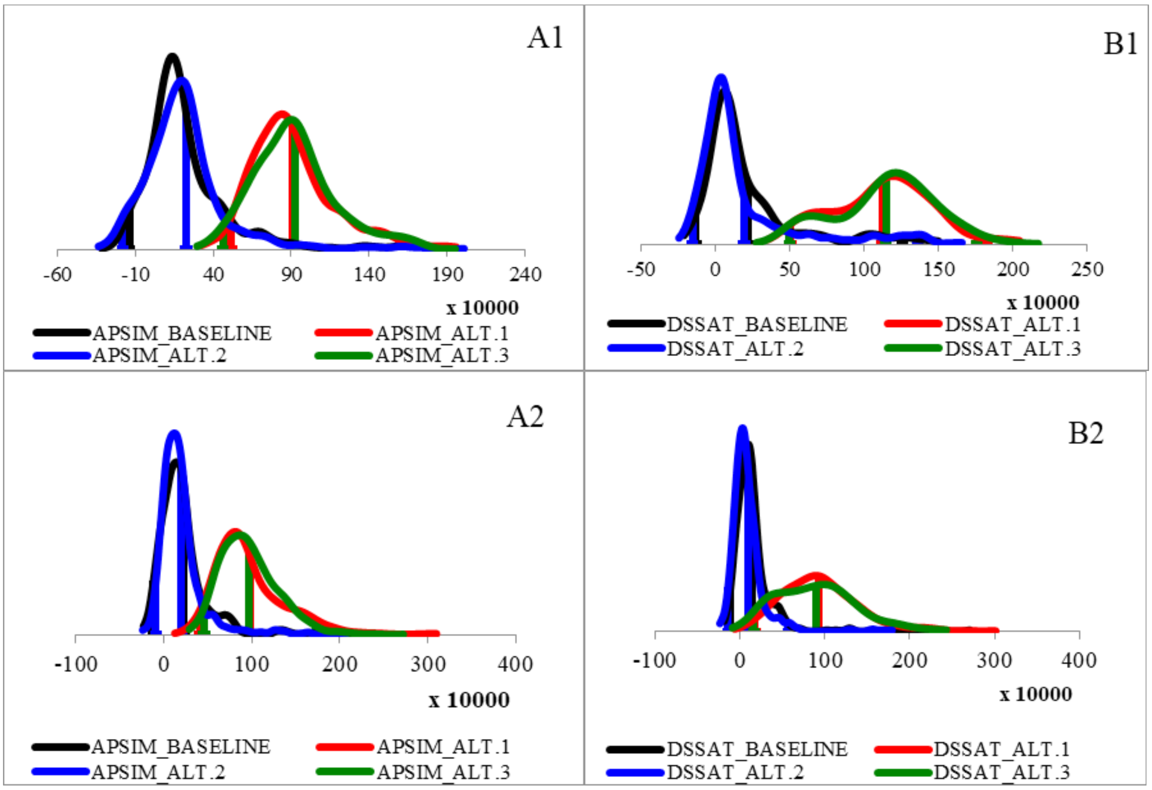

Figure 4.8: PDF of annul maize net return per ha for baseline and alternative scenarios in semi-arid (A1 & B1) sub-humid (A2 & B2) part of the Wami basin: *A1 & A2 =APSIM cropping system model and B1 & B2 = DSSAT cropping system model*

The economic feasibility of the selected options across agro-ecological zones

The simulation results in the baseline scenario (*BASELINE*) for both APSIM and DSSAT confirmed that the sub-humid area has higher probabilities of negative net returns than the semi-arid region. APSIM estimated 18.6% probability of negative net returns for the sub-humid and 13.9% for the semi-arid, with DSSAT estimating 20.2% and 16.6% probabilities for the two zones. When farms are supplemented with *ALT.1*, the two biophysical models suggest a zero probability of negative net returns for both zones except DSSAT in the sub-humid area. DSSAT estimated a small chance (0.4%) of negative net returns. Under *ALT.2*, both models suggest a negative net return for all the agro-ecological zones with sub-humid having the most risk. When the two interventions are applied together (*ALT.3*), both yield models suggest a zero probability of negative net returns.

Still, DSSAT displayed a small probability of 0.7% that the net returns will fall below zero. Although the sub-humid area has the highest maximum net returns, the relative risk measured by the CVs is higher than the semi-arid. For example, the relative variability of the average net return for *BASELINE* and *ALT.2* were above 100% for compared to the *ALT.1* and *ALT.3* which were all less than 53% in all agro-ecological zones. The relative variability of the average net return for *BASELINE* and *ALT.2* was 166% and 230% for DSSAT, and 152% and 191% for APSIM in semi-arid area (Figure 4.9).

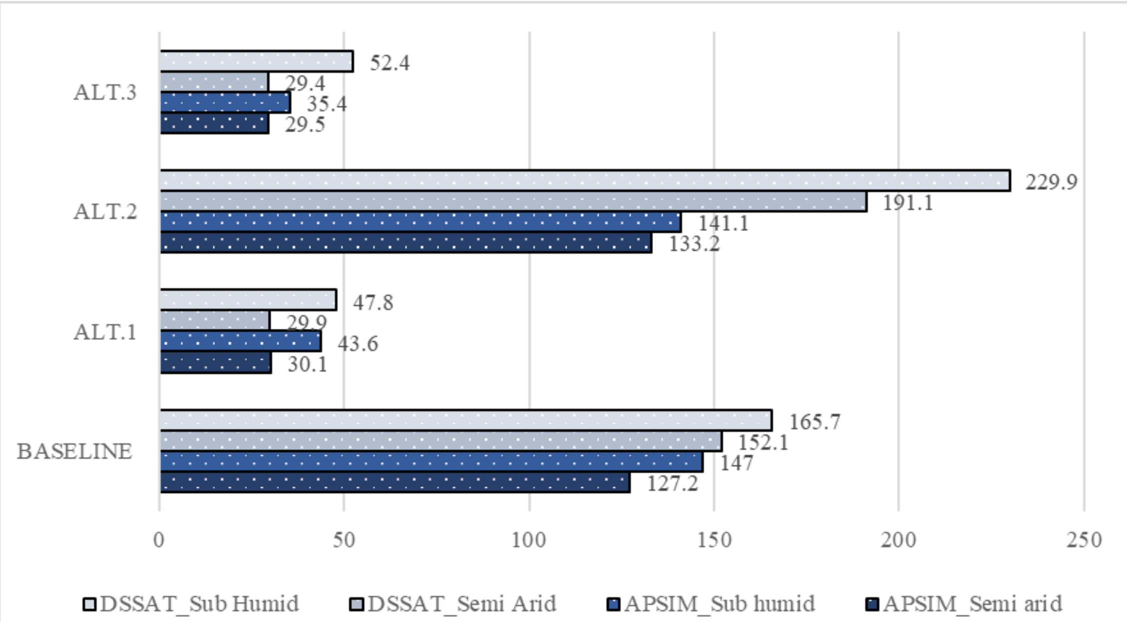

Figure 4.9: Coefficient of variation (CV) of net returns for the semi-arid and sub-humid area in Wami River sub-Basin

Overall results of the economic feasibility assessment of 40 kg N/ha (*ALT.1*) and 3.3 plants/m^2 (*ALT.2*) for maize yield in Wami River sub-Basin, Tanzania indicate that it is worth investing in *ALT.1*. The farms that adopt *ALT.2* as a standalone intervention do not work better for the semi-arid and sub-humid agro-ecological zones within the Wami River sub-Basin. Also, *ALT.3*, which combines *ALT.1* and *ALT.2*, does not result in a significant difference from the application of *ALT.1* alone. Hence, a rational farmer may use *ALT.1* only because *ALT.3* would lead to a higher production cost without an increase in net returns.

Our results are in line with many studies to assess the influence of agronomic practices on the maize sub-sector. Some of these studies include Msongaleli *et al.* (2015), Beletse *et al.* (2015), Masikati *et al.* (2015), Rao *et al.* (2015); Mwinuka *et al.* (2016; 2017). Although these studies did not elaborate on the economic contribution of fertilizer application, they argued that N-fertilizer's use could be one of the fundamental alternatives to reducing risks and uncertainties, especially given climate variability. The studies also claimed that besides the fertilizers' application, adjustments in planting densities should not be ignored.

Additionally, our study agrees with Walker and Schulze (2006), who reported that agronomic practices, especially fertilizer applications, have a more considerable influence, on reducing uncertainty in agricultural production systems. Wilson and Lewis (2015) highlighted that the low production of maize in Tanzania is influenced by limited use of modern inputs like nitrogen fertilizers, which is currently ranging between 9 – 16 kg/ha/year. The low utilization of the N-fertilizer has led to higher uncertainties and lower performance of the sub-sector. Mourice *et al.* (2014) concluded that small nitrogen fertilizer doses would still be beneficial for resource-poor farmers through higher grain yields. However, the Agriculture Climate Resilience Plan (ACRP) 2014-2019 of Tanzania warned that interventions such as improving planting density and the use of fertilizer to increase productivity could show positive outcomes if properly implemented (URT, 2014).

4.6 Conclusions

The purpose of this paper was to contribute to the existing literature a new framework for integrating different biophysical models into economic perspectives in SSA, particularly Tanzania. A bio-economic simulation model was demonstrated under the Monte Carlo simulation protocol for evaluating the economic viability of risk reducing interventions proposed for maize production. Thus, a stochastic bio-economic simulation model of 168 maize plots in the Wami River sub-Basin was developed based on data from two crop models (APSIM and DSSAT). Stochastic values for production costs and prices were incorporated into the model to assess the probable annual net return of maize sub-sector under two crop management alternatives.

First, the Monte Carlo simulation techniques were used to convert the yields from the biophysical models into a stochastic state to capture the risk and uncertainties associated with the yields. Second, the Monte Carlo simulated yields for the baseline and alternatives were validated to ensure that the random variables are simulated correctly. Thirdly, the stochastic annual price of maize was combined with the stochastic yields to simulate stochastic annual revenue. Lastly, the total costs for the baseline and alternatives were used to simulate the empirical distribution of net returns for each scenario. PDFs, CDFs, Tables, and Stoplight charts were developed to rank the targeted options.

Our results suggest that an increase in plant population of 33 000 plants/ha alone, particularly in the Wami River sub-Basin, would have no significant difference in annual net returns from the current maize productivity compared to the application of 40 kg N-fertilizers per ha. In terms of profitability, our bio-economic simulation results suggest an increase in net farm return of up to fivefold when farms are supplemented with the N-fertilizer. Increasing the plant population within the Wami River sub-Basin will likely not increase annual net returns from the baseline unless the two practices are applied concurrently.

The results suggest the importance of emphasizing the application of crop management strategies, especially using at least 40 kg N/ha rate of fertilizers. The economic returns were higher for increased fertilizer application than from increasing plant population. The application of fertilizers may accelerate to achieving improved food availability and reduced poverty to maize-based producers in Tanzania who are mainly small-scale farmers. Moreover, the study contributes to the National Agricultural Policy and the Agriculture Climate Resilience Plan (ACRP) 2014-2019 of Tanzania. For example, the ACRP plan has one of its key messages: "*alternative technologies should focus on boosting cereal crops' productivity to increase yields, enhance food security, and reduce poverty to smallholder farmers*."

This study analysed only two management practices, namely N-fertilizer application and plant population adjustment. There is a need for similar studies on risk-reducing alternatives that could potentially boost productivity and profitability in Tanzania and the rest of SSA. The methodology used in this study was used to assess the economic feasibility of only two technology packages by employing data from two crop models to develop a bio-economic simulation model in a stochastic environment. We argue that the procedures expressed in this study form a basis for more research and include more agricultural practices/technologies that claim to boost productivity, enhance food security, and reduce poverty among the majority of the poor. Similar studies are needed given the absence of integrated assessments that capture agricultural risks by linking appropriate biophysical and economics models. The integrated evaluation can improve decision-making for policy-makers and farmers in Tanzania and the rest of SSA.

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References

Adams, R. M., McCarl, B. A., Segerson, K., Rosenzweig, C., Bryant, K. J., Dixon, B. L., ... and Ojima, D. (1999). *The economic effects of climate change on US agriculture* (pp. 18-54). Cambridge University Press, Cambridge, UK.

Ahmed, M., and Hassan, F. U. (2011). APSIM and DSSAT models as decision support tools. In; *19th International Congress on Modelling and Simulation, Perth, Australia*. pp. 12-16.

Anderson, L., and J.C. Seijo. (2009). Bioeconomics of Fisheries Management. New York: *John* Wiley & Sons, Inc.

Antle, J. M., and Capalbo, S. M. (2001). Econometric-process models for integrated assessment of agricultural production systems. *American Journal of Agricultural Economics*, 83(2), 389-401.

Antle, J. M., Capalbo, S. M., and Crissman, C. C. (1994). Econometric production models with endogenous input timing: an application to Ecuadorian potato production. *Journal of Agricultural and Resource Economics*, 1-18.

Antle, J. M., Capalbo, S. M., and Crissman, C. C. (1998). Tradeoffs in policy analysis: conceptual foundations and disciplinary integration. *Economic, environmental and health tradeoffs in agriculture: pesticides and the sustainability of Andean potato production*, 21-40.

Antle, J. M., and Stoorvogel, J. (2000). Integrating Site-Specific Bio-Physical and Economic Models to Assess Impacts of Policy and Technology on Sustainable Land Use and Soil Quality. *Economic Policy Reforms and Sustainable Land Use in LDCs*.

Antle, J. M., Capalbo, S. M., Johnson, J. B., and Miljkovic, D. (1999). The Kyoto protocol: economic effects of energy prices on northern plains dryland grain production. *Agricultural and Resource Economics Review*, *28*(1), 96-105.

Basso, B., Cammarano, D. and Carfagna, E. (2013). Review of crop yield forecasting methods and early warning systems. In *Proceedings of the first meeting of the scientific advisory committee of the global strategy to improve agricultural and rural statistics, FAO Headquarters, Rome, Italy* (pp. 18-19).

Beletse, Y. G., Durand, W., Nhemachena, C., Crespo, O., Tesfuhuney, W.A., Jones, M.R., Teweldemedhin, M.Y., Gamedze, S.M., Bonolo, P.M., Jonas, S. and Walker, S. (2015). *Projected Impacts of Climate Change Scenarios on the Production of Maize in Southern Africa*. An Integrated Assessment Case Study of the Bethlehem District, Central Free State, South Africa. pp. 125–157.

Bizimana, J.C., and Richardson, J.W. (2019). Agricultural technology assessment for smallholder farms: An analysis using a farm simulation model (FARMSIM). *Computer and Electronics in Agriculture*, 156: 406-425.

Clark, C.W. (1985). Bioeconomic Modelling and Fisheries Management. New York: John Wiley Sons, Inc.

Clark, C.W. (1990). Mathematical Bioeconomics: The Optimal Management of Renewable Resources. New York: John Wiley & Sons, Inc.

Feder, G., Just, R. E., & Zilberman, D. (1985). Adoption of agricultural innovations in developing countries: A survey. *Economic development and cultural change*, *33*(2), 255-298.Hoogenboom, G., Porter, C.H., Shelia, V., Boote, K.J., Singh, U., White, J.W., Hunt, L.A., Ogoshi, R., Lizaso, J.I., Koo, J., Asseng, S., Singels, A., Moreno, L.P. and Jones, J.W. (2017). Decision Support System for Agrotechnology Transfer (DSSAT) Version 4.7 (https://DSSAT.net). DSSAT Foundation, Gainesville, Florida, USA.

Hannesson, R. (1993). Bioeconomic Analysis of Fisheries. New York: John Wiley & Sons, Inc.

Hoogenboom, G., C.H. Porter, K.J. Boote, V. Shelia, P.W. Wilkens, U. Singh, J.W. White, S. Asseng, J.I. Lizaso, L.P. Moreno, W. Pavan, R. Ogoshi, L.A. Hunt, G.Y. Tsuji, and J.W. Jones. (2019). The DSSAT crop modeling ecosystem. *In*: p.173-216 [K.J. Boote, editor] Advances in Crop Modeling for a Sustainable Agriculture. Burleigh Dodds Science Publishing, Cambridge, United Kingdom (http://dx.doi.org/10.19103/AS.2019.0061.10)

Hoogenboom, G., Porter, C.H., Shelia, V., Boote, K.J., Singh, U., White, J.W., Hunt, L.A., Ogoshi, R., Lizaso, J.I., Koo, J., Asseng, S., Singels, A., Moreno, L.P. and Jones, J.W. (2019). Decision Support System for Agrotechnology Transfer (DSSAT) Version 4.7.5 (https://DSSAT.net). DSSAT Foundation, Gainesville, Florida, USA.

Jones, J.W., Hoogenboom, G., Porter, C.H., Boote, K.J., Batchelor, W.D., Hunt, L.A., Wilkens, P.W., Singh, U., Gijsman, A.J. and Ritchie., J.T. (2003). DSSAT Cropping System Model. European Journal of Agronomy 18:235-265.

IFDC (2012). *Tanzania Fertilizer Assessment*. Available at https://africafertilizer.org/en/blog-post/tanzania-fertilizer-market-assessment-ifdc-afap-june-2012

Jones, J.W., Hoogenboom, G., Porter, C.H., Boote, K.J., Batchelor, W.D., Hunt, L.A., Wilkens, P.W., Singh, U., Gijsman, A.J. and Ritchie, J.T. (2003). DSSAT Cropping System Model. *European Journal of Agronomy* 18: 235-265.

Jones, J.W., Keating, B.A., and Porter, C.H. (2001). Approaches to modular model development. *Agricultural Systems*, 70: 421-443.

Just, R. E., and Antle, J. M. (1990). Interactions between agricultural and environmental policies: a conceptual framework. *American Economic Review*, *80*(2), 197-202.

Kaiser, H. M., Riha, S. J., Wilks, D. S., Rossiter, D. G., and Sampath, R. (1993). A farm-level analysis of economic and agronomic impacts of gradual climate warming. *American journal of agricultural economics*, *75*(2), 387-398.

Kadigi, I. L., Richardson, J. W., Mutabazi, K. D., Philip, D., Bizimana, J. C., Mourice, S. K., and Waized, B. (2020). Forecasting yields, prices and net returns for main cereal crops in Tanzania as probability distributions: A multivariate empirical (MVE) approach. *Agricultural Systems*, 180, 102693.

Kahimba, F.C., Sife, A.S., Maliondo, S.M.S., Mpeta, E.J., and Olson, J. (2015). Climate change and food security in Tanzania: Analysis of current knowledge and research gaps. *Tanzania Journal of Agricultural Sciences* 14(1).

Kaufmann, R. K., and Snell, S. E. (1997). A biophysical model of corn yield: integrating climatic and social determinants. *American Journal of Agricultural Economics*, *79*(1), 178-190.

Keating, B.N., Carberry, P.S. and Smith, C.J. (2003). An Overview of APSIM, a model Design for Farming Systems Simulation. *Eur. J. Agron*. 18: 267-272.

Kruseman, G., Ruben, R., Hengsdijk, H., and Van Ittersum, M. K. (1995). Farm household modelling for estimating the effectiveness of price instruments in land use policy. *NJAS wageningen journal of life sciences*, *43*(1), 111-123.

Larkin, S. L., Alvarez, S., Sylvia, G., and Harte, M. (2011). Practical considerations in using bioeconomic modelling for rebuilding fisheries. *OECD Food, Agriculture and Fisheries Working Papers*, No. 38, OECD Publishing.

Macauley, H., and Ramadjita, T. (2015). Cereal crops: Rice, maize, millet, sorghum, wheat. *Feeding Africa*, 36. [https://www.afdb.org/fileadmin/uploads/afdb/Documents/Events/DakAgri2015/Cereal_Crops-_Rice__Maize__Millet__Sorghum__Wheat.pd] site visited on 15/10/2018.

Masikati, P., Tui, S.H.K., Descheemaeker, K., Crespo, O., Walker, S., Lemard, C.J., Claessens, L.F.G., Gama, A.C., Famba, S., van Rooyen, A.F. and Valdivia, R.O. (2015). Crop–Livestock Intensification in the Face of Climate Change: Exploring Opportunities to Reduce Risk and Increase Resilience in Southern Africa by Using an Integrated Multi-modeling Approach', Handbook of Climate Change and Agroecosystems, pp. 159–198.

McCown, R.L., Hammer, G.L. Hargreaves, J.N.G., Holzworth, D.P., and Freebairn, D.M. (1996). APSIM: a novel software system for model development, model testing, and simulation in agricultural systems research. *Agricultural Systems* 50: 255 – 271.

Mourice, S.K., Rweyemamu, C.L., and Tumbo, S.D. (2014). Narrowing Maize Yield Gaps Under Rain-fed conditions in Tanzania: Effect of Small Nitrogen Dose. *Tanzania Journal of Agricultural Sciences* 12(2): 55–65.

Msongaleli, B.M., Rwehumbiza, F., Tumbo, S.D., and Kihupi, N. (2015). Impacts of climate variability and change on rainfed sorghum and maize: implications for food security policy in Tanzania. *Journal of Agricultural Science* 7(5): 124–142. doi: 10.5539/jas.v7n5p124.

Mwinuka, L., Mutabazi, K. D., Makindara, J., and Sieber, S. (2016). Reckoning the risks and rewards of fertilizer micro-dosing in a sub-humid farming system in Tanzania. *African Journal of Science, Technology, Innovation, and Development* 8(5-6): 497-508.

Mwinuka, L., Mutabazi, K. D., Sieber, S., Makindara, J., and Bizimana, J.C. (2017). An economic risk analysis of fertiliser microdosing and rainwater harvesting in a semi-arid farming system in Tanzania. *Agrekon* 56(3): 274-289.

NBS – National Bureau of Statistics. (2012). Tanzania National Panel Survey Report - Wave 2, 2010 – 2011. [https://www.nbs.go.tz/nbs/takwimu/nps/NPS_Report-2010-2011.zip] site visited on 20/01/2015.

Palma, M. A., Richardson, J. W., Roberson, B. E., Ribera, L. A., Outlaw, J., & Munster, C. (2011). Economic feasibility of a mobile fast pyrolysis system for sustainable bio-crude oil production. *International Food and Agribusiness Management Review, 14*(3), 1–16.

Prato, T., Fulcher, C., Wu, S., and Ma, J. (1996). Multiple-objective decision making for agroecosystem management. *Agricultural and Resource Economics Review*, *25*(2), 200-212.

Rao, K.P., Gummadi, S., Mulwa, R.M., Kilavi, M.N., Esilaba, A. and Athanasiadis, I. N. (2015). Impacts of Climate Variability and Change on Agricultural Systems in Eastern Africa. In; *Handbook of Climate Change and Agroecosystems Volume 3*, 75-124.

Segerson, K., and Dixon, B. L. (1999). *Climate change and agriculture: the role of farmer adaptation* (pp. 75-93). Cambridge University Press, Cambridge, United Kingdom and New York, NY, USA.

Rezende, M. L., and Richardson, J. W. (2015). Economic feasibility of sugar and ethanol production in Brazil under alternative future prices outlook. *Agricultural Systems*, 138, 77–87.

Richardson, J.W., and Bizimana, J.C. (2017). *Agricultural Technology Assessment for Smallholder Farms in Developing Countries: An Analysis using a Farm Simulation Model (FARMSIM)*. Working Paper. [https://afpc.tamu.edu/research/ publications/683/FARMSIM.pdf] site visited on 21/03/2018.

Richardson, J.W., Klose, S.L., and Gray, A.W. (2000). An Applied Procedure for Estimating and Simulating Multivariate Empirical (MVE) Probability Distributions In Farm-Level Risk Assessment and Policy Analysis', *Journal of Agricultural and Applied Economics* 32(02): 299–315.

Richardson, J.W., Schumann, K.D., and Feldman, P.A. (2008). Simetar: Simulation and Econometrics to Analyse Risk. *Agricultural and Food Policy Center, Department of Agricultural Economics, Texas A&M University, College Station, TX*.

Rosenzweig, C., Jones, J., Antle, J., and Hatfield, J. (2015). Protocols for AgMIP Regional Integrated Assessments, version 6.0. [http://www.agmip.org/wp-content/uploads/2015/09/AgMIP-RIA-Protocols-V6sm.pdf] site visited on 30/06/2017.

Rötter, R. P., Carter, T.R., Olesen, J.E. and Porter, J.R. (2011). Crop-climate models need an overhaul’, *Nature Climate Change* 1(4): 175–177.

Seijo, J.C., O. Defeo, and S. Salas. (1998). Fisheries Bioeconomics: Theory, Modelling and Management. FAO Fisheries Technical Paper 368. Food and Agriculture Organization of the United Nations (FAO), Rome, Italy.

Thompson, H.E., Berrang-Ford, L., and Ford, J.D. (2010). Climate change and food security in Sub-Saharan Africa: A systematic literature review'. *Sustainability* 2(8): 2719–2733.

Tumbo, S., Mzirai, O., Mourice, S., Msongaleli, B., Wambura, F., Kadigi, I. and Mutabazi, K. (2015). *Assessing the impacts of climate variability and change on agricultural systems in Eastern Africa while enhancing the region's capacity to undertake integrated assessment of vulnerabilities to future changes in climate-Tanzania*. Research gate. [http://www.taccire.sua.ac.tz/xmlui/bitstream/ handle/123456789/516/assessment-report-tanzania.pdf?sequence=1] site visited on 13/04/2017.

Tumbo, S.D., Mutabazi, K.D., Mourice, S.K., Msongaleli, B.M., Wambura, F.J., Mzirai, O.B., Kadigi, I.L., Kahimba, F.C., Mlonganile, P., Ngongolo, H.K. and Sangalugembe, C., (2020). Integrated Assessment of Climate Change Impacts and Adaptation in Agriculture: The Case Study of the Wami River Sub-basin, Tanzania. In *Climate Variability and Change in Africa* (pp. 115-136). Springer, Cham.

URT (2007). National Adaptation Programme of Action (NAPA). Division of Environment, Vice President's Office, Dar es Salaam. [https://unfccc.int/resource/docs/napa/tza01.pdf] site visited on 17/06/2016.

URT (2013). *The United Republic of Tanzania: National Agriculture Policy*. Dar Es Salaam. Available at:

[http://www.tzdpg.or.tz/fileadmin/documents/dpg_internal/dpg_working_groups_clusters/cluster_1/agriculture/2._Ag_policies_and_strategies/National_ag_policies/1._2013_NATIONAL_AGRICULTURAL_POLICY_-_FINALFebruari_2013.pdf] site visited on 12/07/2017.

URT (2014). Ministry of Agriculture, Food Security, and Cooperatives: Agriculture Climate Resilience Plan 2014-2019. [http://extwprlegs1.fao.org/docs/pdf/tan152483.pdf] site visited on 14/06/2016.

URT (2016). Agricultural Sector Development Programme Phase Two (ASDP II). [http://www.tzdpg.or.tz/fileadmin/ documents/external/national_development_frameworks/ASDP2_Final_Document_20_May._2016__after_edit__1_.pdf] site visited on 12/10/2018.

URT (2017). *Climate-Smart Agriculture Guideline of the United Republic of Tanzania*. Available at: [http://www.kilimo. go.tz/uploads/regulations/National_CSA_Guideline.pdf] site visited on 12/07/2017.

Waithaka, M., Nelson, G.C., Thomas, T.S. and Kyotalimye, M. (Eds.). (2013). *East African agriculture and climate change: A comprehensive analysis.* Intl Food Policy Res Inst.

Walker, N.J. and Schulze, R.E. (2006). An assessment of sustainable maize production under different management and climate scenarios for smallholder agroecosystems in KwaZulu-Natal, South Africa. *Physics and Chemistry of the Earth, Parts A/B/C*, 31(15-16): 995-1002.

White, J. W., Hoogenboom, G., Kimball, D.A., and Wall, G.W. (2011). Methodologies for simulating impacts of climate change on crop production, *Field Crops Research* 124(3): 357–368.

Wilson, R.T., and Lewis, J. (2015). The maize value chain in Tanzania. [https://saiia.org.za/wp-content/uploads/2016/06/008-Tanzania_maize.pdf] site visited 15/11/2018.

Wolday, K., and Hruy, G. (2015). A review: performance evaluation of crop simulation model (APSIM) in prediction crop growth, development and yield in semiarid tropics. *Journal of Natural Sciences Research* 5(21): 34-39.

World Bank, (2020). Fertilizer consumption (kilograms per hectare of arable land) – Tanzania. Retrieved from https://data.worldbank.org/indicator/AG.CON.FERT.ZS?locations=TZ

APPENDICES

Appendix 4.1: Comparison of observed data vs. biophysical simulated

This appendix shows how the first step used to develop a bio-economic simulation model (an integrated decision support system). Since the aim of the analysis is to find out the impact of fertilizer application and plant population adjustment were examined using the two models APSIM and DSSAT. The first step in developing an appropriate bio-economic simulation model was to verifying if the baseline data generated by the two models have similar characteristics with the original or site-specific data. Therefore:

a) Yield data from household farm surveys were entered in the two crop models for each field that was surveyed. The models are then calibrated to fit the household farm survey data (matched case). Other variables like climate, soil, and management for each field are added into the models for each field to simulate the productivity that is matched with the observed yield. Other agronomic assumptions based on the advice from agronomists in the regions were also included in the model to obtain the best distribution that fits the observed data. The process continued for including different parameters and opinions until the best baseline that has similar characteristics with the observed data was obtained.

b) After the simulation results from the two crop models are matched with the observed data to be sure that they were correctly produced, the means, standard deviation, variances, and characteristics of bias between observed and simulated yields were computed.

c) The probability distribution functions (PDFs) were drawn to show if the baseline data and observed data has similar shape (Figure 4.1.1). The similarities on the PDFs were enough for the analyst to accept the results of the two models for economic analysis.

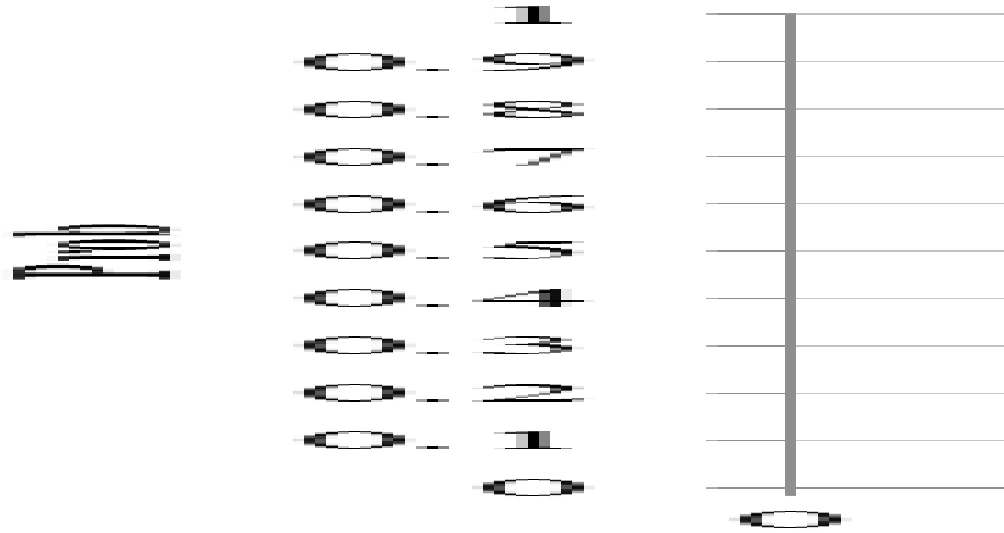

Figure 4.1.110: Relationship between observed and baseline simulated yield for 168 maize plots

d) After the evaluation of the observed and simulated baseline yield, the proposed options were therefore added into the two models to simulate their impact on yield before confirming that they are ready for use in the economic analyses.

This process ends at an agronomic component, and the next step was to use the yield from the two biophysical models along with other variables prices, cost of production, and area planted to analyse the feasibility of the proposed options. All of these variables were made stochastic using the bio-economic simulation. However, assumptions to include the additional costs of the proposed options were made based on the advice from experts, including agronomists.

Appendix 4.2: Validation for process-based data vs. bio-economic simulation model in the semi-arid area of the Wami sub-basin

This appendix shows the validation process to ensure that the data from APSIM and DSSAT process-based models were simulated correctly and demonstrate the appropriate properties of the two models. The probability distribution functions (PDF) in Figure. 4.2.1 and 4.2.2 show that the 500 iterations of the bio-economic simulation model were enough to generate similar shapes like that of parent distribution (process-based). Therefore, the 500 simulated sample for each alternative management was used to capture the risk associated with the proposed options on maize yield.

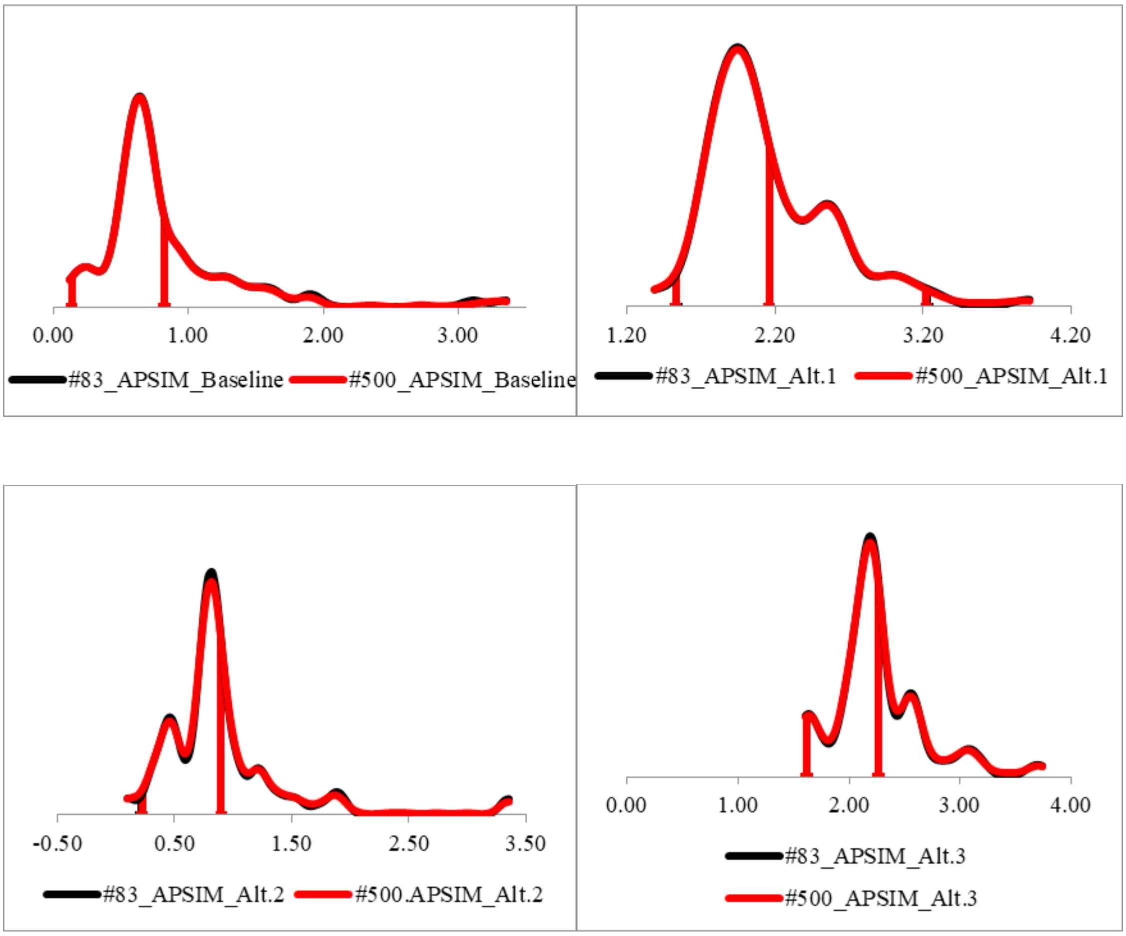

Figure 4.2.1: Data validation of 83 maize plots for APSIM process-based data vs 500 iterations bio-economic simulated data in the semi-arid zone

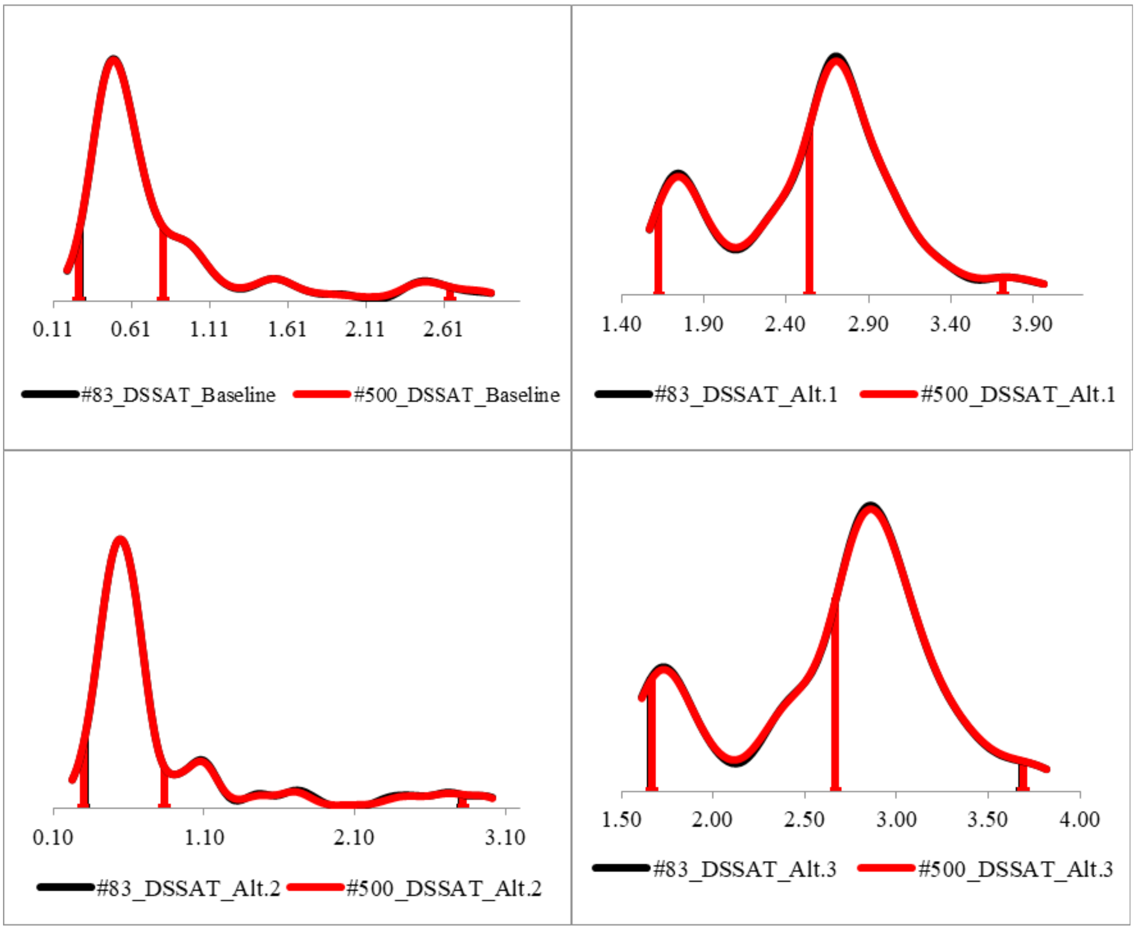

Figure 4.2.2: Data validation of 83 maize plots for DSSAT process-based data vs 500 iterations bio-economic simulated data in semi-arid zone

Appendix 4.3: Distribution of costs for the baseline and the alternative scenarios

This appendix displays per ha costs incurred by small-holder farmers for different operations in maize production in the Wami sub-basin. Table 4.3.1 shows the type of inputs used and the cost incurred and Figure 4.3.1 displays the stochastic total production cost per each alternative. A uniform probability distribution was used to simulated stochastic/random production costs using the =UNIFORM() function in Simetar. The function of production cost for the baseline scenario was programmed using Equation (1) as follows:

$$\tilde{C}_{baseline} = \sum (UNIFORM(Min_k, Max_k)) \qquad (1)$$

where: *k* represents all cost items including land preparation, seeds, planting, weeding, harvesting, and postharvest handling,

Min is the minimum value for the distribution,

Max is the maximum value for the distribution,

The stochastic cost for the baseline scenario was therefore combined with additional costs of 40 kg N/ha (*Alt.1*) and 7 – 10 kilograms of maize seeds (*Alt.2*). The total cost for *Alt.3* was calculated by adding the baseline costs to cost for *Alt.1* and *Alt.2*.

Table 4.3.1: Budgets for maize production per ha in Wami sub-basin for the year 2015/16

	Average (TZS/ha)	Minimum cost (TZS/ha)	Maximum cost (TZS/ha)
Land preparation	40 000	25 000	50 000
Seeds	65 000	60 000	70 000
Planting	25 000	20 000	30 000
Weeding	40 000	30 000	50 000
Fertilizers	50 000	0	50 000
Fertilizer application	20 000	0	20 000
Pesticides	14 000	0	14 000
Pesticides application	6 000	0	6 000
Harvesting	10 000	5 000	20 000
Postharvest handling (transportation and storage)	30 000	15 000	50 000
Total cost	**300 000**	**150 000**	**360 000**

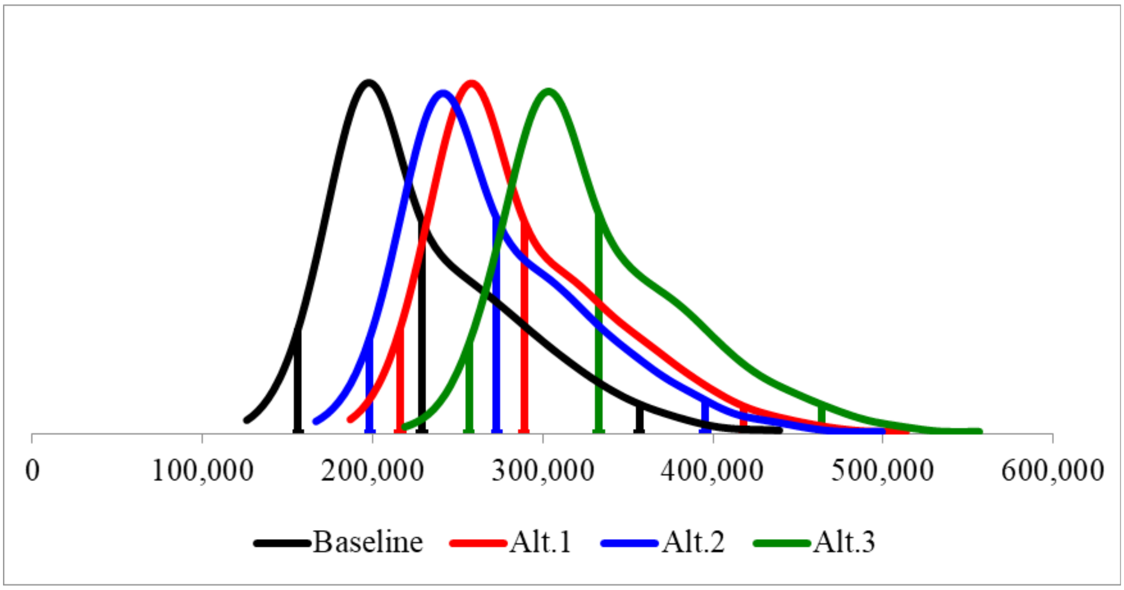

Table 4.3.1: PDF of total production cost per ha per scenario used in the bio-economic model

CHAPTER FIVE

5.0 MANUSCRIPT THREE

sustainability

MDPI

Article

An Economic Comparison between Alternative Rice Farming Systems in Tanzania Using a Monte Carlo Simulation Approach

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5.1 Abstract

Tanzania is the second-largest producer of rice (*Oryza sativa*) in Eastern, Central, and Southern Africa after Madagascar. Unfortunately, the sector has been performing poorly due to many constraints, including poor agricultural practices and climate variability. In addressing the challenge, the government is making substantial investments to speed the agriculture transformation into a more modernized, commercial, and highly productive and profitable sector. Our objective was to apply a Monte Carlo simulation approach to assess the economic feasibility of alternative rice farming systems operating in Tanzania while considering risk analysis for decision-makers with different risk preferences to make better management decisions. The rice farming systems in this study comprise rice farms using traditional practices and those using some or all of the recommended system of rice intensification (SRI) practices. The overall results show 2% and zero probability of net cash income (NCI) being negative for partial and full SRI adopters, respectively. Meanwhile, farmers using local and improved seeds have 66% and 60% probability of NCI being negative, correspondingly. Rice farms which applied fertilizers in addition to improved seeds have a 21% probability of negative returns. Additionally, net income for rice farms using local seeds was slightly worthwhile when the transaction made during the harvesting period compared to farms applied improved varieties due to a relatively high price for local seeds. These results help to inform policymakers and agencies promoting food security and eradication of poverty on the benefits of encouraging improved rice farming practices in the country. Despite climate variability, in Tanzania, it is still possible for rice farmers to increase food production and income through the application of improved technologies, particularly SRI management practices, which have shown a promising future.

Keywords: Rice, Management practices, Risk, stochastic simulation, Tanzania

5.2 Introduction

The population of developing countries is increasing rapidly. Many of these countries rely on rice (*Oryza sativa*) as a staple food, and it is estimated that the demand for rice will increase by up to 70% over the next three decades (Patra and Haque, 2011; Katambara *et* *al.*, 2013). However, the area of land suitable for agriculture, the length of growing seasons and yield potential for cereals including rice are expected to shrink, particularly along semi-arid margins, affecting food availability and exacerbating malnutrition (Maliondo *et al.*, 2012). It is also estimated that 15–20 Mha of the world's 79 Mha of irrigated rice lowlands, which provide three-quarters of the world's rice supply, will suffer some degree of water scarcity (Bouman *et al.*, 2007). These concerns can only be encountered through the application of improved agricultural practices, including rice irrigation schemes and hybrid rice varieties (Ali, 2015). Other scholars (Stoop *et al.*, 2002; Uphoff, 1999; 2003; 2005; 2006; 2007; 2008; Randriamiharisoa *et al.*, 2006; Mishra *et al.*, 2006) have argued that low rice productivity could be addressed through judicious use of agronomic inputs like transplanting young single seedlings with wider spacing, alternating wetting, and drying of fields, and use of fertilizers.

In Tanzania, rice is the second most important staple food and commercial crop after maize (*Zea mays*) and a significant source of employment, income and food security for farming households (Furahisha, 2013; Ram, 2003; Bell, 2016). Tanzania is the second-largest producer of rice in Eastern, Central, and Southern Africa after Madagascar (URT, 2015); about 71% is produced under rain-fed conditions and 29% under irrigation (Ronald *et al.*, 2014). The demand for rice in Tanzania is projected to triple by 2025 and while the yield is still relatively low, (1.6 t/ha) due to increases in temperature and decreases in annual rainfall (URT, 2007; Paavola, 2008). Even with the low performance of the sector, inconsistently Tanzania exports to neighbouring countries like Burundi, Kenya, Rwanda, and Uganda. Additionally, the lower performance of the sector is linked to predominantly rain-fed production, the limited adoption and availability of improved cultivars, low application of fertilizers and intensive use of traditional planting techniques with limited areas for (Wilson and Lewis, 2015). Kahimba *et al.* (2013) argued that, if limited agricultural interventions are to be applied, yields of major cereals, including rice, may halve by 2025 because of climate variability.

Due to these challenges, the Tanzanian government has been struggling to take some measures to stimulate the sector like the imposition of an import tariff of 75 per cent in early 2005 followed by the formulation of policies and programs. These include the National Rice Development Strategy in 2009, National Agricultural Policy (NAP) in 2013, Agricultural Sector Development Strategy – II (2015/16 – 2024/16) and Agricultural Sector Development Programme – II (2015/16 – 2024/25). Among others, these policies emphasize on application of fertilizers, improved seed, development of irrigation infrastructures, and removal of the export ban. Moreover, early in the 2010s, the government through the Ministry of Agriculture Food Security and Cooperatives (MAFSC) involved in the training of extension officers and farmers the System of Rice Intensification (SRI) management practices for enhancing rice production in Tanzania. The SRI practices elaborated by Stoop *et al.* (2009), Kahimba *et al.* (2013), Tusekelege *et al.* (2014) and URT (2015) are the primary campaign by the MAFSC aiming to increase rice yield per ha and in conjunction with the reduction of hunger and poverty by 2025. Even with readily made policies and programs, there has been a slow improvement of the sector mainly due to low adoption of improved farming practices, poor institutional development, limited human, financial and physical resources (Maliondo *et al.,* 2012; Wilson and Lewis, 2015).

Moreover, the low adoption of improved agricultural practices for farmers is due to many factors, including the risks and uncertainties linked to the process of agricultural production and unreliable markets. Diagne *et al.* (2012) argued that the adoption of new agricultural technology depends on farmer’s knowledge of their existence, that is, a farmer adopts a technology if he/she has a complete understanding of new technology. From economic perspectives, farmers decide to choose to adopt a new technology basing on the benefits of the technology (Doss, 2006). Although rice farming systems' agronomic benefits of may be easy to recognize, the economic benefits are not. The unrealized potential of new farming technologies may offset the adoption rate of the respective technologies, especially when the farmer has limited full information about the technology and it's potential.

In this study, we compare the economics of traditional and improved rice farming management practices by considering the risk associated with price, yields, and production costs that affect the net returns of the practices under study. The analysis helps determine the farming system with the highest distribution of profits under different price seasons, such as during harvesting and low supply, when the price is relatively high. We considered price volatility because rice is one of the cash crops to most smallholder farmers in Tanzania. The study also considered that since rice is an essential crop, farmers may sell their produce during harvesting or later when the price is higher. This study employs a Monte Carlo simulation model, which was also applied by Ribera *et al.* (2004), Richardson *et al.* (2007), Rezende and Richardson (2015), and Mwinuka *et al.* (2017) to evaluate the economic performance for each rice farming system.

The contribution of the present study to the body of knowledge in Tanzania is the application of a Monte Carlo simulation approach, which incorporates stochastic/random variables like prices and yields that farmers cannot control with certainty. Data from household surveys, focus group discussions, and secondary sources were used to quantify and parameterize the model. This study informs the rice farming communities and policies that focus on food security and poverty eradication and the suitable agronomic techniques for sustainable agriculture.

5.3 Theoretical and Conceptual Background

In this study, the strong assumption was made that the adoption of viable farm management practices like SRI, improved varieties and application of fertilizers is essential, and will benefit the farmer if the technology is adopted. However, adopting and using new agricultural technologies has never been an easy task because of many factors that are involved in the adoption process like fear of risk and uncertainties (Doss, 2006; Diagne *et al.,* 2012; Bizimana and Richardson, 2019). Mostly, farmers look at some or all of the factors and choose the best alternative based on their utility and profit maximization behaviours (Doss, 2006). The concept is that farmers engage in the adoption of new technology only if the benefits or perceived utility of using the proposed technology outweigh the benefits of the current practices (Mwinuka *et al.,* 2017; Bizimana and Richardson, 2019). This study applies this theoretical background as a guide to building a stochastic simulation model to simulate the economic viability of farming systems so farmers or decision-makers can make better decisions. This background considered relevant and underpinned the theoretical foundation of the study.

5.4 Materials and Methods

5.4.1 Location of the study area

The study was conducted in six villages of the Morogoro region, Tanzania (Figure 5.1) which is in the mid-eastern part of the Tanzania mainland and lies between latitude 7°53′34.80″ south and longitude 36°54′21.60″ East. The region is the largest rice producer in the country, producing between 300 000 to 350 000 tons per year. Rice is the second most dominant crop in the region after maize and is grown on approximately 180 000–250 000 hectares annually. The more substantial part of the study area receives average annual rainfall between 800 and 1100 mm; higher rainfall between 1200–1300 mm is collected around the Nguru mountains. The top of the Nguru mountains receives >1300 mm. The mean annual temperature in the study area ranges between 16 °C and 25 °C (Ndomba, 2014; Gulacha, 2017). The rainfall is bimodal, falling between October and December and March and May (Wambura *et al.*, 2015; Sikay, 2017). The study sites/farms are surrounded by rivers with flowing water throughout the year, making irrigation easier.

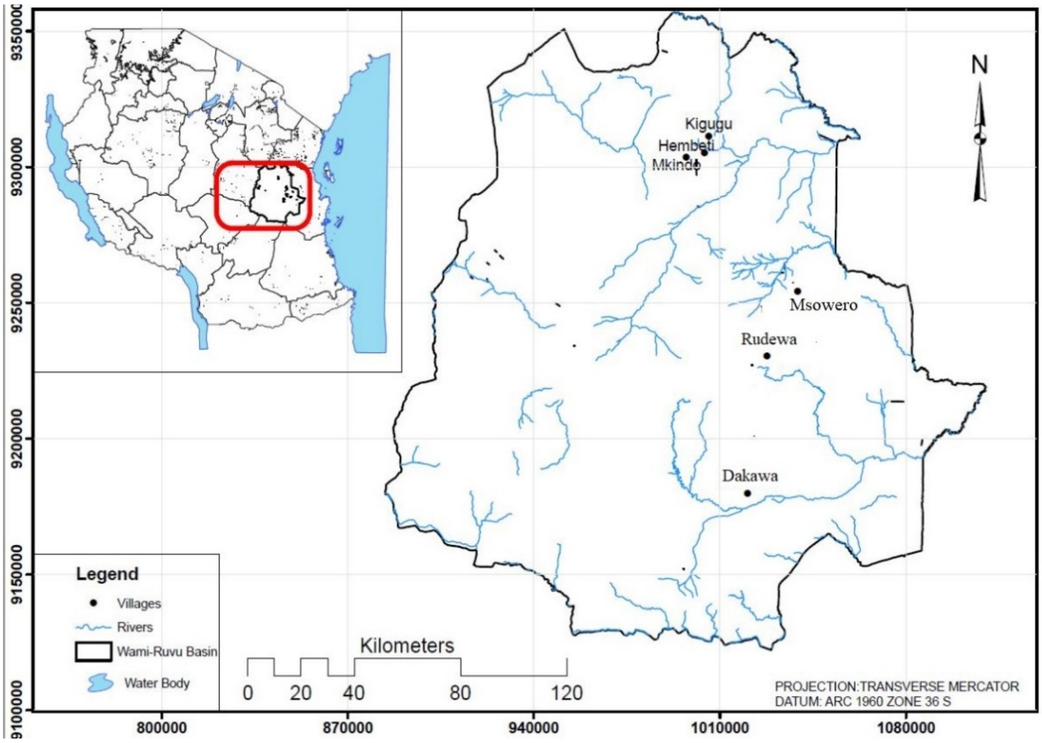

Figure 5.1: Study sites Kigugu, Hembeti, and Mkindo villages (Mvomero district) and Msowero, Rudewa and Dakawa (Kilosa district)

5.4.2 Data type and characteristics

The villages for this study were purposefully selected based on the presence of either traditional or improved rice farming practices. Data were collected using a snowball sampling strategy described in detail by Atkinson and Flint (2001), Browne (2005), Sedgwick (2013), Naderifar *et al.* (2017). A total of six villages: three from Mvomero district (Kigugu, Hembeti, and Mkindo) and three from Kilosa district (Dakawa, Rudewa, and Msowero) were included in the analysis. Although rivers surround the rice farms in the study area, most of the farmers depend on rain-fed farming systems. The data represent farms under different management practices, some of which are better adapted to climate variability, and some grow their rice in both rainy and dry seasons. Rice production in the selected villages is a crucial economic activity generating income and the primary food source. Although there were varying levels of productivity, the households used in the study claimed to be dependent on rice farming for over 80% of their livelihoods

The differences in levels of productivity were linked to the different use of rice-farming technologies, including the application of inorganic fertilizers, the predominant use of local seed varieties, the emerging demand for improved varieties, mainly SARO 5 or TXD 306; and adoption of the System of Rice Intensification (SRI) practices. The SRI is considered a water-saving technology, which has led to a notable increase in crop productivity (Katambara *et al.,* 2013; Kahimba *et al.,* 2013; Ronald *et al.,* 2014). The technology is not only found to be the best farming approach for sustainable agriculture but also used as a coping strategy for climate change and variability, and it has been proved to save up to 50% of water (Diagne *et al.*, 2012). The SRI is a package of practices developed to improve the productivity of rice farming with less water. The technology was introduced in Tanzania in the 2010s and has started to spread throughout the country.

The SRI practice has proved yield levels range from 7.0 to 11.0 tons per ha (Katambara *et al.,* 2013; Diagne *et al.,* 2012; Tusekelege *et al.,* 2014) in Tanzania. Some of the SRI practices include the use of young seedlings of 8–12 days old, wider spacing, transplanting of single seedling, fertilizer alternative wetting and drying, and weed management (Ronald *et al.,* 2014). The SRI does not require more water than traditional farming systems (Tusekelege *et al.,* 2014). Since the study included non-homogeneous rice farmers, the snowball technique was convenience sampling to obtain households with similar characteristics. Five alternative rice farming systems were identified and used to stratify the sampling design within the study area. The five farming systems based on management practices are described as follows:

i) *Baseline* – farms using traditional methods comprising application of saved local seed varieties (*supa shinyanga, mbawa mbili, supa pamba, Kabangala, tule na bwana; kisegese; mwarabu, rangi mbili; ngome*, *zambia*), no fertilizer and higher seed rate between 75–100 kg/ha is used as farmers prefer broadcast planting method. Weeding is done manually and typically done twice before harvest, and no specific spacing is applied. Continuous flooding is dominant with neither irrigation nor water control.

ii) *Alt.1* – applying the traditional practices (*Baseline*), but farmers use improved varieties (mainly SARO5 and IR64) instead of local varieties. Farmers in this group prefer transplanting of seedlings instead of broadcasting, which is done between 21–35 days with limited fertilizer application, and no specific spacing is applied.

iii) *Alt.2* – farms supplemented with improved varieties, transplanting of seedlings (no specific spacing is applied), and application of fertilizer at the rate of 50 kg bags per ha. The main types of fertilizers used are Urea and NPK, and occasionally farmers apply organic fertilizers.

iv) *Alt.3 and Alt.4* – this dedicated group of farmers apply some but not all the SRI practices, i.e., SRI partial adopters (*Alt.3*) and those claiming to use all the specified SRI practices (Alt.4). The specific practices under SRI in Tanzania involve (1) stepwise selection and preparation of quality viable seeds; (2) nursery plot development and careful management; (3) land/field levelling for easy infield water management; (4) transplanting one young seedling (at two leaves) per hill while using 25 cm x 25 cm or 25 cm x 30 cm spacing; (5) quickly transplanting within 30 min of gently removing seedlings from their nursery and not inverting the seedlings; (6) wetting and drying of the field (water control) to improve soil aeration and promote root elongation; (7) timely weeding done every 10–12 days after transplanting and repeated in the same interval until harvest; and (8) intensive application of fertilizer, especially one which is rich in nitrogen and phosphorus. A pictorial demonstration of some necessary steps involved in SRI practices in Tanzania is shown in Appendix 5.1. Also, it should be noted that rice production under SRI is done twice a year. Therefore, yield under SRI scenarios included harvests for both rain and dry seasons as the farmers under SRI have gone a step further to use the water from rivers for irrigation during the dry season.

5.4.3 Yield data

Yields for each scenario were collected through a structured questionnaire along with the area harvested for easier calculation of the amount of rice produced per scenario. For example, production (μ_i) for scenario *i* was calculated as $\mu_i = ha_i * y_i$, where ha is the hectare harvested, and y is the yield in tons. Each scenario has 45 yield data. Yield for *Scenario.0* and *Scenario.1* was low regardless of almost equal land distribution because either of the lower application of improved seeds or fertilizers resulted in lower yields. Table 5.1 displays the distribution of tons harvested per ha and the distribution of the area under rice used in this study.

Yields for three seasons starting from 2015/16, 2016/17, and 2017/18 for each scenario were used for this analysis collected. Each scenario has a total of 45 rice farms per season. The yield data for each scenario, therefore, makes a total of 135 observations (45 x 3 = 135). The main reason for using three seasons' data is to capture the stochastic nature of yield (*y*), which is a random variable. Yield is a vital variable in this analysis. Table 5.1 displays the distribution of yield (t/ha) for different rice farming systems under study.

Table 5.1: Yields distribution (t/ha/year) under different farming systems

	2015/16			2016/17			2017/18		
Scenarios	**Mean**	**Min**	**Max**	**Mean**	**Min**	**Max**	**Mean**	**Min**	**Max**

Baseline	1.66	0.71	3.42	0.88	0.45	1.57	1.64	0.60	3.77
Alt.1	2.32	0.78	3.81	1.02	0.39	1.60	1.99	0.47	3.07
Alt.2	4.34	2.15	5.42	0.93	0.50	2.10	3.03	2.31	5.00
Alt.3	6.58	5.22	8.34	0.79	0.56	2.5	6.72	4.00	8.43
Alt.4	13.47	6.78	19.86	1.14	0.45	2.03	13.47	6.10	19.10

Source: field survey

5.4.4 Price data

The price for rice is also a random variable as it fluctuates with time for each variety (local or improved). For example, during data collection, it was argued by farmers and key informants that the price for local varieties under *Baseline* is, to some extent, higher than the price for improved varieties (under *Alt.1* to *Alt.4*). During the harvesting season (April–September), the price for rice is low. However, the price rises when the supply is low, particularly during October through March for all the scenarios presented in Table 5.2. The table shows the summary statistics in terms of average, minimum, and maximum price per season per variety. For each variety, we collected a total sample of 45 price data. Rice prices for local varieties during low supply (non-harvesting) and high supply (harvesting) seasons are denoted by Local_P1 and Local_P2, respectively. Meanwhile, rice prices for improved varieties are indicated by Improved_P1 and Improved_P2 for low and high supply seasons, correspondingly.

Table 5.2: Summary statistics of rice prices (in US$/ton) in the study area for the year 2018

Statistics	**Low Supply**		**High Supply**	
	Local_P1	***Improved_P1***	***Local_P2***	***Improved_P2***
Average (US$/t)	339.3	531.4	232.0	448.9
Minimum (US$/t)	311.1	488.9	217.8	400.0
Maximum (US$/t)	400.0	577.8	244.4	511.1

Source: Field survey; *Exchange rate: US$ 1.00/TZS2,340*

5.4.5 Cost of production per scenario

Data on production cost and input prices for each scenario were also corrected. These costs include seed, nursery preparation (for SRI farms), land preparation, transplanting/seedling, weeding, post-emergence pesticides, bird scaring, wetting and drying, fertilizers, harvesting/cutting/threshing, postharvest handling, and storage costs (Appendix 5.2). *Alt.1* to *Alt.3* use transplanting means of planting; hence it needs 20 to 50 kg/ha of seeds costing between US$8.9 to 17.8. *Baseline* usually applies traditional (broadcasting) planting and needs 50 to 70 kg/ha of seeds, which cost between US$13.3 to US$21.3 thousand. Of all the farming systems, *Alt.4* needs between 7 and 10 kg/ha of seeds. The seeds are obtained through careful seed selection to get pure and quality seeds for high germination probability. The process costs between US$17.8 to US$35.6, as more than 70 kg is needed to obtain the quality seeds.

Land preparation involves ploughing and harrowing for *Baseline* to *Alt.2*, but *Alt.3* and *Alt.4* go beyond to levelling, puddling, and marking transplanting grids. *Baseline* and *Alt.1* did not use fertilizers, but *Alt.4* used more fertilizers, causing the highest cost of all scenarios. *Alt.4* also involved wetting and drying of the field to improve soil aeration and promote roots elongation that claimed to allow plant root growth and subsequent plant vigor and health. The minimum and maximum cost for all scenarios were US$235.6–416.9, US$262.2–473.3, US$417.8–717.8, US$564.4–962.2, and US$817.8–1213.3 for all scenarios, correspondingly.

5.4.6 Stochastic simulation for economic comparison between rice farming systems

The Monte Carlo simulation procedures outlined by Richardson *et al.* (2007; 2018) was used to evaluate the net cash income (NCI) distributions for each scenario. Since we have a total of 135 production data per scenario, the *first step* was defining, parameterizing, simulating, and validating the stochastic variables. Yields and prices are the key variables in calculating stochastic production and receipts. Typically, yields and prices are correlated with each other. Therefore, a multivariate empirical (MVE) distribution described by Richardson *et al.* (2000) was estimated and employed to simulate the two variables using the observed values. The residuals (deviations from the observed mean) from surveyed yield and price for each scenario were used to estimate the parameters for the MVE yield and price distribution. An MVE distribution is an appropriate tool to account for many variables at once and can eliminate the possibility of values exceeding reasonable values like negatives in surveyed data (Ribera *et al.*, 2004).

An MVE yield and price distribution is presented in Equation (5.1) and Equation (5.2), respectively, and is defined by the fractional deviations from mean and cumulative probabilities. It also accounts for the correlated uniform standard deviates ($CUSD_{yp}$) with *yp* representing the row of the correlation matrix of price and yield. The MVE distribution is simulated in Simetar, an acronym for Simulation and Econometrics To Analyse Risk (or Simulation for Excel to Analyse Risk in an Excel add-in and is available at www.simetar.com). In other words, Simetar is a simulation language written for risk analyses that provides a transparent method for simulating the effects of risk and presents the results as probability distributions (Richardson *et al.*, 2000; 2008).

The *second step* was to simulate the MVE distribution in Equations (5.1) and (5.2) for at least 500 iterations using the Latin Hypercube (LHC) sampling procedures defined by Richardson *et al*. (2008). The LHC procedure ensures that a sample of only 500 iterations is necessary to reproduce the parent distributions. A simulation of 500 iterations was needed to have an adequate sample to capture the inherent risk in the yield and price datasets. The *third step* was to validate the simulated distribution to ensure that the random variables were simulated correctly and demonstrate the appropriate properties of the parent distributions. The probability distribution functions (PDFs) of observed and simulated yields and prices were drawn for comparison; as shown in Appendix 5.3, the

PDFs for LHC 500 simulated values and the observed yields and prices have similar shapes confirming that the LHC simulated the observed distribution accurately.

The *fourth step* involved simulating the stochastic production and receipts in Equations (5.3 and 5.4) for each scenario. Therefore, the stochastic production and revenue were combined with the stochastic cost of production to simulate the probability distribution for net income, our targeted key output variable (KOV) for this study. Likewise, production costs were made stochastic using the GRKS probability distribution as the costs differ from one farmer to another for each scenario analysed. Gray, Richardson, Klose, and Schumann developed GRKS probability distribution to simulate subjective probability distributions based on minimum, average/model, and maximum values (Richardson *et al*., 2008). The GRKS in this study was used to include all the cost options used by smallholder farmers who are pessimistic, average, or optimistic. The GRKS is simulated in Simetar using the command = GRKS (min, midpoint, max) and generates random costs. Equation (5.5) was therefore used to simulate the stochastic production cost for each rice farming scenario. Appendix 5.4 shows the probability distribution functions (PDFs) and the cumulative distribution functions (CDFs) for each scenario with *Alt.4* presenting the highest production cost of all scenarios followed by *Alt.3* and *Alt.2.* Table 5.3 defines the symbols used in the equations.

$$\tilde{y}_i = \bar{y}_i * (1 + EMP(S_y, P(S_y), CUSD_{yp})) \tag{5.1}$$

$$\tilde{p}_\omega = \bar{p}_\omega * (1 + EMP(S_p, P(S_p), CUSD_{yp})) \tag{5.2}$$

$$\tilde{\mu}_i = \tilde{y}_i * a_i \tag{5.3}$$

$$\tilde{R}_i = \tilde{p}_\omega * \tilde{\mu}_i \tag{5.4}$$

$$\tilde{C}_i = \sum (GRKS(Min_{Vi}, Average_{vi}, Max_{Vi})) \tag{5.5}$$

$$N\tilde{C}I_i = \tilde{R}_i - \tilde{C}_i \tag{5.6}$$

The *final step* was to simulate the probability distributions of net income for each of the rice farming systems in Equation (5.6) for over 500 iterations using LHC simulation criteria expressed in *the second step* above. The results of the 500 simulated samples were used to estimate the empirical probability distributions of success (NCI) for each scenario and to compare the scenario with the best distribution per hectare. A comparison of the scenarios is well elaborated in section 5.4.7.

Table 5.3: Definition of symbols used in the model

Symbols	Definitions
~	A tilde represents a stochastic variable
i	Rice farming alternatives (*Baseline*, *Alt.1*, *Alt.2*, *Alt.3*, *Alt.4*)
a_i	Hectares (ha) allocated for each alternative i
$\tilde{y}_i$	Stochastic rice yield per ha for alternative i
$N\tilde{C}I_i$	Stochastic production for alternative i which is the product of hectares and yield [$\tilde{y}_i * a_i$]
ω	Rice variety (local and improved)
$\tilde{p}_\omega$	Stochastic rice price influenced by seasonal volatility for variety ω *(Local_P1, Local_P2, Improved_P1, Improved_P2)*
$\tilde{R}_i$	Stochastic receipt/revenue which is a product of stochastic production and price [$\tilde{p}_\omega * \tilde{\mu}_i$]
Vi	Variable cost (US$/ha) given by the summation of all costs included in rice production per each scenario in a range of Min and Max. [including seed, plow, harrow, planting, weeding, bird scaring, fertilizer, post-emergence herbicides, harvesting/threshing, postharvest handling, and storage]
F_i	The fixed cost which was equated to zero for this analysis [F=0]
$\tilde{C}_i$	Stochastic Total production cost for each rice farming system and was computed as $[a*(\tilde{v}_i + F_i)]$
$\tilde{\pi}_i$	Net income which is calculated as the receipt minus total cost $[\tilde{R}_i - \tilde{C}_i]$
S_y	Fraction deviations from a mean or sorted array of random yields for scenario i
S_p	Fraction deviations from a mean or sorted array of random prices for variety ω
$P(S_y)$	Cumulative probability function for the S_y values
$P(S_p)$	Cumulative probability function for the S_p values
$CUSD_{yp}$	Simetar function to simulate correlated uniform standard deviates of random variables
EMP()	Simetar function used to simulate an MVE distribution

5.4.7 Scenario Ranking

In ranking the scenarios, we used two ranking approaches – the Stoplight function and the stochastic efficiency with respect to a function (SERF). The Stoplight function is a Simetar function that produces charts to summarize the probability that the scenarios will be less than the specified lower target or that the scenarios will exceed the targeted maximum value. It also provides the likelihood of each scenario falling between specified targets (Richardson *et al.,* 2008). The probability of falling below the minimum target (possibility of unfavourable) is presented in red colour, the probability of exceeding the maximum target (probability of favourable) is shown in green, and the probability of falling between the two targets (probability of cautionary) is coloured amber. However, through a participatory discussion with rice farmers, the minimum and maximum targets were set at \$500 and \$1000 to reflect the historical annual rice net returns per ha.

SERF uses certainty equivalents (CEs) and a range of absolute risk aversion coefficients (ARACs) to rank many risky alternatives simultaneously. Each alternative can be compared and ranked at each ARAC (Hardaker *et al.*, 2004; Richardson *et al.*, 2008; Bizimana and Richardson, 2019). The of SERF's advantage over the conventional stochastic dominance analysis with respect to a function (SDFR) is that SERF involves comparing each alternative with all the other alternatives simultaneously, not pairwise. On the other hand, the SERF approach compares the CE of all risky alternative scenarios for all risk ARACs over the range and chooses the scenario with the highest CE at each ARAC value; hence assist decision-makers with different risk attitudes. The ARCs range from zero (risk-neutral), normal, moderate, and extremely risk-averse person. Following the formula proposed by Hardaker *et al.* (2004), the extreme or upper ARAC value for this study was calculated using Equation (7) as follows:

$$ARAC_U = \frac{r_U(w)}{w} \tag{5.7}$$

where $r_U(w)$ is the risk aversion coefficient with respect to wealth (*w*).

The risk aversion coefficient with respect to wealth was proposed by Anderson and Dillon (1992) to be set equal to 4 (very risk-averse). Also, the emphasize was done by Hardaker *et al.* (2004), where they suggested that the average wealth for alternatives can be used to calculate the upper ARAC in Equation (5.7). In this study, scenarios were analysed based on price seasonality (April – September, and October – March). On a yearly basis, the average wealth for each case was therefore used to compute the upper ARAC.

5.5 Results

Simulation results on economic viability for each scenario are presented seasonally (low or high supply) and on an annual basis. Table 5.4 presents the summary statistics for and the probability of generating negative NCI for each scenario. All the five scenarios show positive mean values of NCI for both low and high supply seasons. However, during the low supply, the average NCI is high. The high supply season shows negative minimum values of NCI for the first three scenarios congruently (US$-140.9, US$-289.4, and US$-203.1). In comparison, the low supply season shows negative minimum values for the first two scenarios (US$-14.9 and US$-77.3). Consequently, the first three scenarios for the aggregated/annual price also show negative minimum values of NCI for the first three scenarios (US$-126.2, US$-213.9, and US$-75.3).

Generally, the low supply season has the highest NCI distribution for all scenarios compared to the counterpart with *Alt.4* dominating in terms of average, minimum, and maximum values, followed by *Alt.3* and *Alt.2* (Table 5.4). The high NCI for scenarios 4 and 3 is not only influenced by the highest price offered during low supply but also due to high yield per unit area. On the other hand, during the harvesting season, the results show that *Baseline*, *Alt.1*, and *Alt.2* have 17.9%, 21.6%, and 6.9% likelihood of negative NCI, respectively. *Alt.3* and *Alt.4* have zero probability of negative returns. Meanwhile, the non-harvesting season has 0.43% and 1.14% chances of negative NCI for *Baseline* and *Alt.1* with a zero chance for the last three. For the aggregated/annual results, the table shows 3.59%, 9.62%, and a 0.57% likelihood of negative NCI values for *Baseline, Alt.1,* and *Alt.2*, respectively, with *Alt.3* and *Alt.4* both having a zero probability.

Table 5.4: Summary statistics and the probability of negative annual net income from the stochastic simulation for control and alternative scenarios (US\$ ha^{-1}).

Scenarios	Mean	SD	CV	Min	Max	Probability(NCI<0)
Income during harvesting season (April – September)						
Alt.0	240.2	259.8	108.1	-140.9	1 073.7	17.9
Alt.1	168.6	188.1	111.6	-289.4	645.0	21.6
Alt.2	432.8	266.4	61.5	-203.1	904.6	6.9
Alt.3	765.9	245.3	32.0	227.8	1 401.0	0.0
Alt.4	2 094.5	1 166.3	55.7	283.4	4 016.3	0.0
Income during shortage season (October – March)						
Alt.0	558.0	386.8	69.3	-14.9	1 705.4	0.43
Alt.1	677.8	376.3	55.5	-77.3	1 600.4	1.41
Alt.2	1 370.2	513.6	37.5	221.8	2 274.3	0.00
Alt.3	2 197.2	463.9	21.1	1 178.1	3 496.1	0.00
Alt.4	4 979.7	2 199.7	44.2	1 665.6	8 851.5	0.00
Annual net income						
Alt.0	399.2	338.4	84.8	-126.2	1 516.6	3.59
Alt.1	424.9	318.5	75.0	-213.9	1 348.6	9.62
Alt.2	899.7	470.0	52.2	-75.3	2 227.9	0.57
Alt.3	1 485.7	545.2	36.7	308.6	3 147.2	0.00
Alt.4	3 537.2	1 885.9	53.3	527.7	8 312.9	0.00

Notes: SD = standard deviation, CV = coefficient of variation, NCI = net cash income, Exchange rate: US\$ 1.00/TZS2 340.

Likewise, the Stoplight charts in Figures 5.2–5.4 show the probability of NCI to be less than the lower target of US\$500, the likelihood of exceeding the upper target of US\$1000, and the probability of falling between the two targets. In Figure 5.2, when farmers decide to sell their rice during harvesting season, the probability of NCI being less than the minimum target is 83%, 96%, 46%, 16%, and 3% for *Baseline*, *Alt.1*, *Alt.2*, *Alt.3*, and *Alt.4*, respectively. The probability of exceeding the maximum target is higher for *Alt.4* (71%), followed by *Alt.3* (19%), and 1% for *Baseline*. Meanwhile, *Alt.1* and *Alt.2* have a zero probability. The probability of falling between two targets is lower for *Alt.1* and *Baseline* and higher for the rest of the scenarios.

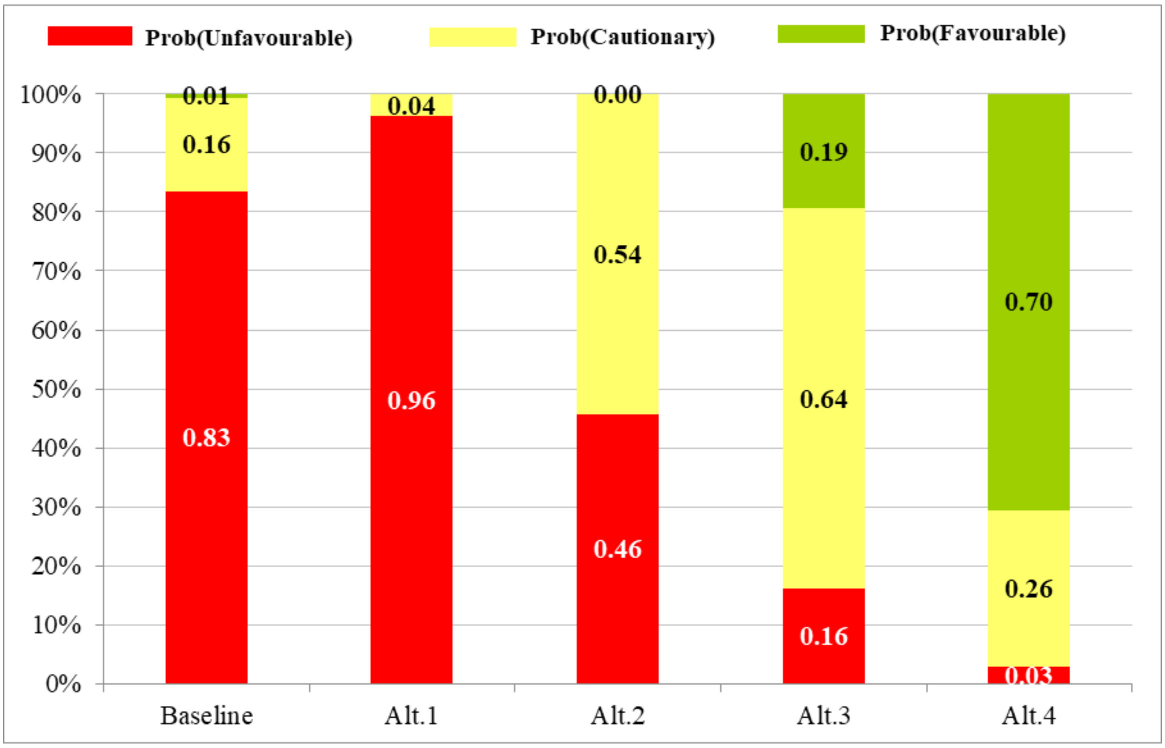

Figure 5.2: **Stoplight chart for probabilities of NCI being less than US$500 and greater than US$1000 for rice farming systems when transactions are made between April – September.**

When farmers sell their rice during low supply season, the results show that the probability of NCI being less than the minimum target decreased to 54%, 34%, and 3% for *Baseline*, *Alt.1*, and *Alt.2*, correspondingly, with a zero probability for the last two scenarios (Figure 5.3). In the meantime, *Alt.3* and *Alt.4* have a 100% probability of exceeding the maximum threshold, followed by *Alt.2* (68%), *Alt.1* (18%), and a 13% probability for *Baseline*. The possibility of falling between the two targets was 32%, 45%, and 29% for *Baseline*, *Alt.1*, and *Alt.2*, respectively.

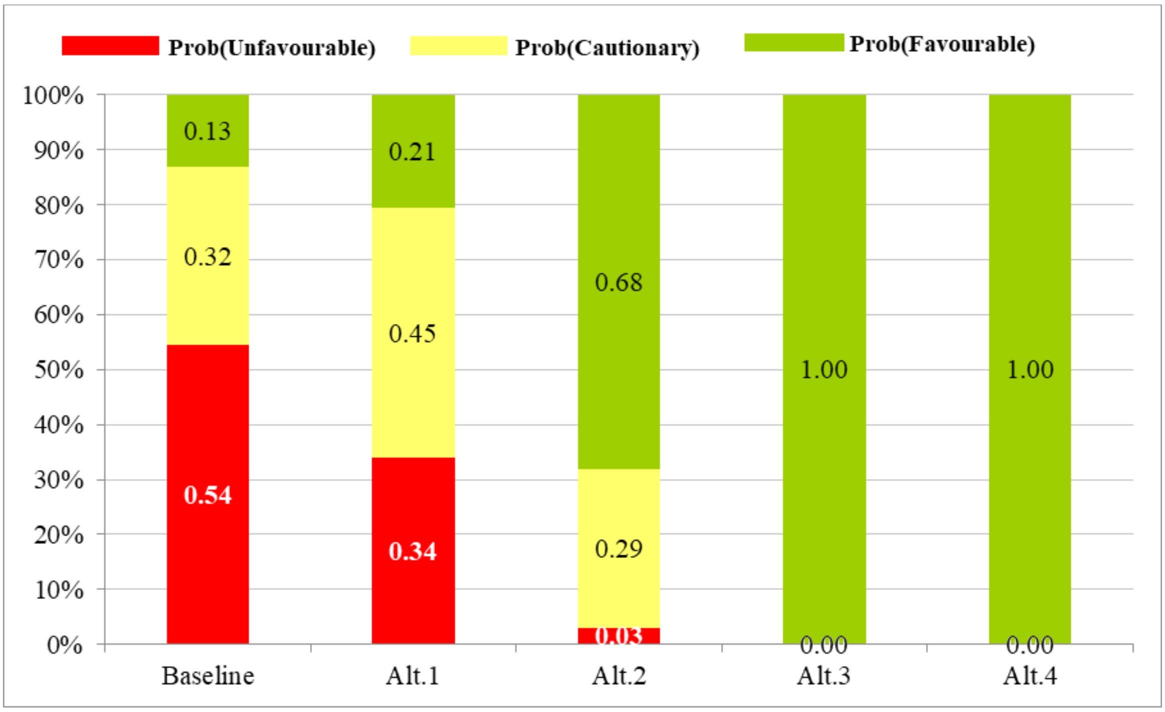

Figure 5.3: Stoplight chart for probabilities of NCI being less than US$500 and greater than US$1000 for alternative rice farming systems when transactions are made between October–March.

Figure 5.4 was developed to show the distribution of NCI of all scenarios annually. The results show that the first four scenarios have a 66%, 60%, 21%, and 2% probability that annual NCI will be less than $500, respectively, with *Alt.4* having a zero probability. The probability of exceeding the maximum target is higher for *Alt.4* (94%), followed by *Alt.3* (80%), and *Alt.2* (41%), while the first two have less than 10% probability of being above the maximum target. It is worth mentioning that the higher NCI for *Alt.4*, *Alt.3*, and *Alt.2* are associated with increased production due to applying SRI technologies, improved seeds, or fertilizers.

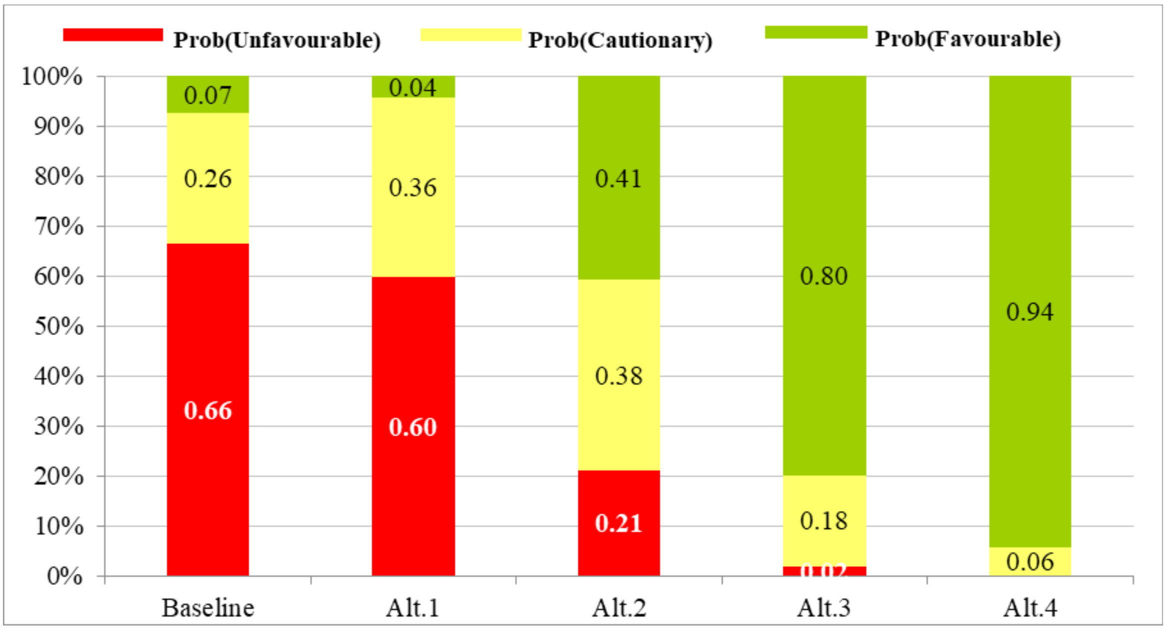

Figure 5.4: Stoplight chart for probabilities of annual NCI being less than US$500 and greater than US$1000 for alternative rice farming systems.

The scenarios were also ranked using a stochastic efficiency with respect to a function (SERF) where the scenarios are ranked based on the decision-maker utility for income and risk. Figures 5.5 and 5.6 present the results for low and high supply seasons, respectively. Regardless of the time of the transaction, *Alt.4* provides the most top certainty equivalents for all realistic risk aversion coefficients, followed by *Alt.3* and *Alt.2*. This indicates that *Alt.4* is highly preferred by all classes (risk-neutral to risk-averse) of decision-makers over all other scenarios analysed, followed by *Alt.3* and *Alt.2*. The certainty equivalents (CEs) for Alt.4 were the highest, followed by *Alt.3* and *Alt.2*. In the meantime, *Alt.1* has the lowest CEs at all levels of ARAC values when the transaction is to be made between April and September (Figure 5.5). In contrast, when the purchase is to be done between October and March, the CEs for *Alt.1* are slightly higher than for *Baseline* due to the relatively high production for Alt.1 (Figure 5.6).

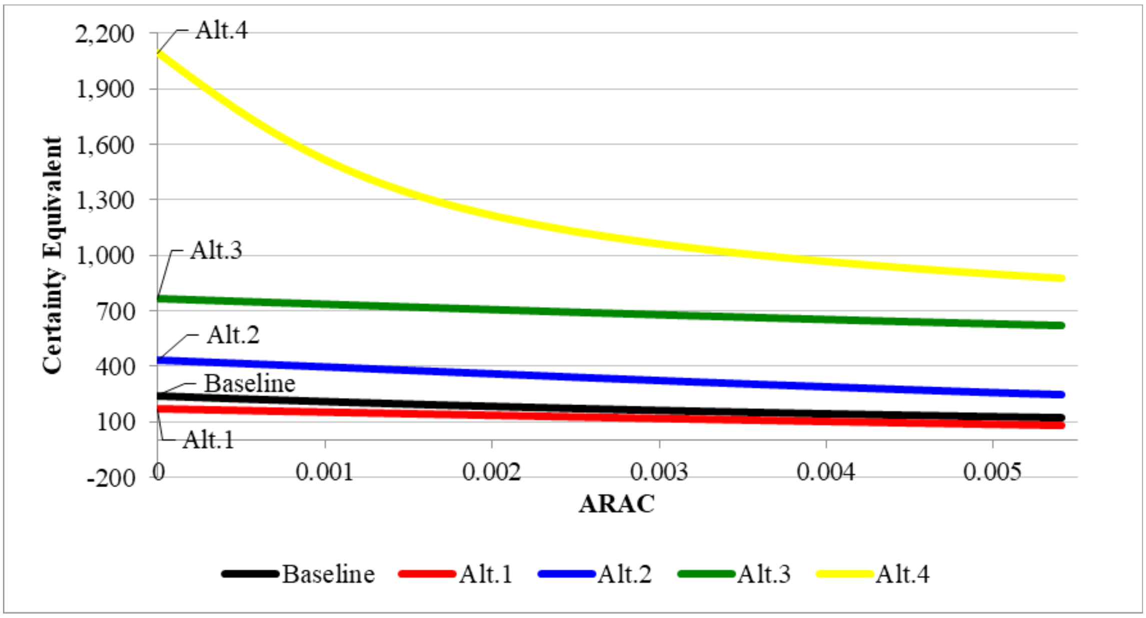

Figure 5.5: **Stochastic efficiency with respect to a function (SERF) under a negative exponential utility function of NCI when the transaction is made between April – September.**

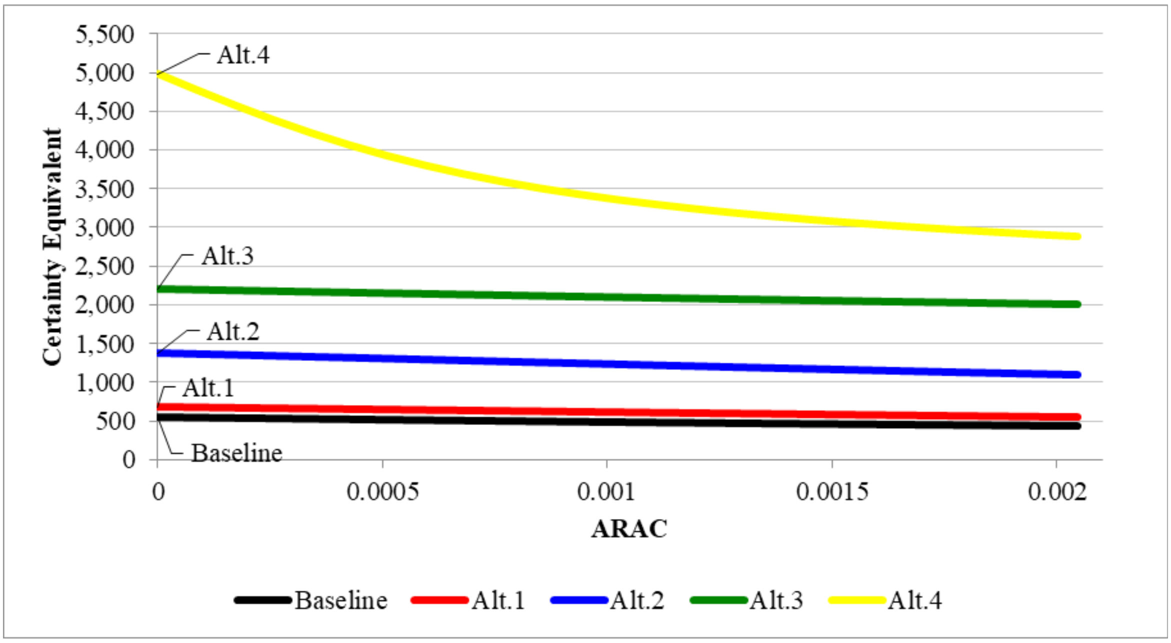

Figure 5.6: **SERF under a negative exponential utility function of NCI when the transaction is made between October–March.**

Figure 5.7 represents the SERF of annual NCI for all scenarios. Likewise, *Alt.4* shows the highest certainty equivalents, followed by *Alt.3* and *Alt.2* correspondingly. This implies that all risk-neutral and risk-averse decision-makers consistently prefer the three scenarios over all other scenarios. The CEs for *Alt.1* are, to some extent, higher than for *Baseline* at all values of ARAC. The differences indicate that all classes of decision-makers prefer less the latter (neutral and risk-averse decisionmakers) because the equivalent certainty line for *Alt.1* is above the certainty equivalent for *Baseline* for ARAC levels of 0 to 0.0030.

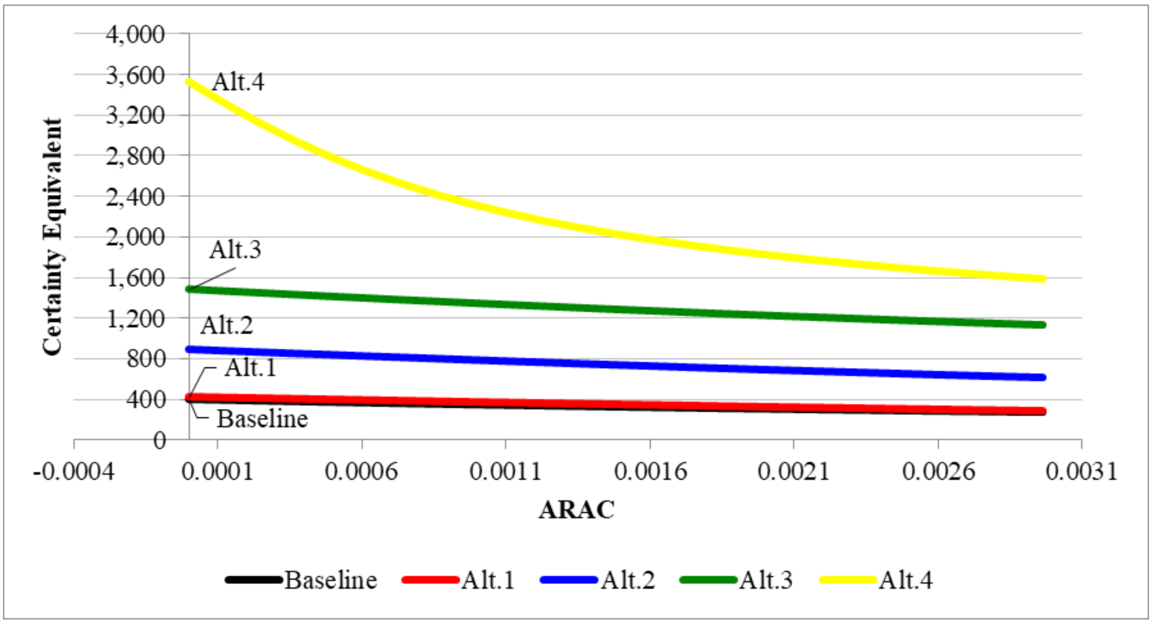

Figure 5.7: SERF under a negative exponential utility function of annual NCI.

5.6 Discussion

By considering the annual net income distribution, rice farms under *Alt.4* (SRI adopters) had the highest income distribution regardless of seasonal variability in price followed by *Alt.3* (partially SRI adopters) and it was relatively low for the non-SRI adopter. The high variation in income depends upon the degree of adoption of the technology (Uphoff, 2007). The income gap between the traditional and improved practices, especially SRI adopters and non-adopters, was consistent with case studies in Asia, Latin America, and Africa (Uphoff, 2007). For example, in the Philippines, Llanto *et al.* (2005) and Cruz *et al.* (2005) assessed the impact of SRI practices under the Australian RiceCheck program. The two studies reported that farmers who adopted at least three key SRI practices earned gross profit margins nearly twice as large compared to farmers under the traditional system. Similar observations were also reported in Sri Lanka (Namara *et al.*, 2003).

In Viet Nam, the same assessment was conducted and revealed that farmers who adopted some of the SRI technologies have seen their income increase between 11% to 40% (Pham *et al.*, 2005). In China, farmers who took the improved farm management practices enjoyed an increase in net income by 48% (Satyanarayana *et al*, 2007).

In India, a study to assess the impact of integrated crop management on rice farms' profitability was conducted and found a massive increase in net income. The study reported a more than threefold profit increase (from US$105/ha to US$369/ha) to farmers who adopted improved management practices like early transplanting, one seedling per hill, square transplanting; early and frequent mechanical weeding; and intermittent irrigation (Balasubramanian *et al.*, 2005; Abdulrachman *et al.*, 2005; Satyanarayana *et al.*, 2007). Although the studies did not report on the economic contribution in Indonesia and Cambodia, the improved rice practices recorded an increase of between 10 - 50% and 50 - 100% on yield/ha to farmers who adopted the program (Anthofer, 2004; Satyanarayana *et al.*, 2007; Glover, 2011). The positive impact of improved rice production practices was also reported in Brazil, Venezuela, Costa Rica, and Nicaragua (Uphoff, 2007). In sub-Saharan Africa, eastern Africa, in particular, studies conducted by Tusekelege *et al.* (2014) and Bell (2016) show that rice farms under SRI practices yielded ≥ 5.5 tons/ha, but the studies did not elaborate on the economic viability of the technologies.

Our results show that rice farms using all the recommended SRI practices generated the highest net cash income, followed by rice farms which partially implemented the principles. Farms under SRI practices have 80% and 94% probabilities of NCI being greater than US$1000 for partial and full adopters. The chances of negative net revenue were low even when transactions were to be made during high supply. The high yield per unit area resulted from the application of a tailor-made improved technology package.

The next-best performing scenario was the farms supplemented with both improved seeds (SARO 5) and fertilizers. The scenario utilizing traditional farming system technologies was the least preferred of the five scenarios analysed. Those using a combination of conventional practices plus improved seed were the second least preferred.

For all scenarios, especially under SRI practices (partially or fully), farmers earn reasonable profits if they store their produce until the peak price season. Although local varieties gained higher prices than the improved varieties, SRI users were economically better off than their counterparts due to higher yields. Women play a significant role in SRI practices as they were observed to be the most critical participants in training and supply of labor. In addition, some of the women are now shifting from traditional methods to applying the new farming system. A successful story in Appendix 5.4 by Mwanaidi H. Hamza was observed in Mkindo village. Mwanaidi received the SRI training in 2011, and she started using the technology with great success, which led her to be the focal person in all issues related to SRI in the country.

Many rice producers (mainly smallholder farmers) in Tanzania continue to use traditional management practices, which has led to the sector’s continuous low performance (URT, 2015; Wilson and Lewis, 2015). The results of this study provide useful information to compare the risks and benefits of producing under traditional management practices and the benefits of producing under improved alternative management practices so that farmers would be able to make better management decisions. These results suggest that even if the rice farmers in Morogoro do not adapt to SRI practices, the technology would still be the preferred technology for risk-neutral and risk-averse decision-makers.

5.7 Conclusions

The purpose of this paper was to compare rice farming systems' economic viability under alternative management practices in the Morogoro region, Tanzania, using a Monte Carlo simulation model. We categorized our sample into five alternative scenarios: (1) farms using traditional management practices; (2) farms using improved seed varieties; (3) farms using improved varieties plus fertilizers; (4) farms applying some of the SRI practices; and (5) farms using all the recommended SRI practices. A Monte Carlo simulation model was developed based on stochastic variables, including yields, prices, input, and labor costs, to estimate distributions of economic returns for alternative strategies for better management decisions. A complete Monte Carlo simulation model was used to simulate the net cash revenue per season and per year. Thus, a Monte Carlo simulation model was considered in this paper to incorporate risk faced by farmers by incorporating probability factors for random variables that farmers cannot control with certainty. The simulation results of the model for all the alternative management practices were presented in charts and probabilities to provide a wide distribution of the key output variables.

The findings of this study have vital policy implications for Tanzania's government as it aims to end hunger and reduce poverty by 50% in 2025 through doubling agricultural production. Considering that rice is one of the crops targeted to drive Tanzania out of hunger and poverty, the results of this study suggest the benefits of investing in improved rice farming technologies, particularly SRI principles. The application of SRI practices has demonstrated the potential to increase rice yields and income of farmers. Given the availability of potential areas (including rivers and nine basins) for rice production in Tanzania, they can be utilized to produce more rice in the country.

Author contributions

Conceptualization, I.L.K.; Data curation, I.L.K. and W.M.; Formal analysis, I.L.K.; Funding acquisition, S.S.; Methodology, I.L.K., J.W.R. and J.-C.B.; Project administration, H.F.M.; Resources, H.F.M.; Software, J.W.R., and J.-C.B.; Supervision, K.D.M., D.P., J.W.R., H.F.M. and S.S.; Validation, J.W.R.; Visualization, I.L.K., and J.-C.B.; Writing—original draft, I.L.K.; Writing—review & editing, I.L.K., K.D.M., D.P. and W.M. All authors have read and agreed to the published version of the manuscript.

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Conflicts of Interest

The authors declare that they have no conflict of interests in relation to this paper.

Reference

Abdulrachman, S., Las, I. and Yuliardi, I. (2005). Development and dissemination of integrated crop management for productive and efficient rice production in Indonesia. *IRC Newsl*, *54*, pp.73-82.

Ali, R.M. (2015). *Evaluation of the performance of the system of rice intensification (SRI) in Bumbwisudi rice irrigation scheme, Zanzibar* (Doctoral dissertation, Sokoine University of Agriculture).

Anderson, J. R., and Dillon, J. L. (1992). *Risk analysis in dryland farming systems* (No. 2). Food and Agriculture Org.

Anthofer, J. (2004). October. The potential of the System of Rice Intensification (SRI) for poverty reduction in Cambodia. In *Deutscher Tropentag* (pp. 5-7).

Atkinson, R. and Flint, J. (2001). Accessing hidden and hard-to-reach populations: Snowball research strategies. *Social research update*, *33*(1), pp.1-4.

Balasubramanian, V., Rajendran, R., Ravi, V., Chellaiah, N., Castro, E., Chandrasekaran, B., Jayaraj, T. and Ramanathan, S. (2005). Integrated crop management for enhancing yield, factor productivity, and profitability in Asian rice farms. *IRC Newsl*, *54*, pp.63-73.

Bell, P. (2016). *Sustainable Intensification for Food Security and Climate Change Adaptation in Tanzania* (Doctoral dissertation, The Ohio State University).

Bizimana, J. C., and Richardson, J. W. (2019). Agricultural technology assessment for smallholder farms: An analysis using a farm simulation model (FARMSIM). *Computers and electronics in agriculture*, *156*, 406-425.

Bouman, B.A., Barker, R., Humphreys, E., Tuong, T.P., Atlin, G., Bennett, J., Dawe, D., Dittert, K., Dobermann, A., Facon, T. and Fujimoto, N. (2007). *Rice: feeding the billions* (No. 612-2016-40554).

Browne, K. (2005). Snowball sampling: using social networks to research non-heterosexual women. *International journal of social research methodology*, *8*(1), pp.47-60.

Cruz, R.T., Llanto, G.P., Castro, A.P., Barroga, K.E.T., Bordey, F.H., Redoña, E.D. and Sebastian, L.S. (2005). PalayCheck: the Philippines rice integrated crop management system. *IRC Newsl*, *20*, pp.83-91.

Diagne, A., Glover, S., Groom, B. and Phillips, J. (2012). *Africa's Green Revolution? The determinants of the adoption of NERICAs in West Africa* (No. 174).

Doss, C.R. (2006). Analyzing technology adoption using microstudies: limitations, challenges, and opportunities for improvement. *Agricultural economics*, *34*(3), pp.207-219.

Furahisha, E.H. (2013). *Farmers adoption of selected recommended rice production practices: a case of Kilombero district of Morogoro Region, Tanzania* (Doctoral dissertation, Sokoine University of Agriculture).

Glover, D. (2011). Science, practice and the System of Rice Intensification in Indian agriculture. Food Policy 36, 749-755.

Gulacha, M.M., and Mulungu, D.M. (2017). Generation of climate change scenarios for precipitation and temperature at local scales using SDSM in Wami-Ruvu River Basin Tanzania. *Physics and Chemistry of the Earth, Parts A/B/C*, *100*, pp.62-72.

Hardaker, J.B., Richardson, J.W., Lien, G., Schumann, K.D. (2004). Stochastic efficiency analysis with risk aversion bounds: a simplified approach. Aust. J. Agric. Resour. Econ. 48 (2), 253–270.

Kahimba, F.C., Kombe, E.E. and Mahoo, H.F. (2013). The Potential of System of Rice Intensification (SRI) to Increase Rice Water Productivity: a Case of Mkindo Irrigation Scheme in Morogoro Region, Tanzania. *Tanzania Journal of Agricultural Sciences*, *12*(2).

Katambara, Z., Kahimba, F.C., Mahoo, H.F., Mbungu, W.B., Mhenga, F., Reuben, P., Maugo, M., and Nyarubamba, A. (2013). Adopting the system of rice intensification (SRI) in Tanzania: A review. *Agricultural Sciences*, *4* (08), p.369.

Llanto, G.P., Castro, A.P., Bordey, F.H., Barroga, K.E.T., Cruz, R.T., Sebastian, L.S. and Redono, E.D. (2005). PalayCheck: the Philippines' rice integrated crop management system. *Philippine Journal of Crop Science (Philippines)*.

Maliondo, S.M.S., Mpeta, E.J., and Olson, J. (2012). Climate change and food security in Tanzania: an analysis of current knowledge and research gaps and recommendations for a research agenda. *iAGRI Reference Background Paper*.

Mishra, A., Whitten, M., Ketelaar, J.W., and Salokhe, V.M. (2006). The System of Rice Intensification (SRI): A challenge for science, and an opportunity for farmer empowerment towards sustainable agriculture, *International Journal of Agricultural Sustainability* 4: 193-212.

Mwinuka, L., Mutabazi, K. D., Sieber, S., Makindara, J., and Bizimana, J. C. (2017). An economic risk analysis of fertiliser microdosing and rainwater harvesting in a semi-arid farming system in Tanzania. *Agrekon*, *56*(3), 274-289.

Mwinuka, L., Mutabazi, K.D., Sieber, S., Makindara, J. and Bizimana, J.C. (2017). An economic risk analysis of fertilizer microdosing and rainwater harvesting in a semi-arid farming system in Tanzania. *Agrekon*, *56*(3), pp.274-289.

Naderifar, M., Goli, H., and Ghaljaie, F. (2017). Snowball sampling: A purposeful method of sampling in qualitative research. *sdmej*, *14*(3).

Namara, R.E., Weligamage, P., and Barker, R. (2003). *Prospects for adopting system of rice intensification in Sri Lanka: A socioeconomic assessment* (Vol.75). IWMI.

Ndomba, P.M. (2014). Streamflow data needs for water resources management and monitoring challenges: A case study of Wami River subbasin in Tanzania. In *Nile River Basin* (pp. 23-49). Springer, Cham.

Paavola, J. (2008). Livelihoods, vulnerability, and adaptation to climate change in Morogoro, Tanzania. *Environmental Science & Policy*, *11*(7), pp.642-654.

Patra, P.S., and Haque, S. (2011). Effect of seedling age on tillering pattern and yield of rice (Oryza sativa L.) under system of rice intensification. *ARPN Journal of Agricultural and Biological Science*, *6*(11), pp.33-35.

Pham, T.S., Trinh, K.Q., and Tran, D.V. (2005). Integrated crop management for intensive irrigated rice in the Mekong Delta of Viet Nam. *IRC Newsl.*, 20: 91-96.

Ram, P.C. (2003). Maclean, JL, Dawe, DC, Hardy, B., and Hettel, GP (eds) Rice almanac. 3rd edn.

Randriamiharisoa, R., Barison, J., and Uphoff, N. (2006). Soil biological contributions to the System of Rice Production, in N. Uphoff *et al*. (eds.), *Biological Approaches to Sustainable Soil Systems*, 409-424, CRC Press, Boca Raton, FL.

Rezende, M.L., and Richardson, J.W. (2015). Economic feasibility of sugar and ethanol production in Brazil under alternative future prices outlook. *Agricultural Systems*, *138*, pp.77-87.

Ribera, L.A., Hons, F.M., and Richardson, J.W. (2004). An economic comparison between conventional and no-tillage farming systems in Burleson County, Texas. *Agronomy Journal*, *96*(2), pp.415-424.

Richardson, J.W., Herbst, B.K., Outlaw, J.L., and Gill II, R.C. (2007). Including risk in economic feasibility analyses: The case of ethanol production in Texas. *Journal of Agribusiness* 25(2): 115–132

Richardson, J.W., Klose, S.L., and Gray, A.W. (2000). An applied procedure for estimating and simulating multivariate empirical (MVE) probability distributions in farm-level risk assessment and policy analysis. *Journal of Agricultural and Applied Economics*, *32*(2), pp.299-315.

Richardson, J.W., Schumann, K., and Feldman, P. (2008). Simulation and econometrics to analyse risk. *Simetar, Inc.: College Station, TX*.

Ronald, B., Dulle, F., and Honesta, N. (2014). Assessment of the information needs of rice farmers in Tanzania: A Case Study of Kilombero district. *Morogoro. Lib. Philos. Pract. 0-1*.

Satyanarayana, A., Thiyagarajan, T.M., and Uphoff, N. (2007). Opportunities for water saving with higher yield from the system of rice intensification. *Irrigation Science*, *25*(2), pp.99-115.

Sedgwick, P. (2013). Snowball sampling. *Bmj*, *347*, p.f7511.

Sikay, F. H. (2017). *The potential of the System of Rice Intensification technique (SRI) in saving irrigation water and its impact on rice yield within Wami Basin in Tanzania: Application of the QSWAT model*. (Master degree dissertation, Aarhus University).

Stoop, W., Uphoff, N., and Kassam, A. (2002). A review of agricultural research issues raised by the System of Rice Intensification (SRI) from Madagascar: Opportunities for improving farming systems for resource-poor farmers. *Agricultural Systems* 71: 249-274.

Tusekelege, H. K., Kangile, R. J., Ng'elenge, H. S., Busindi, I.M., Nyambo, D.B. and Nyiti, E. (2014). Option for increasing rice yields, profitability, and water saving; a comparative analysis of System of Rice Intensification in Morogoro, Tanzania', *Int. J. Rec. Biotech*, *2*(1), pp.4-10.

Uphoff, N. (1999). Agroecological implications of the system of rice intensification (SRI) in Madagascar. *Environment, development, and sustainability*, *1*(3-4), pp. 297-313.

Uphoff, N. (2003). Higher yields with fewer external inputs? The System of Rice Intensification and potential contributions to agricultural sustainability. *International Journal of Agricultural Sustainability* 1: 38-50.

Uphoff, N. (2005). The development of the System of Rice Intensification, in J. Gonsalves *et al*. (eds.), *Participatory Research and Development for Sustainable Agriculture and Rural Development*, Vol. 3, 119-125, International Potato Center-UPWARD and International Development Research Centre, Ottawa.

Uphoff, N. (2006). The System of Rice Intensification: Using alternative cultural practices to increase rice production and profitability from existing yield potentials. *Preface Préface Prefacio*, *55*, pp.103-113.

Uphoff, N. (2007). Reducing the vulnerability of rural households through agroecological practice: Considering the System of Rice Intensification (SRI), *Mondes en Développement*, 35:4.

Uphoff, N. (2008). The System of Rice Intensification (SRI) as a system of agricultural innovation. *Jurnal Ilmu Tanah dan Lingkungan*, *10*(1).

URT (2007). *The United Republic of Tanzania. National Adaptation Programme of Action (NAPA)*, *Prospects*. Dar Es Salaam.

URT (2015). *System of Rice Intensification Training Manual for Extension Staff and Farmers*. The United Republic of Tanzania. [https://sriwestafrica.files.wordpress.com/2014/05/kilimo-booklet-final-sri.pdf]. Site visited on 20/02/2017

Wambura, F.J., Ndomba, P.M., Kongo, V. and Tumbo, S.D. (2015). Uncertainty of runoff projections under changing climate in Wami River sub-basin. *Journal of Hydrology: Regional Studies*, *4*, pp.333-348.

Wilson, R. T., and Lewis, I. (2015). The Rice Value Chain in Tanzania. A Report from the Southern Highlands Food Systems Programme, FAO. pp. 111.

APPENDICES

Appendix 5.1: Important steps in SRI farming system

Plate 5.1: selection and preparation of quality viable seeds (by egg and salt solution); 2: sprouted seed for sowing in the nursery; 3: nursery plots; 4: land/farm preparation for easy water management; 5: marking 25cm x 25 cm transplanting grids in the field; 6: a two-leaf seedling appropriate for transplanting; 7: seedling transplanting and 8: fertilizer application.

Source: Modified from the Tanzania SRI Training Manual for Extension Staff and Farmers (URT, 2015)

Appendix 5.2: Production cost per ha for rice farming systems in Tanzania

This appendix presents the type of input and their respective costs used in rice production for each scenario (Table 5.2.1) and Figure 5.2.1. Displays the distribution of total cost (US$/ha) used per scenario.

Appendix 5.2.1: Estimated costs of production (US$/ha) per hectare for rice under different farming systems in Tanzania.

Variable cost	**Scenario.0**		**Scenario.1**		**Scenario.2**		**Scenario.3**		**Scenario.4**	
	Min	***Max***	***Min***	***Max***	***Min***	***Max***	***Min***	***Max***	***Min***	***Max***
Seed: Traditional	13.3	21.3								
Seed: Improved***			8.9	17.8	8.9	17.8	8.9	17.8	17.8	35.6
Nursery preparation									35.6	44.4
Plowing	17.8	22.2	17.8	22.2	17.8	22.2	17.8	22.2	17.8	22.2
Harrowing	17.8	22.2	17.8	22.2	17.8	22.2	17.8	22.2	17.8	22.2
Leveling and puddling							31.1	44.4	31.1	44.4
Marking transplanting grids							22.2	35.6	22.2	35.6
Planting: Broadcasting	17.8	22.2								
Seedling: Transplanting			31.1	44.4	31.1	44.4	44.4	71.1	80.0	111.1
Weeding: 1st round	44.4	111.1	44.4	111.1	44.4	111.1	66.7	133.3	66.7	133.3
Weeding: 2nd round	35.6	44.4	35.6	44.4	35.6	44.4	44.4	66.7	44.4	66.7
Weeding: 3rd round					35.6	44.4	44.4	66.7	44.4	66.7
Bird scaring	22.2	35.6	22.2	35.6	22.2	35.6	22.2	35.6	22.2	35.6
Post-emergence pesticides			4.4	6.7	4.4	6.7	4.4	6.7	13.3	22.2
Field wetting and drying (water control)									35.6	53.3
Fertilizer: 1st round DAP					26.7	48.9	26.7	48.9	44.4	57.8
Fertilizer: 2nd round UREA					26.7	48.9	26.7	48.9	44.4	57.8
Fertilizer: 3rd round UREA					26.7	48.9	26.7	48.9	44.4	57.8
Harvesting/threshing	44.4	88.9	48.9	111.1	66.7	133.3	88.9	155.6	133.3	177.8
Postharvest handling	13.3	26.7	13.3	31.1	26.7	44.4	35.6	80.0	57.8	88.9
Storage	8.9	22.2	17.8	26.7	26.7	44.4	35.6	57.8	44.4	80.0
Total	235.6	416.9	262.2	473.3	417.8	717.8	564.4	962.2	817.8	1213.3

*** for SRI farming system seed farmers considered a carefully seed selection and preparation to obtain quality seed for high germination probability.

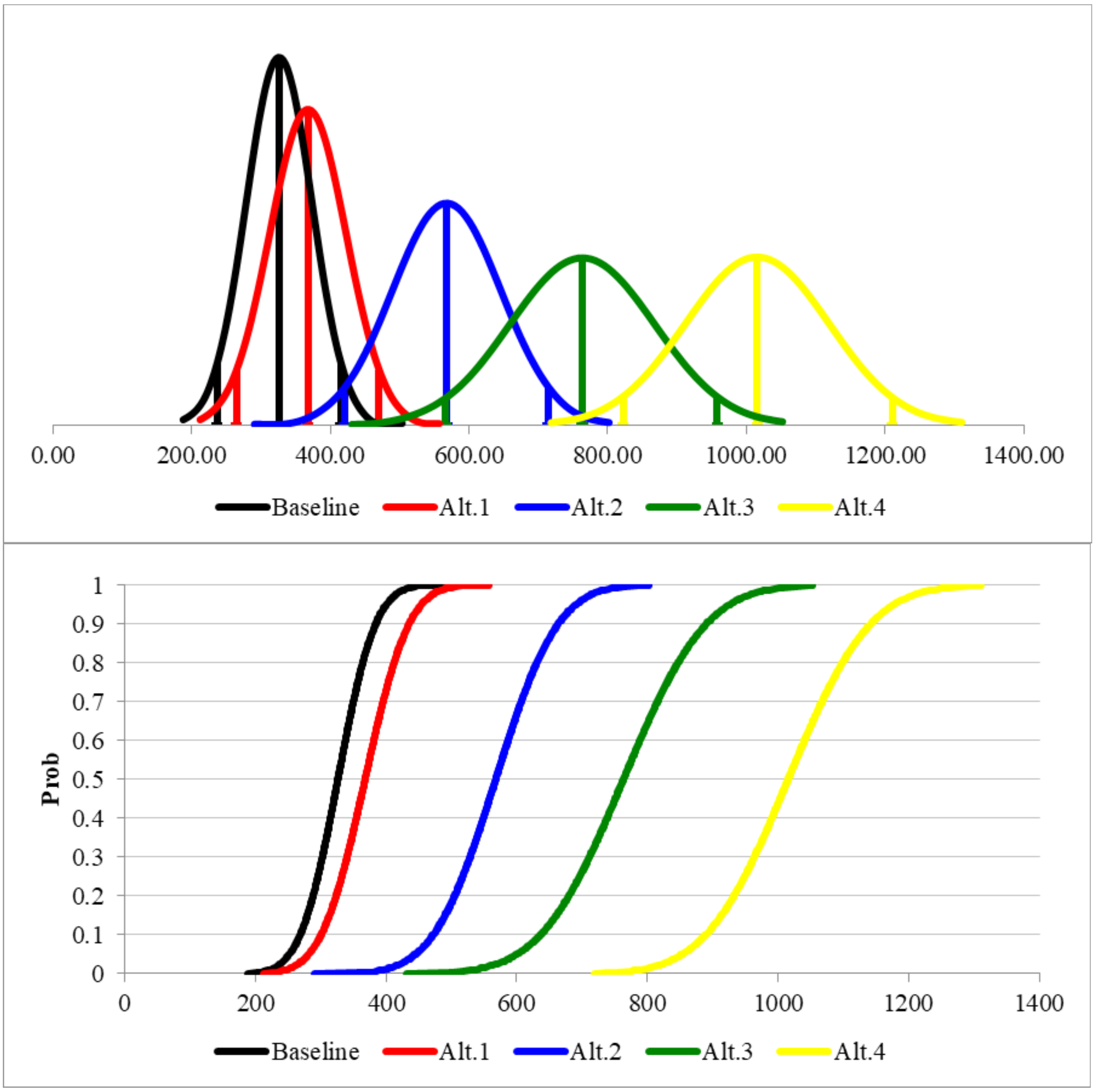

Figure 5.2.1: (a) PDFs of production costs per ha and (b) CDFs of production costs per ha used in the model for each scenario.

Appendix 5.3: Probability Distribution Functions (PDF) Charts for the Simulated Sample (in Red) vs. Observed Yields and Prices Sampled (in Black)

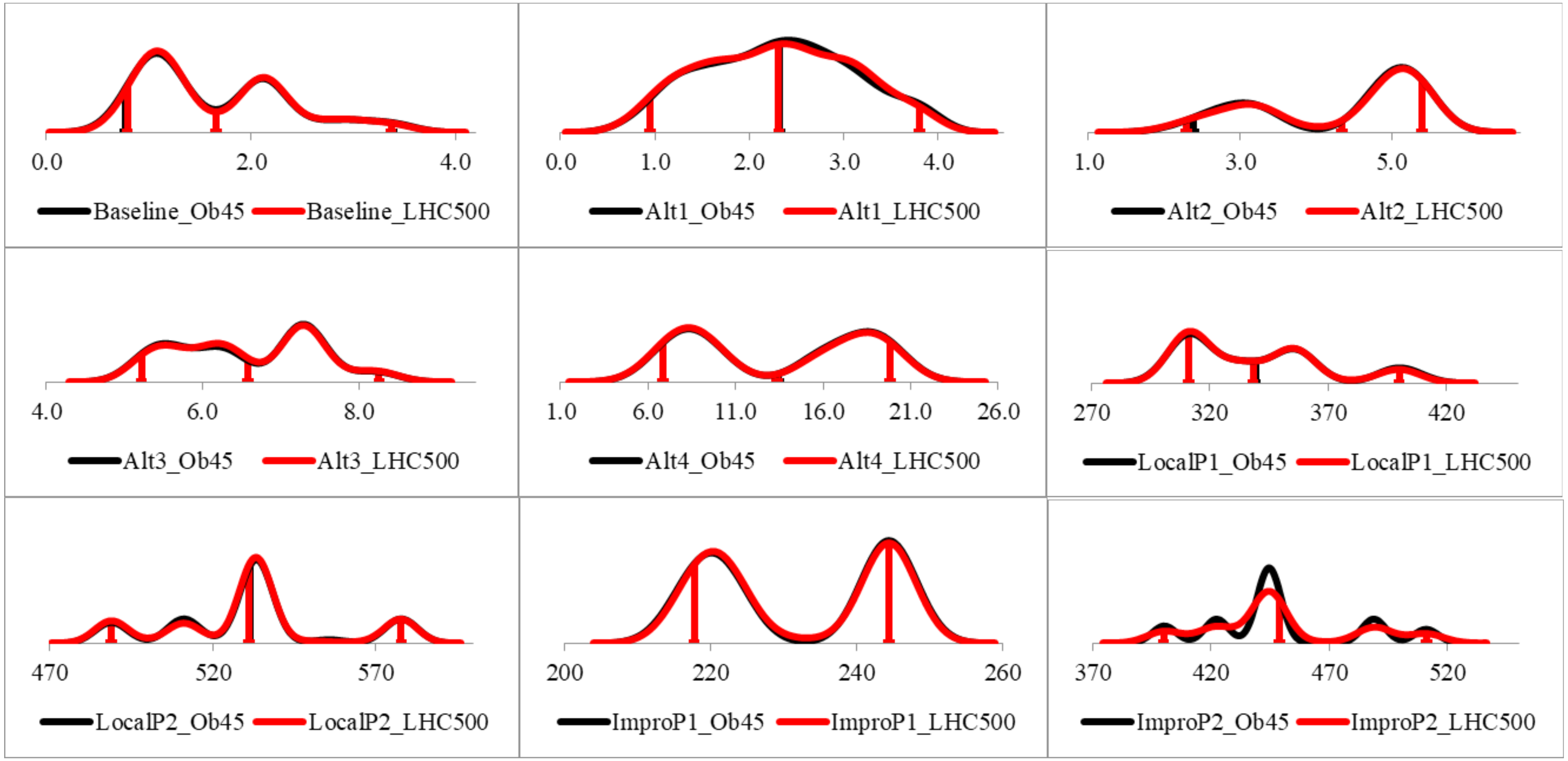

Figure A2. 1. Probability distribution functions for observed vs. 500 simulated stochastic yields and prices: black charts represent the observed sample yields (Baseline_Ob45 to Alt.4_Ob45) and price (LocalP1_Ob45, LocalP2_Ob45, ImproP1_Ob45,ImproP2_Ob45); red charts represent the 500 simulated sample yields (Baseline_LHC500 to Alt.4_LHC500) and price (LocalP1__LHC500, LocalP2__LHC500, ImproP1__LHC500, ImproP2__LHC500). Prices are in TZS. US$1= TZS 2250.

Appendix 5.4. SRI Success Story of Mwanaidi H. Hussen One of the First Farmers to Adopt the Technology

Mwanaidi is one of the first farmers to start using SRI technology soon after she attended the training conducted by the Sokoine University of Agriculture. She is now a focal person in Mkindo village in Mvomero district. The Ministry of Agriculture (MoA) has awarded her prizes for being an example in harvesting more rice per unit area following SRI practices. She is now used by the MoA and other stakeholders to conduct SRI training and demo plots for other farmers. SRI technology has significantly changed her life. Her own success story is as shown in Box 1 below.

"I'm Mwanaidi H. Hussen (Mama Shadidi) joined SRI in 2011 after receiving training from Sokoine University of Agriculture under the supervision of Profs. Mahoo and Kahimba. Since rice farming is my main economic activity, the following year (2012), I applied the knowledge to my own 1 acre. Fortunately, the harvest was four times higher (47 bags) compared to previous yields. In 2013 and 2014, the harvest ranged between 45 to 48 bags and reached 50 bags in 2015. Through SRI, I have achieved the following:

- In the year 2015, I was awarded a prize of 5,500,000 TZS by Morogoro agricultural Authority as the best farmer of the year.
- In terms of food security my family has never suffered from food shortage anymore.
- I always keep ten (10) bags (1 ton) of rice for my family and sell the rest.
- I am now capable of sending my kids to English medium schools and afford the costs.
- I have renovated my house and installed with electricity plus tap water.
- I also conduct SRI pieces of training to my fellow farmers. Taking care of one young orphan boy.
- I built a small fish pond and a vegetable garden around my house, which gives me a small amount of money for my family ...."

CHAPTER SIX

6.0 GENERAL CONCLUSIONS AND RECOMMENDATIONS

The current nature of the agricultural sector and the increased interest in stochastic simulation calls for a review of the techniques available for risk analysis and the viability of agricultural production systems. Likewise, farmers, agribusiness managers, and policymakers are increasingly interested in risk-management tools and policies. One of the main challenges available in the agricultural and agribusiness industry is how to incorporate risk and uncertainties in forecasting and feasibility analyses using time-series or historical data.

The second challenge is how data from biophysical like DSSAT and APSIM can be linked with economic models to can capture risk and uncertainty more comprehensively for better policy decision making. DSSAT and APSIM can be integrated with econometric models and report results beyond the agronomic perspective to socio-economic outlook. The third challenge is how household cross-sectional or panel survey data can be manipulated stochastically to capture the inherent risk and uncertainty. Also, the procedure to incorporate heteroscedasticity of the random variables like prices and yields over time is still a problem.

With the current widespread availability of microcomputers and the increasing computational power of spreadsheets has allowed agricultural analysts to develop stochastic simulation models using Microsoft Excel to meet the growing demand. The current production and price volatilities in the agricultural sector due to climate change and variability, particularly in developing countries, will undoubtedly continue to increase the demand for simulation-based analysis in the future. The main objective of this study was, therefore, to create and demonstrate applied stochastic simulation techniques to be used in addressing the above challenges. Specific objectives of this study were to developed and present user-friendly stochastic models to address these challenges.

The first objective was to develop a stochastic simulation model to evaluate the economic feasibility of three main cereal crops, namely: maize, sorghum and rice for the seven years through 2025. In this regard, a MASORISIM which stands for maize, sorghum and rice simulation model was developed. The MSORISIM designed to incorporate risk and uncertainty associated with productivity and profitability of the selected crops. The model started by converting random variables like prices, yields, production costs, and inflation rates into stochastic form. The stochastic variables were finally used in forecasting and economic analysis. Since the model was simulating random variables (prices and yields) for three crops, it incorporated the correlation among variables and controlled the heteroscedasticity of these variables. Out of this objective, a paper was developed and published to *Agricultural Systems*, a peer-reviewed international journal in the special issue (SI) of Risk Management in Agriculture: what challenges and prospects? The electronic version of the paper is available at [https://doi.org/10.1016/j.agsy.2019.102693]

The second objective was to develop and illustrate a bio-economic simulation model to evaluate the benefits of recommended management practices on maize production. The bio-economic simulation is an integrated decision support system (IDSS) which links data from biophysical and econometric models for comprehensive decision-making. Maize yield data from APSIM and DSSAT crop models were made stochastic using a Monte Carlo simulation procedure. The stochastic yield was combined with other random variables like prices and production costs to develop a complete IDSS for evaluating the economic feasibility of maize with and without farm management practices. A manuscript was produced and published to *Agricultural Systems*, an international peer-reviewed journal and the electronic copy of the paper is available at [https://doi.org/10.1016/j.agsy.2020.102948].

The third objective was to conduct scenario analysis on rice farming systems in Tanzania to identify the system which has the highest potential to farmers. Traditional and improved rice farming systems were analysed and compared to one another using a Monte Carlo simulation protocol. The risk associated with each rice farming system was included in the analysis. A manuscript was developed and published to *Sustainability* a peer-review journal of MDPI. The manuscript belongs to the SI of Suitable Agronomic Techniques for Sustainable Agriculture and can be accessed at [https://doi.org/10.3390/su12166528].

6.1 Contribution of the Study to Knowledge

The vital contribution of this study is the application of a Monte Carlo simulation approach to develop and demonstrate user-friendly stochastic risk simulation tools over deterministic models. Scholarly, the work has increased the number of references on the application of stochastic risk in agricultural production, which were relatively low in Tanzania. Unlike conventional, forecasting methodologies, the MASORISIM helps in the inclusion of risk and uncertainties in the forecasting of stochastic variables that have a critical impact on farm net cash returns.

Moreover, this study's contribution is the development of IDSS model where data from biophysical models like APSIM and DSST are linked with econometric models for enhanced decision making. There are a limited number of studies (if any) in Tanzania and SSA which are linking data from process-based models in simulating risks and uncertainties on crop yields. With the current increase in global concern on integrated risk assessment studies [www.agmip.org], this study, therefore, addresses the existing gap by demonstrating how biophysical models can be linked with economic models to develop a bio-economic IDSS model. The IDSS was then used to assess the economic feasibility of application of 40 kg N-fertilizers per ha and adjustment in plant population of 33 000 plant population per ha on maize sub-sector. The study also performed a scenario analysis which is a state-of-the-art approach to identify rice farming systems with the highest potential in Tanzania.

6.2 Areas for Further Research

The analysis of this study was based only on two agro-ecological zones (semi-arid and sub-humid). Drawing conclusions for policies at the national level could be inappropriate. With the availability of time series and national panel data, it would be essential to conduct similar studies at the national level to include other agro-ecological zones. The developed approach is operationally feasible because the algorithms used in this study are applicable at any scale, including the national. The MASORISIM model can be fabricated to include more crops than only maize, sorghum and rice. The model can also made-up to include all regions of Tanzania than only Dodoma and Morogoro. However, accurate and timely yield and price forecasts for main crops at a national level will provide a reliable roadmap of the whole Tanzania, particularly the Ministry of Agriculture and other agriculture sector development initiatives.

The procedures used in developing the IDSS bio-economic simulation model was based only on two management practices (N-fertilizer and plant population) on maize production. The model can be modified to analyse an array of technologies for different crops and site-specific. Likewise, similar studies on other important crops that are essential in maintain food security in Tanzania can be conducted. The study also did not include cash crops such as cotton, coffee, sisal, and sugarcane, which are critical for generating foreign income. Also, the model applied to this study can be modified to analyse the entire country or all agro-ecological zones.

Since the government aims to end hunger and reduce poverty of the majority by at least 50% in 2025 through doubling agricultural production for sustainable national food security and nutrition, farmer income and economic growth. This calls for different scenario analyses to identify farming systems which are potential for increasing farm productivity and profitability. For example, application of SRI was found to be the best alternative in rice production in Tanzania which needs to be emphasized by the government. This approach can be applied to an array of management practices, including crop rotation, mulching, improved irrigation, agroforestry, terraces, contours, beekeeping, rainwater harvesting, fishing, and tower garden.

With evidence from crop models like APSIM and DSSAT, bio-economic integrated studies are, however, needed to explore the potential of more crop management practices and technologies for better decision-making. This study forms a basis for more risk analysis studies to improved decision marking for farmers, government, and stakeholders in the agricultural sector.

Nevertheless, this study has a vital implication on the policy environment. For instance, the Tanzania Development Vision 2025, emphasizes that by "*2025 the agricultural economy will have been transformed from low productivity to a semi-industrialized sector, led by modernized and highly productive agricultural activities which are effectively integrated and buttressed by supportive industrial and service activities in the rural and urban areas*". Likewise, the ASDP-2, the Tanzania Agriculture and Food Security

Investment Plan (TAFSIP) and the CAADP were formulated to assist the achievement of TDV 2025. However, this study has revealed that there is still uncertainty in productivity and profitability of key crops in Tanzania unless farmers apply are encouraged to use the recommended farm management practices. There is, therefore, a need to conduct similar studies to assess the outlook of agricultural production by 2025 and further and highlight the benefits of different farm options that can be utilized for increased productivity and profitability of the selected sectors.