FORECASTING YIELD AND PROFITABILITY OF MAIZE CROPPING SYSTEM USING SIMULATION MODELS IN UASIN GISHU, KENYA

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Abstract

Simulation models have been used successfully to forecast productivity of cropping systems under various weather, management and policy scenarios. These models have helped farmers make efficient resource allocation decisions. However, in Kenya simulation models have not been used extensively and more specifically in modeling maize cropping system. The study aimed at forecasting productivity and profitability of maize cropping system in Uasin Gishu district, Kenya. Both primary and secondary data were used. Both time series and cross-sectional data for variables of interest were collected and complemented by a survey of 20 maize farmers who were systematically selected to verify information obtained from secondary sources. Cropping Systems simulation model and Monte Carlo simulation were used to determine maize output and profits under alternative price scenarios. Even though, simulated yields under-estimated actual maize yield both at the district and across the four agro-ecological zones, the deviation from the actual yield was marginal. It is recommended that Cropsyst and Monte Carlo models be included among a bundle of tools for decision making. Further research is also required to test the two models under different locations, soil types, management styles and scales of production.

Key Words: Forecasting, Yields, Profits, Maize cropping system, Simulation models

1   Introduction

Mathematical models are now valuable tools for representing the long-term productive and environmental effects of different cropping systems and extrapolating the experimental results in time and space (Grabisch, 2003). Cropping systems are part of Agricultural Systems which all fall under the General systems. According to Dillon (1992), an agricultural system is an assemblage of components which are united by some form of interaction and interdependence and which operate within a prescribed boundary to achieve a specified agricultural objective on

behalf of the beneficiaries of the system. Agricultural systems must therefore be evaluated in order to determine whether or not the desired objectives are being met.

Evaluation of agricultural systems consists essentially of measuring how adequate and effective an existing system has been in achieving its objectives over some past operating phase (season or operating year). There are diverse farming system properties that are normally evaluated, such as generation of maximum net income/profitability of the system in money terms - either directly for market-oriented farms or indirectly by imputation of values for subsistence-oriented farms; sustainability; and environmental compatibility (Dillon and Hardaker, 1993; Upton, 1987). Other key properties of agricultural systems evaluated include productivity, stability, diversity, flexibility, and time-dispersion. In Kenya, Simulation models have not been used on large scale cropping systems as a tool to determine, predict and forecast the behaviour/properties of cropping systems such as crop growth and productivity. Currently, yield from cropping systems is determined only through experimentation, field research or on-farm trials, which are reported to have several shortcomings. There is therefore a need to apply simulation models to cropping systems in Kenya. According to Kothari (1999) and Kelton et al., (2003), simulation is the next best alternative to experimentation or observing a real system and as stated by Staggenborg et al. (2005), crop simulation models assist scientists in making more efficient use of resources by providing an insight on potential plant responses to alterations in cropping systems. Crop simulation models can also be used as decision tools to improve the efficiency of input management for cropping systems and minimize negative environmental impacts (Alva et al., 2004).

2   Theoretical Considerations
2.1   Modeling Production Behavior

Producer's objective in a classical sense is to maximize output so as to reap more profits (Varian, 1992; Jehle et al. 1998 and Mas Collel, 1995). Such behavior can be modeled using a profit function approach, production function approach, cost function approach, or through mathematical optimization and dynamic programming. Given price taking, profit maximizing and a model of the physical production process, it is possible to derive a model of producer output and input decisions. When using the profit function approach, the model can be specified as (equation 2.1):

$$\pi(p,w) = \max \; p.y - c(y,w) \qquad (2.1)$$

Where p, y, w, x and c(y,w) are output price, output, price vector of n inputs($w_1...w_n$), quantity vector of n physical inputs($x_1...x_n$) and cost function -minimum amount of money needed to purchase inputs at input prices, w, that will produce output y. The profit function can be re-stated as (equation 2.2):

$$\pi(p,w) = \max \; p.y - wx(y,w) \qquad (2.2)$$

Maximization of the profit requires that price equals marginal cost and the value of y that maximizes profits is supply (equation 2.3) (Varian, 1992, Jehle and Reny, 1998).

$$\frac{\partial \pi(.)}{\partial y} = p - \frac{\partial c(.)}{\partial y} = p - mc(.) = 0 \qquad (2.3)$$

This can be expressed as $p = mc$, where p is the output price and mc is the marginal cost. Using Hotteling's lemma (Varian, 1992, Jehle and Reny, 1998), the derivative of the profit function, with respect to input price, is a factor demand (equation 2.4) and, with respect to an output price, is the supply function (equation 2.5).

$$\frac{\partial \pi(.)}{\partial w} = - \frac{\partial c(.)}{\partial w} = - x(.) \qquad (2.4)$$

$$\frac{\partial \pi(.)}{\partial p} = y(.) \qquad (2.5)$$

3

In Uasin Gishu district, Kenya, maize farmers are commercial and therefore driven by the profit motive. Therefore, modeling using the profit approach is more appropriate. Production functions and cost function approaches can be used to model producer behaviors in a set up with minimal marketed commodity. However, while stochastic analysis of profit, production and cost functions determines the significance of some variables, it does not tell us how much of each variable input should be used to achieve optimal output. Similarly, stochastic models are deficient in their ability to capture various policy alternatives. This calls for application of other analytical tools for testing alternative policy scenarios and forecasting production dynamics. Such tools include mathematical optimization, dynamic programming and simulation analysis. This study adopted cropping system simulation (Cropsyst) and Monte Carlo models to simulate productivity and profitability of maize production system.

2.2 Model Specification

The study used two simulation models namely Cropsyst and Monte Carlo. The Cropsyst model is premised on the assumption that actual biomass/output growth is a result of interactions involving various independent variables which include weather, soil types, management practices and crop physiology. The Cropsyst model is specified in figure 2.1:
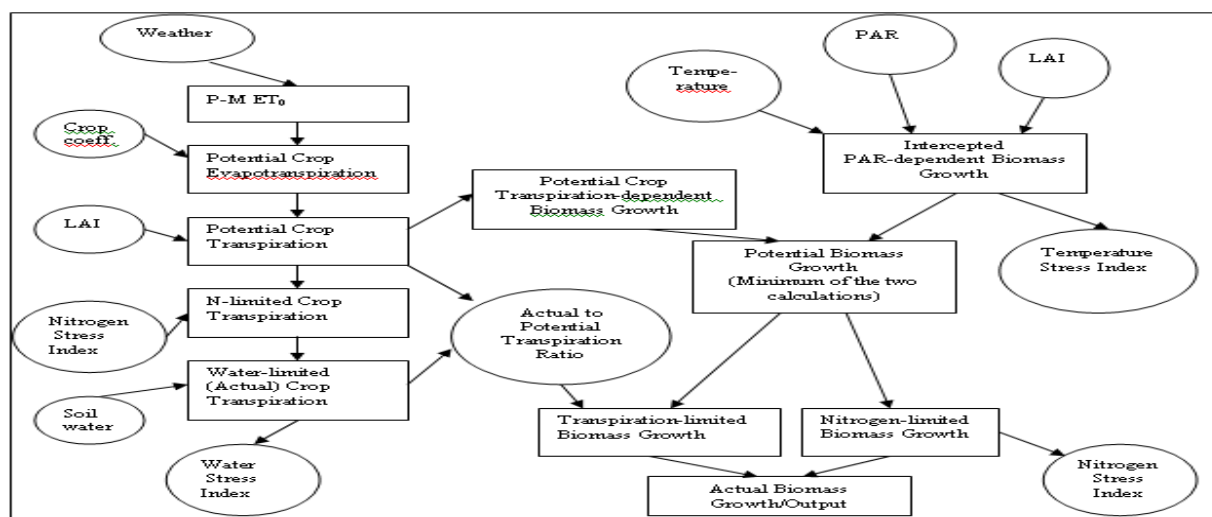

Figure 2.1: Flowchart of biomass growth calculations in CropSyst

Source: Adopted from Stockle et al., 2003

The Monte Carlo Model is premised on the assumption that inputs are fed into the model to generate outputs. The schematic representation of Monte Carlo simulation Model used in this study is as shown in figure 2.2:
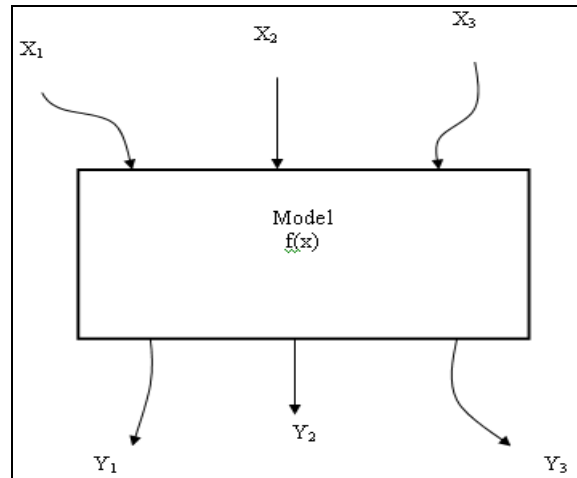

Figure 2.2: Schematic representation of Monte Carlo simulation Model

Source: Adopted from Lordanova, 2007

Where X_i, $f(x)$ and Y_i are inputs, model interactions and output/results respectively. The procedure followed in the Monte Carlo simulation model is as follows:

Step 1: Creation of a parametric model

$$Y = f(X_1, X_2 \cdots X_q) \tag{2.6}$$

Step 2: Generation of a set of random inputs

$$X_1, X_2 \cdots X_3$$

Step 3: Evaluation of the model to give results as Y_i

Step 4: Repeat of steps 2 and 3 for $i = 1$ to n

Step 5: Analysis of the results using histograms and summary statistics.

Triangular distribution can be done for the different input scenarios because it is a continuous distribution whose specification requires elicitation of only three values of the risky variable - its lowest, highest and most likely values denoted in the model matrix as respectively, by *a, b* and

5

m. The formula for the triangular distribution for an uncertain variable *X* is given by equations 2.7 and 2.8:

$$f(X) = 2(X - a)/(b - a)(m - a), X < m \tag{2.7}$$

$$f(X) = 2(b - X)/(b - a)(b - m), X > m \tag{2.8}$$

The formula for its cumulative distribution function *(CDF)* is given by equations 2.9 and 2.10:

$$F(X) = (X - a)^2 / (b - a)(m - a), X < m \tag{2.9}$$

$$F(X) = 1 - (b - X)^2 / (b - a)(b - m), X > m \tag{2.10}$$

The mean *E(X)* and variance *V(X)* of the triangular distribution is found as equations 2.11 and 2.12 respectively:

$$E(X) = (a + m + b)/3 \tag{2.11}$$

$$V(X) = \left[(b - a)^2 + (m - a)(m - b) \right] / 18 \tag{2.12}$$

3   Materials and Methods

The study area was Uasin Gishu District which is located in the Rift Valley Province of Kenya (figure 3.1). The study sites were Turbo, Timboroa, Kuinet and Ilula.
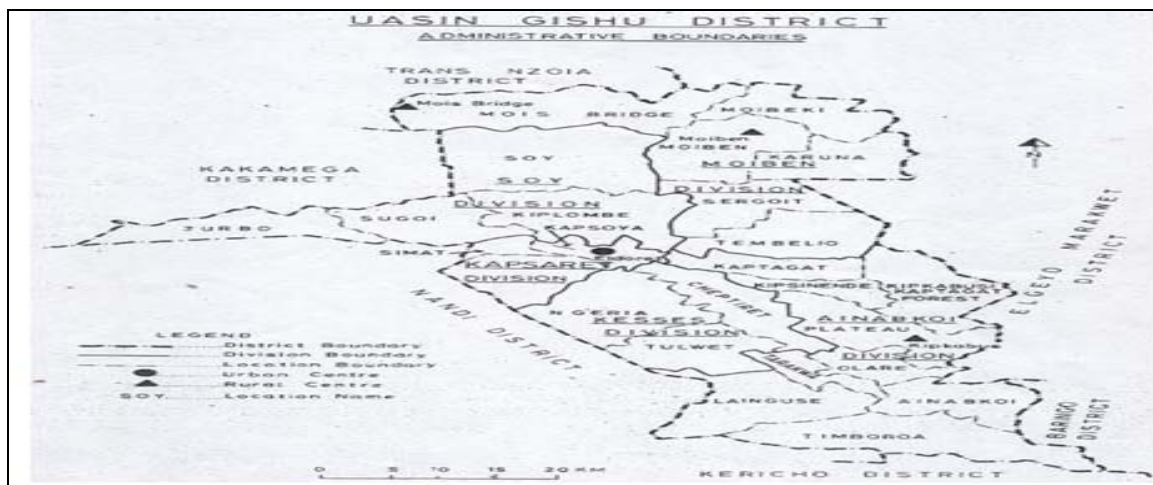

Figure 3.1: Map of Uasin Gishu District

Source: Uasin Gishu District Physical planning department, 2009

Both Primary and Secondary data was used. Data on maize output, prices, input cost, annual rainfall and temperature for the district was used. Secondary data was obtained from statistical abstracts, Uasin Gishu District development plans, and from annual agricultural reports in the Ministry of Agriculture offices in Uasin Gishu District. A survey of 20 maize farmers who were systematically selected was done to verify information obtained from secondary sources before feeding into the Cropsyst and Monte Carlo models. The first farmer was selected randomly and subsequent farmers were selected by skipping every two farmers. An interview schedule was prepared, pre-tested, refined before interviews were held for the selected maize farmers.

CropSyst model was used in the analysis of maize output. CropSyst requires data collected be organized into five input data files that are required to run CropSyst namely; simulation control, location, soil, crop, and management. Similarly, growth in output in the cropping system is a result of interactions between key variables in the cropping system. The output of the maize cropping system, together with other exogenous variables was used to determine other properties of the maize cropping system, such as profitability. Base budgets for simulation analysis of maize cropping system were developed using the profit function. The base budgets were then input into Monte Carlo Simulation Model to determine the profitability of maize farming in Uasin Gishu District through scenario analysis. Different price scenarios, which represented the most common market outlets for maize in Uasin Gishu in 2007, were used in the analysis namely: Scenario 1: Government/National cereals and produce board (NCPB) price of Kshs. 1,300; Scenario 2: Unga Limited (a private company) price of Kshs. 1,450; Scenario 3: private speculators price of Kshs. 1,300 – 1,700 (a triangular distribution of minimum price of Kshs. 1,300, mean price of 1,500, and maximum price of Kshs. 1,700 was adopted); Scenario 4:

middlemen price of Kshs. 800 - 1,000 (a triangular distribution of minimum price of Kshs. 800, mean price of 900 and maximum price of Kshs. 1,000 was adopted).

In Monte Carlo simulation, random inputs (X_{i1}, X_{i2} ------- X_{iq}) used were the base budget inputs and various price scenarios while the parametric model ($y= f(X_1, X_2,.......X_q)$) linked the base budgets and price scenarios to yield the outcome/results. The model was then run to produce results (Yi) in the form of profitability gains of each price scenario for one run. The model was re-run (Repeat of steps 2 and 3 for i = 1 to n) 2,000 times to achieve high degree of accuracy. The results were analyzed and presented as histograms.

4   Results and Discussion

4.1   *Simulated Yield of Maize using CropSyst model*

The actual and simulated yield of maize using CropSyst model for the four locations in Uasin Gishu District is shown in Table 4.1. Results of simulated yield show that Turbo produces the highest yield of maize averaging at 53 bags/ha while Timboroa the lowest yield with only 22 bags/ha which is in line with actual yields reported in the four agro ecological zones in the district which represent different peculiarities in the soil types and microclimates in those zones. The average district simulated yield was estimated at 32 bags/ha which is also consistent with the actual district average figure.

Table 4.1: Yield of Maize under field and CropSyst simulation model by location

Location	Actual Yield (Bags/Ha)	Simulated Yield (Bags/Ha)	% Deviation	d
Kuinet (Ziwa)	32	28.158	(-) 12.006	0.930
Timboroa	29	21.748	(-) 25.007	0.796
Turbo	56	52.641	(-) 5.999	0.958
Illula	31	24.842	(-) 19.865	0.895
District Average	37	31.847	(-) 15.719	0.895

Source: Author's Survey, 2009

Comparison between actual and simulated maize yields revealed that simulated values underestimated actual maize yield in Kuinet, Timboroa, Turbo and Illula by 12, 25, 6 and 20 percent respectively. Similarly, the district actual maize yield is also underestimated by 16 percent. Results also show very high values for Willmott index of agreement (d) (table 4.1) for both the district average and the four agroecological zones signifying a very high level of accuracy. Stokle et al (2003) noted that simulation models can underestimate the yield of maize by upto 27 percent, without necessarily undermining reasonability of estimates obtained. All the simulated yields therefore are within what can be termed as reasonable estimates of the actual farmers' yield and therefore they can be used for planning and decision making. The results have also shown that despite heterogeneity in the four agro ecological zones evaluated, Cropsyst has showed a consistent pattern of estimates which are all in line with observed maize yield.

4.2   *Maize Profitability using Monte Carlo Simulation model*

Figure 4.1 shows probable profitability gains of maize farming under scenario 1, whereby the maize farmer targets to dispose the produce at Kshs.1,300 per bag to the National Cereals and produce Board. The average profitability gain attainable by a maize farmer is estimated at Kshs.

9,782 per hectare with a probability of this scenario occurring estimated at 0.45. However, the maize farmer can make a maximum profit of up to Kshs. 24,835 with a probability of 0.88. Similarly, a maize farmer can also make losses of up to Kshs. 7,551 with a probability of 0.12.
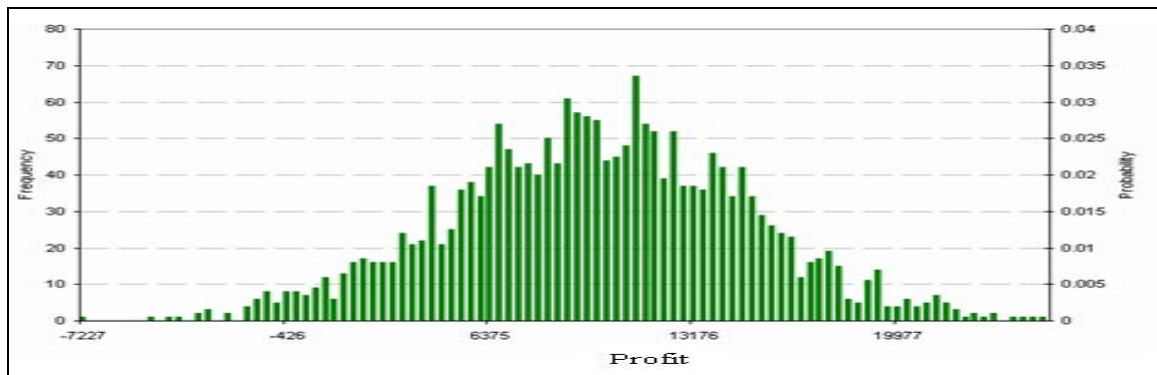

Figure 4.1: Maize net returns/profits in scenario 1 and their probabilities

Source: Author's Survey, 2009

The profitability gains of maize farming in scenario 2, where a maize farmer receives Kshs. 1,450 per bag from Unga Ltd is shown in figure 4.2. Average simulated maize profits are estimated at Kshs. 15,444 per hectare with a probability of 0.45. However, maize profits can go as high as Kshs. 33,319 with a probability of 0.93. Similarly, a maize farmer can also make losses of up to Kshs. 2,548 with a probability of 0.07.
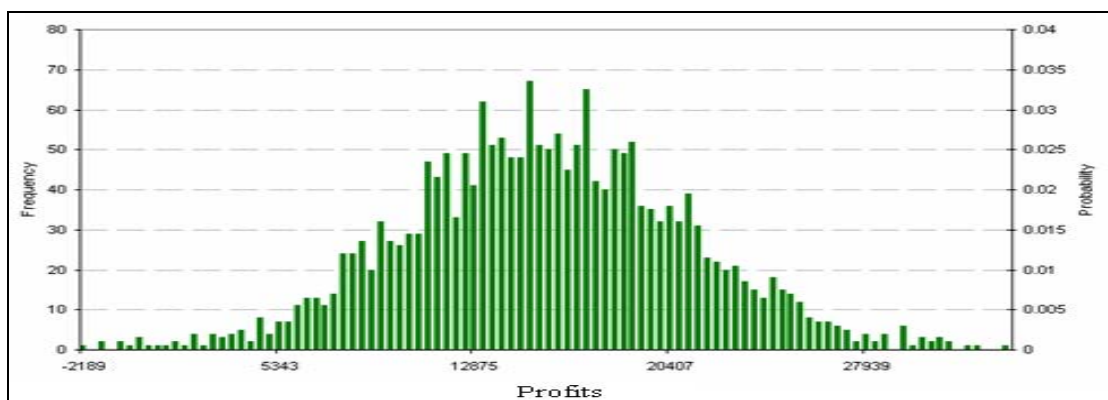

Figure 4.2: Maize net returns/profits in scenario 2 and their probabilities

Source: Author's Survey, 2009

The profitability gains of maize farming in scenario 3, where a maize farmer sells his produce to maize price speculators at a price of Kshs. 1,300 – 1,700 per bag is shown in figure 4.3. In this case, average simulated maize output is a profit of Kshs. 17,128 per hectare with a probability of this occurring being 0.45. Similarly, a maize farmer can make a maximum profit of Kshs. 35,680 with a probability of 0.94. However, losses of up to Kshs. 1,599 can be incurred by maize farmers with a very low probability of 0.06.
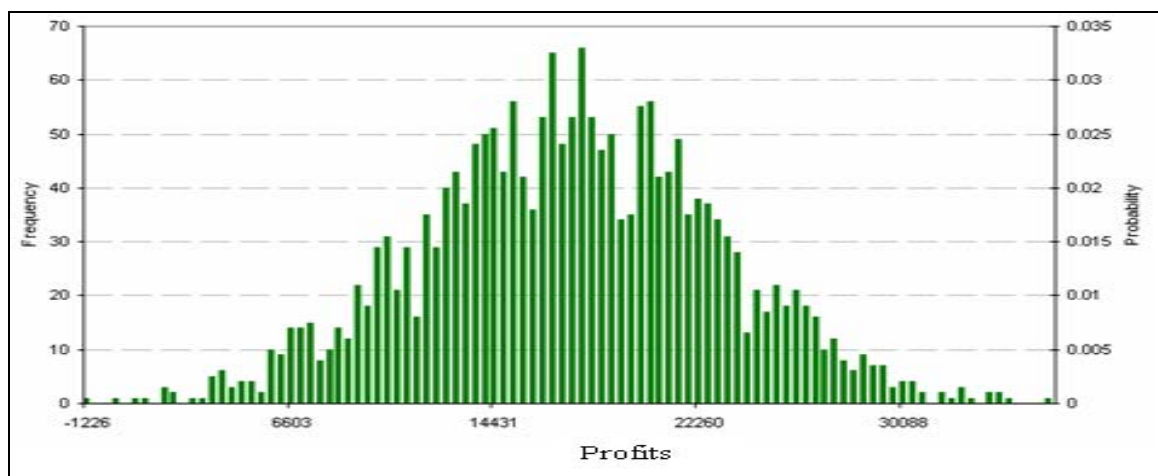

Figure 4.3: Maize net returns/profits of scenario 3 and their probabilities

Source: Author's survey, 2009

The profitability gains of maize farming in scenario 4, where a maize farmer sells his produce to middlemen at a price of Kshs. 800 – 1,000 per bag is shown in figure 4.4. In this case, average simulated maize output is a loss of Kshs. 4,973 per hectare with a probability of this occurring being 0.55 and could go to as high as Kshs. 17,834 with probability of this occurring being 0.95. However, the highest maize profitability realizable under this scenario is Kshs. 6,404 with a remote probability of 0.05.
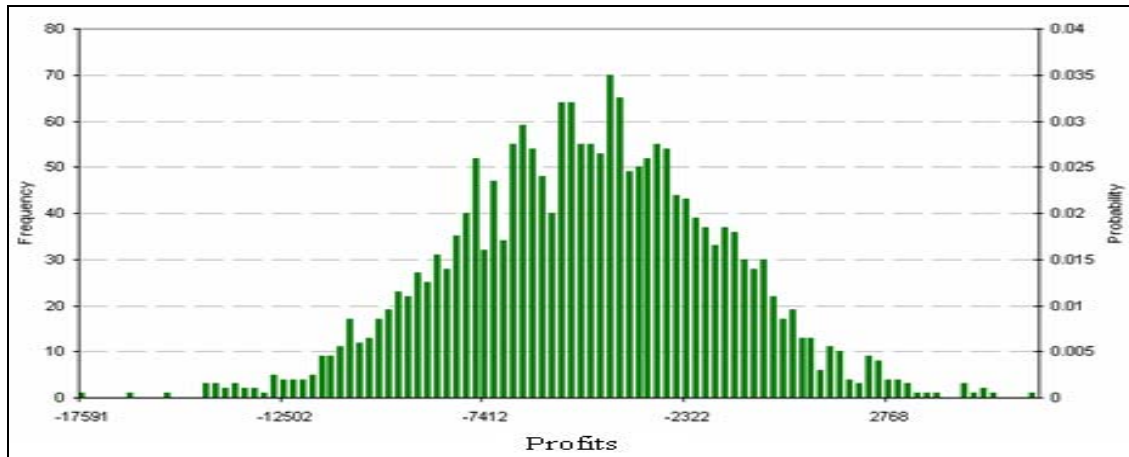
Figure 4.4: Maize net returns/profits of scenario 4 and their probabilities

Source: Author's survey, 2009

Evaluation of the four scenarios shows that their ranking on the basis of maize profitability identified scenario 3, which is associated with the private maize price speculators as the most profitable alternative with a profit of Kshs. 17,128, followed by scenario 2, which is associated with Unga Ltd with a profit of 15,444, scenario 1 which is associated with NCPB with a profit of Kshs. 9,782 and finally scenario 4 associated with middlemen with a loss of 4,973. In addition, chances of the aforementioned scenarios occurring were more or less the same implying that on the basis of profitability alone a policy implication for both farmers and policy makers can be derived from the results. This can, therefore, be used to advise both policy makers and maize farmers on strategies of ensuring maize farming remains a profitable venture despite uncertainties in the farming process as noted by Fleisher (1990) and Giardini, et al (2004). Farmers would, therefore, be advised to choose their selling points wisely given information on prices and other variables such as promptness in payment and reliability of the buying agents. Policy makers would be advised to use institutions such as marketing boards to ensure that players in the maize market do not charge prices below break

even point and information flow is enhanced to elimination of information asymmetry among market stakeholders.

5   Conclusions and Recommendations

It is concluded that simulated maize yield was highest in Turbo and lowest in Timboroa which is consistent with actual yields reported in the district. Similarly, even though, simulated yields under-estimated actual maize yield both at the district and across the four agro-ecological zones, the deviation from the actual yield was marginal. Additionally, CropSyst model can also be used under heterogeneous conditions and still give reasonable estimates of actual farm yields. It is also concluded that among the four maize profitability scenarios evaluated, scenario 3 was most profitable while scenario 1 was least profitable with equal chances of occurrence. However, scenario 4 is unsustainable due to farmers' exposure to losses. This confirms that both CropSyst and Monte Carlo models are efficient and consistent forecasters of productivity and profitability in cropping systems.

It is recommended that both Cropsyst and Monte Carlo models be incorporated among the Ministry of Agriculture decision making tools for facilitating informed decision by maize farmers. It is also recommended that polices be put in place to improve farmers' access to information on alternative causes of action and their consequences thus eliminating risks and uncertainties associated with maize production. Further research is also required to test the two models under different locations, soil types, management styles and scales of production.

REFERENCES

Alva, A. Marcos, J. Stockle, C. Reddy, V. and Timlin, D. 2004. CropSyst VB – Simpotato, a Crop Simulation Model for Potato – Based Cropping Systems: II. Evaluation of Nitrogen Dynamics. *Agronomy Journal*. 84: pp 911 - 915.

Dillon, J.L. and Hardaker, J.B. 1993. *Farm Management Research for Small Farmer Development*, FAO Farm Systems Management Series No. 6, Food and Agriculture Organization of the United Nations, Rome.

Dillon, J.L. 1992. *The Farm as a Purposeful System*, Miscellaneous Publication No. 10, Department of Agricultural Economics and Business Management, University of New England, Armidale.

Giardini, L. Berti, A. and Morari, F. 2004. Simulation of two Cropping Systems with EPIC and CropSyst Models. *Italian Journal of Agronomy*. 2, 1, 29 – 38.

Grabisch, M. 2003. Temporal scenario modeling and recognition based on possibilistic logic. *Elsevier Science Publishers Ltd. Essex, UK*. Pp 261 – 289.

Fleisher, B. 1990. *Agricultural Risk Management*, Lynne Rienner Publishers, Boulder.

Jehle G.A. and P J. Reny(1998): *Advanced Microeconomic Theory*. Addison Wesley Longman, Inc.

Kelton, W. D., Sadowski, R. P. and Sadowski, D. A. 2003. Simulation with Arena. 2nd Edition. McGraw Hill, London.

Kothari, C. R. 1999. Quantitative Techniques. Third Revised Edition.. East African Educational Publishers, Nairobi, Kenya.

Lordanova, T. (2007): Introduction to Monte Carlo Simulation. *The Wall Street Journal*. London Pg 1-4.

0Staggenborg, A. S., and Vanderlip, L. R. 2005. Crop Simulation Models Can be Used as Dryland Cropping Systems Research Tools. *Agronomy Journal*. 97: pp 378 – 384.

Stockle, C. O, Donatelli, M. and Nelson, R. 2003. CropSyst, a cropping systems simulation model. *European Journal of Agronomy* 18 (2003). pp 289 – 307.

Upton, M. 1987. *African Farm Management*, Cambridge University Press.

Varian H.R (1992): *Microeconomic Analysis* 3rd Ed. W.W. Norton & Company, New York.