FORECASTING WHEAT OUTPUT AND PROFITS FROM CROPPING SYSTEMS USING SIMULATION MODELS IN UASIN GISHU, KENYA

By

NYANGWESO, P.M; ODWORI, PAUL OKELO; MAPELU, M.Z;

and ODHIAMBO, M.O

FORECASTING WHEAT OUTPUT AND PROFITS FROM CROPPING SYSTEMS USING SIMULATION MODELS IN UASIN GISHU, KENYA

[1]NYANGWESO, P.M [2]PAUL OKELO ODWORI; [3]MAPELU, M.Z; and [4]ODHIAMBO, M. O

[1;2; 4]Department of Economics and Agricultural Resource Management, Moi University, P.O. Box 1125, Eldoret, Kenya.
[3] Department of Physics, Moi University, P.O. Box 1125, Eldoret, Kenya.
*Corresponding author; Email: philoe2000@yahoo.com

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 large scale cropping systems. The study aimed at forecasting productivity and profitability of wheat cropping systems 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 wheat farmers who were systematically selected to verify information obtained from secondary sources. Cropping Systems simulation model and Monte Carlo simulation were used to determine wheat output and profits under alternative price scenarios. Even though, simulated yields over-estimated actual field wheat yield both at the district and across the four agro-ecological zones, the deviation from the actual field 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, diverse soil types, varied management styles and different scales of production.

Key Words: Wheat, cropping system, simulation, forecasting, productivity, profits.

1   Introduction

Simulation models such as Agricultural Production Systems simulator (APSIM) and Cropping Systems simulation model (CropSyst) have been used successfully in cropping systems in many countries such as Italy, Turkey, United States of America, Spain, and in Tunisia (Giardini et al., 2004; Bocchi et al., 2001; Fila et al., 2003). According to Giardini et al. (2004), these models give reasonable estimates of crop growth and yields.

Models have been used extensively in analysis of agricultural production systems. Models have been used `as decision support tools in dairy nutrient management (Alva et al., 2004); the

simulation model CropSyst has been applied to an intensive forage system in Northern Italy (Grabisch, 2003). A crop simulation model has been used to study the impact of climate change on wheat and sunflower yields (Grabisch, 2003); and the CropSyst simulation model has also been used to study growth of maize under different organic and mineral fertilization regimes (Donatelli et al., 2003; Fila et al., 2003).

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 also 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   =   Price of output.

     y   =   Quantity of output.

     w   =   Price vector of n inputs, (w1...wn).

     x   =   Vector of n physical input quantities used in production, (x1...xn).

     C(y,w) =   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, 1993, 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, 1993, 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).

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

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

In Uasin Gishu district, Kenya wheat farmers are entirely commercial and therefore are driven by the desire to maximize profits. 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 productitivity and profitability of wheat 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:
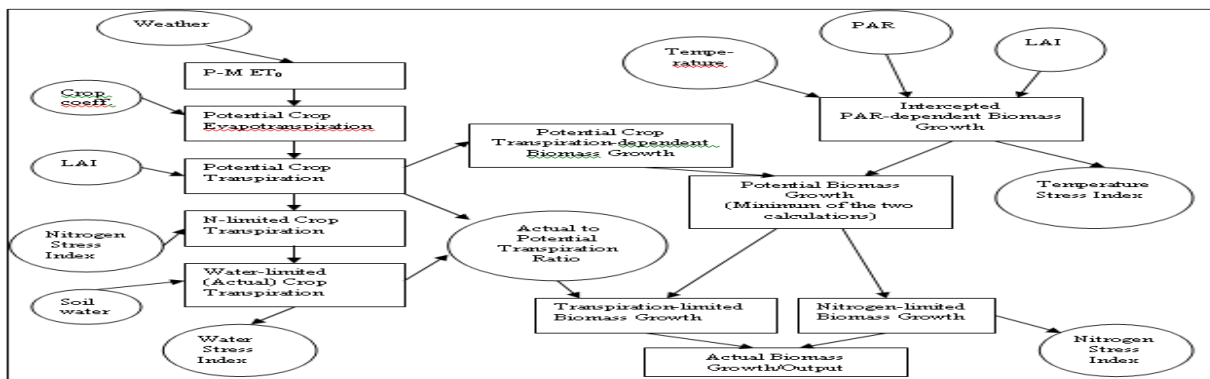
Figure 2.1: Flowchart of biomass growth calculations in CropSyst

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 follows:
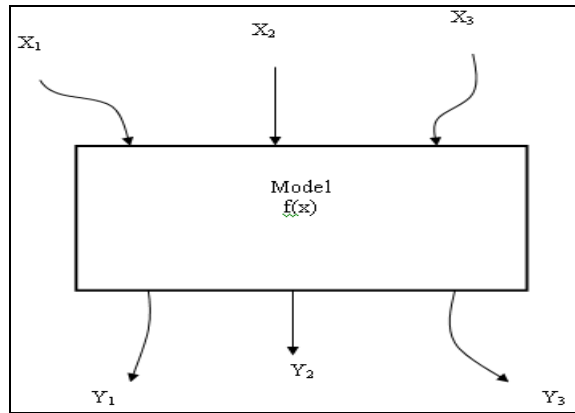
Figure 2.2: Flowchart of biomass growth calculations in CropSyst

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

$$Y = f (X_1, X_2, ...X_q)$$

Step 2: Generation of a set of random inputs
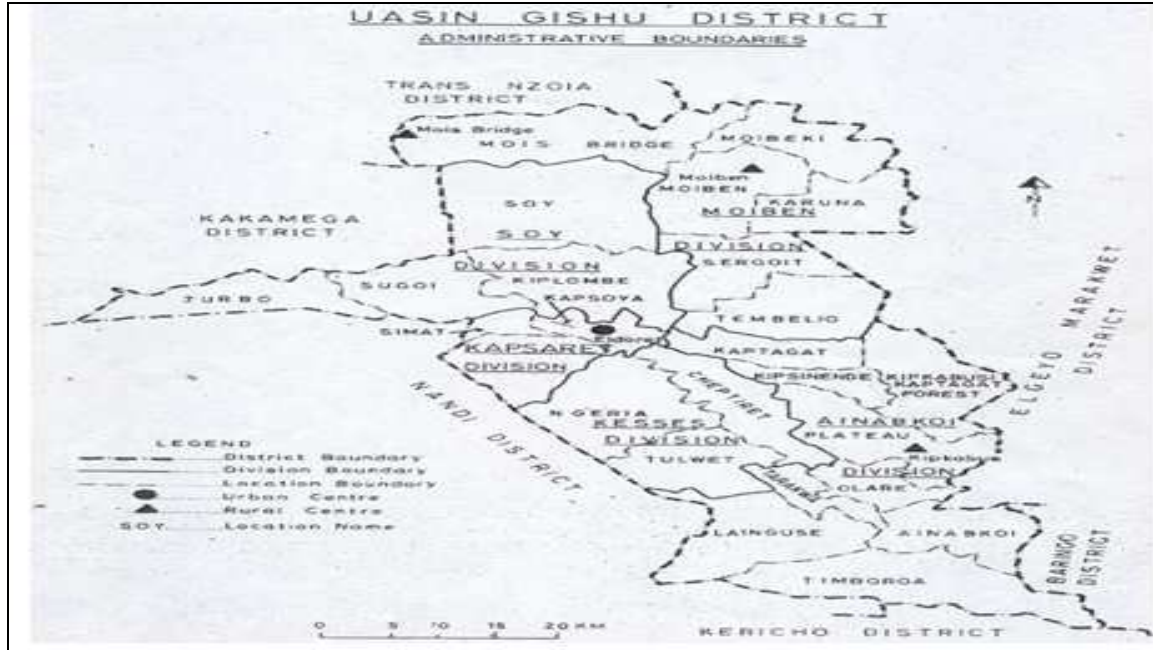
$$X_{i1}, X_{i2},...........X_{i\,q}$$

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.

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 wheat 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 wheat 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, pretested, refined before interviews were held for the selected wheat farmers.

CropSyst model was used in the analysis of wheat 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 wheat cropping system, together with other exogenous variables was used to determine other properties of the wheat cropping system, such as profitability. Base budgets for simulation analysis of wheat cropping systems were developed using the profit function. The base budgets were then input into Monte Carlo Simulation Model to determine the profitability of wheat farming in Uasin Gishu District through scenario analysis. Different price scenarios, which represented the most common market outlets for wheat in Uasin Gishu in 2007, were used in the analysis namely: Scenario 1: Unga Limited (a private company) price of Kshs. 2,600; scenario 2: middlemen price of Kshs. 1,950 and scenario 3: hypothetical case of reduced market price of Kshs. 1,500.

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 Wheat using CropSyst model

The field and simulated yield of wheat using CropSyst model for the four locations in Uasin Gishu District is shown in Table 4.1. Results of simulated yield show that Illula produces the highest yield of wheat averaging at 38 bags/ha while Timboroa the lowest yield with only 25.6 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 30.6 bags per hectare.

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

| Location	Actual Yield (Bags/Ha)	Simulated Yield (Bags/Ha)	% Deviation	d
Kuinet (Ziwa)	26	28.339	(+) 8.996	0.934
Timboroa	24	25.571	(+) 6.546	0.948
Turbo	27	30.686	(+) 13.652	0.928
Illula	32	37.987	(+) 18.709	0.908
District Average	27	30.646	(+) 11.976	0.930

 Source: Author's Survey, 2009

Comparison between actual and simulated yields revealed that simulated yields over-estimated actual field wheat yield in Kuinet, Timboroa, Turbo and Illula by 8.996, 6.546, 13.652 and 18.709 percent respectively. Similarly, simulated district average wheat yield over-estimated actual district wheat yield by 11.976 percent. Results also show very high values for Willmott index of agreement (d) (table 4.1) for Kuinet, Timboroa, Turbo and Illula signifying a very high level of accuracy. Stokle et al (2003) and Staggenborg et al., (2005), noted that simulation

models can over-estimate the yield of wheat by upto 16 % but are still considered reasonable estimates of the actual farmers' yield. All the simulated yields therefore are within what can be termed as reasonable estimates of the actual farmers' yield and can be used for planning and decision making. The results have also shown that though CropSyst model is intended for crop growth simulation over a single land block fragment with uniform soil, weather, crop rotation and management, the model can also be used in some heterogeneous conditions (like the varying soil types of the district) and still give reasonable estimates of actual farm yields that can subsequently be used for making decisions and so act as a support tool for planning at the farm level.

4.2   *Wheat Profitability using Monte Carlo Simulation model*

Figure 4.1 shows probable profitability gains of wheat farming under scenario 1, whereby the wheat farmer targets to dispose the produce at Kshs. 2,600 per bag to Unga Limited.
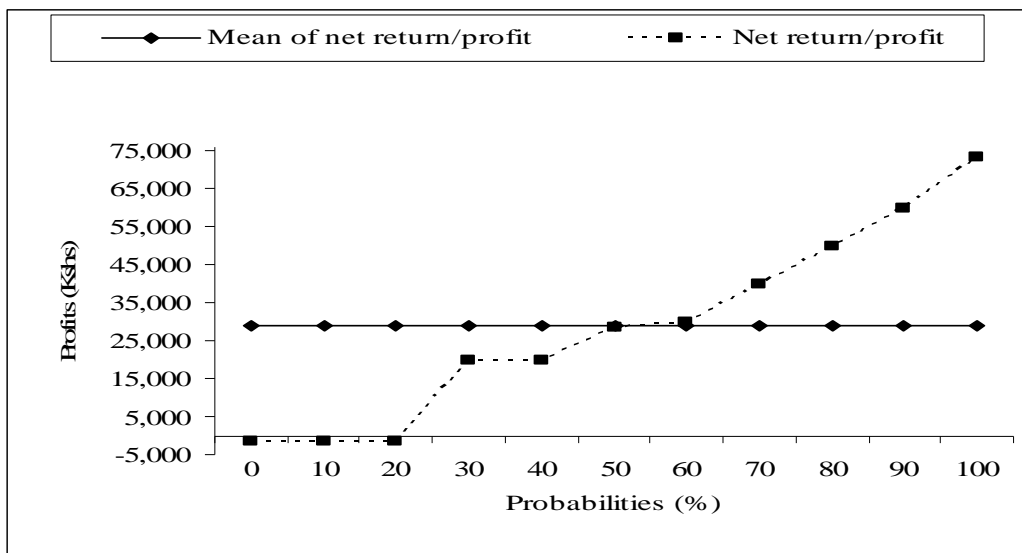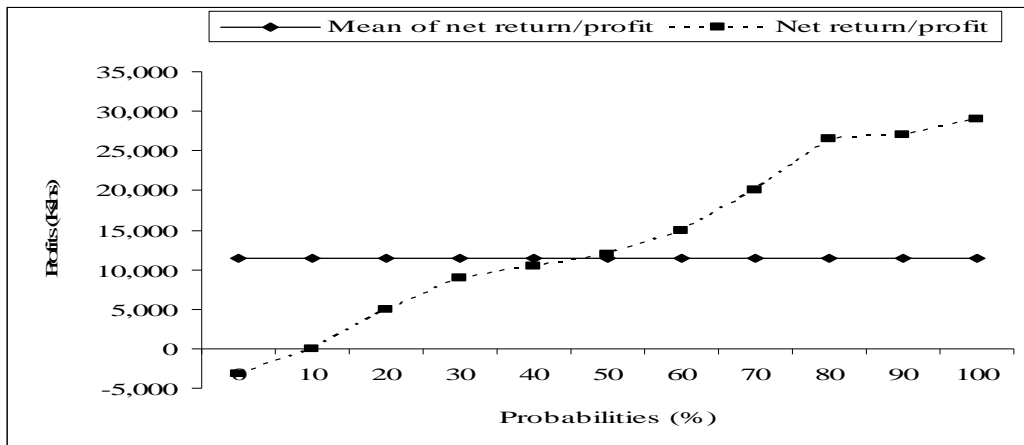

Figure 4.1: Probable wheat net returns/Profits (scenario 1)
Source: Author's Survey, 2009

The average profitability gain attainable by a wheat farmer is estimated at Kshs. 28,957 per hectare with a probability of this scenario occurring estimated at 0.59. However, the wheat

9

farmer can make a maximum profit of up to Kshs. 73,551 with a probability of 0.975. Similarly, a wheat farmer can also make losses of up to Kshs. 1,370 with a probability of 0.16.

The profitability gains of wheat farming in scenario 2, where a wheat farmer receives Kshs. 1,950 per bag from middlemen is shown in figure 4.2. Average simulated wheat profits are estimated at Kshs. 11,407 per hectare with a probability of 0.49. However, wheat profits can go as high as Kshs. 28,974 with a probability of 0.89.

Figure 4.2: Net returns/Profits of scenario 2 and their probabilities in Wheat
Source: Author's Survey, 2009

The profitability gains of wheat farming in scenario 3, where a wheat farmer receives a reduced price of Kshs. 1,500 per bag is shown in figure 4.3. In this case, average simulated wheat output is a net loss of Kshs. 743 per hectare with a probability of this occurring being 0.47. Additionally, losses could be as bad as Kshs. 15,827 with a probability of 0.97. However, the maximum wheat profit achievable is estimated at Kshs. 1,887, with a very low probability of 0.03.
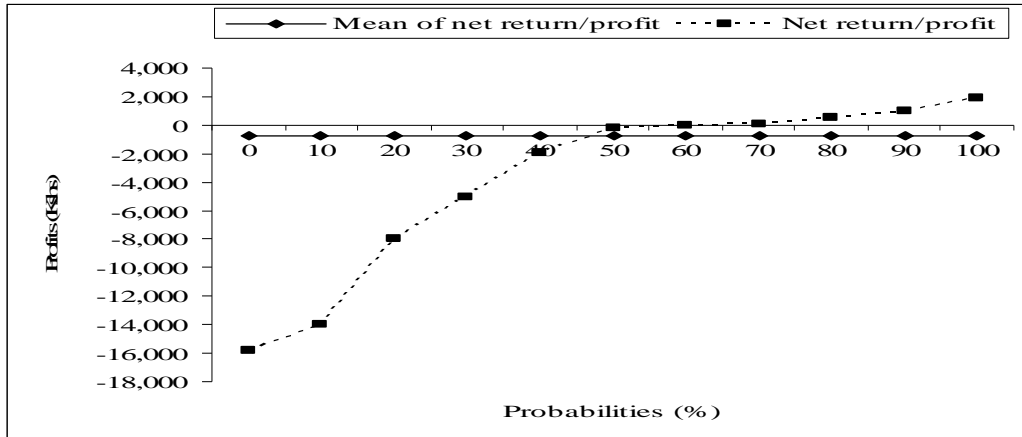
Figure 4.3: Net returns/Profits of scenario 3 and their probabilities in Wheat

Source: Author's Survey, 2009

Evaluation of the three scenarios shows that scenario 1, which is associated with the Unga price of Kshs. 2,600, was the most profitable while scenario 3, which is associated with dropping wheat price below Kshs. 1,500 is unsustainable for wheat farmers. Similarly, the probability of making profits is highest in scenario 1 and lowest in scenario 3. Additionally, the probability of making losses is highest in scenario 3 and lowest in scenario 1. This can be used to advise both policy makers and wheat farmers on strategies of ensuring wheat farming remains a profitable venture. Farmers would, therefore, be advised to sell their wheat to Unga millers as the best alternative, but avoid disposing off their wheat when the price falls below Kshs. 1,500. Policy makers would be advised to use institutions such as marketing boards to ensure that players in the wheat market do not charge prices below Kshs. 1,500 which is likely to drive wheat farmers out of business. This can be compared with other possible investments in the economy as it gives a guide on the likely profitability in wheat farming under different policy scenarios and as noted by Fleisher, (1990) and Giardini, et al (2004), would help the investor in making long-term investment decisions in this environment full of uncertainties.

Conclusions and Recommendations

It is concluded that simulated wheat yield was highest in Illula and lowest in Timboroa which is consistent with actual yields reported in the district. Similarly, even though, simulated yields

over-estimated actual field wheat yield both at the district and across the four agro-ecological zones, the deviation from the actual field 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 three wheat profitability scenarios evaluated, scenario 1 is more profitable and more likely to occur than scenario 2. However, scenario 3 is unsustainable due to farmers' high exposure to losses and the low chances of occurrence.

It is recommended that Cropsyst model be adopted as one of the tools for forecasting productivity to facilitate informed decision by wheat farmers. This can be done by incorporating it among the mainstream decision making tools in the Ministry of agriculture. Similarly, it is also recommended that profitability modeling via Monte Carlo be adopted as a strategy for evaluating alternative policies to enrich a basket of advisory tools at the disposal of extension agents. The government should also put in place polices that cushion farmers from vagaries of markets failure. It is also recommended that further and more extensive research be done to test the two models under different locations, diverse soil types, varied management styles and different 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.

Bocchi, S., Confalonieri, R. and Bechini, L. (2001) CropSyst for rice in Northern Italy. Proceedings. Second Modelling Cropping systems International Symposiun. Florence, Italy. 16 – 18 July 2001. pp 51 – 52.

Donatelli, M., Bellocchi, G. and Fontana, F. (2003) RadEst 3.00: Software to estimate daily radiation data from commonly available meteorological variables. *Eur. J. Agron*. 18: 363 – 367.

Fila, G., Bellocchi, G., Acuti, M., and Donatelli, M. (2003) IRENE: a software to evaluate model performance. *Eur. J. Agron*. 18: 369 – 372.

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.

Staggenborg, 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.

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