Available online at www.elixirpublishers.com (Elixir International Journal)

Agriculture

Elixir Agriculture 119 (2018) 51107-51113

Elixir ISSN: 2229-712X

# Weather Index Based Crop Insurance using Artificial Neural Networks

Willard Zendera[1], Samson Mhlanga[2] and Moses Mutetwa[3]

[1,3]Africa University, Department of Agriculture & Natural Sciences, Box 1320, Mutare - Zimbabwe

[2]National University of Science and Technology, Department of Industrial and Manufacturing Engineering Sciences, PO Box AC 939 Ascot- Zimbabwe.

**ARTICLE INFO**

**Article history:**

Received: 7 May 2018;

Received in revised form: 15 June 2018;

Accepted: 25 June 2018;

**Keywords**

Climate change,
Weather Index Insurance,
Artificial Neural Networks,
Evapotranspiration,
Yield.

**ABSTRACT**

Climate change and climate variability and financial institutions' unwillingness to give loans have resulted in many farmers losing confidence in dry land agriculture. Traditional crop insurance methods have also presented challenges due to the risk related to adverse selection and moral hazard resulting in high transaction costs for individual assessment. This study focused on developing a weather index based insurance model that uses artificial neural networks to estimate potential evapotranspiration ($ET_O$) and consequently yield reduction due to moisture stress. Weather data from 2012 to 2015 for Kutsaga area in Harare was used for the study. Seasonal weather data were used as input data to the first model to predict the $ET_o$. The output $ET_O$ and effective rainfall data together with the crop factor (Kc), yield reduction factor (Ky), root zone depth (RzD) and root zone moisture (RzM)were used as input data for the second network to compute % yield reduction. Data for maize for the 2012-13 growing season was used for training the network and validating the estimated $ET_O$ and % yield reduction. The estimated $ET_O$ compared very well with the calculated values with $R^2$ values of above 0.84. The estimated yield reduction % indicated even high accuracies with $R^2$ values of above 0.91. The 2014-2015 growing season resulted in crop loss due to mid-season dry spells and the model predicted a 100% crop loss which means the farmer had to be compensated for the value equivalent to cost of inputs. The model has got potential to be used by insurance companies using weather based data and with mobile banking transaction costs can be reduced.



## INTRODUCTION

Farmers in many developing countries are exposed to severe income losses due to weather calamities such as drought, floods, and extreme high/low temperatures. Crop insurance programs exist, yet are plagued by fraud, corruption, and adverse selection problems [1]. While weather-based index insurance would avoid much of these problems, its feasibility needs to be established in order to provide a low-cost and effective risk management aid for poor people [2].

Access to agricultural insurance is generally very limited in developing countries including Zimbabwe. Provision of this type of service is challenging for insurers resulting in costs that are normally prohibitive for farmers. Financial institutions are also not willing to give these farmers loans due to the risks and lack of security associated with rain fed agriculture [3]. Insurers have tended to concentrate on urban and industrial risks and therefore often do not have networks in rural areas. Where agricultural insurance can be provided, risks are often highly spatially correlated and therefore difficult for insurers to manage [4]. There is arguably a hesitation among the international reinsurance market to become involved with local insurance companies to enable them to transfer offshore, some of their own risk although this has been less of a constraint.

Farmers insurance works best where and when other services like access to credit, improved seed and inputs, markets and functioning supply chains and advisory services are in place. Insurance often cannot add value to farmers' livelihood unless their income can be enhanced through availability of other services. Many of these services are absent in developing countries.

Most of the traditional crop insurance policies make compensation when the farmer incurs a loss. This usually involves a physical sight visit to the farm to make inspections and estimate the damage or loss of the crop [5].

Index based crop insurance, on the other hand, uses weather observations as proxies for losses in production or quality and does not require loss assessments. With index policy a meteorological measurement is used as the trigger for indemnity payments. These damaging weather events might be extreme temperature, rainfall or hurricanes. The classic insurance policy is replaced with a coupon per hectare basis for a given crop. For losses from specific causes, the coupon gives a monetary value payable on certification that the named weather event, of specified severity, has occurred. This crop insurance system can offer lower administrative costs and are less technically complex than traditional crop insurance as there is no need to do physical loss assessment.

Models being implemented in Africa by Syngeta Foundation in East Africa involves a farmer being registered and purchasing the policy through an agent. At the end of each growing season, weather statistics are analyzed against an index of historical weather data. If a certain weather

Tele: 00263 774 334 486

E-mail address: mosleymute@gmail.com

parameter for example rainfall did not meet a certain minimum threshold then payment is triggered. In Zimbabwe *Econet* through *Ecofarmer* has also introduced a similar package which compensates a farmer against the purchase of specified seed from Seedco [6]. *ZIMNAT*, through its *Pundutso* crop insurance also insures crops against drought [7]. There is a significant need for effective and efficient mechanism for transferring natural disaster risks that negatively impact farmers.

Studies in weather index-based crop insurance have been applied in classifying zones to establish insurability of the crops in the zones or have been applied to trigger compensation if a certain parameter mostly rainfall does not meet the seasonal water requirements [8].

This approach however just considers the total seasonal rainfall but does not consider rainfall distribution. Studies have highlighted the potential of the application of artificial neural networks (ANN) in determining crop loss or reduction in yield due to moisture stress or any other unfavorable weather conditions [9].

Studies that make use of real time weather conditions to monitor the performance of a crop in insurance to compensate a farmer as soon as a certain minimum trigger has been observed in real-time are scanty. It is against this background that this proposal seeks to apply artificial neural networks (ANN) based intelligent control system for crop insurance.

## METHODOLOGY

### Weather Data

Weather data was obtained from the meteorological office in Harare for the period from 2012 to 2015 for the area around Kutsaga. The data was computed into weekly averages for twenty eight weeks starting from early October to mid-April.

### Computation of Potential Evapotranspiration ($ET_O$)

The weekly minimum and maximum temperatures, humidity, wind speed, altitude, longitude, latitude and sunshine hours were used to calculate the $ET_O$ based on the FAO Penman-Monteith formula using CROPWAT 8.0. The Penman-Monteith estimated $ET_O$ values were considered as standard and were used for training of the artificial neural network.

### Computation of the Yield Reduction.

Weekly rainfall data, the crop coefficient factor (Kc), the yield reduction factor Ky, the available moisture content and the potential evapotranspiration were used to compute the percentage yield reduction factor.

Weekly average precipitation was used to compute the effective rainfall (Peff) using the FAO dependable rain formula. The actual crop evapotranspiration (Etc) was computed from the ETo and the crop factor Kc. Predicted ETo values were obtained from the first ANN output and were used to calculate Etc.

Computed actual crop water requirements at each stage of growth linked of the weather parameters to the amount of water used at each stage of growth under standard conditions. For this study maize crop was used as a reference crop for any calculation.

If we consider a crop of maize being grown in Harare (Kutsaga area) for example and planted in early December the actual crop water requirements will be as shown in Table 1.

The actual moisture levels in the soil was linked to the actual crop evapotranspiration for maize, by putting into consideration the water holding capacity of the soil and the rooting depth of the maize crop.

The moisture levels were monitored from field capacity (100%) to 60 % moisture depletion level. In this range the crop evapotranspiration is considered normal and at below 60 % the crop will start having difficulties in absorbing the moisture due to increased soil moisture tension and this will affect the actual evapotranspiration (Eta). The reduced moisture will start having an effect on the plant performance and hence the yield. Yield reduction factor values Ky for maize were used to calculate the % yield reduction.

### Development of the Artificial Neural Network.

Two ANN models were developed which consisted of three layers, input, hidden and output layers respectively. The first model was developed to estimate $ET_O$ based on the maximum and minimum temperature, humidity, sunshine hours and wind speed.

The estimated ETo, effective precipitation, crop factor (Kc) and crop rooting depth where used to estimate the soil moisture. All these were used as input data for the second model and together with the yield reduction factor Ky the values were used to compute the yield reduction factor.

## DESIGN AND CALCULATIONS

### Predicting Potential Yield Using ANN

ANN was used to develop a model that was be used to predict potential evapotranspiration. Weather data was entered into excel spreadsheet with several variables such as humidity, wind speed, sunshine hours, minimum and maximum temperatures. The data was then entered into CROPWAT 8.0 software and was used to compute the calculated potential evapotranspiration ETo (mm/day) based on the Penman-Monteith method.

$$ET_o = \frac{0.408\,\Delta\,(R_n - G) + \gamma \frac{900}{T + 273} u_2\,(e_s - e_a)}{\Delta + \gamma(1 + 0.34 u_2)} \quad (1)$$

Where

$ET_o$ : reference evapotranspiration (mm/day)
$R_n$ : net radiation at the crop surface ($MJm^{-2}$/day)
G : soil heat flux density ($MJm^{-2}$/day)
T : mean daily temperature ($^oC$)
$U_2$ : wind speed ($ms^{-1}$)
$e_s$-$e_a$ : saturation vapour pressure deficit (KPa)
$\Delta$ : Slope of vapour pressure curve (KPa/$^oC$)
$\gamma$ Psychometric constant (KPa/$^oC$)

The aspects of solar radiation and soil heat flux density were accounted for by entering the altitude and the coordinates of Kutsaga Research Station which are 17.9189S, 31.1456E, and altitude*:* 1479 m.

**Table . 1. Typical Crop Water Requirements for Maize Grown in Harare (Kutsaga Area).**

| Crop growth stage | Germination and establishment | Crop development | Tasseling, silking and pollination | Kernel development & maturity |
|---|---|---|---|---|
| Period (days) | 20 | 30 | 40 | 30 |
| Kc | 0.4 | 0.8 | 1.10 | 0.8 |
| ETo | 3.6 | 4.50 | 5.10 | 5.40 |
| Etc (mm/day) | 1.44 | 3.60 | 5.61 | 4.32 |
| Etc (mm/period) | 28.8 | 108.0 | 224.4 | 129.6 |

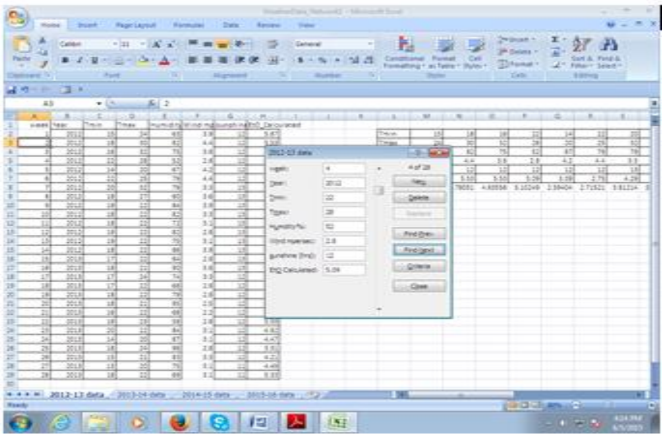

**Figure. 1. Weather Data for Estimating ETo.**

The weather data for 2012-2013 rain season (Fig. 1) was transposed and used as input data for the for the ANN model for predicting potential evapotranspiration and the calculated $ET_O$ values used as the target values for predicting ETo values for the 2013-2014 and 2014-2015 rainfall season. The input layer consisted of measured variables or inputs fed into the input nodes. Various weights were attached to the inputs to determine how the inputs interact, and the sum of the inputs passes through a hidden layer where the network performs problem specific subfunctions and reaches an output value. The output was then compared to a predetermined outcome and the process was repeated through try and error until the optimum solution was attained. This activity constituted the training of the network model. The architecture of the artificial neural network model is as shown in Fig. 2a.

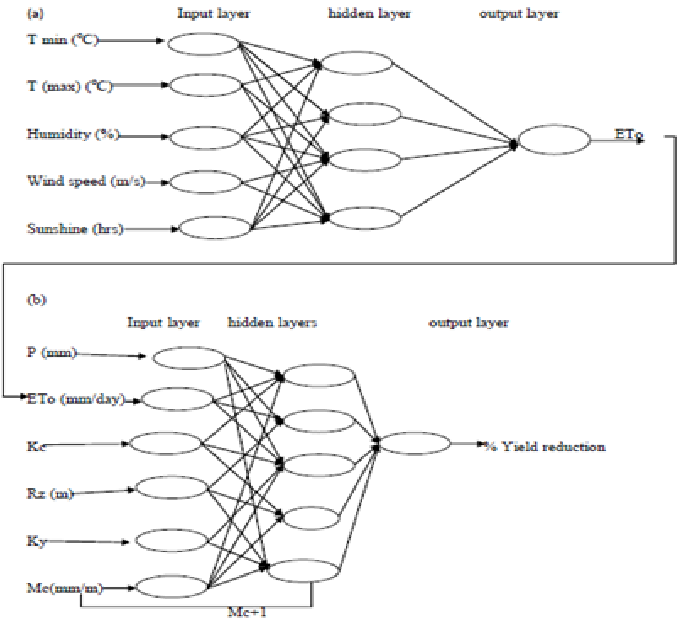


**Figure. 2. ANN Model (a) Estimation of Evapotranspiration (b) % Yield Reduction Estimation (1-Ya/Yb).**

**Predicting Yield reduction Using ANN**

The second step was to use the predicted $ET_O$ and other variables to compute the yield reduction %. The other variables included rainfall, crop factor Kc, soil water holding capacity (mm/m), yield reduction factor Ky and maize rooting depth as shown in Fig. 3. Rainfall data for the 2012-2013 rainfall seasons was used as part of the input data to compute the calculated % yield reduction.

The calculated yield reduction % was then used as target data to predict the yield reduction for the 2013-2014 and 2014-2015 rain season.

The weekly average rainfall was first converted into effective precipitation. The dependable rain formula was used to calculate effective rainfall using the Eq. 2 below.

Effective rainfall = 0.6*Total Rainfall -10(Total rainfall <70 mm)

Effective Rainfall = 0.8*Total Rainfall-24 (total rainfall >70 mm) (2)

The formula was entered into excel using the IF function "=IF(A3<70, 0.6*A3-10, 0.8*A3-24)",and another IF function "=IF(B4>0, 1*B4, B4*0)" was used to remove negative precipitation.

The actual crop evapotranspiration Etc was calculated from the predicted ETo and the Kc values from literature using the Eq. 3 below.

Etc = ETo*Kc * 7 (3)

Where Etc : weekly crop evapotranspiration (mm/week)

ETo: Potential evapotranspiration (mm/day)

Kc : crop factor

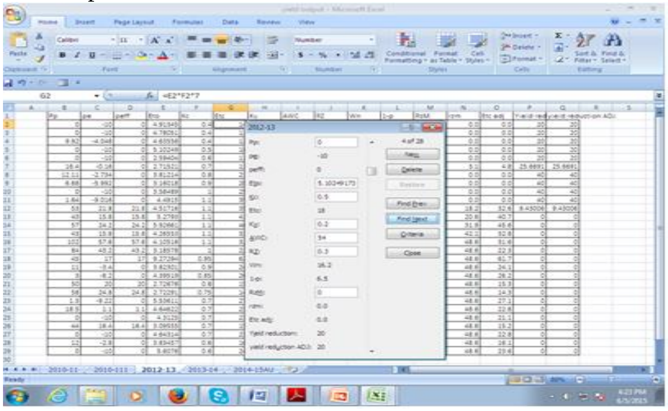

**Figure .3. Weather Data for Estimating Yield Reduction.**

The product was multiplied by 7 in order to give weekly crop evapotranspiration. The formula was also entered into excel spread sheet as follows "=D3*E3*7".The available water content for different soils as shown in Table 2 below (Brouwer *et al*, 1985). The available water content of 54 mm/m was used as it is the one measured for the prevailing soils in Harare area (Nyamapfene, 1992).

**Table. 2. Available Moisture for Different Soils.**

| Soil type | Available water content mm/m |
|---|---|
| sand | 25-100 |
| loam | 100-175 |
| clay | 175-250 |

The available water content was used to calculate the available moisture in the root zone at each stage of growth of the crop. The rooting depth of maize varies from 0.3 m during the initial stages to 0.9 m at maturity.

Available soil moisture was calculated as follows:

Available moisture (mm) = available water content * root zone depth (Rz) (4)

Moisture was only allowed to deplete by 60 % so the yield is not affected by moisture deficit if not less than 40% of the moisture is available in the soil.

Moisture was only allowed to deplete by 60 % so the yield is not affected by moisture deficit if not less than 40% of the moisture is available in the soil.

Allowable moisture depletion = available moisture* 40% (5)

The available moisture and allowable moisture depletion then gives the upper and lower limits of the moisture range that is required by a crop of maize without affecting its yield.

The actual moisture in the soil was calculated using the water balance equation as follows:

RzM =RzM(i-1) + Peff – Etc (6)

Where RzM the root zone moisture content (mm)

RzM(i-1) is the initial moisture content for the week

Peff effective precipitation

Etc crop evapotranspiration for maize

The following function was used in excel to correct the root zone moisture content so that it does not go beyond the water holding capacity of the soil "=IF(L3>J3, J3,L3)"

When the moisture content is below the depletion level (60%) the crop evapotranspiration is affected and therefore the adjusted crop evapotranspiration ETadj is used and was calculated using excel as:

ETadj = RzM/allowable moisture depletion*Etc (7)

The adjusted crop evapotranspiration is the one that helps to establish the % yield loss using equation

$$\left(1-\frac{Ya}{YX}\right) = Ky\left(1-\frac{ETa}{ETx}\right) \quad (8)$$

Where Ya : Actual yield (t/ha)

$Y_x$ : Maximum expected yield (t/ha)

Ky : yield reduction factor

When the ratio (1-Ya/$Y_x$)*100 gives the percentage yield reduction and if it is less than 50% then payment is initiated.

The yield reduction was corrected so that the % yield reduction does not exceed 100%. Using the IF function in excel as follows: "=IF (O3>100, 1*100,O3, O3)"

The variables in Figure 2b, were used as input data to the network model and the calculated ETa was used as the target data. Data for the year 2012-13 rain season was used for training the model

The indemnity payment depends on four factors: threshold, actual value, limit and total liability. The equation of indemnity is therefore:

Indemnity payment = [1-(threshold – actual value)/(threshold-limit)]* liability (9)

Only when actual value =<limit

The threshold value to be used will be the maximum yield to be expected Ym (100%)

The actual yield to be expected Ya =1- yield reduction %

The threshold limit = 50%

Threshold limit can be set as the breakeven point for a particular crop in terms of the minimum yield at which the farmer will start making a loss.

## RESULTS AND DISCUSSION

### Seasonal Weather Conditions

The weather conditions for the period 2012 to 2015 are as shown in Fig. 4 to Fig. 6. Figure 4 shows the variation of rainfall throughout the rain season. Throughout the 3 rainfall season it shows that reasonable rainfall for planting starts during the 9th week that is in early December. Rainfall seasons 2012-13 and 2013-14 was characterized by peak rainfall periods of 80 mm and 100 mm respectively and the rainfall was evenly distributed. Rain season 2014-15 was characterized by a peak rainfall of about 150 mm followed by very low rainfall in the month in January to February.

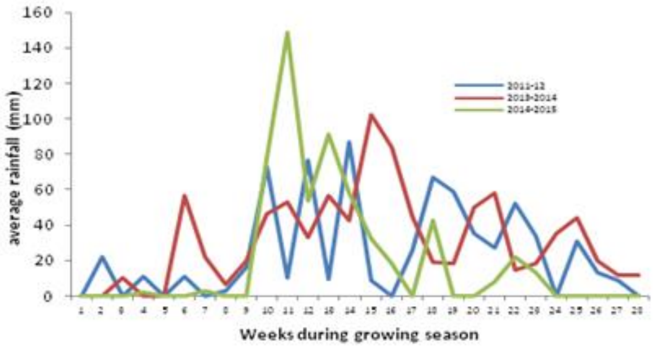


**Figure. 4. Weekly Average Rainfall during the Growing Season.**

Temperature distribution did no differ significantly throughout the three growing seasons with the average temperatures ranging from in October 24° C to about 18° C towards the end of the growing season in March-April. The weekly average temperature is shown in Fig. 5.

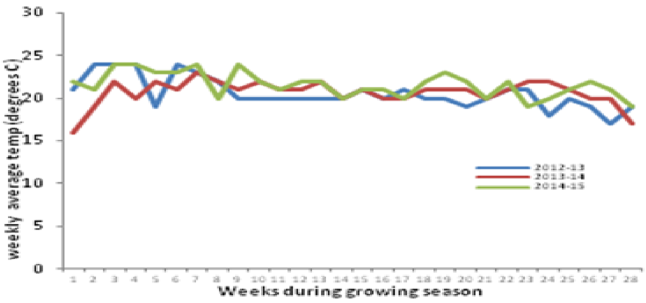


**Figure. 5. Weekly Average Temperature during the Growing Season.**

The sunshine hours were characterized by 12 hour days in November increasing to 13 hours in December to mid February and then decreasing to 11 hours towards the end of the rain season (Fig. 6).

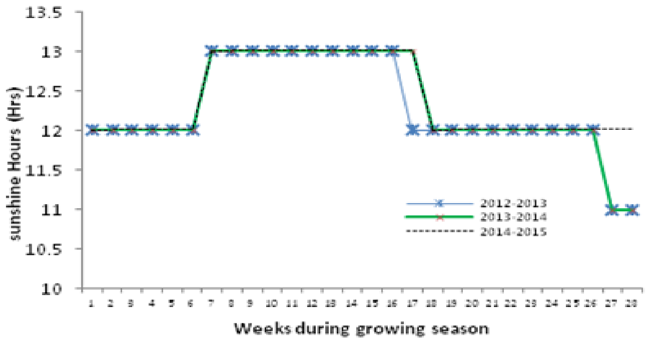


**Figure .6. Weekly Average Sunshine Hours during the Growing Season.**

### Estimation of Reference Evapotranspiration

Weather data for the year 2012-2013 rain seasons was used to as input data for estimating evapotranspiration for the artificial neural network model. The target data was calculated using the Penman-Monteith method and CROPWAT software was used to compute the potential evapotransipirations $ET_O$ for the growing seasons from 2012 - 2015. The weather data for the 2013-2014 and 2014-15 growing seasons were used as sample data for simulating the evapotranspiration. Figure 7 shows the printout of the ANN model from MATLAB R2013 with 6 input variables and 1 output. The ANN was trained using 10 Neurons. In this process several iteration were performed to minimize the error of estimation.

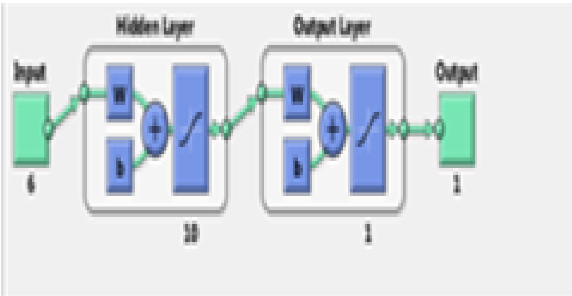


**Figure . 7. ANN Model for Estimation of Potential Evapotranspiration.**

The ANN model estimated $ET_O$ with $R^2$=0.865after 44 epochs as shown in Fig. 8 and Fig. 9. Levenberg-Narquardt (trainlm) algorithm was used as the training function.

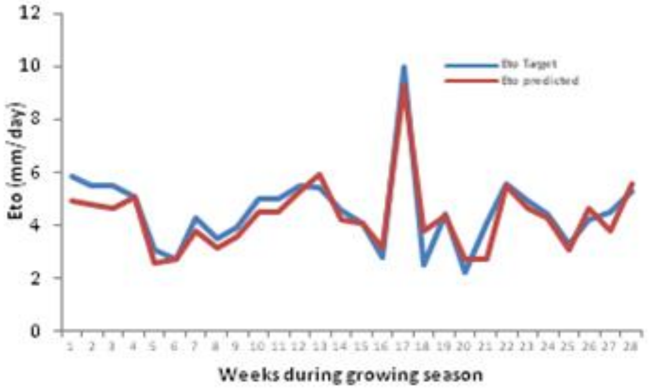


**Figure .8. Comparison of the Calculated and Predicted Reference Crop Evapotranspiration for the 2012-13 Season.**

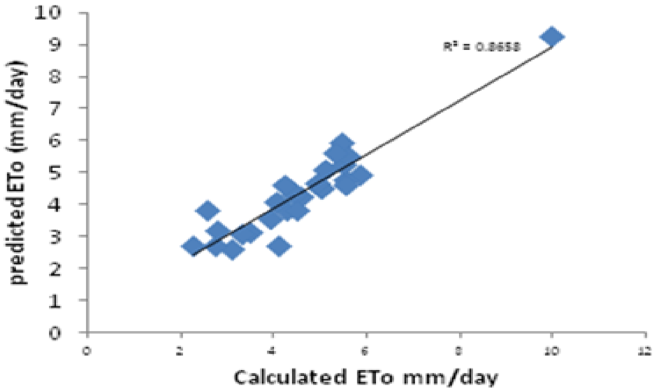


**Figure 9: Regression Analysis between Calculated and Predicted Reference Crop Evapotranspiration for the 2012-2013 Season.**

The comparative analysis of the predicted and calculated $ET_O$ values for the 2013-14 growing season are shown in Fig. 10 below and the $R^2$ value of 0.85 as shown in Fig. 11 below.

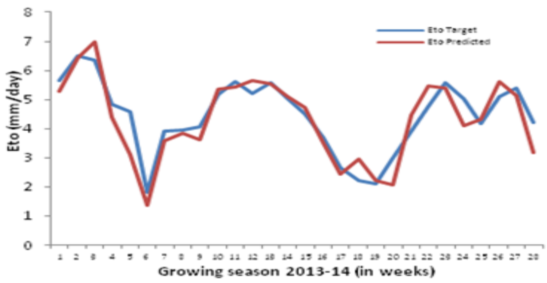


**Figure . 10. Comparison of the Calculated and Predicted Potential Evapotranspiration for the 2013-2014 Growing Season.**

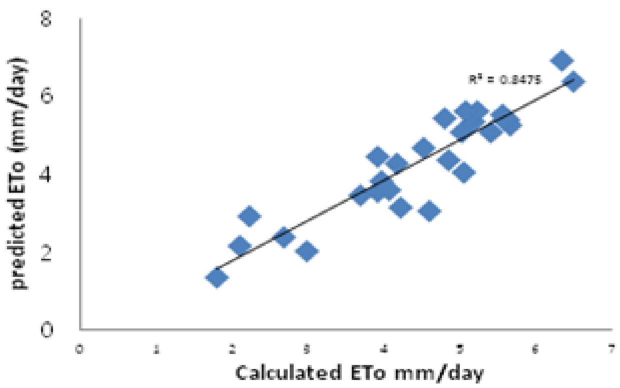


**Figure .11. Regression Analysis of the Calculated and Predicted Potential Evapotranspiration for the 2013-2014 Growing Season.**

The comparative analysis of the predicted and calculated $ET_O$ values for the 2014-15 growing season are shown in Fig. 12 below and the $R^2$ value of 0.84 as shown in Fig. 13 below.

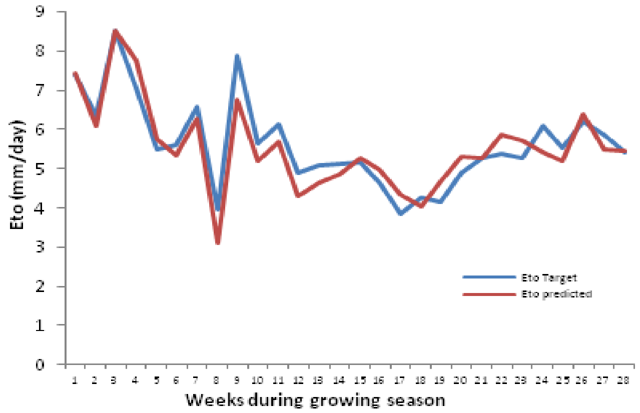


**Figure. 12. Comparison of the Calculated and Predicted Potential Evapotranspiration for the 2014-2015 Growing Season.**

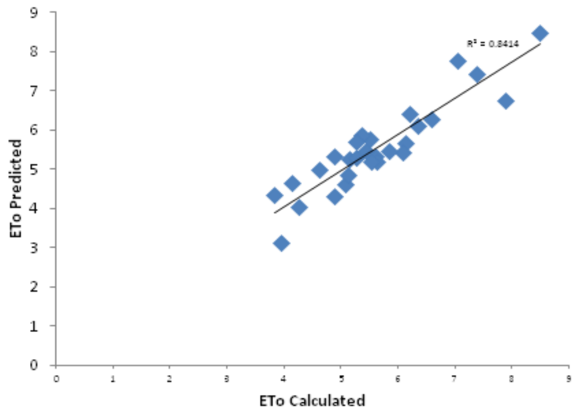


**Figure .13. Regression Analysis of the Calculated and Predicted Potential Evapotranspiration for the 2014-2015 Growing Season.**

**Estimation of Root zone Moisture**

The root zone moisture is an indicator of the possible planting dates and the soil moisture profile which is an indicator of the crop performance. Figure 14 and Figure 15 below shows the root moisture profile for the 2013-2014 and 2014-2015 growing seasons respectively.

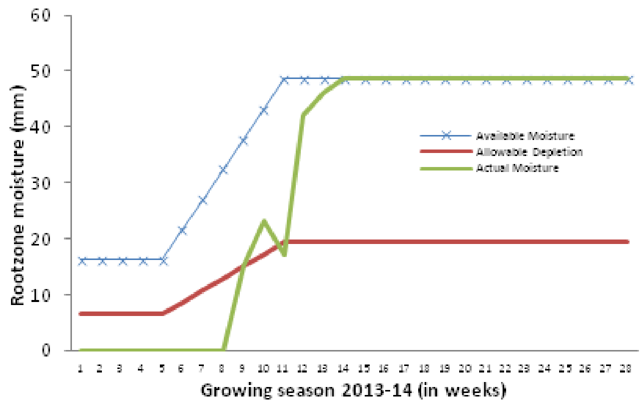


**Figure.14. Root Moisture Profile for the 2013-14 Growing Season.**

Figure 14 indicates that the 2013-14 growing season was a good season as the crop had enough moisture throughout the season. Figure 15 indicates that the moisture content was only adequate between week 9 to week 14. After week 14 the moisture levels depleted to below the allowable moisture depletion and therefore the crop started experiencing moisture stress

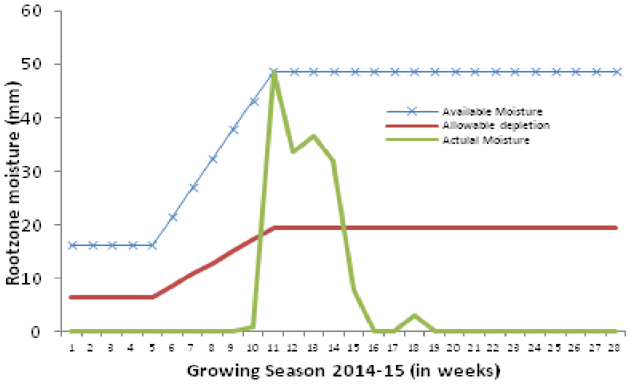


**Figure. 15. Soil Moisture Variation for the 2014-15 Growing Season.**

**Estimation of Yield Reduction**

Predicted $ET_O$ output data from the network was used together with weekly rainfall data for the 2012-13 growing season and other crop and soil variables to estimate the yield reduction due to moisture stress. The artificial neural network that was created is as shown in the network in Fig. 16 below. The network had six input variables and one output. The network used 10 neurons and the TRAINOSS training algorithm. After training with several trial and error an optimum output was reached with a regression $R^2$ value of 0.93.

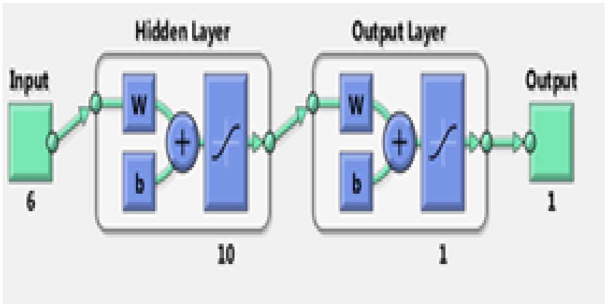


**Figure 16: Artificial Neural Network for Estimating Yield Reduction**

The output yield reduction value for the 2012-13 growing season was used to simulate the yield reduction for the 2013-14 and 2014-15 growing season. The $R^2$ value for the yield reduction calculated and estimated is as shown in Fig. 17 below.

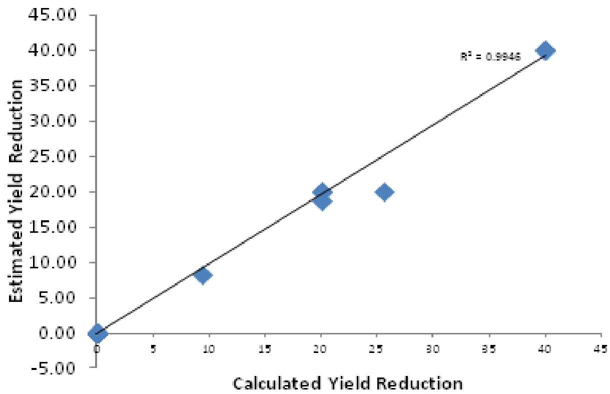


**Figure. 17. Regression Analysis between Estimated and Predicted Yield Reduction Values for the 2012-13 Season.**

The yield reduction % for the 2013-14 growing season was estimated using the artificial neural network and compared to the calculated artificial neural network as is shown in Fig. 18 and Fig. 19 below.

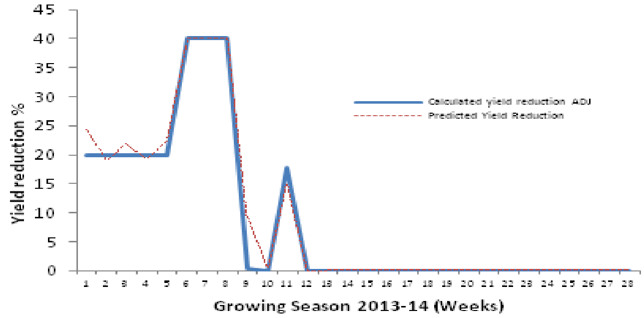


**Figure .18. Calculated and Estimated Yield Reduction % for the 2013-14 Growing Season.**

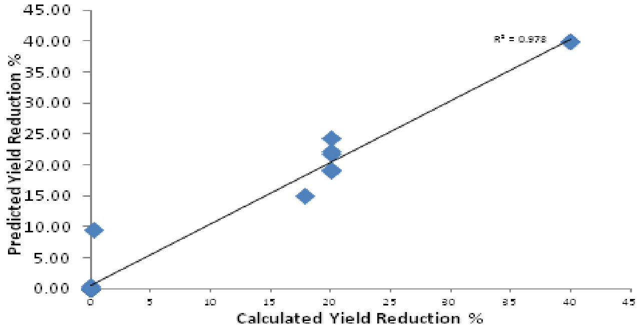


**Figure.19. $R^2$ Values for the Estimated and Calculated Yield Reduction for the 2013-14 Season.**

The yield reduction values for the 2014-15 rainfall season is as shown in Figure 2014-15 growing season. The rainfall was not evenly distributed in this year and % yield reduction values of 100% were experienced in this season Fig. 20.

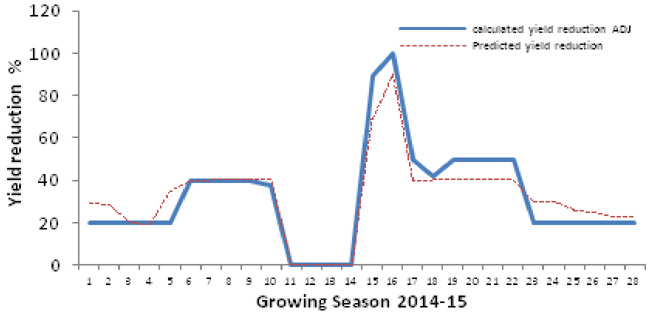


**Figure.20. Calculated and Estimated Yield Reduction Values for the 2014-15 Growing Season.**

The $R^2$ values for the 2014-15 growing season are as shown in Fig. 21 below with an $R^2$ value of 0.92

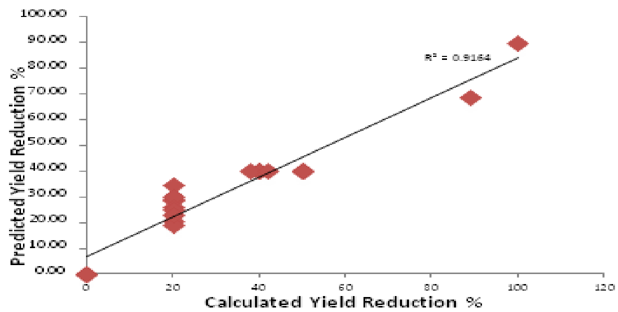


**Figure. 21. Regression Analysis for the Calculated and Estimated Yield Reduction for the 2014-15 Growing Season.**

**Analysis for Indemnity**

The assumption that was used in this study is that a farmer has decided to insure the cost of their inputs per hectare and \$900 was used as the total cost of inputs required to grow one hectare of maize. The indemnity was calculated using Eq. 4-9. The graphs showing yield reduction and indemnity payment for the season 2013-14 and 2014-15 are as shown in Fig. 22 and Fig. 23 respectively.

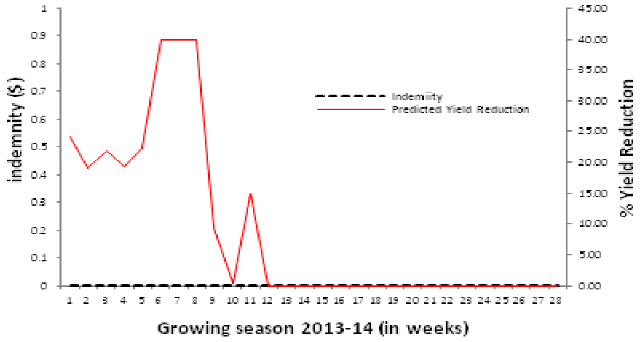


**Figure.22. Indemnity Payment for 2013-14 Growing Season.**

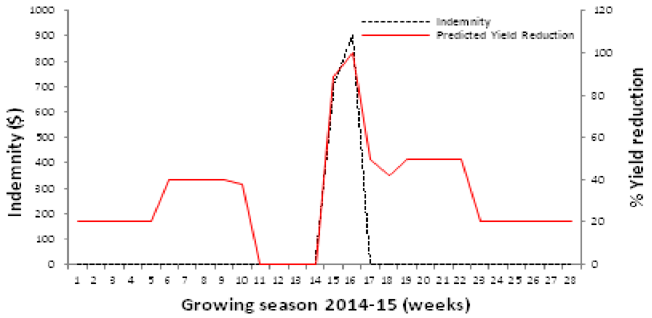


**Figure.23. Indemnity Payment for 2014-15 Growing Season.**

## CONCLUSIONS AND RECOMMENDATIONS

This study aimed at developing a weather index based crop insurance model using artificial neural networks. Two neural network models were developed and were run using MATLAB R2013.

The first model was developed to estimate the potential evapotranspiration using five input variables i.e. maximum and minimum temperature, humidity, wind speed and sunshine hours. Data for the 2012-13 growing season was used for training the neural network and data for 2013-14 and 2014-15 growing season were used for predicting the potential evapotranspiration respectively. The output of the predicted potential evapotranspiration was used as input data for the second network. Potential evapotranspiration was estimated with $R^2$ values of 0.85 and 0.84 for the 2013-14 and 2014-15 growing seasons respectively as compared to the calculated values.

The second artificial neural network was developed to estimate yield reduction due to moisture stress. The network used six input variable i.e. potential evapotranspiration, effective precipitation, yield reduction factor, crop factor, and root zone depth and root zone moisture. Data for the 2012-13 growing season was used for training the network and data for the 2013-14 and 2014-15 growing seasons were used for predicting the yield reduction for the two season. The second model estimated the yield reduction percentages with $R^2$ values of greater than 0.91, for the 2013-14 and 2014-15 growing season. The second model indicated under estimates at higher yield reduction of close to 100%.

The weather conditions for the 2013-14 growing season were conducive for crop growth and therefore no indemnity was expected to be paid to the farmer as indicated by Fig. 20 and Fig. 14. weather conditions for the 2014-15 growing season were characterized by a mid season drought spell that increased to yield loss to above 50% and therefore the farmer is expected to get compensation based on the maximum loss for that season which is 100% for this particular case.

A comparison of the empirical results (Fig. 14, 15, 18 and Figure 20) indicates that the weather index based model has potential to accurately predict yield loss and can be used by agro-insurance companies without the risk of adverse selection and moral hazard at minimum transaction cost Fig. 22 and Fig. 23. The farmer can be compensated using mobile money transfer like Ecocash. This weather index insurance is different from the two locally available packages on the market in that they only put into consideration the total seasonal rainfall, but does not consider the distribution and other weather conditions which also contribute to the crop growth. This disadvantages the farmer in that the total rainfall for the season maybe adequate but the distribution will not be such the crop will be able to produce reasonable yields.

The problem set is realistic and reflects a real life situation that is faced by many farmers especially small holder farmers who find it very difficult to insure their crops and to recover after crop failure. The solution provided can be both a relief to farmers and to insurance companies.

Therefore the study achieved its set objectives and insurance companies can take up the idea for implementation.

### Future work

This study used empirical formulae to estimate soil moisture and consequently yield reduction. Further studies can be carried out to estimate the yield reduction by actually monitoring the soil moisture.

### Acknowledgments

We would like to thank National University of Science and Technology for the opportunity to carry out the study and Walter Mahohoma (PhD) for assisting with weather data.

## REFERENCES

[1]Skees,J.R.Innovation in Index Insurance for the Poor in Lower Income Countries. Agricultural and Resource Economics Review 37/1:1-15, 2008.

[2]Carter, M., de Javavry, A., Sadoulet, E and Sarris, A. Index based weather insurance for developing countries: Areview of evidence and a set of propositions for uo-scaling, 2014.

[3]Worldbank. Weather index insurance for agriculture. Guidance for development practitioners, 2011.

[4]Roberts,R.A.J.Insurance of Crops in Developing Countries.F.A.O.,Rome. 2005.

[5]Fuchs, A. and Wolf, H. Drought and Retribution: Evidence of a Large Scale Rainfall Indexed Insurance Porgram in Mexico. 2014.

[6]Kabweza, L.S.M. Econet announces Ecofarmer, insurance forsmallholderfarmers,2013.(https://www.techzim.co.zw/2013/09/econet-announcesecofarmer-insurance-for-smallholder-farmers.) ACCESSED on 17 April 2015)

[7]Mudariki, G and Mhlanga, F. ZMNAT launches insurance for farmers, Southern Eye, 2013.

[8]Jain, A. Predicting Air Temperature for Frost Warning Using Artificial Neural Networks.MSc Thesis, Athens Georgia. 2003.

[9]Muhammad, S. and R. Usman. Automation of Irrigation Systems Using ANN Based Controller.International Journal of electrical & computer Sciences IJECS-IJECS Vol: 10 no: 02, 2010, pp41-47