A Generalised Regression Neural Network Model For Maize Production In Trans Nzoia County

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Abstract -- *Agriculture plays a pivotal role in the advancement of any country's economy. Its productivity has obvious increase income. However, it is greatly dependent on climatic changes. To help counter this, Artificial Neural Network models have been used as an approach for achieving practical and effective solutions in predicting crop yield using weather conditions and soil parameters as inputs. However, human population as a parameter has not been addressed in Artificial Neural Network models by most researchers. For this reason, this study intends to in-corporates population in a Generalised Regression Neural Network Model in predicting maize yield among other parameters like area of production, amount of rainfall and temperature, by factoring in a connection between the weights the number of neurons. Collected data from Trans-Nzoia County will be used for developing and validating the model. The developed model would be useful in helping the farmers predict the yield of maize for post-harvest management and marketing.*

Keywords — *regression, neural network, population, maize, prediction.*

I. INTRODUCTION

Maize is a major food crop in Kenya that is produced both on small and large scale [1]. A greater percentage of Kenyan population depends on maize farming for both subsistence and income generation. On improved research, maize is adaptive to wide climatic conditions. Consequently, maize is grown in many areas in Kenya, though its chief growth areas still remain Uasin Gishu, Nakuru, Bungoma and Trans Nzoia counties.

Report by the Kenya National Bureau of Statistics (KNBS), suggests that good yields have been obtained over the years through the use of hybrid seeds supplied by the Kenya Seed Company after being developed by the Kenya Agricultural and Livestock Research Organisation (KALRO). Notably, conditions favoring maize farming include: warm temperatures above 15^0 C, high amount of rainfall (1,200 mm - 2,500 mm) depending on different regions, rich and well drained light loam soil and undulating landscape (especially in Trans Nzoia county).

In this study we propose a GRNN model as applied to predicting maize production in Trans Nzoia County. This will help make relevant recommendations pertaining to post harvest management of the crop.

A. ARTIFICIAL NEURAL NETWORKS (ANN)

A new method of information processing is called Neural Network [2]. The complex network system is made up of many simple units called neurons [3]. Modern neuroscience research is the basis on which it works. In most cases, the back - propagation (BP) neural network model (i.e BP network model) is used due to its better functions of self-learning. The standard BP network consists three types of neuron layers namely: input layer, hidden layer(s) and the output layer(s)\cite [4]. Each layer of neurons are fully - connected, while the neurons in each layer are not connected. This learning process of BP algorithm is made up of the propagation and anti - propagation. For propagation process, the input information is transmitted and processed to the hidden layers [5] via the input layer(s). The state of every neural unit layer entirely depends on the state of the next layer. When the expected information is missing in the input layer, the process turns into anti - propagation and the error signal is returned along the initial connection path. By changing the value of the series interconnected weight between each layer(s) in series, the error signal is transmitted in a given order into the input layer, and then sent into the propagation process. Repetition of the application of these two processes makes the error attained much insignificant as it meets the desired value.

B. GENERALISED REGRESSION NEURAL NETWORK (GRNN)

GRNN is a memory - based network which provides estimates of continuous variables and converges to the underlying regression (linear and non - linear) surface. It is based on a learning algorithm with a highly corresponding structure that transmits an information in one – pass [6]. Given a scattered data in a multi - dimensional measurement space, this algorithm gives a seamless transitions from one input value to another. This form of algorithm can be applied in any regression situation whereby assumption where obvious outcomes is not guaranteed. However, this form of a parallel network is applicable in such situations learning a plant model dynamics for forecast or control.

In terms of form, the GRNN and Probabilistic Neural Network (PNN) are similar. However, whereas PNN finds decision boundaries between categories of patterns, GRNN estimates values for continuous dependent variables. Both, however, attain these by using non - parametric estimators of probability density functions. Notably though, advantages of a GRNN relative to the other non - linear regression techniques are as follows: network ``learns'' in a one - pass through the data and generalizes from examples as soon as they are stored. Besides, the estimate is bounded by the minimum and maximum observations. Also the estimate cannot converge to poor solutions corresponding to local minima of the error criterion (as sometimes is observed with iterative techniques). Finally, the software simulation is easy to write and use. However, its disadvantage is that it requires substantial computation to evaluate new points.

C. CROP YIELD PREDICTION USING (ANN)

Pre - requisite intelligence systems has made Artificial Neural Network (ANN) become a novel technology which gives various solutions for the complicated problems in agricultural researchers [7]. According to Shearer, there exit two significant levels to foretell how crop performance would be. These are regression models and application of artificial intelligence techniques. However, problems in agricultural research gave complex models that couldn't be easily analysed using regression analysis techniques. ANN due to its accuracy and non-dependency on statistical assumptions, can be used in crop yield prediction. Though there are many types of ANN, this thesis develops a GRNN model, evaluate its performance and test its efficiency in predicting maize production.

II. RELATED RESEARCH

In this section, we provide literature from previous studies related to this study. Recent trends have seen various artificial intelligence (AI) techniques applied in the related research. A wide range of AI techniques have been applied to model agricultural systems including regression analysis [11], knowledge based models [12], genetic algorithm [13], agent - based system [14] and swarm intelligence [15].

An earlier study by[19] to predict daily grass reference crop evapotranspiration (ETo) as an output using ANN model with observed values as speed of wind, maxima and minima relative humidity, solar radiation, maxima and minimum temperature as input parameters with a standard Back - Propagation (BP). He compared the model with Penman - Monteith (PM) convectional method and found that the ANN model could predict ETo more accurately than the PM convectional method by selecting the best model with the minimum weighted standard error and minimum architecture. He used the learning rates of 0.2 and 0.8 and settled on ANN model of 6 - 7 – 1 layer(s).

Also, Artificial Neural Network model for brown onion harvest prediction based on soil parameters presented by [20], obtained the input parameters using agricultural experiment on soil nutrients. The experiment was carried out in the year 2000 by PAC in a farm located in Shunyi district, Beijing and the experimental data divided into two parts. The first part of 58 samples were used to train the ANN model using BP algorithm and the remaining part (14 samples) for testing. ANN architecture of 6 - 11 – 1 layer(s) model was trained and the training stopped after 2000 times with momentum co - efficient and step length of 0.5 and 0.05 respectively. He recorded correlation co - efficient of 0.916 and average error value of 0.0028 and showed that the ANN model could be used accurately to forecast crop production with soil parameters as the observed inputs.

Besides, [21] considered both surface regression and ANN modelling of wheat yield prediction based on effects of soil and climate factors in Argentine Pampas. To establish the best model, ANN using BP algorithm with input parameters as climate and soil data for 10 different seasons between the year 1995 to 2004 and net grain production as the targeted output was considered. After training the network, rainfall and photo-thermal quotient were the significant factors in wheat yield prediction. There existed a strong correlation between the wheat yield and the soil available water holding capacity and soil organic carbon content in the top soil profile. Regression output of the observed and the predicted values gave a close fit of the data points and showed that the ANN model was superior to surface regression modelling and could predict the wheat yield since the input parameters could be available between 40 to 60 days before harvesting.

ANN models (270) developed by [9], using feed - forward BP Artificial Neural Network with past rainfall data, daily temperature sum, daily sunshine hours, daily wind speed and daily solar radiation, between the year 1993 to 2003 as the input parameters and rice yield over the same period as the targeted output. He focused on investigating whether ANN models could best predict rice yield for climatic conditions of Fujian in mountainous region, evaluated the models performance by varying the developmental parameters and compared the effectiveness to a multiple regression model. Learning rates and number of hidden nodes greatly affected the accuracy of the rice yield predictor, with optimal learning rates resulting between 0.71 - 0.90. His model provided more accurate yield predictions than multiple regression models with R^2 and RMSE of 0.67 and 891 respectively. However, it was more time consuming than multiple linear regression during its development.

ANN of MLFANN type was developed by [10] to predict maize yield and compared its performance with Multiple Linear Regression (MLR) model. He used the maize yield data as the targeted output and fertilizer consumption, pesticide consumption, farm power and human labour as the observed input parameters. With the help of NN tool in MATLAB software, he used Conjugate Gradient Descent and Gradient Descent Algorithms (CGDA and GDA) for training using the data from Natural Agricultural Technology Project Division of Agricultural economics, I.A.R.I, New Delhi. After training, the model was validated and tested and the results showed that MLFANN with 11 - 6 - 1 layers(s) had a minimum MSE and performed better than the MLR model. He finally proposed the use of more advanced ANN models for instance, GRNN for crop yield prediction.

A study by [11] on tomato to determine the best architecture model using feed-forward neural network method using data provided by Crop-Assist stations to predict yield, growth and water consumption in different time intervals with greenhouse environmental inputs as temperature, radiation, carbon (iv) oxide levels, pH and known outputs as actual yield, growth and water consumption. He considered 30 different random seed NN model and best model chosen on the basis of a suitable NN architecture. The model could easily and readily be deployed in commercial greenhouse for prediction and also improved overtime. However, in the study the connections between neurons and weights was not considered.

ANN model considering parameters of soil and atmosphere related, with pH, nitrogen, phosphate, potassium, depth, temperature, rainfall as the input variables using feed-forward propagation method was developed by [12]. Data related to plant nutrients and other parameters from Vidarbh was used to build the model in MATLAB. Even though the model didn't bring in a connection between the neurons and the weights in the model, the study concluded that the model could predict the crop yield based on various parameters using ANN and be useful to farmers who are not economically stable and couldn't afford laboratory test. The study finally proposed to extend the model to other crops and make a model for a single crop by taking care of its nutrients right from planting period to harvesting.

Based on the researches above, an ANN is an effective tool in predicting the crop yield. While there has been a number of studies that have reported on how ANNs may be effectively used for the prediction of crop yield in different environments. A GRNN model has no much information existing in predicting crop yield. However, [13] developed a GRNN model in evapotranspiration modelling and used solar radiation, air temperature, relative humidity and wind speed as the inputs but didn't factor in a connection between the weights and the number of neurons in the model. His model is presented in the equation (1) below.

$$\hat{Y}(\underline{X}) = \frac{\sum_{i=1}^{n} y_i \exp -[\frac{d_i^2}{2\sigma^2}]}{\sum_{i=1}^{n} \exp -[\frac{d_i^2}{2\sigma^2}]} \quad (1)$$

It is on this basis that we use of a GRNN model incorporating human population among other parameters as area of production, amount of rainfall and temperature as the inputs and factor in a connection between the weights and the number of neurons in the model.

III. MODEL CONSTRUCTION

In this section, we present a GRNN model development for predicting the amount of maize produced using area of production (x_1), amount of rainfall (x_2), minimum temperature (x_3) and maximum temperature (x_4), and the human population (x_5) as the observed input parameters.

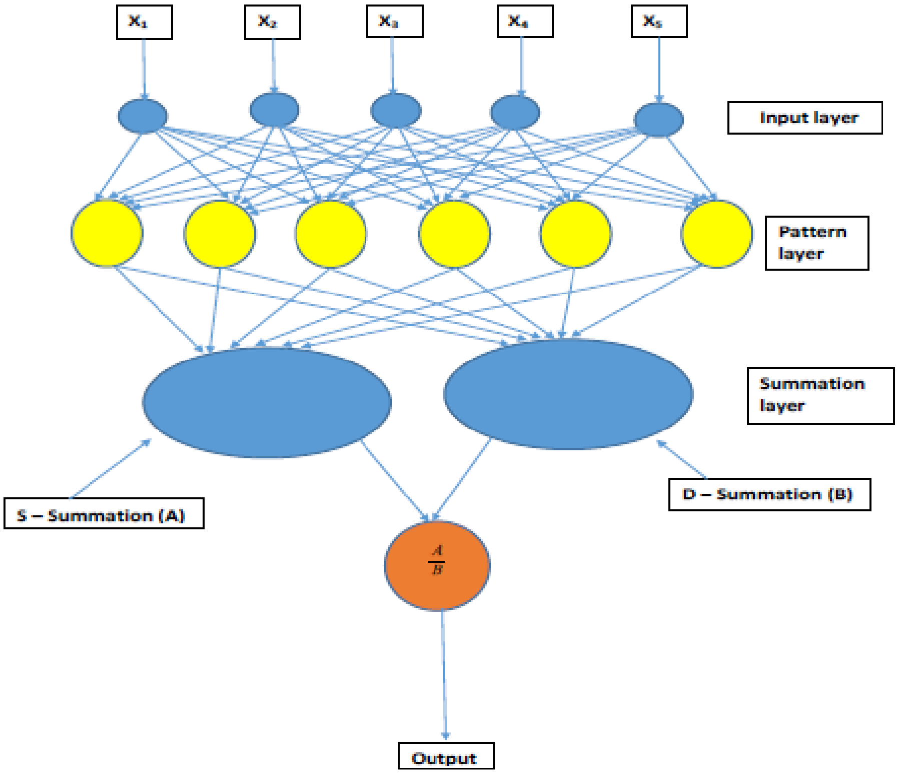
The observed values between the year 1995 to 2018, divided into training and testing sets, are obtained as follows; the data of the area of production and amount of maize produced are obtained from KALRO head office in Trans Nzoia county, amount of rainfall and temperature of the county are obtained from Kenya Meteorological Department (KMD) head office in Nairobi and the human population is obtained from Kenya National Bureau of Statistics (KNBS) office in Trans Nzoia county.

A GRNN model consists of four layers namely; input layer, pattern layer, summation layer and output layer. The number of input units in the input layer are the observed parameters that includes; area of production (x_1), amount of rainfall (x_2), minimum temperature (x_3), maximum temperature (x_4), and the human population (x_5). Table 1 gives a descriptive summary of the state variables and their units of measurement as applied to this model.

Table 1: A descriptive summary of the variables and their units.

Variable	Description	Units
x_1	Area of production	Area $\times 10^5 km^2$
x_2	Amount of rainfall	Volume$\times 10^3 mm^3$
x_3	Minimum temperature	$^0C \times 10^1$
x_4	Maximum temperature	$^0C \times 10^1$
x_5	Human population	Persons $\times 10^6$

As outlined by [19] in other study, a GRNN architecture is made up of layers in a given order (input layer, pattern layer, summation layer and the output layer). Neurons connects each and every layer, processing information and gives their outputs. Summation layer is split into two (summation units and division unit). Normalization of the output set is done by the summation and the output layer. Summation layer is connected with summation neurons (S and D), whereas the sum of the weighted responses is computed by the S - summation neuron, the un-weighted outputs of the pattern neurons are calculated by the D - summation neuron. In the output layer, each S - summation neuron is divided by each D - summation neuron to give an output, $\mathbf{Y_i}$ (predicted value). For training of the network, Radial Basis Function (RBF) and Linear Activation Function (LAF) are used in the hidden and output layers respectively. Figure 1 below depicts this scenario as it presents a GRNN Model architecture in the current study.



If f(x, y) is unknown joint continuous probability density function of a random variable vector, **X**, and a scalar random variable, **Y**. Letting x and y to be a specific measured value of random variable **X** and **Y** respectively. Equation (2) below gives conditional mean of y given x (regression of y on x);

$$E[y/x] = \frac{\int_{-\infty}^{\infty} y f(x,y) dy}{\int_{-\infty}^{\infty} f(x,y) dy} \qquad (2)$$

For unknown density of f(x, y), it is estimated from a sample observations of x and y. For a non - parametric estimate of f'(x, y), a class of consistent estimators proposed by [23] are used and is applicable in multidimensional situation as explained by [24]. These estimators are a better choice for estimating the probability density function, f(x, y) [6], given an assumption that the underlying density is continuous and evaluating the first partial derivatives of the function at any x are small, the probability estimator f(x, y) is dependent on sample values x^i and y^i of the random variables **X** and **Y**, where n is the number of sample observations and p is the dimensional of the vector variable **X**. Equation (3) below gives the probability estimator f'(x , y) as expressed by [6];

$$\hat{f}(x,y) = \frac{1}{(2\Pi)^{\frac{p+1}{2}} \sigma^{(p+1)}} \cdot \frac{1}{n} \sum_{i=1}^{n} \exp -[\frac{(X - X^i)^T (X - X^i)}{2\sigma^2}] . \exp -[\frac{(Y - Y^i)^2}{2\sigma^2}]. \qquad (3)$$

The probability estimate, f'(x, y) assigns sample probabilities with width of σ (spread) for each sample x^i and y^i. Substituting the joint probability estimate f'(x, y) in equation (3) into the conditional mean, in equation (2) yields desired conditional mean of y given x. When equation (2) and (3) are combined and the order of integration interchanged, summation gives the desired conditional mean, denoted Y(X) as expressed by [6].

$$\hat{Y}(\underline{X}) = \frac{\sum_{i=1}^{n} \exp -[\frac{(\underline{X}-\underline{X}^i)^T(\underline{X}-\underline{X}^i)}{2\sigma^2}] \int_{-\infty}^{\infty} y_i \exp -[\frac{(y-Y^i)^2}{2\sigma^2}] dy}{\sum_{i=1}^{n} \exp -[\frac{(\underline{X}-\underline{X}^i)^T(\underline{X}-\underline{X}^i)}{2\sigma^2}] \int_{-\infty}^{\infty} \exp -[\frac{(y-Y^i)^2}{2\sigma^2}] dy} \tag{4}$$

Defining the scalar function d_i^2 as suggested by [6]

$$d_i^2 = (\underline{X} - \underline{X}^i)^T(\underline{X} - \underline{X}^i) \tag{5}$$

Replacing $(\underline{X} - \underline{X}^i)^T(\underline{X} - \underline{X}^i)$ with d_i^2 in equation (4) and introducing η_A and η_B as the number of neurons in the S - summation and the D - summation layers respectively in this study, then;

$$\hat{Y}(\underline{X}) = \frac{\sum_{i=1}^{n} \exp -[\frac{d_i^2}{2\sigma^2}] \int_{-\infty}^{\infty} \eta_A y_i \exp -[\frac{(y-Y^i)^2}{2\sigma^2}] dy}{\sum_{i=1}^{n} \exp -[\frac{d_i^2}{2\sigma^2}] \int_{-\infty}^{\infty} \eta_B \exp -[\frac{(y-Y^i)^2}{2\sigma^2}] dy} \tag{6}$$

Evaluating equation (6), we finally obtain;

$$\hat{Y}(\underline{X}) = \frac{\sum_{i=1}^{n} \eta_A y_i \exp -[\frac{d_i^2}{2\sigma^2}]}{\sum_{i=1}^{n} \eta_B \exp -[\frac{d_i^2}{2\sigma^2}]} \tag{7}$$

The resulting regression in equation (7) is directly applicable to problems involving numerical data. In this study, we use the GRNN network simulated in MATLAB to predict new output after training by introducing new observed values of the input vector, **X**

Parameter determined in this GRNN model during simulation is the spread, σ. There are a number of techniques of determining the spread, σ for instance the use of fruit fly optimization algorithm (FOA) as explained by [25]. However, in this study we have arbitrary varied the spread, σ in the range 0.01 – 1 as suggested by [26]. This is done until the best fitting regression model between the observed outputs and the simulated outputs was achieved at 0.07 for the developed GRNN model.

IV. ANALYSI AND RESULTS

In this section, we present the result and analysis of the study. To numerically describe the goodness of the model, we use mean square error (MSE), root mean square error (RMSE) and the co-efficient of determination R^2 between the modelled output and measures of the training and testing data set. Equations (8), (9) and (10) below defines the performance indicators;

$$MSE = \frac{1}{m}\sum_{i=1}^{m}(Y_i - y)^2 \tag{8}$$

$$RMSE = \sqrt{\frac{1}{m}\sum_{i=1}^{m}(Y_i - y)^2} \tag{9}$$

$$R^2 = 1 - \frac{\sum_{i=1}^{m}(y - \bar{Y}_i)^2}{\sum_{i=1}^{m}(y - \bar{y})^2} \tag{10}$$

Where, m = number of observations, Y_i = predicted value, y = observed value, $\bar{y}$ = mean of observed values and $\bar{Y}_i$ = mean of predicted values.

The table (2) shows the performance indicators between the modelled output and measures of the training and testing data set from the MATLAB after the simulation. The measures remained the same during training for both all the inputs and when human population is excluded as an input.

Table 2: A summary of simulation values from the MATLAB after training process.

Measure	Value
Min - MSE	0.4884
MSE - Training	0.4884
MSEE	0.4884
RMSE - Training	0.6988
SSE - Training	3.4091
R^2	0.9301

A. GRAPHICAL REPRESENTATION OF THE GRNN MODEL SIMULATED OUTPUT

In this section, we present a graphical representation of a GRNN model simulated output from MATLAB.

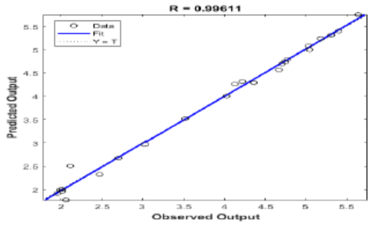


Figure 2: Number of predicted $90kg$ bags $(\times 10^6)$ and Number of observed $90kg$ bags $(\times 10^6)$ Regression for the GRNN model

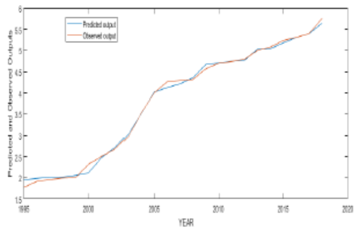


Figure 3: Number of predicted $90kg$ bags $(\times 10^6)$ and Number of observed $90kg$ bags $(\times 10^6)$ plot between $1995 - 2018$ for the GRNN model

In Fig. (2) and Fig. (3), it is evident that the GRNN model developed after simulation gives an accurate performance because the predicted and the observed target values in a graphical representation gives a close fit.

V. CONCLUSIONS

In this section, we have focused on the role of predicting maize production in Trans Nzoia County. We therefore make conclusions in relation to the objectives and give recommendations and future work related to the study.

We have presented a GRNN model by introducing a connection between the weights and the number of neurons in the summation layer by assessing the role of human population in predicting the amount of maize produced using the model. The model responds to both increase in human population and maize productivity i.e as the human population increases over the years, the amount of maize produced also increases. We therefore conclude that; amount of rainfall, temperature and the area cultivated remains the key predictors for a GRNN model for crop prediction.

Any decision to predict maize production should be done in good time. Once a farmer has predicted the amount of maize to be produced before the actual harvest they should immediately plan for the post-harvest management. This will enhance proper storage, marketing and sales. In future, there will be need to model ``A Generalised Regression Neural Network for maize production" and compare its performance with other ANN models e .g BP and MLFNN incorporating human population of the area of study.

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