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Modeling County level maize yields using artificial neural network

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Abstract Maize yield estimates are useful for county food security preparedness. Techniques such as regression and simulation have been used by various studies to model and predict maize yield. This study used a feed-forward, back propagation artificial neural network with levenberg-marquardt algorithm for training. Artificial neural networks framework was chosen because its a data driven method that is relatively less widely used in county level yield prediction. Moreover, neural networks has key merits, such as require less formal statistical training, ability to detect nonlinear relationships by identifying likely interactions between variables and the availability of multiple training algorithms. We modelled historical maize yield between 2005–2016 as function of satellite derived precipitation, temperature, reference crop evapotranspiration, soil moisture and normalized difference vegetation index (NDVI) to predict maize yields at pixel level. The data was obtained with a spatial resolution of $\approx$ 4 km and subsequently, the predictions was done at $\approx$ 4 km pixel size. The historical reference maize yield data was divided into two sets for model training and validation. The model predicted maize yield with R^2 and root mean square error of 0.76 and $0.038 MT/ha$ in Trans-Nzoia county and 0.86 and $0.016 MT/ha$ respectively in Nakuru county. These findings shows a promising future for applications targeting to rapidly assess county level food preparedness in Kenya because maize is a major staple food.

Keywords Boruta algorithm · artificial neural networks · machine learning · maize yield prediction · modeling · remote sensing

Address(es) of author(s) should be given

1 Introduction

There is a linear growth in world population according to data and projections published by United Nations. This data also gives 1.18% as the current world's population growth per year, which approximates to annual population increment of 83 million people (United Nations, 2015). More than half of global population growth between now and 2050 is expected to occur in Africa. Africa has the highest rate of population growth among major areas, growing at a pace of 2.55% annually in 2010–2015. Consequently, of the additional 2.4 billion people projected to be added to the global population between 2015 and 2050, 1.3 billion will be from Africa (United Nations, 2015). This growth in population will directly impact food supply systems.

Africa relies heavily on weather dependant agriculture. It also experiences short-term changes in climate (Stige et al., 2006). These two factors increases stress on food production and food systems. According to (Ahmed et al., 2009) a higher percentage of African population is expected to be below poverty line.

The consequential effects of this stress on food production is, hunger and poverty, which is prevalent in sub-saharan Africa. Therefore, there is need to prioritize strategies and policies to resolve stress and avert poverty in Africa. As well as measure the impact of policies on set objectives, and protect food production from destructive impacts of future climate changes (Lobell and Burke, 2010; Schmidhuber and Tubiello, 2007).

Predicting food production is of significance in solving food problems, but is not easy. This is because food production or yield is a product of climatic and management factors. Weather is a constituent of climate according to (Islam et al., 2020) definition of climate as average weather of an area analyzed for a period of 25–

30 years. while weather as the atmospheric conditions of an area at a given day.

According to (Budyko and Menzhulin, 1996) almost half the total losses in all economic sectors is attributed to unfavorable weather conditions. The management factors are also vital in food production, but these data is not readily available in developing countries. Therefore, it is essential to develop a reliable model of food production using weather parameters.

The inspiration of crop yield prediction is based on needs in food security. The need to achieve competing policy objectives while also protecting public investment in agriculture. Crop yield models help in realizing an equilibrium between various needs such as: increased food production, environment protection, decreased resources, higher farming incomes and climate change mitigation (Lobell and Azzari, 2017).

Crop yield prediction has two main categories namely: statistical and simulation models. The significance of predicting crop yields has been observed. As many studies have modelled yields using statistical methods with various parameters as a means to food security. According to (Zhang et al., 2010) statistical models such as linear regression which is based on ordinary least square (OLS) and autoregressive model can be used for yield prediction. In this study autoregressive model provided a better performance that was attributed to this model ability to adjust for spatial autocorrelation inherent in the data. The only weakness to this model is it's linear combination of variables to a process understood to be quite complex and dynamic in nature and thus not easily modelled into a regression framework (Zhang et al., 2010). A study by (Sellam and Poovammal, 2016) established that variables such as annual rainfall, area under cultivation and food price index explains 70% variability in crop yields.

The study by (Zhang et al., 2010) also demonstrated that Normalized Difference Vegetation Index (NDVI) and precipitation are the major predictors in modelling corn yield. Studies also demonstrated the use of satellite images in agriculture to improve food production and food security. Satellite images provide both extensive spatial coverage and high temporal resolution. These images brought new possibilities such as: to map land cover, detect irrigation, estimate biomass, and survey crop health (Chen and Mcnairn, 2006). Moreover, multiple satellite missions have the capability to regularly monitor phenomena on the Earth surface. These satellites provides a rich source of data that can be ingested into crop yield prediction models (Rémy et al., 2017).

In recent times, statistical models offer better predictions, but still are not effective with complex data set. These limitations has driven crop yields modelling to adopt data-driven models (Kadir et al., 2014) such as machine learning algorithms. In line with this, (Schlenker and Roberts, 2008) found a robust nonlinear relationship between weather and yields that is consistent across space, time, and crops. This introduced non-linear models in crop yields modelling.

The use of satellite data and data-driven models can help address challenges of food production uncertainty. Especially by utilizing the computational capacity of machine learning algorithms such as artificial neural networks (ANNs) to model the relationships between predictors (inputs) and objective variables (outputs) (Deo and Şahin, 2015). The advantages of ANNs in yield prediction are: (1) faster and flexible modeling approach, (2) proper and easy to work nonlinear relationship, and (3) the model structure incorporates expertise and user experiences (Barzegar and Asghari Moghaddam, 2016). Kross et al. (2018) concluded that ANNs can be used to predict yields using satellite images as long as models are created for unique crop types. Hota (2014) established that the neural network-based estimation has technical efficiency that may lead to improved results. In this study, radial basis function networks (RBFN) outperformed other estimation techniques in consideration. The study also established ANNs as a beneficial model for crop yield prediction based on sensing various soil and atmospheric parameters (Dahikar and Rode, 2014). Africa lacks sufficient in-situ data, but satellite data provides a relatively low cost solution. To ensure timely interventions, yield prediction can provide an early warning on imminent food crisis that may face countries in Africa. Data and information models are necessary to sustain all the dimensions of food security; availability, accessibility, utilization and food systems stability. Reports have shown that without the prior information on expected yields with the relevant stakeholders, country suffers from food scarcity shocks annually.

The motivation behind this study is to use satellite data and ANNs model to predict maize yields prior to harvesting period for sustainable food security. We adopt ANNs of multilayer perceptron, feed forward back propagation to predict maize yield at pixel level as function of weather data derived from satellite in Trans Nzoia and Nakuru counties in Kenya.

2 Materials and methods

2.1 Study area

We adopt two counties (Trans-Nzoia and Nakuru as shown in Figure 1) in Kenya for maize prediction due data availability. Trans Nzoia county covers an area of about 2,495 km^2, with a population of approximately 1 million (KNBS, 2019). The climate in Trans Nzoia

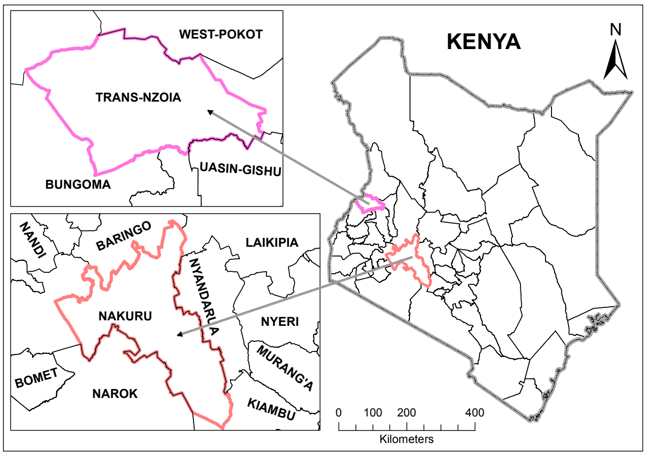


Fig. 1 Study area: Trans Nzoia and Nakuru Counties.

is mild temperatures, with rainfall of around 1097 mm per year. The main activity is largely agriculture and livestock rearing. Large-scale agriculture is mainly on wheat, maize and dairy farming, while small-scale agriculture is on maize, beans and potatoes. On the other hand, Nakuru county lies south east of Trans Nzoia and covers an area of about 7,505 sq km, with a population of approximately 2 million people (KNBS, 2019). The county has also mild temperatures with rainfall of around 895 mm per year. The main activity is agriculture and livestock rearing. Large-scale agriculture is mainly on barley, maize and dairy farming, while small-scale agriculture is on maize, peas and potatoes. Maize is rain-fed in the two counties with the sowing period in March and harvesting in November to December.

2.2 Data

This study used precipitation, minimum temperature, average temperature, maximum temperature, reference crop evapotranspiration, and NDVI derived from Landsat 7 (USGS, 1990). All the primary weather factors such as precipitation, minimum temperature, maximum temperature, and the derived factors such as average temperature, evapotranspiration, and soil moisture were obtained from climatology lab as multi-band raster images. The data has been validated with a number of station-based observations from a variety of networks including the global historical climate Network, SNOTEL, and RAWS (Abatzoglou et al., 2018). All data have monthly temporal resolution and a spatial resolution of ≈4 km. The data cover the period from 1958–2019. The historical maize yield data was obtained from the Ministry of Agriculture in Kenya.

2.3 Data processing

The Landsat images were calibrated so as to convert digital numbers to spectral radiance (Figure 2). We then used the Near Infra-Red (NIR) and red (R) bands to compute NDVI as

$$\mathrm{NDVI} = \frac{\mathrm{NIR} - \mathrm{R}}{\mathrm{NIR} + \mathrm{R}}. \tag{1}$$

NDVI values between -1 to 0.6 were masked out yielding a raster with values from 0.6 up to 1.0 which represents vegetation. The multiband rasters from for weather parameters were converted to single-band raster to unit weights using grayscale function

$$\mathrm{Output} = (B1 \times W2) + (B2 \times W2) \tag{2}$$

where $B1$ is the first raster and $B2$ is the second raster in the multi-band raster, $W1$ and $W2$ were set to 1. The resultant raster, in netCDF file format, was converted to geotiff format. The data was normalized using the min-max transformation, i.e.

$$X = \frac{X - X_{min}}{X_{max} - X_{min}} \tag{3}$$

where X is a variable representing one of the data sets used.

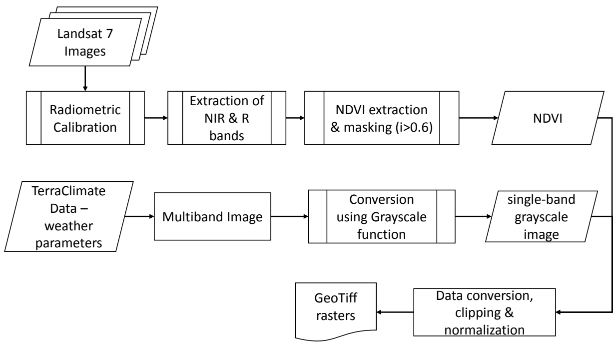


Fig. 2 Data Processing.

2.4 Feature selection

The study adopted boruta algorithm for feature or variable selection because it's based two important concepts namely: shadow features and binomial distribution. Boruta is a feature selection algorithm that works with various data and is capable of working with any prediction method to determine the importance of variable (Kursa and Rudnicki, 2010). Boruta implements the first concept by randomly creating shadow features to compete with original features. The shadow feature with highest recorded importance becomes the threshold. The importance of each original features is compared with this threshold. The original features with performance above this threshold, are selected. Secondly, the variable importance is obtain through an iteration process that follows binomial distribution. The maximum level of uncertainty about the feature is expressed by a 50% probability for selection or elimination (Mazzanti, 2020).

2.5 Yield prediction using ANNs

The study developed an ANN yield prediction model based on selected variables/features (from Section 2.4) of satellite data. Neural network adopts the parallel architecture of our brain and the operation of biological neural networks (Puig-Arnavat and Bruno, 2015). The algorithm is designed to recognize patterns in complex data optimally. Neural networks have neurons with connections. A neuron contain a value and activation function whereas connection holds a weight and bias. The neurons are divided into input, hidden and output layers. Neural networks have three parts; feed forward, activation functions, and back propagation (Kadir et al., 2014).

The term feed forward in neural network refers to the process of updating the neuron in the next layer, by multiply the activations by weights. Activation functions are the logistic functions. They scale the values of updated neurons to be between 0 and 1. The study adopted the sigmoid activation function, i.e.

$$f(x) = \frac{1}{(1 + e^{-x})} \tag{4}$$

where x is the input for the respective input layer of the neural. In the neural networks, back propagation computes the gradient. The neural learns (during model training) by adjusting the weight (w) and bias (b) for each layer using these gradients.

We trained our ANNs model for prediction using the Levenberg-Marquardt algorithm. This is a hybrid technique that uses both Gauss-Newton and gradient descent approaches to achieve optimal solution (Wilson and Mantooth, 2013). The hybrid approach uses the best characteristics of these two techniques. Gauss-Newton technique is normally faster when the initial guess is relatively close to the optimum, otherwise the algorithm uses the gradient descent technique to find an optimum,

$$x_{k+1} = x_k - \left[J^T J + \mu I\right]^{-1} J^T e \tag{5}$$

where J is the jacobian matrix of performance, $J^T J$ is an approximation of the matrix, μ is the adaptive value, x is the variable, e is the error and $J^T e$ is the gradient descend computation. The small values of the parameter μ result in a Gauss-Newton update and large values of μ result in a gradient descent update. This algorithm adaptively varies the parameter updates between the gradient descent update and the Gauss-Newton update making it an efficient method for weights adaptations (Wilson and Mantooth, 2013).

In our study, the learning algorithm was based on feed forward back propagation multi-layer neural networks. The ANN model used in the study has following types of activation functions: tangent sigmoid function, sigmoid function and linear function. In back-propagation, sigmoid function and linear function are used as the activation functions. In the predictive model, the study used the Levenberg-Marquardt algorithm with linear and tangent sigmoid functions as activation functions. The initial step included assigning of model weights and thresholds, followed by neuron activation using the activation functions. The weights were updated based on the 6 neurons for input and hidden layer, and 1 neuron for output layer. The prediction model (Figure 3)

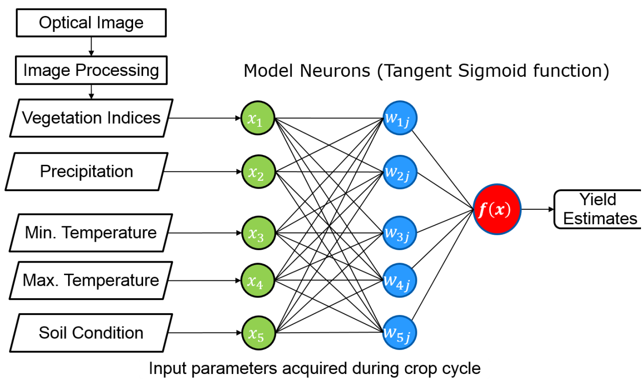
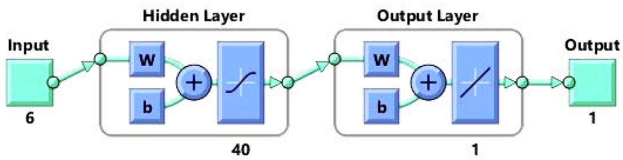


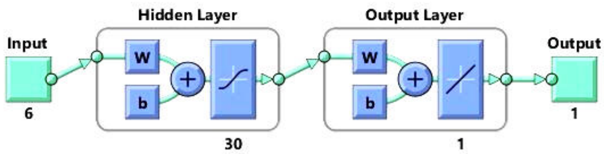
Fig. 3 Artificial neural network (ANN) architecture.

has six input variables which results in total of 6960 ($6 \times 116 \times 10$) data points. The data was normalized between 0 to 1, to neutralize the effect of influence by large data. The input variables were selected based on their influence to yields using boruta algorithm. The data was then divided randomly; 70% for training, 20% for validation and the remaining 10% for testing the model to determine optimum performance in modeling maize yields.

In retrospect, we designed two ANNs model configuration for the two counties. Figure 4a shows the model structure adopted for maize yield prediction in Trans Nzoia county. The best model fit was achieved in 40 iterations and attained a max performance. On the other, hand Figure 4b illustrates the model structure designed for Nakuru county.



(a)



(b)

Fig. 4 Designed ANNs architecture for yield prediction in (a) Trans Nzoia and (b) Nakuru counties.

2.6 Model performance validation

The performance of designed ANNs model was evaluated using coefficient of determination (R^2) and Root Mean Squared Error (RMSE). R^2 is a statistical measure of the goodness of fit of a model with values between 0 and 1. The higher the R^2 the better the model fits the data. For instance, $R^2 = 1$ means the model fits the data perfectly, e.g.

$$R^2 = 1 - \frac{(n-1)}{(n-p)} \times \frac{\text{SSE}}{\text{SST}} \tag{6}$$

where *SSE* is the sum of squared error, *SST* is the sum of squared total, n is the number of observations, and p is the number of regression coefficients. The RMSE provides the difference between the predicted and actual values i.e.

$$\text{RMSE} = \sqrt{\frac{\sum_{t=1}^{2}(y_t - y)^2}{n}} \tag{7}$$

where y_t is the predicted value, y is the actual value and n is the number of samples (Shastry et al., 2017). RMSE is a good measure of how well the model predicts the response, and it is the most important criterion for fit. The lower the RMSE values the better the fit.

3 Results and Discussion

We used historical maize yield from Trans Nzoia and Nakuru counties, in Kenya. Trans Nzoia was used for training and Nakuru to test the model performance as both counties have similar maize growing seasons. Figure 5 shows the normalized variables after min-max transformation. Generally, the maize yields were high in the year 2012 which is also picked by the variables. In other years the variables more or less show the same trend as the historical yields.

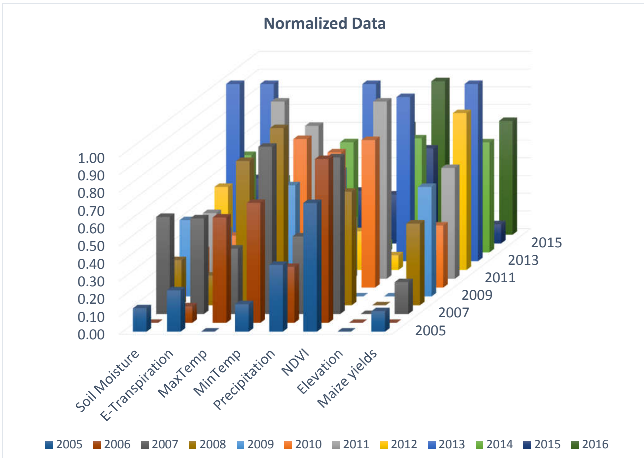


Fig. 5 Normalized variables in Trans Nzoia county: *precipitation, temperature (min, max), evapotranspiration, ndvi, soil moisture, elevation, and yields.*

The normalized variables in Figure 5 were the inputs to boruta algorithm for feature selection. The variable selection results in Figure 6 shows that weather variables and soil moisture have more influence to maize yield. Elevation was not considered as a significant factor. The blue bars represents the randomized shadow features for the minimum, mean and max thresholds. The red bars shows the shadow features of the respective features. The highest blue box plots - shadow maximum, defined the threshold of the features for this study. The green bars are the important features, as they are above the threshold. Consequently, features selected for yield prediction were: NDVI, precipitation, soil moisture, evapotranspiration, minimum and maximum temperature.

Table 1 shows the coefficient of determination R^2 and RMSE obtained from different model structure configurations of ANNs model (Figure 4a) in Trans Nzoia county based on the selected variables. The highest R^2 value which corresponds to the least RMSE was obtained at 40 iterations. There was however no clear

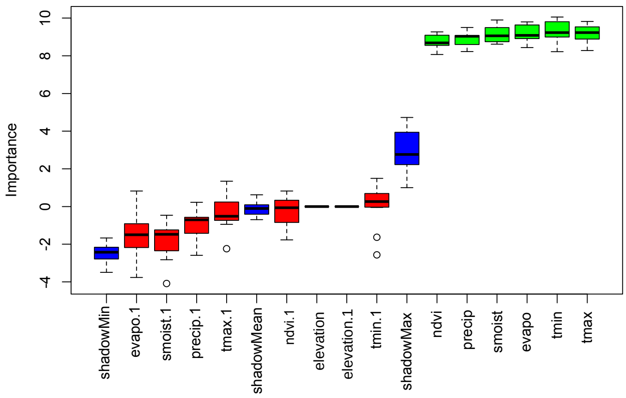


Fig. 6 Feature Selection using boruta algorithm: *where precip (precipitation), smoist (soil moisture), evapo (evapotranspiration), tmin (minimum temperature), tmax(maximum temperature), ndvi and their respective shadow features.*

trend on R^2 and RMSE with increase in the number of iterations.

Table 1 ANN structures with corresponding R^2 and RMSE (MT/ha) in Trans Nzoia County.

Case	Inputs	No. Neurons	Structure	R^2	RMSE
1	6	20	06:20:1	0.67	0.698
2	6	30	06:30:1	0.57	0.344
3	6	40	06:40:1	0.76	0.038

As a test, similar variables for Nakuru county were subjected to the model architecture in Figure 4b which gave the results in Table 2. In this case, the model gave the highest R^2 but coincidentally the RMSE was not the lowest in this case. The least RMSE was obtained at 30 iterations where the R^2 value decreased by 4%.

Table 2 ANN structures with corresponding R^2 and RMSE (MT/ha) in Nakuru County.

Case	Inputs	No. Neurons	Structure	R^2	RMSE
1	6	10	06:10:1	0.85	0.886
2	6	20	06:20:1	0.90	0.127
3	6	30	06:30:1	0.86	0.016

Overall, the best model quality in maize yield prediction is achieved at R^2 of 0.76 and 0.86 with corresponding RMSE values of 0.038 MT/ha and 0.016 MT/ha in Trans Nzoia and Nakuru county respectively (Tables 1–2). This means the model explained a minimum of 76% of maize yield variability based on the NDVI and weather data. This is quite significant given that the highest deviations observed from the ANNs models is ± 0.038 MT/ha of maize yield at county level on average. The lack of standardized and comprehensive reporting of the yields at county levels may have influence model performance. Nonetheless, ANNs computed reasonable yield estimates in the two counties as shown in Table 3.

Table 3 Estimated yield and R^2 values, 2017.

County	Estimated yield (MT/HA)	R^2
Trans Nzoia	4.13	0.76
Nakuru	2.26	0.86

Spatial distribution of final yield estimates are shown in Figure 7 for Trans nzoia and Figure 8 for Nakuru. In Trans-Nzoia county, the Northern and Eastern regions have high estimates of maize yield than Southern and Western regions. On the other hand, Nakuru has high yields in the North western and eastern parts. These areas were noted to receive relatively high rainfall, while areas with low estimates experience high temperature.

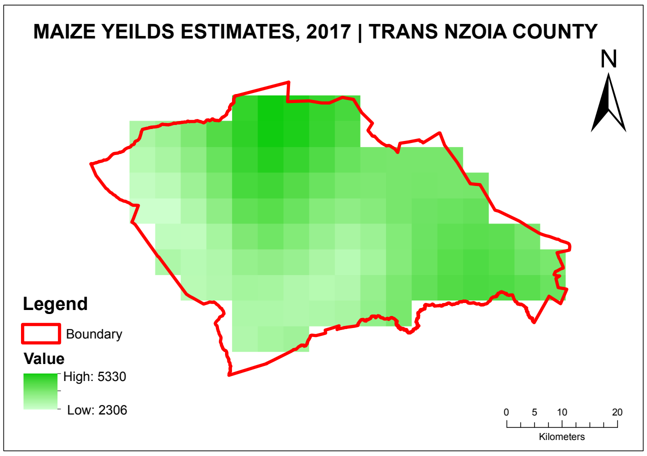


Fig. 7 Predicted maize yield for 2017 Trans Nzoia County.

We further compared ANNs model in Trans Nzoia with ordinary regression and established that ANNs results are better by an R^2 of 0.12 (Table 4). It is probably because the regression model adopts a linear interaction between the factors, e.g., temperature, humidity, rainfall which affects the crop yield. So ANNs still remains a favourable yield estimation tool.

Table 4 R^2 and $RMSE(MT/ha)$ for prediction models.

Model	R^2	$RMSE$
Ordinary regression	0.64	0.089
Artificial neural network	0.76	0.038

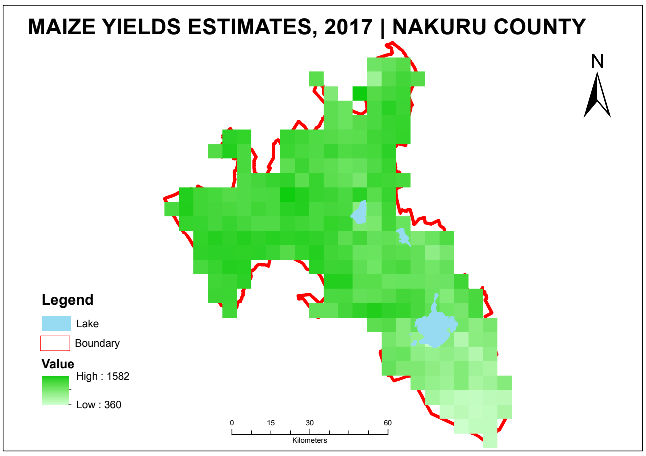


Fig. 8 Predicted maize yield for 2017 in Nakuru County.

4 Conclusion

Yield prediction is beneficial to both farmers and businesses as it provides an opportunity to make decisions and amend or introduce policies before harvest. Thus far, our study has demonstrated that maize yield estimation at county level in Kenya can be achieved at a reasonable prediction accuracy using ANNs and satellite data. In developing countries, this combination presents a solution to food insecurity shocks normally experienced. However, our study mainly used remotely-sensed satellite weather data and NDVI, therefore our future research will integrate physical and management factors for maize yield prediction.

References

Abatzoglou JT, Dobrowski SZ, Parks SA, Hegewisch KC (2018) TerraClimate, a high-resolution global dataset of monthly climate and climatic water balance from 1958-2015. Scientific Data 5(1):170191, DOI 10.1038/sdata.2017.191, URL https://doi.org/10.1038/sdata.2017.191

Ahmed SA, Diffenbaugh NS, Hertel TW (2009) Climate volatility deepens poverty vulnerability in developing countries. Environmental Research Letters 4(3):034004, DOI 10.1088/1748-9326/4/3/034004

Barzegar R, Asghari Moghaddam A (2016) Combining the advantages of neural networks using the concept of committee machine in the groundwater salinity prediction. Modeling Earth Systems and Environment 2(1):26, DOI 10.1007/s40808-015-0072-8, URL https://doi.org/10.1007/s40808-015-0072-8

Budyko MI, Menzhulin GV (1996) Climate Change Impacts on Agriculture and Global Food Production: Options for Adaptive Strategies. Springer, New York, NY, DOI https://doi.org/10.1007/978-1-4613-8471-7_16

Chen C, Mcnairn H (2006) A neural network integrated approach for rice crop monitoring. International Journal of Remote Sensing 27(7):1367–1393, DOI 10.1080/01431160500421507, URL https://doi.org/10.1080/01431160500421507, https://doi.org/10.1080/01431160500421507

Dahikar SS, Rode SV (2014) Agricultural Crop Yield Prediction Using Artificial Neural Network Approach. International Journal of Innovative Research in Electrical, Electronics, Instrumentation and Control Engineering 2(1):683–686

Deo RC, Şahin M (2015) Application of the Artificial Neural Network model for prediction of monthly Standardized Precipitation and Evapotranspiration Index using hydrometeorological parameters and climate indices in eastern Australia. Atmospheric Research 161-162:65–81, DOI https://doi.org/10.1016/j.atmosres.2015.03.018

Hota SK (2014) Artificial neural network and efficiency estimation in rice yield. International Journal of Innovative Research in Science, Engineering and Technology 3(7):14787–14805

Islam R, Islam MM, Islam MN, Islam MN, Sen S, Faisal RK (2020) Climate change adaptation strategies: a prospect toward crop modelling and food security management. Modeling Earth Systems and Environment 6(2):769–777, DOI 10.1007/s40808-019-00708-6, URL https://doi.org/10.1007/s40808-019-00708-6

Kadir MKA, Ayob MZ, Miniappan N (2014) Wheat yield prediction: Artificial neural network based approach. In: 2014 4th International Conference on Engineering Technology and Technopreneuship, pp 161–165, DOI 10.1109/ICE2T.2014.7006239

KNBS (2019) 2019 kenya population and housing census: Volume i. http://www.knbs.or.ke, (Accessed: 2nd March 2020)

Kross A, Znoj E, Callegari D, Kaur G, Sunohara M, Vliet L, Rudy D Hand Lapen, Mcnairn H (2018) Evaluation of an Artificial Neural Network Approach for Prediction of Corn and Soybean Yield. In: 14th International Conference on Precision Agriculture, Montreal, Quebec, Canada

Kursa M, Rudnicki W (2010) Feature selection with the boruta package. Journal of Statistical Software, Articles 36(11):1–13, DOI 10.18637/jss.v036.i11, URL https://www.jstatsoft.org/v036/i11

Lobell DB, Azzari G (2017) Satellite detection of rising maize yield heterogeneity in the U.S. Midwest. Environmental Research Letters 12(1):014014, DOI 10.1088/1748-9326/aa5371, URL https://doi.org/

10.1088%2F1748-9326%2Faa5371

Lobell DB, Burke MB (2010) On the use of statistical models to predict crop yield responses to climate change. Agricultural and Forest Meteorology 150(11):1443–1452, DOI https://doi.org/10.1016/j.agrformet.2010.07.008

Mazzanti S (2020) Boruta explained exactly how you wished someone explained to you. https://towardsdatascience.com, (Accessed: 22nd February 2020)

Puig-Arnavat M, Bruno JC (2015) Artificial neural networks for thermochemical conversion of biomass. In: Recent advances in thermo-chemical conversion of biomass, Elsevier, pp 133–156

Rémy F, Sicre C, Baup F (2017) Estimation of corn yield using multi-temporal optical and radar satellite data and artificial neural networks. International Journal of Applied Earth Observation and Geoinformation 57:14–23, DOI 10.1016/j.jag.2016.12.011

Schlenker W, Roberts MJ (2008) Estimating the Impact of Climate Change on Crop Yields: The Importance of Nonlinear Temperature Effects. Working paper, NATIONAL BUREAU OF ECONOMIC RESEARCH, Cambridge, MA, DOI 10.3386/w13799, URL http://www.nber.org/papers/w13799

Schmidhuber J, Tubiello FN (2007) Global food security under climate change. Proceedings of the National Academy of Sciences 104(50):19703–19708, DOI 10.1073/pnas.0701976104, URL https://www.pnas.org/content/104/50/19703, https://www.pnas.org/content/104/50/19703.full.pdf

Sellam V, Poovammal E (2016) Prediction of Crop Yield using Regression Analysis. Indian Journal of Science and Technology 9(38):1–5, DOI https://doi.org/10.17485/ijst/2016/v9i38/91714

Shastry A, Sanjay H, Bhanusree E (2017) Prediction of crop yield using regression techniques. International Journal of Soft Computing 12(2):96–102, DOI 10.36478/ijscomp.2017.96.102

Stige LC, Stave J, Chan K, Ciannelli L, Pettorelli N, Glantz M, Herren HR, Stenseth NC (2006) The effect of climate variation on agro-pastoral production in Africa. Proceedings of the National Academy of Sciences 103(9):3049–3053, DOI 10.1073/pnas.0600057103, URL https://www.pnas.org/content/103/9/3049, https://www.pnas.org/content/103/9/3049.full.pdf

United Nations (2015) World Population Prospects: The 2015 Revision, Key Findings and Advance Tables. https://www.un.org/en/development/desa/publications/world-population-prospects-2015-revision.html, (Accessed: 29th July 2020)

USGS (1990) Earthexplorer. https://earthexplorer.usgs.gov/, (Accessed: 22nd February 2020)

Wilson P, Mantooth HA (2013) Model-Based Optimization Techniques. Model-Based Engineering for Complex Electronic Systems. Elsevier, DOI 10.1016/b978-0-12-385085-0.00010-5

Zhang L, Lei L, Yan D (2010) Comparison of two regression models for predicting crop yield. IEEE International Geoscience and Remote Sensing Symposium pp 1521–1524, DOI https://doi.org/10.1109/IGARSS.2010.5652764