Journal of the University of Ruhuna
Volume 12 No 2, December, 2024. Pp 110-120
DOI: https://doi.org/10.4038/jur.v12i2.8032
ISSN: 2659-2053

RESEARCH ARTICLE

Forecasting Paddy Yield in Sri Lanka Using Back-propagation Learning in Artificial Neural Network Model

E.J.K.P. Nandani* and T.T.S. Vidanapathirana
Department of Mathematics, University of Ruhuna, Matara, Sri Lanka

Abstract: Climate change has a direct and indirect impact on food production, and food production depends on the available resources such as the quantity of seeds sown, climate, soil moisture, solar radiation, expected carbon, fertilizers, pesticides, government policies, etc. Paddy yield is one of the major contributors to food production, and there are several studies on forecasting paddy yield production in Sri Lanka using common algorithms in ANNs, this study focused on forecasting the paddy yield in Sri Lanka based on some climate factors using the selected best steepest descent optimizer algorithm for Backpropagation learning (BP) in the Artificial Neural Network (ANN) model. The input and output for the ANN model were selected as climate factors and average seasonal paddy yield respectively. The seasonal data from 1981-2020 were collected from the website of the Department of Census and Statistics, Sri Lanka, and the NASA POWER project which provides solar and meteorological data collected from 1981-2023. The min-max normalization process was used to rescale the data in [0,1], and the parameters of the ANN model were selected by trial and error. First, built-up an ANN model to forecast the yield of paddy in key districts in Sri Lanka. The forecasting accuracy of the steepest descent optimizer algorithms which are the Batch Gradient Descent Method (BGD), Stochastic Gradient Descent Method (SGD), and Mini-batch Gradient Descent Method (MBGD), for BP learning in the ANN model was measured by Mean Square Error. The results show that the ANN model with BP learning is suitable for Paddy yield prediction, and BGD was the best optimization algorithm for BP learning in this study. Hence, paddy yields of key districts in Sri Lanka were forecasted from 2021-2023 based on some the climate factors.

***Keywords**: Artificial Neural Network, Climate Factors, Forecasting, Paddy Production, Steepest descent algorith*

Introduction

Agriculture plays a prominent role in the overall growth of Sri Lanka. Over 24% of the total labor force of Sri Lanka is engaged in agriculture, and the agriculture sector contributes 7.42% to the national GDP (Vinushi et al., 2020) . The primary form of agriculture in Sri Lanka is rice production. Rice is the staple and the main carbohydrate source of the Sri Lankan diet since ancient days (Mihiranie et al., 2020). According to the reports 2019 of the Central Bank of Sri Lanka, paddy production contributed 10% to the agricultural GDP and 0.7% to the total GDP in 2017 (Perera et al., 2021). Approximately 800, 000 farmers' and their families' lives depend directly on paddy, which is grown on 30% of the land area (MPDI, 2003). Sri Lanka is a tropical country, the temperature is usually constant with respect to a certain altitude and there are two monsoons which are locally called as "Maha" Season (September-March) and "Yala" season (May-August) caused by the

*corresponding author: nandani@maths.ruh.ac.lk, https://orcid.org/0000-0002-1255-5252

country's rainfall distribution. On the precipitation level, the country has been divided mainly into three climatic zones — Wet Zone, Intermediate Zone, and Dry Zone (Ranathunga et al., 2018). The total area of paddy cultivated in Yala and Maha seasons, exceeded 852, 000 hectares in 2002 (De Silva et al., 2007). Selected key districts given in Fig.1 provide nearly 98% of the total paddy yield in Sri Lanka, and districts in the dry zone give more contribution to the paddy production in Sri Lanka.

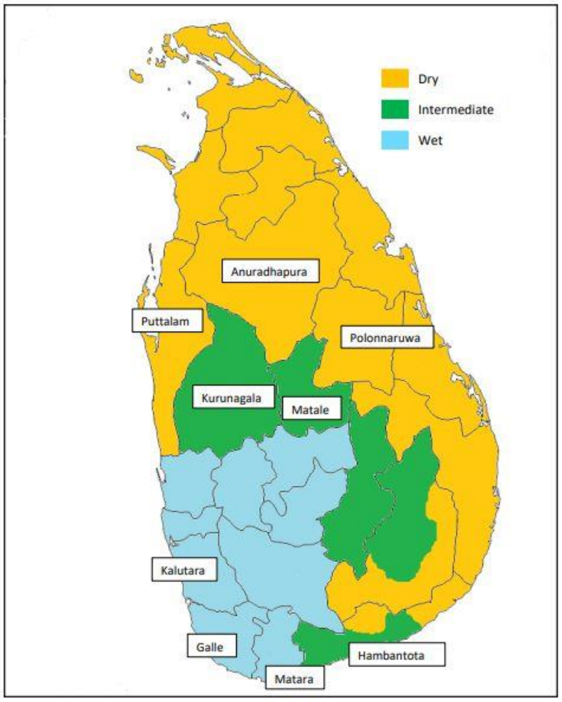

Figure. 1. Selected key districts of paddy production related to weather zones in Sri Lanka.

The demand for food is increasing day by day due to the rapid growth of the population. Climate change could influence food production via direct and indirect effects on crop growth processes (Paltasingh and Goyari, 2018, Worl Bank Group. and Asian Development Bank, 2018) . Especially, the production of paddy yield depends on various factors like the quantity of seeds sown, rainfall, soil moisture, solar radiation, expected carbon, fertilizers, pesticides, as well government policies (Aydinalp and Cresser, 2008, Cumhur and Malcolm, 2008, Banu E. and A., 2021, Perera et al., 2021, Vanitha. and Sivasankari., 2021, Rankothge, 2022) . There are numerous studies have evaluated the climate change impacts on agriculture as local or regional scale, based on various approaches (Reilly, 1995, Dinar and Mendelsohn, 2011, Mendelsohn, 2014, Chen et al., 2016a, Karimi et al., 2018). However, the paddy harvest is extremely vulnerable to climate change and climate variations. Therefore, understanding the relationships between climatic factors and paddy production has become crucial for the sustainability of the agriculture sector (Vinushi et al., 2020) . However, these relationships are usually complex nonlinear relationships.

Artificial Neural Network (ANN) has become increasingly popular in forecasting philosophy, leading to effective implementations in the prediction of time series and explanatory forecasting (Zhang et al., 1998, Abdullah et al., 2019). ANN can handle multi-variate non-linear, non-parametric statistical approaches more efficiently (Vanitha. and Sivasankari., 2021)., and it provides a flexible nonlinear mapping between inputs and outputs (Zhang et al., 1998, Shabri et al., 2009, Jha and Sinha, 2013). Recent research activities in ANN have shown that ANN has powerful pattern recognition, classification, and forecasting capability (Zhang et al., 1998, Abdullah et al., 2019).

Modern technology adoption is very important for agricultural improvement. It always tries to obtain the highest yields and highest economic profit (Rehman et al., 2016) . In the future, there may be mass production of non-driver tractors and other agriculture machinery that use electronic sensors and GPS maps (Vanitha. and Sivasankari., 2021). However, climate change can improve or worsen conditions in the agricultural sector. It has been discussed in numerous studies by exploring the impact of climate change on agriculture, (Reilly, 1995, Mendelsohn, 2009, Dinar and Mendelsohn, 2011, Mendelsohn, 2014, Chen et al., 2016b, Karimi et al., 2018). Climate change may affect not only agriculture but several other economic systems as well (Kane, 1991). So, identifying the relation between climate factors and agriculture will help to reduce the negative effects on agriculture as well as the economy of the country.

Sri Lanka is an agricultural country since ancient times, and the paddy and rice sectors continue to occupy a foremost place in agriculture in Sri Lanka. Gunapala et al., (2022) have noticed that Sri Lanka uses the crop-cutting survey method to estimate the average paddy yield during the harvesting period and it has failed to forecast the yield before harvesting. Therefore, identifying a novel technique for accurate paddy yield prediction before harvesting is worthwhile and it will help to authorities to take decisions. Although several studies on the agriculture field are growing up all over the world, most of the studies on rice prediction in Sri Lanka are still based on traditional time series modeling. For example, most studies have forecasted paddy production in Sri Lanka using Auto Regressive Integrated Moving Average (ARIMA) Model (Karunarathna and Fransisco, 2010, Sivapathasundaram and Bogahawatte, 2012) , that is one of the most important and widely used time series model (Jha and Sinha, 2013). Other approaches for estimating paddy yield are Exponential Smoothing (EXPS) (Shabri et al., 2009) , Auto Regressive Integrated Moving Average (ARIMAX) (Yogarajah et al., 2013), etc.

In recent times, Machine Learning (ML) techniques have been much successful in modelling time series data, and numerous empirical studies have shown that ML approaches outperform time series models in forecasting (Nandani et al., 2015, Paul et al., 2022) . Therefore, most research studies in the agricultural sector have paid particular attention to ML specially ANN which is a multivariate non-linear non-parametric data driven self-adaptive statistical method (Jha and Sinha, 2013, Muthukumaran et al., 2023) As an example, some studies have been undertaken on predicting paddy yield (Ji et al., 2007, Vanitha. and Sivasankari., 2021, Vinson et al., 2021) and forecasting the agricultural price of commodities (Jha and Sinha, 2013, Mahto et al., 2021) using ANN. As well as the value of ANN models in forecasting economic time series has been established for developed countries like the USA, Canada, Germany, etc., but little work has been undertaken for developing countries (Jha and Sinha, 2013). Fortunately, the research on agriculture to date in Sri Lanka has been tended to focus on ANN rather than traditional time series models (Vinushi et al., 2020, Wanninayaka et al., 2020) .

While there are some studies have assessed the suitability of some climate factors such as temperature, relative humidity, etc. (Mendelsohn, 2014, Rathnayake et al., 2016, Ray, 2016, Ekanayake et al., 2021), most studies predicted the paddy yield using the ANN model based on climatic data (Vinushi et al., 2020), historical data (Ji et al., 2007) . Some studies have used remote sensing, weather, and non-weather variables (Wanninayaka et al., 2020). Moreover, related researchers have explored different ANN structures and learning methods (Muthusinghe et al., 2018, Shook et al., 2021). The comparison between traditional methods and ANN techniques in the literature has proven that agricultural commodity prices can be forecasted more accurately using ANN techniques (Vinushi et al., 2020, Vanitha. and Sivasankari., 2021, Vinson et al., 2021, Sandaruwani and Abeygunawardana, 2022). However, several empirical studies have already suggested that by combining several different models, forecasting accuracy can often be improved over the individual model (Shabri et al., 2009).

According to the details given in the above, researchers have been carried out their studies on paddy/agriculture based on traditional time series models and common machine learning techniques. This study attempts to compare the forecasting ability of various forms of weights updating rules (the Batch Gradient Descent Method (BGD), Stochastic Gradient Descent Method (SGD), and Mini-batch Gradient Descent Method (MBGD)) which are related to the gradient descent technique in BP and seeks to forecast paddy yield in Sri Lanka by using the obtained best steepest descent optimizer algorithm in BP learning algorithm in ANN.

Although, there are several studies on forecasting paddy yield production using traditional time series models, and ANN with common learning algorithms (Vinushi et al., 2020), the major objective of this study was to find the better weights update rule (optimization algorithm) for BP learning algorithm in ANN model based on paddy yield forecasting under the climate factors, and forecast the average paddy yield in Sri Lanka more accurately through selected key districts shown in Fig 1, for Yala and Maha seasons separately. According to the precipitation level, Anuradhapura, Polonnaruwa, and Puttalama represent the Dry zone, the wet zone is represented by Galle, Matara, and Kalutara Districts, and Kurunegala, Matale and Hambantota represent the Intermediate zone. This study focused on three tasks, and those were listed below.

1. Forecast the average paddy yield in Sri Lanka seasonally (2011 - 2020) in key districts where Anuradhapura, Polonnaruwa, Puttaluma, Galle, Matara, Kalutara, Kurunegala, Matale, and Hambantota by using BP algorithm in ANN along with various weights updating rules to select the best ANN model,
2. Compare the performance ability of the optimization algorithms which is affected to the weight updated in the back-propagation learning in ANN, using Mean Square Error (MSE),
3. Forecast the paddy yield seasonally in key districts from 2021 to 2023 applying obtained best optimization algorithm results.

The seasonally average paddy yield of each district in Sri Lanka from 1981 to 2020 was collected from the website of the Department of Census and Statistics, Sri Lanka, and the NASA POWER Project which provides solar and meteorological data sets (1981-

2023) from NASA research (http://power.larc.nasa.gov/data-access-viewer).

Among the most influential climatic factors on agricultural productivity some of the commonly used factors average values of minimum temperature, maximum temperature, wind speed, humidity, and total rainfall related to the season are used as input variables, and the amount of seasonal paddy yield is taken as an output variable in the ANN model.

Methodology

Data Collection

The major objective of this study was to forecast the average paddy yield in Sri Lanka in key districts considering the Yala and Maha seasons separately. Therefore, the necessary seasonal average paddy yield of each district in Sri Lanka from 1981 to 2020 was collected from the website of the Department of Census and Statistics, Sri Lanka (http://www.statistics.gov.lk/), and the NASA POWER Project which provides solar and meteorological data sets (1981-2023) from NASA research (http://power.larc.nasa.gov/data-access-viewer). There were no missing values found in the dataset and calculated the correlations between climate factors and paddy yield. The dataset was normalized by min-max normalization given in (1) and the normalized data set was used for further analysis.

$$x' = \frac{x - x_{min}}{x_{max} - x_{min}}(u - l) + 1, \qquad (1)$$

Where x and x' represent original data and normalized data respectively. x_{min} and x_{max} minimum and maximum values of the relevant data and u and l are upper and lower limits of the new range. i.e. $x' \in [l, u]$. After that input and output data were divided into two clusters such that 1981-2010 (80% out of the entire dataset) was used for training the model and 2011-2020 (20% out of the entire dataset) was used for testing the accuracy of the model. Using the training data set built up the corresponding ANN models for each key district and selected the suitable hidden nodes and learning rate by trial and error. Initial weights are selected randomly for the training process.

Interested Model

The universal approximation theorem shows that an ANN model with a single hidden layer with a sufficiently large number of neurons can in principle relate any given set of inputs to a set of outputs to an arbitrary degree of accuracy (Shabri et al., 2009). Therefore, in this study number of hidden layers is limited to one. Five climate factors—average values of maximum temperature, minimum temperature, wind speed, humidity, and total rainfall were used as input variables, and average seasonal paddy yield was the output variable. One of the most important characteristics of the ANN model is the number of neurons in the hidden layer. If an inadequate number of neurons is used, the ANN model will be unable to model data properly, and the accuracy of the model will be poor. So, the number of neurons in the hidden layer and learning rate parameters were selected by trial and error.

The activity function used for each neuron in the ANN model was the logistic sigmoid function given by

$$f(x) = \frac{1}{1+e^{-x}}. \qquad (2)$$

The general expression for j^{th} neuron output, y_j' of the above ANN model is given by (3)

$$y_j' = f\left(\sum_{i=1}^{H_n} v_{ij} \,.\, f\left(\sum_{k=1}^{I_n} w_{x_{ki}}\, x_k\right)\right), \qquad (3)$$

where I_n and H_n are the number of neurons in the input layer and hidden layer respectively. $w_{x_{ki}}$ weight of the connection between network input x_k and neuron i in the hidden layer. The success of the ANN model depends on the training process, where all weights are adjusted repeatedly until the output matches the expected values for all training data.

Weights, w adjustment is followed by one of the optimization algorithms in Back-propagation (BP) learning that is the most popular and widely implemented learning algorithm for all ANN paradigms. It uses gradient descent method defined on the loss function given in equation (4) and the learning rate, η.

$$L = expected\ output\ (y) - ANN\ output\ (y') \quad (4)$$

There are three variant optimization algorithms — Batch Gradient Descent (BGD), Stochastic Gradient Descent (SGD), and Mini Batch Gradient Descent (MBGD), of the gradient descent algorithm which differ in the amount of data used for updating weights iteratively in the BP algorithm.

Batch Gradient Descent Method (BGD):

The loss function value is calculated for each example within the training dataset, but only after all training examples have been evaluated weights are updated using the mean of all the individual losses as in (5)

$$w_{i+1} = w_i - \eta \, \nabla_{w_i} L(w_i) \qquad (5)$$

Stochastic Gradient Descent Method (SGD):

When we train the model to optimize the loss function using only one particular example from our dataset,

$$w_{i+1} = w_i - \eta \, \nabla_{w_i} L(x^i, y^i : w_i) \qquad (6)$$

Mini-batch Gradient Descent Method (MBGD):

MBGD is the cross-over between BGD and SGD. In this approach instead of iterating through the entire dataset or one observation, the dataset is split into subsets (batches) with size n and compute the gradients for each batch as (7).

$$w_{i+1} = w_i - \eta \, \nabla_{w_i} L(x^{i:i+n}, y^{i:i+n} : w_i) \qquad (7)$$

The performance ability of optimization algorithms given (5), (6) and (7) was compared by using MSE given in (8).

$$MSE = \frac{1}{N} \sum_{i=1}^{N} (y_i - y_i')^2 \qquad (8)$$

Finally, forecast the paddy yield seasonally in key districts in Sri Lanka from 2021-2023 applying the obtained best optimization algorithm and parameters to the BP learning in built up ANN model.

Results and Discussion

The collected total paddy yield in Sri Lanka from 1981 to 2020 is shown in Fig.2. Although the Maha season (September-March) is joining the two consecutive years, their paddy yield shown in Figure 2 corresponds to the season started the year. In both seasons produced paddy yield has been increased with a small deviation due to the usage of modern technology.

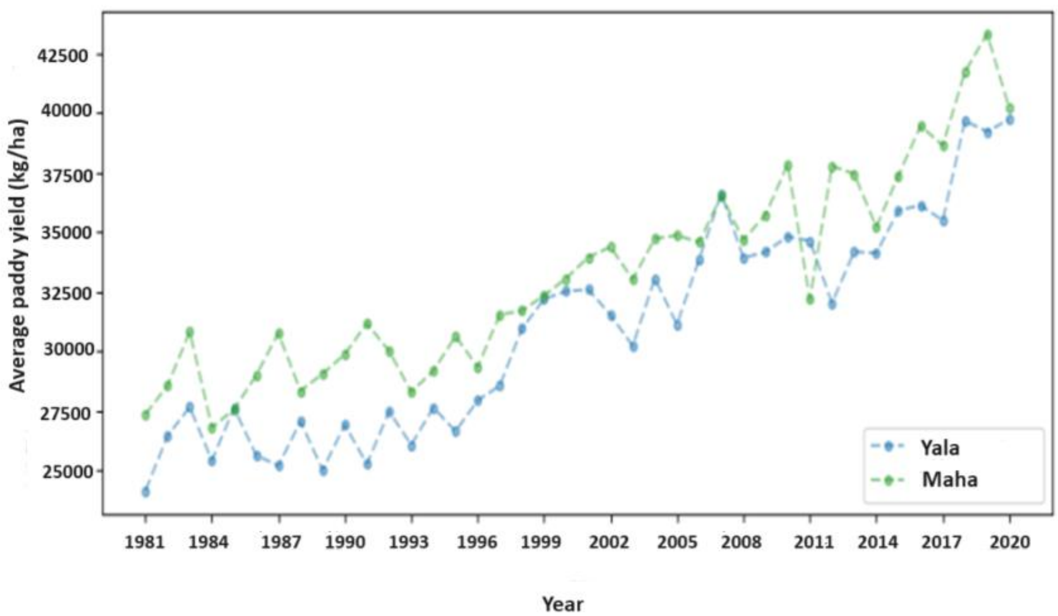

Figure. 2. The produced paddy yield from 1981 to 2020 in Sri Lanka.

Table 1 and Table 2 show the p-value and Pearson's correlation coefficient which gives the details for linear independence between paddy yield and each climate factor for Yala and Maha separately. Here, $\mathbf{v_1}$, $\mathbf{v_2}$ $\mathbf{v_3}$, $\mathbf{v_4}$, and $\mathbf{v_5}$ represent the climate factors that are rainfall, max. temperature, min. temperature, average humidity, and wind speed respectively. When the significant level is α=0.05, they reveal that most of climate variables and paddy yields are not linearly independent in the Yala season, and there are weak/moderate correlated. As well as most of climate variables and paddy yields are linearly independent in the Maha season.

Table 1: P-value and Pearson's correlation coefficient for the Yala season. Each v_i's represents the climate factors

Districts	Yala									
	P-value					Pearson's Correlation Coefficient.				
	v_1	v_2	v_3	v_4	v_5	v_1	v_2	v_3	v_4	v_5
Anuradhapura	0.03	0.03	0.76	0.03	0.00	0.34	-0.05	0.33	0.60	-0.42
Polonnaruwa	0.28	0.28	0.39	0.13	0.05	0.34	-0.05	0.33	0.60	-0.42
Puttalama	0.93	0.93	0.30	0.00	0.13	0.01	0.16	0.55	0.24	-0.10
Galle	0.00	0.00	0.75	0.02	0.00	0.44	0.55	0.37	0.58	0.08
Matara	0.01	0.01	0.14	0.07	0.00	0.39	-0.23	0.29	0.58	-0.03
Kalutara	0.00	0.00	0.54	0.00	0.00	0.44	-0.10	0.49	0.45	-0.23
Kurunegala	0.00	0.00	0.16	0.20	0.01	0.45	-0.22	0.20	0.42	-0.44
Matale	0.02	0.02	0.20	0.13	0.02	0.35	-0.21	0.24	0.36	-0.25
Hambantota	0.02	0.02	0.32	0.00	0.00	0.36	-0.16	0.50	0.48	-0.40

Table 2: Pearson's correlation coefficient and P-value for Maha season. Each v_i's represent the climate factors

Districts	Maha									
	P-value					Pearson's Correlation Coefficient.				
	v_1	v_2	v_3	v_4	v_5	v_1	v_2	v_3	v_4	v_5
Anuradhapura	0.01	0.01	0.02	0.00	0.01	0.42	-0.30	0.38	0.50	-0.43
Polonnaruwa	0.00	0.23	0.11	0.01	0.10	0.48	-0.35	0.25	0.40	-0.26
Puttalama	0.70	0.95	0.50	0.41	0.74	0.060.	0.01	0.11	0.13	0.05
Galle	0.00	0.91	0.42	0.05	0.64	60	0.02	0.13	0.30	-0.07
Matara	0.00	0.27	0.48	0.06	0.15	0.53	-0.18	-0.11	0.30	-0.23
Kalutara	0.00	0.76	0.61	0.59	0.09	0.61	-0.05	0.08	0.09	-0.27
Kurunegala	0.11	0.61	0.48	0.29	0.03	0.25	-0.08	0.11	0.17	-0.34
Matale	0.08	0.75	0.08	0.20	0.35	0.28	-0.05	0.27	0.20	-0.15
Hambantota	0.00	0.64	0.11	0.10	0.01	0.44	-0.07	0.25	0.26	-0.40

Built up 5-HN-1 ANN architecture shown in Fig 3 was trained for 50000 iterations with parameter values which are selected by trial and error, given in Table 3. While the learning rate has been fluctuated between 0.7 - 0.9, mostly it was selected as 0.9, and the number of hidden nodes was always greater than or equal to size of the input layer and less than twice the size of the input layer. After the training process, a testing set was used to measure the performance of the models, and corresponding MSE values are shown in Table 4.

They have been proved that the performance of the ANN model depends on the optimization algorithm of the BP learning, and minimum MSE values corresponding to the Yala and Maha both seasons received from the BGD algorithm applied to BP learning in the ANN model.

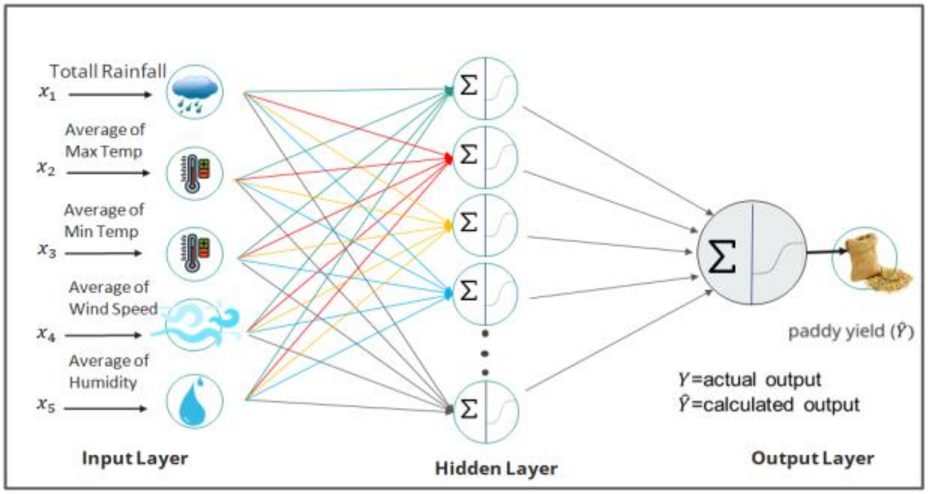

Figure. 3. Optimal ANN architecture for forecasting paddy yield in Sri Lanka.

Table 3. Details of the built up 5-HN-1 ANN model corresponding to each district and weather zone. Here, HN and η represent the number of hidden nodes in the hidden layer and the learning rate respectively.

Districts	**Selected values**			
	Yala		**Maha**	
	HN	η	**HN**	η
Anuradhapura	6	0.9	7	0.8
Polonnaruwa	6	0.9	9	0.9
Puttalam	7	0.9	8	0.9
Galle	7	0.9	5	0.9
Matara	8	0.7	6	0.9
Kalutara	8	0.9	6	0.7
Kurunegala	6	0.9	6	0.7
Matale	6	0.9	7	0.9
Hambantota	9	0.9	7	0.7

Table 4: MSE of ANN model at forecasting district-wise paddy yield in Sri Lanka.

Districts	**MSE of Optimization Algorithms in BP Learning**					
	BGD		***SGD***		***MBGD***	
	Yala	***Maha***	***Yala***	***Maha***	***Yala***	***Maha***
Anuradhapura	0.0399	0.0630	0.0906	0.0802	0.0791	0.0761
Polonnaruwa	0.0690	0.1196	0.1240	0.2080	0.0813	0.1491
Puttalam	0.0672	0.0695	0.1266	0.1283	0.0869	0.0864
Galle	0.0306	0.0716	0.0974	0.1317	0.1147	0.0949
Matara	0.0402	0.0688	0.0719	0.1305	0.0749	0.1071
Kalutara	0.0569	0.0766	0.0638	0.1273	0.1017	0.1252
Kurunegala	0.0540	0.1089	0.0608	0.2832	0.0912	0.1460
Matale	0.0658	0.0486	0.0614	0.1316	0.0859	0.0627
Hambantota	0.0796	0.0995	0.1240	0.1648	0.1288	0.1327

Table 5: Forecasted paddy yield in each key district from 2021-2023.

Districts	Forecasted Paddy Yield (kg per Hectare)				
	Yala (May –August)			Maha (Sept.- March)	
	2021	2022	2023	2021/2022	2022/2023
Anuradhapura	2359.3	5574.0	3740.0	2944.2	3456.8
Polonnaruwa	2632.9	4534.9	4320.0	2853.6	2590.0
Putalam	2537.5	4506.6	3140.0	2583.2	2594.3
Galle	2410.8	4483.6	2430.0	2236.4	3389.7
Matara	2595.1	4309.2	3952.3	2987.7	3098.1
Kalutara	2496.1	3215.8	2987.0	2135.0	2590.9
Kurunegala	2831.0	3740.6	3970.0	3046.6	2590.0
Matale	2831.0	2691.8	3572.0	3125.0	2590.0
Hambantota	2526.0	4534.9	3456.0	2475.2	3292.1

Yala and Maha are the main two seasons in Sri Lankan agriculture, and each season has nearly six months. At present, farmers use scientifically developed new kinds of seeds, and their yield is less than that of the four months. Therefore, it was difficult to define the period for each season exactly.

Although this study mainly focused on the weather effect on paddy yield in Sri Lanka, paddy yield depends on not only weather factors but also external factors such as soil moisture, solar radiation, expected carbon, fertilizers, pesticides, as well government policies quality etc. As an example, farmers obtained more yield after using new technology and scientifically developed seeds. Also paddy yield in Sri Lanka decreased in 2021-2022 due to chemical fertilizer ban. Therefore, results shown in Table II may have some deviation from actual values.

References

Abdullah, S. N. S., A. Shabri, and R. Samsudin. (2019). Use of Empirical Mode Decomposition in Improving Neural Network Forecasting of Paddy Price. Matematika:53-64. https://doi.org/10.11113/matematika.v35.n4.1263.

Aydinalp, C., and M. S. Cresser. (2008). The effects of global climate change on agriculture. American-Eurasian Journal of Agricultural & Environmental Sciences **3**:672-676.

Banu E., and G. A. (2021). Rice crop yield prediction using random forest and deep neural network- An integrated approach. International Conference on Smart Data Intelligence (ICSMDI2021).

Chen, S., X. Chen, and J. Xu. (2016a). Impacts of climate change on agriculture: Evidence from China. Journal of Environmental Economics and Management **76**:105-124. https://doi.org/10.1016/j.jeem.2015.01.005.

Chen, S., X. Chen, and J. Xu. (2016b). Impacts of climate change on agriculture: Evidence from China. Journal of Environmental Economics and Management **76**:105-124. https://doi.org/10.1016/j.jeem.2015.01.005.

Cumhur, A., and S. C. Malcolm. (2008). The effects of global climate change on agriculture. American-Eurasian Journal of Agricultural and Environmental Sciences **3**:672-676.

De Silva, C. S., E. K. Weatherhead, J. W. Knox, and J. A. Rodriguez-Diaz. (2007). Predicting the impacts of climate change—A case study of paddy irrigation water requirements in Sri Lanka. Agricultural Water Management **93**:19-29. https://doi.org/10.1016/j.agwat.2007.06.003.

Dinar, A., and R. O. Mendelsohn. (2011). Handbook on climate change and agriculture. Edward Elgar Publishing.

Ekanayake, P., W. Rankothge, R. Weliwatta, and J. W. Jayasinghe. (2021). Machine Learning Modelling of the Relationship between Weather and Paddy Yield in Sri Lanka. Journal of Mathematics **2021**:9941899. https://doi.org/10.1155/2021/9941899.

Gunapala, P., C. Rupasinghe, and A. Priyankara. (2022). Paddy Yield Estimation Models Using Satellite Data: A Case Study in Kamburupitiya DS Division. Journal of Dry Zone Agriculture **8**. http://doi.org/10.4038/jdza.v8i1.56.

Jha, G. K., and K. Sinha. (2013). Agricultural price forecasting using neural network model: An innovative information delivery system. Agricultural Economics Research Review **26**:229-240.

Ji, B., Y. Sun, S. Yang, and J. Wan. (2007). Artificial neural networks for rice yield prediction in mountainous regions. The Journal of Agricultural Science **145**:249-261. https://doi.org/10.1017/S0021859606006691.

Kane, S. (1991). Climate change: economic implications for world agriculture. US Department of Agriculture, Economic Research Service.

Karimi, V., E. Karami, and M. Keshavarz. (2018). Climate change and agriculture: Impacts and adaptive responses in Iran. Journal of Integrative Agriculture **17**:1-15. https://doi.org/10.1016/S2095-3119(17)61794-5.

Karunarathna, V., and G. Fransisco. (2010). Development of forecasting model for paddy cultivation in Sri Lanka. ASBIRES:142-147.

Mahto, A. K., M. A. Alam, R. Biswas, J. Ahmed, and S. I. Alam. (2021). Short-Term Forecasting of Agriculture Commodities in Context of Indian Market for Sustainable Agriculture by Using the Artificial Neural Network. Journal of Food Quality **2021**:9939906. https://doi.org/10.1155/2021/9939906.

Mendelsohn, R. (2009). The Impact of Climate Change on Agriculture in Developing Countries. Journal of Natural Resources Policy Research **1**:5-19. https://doi.org/10.1080/19390450802495882.

Mendelsohn, R. (2014). The Impact of Climate Change on Agriculture in Asia. Journal of Integrative Agriculture **13**:660-665. https://doi.org/10.1016/S2095-3119(13)60701-7.

Mihiranie, S., J. K. Jayasinghe, C. V. L. Jayasinghe, and J. P. D. Wanasundara. (2020). Indigenous and traditional foods of Sri Lanka. Journal of Ethnic Foods **7**:42. https://doi.org/10.1186/s42779-020-00075-z.

Muthukumaran, S., P. Geetha, and E. Ramaraj. (2023). Multi-Objective Optimization with Artificial Neural Network Based Robust Paddy Yield Prediction Model. Intelligent Automation \& Soft Computing **35**:215--230. https://doi.org/10.32604/iasc.2023.027449.

Muthusinghe, M. R. S., S. T. P, W. A. N. D. Weerakkody, A. M. H. Saranga, and W. H. Rankothge. (2018). Towards Smart Farming: Accurate Prediction of Paddy Harvest and Rice Demand. 2018 IEEE Region 10 Humanitarian Technology Conference (R10-HTC):1-6. http://doi.org/10.1109/R10-HTC.2018.8629843.

Nandani, E., M. Mahinda, and J. Wedagedara. (2015). Comparison of ARIMA and Neural Network Models for S&P SL (20)

Index. Proceedings of 2nd Ruhuna International Science & Technology Conference, University of Ruhuna:22-23.

Paltasingh, K. R., and P. Goyari. (2018). Statistical Modeling of Crop-Weather Relationship in India: A Survey on Evolutionary Trend of Methodologies. Asian Journal of Agriculture & Development **15**.

Paul, R. K., M. Yeasin, P. Kumar, P. Kumar, M. Balasubramanian, H. S. Roy, A. K. Paul, and A. Gupta. (2022). Machine learning techniques for forecasting agricultural prices: A case of brinjal in Odisha, India. PloS one **17**:e0270553. https://doi.org/10.1371/journal.pone.0270553.

Perera, M. D. D., D. A.K.A., U. U.D.R., and W. W.A.R. (2021). Policies that Matter or Are Forgettable-The Evaluation of Paddy Policies in Sri Lanka:1998 to 2018. Hector Kobbekaduwa Agrarian Research and Training Institute, , Sri Lanka, .

Ranathunga, L., W. Wijemanna, M. Sathsara, and R. Gamage. (2018). Agriculture in Sri Lanka: The Current Snapshot. International Journal of Environment, Agriculture and Biotechnology **3**:118-125. https://doi.org/10.22161/ijeab/3.1.15.

Rankothge, W. H. (2022). An Empirical Study on Paddy Harvest and Rice Demand Prediction for an Optimal Distribution Plan. Pages 27-51 *in* R. M. S. Rani, G.R. Kanagachidambaresan, S. Ahuja and D. Gupta, editor. Machine Learning Paradigm for Internet of Things Applications.

Rathnayake, W., R. De Silva, and N. Dayawansa. (2016). Assessment of the suitability of temperature and relative humidity for rice cultivation in rainfed lowland paddy fields in Kurunegala district. Tropical Agricultural Research **27**:370– 388.

Ray, M. (2016). Influence of different weather parameters on rice production-A review. Advances in Life Sciences **5**:5776-5782.

Rehman, A., L. Jingdong, R. Khatoon, I. Hussain, and M. S. Iqbal. (2016). Modern agricultural technology adoption its importance, role and usage for the improvement of agriculture. Life Science Journal **14**:70-74.

Reilly, J. (1995). Climate Change and Global Agriculture: Recent Findings and Issues. American Journal of Agricultural Economics **77**:727-733. https://doi.org/10.2307/1243242.

Sandaruwani, I., and R. Abeygunawardana. (2022). A Comparison of Classical Time Series Models and Machine Learning LSTM Model to Forecast Paddy Production in Sri Lanka.

Shabri, A., R. Samsudin, and Z. Ismail. (2009). Forecasting of the rice yields time series forecasting using artificial neural network and statistical model. Journal of Applied Sciences **9**:4168-4173. https://doi.org/10.3923/jas.2009.4168.4173.

Shook, J., T. Gangopadhyay, L. Wu, B. Ganapathysubramanian, S. Sarkar, and A. K. Singh. (2021). Crop yield prediction integrating genotype and weather variables using deep learning. PloS one **16**:e0252402. https://doi.org/10.1371/journal.pone.0252402.

Sivapathasundaram, V., and C. Bogahawatte. (2012). Forecasting of paddy production in Sri Lanka: A time series analysis using ARIMA model. Tropical Agricultural Research **24**:21-30.

Vanitha., G., and B. Sivasankari. (2021). Prediction of Paddy Yield in Thiruvarur District using Artificial Neural Network. International Journal of Current

Microbiology and Applied Science **10**:47-56.

Vinson, J., S. M. Priyadharson, and R. Kannadasan. (2021). Exploration of Machine Learning Approaches for Paddy Yield Prediction in Eastern Part of Tamilnadu. Agronomy **11**:2068. https://doi.org/10.3390/agronomy11102068.

Vinushi, A., L. Wickramasinghe, A. Perera, J. Jayasinghe, and U. Rathnayake. (2020). Artificial Neural Network to Estimate the Paddy Yield Prediction Using Climatic Data. Mathematical Problems in Engineering **2020**:8627824. https://doi.org/10.1155/2020/8627824.

Wanninayaka, W. K., R. T. Rathnayaka, and E. N. Udayakumara. (2020). Artificial neural network to estimate the paddy yield prediction using remote sensing, weather and non weather variable in Ampara district, Sri Lanka. 2020 5th International Conference on Information Technology Research (ICITR):1-6. https://doi.org/10.1109/ICITR51448.2020.9310894.

Worl Bank Group., and Asian Development Bank. (2018). Climate Risk Country Profile: Sri Lanka. World Bank.

Yogarajah, B., C. Elankumaran, and R. Vigneswaran. (2013). Application of ARIMAX model for forecasting paddy production in Trincomalee district in Sri Lanka. Third International Symposium. :21-25.

Zhang, G., B. Eddy Patuwo, and M. Y. Hu. (1998). Forecasting with artificial neural networks:The state of the art. International Journal of Forecasting **14**:35-62. https://doi.org/10.1016/S0169-2070(97)00044-7.