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Wheat Yield Prediction in Bangladesh using Artificial Neural Network and Satellite Remote Sensing Data

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Strictly as per the compliance and regulations of:

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I. Introduction

Agriculture is the most influential strategic sector all over the world; this sector provides food and the prime means of livelihood 7.6 billion people. Wheat is one of the most important staple foods; it is ranked second as cereal grain after rice and consumes throughout the world. It is not only a staple food, but it is also an excellent cash crop because of its dominance in world trade and commerce. Besides this, the cultivation of wheat is comparatively easier than the other grain crops, has a relatively short duration of growing period and has very fair yield rate. It is currently the most widely cultivated crop, and it covers more area than any other food crop in the world. It is an abundant source of carbohydrates and protein. It provides 20% of the daily food calories and protein for 4.5 billion people all around the world [1].

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According to the Food and Agriculture Organization (FAO) of United Nations, rice and wheat are the world's two most important food grains; their respective scenarios in production are 493.7 & 732.4 million tons, in cultivated area are 163.19 & 220.41 million hectare and in trade are 45 & 156 million tons in the year 2014/15 which clearly indicates the dominance of wheat in global food security.

Bangladesh is known to be a densely populated country in the world; about 160 million people live on a small land 147,570 km^2, where the agricultural sector is under immense pressure to meet the increasing demand of food for its big amount, and ever-increasing population. Fundamentally, Bangladesh has an agro-based economy and agriculture plays a vital role in its economy, food security, employment and poverty reduction. As the single largest contributor to the national economy and employment generation, agriculture contributes about 17% to Gross Domestic Product (GDP), and around 45% of the total labor force is employed in this sector [2]. Wheat is the second most important cereal crop in Bangladesh next to rice. It is known to be the food supplement to rice as dietary preferences of Bangladeshi people and in economic and consumption importance.

An accurate, authentic and timely prediction of crop yield is of fundamental importance to the government, growers, stakeholders, and policymakers for monitoring food security and planning about crop markets. The statistical yield data is a manual collection of field data done via an annual/seasonal sample survey which is labor and time intensive and requires several months after harvest to release officially. On the other hand, crop yield can be effectively forecast before harvest using remote sensing technology. Yield forecast provides valuable information that can be used to maintain adequate food stocks, make appropriate food policies, improve market transactions, set national prices, optimize the utilization of storage, transaction and processing facilities, and make effective decisions regarding the export or import trade [3]. At present, different methodologies and models are used by researchers to predict agriculture production. These include multiple regression, exponential smoothing, adaptive, stochastic time series, iterative, least-squares, fuzzy logic, expert system and artificial neural network

[4]. ANN uses widely as a crop yield forecasting application because of its ability to learn complicate and nonlinear relationships between the different parameters of crop growth and yield such as temperature, plant biomass, leaf area index, moisture, solar radiation, and photosynthesis. These parameters also use as variables for crop simulation model [5].

Agricultural production is intensely influenced by weather components like the temperature, solar energy, humidity, precipitation, atmospheric gases, etc., of an area and wheat yields are controlled by them [6]. The weather network in Bangladesh is not sufficient for the timely and efficient collection of weather information regarding crop development. On the other hand, satellite remote sensing technologies are capable, available and cost-effective for monitoring and identifying crop growth stages, phenology, yield and classes in a timely fashion [7]. Besides this, NOAA developed vegetation health indices VCI and TCI estimating cumulative moisture and temperature respectively of an area which are very useful for remote sensing researchers in the agriculture field. Normalized Difference Vegetation Index (NDVI) and Brightness Temperature (BT) characterize healthy and unhealthy vegetation of the area and VCI and TCI are derived from them. VCI and TCI values have a strong correlation with these indices and agricultural crop production during the critical period of crop development [8]. In this study, we developed a methodology for predicting wheat yield in Bangladesh using remote sensing technology and ANN simulation tool, and we also examined the usability of AVHRR-based vegetation health products VCI and TCI indices as predictors for early estimation of wheat yield in Bangladesh at approximately six to eight weeks before harvest. The efficiency of this model was evaluated for different hidden neurons to determine the optimum performance.

II. Study Area

The study area is Bangladesh, located in South Asia between 20°34′ to 26°38′ North latitudes and 88°01′ to 92°42′ East longitudes. Bangladesh has a total area of 147,570 km^2 and is bordered by India in the West, North, and East by a 4,095 km land frontier and by Myanmar in the Southeast by 193 km land and water frontier. The climate of Bangladesh is tropical monsoon, with three main seasons: a hot and humid summer season (March-May), a warm and humid monsoon season (June-October) and a cold and dry winter season (November-February). The Country's temperature falls between 12-35°C, humidity range is 65-90%, and the annual average rainfall varies from 1500 mm to 5000mm [9]. There is a perfect relationship between optimum wheat cultivation weather and the weather of Bangladesh. Notably, Bangladeshi weather is favorable for wheat cultivation. Wheat is grown well in the temperate and sub-temperate zones of the world. It is a cold-loving crop, and a high level of moisture requires in the early period of the plantation. Every crop has an optimum temperature range for its maximum production. The optimum temperature for wheat growing is 25°C with minimum and maximum growing temperature is 3-4°C and 32°C respectively [10]. Wheat is one of the principal winter crops in Bangladesh and is planted in November/December and harvested in March/April. The lifetime of the wheat crop is approximately 90-120 days depending on the wheat variety and local weather conditions. During the cultivation season, November to February is the cooler and drier winter, and March-April is the hot and humid summer season. Temperature has a significant impact on wheat cultivation such as high-temperature stresses during reproduction and grain filling stages are some of the key concerns of yield loss. On the other hand, the higher temperature boosts plant growth, flowering, and maturation. Optimum yield also requires an adequate source of moisture availability during the growing season. Therefore, seeding time is very crucial for optimum yield and the optimum seeding time is between 15th-30th November [11]. Wheat plants are affected by cold or frost injury at any stage of growth and grow slowly during winter. Maximum production depends on tillers/plant, optimum plant population, grains/spike and healthy vegetation which are related to temperature and moisture conditions of the cultivated area. A maximum of 5-7 tillers/plant form throughout the life of wheat plants. The maximum number of tillers mature, and optimum plant populations occur within 50 days of sowing which is until January [12]. For this study, we used VCI and TCI data for weeks 1-4 which are the month of January because this month is most sensitive for crop condition such as the development of healthy vegetation and better production of wheat yield.

III. Remote Sensing and Agriculture

Remote Sensing (RS) is the science of obtaining information about an area, object or phenomenon from a distant location without having physical contact or interfering with that area, object or phenomenon similar to the human acquisition of information through the sense of sight. RS is a technique that makes it possible to monitor the earth's resources and to gather real-time data from unreachable and dangerous areas. The dominant principle of RS is the spectral signature of the object because every object responds differently based on the different regions of the electromagnetic spectrum. By spectral signature characteristic RS responses are used to distinguish different materials and their properties such as vegetation, bare soil, cloud, and water. In remote sensing methods, data acquire as an image which represents the area being observed using special types of sensors such as aerial cameras, scanners, and radar mounted on a satellite, aircraft or other spacecraft. To extract the required information from the image which will reflect the properties of the observed area, image analysis and interpretation requires. Therefore, RS is also known as a multi-disciplinary science which is a combination of optics, electronics, spectroscopy, photography, computer, satellite, and telecommunication, etc. [13]. RS applications are successfully devoted to agricultural sector which includes: (a) estimation of crop yield, biomass and crop acreage (b) monitoring vegetation vigor and thermal stress (c) assessment of crop phonological development and (d) mapping cropland and land use/land cover changes [14].

IV. Data Acquisition

Wheat yield statistical data and AVHRR sensor based remote sensing satellite data for 24 years (1988-2011) are used in this research.

a) *Wheat Yield Official Statistical Data*

Wheat yield data are collected from 'The Yearbook of Agricultural Statistics of Bangladesh' which contains exclusively agriculture-related data and is regularly published by the Bangladesh Bureau of Statistics (BBS). BBS conducts the core agricultural statistics and generates data on the types of crop, production, yield, cultivation area, etc., and is responsible for accumulation, compilation, and dissemination of statistical data for the entire national system. It is a governmental authority and provides reliable, accurate and timely statistics of agricultural production. It conducts two types of agricultural statistics (a) structural and (b) annual. Structural statistics performs according to Food and Agriculture Organization (FAO) guidelines by collecting data through full count/sample census, normally at an interval of 10-year. The annual statistics performs by collecting data through annual/seasonal sample surveys. In this paper, we used annual statistical yield data. Yield (ton/hectare) was calculated by dividing total wheat production (tons) by the total sown area (hectare) [2].

b) *Satellite-Based Remote Sensing Data*

In this study, AVHRR sensor based vegetation health product (VHP) developed by NOAA was used to develop a model for predicting wheat yield in Bangladesh. The AVHRR flown on NOAA polar-orbiting satellites is a scanning radiometer (sensor) which has six channels three solar (visible-near infrared) and three thermal infrared to measure solar energy reflected/emitted from the earth surface. VHP derived products vegetation condition index (VCI) characterizing moisture condition and temperature condition index (TCI) characterizing thermal condition derived from NDVI and BT values acquired from the AVHRR onboard NOAA polar-orbiting satellites. The detailed methods and algorithms for calculating weekly VCI and TCI values are presented in Kogan [15, 16, 17, 18]. This paper briefly mentions some steps which are: (a) the VHP data were developed from Global Area Coverage (GAC) data, which was generated by sampling and mapping the AVHRR 1 km daily reflectance in visible (ch1, 0.58–0.68μm), near infrared (ch2, 0.72–1.00μm), and two infrared bands (ch4, 10.3–11.3μm and Ch5, 11.5–12.5μm) to a 4 km map; (b) NDVI was calculated from pre and post launch calibrated visible and near infrared reflectance using the formula:

$$\text{NDVI} = (\text{NIR} - \text{VIS}) / (\text{NIR} + \text{VIS}) \tag{1}$$

(c) The ch4 IR values were converted into BT, which were corrected for sensor's non-linear behavior; (d) the weekly composite value of NDVI was generated by selecting the largest NDVI for each pixel. NDVI was adjusted using statistical techniques; (e) a digital smoothing filter was used to eliminate the high-frequency noise (clouds, Sun, and sensor angular effects, etc.) from NDVI and BT weekly time series; (f) NDVI and BT climatology were calculated from multi-year smoothed NDVI and BT. Climatology variables the maximum and minimum values of NDVI and BT during 1988-2011 were calculated for each of 52 weeks on a pixel by pixel basis.

Vegetation health products (VHP) VCI and TCI characterize moisture, and thermal conditions respectively were calculated as:

$$VCI = \frac{NDVI - NDVI_{min}}{NDVI_{max} - NDVI_{min}} \times 100 \tag{2}$$

$$TCI = \frac{BT_{max} - BT}{BT_{max} - BT_{min}} \times 100 \tag{3}$$

Where, NDVI, NDVImin, and NDVImax (BT, BTmin, and BTmax) represent the smoothed weekly NDVI (BT), their multi-year absolute minimum and maximum respectively. VCI and TCI indices are numeric values on a scale of 0 to 100. VCI changes from 0 to 100, reflecting moisture condition changes from extreme stress to favorable and TCI changes from 0 to 100 reflecting thermal condition changes from dryness (extreme stress) to healthy (favorable). The value 50 for both VCI and TCI corresponds to an average condition [15].

V. Materials and Methods

a) *ANN for Predicting Wheat Yield*

ANN is a mathematical model motivated from the human central nervous system in the same manner as the brain process information, and it consists of an interconnecting group of simple elements known as 'nodes', 'neurons', and 'processing elements'. It is an intelligent system that can manipulate complex data and to learn input-output correlation by adjusting the weight and bias values to produce targeted output. As a

Global Journal of Science Frontier Research (D) Volume XVIII Issue II Version I Year 2018

processing unit of NN, each neuron consists of input, a summer, a bias, a transfer function and an output to process and compute values provide from connected inputs. A particular targets lead to desire outputs by adjusting or training the network [19]. The network adjustment process accomplishes based on a comparison between the targets and predicted values as demonstrated in Fig. 1.

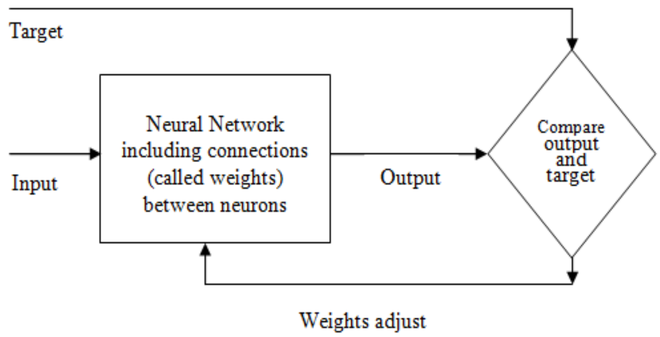

Fig. 1: Artificial neural network generic structure

A nonlinear autoregressive with external (exogenous) input or NARX neural network time series tool was used to develop a wheat yield prediction model for this study. It can be written as the Equation 4 below:

$$y(t)=f(y(t-1),y(t-2),\ldots,y(t-d),x(t-1),x(t-2),\ldots x(t-d)) \quad (4)$$

Here x(t) is the input time series, and y(t) is the target time series. The model predicts the time series value of y(t) from 'd' past values of y(t) and the same period of past values of another time series x(t). For our study, x(t) is the vegetation health indices weekly VCI and TCI, and y(t) is the wheat yield statistical data. The simulated view of the NN model is shown in Fig. 2.

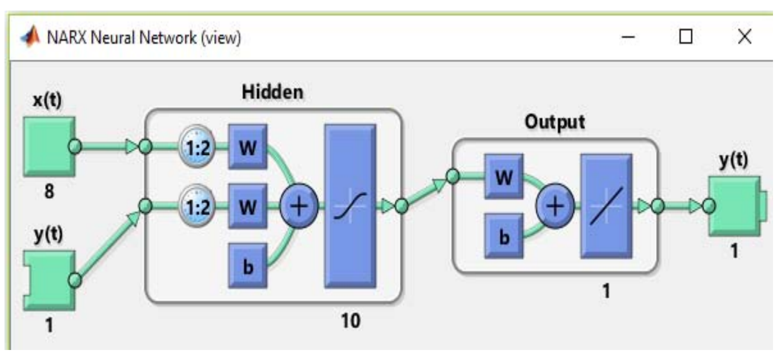

Fig. 2: Simulated diagram of wheat yield prediction model

b) *Input Parameters*

In this study, we used an AVHRR sensor based satellite data products weekly VCI and TCI data for weeks 1-4 as inputs and statistical wheat yield data as the target for the same period of 24 years from 1988-2011. Here a week is defined is based on the year such as week 0ne covers days of the year 1 to 7 (1^{st} week of January). The input is a 1×24 cell array of 8×1 matrices, representing dynamic data 24-time steps of 8 elements (VCI1-VCI4 and TCI1-TCI4) and the target (wheat yield) is a 1×24 cell array of 1×1 matrices, representing dynamic data 24-time steps of 1 element. For training, validation and testing of the network the input and target data were randomly divided into 70% for training, 15% for validating and 15% for testing.

c) *Weight and Bias*

Weight and bias are two significant parameters, and they are known to be the adjustable variables for NN training process. They are changed according to the error (reduce error) between the target and predicted values to generate the optimum output [20]. Each element of the input vector connects with every neuron in the hidden layer through input weight matrix **IW**, and hidden layer output connects to output neuron through a layer weight matrix **LW**. Every neuron has its own bias. Fig. 3 shows the connection between weight and bias values. There are total 201 weight and bias values that come up from the proposed model network simulation. As each neuron has its own bias out of 201, there are 11 bias values (10 hidden and 1 output neurons), and remaining 190 are weight values. Weight and bias matrices generated by a Matlab simulation illustrate below where **b**, **IW**, and **LW** represent the bias, input weight and layer weight respectively.

b = 2×1 cell array: {10×1 double}
{[-1.0073]}
IW = 2×2 cell array: {10×16 double} {10×2 double}
{0×0 double} {0×0 double}
LW = 2×2 cell array: {0×0 double} {0×0 double}
{1×10 double} {0×0 double}

d) ANN Model Architecture

The proposed model is a two-layer (hidden layer and output layer) feed-forward Artificial Neural Network with a back-propagation learning algorithm as illustrated in Fig. 3. The connections of weights between inputs and hidden nodes, hidden nodes to the output node and biases with nodes are shown in Fig. 3.

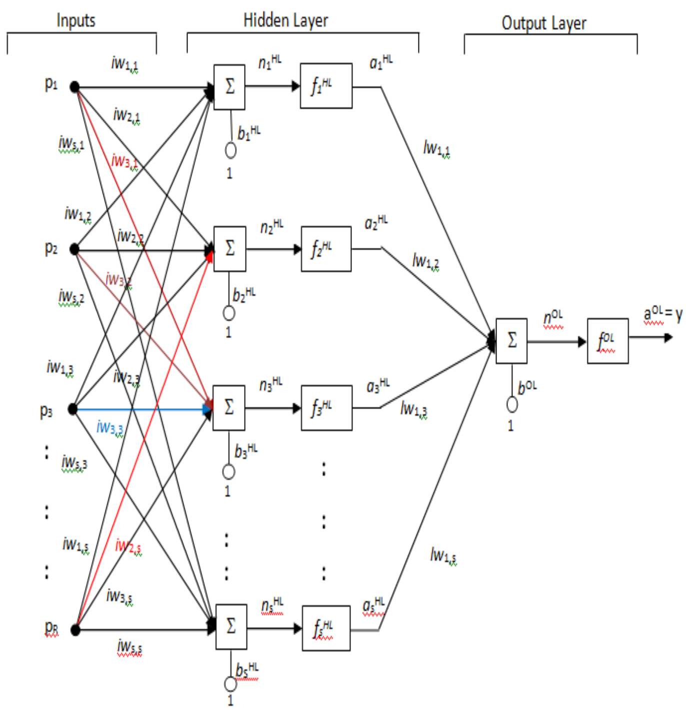

Fig. 3: Schematic diagram of feed-forward back propagation ANN with layers and connections

The output of this model is also known as the network simulation output and is produced according to the following equation:

$$y = \mathbf{f}^{\mathrm{OL}}(\mathbf{LW}^{\mathrm{OL}}\ \mathbf{f}^{\mathrm{HL}}(\mathbf{IW}^{\mathrm{HL}}\ \mathbf{p} + \mathbf{b}^{\mathrm{HL}}) + \mathbf{b}^{\mathrm{OL}}) \qquad (5)$$

Here,
HL- Hidden layer
OL- Output layer
y = Model output (simulated output)
f^{OL} = Linear transfer function for output layer neuron
f^{HL} = Log-sigmoid transfer function for hidden layer's neuron
LW^{OL} = Layer weight matrix for the hidden layer to the output layer
IW^{HL} = Input weight matrix for hidden layer (from input variables to hidden layer's neurons)
p = Input vector (R × Q matrix, R is the number of input variables, and Q is the number of elements each variable has)
b^{HL} = Bias vector for hidden layer neurons
b^{OL} = Bias vector for the output layer

The key issues around to designing a neural network-based prediction model are to select the appropriate number of neurons for hidden layer and activation function for both hidden and output layer because the optimum performance of the model depends on them. For our model, we chose the trial and error method to select the optimum number of neurons for hidden layer. We tested 4,6, 8, 10, 12, 15, 20 and 25 neurons for hidden layer and selected 10(ten) neurons for our proposed model as it provides less mean squared error compared to others as well as less error of prediction. We used 1 (one) neuron for the output layer because it was selected based on the number of element category in the target. Since transfer function, also known as activation function, has a dominant impact on the neuron's output we used sigmoid transfer function for the hidden layer and linear transfer function for output layer neuron. A characteristic of the sigmoid transfer function is that it takes input values between plus and minus infinity and compresses the output into a range between 0 & 1 and the linear transfer function which produce its input as the output.

e) Training The Network

Training is a paramount attribute of the neural network simulation software. Therefore, selection of appropriate training functions is a vital feature of NN based model development. Training function *'trainlm'* was used to develop wheat yield prediction model. It is the fastest training function for the back-propagation algorithm in the NN toolbox software which updates weights and biases according to the Levenberg-Marquardt optimization [21]. The back-propagation algorithm is used to calculate the error between the output and target by randomly initializing the weight and biases for each neuron; then the weight will be updated until the network generalization stops as an indication of increase the mean square error of the validation sample. During the network training process, the data are randomly divided according to pre-specified percent, in this model for training 70% that are used to adjust the network according to its error, for validation 15% that are used to measure network generalization and stops training when generalization stops improving, for testing 15% are used to measure network performance. Every training attempt will produce completely different outcomes because of different initial conditions of weights and biases values and random sampling of data. The network is retrained when the first try did not generate desired results or need to improve the predicted results.

VI. Results and Discussion

The purpose of this model was to develop a satellite-based prediction model for predicting wheat yield in Bangladesh using the artificial neural network. We tested AVHRR-sensor derived vegetation health products VCI and TCI indices for wheat yield prediction six to eight weeks before harvest. The precision of this model was evaluated based on the Mean Square Error (MSE), regression values between actual and predicted data and prediction accuracy. The simulated results obtained from the model are illustrated in Tables 1 through 5. It was found that the model for 10 hidden neurons provided optimum performance.

a) Model Performance Evaluation

The model performance was evaluated by calculating the Mean Square Error (MSE), which is the average squared difference between the output (predicted) and targets (actual) for different hidden neurons. MSE is defined by the following equation, and the results for different hidden neurons are shown in Table 3.

$$F = MSE = \frac{1}{N}\sum_{i=1}^{N}(y_a - y_p)^2$$

Where N denotes the number of samples; for this study N is 22 (22 years from 1990-2011) shown in column 1, y_a represents the actual wheat yield statistical data shown in column 2, y_p represents the predicted (simulated) wheat yield shown in column 3-10 in Table 1, and $e_y = (y_a - y_p)$ denotes the error between the actual and predicted wheat yield as shown in column 3-10 in Table 2. The performance (MSE) of the neural network for different hidden neurons shown in Table 3, it demonstrates that the best outcome (less MSE value) occurs for 10 neurons which were selected for our wheat yield prediction model. The model performance is reliable because the final MSE is very small. Fig. 4 shows the performance curve which is plotted between MSE and epochs for training, validation and test data set. It is seen that the best validation performance occurs at epoch 3 and training, validation and testing error all decreased until epoch 3, after that only training error decreases but validation and testing error increase until epoch 5, after that network training was stopped because network generalization stops improving, such as validation error increase which occurred after epoch 5. It does not appear that any overfitting had occurred since neither the validation nor testing error increased before epoch 3 where the best validation performance occurred.

Table 1: Wheat Yield Statistical Data and ANN Model Predicted Yield Data for Different Hidden Neurons

Year	Actual/Target yield (Ton/Hectare)	Model output (prediction) for different no. of neurons (Ton/Hectare)							
		4	6	8	10	12	15	20	25
1988	1.7542								
1989	1.8246								
1990	1.5034	1.7802	1.5166	1.9362	1.4965	1.7520	1.5153	1.6129	1.9472
1991	1.6767	1.6806	1.5486	1.8474	1.6794	1.7285	1.6631	1.7947	1.6849
1992	1.8534	1.6951	1.5292	2.0497	1.8196	1.8934	1.8538	1.8220	1.8009
1993	1.8457	1.8443	1.5796	2.1140	1.8447	1.8469	1.8593	1.6893	1.7828
1994	1.8390	1.9142	1.7635	2.0322	1.8423	2.1320	2.1175	1.9430	2.2676
1995	1.9483	1.9035	1.9717	1.9596	1.9101	2.0457	2.0019	2.5071	1.9762
1996	1.9531	1.9733	1.9918	1.9199	1.9558	1.8544	1.9787	1.9369	2.2910
1997	2.0544	1.9723	2.1917	2.0840	2.0485	2.1589	2.0942	1.7950	1.9951
1998	2.2408	2.1989	2.1084	1.9152	2.1308	2.2660	2.2680	2.0155	2.0965
1999	2.1627	2.1214	1.8755	2.0933	2.1746	2.1670	1.6381	2.0801	2.2364
2000	2.2104	2.0434	1.9515	2.0406	2.0482	2.1870	2.2191	2.2084	2.1723
2001	2.1643	2.0971	2.1725	2.1424	2.2568	2.1267	2.2001	2.0227	2.0299
2002	2.1644	2.0702	1.7535	2.1669	2.1832	2.3149	2.2459	2.2901	2.1281
2003	2.1327	2.0644	2.1755	1.9896	2.141	2.0565	2.1589	2.0249	2.1487
2004	1.9527	1.9863	1.9084	2.0426	1.953	1.8946	1.9619	1.7711	1.9237
2005	1.7478	1.9059	1.5999	2.1310	1.7509	1.9259	1.7470	1.7390	1.7556
2006	1.5344	1.7583	1.4616	1.9529	1.532	1.8190	1.7903	1.4525	1.8878
2007	1.8471	1.7406	1.2239	1.7662	1.7306	1.6042	1.8666	1.2041	1.8411
2008	2.1753	1.7897	1.9408	2.2069	2.2457	2.0687	2.2180	2.0361	2.0611
2009	2.1516	2.1525	1.7584	2.1460	2.1468	1.8298	1.4462	2.0466	2.0964
2010	2.3959	2.4095	1.9181	2.2030	2.4046	2.0512	2.4147	2.1965	2.4166
2011	2.6012	2.2831	2.0304	2.5152	2.5856	2.5134	2.6263	2.3625	2.4391

Table 2: Wheat Yield Error of Prediction for Different Hidden Neurons

Year	Target/Actual yield (Ton/Hectare)	Model prediction error for different hidden layer neurons							
		4	6	8	10	12	15	20	25
1988	1.7542								
1989	1.8246								
1990	1.5034	-0.2768	-0.0132	-0.4328	0.0069	-0.2486	-0.0119	-0.1095	-0.4438
1991	1.6767	-0.0039	0.1281	-0.1707	-0.0027	-0.0518	0.0136	-0.1180	-0.0082
1992	1.8534	0.1583	0.3242	-0.1963	0.0338	-0.0400	-0.0004	0.0314	0.0525
1993	1.8457	0.0014	0.2661	-0.2683	0.001	-0.0012	-0.0136	0.1564	0.0629
1994	1.8390	-0.0752	0.0755	-0.1932	-0.0033	-0.2930	-0.2785	-0.1040	-0.4286
1995	1.9483	0.0448	-0.0234	-0.0113	0.0382	-0.0974	-0.0536	-0.5588	-0.0279
1996	1.9531	-0.0202	-0.0387	0.0332	-0.0027	0.0987	-0.0256	0.0162	-0.3379
1997	2.0544	0.0821	-0.1373	-0.0296	0.0059	-0.1045	-0.0398	0.2594	0.0593
1998	2.2408	0.0419	0.1324	0.3256	0.1100	-0.0252	-0.0272	0.2253	0.1443
1999	2.1627	0.0413	0.2872	0.0694	-0.0119	-0.0043	0.5246	0.0826	-0.0737
2000	2.2104	0.167	0.2589	0.1698	0.1622	0.0234	-0.0087	0.0020	0.0381
2001	2.1643	0.0672	-0.0082	0.0219	-0.0925	0.0376	-0.0358	0.1416	0.1344
2002	2.1644	0.0942	0.4109	-0.0025	-0.0188	-0.1505	-0.0815	-0.1257	0.0363
2003	2.1327	0.0683	-0.0428	0.1431	-0.0083	0.0762	-0.0262	0.1078	-0.0160
2004	1.9527	-0.0336	0.0443	-0.0899	-0.0003	0.0581	-0.0092	0.1816	0.0290
2005	1.7478	-0.1581	0.1479	-0.3832	-0.0031	-0.1781	0.0008	0.0088	-0.0078
2006	1.5344	-0.2239	0.0728	-0.4185	0.0024	-0.2846	-0.2559	0.0819	-0.3534
2007	1.8471	0.1065	0.6232	0.0809	0.1165	0.2429	-0.0195	0.6430	0.0060
2008	2.1753	0.3856	0.2345	-0.0316	-0.0704	0.1066	-0.0427	0.1392	0.1142
2009	2.1516	-0.0009	0.3932	0.0056	0.0048	0.3218	0.7054	0.1050	0.0552
2010	2.3959	-0.0136	0.4778	0.1929	-0.0087	0.3447	-0.0188	0.1994	-0.0207
2011	2.6012	0.3181	0.5708	0.0860	0.0156	0.0878	-0.0251	0.2387	0.1621

Table 3: The Performance (MSE) of ANN Model for Different Neurons in the Hidden Layer

NN Prediction Model performance	Neurons in the hidden Layer							
	4	6	8	10	12	15	20	25
MSE	0.0228	0.0790	0.0413	0.0062	0.0286	0.0424	0.0512	0.0328

Table 4: Regression Performance of ANN Model for Different Neurons in the Hidden Layer

	Regression (R) value for different neurons in hidden layer							
	4	6	8	10	12	15	20	25
Training	0.91	0.77	0.79	0.99	0.88	0.99	0.88	0.97
Validation	0.96	0.95	0.83	0.96	0.83	0.69	0.91	0.82
Test	0.76	0.80	0.85	0.92	0.82	0.96	0.82	0.97
All	0.83	0.67	0.66	0.86	0.76	0.72	0.70	0.73

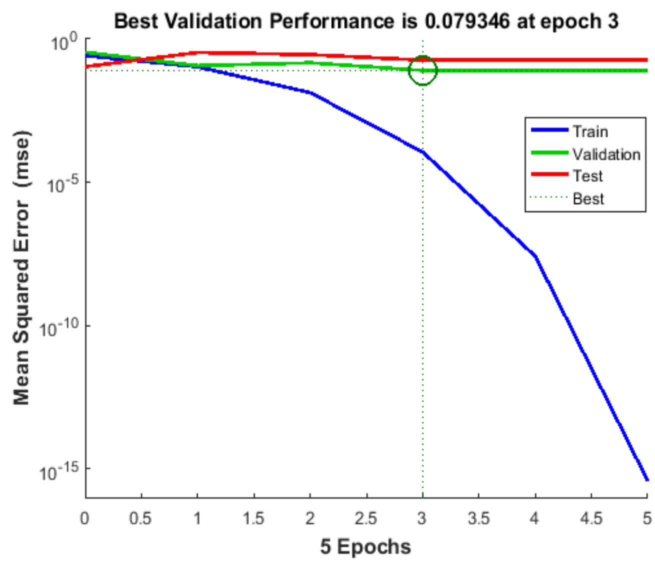

Fig. 4: Performance curve of NN with the best validation

b) Model Regression Evaluation

The correlation between wheat yield target and predicted data were determined by the regression value generated from the NN simulation shown in Table 4. It is seen that for our wheat yield prediction model there are strong correlations between the predicted and actual yield. The regression (R) value for training, validation and test dataset are greater than 0.92 and for all data response is 0.86 shown in Table 4. The regression value is a good indicator of the strength of the correlation between them. An R-value of 1 (one) indicates the best relationship and an R-value close to 0 (zero) indicates a random relationship. Regression plots for training, validation, testing and all data sets are demonstrated by four axes shown in Fig. 5. The dashed line in each plot represents the perfect correlation when the predicted yield is exactly equal to the target whereas the solid line represents the model's best fit between target and output. The regression plots depict that there are strong linear relationships between the predicted and the target data for all four situations. Therefore, it is proven that the ANN-based wheat yield prediction model is a successful model.

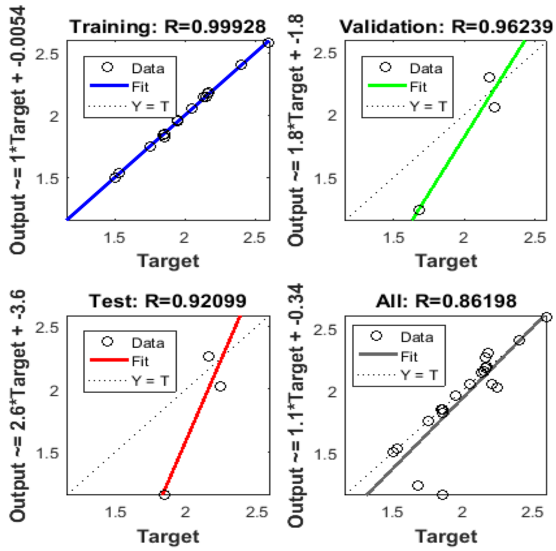

Fig. 5: Relationship between predicted (output) and actual (target) wheat yield data

c) Model Accuracy Evaluation

The reliability of the proposed wheat yield prediction model was assessed by comparing the target and output data. To determine the appropriate number of neurons for model development, we examined the ANN for different neurons in the hidden layer. We tested for 4, 6, 8, 10, 12, 15, 20 and 25 hidden neurons and computed the error of prediction to choose the proper hidden neurons to achieve optimum model performance. Based on the MSE and percentage error of prediction we selected 10 neurons for hidden layer because the model with 10 hidden neurons provides optimum performance in comparison to others. The accuracy of our proposed model was evaluated by calculating the percentage error of prediction using the following formula and the results are demonstrated in Table 5.

$$\% \, error = \frac{\text{Actual yield} - \text{Predicted yield}}{\text{Actual yield}} \times 100$$

From column 5 of Table 5, it can be seen that the model provides a high degree of accuracy because the percentage error of prediction for all 22 years from 1990-2011 are very reasonable. The minimum error is 0.0003 (0.02%), and the maximum error is 0.1622 (7.33%). Besides this, the error of prediction in each year is less than 8% and 91% of the errors of prediction is less than 5%. These explanations regarding model outcomes specify that our proposed wheat yield prediction model has a high level of accuracy in its capacity to predict wheat in Bangladesh. A comparison graph is plotted using actual and predicted wheat yield data to show the model accuracy in a more effective way is shown in Fig. 6. The graph indicates a high level of similarity between the actual and predicted yield. Thus, it can be said that the model is highly capable of predicting wheat yield in Bangladesh. Therefore, we can deduce that our ANN based prediction model, which uses satellite remote sensing data, is a reliable, accurate and highly promising wheat yield prediction model. Furthermore, this model can be used for other crops in Bangladesh to predict in the same fashion.

Table 5: Statistical Wheat Yield and Predicted Wheat Yield with the Error of Prediction in Bangladesh

Year	Target/Actual	Predicted	error	% of error
1988	1.7542			
1989	1.8246			
1990	1.5034	1.4965	0.0069	0.45%
1991	1.6767	1.6794	-0.0027	-0.16%
1992	1.8534	1.8196	0.0338	1.82%
1993	1.8457	1.8447	0.0010	0.05%
1994	1.8390	1.8423	-0.0033	-0.17%
1995	1.9483	1.9101	0.0382	1.96%
1996	1.9531	1.9558	-0.0027	-0.13%
1997	2.0544	2.0485	0.0059	0.28%
1998	2.2408	2.1308	0.1100	4.90%
1999	2.1627	2.1746	-0.0119	-0.55%

2000	2.2104	2.0482	0.1622	7.33%
2001	2.1643	2.2568	-0.0925	-4.27%
2002	2.1644	2.1832	-0.0188	-0.86%
2003	2.1327	2.1410	-0.0083	-0.38%
2004	1.9527	1.9530	-0.0003	-0.02%
2005	1.7478	1.7509	-0.0031	-0.17%
2006	1.5344	1.5320	0.0024	0.15%
2007	1.8471	1.7306	0.1165	6.30%
2008	2.1753	2.2457	-0.0704	-3.23%
2009	2.1516	2.1468	0.0048	0.22%
2010	2.3959	2.4046	-0.0087	-0.36%
2011	2.6012	2.5856	0.0156	0.59%

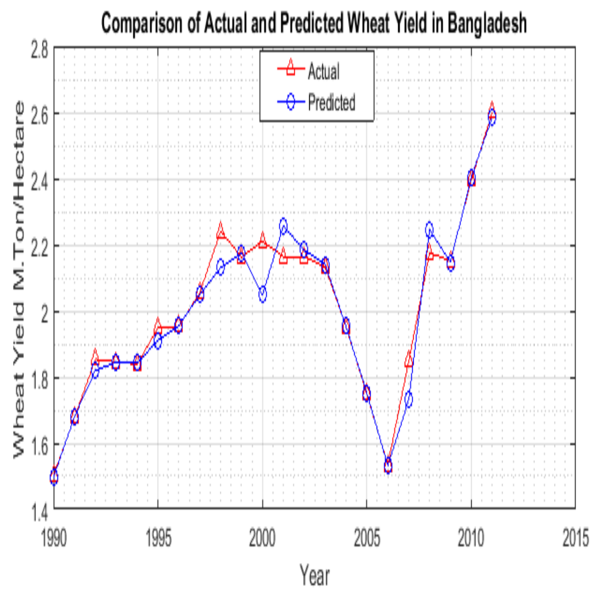

Fig. 6: Comparison graph of actual and predicted wheat yield in Bangladesh

VII. Conclusion

This study showed that wheat yield in Bangladesh could be predicted at approximately six to eight weeks before harvest time. The predicted yields are very close to the government-led statistical yields with an error of prediction less than 8%. Therefore, it is proven that AVHRR sensor based satellite data products vegetation health indices VCI and TCI characterizing moisture and thermal conditions respectively can be used as ideal predictors to predict wheat yield in Bangladesh. The study also showed that ANN is a potential tool for model development. We used the method of trial and error to select hidden layer neurons for developing an appropriate model, and it was found that the hidden layer with ten neurons produced the optimum result. It was observed that increasing the number of hidden neurons did not generate better outcomes. The methods and results of this model will serve as a prototype for other wheat-producing countries where remote sensing and historical data are available for use. The developed model has the ability for reliable, transparent and timely prediction of wheat yield in Bangladesh that can provide valuable information to the policymakers, government planners, agricultural stakeholders, researchers and any other concerned party.

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