QUANTIFYING IMPACT OF DROUGHTS ON BARLEY YIELD IN NORTH DAKOTA, USA USING MULTIPLE LINEAR REGRESSION AND ARTIFICIAL NEURAL NETWORK

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Abstract: This research investigated the effect of different drought conditions on Barley (*Hordeum vulgare* L.) yield in North Dakota, USA, using Multiple Linear Regression (MLR) and Artificial Neural Network (ANN) methods. Though MLR method is widely used, the ANN method has not been used in the past to investigate the effect of droughts on barley yields to the best of authors' knowledge. It is found from this study that the ANN model performs better than MLR in estimating barley yield. In this paper, the ANN is proposed as a viable alternative method or in combination with MLR to investigate the impact of droughts on crop yields.

Key words: *Barley yield, multiple linear regression, artificial neural network, drought impact*

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1. Introduction

Impact of drought on various sectors has long been recognized. Agriculture is one of the major sectors that experiences significant loss during drought events. Agriculture also is the first sector to be affected at the onset of drought because crops at various stages of their growth depend on water and soil moisture [23]. Impact of drought on agriculture has been studied by several investigators [17, 18, 21]. Li et al. [17] studied the drought risk for global crop production under current and future climatic conditions by using historical crop yield and meteorological drought. It is anticipated significant losses in yields of major crops in the future due to drought events. There was $145 billion loss in crop production across the United States during the last three decades [18]. A better understanding of the

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historical drought damages and drought-yield relationship could help reduce any future losses. According to Thomson et al. [37] crop yield variability is mainly influenced by local weather and climate rather than by large scale climatic patterns. The State of North Dakota, USA, is a leading producer of many crops. Particularly, it is a leading producer of barley in the nation accounting for 24% of nation's barley production. Since North Dakota is also a drought prone state, it is important to study the drought-barley yield relationship in particular [12, 15].

Multiple Linear Regression (MLR) and Artificial Neural Network (ANN) models are both widely used in many areas for prediction and classification purposes. MLR is a traditional statistical technique, and it has an established methodology. However, ANN is relatively a recent computational modeling tool that is used to solve many complex real world problems due to its remarkable learning and generalization capabilities [5, 31]. ANN has been used in water quality and water resources area to estimate evaporation, evapotranspiration, rainfall, runoff, and nutrient transportation [36, 38], accounting and finance [16], health and medicine [30, 33], engineering and manufacturing [8, 40], marketing [2, 9], agriculture [26], and forestry science [1, 28].

There are ample information in the literature about the application and capabilities of ANN and MLR [2, 4, 19, 31, 32, 41]. A detailed review of neural networks and statistical techniques can be found in Paliwal and Kumar [31]. A comprehensive list of comparative studies of applications of neural networks and other statistical techniques from various fields can be found in their study. They also discuss the capabilities of each method. Mekanik et al [19] investigated the capabilities of ANN and MLR to forecast long-term seasonal spring rainfall in Victoria, Australia using lagged El Nino Southern Oscillation (ENSO) and Indian Ocean Dipole (IOD). They found that ANN is a better model to find the pattern and trend of observations, and generally had lower error compared to MLR.

Kaul et al. [13] conducted a study to predict the corn and soybean yield using field-specific rainfall, and Soil Rating for Plant Growth (SRPG), and concluded that ANN has a better prediction capability compared to MLR. Ayoubi and Sahrawat [4] used ANN and MLR to predict the biomass and grain yield of barley in relation to soil properties. They found that ANN outperformed MLR. There are numerous studies on quantifying barley yield using different input characteristics and methodologies [4, 22, 27, 29]. For example, Mkhabela et al [22] developed statistical models to predict the yield of different crops including barley using MODIS NDVI data for Canadian Prairies. However, the relationship between different drought conditions and barley yield has not been studied using ANN to the best of authors' knowledge. Though MLR models have been used, the complex nature of drought-yield relationship need better methods of prediction and interpretation [15].

ANN methodology is a non-linear data driven self-adaptive approach. ANN can identify and learn correlation patterns between variables (independent) and corresponding target variables (dependant) when the underlying relationship is unknown and consequently can predict the dependent variables based on new independent variable data sets [34]. Basically, ANN performs the function of nonlinear mapping or pattern recognition. If a set of input data corresponds to a definite signal pattern, the network can be trained to give correspondingly a desired pattern at the output. The network has the capability to learn and estimate the output [7].

The objective of this study is to quantify and compare the impact of different drought conditions on barley (*Hordeum vulgare* L.) yield using the MLR and ANN models. Though there are few studies relating yield with climate variables using ANN and MLR, the method has not been used to quantify the drought impact on barley yields to the best of our knowledge. In addition, this study uses the U.S. Drought Monitor data which account for areal coverage and severity of drought. This drought data is relatively new (2000–present), and has not been used for similar past studies. North Dakota State is one of the leading producers of barley in USA. Therefore, it is only appropriate to use data from North Dakota. However, the methodology used in this study can be used for other areas.

2. Material and Methods

2.1 Drought Data

This study uses the U.S. Drought Monitor (USDM) drought data, a major source of drought data in the USA available to the public from the National Drought Mitigation Center (NDMC), University of Nebraska, Lincoln [25]. The USDM is developed as a comprehensive tool to reflect the existing drought condition across the United States [11]. Several federal agencies including U.S. Department of Agriculture (USDA), and National Oceanic and Atmospheric Administration (NOAA), and NDMC contribute to produce drought monitor data products. The simplicity of the USDM is the reason behind why many federal and state agencies use these data products [35]. The USDM releases its products (map and tabular data) every week, which reflect the drought condition of the U.S. A slightly adapted sample version of the map is shown in Fig. 1. In this study, the USDM countywide weekly

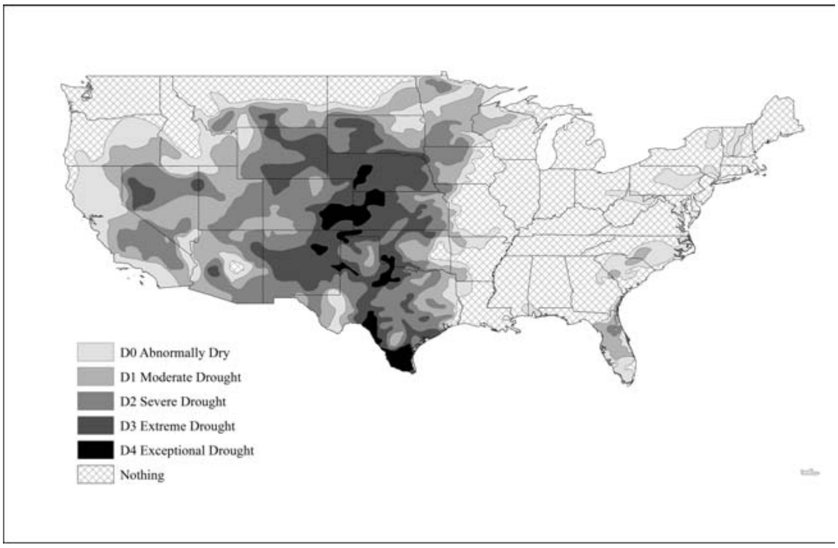

Fig. 1 *A Sample USDM weekly map.*

percent areal coverage values (A_{D0}, A_{D1}, A_{D2}, A_{D3}, and A_{D4}), were used as input for different drought intensity categories D0, D1, D2, D3, and D4 for the years 2000 to 2012. D0, D1, D2, D3, and D4 represent different drought intensity categories: abnormally dry, moderate drought, severe drought, extreme drought, and exceptional drought respectively.

This data is classified based on multiple drought indices. The use of multiple indicators is one of the key strengths of USDM data because it is difficult to represent the complex characteristics of drought using a single drought indicator [11]. D0, D1, D2, D3, and D4 were categorized using the key indicators such as Palmer Drought Index, Climate Prediction Center (CPC) Soil Moisture Model (Percentiles), USGS Weekly Stream flow (Percentiles), Standardized Precipitation Index (SPI), and Objective Short and Long-term Drought Indicator Blends (Percentiles) and numerous supplementary indicators.

2.2 Crop Data

Barley is one of the major agricultural crops grown in North Dakota. County-by-county yield data of barley is derived from USDA National Agricultural Statistics Service (NASS) web portal for the study period (2000 – 2012) [24]. Generally, Barley planting will start in later part of April, and harvesting end in early part of September in North Dakota. Fig. 2 shows the North Dakota counties and barley yield in 2010. North Dakota is one of the north-central states of the USA and has 53 counties.

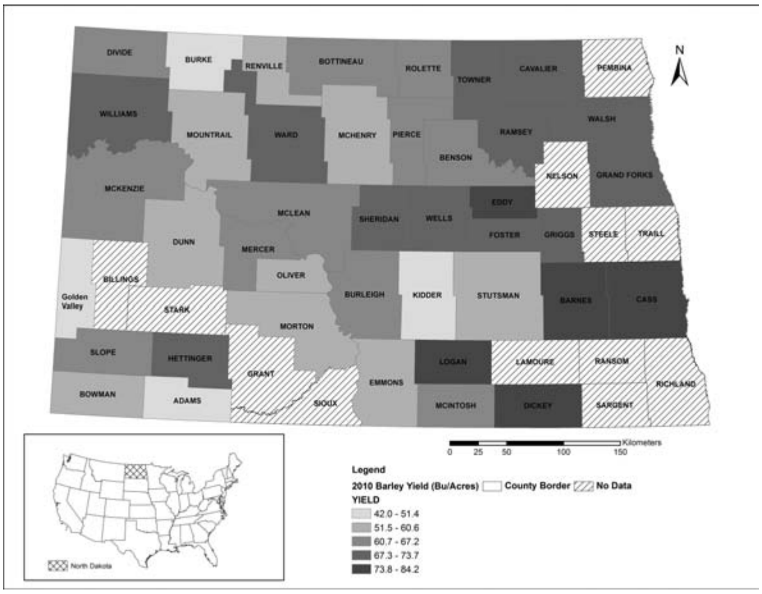

Fig. 2 *The North Dakota counties and barley yield in Bushel/Acres (1 Bushel = 0.03524 m^3; 1 Acre = 4046.86 m^2) for year 2010 (barley yield data is derived from USDA NASS web portal).*

Tab. I shows the barley yield details in ND, USA for years 2000 to 2012. For each year, number of counties reported yield (out of 53 counties in ND), average yield, maximum and minimum yield, and corresponding counties are listed. Fig. 3 shows the average yield variation of barley yield for year 2000 to 2012. The maximum average yield is reported in 2009 (69.22 bu/acres), and minimum average yield is reported in 2002 (40.02 bu/acres) in ND.

Year	Number of county reported	Average yield	Maximum yield (County)	Minimum yield (County)
2000	53	54.91	71.4 (Pembina)	42.3 (Divide)
2001	53	55.68	66.0 (Slope)	46.0 (Burke/Mckenzie)
2002	51	40.02	55.7 (Traill)	12.6 (Grant)
2003	53	57.60	77.8 (Steele)	29.9 (Grant)
2004	51	59.02	81.6 (Dickey)	27.3 (Grant)
2005	51	53.50	73.3 (Emmons)	40.0 (Divide)
2006	48	46.15	68.6 (Traill)	21.8 (Emmons)
2007	51	53.17	63.3 (Emmons)	37.5 (Richland)
2008	40	54.75	81.1 (Traill)	23.9 (Mckenzie)
2009	41	69.22	91.0 (Emmons)	51.0 (Bowman)
2010	41	64.92	84.2 (Dickey)	42.0 (Golden Valley)
2011	27	43.47	67.1 (Ramsey)	23.3 (Morton)
2012	31	59.01	79.8 (Traill)	31.0 (Slope)

Tab. I *Barley yield (in Bushel/acres) details in ND, USA for year 2000 – 2012.*

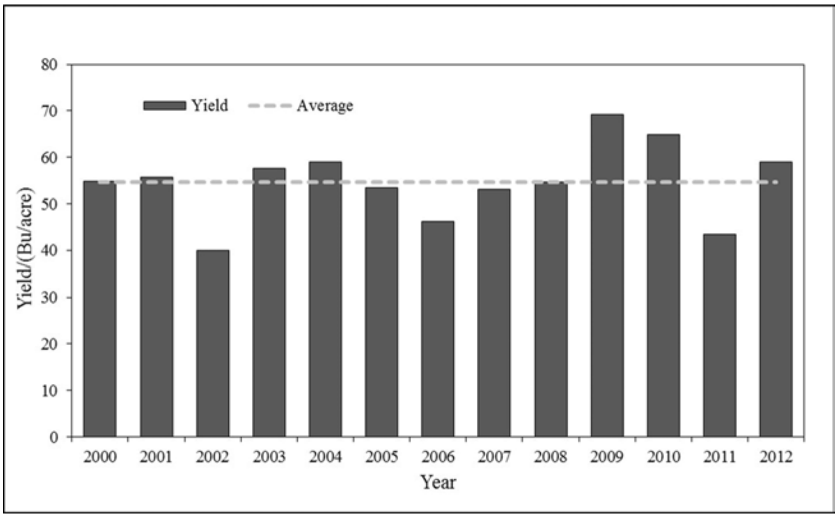

Fig. 3 *Annual average barley yield in ND, USA for year 2000 – 2012.*

2.3 Multiple Linear Regression (MLR)

MLR is a statistical method used to investigate the relationship between several independent variables and a dependent variable. A linear regression model assumes that the relationship between the dependent variable and the *p*-vector of regressors is linear, where p is the number of independent variables. Thus the model takes the form

$$y_i = \beta_1 \chi_{i1} + \cdots + \beta_p \chi_{ip} + \varepsilon_i = \chi_i \prime \beta + \varepsilon_i i = 1, \ldots, n \tag{1}$$

where $\prime$ denotes the transpose, so that $x_i \prime \beta$ is the inner product between vectors x_i and β. The y_i is called the *regressand* or *dependent* variable. The decision as to which variable in a data set is modeled as the dependent variable and which are modeled as the independent variables may be based on a presumption that the value of one of the variables is caused by, or directly influenced by the other variables. The χi is called regressor or independent variable [39]. To ascertain the dependency of barley yield on drought categories, Eq. (1) was utilized. Average values of A_{D0}, A_{D1}, A_{D2}, A_{D3} and A_{D4} were calculated between planting and harvesting period from collected data for different drought intensity categories of areal coverage values, where A_{D0}, A_{D1}, A_{D2}, A_{D3} and A_{D4} are percentage area coverage values for D0, D1, D2, D3, and D4 respectively. Then panel data set was constructed using barley yield, Avg(A_{D0}), Avg(A_{D1}), Avg(A_{D2}), Avg(A_{D3}) and Avg(A_{D4}). For $i = 1, 2, \ldots 53$ counties and $t = 1, 2, \ldots 13$ years (2000–2012) of observation.

$$\begin{aligned} Yield_{it} &= \alpha + \alpha_1 \times Avg(A_{D0})_{it} + \alpha_2 \times Avg(A_{D1})_{it} + \alpha_3 \times Avg(A_{D2})_{it} + \\ &\quad + \alpha_4 \times Avg(A_{D3})_{it} + \alpha_5 \times Avg(A_{D4})_{it} + \varepsilon \end{aligned} \tag{2}$$

where $\alpha_1, \alpha_2, \alpha_3, \alpha_4, \alpha_5$ coefficients were tested for statistical significance at the 5% level fitted models of equation 2. Though drought is a continuous phenomenon in terms of space and intensity, the drought monitor data account for areal coverage of drought for defined drought intensity categories. Therefore, it is appropriate to use the drought monitor data to quantify the impact of different drought intensity categories on barley yield.

2.4 Artificial Neural Network (ANN)

ANN has been widely used to model complex and non-linear processes and systems [34]. ANNs are non-linear data driven self-adaptive systems that can identify and learn correlated patterns between input data sets and corresponding output values, even when the underlying data relationship is unknown. ANN resembles human brain in two respects; the network acquires knowledge through a learning process, and the interconnection strengths known as synaptic weights are used to store the knowledge [6, 41]. The ANN can be explicitly programmed to perform a task by manually creating the topology and then setting the weights and thresholds of each link. The process of determining weights and biases is called training. The observed data set used to train the ANN is called the training data set. The training data set consists of input signals assigned with corresponding target (desired) output. The network training is an iterative process. In each iteration weights coefficients of nodes are modified using new data from training data set. The weight coefficients and biases are adjusted in each iteration so as to minimize the error of prediction of target value. In this study, Levenberg-Marquardt (LM) algorithm was used to train the network.

The Levenberg-Marquardt (LM) algorithm is an intermediate optimization algorithm between the Gauss–Newton (GN) method and Gradient Descent (GD) algorithm [3]. It combines the speed of the Newton algorithm with the stability of the GD method. The LM algorithm can be considered a trust-region modification to Gauss-Newton [10].

3. Results and Discussion

In this study, the ANN and MLR models were compared for their performance in explaining the influence of drought conditions on the variability of barley yield in North Dakota. In the MLR analysis, the yield of barley was used as the dependent variable and drought conditions were used as the independent variables.

The following tables list parameters derived from MLR model (Eq. 2) for barley using MINITAB® statistical software (Tab. II, III, and IV).

The regression equation can be written as:

$$\begin{aligned} Yield \quad = \quad & (58.6) - 0.0688 \times Avg(A_{D0}) - 0.0959 \times Avg(A_{D1}) - 0.191 \times \\ & \times Avg(A_{D2}) - 0.239 \times Avg(A_{D3}) - 5.16 \times Avg(A_{D4}) \qquad (3) \end{aligned}$$

Negative values for coefficients suggest that yield reduces with increasing drought severity as expected.

Source	DF	SS	MS	F	P
Regression	5	12656.2	2531.2	18.88	0.000
Residual Error	585	78439.6	134.1		
Total	590	91095.8			

Tab. II *Results of analysis of variance.*

Tab. II shows the Analysis of Variance (ANOVA) results for the regression model (Eq.02). The ANOVA table lists the Degree of Freedom (DF), Sum of Square (SS), and Mean Square (MS) for regression model and residual error. The Mean Square for Error (MSE) for the regression model is 134.1. It is high for barley yield value prediction. Overall average barley yield in North Dakota for the study period is only 54.67 bu/acre (1 US Bushel = 0.03524 m^3 and 1 acre = 4046.86 m^2). Thus, prediction results will be unreliable (Tab. II). However, global F-test indicates that MLR is useful. The observed significance level for F statistic (p = 0.000) implies there is strong evidence that at least one of the model coefficient is nonzero, and overall model is useful to predict yield (Tab. II).

Table III shows the estimated coefficients for the regression model (Eq.03), estimated standard error (SE) of coefficients, t-test statistic values, P-values, and

Predictor	Coefficient	SE coefficient	T	P	VIF
Constant	58.6	0.7584	77.24	0.000	
$AvgD_0$	-0.0688	0.0265	-2.60	0.010	1.176
$AvgD_1$	-0.0959	0.0380	-2.52	0.012	1.494
$AvgD_2$	-0.191	0.0483	-3.95	0.000	1.579
$AvgD_3$	-0.239	0.0657	-3.64	0.000	1.171
$AvgD_4$	-5.16	2.4930	-2.07	0.039	1.009

$S = 11.5795$ $R^2 = 13.9\%$, R^2 (adj) = 13.2%

Tab. III *Results of regression analysis.*

	AvgD0	AvgD1	AvgD2	AvgD3
AvgD1	0.264			
AvgD2	-0.119	0.472		
AvgD3	-0.128	0.091	0.361	
AvgD4	0.016	0.046	0.054	0.084

Tab. IV *Pearson correlation matrix.*

Variance Inflation Factor (VIF) for coefficients. Results of regression analysis show that all the drought categories coverage has a significant influence in barley yield (Tab. III). The observed significant values (p-values) in t-tests for all individual coefficients show that all the drought severity coverage categories are significant (at $\alpha \quad = 0.05$) in barley yield prediction (Tab. III). Negative values suggest that yield reduces with increasing drought severity as expected. Multiple coefficient of determination (R^2) for this model implies that only 13.9 % variation in yield can be explained by drought severity coverage (Tab. III). It should be noted that the study area experienced only few D4 drought conditions during growing period of barley within the selected time frame for this study.

Low values of Variance Inflation Factor (VIF) for coefficient (<10), and Pearson correlation values between the drought severity coverage categories (Tab. IV) suggest no serious multicollinearity in the model.

The ANN scheme for the problem at hand is shown in Fig. 4.

ANNs can detect the important features of the input-output relationships with the help of nodes in the hidden layer. The hidden layer and nodes are very important for ANN. The nodes in the hidden layer capture the pattern in the data used [20]. Best fitting results were obtained for the five inputs AvgD0, AvgD1, AvgD2, AvgD3, and AvgD4, and the one output (yield of barley) using one hidden layer and ten neurons with logsig transfer function, $y=1/(1+e^{-x})$. For many practical problems where we need to approximate any function that contains a continuous mapping from one finite space to another, there is no reason to use any more than one hidden layer. The number of neurons used was determined by trial and error. Transfer functions calculate a layer's output from its net input. The function logsig generates outputs between 0 and 1 as the neuron's net input goes from negative to positive infinity. Logsig function is generally used when the network is used for pattern recognition problems such as this.

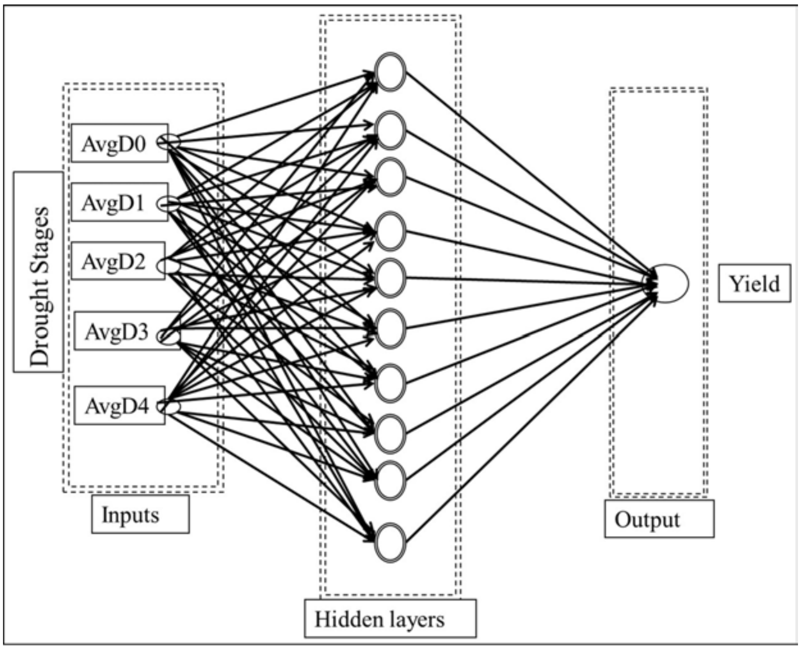

Fig. 4 *ANN Scheme for the study problem.*

Predetermined values for the output error (MSE) and maximum iteration number were set to 0.001 and 1000 epoch, respectively. MATLAB® software was used for this analysis. Since the accuracy of estimation is highly dependent on covering all level of data, the randomization process was repeated until a satisfactory level of data distribution was reached. The training process will be completed when all weighing indices are fixed and the ANN model can accurately estimate the output data as a function of input values [14]. Randomly chosen 70% of the data set (414 data) was selected as training data for ANN model. The rest 30% of data set (177 data) was used for testing and validation. An output error of 0.007 mse was determined for generated outputs by logsig transfer function with a maximum iteration number of 300 epochs. The R^2 of ANN was found 0.61 for training, 0.59 for testing, 0.61 for validation and 0.60 for all (Fig. 5). The MSE value of ANN model for the barley prediction is 4.523 for all data.

Zaefizadeh et al. [42] conducted a research to predict yield in barley using MLR and ANN methods. They determine the relationship between genotypes and genotype interaction in the environment and its impact on barley yield. They stated that ANN is more effective than MLR for the estimating barley yield since the error for the estimation of barley yield was higher in MLR compared to the error in ANN method. Many researchers agree that ANN is superior to MLR with regard to prediction accuracy since the accuracy in ANN increases as the dimensionality and nonlinearity of the problem increases [5, 31]. Overall, many researchers agree that ANN is an intelligence technique and it is superior to MLR in some aspects.

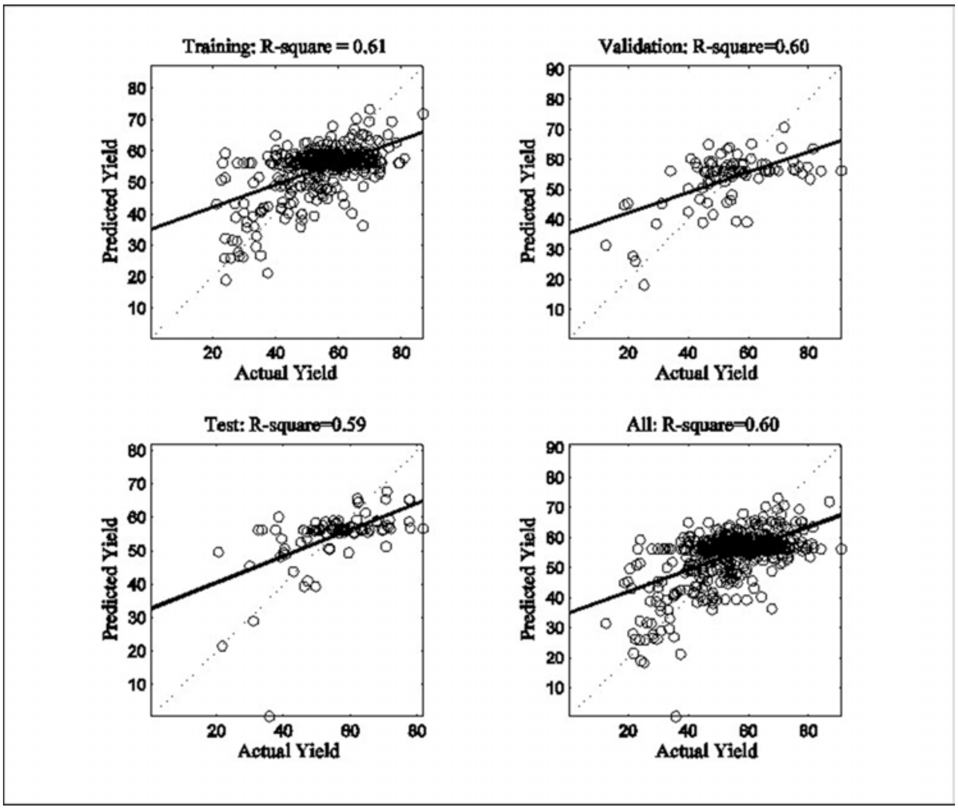

Fig. 5 *The relationship between actual and predicted yield of barley using ANN.*

The precision of the approximation is based on the number of iterations of the simulation done. But the relationship between iterations and precision depends on the relationship between the input and output variables. According to R^2 results, ANN model has been found to quantify better the impact of the different drought conditions on barley yield.

4. Conclusion

This study quantified the impact of drought on barley yield in North Dakota, USA, using MLR and ANN models and compared the results. The developed ANN model is trained using different drought conditions. The ANN model coefficient of determination (R^2) indicates that 60 percent of the variation in yield can be explained by drought whereas only 13 percent by multiple regression. It should be noted that barley yield also depends on other variables such as soil characteristics, and management practices. A perfect prediction model should account for all the variables that influence the yield. However, quantification of drought impact on yield is vital in order to develop more powerful predictive models. Massive parallelism, distributed representation, learning ability, generalization ability, and fault tolerance are some of the attractive features of ANN. When the input and output of the system are complicated (multiple input and output, nonlinearity, etc.), ANN can perform better with the help of its inherent structural advantages. Overall, the information processing capabilities and the ability to recognize and learn from input and output regardless of the problem's dimensionality and nonlinearity makes ANN a more efficient method compared to MLR for estimation of impact of different drought conditions on barley yield. While finding of this study emphasis the need of similar studies in different part of the world in order to proper mitigation strategies to address the drought, this study demonstrates how recent computational tools such as ANN can be effectively used to address this kind of problems. The issues associated with and caused by drought have started to be very real even in world regions where these problems have not been viewed, as yet, important. As drought becomes one of the foremost problems of modern agriculture, the application of ANN or in combination with MLR to investigate the impact of droughts on crop yields would be a promising subject for further research.

References

[1] AERTSEN W., KINT V., VAN ORSHOVEN J., OZKAN K., MUYS B. Comparison and ranking of different modelling techniques for prediction of site index in Mediterranean mountain forests. *Ecological Modelling.* 2010, 221(8), pp. 1119–1130, doi: 10.1016/j.ecolmodel.2010.01.007.

[2] AINSCOUGH T.L., ARONSON J.E. An empirical investigation and comparison of neural networks and regression for scanner data analysis. *Journal of Retailing and Consumer Services* 1999, 6(4), pp. 205–217, doi: 10.1016/s0969-6989(98)00007-1

[3] ARFKEN G. The Method of Steepest Descents. – In: *Mathematical Methods for Physicists, 3rd (ed.)*: Academic Press, Orlando, USA. 1985, pp. 428–436.

[4] AYOUBI S., SAHRAWAT K.L. Comparing multivariate regression and artificial neural network to predict barley production from soil characteristics in northern Iran. *Archives of Agronomy and Soil Science* 2011, 57(5), pp. 549–565 doi: 10.1080/03650341003631400.

[5] BASHEER I. Selection of Methodology for Neural Network Modeling of Constitutive Hysteresis Behavior of Soils. *J. Comput.-aided Civil Infrastruct. Eng.* 2000, 15(6), 445–463 doi: 10.1111/0885-9507.00206

[6] BEKAT T., ERDOGAN M., INAL F., GENC A. Prediction of the bottom ash formed in a coal-fired power plant using artificial neural networks. *Energy* 2012, 45(1), pp. 882–887, doi: 10.1016/j.energy.2012.06.075

[7] BOSE B.K. Expert-System, Fuzzy-Logic, and Neural-Network Applications in Power Electronics and Motion Control. *Proceeding of the IEEE.* 1994, 82(8), pp. 1303–1323, doi: 10.1109/5.301690.

[8] FENG C.X., WANG X. Digitizing uncertainty modeling for reverse engineering applications: Regression versus neural networks. *Journal of Intelligent Manufacturing.* 2002, 13(3), pp. 189–199, doi: 10.1023/A:1015734805987

[9] FISH K.E., BARNES J.H., AIKEN M.W. Artificial neural networks – A new methodology for industrial market segmentation. *Industrial Marketing Management* 1995, 24(5), pp. 431–438, doi: 10.1016/0019-8501(95)00033-7

[10] HAGAN M.T., MENHAJ M.B. Training feedforward networks with the marquardt algorithm. *IEEE Transactions on Neural Networks.* 1994, 5(6), pp. 989–993, doi: 10.1109/72.329697

[11] HAYES M.J., SVOBODA M., COMTE D.L., REDMOND K.T., PASTERİES P. Drought Monitoring: New Tools for the 21st century, in: Wilhite, D.A (eds.), *Drought and Water Crises: Science, Technology, and Management Issues.* 2005, 1, pp. 53–69.

[12] KARETINKOV D., PARRA N., BELL B., RUTH M., ROSS K., IRANI D. Economic Impacts of Climate Change on North Dakota. *A Review and Assessment Conducted by the Center for Integrative Environmental Research (CIER).* 2008, University of Maryland, USA.

[13] KAUL M., HILL R.L., WALTHALL C. Artificial neural networks for corn and soybean yield prediction. *Agricultural Systems* 2005, 85(1), pp. 1–18, doi: 10.1016/j.agsy.2004.07.009

[14] KAWASHIMA S., NAKATANI M. An algorithm for estimating chlorophyll content in leaves using a video camera. *Annals of Botany* 1998, 81(1), pp. 49–54, doi: 10.1006/anbo.1997.0544

[15] LEELARUBAN N., ODUOR P., AKYUZ A., SHAIK S., PADMANABHAN G. Leveraging a Spatio-Temporal Drought Severity and Coverage Index with Crop Yield Modeled as a Stochastic Process. *International Journal of Hydrology Science and Technology (IJHST)* 2012, 2(3), pp. 219–236, doi: 10.1504/ijhst.2012.049184

[16] LENARD M.J., ALAM P., MADEY G.R. The application of neural networks and a qualitative response model to the auditor's going concern uncertainty decision. *Decision Sciences.* 1995, 26(2), pp. 209–227, doi: 10.1111/j.1540-5915.1995.tb01426.x

[17] LI Y., YE W., WANG M., YAN X. Climate change and drought: a risk assessment of crop-yield impacts. *Climate Research* 2009, 39, pp. 31–46, doi:10.3354/cr00797

[18] LOTT N., ROSS T. Tracking and evaluating U.S. billion dollar weather disasters, 1980–2005. *86th AMS Annual Meeting.* 2006 January 29–February 2, Atlanta, Georgia, p. 7.

[19] MEKANIK F., IMTEAZ M.A., GATO-TRINIDAD S., ELMAHDI A. Multiple regression and Artificial Neural Network for long-term rainfall forecasting using large scale climate modes. *Journal of Hydrology.* 2013, 503, pp. 11–21, doi: 10.1016/j.jhydrol.2013.08.035.

[20] MISHARA A.K., DESAI V.R. Drought forecasting using feed-forward recursive neural network. *Ecological Modelling* 2006, 198(1–2), pp. 127–138 doi: 10.1016/j.ecolmodel.2006.04.017.

[21] MISHRA V., CHERKAUER K.A. Retrospective droughts in the crop-growing season: Implications to corn and soybean yield in the Midwestern United States. *Agricultural and Forest Meteorology* 2010, 150(7–8), pp. 1030–1045 doi: 10.1016/j.agrformet.2010.04.002

[22] MKHABELA M.S., BULLOCK P., RAJ S., WANG S., YANG Y. Crop yield forecasting on the Canadian Prairies using MODIS NDVI data. *Agricultural and Forest Meteorology.* 2011, 151(3), pp. 385–393, doi: 10.1016/j.agrformet.2010.11.012.

[23] NARASIMHAN B., SRINIVASAN R. Development and evaluation of Soil Moisture Deficit Index (SMDI) and Evapotranspiration Deficit Index (ETDI) for agricultural drought monitoring. *Agricultural and Forest Meteorology* 2005 133(1–4), pp. 69–88 doi: 10.1016/j.agrformet.2005.07.012.

[24] National Agricultural Statistics Service (NASS). *United States Department of Agriculture (USDA)*, 2014 [viewed 11 August 2014]. Available from: http://www.nass.usda.gov/

[25] National Drought Mitigation Center (NDMC), ©2014 [viewed 11 August 2014] Available from: `http://www.drought.unl.edu/`

[26] ODABAS M.S., TEMIZEL K.E., CALISKAN O., SENYER N., KAYHAN G., ERGUN E. Determination of reflectance values of *hypericum*'s leaves under stress condıtıons usıng adaptıve network based fuzzy interface system. *Neural Network World.* 2014, 24(1), pp. 79–87, doi: 10.14311/nnw.2014.24.004.

[27] OGUNKUNLE A.O., BECKETT P.H.T. Combining soil map and soil analysis for improved yield prediction. *Catena.* 1988, 15(6), pp. 529–538, doi: 10.1016/0341-8162(88)90004-5.

[28] OSTENDORF B., HILBERT D.W., HOPKINS M.S. The effect of climate change on tropical rainforest vegetation pattern. *Ecological Modelling.* 2001, 145(2–3), pp. 211–224, doi: 10.1016/s0304-3800(01)00392-1.

[29] OSTERGARD H., KRISTENSEN K., PINNSCHMIDT H.O., HANSEN P.K., HOVMOLLER M.S. Predicting spring barley yield from variety-specific yield potential, disease resistance and straw length, and from environment-specific disease loads and weed pressure. *Euphytica.* 2008, 163(3), pp. 391–408, doi: 10.1007/s10681-008-9714-5.

[30] OTTENBACHER K.J., SMITH P.M., ILLIG S.B., LINN R.T., FIEDLER R.C., GRANGER C.V. Comparison of logistic regression and neural networks to predict rehospitalization in patients with stroke. *Journal of Clinical Epidemiology* 2001, 54(11), pp. 1159–1165, doi: 10.1016/s0895-4356(01)00395-x

[31] PALIWAL M., KUMAR U.A. Neural networks and statistical techniques: A review of applications. *Expert systems with applications* 2009, 36(1), pp. 2–17 doi: 10.1016/j.eswa.2007.10.005.

[32] PAO H.T. A comparison of neural network and multiple regression analysis in modeling capital structure. *Expert Systems with Applications.* 2008, 35(3), pp. 720–727, doi: 10.1016/j.eswa.2007.07.018.

[33] REGGIA J.A. Neural computation in medicine. *Artificial Intelligence Medicine.* 1993, 5(2), pp. 143–157, doi: 10.1016/0933-3657(93)90014-t

[34] SUO X.M., JIANG Y.T., YANG M., LI S.K., WANG K.R., WANG C.T. Artificial Neural Network to Predict Leaf Population Chlorophyll Content from Cotton Plant Images. *Agric. Sci. in China* 2010, 9(1), pp. 38–45, doi: 10.1016/s1671-2927(09)60065-1

[35] SVOBODA M. An introduction to the drought monitor. *Drought Network News.* 2000, 12(1), pp. 15–20.

[36] TAYFUR G., GULDAL V. Artificial neural networks for estimating daily total suspended sediment in natural streams. *Nordic Hydrology.* 2006, 37, pp. 69–79.

[37] THOMSON A.M., BROWN R.A., ROSENBERG N.J., IZAURRALDE R.C., BENSON V. Climate change impacts for the conterminous USA: an integrated assessment. *Climatic Change* 2005, 69(1), pp. 43–65, doi: 10.1007/1-4020-3876-3_4

[38] TOKAR A.S., JOHNSON P.A. Rainfall–runoff modelling using artificial neural networks. *Journal of Hydrologic Engineering, ASCE* 1999, 4(3), pp. 232–239, doi: 10.1061/(asce)1084-0699(1999)4:3(232)

[39] WEISBERG S. Applied linear regression. *A John Wiley & Sons, Inc. Pub., USA* 2005, pp. 310, doi: 10.1002/0471704091

[40] YESILNACAR E., TOPAL T. Landslide susceptibility mapping: A comparison of logistic regression and neural networks methods in a medium scale study, Hendek region, Turkey. *Engineering Geology.* 2005 79(3–4), pp. 251–266, doi: 10.1016/j.enggeo.2005.02.002

[41] YILMAZ I., KAYNAR O. Multiple regression, ANN (RBF, MLP) and ANFIS models for prediction of swell potential of clayey soils. *Expert Systems with Applications* 2011, 38(5), pp. 5958–5966, doi: 10.1016/j.eswa.2010.11.027

[42] ZAEFIZADEH M., KHAYATNEZHAD M., GHOLAMIN R. Comparison of Multiple Linear Regressions (MLR) and Artificial Neural Network (ANN) in Predicting the Yield Using its Components in the Hulless Barley. *American-Eurasian J. Agric. & Environ. Sci.* 2011, 10(1), pp. 60–64.