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Modeling of Soil Temperature by Generalized Regression Neural Network in Bathalagoda Area of Sri Lanka

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ABSTRACT

Regression is the data analysis component of statistics. The application of neural networks for regression problems is a popular technique. Even though neural networks have complex structures, and various parameters, they perform well in regression problems. The generalized regression artificial neural network (GRNN) is a well-known and widely applied mathematical model for forecasting of nonlinear functions. This study presents the application of GRNN models to predict the weekly morning and evening soil temperatures at a depth of 5cm on the weekly agro-climatic data collected from Bathalagoda. This paper investigates the potential of using a GRNN for reference soil temperature estimation. Weekly data collected at Bathalagoda Rice Research and Development Institute wasanalyzed in this study. Serial cross correlation and autocorrelation analysis were used to select the most suitable input variables for the network models. Models with different combinations of input variables were tested and the best sets of input variables were selected based on the prediction accuracy. The Mean Square Error (MSE) and the coefficient of determination (R^2) of the model of predicted values on actual values were employed to compare the performances of different neural networks. Determination coefficients of GRNN models of morning and evening soil temperatures were found to be 0.71 and 0.68 respectively. The GRNN model yields the best result of minimum mean square errors values of 0.358 and 0.447 for the morning and evening soil temperatures respectively. The results suggest that using GRNN with minimum climatic variables for soil temperature forecasting is a reliable method.

KEYWORDS: - Generalized Regression Neural Network, Soil temperature

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INTRODUCTION

Primary objective of regression based on Artificial Neural Networks (ANN) is identifying the underlying relationships among observed values and predicted values in data. Identifying structures in data based on neural networks is a novel application of ANN. The goal of regression based on ANN is to improve the quality of the association of data between the predicted values and the actual values. The knowledge acquired using ANN gives a competitive advantage over traditional methods.

Regression based on ANN needs tools to analyze and model the data. Regression tools can forecast the future trends and build up the model in data. The discord of aims between regression and neural networks has naturally caused some complications when applying ANN for regression.Regression has formal structure of the statistics but the appearance of this new discipline does not have the methodical manner to solve problems. Regression modeling is a very powerful technique. However; its main limitation is the assumption of linearity of relations between responses and predictor variables. In real worldscenarios this assumption is rarely satisfied. Furthermore, when there are several predictors, it is unlikely to discoverany underlying non-linear functional relationships between response and predictor variables. Fortunately, ANN'shave been shown to beable to map any non-linear mappings[1]. ANN based modeling approach with the ability to learn from experience is very useful in many practical problems since it is often easier to find data than to develop theoretical models about the underlying laws governing the systems from which data are generated.

There are several local ANN universal approximators such as, radial basis function (RBF) neural networks and general regression neural networks (GRNN) [2, 3]. GRNN belongs to the well-known non-parametric kernel regression models[4, 5]. A comprehensive study of local modeling approaches and their applications can be found in [5]. Some extensions of these non-parametric regression approaches have also been made which can be found in [6].

Artificial Neural Networks (ANN)

ANN's attempt to mimic the functionalities of the human brain. An ANN comprises a number of artificial neurons in a specific architecture in order to process data. These artificial neurons are simple elements that are interconnected by links and determine an empirical relationship between the inputs and outputs of a given system [1]. The structure of ANN usually consists of a few layers withspecific numbers of neurons, where the inputs are independent variables and the outputs are dependent. The first layer consists of elements in the input layer and cannot perform any other functions. The next layer is called the hidden layers and the output layer is the last layer. The network then applies the parameters it has learned to a new input pattern to predict the appropriate output.

Statistical neural networks are interesting because of their application in prediction and classification problems.Statisticiansusually apply discriminant analysis, logistic regression, Bayesian analysis, multiple regression and time series models to predict forecast values. In cases where it is difficult to apply conventional approaches such as control, optimization, pattern recognition, classification, and regression, ANN models can be applied.

MATERIALS AND METHODS

Materials

The weekly agro-climatic data (Minimum and maximum air temperatures, rainfall, sun shine hours, relative humidity (morning and evening) , pan evaporation , wind velocity) from 1990 to 2010 provided by the Rice Research and Development Institutes (RRDI) located in Bathalagoda, were used for this study. The soil temperature data at depths of 5cm measured by the RRDI will also be used. The outputs were soil temperature in morning and evening. All the agro climatic factors except relative humidity at evening of a given day are measured only on the next day morning. Therefore the soil temperature at morning depends on the agro climatic factors of previous day.

There are a few different types of neural networks. Each differs from the others in network structure and parameters. In this study, the Generalized Regression Neural Network (GRNN) was applied to predict the soil temperature in morning and evening at the 5cm depth.

Generalized Regression Neural Network (GRNN)

The GRNN consists four layers: input layer, pattern layer, summation layer and output layer. The number of input units in the first layer is equal to the total number of parameters. The first layer is fully connected to the second, pattern layer, where each unit represents a training pattern and its output is a measure of the distance of the input from the stored pattern. Each pattern layer unit is connected to the two neurons in the summation layer.The GRNN can be treated as a normalized radial basis function network in which the hidden unit is centered at every training case. The GRNN is based on nonlinear regression theory for function estimation.

EXPERIMENTS

Proposed ANN models

The data was partitioned into training (1990-2005), validation (2006-2008) and test sets (2009-2010). Input variables were added according to the strength of correlations between the response variable and the predicted variables. The ANNs used in this analysis were fully connected with a single input layer consisting of selected number of input neurons, a single hidden layer with a selected number of hidden neurons and a single output layer with one output neuron.

Predicted values of soil temperatures in the morning and evening were compared using the coefficient of determination (R^2). The ANN models were implemented based on the R^2 values.

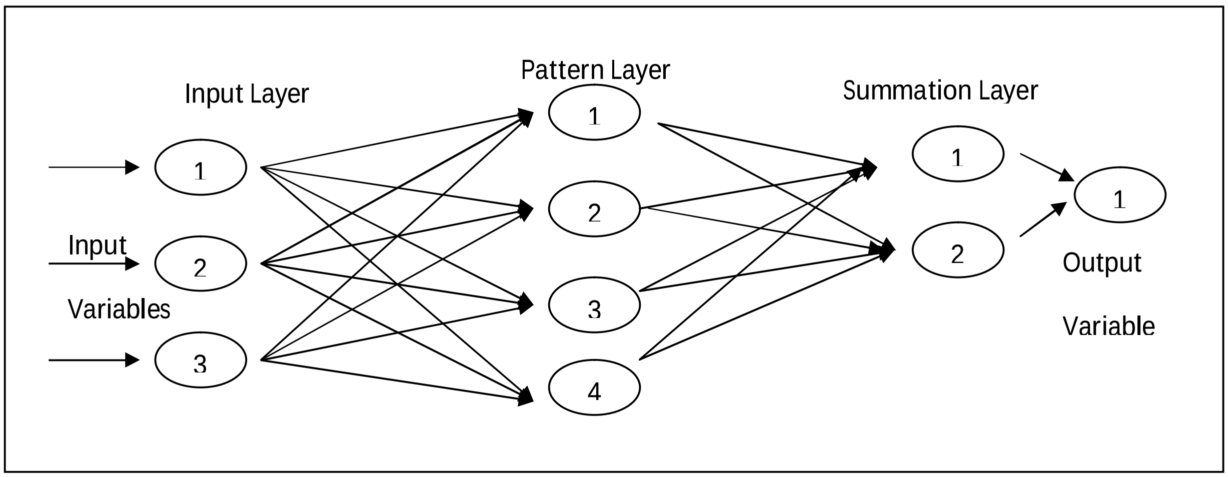


Figure No.1: Architecture of a GRNN

RESULTS AND DISCUSSION

Two GRNN models were selected for the dependent variables, i.e. morning and evening soil temperatures at depths of 5cm. The results are summarized in Table 1.

As shown in Table 1, the network architectures achieved best potential within a short training and testing period.The trained networks were considered as the final ANN networks for modeling soil temperature at depth of 5cm.

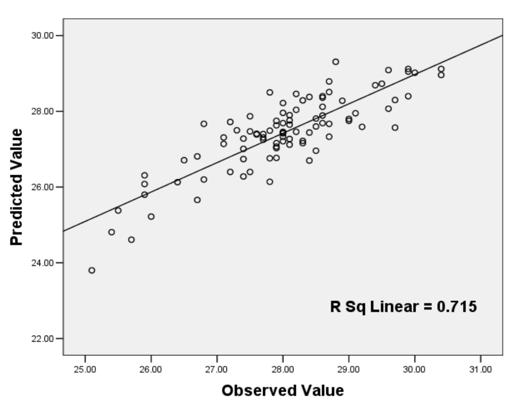
The scatter plots of the measured soil temperature against predicted soil temperature for the test data set for the GRNN models are shown in Figure 02. These figures depict that GRNN models predict soil temperature with reasonably high accuracy.

The estimated values are found to be close to the measured values. As shown in Table 01, the mean-square errors for the two models of GRNN are 0.358 and 0.447 respectively for morning and evening. The R^2 values of predicted values on actual values for the two models built using GRNN are 0.71 and 0.68 respectively for morning and evening. The results demonstrate the applicability and performance of GRNN models for prediction of soil temperature at morning and evening at a depth of 5cm.

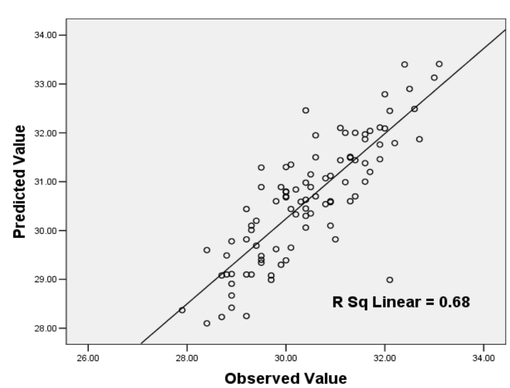
Table 1: Soil temperature models in morning and evening at Depth of 5cm

	Soil -5cm at morning	**Soil -5cm at evening**
Input Layer Nodes	6 (minimum and maximum temperature, pan evaporation, sun shine hours, Relative humidity at evening) of previous week and Relative humidity at morning of present week	7 (maximum temperature, Relative humidity at evening, sun shine hours, ,pan evaporation, wind velocity, Relative humidity at morning ,minimum temperature) of present week
Output Layer	Nodes 1 (soil Temperature at morning)	Nodes 1 (soil Temperature at evening)

Regression scatter plots of GRNN



(a)



(b)

Figure No.2: Comparison between exact and predicted soil temperature values at (a) morning and (b) evening in 5 cm for 2009-2010 of GRNN

CONCLUSIONS AND FURTHER RESEARCH

The results demonstrate that GRNN models produce reasonably high prediction accuracieswhen forecasting morning and evening soil temperatures at a depth of 5cm. Results also indicate that soil temperature can be modeled as a non-linear function of a few selected weather variables.

Minimum and maximum temperature, pan evaporation, relative humidity in the morning and evening during the previous week and present week were found to affect morning and evening soil temperature models at depths of 5cm according to theconsidered data set. Sun shine hours during the previous week and present week were also found to affect the soil temperature both in the morning and evening at 5cm depth. Wind velocity during current week was found to affect soil temperature at a depth of 5cm only in the evening.

Data collected on a daily basis would have been more appropriate and might have yielded more accurate forecasting model(s) for morning and evening soil temperatures.

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