Estimating daily solar radiation using soft computing method

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ABSTRACT

The objective of this study is to develop generalized regression neural networks (GRNN) model for estimating daily solar radiation using limited weather variables at Champaign and Springfield stations in Illinois. The best input combinations (one, two, and three inputs) can be identified using GRNN model. From the performance evaluation and scatter diagrams of GRNN model, GRNN 3 (three input) model produces the best results for both stations. Results obtained indicate that GRNN model can successfully be used for the estimation of daily global solar radiation at Champaign and Springfield stations in Illinois. These results testify the generation capability of GRNN model and its ability to produce accurate estimates in Illinois.

Keywords: generalized regression neural networks, daily solar radiation, Illinois, limited weather variables

INTRODUCTION

Solar radiation intercepted at the earth's surface is important for various applications, such as in the infrastructure and construction industry, estimation of crop productivity, environmental and agrometeorological research, atmospheric physics and the practical utilization of renewable energy resources. Solar radiation data are required by solar engineers, architects and agriculturists for many applications such as solar heating, cooking, drying and interior illumination of buildings. Solar radiation plays an important role in the design and analysis of energy efficient buildings in different climates. Artificial neural networks (ANN) models were used by many researchers to estimate global solar radiation. Almost all the literatures concluded that ANN model is superior to other empirical regression models. The objective of the present study is to develop GRNN model that can be used to estimate daily solar radiation at two locations (Champaign and Springfield stations) in Illinois.

GENERALIZED REGRESSION NEURAL NETWORKS

GRNN is a neural networks model based on the nonlinear regression theory. GRNN model, as a universal approximation for smooth functions, is capable of solving any smooth function approximation problem. The process of GRNN modeling can solve the problem of local minimum (Specht 1991; Sudheer *et al.* 2003). The parameters that need to be optimized during the training performance are centers, widths/spreads, and connection weights. The radial basis function (RBF) is widely used for the transfer function of the hidden layer. Determining parameters of the RBF between the input layer and

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the hidden layer implies the finding of suitable centers and widths/spreads. The connection weights between the hidden layer and the summation layer are determined using the supervised training performance (Kim and Kim 2008). A GRNN model has been successfully developed and investigated for hydrological modeling (Kisi 2006; Kim and Kim 2008; Kim *et al*. 2012; 2013). Detailed information on the GRNN model can be found in Tsoukalas and Uhrig (1996), Kim and Kim (2008), and Kim *et al*. (2012, 2013).

CASE STUDY

The daily weather data obtained from two weather stations (Fig. 1), Champaign (latitude, 40.0840° N; longitude, 88.2404° W; altitude, 219 m) and Springfield (latitude, 39.7273° N; longitude, 89.6106°W; altitude, 177 m) operated by the Illinois State Water Survey (ISWS), were used in this study (http://www.isws.illinois.edu/warm/). The ISWS is a division of the Prairie Research Institute of the University of Illinois at Urbana-Champaign and has flourished for more than a century by anticipating and responding to new challenges and opportunities to serve the citizens of Illinois. The weather data consisted of six years (January 2007 to December 2012, N=2,192 days) of daily records of air temperature (TEM), solar radiation (RAD), relative humidity (HUM), dew point temperature (DEW), wind speed (WIN), and potential evapotranspiration (ETO). Air temperature and relative humidity have been measured at 2 m above the ground, whereas wind speed has been measured at 10 m above the ground (prior to winter 2011/2012 measurement made at 9.1 m). Potential evapotranspiration has been calculated using the Food and Agricultural Organization (FAO) of the United Nations Penman–Monteith equation as outlined in FAO Irrigation and Drainage Paper No. 56 "Crop Evapotranspiration" (Allen et al. 1998) since 1 December 2012 (Water and Atmospheric Resources Monitoring Program 2011). Prior to that time, the Van Bavel method was used for calculating potential evapotranspiration (Van Bavel 1956).

For a data-driven model, data was split into training, cross-validation, and testing data. The training data were used for optimizing the connection weights and bias of the data-driven model, the cross-validation data were used to select the model variant that provides the best level of generalization, and the testing data were used to evaluate the chosen model against unseen data (Dawson and Wilby 2001; Izadifar and Elshorbagy 2010). The cross-validation method provides a rigorous test of data-driven model's skill (Dawson and Wilby 2001) and is generally used to overcome the overfitting problem inherent in the data-driven models (Haykin 2009). This technique has been often applied at the end of training performance in the literature (Smith, 1993; Haykin, 2009) and is also employed for data-driven model's selection (Stone, 1974). In all of these applications, the first 4 years data (2007–2010, N=1,461 days) was applied for training, 1 year (2011, N=365 days) and 1 year (2012, N=366 days) for cross-validation and testing. The estimated solar radiation values were compared with observed ones using 5 performance evaluation criteria: the correlation coefficient (CC), root mean square error (RMSE), Nash-Sutcliffe coefficient (NS) (Nash and Sutcliffe 1970; ASCE 1993), mean absolute error (MAE), and average performance error (APE). Although CC is one of the most widely used criteria for calibration and evaluation of hydrological models with observed data, it alone cannot discriminate which model is better than others. Since the standardization inherent in CC as well as its sensitivity to outliers yields high CC values, even when the model performance is not perfect. Legates and McCabe (1999) suggested that various evaluation criteria (e.g., RMSE, MAE, NS, and APE) must be used to evaluate model performance. Figure 2 shows the comparison of the observed and estimated daily solar radiation values using GRNN models (two and three inputs).

CONCLUSIONS

This study develops and evaluates data-driven models for estimating daily solar radiation at Champaign and Springfield stations in Illinois. The GRNN model is developed for the best input combinations (one, two, and three inputs), respectively. Adding other input variables to the best input combinations (one, two, and three inputs) improves GRNN model performance. In this study, it can be found that the data-driven models can estimate daily solar radiation.

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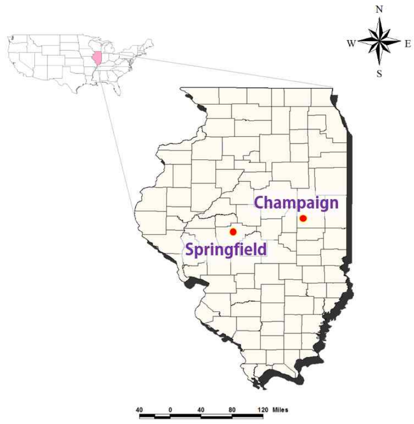
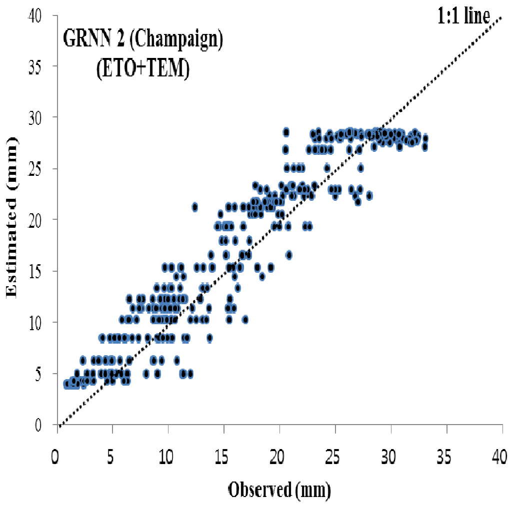
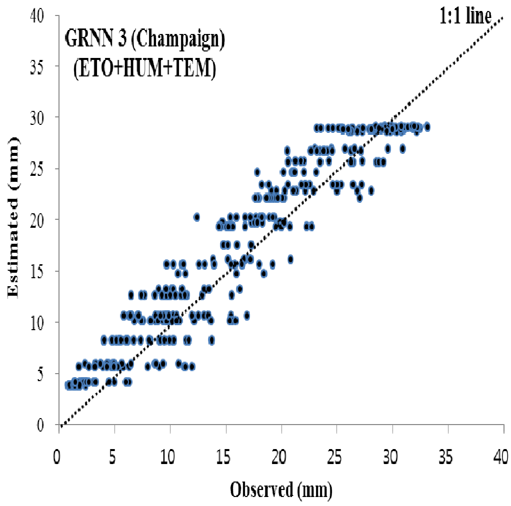


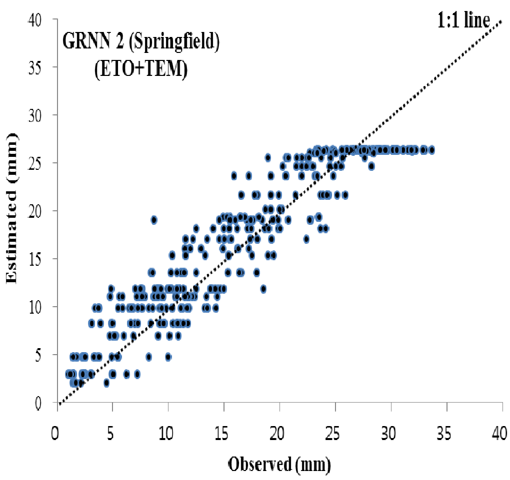
Figure 1 Schematic map of two weather stations



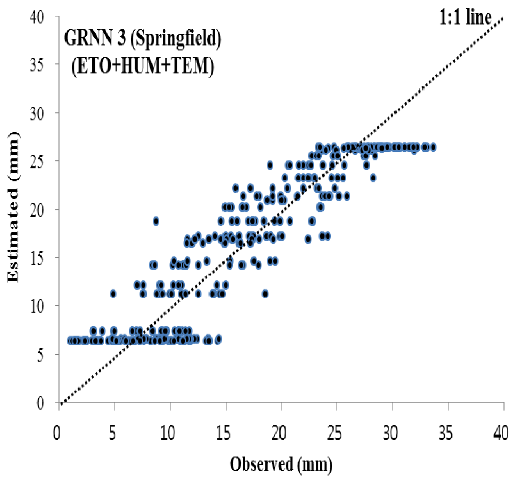
(a) GRNN 2 (Champaign)



(b) GRNN 3 (Champaign)



(c) GRNN 2 (Springfield)



(d) GRNN 3 (Springfield)

Figure 2 Comparison of the observed and estimated daily solar radiation values using GRNN models