Atmospheric Research 161–162 (2015) 65–81

Contents lists available at ScienceDirect

Atmospheric Research

journal homepage: www.elsevier.com/locate/atmos

Application of the Artificial Neural Network model for prediction of monthly Standardized Precipitation and Evapotranspiration Index using hydrometeorological parameters and climate indices in eastern Australia

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ARTICLE INFO

Article history:
Received 7 November 2014
Received in revised form 8 March 2015
Accepted 27 March 2015
Available online 8 April 2015

Keywords:
Artificial Neural Network
Drought prediction in Australia
Data-driven model
Standardized Precipitation and Evapotranspiration Index (*SPEI*)

ABSTRACT

The forecasting of drought based on cumulative influence of rainfall, temperature and evaporation is greatly beneficial for mitigating adverse consequences on water-sensitive sectors such as agriculture, ecosystems, wildlife, tourism, recreation, crop health and hydrologic engineering. Predictive models of drought indices help in assessing water scarcity situations, drought identification and severity characterization. In this paper, we tested the feasibility of the Artificial Neural Network (ANN) as a data-driven model for predicting the monthly Standardized Precipitation and Evapotranspiration Index (*SPEI*) for eight candidate stations in eastern Australia using predictive variable data from 1915 to 2005 (training) and simulated data for the period 2006–2012. The predictive variables were: monthly rainfall totals, mean temperature, minimum temperature, maximum temperature and evapotranspiration, which were supplemented by large-scale climate indices (Southern Oscillation Index, Pacific Decadal Oscillation, Southern Annular Mode and Indian Ocean Dipole) and the Sea Surface Temperatures (Nino 3.0, 3.4 and 4.0). A total of 30 ANN models were developed with 3-layer ANN networks. To determine the best combination of learning algorithms, hidden transfer and output functions of the optimum model, the Levenberg–Marquardt and Broyden–Fletcher–Goldfarb–Shanno (BFGS) quasi-Newton backpropagation algorithms were utilized to train the network, tangent and logarithmic sigmoid equations used as the activation functions and the linear, logarithmic and tangent sigmoid equations used as the output function. The best ANN architecture had 18 input neurons, 43 hidden neurons and 1 output neuron, trained using the Levenberg–Marquardt learning algorithm using tangent sigmoid equation as the activation and output functions. An evaluation of the model performance based on statistical rules yielded time-averaged Coefficient of Determination, Root Mean Squared Error and the Mean Absolute Error ranging from 0.9945–0.9990, 0.0466–0.1117, and 0.0013–0.0130, respectively for individual stations. Also, the Willmott's Index of Agreement and the Nash–Sutcliffe Coefficient of Efficiency were between 0.932–0.959 and 0.977–0.998, respectively. When checked for the severity (S), duration (D) and peak intensity (I) of drought events determined from the simulated and observed *SPEI*, differences in drought parameters ranged from −1.41–0.64%, −2.17–1.92% and −3.21–1.21%, respectively. Based on performance evaluation measures, we aver that the Artificial Neural Network model is a useful data-driven tool for forecasting monthly *SPEI* and its drought-related properties in the region of study.

Abbreviations: ANN, Artificial Neural Network; BOM, Bureau of Meteorology; d, Willmott's Index of Agreement; D, duration of drought; E, Nash–Sutcliffe Coefficient of Efficiency; GCM, global circulation model; Hardlim, hard limit; I, peak intensity of drought; IOD, Indian Ocean Dipole; JISAO, Joint Institute of the Study of the Atmosphere and Ocean; Logsig, logarithmic sigmoid; *MAE*, mean absolute error; POAMA, Predictive Ocean Atmosphere Model of Australia; R^2, Coefficient of Determination; Radbas, radial bias; *RDDI*, Rainfall Decile Drought Index; *RMSE*, Root Mean Square Error; S, severity of drought; SAM, Southern Annular Mode; SLFM, Single Layer Feedforward Neural Network; SOI, Southern Oscillation Index; *PCN*, precipitation; *PE*, prediction error; *PET*, potential evapotranspiration DO; PDO, Pacific Decadal Oscillation; *SPI*, Standardized Precipitation Index; *SPEI*, Standardized Precipitation and Evapotranspiration Index; SPOTA, Seasonal Pacific Ocean Temperature Analysis; SST, Sea Surface Temperature; ST, standard deviation; SVD, singular value decomposition; SVM, support vector machine; Tansig, training hyperbolic-tangent sigmoid; Trainbfg, training BFGS quasi-Newton; Trainbr, training Bayesian regulation; Trainlm, training Levenberg–Marquardt; Trainoss, training one-step secant; Trainscg, training scaled conjugate gradient; Tribas, training triangular basis.

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http://dx.doi.org/10.1016/j.atmosres.2015.03.018
0169-8095/

1. Introduction

A drought is a chronic, albeit a natural climatic feature in most climates, although it may occur with varying frequencies, intensities or durations (Wilhite, 1996). Droughts pose detrimental impacts on agriculture, economy, recreation, hydropower generation and environments (Mpelasoka et al., 2008; Riebsame et al., 1991). By definition, drought results from temporary imbalance of water resources due to persistently lower than average rainfall (Pereira et al., 2009). Water resources are also affected by aridity, which is a permanent climatic feature with an imbalance in water availability or low average annual rainfall and soil moisture expressed through precipitation and evapotranspiration ratios (Arora, 2002). Nonetheless, both drought and aridity are intrinsically driven by a shortage of usable water, and may be exacerbated due to higher surface temperatures and evaporation rates. Hence, a combination of both abnormal patterns of precipitation and evapotranspiration changes is a potential indicator of aridity or dry conditions. One particular drought index (*DI*) for such assessments is the Standardized Precipitation Evapotranspiration Index (*SPEI*), which incorporates precipitation and potential evapotranspiration (*PET*) in its formulation to express the water supply–demand relationships in order to accommodate for climate change influences (Vicente-Serrano et al., 2010a,b, 2012a,b). In circumstantial challenges posed by a drying climate, scientists and engineers responsible for planning, management and adjudicating the distribution of water resources must have an understanding of rainfall and evapotranspiration changes and knowledge about their spatial and temporal distributions and the predicted trends. Thus, predictive models of the *SPEI* may greatly help stakeholders in assessing drought and aridity impacts due to unexpected changes in rainfall, temperature and evapotranspiration. Models based on water scarcity conditions can assist in risk management, developing mitigation, forewarning and response systems (Wilhite, 1996; Wilhite and Hayes, 1998; Wilhite et al., 2000).

In forecasting key parameters of drought such as rainfall or evaporation, basically two kinds of models are considered in literature: physical model (or global circulation model, GCM), which is based on the interactive behavior of the ocean, atmosphere, sea ice and land surface, and data-driven (or statistical) model which assimilates the trends in observed climatic parameters (e.g. rainfall), climate indices and Sea Surface Temperatures to make future predictions. However, physical model provides reliable forecast for ancillary atmospheric variables like temperature but less reliable information can be obtained for variables that are crucial determinants of drought (e.g. rainfall) (Hudson et al., 2011; Kuligowski and Barros, 1998). Therefore, the development of robust predictive models as alternatives to physical models is desirable for improving confidence in rainfall projections and assessment of future drought.

For Australia specifically, the Predictive Ocean Atmosphere Model for Australia (POAMA) (Hudson et al., 2011; Zhao and Hendon, 2009) and Seasonal Pacific Ocean Temperature Analysis (SPOTA-1) (Day et al., 2010) are used as predictors of seasonal climates. However, studies that compared forecast of precipitation using data-driven models with physical models such as the POAMA have found significant improvement in the predictions from the former type of model (e.g. Abbot and Marohasy, 2014; Hudson et al., 2011; Inquiry, 2011; Seqwater, 2011). In order to improve and enhance the fidelity of modeling framework for forecasting hydro-meteorological variables, many researchers are testing the viability of data-driven models as alternative premises for predicting future changes in hydrological, atmospheric and climatic parameters.

Data-driven models utilize the computational capacity of machine learning algorithms and mathematical equations that are not based on the physical interactions of the ocean, atmosphere or sea ice as with the case of physical models but instead employ historical datasets to deduce the relationships between predictor (inputs) and objective variables (outputs) (Acharya et al., 2013; Deo and Sahin, 2015; Şahin, 2012; Şahin et al., 2014). Consequently, the advantages of such models are: the explanation of future trends in climate parameters with less complexities in executing the model or comprehension of the model output compared with physical models, easy experimentation or evaluation, low computational cost and less data requirements than the physical model, efficiency in training and the testing phase (e.g. shorter execution time), applicability to specific areas and the competitive performance relative to physical models (Abbot and Marohasy, 2012, 2014; Ortiz-García et al., 2014). More importantly, for the purpose of predicting temperature or precipitation, significant improvements in performance of data-driven models have been noted in recent studies (e.g. Abbot and Marohasy, 2012, 2014).

A longstanding well-established data-driven model is the Artificial Neural Network (ANN), which was developed in the early 1950s. The ANN is a computational paradigm that mimics the biological structure of the brain (McCulloch and Pitts, 1943). It operates like a black box, and does not require detailed information about the inputs as with the case of physical models. Instead, the ANN learns from the relationships between input parameters and controlled or uncontrolled variables by checking previous trends in data as non-linear regression. ANN also has the capability for managing very large and complex datasets with several interrelated parameters (Şahin et al., 2013). Therefore, the use of ANN for prediction of complex climatic phenomenon (e.g. drought) is not a new but an enlightening research endeavor.

ANN has been applied extensively in many parts of the world including Greece (Nastos et al., 2014), China (Wu et al., 2011), India (Chattopadhyay, 2007; Chattopadhyay and Chattopadhyay, 2008), Iran (Morid et al., 2007), Ethiopia (Belayneh and Adamowski, 2012), Kenya (Masinde, 2013), Turkey (Şenkal et al., 2012; Şenkal, 2010; Şenkal and Kuleli, 2009) and Australia where recent research is showing the relatively good performance of ANN models for drought forecasting. Mekanik et al. (2013) used ANN and Multiple Regression models with lagged relationships of the El Nino Southern Oscillation (ENSO) and Indian Ocean Dipole (IOD) as predictors for forecasting rainfall in Victoria. The study found smaller predictive errors using the ANN approach. In two separate studies in Queensland, Abbot and Marohasy (2012, 2014) used the ANN model to demonstrate the relatively smaller mean square errors of precipitation predictions compared to the official predictive model used by the Bureau of Meteorology (POAMA-1.5). For a study focusing on Yarra River catchment in Victoria (Australia), Barua et al. (2010, 2012) applied the recursive multistep neural network (RMSNN) and the direct multistep neural network (DMSNN) approaches to predict nonlinear aggregated drought index (NADI) for assessing drought conditions considering all significant hydrometeorological variables. Overall, the ANN model was highly capable of forecasting drought conditions up to 6 months in advance. Quite recently, the work of Mekanik and Imteaz (2014) attempted to find the effects of past values of El Nino southern Oscillation (ENSO) and Indian Ocean Dipole (IOD) on rainfall in Horsham, Melbourne and Orbost in Victoria, Australia. Using ANN models, they investigated lagged-time relationships of single and combined climate mode indices with Victorian rainfall. Interestingly, the use of ENSO and IOD indices appeared to increase the ANN model correlation up to 0.99, 0.98 and 0.30 in the three tested regions.

In forecasting problems based on data-driven paradigms, synoptic-scale indices are often used as predictants for medium-range forecasting to explain the behavior of future climate (Dijk et al., 2013; McAlpine et al., 2009; Timbal and Fawcett, 2013; Ummenhofer et al., 2009; Franks and Kuczera, 2002; Kiem and Franks, 2004; Kiem et al., 2003; Verdon-Kidd and Kiem, 2009, 2010). For the case of Australia, researchers have found that the Millennium drought was related to a combination of intensified sea level pressure across southern Australia (Hope et al., 2010), the subtropical ridge (belt of high-pressure systems representing the descending Hadley cell) (Timbal et al., 2010) and the ENSO cycle (Verdon-Kidd and Kiem, 2009; Verdon-Kidd and Kiem,