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Research paper

Wavelet based analysis on rainfall and water table depth forecasting using Neural Networks in Kanyakumari district, Tamil Nadu, India

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ABSTRACT

Rainfall is one of the most complex phenomenons occurring on earth to study with extreme and advanced soft computing engine that can perform well with adaptive perception. Water table depth is more or less proportionate to the rainfall occurring on the study area. Some other factors involved in it are climate change, soil characteristics and human activities. Here in this research, an attempt has been made to study the behaviour of rainfall in Kanyakumari district, Tamil Nadu, India. The study region is one of the most agricultural favourable climatic districts with large area of cultivating lands. Unlike the other districts in Tamil Nadu, this district gets rainfall from both south west and north east monsoons. For this analysis, wavelet tool has been used. Apart from analysing it, short term forecasting has been attempted with efficient soft computing tool, Artificial Neural Networks (ANN). This method has been validated with the actual water table depth with respect to the rainfall. This approach applied to the data works well for short term forecasting. The performance of the model was evaluated using the regression coefficients and Mean Absolute Percent Error (MAPE) reveals the success of the working integrated model.

1. Introduction

In this research work, Kanyakumari study area is chosen to predict the water table depth with respect to the rainfall in the region, irrespective of its domain, using Artificial Neural Networks (ANN). Rainfall behaviour was studied with ANN model and the prediction results were compared with the actual result.

Wavelet transforms draws attention after Grossman and Morlet's (1984) development on signal processing. After it becomes a common tool, researchers applied it in many fields such as data analysis, modelling, neurophysiology, data compression, nuclear science, pure mathematics, speech analysis, radar, human vision, atmospheric science, ocean wave analysis, temporal analysis, turbulent and stream flow characterization (Santos et al., 2001).

There are large number of conceptual basis of wavelet and NNs used for forecasting rainfall and groundwater table (e.g., Maskey et al., 2000; Daliakopoulos, 2005; Mohammadi, 2008).

Wavelet analysis has been applied by various researchers in the field of hydrological modelling. A hybrid model by Cannas et al. (2006) applied to predict monthly rainfall–runoff forecasting in Italy. Adamowski (2007, 2008a, 2008b) applied a wavelets for flood forecasting. Kisi (2008) and Partal (2009) adapted wavelets for monthly flow forecasting in Turkey. Kisi (2009) approached daily inflow of water in intermittent rivers. Wang et al. (2009) applied wavelet for forecasting inflow in Yangtze River. Adamowski and Sun (2010) applied integrated approach with wavelets for lead times of three different rivers in Cyprus.

Wavelet transform used for many multi scale characteristics of rainfall, temperature, etc., (Deng et al., 1997; Dai et al., 2003; Tan et al., 2001; You et al., 1999; Yang and Song, 1999; Zhu et al., 2003; Yao and Qian, 2001; Wang et al., 2000).

New methods were developed for different level of forecasting. Lallahemea et al. (2005) analysed level of groundwater level variations using Artificial Neural Networks. Coppola et al. (2003) and Dalyakapulus et al. (2005) applied ANN for studying instability in groundwater level. Dehghani et al. (2009) applied different soft computing tools to interpolate levels of groundwater. Nakhaee et al. (2011) applied neural-wavelet analysis on groundwater level. To interpolate the transfer coefficient, Kholghi and Hosseini (2009) applied geostatistics, ANN and ANFIS for better solution. Zohreh et al. (2014) modelled groundwater level using ANN, ANFIS and time series analysis.

ANN is proved to the best tool in forecasting models. Its basics

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Table 1
Land classification of Kanyakumari district.
[source: http://www.kanyakumari.tn.nic.in/agri.html]

S.No	Classification	2010-11	2011–2012
1.	Forest	4772.3	4772.3
2.	Barren and Uncultivable waste	4000.8	4000.8
3.	Land put to non-agricultural use	28409.0	28487.9
4.	Cultivable waste	101.7	83.1
5.	Permanent pasture and other grazing lands	103.6	103.6
6.	Land under miscellaneous tree crops not included under net area sown	733.5	623.7
7.	Current fallows	428.7	644.5
8.	Other fallow lands	476.1	577.1
9.	Net area sown	78791.4	78524.3

structure consists of computing elements called neurons interconnected with parallel distributed processing (Rummelhart and McClelland, 1996). This network was successfully applied by several researchers to produce significant results (Mary, 2002; Singh and Chowdhury, 1986; Cigizoglu, 2002).

The objectives of the study are

1. Analysing rainfall and water table depth data in Kanyakumari district using wavelet transforms
2. Training Artificial Neural Networks with rainfall data to predict water table depth
3. Analysing and justifying the tested results of ANN.
4. Land Use Land Change (LULC) classification has been done for the study area to understand the results obtained from the ANN testing.

2. Study area

Kanyakumari is located in the border of Western Ghats having a elevation of 200 m from the foothills in the west side with ridges and complex valleys. The slope of southeast of Knayakumari extends towards the Gulf of Mannar. Land classification details are shown in Table 1. The central and eastern sides are barren lands with some hillocks. Marshy swaps on the coastal side occupied with some sand dunes (Teri sands). From the knowledge of satellite imagery the geomorphology of Kanyakumari is classified as

1) Structural Hills
2) Bazada
3) Valley Fill,
4) Flood Plain
5) Pediment,
6) Shallow Buried Pediments,
7) Deep Buried Pediments, and
8) Coastal Plain.

2.1. Rainfall and climate

Rainfall in Kanyakumari is due to the influence of both southwest and northwest monsoons. More amount of rainfall is coming from southwest monsoon. Annual rainfall over the district varies from 826 to 1456 mm. South-eastern part of Kanyakumari receives low rainfall. But the trend increases from west, north and northwest. Highest recorded humidity is 95% in the month May and 45 in February. Only during monsoon higher and lower temperatures were recorded. Minimum temperature recorded is 23.85°C during January. Annual minimum temperature is 23.78°C and maximum temperature is 33.95°C

2.2. Groundwater scenario

The Kanyakumari district is underlain with both porous and fissured formations. Aquifer system in the district is composed of i) unconsolidated & semi consolidated formations (ii) weathered, fissured, and fractured crystalline rocks. In the regions of crystalline rocks the groundwater occurrence is limited to zone of weathering and fracturing. Generally the district is covered with heterogeneous rocks structures with hard rock aquifers indicated by the variation in litholog structure and texture. Groundwater occurrence in weathered mantle and semi-confined to confined in the regions of fracture and some fissured zones of the rocks. The thickness varies from less than one meter to 20 m. Therefore the depth of water levels varies from 8 to 18 m bgl.

3. Methodology

In this research work, rainfall data from Kanyakumari district were collected and analysed using wavelet transform. Wavelet analysis, an advance tool, is used for understanding time varying input data. Many applications have been increasing nowadays using wavelet in the field of communications engineering, signal processing, optical engineering, image processing, etc.,. There are certain advantages in using wavelets instead of Fourier transforms. Main advantage is wavelet can provide the exact locality of changes in varying patterns of input signal whereas in Fourier transform concern only on frequency domain. Information on spectral components with time localization can be obtained using multiresolution wavelet analysis. Multiresolution wavelet analysis produced the power spectrum of rainfall and water table depth data.

After analysing the data, ANN is initiated with pre processing training elements like number of epochs, number of data available for training and testing, performance criteria based on minimum error percent and correlation coefficient (R). Rainfall data and Water table depth data were used for input and output parameters respectively, to train ANN. For training monthly rainfall data and water table depth data of Kanyakumari district from 2004 to 2009 has been used. For testing rainfall data from 2010 to 2014 has been applied and the optimised results were obtained. Root Mean Square Error (RMSE) helps to converge the result by applying it in particular number of iterations. The algorithm is also checked for validation using Mean Absolute Percent Error (MAPE).

4. Wavelet and artificial neural networks

4.1. Wavelet analysis

Wavelet transform plays major role in analysing the data in broad spectrum of time-frequency. Event related potential determination can be easily done through this transformation more clearly. The spatial and temporal information will provide the real time data strategy in eagle's eye. Advantages over the conventional time-frequency analysis lies in decompose the signal of any time-frequency multiresolution functions (Mallat, 2009). The admissibility condition is as follows

ψ (t) ϵ L^2 (R) satisfies certain admissibility conditions as

$$C\psi = \int_R \frac{|\hat{\Psi}(\omega)|^2}{|\omega|} d\omega < \infty \tag{1}$$

$\Psi(t)$ is called wavelet; $\hat{\Psi}$ (ω) is fourier transform of $\Psi(t)$. The Continuous Wavelet Transform (CWT) is defined as the sum over all time of the signal multiplied by scaled, shifted versions of the wavelet function,

$$\Psi_{a,b}(t) = |a|^{-\frac{1}{2}} \Psi\left(\frac{t-b}{a}\right) \tag{2}$$

$$W_f(a, b) = \langle f(t), \Psi_{a,b}(t)\rangle = |a|^{-\frac{1}{2}} \int_R f(t) \Psi\left(\frac{t-b}{a}\right) dt \tag{3}$$

Wavelet coefficients of rainfall and water table depth showed in Fig. 1a and Fig. 1b respectively. CWT uses discrete sampling of data in order to obtain the finer details depends on the scaling parameter of the wavelet. Wavelet coefficients are used to transform the signal to