Applications of Wavelet Transform Technique in Hydrology—A Brief Review

Khandekar Sachin Dadu and Paresh Chandra Deka

Abstract Recently, wavelet transform analysis has become a popular analysis tool due to its ability to elucidate simultaneously both spectral and temporal information within the signal. This overcomes the basic shortcoming of Fourier analysis, which is that the Fourier spectrum contains only globally averaged information. Therefore, a data preprocessing can be performed by time series decomposition into its subcomponents using wavelet transform analysis. Wavelet transforms provide useful decompositions of the main time series, so that wavelet-transformed data improve the ability of a forecasting model by capturing useful information on various resolution levels. The wavelet decomposition of a nonstationary time series into different scales provides an interpretation of the series structure and extracts significant information about its history, using few coefficients. For these reasons, this technique is largely applied to time series analysis of nonstationary signals. In terms of hydrologic applications, this modeling tool is still in its nascent stages. The practicing hydrologic community is just becoming aware of the potential of wavelet transform as an analyzing tool. This paper is intended to serve as an introduction to wavelet transformation for hydrologists. Apart from descriptions of various aspects of wavelet transform and some guidelines on their usage, this paper offers brief comparisons of the nature of wavelet transformations and other modeling philosophies in hydrology. The merits of wavelet transform applications have been discussed.

Keywords Wavelet transform · Artificial neural network · Hydrology · Streamflow · Time series · Forecasting

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1 Introduction

The hydrology system is a highly complex nonlinear system under the influence of rain-bearing system and underlying surface system. It is influenced by many factors, such as weather, land with vegetal cover, infiltration, evapotranspiration, so it includes the good deal of stochastic dependent component, multi-time scale, and highly nonlinear characteristics. Forecasting of hydrological time series can be done using stochastic models like Auto regressive (AR), Auto regressive moving average (ARMA), Auto regressive integrated moving average (ARIMA), etc. These models are basically time series models and have a limited ability to capture nonstationarities and nonlinearities.

A nonstationary time series can be decomposed into certain number of stationary time series by wavelet transform (WT). Then different single prediction methods are combined with WT to improve the prediction accuracy. In most of the hybrid models, WT is used as preprocessing technique. The wavelet-transformed data aid in improving the model performance by capturing helpful information on various resolution levels. Due the above-mentioned advantages of WT, it has been found that the hybridization of wavelet transformation with other models like ANN, FL, ANFIS, linear models, etc., improved the results significantly than the single regular model (Prahlada and Deka 2011).

Wavelet theory (Mallat 1989) is first developed in the end of 1980s of last century. Nowadays, it has been applied in many fields, such as signal process, image compression, voice code, pattern recognition, hydrology, earthquake investigation, and many other nonlinear science fields. The objective of this paper is to examine how successfully WT has been used in hydrologic problem. The researches and applications of wavelet analysis have already begun in hydrology and water resources. The document (Li et al. 1997) points out the potential applications of wavelet analysis to hydrology and water resources. Li et al. (1999) probed longtime interval forecast of hydrological time series with combining neural network models based on WT. Wang et al. (2000) have proposed a wavelet transform stochastic simulation model, which generates synthetic streamflow sequences that are statistically similar to observed streamflow sequences. The multi-time scale characteristics of hydrological variable have been studied by Wang et al. (2002). Wavelet analysis has been a hot research point in prediction of time series analysis due to its multiresolution function (Zhou et al. 2008). In this study, general applications of WT are discussed briefly. However, this study did not present any detail on hydrologic applications. Rather, it complements earlier studies.

2 Wavelet Transformation Basics

2.1 General

In the last decade, WT has become a useful technique for analyzing variations, periodicities, and trends in time series. A wavelet transformation is a strong mathematical signal processing tool like Fourier transformation with the ability of analyzing both stationary as well as nonstationary data, and to produce both time and frequency information with a higher resolution, which is not available from the traditional transformation. WT provides multiresolution analysis, i.e., at low scales (high frequency) it gives better time resolution and poor frequency resolution and at high scales (low frequency) it gives better frequency resolution and poor time resolution and in actual practice for all the time series signals such information is important. The lower scales (i.e., compressed wavelet) trace the abrupt change or high frequency of a signal and the higher scales (i.e., stretched wavelet) trace slowly progressing occurrences or low-frequency component of the signal.

Signals whose frequency content does not change with time are called stationary signals. In other words, the frequency content of stationary signals does not change in time. In stationary signals it is not necessary to know at what times frequency components exist, since all frequency components exist at all times.

Mathematical transformations (viz., Fourier transform (FT), Short Time Fourier transform (STFT), WT, etc.) are applied to time domain signals (raw signals) to obtain further information from that signal that is not readily available in the raw signals. The above-mentioned mathematical transformation techniques are briefly described in the following sections.

2.2 Fourier Transform (FT)

If the FT of a signal in time domain is taken, the frequency–amplitude representation of that signal is obtained. That is, we have a plot with one axis being the frequency and the other being the amplitude. This plot tells us how much of each frequency exists in the raw signal. But it does not tell about what spectral component exist at any given time instant, i.e., the time information is lost. So FT is not suitable for nonstationary data. The FT is defined by the following two equations:

$$F(\omega) = \int_{-\infty}^{\infty} x(t) \cdot \mathrm{e}^{-2j\pi\omega t} \mathrm{d}t \tag{1}$$

$$x(t) = \int_{-\infty}^{\infty} F(\omega) \cdot \mathrm{e}^{2j\pi\omega t} \mathrm{d}\omega \tag{2}$$

In the above equation ω stands for frequency, t stands for time, and $x(t)$ denotes time domain signal. Equation (1) is FT of $x(t)$ and Eq. (2) is inverse FT of $F(\omega)$. In Eq. (1), the signal $x(t)$, is multiplied with an exponential term, at some certain frequency "ω", and then integrated over all the times. This integral is calculated for every value of "ω". If the value of this integration is large, then this means that the signal have a major component of "ω" in it.

2.3 Short Time Fourier Transform (STFT)

The STFT is an improvement on the FT (frequency) because it provides a measure of time and frequency resolutions. The difference between STFT and FT is that in STFT, the signal is divided into small enough segments, where these segments (portions) of the signal can be assumed to be stationary. For this purpose, a window function "***w***" is chosen. The width of this window must be equal to the segment of the signal where its stationarity is valid. This window is first located to very beginning of signal. The window function and signal are then multiplied. This product is assumed to be another signal, whose FT is to be taken. In other words, FT of this product is taken, just like taking FT of any signal. The next step is shifting this window to new location, multiplying with the signal, and taking FT of the product. This procedure is followed until the end of the signal is reached.

STFT is defined as

$$\mathrm{STFT}(t,\omega) = \int_t [x(t) \cdot w^*(t)] \cdot \mathrm{e}^{-2j\pi\omega t} \cdot \mathrm{d}t \tag{3}$$

In the above equation $x(t)$ denotes raw signal, $w(t)$ denotes window function, and * is complex conjugate.

Wide window gives good frequency resolution, but poor time resolution. Narrow window gives good time resolution, but poor frequency resolution. The use of a fixed window size at all times and for all frequencies is a limitation of this method.

2.4 Wavelet Transformation

The wavelet representation addresses the above limitation, by *adaptively* partitioning the time–frequency plane, using a range of window sizes. At high frequencies, the WT gives up some frequency resolution compared to the FT. Figure 1 shows representation of the effect of using FT and WT.

The WT breaks the signal into its wavelets (small wave) which are scaled and shifted versions of the original wavelet so-called mother wavelet.

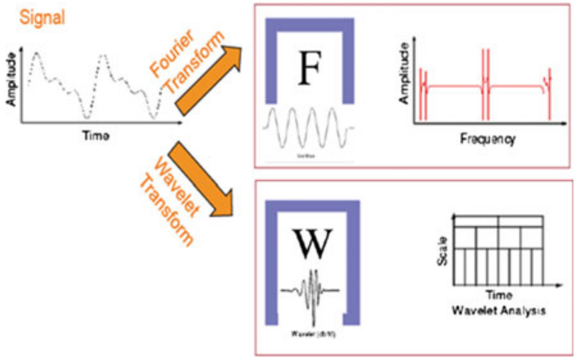

Fig. 1 Fourier Transform and wavelet transformation

The generation of wavelet coefficients for a time series involves five steps (The Mathworks 2010):

(i) Given a signal X_t and a wavelet function $\Psi j,k$ compares the wavelet to a section at the start of the signal (Fig. 2a).
(ii) Compute the coefficient, $c_{j,k}$, which is an indication of the correlation of the wavelet function with the selected section of the signal.
(iii) Shift the wavelet to the right and repeat steps (i) and (ii) until the entire signal is covered (Fig. 2b).
(iv) Dilate (scale) the wavelet and repeat steps (i) through (iii) (Fig. 2c).
(v) Repeat steps (i) through (iv) for all scales to obtain coefficients at all scales and at different sections of the original signal.

The wavelet transformation is divided into two types:

1. Continuous wavelet transform (CWT)
2. Discrete wavelet transform (DWT).

2.4.1 Continuous Wavelet Transform (CWT)

The Continuous Wavelet Transform (CWT) of a signal $x(t)$ is given by Eq. 4.

$$\mathrm{CWT}(a,b) = \frac{1}{\sqrt{a}} \int_{-\infty}^{\infty} x(t) \cdot \psi^{*}\left(\frac{t-b}{a}\right) \cdot \mathrm{d}t \tag{4}$$

In the above equation, the transformed signal is a function of two variables, a and b, the scale and translation factor, respectively, of the function $\psi(t)$. * corresponds to complex conjugate. $\psi(t)$ is the transforming function, and is called the mother wavelet, which is defined mathematically as

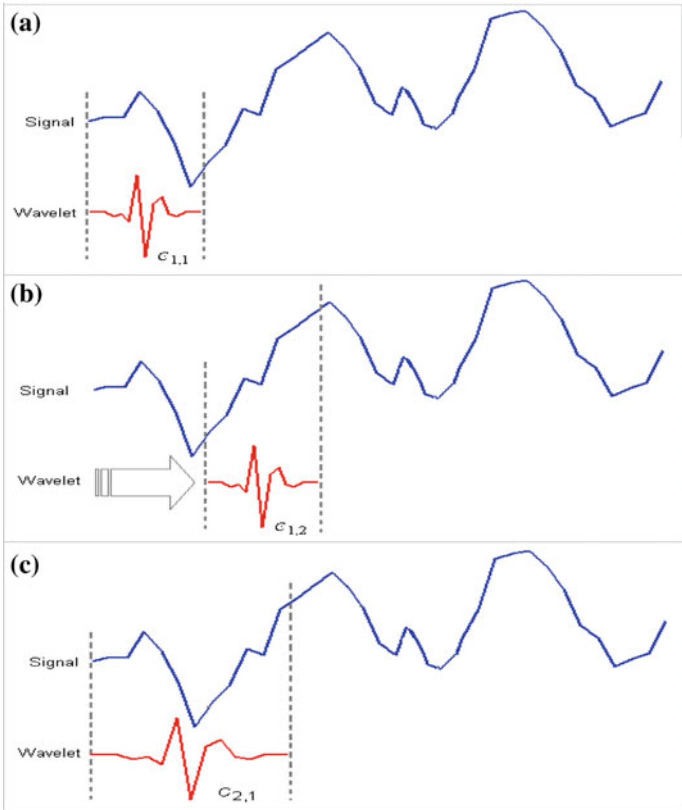

Fig. 2 Generating wavelet coefficients from a time series

$$\int_{-\infty}^{\infty} \psi(t)\mathrm{d}t = 0 \tag{5}$$

The term translation is related to the location of the window, as the window is shifted through the signal. This term, obviously, corresponds to time information in the transform domain. The scale parameter is defined as 1/frequency. Low frequencies (high scales) correspond to a global information of a signal (that is usually spans the entire signals), whereas high frequencies (low scales) correspond to a detailed information of a hidden pattern in the signal (that usually lasts a relatively short time).

The CWT is computed by changing the scale of the analysis window, shifting the window in time, multiplying by the signal, and integrating over all times.

The original signal is reconstructed using the inverse wavelet transform as

$$x(t) = \frac{1}{C_\psi} \int_{-\infty}^{\infty} \int_{0}^{\infty} \frac{1}{\sqrt{a}} \psi\left(\frac{t-b}{a}\right) \cdot \mathrm{CWT}(a,b) \frac{\mathrm{d}a \cdot \mathrm{d}b}{a^2} \tag{6}$$

where C_ψ is admissibility constant.

2.4.2 Discrete Wavelet Transform (DWT)

Calculating the wavelet coefficients at every possible scale is a fair amount of work, and it generates a lot of data. If one chooses scales and positions based on the powers of two (dyadic scales and positions) then the analysis will be much more efficient as well as accurate. This transform is called discrete wavelet, and has the form as

$$\psi_{m,n}(\frac{t-b}{a}) = \frac{1}{\sqrt{a_o^m}} \psi\left(\frac{t - nb_o a_o^m}{a_o^m}\right) \tag{7}$$

where m and n are integers that control the wavelet dilation and translation, respectively; b_o is the location parameter and must be greater than zero; a_o is a specified fixed dilation step greater than 1. From this equation, it can be seen that the translation step $nb_o a_o^m$ depends upon the dilation, a_o^m. The most common and simplest choice for parameters a_o and b_o are 2 and 1 (time steps), respectively. This power of two logarithmic scaling of the translations and dilations is known as the dyadic grid arrangement. The dyadic wavelet can be written in more compact notation as

$$\psi_{m,n}(t) = 2^{-m/2} \psi(2^{-m} t - n) \tag{8}$$

Discrete dyadic wavelets of this form are usually chosen to be orthonormal. This allows for the complete regeneration of the original signal as an expansion of a linear combination of translate and dilate orthonormal wavelets. For discrete time series x_i, where x_i occurs at discrete time i, the dyadic wavelet transform becomes

$$T_{m,n} = 2^{-m/2} \sum_{i=0}^{N-1} \psi(2^{-m} i - n) x_i \tag{9}$$

where $T_{m,n}$ = wavelet coefficient for the discrete wavelet of scale $a = 2^m$ and location $b = 2^m n$. Equation (9) considers a finite time series, x_i, $i = 0, 1, 2, \ldots, N-1$, and N is an integer power of 2: $N = 2^M$. This gives the range of m and n as, respectively, $0 < n < 2^{M-m} - 1$ and $1 < m < M$. At the largest wavelet scale (i.e., 2^m, where $m = M$), just one wavelet is needed to cover the time interval and only one coefficient is produced. At the next scale (2^{M-1}), two wavelets cover the time interval, therefore two coefficients are produced, and so on down to $m = 1$. At $m =$

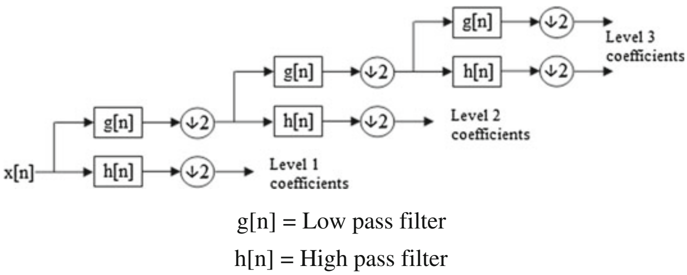

Fig. 3 Wavelet decomposition tree

1, the *a* scale is 2^1, i.e., $2^M/2^1$, i.e., 2^{M-1} or $N/2$ coefficients are needed to describe the signal at this scale. The total number of wavelet coefficients for a discrete time series of length $N = 2^M$ is then $1 + 2 + 4 + 8 + \cdots + 2^{M-1} = N-1$ (Addison et al. 2001).

DWT operates two sets of function viewed as high-pass and low-pass filters (see Fig. 3). The original time series are passed through high-pass and low-pass filters and separated at different scales. The time series is decomposed into one comprising its trend (the approximation) and one comprising the high frequencies and the fast events (the detail).

3 Applications of Wavelet Transform in Hydrology

Recently, WT analysis has become a popular analysis tool due to its ability to elucidate simultaneously both spectral and temporal information within the signal. Some of the recent works carried out in the Hydrology are discussed below.

Addison et al. (2001) used WT analysis to a variety of open channel wake flows. Feature location was undertaken using a continuous WT, and both turbulent statistical analysis and thresholding of the turbulent signal components are undertaken using a discrete WT. It was found that the CWT is the preferred method for feature detection within fluid velocity time signals.

Wensheng and Ding (2003) carried out a multi-time scale prediction of ground water level at Beijing and daily discharge of Yangte River Basin at China using Hybrid Model of Wavelet-Neural Network. Through a Trous algorithm and three-layer neural network forecasting results were carried out. Twelve years of shallow monthly ground water level data were used, 9 years for calibration, and 3 years for validation. Daily discharge data of 8 years were used for training and 2 years for testing. The comparisons revealed that the model increase the forecasted accuracy and prolong the length time of prediction. The proposed WLNN model focused on improving the precision and prolonging the forecasting time period.

Kim and Valdes (2003) developed nonlinear model for drought forecasting based on a conjunction of wavelet transforms and neural networks in the Conchos river basin in Maxico. The results indicate that the conjunction model using dyadic wavelet transform significantly improves the ability of neural network in forecasting.

Cannas et al. (2005) studied the river flow forecasting 1 month ahead with Neural Networks and Wavelet Analysis using monthly runoff data for the Tirso Basin, Italy. The dataset was split into three parts, first 40 years was used for training, next 9 years for cross validation, and last 20 years for testing. The reconstruction of the data was done by traditional feed forward, MLP networks. For the nonstationary and seasonal irregularity of runoff time series, the best results were obtained using data clustering and DWT combination. Tests showed that neural networks trained with preprocessed data showed better performance.

Zhou et al. (2008) developed monthly discharge predictor–corrector model based on wavelet decomposition using 52 years records of monthly discharge at Yichang station of Yangtse river. The decomposed times series data were used as input to ARMA model for prediction which improves the prediction accuracy.

Rao and Krishna (2009) carried out modeling using Hydrological Time Series data adopting Wavelet-Neural Network for four west flowing rivers in India namely Kollur, (22 years data from 1981 to 2002), Seethanadi (26 years data from 1973 to 1998), Varahi (26 years 1978–2003), and Gowrihole (25 years data from 1979 to 2003). The results of daily Streamflow and monthly Groundwater level series modeling indicated that the performances of WNN Models are more effective than ANN Models.

Nourani et al. (2009a, b) studied the rainfall–runoff modeling using Wavelet–ANN approach for predictions of runoff discharge 1 day ahead of the Ligvanchai watershed at Tabriz, Iran. The daily rainfall and runoff time series for 21 years were used. The time series were decomposed up to four levels using Haar, Daubechies (db2), Symlet (sym3), and Coiflet (coif1). The Study showed that both short- and long-term runoff discharges could be predicted considerably. The model results show the high merit of Haar wavelet in comparison with the others. Authors also recommended that WT could be used for trend analysis in watersheds.

Kisi (2009) developed neuro-wavelet (NW) model by combining two methods DWT and artificial neural network (ANN), for 1 day ahead intermittent streamflow forecasting and results were compared with those of the single ANN model. Intermittent streamflow data from two stations in the Thrace Region, the European part of Turkey, in the northwest part of the country were used in the study. In NW model, the original time series were decomposed into a five number of subtime series components by Mallat DWT algorithm. The correlation coefficients between each subtime series and original intermittent streamflow time series were found. These correlation values provide information for the determination of effective wavelet components on streamflow. The new subtime series having high correlation coefficient was used as input to the ANN model. The NW model was found to be much better than the ANN in high flow estimation. The test results showed that the DWT could significantly increase the accuracy of the ANN model in modeling intermittent streamflows.

Rajaee et al. (2010) investigated the Prediction of daily suspended sediment load 1 day ahead with wavelet and neuro-fuzzy combination model using time series data of discharge and suspended sediment load as input in a gauging station from the Pecos River in USA. Results showed that the wavelet analysis and neuro-fuzzy model performed better predictions rather than neuro-fuzzy and sediment rating curve (SRC). The cumulative suspended sediment load estimated by this technique was closer to the actual data. The WNF model considers periodic and stochastic characteristics of suspended sediment phenomenon and may provide suitable constructions not clearly seen in the suspended SRC. The model also could be employed to stimulate hysteresis phenomenon, while the SRC method is incapable in this event.

Shiri and Kisi (2010) studied short-term and long term streamflow forecasting using a wavelet and neuro-fuzzy conjunction model to investigate the daily, monthly, and yearly streamflow of Derecikviran station on Filyos River in the Western Black Sea region of Turkey using 31 years of streamflow data. The results obtained showed that the neuro-fuzzy (NF) and wavelet–neuro-fuzzy (WNF) models increased the accuracy of the single NF models especially in forecasting yearly streamflow. Also the single NF and WNF models were compared with each other by adding periodicity components into the inputs. The comparison results indicated that adding periodicity component generally increased the models accuracy.

Kisi (2010) developed neuro-wavelet models for daily suspended sediment estimation for two stations on tongue river in montana using daily streamflow and suspended sediment data. The comparison results reveal that the developed model could increase the estimation accuracy.

Adamowski and Sun (2010) investigated a method based on coupling discrete wavelet transform (WA) and ANN for flow forecasting applications in nonperennial rivers in semiarid watersheds at lead times of 1 and 3 days for two different rivers in Cyprus. The discrete trous wavelet transform was used to decompose flow time series data into eight levels of wavelet coefficients which are used as inputs to Levenberg Marquardt artificial neural network models to forecast flow. WA–ANN model provided more accurate results than regular ANN.

Nourani et al. (2011) studied two hybrids for two watersheds located in Azerbaijan, Iran. Artificial Intelligence approaches for modeling rainfall–runoff process. Two hybrid AI-based models which are reliable in capturing the periodicity features of the process are introduced for modeling. In the first model, the SARIMAX (Seasonal Auto Regressive Integrated Moving Average with exogenous input)–ANN model, an ANN is used to find the nonlinear relationship among the residuals of the fitted linear SARIMAX model. In the second model, the wavelet–ANFIS model, WT is linked to the ANFIS concept and the main time series of two variables (rainfall and runoff) are decomposed into some multifrequency time series by WT. Afterward, these time series are imposed as input data to the ANFIS to predict the runoff discharge one time step ahead. The obtained results showed that, although the proposed models can predict both short and long terms runoff discharges by considering seasonality effects, the second model is relatively more appropriate because it uses the multiscale time series of rainfall and runoff data in the ANFIS input layer.

Kisi and Shiri (2011) developed precipitation forecasting model using wavelet–genetic programming and WNF conjunction. They found that hybrid wavelet–genetic programming model was of better performance than hybrid wavelet–neuro-fuzzy model.

Rajaee et al. (2011) developed ANN, wavelet analysis and ANN combination (WANN), multilinear regression (MLR), and SRC models for daily suspended sediment load (*S*) modeling in the Iowa gauging station in the US. In the WANN model, DWT was linked to the ANN method. For this purpose, the observed time series of river discharge (*Q*) and *S* were decomposed into five levels by DWT which were imposed as input to ANN to predict 1 day ahead *S*. A complex Morlet wavelet technique was applied to analyze wavelet construction of daily *Q* and *S*. The number of nodes in the input in WANN model was determined by $(i + 1) \times 2$, because this model uses two variables (*Q* and *S*) and each time series is decomposed into *i*, $i = (1,2,\ldots,5)$ detailed time series and approximation time series.

This study was aimed at examining the effects of employed mother wavelet type on the proposed WANN model efficiency. Seven different mother wavelets were used [viz., Daubechies-2 (db2) (the most popular wavelet), the Haar wavelet (a simple wavelet), and some irregular wavelet such as Bior1.1, Rboi1.1, Coif1, Sym1, and Mayer wavelets].

It was found that, increasing the decomposition level, in levels over Level 1, decreases the model's performance, because high decomposition levels lead to a large number of parameters with complex nonlinear relationships in the ANN technique. The WANN model was more accurate in predicting the *S* and its performance was better than the ANN, MLR, and SRC models.

Wang et al. (2011) utilized wavelet transform method for synthetic generation of daily streamflow in Jinsha river of China. Daily streamflow sequences with different frequency components are decomposed into the series of wavelet coefficients at various resolution levels using wavelet decomposition algorithm. Based on these sampled subseries, a large number of synthetic daily streamflow sequences are obtained using wavelet reconstruction algorithm. They concluded that this newly developed method is able to generate streamflow sequences based on probability distributions and type of dependence structure.

4 Conclusion

This paper serves as an introduction to WT with emphasis on their application to hydrologic problems. It presents brief description of WT, the underlying concept, and mathematical aspects, and the role of WT relative to other approaches in hydrology. Guidelines for application of WT to hydrological problems are presented. The role of WT in various branches of hydrology has been examined here and found that WT is robust tool in analysis of many nonlinear and nonstationary hydrologic processes such as rainfall–runoff, streamflow, groundwater modeling, precipitation, evaporations. However, WT tends to be data (signal) intensive and prudent on statistical properties of dataset. For this emerging technique, still more questions arises which must be further studied.

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