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Review Paper

Applications of hybrid wavelet–Artificial Intelligence models in hydrology: A review

Vahid Nourani [a,*], Aida Hosseini Baghanam [a], Jan Adamowski [b], Ozgur Kisi [c]

[a] Dept. of Water Resources Eng., Faculty of Civil Eng., Univ. of Tabriz, Iran
[b] Dept. of Bioresource Eng., McGill Univ., Quebec, Canada
[c] Eng. Faculty, Canik Basari University, Samsun, Turkey

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SUMMARY

Accurate and reliable water resources planning and management to ensure sustainable use of watershed resources cannot be achieved without precise and reliable models. Notwithstanding the highly stochastic nature of hydrological processes, the development of models capable of describing such complex phenomena is a growing area of research. Providing insight into the modeling of complex phenomena through a thorough overview of the literature, current research, and expanding research horizons can enhance the potential for accurate and well designed models.

The last couple of decades have seen remarkable progress in the ability to develop accurate hydrologic models. Among various conceptual and black box models developed over this period, hybrid wavelet and Artificial Intelligence (AI)-based models have been amongst the most promising in simulating hydrologic processes. The present review focuses on defining hybrid modeling, the advantages of such combined models, as well as the history and potential future of their application in hydrology to predict important processes of the hydrologic cycle. Over the years, the use of wavelet–AI models in hydrology has steadily increased and attracted interest given the robustness and accuracy of the approach. This is attributable to the usefulness of wavelet transforms in multi-resolution analysis, de-noising, and edge effect detection over a signal, as well as the strong capability of AI methods in optimization and prediction of processes. Several ideas for future areas of research are also presented in this paper.

Contents

Abbreviations: ACO, Ant Colony Optimization; AI, Artificial Intelligence; ANFIS, Adaptive Neuro-Fuzzy Inference System; ANN, Artificial Neural Network; AR, Auto Regressive; ARIMA, Auto Regressive Integrated Moving Average; ARIMAX, ARIMA with exogenous input; CWT, Continues Wavelet Transform; DWT, Discrete Wavelet Transform; dbn, Daubechies order *n* wavelet; GA, Genetic Algorithm; GEP, Gene-Expression Programming; GP, Genetic Programming; GWL, Groundwater Level; LR, Linear Regression; MA, Moving Average; MAE, Mean Absolute Error; MARS, Multivariate Adaptive Regression Spline; MLP, Multi-Layer Perceptron; MLR, Multiple Linear Regression; NF, Neuro Fuzzy; NN, Neural Network; PSO, Particle Swarm Optimization; RMSE, Root Mean Square Error; SOM, Self-Organizing Map; SPI, Standard Precipitation Index; SRC, Sediment Rating Curve; SSA, Singular Spectrum Analysis; SSC, Suspended Sediment Concentration; SSL, Suspended Sediment Load; SST, Sea Surface Temperature; SVM, Support Vector Machine; SVR, Support Vector Regression; WANFIS, Wavelet–ANFIS; WANN, Wavelet–artificial neural network; WBANN, Wavelet–Bootstrapping ANN; WGRNN, Wavelet–Generalized Regression NN; WMF, Wavelet Modeling Framework; WMRA, Wavelet Multi-Resolution Analysis; WNF, Wavelet–Neuro Fuzzy; WR, Wavelet–Regression; WVC, Wavelet–Volterra.

* Corresponding author. Tel.: +98 914 403 0332; fax: +98 411 334 4287.
E-mail addresses: vnourani@yahoo.com, vnourani@umn.edu (V. Nourani), hosseinibaghanam@gmail.com (A. Hosseini Baghanam), jan.adamowski@mcgill.ca (J. Adamowski), okisi@basari.edu.tr (O. Kisi).

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1. Introduction

Characterized by high complexity, dynamism and non-stationarity, hydrological and hydro-climatologic forecasting has always presented a challenge to hydrologists who recognize its essential role in environmental and water resources management as well as in water-related disaster mitigation. Recent years have seen a significant rise in the number of scientific approaches applied to hydrologic modeling and forecasting, including the particularly popular 'data-based' or 'data-driven' approaches. Such modeling approaches involve mathematical equations drawn not from the physical process in the watershed but from an analysis of concurrent input and output time series (Solomatine and Ostfeld, 2008). Such models can be defined on the basis of connections between the system state variables (input, internal and output variables) with only a limited number of assumptions being made regarding the physical behavior of the system. Typical examples of data-driven models are rating curves, the unit hydrograph method and various statistical models (Linear Regression; LR, multi-linear, Auto Regressive Integrated Moving Average; ARIMA) and methods of machine learning. The conventional black box time series models such as ARIMA, ARIMA with exogenous input (ARIMAX) and Multiple Linear Regression (MLR) are linear models and assume stationarity of the dataset. Such models are unable to handle non-stationarity and non-linearity involved in hydrological processes. As a result, many researchers have focused on developing models that are able to model non-linear and non-stationary processes.

The data-driven methods of Artificial Intelligence (AI) have shown promise in modeling and forecasting non-linear hydrological processes and in handling large amounts of dynamicity and noise concealed in datasets. Such properties of AI-based models are well suited to hydrological modeling problems. Numerous AI tools or techniques have been used, including versions of search optimization, mathematical optimization, as well as logic-, classification-, statistical learning- and probability-based methods (Luger, 2005). In particular, three sub-sets of AI have been widely used in the hydro-climatologic and environmental fields:

(1) *Evolutionary computation:* A branch of optimization methods that includes swarm intelligence algorithms such as Ant Colony Optimization (ACO; Dorigo et al., 1996) or Particle Swarm Optimization (PSO; Kennedy and Eberhart, 1995) and evolutionary algorithms such as Genetic-Algorithms (GA; Goldberg, 2000), Gene-Expression Programming (GEP), and Genetic-Programming (GP; Koza, 1992).
(2) *Fuzzy logic:* Fuzzy systems (Zadeh, 1965) can be used for uncertain reasoning, which provide a logic perspective in AI techniques.
(3) *Classifiers and statistical learning methods:* These models employ statistical and machine-learning approaches. The most widely used classifiers are Neural Networks (NNs; Haykin, 1994), kernel methods such as the Support Vector Machine (SVM; Vapnik, 1995), *k*-nearest neighbor algorithms such as Self-Organizing Map (SOM; Kohonen, 1997), Gaussian mixture model, naive Bayes classifier, and decision tree. NNs, the predominant AI method, are used in hydrology via two approaches: (i) supervised, including acyclic or feed-forward NNs (where the signal passes in only one direction) and recurrent NNs (which allow feedback), and (ii) unsupervised (*e.g.*, SOM).

Among the broader applications of AI methods, GA, GP, Fuzzy, NNs, and SVM are widely used in different fields of hydrology. Since their emergence in hydrology, the efficient performance of AI techniques such as data-driven models has been reported over a wide range of hydrological processes (*e.g.*, precipitation, stream-flow, rainfall–runoff, sediment load, groundwater, drought, snowmelt, evapotranspiration, water quality, *etc.*). The number of researchers active in this area has increased significantly over the last decade, as has the number of publications. Several dozen successful applications for hydrological process modeling (*e.g.*, stream-flow, rainfall–runoff, sediment, groundwater, water quality) using ANN, Fuzzy, GP, GA, and SVM have been reported, with some examples listed in Table 1.

Despite the flexibility and usefulness of AI-based methods in modeling hydrological processes, they have some drawbacks with highly non-stationary responses, *i.e.*, which vary over a wide scale of frequencies, from hourly to multi-decadal. In such instances of 'seasonality', a lack of input/output data pre/post-processing, may not allow AI models to adequately handle non-stationary data. Here, hybrid models which combine data pre/post-processing schemes with AI techniques can play an important role.

Hybrid hydrological models may take advantage of black box (here AI-based) models and their ability to efficiently describe observed data in statistical terms, as well as other prior information, concealed in observed records. The hybrid models discussed here represent the joint application of AI-based methods with the wavelet transform to enhance overall model performance.

As an advance in signal processing, wavelet transforms can reliably obviate AI model shortcomings in dealing with non-stationary behavior of signals. A mathematical technique useful in numerical analysis and manipulation of multidimensional signal sets, wavelet analysis provides a time-scale representation of the process and of its relationships. Indeed, the main property of the wavelet transform is its ability to provide a time-scale localization of a process. The wavelet transform has attracted significant attention since its theoretical development in 1984 (Grossmann and Morlet, 1984). A number of recent hydrological studies have implemented wavelet analysis (*e.g.*, Adamowski and Sun, 2010; Kim and Valdes, 2003; Kisi, 2009a,b, 2010; Nourani et al., 2009a,b, 2011; Maheswaran and Khosa, 2012a; Partal and Kisi, 2007; Sang, 2012; Tiwari and Chatterjee, 2010; Zhou et al., 2008).

The Wavelet transform is applicable in extracting nontrivial and potentially useful information, or knowledge, from the large data sets available in experimental sciences (historical records, reanalysis, global climate model simulations, *etc.*). Providing explicit information in a readable form, it can be used to solve diagnostic, classification or forecasting problems. In a review of the applications of the wavelet transform in hydrologic time series modeling, Sang (2013a) highlighted the multifaceted information that can be drawn from such analysis: characterization and understanding of hydrologic series' multi-temporal scales, identification of seasonalities and trends, and data de-noising. Therefore, the ability of the wavelet transform to decompose non-stationary signals into

Table 1
Examples of some AI applications in hydrological process modeling.

Hydrologic process	ANN	Fuzzy	GP	GA	SVM
Stream-flow modeling	Sudheer et al. (2008)	Chang and Chen (2001)	Ni et al. (2010)	Parasuraman and Elshorbagy (2007)	Li et al. (2010)
Rainfall–runoff modeling	Hsu et al. (1995)	Savic et al. (1999)	Gautam and Holz (2001)	Cheng et al. (2002)	Elshorbagy et al. (2010)
Sediment modeling	Sarangi et al. (2005)	Aytek and Kisi (2008)	Altunkaynak (2009)	Rajaee et al. (2009)	Misra et al. (2009)
Groundwater modeling	Bhattacharjya and Datta (2009)	He et al. (2008)	Fallah-Mehdipour et al. (2013)	Bhattacharjya and Datta (2009)	Yoon et al. (2011)
Water quality modeling	Singh et al. (2009)	Pai et al. (2009)	Eslamian and Lavaei (2009)	Dhar and Datta (2009)	Singh et al. (2011)

sub-signals at different temporal scales (levels) is helpful in better interpreting hydrological processes (Adamowski, 2008a,b; Adamowski et al., 2009; Kisi, 2010; Mirbagheri et al., 2010; Nason and Sachs, 1999; Sang, 2012).

Depending on wavelet and AI methods' individual capacities, it can be inferred that a hybrid model comprised of both would simultaneously have the advantages of both techniques. The combined wavelet–AI approach is a useful methodology, grounded on both wavelet transform and various AI modeling techniques. It allows for the construction of tractable joint models with such broad applications in hydrology as de-noising, optimization, remediation of active Artificial NN (ANN) functions, as well as hydrological process forecasting. In the latter case, wavelet–AI models have been explored by hydrologists, as the combination allows for a detailed elucidation of signals, making the hybrid method an effective tool for predicting hydrological phenomena. In forecasting tasks, the hybrid wavelet–AI method follows a two-step procedure (Fig. 1):

(i) Use of the wavelet transform to pre-process input data. This includes providing a time–frequency representation of a signal at different periods in the time domain, as well as considerable information about the physical structure of the data.
(ii) Extraction of features from the main signal to serve as AI inputs, and allowing the full model to process the data.

The selection of an efficient mother wavelet and decomposition level are two important issues in the first step. Appropriate selection of the mother wavelet constitutes the most important decision associated with the first step; both in the case of discrete and continuous wavelet transforms (DWT and CWT, respectively). CWT and DWT construct a time–frequency representation in the form of a continuous or discrete signal, respectively. Detailed analyses regarding the performance of different mother wavelets in hydrological simulations have led to the conclusion that to determine the ideal mother wavelet for a given problem a variety of mother wavelets should be tested through a trial and error process (Maheswaran and Khosa, 2012a; Nalley et al., 2012; Nourani et al., 2011; Sang, 2012). Nevertheless, similarity in shape between the mother wavelet and the raw time-series is often the best guideline in choosing a reliable mother wavelet. Generally, mother wavelets with a compact support form (*e.g.*, Daubechies-1, Haar; and Daubechies-4, db4) are the most effective in generating time localization characteristics for time series which have a short memory and short duration transient features. In contrast, mother wavelets with a wide support form (*e.g.*, Daubechies-2, db2) yield reliable forecasts for time series with long term features (Maheswaran and Khosa, 2012a).

Since DWT starts with a discrete set of data and considers a dyadic set of scales, it is compatible with the discrete observation of hydrological signals. In order to study the signal, discretisation comes first, and as a result decomposition levels follow. Although appropriate selection of the maximum scale is also important in CWT, it plays an essential role in DWT due to the decomposition procedure and extraction of dominant sub-series which can not be depicted as easily as with the CWT. Therefore, along with mother wavelet type selection, determination of the appropriate decomposition level (scale) is another important sub-step within the first step when DWT is applied (Fig. 1.). In early studies, the optimum decomposition level was usually determined through a trial-and-error process, but afterwards a formula which relates the minimum level of decomposition, L, to the number of data points within the time series N_s, was introduced in the literature (Aussem et al., 1998; Nourani et al., 2009b; Wang and Ding, 2003):

$$L = int[\log N_s] \tag{1}$$

Later, Nourani et al. (2011) criticized the outcome of this formula, stating that, having been derived for fully autoregressive (AR) signals, it only considers time series length, without paying

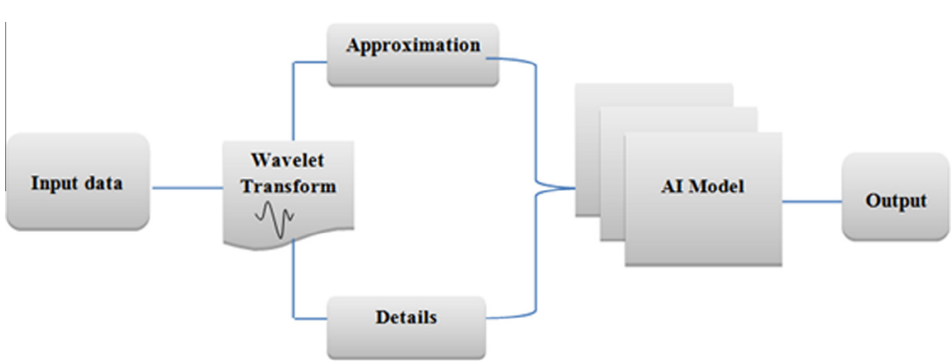

Fig. 1. Schematic diagram of hybrid wavelet–AI forecasting model.

any attention to seasonal effects. Since many seasonal characteristics may be embedded in hydrological signals, a precise insight into the process under study and attention to the periodicity of the process might be helpful in the selection of an appropriate decomposition level for dyadic DWT analysis. Decomposition level l contains l details and as an example in the case of daily modeling denotes 2^n-day mode where $n = 1, 2, \ldots, l$ (*e.g.*, 2^1-day mode, 2^2-day mode, 2^3-day mode which is nearly weekly mode, 2^4-day mode, 2^5-day mode which is nearly monthly mode, *etc.*), therefore, the seasonal and scale dependency of the process can be handled by the model.Depending on the wavelet type, the decomposition level and the type of AI method applied, several approaches can be examined according to the aim in developing the hybrid wavelet–AI model. In this context, AI methods can be seen to fall into three basic categories: optimization, logic, classification and statistical learning; based on the utilization of AI over one of these three fields, different purposes for the hybrid wavelet–AI model can be inferred. Generally, the collective application of optimization methods and wavelet analysis leads to recognition of optimal inputs for AI models (Kuo et al., 2010a,b; Wang et al., 2011a). Feature extraction and classification of dominant inputs to be used in forecasting (Hsu and Li, 2010; Nourani et al., 2013, 2014) along with seasonality detection (Nourani and Parhizkar, 2013; Nourani et al., 2009a,b, 2011, 2012) as well as noise reduction/removal from the hydrologic time series (Campisi et al., 2012; Guo et al., 2011) are important elements contributing to better forecasting for future planning through hybrid wavelet–AI models.

Given the rapidly evolving field of wavelet-AI approaches in hydrology, it is important to survey what has been done with wavelet–AI models and current research trends. Several review papers (see Table 2) concerning particular sub-sets of AI models used in hydrology or specifically on hydrological modeling have explored this topic (Abrahart et al., 2012; ASCE, 2000; Dawson and Wilby, 2001; Kalteh et al., 2008; Maier and Dandy, 2000; Maier et al., 2010; Solomatine and Ostfeld, 2008). While general reviews of wavelet applications in hydrology (Kumar and Foufoula-Georgiou, 1997; Labat, 2005; Schaefli et al., 2007; Sang, 2013a) have surveyed wavelet analysis methods (see Table 2), no reviews have centered on the specific use of wavelet–AI models. Maier et al. (2010), in their review paper on methods used in developing NNs for the prediction of water resource variables in river systems, suggested that

> "...*work should continue on the development and evaluation of hybrid model architectures that attempt to draw on the strengths of alternative modeling approaches. Given the amount of work that has already been done in this area, a review of this emerging field of research would seem timely.*"

The lack of review papers evaluating the simultaneous application of AI models and wavelets in hydrology led to the collective preparation of the current review paper, which is an updated assessment of coupled AI and wavelet applications in various fields of hydrology. The advances in hydrological modeling and simulation achieved through wavelet–AI models have largely outstripped conventional models in terms of performance, and led to an increase in associated research and resulting publication numbers since 2003 (Fig. 2). While such publications remained low from 2003 until 2007, there was a 10-fold increase over the next two years, which represents a turning point in wavelet–AI research. Articles up to 2007 played an innovator role, with the paper of Labat et al. in 2004 representing the pioneering work of wavelet applications to hydrology (with 152 citations in Scopus) and Labat's review on the wavelet concept (with 114 citations) providing further incentive to research the application of wavelet–AI systems in hydrological modeling (Labat, 2005). In 2006, Partal and Küçük (with 44 citations) demonstrated the merits of wavelet trend analysis in determining possible trends in annual total precipitation series, while the work of Cannas et al. (with 38 citations) further developed the hybrid wavelet–AI model. Since 2007, there has been an increase in the number of papers dealing with wavelet-AI modeling of hydrological processes, as can be seen from Fig. 2.

The principal objectives of the current review paper are to comprehensively categorize wavelet–AI models and enumerate their novel applications in hydrology along with their benefits. In turn, this assessment will provide some ideas on future areas of research in the field. This review focuses on their extensive use in hydroclimatology, and further restricts itself to the main hydrologic parameters of interest, *i.e.*, (i) precipitation, (ii) stream-flow, runoff, (iii) rainfall–runoff, (iv) sediment, (v) groundwater, (vi) miscellaneous: drought, snowmelt, evapotranspiration, water quality, wave height, *etc.* These selected parameters of review were drawn from a review of NN hydrological modeling undertaken by the ASCE Task Committee (ASCE, 2000). The present sources consulted were drawn from the Scopus abstract and citation database (www.scopus.com). Conference proceedings are not included in

Table 2
Review papers concerning particular sub-sets of AI models and the wavelet transform used in hydrology.

Review subject	Authors (year)	Paper/book title
Reviews on hydrological applications of AI	ASCE Task Committee on Application of Artificial Neural Networks in Hydrology (2000)	Artificial neural networks in hydrology ii: hydrologic applications
	Maier and Dandy (2000)	Neural networks for the prediction and forecasting of water resources variables: a review of modeling issues and applications
	Govindaraju and Rao (2000)	Artificial neural networks in hydrology
	Dawson and Wilby (2001)	Hydrological modeling using artificial neural networks
	Solomatine (2005)	Data-driven modeling and computational intelligence methods in hydrology
	Cherkassky et al. (2006)	Computational intelligence in earth sciences and environmental applications
	Kalteh et al. (2008)	Review of self-organizing map (SOM) in water resources: analysis, modeling, and application
	Solomatine and Ostfeld (2008)	Data-driven modeling: some past experiences and new approaches
	Maier et al. (2010)	Methods used for the development of neural networks for the prediction of water resource variables in river systems: Current status and future directions
	Abrahart et al. (2012)	Two decades of anarchy? Emerging themes and outstanding challenges for neural network river forecasting
Reviews on hydrological applications of wavelets	Kumar and Foufoula-Georgiou (1997)	Wavelet analysis for geophysical applications
	Labat (2005)	Recent advances in wavelet analyses: Part 1. A review of concepts
	Schaefli et al. (2007)	What drives high flow events in the Swiss Alps? Recent developments in wavelet spectral analysis and their application to hydrology
	Sang (2013a)	A review on the applications of wavelet transform in hydrology time series analysis

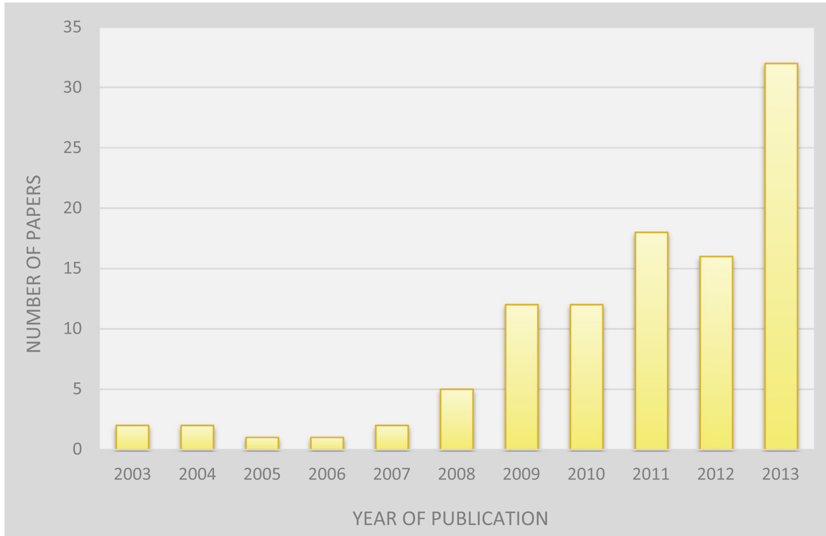

Fig. 2. Number of published papers regarding wavelet–AI applications in hydro-climatology (indexed in Scopus) with respect to year of publication.

this review. Details of the selected papers, including year of publication, authors, AI methods used and variables predicted are given in Table 3. This is followed by sections on the basic concepts of the wavelet transform (Section 2), and the applications of hybrid models in various fields of hydrology (Section 3). A summary and suggestions for future avenues of research are presented in the last sections of the paper.

2. Wavelet transform

The wavelet transform has increased in usage and popularity in recent years since its inception in the early 1980s, yet it is still not as widely used as the Fourier transform. However, Fourier analysis has a significant drawback: a signal's Fourier transform into the frequency domain results in the loss of time information, such that it becomes impossible to tell when a particular event took place. In contrast, wavelet analysis allows for the use of long time intervals when more precise low-frequency information is needed, and shorter regions when high-frequency information is of interest.

In the field of earth sciences, Grossmann and Morlet (1984), who worked especially on geophysical seismic signals, introduced the wavelet transform. A comprehensive literature survey of wavelet use in the geosciences can be found in Foufoula-Georgiou and Kumar (1995) and most recent contributions are cited by Labat (2005). As there are many good books and articles introducing the wavelet transform, this paper will not delve into the theory behind wavelets and only present the main concepts of the transform; recommended literature for more information on the wavelet transform includes Mallat (1998) or Labat et al. (2000).

The time-scale wavelet transform of a continuous time signal, $x(t)$, is defined as (Mallat, 1998):

$$T(a,b) = \frac{1}{\sqrt{a}} \int_{-\infty}^{+\infty} g^*\left(\frac{t-b}{a}\right) x(t) \cdot dt \tag{2}$$

where a is a dilation factor, b is the temporal translation of the function $g(t)$, which allows for the study of the signal around b, $*$ corresponds to the complex conjugate and $g(t)$ is the wavelet function or mother wavelet.

The main property of the wavelet transform, which is derived from the compact support of its basic function, is to provide a time-scale localization of processes. This is in contrast to the classical trigonometric functions of Fourier analysis. The wavelet transform searches for correlations between the signal and wavelet function. This calculation is done at different scales of a and locally around the time of b. The result is a wavelet coefficient ($T(a,b)$) contour map known as a scalogram. In order to be classified as a wavelet, a function must have finite energy, and it must satisfy the following "admissibility conditions" (Mallat, 1998):

$$\int_{-\infty}^{+\infty} g(t)dt = 0, \quad C_g = \int_{-\infty}^{+\infty} \frac{|\hat{g}(w)|^2}{|w|} dw < \infty \tag{3}$$

where $\hat{g}(w)$ is Fourier transform of $g(t)$; *i.e.*, the wavelet must have no zero frequency component.

In order to obtain a reconstruction formula for the studied signal, it is necessary to add "regularity conditions" to the previous conditions (Mallat, 1998):

$$\int_{-\infty}^{+\infty} t^k g(t)dt = 0 \quad \text{where } k = 1, 2, \ldots, n-1 \tag{4}$$

So the original signal may be reconstructed using the inverse wavelet transform as (Mallat, 1998):

$$x(t) = \frac{1}{C_g} \int_{-\infty}^{+\infty} \int_0^{\infty} \frac{1}{\sqrt{a}} g\left(\frac{t-b}{a}\right) T(a,b) \frac{da \cdot db}{a^2} \tag{5}$$

For practical applications, the hydrologist does not have at their disposal a continuous-time signal process but rather a discrete-time signal. A discretization of Eq. (2) based on the trapezoidal rule may be the simplest discretization of the continuous wavelet transform, producing N^2 coefficients from a data set of length N. Redundant information is therefore locked up within the coefficients, which may or may not be a desirable property (Addison et al., 2001).

To overcome this redundancy, a logarithmically uniform spacing can be used for the a scale discretization with a correspondingly coarser resolution of the b locations, which allows for N transform coefficients to completely describe a signal of length N. Such a discrete wavelet has the form (Mallat, 1998):

$$g_{m,n}(t) = \frac{1}{\sqrt{a_0^m}} g\left(\frac{t - nb_0 a_0^m}{a_0^m}\right) \tag{6}$$

where a_0 is the specified fine dilation, where $a_0 > 1$, with a_0 usually equal to 2, b_0 is the location parameter, where $b_0 > 0$, with b_0 usually equal to 1, and m and n are integers that control the wavelet dilation and translation respectively.

Table 3
Details of the surveyed papers, including year of publication, authors, where hybrid wavelet–AI methods were used to predict hydrological variables.

Paper No.	Author (year)	Type of AI technique	Wavelet transform type	Variables	Time scale
9	Mwale and Gan (2005)	ANN, GA	CWT	Precipitation	Monthly
	Mwale et al. (2007)	ANN, GA	CWT	Precipitation	Monthly
	Partal and Kisi (2007)	ANFIS	DWT	Precipitation	Daily
	Nourani et al. (2009a)	ANN	DWT	Precipitation	Monthly
	Partal and Cigizoglu (2009)	ANN	DWT	Precipitation	Daily
	Kuo et al. (2010a)	ANN, GA	CWT	Precipitation	Seasonal
	Kisi and Shiri (2011)	GEP, NF	DWT	Precipitation	Daily
	Kisi and Cimen (2012)	SVM	DWT	Precipitation	Daily
	Ramana et al. (2013)	ANN	DWT	Precipitation	Monthly
35	Cannas et al. (2006)	ANN	DWT,CWT	Runoff	Monthly
	Kisi (2008)	ANN	DWT	Stream-flow	Monthly
	Wang et al. (2009)	ANN	DWT	Runoff	Daily, annually
	Wu et al. (2009)	ANN	DWT	Runoff	Daily
	Adamowski (2008a)	ANN	CWT	Stream-flow, meteorological data	Daily
	Zhou et al. (2008)	ANN	DWT	Discharge	Monthly
	Kisi (2009a)	ANN	DWT	Stream-flow	Daily
	Partal (2009a)	ANN	DWT	Stream-flow	Monthly
	Mwale and Gan (2010)	ANN, GA	CWT	Runoff	Monthly
	Adamowski and Sun (2010)	ANN	DWT	Stream-flow	Daily
	Kuo et al. (2010b)	ANN,GA	CWT	Stream-flow, rainfall, air temperature	Seasonal, daily
	Pramanik et al. (2010)	ANN	DWT	Stream-flow	Daily
	Tiwari and Chatterjee (2010)	ANN- Bootstrap	DWT	River water level	Hourly
	Shiri and Kisi (2010)	ANFIS	DWT	Stream-flow	Daily, monthly, yearly
	Wang et al. (2011a,b)	Statistical method	DWT	Streamflow	Daily
	Kisi (2011a)	ANN	DWT	Stream-flow	Monthly
	Kisi and Partal (2011)	NF	DWT	Stream-flow	Monthly
	Guo et al. (2011)	SVM	DWT	Stream-flow	Monthly
	Kisi and Cimen (2011)	SVM	DWT	Stream-flow	Monthly
	Tiwari and Chatterjee (2011)	ANN-Bootstrap	DWT	Discharge	Daily
	Krishna et al. (2011)	ANN	DWT	Stream-flow	Daily
	Tiwari et al. (2012)	ANN, SOM	DWT	Discharge	Daily
	Kalteh (2013)	SVR, ANN	DWT	Stream-flow	Monthly
	Wei et al. (2012)	ANN	DWT	River discharge	Monthly
	Ren et al. (2011)	ANFIS	DWT, CWT	Runoff	Monthly
	Adamowski and Prokoph (2013)	ANN	CWT	Stream-flow	Daily
	Maheswaran and Khosa (2013a)	ANN	DWT, WVC	Stream-flow	Daily
	Maheswaran and Khosa (2012b)	ANN	DWT, WVC	Stream-flow	Monthly
	Krishna (2013)	ANN	DWT	Inflow	Daily
	Badrzadeh et al. (2013)	ANN, ANFIS	DWT	River flow	Daily
	Danandeh Mehr et al. (2013a)	ANN, GP	DWT	Stream-flow	Monthly
	Danandeh Mehr et al. (2013b)	ANN	DWT	Stream-flow	Monthly
	Sahay and Srivastava (2013)	ANN, GA	DWT	Flood	Daily
	Sang (2013b)	WMF	DWT	Rainfall, runoff	Monthly, daily
	Maheswaran et al. (2013)	ANN	DWT, WVC	Stream-flow	Daily, weekly, monthly
12	Anctil and Tape (2004)	ANN	CWT	Stream-flow, rainfall, evapotranspiration	Daily
	Remesan et al. (2009)	ANN	DWT	Rainfall, runoff	Daily
	Nourani et al. (2009b)	ANN	DWT	Rainfall, runoff	Daily
	Nourani et al. (2011)	ANN, ANFIS	DWT	Rainfall, runoff	Daily, monthly
	Wang et al. (2011a,b)	ANN, GA	DWT	Rainfall, stream-flow	Hourly
	Adamowski et al. (2011)	ANN-MARS	DWT	Morphological data, rainfall, runoff	Daily
	Nourani et al. (2012)	ANN, GP	DWT	Rainfall, runoff	Daily, monthly
	Adamowski and Prasher (2012)	SVR, ANN	DWT	Rainfall, runoff	Daily
	Nayak et al. (2013)	ANN	DWT	Rainfall, discharge, evaporation	Daily
	Nourani et al. (2013)	ANN, SOM	DWT	Rainfall, runoff	Daily
	Kamruzzaman et al. (2013)	AR	DWT	Rainfall, stream	
	Nourani and Parhizkar (2013)	ANN, SOM	DWT,CWT	Rainfall, runoff	Daily, monthly
10	Partal and Cigizoglu (2008)	ANN	DWT	SSL	Daily
	Mirbagheri et al. (2010)	ANN, NF	DWT	SSL, discharge	Daily
	Kisi (2010)	ANN	DWT	SSL	Daily
	Rajaee (2010)	NF	DWT	SSL	Daily
	Rajaee et al. (2010)	NF	DWT	SSL	Daily
	Rajaee et al. (2009)	ANN,NF	DWT	SSL	Daily
	Rajaee et al. (2011)	ANN	DWT	SSL	Daily
	Shiri and Kisi (2012)	ANN, GEP, NF	DWT	SSL, discharge	Daily

(continued on next page)

Table 3 (*continued*)

Paper No.	Author (year)	Type of AI technique	Wavelet transform type	Variables	Time scale
	Liu et al. (2013a,b)	ANN	DWT	SSC	Daily
	Nourani et al. (2014)	ANN	DWT	Stream-flow, SSL	Daily
5	Adamowski and Chan (2011)	ANN	DWT	GWL	Monthly
	Maheswaran and Khosa (2013b)	ANN	WVC	GWL	Monthly
	Kisi and Shiri (2012)	ANFIS	DWT	GWL	Daily
	Moosavi et al. (2013a)	ANN, ANFIS	DWT	GWL	Monthly
	Moosavi et al. (2013b)	ANN, ANFIS	DWT	GWL	Monthly
32	Kim and Valdes (2003)	ANN	DWT	Drought	Monthly
	Belayneh and Adamowski (2013)	AN	DWT	SPI, drought	Monthly
	Belayneh et al. (2014)	ANN, SVR	DWT	SPI, drought	Monthly
	Shirmohammadi et al. (2013)	ANN, ANFIS	DWT	Drought	Monthly
	Wang and Ding (2003)	ANN	DWT	Shallow GWL, discharge	Daily, monthly
	Lauzon et al. (2004)	SOM	CWT	Soil moisture-precipitation-flow	Daily
	Deng et al. (2011)	SVM	DWT	Soil water content, precipitation, temperature, evaporation	Daily
	Adamowski (2008b)	ANN	CWT	Snowmelt river flood	Daily
	Noori et al. (2009)	ANN, ANFIS	CWT	Waste Generation	Weekly
	Partal (2009b)	ANN	DWT	Evapotranspiration	Daily
	Shankar et al. (2011)	Fuzzy	DWT	Land cover	–
	Abghari et al. (2012)	ANN	Active function	Evapotranspiration	Daily
	Adamowski et al. (2012)	ANN	DWT	Urban water demand, precipitation, temperature	Daily
	Kisi (2009b)	ANN	DWT	Lake level	Monthly
	Campisi et al. (2012)	ANN	DWT	Urban water demand	Monthly
	Tiwari and Adamowski (2013)	Bootstrap-ANN	DWT	Urban water demand	Daily, monthly
	Ozger (2010)	ANN, ANFIS	CWT	Wave height	Hourly
	Kisi (2011b)	ANN	DWT	River-stage	Daily
	Deka and Prahlada (2012)	ANN	DWT	Wave height	Hourly
	Shekarrizfard et al. (2012)	ANN	DWT	Meteorological data	Daily
	Siwek and Osowski (2012)	ANN, SVM	DWT	Meteorological data	Daily
	Najah et al. (2012)	ANFIS	DWT	Water quality parameters	Monthly
	Karran et al. (2013)	ANN,SVR	DWT	Climate regimes	Daily
	Yu et al. (2013)	NF	DWT	Hydro-meteorological data	Daily
	Nalley et al. (2013)	Trend test	DWT	Air temperature	Monthly, seasonally, annually
	Pingale et al. (2013)	Trend test	DWT	Temperature, rainfall	Monthly, seasonally, annually
	Eynard et al. (2011)	ANN	DWT	Temperature and thermal power consumption	Monthly
	Liu et al. (2013a)	GA, PSO	DWT	Wind speed	Sampling
	Liu et al. (2013b)	ANN	DWT, Packet	Wind speed	Sampling
	Liu et al. (2014)	SVM	DWT	Wind speed	Sampling
	Evrendilek (2012)	ANN	DWT	Heat fluxes, evapotranspiration	Sampling
	Wang et al. (2013)	ANN, ARIMA	DWT	Water quality properties	Monthly

This power of two logarithmic scaling of the translation and dilation is known as the dyadic grid arrangement. The dyadic wavelet can be written in more compact notation as (Mallat, 1998):

$$g_{m,n}(t) = 2^{-m/2} g(2^{-m}t - n) \tag{7}$$

Discrete dyadic wavelets of this form are commonly chosen to be orthonormal; *i.e.*, (Mallat, 1998):

$$\int_{-\infty}^{+\infty} g_{m,n}(t) g_{m',n'}(t) dt = \delta_{m,m'} \delta_{n,n'} \tag{8}$$

where δ is the Kronecker delta.

This allows for the complete regeneration of the original signal as an expansion of a linear combination of translates and dilates of orthonormal wavelets.

For a discrete time series, x_i, the dyadic wavelet transform becomes (Mallat, 1998):

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

where $T_{m,n}$ is the wavelet coefficient for the discrete wavelet of scale $a = 2^m$ and location $b = 2^m n$. Eq. (9) considers a finite time series, x_i, where $i = 0, 1, 2, \ldots, N - 1$; and N is an integer power of 2, *i.e.*, $N = 2^M$. This gives the ranges 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 when $m = M$) only one wavelet is required to cover the time interval, and only one coefficient is produced. At the next scale (2^{m-1}), two wavelets cover the time interval, hence two coefficients are produced, and so on down to $m = 1$. At this point, the a scale is 2^1, *i.e.*, 2^{M-1} or $N/2$ coefficients are required 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 $1 + 2 + 4 + 8 + \cdots + 2^{M-1} = N - 1$.

In addition to this, a signal smoothed component,$\overline{T}$, remains, which is termed the signal mean. Thus, a time series of length N is broken into N components, *i.e.*, with zero redundancy. The inverse discrete transform is given by (Mallat, 1998):

$$x_i = \overline{T} + \sum_{m=1}^{M} \sum_{n=0}^{2^{M-m}-1} T_{m,n} 2^{-m/2} g(2^{-m}i - n) \tag{10}$$

or in a simpler format as (Mallat, 1998):

$$x_i = \overline{T}(t) + \sum_{m=1}^{M} W_m(t) \tag{11}$$

where $\overline{T}(t)$ is the approximation sub-signal at level M, representing the background information of data, and $W_m(t)$ are wavelet coefficients which provide the detail sub-signals at levels $m = 1, 2, \ldots, M$ and can capture small features of interpretational value in the data.

Because of the simplicity of $W_1(t)$, $W_2(t)$, $\ldots$, $W_M(t)$, $\overline{T}(t)$, some interesting characteristics, such as period, hidden period, dependence and jump can be diagnosed easily through wavelet components.

3. Hydro-climatologic applications of wavelet–AI models

This review is a complement to recent surveys such as Maier et al. (2010) and Abrahart et al. (2012) who mainly focused on either technical or historical reviews of the use of ANNs in the prediction of water resource variables in river systems and river forecasting, respectively. The current review deals with various hydro-climatologic processes. Moreover, it goes through applications of not only the ANN technique but also other data-driven AI techniques (*e.g.*, SOM, Fuzzy logic, GA, GP, SVM, *etc.*) coupled with wavelet transform. Approximately 105 papers on the subject of wavelet–AI for several hydro-climatologic issues were investigated. Table 3 compares the type of utilized AI techniques, wavelet types, applied hydrological variables and time scales of the reviewed papers.

3.1. Topic 1: Wavelet–AI approach for precipitation modeling

Precipitation is needed to replenish water to the earth and is important because it helps maintain the atmospheric balance. The amount and duration of precipitation events affect both water level and water quality. Precipitation can also be damaging; for example, too much rain can cause severe flooding. Therefore, an accurate estimate of precipitation is essential in water resources management, particularly with respect to flood mitigation. However, the wide spatiotemporal variation in rainfall makes its prediction particularly challenging. Numerous numerical, physical and data-driven-based models have been developed to provide an accurate estimation model for precipitation. Mwale and Gan (2005) used wavelet spectra information to identify and analyze the variety in space, time and frequency of dominant oscillations in the rainfall of East Africa, along with the relationships existing between September–November rainfall in that region and Sea Surface Temperature (SST) of the Indian and South Atlantic Oceans. Their wavelet-based analysis discerned homogeneous zones of rainfall variability over various parts of the Oceans. In order to accurately predict rainfall with a 2-month lead time, linear (*i.e.*, canonical correlation analysis) and non-linear (*i.e.*, ANN–GA) statistical tele-connection models were applied. A non-linear ANN–GA model was the most accurate in predicting rainfall over most of East Africa, whereas a model based on linear canonical correlation analysis performed poorly over the same region. Mwale et al. (2007) then expanded their models two years later using wavelet empirical orthogonal functions of space–time-Frequency regimes for examining the predictability of southern Africa summer rainfall.

Partal and Kisi (2007) proposed a wavelet–NF method to predict precipitation values. As choosing appropriate model inputs is one of the most critical steps in building an accurate forecasting model, DWT was used to present the original precipitation signal under different resolution intervals, such that daily, monthly, and annual sub-series' characteristics could be more clearly delineated than in the original signal. Subsequently, the correlation coefficients between sub-series and the original precipitation series provided information for the selection of the NF model inputs and for the determination of the effective wavelet components to use in predicting precipitation values at a daily scale. Their wavelet–NF model provided a good fit with the observed data, especially for time series which had zero precipitation in the summer months as well as for the peaks within the testing period. This result was interesting since classical NF models have usually faced difficulties in forecasting extreme values of observed precipitation series. Nourani et al. (2009a) linked wavelet analysis to a non-linear inter-extrapolator ANN for monthly precipitation prediction. A wavelet transform, capable of capturing signals' multi-scale features, served to decompose the precipitation time series into sub-signals. Using an ANN model with a non-linear kernel to reconstruct the signal better simulated the non-linear behavior of the phenomenon than did other linear models such as seasonal ARIMA. This was largely because the dominant seasonalities extracted via wavelet analysis were assigned greater weights. Furthermore, in investigating the effect of wavelet transform type and optimum decomposition level on model performance, they confirmed the model's accuracy in forecasting short- (one month ahead) and long-term precipitation events. A similar methodology was also followed by Ramana et al. (2013) to model monthly rainfall values using both rainfall and temperature data as inputs for a WANN model.

Partal and Cigizoglu (2009) predicted daily precipitation via a wavelet–NN method, which provided a good fit with observed data. Kisi and Shiri (2011) used the advantage of several AI-based methods in order to model daily precipitation. They compared the abilities of single GEP, NF models, with the linked form of GEP and NF with wavelet analysis. The results of daily precipitation forecasts via single GEP and NF were weak, and the use of wavelet coefficients did not satisfactorily improve the forecasting results, although the accuracies increased to a great extent. Finally, they obtained good precipitation forecasting results by merging the best single and hybrid models' inputs and introducing them as the model inputs. Among the outcomes of later models, the hybrid wavelet–GEP model had superior performance in forecasting daily precipitation than the wavelet–NF model which was unable to learn the non-linear nature of the process.

Kuo et al. (2010a) investigated the seasonal predictability of rainfall via the wavelet–AI approach. Wavelet analysis was employed on seasonal rainfall and Pacific Ocean SST data, and the results revealed strong 2–4-year cycles in rainfall data as well as high wavelet coherence between the selected SST and seasonal rainfall. They went on to use an ANN-GA model to predict seasonal precipitation with a one-season lead time, using the GA to calibrate ANN parameters. As a result, model parameters and coefficients for the different layers were optimized by minimizing an objective function that, in turn, maximized the correlation between simulated and observed seasonal rainfall values. Their study demonstrated a strong relationship between seasonal Pacific SST anomalies and seasonal rainfall at the study site, and this link was effectively captured by an ANN–GA model.

Kisi and Cimen (2012) used a joint wavelet–SVM model for the prediction of daily precipitation and found that the hybrid method could increase the forecasting accuracy of one-day-ahead precipitation better than single SVM and ANN models.

An assessment of the various studies on precipitation modeling revealed two issues regarding AI and wavelet transforms, respectively:

(i) Since an averaged value of the pointy measured rainfalls of the rain gauges over a watershed is usually assigned to the whole of the watershed, the data and subsequently the model used for forecasting and simulation of the rainfall process usually contain uncertainties. In such uncertain situations, Fuzzy-based models may be employed in the estimation of uncertainties in real world problems.

(ii) It can be deduced that although the data pre-processing process by the wavelet transform can improve the precipitation modeling performance at different time scales, this improvement is greater for large scales such as monthly or seasonal data compared to hourly, daily or weekly. Such an outcome is reasonable because the seasonality pattern in large time scales are more highlighted compared to the small time scales. In other words, the Auto Regressive (AR) or Markovian property of precipitation is more significant in small time scales such as the daily scale in which the process does not present a strong Markov chain, whereas the seasonality feature is the dominant factor in large time scales such as monthly or seasonal. In such cases precipitation forecasting at a daily scale might not result in useful outcomes. On the other hand, precipitation time series analysis via wavelets is not only considered a temporal pre-processing technique, but it also reveals effective information about the precipitation background of a specific area. Accordingly, the scalogram of CWT specifies the dominant daily, monthly, seasonal and yearly periods, as well as the failure or increase in the precipitation. In this way, droughts and floods can be distinguished clearly. Thus, in using the hybrid wavelet–AI models for rainfall prediction, more refined time steps can be recognized and used to drive certain hydrologic models in order to predict droughts and floods according to the declining and rising trends of rainfall values. Such information should benefit the water resources management of any watershed.

3.2. Topic 2: Wavelet–AI models for flow forecasting

Simulations and predictions of stream-flow is one of the most active research areas in surface water hydrology. Given its potential consequences (e.g., flooding, erosion), stream-flow is the generated component of the rainfall–runoff process and needs precise prediction; therefore, short- and long-term forecasting models are extremely important for the sustainable management of water resources. Given the influence of such varied phenomena as precipitation, evaporation, and temperature in stream-flow generation, the relevant observed time series tend to be non-linear, temporally variable and indeterminate. The underlying mechanisms of stream-flow generation are likely to be quite different during low, medium, and high flow periods, especially when extreme events occur. It is therefore very difficult to forecast stream-flow (Guo et al., 2011). In several studies the efficiency and accuracy of stream-flow models using a wavelet–AI approach has been compared to those of single AI or conventional regression-based models. Typically, such models first decompose a time series into multiple levels of detail, and then implement a multi-resolution analysis which can effectively diagnose the signal's main frequency components, as well as abstract local information from the time series. Subsequently, the appropriate sub-series are utilized in the AI model.

Cannas et al. (2006) investigated the effects of wavelet-based data pre-processing on NNs' ability to predict the hydrologic behavior of runoff. Employing DWT and CWT to account for non-stationarity and seasonal irregularity of runoff time series, they showed that networks trained with pre-processed data performed better in predicting monthly runoff than did networks trained with non-decomposed, noisy raw signals.

Adamowski (2008a) developed short-term river flood forecasting models based on wavelet and cross-wavelet components and evaluated their accuracy, compared with ANN models and simple perseverance models, in forecasting daily stream-flows with lead times of 1, 3, and 7 days. The wavelet based models showed great accuracy as a stand-alone forecasting method for 1- and 3-day lead times river flood forecasting, provided no significant trends in the amplitude occurred for the same Julian day year-to-year, and a relatively stable phase shift existed between the flow and meteorological time series. However, such river flood forecasting models, based on wavelet and cross-wavelet constituent components, were not accurate for longer lead time forecasting (*e.g.*, 7 days).

In order to forecast monthly stream-flows, Kisi (2008) used a neuro-wavelet model. Comparing these results with those of a Multi-Layer Perceptron (MLP), a MLR and AR models, he found the neuro-wavelet model outperformed the MLP, MLR and AR models.

In a further study, Wang et al. (2009) applied the multi-resolution characteristic of wavelet analysis and the non-linear capability of ANN to predict inflow of Three Gorges Dam in Yangtze River, China. Using both a wavelet network model and a type of threshold AR model to predict short- and long-term runoffs, they found the wavelet network model to be more accurate, leading them to suggest that future research should focus on functional and feasible wavelet network models.

In another study, Wu et al. (2009) explored the efficiency of various methods in improving the ANN performance in daily flow prediction. The objective of their research was to determine whether data pre-processing techniques such as Moving Average (MA), Singular Spectrum Analysis (SSA), and Wavelet Multi-Resolution Analysis (WMRA), coupled with ANN, might improve the estimation accuracy of daily flows. These data pre-processing techniques were used to improve and highlight the mapping relationship between inputs and output of the ANN model by smoothing raw flow data. The hybrid models showed noticeable improved performance over the ANN model and considering the performance and complexity of the linkage of ANN to the data pre-processing methods, MA, SSA and WMRA yielded better efficiency, respectively.

Zhou et al. (2008) used a wavelet predictor–corrector model to decompose a time series into an approximation series and several stationary detailed sub-series. Each sub-series was then predicted individually using an ARMA model, and a correction procedure was implemented for the sum of the prediction results. Finally, simulating monthly discharge with ARMA, seasonal ARIMA, and an ANN model, they found the wavelet predictor–corrector model to have the greatest prediction accuracy. In addition, the decomposition scale showed no obvious effect on the prediction for the monthly discharge time series.

Kisi (2009a), comparing the ability of a joint wavelet–ANN model to an ANN alone in predicting 1-day-ahead intermittent stream-flow, tested the models by applying different input combinations of decomposed time series. He ultimately showed that the wavelet–ANN provided significantly better forecasting accuracy than the ANN alone, particularly for high flow estimates.

Partal (2009a) evaluated the efficiency of several ANNs (*i.e.*, feed forward back propagation, generalized regression NN, radial based function-based NN) combined with a wavelet transform to predict river flow in future months. Periodic components obtained via wavelet decomposition were fed to the NNs to improve river flow forecasting. The combination of hybrid wavelet and the feed forward back propagation model outperformed all other models examined in the study.

Adamowski and Sun (2010) coupled DWT and ANN for flow forecasting in non-perennial rivers in semi-arid watersheds. The decomposition process of original flow time series into sub-series was iterated, with successive approximation signals being decomposed in turn, so that the original flow time series were broken down into many lower resolution components. The sub-series used in the ANN model led to efficient forecasting outcomes. WANN models were found to provide more accurate flow forecasts than the regular ANN models, since wavelet transforms provided useful decompositions of the original time series, and the wavelet-transformed data improved the ability of the ANN forecasting model by capturing useful information on various resolution levels.

Using a wavelet-based ANN–GA model, Kuo et al. (2010b) predicted stream-flow with a one season (3-month) lead time-based on SST. Wavelet analysis was first applied to select sectors of SST that were related to the rainfall data of the study sites at a seasonal time scale, and then the selected SST was used as predictors in the ANN–GA model to predict seasonal rainfall at a one-season lead time. The GA portion of the model served to calibrate the parameters of the ANN with a feed forward structure and three layers. This resulted in an efficient stream-flow prediction methodology.

Pramanik et al. (2010) concluded that advance time step stream-flow forecasting was of critical importance in controlling flood damage, while applying a hybrid wavelet–AI model to stream-flow forecasting. They proposed models which used DWT functions to pre-process the flow time series into wavelet coefficients of different frequency bands, leading to the creations of WANN models with 1-, 2- and 3-day lead times to forecast flow. The hybrid models were trained using the Levenberg–Marquardt algorithm and results were compared with simple ANN models. Confirming previous studies' results, the WANN models provided better prediction of peaks in stream-flow than individual ANN models.

In order to develop an accurate and reliable ANN model for hourly flood forecasting, the potential of wavelet and bootstrapping techniques linked to ANN (WBANN) was explored by Tiwari and Chatterjee (2010). To capture useful information, the time series was decomposed into different components and then appropriate sub-series were added up to develop new time series. Finally a bootstrap-based ANN model was constructed. Overall, the WBANN model was found to be accurate and reliable in simulating peak water levels, and outperformed the ANN, WANN and BANN models, indicating that while wavelet decomposition improved the performance of ANN models, the bootstrap re-sampling technique produced more consistent and stable solutions.

To study short- and long-term stream-flow forecasting, Shiri and Kisi (2010) used recorded stream-flow values to compare the performance of a combined wavelet–NF model, which took into account the periodicity of the data, to an unenhanced NF model. The comparison of results showed that adding the periodicity component into the input layer generally increased modeling accuracy; such the wavelet–NF model can be considered as an appropriate model to simulate daily, monthly and especially yearly streamflows.

Synthetic generation of daily streamflow sequences via the wavelet transform was explored by Wang et al. (2011b). The method firstly decomposes the daily streamflow sequences with different frequency components into the series of wavelet coefficients $W_1(t)$, $W_2(t)$, ..., $W_P(t)$ and scale coefficients (the residual) $CP(t)$ at a specific resolution of P. Secondly, the series of $W_1(t)$, $W_2(t)$, ..., $W_P(t)$ and $CP(t)$ are divided into a number of sub-series based on a yearly period. Thirdly, random sampling is performed from sub-series of $W_1(t)$, $W_2(t)$, ..., $W_P(t)$ and $CP(t)$, respectively. Finally, based on these sampled sub-series, a large number of synthetic daily streamflow sequences are obtained using the wavelet reconstruction algorithm. Regarding the advantages of the developed method, Wang et al. (2011b) indicated that: (1) the approach is nonparametric; (2) it is able to avoid assumptions of probability distribution types (Normal or Pearson Type III) and of dependence structure (linear or non-linear); (3) it is not sensitive to the original data length and suitable for any hydrological sequences; and (4) the generated sequences by the method could capture the dependence structure and statistical properties presented in the data.

The ability of a combined model, Wavelet–Generalized Regression NN (WGRNN), was investigated by Kisi (2011a) for prediction of one-month-ahead stream-flow. The WGRNN, by combining DWT and GRNN, performed better than the GRNN and feed forward NN models for forecasting monthly stream-flow. Since several features of the original signal, such as its daily, monthly and annual periods, could be discerned more clearly than in the original signal, therefore, estimates were more accurate than those obtained directly by the original signals. Through a similar study, Kisi and Partal (2011) developed a forecasting model for monthly stream-flow via NF coupled to DWT. Comparison results indicated that the wavelet–NF model was superior to the classical NF method, especially in detecting the peak values of stream-flow.

Guo et al. (2011) used an SVM model improved by the addition of an adaptive insensitive factor to improve the performance of the SVM in predicting monthly stream-flow. Considering the presence of noise in the runoff time series and its potential negative influence on model performance, a wavelet de-noising method was applied to reduce or eliminate the noise. Furthermore, given the PSO algorithm's strong searching ability, an improved PSO was applied to optimize the parameters of the forecasting model. The improved SVM model combined with wavelet analysis was able to process a complex hydrological data series (*e.g.*, monthly stream-flow) better than ANN and conventional SVM models.

In a similar study, Kisi and Cimen (2011) investigated the accuracy of a combined wavelet and SVM model in forecasting monthly stream-flow. They implemented their study in 5 steps: (i) wavelet de-noising, (ii) determination of best delay time and embedding dimension, (iii) phase-space reconstruction, (iv) model fitting, (v) stream-flow forecasting with different models. With an ANN model serving as the basis of comparison for conventional and improved SVM models, they found that coupling with a DWT significantly increased the accuracy of the Support Vector Regression (SVR) model in forecasting monthly stream-flow.

With the goal of forecasting daily discharge, Tiwari and Chatterjee (2011) explored a WBANN model, comparing its performance to that of a traditional ANN, WANN and bootstrap-based ANN. The WBANN and WANN models produced significantly better results than the traditional ANN and bootstrap-based ANN models, particularly in terms of peak discharge forecasting. Similarly, Krishna et al. (2011) employed a hybrid WANN model to forecast daily river flow, achieving good forecasting accuracy, especially with respect to peak points.

Ren et al. (2011) used the advantage of localized characteristics of wavelet transform and approximation function of an Adaptive Neuro-Fuzzy Inference System (ANFIS) in order to establish a combined wavelet–ANFIS (WANFIS) model for monthly runoff prediction. Issues arising from the large amplitude of intra- and inter-annual variation in monthly runoff were avoided through the use of a wavelet analysis-based resolving and reconstruction technique allowing the decomposition of signals with different frequencies. Based on a comparison of measured and simulated values this modeling approach produced acceptable predictions.

Tiwari et al. (2012) investigated AI-based (*i.e.*, NN and SOM) and wavelet-based daily river discharge forecasting models. SOM was used to homogeneously classify the data sets, while the NN models served for prediction. The NN models were supplemented by a wavelet approach, which served to enhance forecasting performance with respect to long datasets. The SOM's effectiveness in clustering data into different groups and the superiority in forecasting river flow of WBANN models over simple NN models were noted.

In a recent study, Kalteh (2013) forecasted monthly river flow by using the capabilities of AI-based (*i.e.*, SVR and ANN) models coupled with the wavelet transform. Coupled with a wavelet transform process, ANN and SVR models provided more accurate forecasts than non-coupled ANN or SVR models. The performance of the hybrid wavelet–SVR model exhibited greater reliability than the WANN model.

In order to accurately simulate and predict the dynamic behavior of river discharge over a wide range of time intervals, Wei et al. (2012) proposed a hybrid WANN method capable of reliably capturing the high-frequency characteristics of river discharge on a monthly time scale. As a basis for comparison, the WANN model was used to predict river discharge 48 months in advance. The WANN model decomposed by db5 mother wavelet at level 4 resulted in the most accurate river discharge predictions.

To forecast daily inflow with lead times of 1–5 days, Maheswaran and Khosa (2013a) established a multi-scale non-linear model based on coupling a DWT and a second-order Volterra (WVC) model, and compared its performance to that of conventional ANN and WANN models, as well as other baseline models. The WVC performed well in short-term flow forecasting, especially when compared with the WANN model. This may be attributed to the ability of the former approach to provide a better scale-specific description of the original time series. It is noted that Maheswaran and Khosa (2012b) extended the 1-month ahead streamflow forecasting method using the wavelet based multi-scale non-linear model linked to the second order non-linear Volterra kernel estimated by Kalman filter formulation. The proposed model was compared with wavelet based linear regression models and other non-linear approaches such as WANN based models, and was found to provide the best performance.

Adamowski and Prokoph (2013) used the multi-scale resolution features of CWT analysis and cross wavelet analysis to determine the amplitude and timing of stream-flow discontinuities for specific wavebands. The cross wavelet-based method was able to detect the strength and timing of abrupt shifts to new stream-flow levels, gaps in data records longer than the waveband of interest, as well as a sinusoidal discontinuity curve following an underlying modeled annual signal at ±0.5 year uncertainty. Parameter testing of the time–frequency resolution demonstrated that high temporal resolution using narrow analysis windows was favorable to high-frequency resolution for detection of waveband-related discontinuities. Discontinuity analysis on observed daily stream-flow records showed that there was at least one discontinuity-year related to the annual spring flood in each record studied, and that neighboring stream-flows had similar discontinuity patterns.

Badrzadeh et al. (2013) investigated WANN and WANFIS models provided originally by Nourani et al. (2011), for river flow forecasting. Outcomes indicated that the hybrid WANN model produced better results, especially for the peak values and longer lead-times.

Krishna (2013) explored the capability of two pre-processing techniques of wavelets and MA in combination with ANN and MLR models for prediction of daily inflow values. The study demonstrated the superiority of the wavelet pre-processing technique and owing to the model performance, the wavelet–MLR was considered better than the WANN model.

Danandeh Mehr et al. (2013a) applied WANN and linear GP techniques to forecast monthly streamflow values. In contrast to the results of the majority of previous research studies, in this study, WANN model performed poorly in comparison to linear GP. An explicit linear GP model constructed by only basic arithmetic functions including one month-lagged records of both target and upstream stations resulted in the best prediction model for the study catchment. In another similar study, Danandeh Mehr et al. (2013b) explored the prediction of monthly streamflow at successive stations using the WANN model.

The comprehensive study of Sang (2013b) led to an improved Wavelet Modeling Framework in conjunction with AI-based black box models for precipitation and discharge time series forecasting. He developed a method for DWT decomposition of time series termed the Wavelet Modeling Framework (WMF). In this light, Sang firstly separated different deterministic components and removed noise involved in the original time series using DWT to obtain deterministic forecasting results; then, he forecasted the former and quantitatively described noise's random characteristics to estimate uncertainty and then summed them up to attain the final forecasting result. He applied the WMF to four hydrologic cases and found that wavelet-based AI models perform more effectively than single AI models.

Sahay and Srivastava (2013) developed a wavelet–GA–NN model for forecasting 1-day-ahead monsoon river flows which are difficult to model due to the irregularly spaced spiky large events and sustained flows of varying duration. In this regard, GA was used for optimizing the initial parameters of an ANN training scheme. The results indicated that wavelet–GA–NN model could outperform the AR and GA-optimized ANN models, which used original streamflow time series as inputs.

Although the majority of wavelet–AI-based models in streamflow forecasting used a particular set of wavelet decomposition sub-series as the 'optimal' wavelet transform to be used for forecasting purposes, relying on a specific wavelet sub-series often leads to predictions that capture some phenomena at the expenses of others. However, different sub-series play different roles in capturing the different characteristics of a particular hydrological process. Therefore, ensemble approaches based on the use of multiple different wavelets, in conjunction with a multi-model setup, could potentially improve the modeling performance and also allow for uncertainty estimation. This was a novel idea in the wavelet–AI field developed by Maheswaran et al. (2013) which involved proposing a new multi-wavelet based ensemble method for the wavelet Volterra coupled model. The ensemble-based multi-wavelet Volterra approach was applied for forecasting streamflow at different scales (daily, weekly and monthly) and the outcomes revealed the superiority of the new approach in comparison to non-ensemble wavelet Volterra models.

An assessment of the various papers that have been reviewed in this sub-section reveals the following:

(i) Single AI-based models with short-term memory can usually handle the AR property of the process; thus, in modeling, each value of a series can only be related to the prior values, and subsequently, the peak and maximum values of flow which are important in water resources management and particularly in flood mitigation are underestimated. Combining wavelet and AI methods can help handle long term seasonality and reveal proper outcomes for peak flows. It is noted that classic models such as seasonal ARIMA can also handle the long term seasonality, but the advantage of wavelet–AI models is the simultaneous consideration of several short- and long-term seasonalities in the modeling process, which may lead to better estimation of peak points.

(ii) Hydrologic time series in general, and flow time series in particular, consist of measurement and/or dynamical noise. In this regard, the wavelet transform is capable of de-noising the time series to improve the AI-based modeling performance, in addition to extracting dynamic and multi-scale features of the non-stationary time series.

(iii) According to Table 3, among the reviewed papers, the DWT has been applied more than CWT for flow forecasting. This can be related to the nature of flow which is less stochastic, so, the Markovian property of flow time series is more perceptible in comparison to rainfall. In this way, application of DWT at specific levels which refer to daily, weekly, monthly, and yearly seasonalities appears to be more useful than application of CWT which exhibits much more redundant seasonalities.

(iv) One of the important concerns in flow forecasting is the selection of a proper lead time. At a daily time scale it is considered that longer lead times (*e.g.*, 7 days) for flow forecasting using wavelet-AI approaches could not lead to accurate forecasting results, while 1-, 2- or 3-day ahead forecasting was usually more effective.

3.3. Topic 3: Wavelet–AI models for rainfall–runoff modeling

For any watershed, accurate rainfall–runoff modeling is a key issue in water resource planning, as it provides vital information for flood mitigation, the design of hydraulic structures, and overall watershed management. The highly complex, dynamic and nonlinear nature of the process on both spatial and temporal scales has led to the scientific investigation of hybrid models.

In a preliminary study, Anctil and Tape (2004) explored the use of an ANN rainfall–runoff model combined with wavelet decomposition in an effort to forecast next-day stream-flow, based on stream-flow, rainfall, and potential evapotranspiration time series. Three wavelet decomposed components (*i.e.*, short, intermediate, and long wavelet periods) were used to depict the rainfall–runoff process. An ANN was then trained for each wavelet sub-series. Short wavelet periods were found to be ultimately responsible for most of the WANN hybrid forecasting error. The slight advantage in performance of the WANN over non wavelet-assisted models might be attributed to a better usage of the evapotranspiration time series.

Later, Remesan et al. (2009) described a new hybrid model based on the Gamma Test, ANN and DWT, evaluated for daily rainfall–runoff modeling. They identified input combinations composed of antecedent rainfall and runoff values using Gamma Test analysis. The proposed hybrid model outperformed other popular AI models (*i.e.*, local LR, NNAR with exogenous input and ANFIS models), as well as basic benchmark models (*i.e.*, a naive model in which the predicted runoff value is equal to the latest measured value) and a trend model (in which the predicted runoff value is based on a linear extrapolation of the two previous runoff values). They observed significant modeling improvement by purposely decomposing input signals into different frequency bands to be modeled separately, although it has been known for decades that hydrological catchments can act as low-pass filters in converting high frequency rainfall signals into low frequency river flows. The wider implication of their study in the field of hydrological modeling was that its general framework could be applied to other model combinations in which the model engine could consist of other AI techniques, such as SVM, NF systems, or even a conceptual model.

Mwale and Gan (2010) integrated wavelet empirical orthogonal function analysis, GA driven ANN, statistical disaggregation and hydrologic modeling into a hydrologic framework to a model weekly rainfall–runoff process. They found that the statistical properties of the hydro-climatic process in their case study are approximately stationary, and so statistically generated rainfall values may be used to predict the basin runoff with considerable skill.

In developing a WANN model to simulate flooding on an arid flood plain, Wang et al. (2011a) implemented a GA in order to gain the ability to achieve a global optimum and avoid a local optimum. This hybrid GA-WANN model showed a strong capacity for rainfall–runoff mapping and computational efficiency as well as being suitable for flood simulation in arid areas.

Nourani et al. (2009b) coupled wavelets and ANN to model the rainfall–runoff process. Given the extraction via wavelets of the time series' multi-scale characteristics, the model was capable of predicting both short and long term runoffs. In a further study, Nourani et al. (2011) investigated the rainfall–runoff process using two hybrid wavelet–AI models (*i.e.*, WANN and WANFIS) and found that considering seasonality effects extracted through wavelet decomposition, the hybrid WANFIS model outperformed individual AI-based models. They attributed this to the strength of wavelet analysis in extracting dominant frequencies, and fuzzy analysis in handling the uncertainties involved in the relevant phenomena.

Given the complexity of rainfall–runoff relationships in mountainous watersheds and the lack of hydrological data in such watersheds, process-based models have a limited applicability for runoff forecasting. In light of this, Adamowski et al. (2011) proposed a methodology where extensive data sets were not required for runoff forecasting in mountainous watersheds; Multivariate Adaptive Regression Spline (MARS), WANN, and regular ANN models were developed and compared for runoff forecasting applications in a mountainous watershed with limited data. The best WANN and MARS models were found to be comparable in terms of forecasting accuracy, both providing very accurate runoff forecasts compared to the best ANN model, particularly in the case of short-term runoff. Adamowski and Prasher (2012) employed SVR and WANN for daily runoff forecasting in a mountainous region supported by antecedent precipitation index, rainfall, and day of the year data. Both methods provided accurate results, with the best WANN model slightly outperforming the best SVR model in terms of accuracy, leading them to suggest that to further assess the suitability in forecasting runoff these methods should be tested in other mountainous watersheds where only limited data are available.

Nourani et al. (2012) investigated the linkage of wavelet analysis to GP in constructing a hybrid model to detect seasonality patterns in rainfall–runoff. The hybrid model was useful in forecasting runoff. Nourani et al. (2013) went on to confirm the superiority of a SOM–ANN model coupled with wavelet transform in rainfall–runoff modeling using satellite data. A two-level SOM clustering technique served to identify spatially homogeneous clusters of satellite precipitation data, and the most operative and effective data were selected for the ANN to model the rainfall–runoff process on daily and multi-step scales. Besides removing noise, the wavelet transform served to extract dynamic and multi-scale features from the non-stationary runoff time series. Spatiotemporal pre-processing of ANN model inputs led to a promising improvement in the performance of rainfall–runoff forecasting compared to ANN and simple WANN models. The forecasting outcomes indicated that the ANN forecasting model coupled with the SOM clustering method decreased the dimensionality of the input variables and consequently the complexity of the ANN model. On the other hand, by removing noise and revealing the dominant periods, wavelet transformation of runoff data increased the forecasting performance of the model, particularly with respect to peak runoff values. Using a wavelet transform to capture multi-scale features of the rainfall–runoff process, a SOM to classify the extracted features and select the dominant ones and an ANN to predict runoff discharge, Nourani and Parhizkar (2013) applied the resultant wavelet–SOM–ANN model for modeling the rainfall–runoff process. The two-stage procedure (*i.e.*, data pre-processing and model building stages) was implemented in the rainfall–runoff forecasting model. Since one of the essential steps in any ANN-based model is determination of dominant input variables, independent rainfall and runoff sub-series obtained via wavelet analysis were evaluated and classified with SOM, a strong non-linear classifier. The newly developed model led to better predictions, especially for peak points.

Nayak et al. (2013) demonstrated the potential use of WANN for daily river flow forecasting by developing a rainfall–runoff model and compared the WANN with the single ANN and the NAM (*i.e.*, NAM describes the behavior of each individual component in the hydrological cycle, at catchment level, using a group of interconnected conceptual elements) models. The WANN model performed better compared to the ANN and NAM model which includes physical elements such as moisture content in estimating the hydrograph characteristics such as the flow duration curve.

Kamruzzaman et al. (2013) considered a novel aspect, which exploits the relationship between stream flow on day t and a DWT of the rainfall from day t back as far as day $t–k$. Then, a multi-scale transform is also included in the modeling framework as a moving DWT. Although the authors indicated that their aim was to find relatively few wavelet coefficients based on rainfall back as far as day $t–k$ that could be used as linear predictors for stream flow on day t, the application of the moving method to the decomposed wavelet time series appears not to be a good approach, since each value of the wavelet coefficient time series denotes a specific period of the process.

The review of papers in this sub-section showed that:

(i) The majority of researchers applied a daily time scale in order to model the rainfall–runoff process. Rainfall–runoff models are used extensively in flood studies and forecasting, and that is why it is important to investigate the rainfall–runoff process at short-term scales such as daily. Since the Markovian property of runoff is more perceptible in comparison to rainfall, the combination of runoff antecedents and rainfall data can appropriately produce rainfall–runoff patterns.

(ii) Moreover, comparison of both daily and monthly time scales for rainfall–runoff modeling in a watershed revealed that the determination coefficients for peak values were more precise at a monthly time scale compared to a daily time scale. Since at the monthly scale modeling the AR characteristic of the time series is decreased by averaging the time series data over a month, the seasonal pattern is highlighted as the main characteristic of the time series which can be captured by wavelet analysis in terms of sub-signals.

(iii) Rainfall–runoff model performances for various watersheds with similar climate and markedly distinct topography conditions are different. The properties of a flat sub-basin can be handled with simple AI models such as ANN; however, a 'wild' watershed (*i.e.*, a more steep and large watershed with elevation variety) can be more accurately modeled via ANFIS. In addition to uncertainties relevant to pointy rainfall measurement and spatiotemporal variation over the study area, wild watersheds involve more uncertain and ambiguous hydrological characteristics. Therefore, models based on the fuzzy theory concept might lead to more reliable results than other AI models. The application of wavelets which provide dominant sub-series as inputs to the model to have insight into the physics of the process, can effectively decrease the undesirable effects of topographic variety of the study area. From the point of uncertainty view, the WANFIS model seems to perform more effectively than other wavelet–AI models in modeling 'wild' watersheds.

(iv) One of the important issues in rainfall–runoff models is the accurate modeling of peak values in order to designs an appropriate flood alert and management system. The wavelet-based seasonal models are more efficient than only AR models (*i.e.*, ANN and ANFIS) in monitoring peak values. It is evident that extreme or peak values in the rainfall and runoff time series, which occur in a periodic pattern, can be detected by the seasonal models accurately. When comparing flat and 'wild' watersheds, the wild watershed shows quicker responses for a precipitation event towards a watershed with a mild slope and fairly small area, so, more instantaneous jumps may appear in the wild watershed's time series. WANFIS can model such extreme values more accurately due to being compatible with the uncertainty involved. By employing fuzzy and wavelet concepts linked to the ANN framework, the uncertainty and seasonality of the phenomena can respectively be better handled.

3.4. Topic 4: Wavelet–AI models for sediment modeling

In terms of assessing sediment impacts on design and management of water resources projects, the estimation and simulation of Suspended Sediment Load (SSL) at a watershed outlet is vital to water and environmental engineers. Unlike many chemical pollutants, sediment is a vital natural component of water bodies; however, particularly in excessive amounts, they can be of concern, either as a contaminant affecting water quality, or by interfering with the efficient performance of hydraulic structures such as dams.

Partal and Cigizoglu (2008) estimated the SSL in rivers via a hybrid WANN method. The dominant wavelet components obtained via DWT were summed up and served as an input for the ANN model. The WANN model provided a good fit to observed data, particularly in the case of peak values and cumulative sediment loads. Rajaee (2010) compared NF, wavelet–NF (WNF), MLR, and Sediment Rating Curve (SRC) models in forecasting SSL. The observed time series of river flow discharge and SSL were decomposed into sub-series via DWT, and the effective sub-series were added together and used as inputs to the NF model for daily SSL prediction. The results illustrated the efficiency of WNF model, while NF, MLR, and SRC models provided unacceptable predictions. In a similar study, Rajaee et al. (2010) explored the efficiency of WNF model for SSL forecasting in a larger study area with a lower discharge and SSL amount and achieved promising results in a 'wild' watershed. The observed time series of river discharge and SSL were decomposed by the db4 wavelet and the useful wavelet components were summed and used in the NF model. Results showed that the WNF model performance was better in prediction compared to the NF and SRC models, particularly in extreme value prediction. Moreover, the model could be employed to simulate the hysteresis phenomenon, while the SRC method was not able to handle the involved hysteresis.

Using a coupled WANN, NF model and a conventional SRC, Mirbagheri et al. (2010) forecasted SSL. Their WNF model satisfactorily predicted sediment loads underestimated by ANN, NF and SRC models alone. Besides being good at predicting load, the WNF model was successful in reproducing the hysteresis phenomenon. Hysteresis is a secondary relationship between sediment and river discharge values which can be detected in a scatter plot of discharge vs. sediment, where above a certain threshold, increasing the discharge diminishes sediment loads. The WNF model was capable of simulating this hysteresis and while its simulation yielded loads rather unlike those measured, the SRC method was unable to model this behavior, and the ANN and NF models were only somewhat able to regenerating the hysteresis effect. Overall, the WNF model, which used decomposed data to extract important characteristics embedded in the Suspended Sediment Concentration (SSC) signal, outperformed other models that employed raw data.

Applying a WANN technique for modeling the daily suspended sediment-discharge relationship, Kisi (2010) showed that the hybrid model could increase estimation accuracy. Considering WANN, MLR, and SRC models for daily SSL modeling, Rajaee et al. (2011) showed that the WANN model outperformed the other models, generated reasonable predictions for extreme sediment loads, acceptably simulated the hysteresis phenomenon, and satisfactorily estimated the cumulative SSL.

Employing GEP, NF, and ANN techniques to estimate SSL using daily river discharge and sediment load records, Shiri and Kisi (2012) showed that the GEP model outperformed the NF and ANN models. Combining these models with DWT analysis improved all model performances while the wavelet–GEP model outperformed the wavelet–NF and WANN models.

Due to the complexity of the relationship between SSC and river discharge, Liu et al. (2013c) constructed a WANN model to predict next day SSC. Observed river discharge and SSC time series were decomposed into seven sub-series via the DWT using the db4 mother wavelet. Effective sub-series were selected by cross-correlation analysis and summed to reconstruct noise-free time series to serve as ANN inputs for SSC prediction. The WANN model was better able to predict the highly non-linear and non-stationary SSC time series than ANN or SRC models. Noise removal using the WANN approach dramatically improved the fit of the predicted SSC time series to the observations. Additionally, error autocorrelation and the correlation between input and error time series in the WANN model showed it to be more robust than either the SRC or ANN models.

Nourani et al. (2014) developed an ANN-based stream-flow-sediment model by focusing on a wavelet-based global soft thresholding method to de-noise hydrological time series at the daily scale. Since the appropriate selection of the decomposition level and mother wavelet type are important in thresholding results, sensitivity analysis was performed over different levels and several Daubechies type mother wavelets (Haar, db2, db3, db4 and db5) to choose the proper variables. De-noised time series were applied to the ANN model to forecast flow discharge and sediment values. The results indicated that, the wavelet-based de-noising approach, as a pre-processing method, could improve the ANN-based stream-flow-sediment forecasting models; in addition, the wavelet de-noising was significantly dependent on the chosen mother wavelet whereas forecasting results varied with the alteration of mother wavelets.

According to the reviewed papers regarding sediment modeling, one of the important issues in sediment modeling is the hysteresis phenomenon in which the SSL depends not only on the water discharge amount and flow capability, but also on the load availability, which is complexly related to the season or month of occurrence. Thus, the application of a solely AR model such as various AI methods (*e.g.*, ANN, ANFIS) that relates discharge and SSL to their antecedents is not sufficient in the presence of factors such as hysteresis. In this regard, the application of the wavelet transform which considers the seasonality of the process in order to handle hysteresis is advantageous.

3.5. Topic 5: Wavelet–AI models for groundwater modeling

In many watersheds, groundwater is often one of the major sources of water supply for domestic, agricultural and industrial users. In many such regions, groundwater has been withdrawn at rates far in excess of recharge, leading to harmful environmental side effects such as major water-level declines, drying up of wells, reduction of water in streams and lakes, water-quality degradation, increased pumping costs, land subsidence, and decreased well yields (Adamowski and Chan, 2011). To effectively manage groundwater, the ability to predict Groundwater Level (GWL) fluctuations and quantify environmental threats (*e.g.*, contamination, salinization) and their potential to expand are key hydrological issues.

Adamowski and Chan (2011) developed a one month-ahead GWL forecasting model using a coupled DWT–ANN method. The DWT decomposed each original data series into information bearing component series, which then served as inputs to the ANN-based forecasting portion of the model. The DWT allowed most of the 'noisy' data to be removed and facilitated the extraction of quasi-periodic and periodic signals from the original time series.

Maheswaran and Khosa (2013b) compared the GWL forecasting abilities of three hybrid wavelet models; WVC, WANN, and wavelet–LR as well as ANN and dynamic AR models. Compared to the wavelet–LR and WANN models, the WVC model performed better in forecasting GWL characterized by non-linearity and non-stationarity. With an increase in lead time, the wavelet based models performed progressively better than the regular models. Overall, accurate long term GWL forecasting was best provided using the WVC model.

Investigating the ability of a joint wavelet and NF model to perform one-, two- and three-day-ahead groundwater depth forecasting, Kisi and Shiri (2012) found that the joint model outperformed the NF model, particularly for two- and three-day-ahead forecasts.

Moosavi et al. (2013a) compared several data-driven models (*i.e.*, ANN, ANFIS, WANN and WANFIS models) for forecasting GWL at a monthly scale. The comparison of results demonstrated that the WANFIS model outperformed the other models since it could handle both uncertainty and seasonality involved in the process.

The low number of papers on groundwater modeling via wavelet–AI demonstrates the need to consider groundwater and relevant issues. Meanwhile, it can be inferred that the monthly time scale or any long-term scale is the appropriate scale for modeling groundwater, since such scales coincide with the nature of the process, notwithstanding the study of Kisi and Shiri (2012) who performed daily groundwater modeling.

Through a comparative study, Moosavi et al. (2013b) investigated the optimum structures of WANN and WANFIS models for GWL forecasting. Their research revealed that transfer functions of ANN and membership function types of ANFIS besides the mother wavelet type are the most important factors in the performance of WANN and WANFIS models, respectively. Comparison of optimal WANN and WANFIS demonstrated the better performance of WANFIS.

Since groundwater is recharged by flow or any precipitation that seeps into the ground, the periodic characteristic of groundwater is relevant to rainfall and runoff processes as well as climatic parameters. Therefore, it is suggested that wavelet-AI methods be explored in order to determine the lags, correlation and interaction between climatic parameters and GWL as well as groundwater quality factors. On the other hand, because groundwater is susceptible to pollutants which may follow a periodic pattern to soak into the underground, the wavelet–AI approach can simulate and extract effective features and patterns among GWL, climatic parameters and contaminants.

3.6. Topic 6: Other hydro-climatologic applications of wavelet–AI models

Besides the detailed investigations of wavelet–AI model applications to forecast various hydrological processes, they have been also successfully applied to model other hydro-climatologic processes (*i.e.*, shallow watertable depths, drought, snowmelt, evapotranspiration, *etc.*)

Wang and Ding (2003) proposed hybrid WANN models to predict monthly mean water table depths and daily discharge. In terms of prediction accuracy, the hybrid model outperformed ARMA and threshold AR models, trained with the GA optimization technique. The results implied that when the forecasting horizon was extended the fitting and testing precision of the hybrid model outstripped that of the other models.

Kim and Valdes (2003) linked dyadic wavelet transforms and NNs to generate a WANN model capable of forecasting the Palmer drought severity index at various lead times. In order to reduce the inconsistency of the sub-signal, a wavelet transform based on the dyadic algorithm was used. They concluded that the hybrid approach enhanced the ability of NNs to forecast the indexed regional drought. Moreover, based on several accuracy statistics, the forecasting skill of the hybrid model for lead times up to 6 months was much better (4–60%) compared to the other statistical prediction methods. Following the previous study, Belayneh and Adamowski (2013) and Belayneh et al. (2014) investigated the ability of data driven models such as ARIMA, ANN, and SVR and WTs to forecast long-term (6 and 12 months lead times) drought. Belayneh et al. (2014) proposed the wavelet–SVR model in addition to WANN model to forecast long term drought. They applied Standard Precipitation Index (SPI) 12 and 24 as indicators of long-term drought conditions. The forecast results for WANN and wavelet–SVR models were improved compared to models without any wavelet based pre-processing, and the WANN model was better than the WSVR model.

This study indicated that the approximation time series component in wavelet decomposition is the most effective component in forecasting SPI time series, which adequately de-noises the data and avoids any discontinuities within the SPI time series.

Another study which modeled drought was conducted by Shirmohammadi et al. (2013). The research was carried out to evaluate the ability of WANN and ANFIS techniques for meteorological drought forecasting at one, two, and three time steps (6 months) ahead. WANFIS was found to be more accurate than the WANN model.

Given the importance and advantage of considering soil moisture information in a variety of hydrologic models, Lauzon et al. (2004) proposed the analysis of soil moisture conditions based on wavelet analysis and SOM through Kohonen NNs. Through these techniques, the influence of soil moisture on the hydrologic regime could be assessed and relevant information could be extracted for the development of a stream-flow model. Based on results inferred from wavelet analysis, soil moisture supported the annual cycle in observed flows. The links between precipitation events, the short-term behavior of soil moisture and the inflow regime could be clearly seen through wavelet analysis. A comprehensive description of the soil moisture profile, its evolution over time, and its relation to precipitation, temperature and flow observations were performed via wavelet analysis and SOM.

Since seasonal drought usually originates from low availability of soil moisture, Deng et al. (2011) predicted the dynamic changes of soil water in the field via daily soil water content simulated by least squares SVM with meteorological factors. Wavelet-based de-noising was applied to pre-process the original chaotic soil water signal and the results of the prediction showed improvement of the model in comparison to ANN and ANFIS models.

Adamowski (2008b) proposed a method of stand-alone short-term spring snowmelt river flood forecasting based on wavelet and cross-wavelet analysis. The accuracy in forecasting daily stream-flows with lead-times of 1, 2, and 6 days of the new wavelet forecasting method was compared to that of MLR analysis, ARIMA analysis, and ANN. The wavelet-based forecasting method was shown to accurately forecast river flooding for 1 and 2-day lead-times, but was not particularly accurate for longer lead-time forecasts (*e.g.*, 6 days).

Accurate prediction of solid waste generation is an important issue in the planning and design of municipal water purification systems. Noori et al. (2009) applied hybrid WANFIS and WANN models to predict the weekly waste generation from a municipal solid waste management system. Input data pre-processing via wavelet analysis clearly improved prediction accuracy. Of the two models tested, the WANFIS model, by reason of its effective handling of uncertainties involved in the process, exhibited a better performance than the WANN model.

Evapotranspiration is a complex process affected by a variety of climatologic factors. Hybrid wavelet–NN models provide an alternative way of exploring the underlying mechanisms of evapotranspiration. In consideration of this, Partal (2009b) tested the ability of a WANN model in estimating reference evapotranspiration. Applying wavelet analysis to raw data of climatic data (*i.e.*, air temperature, solar radiation, wind speed, relative humidity) as a pre-processing approach allowed the ANN model to equal or outperform a MLR and the empirical Hargreaves method in daily evapotranspiration forecasting. This confirmed that the hybrid WANN method could be successfully applied to model reference evapotranspiration based on climatic data.

In another study, the use of wavelet analysis in conjunction with AI was employed to predict daily evaporation (Abghari et al., 2012). Mexican Hat and poly WOG1 mother wavelet activation functions were used in an ANN instead of the commonly used Sigmoid function, and differences in terms of daily pan evaporation predictions were noted. In terms of the accuracy of daily pan evaporation forecasts, the WANN model outperformed any single ANN model.

Applying a hybrid WANN model to 1- and 6-month-ahead forecasting of mean monthly lake levels, Kisi (2009b) found that WANN significantly increased the short- and long-term forecast accuracy over wavelet-free models.

Campisi et al. (2012) explored the problem of forecasting urban water demand by means of a back-propagation ANN coupled with a wavelet de-noising technique. The forecasting horizon varied from 1 to 6 months and the impact of five different wavelet filter-banks on ANN outcomes was explored. ANNs coupled with Haar and db2 and db3 filter-banks outperformed non-coupled ANN, MLR and ANN models coupled with db4 and db5 filters. Overall, they found that the de-noising impact gained via wavelet-attributable reduction in training set variance could improve forecasting accuracy; however an oversimplification of the input-matrix could lead to a deterioration in the forecasting accuracy and induce network instability.

Short term (1, 3, and 5 days; 1 and 2 weeks; and 1 and 2 months) urban water demand forecasting was also explored by Tiwari and Adamowski (2013) via a WBANN model. The results demonstrated that the hybrid WBANN and WANN models produce significantly more accurate forecasting results than the traditional NN, BNN, ARIMA, and ARIMAX models. It was also found that the WBANN model reduces the uncertainty associated with the forecasts, and the performance of WBANN forecasted confidence bands were found to be more accurate and reliable than BNN forecasted confidence bands.

For coastal and ocean engineering applications, Ozger (2010) employed a combination of wavelet and fuzzy logic approaches to forecast wave heights and periods with lead times up to 48 h. A wavelet technique was used to separate time series into spectral bands, which were subsequently estimated individually through a fuzzy logic approach. The hybrid wavelet-fuzzy logic model outperformed the single fuzzy logic, ANN and ARMA models. The superiority of the wavelet-fuzzy logic model in terms of model performance was particularly notable for longer lead times (*e.g.*, 48 h).

Kisi (2011b) compared the performance of a Wavelet Regression (WR) technique with ANN models for daily river-stage forecasting. In order to create the forecasting models, two different WR models were developed using the stage sub-time series. The sum of effective decomposed details and the approximation components were used as inputs to the WR1 model, while in the WR2 model, the effective details and the approximation components were used as separate inputs. Under these circumstances, the WR models outperformed the single ANN models, and the WR2 model outperformed the WR1 model.

Adamowski et al. (2012) proposed an urban water demand forecasting method based on coupling a DWT and ANN for a lead time of one day over the summer months (May–August). The key variables used to develop and validate the models were daily total precipitation, daily maximum temperature, and daily water demand data. The WANN model was found to provide more accurate urban water demand forecasts than the MLR, MNLR, ARIMA or ANN models.

Deka and Prahlada (2012) employed a WANN model to forecast the occurrence of waves of significant height reaching the west coast of India for lead times up to 48 h. A WANN drawing on a multi-resolution time series for input data to its ANN component provided more accurate forecasts than a single ANN.

Land cover assessment as a hydro-climatologic related field has been considered in various hydrological studies. In this light, a wavelet feature based supervised scheme for fuzzy classification of land cover multispectral remote sensing images was proposed by Shankar et al. (2011). In a distinct application of wavelet transforms, the obtained wavelet features from land cover images provided important information about the spatial and spectral characteristics of image pixels and hence could be used in fuzzy based land cover classification. The classification results compared to original spectral feature based methods demonstrated the high efficiency of wavelet-based fuzzy classification of land cover.

A wavelet-based NN model was developed by Shekarrizfard et al. (2012) in order to model the relationship between PM_{10} (a major air pollutant) levels and meteorological data including several parameters, such as wind speed, wind direction, moisture, and temperature. Due to the reduction in the noise inherent in most meteorological data by means of the wavelet transform, the wavelet-enhanced ANN generated accurate predictions of PM_{10} levels, compared to a wavelet-free ANN method. They concluded that the proposed WANN model was generally an effective method for PM_{10} level prediction. In a similar parameter prediction, Siwek and Osowski (2012) used several AI methods (*i.e.*, MLP, radial basis function, Elman network and SVM) as well as a linear AR model in conjunction with DWT to forecast the daily average concentration of PM_{10}. Application of wavelets and an ensemble of many individual prediction results led to an accurate method of prediction.

Karran et al. (2013) conducted an exploration of how well wavelet–AI models perform in different climate regimes with differing hydrological characteristics and studied the performance of such models for lead times of less than one month. Their study compared the use of ANNs, SVR, WANN, and wavelet–SVR in Mediterranean, Oceanic, and Hemiboreal watersheds. The results indicated that SVR based models overall performed well, but no one model outperformed the others in more than one watershed, suggesting that some models may be more suitable for certain types of data. Overall, model performance varied greatly between climate regimes and they suggested that higher persistence and slower hydrological processes (*i.e.*, snowmelt, glacial runoff, and subsurface flow) support reliable forecasting in daily and multi-day lead times.

Water quality modeling via hybrid wavelet–AI models has not been explored in much detail in the literature. In Najah et al. (2012), monthly water quality parameters of a river were predicted utilizing an ANFIS model. Since the observational water quality data might be polluted by noise owing to systematic and random errors, the wavelet de-noising technique in conjunction with the ANFIS model was applied.

Overall, based on the reviewed studies, the application of wavelets as a pre-processing technique, usually improves modeling performance after decomposition of the main signal to seasonal sub-series at different scales via one of three scenarios:

(i) Use of all decomposed time series as inputs of the AI model.
(ii) Use of only the dominant sub-series as inputs of the AI model.
(iii) Use of the original signal as the input of the AI model, reconstructed by using only selected dominant sub-series.

Comparison of the reported results in the reviewed papers demonstrates that the application of the second scenario due to the simplicity of the structure and reduction of redundant and non-relevant data as well as accurate performance, may lead to more accurate results in hydro-climatologic applications of wavelet–AI methods.

4. Summary and conclusions

Since the emergence of AI techniques in hydro-climatology, research activity in the field of modeling, analyzing, forecasting and prediction of water quantity and quality variables has increased dramatically. Wavelet–AI applications have increased in modeling various hydrological processes such as rainfall–runoff, stream-flow, precipitation, sediment, groundwater and others. Among the processes involved in the hydrologic cycle, extensive research has been conducted on stream-flow modeling, with fewer papers focused on other processes of the hydrologic cycle, and even fewer have focused on water quality and water resources management issues.

Given, on the one hand, the capacity and robustness of AI models in coping with the non-linear and dynamic nature of hydrologic processes, and on the other hand the ability of wavelet analysis to extract the prominent periodicities and seasonalities from a time series, a greater understanding and ability to predict various hydrological processes can be achieved. The results of many of the studies explored in this review paper have revealed the relative efficiency of wavelet–AI models compared with other methods in accurately forecasting hydrological variables. These improvements in hydrological forecasting can lead to a better interpretation of phenomena and inform the development of appropriate water and environmental resource planning and management policies.

In the current review paper several papers were investigated and compared that used wavelet–AI based models with great operation or forecasting ability in order to model several hydro-climate processes. One of the more important issues was exploring which AI method can best fit the specific hydro-climate process. A lack of attention regarding this issue has led to the use of various AI methods without any consideration as to the appropriateness of the model. As an example (see Table 3), among 34 papers that modeled flow, 25 of them solely used ANN, as the appropriate AI method. The other 9 papers used GP, SVM, SVR and ANFIS. Based on the review conducted in this study, it appears that for applications with high levels of uncertainty, the ANFIS approach can provide better results. Rainfall–runoff modeling in a very large watershed with sparse sampling gauges, or sediment amount prediction in various watersheds with different beds, are examples of modeling in situations of high uncertainty where the ANFIS approach might be useful to explore.

It was also found that, wavelet-based seasonal models are more efficient than AR models (*i.e.*, ANN and ANFIS) in monitoring peak values. It is evident that extreme or peak values in the rainfall, runoff or sediment time series, which occur in periodic patterns, can be detected by the seasonal models more accurately. For short term real time forecasting or for modeling at a fine time resolution (*e.g.*, hourly, daily), an AR model or WANN model with low decomposition levels which uses current and only a few previous state values of the process as inputs is likely to be the most useful model. But for long term, seasonal forecasting or modeling in monthly or seasonal time scales, a hybrid wavelet–AI model which decomposes the time series at high levels can detect the long term memory of the process. Furthermore, the study parameter has a significant role in the selection of a reliable modeling tool. For example, for modeling a highly stochastic process (*e.g.*, event-based precipitation) probabilistic-based pre-processing (*e.g.*, bootstrapping-based simulation) could also be helpful.

Maier and Dandy (2000) identified the adoption of appropriate input determination approaches, as one of the main concerns in hydro-climatologic models. Moreover, Maier et al. (2010), in a recent review on ANN methods indicated two deficiencies of ANN-based hydrologic modeling; firstly, evaluating the relationship between input variables with the model output, secondly, investigating input independence and avoiding redundant inputs even if they help the performance of an ANN model, since they might increase model complexity and parameter uncertainty. If these two issues are addressed in other AI-based models in addition to ANN, increased attention should be devoted to reduce the uncertainty surrounding model outputs and to enable AI-based models to extract more confident knowledge from the data. In this way, wavelet-based pre-processing as well as various AI-based optimization techniques are capable of addressing the aforementioned two issues by:

(i) Wavelet transform breaks down the signal into periods involved in the process, then via an AI-based optimization technique (*e.g.*, GA) the potential sub-signals having a significant relationship with the model output can be determined. Thus, the use of a wavelet–AI approach not only tackles non-linear model input selection, but also provides pre-processing on each input signal via wavelet analysis.

(ii) Application of the wavelet transform leads to identification of various periods as sub-signals, subsequently, the selection of dominant sub-signals (as inputs to the AI models) having an insight into model scale or entity, prevents the interference of redundant information and reduces the uncertainty surrounding AI-based model output.

The future of predicting hydrological processes through wavelet–AI approaches can be anticipated if one looks at how the field evolved over the past decade. Firstly, in almost all hydrologic signals, the underlying complex non-linear seasonalities and relationships have been extracted through the implementation of the wavelet transform. Secondly, according to the task at hand (*e.g.*, forecasting, optimization, or classification), one or another AI-based technique can be applied in order to fulfill the purpose of modeling. In general, it can be concluded that recently implemented wavelet-based models have principally focused on improving the accuracy of hydrologic process modeling. Through the application of a hybrid wavelet–AI model to improve modeling performance, the classic concerns of data-driven modeling (*i.e.*, well established data division to have the requisite training and validation sub-sets, optimal network structure of the AI technique, *etc.*) should be regarded to acquire a precise hybrid model.

According to Table 3, the dominant field of application of hybrid wavelet–AI models in hydrological studies is forecasting and prediction. Stream-flow forecasting via wavelet–AI models has been the focus of several studies, whereas their use in predicting water quality parameters has attracted less attention. There is therefore a need to broaden the range of application of wavelet–AI models to focus on other predictive variables, especially those concerned with water quality. However, one factor limiting the application of wavelet–AI models in water quality modeling could be the lack of good quality, long-term data to detect the long-term seasonality signature of the process.

Among the reviewed papers, only about 20% of studies used the CWT for decomposing hydrological time series, and the majority of studies utilized the DWT. This is because real world observed hydrologic time series are measured and gathered in discrete form rather in a continuous format. So, the dyadic DWT is more suitable for decomposition of time series into trend and detail sub-signals comprising high frequencies and fast events, and also to reconstruct the original time series from sub-signals. Each resolution level in DWT represents a dyadic period based on the scale of data. Considering a set of daily data, DWT decomposition leads to 2^n-day mode resolutions (*e.g.*, 2^1 -day mode, 2^2-day mode, 2^3-day mode which is nearly weekly mode, 2^4-day mode, 2^5-day mode which is nearly monthly mode, and …, 2^6-day mode which is nearly yearly mode, *etc.*) which approximately denote the periodicity of a hydrologic process. Although 2^3 day mode and 2^5-day mode are fairly accurate for the weekly and monthly periods, 2^8-day mode represents the yearly periodicity with a 30% error. Therefore, it is unlikely that DWT can represent the yearly periodicity as well as CWT which is able to depict exact periods. On the other hand, although CWT provides a time–frequency representation of a signal at many different and exact periods in the time domain, redundant information is locked up within the coefficients, which may or may not be a desirable property. Thus, it is inferred that according to the considered hydrologic time series and its scale, the DWT or CWT should be selected and applied.

In the majority of reviewed papers, the Nash-Sutcliff evaluation criterion (Nash and Sutcliffe, 1970) was applied in addition to other efficiency criteria (*e.g.*, Mean Absolute Error; MAE, Root Mean Square Error; RMSE) to evaluate the model performance. According to Legates and McCabe (1999) a good evaluation of model performance should include at least one 'goodness-of-fit' or relative error measure (*e.g.*, Nash-Sutcliff criterion) and at least one absolute error measure (*e.g.*, RMSE or MAE), thus, a hydrological model can be sufficiently evaluated by Nash-Sutcliff and RMSE but due to the importance of peak and extreme values in hydrologic processes other criteria (*e.g.*, Ratio of Absolute Error of Peak value) may also be applied. For the design of a disaster alert system (*e.g.*, flood alert system), in addition to the measure of peak value error (error between observed and computed peak values), the occurrence time of such extreme conditions should also be regarded. In this regard, Dawson et al. (2007) developed a scope to evaluate metrics for the standardized assessment of hydrological forecasts.

In spite of the black box nature of AI methods, the use of wavelet analysis with AI methods makes it possible to provide some insight into the physics of the process in both time and space. For example, due to urbanization and land use/cover changes, a watershed's lag time and response to the inputs (*e.g.*, rainfall) may be changed and in turn, the calibrated parameters of the employed wavelet–AI model (*e.g.*, decomposition level, mother wavelet, input lags, etc.) can change. To monitor such changes, the time series of the studied process should be split into specific sub-series and by comparing the calibrated parameters of the model by sub-series, the trend in land cover/use can be detected. A similar methodology can be used to detect spatial changes of land uses by dividing the watershed into sub-basins.

5. Recommendations for future research

Based on the review of almost 105 papers regarding applications of wavelet–AI methods in hydro-climatology, the following recommendations for future research are provided:

1. Given the discrete nature of hydrologic time series, applications of the wavelet transform in hydrology mainly concentrate on the use of DWT. A broader use of CWT is suggested in order to exploit its properties over all time scales, such as with dyadic scales in DWT.
2. Considering the importance of the wavelet transform for temporal pre-processing, it is a useful tool in extracting the underlying features and de-noising time series. While such applications have been explored in hydrological modeling in recent years, it could be useful to explore the use of the wavelet transform for pre-processing of spatial data (*e.g.*, digital elevation model) employed in hydrological models.

3. The main concerns regarding wavelet-based models are the appropriate selection of the mother wavelet and decomposition level according to the hydrological process and the scale of the process. While Nourani et al. (2011, 2013) stated that similarity in shape between the mother wavelet and that of the time series under study is the best guideline in choosing the proper mother wavelet, it would be useful to investigate similarities from another point of view than form (*e.g.*, energy). Although the selection of mother wavelet and decomposition level have been studied (Nourani et al., 2011; Sang, 2012), a more thorough investigation could lead to the selection of a specific mother wavelet according to the nature of the hydrologic process investigated, and the use of an algorithm based on historical data length to select the decomposition level.
4. Due to the low number of papers in the field of groundwater and water quality modeling via wavelet–AI models, it is suggested that additional research be conducted on this topic.
5. In addition to the suggestion of Abrahart et al. (2012) to create benchmark data sets, it would be useful to develop an archive of appropriate wavelet–AI models for specific hydro-climatologic processes, with transparency in the application of different types of wavelet transforms (*i.e.*, DWT, CWT), efficient mother wavelet type and finally appropriate AI techniques for each hydro-climatologic process at a desired time scale.
6. In addition to the ability of wavelet–AI models for black box modeling of hydrological processes, they can also be linked to physically-based models (*e.g.*, TOPMODEL; Beven and Kirkby,1979) to develop integrated modular models. For this purpose, the geomorphologic characteristics of the study area at a sub-grid scale can be extracted and represented via geographic information system tools, pre-processed by wavelets, and then used in the model to estimate the spatiotemporal variability of parameters (*e.g.*, soil moisture, GWL, recharge, transmissivity). In a similar way, other AI methods such as SOM-based spatial clustering of grids into homogeneous zones can also be used.
7. It would also be useful to prepare other review papers to survey hydro-climatologic applications of different hybrid models constructed via the conjunction of AI models with other commonly used data pre/post-processing techniques.

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