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REVIEW ARTICLE - HYDROLOGY

River/stream water temperature forecasting using artificial intelligence models: a systematic review

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Abstract
Water temperature is one of the most important indicators of aquatic system, and accurate forecasting of water temperature is crucial for rivers. It is a complex process to accurately predict stream water temperature as it is impacted by a lot of factors (e.g., meteorological, hydrological, and morphological parameters). In recent years, with the development of computational capacity and artificial intelligence (AI), AI models have been gradually applied for river water temperature (RWT) forecasting. The current survey aims to provide a systematic review of the AI applications for modeling RWT. The review is to show the progression of advances in AI models. The pros and cons of the established AI models are discussed in detail. Overall, this research will provide references for hydrologists and water resources engineers and planners to better forecast RWT, which will benefit river ecosystem management.

Keywords River water temperature forecasting · Artificial intelligence models · Hybrid model · Review

Introduction

Water temperature is one of the most important indicators for river systems, which controls many physical and biogeochemical processes within the waterbody, such as the reaeration process of oxygen (Gualtieri et al. 2002), decay process of organic matter (Matsumoto et al. 2007), nitrification kinetics (Zhang et al. 2014), etc. All the aquatic species have the specific water temperature ranges for development and production, and significant variations in water temperature may bring serious consequences to the ecosystem. For example, Quinn et al. (1994) indicated that water temperatures that occur in summer in many New Zealand rivers may limit the distribution and abundance of some invertebrate species. Lessard and Hayes (2003) found that increasing temperatures downstream of the dams impacted the densities of several cold-water fish species and the community composition of macroinvertebrates. It is therefore of great significance to study the thermal regime of rivers.

Mathematical models are important tools to evaluate the thermal dynamics in rivers. In the past decades, many models were developed and applied in different regions. Generally, these models can be classified into two categories: (1) statistical/stochastic models and (2) process-based deterministic models.

For statistical/stochastic models, there are many types available, such as the simple linear regression models (Smith 1981; Crisp and Howson 1982; Stefan and Preud'homme 1993; Pilgrim et al. 1998; Erickson and Stefan 2000; Sohrabi et al. 2017; Laanya et al. 2017), logistic nonlinear models (Mohseni et al. 1998; Webb et al. 2003; Koch and Grunewald 2010; van Vliet et al. 2011; Soto 2016; Piotrowski and Napiorkowski 2019), autoregressive models (Kothandaraman 1971; Cluis 1972; Caissie et al. 1998, 2001, 2017), and hybrid models (Toffolon and Piccolroaz 2015).

The process-based deterministic models are based on the energy balance equations, and they consider the heat fluxes between the river and the surrounding environment (Sinokrot and Stefan 1993; Benyahya et al. 2007; Wright et al. 2009; Dugdale et al. 2017). These models are generally complex, and they need a lot of data as model inputs, such as river bathymetry, hydrological information, and a set

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of meteorological variables, which limit their applications, especially in areas with limited available data. This helps to boost another type of statistical model, namely the artificial intelligence (AI) models.

Recent advances in computational algorithms and computation capacity of modern computers have significantly contributed to the development and applications of various types of artificial intelligence models. These AI models require fewer input variables compared with the process-based deterministic models and may outperform the traditional statistical models (Sahoo et al. 2009; Faruk 2010; Hadzima-Nyarko et al. 2014; Piotrowski et al. 2015; Zhu et al. 2018, 2019a; Graf et al. 2019). Previously, Benyahya et al. (2007) briefly reviewed the statistical water temperature models for rivers; Dugdale et al. (2017) conducted a review of process-based deterministic approaches and future directions for river temperature modeling. However, a comprehensive review of the available studies on developing and applying AI models for river water temperature forecasting has never been conducted.

This study aims to fill this research gap by conducting a review of the available studies on river water temperature forecasting using AI models. This review introduces how effectively the applied AI models have accomplished proper predictive river water temperature models, particularly in relation to the external or internal structure of the AI models, input variables, and the efficiency of AI integrated modeling.

Artificial intelligence models

We use the scientific databases, Web of Science and Google Scholar, and set the keywords/terms as "stream/river water temperature, modeling/forecasting, artificial intelligence" in the period of 2000–2020. After screening, we get 36 studies (see Table 1). These AI models can be divided into the following groups: (1) artificial neural networks, (2) adaptive neuro-fuzzy inference system, (3) Gaussian process regression, (4) Wavelet Transform (WT)-Artificial Intelligence integrated model, and (5) other AI models.

Artificial neural networks

During the last two decades, artificial neural networks (ANNs) (Haykin 1999) become a classical modeling tool for regression problems in hydrology. ANN architecture often consists of a number of nodes structured in consecutive layers that perform various mathematical computational tasks. In recent years, to solve complex environmental problems, various variants of "shallow" neural networks were used. These networks are relatively simple, with easily understandable features. However, with the development of AI, deep learning networks (LeCun et al. 2015; Goodfellow 2016) become increasingly popular in almost every field of science, and this trend is slowly impacting hydrological researches as well (Shen 2018; Shen et al. 2018; Sun et al. 2019; Hu et al. 2019; Lee et al. 2020; Bui et al. 2020; Zhu et al. 2020a; Lu and Ma 2020). Nonetheless, so far there is limited application of deep learning networks in stream temperature modeling, what may be easily justified by the limited number of available stream temperature data and huge number of parameters that need calibration in deep learning models (Lu and Ma 2020). Although we hope for future implementations of deep learning networks into river water temperature modeling, while in hydrology, the most widely used ANN type is still the so-called multilayer perceptron neural network (MLPNN) with three layers, which may be easily considered as a classical "shallow" neural network. In Table 1, we show that although "shallow" ANNs have been widely used for stream temperature modeling, with a few exceptions that introduce radial basis function networks (RBFNs) (Bromhead and Lowe 1988) or product-units neural networks (PUNNs) (Durbin and Rumelhart 1989) to the topic, majority of studies considered only MLPNN variants.

The MLPNN architecture often consists of three layers: input, hidden, and output ones. The input data are fed to the input layer and computation of weighted sum is performed; then, the data are processed in the hidden layer, which can be converted to multiple layers depending on the complexity of the problem; and lastly, the result is produced in the output layer.

Majority of MLPNN applications (see Table 1) concerned classical stream temperature modeling for the particular river based on exogenous variables such as air temperature or flow discharge. However, ANNs were also used for predicting specific dates at which particular stream temperatures are expected. For example, Daigle et al. (2009) used MLPNN to evaluate the date of the beginning of the seasonal cycle of stream temperature in different streams located in Canada and Northern USA and showed that they perform favorably against simple regression models (Daigle et al. 2010). Faruk (2010) coupled MLPNN with ARIMA models for autoregressive modeling of stream temperature. Tao et al. (2008) applied MLPNN for both autoregressive stream temperature modeling with exogenous inputs and for modeling the specific dates at which ice cover appears and melts on particular rivers.

Among large number of studies devoted to assessing the impact of projected climatic changes on stream temperatures (Webb et al. 2008; Watts et al. 2015; Arora et al. 2016; Knouft and Ficklin 2017; Soto 2018; Du et al. 2019), many are based on MLPNN models (Jeong et al. 2013; Liu et al. 2018b). MLPNN is attractive for this task, as it requires information only on a few variables that may be obtained or evaluated from climate models. In this respect, it is somehow in-between physically based models that require too much

Table 1 Applications of artificial intelligence (AI) models for river water temperature forecasting

Model type	Input variables	Time scale	Reference
Artificial neural network (ANN)			
MLPNN	Air temperature, dew-point temperature, solar radiation, wind speed, discharge, cloud cover	Daily	Foreman et al. (2001)
MLPNN	Air temperature, rainfall, pH, dissolved oxygen	Monthly	Sivri et al. (2007)
MLPNN	Air temperature	Daily	Chenard and Caissie (2008)
MLPNN	Air temperature, discharge, past river temperature	Daily	Tao et al. (2008)
RBFNN, MLPNN	Air temperature, short wave radiation	Daily	Sahoo et al. (2009)
MLPNN	Air temperature, sea temperature, past stream temperature	Monthly	Sivri et al. (2009)
MLPNN	Air temperature, barometric pressure, wind speed, wind direction, solar radiation reflected from the river, humidity, autoregressive water temperature, water temperature spilled from the artificial dam	10-min	Hong (2012)
MLPNN	Air temperature, precipitation	Daily	Jeong et al. (2013)
MLPNN	Air temperature, landform attributes, riparian forest and network forest land cover, local catchment agriculture	Daily	DeWeber and Wagner (2014)
MLPNN	Air temperature	Daily	Hadzima-Nyarko et al. (2014)
MLPNN	Air temperature, water level	Hourly	Hebert et al. (2014)
MLPNN	Air temperature, solar radiation, wind speed, discharge, cloud cover, precipitation, barometric pressure	Daily	Cole et al (2014)
MLPNN	Air temperature	Daily	Rabi et al. (2015)
MLPNN, PUNN	Air temperature, flow discharge, declination of the Sun	Daily	Piotrowski et al. (2014, 2015, 2016)
MLPNN	Air temperature, precipitation	Hourly	Jeong et al. (2016)
MLPNN	Air temperature, wind speed, relative humidity	Monthly	Temizyurek and Dadaser-Celik (2018)
MLPNN	Air temperature	Daily	Zhu et al. (2018)
MLPNN	Air temperature, discharge, relative humidity, wind speed, sunshine duration	Daily	Liu et al. (2018a)
MLPNN	Various water quality indicators	Monthly	Voza and Vukovic (2018)
MLPNN	Air temperature, flow discharge, the components of the Gregorian calendar (day of the year)	Daily	Zhu et al. (2019b, c)
FFNN	Air temperature, flow discharge, day of the year	Daily	Zhu et al. (2019d)
RBFNN	Air temperature, flow discharge, day of the year	Daily	Zhu and Heddam (2019)
MLPNN	Air temperature, flow discharge, declination of the Sun	Daily	Piotrowski et al. (2020)
BPNN, RBFNN, WNN, GRNN, ELMNN	Air temperature, flow discharge, day of the year	Daily	Qiu et al. (2020)
Adaptive neuro-fuzzy inference system (ANFIS)			
DNFIS	Air temperature, barometric pressure, wind speed, wind direction, solar radiation reflected from the river, humidity, autoregressive water temperature, water temperature spilled from the artificial dam	10-min	Hong and Bhamidimarri (2012)

Table 1 (continued)

Model type	Input variables	Time scale	Reference
ANFIS	Air temperature, flow discharge, declination of the Sun	Daily	Piotrowski et al. (2015)
ANFIS	Air temperature, flow discharge, the components of the Gregorian calendar	Daily	Zhu et al. (2019b)
Gaussian process regression (GPR)			
GPR	Air temperature, flow discharge	Daily	Grbic et al. (2013)
GPR	Air temperature	Daily	Zhu et al. (2018)
GPR	Air temperature, flow discharge, day of the year	Daily	Zhu et al. (2019d)
Wavelet Transform (WT)-Artificial Intelligence integrated model			
WT-MLPNN	Air temperature, flow discharge, declination of the Sun	Daily	Piotrowski et al. (2015)
WT-MLPNN, WT-ANFIS	Air temperature, day of the year	Daily	Zhu et al. (2019e)
WT-MLPNN	Air temperature	Daily	Graf et al. (2019)
Other AI models			
DT	Air temperature, flow discharge, day of the year	Daily	Zhu et al. (2018, 2019d)
SVM	Air temperature, flow discharge	Daily	Rehana (2019)
ELM	Air temperature, flow discharge, day of the year	Daily	Zhu et al. (2019a), Zhu and Heddam (2019)
DT, RF, SVM, RBFNN, LSTM	Water temperature	Hourly	Lu and Ma (2020)

Multilayer perceptron neural network (MLPNN), radial basis function neural network (RBFNN), product-unit artificial neural network (PUNN), feedforward neural network (FFNN), back-propagation neural network (BPNN), wavelet neural network (WNN), general regression neural network (GNN), Elman neural network (ELMNN), decision trees (DT), extreme learning machine (ELM), random forests (RF), support vector machine (SVM), and long short-term memory (LSTM)

information unavailable for the future, and simple regression models that are based solely on air temperature which is highly doubtful (Arismendi et al. 2014). Moreover, MLPNN may relatively easily be coupled with more-physical ones, e.g., Stewart et al. (2014) presented a hybrid approach that coupled Soil-Water-Balance Model with MLPNN in order to evaluate stream temperatures in various locations across the State of Wisconsin (USA) in future climatic conditions based on geographical features.

Adaptive neuro-fuzzy inference systems

Fuzzy logic models have been useful tools in solving difficult computational problems (Zadeh 1988; Zhai and Williams 2012; Petrović et al. 2014). Among the fuzzy logic models, the most popularly applied one is the adaptive neuro-fuzzy inference system (ANFIS) model (Jang 1993; Kurnaz et al. 2010; Bui et al. 2012). ANFIS is a multilayer feedforward network, which utilizes a neural network learning algorithm and is able to identify nonlinear boundaries. It has the ability to achieve a highly nonlinear mapping and nonlinear time series. The stages of ANFIS consist of choosing the type of interfering systems such as Mamdani, Sugeno, and Tsumoto, as well as aggregation, and defuzzification procedures.

The applications of the ANIFS models for river water temperature forecasting are also summarized in Table 1. For example, the dynamic version of neuro-fuzzy inference systems (DNFIS) has been developed for stream temperature forecasting at specific river reach located under the artificial dam which spills waters of modified temperatures into the river (Hong and Bhamidimarri 2012). As seen, compared with the ANN models, applications of the ANIFS models in the area of river water temperature forecasting are quite limited, even though the ANFIS models have been widely used in other scientific fields (Kurnaz et al. 2010; Mohandes et al. 2011; Bui et al. 2012; Razavi Termeh et al. 2018).

Gaussian process regression

Gaussian process regression (GPR) is a Bayesian learning algorithm. It has been widely used in hydrological studies, such as streamflow forecasting (Sun et al. 2014), reference evapotranspiration estimation (Holman et al. 2014), or precipitation simulation (Kleiber et al. 2012). It is based on the assumption that the joint probability distribution of model outputs is Gaussian. It combines various machine learning tasks, including model training, uncertainty estimation, and hyperparameter estimation, which is its major advantage over the other machine learning methods. However, currently, GPR model has been applied in river water temperature forecasting several times, as summarized in Table 1.

Wavelet-artificial intelligence integrated model

Wavelet transform is a preprocessing method capable of doing wavelet decomposition, wavelet de-noising, wavelet aided complexity description, and wavelet aided forecasting (Sang 2013). It can help to overcome the limitation of various AI models to handle nonstationary data. Due to this, a lot of researches employ the hybrid wavelet-artificial intelligence integrated models for hydrological studies (Nourani et al. 2009, 2014; Guimarães Santos and da Silva 2014; Quilty and Adamowski 2018; Poul et al. 2019).

There are two common forms of wavelet analysis: (1) One is discrete wavelet analysis which deals with discrete signals and decomposes the time series into sub-signals at a specific wavelet and decomposition level. (2) The other one is continuous wavelet transform which deals with continuous signals and is applied for disclosing time series features under multi-temporal scales. The applications of the hybrid wavelet-AI model for river water temperature forecasting are also summarized in Table 1. As seen, compared with its applications in other hydrological time series forecasting (Nourani et al. 2014), applications of this modern method in river water temperature modeling are relatively limited.

Other artificial intelligence models

Applications of the other AI models for river water temperature forecasting are also summarized in Table 1. Unlike the other hydrological time series modeling (e.g., modeling of suspended sediment concentrations, rainfall-runoff forecasting), for which a lot of AI models have been used (Chandwani et al. 2015; Afan et al. 2016), for river water temperature modeling, AI models, which are not based on neural networks, fuzzy sets or wavelet transformations, are very rarely applied. This may be simply the effect of the dominance of neural networks-based approaches in the hydrological literature.

Evaluation and assessment

Model inputs

As summarized in Table 1, most of the available studies evaluate river thermal dynamics at daily time scale. For high-frequency data (e.g., hourly), the available studies are limited (Hong and Bhamidimarri 2012; Hebert et al. 2014; Jeong et al. 2016; Lu and Ma 2020). This may be induced by the data availability (e.g., high-frequency data are rarely measured) as in many parts of the world, water temperature in rivers is measured once per day.

Physical interpretation of various variables that affect the relation between air and stream temperature has been given in Mohseni et al. (1999). Since then, different studies may use different input variables; however, air temperature needs to be used due to the strong correlations between river water temperature and air temperature. In order to consider the time lags between water temperature and air temperature (Letcher et al. 2016), air temperatures from the past few time intervals are often used as model inputs (Sahoo et al. 2009; Piotrowski et al. 2015; Graf et al. 2019).

Except air temperature, the role of flow discharge as an input to AI models was assessed in many studies (Foreman et al. 2001; Grbic et al. 2013; Piotrowski et al. 2014, 2015; Zhu et al. 2019b, c, d; Graf et al. 2019; Qiu et al. 2020). It was found that flow discharge plays an important role mainly in snow-fed and regulated rivers with higher-altitude hydropower reservoirs, while it improved to a lower extent model performance in lowland rivers (Zhu et al. 2019b). Some authors also use the information on precipitation (Jeong et al. 2013, 2016; Cole et al. 2014), barometric pressure (Hong 2012; Cole et al. 2014), humidity (Hong 2012), or wind velocity (Foreman et al. 2001; Hong 2012; Cole et al. 2014), but the importance of these factors for stream temperature modeling is rather limited for specific locations. Temperature of spilled water from artificial dams has also been considered for specific rivers (Hong 2012), which is of no importance in most cases.

On the contrary, model input that can significantly improve model performance is solar radiation (Foreman et al. 2001; Cole et al. 2014) coupled with cloud cover. For daily river water temperature forecasting, Sahoo et al. (2009) also used short wave radiation as model input because this variable impacts thermal balance of rivers, and the model results showed that the prediction performance was somewhat higher if short wave radiation was included. However, longer time series of such data are frequently unavailable for vast majority of locations of interest. As a result, some substitutes have to be used. One of the simplest is the components of the Gregorian calendar (CGC), such as day of the year (DOY). The modeling results showed that the addition of CGC contributes to better capture the seasonal pattern of river water temperature (Zhu et al. 2019b, c, d; Qiu et al. 2020) as it can provide additional relevant information on the seasonality of the river thermal dynamics, possibly mimicking the effect of lateral and upstream water and heat inputs. The results are the same as in other studies for water quality modeling (Heddam 2016; Heddam and Kisi 2017). In the studies of Piotrowski et al. (2014, 2015, 2020), declination of the Sun is used as model input, and the model results showed that it helped to improve the model performance. In a recent publication (Piotrowski and Napiorkowski 2019), the role of this variable was further studied in the nonlinear regression stream temperature model. However, to what extent the use of declination of the Sun, or day of the year may substitute the direct measurement of solar radiation has never been researched so far, which needs further investigations.

Comparison of different models

For stream temperature modeling, in most studies, more than a single model is used. However, the intercomparison among various models is rarely conclusive. The clear exceptions are linear, nonlinear regression, and the other statistical models, which were shown to be outperformed by MLPNN or the other AI models (Foreman et al. 2001; Sahoo et al. 2009; Zhu et al. 2018, 2019a, b). This finding was easily confirmed in some more recent studies, e.g., Jeong et al. (2013). For example, Sahoo et al. (2009) showed that artificial neural network models performed far better than the traditional regression analysis and chaotic nonlinear dynamic models. Zhu et al. (2019a) found that the AI models (e.g., MLPNN and ELM) improved the accuracy of river water temperature modeling (20–35%) compared with the traditional statistical models.

Intercomparison among the other stream temperature AI models is less conclusive. Cole et al. (2014) found that MLPNN performs better than statistical models, but is outperformed by heat budget-based approach. However, Hong and Bhamidimarri (2012) claimed that DNFIS model outperforms not only classical ANFIS, but also MLPNN, at least for short-term stream temperature forecasting. Zhu et al. (2019b) compared the performances of MLPNN and ANFIS models. In their study, three identification methods used for the ANFIS model, including fuzzy c-mean clustering, grid partition method, and subtractive clustering, were compared. The results indicated that the MLPNN model provides the best performance in general, and the choice of the identification method significantly impacts the performance of the ANFIS model. The evaluation results in Zhu et al. (2019d) showed that the feedforward neural network performed better than the GPR and DT models. Piotrowski et al. (2015) compared various artificial neural network types and found that the choice of neural network is dependent on the way the models are compared, and this may be a warning for anyone who wishes to promote their own models, and their superiority should be verified in different ways.

Zhu et al. (2019e) integrated wavelet transform with MLPNN and ANFIS models, and the results indicate that the combination of WT and AI models yields better models than the conventional forecasting models. The performance of the hybrid model is based on the mother wavelet and decomposition level. In order to assess the impact of mother wavelet and decomposition level on the performance of the hybrid model, Graf et al. (2019) developed a hybrid WT and MLPNN model and found that among the four mother wavelets applied, the discrete Meyer performs the best, slightly better than the Daubechies at level 10 and Symlet, while the Haar mother wavelet has the lowest accuracy. Also, the model performance improves with an increase in the decomposition level, indicating the importance of the choice of decomposition level.

In a recent study by Qiu et al. (2020), particle swarm optimization (PSO) was coupled with the back-propagation neural network (BPNN) to forecast water temperature in two river stations of the Yangtze River, and the modeling results were compared with that of RBFNN, wavelet neural network (WNN), general regression neural network (GRNN), and Elman neural network (ELMNN). The results showed that with the optimization of the PSO algorithm, the BPNN model can better capture river thermal dynamics.

Model calibration

AI models applied for stream temperature simulations often require calibration (frequently the term training is used in case of neural networks). Because MLPNNs are universal approximators (Hornik et al. 1989), they may be fitted to any continuous and differentiable functions. This means that during calibration, such model may be fitted to not only the signal, but also the noise presented in the training data sample, which may negatively affect the possibility of using such calibrated model to independent data. This is especially important for stream temperature modeling, for which often there is scarcity of available data and the number of spectacular events (with rapid heating or cooling of stream waters) is low. Hence, the performance of the calibrated models on unseen data depends on both calibration algorithm and possibility to avoid overfitting.

Comparison of training algorithms for stream temperature modeling has been done in a few studies. Hong and Bhamidimarri (2012) verified two training methods of the dynamic neuro-fuzzy inference systems: extended Kalman filter approach with and without back-propagation algorithm. Authors also showed the performance of MLPNN trained with back-propagation algorithm for comparison. Dynamic neuro-fuzzy model with hybrid training turned out to be the best choice. In another study, Hong (2012) compared the performance obtained by MLPNN trained by sequential learning with extended Kalman filter, extended Kalman filter with noise updating, and classical (nonsequential) back-propagation algorithm. In the sequential learning approach, instead of dividing data set into calibration and independent subsets, authors assumed that the new information is added into training sample each time it is collected. The superiority of the proposed approach is confirmed by the experiments. Piotrowski et al. (2014) presented a wide-scale comparison among MLPNN trained by means of various metaheuristic algorithms and Levenberg–Marquardt approach. Although some metaheuristics showed promising performance, it was concluded that majority of them are unable to outperform the Levenberg–Marquardt algorithm and that more consistent performance may rather be achieved by ensemble averaging than searching for newer optimization methods.

A possibility to mitigate the effect of overfitting in MLPNN models applied for stream temperature simulations by means of deep-learning-based technique called dropout has been studied in Piotrowski et al. (2020). It was shown that by temporarily dropping out nodes with small probability (1%) during MLPNN training by means of Levenberg–Marquardt algorithm (Levenberg 1944), the probability of getting poorly calibrated models may be highly reduced, and hence, the performance of an average calibrated model is improved.

Recommendations for future research

Wavelet transform, as a good preprocessing method, helps to improve the performance of the traditional AI models for river water temperature forecasting, as revealed in Zhu et al. (2019e, 2020b) and Graf et al. (2019). However, currently, WT has only been coupled with the MLPNN and ANIFS models, and further researches are needed to investigate its coupling with some modern AI models. Additionally, a recent study by Quilty and Adamowski (2018) showed that some of the recent researches incorrectly developed wavelet-based AI models, which cannot be properly used for practical applications. The errors made by these researchers are: (1) the use of future data as input to the developed models, (2) inappropriate selection of decomposition level and wavelet filter, and (3) not carefully partitioning training and testing data. Because of not addressing the boundary conditions in applying wavelet decomposition, some researchers incorrectly implemented wavelet-based AI models, which resulted in much better accuracy than what is realistically achievable. In Quilty and Adamowski (2018), a new strategy for avoiding such errors and adequately using wavelet decomposition method was reported that should be considered in future studies related to wavelet-based complementary modeling approach.

Overfitting is a common issue for AI models (Schaffer 1993), and in order to avoid overfitting, several methods are available. Early stopping is a simple approach to avoid overfitting, frequently used in stream temperature simulations (Piotrowski et al. 2015; Graf et al. 2019). However, to mitigate the possibility of poor performance on independent data, Piotrowski et al. (2019) investigated the impact of deep learning-based dropout on shallow neural networks for river water temperature modeling. They found that dropout reduces the number of models that perform poorly on testing data and hence improves the mean performance. Dropout is a method to avoid overfitting for deep learning, and its applications in shallow neural networks for river water temperature modeling are worth further researches.

Some new AI models, such as the extreme learning machine (Huang et al. 2006), a recent extension of the ANN model, is known as a fast-computational learning model, which has been certified as an online expert predictive system with great real-time application potential. It has been widely used in other hydrological studies (Atiquzzaman and Kandasamy 2016; Rezaie-Balf and Kisi 2017; Yaseen et al. 2018, 2019), however, there are only two attempts for river water temperature simulations (Zhu et al. 2019a; Zhu and Heddam 2019), and its potential for river water temperature forecasting worth further studies.

Finally, the usefulness of deep learning networks in stream temperature modeling needs to be verified. Of much interest are studies that could compare a few deep learning methods on larger number of rivers and possibly relate the results with those obtained by means of physically based models.

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Compliance with ethical standards

Conflict of Interest On behalf of all authors, the corresponding author states that there is no conflict of interest.

References

Afan HA, El-shafie A, Mohtar WHMW, Yaseen ZM (2016) Past, present and prospect of an Artificial Intelligence (AI) based model for sediment transport prediction. J Hydrol 541:902–913

Arismendi I, Safeeq M, Dunham JB, Johnson SL (2014) Can air temperature be used to project influences of climate change on stream temperature? Environ Res Lett 9:084015

Arora R, Tockner K, Venohor M (2016) Changing river temperatures in northern Germany: trends and drivers of change. Hydrol Processes 30:3084–3096

Atiquzzaman M, Kandasamy J (2016) Prediction of hydrological time-series using extreme learning machine. J Hydroinform 18(2):345–353

Benyahya L, Caissie D, St-Hilaire A, Ouarda TBMJ, Bobée B (2007) A review of statistical water temperature models. Can Water Resources J 32(3):179–192

Bromhead DS, Lowe D (1988) Multivariable functional interpolation and adaptive networks. Complex Syst 2:321–355

Bui QT, Nguyen QH, Nguyen XL, Pham VD, Nguyen HD, Pham VM (2020) Verification of novel integrations of swarm intelligence algorithms into deep learning neural network for flood susceptibility mapping. J Hydrol 581:124379

Bui TD, Pradhan B, Lofman O, Revhaug I, Dick OB (2012) Landslide susceptibility mapping at Hoa Binh province (Vietnam) using an adaptive neuro-fuzzy inference system and GIS. Comput Geosci 45:199–211

Caissie D, El-Jabi N, St-Hilaire A (1998) Stochastic modelling of water temperatures in a small stream using air to water relations. Can J Civil Eng 25(2):250–260

Caissie D, El-Jabi N, Satish MG (2001) Modelling of maximum daily water temperatures in a small stream using air temperatures. J Hydrol 251(1–2):14–28

Caissie D, Thistle ME, Benyahya L (2017) River temperature forecasting: case study for Little Southwest Miramichi River (New Brunswick, Canada). Hydrol Sci J 62(5):683–697

Chandwani V, Vyas SK, Agrawal V, Sharma G (2015) Soft computing approach for rainfall-runoff modelling: a review. Aquatic Procedia 4:1054–1061

Chenard J, Caissie D (2008) Stream temperature modelling using artificial neural networks: application on Catamaran Brook, New Brunswick, Canada. Hydrol Processes 22:3361–3372

Cluis DA (1972) Relationship between stream water temperature and ambient air temperature. Hydrol Res 3(2):65–71

Cole JC, Maloney KO, Schmid M, McKenna JE Jr (2014) Developing and testing temperature models for regulated systems: a case study on the Upper Delaware River. J Hydrol 519:588–598

Crisp DT, Howson G (1982) Effect of air temperature upon mean water temperature in streams in the north Pennines and English Lake District. Freshw Biol 12(4):359–367

Daigle A, St-Hilaire A, Ouellet V, Corriveau J, Ouarda TBMJ, Bilodeau L (2009) Diagnostic study and modeling of the annual positive water temperature onset. J Hydrol 370:29–38

Daigle A, Ouarda TBMJ, Bilodeau L (2010) Comparison of parametric and non-parametric estimations of the annual date of positive water temperature onset. J Hydrol 390:75–84

DeWeber JT, Wagner T (2014) A regional neural network ensemble for predicting mean daily river water temperature. J Hydrol 517:187–200

Du X, Shrestha NK, Wang J (2019) Assessing climate change impacts on stream temperature in the Athabasca River basin using SWAT equilibrium temperature model and ist potential impacts on stream ecosystem. Sci Total Environ 650(2):1872–1881

Dugdale SJ, Hannah DM, Malcolm IA (2017) River temperature modelling: a review of process-based approaches and future directions. Earth-Sci Rev 175:97–113

Durbin R, Rumelhart DE (1989) Product Units: a computationally powerful and biologically plausible extension to backpropagation networks. Neural Comput 1:133–142

Erickson TR, Stefan HG (2000) Linear air/water temperature correlations for streams during open water periods. J Hydrol Eng 5(3):317–321

Faruk DO (2010) A hybrid neural network and ARIMA model for water quality time series prediction. Eng Appl Artificial Intell 23:586–594

Foreman MGG, Lee DK, Morrison J, Macdonald S, Barnes D, Williams IV (2001) Simulations and retrospective analyses of Fraser watershed flows and temperatures. Atmos Ocean 39(2):89–105

Goodfellow I, Bengio Y, Courville A (2016) Deep Learning. MIT Press, Cambridge

Graf R, Zhu S, Sivakumar B (2019) Forecasting river water temperature time series using a wavelet–neural network hybrid modelling approach. J Hydrol 578:124115

Grbic R, Kurtagic D, Sliškovic D (2013) Stream water temperature prediction based on Gaussian process regression. Expert Syst Appl 40:7407–7414

Gualtieri C, Gualtieri P, Doria GP (2002) Dimensional analysis of reaeration rate in streams. J Environ Eng 128(1):12–18

Guimarães Santos CA, da Silva GBL (2014) Daily streamflow forecasting using a wavelet transform and artificial neural network hybrid models. Hydrol Sci J 59(2):312–324

Hadzima-Nyarko M, Rabi A, Šperac M (2014) Implementation of artificial neural networks in modeling the water-air temperature relationship of the River Drava. Water Resources Manag 28(5):1379–1394

Haykin S (1999) Neural networks a comprehensive foundation. Prentice Hall, Upper Saddle River

Hebert C, Caissie D, Satish MG, El-Jabi N (2014) Modeling of hourly river water temperatures using artificial neural networks. Water Qual Res J Can 49(2):144–162

Heddam S (2016) New modelling strategy based on radial basis function neural network (RBFNN) for predicting dissolved oxygen concentration using the components of the Gregorian calendar as inputs: case study of Clackamas River, Oregon, USA. Model Earth Syst Environ 2:1–5

Heddam S, Kisi O (2017) Extreme learning machines: a new approach for modeling dissolved oxygen (DO) concentration with and without water quality variables as predictors. Environ Sci Pollut Res 24:16702–16724

Holman D, Sridharan M, Gowda P, Porter D, Marek T, Howell T, Moorhead J (2014) Gaussian process models for reference ET estimation from alternative meteorological data sources. J Hydrol 517:28–35

Hong YST (2012) Dynamic nonlinear state-space model with a neural network via improved sequential learning algorithm for an online real-time hydrological modeling. J Hydrol 468–469:11–21

Hong YST, Bhamidimarri R (2012) Dynamic neuro-fuzzy local modeling system with a nonlinear feature extraction for the online adaptive warning system of river temperature affected by waste cooling water discharge. Stochastic Environ Res Risk Assess 26:947–960

Hornik K, Stinchcombe M, White H (1989) Multilayer feedforward networks are universal approximators. Neural Netw 2:359–366

Hu R, Fang F, Pain CC, Navon IM (2019) Rapid spatio-temporal flood prediction and uncertainty quantification using a deep learning method. J Hydrol 575:911–920

Huang GB, Zhu QY, Siew CK (2006) Extreme learning machine: theory and applications. Neurocomputing 70(1–3):489–501

Jang JSR (1993) ANFIS: adaptive-network-based fuzzy inference systems. IEEE Trans Syst Man Cybern 23:665–685

Jeong DI, Daigle A, St-Hilaire A (2013) Development of a stochastic water temperature model and projection of future water temperature and extreme events in the Ouelle River basin in Quebec, Canada. River Res Appl 29:805–821

Jeong K, Lee J, Lee KY, Kim B (2016) Artificial neural network-based real time water temperature prediction in the Soyang River. Trans Korean Institute Electrical Eng 65(12):2084–2093

Kleiber W, Katz RW, Rajagopalan B (2012) Daily spatiotemporal precipitation simulation using latent and transformed Gaussian processes. Water Resources Res 48(1):W01523

Knouft JH, Ficklin DL (2017) The potential impacts of climate change on biodiversity in flowing freshwater systems. Ann Rev Ecol Evolut Syst 48:111–133

Koch H, Grunewald U (2010) Regression models for daily stream temperature simulation: case studies for the river Elbe, Germany. Hydrol Process 24:3826–3836

Kothandaraman V (1971) Analysis of water temperature variations in large rivers. J Sanitary Eng Division 97(1):19–31

Kurnaz S, Cetin O, Kaynak O (2010) Adaptive neuro-fuzzy inference system based autonomous flight control of unmanned air vehicles. Expert Syst Appl 37(2):1229–1234

Laanya F, St-Hilaire A, Gloaguen E (2017) Water temperature modelling: comparison between the generalized additive model,

logistic, residuals regression and linear regression models. Hydrol Sci J 62(7):1078–1093
LeCun Y, Bengio Y, Hinton G (2015) Deep learning. Nature 521:436–444
Lee T, Shin JY, Kim JS, Singh VP (2020) Stochastic simulation on reproducing long-term memory of hydroclimatological variables using deep learning model. J Hydrol 582:124540
Lessard JL, Hayes DB (2003) Effects of elevated water temperature on fish and macroinvertebrate communities below small dams. River Res Appl 19(7):721–732
Letcher BH, Hocking DJ, O'Neil K, Whiteley AR, Nislow KH, O'Donnell MJ (2016) A hierarchical model of daily stream temperature using air-water temperature synchronization, autocorrelation, and time lags. PeerJ 4:e1727
Levenberg K (1944) A method for the solution of certain problems in least squares. Quart Appl Math 5:164–168
Liu H, Sun S, Zheng T, Li G (2018a) Prediction of water temperature regulation for spawning sites at downstream of hydropower station by artificial neural network method. Trans Chin Soc Agricult Eng 34(4):185–191
Liu D, Xu Y, Guo S, Xiong L, Liu P, Zhao Q (2018b) Stream temperature response to climate change and water diversion activities. Stochastic Environ Res Risk Assess 32:1397–1413
Lu H, Ma X (2020) Hybrid decision tree-based machine learning models for short-term water quality prediction. Chemosphere 249:126169
Matsumoto K, Hashioka T, Yamanaka Y (2007) Effect of temperature-dependent organic carbon decay on atmospheric pCO_2. J Geophys Res Biogeosci 112(2):G02007
Mohandes M, Rehman S, Rahman SM (2011) Estimation of wind speed profile using adaptive neuro-fuzzy inference system (ANFIS). Appl Energy 88(11):4024–4032
Mohseni O, Stefan HG, Erickson TR (1998) A nonlinear regression model for weekly stream temperatures. Water Resources Res 34(10):2685–2692
Nourani V, Alami MT, Aminfar MH (2009) A combined neural-wavelet model for prediction of Ligvanchai watershed precipitation. Eng Appl Artif Intell 22(3):466–472
Nourani V, Hosseini Baghanam A, Adamowski J, Kisi O (2014) Applications of hybrid wavelet-Artificial Intelligence models in hydrology: a review. J Hydrol 514:358–377
Petrović DV, Tanasijević M, Milić V, Lilić N, Stojadinović S, Svrkota I (2014) Risk assessment model of mining equipment failure based on fuzzy logic. Expert Syst Appl 41(18):8157–8164
Pilgrim JM, Fang X, Stefan HG (1998) Stream temperature correlations with air temperatures in Minnesota: implications for climate warming. J Am Water Resources Assoc 34(5):1109–1121
Piotrowski AP, Napiorkowski JJ (2019) Simple modifications of the nonlinear regression stream temperature model for daily data. J Hydrol 572:308–328
Piotrowski AP, Napiorkowski MJ, Kalinowska M, Napiorkowski JJ, Osuch M (2016) Are evolutionary algorithms effective in calibrating different artificial neural network types for streamwater temperature prediction? Water Resources Manage 30(3):1217–1237
Piotrowski AP, Napiorkowski MJ, Napiorkowski JJ, Osuch M (2015) Comparing various artificial neural network types for water temperature prediction in rivers. J Hydrol 529:302–315
Piotrowski AP, Napiorkowski MJ, Piotrowska AE (2020) Impact of deep learning-based dropout on shallow neural networks applied to stream temperature modelling. Earth-Sci Rev 201:103076
Piotrowski AP, Osuch M, Napiorkowski MJ, Rowinski PM, Napiorkowski JJ (2014) Comparing large number of metaheuristics for artificial neural networks training to predict water temperature in a natural river. Comput Geosci 64:136–151
Poul AK, Shourian M, Ebrahim H (2019) A comparative study of MLR, KNN, ANN and ANFIS models with wavelet transform in monthly stream flow prediction. Water Resources Manag 33:2907–2923
Qiu R, Wang Y, Wang D, Qiu W, Wu J, Tao Y (2020) Water temperature forecasting based on modified artificial neural network methods: two cases of the Yangtze River. Sci Total Environ 737:139729
Quilty J, Adamowski J (2018) Addressing the incorrect usage of wavelet-based hydrological and water resources forecasting models for real-world applications with best practices and a new forecasting framework. J Hydrol 563:336–353
Quinn JM, Steele GL, Hickey CW, Vickers ML (1994) Upper thermal tolerances of twelve New Zealand stream invertebrate species. N Z J Mar Freshw Res 28(4):391–397
Rabi A, Hadzima-Nyarko M, Šperac M (2015) Modelling river temperature from air temperature: case of the River Drava (Croatia). Hydrol Sci J 60(9):1490–1507
Rehana S (2019) River water temperature modelling under climate change using support vector regression. In Hydrology in a Changing World. Springer, Cham, pp 171–183.
Rezaie-Balf M, Kisi O (2017) New formulation for forecasting streamflow: evolutionary polynomial regression vs. extreme learning machine. Hydrol Res 49(3):939–953.
Razavi Termeh SV, Kornejady A, Pourghasemi HR, Keesstra S (2018) Flood susceptibility mapping using novel ensembles of adaptive neuro fuzzy inference system and metaheuristic algorithms. Sci Total Environ 615:438–451
Sahoo GB, Schladow SG, Reuter JE (2009) Forecasting stream water temperature using regression analysis, artificial neural network, and chaotic non-linear dynamic models. J Hydrol 378(3–4):325–342
Sang YF (2013) A review on the applications of wavelet transform in hydrology time series analysis. Atmos Res 122:8–15
Schaffer C (1993) Overfitting avoidance as bias. Mach Learn 10:153–178
Shen C (2018) A transdisciplinary review of deep learning research and its relevance for water resources scientists. Water Resources Res 54(11):8558–8593
Shen C, Laloy E, Elshorbagy A, Albert A, Bales J, Chang FJ, Ganguly S, Hsu KL, Kifer D, Fang Z, Fang K, Li D, Li X, Tsai WP (2018) HESS opinions: incubating deep-learning-powered hydrologic science advances as a community. Hydrol Earth Syst Sci 22:5639–5656
Sinokrot BA, Stefan HG (1993) Stream temperature dynamics: measurements and modeling. Water Resources Res 29(7):2299–2312
Sivri N, Kilic N, Ucan ON (2007) Estimation of stream temperature in Firtina Creek (Rize-Turkiye) using artificial neural network model. J Environ Biol 28(1):67–72
Sivri N, Ozcan HK, Ucan ON, Akincilar O (2009) Estimation of stream temperature in Degirmendere River (Trabzon-Turkey) using artificial neural network model. Turkish J Fish Aquat Sci 9:145–150
Smith K (1981) The prediction of river water temperatures. Hydrol Sci J 26(1):19–32
Sohrabi MM, Benjankar R, Tonina D, Wenger SJ, Isaak DJ (2017) Estimation of daily stream water temperatures with a Bayesian regression approach. Hydrol Processes 31:1719–1733
Soto B (2016) Assessment of trends in stream temperatures in the north of the Iberian peninsula using a nonlinear regression model for the period 1950–2013. River Res Appl 32:1355–1364
Soto B (2018) Climate-induced changes in river water temperature in North Iberian Peninsula. Theor Appl Climatol 133:101–112
Stefan HG, Preud'homme EB, (1993) Stream temperature estimation from air temperature. J Am Water Resources Assoc 29(1):27–45
Stewart JS, Westenbroek SM, Mitro MG, Lyons JD, Kammel LE, Buchwald CA (2014) A model for evaluating stream temperature

response to climate change in Wisconsin. USGS Report 2014–5186.
Sun AY, Wang D, Xu X (2014) Monthly streamflow forecasting using Gaussian process Regression. J Hydrol 511:72–81
Sun AY, Scanlon BR, Zhang Z, Walling D, Bhanja SN, Mukherjee A, Zhong Z (2019) Combining physically based modeling and deep learning for fusing GRACE satellite data: can we learn from mismatch? Water Resources Res 5:1179–1195
Tao W, Kailin Y, Yongxin G (2008) Application of artificial neural networks to forecasting ice conditions of the Yellow River in the Inner Mongolia reach. J Hydrol Eng ASCE 13(9):811–816
Temizyurek M, Dadaser-Celik F (2018) Modelling the effects of meteorological parameters on water temperature using artificial neural networks. Water Sci Technol 77(6):1724–1733
Toffolon M, Piccolroaz S (2015) A hybrid model for river water temperature as a function of air temperature and discharge. Environ Res Lett 10(11):114011
Voza D, Vukovic M (2018) The assessment and prediction of temporal variations in surface water quality—a case study. Environ Monit Assess 190:434
van Vliet MTH, Ludwig F, Zwolsman JJG, Weedon GP, Kabat P (2011) Global river temperatures and sensitivity to atmospheric warming and changes in river flow. Water Resources Res 47:W02544
Watts G, Battarbee RW, Bloomfield JP, Crossman J, Daccache A, Durance I, Elliott JA, Garner G, Hannaford J, Hannah DM, Hess T, Jackson CR, Kay AL, Kernan M, Knox J, Mackay J, Monteith DT, Ormerod SJ, Rance J, Stuart ME, Wade AJ, Wade SD, Weatherhead K, Whitehead PG, Wilby RL (2015) Climate change and water in the UK—past changes and future prospects. Progress Phys Geogr 39(1):6–28
Webb BW, Clack PD, Walling DE (2003) Water-air temperature relationships in a Devon river system and the role of flow. Hydrol Process 17(15):3069–3084
Webb BW, Hannah DM, Moore RD, Brown LE, Nobilis F (2008) Recent advances in stream and river temperature research. Hydrol Process 22:902–918
Wright SA, Anderson CR, Voichick N (2009) A simplified water temperature model for the Colorado River below Glen Canyon Dam. River Res Appl 25(6):675–686
Yaseen ZM, Allawi MF, Yousif AA, Jaafar O, Hamzah FM, El-Shafie A (2018) Non-tuned machine learning approach for hydrological time series forecasting. Neural Comput Appl 30(5):1479–1491
Yaseen ZM, Sulaiman SO, Deo RC, Chau KW (2019) An enhanced extreme learning machine model for river flow forecasting: State-of-the-art, practical applications in water resource engineering area and future research direction. J Hydrol 569:387–408
Zadeh LA (1988) Fuzzy logic. Computer 21(4):83–93
Zhai P, Williams ED (2012) Analyzing consumer acceptance of photovoltaics (PV) using fuzzy logic model. Renewable Energy 41:350–357
Zhang S, Wang Y, He W, Wu M, Xing M, Yang J, Gao N, Pan M (2014) Impacts of temperature and nitrifying community on nitrification kinetics in a moving-bed biofilm reactor treating polluted raw water. Chem Eng J 236:242–250
Zhu S, Bonacci O, Oskoruš D, Hadzima-Nyarko M, Wu S (2019a) Long term variations of river temperature and the influence of air temperature and river discharge: case study of Kupa River watershed in Croatia. J Hydrol Hydromech 67(4):305–313
Zhu S, Hadzima-Nyarko M, Gao A, Wang F, Wu J, Wu S (2019b) Two hybrid data-driven models for modeling water-air temperature relationship in rivers. Environ Sci Pollut Res 26:12622–12630
Zhu S, Heddam S (2019) Modelling of maximum daily water temperature for streams: optimally pruned extreme learning machine (OPELM) versus radial basis function neural networks (RBFNN). Environ Process 6(3):789–804
Zhu S, Heddam S, Nyarko EK, Hadzima-Nyarko M, Piccolroaz S, Wu S (2019c) Modeling daily water temperature for rivers: comparison between adaptive neuro-fuzzy inference systems and artificial neural networks models. Environ Sci Pollut Res 26:402–420
Zhu S, Heddam S, Wu S, Dai J, Jia B (2019d) Extreme learning machine-based prediction of daily water temperature for rivers. Environ Earth Sci 78(6):202
Zhu S, Hrnjica B, Ptak M, Choiński A, Sivakumar B (2020a) Forecasting of water level in multiple temperate lakes using machine learning models. J Hydrol 585:124819
Zhu S, Nyarko EK, Hadzima-Nyarko M (2018) Modelling daily water temperature from air temperature for the Missouri River. PeerJ 6:e4894
Zhu S, Nyarko EK, Hadzima-Nyarko M, Heddam S, Wu S (2019e) Assessing the performance of a suite of machine learning models for daily river water temperature prediction. PeerJ 7:e7065
Zhu S, Ptak M, Yaseen ZM, Dai J, Sivakumar B (2020b) Forecasting surface water temperature in lakes: a comparison of approaches. J Hydrol 585:124809