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Research papers

A stacking ensemble learning framework for annual river ice breakup dates

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ABSTRACT

River ice breakup dates (BDs) are not merely a proxy indicator of climate variability and change, but a direct concern in the management of local ice-caused flooding. A framework of stacking ensemble learning for annual river ice BDs was developed, which included two-level components: member and combining models. The member models described the relations between BD and their affecting indicators; the combining models linked the predicted BD by each member models with the observed BD. Especially, Bayesian regularization back-propagation artificial neural network (BRANN), and adaptive neuro fuzzy inference systems (ANFIS) were employed as both member and combining models. The candidate combining models also included the simple average methods (SAM). The input variables for member models were selected by a hybrid filter and wrapper method. The performances of these models were examined using the leave-one-out cross validation. As the largest unregulated river in Alberta, Canada with ice jams frequently occurring in the vicinity of Fort McMurray, the Athabasca River at Fort McMurray was selected as the study area. The breakup dates and candidate affecting indicators in 1980–2015 were collected. The results showed that, the BRANN member models generally outperformed the ANFIS member models in terms of better performances and simpler structures. The difference between the R and MI rankings of inputs in the optimal member models may imply that the linear correlation based filter method would be feasible to generate a range of candidate inputs for further screening through other wrapper or embedded IVS methods. The SAM and BRANN combining models generally outperformed all member models. The optimal SAM combining model combined two BRANN member models and improved upon them in terms of average squared errors by 14.6% and 18.1% respectively. In this study, for the first time, the stacking ensemble learning was applied to forecasting of river ice breakup dates, which appeared promising for other river ice forecasting problems.

1. Introduction

The long-term trends of river ice breakup dates (BDs) have been demonstrated as good proxy indicators of climate variability and change (Cooley and Pavelsky, 2016; de Rham et al., 2008a,b; DeBeer et al., 2016; Fu and Yao, 2015; Lesack et al., 2013, 2014; Magnuson et al., 2000; Pavelsky and Smith, 2004; Shi et al., 2015; Yang et al., 2015). However, as an indicator of an annual event at high-latitude regions, the river ice BDs are a direct input to the management of local ice-caused flooding (Beltaos and Prowse, 2001; Beltaos et al., 2006; Nafziger et al., 2016; Prowse et al., 2010; Wang et al., 2013; Zhao et al., 2012, 2015). Since breakup may cause water level increases of several metres in minutes, a long-lead accurate forecasting of breakup dates is valuable. Earlier forecasts can provide greater preparedness time for the local emergency response authorities, which is thus helpful for mitigating potential economic losses and protection of the public. It is evident that many factors affecting river ice breakup dates include spring surface air temperatures and downstream/upstream river ice conditions (Beltaos and Burrell, 2015; Bieniek et al., 2011; Cooley and Pavelsky, 2016). Thus, development of powerful forecasting tools is crucial in river ice-caused flood management (Warren et al., 2017).

Previously, data-driven and hydraulic models were applied to breakup prediction. However, most of these models focus on predicting breakup severity (Mahabir et al., 2005; Mahabir et al., 2006a, 2007, 2003, 2006b, 2008; Mahabir, 2007). A limited number of studies on the prediction of breakup dates have been reported. For instance, an artificial neural network (ANN) model was proposed to forecast ice run, freeze-up, and breakup dates in the Inner Mongolia Reach of the Yellow River (Tao et al., 2008). An ANN model coupling particle swarm optimization and back propagation was developed for ice breakup date forecast in the top reach of the Yellow River, China (Hu et al., 2008). A support vector machine optimized by a multi-objective shuffled

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complex evolution metropolis algorithm was developed for prediction of ice breakup dates in the Inner Mongolia section of the Yellow River (Zhou et al., 2009). A three-layer feed-forward ANN model was proposed for predicting the onset of breakup, using the Hay River in northern Canada (Zhao et al., 2012). Besides, due to the complicated breakup mechanism and the site-specific characteristics, prediction of breakup dates is a challenge.

To further improve the performance of prediction models, one possible solution is application of more advanced prediction methods to river ice breakup timing. Effectiveness of these new methods needs to be demonstrated through their comparisons with other conventional methods (Alvisi et al., 2006; Sun and Trevor, 2015). Instead of selecting the best model, an alternative solution is to combine the current prediction models in a manner that each advantage can be merged within an integrated framework (Sun and Trevor, 2017a,b). Stacking ensemble learning is such a type of method, which uses combining models to combine member models. Various ensemble learning methods have been applied to various fields of hydrological and meteorological modeling, such as satellite precipitation estimation (Hong et al., 2006), daily streamflow prediction (Dhanya and Kumar, 2011), urban water demand forecasting (Tiwari and Adamowski, 2013), soil moisture estimation (Kornelsen and Coulibaly, 2014), groundwater level prediction (Sun, 2013), salinity intrusion in coastal aquifers (Sreekanth and Datta, 2011), flood frequency analysis (Ouarda and Shu, 2009; Shu and Ouarda, 2007) and irrigation demands (Perera et al., 2016). Among them, the advantages of stacking learning lie in the performance improvement due to possible variance reduction of forecast errors or correction of biases. However, its application to river ice breakup timing has limited reporting.

To this end, the objective of this study is to develop a stacking ensemble learning framework (SELF) of annual river ice breakup dates and to apply it to the community of Fort McMurray on the Athabasca River, Canada. This will entail: (1) the development of member prediction models for river ice breakup dates, including Bayesian Regulated back-propagation artificial neural network (BRANN), and adaptive Neuro Fuzzy Inference System (ANFIS); (2) the selection of input variables for member models by a hybrid filter and wrapper method; (3) the use of outputs of certain combinations of member models as further inputs for combining models, verifying the roles of BRPANN, ANFIS, and simple average methods (SAM) as combining models within the SELF; and (4) the application of the proposed SELF to a representative unregulated river in Alberta, Canada, where frequent ice-caused floods are a concern.

2. Methods

2.1. Stacking ensemble learning

The stacking ensemble learning framework (SELF) for annual river ice breakup dates has a two-level structure, which includes member and combining models (Fig. 1). In terms of its functions, the member models link the BDs with their affecting indicators; the combining models quantify the relations between the predicted BDs by each member models and the observed BDs. In this study, the BRANN and ANFIS are tested in terms of their performances as not only member models but also combining models. The SAM is selected only for the combining model as a comparison basis.

2.2. Input variable selection (IVS)

Input variable selection (IVS) is one of the most important steps for building the member models. There are three basic types of IVS methods, which are filter, wrapper and embedded methods (May et al., 2011; Vergara and Estévez, 2014). For the member model of annual river ice forecasting, the data sample number is relatively small as the period of monitored historical record is typically short. It has been reported that when the ratio of the sample number to the input variable number is less than 5, it may affect the performance of more advanced IVS methods (Galelli et al., 2014). Considering the relatively small river ice data set, a hybrid filter-wrapper method was proposed. Firstly, the linear correlation coefficients (R) and the mutual information (MI) indices were calculated to evaluate the separate ranking of all input variables. A certain number of inputs variables with higher rankings were reserved as candidate ones. This filter method is merely to narrow down the range of candidate input variables. Furthermore, in the wrapper step, a greedy search-based leave-one-out cross validation (LOOCV) method is employed to evaluate the performances of each type of models under all possible combinations of filtered input variables and inherent parameters. The calculation load of this wrapper method is acceptable. This is because the number of all candidate input variables is reduced to a reasonable level by the filter method; meanwhile, the data sample number is small which constrains the maximum of input variable number employed in the models. The detailed equations for R and MI can be referred to the reference (Guyon and Elisseeff, 2003).

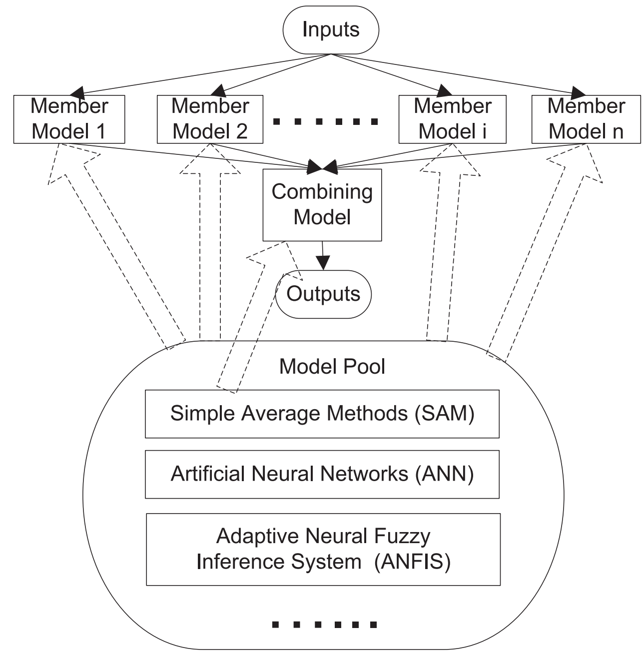

Fig. 1. Structure of stacking ensemble learning framework (SELF).

2.3. Bayesian regularization back-propagation artificial neural network (BRANN)

The Bayesian regularization back-propagation artificial neural network (BRANN) is proposed as one of the member or combining models within the SELF. Although conventional back-propagation ANN is demonstrated as universal approximators, it often suffers from the overfitting problems (Abrahart et al., 2012; Anctil and Lauzon, 2004; Hsu et al., 1995; Maier et al., 2010; Zhang et al., 2009). BRANN uses the Bayesian theory to balance the structure size and prediction accuracy (Foresee and Hagan, 1997). BRANN follows a typical three-layer structure with logistic and linear transfer functions in hidden and output layers, respectively. Especially, the number of either factors affecting BDs or member models determines the number of neurons in the input layer; the number of neurons in the hidden layer needs to be adjusted by trial and error to maximize the model's performance; and the number of neurons in output layer is usually one, which is same as the number of predicted BDs. During the calibration process, the objective function is as follows: