An Improved Model for Sap Flow Prediction Based on Linear Trend Decomposition

Bo Li[1,2,3,4], Yane Li[1,2,3,4], Hailin Feng[1,2,3,4](✉), Bin Wu[1,2,3,4], Qiang Zhu[1,2,3,4], Xiang Weng[1,2,3,4], and Yaoping Ruan[1,2,3,4]

[1] College of Mathematics and Computer Science, Zhejiang A&F University, 666 Wusu Street, Hangzhou 311300, China
2021611011039@stu.zafu.edu.cn, {yaneli,hlfeng,wubin,woodweng, 20182018}@zafu.edu.cn

[2] Key Laboratory of Forestry Intelligent Monitoring and Information Technology of Zhejiang Province, Hangzhou 311300, China

[3] China Key Laboratory of State Forestry and Grassland Administration on Forestry Sensing Technology and Intelligent Equipment, Hangzhou 311300, China

[4] College of Optical, Mechanical and Electrical Engineering, Zhejiang A&F University, Hangzhou 311300, China

Abstract. Tree transpiration plays an important role in environmental change, which mainly assessed by sap flow. It is great significance to predict sap flow accurately for estimation of water consumption, management of water resource and making of sustainable development strategy for geohydrological balance under climate change. In this study, an improved prediction model was built with Dilnear algorithm using historical environment factors to assess short-term sap flow. Specifically, a public dataset including 17568 records was used. One record have one sap flow value and 9 environment factors which measured from January 1, 2016 to December 31, 2016 at 30 min interval in Canada for Tsuga canadensis (*L.*) Carriere. After data processed with missing value padding and normalization, seven factors was extracted with fusion of Pearson correlation and Grey correlation method. Then, sap flow prediction model was established with Dlinear algorithm. For comparison and analysis, five other deep learning networks of CNN, GRU, LSTM, Transformer and Informer were used to built sap flow prediction model respectively. Results shown that Dlinear based model has better performance than other models established in this paper. The coefficient of determination (R^2), the Mean Absolute Error (*MSE*) and the Mean Square Error (*MAE*) achieved 0.9568, 0.0282 and 0.0017 for Dlinear based model. R^2 of Dlinear based model is of 20.37%, 14.9% and 21.93% higher than CNN, GRU and LSTM based model respectively. In addition, we also analyzed length of look-back window and prediction window. Results shown that when length of look-back window was set as 720, Dlinear based model has better performance with R^2 of 0.9568, which higher of 2.62%, 7.75%, 18.95% and 35.46% than length of 336, 192, 96, and 48. When the prediction window length was set as 96, Dlinear based model has higher of R^2 and smaller of *MSE* and *MAE* than length of 240, 336 and 720. At the

B. Li and Y. Li—Co-first author, whom make the equal contribution to this paper.

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same time, we compared performance of models established with seven selected factors and all nine factors. Results shown that model with seven selected factors have slight higher of R^2 than model with all nine factors. Results indicate that the model established in this paper can accurately predict sap flow, especially for short-term sap flow, which has great application value and practical significance for management of trees and forests.

Keywords: Deep Learning · Sap flow · Dlinear · Environment factors · Short-term prediction

1 Introduction

Forest is an indispensable part of the Earth's ecosystem, and the forest systems composed of various tree species occupies about 1/3 of the Earth's total land area [1]. Transpiration of trees plays a crucial role in environmental change. Therefore, an accurate predicting of transpiration for forest is of great significance for the Earth's hydrological balance and the formulation of sustainable development strategies under climate change [2–4]. The quantitative assessment measures of forest transpiration mainly include water balance, micrometeorology and sap flow based method [1, 5]. Changes of sap flow are directly physiological features for trees' response to the environment. As a result, the accurate prediction of trunk sap flow is helpful to analyze transpiration and hydrological changes for forest and environmental workers.

Many research findings revealed that diurnal variations of sap flow are closely related to physiological factors such as saturated vapor pressure deficit (VPD), canopy width and leaf area index, and environmental variables such as solar radiation, relative humidity (RH), air temperature (Ta) and soil water content (SWC) [6]. In addition, xylem characteristics of vessel density, size, and fibrosis are physiological structural factors which affect trunk sap flow [7]. In arid areas, environmental factors such as transpiration, high temperature and low humidity have an important impact on changes of trunk sap flow in arid areas [8]. The sap flow of the plant itself will also change correspondingly with the changes of the environment, such as maintaining the same, decreasing or increasing [9].

Under the background of global climate warming and urban heat island effect increasing, the sap flow of urban green tree species changes under the influence of environment and the demand for water increases [10]. Because the research on the sap flow of trees during the day is mainly carried out in artificial forests [11], there is a lack of information and research on the daily sap flow of urban garden trees. The underestimation of water consumption of urban trees leads to the limitation of their physiological process and growth, and even the reduction of tree life [12]. Su et al. studied the sap flow driving and changing factors for F. pennsylvanica, one of the common green tree species in northern China [11]. The purpose of this study was to investigate the water requirement of F. pennsylvanica to further provide theoretical basis for local greening irrigation. Results indicated that high nighttime sap flow velocity might be produced under the water stress condition [11]. Zhang et al. investigated a long short term memory (LSTM)-transformer based Larix olgensis sap flow prediction model, which shown better performance than

Back-Propagation (BP) neural network, deep neural network (DNN), LSTM and Transformer based models in terms of correlation coefficient (R^2), root mean square error (RMSE) and Mean absolute error (MAE) [13]. Granata et al. compared methods of random forest, weighted regression of decision tree, multi-layer perceptron (MLP) and k-neighbor algorithm in the prediction of wetland evaporation in Indian River County, Florida, and found that the performance of k-neighbor and random forest based models were better than other two algorithms based models [14]. Vishwakarma et al. found that the FAO-56 Penman–Monteith (FAO56-PM) method performed better than all 30 applied models in their empirical model of plant water evaporation in subtropical humid environments [15]. Unfortunately, the workload and effort of the empirical model were much higher than those of machine learning methods. During this period, Elbeltagi studied an MLP-artificial neural network (ANN) based model to compare with the empirical model, which shown that the performance of MLP-ANN is higher than the empirical model [16]. Tu et al. established a 3- layer BP neural network based on Levenberg-Marquardt to predict sap flow of Pinus massoniana, which have better performance than multiple linear regression (MLR) technology. The performance of BPNN based model is better than Mixed Logistic Regression (MLR) based model, especially after introducing phenological index and delay effect [17]. Han et al. found that the BPNN has higher prediction accuracy than MLR and FAO-56 in prediction of crop evaporation by using factors of dynamic changes of crop coefficient and precipitation changes [18]. Roy compared the applicability of LSTM and Bi-LSTM based models to predict evaporation, which shown that the prediction ability of LSTM or Bi-LSTM based model is all better than models of support vector machine regression (SVR), M5 model tree (M5 tree), Multiple Adaptive regression curves (MARS), probabilistic linear regression (PLR), adaptive Neuro-fuzzy inference system (ANFIS) and Gaussian process regression (GPR). LSTM and Bi-LSTM have the same prediction performance on the unknown data obtained from the test station Ishurdi (the entire data set was not used for model training) [19]. Li et al. explored the relationship between sap flow and environmental variables of Piceacrassifolia Kom, and concluded that BPNN could more rationally explain the nonlinear relationship between transpiration and impact factors than MLR [20]. Feng et al. showed that abandoning the multicollinear factors has little effect on the prediction accuracy [21]. Zhao et al. studied the relationship between sap flow and tree diameter and its influencing factors. Results showed that the tree diameter influenced the variation of sap flow between trees in large intra-year and inter-year variations. The potential transom demand of trees mainly determined the intra-year variation of tree diameter explanatory power, and the interannual variation of diameter explanatory power was mainly controlled by environmental water supply. The pattern of the relationship between sap flow and diameter also showed large inter-annual variation [1]. Loritz et al. showed that recurrent neural network (RNN) can better predict the eco-hydrological characteristics of plant water stress in dry periods, especially with the addition of improved seasonal and daily models [22]. In addition to the algorithms applied by many scholars, it is worth to discuss whether the new time series algorithm can also get better results in sap flow prediction.

Time series prediction model is used to assess current or future data based on historical data, which contains a lot of information, noise and other uncertainties, fulling of difficulties. For example, the difficulty of accurately predicting stock prices is that the stock market is non-parametric and non-linear, and there is a lot of noise and uncertainty [23]. Wang et al. found that the direct input-output connection backpropagation neural network (BPNN-DIOC) performed well on commonly time series data sets (such as CO2 concentration, Milk production, Atvinnulausir eftirmenntun, Number of unemployed, Monthly lake erie levels, Social media payroll index, Electricity load demand and Electricity price) has higher accuracy than the traditional BPNN based prediction model [24]. Niu et al. found that the performance of Informer based model is 19% to 35% higher than that of LSTM alone and LSTM combined with attention mechanism based model for prediction of PM2.5, especially for 30-day long-term prediction [25]. Wang et al. proposed a BHT-autoregressive moving average (ARIMA)-GRU (BAG) based model to solve the linear and nonlinear relationship for soil moisture prediction. BHT-ARIMA was used to predict the linear part of soil moisture, and GRU was used to predict the residual sequence. The residual sequence is the nonlinear part and the two results are added by weight to obtain the final result [26]. Hu et al. proposed a GRP-LSTM-GAN based model to realize the important information of time scale and analyze and interpret the global and local information in the prediction of the temperature of the rotary drying furnace [27]. Wang et al. proposed a transformer-based InSAR integrated prediction model for short-term assessment in permafrost areas, and the effect of this method is better than that of RNN and LSTM in long-term time series variant modeling [28]. Li et al. proposed a predict model by combining ARIMA and LSTM networks. In this model, the ARIMA model was used to process the historical data of gas time series, and the corresponding linear prediction results and residual series were obtained. The LSTM model is used for further analysis of the residual series to predict the nonlinear factors in the residual series [29]. Lu et al. first applied Informer to flexion force prediction (FFP), and found that the buckling force error predicted by Informer based model was smaller than correlation based prediction methods [30]. Recent deep learning models such as Transform have achieved great success in the fields of natural Language Processing (NLP), computer vision (CV), speech, etc. [31], but Transformer without combining with other methods has not been verified for its usability in sap flow prediction.

Although many deep learning based models have been applied to the prediction of sap flow, the recently developed algorithms which fittable for time series data have not been more widely used in field of sap flow prediction. The goal of this research is to investigate a more accurate prediction model for assessment of time series of sap flow value with historical environment factors. In this study, a new Dlinear algorithm was applied to establish sap flow prediction model. After sap flow and environment factors preprocessing, an improved sap flow prediction model was proposed with the new Dlinear algorithm, which has higher precision for the assessment of sap flow with environment factors. The R^2, MSE and MAE of the model reached 0.9568, 0.0017 and 0.0282 respectively. In the process of this model developing, we compared and analyzed the performances of different models constructed with CNN, GRU, LSTM, Transformer and Informer respectively. Results shown that the prediction performance of the Dlinear based model was better than other models established in this paper. There is a specific relationship between sap flow and environmental factors. The prediction model can assess the current sap flow by learning the relationship between historical records of sap flow and environment variables, which involves the setting of time window's length. Assuming that the model predicts the sap flow at the current moment, it needs to observe the relationship between the sap flow value and various environmental factors measured at previous historical moments. Theoretically, the longer the look-back window length, the more information the model can learn [32]. In this study, we compared and analyzed performance of models established under different window lengths. The model we established in this study has practical significance in that it helps to accurately predict sap flow for further assessment of stand transpiration, water consumption and intelligent management of water resources. The overall flow chart of this study is shown in Fig. 1.

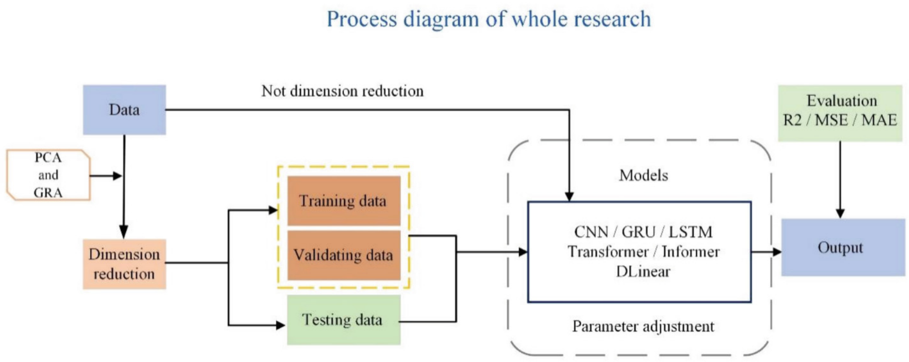

Fig. 1. Process diagram of this study. PCA and GRA stands for the Pearson correlation analysis and Grey relational analysis respectively.

2 Materials and Methods

2.1 Dataset Source and Data Processing

The sap flow dataset used in this study is selected from a public dataset of SAPFLUXNET (Global Stem Sap Flow Testing Database) which uploaded by Beamesderfer·Eric and Arain·Altaf of McMaster University. SAPFLUXNET is a global database that contains sap flow data, environmental variables and different levels of metadata. It is compiled from data and materials provided by researchers around the world. The database contains sap flow data for 2714 plant species (1584 angiosperms and 1130 gymnosperms), which are divided into 174 species (141 angiosperms and 33 gymnosperms), 95 different genus and 45 different families. The sap flow data of Tsuga canadensis (L.) Carriere and the corresponding environmental variables which measured from January 1, 2016 to December 31, 2016 was used to establish sap flow prediction model. There are 17568 records in this dataset. Each record including one sap flow value and nine environmental factors with measuremental interval of 30 min. Among them, the environmental variables include temperature (Ta, °C), saturated vapor pressure deficit (VPD, kPa), wind speed (WS, m·s-1), Photon Flux Density, (PPFD, umol ·m-2 ·s-1), shallow soil water content(SWC_Shallow, cm3·cm-3), deep soil water content (SWC_Deep, cm3 · cm-3), Shortwave Incoming Radiation (SW_in, W·m-2), relative humidity (RH,%) and Extraterrestrial radiation (Ext_rad, W·m-2). These 17568 time series records were divided into three groups in a ratio of 7:2:1 as the training set, test set and validation set, including 12297, 3513 and 1756 records respectively.

For missing values present in the data set, we use data from the nearest Canadian hemlock tree at the same distance to fill in the missing values. In addition, due to the different basic units and representations of each variable, not only the values of a single variable vary greatly throughout the year, but also the differences between the values of each variable are large. In order to reduce the loss of computing power and let the model learn more information from data, the data was normalized with the max-min standardization function which between [0,1], as shown in formula (1).

$$X' = \frac{X - \mathrm{X_{min}}}{X_{\mathrm{max}} - X_{\mathrm{min}}} \tag{1}$$

where X' represents the normalized value, X stands for the original value, Xmin and Xmax represents the minimum and the maximum value respectively.

2.2 Methods

LSTM: An unit gate network model composed of input gate, output gate and forgetting gate, which solves the problem of gradient disappearance and gradient explosion in the training process of traditional RNN [33].

CNN: Convolutional Neural Network is a kind of feedforward neural network composed of convolutional layer, pooling layer and fully connected layer with the main function of feature extraction, downsampling and classification respectively. The difference between CNN and other ANN is that the CNN can automatically extract features from data with the convolutional layer and pooling layer to learning, instead of extracting features manually. Specifically, the convolutional layer multiplizes the local sum of the input matrix and the convolution kernel matrix, and then adds it to get a new matrix. The pooling layer compreses the matrix obtained by the convolutional layer. Based on calculation of convolution and downsampling, the feature map computed and used for further classification or regression [34].

GRU: Gate Recurrent Unit (GRU), like LSTM, is proposed to solve the problem of long-term memory and gradient in backpropagation. Compared with LSTM, GRU is composed of reset gate and update gate to realize forgetting and selective memory with more efficient in hardware computing power and time cost. However, LSTM requires multiple gates to achieve it [35].

Transformer: Transformer is a classic NLP model proposed by the Google team in 2017. The design idea is to use the self-attention mechanism to propagate in the vertical direction, so that all computing layers run simultaneously to obtain global information, completely abandoning the horizontal propagation of traditional RNN. This parallel computation can be accelerated by GPU, which greatly improves computing efficiency. The reason why self-attention mechanism has this advantage is that the attention calculation is carried out for each input unit and surrounding units, which establishes a direct link between all units and can capture information over a longer distance [36].

Informer: Informer reduces the time and space complexity O (L2) of self-attention mechanism, where L is the sequence length. The encoder-decoder structure iterates in multiple steps during decoding so that the longer the prediction sequence is, the longer the prediction time is. In order to solve the above problems of Transformer, Informer used ProbSparse self-attention strategy to reduce the time complexity to O (L·logL). A self-attention distillation mechanism is proposed to shorten the input sequence length of each layer to reduce the amount of computation and spending time. A generative decoder mechanism is proposed for Informer to make direct multi-step prediction [37].

Dlinear: Dlinear is a new baseline model jointly proposed for digital economy. This algorithm combines the position encoding strategy with the linear layer of Autoformer and FEDformer to decompose the time series into trend series and residual series. Then, the direct multistep prediction of the decomposed sequences is carried out by using two single-linear networks. Taking into account the different seasonality and trend of variables in the data set, the authors set a separate linear layer for each variable. The advantage of Dlinear is that the shorter the traversal path, the better the dependencies between variables are captured, which enables Dliearn to capture both short-term and long-term temporal relationships. The seasonality and trend of time series are decomposed and the weights are visualized to help analyze the characteristics of the predicted values. Because it is a single linear network, it is convenient to optimize the model with fewer parameters [32]. The Dlinear model framework is shown in Fig. 2.

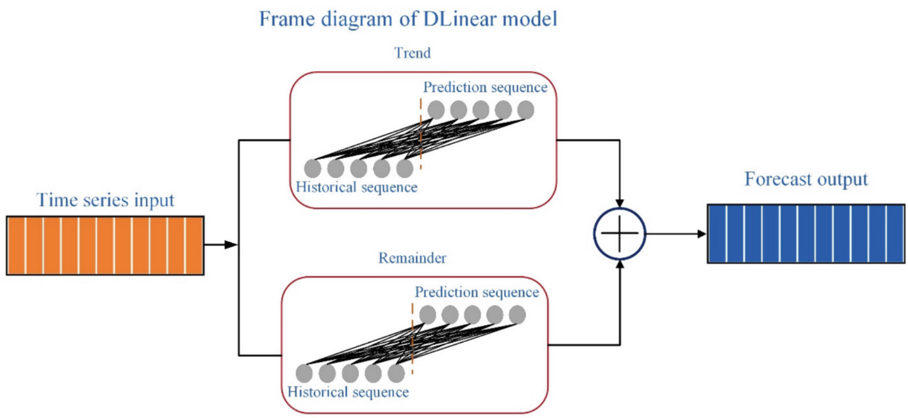

Fig. 2. Framework of Dlinear model. For multivariable prediction tasks, multiple figure core frameworks can be used.

2.3 Performance Assessment Indices

In this study, the Mean Square Error (MSE) and Mean Absolute Error (MAE) were used to assess performance of sap flow prediction models, following the work of time series prediction algorithm [32, 36–39]. In addition, the coefficient of determination (R^2) was applied to evaluate the interpretability of the real and predicted flow values.

Calculation formulas of indices used in this paper are shown in Formulas of (2), (3) and (4) respectively.

$$MSE = \frac{1}{\mathrm{m}}\sum_{i=1}^{m}(y_i - \hat{y}_i)^2 \tag{2}$$

$$MAE = \frac{1}{\mathrm{m}}\left|\sum_{i=1}^{m}(y_i - \hat{y}_i)\right| \tag{3}$$

In formulas (2) and (3), yi represents the ture value and $\hat{y}_i$ represents the predicted value.

$$R^2 = 1 - \frac{\sum_i (\hat{y}_i - y_i)^2}{\sum_i (\overline{y}_i - y_i)^2} \tag{4}$$

In the formula (4), y_i is the ture value, $\hat{y}_i$ means the predicted value, $\overline{y}_i$ is the sample mean, $\sum_i (\hat{y}_i - y_i)^2$ is the forecasting error, $\sum_i (\overline{y}_i - y_i)^2$ is the average error.

3 Results

3.1 Data Dimensionality Reduction

After data preprocessing, data dimensionality reduction was carried out with fusion of Pearson correlation analysis (PCA) and Grey relational analysis (GRA) based methods. GRA is a tool to evaluate the correlation degree based on the distance between the reference sequence and the comparison sequence, which has been more widely used in many scientific decision-making problems [40]. Asgharnezhad and Darestani analyzed Dempster-Shafer theory and GRA and found that GRA was more reliable and robust [41]. Gerus Gościewska and Gościewski believed that GRA can be applied in more aspects by virtue of its advantages [42]. In this study, we selected environmental factors by combining results of PCA and GRA. Specifically, we first used GRA to analyze the relationship between subsystems and the parent system. The sap flow and environmental factors were assumed to be the parent sequence. The mother sequence M is divided into a single subsystem A. For example, the annual temperature series was divided into AT, the annual RH series was divided into AR, and so on. After divided the series into 10 subsystems according to environment factors, including the sap flow series, and then relationships between the subsystems each other and the subsystems with the parent sequence were computed. Results shown the ranking of environment factors from high to low computed with GRA was as follows: VPD > Ext_rad > PPFD_in > SW_in > Ta > RH > SWC_shallow > SWC_deep > WS. The heat map of GRA is shown in Fig. 3(a). Second, PCA was carried out for 9 factors and sap flow value. Results shown that the sap flow of Tsuga canadensis (L.) Carriere was strongly correlated with VPD, PPFD_in and Ext_rad, moderately correlated with RH, Ta and SW_in, weakly correlated with SWC_shallow and extremely weekly correlated with WS and SWC_deep. The heat map of Pearson correlation coefficient is shown in Fig. 3(b). Combined with results of GRA and PCA, environment factors of SWC_deep and WS were removed. Seven environment factors including VPD, Ext_rad, PPFD_in, SW_in, Ta, RH and SWC_shallow were used to establish sap flow prediction based model.

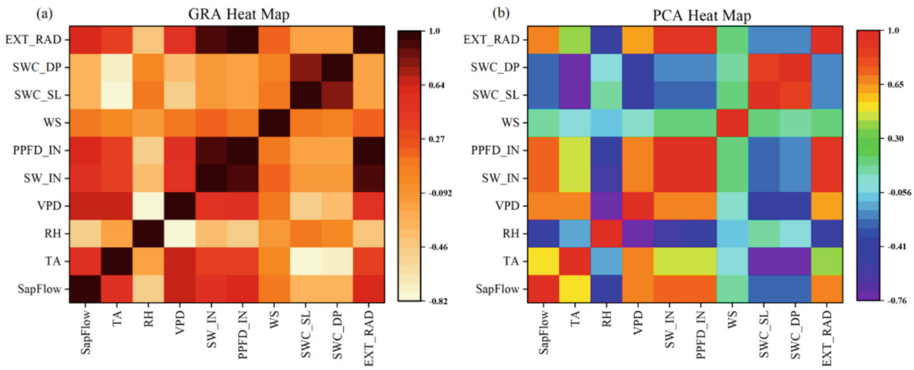

Fig. 3. GRA and PCA obtain the heat map of the interrelation of each variable. The stronger the positive correlation between variables in Figure (a), the darker the color; The stronger the negative correlation, the lighter the color. The stronger the positive correlation between variables in Figure (b), the closer the color is to red; The stronger the negative correlation, the closer the color is to purple.

3.2 Comparison of Performance Between Different Sap Flow Prediction Models

In order to verify and compare the applicability of the new baseline Dlinear algorithm for sap flow prediction, three classical deep learning models, namely CNN, GRU and LSTM, and two newer time series prediction models Transformer and Informer as well as the new baseline Dlinear algorithm were used to establish sap flow prediction models respectively. When the optimal window length of each model was set as 96, the loss value almost no longer fluctuates after 15 times of training. The prediction length of 96 is chosen because the environmental value changes are moderate and it is suitable to explore the sensitivity of the model to subtle changes. The optimal performance of R^2, MSE, and MAE for each model established with seven selected environment factors was shown in Table 1. In addition, the time consumption was also introduced to evaluate the operation efficiency of models.

As shown in Table 1, performance of R^2, MSE and MAE for the new baseline Dlinear model are superior to other models established in this paper. While this new baseline Dlinear model spend longer time for training than other models, which need to reduce the operation time for further study. In addition, R^2 of Transformer and Informer based prediction model is negative, and the MSE and MAE are also within the range of previous research results [36, 37], indicating that these two models cannot play their performance well in prediction of sap flow. Thus, Transformer and Informer based models are not suitable for prediction of sap flow, so these two models will not be discussed in the subsequent results.

Table 1. Optimal performance index of each model.

Models	R^2	*MSE*	*MAE*	Spending time (s)
CNN	0.7972	0.0038	0.0306	**212.62**
GRU	0.8078	0.0036	0.0295	198.17
LSTM	0.7357	0.0049	0.0335	559.32
Transformer	−0.5623	0.0603	0.2312	381.39
Informer	−0.6449	0.0636	0.2364	813.21
Dlinear	**0.9568**	**0.0017**	**0.0282**	612.52

3.3 Effect of Feature Screening on Sap Flow Prediction Model

In order to verify and analyze how much impact of the features eliminated by data dimensionality reduction on model performance, 7 environment factors we selected with fusion method of GRA and PCA and all 9 environment factors were used to establish sap flow prediction model with CNN, GRU, LSTM and DLinear respectively. The comparison and analysis results are shown in Table 2. All the selected evaluation indexes in the table are the prediction length of 96 and the optimal look-back windows length.

Table 2. Comparison of performance for models established with 7 selected factors and all 9 factors.

Models		R^2	*MSE*	*MAE*	Spending times (s)
CNN	7 selected factors	0.7531	0.0046	0.0322	**111.44**
	All 9 factors	0.7972	0.0038	0.0306	**212.62**
GRU	7 selected factors	0.8078	0.0036	0.0295	1083.34
	All 9 factors	0.7817	0.0041	0.0302	1090.25
LSTM	7 selected factors	0.7375	0.0049	0.0335	392.63
	All 9 factors	0.7317	0.005	0.0322	483.89
DLinear	7 selected factors	**0.9568**	**0.0017**	**0.0282**	612.52
	All 9 factors	**0.9479**	**0.0019**	**0.0285**	638.76

As shown in Table 2, performance of GRU, LSTM and Dlinear based models all have a small increase after reducing the feature dimension. At the same time, the spending time also reduced after processed of data dimensionality reduction. Performance of CNN based sap flow prediction model has declined with low-dimensional features. The possible reason is that structure of CNN determines that it needs more information, after removing some features, even if the removed features have only a small amount of usable information for sap flow prediction, the weights have changed. The forgetting characteristics of LSTM and GRU make the model selectively abandon the noise information or the very weak correlation features, which leads to a little improvement for performance of model after removing the two environment factors of SWC_deep and WS. The very weak correlation features have been automatically forgotten during the model calculation process. The advantage of Dlinear model is that its direct multi-step prediction reduces the error accumulation, the linear layer combination of location strategy and trend decomposition makes the sharing of information closer which can learn more available information. In addition, trend decomposition was performed for each environment factor and sap flow, which makes the data more continuous, smooth and easy to predict. The final result is that the trend prediction and the residual sequence prediction are added with different weights. After the above operation, the relationship between the characteristics and the predicted value is more obvious, so the performance of the prediction model is improved.

3.4 Effect of Look-Back Window Length on Performance of Sap Flow Prediction Models

Suppose the length of look-back window is N, which means N records measured from closest to the current time used to predict sap flow measured at current time. Length of look-back window is a key parameter of model construction, which determines how much information the model can learn from the historical period. The influence of different look-back window lengths on performance of each prediction model is analyzed in this paper. As a result, we established sap flow prediction models with different length of look-back window using 7 and 9 factors respectively. Other parameters are consistent for each model, as shown in Table 3. Performance of models with different length of lookback window are shown in Fig. 4.

Table 3. Network parameter Settings of each model.

Parameter	Method or value
Predicted length	96
Learning rate	0.01
Optimization iteration algorithm	Adam
Loss function	MSE
Activation function	ReLu
Epochs	800

From Fig. 4, we observe the following. First, performance of the model is correlated with the length of look-back window, no matter whether the factors adopted changed (7 selected or all 9 factors) or methods used changed (CNN, GRU, LSTM or Dlinear). Second, for different networks of Dlinear, LSTM, CNN and GRU, the optimal lengths of windows is different. Specifically, when all 9 factors used, the look-back window lengths at the highest performance are 336, 720, 24 and 720 for CNN, GRU, LSTM and Dlinear based models respectively. When 7 selected factors used, the look-back window lengths at the highest performance are 48, 720, 96 and 720 for CNN, GRU, LSTM and Dlinear

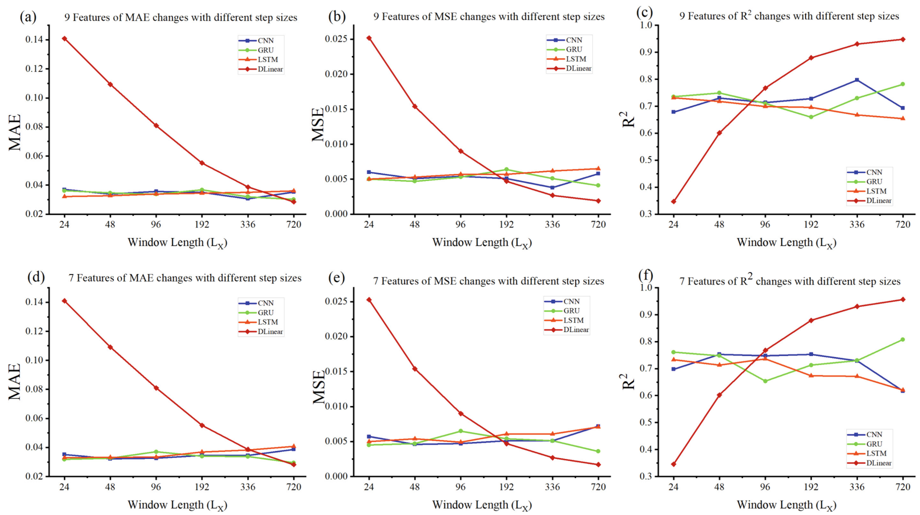

Fig. 4. Influence of different number of features and different length of look-back window on the model. This figure can compare the change trend of the model under the same number of features and the influence of different number of features on the model.

based models respectively. Third, performance trends are slightly different for models established with different factors. Performance changes of models constructed with 7 factors and 9 factors under different length of look-back windows are shown in Table 4. R^2, MSE and MAE varies between 0.0089 and −0.076, 0.0014 and −0.0026, as well as 0.0047 and −0.0044 respectively under different retrospective windows before and after data dimension reduction with different networks. In Table 4, negative numbers indicate decrease, positive numbers indicate increase, the maximum changes of R^2, MSE, and MAE are shown in black, and the minimum changes are shown in underlined.

Table 4. Changes of evaluation indexes in different lengths of look-back windows.

Models	Dlinear			LSTM			CNN			GRU		
Indexes	R^2	*MSE*	*MAE*	R^2	*MSE*	*MAE*	R^2	*MSE*	*MAE*	R^2	*MSE*	*MAE*
24	0.0010	−0.0001	0.0001	0.0014	0	0.0009	0.0191	−0.0003	−0.0017	0.0254	−0.0005	<u>−0.0044</u>
48	0.0011	0	−0.0002	−0.0049	−0.0001	0.0003	0.0228	−0.0005	−0.0016	−0.0014	0	−0.0019
96	−0.0001	0	0	0.0370	−0.0004	−0.0003	0.0337	−0.0004	−0.0031	−0.0567	0.0012	0.0033
192	0.0001	0	0	−0.0224	0.0004	0.0023	0.0253	0	−0.0006	0.0531	−0.001	−0.0028
336	0.0001	0	0	0.0030	0.0001	0.0032	−0.069	0.0013	0.0039	0.0001	0	0.0017
720	**0.0089**	−0.0002	−0.0003	−0.0342	0.0006	**0.0047**	<u>−0.076</u>	**0.0014**	0.0034	0.0261	<u>−0.0026</u>	−0.0007

3.5 Performance of DLinear with Different Prediction Window Lengths

Suppose lengths of prediction window and look-back window are M and N respectively, which means N records of environment factors measured from closest to the current time used to predict sap flow value at future moments away from the present M time intervals. Length of prediction window is important for sap flow prediction model. In order to explore the model performance changes under different prediction window lengths, we established different Dlinear based sap flow prediction models with different prediction window lengths using 7 selected factors. Among them, the length of look-back window was set as 720 which can reflect the optimal performance of the model, and the prediction lengths are set as 96, 240, 336 and 720 respectively [32, 38, 39]. The dropout is set to 0.3, the epochs is set to 300, the early-stop policy is set to 15, and other major parameters are set as shown in Table 3. Comparison and analysis for performance of models built with different prediction window lengths are shown in Table 5.

Table 5. Comparison and analysis for performance of models built with different prediction window lengths.

Prediction length	R^2	*MSE*	*MAE*
96	**0.9568**	**0.0019**	**0.0285**
240	0.9262	0.0028	0.0302
336	0.903	0.0037	0.0435
720	0.8142	0.0069	0.0667

Results shown that performance of models gradually decreases with the increase of prendition length. When the predicted length is 720, which means the future sap flow at 15 days from the current moment was predict, the R^2 is lowest with 0.8142, the MSE and MAE is the largest with 0.0069 and 0.0667 respectively. When the prediction length set as 96, which means the model predict the future sap flow at 2 days from the current moment, R^2 of this model is highest with 0.9568, the MSE and MAE is the smallest with 0.0019 and 0.0285 respectively. Figure 5 shows sap flow values of predicted with models and measured with sensors in different prediction lengths. Due to the large difference between the maximum and minimum sap flow values, the normalized data is selected for plotting.

From Fig. 5 we can see that the model fit degree gradually decreases with the increase of the predicted length, and the model fit degree is the lowest when the predicted length is 720 and the model fit degree best when the predicted length is 96. The possible reason is that the increase of the length of prediction window makes the amount of required information larger. However, there is a certain phenomenon of information loss in the path of information acquisition, and noise and sequence decomposition are the important factors causing this phenomenon. Although the R^2 of the Dlinear model failed to reach 0.9 in the prediction of the future 15 days, it proves the applicability of the new baseline Dlinear algorithm for establishment of sap flow prediction model. This algorithm can used to built new convenient time series prediction model, and more time can be invested in its research to fully develop the model potential.

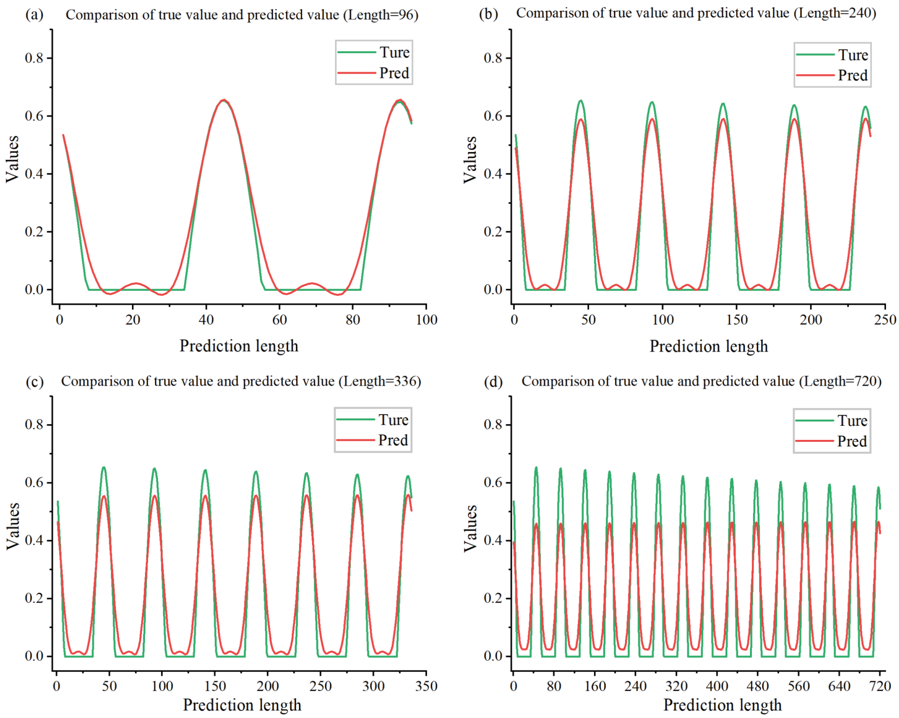

Fig. 5. Comparison of measured sap flow values and predicted sap flow values of different prediction lengths.

4 Discussion

Although the performance of different deep learning algorithms is different, it is not a denial of them, but whether the application field of the model affects its performance. This study mainly discusses from four aspects.

First, six sap flow prediction models were established with algorithms of Dlinear, CNN, GRU, LSTM, Transformer and Informer respectively. Results shown that although Transformer and Informer algorithms have excellent performance in natural language processing, image processing, power and transportation, etc., they perform poorly in this study. The R^2 of Dlinear based model is the best, whch 20.37%, 21.93% and 14.9% higher than CNN, LSTM and GRU based models, respectively. In terms of time consumption, Dlinear model only takes less time than GRU. Although previous models can be used in combination to get a good effect, there is a simple and convenient algorithm of Dlinear, so why not use? Therefore, in the selection of algorithm to establish sap flow prediction model, we should first consider the impact of environmental factors, physiological structure of the plant itself and life characteristics on model performance, and then consider whether the application field is the cause of model performance decline.

Second, environment factors were selected with fusion method of Pearson correlation analysis and Grey relational analysis. Results shown that there are consistent in feature selection of PCA and GRA, but there are some differences in the interpretability between factors. Performance of LSTM, GRU and Dlinear based models established with factors selected with PCA and GRA are slightly higher than models established with all 9 environment factors. While it is obviously that there is less computation and less spending time of models built with fewer factors. Different factor selected methods should be compared and analyzed for further studies.

Third, effect of look-back windows length was analyzed in this study. Results shown that there has great influence on performance of models established with different length of look-back windows. Dlinear algorithm adopts the direct multi-step prediction method, and the model performance improves with the increase of the length of look-back windows, while the performance of CNN, LSTM and GRU based models decreases first and then improves or improves first and then decreases. This phenomenon may caused by the model network structure, which also indicates that the Dlinear method has high reliability for prediction of sap flow, especially for short-term prediction of 1 to 5 days, which also confirms the argument in the paper that the correlation capture is stronger under the short path [32].

Fourth, effect of prediction window length was compared and analyzed in this paper. Results shown that the performance of Dlinear based model gradually declines with the increase of the prediction length. The possible reason for this result is not only that the model has not been fully verified for correct application, but also the shortcomings of trend decomposition and direct multi-step prediction. Trend decomposition can make the data smoother, which is convenient for prediction, but at the same time, part of the information will be lost. However, the disadvantage of Dlinear is that the required information will increase with the increase of the prediction length, which leads to the error of the model when predicting the longer time.

In short, the Dlinear based model has high applicability in sap flow prediction, which provides a simple and convenient method for tree water consumption, evaporation and hydrology. At the same time, it provides a new model idea for sap flow prediction. For example, the Dlinear model sets a linear layer based on a new baseline for each variable, which is similar to Channel Independent (CI), that is, multiple sequences are regarded as a single variable prediction and each variable is modeled separately. Recently, Lu et al. studied the gap between Channel Independent (CI) and Channel Dependent (CD), and found that MAE, MSE and other indicators of CI method were lower than those of CD method in most prediction tasks through multiple data set experiments [43]. The core conclusion mentioned in this paper is that real data tend to have Distribution Drift, and CI method is helpful to alleviate this problem and improve model generalization [43]. Different from Channel Independent, there is a certain correlation between Dlinear network structure, which is more in line with the mutual influence relationship between natural environments. Although trend decomposition may cause some information loss, it is also worth considering whether it can be applied in traditional time series prediction algorithms of LSTM and GRU. For example, when inputting data after trend decomposition, the operation time of forgetting layer can be reduced to improve the operation efficiency.

5 Conclusion

The new baseline model Dlinear algorithm shows reliable and efficient performance in sap flow prediction, even under the influence of different look-back windows. At the same time, the direct multi-step prediction strategy has a good effect on short-term sap flow prediction, but it still has a large room for improvement in long-term sap flow prediction. In the further studies, the network structure will be improved (based on the combination of time sequence and linear layers) to adapt to the data-type time series in nature, hoping to achieve a higher degree of fit, or adjust the decomposition intensity to make the trend and seasonality of data more obvious, the connection between data more clear, and reduce the spending time. In addition, the following issues need to be further discussed in further researches. First, the dataset is only available for one year. Second, only environmental factors were considered in this study, other factors, such as tree characteristics, physiological structure and woodland density, should be considered.

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