WOOD RESEARCH doi.org/10.37763/wr.1336-4561/67.5.875887
e-ISSN 2729-8906
67(5): 2022 875-887 pp.

A DEEP LEARNING PROGRAM FOR PREDICTING SAP FLOW OF *LARIX OLGENSIS*

YANWEN ZHANG, ZIXUAN WANG, ZHIHU SUN, JIANPING HUANG
NORTHEAST FORESTRY UNIVERSITY
P. R. CHINA

(RECEIVED APRIL 2022)

ABSTRACT

Plant sap flow is crucial to understanding plant transpiration, plant hydraulic functioning and physiological properties. In this study, a method for predicting trunk sap flow of *Larix olgensis* using deep learning was proposed. The method is based on the combined use of Long-short term memory network (LSTM) and transformer model, noted as LSTM-transformer model. The experimental results show that the proposed method provides more accurate prediction quality in terms of correlation coefficient (R^2), root mean square error (RMSE) and mean absolute error (MAE), compared to the state of the art forecast methods such as BP, DNN, LSTM, and transformer models.

KEYWORDS: *Larix olgensis*, stem sap flow density, sap flow prediction, LSTM-transformer model.

INTRODUCTION

Trunk sap density is an important factor affecting plant transpiration and can be an accurate long-term reflection of plant trunk transpiration. Trunk sap density results from water loss from leaves due to transpiration, allowing plant roots to absorb soil water and transport water through the xylem of the trunk to the leaves. Accurate measurement of trunk sap density is essential for the analysis of plant water consumption patterns, ecosystem water cycles, and the evaluation of water use in terrestrial ecosystems (Si et al. 2005). However, direct measurements of trunk sap density are time consuming and high labour consumption (Roy et al. 2022). Therefore, it is crucial to develop a model for predicting trunk sap flow density.

Rosa et al. (2012), Wang et al. (2016) used the SIMDualKc model to estimate transpiration. Jiang et al. (2016) proposed a Multiple linear regression (MLR) model to analyze evapotranspiration and sap flow variation in hybrid maize. Whitley et al. (2013) used modified

Jarvis-Stewart (MJS) and MLR models to estimate trunk sap flow density. Vishwakarma et al. (2022) used 30 empirical models to estimate plants transpiration in subtropical India, although estimations of transpiration and sap flow was achieved to some extent, empirical or physically based models required a large number of observations, and more importantly, it was difficult to achieve a complex regression process between transpiration and trunk sap flow determined by many variables.

To overcome the limitations of traditional statistic methods, the machine learning has become a widely used method. Zheng et al. (2021) proposed a whale-optimized Support vector machine (SVM) model based on maize transpiration, and the results showed that the SVM-WOA model was more effective than the MLP model in prediction. Granata et al. (2020) evaluated the applicability of random forest, ARDS, MLP and KNN in estimating sap flow in US wetlands and found that RF and KNN models were slightly better than ARDS and MLP models. Artificial neural network was used to predict sap flow of pear trees based on climatic factors and soil moisture (Liu et al. 2009), the results showed that the prediction accuracy of the ANN model was better than that of the traditional MLR prediction model. Tang et al. (2018) proposed a GANN model with two additional variables, leaf area index and plant height, to estimate maize sap flow, and showed that using both environmental factors and maize growth data as input variables could improve accuracy. Elbeltagi et al. (2022) developed an MLP-ANN to estimate sap flow in the Beas-Sutlej basin, and the prediction accuracy was significantly improved.

Among various ANNs, the back-propagation neural network or its modified form has been considered as one of the most popular methods. Tu et al. (2019) used back-propagation artificial neural network model to estimate the trunk sap flow of *Pinus sylvestris*, and showed that the accuracy of the model was higher than that of the model without the incorporation of the phenological index. Han et al. (2021) built a three-layer BP models trained by the Levenberg-Marquardt algorithm and added crop coefficients and precipitation as input variables, the results showed that the BP model was more effective in areas with sufficient precipitation. Han et al. (2020) proposed the models for water consumption with back propagation neural network (BPNN) and Elman neural network (ENN) based on fuzzy rules, the results of ENN model showed that the relative error was reduced by 27.0% compared with the BP neural network model.

Recently, deep learning has emerged as a new approach for predicting trunk sap flow. Elbeltagi et al. (2020) used Deep neural network (DNN) to predict crop sap flow values in semi-arid areas, and the prediction results reached 0.95, 0.96, and 0.97 in three provinces. Elbeltagi et al. (2020) used DNN model to simulate the water footprint of maize and wheat, the results showed that DNN models are good for predicting water footprints using historical data.

RNN networks have also become a widespread approach due to their unique information memory capabilities. Feng et al. (2017) used ELM and generalized regression neural network (GRNN) models to estimate maize transpiration on the Loess Plateau in China based on climate variables, LAI and plant height, the experimental results showed that the ELM and GRNN models can accurately estimate maize sap flow using both climate and crop data as inputs. Roy et al. (2021) proposed a subtropical evapotranspiration prediction model based on Bi-LSTM, the results showed that Bi-LSTM was more effective than SSR-LSTM and LSTM networks. Roy et al. (2022) proposed daily and multi-step forward-looking predictions of evapotranspiration based on Bi-LSTM, and the results showed that deep learning models (LSTM and Bi-LSTM) were more effective than classical methods in transpiration prediction problems. Chen et al. (2020) combined two feature engineering methods, principal component analysis and maximum information coefficient, to build a temporal convolution network (TCN) for predicting maize transpiration, and their experimental results showed that the coefficients of determination using the TCN network were higher than those of the LSTM and DNN networks. Xie et al. (2020) used LSTM model to predict transpiration in citrus orchards and found that the LSTM model had high accuracy with different number of input features.

Several studies have been predicting the sap flow denstity of trunk, or predicting sap flow based on machine learning and deep learning. But there is a lack of studies on predicting sap flow of trunks such as *Larix olgensis* using deep learning. Therefore, the objectives of the present study were to: *(1)* explore the applicability of BP, DNN, LSTM and transformer models for trunk sap flow prediction in *Larix olgensis*; *(2)* propose the LSTM-transformer prediction model which can improve the accuracy of trunk sap flow prediction in *Larix olgensis.*

MATERIAL AND METHODS

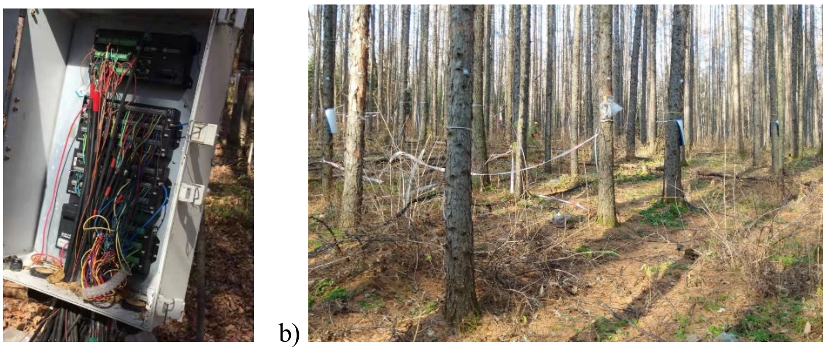
Site description

In this study, a five-month (2020.4-9) experiment was conducted on *Larix olgensis* in Mengjiagang Forestry, Jiamusi City, Heilongjiang Province (130°32′42″E - 130°52′36″E, 46°20′16″N - 46°30′50″N). This region experiences an East Asian continental temperate monsoon climate with annual precipitation ranges between 450 mm and 550 mm, annual temperature of around 2.7°C to 3.5°C and extremes that can reach a maximum of 35.6°C and a minimum of -34.7°C. The annual sunshine hours are around 1955 h and the annual frost-free period is around 116 to 125 days (Shao et al. 2017). The soil is classified as brown loam, white pulpy, meadow, boggy and peat soils. The most widely distributed soil is typical dark brown loam, followed by white pulpy dark brown, and a small amount of submerged dark brown, primitive dark brown and meadow dark brown loams (Zhou et al. 2019). Six *Larix olgensis* of good growth and similar morphology were selected as experimental samples. 32 years old, the diameter at breach height 13.98 ± 3.67 cm, the average tree height is 19.12 ± 2.82 m and the average crown width is 2.78 ± 0.79 m.

Environmental variables and *Larix olgensis* transpiration measurement

Vapor pressure deficit (VPD), air humidity, solar radiation, temperature, soil water content and soil temperature were recorded by climate factor monitoring stations which were recorded at 10 min intervals. The ZDR-20 probe was buried at a depth of 20 cm on the upper and lower slopes of the sample plots to determine the soil water content and soil temperature.

Sap flow rates of *Larix olgensis were* monitored using TDP sensors. Six *Larix olgensis* were chosen for sap flow measurements from April 1st to August 31st. The sensor was placed on the north side of the experimental sample, at a height of 1.3 m from the ground. The rough bark on the surface of *Larix olgensis* was scraped off to expose the fresh wood which can ensure that the pressure would not cause the bark to produce sap flow during the experiment. The holes were then drilled vertically to a depth of 2 cm using a specific size drill. The heating probe is placed at the top and two TDP probes are inserted into the tree sapwood in sequence. The contact between the probes and *Larix olgensis* was sealed with silicone, thus avoiding thermal influences. Aluminium foil is also wrapped around the outside to protect the sensors from rain. Finally, connect the TDP probe to the CR1000X data collector. The physical diagram of the trunk sap collection is shown in Fig. 1.



a) b)

Fig. 1: The physical diagram of the trunk sap collection: (a) data collector, (b) physical view of sap flow collection.

Sap flux density can be formulated by Granier (1988) (Eq. 1) and VPD by Zhang et al. (2014) (Eq. 2):

$$J_s = 11.9\left(\frac{\Delta T_m - \Delta T}{\Delta T}\right)^{1.231} \tag{1}$$

where: J_s is instantaneous sap flow density (g·m^{-2}·s^{-1}), which meant liquid flow per unit time through unit sapwood area; ΔT_m is maximum temperature difference between day and night, ΔT is instantaneous temperature difference, and ΔT_m is determined with a 10 min intervals.

$$VPD = 0.611 \times (1 - RH) \times e^{\left[\frac{17.502T}{T+240.97}\right]} \tag{2}$$

where: VPD - vapor pressure deficit (-), T is the atmospheric temperature (°C), and RH is the relative atmospheric humidity (%).

LSTM-transformer

In this paper, a model combined the LSTM and transformer network model was proposed for prediction of trunk sap flow density in *Larix olgensis*. This provides access to both the sequential relationships of the LSTM network capturing temporal information and the transformer's ability to model the relationships at time steps, which can improve the accuracy of the predictions. The proposed model in this paper is referred to as the LSTM-transformer. The architecture of the proposed method as illustrated in Fig. 2. The input was the sap flow and environmental factors, the length and timestamp of the series can be defined, then the time series were input into the LSTM and transformer networks for feature extraction. The input variables were extracted for the sequence and the time step information features, two hidden features were spliced into a vector as the final feature for the sap flow density. The Dense layer took the previously extracted features and extracted the correlations between the features after non-linear changes. The Dropout layer served to prevent overfitting, the loss function was chosen as MSE, the optimizer was chosen as Adam and the activation function was chosen as ReLU.

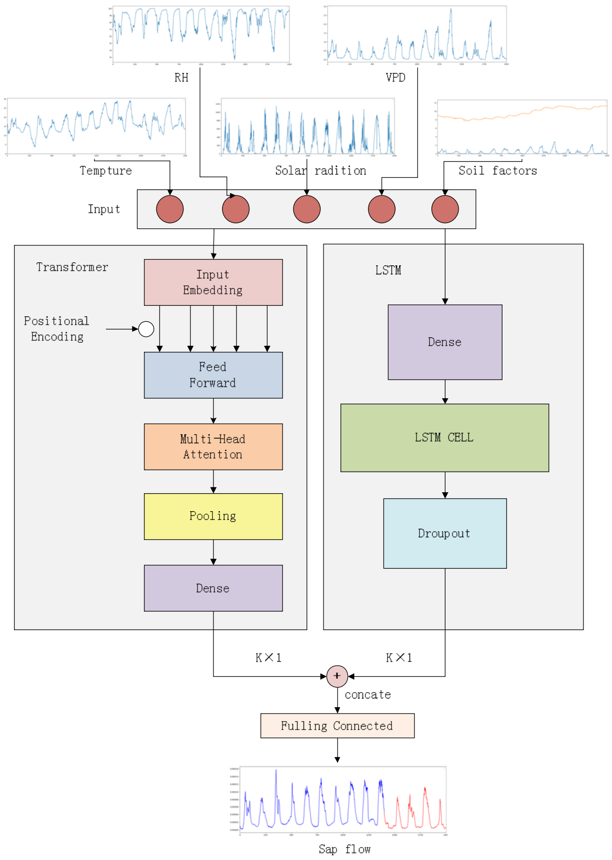


Fig. 2: The architecture of the proposed method.

Long short-term memory network (LSTM) was proposed by Hochreiter (Hochreiter and Schmidhuber 1997) in 1997 as a special variation of RNN network, which can well solve the stability and accuracy of long-term dependency relationship problem. The structure diagram of LSTM network is shown in Fig. 4. The core idea of LSTM is the introduction of cell state, which can transfer sequence relevant information during processing all the way through and overcome the effect of short term memory. The LSTM network is set up with three gate structures of input, output and forget gates to add and remove information respectively, and can learn which information is saved or forgotten during the training process. Zhu (2019) showed that LSTM networks can effectively capture time-series features with different inputs. Wu (2020) showed that complex dependencies of various lengths can be learned from time-series data using a self-attentive mechanism. This transformer model-based approach is a general-purpose approach for modelling various nonlinear dynamic systems framework. Due to the special structure of the LSTM network memory cells are able to input sequential data in a sequential order. The output state of each time step is influenced by both the input of the current time step and the output of the previous time step, thus allowing sequential features to be extracted. But this special structure also makes it possible for some information to be lost in the information transfer, parallel operations are not possible in LSTM networks. Based on the connections shown in Fig. 3a, the LSTM cell can be mathematically expressed as follows:

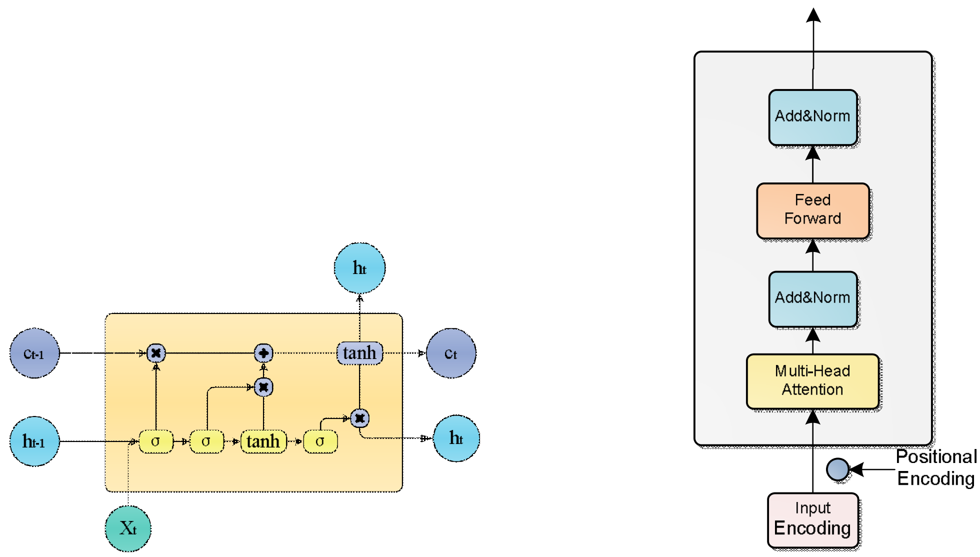


Fig. 3: a) Architecture of LSTM, b) architecture of encoder.

The transformer model was first proposed by the Google team (Vaswani et al. 2017) for the machine translation problem. Transformer model discards the traditional way of extracting sequence information from neural networks and proposes to use attention mechanism for parallel computing, which improves the traditional recurrent neural network training. The stronger long-term dependency modelling capability works better on long sequences. As is mentioned earlier, the RNN-based approach cannot completely eliminate the problem of gradient disappearance and gradient explosion for long sequences, but the transformer architecture can solve this problem. The transformer model, which is able to perform parallel operations and model the relationship between time steps, can compensate for the shortcomings of the LSTM networks. Therefore, some scholars proposed a network framework in which two network models are serial. The transformer model mainly consists of encoder and decoder. But for the sap flow prediction in this paper, which is a time-series deep learning characterisation problem, the encoder can perform the function very well, so the decoder part is not used in this study. This paper focuses on the transformer encoder structure for analysis, and its structure diagram is shown in Fig. 3b.

Experimental setup

In this study, all the experiments were performed with Jupyter Notebook software and Python 3.7.10 on a laptop equipped with the CPU was Intel(R) Core(TM) i5-6300HQ, 2.30GHz processor, the RAM was 16GB.

The dataset was divided into training, validation and test sets at 8:1:1. Due to different dimensions and greater magnitude of value in the input variables, to standardizing the values of the input variables was necessary before training the neutral network. All the input values were standardized into (0, 1) with respect to the maximum and minimum values. The training parameters were set as follows: the time step size was 5, the learning rate was 0.001, the dropout coefficient was 0.1, the maximum number of iterations was 1000, and the batch size was 256. Moreover, an early stopping strategy was adopted in the training phase, the model was stopped if the validation error did not drop in the last ten steps during the training process.

To evaluate the performance of the proposed method (LSTM-transformer), we compared with the methods commonly used in stem sap flow density prediction, including BP, DNN, LSTM and Transformer methods. The performances of proposed method for predicting sap flow of *Larix olgensis* were evaluated by three widely used statistical indicators, i.e. correlation coefficient (R^2), root mean square error (RMSE), and mean absolute error (MAE).

Correlation coefficient is formulated by Eq. 3, RMSE and MAE are defined by Eq. 4 and Eq. 5, respectively:

$$R^2 = \frac{\left[\sum_{i=1}^{n}(a_i - \tilde{a}_i)(s_i - \tilde{s}_i)\right]^2}{\sum_{i=1}^{n}(a_i - \tilde{a}_i)^2 \sum_{i=1}^{n}(s_i - \tilde{s}_i)^2} \tag{3}$$

$$RMSE = \sqrt{\frac{1}{n}\sum_{i=1}^{n}\left(s_i - a_i\right)^2} \tag{4}$$

$$MAE = \frac{1}{n}\sum_{i=1}^{n}\left|s_i - a_i\right| \tag{5}$$

where: α_i is the measured sap flow, s_i is the predicted sap flow, $\tilde{a}_i$ is the averaged measured sap flow, and $\tilde{s}_i$ is the averaged predicted sap flow. The higher R^2 (close to 1) and lower values of RMSE and MAE indicate the high predictive accuracy of the trunk sap flow model.

RESULTS AND DISCUSSION

Visual comparisons

BP and DNN models, which are traditional models for sap flow prediction, were chosen to compared with deep learning models. As can be seen from Fig. 5, the LSTM and transformer models fitted significantly better than the BP and DNN models. The BP model fitted the worst, with the largest difference between predicted and measured values. The DNN network showed a large error in prediction when the trunk sap flow fluctuated (e.g. sample number 300-500 in Fig. 5). The LSTM and transformer models fitted better, while the transformer model fitted better when the trunk sap flow was rising and falling, but the predictions showed large fluctuations and errors in the low part of the sap flow.

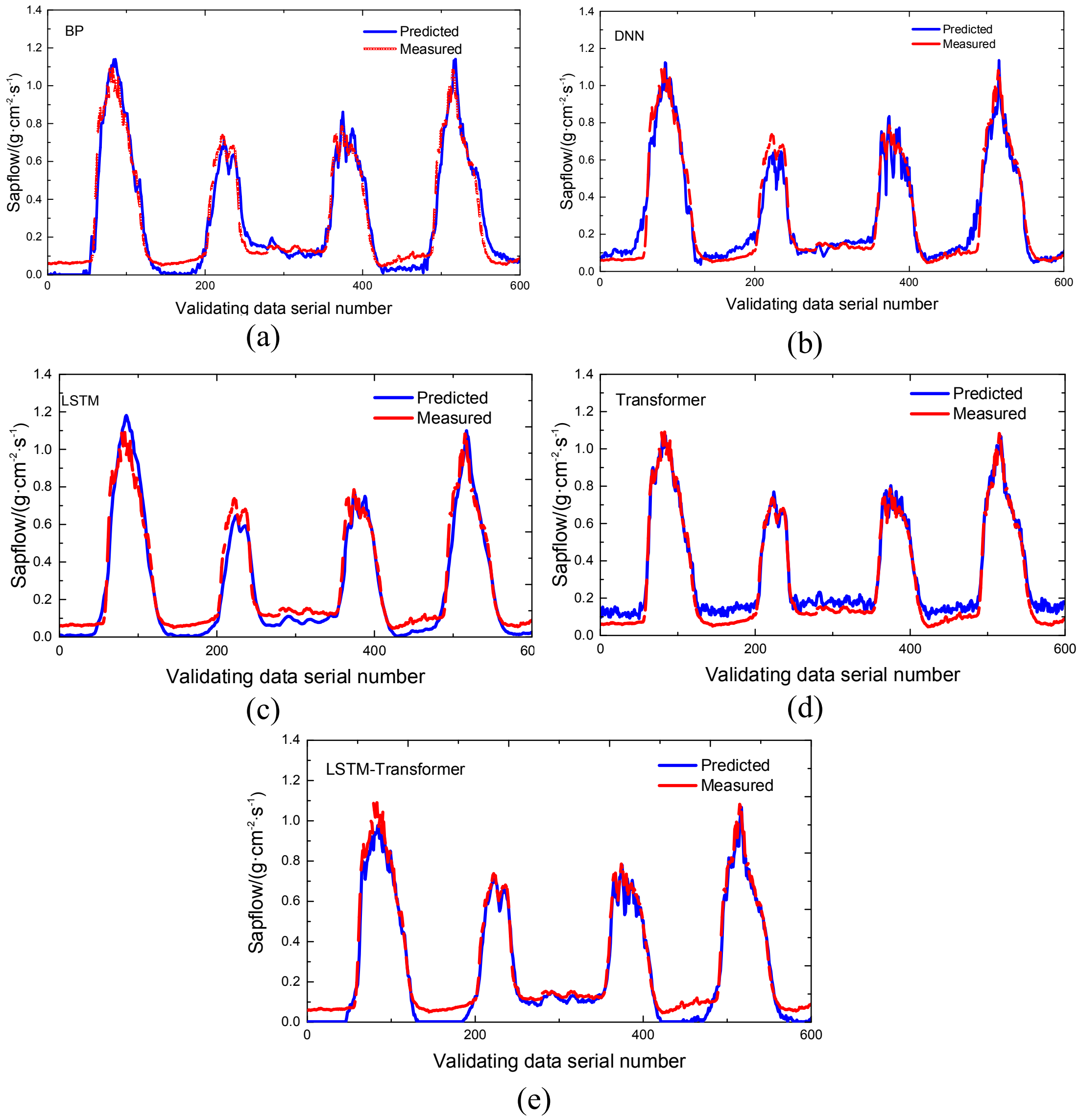


Fig. 5: Goodness of fits between the measured and predicted sap flow density by BP, DNN, LSTM, Transformer and LSTM-transformer.

Quantitative comparison

The scatter plots of sap flow of *Larix olgensis* prediction by BP, DNN, LSTM and Transformer models against their corresponding measured values in the testing data are given in Fig. 6. As observed, machine learning showed a lower dipersion degree of data points, as compared with deep learning models. It is clearly seen that, the deep learning model predicts the smallest distribution difference of measured and predicted sap flow. The proposed method (LSTM-transformer model) (R^2 = 0.955, RMSE = 6.70, MAE = 5.29 during testing) achieves the best performance than LSTM and transformer models. Compared to the LSTM model and the transformer model, the prediction accuracy of the LSTM-transformer model increased by 1.6% and 1.4%. Obviously, the LSTM-transformer model was more suitable for sap flow of *Larix olgensis* prediction due to the LSTM-transformer model can model complex nonlinear relationships between sap flow and environmental factors.

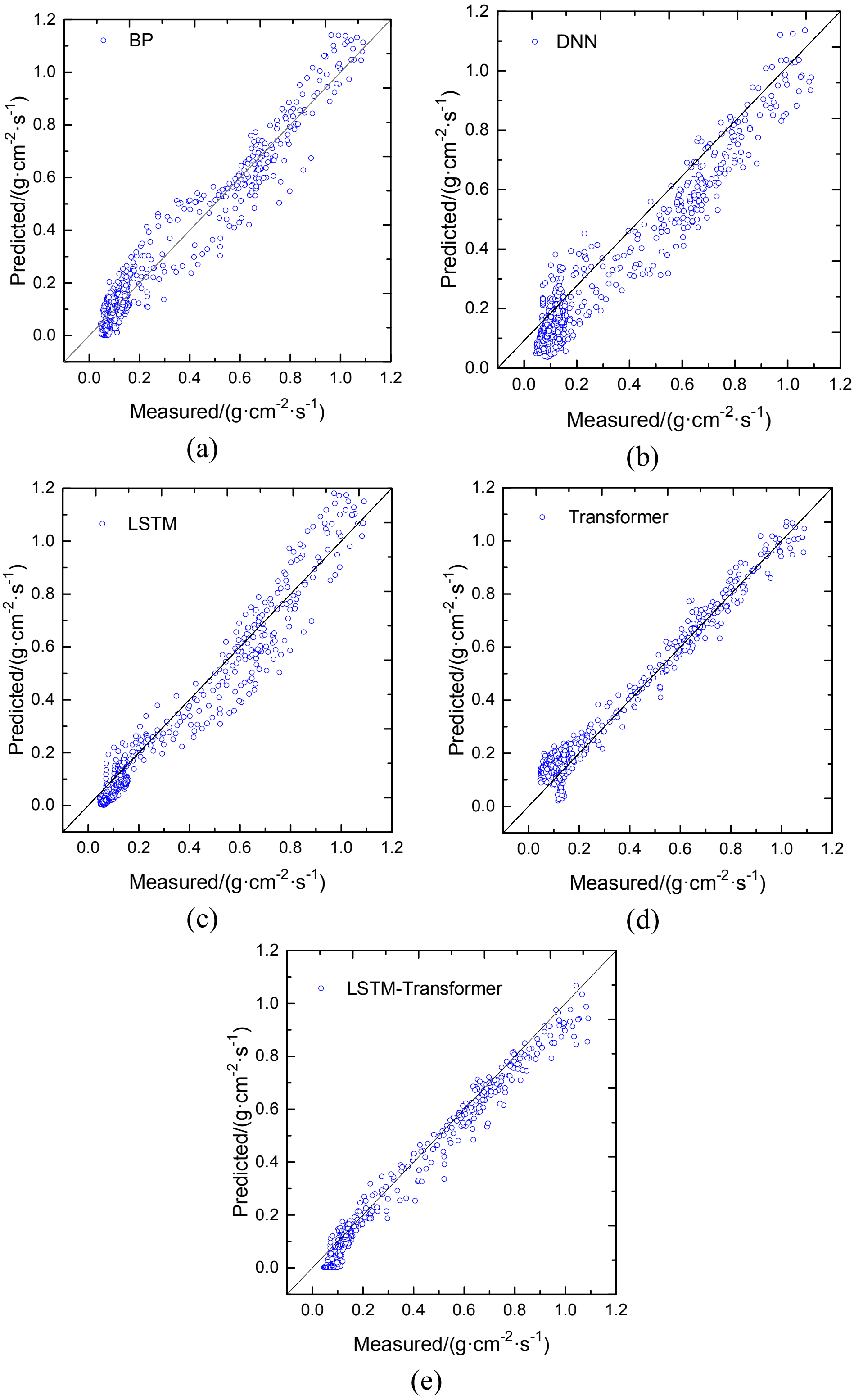


Fig. 6: Scatter plots of measured and predicted Larix olgensis transpiration by BP, DNN, LSTM, transformer and LSTM-transformer.

The statistical results are presented in Tab. 1. As shown the table, estimated sap flow of *Larix olgensis* differed among BP, DNN, LSTM and transformer models. It was cleared that transformer model exhibited the best estimation accuracy during testing (R^2 = 0.955, RMSE = 6.70, MAE = 5.29). LSTM model (R^2 = 0.953, RMSE = 6.77, MAE = 5.03 during testing) slightly outperformed DNN model (R^2 = 0.932, RMSE = 8.18, MAE = 5.99 during testing), followed by BP model (R^2 = 0.918, RMSE = 9.0, MAE = 6.87 during testing). Compered to BP model, the estimation accuracy of DNN, LSTM and transformer models increased by 4%, 2.5% and 0.2% in terms of R^2. Obviously, the transformer model was more suitable for sap flow of *Larix olgensis* prediction due to attention mechanisms was better to capture complex dynamic patterns. And then, DNN model was better than BP model due to DNN model structure with multi-level feature extraction, which can extract features better than BP model, LSTM model was better than BP and DNN models due to LSTM model can effectively capture sequence information and remove certain redundant information.

While BP networks and DNN networks, common methods in the field of sap flow prediction, are able to predict stem sap flow density, this paper finds that predictions can be made more effectively using deep learning models. Although the LSTM network is widely used in stem sap flow density prediction and is able to obtain good predictions, it was less effective compared to the transformer model. The LSTM-transformer model proposed in this paper was more effective than the above models in predicting the sap flow density of *Larix olgensis*.

Tab. 1: Statistical values of BP, DNN, LSTM, transformer and LSTM-transformer models during testing under various input combinations.

Model	R^2	RMSE	MAE
BP	0.918	9.0	6.87
DNN	0.932	8.18	5.99
LSTM	0.953	6.77	5.03
Transformer	0.955	6.70	5.29
LSTM-Transformer	**0.968**	**5.67**	**4.14**

CONCLUSIONS

This work has proposed an efficient method for forecasting sap flow of *Larix olgensis* using the LSTM and transformer model. The results showed that the LSTM and transformer models outperformed the BP and DNN models in predicting *Larix olgensis* sap flow density; the coefficients of determination of the LSTM and transformer models reached 0.953 and 0.955, which were 3.8% and 4.03% higher compared to the BP model, 2.25% and 2.47% higher compared to the DNN model. The coefficient of determination of the combined the LSTM-transformer model reached 0.968, which was 1.6% and 1.4% higher than that of the LSTM and transformer models. The results illustrate that the combined LSTM-transformer model can achieve accurate prediction of sap flow density in *Larix olgensis*.

ACKNOWLEDGEMENTS

This research is partially supported by the National Natural Science Foundation of China (31770670) and the Natural Science Foundation of Heilongjiang Province of China (Grant No. TD2020C001), The authors have no conflict of interest to declare.

REFERENCES

1. Si, J.H., Feng, Q., Zhang, X.Y., Zhang, Y.W., Su, Y.H., 2005: Research progress on surveying and calculation of evapotranspiration of plants and its prospects. Advances in Water Science 03: 450-459.
2. Roy, D.K., Sarkar, T.K., Kamar, S.S.A., Goswami, T., Muktadir, M.A., AI-Ghobari, H.M., Alataway, A., Dewidar, A.Z., EI-Shafei, A., Mattar, M.A., 2022: Daily prediction and multi-step forward forecasting of reference evapotranspiration using LSTM and Bi-LSTM models. Agronomy 12(3): 594.
3. Rosa, R.D., Paredes, P., Rodrigues, G.C., Alves, I., Fernando, R.M., Pereira, L.S., Allen, R.G., 2012: Implementing the dual crop coefficient approach in interactive software. 1. Background and computational strategy. Agricultural Water Management 103: 8-24.
4. Wang, Z.S., Cai, H.J., Yu, L.Y., Wang, X.W., Shi, X.H., 2016: Estimation of evapotranspiration and soil evaporation of winter wheat in arid region of Northwest China based on SIMDualKc model. Transactions of the Chinese Society of Agricultural Engineering 32(5):126-136
5. Jiang, X.L., Kang, S.Z., Li, F.S., Du, T.S., Tong, L., Comas, L., 2016: Evapotranspiration partitioning and variation of sap flow in female and male parents of maize for hybrid seed production in Arid region. Agricultural Water Management 176: 132-141.
6. Whitley, R., Taylor, D., Macinnis-Ng, C., Zeppel, M., Yunusa, I., O'Grady, A., Froend, R., Medlyn, B., Eamus, D., 2013: Developing an empirical model of canopy water flux describing the common response of transpiration to solar radiation and VPD across five contrasting woodlands and forests. Hydrological Processes 27(8): 1133-1146.
7. Vishwakarma, D.K., Pandey, K., Kaur, A., Kushwaha, N.L., Kumar, R., Ali, R., Elbeltagi, A., Kuriqi, A., 2022: Methods to estimate evapotranspiration in humid and subtropical climate conditions. Agricultural Water Management 261: 107378.
8. Zheng, J., Fan, J.L., Zhang, F.C., Wu, L.F., Zou, Y.F., Zhuang, Q.L., 2021: Estimation of rainfed maize transpiration under various mulching methods using modified Jarvis-Stewart model and hybrid support vector machine model with whale optimization algorithm. Agricultural Water Management 249: 106799.
9. Granata, F., Gargano, R., de Marinis, G., 2020: Artificial intelligence based approaches to evaluate actual evapotranspiration in wetlands. Science of the Total Environment 703: 135653.
10. Liu, X., Kang, S., Li, F., 2009: Simulation of artificial neural network model for trunk sap flow of *Pyrus pyrifolia* and its comparison with multiple-linear regression. Agricultural Water Management 96(6): 939-945.
11. Tang, D.H., Feng, Y., Gong, D.Z., Hao, W.P., Cui, N.B., 2018: Evaluation of artificial intelligence models for actual crop evapotranspiration modeling in mulched and non-mulched maize croplands. Computers and Electronics in Agriculture 152: 375-384.
12. Elbeltagi, A., Kumar, N., Chandel, A., Arshad, A., Pande, C.B., Towfiqul Islam, A.R., 2022: Modelling the reference crop evapotranspiration in the Beas-Sutlej basin (India): An artificial neural network approach based on different combinations of meteorological

data. Environmental Monitoring and Assessment 194(3): 1-20.
13. Tu, J., Wei, X.H., Huang, B.B., Fan, H.B., Jian, M.F., Li, W., 2019: Improvement of sap flow estimation by including phenological index and time-lag effect in back-propagation neural network models. Agricultural and Forest Meteorology 276: 107608.
14. Han, X., Wei, Z., Zhang, B.Z., Li, Y.N., Du, T.S., Chen, H., 2021: Crop evapotranspiration prediction by considering dynamic change of crop coefficient and the precipitation effect in back-propagation neural network model. Journal of Hydrology 596: 126104.
15. Han, Y.G., Gao, Y., Han, L., Huang, X.Y., 2020: Modeling water consumption of *Populus bolleana* by artificial neural network based on fuzzy rules. Chinese Journal of Applied Ecology 31(05): 1525-1534.
16. Elbeltagi, A., Deng, J.S., Wang, K., Malik, A., Maroufpoor, S., 2020: Modeling long-term dynamics of crop evapotranspiration using deep learning in a semi-arid environment. Agricultural Water Management 241: 106334.
17. Elbeltagi A, Aslam M R, Malik A, Mehdinejadiani, B., Srivastava, A., Bhatia, A.S., Deng, J.S., 2020: The impact of climate changes on the water footprint of wheat and maize production in the Nile Delta, Egypt. Science of the Total Environment 743: 140770.
18. Feng, Y., Gong, D.Z., Mei, X.R., Cui, N.B., 2017: Estimation of maize evapotranspiration using extreme learning machine and generalized regression neural network on the China Loess Plateau. Hydrology Research 48(4): 1156-1168.
19. Roy, D.K., 2021: Long short-term memory networks to predict one-step ahead reference evapotranspiration in a subtropical climatic zone. Environmental Processes 8(2): 911-941.
20. Chen, Z.J., Sun, S.J., Wang, Y.X., Wang, Q.Y., Zhang, X.D., 2020: Temporal convolution-network-based models for modeling maize evapotranspiration under mulched drip irrigation. Computers and electronics in agriculture 169: 105206.
21. Xie, J.X., Gao, P., Sun, D.Z., Chen, W.B., Chen, S.N., Wang, W.X., 2020: Modeling on prediction of evapotranspiration of citrus orchard based on LSTM. Transactions of the Chinese Society for Agricultural Machinery 51(S2): 351-356.
22. Shao, Y.N., Tian, S.Y., Liu, Y.K., Chen, Y., Sun, Z.H., 2017: Effects of density control on soil respiration in Larix olgensis plantation. Journal of Beijing Forestry University 39(06): 51-59.
23. Zhou, T., Wang, C.K., Zhou, Z.H., Sun, Z.H., 2019: Effects of thinning on soil carbon and nitrogen fractions in a *Larix olgensis* plantation. Chinese Journal of Applied Ecology 30(05): 1651-1658.
24. Granier, A., 1988: Evaluation of transpiration in a Douglas-fir stand by means of sap flow measurements. Tree Physiology 3(4): 309-320.
25. Zhang, H., Wu, B., Yan, N., 2014: Remote sensing estimates of vapor pressure deficit: An overview. Advances in Earth Science 29(05): 559-568.
26. Hochreiter, S., Schmidhuber, J., 1997: Long short-term memory. Neural computation 9(8): 1735-1780.
27. Zhu, X.L., Fu, B.F., Yang, Y.D., Ma, Y., Hao, J.Y., Chen, S.Q., Liu, S., Li, T.G., Liu, S., Guo, W.M., Liao, Z.Y., 2019: Attention-based recurrent neural network for influenza epidemic prediction. BMC Bioinformatics 20(18): 1-10.

28. Wu, N., Green, B., Ben, X., O'Banion, S., 2020: Deep transformer models for time series forecasting: The influenza prevalence case. arXiv preprint arXiv: 200108317.
29. Vaswani, A., Shazeer, N., Parmar, N., Uszkoreit, J., Jones, L., Gomea,A.N., Kaiser, L., Polosukhin, I., 2017: Attention is all you need, proceedings of the Advances in neural information processing systems.

YANWEN ZHANG, JIANPINGHUANG*
NORTHEAST FORESTRY UNIVERSITY
SCHOOL OF MECHANICAL AND ELECTRICAL ENGINEERING
HARBIN 150040
CHINA

ZIXUAN WANG, ZHIHU SUN
NORTHEAST FORESTRY UNIVERSITY
SCHOOL OF FORESTRY
HARBIN 150040
CHINA
*Corresponding author: jphuang@nefu.edu.cn