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Evaluation of water flux predictive models developed using eddy-covariance observations and machine learning: a meta-analysis

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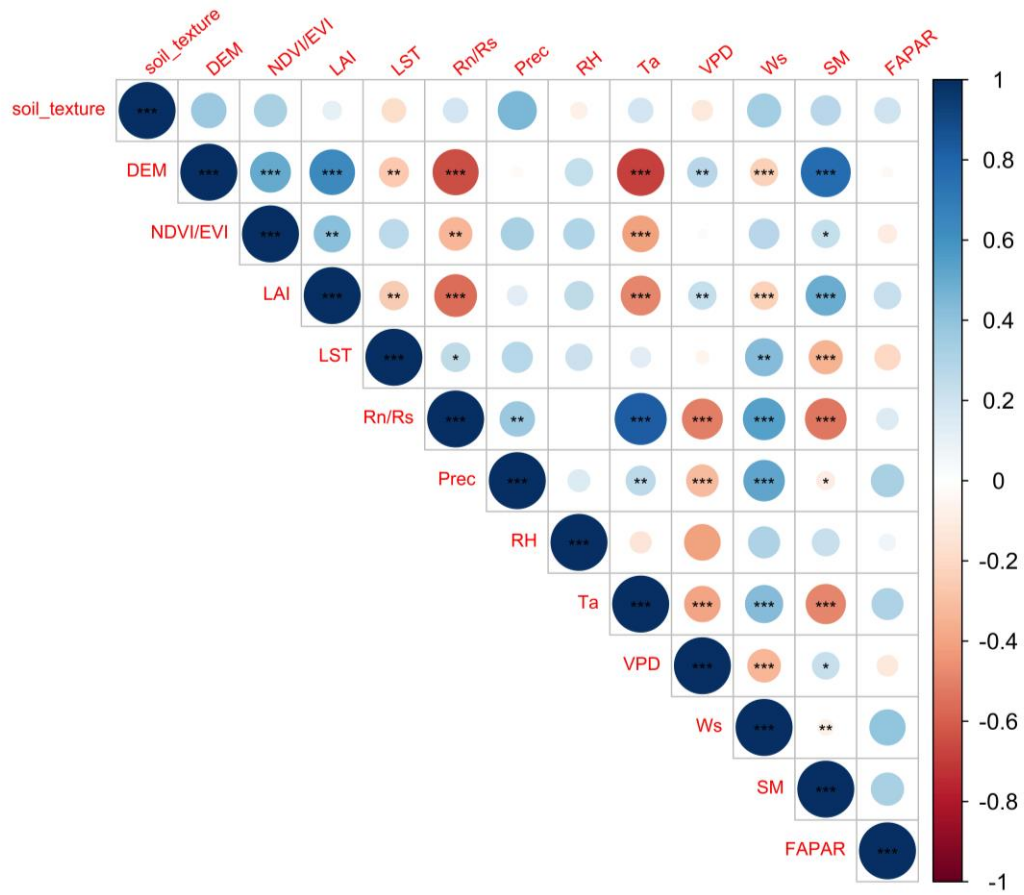

Figure S1. Correlation matrix between the use of various predictors (not used is set as 0 and used is set as 1) which may introduce uncertainty in the assessment of the impact of an individual predictor on model performance. Significance: the p-value < 0.01 (***), 0.05 (**), and 0.1 (*).

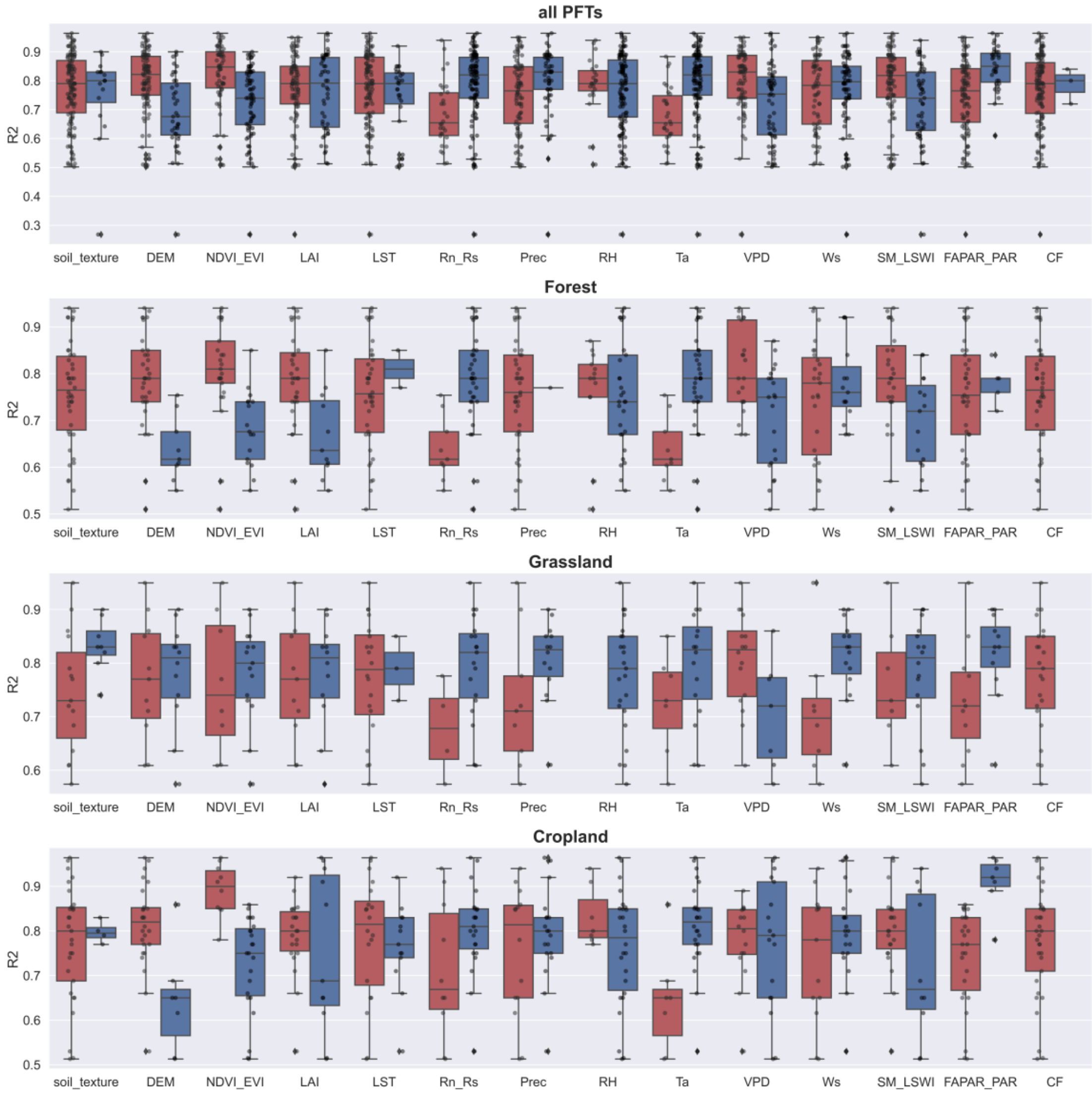

Figure S2. The impact of the various predictors used in models of different PFTs (all data, forest, grassland, and cropland) on R-squared. Dark blue boxes indicate that the predictor was used in the model, while dark red boxes indicate that the predictor was not used. Predictors: precipitation (Prec), soil moisture/land surface water index (SM_LSWI), net radiation/solar radiation (Rn_Rs), enhanced vegetation index (EVI), air temperature (Ta), vapor-pressure deficit (VPD), the fraction of absorbed photosynthetically active radiation/photosynthetically active radiation (FAPAR_PAR), relative humidity (RH), carbon flux (CF), leaf area index (LAI).

Table S1. Papers included in this meta-analysis

Papers	References
32 papers included in the meta-analysis	(Bai et al., 2021; Dou and Yang, 2018, 2017; Fang et al., 2020; Feng et al., 2020; Gerken et al., 2019; Granata, 2019; Granata and Di Nunno, 2021; Guo et al., 2019; Jung et al., 2011; Kafer et al., 2020; Li et al., 2018, 2021; Lu and Zhuang, 2010; Pang et al., 2021; Papale et al., 2015; Qin et al., 2005b, a; Safa et al., 2018; Shang et al., 2021; Van Wijk and Bouten, 1999; Vrugt et al., 2002; Vulova et al., 2021; Wang et al., 2021a, b; Xie et al., 2021; Xu et al., 2018; Yin et al., 2021; Zhang et al., 2021, 2020; Zhao et al., 2019)

References

Bai, Y., Zhang, S., Bhattarai, N., Mallick, K., Liu, Q., Tang, L., Im, J., Guo, L., and Zhang, J.: On the use of machine learning based ensemble approaches to improve evapotranspiration estimates from croplands across a wide environmental gradient, 298–299, https://doi.org/10.1016/j.agrformet.2020.108308, 2021.

Dou, X. and Yang, Y.: Modeling and predicting carbon and water fluxes using data-driven techniques in a forest ecosystem, https://doi.org/10.3390/f8120498, 2017.

Dou, X. and Yang, Y.: Evapotranspiration estimation using four different machine learning approaches in different terrestrial ecosystems, https://doi.org/10.1016/j.compag.2018.03.010, 2018.

Fang, B., Lei, H., Zhang, Y., Quan, Q., and Yang, D.: Spatio-temporal patterns of evapotranspiration based on upscaling eddy covariance measurements in the dryland of the North China Plain, 281, https://doi.org/10.1016/j.agrformet.2019.107844, 2020.

Feng, J., Wang, W., Xu, F., and Sun, S.: Estimating surface heat and water vapor fluxes by combining two-source energy balance model and back-propagation neural network, 729, https://doi.org/10.1016/j.scitotenv.2020.138724, 2020.

Gerken, T., Ruddell, B. L., Yu, R., Stoy, P. C., and Drewry, D. T.: Robust observations of land-to-atmosphere feedbacks using the information flows of FLUXNET, https://doi.org/10.1038/s41612-019-0094-4, 2019.

Granata, F.: Evapotranspiration evaluation models based on machine learning algorithms—A comparative study, https://doi.org/10.1016/j.agwat.2019.03.015, 2019.

Granata, F. and Di Nunno, F.: Forecasting evapotranspiration in different climates using ensembles of recurrent neural networks, https://doi.org/10.1016/j.agwat.2021.107040, 2021.

Guo, L., Shan, N., Zhang, Y., Sun, F., Liu, W., Shi, Z., and Zhang, Q.: Separating the effects of climate change and human activity on water use efficiency over the Beijing-Tianjin Sand Source Region of China, https://doi.org/10.1016/j.scitotenv.2019.07.067, 2019.

Jung, M., Reichstein, M., Margolis, H. A., Cescatti, A., Richardson, A. D., Arain, M. A., Arneth, A., Bernhofer, C., Bonal, D., Chen, J., Gianelle, D., Gobron, N., Kiely, G., Kutsch, W., Lasslop, G., Law, B. E., Lindroth, A., Merbold, L., Montagnani, L., Moors, E. J., Papale, D., Sottocornola, M., Vaccari, F., and Williams, C.: Global patterns of land-atmosphere fluxes of carbon dioxide, latent heat, and sensible heat derived from eddy covariance, satellite, and meteorological observations, 116, https://doi.org/10.1029/2010JG001566, 2011.

Kafer, P. S., Da Rocha, N. S., Diaz, L. R., Kaiser, E. A., Santos, D. C., Veeck, G. P., Roberti, D. R., Rolim, S. B. A., and De Oliveira, G. G.: Artificial neural networks model based on remote sensing to retrieve evapotranspiration over the Brazilian Pampa, https://doi.org/10.1117/1.JRS.14.038504, 2020.

Li, X., Liu, S., Li, H., Ma, Y., Wang, J., Zhang, Y., Xu, Z., Xu, T., Song, L., Yang, X., Lu, Z., Wang, Z., and Guo, Z.: Intercomparison of Six Upscaling Evapotranspiration Methods: From Site to the Satellite Pixel, https://doi.org/10.1029/2018JD028422, 2018.

Li, Z., Chen, C., Nevins, A., Pirtle, T., and Cui, S.: Assessing and modeling ecosystem carbon exchange and water vapor flux of a pasture ecosystem in the temperate climate-transition zone, https://doi.org/10.3390/agronomy11102071, 2021.

Lu, X. and Zhuang, Q.: Evaluating evapotranspiration and water-use efficiency of terrestrial ecosystems in the conterminous United States using MODIS and AmeriFlux data, https://doi.org/10.1016/j.rse.2010.04.001, 2010.

Pang, X., Lei, H., Cong, Z., Yang, H., Duan, L., and Yang, D.: Long term variation of evapotranspiration and water balance based on upscaling eddy covariance observations over the temperate semi-arid grassland of China, 308–309, https://doi.org/10.1016/j.agrformet.2021.108566, 2021.

Papale, D., Black, T. A., Carvalhais, N., Cescatti, A., Chen, J., Jung, M., Kiely, G., Lasslop, G., Mahecha, M. D., Margolis, H., Merbold, L., Montagnani, L., Moors, E., Olesen, Jø. E., Reichstein, M., Tramontana, G., Van Gorsel, E., Wohlfahrt, G., and Ráduly, B.: Effect of spatial sampling from European flux towers for estimating carbon and water fluxes with artificial neural networks, 120, 1941–1957, https://doi.org/10.1002/2015JG002997, 2015.

Qin, Z., Yu, Q., Li, J., Wu, Z.-Y., and Hu, B.-M.: Application of least squares vector machines in modelling water vapor and carbon dioxide fluxes over a cropland, https://doi.org/10.1631/jzus.2005.B0491, 2005a.

Qin, Z., Su, G.-L., Yu, Q., Hu, B.-M., and Li, J.: Modeling water and carbon fluxes above summer maize field in North China Plain with back-propagation neural networks, https://doi.org/10.1631/jzus.2005.B0418, 2005b.

Safa, B., Arkebauer, T. J., Zhu, Q., Suyker, A., and Irmak, S.: Latent heat and sensible heat flux simulation in maize using artificial neural networks, https://doi.org/10.1016/j.compag.2018.08.038, 2018.

Shang, K., Yao, Y., Liang, S., Zhang, Y., Fisher, J. B., Chen, J., Liu, S., Xu, Z., Zhang, Y., Jia, K., Zhang, X., Yang, J., Bei, X., Guo, X., Yu, R., Xie, Z., and Zhang, L.: DNN-MET: A deep neural networks method to integrate satellite-derived evapotranspiration products, eddy covariance observations and ancillary information, 308–309, https://doi.org/10.1016/j.agrformet.2021.108582, 2021.

Van Wijk, M. T. and Bouten, W.: Water and carbon fluxes above European coniferous forests modelled with artificial neural networks, https://doi.org/10.1016/S0304-3800(99)00101-5, 1999.

Vrugt, J. A., Bouten, W., Dekker, S. C., and Musters, P. A. D.: Transpiration dynamics of an Austrian Pine stand and its forest floor: Identifying controlling conditions using artificial neural networks, 25, 293–303, https://doi.org/10.1016/S0309-1708(01)00061-6, 2002.

Vulova, S., Meier, F., Rocha, A. D., Quanz, J., Nouri, H., and Kleinschmit, B.: Modeling urban evapotranspiration using remote sensing, flux footprints, and artificial intelligence, 786, https://doi.org/10.1016/j.scitotenv.2021.147293, 2021.

Wang, L., Zhang, Y., Yao, Y., Xiao, Z., Shang, K., Guo, X., Yang, J., Xue, S., and Wang, J.: GBRT-based estimation of terrestrial latent heat flux in the haihe river basin from satellite and reanalysis datasets, https://doi.org/10.3390/rs13061054, 2021a.

Wang, R., Gentine, P., Yin, J., Chen, L., Chen, J., and Li, L.: Long-term relative decline in evapotranspiration with increasing runoff on fractional land surfaces, https://doi.org/10.5194/hess-25-3805-2021, 2021b.

Xie, M., Luo, G., Hellwich, O., Frankl, A., Zhang, W., Chen, C., Zhang, C., and De Maeyer, P.: Simulation of site-scale water fluxes in desert and natural oasis ecosystems of the arid region in Northwest China, 35, e14444, https://doi.org/10.1002/hyp.14444, 2021.

Xu, T., Guo, Z., Liu, S., He, X., Meng, Y., Xu, Z., Xia, Y., Xiao, J., Zhang, Y., Ma, Y., and Song, L.: Evaluating Different Machine Learning Methods for Upscaling Evapotranspiration from Flux Towers to the Regional Scale, 123, 8674–8690, https://doi.org/10.1029/2018JD028447, 2018.

Yin, L., Tao, F., Chen, Y., Liu, F., and Hu, J.: Improving terrestrial evapotranspiration estimation across China during 2000–2018 with machine learning methods, 600, https://doi.org/10.1016/j.jhydrol.2021.126538, 2021.

Zhang, C., Luo, G., Hellwich, O., Chen, C., Zhang, W., Xie, M., He, H., Shi, H., and Wang, Y.: A framework for estimating actual evapotranspiration at weather stations without flux observations by combining data from MODIS and flux towers through a machine learning approach, Journal of Hydrology, 603, 127047, https://doi.org/10.1016/j.jhydrol.2021.127047, 2021.

Zhang, L., Xiao, J., Zheng, Y., Li, S., and Zhou, Y.: Increased carbon uptake and water use efficiency in global semi-arid ecosystems, https://doi.org/10.1088/1748-9326/ab68ec, 2020.

Zhao, W. L., Gentine, P., Reichstein, M., Zhang, Y., Zhou, S., Wen, Y., Lin, C., Li, X., and Qiu, G. Y.: Physics-Constrained Machine Learning of Evapotranspiration, 46, 14496–14507, https://doi.org/10.1029/2019GL085291, 2019.