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Editorial

Evapotranspiration Measurements and Modeling

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Evaporation is the conversion process of liquid water into vapor and the consequent transport of that vapor into the atmosphere. In vegetation systems, water vapor flux can emerge from two sources. Water vapor flux directly from soil, canopies, or free water surfaces is known as evaporation. On the other hand, water movement through plant roots, stems, and consequent evaporation into the atmosphere through foliage is termed transpiration. It is sometimes difficult to distinguish between these two processes in vegetated systems. Therefore, the term evapotranspiration (ET), which combines evaporation and transpiration, was coined.

Water that evaporates from the surface to the atmosphere is lost and cannot be used anymore. Therefore, evapotranspiration is a significant component of water balance, along with precipitation, seepage, and surface flow. Hence, understanding ET is vital in order to optimize irrigated agriculture water use efficiency and manage natural ecosystems such as forests or grasslands. In the context of climate change and the growing interest in global climate models (GCMs), evapotranspiration plays a vital role as a boundary condition in atmospheric or soil water modeling.

One of the pioneering studies on evaporation dates back to 1802 [1], where the roles of wind speed and vapor pressure deficit in the evaporation process were illustrated. Later studies elaborated on the governing factors influencing evaporation and transpiration, including solar radiation, air temperature, air humidity, wind speed, and plant characteristics [2,3]. The FAO used the Penman–Monteith ET model [4] to establish guidelines for crop irrigation, which became a world standard.

This Special Issue (SI), entitled "Evapotranspiration Measurements and Modeling", contains fifteen papers that cover various experimental, modeling, and remote sensing approaches.

Experimental methods reported in this SI include wrapped sap flow sensors [5], eddy covariance systems [6–13], water balance and a porometer to measure stomatal conductance [14], and meteorological measurements [10,12,15,16]. Modeling studies include the MODFLOW model [17], machine-learning approaches [7,8,12], the Penman–Monteith model [14,16], a canopy transpiration model [14], and multi-model ensemble methods including random forest [18]. Remote sensing approaches are utilized by [12,13,17,19].

Ghiat et al. [19] introduced a comprehensive review of evapotranspiration measurements and modeling. Their study offers essential directions for the estimation of evapotranspiration rates depending on the agricultural setting and the available climatological and physiological data. In this article, various mechanistic and empirical models were reviewed, as well as a variety of experimental methods for ET measurements.

Ndiaye et al. [15] analyzed the trend of reference evapotranspiration (ET_0) and its sensitivity to climatic variables in the Senegal River basin using a data set composed of 33 years of data. Analyses of long-term trends of regional ET_0 are essential for water cycle studies, modeling, and water uses. The results revealed an increase in the ET_0 at the annual and dry season scales for 32% of the Senegal River basin area.

Liu et al. [16] investigated microclimate and evapotranspiration in a new type of solar greenhouse—the sunken solar greenhouse (SSG). They showed that the SSG is environ-

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mentally friendly, is preferable for winter vegetable cultivation in north China, and can be helpful in other regions with cold winter conditions.

Lu et al. [13] used meteorological observations from a geostationary satellite to develop an improved daily ET cycle estimation scheme. The approach solved the surface energy balance equation combined with simplified parameterization. Ground measurements from 35 sites were used for comparison, and reasonable agreement was obtained between the two methods.

Ruiz-Alverez et al. [18] investigated the response of ET_0 to climate change using 11 multi-model ensemble (MME) methods, including random forest. The study was carried out in the Segura Hydrographic Demarcation (SE of Spain), a typical Mediterranean semiarid area. A spatially calibrated Hargreaves model was used to estimate ET_0 from 1970 to 2000. The results demonstrated the superiority of random forest over the other methods used.

Alam et al. [14] developed a model to predict canopy transpiration based on radiation intercepted at various canopy leaf area index (LAI) levels in a controlled environment. They implemented the model for a tall grass crop in a greenhouse. Model-derived values of transpiration were found to agree to within 20% of the measured values.

Mosre and Suarez [12] studied actual evapotranspiration (ET_a) in cold arid regions. They used machine learning algorithms—through the implementation of empirical linear regression formulae—to identify the main variables that control daily and monthly ET_a. The authors combined meteorological data with remote sensing vegetation indices (VIs) to estimate ET_a. The results showed that the best performance of the regression equations in the validation sites was obtained for monthly estimates with the incorporation of VIs.

Colombani et al. [17] investigated the impact of evapotranspiration on the hydro-ecological balance of shallow aquifers. They applied a numerical flow model using MODFLOW for the Tronto river alluvial aquifer (Italy), combined with MODIS data. The results showed that ET accounted for up to 21% of the aquifer water balance.

Dare-Idowu et al. [11] evaluated the energy budget for an irrigated maize crop using various land surface models. They evaluated the results against eddy covariance measurements. They concluded that multi-energy approaches should be favored over single-source models for the future projection of water consumption in irrigated maize, even for presumably homogeneous canopies.

Ferreira et al. [10] evaluated the Soil and Water Assessment Tool (SWAT) model's capability of simulating evapotranspiration in a watershed with the predominance of the Brazilian Cerrado biome. They conducted eddy covariance measurements and applied various evapotranspiration models. Comparing observations and simulations, they found that the Penman–Monteith method provided the best fit.

Grape sap flow in a greenhouse and the influencing environmental factors were studied by Peng et al. [5]. They examined random forest (RF) and partial least squares (PLS) models. Based on model error and uncertainty analyses, the RF model provided better simulation results in the grape growth stages than the PLS model. These results are essential for greenhouse grape irrigation.

Wang et al. [6] investigated energy and water vapor exchange in oasis riparian forest ecosystems using a network of eddy covariance systems. The authors explored the spatio-temporal patterns of heat and water vapor fluxes over the Ejina Oasis riparian forest ecosystem with five different surface types throughout a growing season in 2014. They reported the energy balance components and meteorological data for the examined land-cover types.

Improvements in scintillometer data were presented by Aguirre et al. [9]. Scintillometer data showed unrealistic heat flux values. Thus, the authors reprocessed the data through spectral analysis to eliminate unwanted contributions from electronic noise, absorption, and tripod vibrations using a newly proposed data cleaning method. Corrected sensible heat flux estimations agreed well with those obtained with an eddy covariance system. However, the latent heat flux was sensitive to the theoretical approach used to analyze the scintillometer data.

Fine et al. [8] utilized an innovative deep learning technique to gap-fill eddy covariance evapotranspiration data. They examined the process in different crops—cotton, tomato, and wheat—during several growing seasons. The proposed method was superior to the standard approach based on lookup tables. The results of this study suggested that the deep learning method is reliable and more consistent than the common gap-filling method.

Other machine learning approaches were used by Yohanani et al. [7] to estimate banana plants' evapotranspiration in screenhouses. Measurements were carried out using eddy covariance systems, and the estimations used artificial neural network (ANN) and multiple linear regression (MLR) models. The results showed that in most cases, the ANN model was superior to the MLR model.

In summary, the studies included in this SI cover various measurements and modeling approaches. These were used to determine the evapotranspiration of different agricultural and natural systems under various spatial and temporal scales. This SI will promote our understanding of the evapotranspiration process, its governing factors, and its estimation methods.

Conflicts of Interest: The authors declare no conflict of interest.

References

1. Dalton, J. Experimental essays, on the constitution of mixed gases; on the force of steam or vapour from water and other liquids in different temperatures, both in a Torricellian vacuum and in air; on evaporation; and on the expansion of gases by heat. *Mem. Lit. Philos. Manch.* **1802**, *5*, 535–602.
2. Penman, H.L. Natural Evaporation from Open Water, Bare Soil and Grass. *Proc. R. Soc. Lond. Ser. A Math. Phys. Sci.* **1948**, *193*, 120–145.
3. Monteith, J. Evaporation and environment. In *Symposia of the Society for Experimental Biology*; Cambridge University Press: Cambridge, UK, 1965; Volume 19, pp. 205–234.
4. Allen, R.G.; Pereira, L.S.; Raes, D.; Smith, M. *Crop Evapotranspiration—Guidelines for Computing Crop Water Requirements—FAO Irrigation and Drainage Paper 56*; FAO: Rome, Italy, 1998.
5. Peng, X.; Hu, X.; Chen, D.; Zhou, Z.; Guo, Y.; Deng, X.; Zhang, X.; Yu, T. Prediction of Grape Sap Flow in a Greenhouse Based on Random Forest and Partial Least Squares Models. *Water* **2021**, *13*, 3078. [CrossRef]
6. Wang, W.; Xu, F.; Wang, J. Energy Exchange and Evapotranspiration over the Ejina Oasis Riparian Forest Ecosystem with Different Land-Cover Types. *Water* **2021**, *13*, 3424. [CrossRef]
7. Yohanani, E.; Frisch, A.; Lukyanov, V.; Cohen, S.; Teitel, M.; Tanny, J. Estimating Evapotranspiration of Screenhouse Banana Plantations Using Artificial Neural Network and Multiple Linear Regression Models. *Water* **2022**, *14*, 1130. [CrossRef]
8. Fine, L.; Richard, A.; Tanny, J.; Pradalier, C.; Rosa, R.; Rozenstein, O. Introducing State-of-the-Art Deep Learning Technique for Gap-Filling of Eddy Covariance Crop Evapotranspiration Data. *Water* **2022**, *14*, 763. [CrossRef]
9. Aguirre, F.; Hartogensis, O.; Meza, F.; Suárez, F. Refinements and Analysis of the Optical-Microwave Scintillometry Method Applied to Measurements over a Vineyard in Chile. *Water* **2022**, *14*, 474. [CrossRef]
10. Ferreira, A.d.N.; de Almeida, A.; Koide, S.; Minoti, R.T.; de Siqueira, M.B.B. Evaluation of Evapotranspiration in Brazilian Cerrado Biome Simulated with the SWAT Model. *Water* **2021**, *13*, 2037. [CrossRef]
11. Dare-Idowu, O.; Jarlan, L.; Le-Dantec, V.; Rivalland, V.; Ceschia, E.; Boone, A.; Brut, A. Hydrological Functioning of Maize Crops in Southwest France Using Eddy Covariance Measurements and a Land Surface Model. *Water* **2021**, *13*, 1481. [CrossRef]
12. Mosre, J.; Suárez, F. Actual Evapotranspiration Estimates in Arid Cold Regions Using Machine Learning Algorithms with In Situ and Remote Sensing Data. *Water* **2021**, *13*, 870. [CrossRef]
13. Lu, J.; Jia, L.; Zheng, C.; Tang, R.; Jiang, Y. A Scheme to Estimate Diurnal Cycle of Evapotranspiration from Geostationary Meteorological Satellite Observations. *Water* **2020**, *12*, 2369. [CrossRef]
14. Alam, M.S.; Lamb, D.W.; Warwick, N.W.M. A Canopy Transpiration Model Based on Scaling Up Stomatal Conductance and Radiation Interception as Affected by Leaf Area Index. *Water* **2021**, *13*, 252. [CrossRef]
15. Ndiaye, P.M.; Bodian, A.; Diop, L.; Deme, A.; Dezetter, A.; Djaman, K.; Ogilvie, A. Trend and Sensitivity Analysis of Reference Evapotranspiration in the Senegal River Basin Using NASA Meteorological Data. *Water* **2020**, *12*, 1957. [CrossRef]
16. Liu, H.; Yin, C.; Hu, X.; Tanny, J.; Tang, X. Microclimate Characteristics and Evapotranspiration Estimates of Cucumber Plants in a Newly Developed Sunken Solar Greenhouse. *Water* **2020**, *12*, 2275. [CrossRef]
17. Colombani, N.; Gaiolini, M.; Busico, G.; Postacchini, M. Quantifying the Impact of Evapotranspiration at the Aquifer Scale via Groundwater Modelling and MODIS Data. *Water* **2021**, *13*, 950. [CrossRef]
18. Ruiz-Álvarez, M.; Gomariz-Castillo, F.; Alonso-Sarría, F. Evapotranspiration Response to Climate Change in Semi-Arid Areas: Using Random Forest as Multi-Model Ensemble Method. *Water* **2021**, *13*, 222. [CrossRef]
19. Ghiat, I.; Mackey, H.R.; Al-Ansari, T. A Review of Evapotranspiration Measurement Models, Techniques and Methods for Open and Closed Agricultural Field Applications. *Water* **2021**, *13*, 2523. [CrossRef]