

Survey on Machine Learning Techniques on Evapotranspiration Method in Agriculture

Sivasankari N ^{*1}

^{*1}Associate Professor, Department of ECE, Mepco Schlenk Engineering College, Sivakasi, Tamilnadu, India

ABSTRACT

Artificial intelligence models (AI-M), Machine learning Models, Neural networks model (NN-M) and adaptive neuro fuzzy interface systems (ANFIS-M) methods gained attention now to provide accurate prediction. These prediction methods are utilized in all fields, medical fields, cyber security fields, Astronomical fields. Anyway, these models may produce some inconsistent results. To overcome these results inconsistency, hybridization in the of ML-M, AI-M, ANFIS-M models are coming one by one with their own innovations. This paper aims to consolidate the works to predict daily evapotranspiration level that will manage the water requirements appropriately.

Keywords: Full duplex, self-interference, mutual coupling, envelope correlation coefficient, Gain

I. INTRODUCTION

Evapotranspiration (ET) is the process by which water is transferred from the land to the atmosphere by evaporation from the soil and other surfaces and by transpiration from plants. It is a crucial component of the water cycle and influences weather patterns, climate, and agricultural practices.

Evaporation: The process by which water changes from a liquid to a vapor. This occurs on the surface of water bodies, soil, and vegetation.

Transpiration: The process by which water absorbed by plants, usually through the roots, is evaporated into the atmosphere from the plant's surface, primarily through small openings called stomata in the leaves. This process gets affected by some factors such as Climate: Temperature, humidity, wind speed, and solar radiation significantly impact evapotranspiration rates. Higher temperatures and wind speeds increase evapotranspiration, while higher humidity decreases it. Plant Characteristics: Different plants have varying rates of transpiration. Factors include the type of plant, its stage of growth, and the density of vegetation. Soil Moisture: The availability of water in the soil affects both evaporation and transpiration. Dry soil reduces evaporation and can limit plant growth, thus reducing transpiration. Land Use and Cover: Urbanization, deforestation, and agricultural practices can alter evapotranspiration rates by changing the surface characteristics and plant cover.

Here's how agriculture influences this process:

Crop Type and Canopy Structure: Different crops have varying rates of transpiration based on their leaf area, root structure, and growth stage. For instance, crops like alfalfa or maize have high transpiration rates compared to crops like wheat or barley.

Irrigation Practices: Irrigation increases soil moisture availability, which can enhance both evaporation and transpiration. Over-irrigation can lead to higher evaporation losses, while efficient irrigation methods like drip irrigation minimize evaporation and target water delivery to plant roots, thus optimizing transpiration.

Soil Management: Tillage practices can influence soil moisture retention. No-till or reduced-till practices help maintain soil structure and organic matter, reducing evaporation. On the other hand, conventional tillage can increase evaporation rates by disturbing the soil.

Planting Density and Crop Rotation: Dense planting can create a microclimate that reduces soil evaporation but increases transpiration due to higher plant biomass. Crop rotation with deep-rooted plants can improve soil structure and moisture retention, influencing evapotranspiration rates.

Mulching: Applying mulch reduces soil evaporation by providing a physical barrier that reduces direct sunlight and wind exposure. This practice can also moderate soil temperature and improve water use efficiency.

Climate and Weather Conditions: Agricultural activities are influenced by local climate conditions, which in turn affect evapotranspiration rates. Higher temperatures and wind speeds increase evapotranspiration, while higher humidity decreases it.

Use of Cover Crops: Cover crops can reduce soil evaporation during off-seasons by maintaining soil cover and improving soil health, thus enhancing overall water retention and availability for future crops.

Soil Moisture Conservation Techniques: Techniques like contour farming, terracing, and the use of organic matter improve soil moisture retention and reduce evaporation losses, positively influencing the balance of evapotranspiration.

Managing these factors effectively can optimize water use in agriculture, improving crop yields while conserving water resources. Evapotranspiration (ET) rates vary widely across the world due to differences in climate, vegetation, soil types, and land management practices. Here are some general trends and examples of ET rates in different regions:

1. Tropical Rainforests:

- ET rates are very high due to abundant vegetation and high temperatures.
- Annual ET can exceed 1,500 mm in places like the Amazon Basin.

2. Temperate Regions:

- ET rates are moderate and vary with the seasons.
- In the Midwest United States, annual ET can range from 500 to 800 mm.

3. Arid and Semi-Arid Regions:

- ET rates are generally low due to limited water availability.
- In deserts like the Sahara, ET can be less than 100 mm per year.

4. Mediterranean Climates:

- ET rates are moderate to high, with a strong seasonal variation.
- Southern California has ET rates around 700 to 900 mm annually.

5. Boreal Forests and Tundra:

- ET rates are low due to cold temperatures and short growing seasons.
- In northern Canada and Siberia, ET can be less than 300 mm per year.

6. Monsoon Regions:

- ET rates can be high during the wet season and lower during the dry season.
- In parts of India and Southeast Asia, annual ET can range from 800 to 1,200 mm.

7. Sub-Saharan Africa:

- ET rates vary widely depending on the specific region.
- In the Sahel, ET can be around 200-400 mm, while in more humid regions, it can exceed 1,000 mm.

8. High Altitude Regions:

- ET rates can be lower due to cooler temperatures and shorter growing seasons.
- In the Andes or the Himalayas, ET rates might range from 300 to 600 mm.

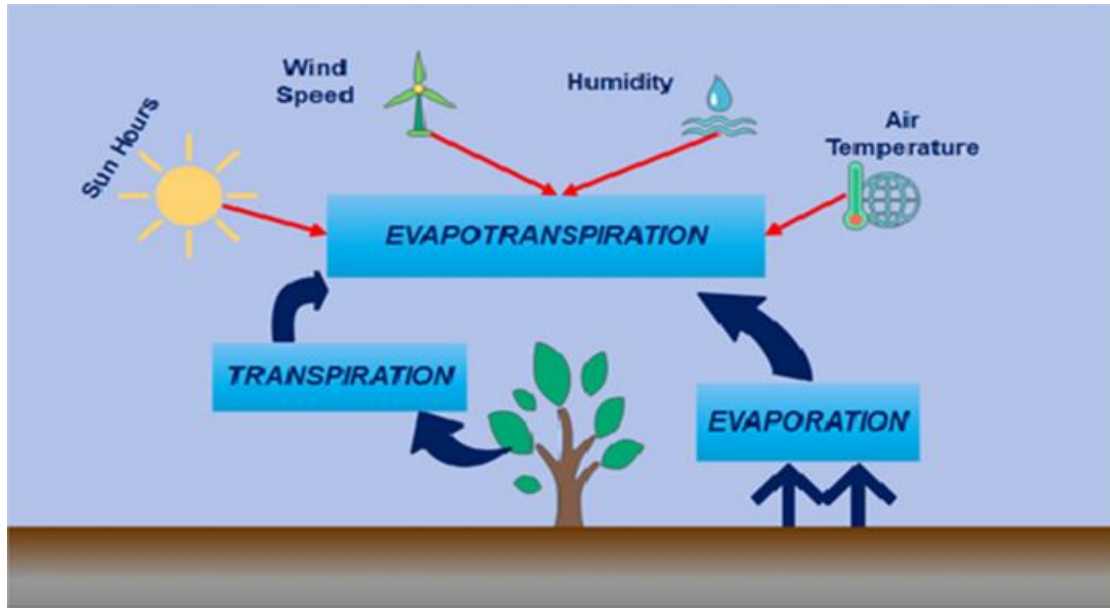


Figure 1: Evapotranspiration method for

Let us see the evapotranspiration rate in different region

Usually, Potential evapotranspiration is higher in the summer, on clearer and less cloudy days, and closer to the equator, because of the higher levels of solar radiation that provides the energy (heat) for evaporation.

Table 1 : Different evapotranspiration rate across the world

Country	Evapotranspiration rate
South Africa	303 mm-a ⁻¹ (2000-2012)
India	573 mm/yr (1980-2018)
United States	0.9 ± 0.4 mm d ¹ in mesic cities/2.9 ± 0.7 mm d ⁻¹
North Fennoscandia	0.3 mm/day
Mediterranean region of Europe	1.6 mm/yr
China	0.93 mm/year
Australia	1.54 mm/day
Soviet Union	4–5 mm/day
Singapore	8.7 g m ⁻² h ⁻¹ to 25.5 g m ⁻² h ⁻¹
Malaysia	4-5 mm/day

The Moderate Resolution Imaging Spectroradiometer (MODIS) is a key instrument aboard NASA's Terra and Aqua satellites. MODIS plays a crucial role in studying global dynamics and processes on the land, in the oceans, and in the atmosphere.

Table 2: evapotranspiration rate for specific plants

Plants	Evapotranspiration rate (Growing stage average)
corn and apple tree	400 – 500 mm
Peas	360 – 400 mm
Grass	310-330 mm
Basil	4.2 mm/day
Neem tree	0.8 cups of water every 12 days neem
Banyan tree	1.95 kg m ⁻² h ⁻¹
Banana tree	5 to 6 mm/day

Machine learning methods of calculating evapotranspiration

A landscape plant's rate of evapotranspiration is equal to the local reference evapotranspiration multiplied by the appropriate plant adjustment factor. Or, expressed with symbols: $ET_L = ET_0 \times K$. The procedure for measuring ET rate is given below:

Key Input Variables for ET Estimation

The accuracy of machine learning models for ET estimation depends on the quality and relevance of input variables. Commonly used inputs include:

Meteorological data: Temperature, humidity, wind speed, solar radiation, and precipitation.

Remote sensing data: Satellite images providing vegetation indices (e.g., NDVI), land surface temperature, and soil moisture.

Hydrological data: Soil properties, groundwater levels, and surface water availability.

Example Workflow for ET Estimation Using Machine Learning

Data Collection: Gather historical data on meteorological, remote sensing, and hydrological variables.

Data Preprocessing: Clean the data, handle missing values, normalize/standardize features, and perform feature selection.

Model Selection: Choose a suitable ML model (e.g., RF, ANN) based on the data characteristics and the problem requirements.

Model Training: Split the data into training and testing sets, train the model on the training set, and validate it on the testing set.

Model Evaluation: Use performance metrics such as RMSE, MAE, and R² to evaluate the model.

Model Deployment: Deploy the trained model for operational ET estimation and integrate it with water resource management systems.

Machine learning methods play the important role in predicting ET rate in every place, but according to data some specific methods have to be applied. Some of the methods are described below:

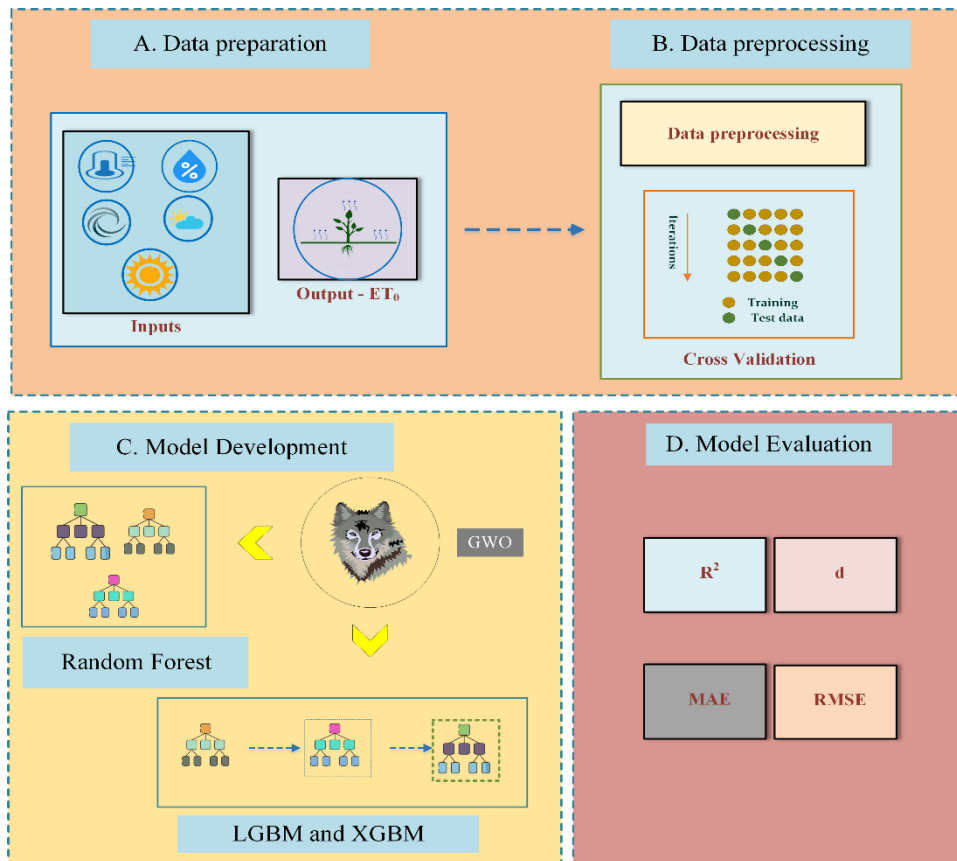


Figure 2: Machine learning models for evapotranspiration methods

1. Artificial Neural Networks (ANNs)

Feedforward Neural Networks (FNN): These are the simplest type of ANN, consisting of an input layer, one or more hidden layers, and an output layer. They are widely used for ET estimation due to their ability to model nonlinear relationships. Various methods regarding this for evapotranspiration methods are discussed from [6-11]

Recurrent Neural Networks (RNN) and Long Short-Term Memory Networks (LSTM): These are suitable for time-series data, making them useful for ET estimation based on historical data. At different climates, how these networks can combine in hybrid manner are described in [12]. Time lagged recurrent neural network T-RNN, [13], enhanced RNN [14], bidirectional LSTM [15], [16] are described.

2. Support Vector Machines (SVM)

SVMs are used for regression tasks (Support Vector Regression - SVR) and are effective in high-dimensional spaces. They have been applied to ET estimation with good results, especially when the data is not linearly separable. MODIS and AmeriFlux data are used with satellite data, terrestrial data using support vector machine for evapotranspiration method are described in the references [17-20].

3. Random Forests (RF)

RF is an ensemble learning method that builds multiple decision trees and merges them to get a more accurate and stable prediction. They are robust to overfitting and can handle large datasets, making them suitable for ET estimation. Boruta RF for agricultural evapotranspiration method is described in [21]. RF with coupled wavelet method [22], combined trapezoidal method is described in [23]

4. Gradient Boosting Machines (GBM)

GBMs build trees sequentially, with each tree correcting the errors of the previous one. Variants like XGBoost and LightGBM have been used for ET estimation due to their high accuracy and efficiency. Agricultural field is combined with cyber physical systems is described in [24]. Some other ensembled algorithms with ET methods are

described in [27]. Maize evapotranspiration rate is estimated with SVM, GBM, artificial and deep learning models also described in [28]. Some other hydrological parameters also described in [29].

5. k-Nearest Neighbors (k-NN)

k-NN is a simple, instance-based learning algorithm that predicts the ET by averaging the values of the k-nearest neighbors in the training data. It's easy to implement and understand but may be computationally expensive for large datasets. Semi-arid continental climate has been described with K-nearest neighbor algorithm is described in [30]. self-optimizing nearest neighbor algorithms based arid-semiarid environment has been described in [31]. Swarm based optimization on k-nearest algorithm also described in [32].

6. Gaussian Processes (GP)

GPs are non-parametric, probabilistic models that are useful for regression tasks. They provide uncertainty estimates along with predictions, which can be valuable for ET estimation. Gaussian process with other deep learning models also described in [33],[34]

7. Deep Learning Models

Convolutional Neural Networks (CNNs): Primarily used for image data, CNNs can also be applied to spatial data in ET estimation. For Punjab regional plants, evapotranspiration methods are described in [35]. Other deep learning models also described in [36],[37].

Autoencoders: These are used for dimensionality reduction and feature learning, which can improve the performance of other ML models in ET estimation. This scheme with satellite image data prediction is described in [38] and [39].

CONCLUSION

In this paper, estimating evapotranspiration (ET) accurately is critical for effective water resource management, irrigation planning, and understanding the hydrological cycle. Traditional methods for ET estimation, such as empirical formulas and physically-based models, often require extensive data and are limited in capturing complex nonlinear relationships. Machine learning (ML) methods offer a promising alternative due to their ability to model these complexities and handle diverse datasets.

In future, hybrid models for more accurate and reliable ET estimates can be made. Improved Data Integration for data for ML models can be created. **Real-time Applications can be developed.**

REFERENCES

- [1] Influence of evaporative cooling by urban forests on cooling demand in cities Article in Urban Forestry & Urban Greening · August 2018
- [2] Allen, R. G., Pereira, L. S., Raes, D., & Smith, M. (1998). Crop Evapotranspiration - Guidelines for Computing Crop Water Requirements - FAO Irrigation and Drainage Paper 56. FAO, Rome.
- [3] Monteith, J. L. (1965). Evaporation and environment. In: The state and movement of water in living organisms. Symposia of the Society for Experimental Biology, 19, 205-234.
- [4] Shuttleworth, W. J. (1993). Evaporation. In D. R. Maidment (Ed.), Handbook of Hydrology (pp. 4.1-4.53). McGraw-Hill, Inc.
- [5] Kustas, W. P., & Norman, J. M. (1996). Use of remote sensing for evapotranspiration monitoring over land surfaces. Hydrological Sciences Journal, 41(4), 495-516
- [6] Farooque, A.A., Afzaal, H., Abbas, F., Bos, M., Maqsood, J., Wang, X. and Hussain, N., 2022. Forecasting daily evapotranspiration using artificial neural networks for sustainable irrigation scheduling. Irrigation Science, pp.1-15.
- [7] Vaz, Pedro J., Gabriela Schütz, Carlos Guerrero, and Pedro JS Cardoso. "Hybrid neural network based models for evapotranspiration prediction over limited weather parameters." IEEE Access 11 (2022): 963-976.
- [8] Chia, Min Yan, Yuk Feng Huang, Chai Hoon Koo, and Kit Fai Fung. "Recent advances in evapotranspiration estimation using artificial intelligence approaches with a focus on hybridization techniques—a

- review." *Agronomy* 10, no. 1 (2020): 101.
- [9] Liu, Y., Zhang, S., Zhang, J., Tang, L., & Bai, Y. (2021). Using artificial neural network algorithm and remote sensing vegetation index improves the accuracy of the penman-monteith equation to estimate cropland evapotranspiration. *Applied Sciences*, 11(18), 8649.
- [10] Chen, Zhuoqi, Runhe Shi, and Shupeng Zhang. "An artificial neural network approach to estimate evapotranspiration from remote sensing and AmeriFlux data." *Frontiers of earth Science* 7 (2013): 103-111.
- [11] Rahimi Khoob, A. (2008). Comparative study of Hargreaves's and artificial neural network's methodologies in estimating reference evapotranspiration in a semiarid environment. *Irrigation Science*, 26, 253-259.
- [12] Granata, Francesco, and Fabio Di Nunno. "Forecasting evapotranspiration in different climates using ensembles of recurrent neural networks." *Agricultural Water Management* 255 (2021): 107040.
- [13] Proias, G. E. O. R. G. I. O. S., et al. "Forecasting reference evapotranspiration using time lagged recurrent neural network." *Wseas Trans. Environ. Dev* 16 (2020): 699-707.
- [14] Karbasi, M., Jamei, M., Ali, M., Malik, A., Chu, X., Farooque, A. A., & Yaseen, Z. M. (2023). Development of an enhanced bidirectional recurrent neural network combined with time-varying filter-based empirical mode decomposition to forecast weekly reference evapotranspiration. *Agricultural Water Management*, 290, 108604.
- [15] Jiménez, Andrés F., Brenda V. Ortiz, Luca Bondesan, Guilherme Morata, and Damianos Damianidis. "Evaluation of two recurrent neural network methods for prediction of irrigation rate and timing." *Transactions of the ASABE* 63, no. 5 (2020): 1327-1348.
- [16] Yin, J., Deng, Z., Ines, A. V., Wu, J., & Rasu, E. (2020). Forecast of short-term daily reference evapotranspiration under limited meteorological variables using a hybrid bi-directional long short-term memory model (Bi-LSTM). *Agricultural Water Management*, 242, 106386.
- [17] Yang, Feihua, et al. "Prediction of continental-scale evapotranspiration by combining MODIS and AmeriFlux data through support vector machine." *IEEE Transactions on Geoscience and Remote Sensing* 44.11 (2006): 3452-3461.
- [18] Liu, Meng, et al. "Global land surface evapotranspiration estimation from meteorological and satellite data using the support vector machine and semiempirical algorithm." *IEEE Journal of Selected Topics in Applied Earth Observations and Remote Sensing* 11.2 (2018): 513-521.
- [19] Yao, Yunjun, et al. "Improving global terrestrial evapotranspiration estimation using support vector machine by integrating three process-based algorithms." *Agricultural and Forest Meteorology* 242 (2017): 55-74.
- [20] Tejada Jr, Allan T., et al. "Modeling reference crop evapotranspiration using support vector machine (SVM) and extreme learning machine (ELM) in region IV-A, Philippines." *Water* 14.5 (2022): 754.
- [21] Jayasinghe, WJM Lakmini Prarthana, et al. "Deep multi-stage reference evapotranspiration forecasting model: Multivariate empirical mode decomposition integrated with the boruta-random forest algorithm." *IEEE Access* 9 (2021): 166695-166708.
- [22] Shiri, Jalal. "Improving the performance of the mass transfer-based reference evapotranspiration estimation approaches through a coupled wavelet-random forest methodology." *Journal of Hydrology* 561 (2018): 737-750.
- [23] Hao, Pengyu, Liping Di, and Liying Guo. "Estimation of crop evapotranspiration from MODIS data by combining random forest and trapezoidal models." *Agricultural Water Management* 259 (2022): 107249.
- [24] Feng, Yu, et al. "Evaluation of random forests and generalized regression neural networks for daily reference evapotranspiration modelling." *Agricultural Water Management* 193 (2017): 163-173.
- [25] Ying, Wangmin, Hua Wu, and Zhao-Liang Li. "Net surface shortwave radiation retrieval using random forest method with MODIS/Aqua data." *IEEE Journal of Selected Topics in Applied Earth Observations and Remote Sensing* 12.7 (2019): 2252-2259.
- [26] Wang, Tianteng, et al. "Hybrid Machine Learning Approach for Evapotranspiration Estimation of Fruit Tree in Agricultural Cyber-Physical Systems." *IEEE Transactions on Cybernetics* 53.9 (2022): 5677-5691.

- [27] Fan, Junliang, et al. "Evaluation of SVM, ELM and four tree-based ensemble models for predicting daily reference evapotranspiration using limited meteorological data in different climates of China." *Agricultural and forest meteorology* 263 (2018): 225-241.
- [28] Fan, Junliang, et al. "Estimation of daily maize transpiration using support vector machines, extreme gradient boosting, artificial and deep neural networks models." *Agricultural Water Management* 245 (2021): 106547.
- [29] Song, Zhihong, et al. "Regionalization of hydrological model parameters using gradient boosting machine." *Hydrology and Earth System Sciences* 26.2 (2022): 505-524.
- [30] Genc, Onur, Ali Dag, and Mehmet Ardiclioglu. "A novel study for the modeling of monthly evaporation using k-nearest neighbor algorithms for a semi-arid continental climate." *2015 IEEE 14th International Conference on Machine Learning and Applications (ICMLA)*. IEEE, 2015.
- [31] Feng, Kepeng, and Juncang Tian. "Estimating potential evapotranspiration based on self-optimizing nearest neighbor algorithms: a case study in arid–semiarid environments, Northwest of China." *Environmental Science and Pollution Research* 27 (2020): 37176-37187.
- [32] Majumdar, Parijata, Diptendu Bhattacharya, and Sanjoy Mitra. "Prediction of evapotranspiration and soil moisture in different rice growth stages through improved salp swarm-based feature optimization and ensembled machine learning algorithm." *Theoretical and Applied Climatology* 153.1 (2023): 649-673.
- [33] Karbasi, Masoud. "Forecasting of multi-step ahead reference evapotranspiration using wavelet-Gaussian process regression model." *Water resources management* 32 (2018): 1035-1052.
- [34] Holman, Daniel, et al. "Gaussian process models for reference ET estimation from alternative meteorological data sources." *Journal of Hydrology* 517 (2014): 28-35.
- [35] Saggi, Mandeep Kaur, and Sushma Jain. "Reference evapotranspiration estimation and modeling of the Punjab Northern India using deep learning." *Computers and Electronics in Agriculture* 156 (2019): 387-398.
- [36] Alibabaei, Khadijeh, Pedro D. Gaspar, and Tânia M. Lima. "Modeling soil water content and reference evapotranspiration from climate data using deep learning method." *Applied Sciences* 11.11 (2021): 5029.
- [37] Sharma, Gitika, Ashima Singh, and Sushma Jain. "DeepEvap: Deep reinforcement learning based ensemble approach for estimating reference evapotranspiration." *Applied Soft Computing* 125 (2022): 109113.
- [38] Karbasi, Masoud, et al. "Forecasting weekly reference evapotranspiration using Auto Encoder Decoder Bidirectional LSTM model hybridized with a Boruta-CatBoost input optimizer." *Computers and Electronics in Agriculture* 198 (2022): 107121.
- [39] Shi, Changjiang, et al. "Enhancing Global Surface Soil Moisture Estimation from ESA CCI and SMAP Product with Conditional Variational Auto-Encoder." *IEEE Journal of Selected Topics in Applied Earth Observations and Remote Sensing* (2024).