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Estimating the Evapotranspiration Using Hybrid Artificial Intelligence Techniques in Arid and Semi-Arid Regions of India

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Abstract
Evapotranspiration (ET) is a crucial component of the hydrological cycle, particularly in arid and semi-arid regions where water resources are limited. Accurate estimation of ET is essential for effective water resource management and agricultural planning. This review explores the application of hybrid artificial intelligence (AI) techniques for estimating ET in the arid and semi-arid regions of India. By combining traditional AI methods, such as artificial neural networks (ANNs) and support vector machines (SVMs), with advanced optimization algorithms like genetic algorithms (GA), particle swarm optimization (PSO), and evolutionary strategies, researchers have enhanced the accuracy and reliability of ET predictions. This paper summarizes the state-of-the-art hybrid AI models, their methodologies, and the challenges and opportunities they present for managing water resources in India's arid and semi arid zones.

Keywords: Evapotranspiration, Artificial neural networks, hybrid AI models

1. INTRODUCTION: -

Large amounts of water are evaporated from ponds and lakes, particularly in arid climates. Crops and trees transpire large portions of water that is applied through irrigation or is received through rainfall. Evaporation and transpiration together is called evapotranspiration (ET). The importance of ET depends upon the time scale and the type of hydrologic event.

India's arid and semi-arid regions face significant challenges due to limited water availability and climate variability. Evapotranspiration is a key factor influencing water balance, agricultural productivity, and ecosystem sustainability. Traditional ET estimation methods, such as lysimeters and empirical models like the Penman-Monteith equation, are resource-intensive or lack generalizability across diverse climatic conditions. Hybrid AI techniques offer an innovative alternative, combining the strengths of individual models to provide robust and scalable solutions for ET estimation.

Evapotranspiration is the sum of water evaporation from soil and transpiration by plants, a vital component of the hydrological cycle. In semi-arid and arid regions, accurate ET estimation informs water resource management and agricultural planning. Traditional methods, such as empirical equations (e.g., Penman-Monteith, Hargreaves), often fail to capture spatial and temporal variations due to limited meteorological data. AI models offer a data-driven alternative, leveraging diverse datasets to provide robust ET estimates.

- **Impact of evapotranspiration:**

During dry periods, plants struggle with the availability of water. If the rate of evapotranspiration is higher than the rate at which a plant can draw up water, the plant will dehydrate and eventually suffer irreversible damage. The amount of water a plant uses is almost equal to the amount of water it transpires. This is because it holds only between 0.1 and 5% of the water drawn in through its roots as part of its structural integrity. An increase in average global surface temperatures over the past decades of climate change has led to an increase in unpredictability of the factors affecting ET as well as the likelihood that extreme cases will occur.

- **Weather Parameters:**

The principal weather parameters affecting evapotranspiration are:
1. **Solar Radiation:** The evapotranspiration process is determined by the amount of energy available to vaporize water. Solar radiation is the largest energy source and is able to change large quantities of liquid water into water vapour. The potential amount of radiation that can reach the evaporating surface is determined by its location and time of the year. Due to differences in the position of the sun, the potential radiation differs at various latitudes and in different seasons.
2. **Air temperature:** The solar radiation absorbed by the atmosphere and the heat emitted by the earth increase the air temperature. The sensible heat of the surrounding air transfers energy to the crop and exerts as such a controlling influence on the rate of evapotranspiration. In sunny, warm weather the loss of water by evapotranspiration is greater than in cloudy and cool weather.
3. **Humidity:** While the energy supply from the sun and surrounding air is the main driving force for the vaporization of water, the difference between the water vapour pressure at theevapotranspiring surface and the surrounding air is the determining factor for the vapour removal. Well-watered fields in hot dry arid regions consume large amounts of water due to the abundance of energy and the desiccating power of the atmosphere. In humid tropical regions, notwithstanding the high energy input, the high humidity of the air will reduce the evapotranspiration demand. In such an environment, the air is already close to saturation, so that less additional water can be stored and hence the evapotranspiration rate is lower than in arid regions.
4. **Wind speed:** The process of vapour removal depends to a large extent on wind and air turbulence which transfers large quantities of air over the evaporating surface. When vaporizing water, the air above the evaporating surface becomes gradually saturated with watervapour. If this air is not continuously replaced with drier air, the driving force for water vapourremoval and the evapotranspiration rate decreases.

- **Present Scenario in India regarding Evapotranspiration:**

The Earth's climate, including India's, is changing due to natural and human-made factors, leading to faster water cycles, harm to ecosystems, and extreme weather events. Understanding these changes helps us assess current weather conditions and predict future climate scenarios, crucial for preparing for and mitigating the impacts of climate change.

2. Artificial neural network (ANN) for modelling evapotranspiration

Sudheer et al. (2003) utilized radial-basis function (RBF) artificial neural networks (ANNs) to estimate daily evapotranspiration (ET) under conditions of limited data availability. By adjusting the interconnection weights during training through an error convergence method, various ANN models were developed using different combinations of weather parameters as inputs. The study highlighted that reducing the number of input variables negatively impacted model performance, emphasizing the significance of individual climatic variables in ET estimation. Interestingly, it was found that an ANN model relying solely on temperature data could satisfactorily estimate ET, demonstrating the potential of ANN approaches for estimating crop ET with minimal data.

Kisi (2006) applied a generalized regression neural network (GRNN) to estimate reference evapotranspiration (ETo), comparing models with varying combinations of input variables such as solar radiation, air temperature, relative humidity, and wind speed. The study evaluated the impact of these variables on estimation accuracy by analyzing changes in error metrics as each variable was added. The four-variable model outperformed traditional methods like Hargreaves and Turc in estimating FAO-56 PM ETo. However, as Aksoy et al. (2007) pointed out, the sensitivity of individual variables was not assessed prior to their inclusion in the models

Zanetti et al. (2007) demonstrated that a multilayer perceptron (MLP) ANN model using maximum and minimum air temperatures, extraterrestrial radiation, and daylight hours can effectively estimate reference evapotranspiration (ETo). Similarly, Kumar et al. (2008) observed that the performance of ANN models is influenced more by the input nodes and associated climatic variables rather than by increasing the number of nodes in hidden layers.

Kim and Kim (2008) developed a GRNN model optimized with a genetic algorithm (GA) to estimate pan evaporation and ETo. They conducted uncertainty analysis on input variables to identify the most critical factors for model optimization, finding that maximum temperature and sunshine hours are essential. Aytek et al. (2008) evaluated the potential of ANNs in humid subtropical climates and found that air temperature alone provided better ETo estimates than the Hargreaves equation, though the ANN model's accuracy was limited to the specific region it was trained on.

Abudu and King (2010) used ANNs to fill gaps in daily ET data measured by the eddy covariance method. They showed that ANN models, when using weather data available before and after missing intervals, could reliably reconstruct missing data. Marti et al. (2010) extended the ANN model by Zanetti et al. (2007) by adding relative humidity and ETo data from locations with similar thermal patterns, demonstrating that models with supplemented data from such regions performed comparably to the original model.

Ozkan et al. (2010) applied artificial bee colony (ABC) optimization to train ANN models for estimating daily ETo. These ANN-ABC models outperformed other ANN and empirical approaches, even in cross-station applications. Lastly, Wang et al. (2013) developed a generalized ANN model using weather data from various climates. While the model struggled in arid and semi-arid regions, they emphasized the need for longer time-series data from diverse climatic zones to enhance ANN reliability for ETo estimation.

3. METHODOLOGY USED: -

Efficient evapotranspiration (ET) estimation involves leveraging advanced computational methods to address data variability and enhance prediction accuracy. The methodology outlined in the flowchart integrates traditional machine learning, neuro-fuzzy systems, and wavelet-based hybrid models for accurate ET estimation.

1. **Data Collection**:
   - Meteorological data is collected, including key parameters such as temperature, humidity, solar radiation, and wind speed, which are critical for estimating evapotranspiration (ET).
2. **Input Selection**:
   - Relevant input variables are selected from the meteorological data, ensuring they have significant influence on ET estimation. This step involves preprocessing and feature selection to optimize model performance.
3. **Model Development**:
   - **Artificial Neural Networks (ANN)**: A Levenberg-Marquardt algorithm is employed to train the ANN model for ET estimation.
   - **Support Vector Machines (SVM)**: Different kernel functions (e.g., linear, polynomial, radial basis function) are tested to train the SVM model for improved accuracy.
   - **Adaptive Neuro-Fuzzy Inference System (ANFIS)**: Grid partitioning and subtractive clustering methods are used to train ANFIS, integrating fuzzy logic with neural network capabilities.
4. **Wavelet Transform**:
   - Discrete wavelet transforms (Db2, Db3, Db4) are applied to decompose the meteorological data into different frequency components, enhancing the model's ability to capture temporal features.
5. **Hybrid Model Development**:
   - The wavelet-transformed data is used to train hybrid models:
     - **Wavelet-ANN**: Combines wavelet transforms with ANN for improved pattern recognition.
     - **Wavelet-SVM**: Integrates wavelet transforms with SVM to enhance the prediction accuracy of ET.
     - **Wavelet-ANFIS**: Merges wavelet analysis with ANFIS to model nonlinear relationships in the data.
6. **Performance Analysis**:
   - The performance of all models (ANN, SVM, ANFIS, and their wavelet-integrated versions) is evaluated using statistical metrics such as root mean square error (RMSE), mean absolute error (MAE), coefficient of determination (R^2), and Nash-Sutcliffe efficiency (NSE).
7. **Selection of Best Model**:
   - Based on the performance metrics, the most accurate and reliable model for ET estimation is selected. This model is considered optimal for capturing the variability and complexity of ET in the given context.
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4. Formulation of Various Reference Evapotranspiration Equations:

I. FAO-56 Penman Monteith Method:

This method is universally accepted method for calculating the reference evapotranspiration as it is suitable for all climatic conditions which is revealed from the research conducted worldwide. The FAO-56 Penman Monteith equation for calculating the reference evapotranspiration is given by equation number

$$ET_o = \frac{0.408\,\Delta(R_n - G) + \gamma \frac{900}{T+273} u_2 (e_s - e_a)}{\Delta + \gamma(1 + 0.34\,u_2)}$$

Where, ET0 = reference evapotranspiration in mm/day
Rn = net radiation at the crop surface (MJ/m2/day)
G = soil heat flux density (MJ/m2/day)
T = mean daily air temperature at 2m height (°C)
u2= wind speed at 2m height
es = saturation vapour pressure (KPa)
ea= actual vapour pressure (KPa)
es-ea = saturation vapour pressure deficit (KPa)
Δ = slope of vapour pressure curve (KPa/°C)
γ = Psychrometric constant (KPa/°C)

II. Hargreaves Method:

Hargreaves proposed a simple method for calculating reference evapotranspiration by using temperature and radiation as parameters. He derived an equation for calculation of reference evapotranspiration.

ETo=0.0023(T1+17.8)(Tmax−Tmin)0.5*R'a

Where, ETo is reference evapotranspiration in mm/day, R'a is extraterrestrial radiation at top of atmosphere in mm/day, T1 is average temperature, Tmax and Tmin are maximum and minimum temperature respectively.

III. Blaney Criddle Method :

$$ETo = c\left[p\left(0.4T + 8.13\right)\right]$$

where, ETo = crop evapotranspiration (mm/day) for the month considered. T = daily temperature (°C) over the month considered. p = daily percentage of total annual daytime hours. c = sunshine hours and daytime wind estimates.

The equation includes N/n ratio, Relative Humidity (RH) and windspeed (U) in meter/second parameters in addition to the mean daily temperature which are explained below: n =Actual daily sunshine duration (hours) N=Maximum possible daily sunshine hours R.H. =Minimum relative humidity (%) during the day U= Mean daytime wind-speed (meter per second) at 2 meters height above the ground.

IV. Jansen-Haise Method (1963):-

Jansen and Haise proposed a simple equation based on the temperature and radiation as follows: ETo = CT (Tmean-Tx)*Rs Where CT, Tx are constants

$$C_T = \frac{1}{\left[\left(45 - \frac{h}{137}\right) + \left(\frac{365}{e^{o}(T_{max}) - e^{o}(T_{min})}\right)\right]}$$

$$T_x = -2.5 - 0.14 \times (e^{o}(T_{max}) - e^{0}(T_{min})) - \frac{h}{500}$$

5. CONCLUSION: -

The methodologies and studies reviewed highlight the effectiveness of artificial neural networks (ANNs) and hybrid models in estimating evapotranspiration (ET) with varying levels of input data and climatic conditions. ANN-based approaches, including radial-basis function networks, generalized regression neural networks, and multilayer perceptron models, have demonstrated robust performance in capturing the nonlinear relationships between meteorological variables and ET. Key findings from the research include:

1. **Relevance of Input Variables**: The performance of ANN models heavily depends on the selection of input variables. Studies have shown that reducing input variables negatively impacts model accuracy, emphasizing the importance of individual climatic factors such as temperature, solar radiation, and humidity in ET estimation.
2. **Hybrid Approaches Enhance Performance**: Integrating wavelet transforms and optimization algorithms like genetic algorithms (GA) or artificial bee colony (ABC) optimization with ANNs has significantly improved the accuracy and reliability of ET estimation models. These hybrid approaches capture complex temporal patterns and nonlinear relationships effectively.
3. **Regional and Data-Specific Challenges**: While ANN models perform well in specific regions or under certain climatic conditions, their accuracy often depends on the availability of localized training data. Studies indicate limitations in generalizing ANN models to diverse climatic zones without extensive and representative datasets.
4. **Practical Applications**: ANN models have proven to be effective for tasks such as gap-filling in ET datasets, estimating crop water requirements under limited data conditions, and providing better accuracy than traditional empirical methods like the Hargreaves equation.

Overall, the studies demonstrate that ANN and its hybrid models are reliable tools for ET estimation when supported by careful input selection, data preprocessing, and performance optimization. However, further work is required to enhance their adaptability across diverse climatic conditions, particularly in arid and semi-arid regions, by incorporating larger and more diverse datasets.

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