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REFERENCE EVAPOTRANSPIRATION ESTIMATION IN BENIN-OWENA RIVER BASIN USING DEEP LEARNING APPROACHES: A REVIEW

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Abstract: Reference evapotranspiration (ETo) is essential for water resource management. Yet, its accurate estimation in the Benin-Owena River Basin Development Authority (BORBDA) is constrained by sparse meteorological networks and incomplete data records. While the FAO Penman-Monteith method remains the standard, its application is limited by data scarcity. This literature review synthesizes existing research on ETo estimation within the BORB and examines the emerging potential of deep learning (DL) approaches. Conventional studies in the basin have primarily relied on empirical and basic machine learning models, revealing systematic data gaps and limited spatial coverage. In contrast, recent DL applications in similar humid tropical regions—such as the Amazon and Southeast Asia-have demonstrated superior performance, with architectures like Long Short-Term Memory (LSTM) and hybrid models effectively capturing complex temporal dependencies and achieving high accuracy even with limited inputs. Despite this success, a significant research gap remains: no comprehensive study has applied advanced DL techniques to ETo modelling in the BORB. This review highlights the critical opportunity to develop robust, DL-based tools tailored to the basin's unique climatic and data conditions. Advancing such methodologies could significantly enhance irrigation scheduling, agricultural water management, and climate adaptation strategies across one of Nigeria's most vital agricultural regions.

Keywords: *Reference evapotranspiration (ETo), Deep learning, Benin-Owena River Basin, Hydrological modeling, Data scarcity.*

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INTRODUCTION

Reference evapotranspiration (ETo) is a critical hydrological parameter for water resources planning, irrigation scheduling, and agricultural water management. Accurate estimation of ETo is particularly vital in river basins like the Benin-Owena River Basin Development Authority (BORBDA) in Nigeria, where rain-fed agriculture dominates and water scarcity increasingly threatens food security.

The Benin-Owena River Basin, covering approximately 33,700 km² across Edo, Delta, Ondo, and Ekiti States, experiences a humid tropical climate with distinct wet and dry seasons, making accurate ETo estimation essential for sustainable water resource management.

Traditional ETo estimation methods, particularly the Food and Agriculture Organization (FAO) Penman-Monteith (PM) equation, require extensive meteorological data, including temperature, humidity, wind speed, and solar radiation. However, many stations within the BORB suffer from incomplete data records, necessitating alternative estimation approaches.

In recent years, deep learning (DL) techniques have emerged as powerful tools for ETo modeling, capable of capturing complex nonlinear relationships between meteorological variables and evapotranspiration without requiring full parametric specifications.

This literature review synthesizes existing research on ETo estimation within the Benin-Owena River Basin context and examines the application of deep learning approaches for evapotranspiration modeling, identifying research gaps and opportunities for advancing hydrological prediction in the region.

OVERVIEW OF THE BENIN-OWENA RIVER BASIN

Geographic and Climatic Characteristics

The Benin-Owena River Basin is situated in southwestern Nigeria, bounded approximately by latitudes 5°50′N to 7°30′N and longitudes 4°30′E to 6°00′E. The basin encompasses major river systems including the Benin River, Owena River, and their tributaries, draining into the Atlantic Ocean.

Topography ranges from coastal lowlands in the south to undulating hills in the north, with elevations varying from sea level to approximately 600 meters.

The climatic regime is characterized by a tropical monsoon pattern with mean annual rainfall ranging from 1,500 mm in the northern sections to over 2,500 mm along the coastal areas. The region experiences two distinct seasons: a wet season spanning April to October and a dry season from November to March. Mean annual temperatures range from 25°C to 28°C, with relative humidity typically exceeding 80% during the wet season [1].

Agricultural and Water Resources Significance

The Benin-Owena River Basin supports diverse agricultural activities including oil palm cultivation, rubber production, rice farming, and mixed cropping systems. The basin is also home to several major dams, including the Owena Dam (Ondo State) and the Ikpoba Dam (Edo State), which provide water for irrigation, domestic supply, and industrial uses. Accurate ETo estimation is essential for optimizing irrigation schedules, particularly during the dry season when water demand peaks and supplies become constrained.

Despite its agricultural significance, the basin faces challenges, including limited meteorological stations, data gaps, and inadequate water management infrastructure.

The Nigerian Hydrological Services Agency (NIHSA) operates limited stations within the basin, and many existing stations suffer from instrumentation failures and data discontinuity, creating significant challenges for conventional ETo estimation methods [2].

REFERENCE EVAPOTRANSPIRATION: CONCEPTS AND ESTIMATION METHODS

Definition and Importance

Reference evapotranspiration (ETo) represents the evapotranspiration rate from a hypothetical grass reference surface with specific characteristics: a height of 0.12 m, surface resistance of 70 s m^{-1}, and albedo of 0.23 [3]. ETo serves as a baseline for estimating crop water requirements when combined with crop coefficients (*Kc*). Accurate ETo estimation directly influences irrigation scheduling, water allocation, and agricultural productivity.

Conventional Estimation Methods

Several empirical and physically based methods exist for ETo estimation, ranging from simple temperature-based approaches to complex combination equations:

Temperature-Based Methods: The Hargreaves-Samani equation, requiring only temperature data, remains widely used in data-scarce regions. However, its accuracy varies significantly across climatic conditions and often underestimates ETo in humid tropical environments [4].

Radiation-Based Methods: The Priestley-Taylor and Turc methods utilize solar radiation and temperature data. While simpler than combination methods, they perform variably under different humidity regimes [5].

Combination Methods: The FAO-56 Penman-Monteith equation is the standard method for ETo estimation, combining energy-balance and aerodynamic components. It requires data on temperature, humidity, wind speed, and solar radiation, providing reliable estimates across diverse climatic conditions [3].

Limitations in Data-Scarce Environments

Within the Benin-Owena River Basin, meteorological stations are sparse and unevenly distributed.

The Nigerian Meteorological Agency (NIMET) operates limited synoptic stations in Benin City, Akure, and Warri, while many agricultural stations lack complete instrumentation. This data scarcity poses significant challenges for implementing the FAO-56 Penman-Monteith method, necessitating alternative approaches that can operate with limited inputs [6].

DEEP LEARNING APPROACHES FOR EVAPOTRANSPIRATION ESTIMATION

Overview of Deep Learning in Hydrology

Deep learning, a subset of machine learning employing artificial neural networks with multiple hidden layers, has demonstrated remarkable capabilities in hydrological modeling.

Unlike traditional statistical methods, deep learning models can automatically extract relevant features from input data, capture complex temporal dependencies, and model nonlinear relationships without requiring explicit physical parameterization [7].

In evapotranspiration modeling, deep learning approaches have shown superior performance compared to conventional empirical equations, particularly in data-limited settings where complete meteorological observations are unavailable [8].

Deep Learning Architectures for ETo Estimation

Artificial Neural Networks (ANNs): The earliest deep learning applications for ETo utilized feedforward ANNs with multiple hidden layers. These models have demonstrated effectiveness in estimating ETo from limited meteorological inputs, often achieving lower error metrics than empirical equations. [9] reported that ANNs outperformed Hargreaves-Samani and Blaney-Criddle methods across multiple climatic zones in Iran.

Recurrent Neural Networks (RNNs): RNNs, particularly Long Short-Term Memory (LSTM) networks, are specifically designed to handle sequential data and capture temporal dependencies. Given the inherent temporal structure of meteorological processes, LSTMs have shown particular promise for ETo modeling. For example, [10] demonstrated that LSTM models achieved higher accuracy than ANNs for daily ETo estimation in the Yellow River Basin, China.

Convolutional Neural Networks (CNNs): While primarily developed for image processing, CNNs have been adapted for time-series analysis in hydrology. Their ability to extract local patterns from sequential data makes them suitable for capturing periodic meteorological patterns. [11] successfully applied hybrid CNN–LSTM architectures for ETo estimation in Brazilian watersheds.

Hybrid and Ensemble Approaches: Recent research has explored hybrid architectures combining multiple deep learning techniques with wavelet transforms, genetic algorithms, or physical constraints. These approaches aim to leverage the strengths of different methods while compensating for individual limitations. [12] reported that wavelet-coupled ANNs improved ETo estimation accuracy compared to standalone models in Mediterranean climates.

Performance Comparison with Conventional Methods

Extensive comparative studies have evaluated deep learning (DL) performance against conventional ETo estimation methods (Table 1):

Table 1. Performance of deep learning methods compared to FAO-56 PM

Study	Location	DL Method	Performance vs FAO-56 PM
Ferreira et al., [71]	Brazil	LSTM	RMSE reduced by 25–40%
Wang et al., [10]	China	LSTM	R^2 = 0.92–0.96 with limited inputs
Gocić et al., [12]	Serbia	Wavelet-ANN	$R^2 \approx 0.94$, outperformed Hargreaves
Majhi et al., [13]	India	CNN–LSTM	MAE reduced by 35% vs empirical methods

EXISTING ETO STUDIES IN THE BENIN-OWENA RIVER BASIN

Conventional Estimation Studies

Several studies have evaluated ETo estimation methods within the Benin-Owena River Basin:

[14] compared the FAO-56 PM, Hargreaves-Samani, and Blaney-Criddle methods at stations in Benin City and Akure. Their results indicated that FAO-56 PM provided the most consistent estimates, while Hargreaves-Samani exhibited systematic underestimation during the wet season. The study recommended calibration of temperature-based methods for local conditions.

[15] assessed seasonal variability of ETo across the BORB using 20-year meteorological records from NIMET stations. Their analysis revealed distinct spatial patterns, with higher ETo values in the northern basin (up to 4.5 mm day^{-1} during the dry season) and lower values near the coast (3.2–3.8 mm day^{-1}). The study noted significant data gaps that limited a comprehensive basin-wide assessment.

[16] developed regional calibration coefficients for the Hargreaves-Samani equation using data from six stations across Edo and Ondo States. Their calibrated model achieved an R^2 of 0.81 compared to FAO-56 PM, a significant improvement over the uncalibrated version (R^2 = 0.64). However, validation at independent stations showed reduced performance, highlighting the need for robust methods that generalize across the basin.

Machine Learning Applications

Recent studies have explored the use of machine learning (ML) techniques for ETo estimation within and beyond the Benin-Owena River Basin, particularly in response to data limitations associated with conventional methods.

[17] Applied Support Vector Machines (SVM) and Random Forest (RF) models for ETo estimation using limited climatic variables from stations in southern Nigeria.

Their findings indicated that RF outperformed SVM and traditional empirical methods, achieving higher accuracy and better generalization across seasons.

[18] investigated the performance of Artificial Neural Networks (ANNs) for ETo prediction in Ondo State using temperature and relative humidity data. The ANN model demonstrated strong predictive capability, with results closely matching FAO-56 PM estimates despite reduced input requirements.

Furthermore,[19] compared multiple machine learning algorithms, including Gradient Boosting and Extreme Learning Machines (ELM), for ETo estimation across southwestern Nigeria. Their results showed that ensemble-based models provided improved accuracy and robustness, particularly under conditions of missing or incomplete meteorological data.

Despite these advancements, the application of advanced deep learning architectures such as LSTM and CNN within the Benin-Owena River Basin remains limited. Most existing studies rely on relatively simple ML models and short-term datasets, highlighting a significant research gap in the adoption of more sophisticated techniques capable of capturing temporal dynamics and spatial variability.

1. Absence of deep learning applications: No published study has applied advanced deep learning (DL) architectures (LSTM, CNN, hybrid models) for ETo estimation within the Benin-Owena River Basin.

2. Limited basin-wide assessments: Existing studies typically focus on individual stations or small clusters, lacking a comprehensive basin-wide evaluation.

3. Inadequate temporal analysis: The temporal structure of ETo patterns, including seasonal and interannual variability, remains underexplored.

4. Uncertainty quantification: Limited attention has been paid to quantifying prediction uncertainty in ETo estimates.

5. Integration with water management: Few studies have linked ETo estimation with practical water management applications within the basin.

COMPARATIVE ANALYSIS: DEEP LEARNING STUDIES IN SIMILAR CLIMATIC REGIONS

To contextualize potential DL applications in the BORB, it is valuable to examine studies from regions with similar tropical humid climates:

West Africa Region: [20] applied LSTM networks for ETo estimation across Senegal using satellite-derived meteorological inputs. Their model achieved R^2 values exceeding 0.90 across multiple stations, demonstrating the feasibility of DL approaches in West African contexts. The study highlighted the importance of proper model architecture selection for regional applications.

Southeast Asia: [21] evaluated multiple deep learning (DL) architectures for ETo estimation in Vietnam's Mekong Delta, a region with similar humid tropical characteristics to the BORB. Their results showed that LSTM models significantly outperformed ANNs and empirical equations, with the greatest improvements observed during periods of limited data availability.

Amazon Basin: [22] conducted a comprehensive benchmarking of DL methods for ETo across Brazilian Amazon stations. They found that ensemble approaches combining multiple DL architectures produced the most robust estimates, with prediction intervals effectively capturing uncertainty.

Table 2. Key Lessons for Benin-Owena Applications

Factor	Lesson	Implication for BORBDA
Data scarcity	LSTM effective with limited inputs	Suitable for sparse station network
Tropical variability	Models capture seasonal patterns	Applicable to BORB bimodal rainfall
Transfer learning	Pre-trained models reduce data needs	Potential for regional generalization
Uncertainty	Quantification improves decision-making	Critical for irrigation management

METHODOLOGICAL FRAMEWORK FOR DEEP LEARNING ETO MODELING

Data Requirements and Sources

For successful DL implementation in the BORB, the following data sources are available (Table 3):

Table 3. Data Sources and Availability

Data Type	Source	Availability
Temperature	NIMET, NIHSA	Daily records, 1970–present
Humidity	NIMET	Daily records, gaps present
Wind speed	NIMET	Limited stations
Solar radiation	NIMET (computed)	Derived from sunshine hours
Evaporation	NIHSA	Pan evaporation data

Model Development Considerations

Input Selection: Optimal input combinations for DL models in tropical environments typically include daily maximum and minimum temperature, relative humidity, wind speed, and extraterrestrial radiation. Studies suggest that models using 3–5 input variables achieve performance approaching full-input models in humid tropical settings [8].

Temporal Resolution: Daily ETo estimation requires consideration of temporal dependencies. LSTM models typically utilize input sequences of 7–30 days to capture antecedent conditions and seasonal patterns.

Validation Strategies: Given the limited station network, cross-validation across stations and temporal hold-out periods is essential for assessing model generalization. K-fold validation with spatial separation ensures robust performance evaluation.

Proposed Architectural Approaches

Based on successful applications in analogous regions, the following architectures are recommended for BORB applications:

1. LSTM networks: For capturing temporal dependencies in meteorological sequences
2. Hybrid CNN-LSTM: For extracting local patterns while maintaining temporal memory
3. Attention-based models: For identifying critical time steps influencing ETo
4. Ensemble methods: For improving robustness and uncertainty quantification

CHALLENGES AND FUTURE DIRECTIONS

Data Challenges

- Sparse observations: Limited meteorological stations constrain model training and validation.
- Data quality issues: Instrument failures, inconsistent recording, and missing values require robust preprocessing.
- Temporal inconsistency: Changing instrumentation and measurement protocols create inhomogeneities.

Future Research Directions

1. Satellite data integration: Incorporating remote sensing products (e.g., MODIS, Landsat) for spatial coverage.
2. Climate change applications: Assessing ETo trends under changing climatic conditions.
3. Real-time forecasting: Developing operational systems for irrigation scheduling.
4. Hybrid physics-DL models: Incorporating physical constraints to improve accuracy and generalizability.
5. Regional model development: Creating basin-specific models that generalize across the BORB.

CONCLUSIONS

Reference evapotranspiration estimation remains a critical challenge for water resources management in the Benin-Owena River Basin. Conventional methods, while established, face limitations due to data scarcity and the complex climatic characteristics of the region. Deep learning approaches offer promising alternatives, with demonstrated success in similar tropical environments across West Africa, Southeast Asia, and South America.

The existing literature reveals a significant research gap: no comprehensive deep learning-based ETo modelling has been conducted for the Benin-Owena River Basin. This gap presents an opportunity to develop advanced estimation tools that can improve water management, enhance agricultural productivity, and contribute to climate adaptation efforts in one of Nigeria's most important agricultural regions.

Future research should focus on developing and validating LSTM-based and hybrid deep learning architectures specifically tailored to the BORB's climatic and data characteristics, integrating available meteorological records, satellite products, and domain knowledge to produce robust, operational ETo estimation tools.

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PROCENA REFERENTNE EVAPOTRANSPIRACIJE U BASENU REKE BENIN-OVENA KORIŠĆENJEM PRISTUPA DUBOKOG UČENJA: - PREGLED

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Apstrakt: Referentna evapotranspiracija (ETo) je neophodna za upravljanje vodnim resursima. Međutim, njena tačna procena u Upravi za razvoj sliva reke Benin-Ovena (BORBDA) je ograničena oskudnim meteorološkim mrežama i nepotpunim zapisima podataka.

Iako Penman-Montejt metoda FAO ostaje standard, njena primena je ograničena nedostatkom podataka.

Ovaj pregled literature sintetiše postojeća istraživanja o proceni ETo unutar BORBDA (Benin-Owena River Basin Development Authority) i ispituje novi potencijal pristupa dubokog učenja DL (Deep Learning).

Konvencionalne studije o slivu reke su se prvenstveno oslanjale na empirijske i osnovne modele mašinskog učenja, otkrivajući sistematske nedostatke u prikupljenim podacima i ograničenu prostornu pokrivenost.

Nasuprot tome, nedavne primene dubokog učenja (DL) u procesu evapotranspiracije u sličnim vlažnim tropskim regionima – kao što su Amazon i Jugoistočna Azija – pokazale su superiorne performanse, sa arhitekturama poput dugoročno-kratkoročno memorije Long Short-Term Memory (LSTM) i hibridnim modelima koji efikasno obuhvataju složene vremenske zavisnosti i postižu visoku tačnost, čak i sa ograničenim ulaznim podacima.

Uprkos ovom uspehu, ostaje značajan istraživačka prepreka: nijedna sveobuhvatna studija nije primenila napredne tehnike DL (Deep Learning) na ETo modeliranje u slivu BORB (Benin-Owena River Basin).

Ovaj pregled ističe kritiku prilike za razvoj robusnih, DL (Deep Learning) baziranih alata, prilagođenih jedinstvenim klimatskim i podacima uslovima basena reke Benin-Ovena. Unapređenje takvih metodologija moglo bi značajno poboljšati postavljanje i kontrolu navodnjavanja, upravljanje poljoprivrednim vodama i strategije prilagođavanja klimatskim promenama u jednom od najvitalnijih poljoprivrednih regiona Nigerije.

Ključne reči: *Referentna evapotranspiracija (ETo), duboko učenje, basen reke Benin-Ovena, hidrološko modeliranje, nedostatak podataka.*

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