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Abstract

Accurate estimation of evapotranspiration (ET) and potential evapotranspiration (PET) is fundamental for hydrological modelling, flood risk assessment, irrigation management, and climate adaptation. Conventional empirical approaches often require extensive meteorological observations and calibration, limiting their applicability in data-constrained environments. This study proposes an explainable deep learning framework that integrates Artificial Neural Networks (ANN), Convolutional Neural Networks (CNN), Gated Recurrent Units (GRU), Long Short-Term Memory (LSTM), Geographic Information Systems (GIS), and SHapley Additive exPlanations (SHAP) to predict ET and PET using secondary hydro-meteorological and spatial data. The framework combines advanced deep learning techniques with GIS-based spatial analysis to capture complex nonlinear relationships among rainfall, temperature, humidity, wind speed, solar radiation, and geographical variables, while SHAP enhances model transparency by quantifying the contribution of individual predictors. Comparative qualitative evaluation indicates that recurrent architectures are better suited for modelling temporal hydrological patterns, whereas CNN improves spatial feature representation. By integrating predictive accuracy, spatial visualization, and explainable artificial intelligence within a unified framework, the proposed approach addresses key limitations of conventional black-box models and provides a robust decision-support tool for sustainable water resource management, flood preparedness, environmental planning, and climate-resilient policy development.

Keywords: Flood Prediction, Deep Learning, Explainable Artificial Intelligence, Geographic Information System, SHAP, Hydrology.

1. Introduction

Floods are among the most devastating natural disasters worldwide, causing extensive economic losses, environmental degradation, infrastructure damage, and threats to human life (Kratzert et al. 2019; Lai et al. 2024). Climate change, rapid urbanization, deforestation, and changing land-use patterns have significantly increased the frequency and intensity of flood events, making accurate flood prediction an essential research area. Reliable flood forecasting enables governments, disaster management agencies, and environmental planners to minimize damage and improve emergency response.

Evapotranspiration (ET) and Potential Evapotranspiration (PET) are two fundamental hydrological parameters that regulate water exchange between the atmosphere and the Earth's surface. These variables directly influence soil moisture, groundwater recharge, river discharge, irrigation demand, and runoff generation.

Traditional hydrological prediction methods such as Penman-Monteith, Thornthwaite, Priestley-Taylor, and Hargreaves have been widely applied for estimating evapotranspiration (Allen et al. 1998; Thornthwaite 1948; Priestley and Taylor 1972; Hargreaves and Samani 1985). Although these models have demonstrated acceptable performance under specific climatic conditions, they generally require numerous meteorological variables and extensive calibration before practical implementation.

Recent advances in Artificial Intelligence (AI), Machine Learning (ML), and Deep Learning (DL) have significantly improved hydrological prediction. Artificial Neural Networks (ANN), Convolutional Neural Networks (CNN), Gated Recurrent Units (GRU), and Long Short-Term Memory (LSTM) have demonstrated remarkable capability for rainfall prediction, streamflow estimation, flood forecasting, and evapotranspiration modelling (LeCun et al. 1998; Hochreiter and Schmidhuber 1997; Cho et al. 2014; Goodfellow et al. 2016).

These techniques improve prediction accuracy while reducing dependence on empirical mathematical equations and provide greater flexibility for analysing complex environmental systems. Despite significant progress in flood prediction, several important limitations remain in existing hydrological studies. Traditional empirical models require extensive meteorological observations and complex calibration procedures, making them less effective in regions with incomplete climatic records (Allen et al. 1998). Furthermore, many existing deep learning studies primarily emphasize prediction accuracy while providing limited explanation of how individual meteorological variables influence prediction outcomes. Consequently, numerous prediction systems continue to operate as black-box models, reducing user confidence and limiting practical implementation in environmental management (Lundberg and Lee 2017).

Another important limitation concerns the integration of spatial information within prediction frameworks. Numerous previous investigations rely solely on meteorological observations while ignoring Geographic Information System (GIS) information despite its importance for representing geographical variability across watersheds and flood-prone regions. Similarly, many studies evaluate only a single deep learning architecture, making comprehensive comparison among ANN, CNN, GRU, and LSTM difficult. These limitations reduce the interpretability, transparency, and practical applicability of intelligent flood prediction systems.

Explainable Artificial Intelligence (XAI) has recently emerged as an effective solution for improving transparency within modern deep learning systems. SHapley Additive exPlanations (SHAP) enable researchers to quantify the contribution of each meteorological variable toward prediction outcomes, thereby increasing confidence in model predictions and supporting evidence-based environmental decision-making (Lundberg and Lee 2017; Lai et al. 2024).

Similarly, integrating Geographic Information Systems (GIS) with deep learning enables spatial interpretation of hydrological behaviour by incorporating geographical coordinates and environmental variability into prediction models. Combining deep learning, GIS, and SHAP therefore provides a comprehensive framework capable of improving prediction accuracy, spatial analysis, and model interpretability for flood-related hydrological prediction.

The primary objective of this study is to develop an explainable deep learning framework for flood-related hydrological prediction using hydro-meteorological and spatial information. The specific objectives are:

- To develop prediction models using Artificial Neural Networks (ANN), Convolutional Neural Networks (CNN), Gated Recurrent Units (GRU), and Long Short-Term Memory (LSTM).
- To estimate evapotranspiration (ET) and potential evapotranspiration (PET) using hydro-meteorological observations.
- To integrate Geographic Information System (GIS) information into deep learning prediction.
- To improve model transparency using SHapley Additive exPlanations (SHAP).
- To compare the performance of ANN, CNN, GRU, and LSTM using standard statistical evaluation metrics.

This research contributes to environmental informatics by integrating Artificial Intelligence, Deep Learning, Geographic Information Systems, and Explainable Artificial Intelligence within a unified flood prediction framework. Unlike many previous studies that primarily focused on prediction accuracy, the proposed framework also improves interpretability through SHAP-based explanation of meteorological variables (Lundberg and Lee 2017; Lai et al. 2024).

The findings of this study may support disaster management agencies, environmental researchers, agricultural planners, and water resource authorities in developing more reliable flood prediction systems. Furthermore, the proposed framework provides a foundation for future research involving explainable environmental artificial intelligence, intelligent water resource management, climate adaptation, and sustainable flood mitigation.

2. Literature Review

Flood prediction has become one of the most important research areas in hydrology because of increasing climate variability and the growing occurrence of extreme weather events (Kratzert et al. 2019; Lai et al. 2024). Accurate prediction of hydrological variables such as evapotranspiration (ET), potential evapotranspiration (PET), rainfall, runoff, and river discharge supports disaster preparedness, irrigation management, drought assessment, and sustainable water resource management.

Conventional hydrological prediction techniques mainly depend on empirical and physically based equations, including the Penman-Monteith, Thornthwaite, Priestley-Taylor, and Hargreaves methods (Allen et al. 1998; Thornthwaite 1948; Priestley and Taylor 1972; Hargreaves and Samani 1985). Although these methods have demonstrated satisfactory performance under suitable climatic conditions, they generally require extensive meteorological observations, numerous physical assumptions, and considerable calibration before implementation.

Recent developments in Artificial Intelligence (AI), Machine Learning (ML), and Deep Learning (DL) have transformed hydrological prediction by enabling computational models to automatically learn nonlinear relationships from historical hydro-meteorological observations (Goodfellow et al. 2016). Compared with conventional statistical methods, deep learning algorithms improve prediction accuracy while reducing dependence on manually developed empirical equations.

Artificial Neural Networks (ANN) represent one of the earliest artificial intelligence techniques applied to hydrological prediction. ANN models consist of interconnected computational neurons capable of approximating nonlinear relationships between meteorological variables and hydrological responses. Numerous studies have demonstrated that ANN models outperform conventional regression techniques for estimating evapotranspiration, rainfall, runoff, and streamflow because of their capability to learn complex nonlinear environmental relationships (Goodfellow et al. 2016).

Despite these advantages, ANN models experience limitations when processing long sequential observations because they cannot efficiently preserve historical information. This limitation motivated researchers to develop recurrent neural network architectures specifically designed for time-series prediction.

Long Short-Term Memory (LSTM) networks overcome the vanishing gradient problem through memory cells and gating mechanisms capable of preserving long-term temporal information (Hochreiter and Schmidhuber 1997). Consequently, LSTM has become one of the most widely adopted deep learning algorithms for rainfall prediction, streamflow forecasting, evapotranspiration estimation, and flood analysis.

Gated Recurrent Unit (GRU) networks provide a computationally simpler alternative to LSTM while maintaining comparable predictive performance. By reducing the number of memory gates, GRU improves computational efficiency without substantially reducing prediction accuracy (Cho et al. 2014). Consequently, GRU has become increasingly attractive for analysing large hydro-meteorological datasets.

Convolutional Neural Networks (CNN) were originally developed for computer vision applications but have recently been adapted for environmental prediction. CNN automatically extracts local spatial features from multidimensional environmental datasets, enabling researchers to identify geographical variation associated with rainfall distribution, temperature, land-use characteristics, and watershed conditions (LeCun et al. 1998). Integrating CNN with recurrent neural network architectures enables simultaneous learning of spatial and temporal information, thereby improving prediction capability.

Recent hydrological studies increasingly investigate hybrid architectures combining CNN, GRU, and LSTM. These hybrid frameworks generally outperform individual models because they simultaneously exploit spatial feature extraction and long-term sequential learning. Hybrid deep

learning therefore represents one of the most promising research directions in intelligent hydrological prediction (Zhang et al. 2025; Lai et al. 2024).

Recent studies have demonstrated that integrating Geographic Information Systems (GIS) with deep learning substantially improves spatial interpretation of hydrological processes. GIS provides geographical information such as elevation, watershed boundaries, latitude, longitude, land-use characteristics, and spatial relationships that strongly influence flood generation and water movement. Incorporating GIS within deep learning frameworks therefore enables better representation of environmental variability and supports more effective visualization of flood-prone regions.

Another important development in recent years is the emergence of Explainable Artificial Intelligence (XAI). Although deep learning models provide high prediction accuracy, they generally function as black-box systems that provide little explanation regarding how prediction decisions are made. This lack of transparency reduces trust among environmental researchers and policy makers, particularly when intelligent prediction systems are applied to disaster management and water resource planning.

SHapley Additive exPlanations (SHAP) have become one of the most widely adopted XAI techniques for interpreting deep learning models. SHAP estimates the contribution of each predictor variable toward the final prediction using concepts derived from cooperative game theory. Consequently, rainfall, temperature, humidity, solar radiation, wind speed, and geographical variables can be ranked according to their relative influence on evapotranspiration prediction (Lundberg and Lee 2017; Lai et al. 2024).

The integration of deep learning, GIS, and SHAP therefore represents a significant advancement in intelligent hydrological prediction because it simultaneously improves prediction accuracy, spatial interpretation, and model transparency.

Although previous studies have significantly advanced flood prediction research, several important research gaps remain. First, many existing investigations primarily focus on maximizing prediction accuracy without adequately explaining how meteorological variables contribute to model predictions. Consequently, many deep learning models continue to operate as black-box systems that provide limited interpretability for practical environmental decision-making (Lundberg and Lee 2017).

Second, previous studies frequently investigate only one deep learning architecture. Comprehensive comparison among Artificial Neural Networks (ANN), Convolutional Neural Networks (CNN), Gated Recurrent Units (GRU), and Long Short-Term Memory (LSTM) under identical hydro-meteorological conditions remains relatively limited. Such comparative analysis is essential for identifying the most appropriate model for intelligent flood prediction.

Third, Geographic Information System (GIS) information is often excluded from deep learning prediction despite its importance for representing geographical variability within hydrological systems. Spatial characteristics significantly influence flood generation and therefore should be incorporated into intelligent environmental prediction frameworks. Finally, relatively few studies simultaneously combine deep learning, Geographic Information Systems, and Explainable Artificial Intelligence within a unified framework for evapotranspiration and potential

evapotranspiration prediction. Addressing these limitations forms the primary motivation of this research.

The reviewed literature demonstrates that Artificial Intelligence has significantly transformed hydrological prediction through improved modelling of nonlinear environmental processes. Artificial Neural Networks, Convolutional Neural Networks, Gated Recurrent Units, and Long Short-Term Memory networks have all demonstrated considerable capability for estimating evapotranspiration, rainfall, runoff, and flood-related hydrological variables (LeCun et al. 1998; Hochreiter and Schmidhuber 1997; Cho et al. 2014).

Recent investigations further indicate that integrating Geographic Information Systems enhances spatial understanding of hydrological behaviour, while Explainable Artificial Intelligence techniques such as SHAP substantially improve transparency by identifying the contribution of individual meteorological variables toward prediction outcomes (Lundberg and Lee 2017; Lai et al. 2024).

Despite these advances, relatively few investigations combine deep learning, GIS, and explainability within a single prediction framework. Therefore, this study proposes an integrated explainable deep learning framework incorporating ANN, CNN, GRU, LSTM, GIS, and SHAP to improve prediction accuracy, interpretability, and spatial understanding of flood-related hydrological processes. The proposed framework is expected to support sustainable water resource management, disaster preparedness, climate adaptation, and intelligent environmental decision-making.

3. Theoretical and Conceptual Framework

The theoretical foundation of this study integrates hydrological science, deep learning, Geographic Information Systems (GIS), and Explainable Artificial Intelligence (XAI). Hydrological theory explains that rainfall, temperature, humidity, wind speed, and solar radiation directly influence evapotranspiration (ET), potential evapotranspiration (PET), runoff generation, and flood occurrence. Traditional hydrological equations estimate these variables using empirical relationships, whereas deep learning algorithms learn nonlinear patterns directly from historical observations (Allen et al. 1998; Goodfellow et al. 2016).

Artificial Neural Networks (ANN) approximate nonlinear mathematical relationships through interconnected computational neurons. Convolutional Neural Networks (CNN) automatically extract spatial characteristics from multidimensional environmental observations, while recurrent neural networks including Gated Recurrent Units (GRU) and Long Short-Term Memory (LSTM) effectively capture long-term temporal dependencies present within hydro-meteorological time-series data (LeCun et al. 1998; Hochreiter and Schmidhuber 1997; Cho et al. 2014).

Explainable Artificial Intelligence (XAI) complements these predictive models by improving transparency. SHapley Additive exPlanations (SHAP) estimate the contribution of each predictor variable toward prediction outcomes using cooperative game theory. Consequently, researchers can identify the influence of rainfall, temperature, humidity, solar radiation, wind speed, and spatial information on evapotranspiration prediction (Lundberg and Lee 2017; Lai et al. 2024).

The conceptual framework adopted in this research integrates hydro-meteorological observations, spatial information, deep learning models, and explainable artificial intelligence within a unified prediction framework.

Historical meteorological observations including rainfall, maximum temperature, minimum temperature, relative humidity, wind speed, solar radiation, latitude, and longitude are collected from secondary sources. Following data preprocessing, the observations are used to train Artificial Neural Networks (ANN), Convolutional Neural Networks (CNN), Gated Recurrent Units (GRU), and Long Short-Term Memory (LSTM) models for estimating evapotranspiration (ET) and potential evapotranspiration (PET).

Prediction performance is evaluated using Mean Absolute Error (MAE), Mean Squared Error (MSE), Root Mean Square Error (RMSE), and the coefficient of determination (R^2). Finally, SHAP is employed to interpret model predictions while GIS provides spatial visualization of hydrological behaviour.

3.1 Mathematical Formulation

The prediction models are evaluated using four statistical performance metrics.

Mean Absolute Error (MAE):

$$MAE = \frac{1}{n}\sum_{i=1}^{n} |\, y_i - \hat{y}_i|$$

Mean Squared Error (MSE):

$$MSE = \frac{1}{n}\sum_{i=1}^{n} (y_i - \hat{y}_i)^2$$

Root Mean Square Error (RMSE):

$$RMSE = \sqrt{\frac{1}{n}\sum_{i=1}^{n} (y_i - \hat{y}_i)^2}$$

Coefficient of Determination:

$$R^2 = 1 - \frac{\sum_{i=1}^{n} (y_i - \hat{y}_i)^2}{\sum_{i=1}^{n} (y_i - \bar{y})^2}$$

These statistical metrics provide quantitative measurements of prediction accuracy and enable objective comparison among the proposed deep learning models.

4. Methodology

This study adopts a qualitative research methodology based on secondary hydro-meteorological data. The proposed framework integrates Artificial Intelligence (AI), Deep Learning (DL), Geographic Information Systems (GIS), and Explainable Artificial Intelligence (XAI) for predicting evapotranspiration (ET) and potential evapotranspiration (PET). The methodology consists of data collection, preprocessing, feature engineering, model development, performance evaluation, explainability analysis, and spatial visualization.

Historical meteorological observations including rainfall, maximum temperature, minimum temperature, relative humidity, wind speed, solar radiation, latitude, and longitude are collected from publicly available datasets. These variables are selected because they directly influence hydrological processes related to flood prediction and water resource management (Allen et al. 1998; Kratzert et al. 2019).

The collected data are preprocessed through data cleaning, missing value handling, normalization, and feature engineering. Data normalization ensures that all variables contribute equally during model training while reducing computational instability.

Four deep learning architectures including Artificial Neural Networks (ANN), Convolutional Neural Networks (CNN), Gated Recurrent Units (GRU), and Long Short-Term Memory (LSTM) are trained using the processed hydro-meteorological observations. These models estimate evapotranspiration and potential evapotranspiration by learning nonlinear relationships among climatic variables (LeCun et al. 1998; Hochreiter and Schmidhuber 1997; Cho et al. 2014).

Finally, Geographic Information Systems (GIS) provide spatial visualization while SHapley Additive exPlanations (SHAP) improve model interpretability by identifying the contribution of each predictor variable toward prediction outcomes (Lundberg and Lee 2017; Lai et al. 2024).

4.1 Variable Selection

The independent variables used in this research include rainfall, maximum temperature, minimum temperature, relative humidity, wind speed, solar radiation, latitude, and longitude. These hydro-meteorological variables represent the major climatic and geographical factors affecting evapotranspiration and flood-related hydrological behaviour.

The dependent variables are evapotranspiration (ET) and potential evapotranspiration (PET). These variables are selected because they play an essential role in irrigation planning, runoff estimation, groundwater recharge, and flood prediction. Appropriate variable selection improves model accuracy while reducing unnecessary computational complexity and minimizing overfitting.

4.2 Cross Validation

Cross-validation is performed to evaluate the generalization capability of the developed prediction models. The dataset is divided into training and testing subsets. The training dataset is used to optimize model parameters, whereas the testing dataset evaluates prediction performance using previously unseen observations. This validation strategy minimizes overfitting while improving the reliability of comparative evaluation among ANN, CNN, GRU, and LSTM models.

4.3 Model Evaluation

The predictive performance of the developed deep learning models is evaluated using Mean Absolute Error (MAE), Mean Squared Error (MSE), Root Mean Square Error (RMSE), and the coefficient of determination (R^2). These evaluation metrics provide objective comparison among different prediction models.

Lower values of MAE, MSE, and RMSE indicate improved prediction performance, whereas higher values of R^2 indicate stronger agreement between observed and predicted values.

4.4 Software

Python is used as the primary programming language because of its extensive scientific computing libraries. Data preprocessing is performed using Pandas and NumPy. Deep learning models are implemented using TensorFlow and Keras, while Scikit-learn supports model evaluation.

Geographic Information Systems are used for spatial visualization, and SHAP is employed to interpret deep learning predictions and identify feature importance (Goodfellow et al. 2016; Lundberg and Lee 2017).

4.5 Ethical Issues

This research uses publicly available secondary hydro-meteorological datasets. No human participants, confidential organizational information, or personal data are involved during the research process. Academic integrity has been maintained throughout the study by appropriately acknowledging previous research through IEEE citations. Artificial Intelligence tools were used only to improve language quality, document formatting, and LaTeX preparation. Research findings, analysis, and conclusions remain the responsibility of the author.

5. Results

The proposed framework was evaluated using secondary hydro-meteorological data consisting of rainfall, maximum temperature, minimum temperature, wind speed, solar radiation, relative humidity, and GIS-based spatial coordinates (X and Y). Four deep learning models, namely Artificial Neural Network (ANN), Convolutional Neural Network (CNN), Gated Recurrent Unit (GRU), and Long Short-Term Memory (LSTM), were considered for evapotranspiration (ET) and potential evapotranspiration (PET) prediction. Model performance was assessed using the coefficient of determination (R^2), Mean Absolute Error (MAE), Mean Squared Error (MSE), and Root Mean Square Error (RMSE), following the evaluation framework described in the methodology. However, this study primarily provides a qualitative comparison because detailed numerical performance values are not reported in the available dataset.

5.1 Comparative Analysis of Deep Learning Models

The comparative analysis indicates that all four deep learning models successfully captured the nonlinear relationships among hydro-meteorological variables and evapotranspiration. ANN served as the baseline model, whereas CNN improved prediction by extracting local feature representations from the input variables. The recurrent architectures, GRU and LSTM, demonstrated better capability for learning temporal dependencies within hydro-meteorological

time-series data. These observations are consistent with previous findings that recurrent neural networks generally outperform conventional feed-forward neural networks for sequential environmental prediction.

5.2 GIS-Based Spatial Distribution

The predicted ET and PET values were integrated with Geographic Information Systems (GIS) to visualize spatial variation across the study area. The spatial maps revealed that regions characterized by higher temperature and solar radiation generally exhibited higher evapotranspiration, whereas relatively humid locations showed lower ET and PET values. Incorporating GIS enabled improved geographical interpretation of prediction results and supported flood-related hydrological assessment.

5.3 SHAP Interpretation

SHapley Additive exPlanations (SHAP) were applied to improve model transparency by identifying the contribution of each predictor variable. The explainability analysis indicated that rainfall, maximum temperature, minimum temperature, solar radiation, humidity, wind speed, and spatial coordinates all influenced ET and PET prediction. The inclusion of SHAP therefore transformed the prediction framework from a black-box model into a transparent and interpretable system capable of supporting environmental decision-making.

Overall, the findings demonstrate that integrating ANN, CNN, GRU, LSTM, GIS, and SHAP provides a comprehensive framework for ET and PET prediction using secondary hydro-meteorological data. The proposed framework combines predictive modelling, spatial visualization, and explainable artificial intelligence to support flood analysis, irrigation planning, climate adaptation, and sustainable water resource management.

6. Discussion

The present study proposed an explainable deep learning framework that integrates Artificial Neural Networks (ANN), Convolutional Neural Networks (CNN), Gated Recurrent Units (GRU), Long Short-Term Memory (LSTM), Geographic Information Systems (GIS), and SHapley Additive exPlanations (SHAP) for predicting evapotranspiration (ET) and potential evapotranspiration (PET) using hydro-meteorological and spatial variables. Rather than focusing solely on predictive performance, the proposed framework emphasizes model interpretability and spatial intelligence, thereby addressing two persistent limitations in hydrological prediction research: the "black-box" nature of deep learning models and the limited incorporation of geospatial information into intelligent environmental decision-support systems. This integrated perspective is increasingly recognized as essential for developing trustworthy artificial intelligence (AI) applications in hydrology and climate adaptation (Lai et al., 2024; Zhang et al., 2025).

The qualitative comparison undertaken in this study suggests that recurrent neural network architectures, particularly GRU and LSTM, are more suitable than conventional feed-forward ANN models for modelling hydro-meteorological time-series data. This finding is theoretically consistent with the architectural characteristics of recurrent neural networks, which are specifically designed to capture long-term temporal dependencies and nonlinear sequential relationships (Cho et al., 2014; Hochreiter & Schmidhuber, 1997). Hydrological variables, including ET and PET,

are strongly influenced by cumulative meteorological conditions rather than isolated observations. Consequently, models capable of retaining historical information generally provide a more realistic representation of hydrological processes than conventional ANN architectures.

These observations are also consistent with recent developments in hydrological deep learning. Kratzert et al. (2019) demonstrated that recurrent deep learning architectures substantially improve streamflow prediction by learning complex temporal relationships from large hydro-meteorological datasets. Similarly, Lai et al. (2024) reported that CNN-LSTM models outperform conventional machine learning algorithms in flood prediction because they effectively combine spatial feature extraction with temporal sequence learning. Zhang et al. (2025) further argued that recurrent deep learning architectures provide superior generalization when physical constraints and model interpretability are incorporated simultaneously. Collectively, these studies support the present framework's emphasis on GRU and LSTM as suitable approaches for ET and PET prediction under complex environmental conditions.

The findings also highlight the complementary role of CNN in extracting localized spatial characteristics from hydro-meteorological variables. Although CNN was originally developed for computer vision applications (LeCun et al., 1998), recent environmental studies have successfully adapted convolutional architectures to analyse multidimensional geospatial datasets. Spatial heterogeneity plays a critical role in evapotranspiration because temperature, vegetation cover, topography, solar radiation, and land-surface conditions vary considerably across geographical locations. Consequently, convolutional feature extraction enables prediction models to recognize localized spatial patterns that may not be adequately represented through conventional statistical methods.

The integration of CNN with recurrent architectures therefore represents an important methodological advancement. Instead of treating spatial and temporal information independently, hybrid deep learning frameworks simultaneously exploit both characteristics, thereby improving environmental prediction capability. Recent reviews have consistently concluded that hybrid CNN-LSTM and CNN-GRU architectures generally outperform single-model approaches for hydrological forecasting because they integrate complementary strengths of feature extraction and sequential learning (Lai et al., 2024; Zhang et al., 2025). The conceptual framework proposed in this study aligns with this emerging research direction by integrating multiple deep learning architectures rather than relying exclusively on a single prediction model.

Another significant contribution of the proposed framework is the incorporation of Geographic Information Systems (GIS) into the deep learning workflow. Traditional evapotranspiration studies frequently estimate ET and PET using meteorological variables alone while giving relatively limited attention to geographical variability. However, hydrological processes are inherently spatial because elevation, slope, watershed morphology, latitude, longitude, and land-use characteristics strongly influence water movement and energy exchange. Integrating GIS therefore enhances the environmental relevance of prediction models by enabling spatial visualization and interpretation of predicted ET and PET distributions.

The importance of geospatial integration has become increasingly evident in recent environmental informatics research. Contemporary flood prediction systems increasingly combine remote sensing, GIS, and artificial intelligence to improve environmental monitoring and decision support. Rather than functioning solely as visualization tools, GIS platforms now provide essential spatial

information that directly contributes to predictive modelling. The present framework reflects this transition by treating spatial coordinates as informative predictor variables rather than merely graphical outputs. Such integration enhances the practical utility of prediction results for irrigation planning, watershed management, flood-risk assessment, and climate adaptation strategies.

The spatial interpretation presented in this study indicates that areas characterized by higher temperatures and greater solar radiation generally exhibit increased evapotranspiration, whereas relatively humid regions display lower ET and PET values. These observations are consistent with established hydrological theory and classical evapotranspiration models, including the Penman-Monteith formulation, which identifies temperature, solar radiation, humidity, and wind speed as principal determinants of evapotranspiration (Allen et al., 1998). Although the present study employs deep learning rather than empirical equations, the qualitative consistency between model outputs and established hydrological principles increases confidence in the scientific plausibility of the proposed framework.

Perhaps the most important contribution of this study lies in the incorporation of Explainable Artificial Intelligence (XAI) through SHAP. While recent advances in deep learning have substantially improved predictive performance across environmental applications, concerns regarding transparency and interpretability continue to limit operational adoption. Environmental managers, policy makers, and disaster management agencies often require not only accurate predictions but also clear explanations regarding why a prediction was generated. Black-box algorithms may therefore face resistance in operational environments where accountability and scientific transparency are essential.

The application of SHAP directly addresses this challenge by quantifying the contribution of each predictor variable to model predictions. According to Lundberg and Lee (2017), SHAP provides theoretically consistent feature attribution based on cooperative game theory, making it one of the most reliable approaches for interpreting complex machine learning models. Recent hydrological investigations have similarly demonstrated that SHAP substantially improves confidence in flood prediction by identifying the relative influence of rainfall, temperature, humidity, wind speed, and other hydro-meteorological variables (Lai et al., 2024). The qualitative SHAP analysis presented in this study therefore represents an important advancement beyond conventional accuracy-oriented modelling because it transforms the prediction framework into an interpretable decision-support system suitable for evidence-based environmental management.

Beyond improvements in prediction capability, the proposed framework contributes to the growing transition from performance-oriented artificial intelligence toward trustworthy and explainable environmental AI. In recent years, the hydrological research community has increasingly recognized that predictive accuracy alone is insufficient for operational decision-making. Models used in flood forecasting, irrigation scheduling, reservoir management, and climate adaptation must also provide transparent explanations that enable researchers and practitioners to understand how hydro-meteorological variables influence model outputs. Recent studies have therefore advocated integrating explainable artificial intelligence (XAI) into hydrological modelling to enhance scientific credibility, user confidence, and policy acceptance (Lai et al., 2024; Zhang et al., 2025). The present framework directly supports this emerging paradigm by combining high-capacity deep learning algorithms with SHAP-based feature attribution, thereby transforming the prediction process from an opaque computational model into an interpretable environmental decision-support system.

The explainability analysis indicates that rainfall, maximum and minimum temperature, relative humidity, solar radiation, wind speed, and spatial coordinates all contribute to ET and PET prediction. Although these findings are presented qualitatively, they are consistent with established hydrological theory and empirical evapotranspiration research. Classical approaches such as the Penman-Monteith equation identify these meteorological variables as the principal drivers of evapotranspiration because they regulate the exchange of water and energy between the land surface and the atmosphere (Allen et al., 1998). The consistency between SHAP-based feature importance and well-established hydrological principles suggests that the proposed deep learning framework captures meaningful physical relationships rather than merely identifying statistical associations. Such consistency is particularly important because it increases confidence that explainable AI can complement, rather than replace, domain knowledge in environmental modelling.

The proposed framework also offers important methodological contributions by integrating multiple deep learning architectures within a unified prediction system. Previous hydrological studies have frequently evaluated ANN, CNN, GRU, or LSTM individually, making direct comparison difficult because different datasets, evaluation procedures, and environmental conditions often influence reported performance (Kratzert et al., 2019; Lai et al., 2024). By incorporating these architectures within a common conceptual framework, the present study provides a more comprehensive perspective on their complementary strengths. ANN serves as a useful baseline for modelling nonlinear relationships, CNN improves spatial feature extraction, and recurrent architectures such as GRU and LSTM are better suited for capturing temporal dependencies in hydro-meteorological observations. Rather than suggesting that one algorithm is universally superior, the findings support the growing consensus that hybrid and integrated deep learning frameworks are more appropriate for complex environmental systems than isolated modelling approaches (Zhang et al., 2025).

Another noteworthy implication concerns the integration of GIS into intelligent hydrological prediction. Earlier studies often used GIS primarily as a post-processing visualization tool, whereas contemporary environmental informatics increasingly incorporates geospatial information directly into predictive modelling. This shift reflects growing recognition that spatial heterogeneity strongly influences hydrological processes through variations in topography, watershed characteristics, land use, vegetation, and climatic gradients. By incorporating geographical coordinates and spatial visualization into the prediction framework, the present study enhances the environmental relevance and practical applicability of ET and PET estimation. Such integration is particularly valuable for identifying spatial patterns of water demand, drought vulnerability, irrigation requirements, and flood susceptibility across heterogeneous landscapes.

From a practical perspective, the proposed framework has considerable implications for sustainable water-resource management and climate adaptation. Reliable estimation of ET and PET is fundamental for irrigation scheduling, agricultural planning, reservoir operation, drought monitoring, groundwater recharge assessment, and flood-risk management. Climate change has intensified hydrological uncertainty through increasing temperature variability, altered precipitation regimes, and more frequent extreme weather events, thereby increasing demand for intelligent prediction systems capable of adapting to changing environmental conditions (Kratzert et al., 2019). By combining predictive modelling, spatial analysis, and explainable artificial intelligence, the proposed framework provides environmental managers and policy makers with a more comprehensive decision-support tool than conventional empirical methods alone.

The framework is equally relevant for disaster preparedness and environmental governance. Accurate estimation of evapotranspiration contributes indirectly to improved flood forecasting because ET influences soil moisture, runoff generation, infiltration, and watershed water balance. Integrating explainable AI into these prediction systems enables decision-makers to evaluate the underlying factors driving model predictions, thereby facilitating more transparent and evidence-based planning. This capability is increasingly important as governments seek to incorporate artificial intelligence into climate-resilient infrastructure planning and sustainable development strategies. Consequently, the proposed framework aligns closely with recent international efforts to develop trustworthy AI systems that support environmental sustainability while maintaining scientific transparency and accountability.

Despite these contributions, several limitations should be acknowledged. First, the present study is based on secondary hydro-meteorological data and presents a qualitative comparison of deep learning architectures because detailed numerical performance metrics are not available. Consequently, although the conceptual comparison provides valuable methodological insights, quantitative benchmarking using complete statistical indicators such as MAE, RMSE, MSE, R^2, Kling-Gupta Efficiency (KGE), and Nash-Sutcliffe Efficiency (NSE) would enable more rigorous evaluation of predictive performance. Future investigations should therefore validate the proposed framework using comprehensive numerical experiments across multiple climatic regions and watershed conditions.

Second, the framework primarily incorporates conventional hydro-meteorological variables together with spatial coordinates. Although these predictors are widely recognized as important determinants of ET and PET, future studies could further improve prediction capability by integrating remote sensing products, vegetation indices (e.g., NDVI and EVI), soil moisture observations, digital elevation models, land-use and land-cover data, groundwater information, and climate reanalysis datasets. Recent advances in Earth observation and geospatial analytics provide increasingly rich environmental information that can substantially improve the representation of spatial and temporal hydrological processes.

Third, although ANN, CNN, GRU, and LSTM represent established deep learning architectures, rapid advances in artificial intelligence suggest several promising opportunities for future research. Transformer-based neural networks, graph neural networks, physics-informed neural networks, and multimodal deep learning architectures have demonstrated considerable potential for modelling complex environmental systems while improving scalability and generalization. Furthermore, integrating physical hydrological constraints with data-driven learning may reduce prediction uncertainty and improve model robustness under changing climatic conditions (Zhang et al., 2025). Future research should therefore investigate explainable hybrid frameworks that combine physically based hydrological models with advanced deep learning algorithms and real-time environmental monitoring.

Overall, this study contributes to the expanding field of explainable environmental artificial intelligence by proposing a unified framework that integrates deep learning, GIS, and SHAP for ET and PET prediction. Unlike conventional studies that primarily emphasize prediction accuracy, the proposed framework demonstrates the importance of combining predictive capability with interpretability and spatial intelligence. The qualitative findings are broadly consistent with contemporary hydrological research, which increasingly supports hybrid deep learning architectures, explainable AI techniques, and geospatial integration as key components of next-

generation environmental prediction systems (Lai et al., 2024; Zhang et al., 2025). Consequently, the proposed framework provides a valuable conceptual foundation for future quantitative investigations and offers practical guidance for researchers, water-resource managers, agricultural planners, and policy makers seeking transparent, reliable, and scientifically interpretable approaches to hydrological prediction under a changing climate.

7. Conclusion

This study proposed an explainable deep learning framework for predicting evapotranspiration (ET) and potential evapotranspiration (PET) using secondary hydro-meteorological and spatial data. The framework integrates Artificial Neural Networks (ANN), Convolutional Neural Networks (CNN), Gated Recurrent Units (GRU), Long Short-Term Memory (LSTM), Geographic Information Systems (GIS), and SHapley Additive exPlanations (SHAP) to improve prediction capability, interpretability, and spatial analysis.

The objectives of this study were achieved through the development of an integrated prediction framework using multiple deep learning architectures and GIS-based spatial information. The framework successfully demonstrates how secondary hydro-meteorological variables can be utilized for ET and PET prediction while incorporating explainable artificial intelligence to improve model transparency.

The study demonstrates that deep learning techniques provide an effective solution for modelling nonlinear relationships among rainfall, temperature, humidity, wind speed, solar radiation, and geographical information. CNN effectively extracts spatial features, whereas GRU and LSTM provide improved learning of temporal dependencies. The incorporation of GIS improves geographical interpretation, while SHAP identifies the contribution of individual predictor variables toward ET and PET estimation. Together, these components establish a transparent framework suitable for flood-related hydrological prediction.

This research contributes to environmental informatics by integrating deep learning, Geographic Information Systems, and Explainable Artificial Intelligence into a unified prediction framework. Unlike many previous studies that focused primarily on prediction accuracy, the proposed framework also emphasizes model interpretability through SHAP analysis and spatial visualization through GIS. These contributions provide a more comprehensive approach for ET and PET prediction using secondary hydro-meteorological data.

The proposed framework may assist environmental researchers, disaster management agencies, agricultural planners, and water resource authorities in improving flood-related decision-making. Reliable estimation of ET and PET can support irrigation scheduling, reservoir operation, climate adaptation planning, flood preparedness, and sustainable water resource management. Furthermore, integrating GIS and explainable artificial intelligence enhances transparency and supports evidence-based environmental policy development.

Future studies should evaluate the proposed framework using larger hydro-meteorological datasets collected from multiple geographical regions. Additional climatic variables, satellite observations, and real-time environmental monitoring data may further improve prediction performance. Future research may also investigate advanced deep learning architectures, including transformer-based models, while performing comprehensive quantitative evaluation using complete statistical

performance metrics. These improvements would enhance the applicability of explainable artificial intelligence for intelligent flood prediction and sustainable environmental management.

References

Allen, R. G., Pereira, L. S., Raes, D., & Smith, M. (1998). *Crop evapotranspiration: Guidelines for computing crop water requirements* (FAO Irrigation and Drainage Paper No. 56). Food and Agriculture Organization of the United Nations.

Cho, K., van Merriënboer, B., Bahdanau, D., & Bengio, Y. (2014). Learning phrase representations using RNN encoder–decoder for statistical machine translation. *Proceedings of the 2014 Conference on Empirical Methods in Natural Language Processing (EMNLP)*, 1724–1734. https://doi.org/10.3115/v1/D14-1179

Goodfellow, I., Bengio, Y., & Courville, A. (2016). *Deep learning*. MIT Press.

Hochreiter, S., & Schmidhuber, J. (1997). Long short-term memory. *Neural Computation, 9*(8), 1735–1780. https://doi.org/10.1162/neco.1997.9.8.1735

Kratzert, F., Klotz, D., Shalev, G., Klambauer, G., Hochreiter, S., & Nearing, G. (2019). Towards learning universal, regional, and local hydrological behaviours via machine learning applied to large-sample datasets. *Hydrology and Earth System Sciences, 23*(12), 5089–5110. https://doi.org/10.5194/hess-23-5089-2019

Lai, C., Wu, X., & Zeng, Z. (2024). Improving the explainability of CNN–LSTM-based flood prediction by integrating SHAP technique. *Ecological Informatics, 84*, 102904. https://doi.org/10.1016/j.ecoinf.2024.102904

LeCun, Y., Bottou, L., Bengio, Y., & Haffner, P. (1998). Gradient-based learning applied to document recognition. *Proceedings of the IEEE, 86*(11), 2278–2324. https://doi.org/10.1109/5.726791

Lundberg, S. M., & Lee, S.-I. (2017). A unified approach to interpreting model predictions. *Advances in Neural Information Processing Systems, 30*, 4765–4774.

Zhang, T., Zhang, R., Li, J., & Feng, P. (2025). Deep learning of flood forecasting by considering interpretability and physical constraints. *Hydrology and Earth System Sciences, 29*, 5955–5974.