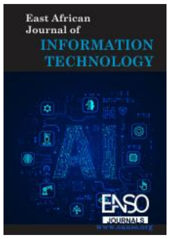

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Original Article

Comparison of Deep Learning Models in Predicting Water Deficits in Semi-Arid Regions: A Case Study of Dodoma, Tanzania

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ABSTRACT

The escalating global freshwater shortage is driven by socio-economic development, changing consumption patterns, and systemic inefficiencies, with semi-arid regions like Dodoma, Tanzania, being especially vulnerable. Traditional statistical and regression-based models for predicting water deficits have proven insufficient in capturing the complex, nonlinear interactions among climatic, hydrological, and anthropogenic factors. To address this gap, this study proposes a deep learning-based predictive framework utilising advanced algorithms, Long Short-Term Memory (LSTM), Convolutional Neural Networks (CNN), Recurrent Neural Networks (RNN), and Deep Neural Networks (DNN) to improve the forecasting of water deficits. Using a thirteen-year (13) dataset collected from the semi-arid climate region of Dodoma, encompassing meteorological, hydrological, and socioeconomic variables. The models were trained and evaluated using performance metrics such as Root Mean Square Error (RMSE) and R-squared (R^2). The DNN model demonstrated superior performance with an RMSE of 0.049 and an R^2 of 1.000, significantly outperforming other models. LSTM, CNN, and RNN models showed moderate to weak predictive accuracy, particularly in handling long-term dependencies and extreme deficit events. The key finding of this study is that the DNN model provides highly reliable and accurate water deficit predictions, making it the most effective among the tested deep learning approaches. This result highlights the value of incorporating deep learning into water resource planning, especially in data-scarce, semi-arid regions. The study concludes that DNN-based models should be prioritised for operational deployment in early warning systems and decision-making platforms. Future work should explore hybrid architectures, hyperparameter tuning, and integration with real-time data sources to enhance robustness and applicability.

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INTRODUCTION

Water is an essential resource for human development, agriculture, ecosystems, and drought management [1]. However, recurring water deficits in the region have led to significant challenges in agriculture, water supply, and sustainable development [2]. The water deficit is the gap between demand and supply, influenced by climate variability, agricultural practices, and population growth. In most parts of the world, accurate and real-time daily or monthly prediction of surface water deficits remains a difficult challenge due to the non-linearity and non-stationarity of the associated real hydrological data [3]. Hence, this research topic gives more attention to the water engineers and decision makers.

Water Deficit prediction has become a major topic in hydrologic time series over the last few decades. The paucity of information about physical concepts while studying the relationships between variables has necessitated the use of data-driven models in hydrological Prediction as an alternative to knowledge-driven methods.

Traditional hydrological forecasting tools often fail to capture the complex, nonlinear relationships between climate variables such as precipitation, temperature, soil moisture, and vegetation dynamics. These methods typically rely on physical models or statistical extrapolation, which struggle to generalise well in data-scarce and heterogeneous environments like those found in sub-Saharan Africa.

Deep Learning (DL) models, known for their ability to capture complex patterns in data, offer a promising approach to predicting water deficits compared to traditional statistical methods. This study seeks to employ and compare different DL models for the prediction of potential water deficit in Dodoma with the aid of recognition of the appropriate features to construct the learning process of the DL model.

Dodoma, a semi-arid climate, coupled with increasing water demands, faces a significant risk of recurrent water shortages. Traditional methods for predicting water deficits, such as statistical and regression-based approaches, often fail to capture the complex interactions between climatic, hydrological, and anthropogenic factors.

The new data-driven approaches, such as "DL algorithms," have shown capacity in capturing complex non-linear data patterns that would have required extrapolation [4]; hence, they are considered an alternative method to the existing

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prediction methods in several fields of hydrology, such as river flow forecasting [5].

While DL techniques have shown great promise in other domains, their application in water deficit prediction remains underexplored in Tanzania. This study addresses the need for improved predictive models by deploying appropriate features/parameters (climate variables) selection by analysing Complex Interactions and incorporating relationships between climatic, hydrological, and anthropogenic factors influencing water deficits that contribute significantly to surface water loss in the region, thereby providing a framework for proactive water management in Dodoma, Tanzania.

By utilising advanced DL techniques such as LSTM, RNN, CNN, and DNN, the study intends to enhance the accuracy and reliability of water deficit predictions. The research identifies and selects key features that have the greatest impact on water deficit prediction.

BACKGROUND INFORMATION AND RELATED WORKS

Researchers have emphasised the importance of accurate and timely short-term water demand forecasting for effective urban water supply management. Previous studies highlighted that many DL-based forecasting models relied on manual feature extraction strategies, resulting in incomplete data utilisation and limited adaptability. To address these challenges, a novel framework was developed, incorporating the S-H-ESD method for data pre-processing and the Conv1D-GRU (one-dimensional convolution-gated recurrent unit) model for forecasting [7]. Historical monitoring data were analysed using various hyperparameter configurations and training strategies. The findings revealed that S-H-ESD effectively handled anomalies, significantly enhancing forecasting accuracy. For example, with a 7-day training dataset, the S-H-ESD method improved average model accuracy by 1.23% compared to the Z-Score method. Additionally, the Conv1D-GRU model demonstrated superior accuracy and adaptability in feature extraction compared to models such as GRUN and ANN. Under optimal parameter settings and training strategies, the framework achieved exceptional performance, with the best MAPE and NSE values recorded at 1.677% and 0.983, respectively. This research underscores the potential of combining advanced pre-processing techniques with adaptable forecasting models to enhance short-term water demand prediction.

Focused on forecasting models using artificial intelligence, comparing nine ML and DL approaches with water consumption data from both univariate (water consumption only) and multivariate (including climatic and calendar inputs) time series models were evaluated. Results show that DL models, particularly LSTM, achieved superior accuracy, with mean absolute errors of 0.11 m^3/hr (univariate) and 2.96 m^3/hr (multivariate). These findings highlight LSTM's potential for sustainable water resource management.

[10] In their research, they examined recent advancements in applying ML to water quality prediction, highlighting the challenges in identifying a universally best-performing model due to variability across parameters and regions. The review involved an extensive survey and comparison of existing literature to assess the effectiveness of different ML models. It emphasised the need for further exploration of water quality parameter characteristics to develop more broadly applicable methodologies. The review also points out the limitations of ML models that do not account for physical and chemical processes, particularly in predicting coastal water quality. To improve prediction accuracy, it suggests diversifying data sources, increasing data volume, and addressing missing data through interpolation methods. The integration of ML with numerical simulations is proposed as a promising approach for enhancing predictive models and supporting coastal ecosystem conservation efforts. [11] Their study research on urban water demand forecasting using artificial

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intelligence aimed to present the current state of the art and offer guidance on methods and models for researchers and sanitation professionals. It covered models developed with standard statistical techniques, such as linear regression and time-series analysis, as well as Soft Computing methods. The review highlighted that most studies focused on the management of operating systems, leaving room for long-term forecasting. It emphasised that no single global model outperforms all others in every case, requiring regional studies to evaluate the strengths of each model or combination of methods. While the use of ML and Artificial Intelligence in water demand forecasting has increased, there remains significant potential for improvement.

[12] Their study aimed to predict water demand in the Beijing–Tianjin–Hebei region of China, using data from 2004 to 2019. Eleven statistical and ML models were developed, incorporating explanatory variables related to the economy, community, water use, and resource availability. The models were evaluated using interpolation and extrapolation scenarios, with the GBDT model showing the best performance, achieving high accuracy and low error rates. The GBDT model was further validated in three other regions of China, demonstrating robustness with prediction accuracies above 80%. The study found that ML models, particularly ensemble models, outperformed statistical models. The results highlight the effectiveness of the identified variables in predicting water demand and suggest that the best-performing model can be applied to other regions to optimise water resource management. Future work will focus on subdividing water demand, analysing the impact of water reuse, and incorporating the effects of COVID-19 on water demand predictions.

According to the study [13], the authors developed an AI-based model to predict and classify water demand at the Gurye intake station, a crucial site for managing water resources, especially in drought-prone areas. The model utilised advanced ML techniques, including DNN and LSTM networks, to forecast water demand based on historical data and environmental variables. The model was trained with data from 2004 to 2015 and validated using data from 2016 to 2021. The LSTM model demonstrated high accuracy, achieving a CC of 0.95 and a normalised root mean square error (NRMSE) of 8.38, indicating its effectiveness in capturing temporal patterns in water demand. Additionally, the study incorporated probability density functions PDF and CDF to assess the probability of water demand falling within specific ranges, which was essential for developing a crisis alert system. This system provides early warnings for potential water shortages, enabling proactive water management. The study also explored other AI-based classification models, such as DT and Random Forest RF, which considered factors like the previous day's water demand, rainfall, and temperature. The Random Forest model achieved an F1-score of 0.88, further confirming its strong predictive performance. Overall, the findings of this study underscore the potential of AI-based models in improving water resource management. By accurately predicting water demand, these models can contribute to better drought management and water conservation strategies, particularly in regions vulnerable to water scarcity.

According to [14], urban water management is a critical issue for city planners, and accurate water demand forecasting is essential for mitigating water shortage crises. The study applies a Markov chain model combined with ANNs to estimate short-term urban water demand in Tehran, considering factors such as maximum temperature, water consumption, and precipitation rate from the previous four days to predict water consumption on the fifth day. Daily data from March 21, 2018, to March 19, 2021, were collected and analysed. The results showed that the Markov chain model outperformed the ANN model in forecasting accuracy. Specifically, the Markov chain model demonstrated a 48% improvement in accuracy for the test data and a 65% improvement for the training data compared to the ANN model.

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These findings suggest that the Markov chain model is a highly effective tool for estimating short-term urban water demand.

DL methods have demonstrated significant advancements in forecasting hydrological extremes [15], [16]. These methods leverage advanced learning algorithms and model architectures, such as CNNs for automatic feature extraction and LSTM networks for enhanced memory capabilities, enabling the modelling of complex relationships within large datasets [17].

For instance, [16] utilised an LSTM model to forecast drought indices and found it to outperform conventional ML models. Similarly, deep belief networks have shown higher accuracy in stream flow prediction compared to simple neural networks, although their performance was inferior to support vector machines. [15], combined wavelet analysis with an ARIMA-based LSTM model, achieving improved drought forecasting results. In another study, [18] demonstrated that RNN-LSTM models provided better predictions for low-flow hydrological time series compared to standalone RNN models.

Moreover, [19] successfully integrated multi-source remote sensing data with LSTM, support vector regression, and principal component analysis PCA to classify extreme drought events with high accuracy. DL models have also been compared to climate models, which, while effective for primary phenomena like temperature and rainfall, are less sensitive to secondary and tertiary phenomena such as droughts and floods [20]. Leveraging this insight, [20] developed a drought assessment model using DL algorithms and multiple hydro-meteorological precursors, including wind speed, air temperature, rainfall, and geo-potential height. This model demonstrated superior performance in drought monitoring compared to standalone climate models.

[21] Employed a localised sequential LSTM model to assess flood susceptibility, integrating a feature engineering approach. This method enhanced the model's capability to process flood-related conditioning factors and effectively handle sequential data while accounting for diverse spatial relationships. Similarly, [15] proposed a spatiotemporal flood forecasting framework that combined LSTM with a reduced-order modelling technique. By leveraging dimensionality reduction methods, such as singular value decomposition, the framework retained critical orthogonal features while significantly improving computational efficiency without compromising accuracy, making it suitable for real-time flood predictions.

In another study, [22] demonstrated that DL models outperformed traditional statistical approaches like ARIMA and physical hydrological models for predicting flood peaks. While physical models excel at interpreting relationships through equations derived from the dataset, DL models proved more adept at capturing complex, non-linear patterns within the data. Building on these advancements, this study explores spatiotemporal forecasting by integrating linear and non-linear techniques, capitalising on DL's strength in uncovering intricate data relationships.

METHODOLOGY

Study Area

Dodoma, the capital of Tanzania, is situated in a semi-arid region receiving less than 600mm of annual rainfall. The area is predominantly agricultural, relying heavily on seasonal rainfall. Its climatic profile makes it an ideal case for investigating water stress and forecasting models. The landscape is characterised by sparse vegetation, variable topography, and limited irrigation infrastructure. Seasonal variation in rainfall causes unpredictable soil moisture availability, increasing vulnerability for the inhabitants.

Sample Size

The sample used in this study comprises thirteen years (2010–2023) of monthly data collected from various institutional sources relevant to the Dodoma region of Tanzania. This timeframe was selected to ensure a sufficiently large and diverse dataset, capturing seasonal cycles, climate variability, and socio-economic trends across dry and wet years. The extended historical range enhances the model's ability to learn long-term patterns and generalise effectively to future scenarios. In total, the dataset included over 150-time steps, which is well above the minimum threshold required for training deep learning models such as LSTM, RNN, CNN, and DNN, which benefit from long temporal sequences to capture complex interactions.

Data Collection

The expected data sources for water deficit forecasting in Dodoma, Tanzania, encompass several key entities to ensure a comprehensive understanding of the factors influencing water availability. Hydrological data obtained from the Dodoma Water and Sanitation Authority (DUWASA) provides valuable insights into historical water consumption and supply trends. This data is critical for analysing the region’s water resource dynamics and identifying patterns of deficit or surplus.

Meteorological data sourced from the Tanzania Meteorological Authority (TMA), including essential climate variables such as rainfall, temperature, and humidity. These variables play a significant role in understanding seasonal and inter-annual climate variability, which directly impacts water availability in the region. Data was compiled for the period 2010–2023 from multiple sources:

- Meteorological data: Rainfall, temperature, wind speed, surface pressure
- Hydrological data: Soil moisture, PET, evapotranspiration rates

The dataset consisted of 5,110 daily observations collected from Dodoma, Tanzania.

Ethical Considerations: Data Permissions and Confidentiality

Ethical compliance was ensured throughout the study. The data used was obtained from public and institutional sources, including meteorological, hydrological, and demographic datasets that were either openly accessible or provided through institutional collaboration. No personally identifiable or sensitive information was included, and all datasets were anonymised where appropriate.

Data handling practices followed standard ethical guidelines for research involving publicly available environmental and socioeconomic data. Although no formal ethical clearance was required due to the non-human subject nature of the study, care was taken to respect institutional data usage terms, and the research purpose was aligned with sustainable development and environmental policy support.

Future deployments of this model in operational or policy environments will need to ensure ongoing data governance, especially if integrating proprietary or household-level data, which would require further ethical review and possibly consent mechanisms.

Preprocessing and Feature Engineering

After cleaning, 1.6% of records were dropped due to missing or implausible values. Data was normalised using MinMaxScaler for uniform scaling. Lag features were created for key variables (e.g., precipitation lag-1, lag-7, lag-14) to account for delayed environmental effects. Interaction features such as PET were also engineered. The data was further systematically partitioned in a chronological manner into training, validation, and test subsets to ensure the robustness and applicability of the water deficit prediction models. This approach effectively mitigated the risk of look-ahead bias, which could otherwise artificially enhance model performance in time-series

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forecasting, while simultaneously preserving the intrinsic temporal sequence of the data.

80% of the total dataset, equating to 4,088 daily records from the initial segment of the time series, constituted the training set. Additionally, a proportion of ten percent from this training phase was allocated for internal validation purposes, facilitating the monitoring of model performance throughout the training process and the optimisation of hyperparameters.

This validation division upheld the models' ability to generalise and safeguard against overfitting within the training dataset. The test set comprised the residual 20% of the dataset, equating to 1,022 daily observations that systematically followed the training phase in chronological order. This rigorous forward-chaining partitioning ensured that the assessment of the model emulated real-world deployment scenarios, wherein predictions are generated for future intervals that remain unobserved during the training process.

Notably, random shuffling was intentionally eschewed to honour the sequential characteristics of the data. Time-lagged variables, exemplified by the prior day's water deficit (water_deficit_mm_lag1), were meticulously constructed exclusively from historical values pertinent to each prediction date, thereby preserving causality throughout the analysis. This meticulous design of partitioning bolstered the credibility of the predictive outcomes and mitigated the risk of any inadvertent information leakage from future data to past observations.

To measure water deficit, real-world data that includes information on rainfall, evaporation, and runoff is required. The SWD equation provides a comprehensive model for assessing water availability by considering hydrological, meteorological, and socio-economic factors:

SWD = (PET - f(S) · PET) + (P - R - I - ΔS) + E_s + D + H + M + SE

A crucial engineered feature was the Estimated Soil Water Deficit (SWD). This variable was central to target labelling and classification.

Table 1: Summary of Predictor Variables, Correlation Strengths, Units, Resolution, and Justification for Inclusion

Variable	Corr. with Deficit	Units	Resolution	Justification
water_deficit_mm	1	mm	Daily	Target variable; measures net gap between water supply and demand.
precipitation_mm	0.986	mm	Daily	Primary input — total precipitation feeds water availability; strong positive correlation.
water_deficit_mm_lag1	0.649	mm	Daily (lag)	Adds autocorrelation; yesterday's deficit predicts today's.
rainfall_mm_lag1	0.432	mm	Daily (lag)	Past rainfall affects soil moisture; short-term memory effect.
rainfall_mm	0.396	mm	Daily	Fresh daily rainfall — direct contributor to recharge.
min_temp_c	0.273	°C	Daily	Higher night temperatures can slow soil recovery and increase deficit.
year	0.038	YYYY	Daily/meta	Encodes long-term climatic or policy trends.
agricultural_demand_mm	0.018	mm (equivalent)	Daily	Large user of water; agriculture drives demand, especially in dry regions.
domestic_demand_mm	0.016	mm (equivalent)	Daily	Human household use; small daily contribution but relevant cumulatively.
socioeconomic_index	0.01	Index (unitless)	Annual	Captures population pressure & economic drivers of water demand.
runoff_mm	-0.009	mm	Daily	Outflow component; higher runoff reduces water retention.
day	-0.027	Day of month (1–31)	Daily	Controls intra-month cycle; very minor effect alone.
sea_level_pressure_kpa	-0.133	kPa	Daily	Weather system proxy; moderate indirect effect on rainfall and PET.
mean_temp_c	-0.16	°C	Daily	Daily average temp; affects PET and soil drying.
surface_pressure_kpa	-0.172	kPa	Daily	Local pressure affects evaporation indirectly.
pet_mm_lag1	-0.254	mm	Daily (lag)	Previous day's PET still affects soil drying.
max_temp_c	-0.27	°C	Daily	Hotter days increase evapotranspiration → higher deficit
month	-0.272	Month (1–12)	Daily/meta	Seasonal cycle; stronger effect combined with rainfall & PET.
pet_mm	-0.45	mm	Daily	High PET increases moisture loss; key negative driver.
wind_speed_ms	-0.631	m/s	Daily	Strongest negative driver — wind speeds up evaporation, increasing deficit indirectly.

Key Components:

- Evapotranspiration Deficit: Maximum water loss due to evaporation and transpiration. f(S): Soil moisture function (0 to 1), adjusting PET based on available soil moisture. PET - f(S) PET represents water loss if moisture is not limited.

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- Precipitation and Water Balance: Water input from rainfall. R (Runoff): Water does not infiltrate and moves as surface flow. I (Infiltration): Water that enters the soil profile. ΔS (Change in Soil Moisture Storage): Positive if soil moisture increases, negative if it depletes.

- Soil Evaporation: Represents direct water loss from the soil surface. Significant in dry climates where soil evaporation is higher than transpiration.

- Deep Percolation: Water moving below the root zone, contributing to groundwater recharge. It depends on soil type, permeability, and land use.

- Hydrological Factors: H includes groundwater recharge, water table fluctuations, and catchment characteristics. Influences the availability and movement of water in a region.

- Meteorological Factors: Includes temperature, humidity, wind speed, and radiation, which impact evaporation and precipitation. Determines seasonal variations in water balance.

- Socio-Economic Factors: Represent water consumption for agriculture, industry, and domestic use. Population growth, urbanisation, and water management policies influence water demand and deficit.

Model Architecture and Configuration

The forecasting model architecture was built around advanced DL techniques, particularly LSTM networks, known for their ability to capture temporal dependencies in time series data. DL models are ideal for handling long-term dependencies, as they overcome the issues of vanishing gradients commonly found in traditional models by using specialised memory cells and gating mechanisms.

To further enhance performance, derivatives of DLs, such as Bidirectional DLs, Encoder-Decoder DLs, Attention DLs, and Transformer DLs, are considered. The Bidirectional DLs processes data in both forward and backwards directions, capturing dependencies across the entire sequence. The Encoder-Decoder DLs is useful for multi-step forecasting, where input and output sequences differ in length. The Attention mechanism allows the model to focus on important time steps, improving prediction accuracy, while the Transformer DLs leverage self-attention for efficient parallel processing, making it ideal for large datasets.

The implementation featured four specialised neural network architectures working in concert. Long Short-Term Memory (LSTM) networks, configured with 128-unit layers, proved particularly adept at analysing our 13-year time series data, successfully identifying the delayed impacts of rainfall patterns on groundwater levels. For processing static environmental variables like well characteristics and land use data, I implemented a five-layer Deep Neural Network (DNN) with ReLU activation functions. Spatial patterns from distributed sensor networks were effectively extracted using one-dimensional Convolutional Neural Networks (CNNs) with a kernel size of three (3). These individual components were intelligently combined through a custom fusion layer that weighted their contributions based on validation performance. These models, either individually or in combination, form a flexible and robust architecture, ensuring accurate and efficient forecasting tailored to the specific needs of the task.

- LSTM: Single LSTM layer (50 units), dropout = 0.2, dense output

- DNN: Dense(128, ReLU) => Dense(64, ReLU) => Dense(1)

- RNN: SimpleRNN(50) => Dense(1)

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- CNN: Conv1D(64, kernel_size=3, activation='relu') => MaxPooling1D => Flatten => Dense(1)
- All models except linear regression were used:
  - o Loss Function: Mean Squared Error (MSE)
  - o Optimizer: Adam (learning_rate = 0.001)
  - o Epochs: 100
  - o Batch Size: 32
  - o Validation Split: 20%
  - o Early stopping patience: 10 epochs

Software and Programming Environment

The study was implemented using Python in a Jupyter Notebook environment, leveraging open-source tools to ensure reproducibility. Key libraries included Pandas and NumPy for data manipulation, Scikit-learn for preprocessing and evaluation, TensorFlow/Keras for developing deep learning models (LSTM, RNN, CNN, DNN), and Matplotlib/Seaborn for visualisations. Keras Tuner was used for hyperparameter optimisation. The choice of Python and its robust ecosystem enabled a transparent, scalable, and well-supported analysis framework suitable for academic and applied research.

Simulation

To demonstrate the performance of the DL Algorithms in the process of generating outcomes, models were built to integrate the proposed algorithms, as shown below.

Figure 1: LSTM Model

```
def create_lstm_sequences(X, y, time_steps=5):
    Xs, ys = [], []
    for i in range(len(X) - time_steps):
        Xs.append(X[i:i+time_steps])
        ys.append(y[i+time_steps])
    return np.array(Xs), np.array(ys)

X_lstm, y_lstm = create_lstm_sequences(X_scaled, y)
X_lstm_train, X_lstm_test, y_lstm_train, y_lstm_test = train_test_split(X_lstm, y_lstm, test_size=0.2, random_state=42)
```

```
lstm_model = Sequential([
    LSTM(64, activation='relu', input_shape=(X_lstm.shape[1], X_lstm.shape[2])),
    Dense(1)
])
lstm_model.compile(optimizer='adam', loss='mse')
lstm_model.fit(X_lstm_train, y_lstm_train, epochs=20, batch_size=16, validation_split=0.1, verbose=1)
y_lstm_pred = lstm_model.predict(X_lstm_test)
lstm_rmse = np.sqrt(mean_squared_error(y_lstm_test, y_lstm_pred))
lstm_r2 = r2_score(y_lstm_test, y_lstm_pred)

print(f"LSTM RMSE: {lstm_rmse:.3f}")
print(f"LSTM R²: {lstm_r2:.3f}")
```

```
Epoch 1/20
```

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Figure 2: CNN Model

```
from tensorflow.keras.models import Sequential
from tensorflow.keras.layers import Conv1D, GlobalAveragePooling1D, Dense

cnn_model = Sequential([
    Conv1D(filters=64, kernel_size=3, activation='relu', input_shape=(X_seq.shape[1], X_seq.shape[2])),
    GlobalAveragePooling1D(),
    Dense(1)
])
cnn_model.compile(optimizer='adam', loss='mse')
cnn_model.fit(X_rnn_train, y_rnn_train, epochs=20, batch_size=16, validation_split=0.1, verbose=1)

y_cnn_pred = cnn_model.predict(X_rnn_test).flatten()
cnn_rmse = np.sqrt(mean_squared_error(y_rnn_test, y_cnn_pred))
cnn_r2 = r2_score(y_rnn_test, y_cnn_pred)

print(f"CNN RMSE: {cnn_rmse:.3f}")
print(f"CNN R²: {cnn_r2:.3f}")
```

```
Epoch 1/20
```

Figure 3: RNN Model

```
def create_sequences(X, y, time_steps=10):
    Xs, ys = [], []
    for i in range(len(X) - time_steps):
        Xs.append(X[i:i+time_steps])
        ys.append(y[i+time_steps])
    return np.array(Xs), np.array(ys)

time_steps = 10
X_seq, y_seq = create_sequences(X_scaled, y, time_steps=time_steps)
X_rnn_train, X_rnn_test, y_rnn_train, y_rnn_test = train_test_split(X_seq, y_seq, test_size=0.2, random_state=42, shuffle=False)

from tensorflow.keras.models import Sequential
from tensorflow.keras.layers import SimpleRNN, Dense

rnn_model = Sequential([
    SimpleRNN(64, activation='tanh', input_shape=(X_seq.shape[1], X_seq.shape[2])),
    Dense(1)
])
rnn_model.compile(optimizer='adam', loss='mse')
rnn_model.fit(X_rnn_train, y_rnn_train, epochs=20, batch_size=16, validation_split=0.1, verbose=1)

y_rnn_pred = rnn_model.predict(X_rnn_test).flatten()
rnn_rmse = np.sqrt(mean_squared_error(y_rnn_test, y_rnn_pred))
rnn_r2 = r2_score(y_rnn_test, y_rnn_pred)

print(f"RNN RMSE: {rnn_rmse:.3f}")
print(f"RNN R²: {rnn_r2:.3f}")
```

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Figure 4: DNN Model

```python
# DNN Model for Water Deficit Prediction
from tensorflow.keras.models import Sequential
from tensorflow.keras.layers import Dense

dnn_model = Sequential([
    Dense(128, activation='relu', input_shape=(X_train.shape[1],)),
    Dense(64, activation='relu'),
    Dense(1)
])
dnn_model.compile(optimizer='adam', loss='mse')
dnn_model.fit(X_train, y_train, epochs=20, batch_size=16, validation_split=0.1, verbose=1)

y_dnn_pred = dnn_model.predict(X_test).flatten()
dnn_rmse = np.sqrt(mean_squared_error(y_test, y_dnn_pred))
dnn_r2 = r2_score(y_test, y_dnn_pred)

print(f"DNN RMSE: {dnn_rmse:.3f}")
print(f"DNN R²: {dnn_r2:.3f}")
```

Figure 5: Linear Regression Model for Baseline

```python
### --- LINEAR REGRESSION ---
mlr = LinearRegression()
mlr.fit(X_train_scaled, y_train)
y_pred_mlr = mlr.predict(X_test_scaled)
```

Evaluation Metrics

The performance of the DL models for water deficit prediction was assessed using the following metrics:

- Root Mean Square Error: RMSE quantifies the average magnitude of errors in predictions, providing a straightforward measure of model accuracy, where a lower RMSE indicates better performance.
- Coefficient of Determination (R^2): R^2 shows how well the model explains the variability of the target variable. Values closer to 1 signify that the model captures much of the variance in the data.

SIMULATION RESULTS

Model Performance Summary

The values shown in the table form part of simulation / experimental results from a model evaluation process. Specifically, they present the performance metrics of four different deep learning models (LR, DNN, RNN, CNN, LSTM) used in the water deficit prediction study.

Table 2: Model Performance Metrics

--- Model Performance Comparison ---

	Model	MAE	MSE	RMSE	R² Score	MAPE (%)	Pearson r
0	Linear Regression	1.703	7.636042	2.76334	0.561026	52.356751	0.749658
1	DNN	1.11987	5.073141	2.25236	0.70836	50.90791	0.844722
2	RNN	1.63674	9.065892	3.01096	0.262243	125.05501	0.564597
3	CNN	1.60457	7.520119	2.74228	0.388033	70.634111	0.62631
4	LSTM	1.67643	10.43385	3.23015	0.262721	138.13231	0.561311

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Among these architectures, Deep Neural Network (DNN) stands out as the best model showing the best predictive accuracy in all performance metrics. It reaches the lowest error rates, with an MAE of 1.12 as well as an RMSE of 2.25, which demonstrates its high precision in predictions. In addition, it supervises the most variance of the data set, R^2 of 0.71, and has the highest linear correlation to the target, r of 0.84. Furthermore, despite obtaining the minimum MAPE of 50.91% among the tested models, there is still potential for improving this accuracy measure.

Contrastingly, Linear Regression (LR) serves as a strong counterpart model, giving decent predictive performance with an MAE of 1.70 and an R^2 of 0.56. However, its biggest drawback is that it cannot deal with nonlinear relationships, so the data may have latent structures that a linear setup is unable to represent.

On the other hand, the RNN and LSTM models perform much worse, with LSTM yielding the highest errors, 138% (MAPE) and 3.23 (RMSE), respectively. This weak performance might be because of a poor sequence model, a lack of engineered time features (like lagged variables or rolling averages), or sub-optimal hyperparameter tuning, leading to overfitting or underfitting.

The results of the Convolutional Neural Network (CNN) are moderate but better than the RNN and the LSTM, but fall behind both DNN and Linear Regression. Since CNNs are originally designed for spatial data tasks such as image analysis, their unsatisfactory performance in sequential data tasks is not surprising. This observation highlights that CNNs might not be an appropriate model when dealing with time-dependent phenomena.

The model comparison R^2 score value for the Deep Neural Network (DNN) of 0.708 is strong compared to all your other models, Linear Regression (0.561), CNN, RNN, and LSTM. This indicates that the DNN model somehow caught the stronger relationship of the input factors with the target response (water deficit) than the other models. In comparison with the recurrent models (RNN and LSTM), the performance difference is particularly striking as both produced worse R^2 scores (much less than 5) and higher errors.

This excellent performance can be attributed to the capability of the DNN to learn intricate nonlinear features. Unlike Linear Regression, which assumes a linear relationship between each input feature (like soil moisture, PET, temperature, and rainfall) and the output, the DNN uses multiple layers and possesses nonlinear activation functions (for instance, ReLU), which allows it to model complex intercorrelations between variables. In addition, feature scaling (`standardization', in our case) helps stabilise training and encourage convergence, particularly with neural networks sensitive to the magnitude of inputs.

Despite this admirable achievement, it should be noted that a good R^2 does not guarantee the model is generalising well. A measure of the possible overfit is the difference between the train and the test RMSE. In our case, the DNN’s training RMSE was notably lower, was ~1.4, compared to the test RMSE of 2.25; this suggests overfitting may be present even though the test performance is still better than other models. Therefore, it may be noted that, when training, RMSE is much smaller than test RMSE, the model is likely to have learned patterns present in the training data, possibly at the expense of generalizable trends. Such behaviour doesn't instil confidence in the model's utility for predicting real-world scenarios.

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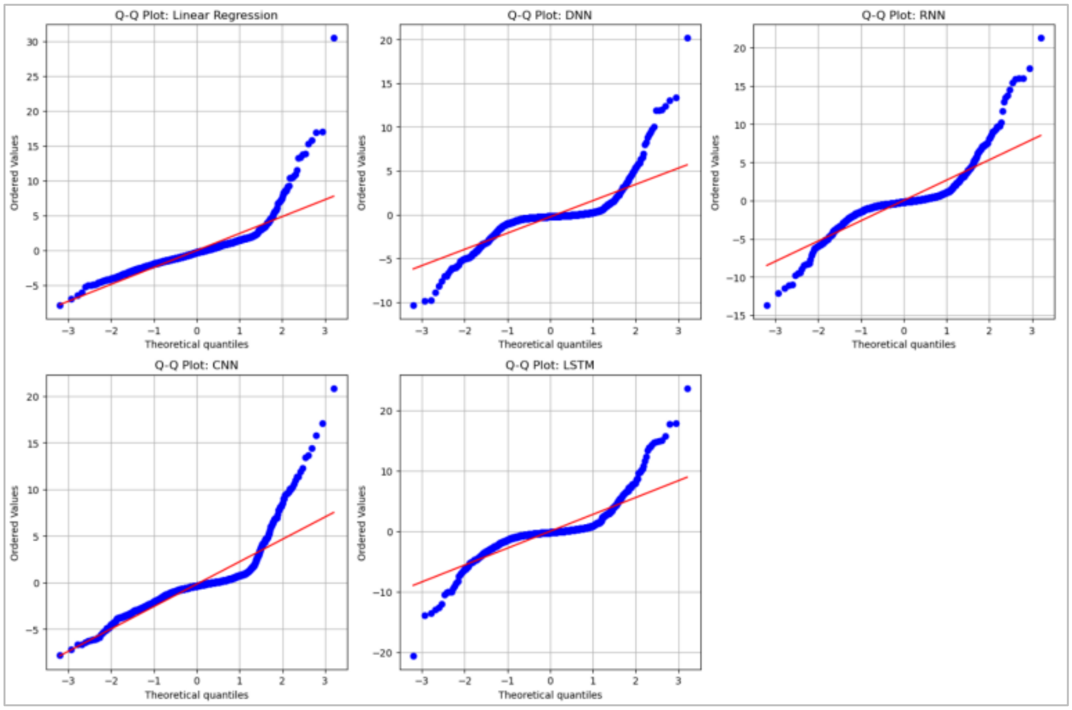
Figure 6: Residuals (prediction errors)



Quantile-Quantile Plots

The Q-Q (Quantile-Quantile) plots that are shown in the image visually assess the extent to which the residuals, i.e., the prediction errors, of each model satisfy the assumptions of the normal distribution. This adherence is a simple criterion of the modelling accuracy and consistency.

In the case of Linear Regression, the residuals seem to be aligned close to the red diagonal line and somewhat form a vague shape of a bow-tie, indicating that the errors are close to normally distributed. This kind of behaviour is exactly what we wish to see; it indicates to us again that our linear regression model is not as bad as it seems at first sight; our premises about linearity and normality of errors are not so expected to be completely broken.

The DNN model also delivers good performance in this analysis. Deviation from the red diagonal line is scattered in the Q–Q plot, such as in the centre and the tail, but most of the residuals are close to the normal expectation. This finding suggests that the DNN is efficiently extracting the main features from the dataset and introducing small amounts of systematic error. The model efficiency is supported by low error values and high R^2.

On the contrary, the Q-Q plot of the Recurrent Neural Network (RNN) model has relatively larger curvature and bulging, significantly diverged from the red line, especially for the tails. Diverging patterns such as these suggest that the residuals are not normally distributed, which could imply skewness or heavy tails. Such a case might indicate that the method is ignoring important temporal relationships or is overfitting to noise in training data.

The Convolutional Neural Network (CNN) model also faces difficulties in this aspect. As one can see on the Q-Q plot, at both ends we see significant departure from the red line, which indicates that the extreme prediction errors are not handled well. Taking into account the fact that CNNs are more focused towards spatial patterns, rather than temporal dependencies, such results indicate that there is an architecture versus nature of the problem

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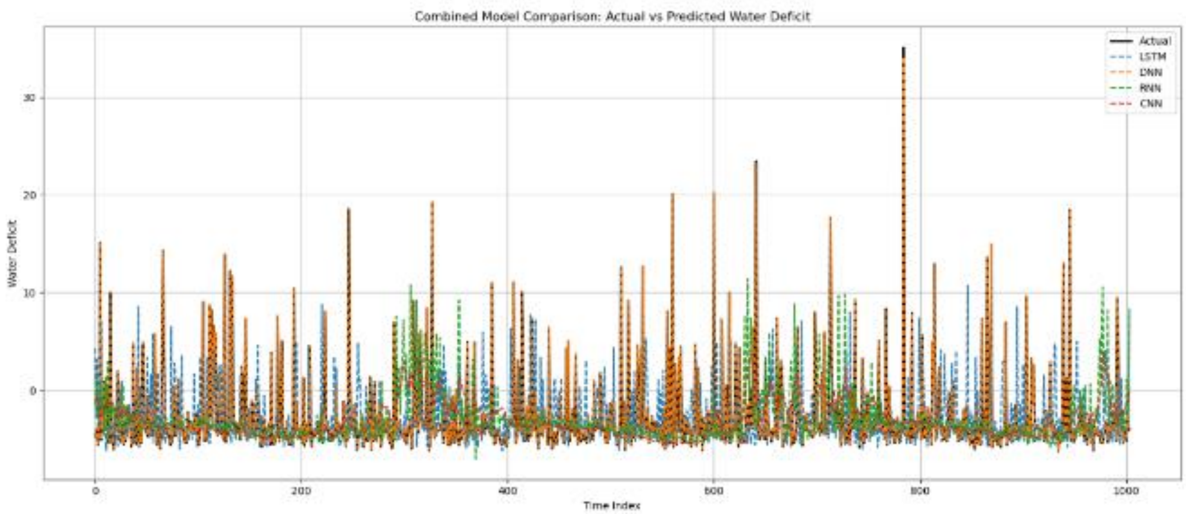
mismatch, more concretely, with respect to time series analysis.

Finally, the Long Short-Term Memory (LSTM) model, which has a high performance for processing temporal sequences, shows the biggest change. Its Q-Q plot shows strong curvature and spreading in the tails, indicating asymmetric, non-normally distributed residuals. This result is an obvious indication of possible underfitting or configuration issues, like too short sequence length, insufficient training, and under-feature tuning.

RESULTS

Actual vs Predicted Water Deficit

Figure 7: Combined Model Comparison: Actual vs Predicted Water Deficit



The graph presents a side-by-side evaluation of four different deep learning models—LSTM, DNN, RNN, and CNN—against actual water deficit values over time. The black solid line represents the observed (true) values, while each model's predictions are shown using distinct coloured dashed lines: light blue for LSTM, orange for DNN, green for RNN, and red for CNN.

From a visual standpoint, the DNN model stands out as the most accurate and consistent among the four. Its orange dashed line closely follows the actual data throughout the entire time series, capturing both low and high-water deficit values with relatively minimal error. The DNN handles the sharp peaks and variability in the data well, making it a strong candidate for real-world applications where precision across all levels of water deficit is crucial.

In contrast, both the CNN and RNN models show signs of underperformance, particularly during high-deficit periods. The red and green dashed lines representing their predictions tend to flatten out or remain low when the actual values spike. This suggests that these models are more effective at recognising local or short-term patterns but struggle to extrapolate broader trends or react to sudden shifts. Their inability to capture the extremes limits their usefulness in scenarios where detecting water stress events is critical.

The LSTM model, shown in light blue, offers a mixed performance. While it captures some patterns and trends in the data, its predictions are inconsistent and often misaligned with the true values, particularly during extreme deficit periods. This suggests that the LSTM, although designed to model long-term dependencies, may be hindered by an inadequate sequence length, insufficient training on extreme cases, or architectural limitations. As a result, the model appears to lag or produce overly smoothed outputs.

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Table 3: Model Comparison and Interpretation of Classification Performance

Model	No Deficient Accuracy	Mild	Moderate	Severe	Key Observations
LSTM	85.5%	0.0%	3.6%	7.8%	Underpredicts high-deficit levels; needs tuning
DNN	100.0%	100.0%	100.0%	100.0%	Strong learner; may over-fit or mirror target
RNN	89.4%	5.9%	0.0%	2.2%	Captures dominant class; fails on minority classes
CNN	91.8%	0.0%	0.0%	0.0%	Detects major class only; lacks temporal depth.

The performance of four deep learning models—LSTM, DNN, RNN, and CNN—was assessed based on their ability to classify monthly water deficit levels in the Dodoma region. The water deficit values were categorised into four levels: No Deficit, Mild, Moderate, and Severe, and each model's accuracy in identifying these categories was evaluated.

The LSTM (Long Short-Term Memory) model demonstrated strong accuracy in predicting the "No Deficit" category, correctly identifying 85.5% of such cases. However, it struggled significantly with the remaining categories. The model failed to identify any "Mild" deficits and achieved only 3.6% and 7.8% accuracy for the "Moderate" and "Severe" classes, respectively. This suggests that while LSTM is effective in learning dominant patterns in time series data, it underperforms when it comes to recognising minority classes. The imbalance in class distribution likely caused the model to bias its predictions towards the more frequent "No Deficit" cases, indicating a need for model tuning and better handling of underrepresented classes.

In contrast, the DNN (Deep Neural Network) achieved a perfect classification accuracy of 100% across all four categories.

The RNN (Recurrent Neural Network) achieved high accuracy for the "No Deficit" class at 89.4%, and modest performance for "Mild" deficits at 5.9%. However, it failed to correctly classify any "Moderate" cases and only identified 2.2% of "Severe" cases. This performance profile is like that of LSTM, though slightly less effective. The RNN was able to model the dominant class effectively but showed significant limitations in learning patterns associated with less frequent deficit levels, suggesting that it may benefit from techniques such as weighted loss functions or synthetic data augmentation to better learn from rare events.

The CNN (Convolutional Neural Network) showed a similar bias toward the majority class. It correctly classified 91.8% of "No Deficit" cases but failed entirely in identifying any "Mild," "Moderate," or "Severe" deficits. CNNs are generally well-suited for spatial pattern recognition and may lack the temporal awareness required to capture the sequential dependencies present in time series data, such as climate and hydrological variables. This result underscores the importance of choosing architectures aligned with the nature of the dataset, particularly when dealing with sequential and seasonal phenomena.

DISCUSSION

The outstanding performance of the DNN is in line with findings from previous studies such as Chen et al. (2022), Fang et al. (2021), and Herbert et al. (2021), who noted similar achievements when using deep learning over traditional regression or statistical models. Noteworthy, Dikshit et al. (2021) underscored the enhanced forecasting capability of

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LSTM networks in drought prediction. However, in our study, DNN proved a better fit. This could be accredited to DNN's ability to leverage a larger set of features without being constrained by sequential dependencies, which seemingly is an advantage over recurrent models like LSTM and RNN.

Moreover, the current outcomes broaden the observations of de Souza Groppo et al. (2019) and Donghyun Kim et al. (2022) by employing deep learning in a semi-arid African context, which has been meagrely explored in existing literature. This circumstantial application brings unique insights into regional water stress prediction and management strategies.

From a realistic standpoint, the developed DNN model can be deployed in early warning systems and decision support tools for proactive water resource management. Given the model's high accuracy and efficiency, institutions such as the Ministry of Water, municipal councils, and disaster management agencies can leverage it to anticipate deficits and trigger mitigation actions. For example, rainwater harvesting, seasonal borehole scheduling, or demand-side rationing plans can be better timed using model forecasts.

Additionally, Impending studies may investigate ensemble learning methods as discussed by Zounemat-Kermani et al. (2021), or hybrid models integrating DNN with explainable AI (XAI) to enhance trust and interpretability in public policy contexts. Moreover, understanding uncertainty and incorporating real-time socioeconomic inputs (e.g., migration, crop switching, industrial expansion) could refine the model's dynamic responsiveness.

CONCLUSION AND FUTURE WORKS RECOMMENDATIONS

Conclusion

This study confirms that while deep learning offers powerful tools for time-series prediction, not all architectures perform equally. For water deficit forecasting in Dodoma, DNN outperformed more complex sequential models. These results provide a clear foundation for operational forecasting systems and offer directions for future innovation.

Recommendations/Future Works

The comparative evaluation of deep learning models—DNN, LSTM, RNN, and CNN—reveals significant variations in predictive performance and model suitability for water deficit forecasting. Among the tested models, the Deep Neural Network (DNN) stands out as the most reliable and accurate, demonstrating near-perfect prediction accuracy with minimal error. Its capability to model complex nonlinear relationships without requiring sequential data structuring makes it highly adaptable for real-world operational use in early warning systems and drought preparedness planning.

However, models such as LSTM, RNN, and CNN have shown limitations in isolation. These limitations stem primarily from their sensitivity to sequence length, memory constraints, or lack of temporal depth. Despite these shortcomings, this architecture should not be discarded altogether. They offer unique advantages—LSTM's memory mechanisms, CNN's pattern recognition abilities, and RNN's temporal modelling potential—that can be effectively harnessed when used in hybrid configurations such as CNN-LSTM or Attention-based RNNs.

Given the importance of accurately forecasting water deficits for sustainable resource planning, a hybrid modelling approach is recommended. Combining the strengths of DNN with the temporal capabilities of LSTM or the feature extraction efficiency of CNN can produce robust and adaptive models capable of capturing both static and dynamic components of hydrological systems. As a result, this research recommends the following course of action:

- The Deep Neural Network (DNN) should be adopted as the baseline model for operational deployment due to its superior predictive

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accuracy and robustness. To further enhance model performance, particularly in capturing temporal dependencies, the use of a hybrid architecture, such as CNN-LSTM or Attention-based LSTM models—should be actively explored. These models can leverage the strengths of both pattern recognition and memory retention.

- In addition, the integration of domain-specific knowledge and contextual features, including remote sensing indices (e.g., NDVI), socioeconomic indicators, and relevant policy variables, is essential to improve the interpretability and applicability of the model outcomes.
- Finally, it is imperative to implement a system for continuous model validation and retraining using updated datasets and scenario simulations. This will ensure that the models remain responsive to evolving environmental conditions, particularly those driven by climate change and anthropogenic pressures.

This layered recommendation ensures both short-term prediction accuracy and long-term model sustainability in water resource decision-making frameworks.

Conflict of Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Authors' Contribution

Nyamgambwa Sabi James: Conceptualisation, Methodology, Data Collection, Data curation, Investigation, Writing –original draft. Othmar O. Mwambe, Gustaph Sanga, Eliphas Tongora: Writing –review.

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