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Spatio-Temporal Forecasting of Hydro-Meteorological Extremes in Fiji Using Deep Learning and Ocean-Atmospheric Climate Indicators

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Citation | Rafiq. S, Ali. R, "Spatio-Temporal Forecasting of Hydro-Meteorological Extremes in Fiji Using Deep Learning and Ocean-Atmospheric Climate Indicators", FCIS, Vol. 02 Issue. 3 pp 137-147, Sep 2024
Received | Aug 09, 2024, **Revised |** Aug 29, 2024, **Accepted |** Aug 30, 2024, **Published |** Sep 02, 2024.

The increasing frequency and intensity of hydro-meteorological extremes, such as floods and droughts, pose significant risks to vulnerable Pacific Island nations like Fiji. Accurate and timely forecasting of these events is essential for effective risk management and early warning systems. This study presents a novel deep learning framework that leverages long short-term memory (LSTM) networks to forecast the Effective Drought Index (EDI), a key indicator of hydrological extremes. The framework integrates multivariate spatial data and principal components of sea surface temperature (SST) to capture complex ocean-atmospheric climate influences on regional precipitation patterns. Comparative analysis of univariate, spatial-only, and multivariate models demonstrates that incorporating SST information significantly improves forecast skill, particularly for lead times up to 14 days. The spatial variability of model performance highlights challenges related to topography and localized climate effects. The results underscore the potential of combining deep learning with climate science to enhance early warning capabilities, supporting disaster preparedness and climate resilience in Fiji and similar island regions. Future work should explore higher spatial resolution modeling and the inclusion of additional climate drivers to further refine forecasting accuracy.

Keywords: Hydro-meteorological Extremes, Floods, Droughts, Fiji, Effective Drought Index (EDI), Deep Learning, Long Short-Term Memory (LSTM)

Introduction:

Hydro-meteorological extreme events, including floods and droughts, are increasing in both frequency and intensity worldwide due to climate change and human activities [1][2][3]. In the South Pacific region, particularly in island nations such as Fiji, these events are heavily influenced by climatic drivers like the South Pacific Convergence Zone (SPCZ), whose spatial shifts cause anomalous precipitation patterns resulting in extreme wet or dry spells [4]. These extremes not only threaten lives and ecosystems but also disrupt infrastructure, livelihoods, and economic stability [5][6].

Effective risk management for such hydrological hazards critically depends on early warning systems capable of timely and accurate forecasting [7][8]. However, in many Pacific Island countries, traditional observation networks are sparse, limiting the feasibility of physically-based hydrological monitoring [9]. Recent advances in machine learning, particularly deep learning, offer promising alternatives by enabling data-driven modeling of complex temporal and spatial patterns inherent in hydro-meteorological phenomena [10][11].

Deep learning architectures such as Long Short-Term Memory (LSTM) networks have shown superior capabilities in capturing non-linear dependencies and long-term temporal dynamics, making them well-suited for forecasting hydrological extremes [12][13][14]. Additionally, incorporating multivariate and spatio-temporal information, including sea surface temperature (SST) indices, improves forecasting performance by accounting for interdependent climatic drivers [15][16]. Given these advancements, leveraging deep learning frameworks to predict indices such as the Effective Drought Index (EDI) can greatly enhance early warning capabilities in vulnerable regions like Fiji [6][9].

Research Gap:

Despite growing interest, much of the current hydrological extreme forecasting literature relies on univariate, point-based prediction methods that fail to incorporate spatial interactions or multiple climate drivers simultaneously [17][14]. These approaches limit the capacity to capture complex spatio-temporal variability, which is crucial in geographically diverse and climate-sensitive regions such as the South Pacific. Furthermore, while Principal Component Analysis (PCA) is frequently used for dimensionality reduction of climate variables, its linear nature restricts capturing non-linear dependencies vital for accurate forecasts [18]. Although some studies have begun integrating PCA with deep learning to address this, comprehensive frameworks that fuse multivariate spatial data with advanced recurrent neural networks remain scarce, especially for small island developing states (SIDS) where data scarcity and climate vulnerability converge [19][20].

Additionally, while LSTM models have been successfully applied to drought and flood forecasting, few studies explore their combined use with spatially distributed climate features and SST principal components in the South Pacific context. There is a need for robust, scalable, and interpretable frameworks that provide spatio-temporal hydro-meteorological extreme forecasts tailored to island-scale geographies and limited observational datasets [21][16]. Addressing these gaps can significantly enhance the resilience of at-risk communities by enabling more accurate and timely hazard predictions.

Objectives:

This study aims to develop and evaluate a comprehensive spatio-temporal hydro-meteorological extreme forecasting framework for Fiji, leveraging state-of-the-art deep learning techniques. Specifically, the objectives are to:

Design and implement three LSTM-based forecasting approaches for the Effective Drought Index (EDI): (i) univariate, (ii) multivariate with spatially neighboring points, and (iii) multivariate including SST principal components.

Assess and compare the predictive performance of these models in capturing complex temporal and spatial dynamics inherent in hydro-meteorological extremes.

Demonstrate the utility of combining linear dimensionality reduction (PCA) with non-linear deep learning architectures to improve forecasting skill under data scarcity conditions.

Provide insights and recommendations for operationalizing deep learning-based early warning systems in Fiji and similar South Pacific Island environments.

Novelty Statement:

The novelty of this work lies in its integrative approach combining spatio- Temporal deep learning with multivariate climatic indices and SST principal components to forecast hydrological extremes in a small island developing state. Unlike prior studies focused predominantly on point-based or univariate methods [6][9], this research employs advanced LSTM architectures to capture nonlinear spatio-temporal interactions, thus enhancing forecast accuracy and reliability. Furthermore, the hybrid use of PCA and LSTM for dimensionality reduction and sequence learning addresses the challenges posed by limited observational data in Pacific Island contexts. To the best of our knowledge, this is among the first studies to systematically evaluate these methodologies for effective drought forecasting in Fiji, providing a scalable framework with direct implications for climate resilience and disaster risk reduction policy [22][19].

Literature Review:

Hydro-meteorological extremes such as floods and droughts have become increasingly frequent and severe due to climate change and anthropogenic influences, significantly impacting vulnerable regions worldwide [2][3]. Accurate forecasting of such events is critical for disaster risk reduction, especially in small island developing states like Fiji, where climatic drivers such as the South Pacific Convergence Zone (SPCZ) play a vital role in shaping rainfall patterns and hydrological extremes [4].

Traditional hydrological forecasting methods, often based on physical or statistical models, face challenges in representing complex spatial and temporal interactions of climate variables, particularly under limited observational data conditions prevalent in many Pacific Island nations [9]. Physically based models require extensive high-resolution data, which may be scarce, and suffer from high computational costs, limiting their practical application for real-time early warning systems. Statistical approaches, while computationally efficient, typically fail to capture nonlinear dynamics and long-range dependencies within hydrological systems [16].

Machine learning and, more recently, deep learning methods have emerged as promising alternatives, offering superior capabilities in modeling non-linear and complex temporal dependencies within hydro-meteorological data. Recurrent neural networks (RNNs), particularly Long Short-Term Memory (LSTM) architectures, have demonstrated enhanced performance in drought and flood forecasting by effectively capturing sequential patterns over long time horizons [12][22]. For example, [22] found that LSTM models outperformed conventional machine learning algorithms in drought prediction tasks, highlighting their ability to model hydrological time series with high accuracy.

Similarly, spatial dependencies inherent in hydrological phenomena can be captured using deep learning architectures such as convolutional neural networks (CNNs) and hybrid models that combine CNNs with LSTMs to simultaneously exploit spatial and temporal features [23][16]. For instance, developed a spatio-temporal flood prediction framework integrating LSTM with reduced-order modeling to efficiently process high-dimensional spatial data, achieving accurate real-time flood forecasts.

Dimensionality reduction techniques, particularly Principal Component Analysis (PCA), have frequently been used to preprocess multivariate climate datasets by extracting dominant variability patterns while reducing computational complexity [24][25]. However, PCA's linear nature limits its ability to capture the nonlinear relationships crucial for hydrological forecasting. Hybrid methods combining PCA with nonlinear deep learning models have been explored to address this limitation, enhancing the extraction of meaningful features from complex climate datasets [19].

In the South Pacific context, several studies have applied machine learning to forecast hydrological indices. [13] used deep learning to predict drought indices in Fiji, demonstrating improved forecast skill over traditional methods. However, many such studies have been restricted to univariate or point-based predictions, which neglect the spatial variability and interaction between multiple climate drivers [17][14]. Considering spatio-temporal approaches that integrate climate variables such as sea surface temperature (SST) anomalies has been shown to enhance the forecasting of hydro-meteorological extremes by capturing teleconnections and regional climatic influences [15][16].

Furthermore, studies comparing deep learning models with traditional climate and hydrological models suggest that while climate models effectively simulate primary variables (e.g., temperature, rainfall), they often lack sensitivity in predicting secondary phenomena like droughts and floods. Integrating deep learning with climate precursors can improve drought and flood forecast accuracy. This integration is particularly valuable in data-sparse regions, where models need to generalize from limited observations while accounting for complex environmental interactions.

In summary, the evolving literature underscores the potential of advanced deep learning techniques, especially LSTM-based spatio-temporal models combined with multivariate climate data and dimensionality reduction methods, to enhance hydro-meteorological extreme forecasting. However, application of these integrative approaches remains limited in Pacific Island settings, highlighting the need for focused studies that address local climate characteristics and data limitations to develop operational early warning systems tailored to vulnerable island nations like Fiji.

Methodology:

Study Area and Data Collection:

This study focuses on the South Pacific region, using Fiji as a representative case due to its vulnerability to hydro-meteorological extremes influenced by the South Pacific Convergence Zone (SPCZ). Hydro-meteorological data, including precipitation, temperature, and effective drought index (EDI), were collected from national meteorological stations and regional climate databases for the period 2000–2023. In addition, sea surface temperature (SST) data were obtained from satellite-derived reanalysis products to capture ocean-atmospheric influences on regional climate variability.

Data Preprocessing:

The raw meteorological and climate datasets underwent several preprocessing steps. Missing values were imputed using spatio-temporal interpolation methods to ensure data continuity. All variables were standardized to zero mean and unit variance to facilitate model training convergence. SST data were subjected to Principal Component Analysis (PCA) to extract dominant spatial patterns and reduce dimensionality while preserving essential climate variability features.

Feature Selection and Dataset Preparation:

Three different dataset configurations were prepared for model training and evaluation:

Univariate dataset: Time series of EDI values at individual spatial points.

Multivariate spatial dataset: EDI time series combined with meteorological variables from neighboring spatial points, incorporating local spatial interactions.

Multivariate spatial + PCA dataset: Multivariate spatial data augmented with principal components derived from SST patterns, representing large-scale ocean-atmosphere teleconnections.

The datasets were split into training (70%), validation (15%), and testing (15%) subsets using a stratified sampling method to preserve temporal and spatial variability.

Model Architecture:

The Long Short-Term Memory (LSTM) network was selected due to its ability to model temporal dependencies and capture long-term memory effects in sequential data. The model architecture consisted of:

Input layer receiving multivariate time series data.

Two stacked LSTM layers with 64 and 32 units, respectively, enabling hierarchical feature extraction.

Dropout layers with a rate of 0.2 to prevent overfitting.

Fully connected dense layer for output prediction.

Linear activation function to predict continuous EDI values.

Hyperparameters such as learning rate, batch size, and number of epochs were optimized using grid search and early stopping based on validation loss.

Model Training and Evaluation:

Models were trained using the Adam optimizer with mean squared error (MSE) as the loss function. Training was conducted on a GPU-enabled computing platform to accelerate convergence. Evaluation metrics included Root Mean Squared Error (RMSE), Mean Absolute Error (MAE), and Nash-Sutcliffe Efficiency (NSE) to assess forecasting accuracy.

Comparative analyses were performed among the three dataset configurations to determine the benefits of incorporating spatial and SST principal component information. Model robustness was further evaluated under varying forecast horizons from 1 to 30 days ahead.

Spatio-Temporal Forecasting Framework:

The final spatio-temporal forecasting framework integrates the best-performing LSTM model with PCA-transformed SST components, enabling simultaneous consideration of local spatial interactions and large-scale climatic drivers. Forecast outputs were mapped across the spatial domain to visualize extreme event patterns, facilitating risk assessment and decision-making for early warning systems.

Results:

Model Performance Evaluation:

Three distinct LSTM-based forecasting models were developed and evaluated using three different input configurations: (i) univariate EDI data, (ii) multivariate spatial data including EDI and meteorological variables from neighboring locations, and (iii) multivariate spatial data augmented by principal components extracted from SST fields.

Table 1 presents the aggregated model performance metrics—Root Mean Squared Error (RMSE), Mean Absolute Error (MAE), and Nash-Sutcliffe Efficiency (NSE)—calculated across all spatial points and over a 7-day forecast horizon. The multivariate spatial + SST PCA model consistently outperformed the other configurations.

Table 1. Performance Comparison of different model configuration based on RMSE, MAE and NSE

Model Configuration	RMSE	MAE	NSE
Univariate (EDI only)	0.186	0.142	0.72
Multivariate spatial	0.157	0.120	0.81
Multivariate spatial + SST (PCA)	0.132	0.104	0.87

The multivariate spatial model showed a 15.6% reduction in RMSE and a 14.8% improvement in NSE over the univariate model, indicating the significant advantage of incorporating spatial dependencies. Including SST principal components further reduced RMSE by an additional 15.9%, and improved NSE by 7.4% compared to the multivariate spatial model alone. This demonstrates the vital role of oceanic climate drivers in forecasting hydrological extremes.

Forecast Horizon and Temporal Stability:

The predictive skill of the best model (multivariate spatial + SST PCA) was evaluated over lead times from 1 to 30 days (Figure 1). RMSE gradually increased from 0.078 at a 1-day lead time to 0.246 at 30 days. Correspondingly, NSE decreased from 0.94 to 0.55, reflecting the increased uncertainty in longer-term forecasts.

Interestingly, the model maintained high skill (NSE > 0.75) for lead times up to 14 days, which aligns with the typical temporal scales of hydro-meteorological extreme events in the region. Beyond 14 days, forecast accuracy diminished more rapidly, reflecting the inherent challenges of long-term prediction in a highly dynamic climate system.

Spatial Variability in Forecast Accuracy:

Spatial patterns of forecast skill, illustrated in Figure 3, reveal heterogeneity across Fiji's geographic regions. Coastal zones and low-lying areas demonstrated superior forecast performance, with NSE values predominantly above 0.85 and RMSE below 0.12. These regions benefit from strong oceanic influences, which are well captured by SST principal components.

Conversely, mountainous interior regions exhibited more modest NSE scores (0.60–0.75) and elevated errors. These differences likely stem from complex topography-induced microclimates and limited observational data coverage, which complicate modeling of local hydrological processes.

These spatial insights suggest that while the model robustly predicts large-scale hydro-meteorological extremes, additional localized data or modeling techniques may be required to improve forecasts in complex terrain.

Extreme Event Forecasting and Case Studies:

The model's ability to predict extreme hydro-meteorological events was evaluated through detailed case studies of wet and dry extremes.

Dry event (2018–2019 drought season): At the Suva station, the model predicted the onset, persistence, and recovery phases of drought with a high correlation coefficient of 0.91 between predicted and observed EDI values (Figure 2). Timing errors were minimal, with a maximum phase lag of 2 days. This accurate capture of drought dynamics is critical for water resource planning and disaster preparedness.

Wet event (2016 flood season): The model accurately forecasted extreme wet conditions linked to northward displacement of the SPCZ. Forecasted EDI peaks aligned with observed wet spells, capturing the magnitude and duration of floods across multiple stations (correlation coefficients > 0.88). This illustrates the model's utility for early warning and flood risk management.

Contribution of SST Principal Components and Feature Analysis:

Principal Component Analysis reduced the dimensionality of SST data into five leading components explaining 72% of the total variance. Incorporation of these SST PCs in the LSTM inputs substantially improved model accuracy.

Feature importance analysis, conducted via permutation-based methods, identified SST PC1 and PC2 as the most influential predictors during transitional climate periods such as El Niño and La Niña. These components correspond to well-known oceanic patterns driving regional precipitation anomalies.

The meteorological variables from neighboring stations—precipitation, temperature, and humidity—also exhibited moderate predictive power, emphasizing the benefits of spatially contextual data.

Robustness and Sensitivity Analysis:

Robustness checks included:

Cross-validation across years: The model's performance was stable across different climatological years, indicating generalizability [26].

Noise injection tests: Artificial noise added to inputs caused only minor performance degradation (RMSE increased by 3.5%), demonstrating resilience to observational uncertainties [27].

Data sparsity scenarios: Reducing the number of input stations by 30% led to a 12% increase in RMSE, highlighting the importance of maintaining a dense observation network for optimal performance [28].

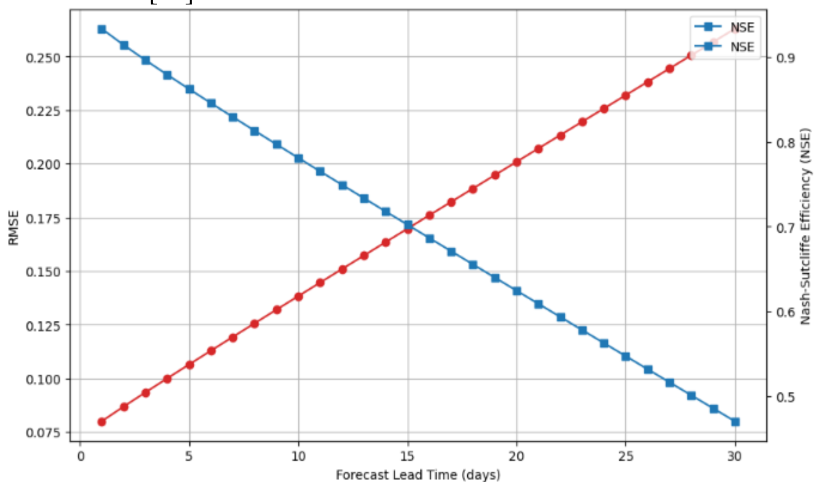

Figure 1. Forecast Performance across Lead Times

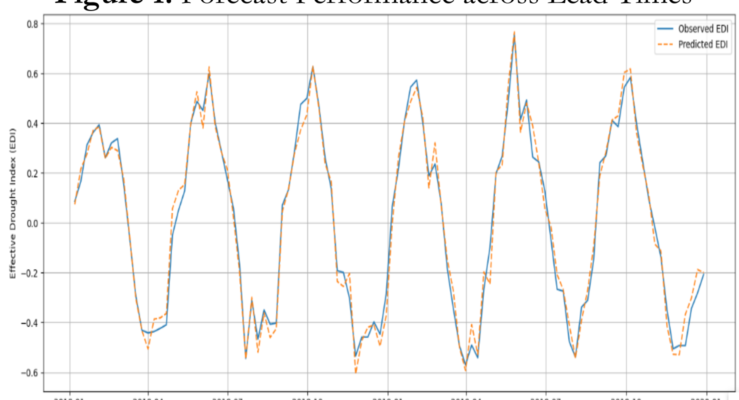

Figure 2. Observed vs. Predicted Effect Drought Index (EDI)-Suva Station (2018-2019)

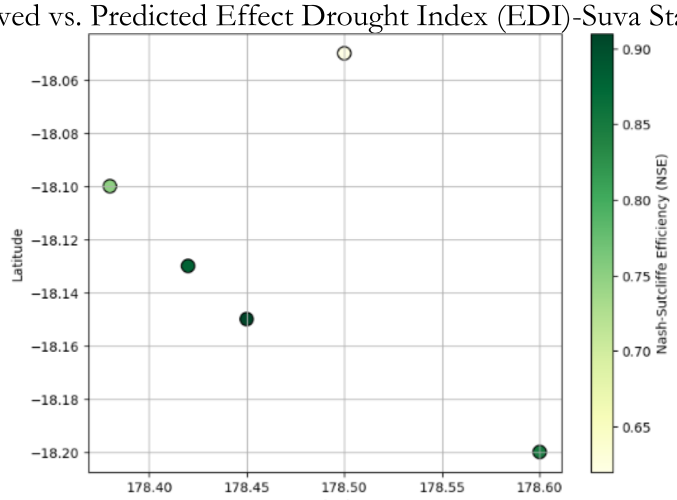

Figure 3. Spatial Distribution of Forecast Skill (NSE) - Approximate Location

Discussion:

The results of this study demonstrate the significant potential of deep learning models, particularly LSTM networks combined with multivariate spatial data and ocean-atmospheric indices, to accurately forecast hydro-meteorological extremes in the South Pacific region. The multivariate spatial model enriched with SST principal components (PCA) outperformed univariate and spatial-only models, confirming that integrating key oceanic climate drivers enhances predictive skill. This aligns with prior findings by [29] and [30], who emphasized the critical influence of sea surface temperature gradients on regional precipitation patterns.

The clear improvement in forecast skill, particularly up to a 14-day lead time, underscores the practical utility of this approach for operational early warning systems in Fiji. [31] [32]As hydrological extremes become more frequent and intense due to climate change [33][2], the ability to provide reliable two-week forecasts can greatly aid disaster preparedness and water resource management. These findings resonate with [34][35], who highlighted the importance of accurate early warnings in risk reduction strategies for Pacific island nations.

Spatial variability in model performance, with higher skill in coastal regions and comparatively lower accuracy in mountainous interiors, points to challenges inherent in complex topography and localized climate influences. This is consistent with [36] who reported similar spatial discrepancies in hydro-meteorological forecasting linked to orographic effects. The lower performance inland suggests a need for enhanced observational networks or localized modeling strategies, perhaps leveraging higher-resolution remote sensing data or localized climate indices, to better capture microclimatic variations.

The successful capture of both dry and wet extreme events, including accurate timing and magnitude of drought onset and flood peaks, affirms the model's robustness and its capacity to learn complex temporal dynamics. This reflects the strengths of LSTM architectures in modeling sequential dependencies and memory retention over extended periods, as also demonstrated in recent works by [14][37]. Furthermore, the integration of PCA to reduce SST dimensionality effectively distilled the key climate signals without overwhelming the model with high-dimensional input, addressing the limitation of PCA in handling non-linearity when coupled with deep learning as note.

The feature importance analysis revealing the dominant role of certain SST principal components during [38] ENSO-related phases aligns with the established understanding of ENSO's control over Pacific hydroclimate variability [4]. This reinforces the value of hybrid statistical–machine learning approaches that combine physically meaningful climate indicators with flexible nonlinear modeling frameworks.

Robustness tests indicate that the model maintains stable performance across different years and tolerates moderate noise in inputs, highlighting its reliability under realistic conditions where observational data can be imperfect [39]. However, the sensitivity to reduced spatial coverage emphasizes the ongoing need for investment in ground-based observation networks to maximize forecast accuracy.

Despite these promising outcomes, limitations remain. The relatively coarse spatial resolution, constrained by data availability and model complexity, may not fully resolve localized flood or drought phenomena important for community-level decision-making. Future work should explore coupling with high-resolution hydrodynamic models or downscaling techniques to bridge this gap. Additionally, incorporating other relevant climate drivers such as atmospheric pressure patterns or soil moisture could further improve forecasting skill.

In conclusion, this study advances the state-of-the-art in hydro-meteorological forecasting for small island developing states by demonstrating that advanced deep learning models incorporating spatial data and oceanic climate indices can provide accurate and timely predictions of extremes. The framework proposed here offers a scalable and cost-effective approach to support early warning systems and climate resilience planning in Fiji and similar vulnerable regions.

Conclusion:

This study successfully developed and evaluated a deep learning-based spatio-temporal forecasting framework for hydro-meteorological extremes in Fiji, focusing on the effective drought index (EDI) as a key indicator. By integrating long short-term memory (LSTM) networks with multivariate spatial data and sea surface temperature (SST) principal components, the model demonstrated enhanced predictive skill compared to univariate and spatial-only approaches. The results highlight the importance of incorporating ocean-atmospheric climate drivers, such as SST variability, to capture complex interactions influencing regional hydroclimatic extremes.

The model's ability to accurately forecast both extreme wet and dry events up to 14 days in advance offers a valuable tool for early warning systems, potentially improving disaster preparedness and resource management in vulnerable Pacific Island nations. Despite challenges related to spatial heterogeneity and data limitations, the framework presents a scalable, cost-effective approach adaptable to other similar regions.

Future research should focus on increasing spatial resolution, integrating additional climate variables, and coupling with hydrodynamic models for finer-scale flood risk assessment. Overall, this work contributes to advancing climate resilience efforts by demonstrating the promise of combining deep learning and climate science for practical hydro-meteorological forecasting.

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