



**Sandia National Laboratories**



# Machine Learning and Reservoir Computing for Watershed-Scale Drought Prediction

**Nicole D. Jackson, Ph.D.**

**Climate Security Center**

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The EPIC PLANN (Enhanced Prediction in Chaotic Systems with Physics-learned Autonomous Neural Networks) team



- William Chapman<sup>†</sup>                      ‡
- Josh Mott<sup>‡</sup>
- J. Darby Smith
- Corinne Teeter



- Louis Scuderi
- Zach Strasberg<sup>‡</sup>

<sup>†</sup> postdoc , <sup>‡</sup> Ph.D. student



Sandia Earth Science Research Foundation

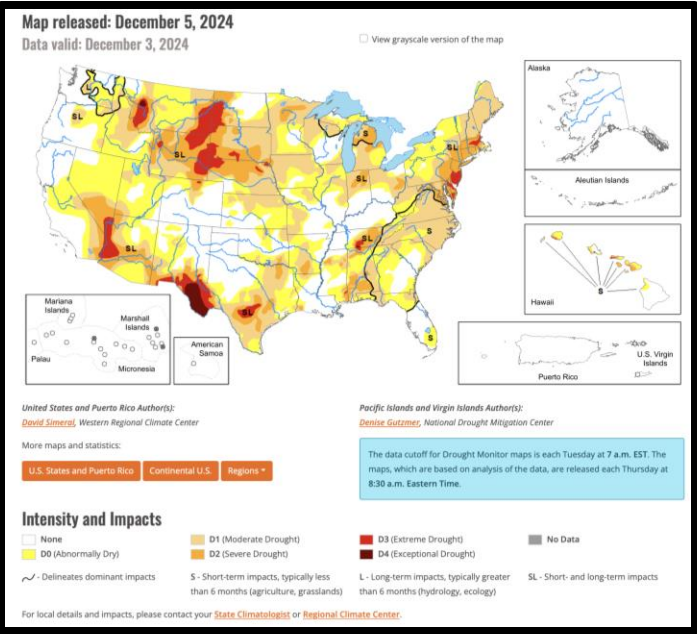
- Program Manager: Stephanie Kuzio

# The US Drought Monitor provides weekly drought estimates



## U.S. Drought Monitor

### Last week's report



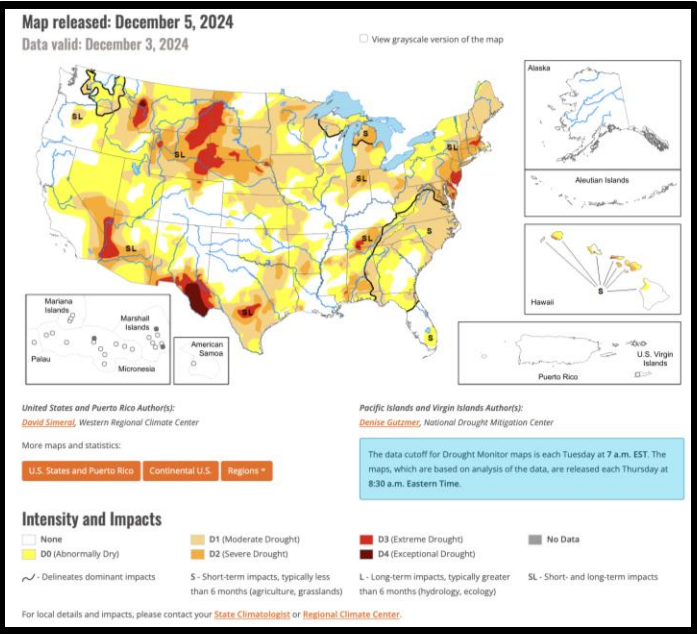
Source: [U.S. Drought Monitor](#)

# The US Drought Monitor provides weekly drought estimates as well as monthly forecasts

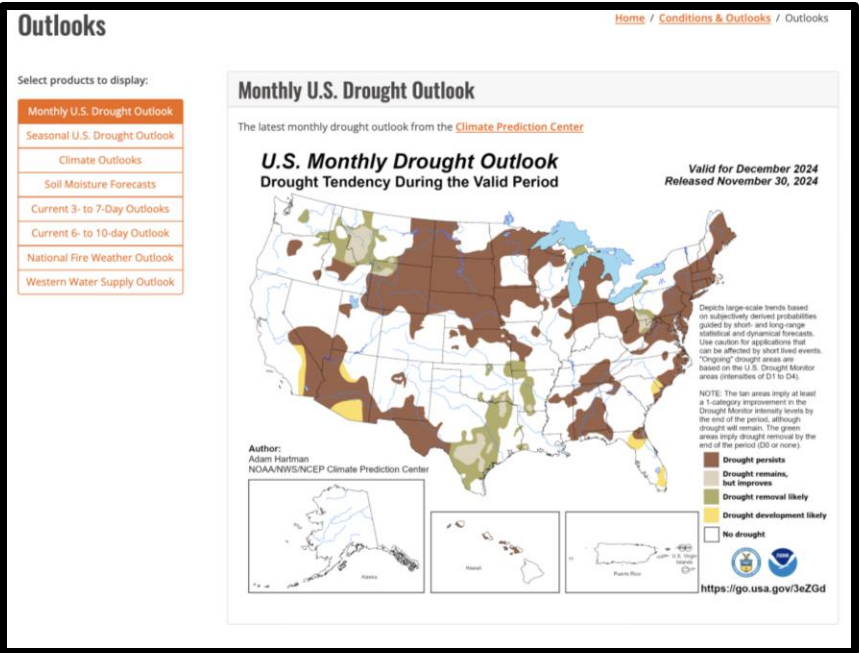


## U.S. Drought Monitor

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### Monthly Outlook



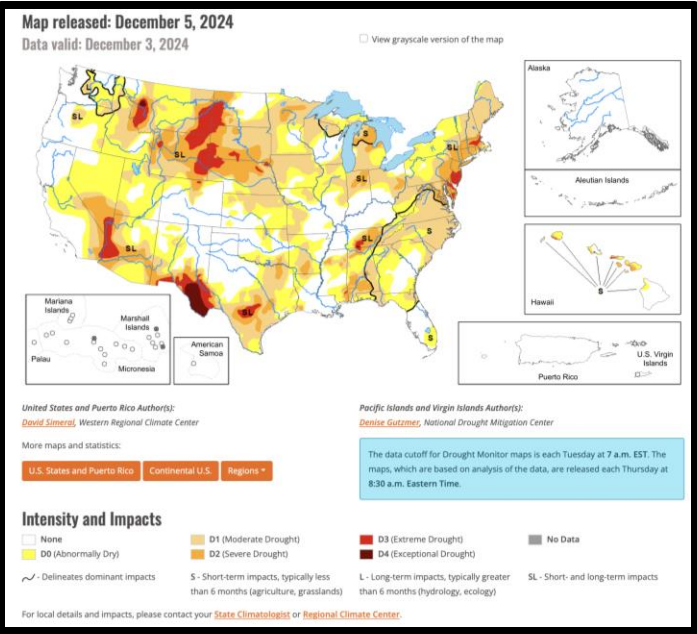


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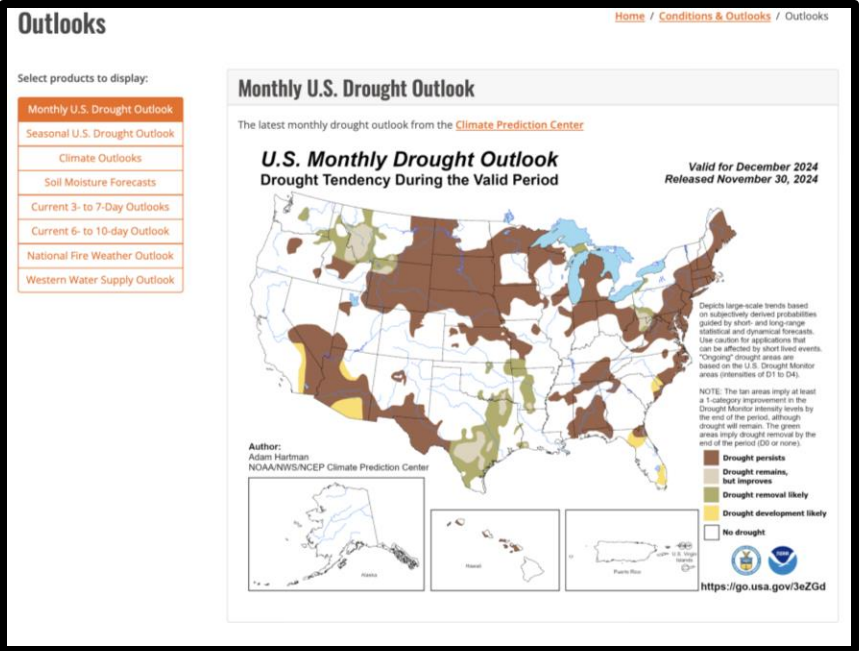


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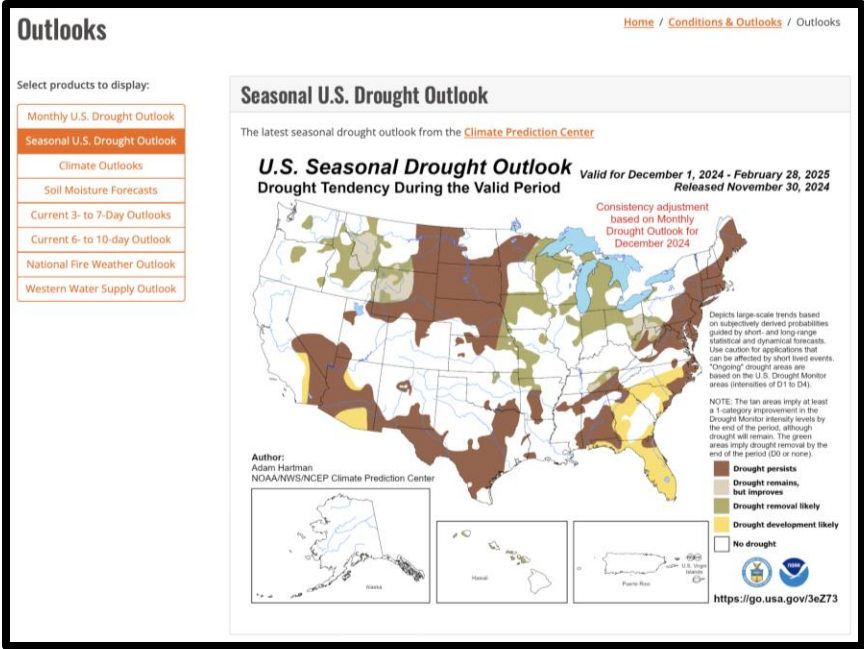
### Last week's report



### Monthly Outlook



### Seasonal Outlook

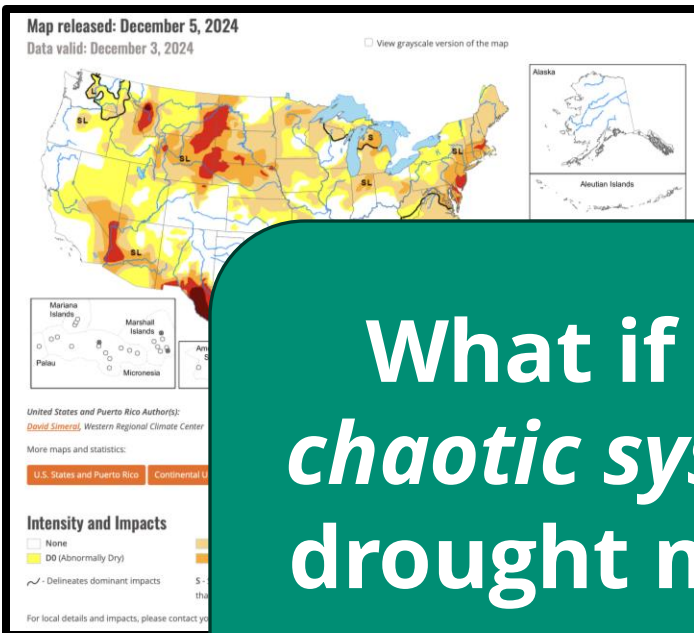


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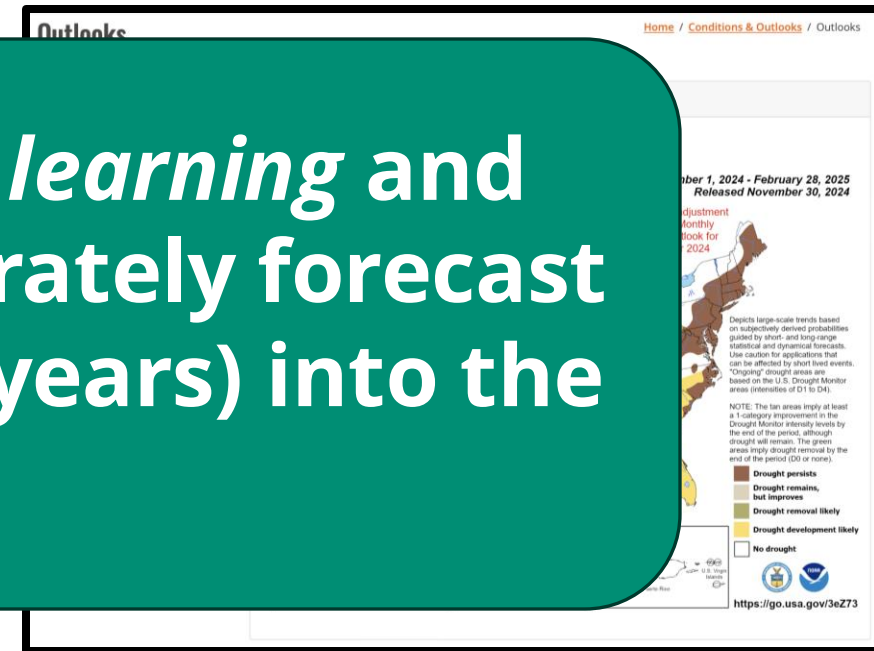
Last week's report



Monthly Outlook



Seasonal Outlook



What if we could use *machine learning* and *chaotic system modeling* to accurately forecast drought much farther (e.g., 1-2 years) into the future?

# Multiple machine learning—based algorithms have been used to forecast meteorological drought



## A Deep Learning Based Approach for Long-Term Drought Prediction

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**Abstract**—Drought is a natural disaster that comes with high hazardous impacts on the society. Its effects are mostly manifested as hydrological drought. Identifying past droughts and predicting future ones is very vital in limiting their effects. However, the random and nonlinear nature of drought variables makes accurate drought prediction remain a challenging scientific problem. Neural networks have shown great promise over the last two decades in modeling nonlinear time series. But the issue of nonconvex optimization ensues when two or more hidden layers are required for highly complex phenomena. This research looks into the drought prediction problem using deep learning algorithms. We propose a Deep Belief Network consisting of two Restricted Boltzmann Machines for long-term drought prediction using lagged values of Standardized Streamflow Index (SSI) as inputs. The proposed model is applied to predict different time scale drought indices across the Gunnison River Basin located in the Upper Colorado River Basin. The study compares the efficiency of the proposed model to that of traditional approaches such as Multilayer Perceptron (MLP) and Support Vector Regression (SVR) for predicting the different time scale drought conditions. The proposed model shows an edge in performance over the traditional methods using Root Mean Square Error and Mean Absolute Error as metrics.

**Index Terms**—Deep Belief Network, unsupervised pre-training.

[6]. Of the total 58 weather-related disasters recorded within the period, 10 were as a result of droughts and other related heat waves [6]. The ability to design models that can make reliable future predictions constitutes a significant progress in the drought management process. However, the random and nonlinear nature of drought variables makes accurate drought prediction remain a challenging scientific problem.

Several studies conducted in recent years have proposed methods to improve drought forecasting [7]–[18]. In [11], a seasonal drought prediction model based on a Bayesian framework, was used to characterize hydrologic drought across the Gunnison River Basin. The authors used standardized streamflow index (SSI) for their analysis. In [12], a wavelet-linear genetic programming (WLGPM) model was used for long lead-time drought forecasting (with 3, 6, and 12-month lead times) in the state of Texas. They demonstrated that the standard linear genetic programming model is unable to learn the non-linear structure of drought in lead times more than three months. An autoregressive integrated moving average (ARIMA), recursive multistep neural network (RMSNN) as well as a direct multistep neural network (DMSSNN) were also

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**RESEARCH ARTICLE**  
10.1029/2020WR028413

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- Ensemble learning machine predicts drought more effectively than support vector regression and random forest
- The new approach allows for ensemble, probability, and deterministic drought predictions

**Supporting Information:**  
Supporting information may be found in the online version of this article.

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**Citation:**  
Li, J., Wang, Z., Wu, X., Xu, C.-Y., Guo, S., Chen, X., & Zhang, Z. (2021). Robust meteorological drought prediction using antecedent SST fluctuations and machine learning. *Water Resources Research*, 57, e2020WR028413. <https://doi.org/10.1029/2020WR028413>

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- SVR
- Random Forest (RF)
- Extreme Learning Machine (ELM)

## Estimation of SPEI Meteorological Drought Using Machine Learning Algorithms

**ALI MOKHTAR<sup>1,2</sup>, MOHAMMADNABI JALALI<sup>3</sup>, HONGMING HE<sup>4</sup>, NADHIR AL-ANSARI<sup>5,6</sup>, AHMED ELBELTAGI<sup>7</sup>, KARAM ALSAFADI<sup>8</sup>, HAZEM GHASSAN ABD<sup>9</sup>, SAAD SH. SAMMEN<sup>10</sup>, YEOBAH CYASI-ABDO<sup>11</sup>, AND JESU'S RODRIGO-COMINO<sup>12,13</sup>**

<sup>1</sup>State Key Laboratory of Soil Erosion and Dryland Farming on the Loess Plateau, Institute of Soil and Water Conservation, Northwest Agriculture and Forestry University, Chinese Academy of Sciences and Ministry of Water Resources, Yangling 712100, China

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Source: [Mokhtar et al. \(2021\)](#)

- RF
- Extreme Gradient Boost (XGB)
- Convolutional neural network (CNN)
- Long-term short memory (LSTM)



A review of machine learning methods for drought hazard monitoring and forecasting: Current research trends, challenges, and future research directions

Foyez Ahmed Prodhon<sup>a,b,c</sup>, Jiahua Zhang<sup>a,b,c</sup>, Shaikh Shamin Hasan<sup>a</sup>, Til Prasad Pangali Sharma<sup>a,1</sup>, Hasiba Pervin Mohana<sup>a</sup>

<sup>a</sup>Key Laboratory of Digital Earth Science, Aerospace Information Research Institute, Chinese Academy of Sciences, Beijing, 100049, China

<sup>b</sup>University of Chinese Academy of Sciences, Beijing, 100049, China

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**ARTICLE INFO**

**Keywords:**  
Machine learning  
Deep learning  
Forecasting  
Drought  
Big data

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Machine learning is a dynamic field with wide-ranging applications, including drought modeling and forecasting. Drought is a complex, devastating natural disaster for which it is challenging to develop effective prediction models. Therefore, our review focuses on basic information about machine learning methods (MLMs) and their potential applications in developing efficient and effective drought forecasting models. We observed that MLMs have achieved significant advances in the robustness, effectiveness, and accuracy of the algorithms for drought modeling in recent years. The performance comparison of MLMs with other models provides a comprehensive conception of different model evaluation metrics. Further challenges of MLMs, such as inadequate training data sets, noise, outliers, and observation bias for spatial data sets, are explored. Finally, our review covers in-depth understanding to researchers on machine learning applications in forecasting and modeling and provides drought mitigation strategy guidance for policymakers.

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Gap: forecasting for periods beyond 3-6 months

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# Modeling supported by the high spatial resolution (4 km) NCAR/USGS CONUS404 dataset for period 1979-2021



- Climate Data (CONUS404)
- Drought Metrics



>100 including...



Precipitation



Temperature



Transpiration



Wind speed

Calculated **meteorological drought** metrics:

- Standardized Precipitation Index (SPI)
- Standardized Precipitation Evapotranspiration Index (SPEI)

# Data is statistically reduced to the weekly timescale at the HUC4 and HUC8 spatial scales

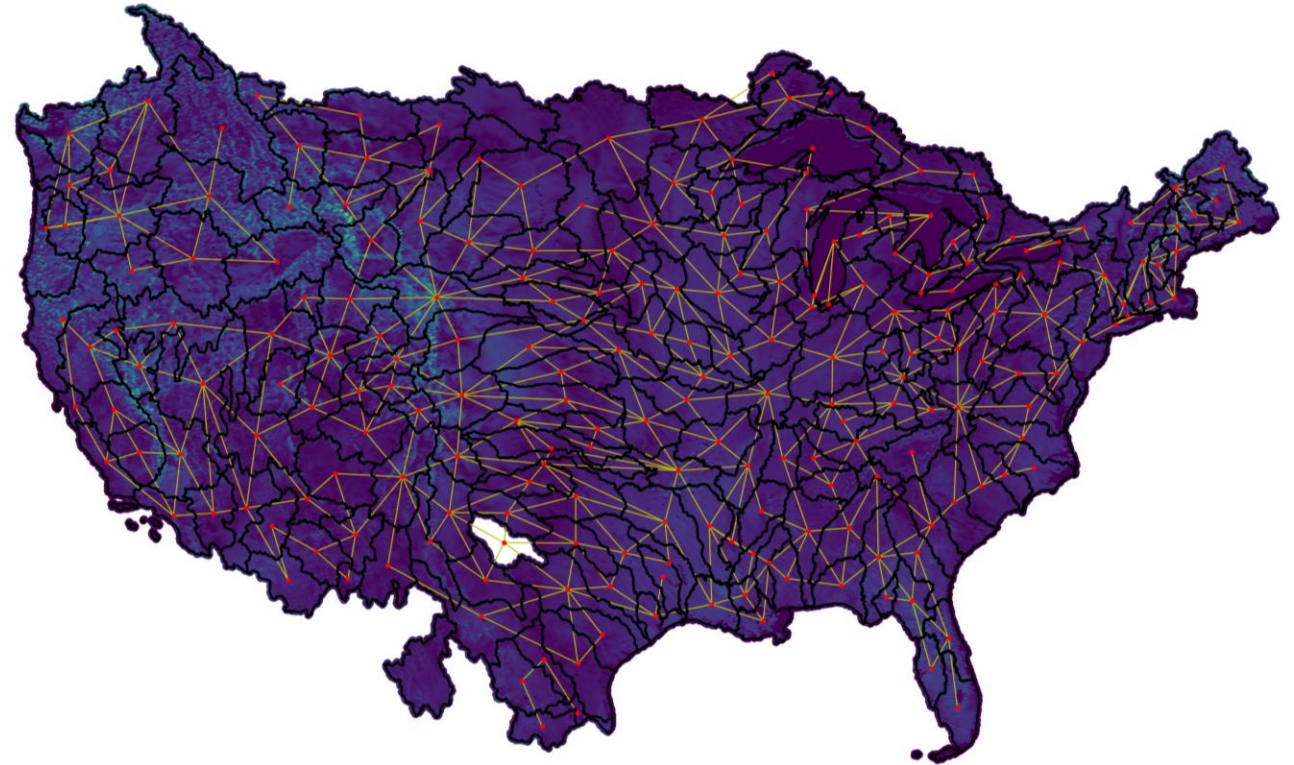


- Climate Data (CONUS404)
- Drought Metrics



Watershed-scale Spatial Aggregation

Sample HUC8 aggregation for precipitation



Connections across watersheds

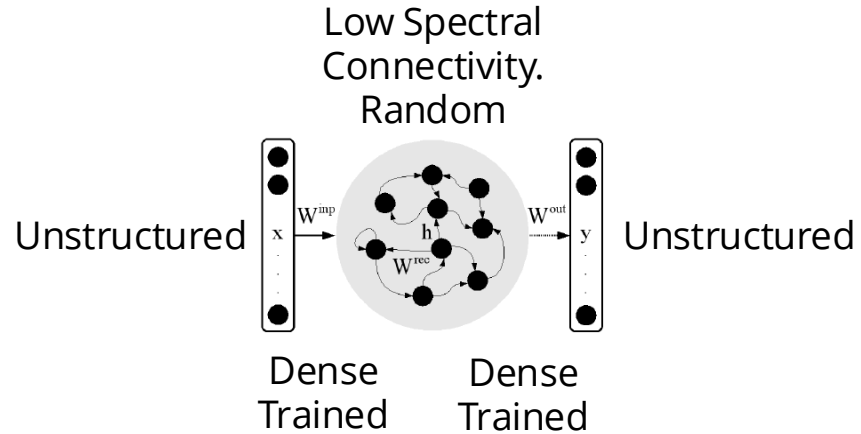
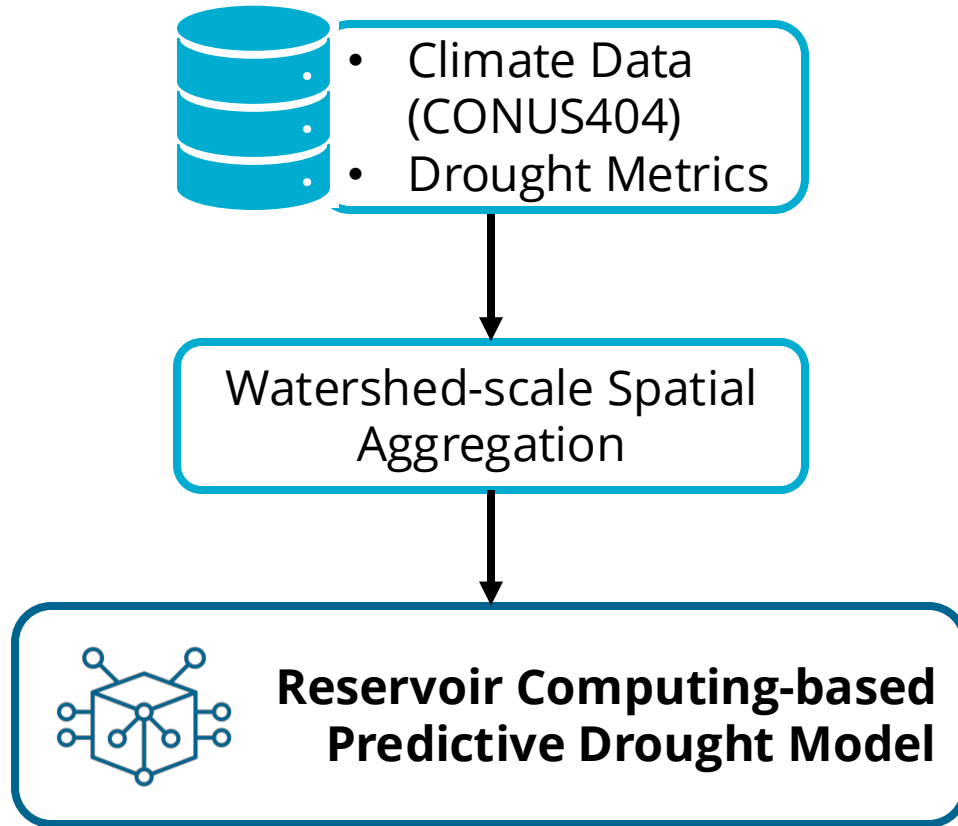


Watershed centroid

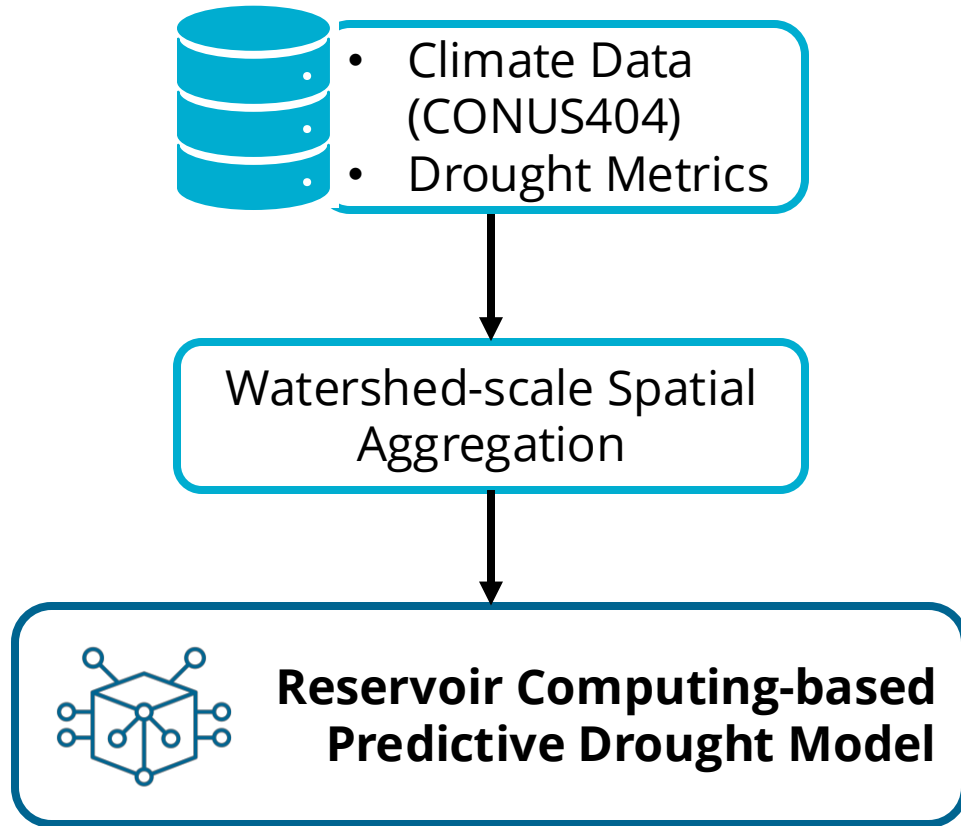
Precipitation



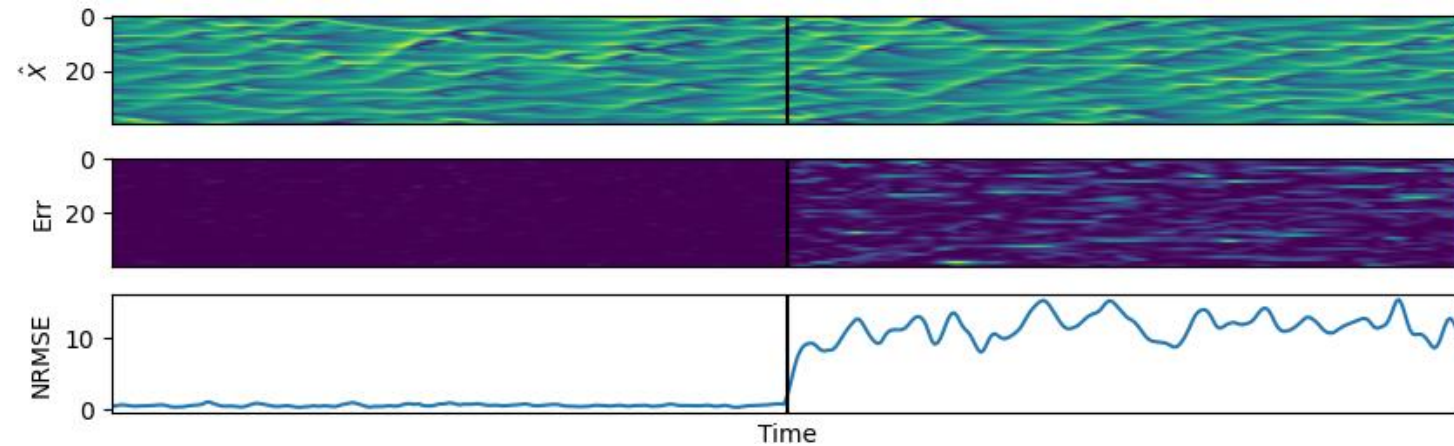
# Reservoir networks use spectral normalization and random connectivity to autonomously mimic chaotic system



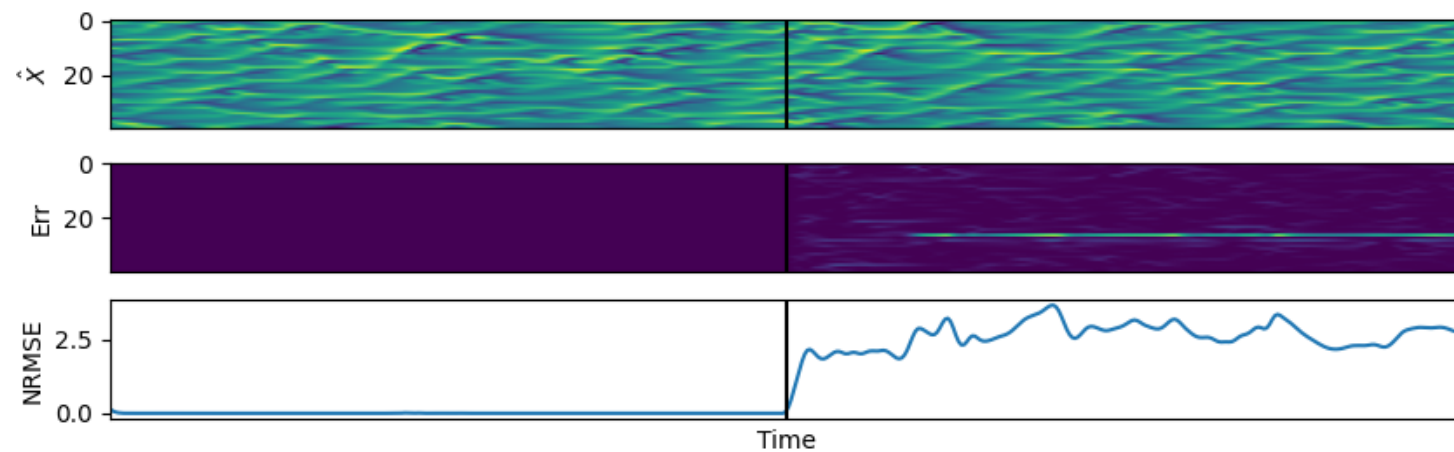
# Graph-based reservoirs reduce normalized root mean square error during prediction period versus a single reservoir



## Single Reservoir

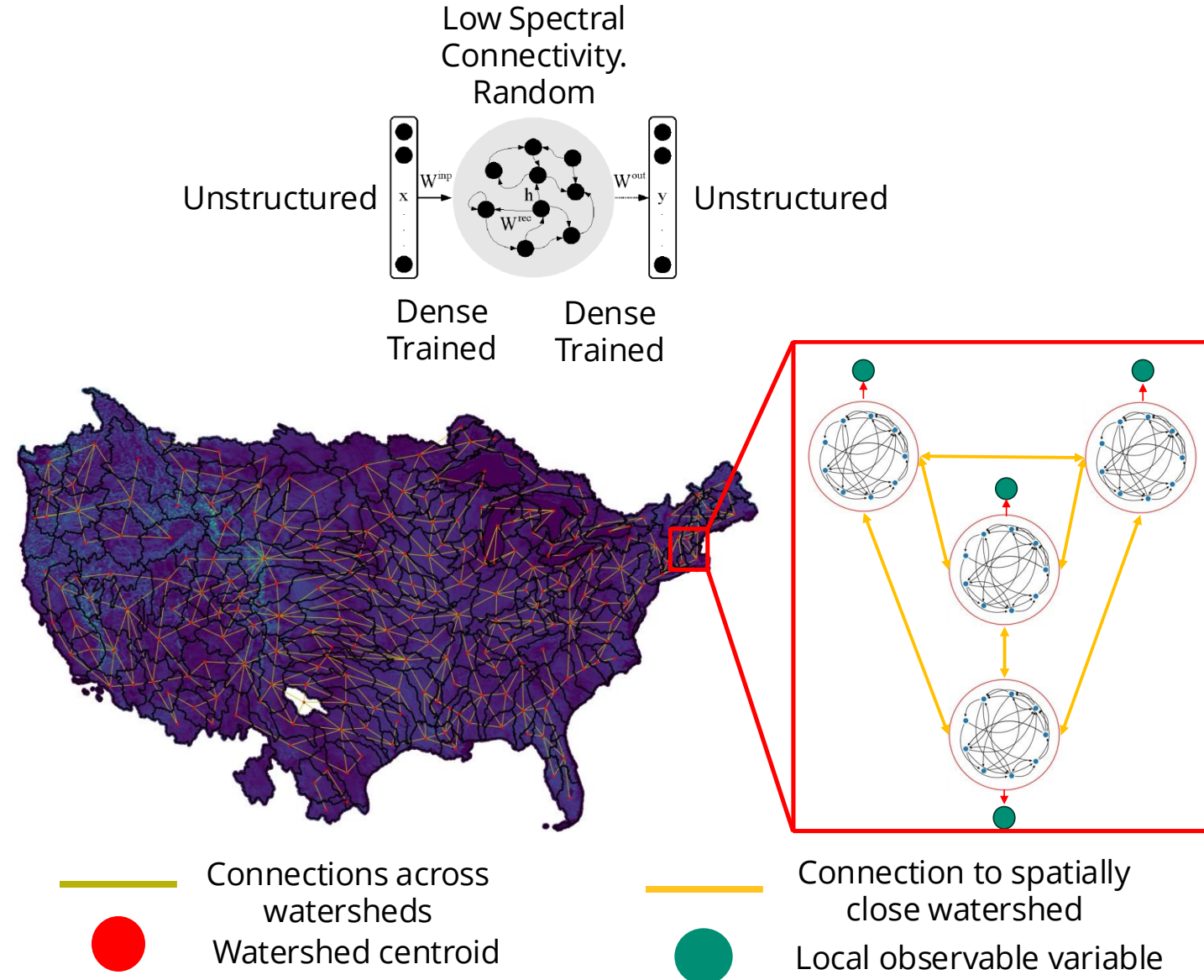
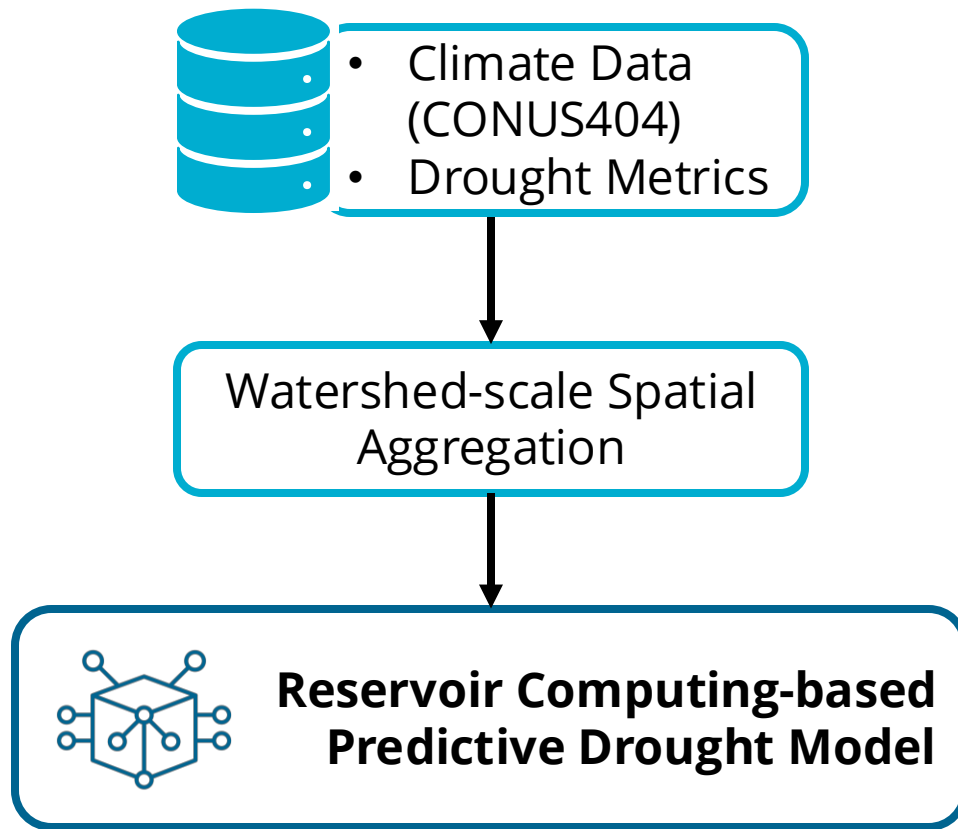


## Graph Reservoir

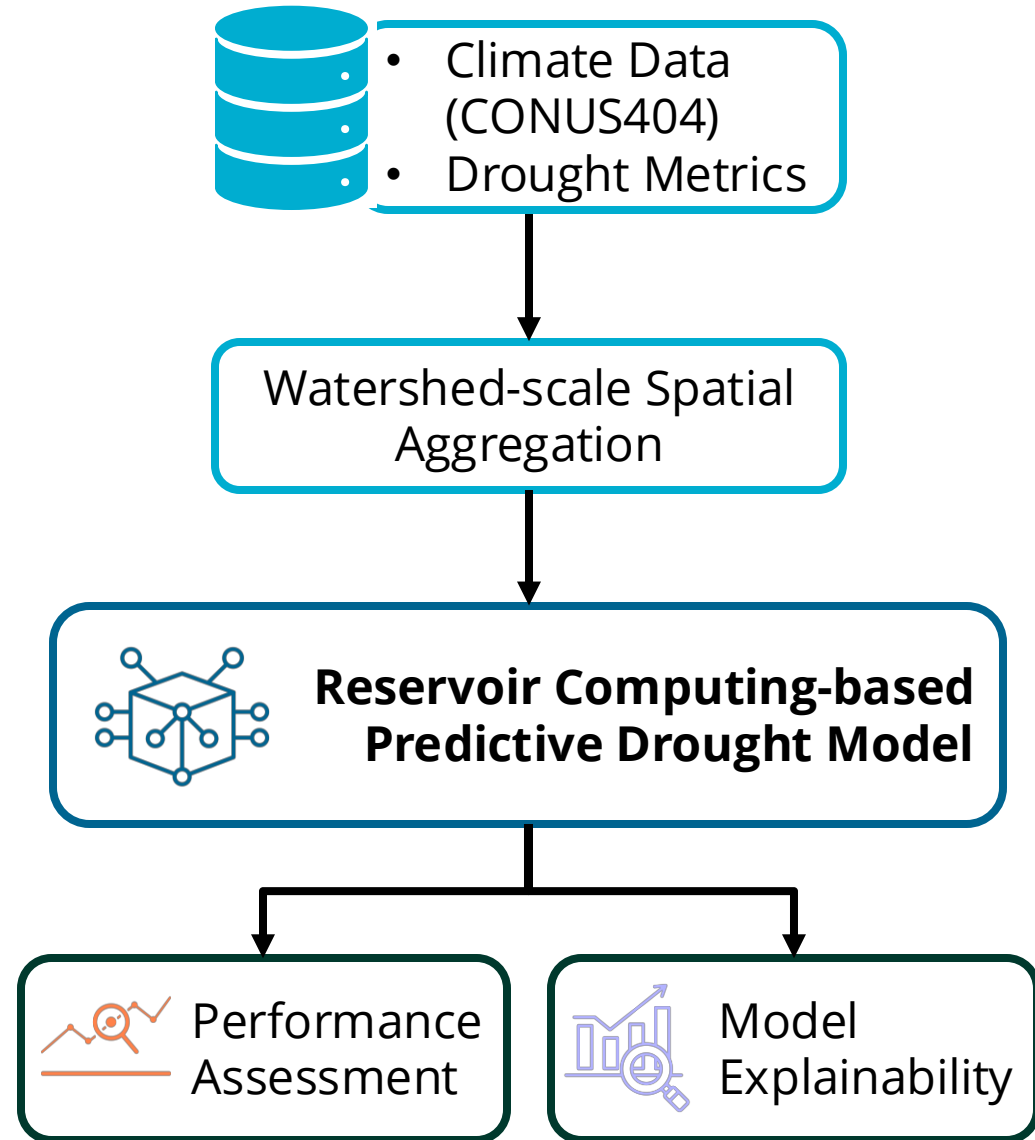




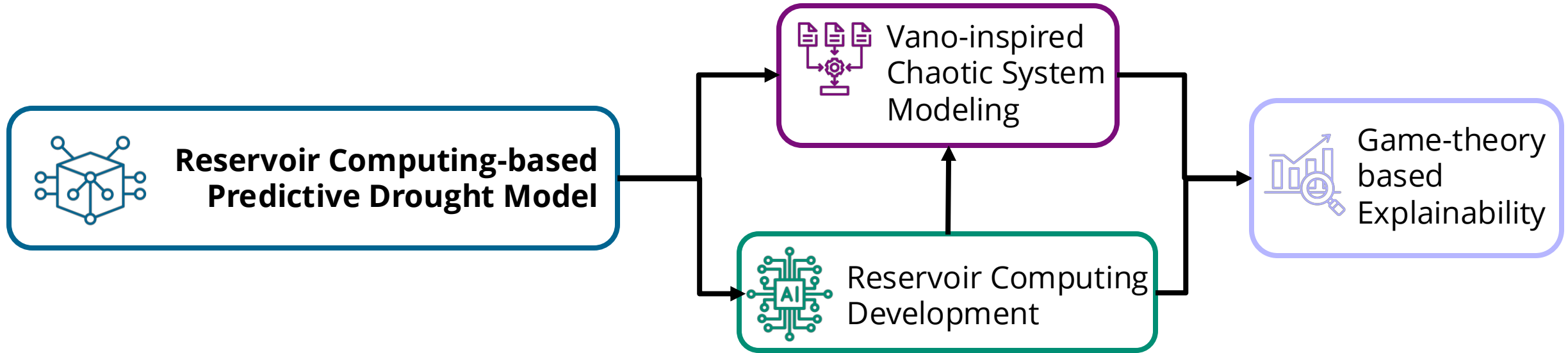
# Graph reservoir nodes are generated for each watershed while maintaining the input layer's spatial structure



# The EPIC PLANN project is using a standard framework to develop its ML-based predictive model for drought



# Reservoir model development inspired by chaotic systems modeling and game theory



# A graph-based reservoir network is trained to predict two sets of Vano models side by side



## Input layer

$X_1(t_0), \dots, X_1(t_{N_k})$

$X_2(t_0), \dots, X_2(t_{N_k})$

$X_3(t_0), \dots, X_3(t_{N_k})$

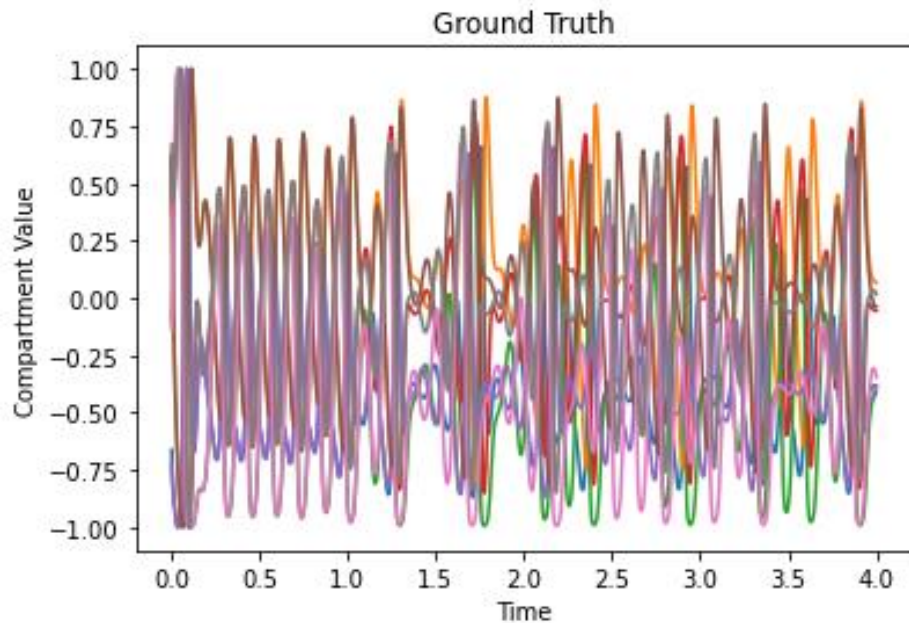
$X_4(t_0), \dots, X_4(t_{N_k})$

$Y_1(t_0), \dots, Y_1(t_{N_k})$

$Y_2(t_0), \dots, Y_2(t_{N_k})$

$Y_3(t_0), \dots, Y_3(t_{N_k})$

$Y_4(t_0), \dots, Y_4(t_{N_k})$



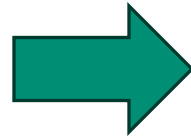


# A graph-based reservoir network is trained to predict two sets of Vano models side by side

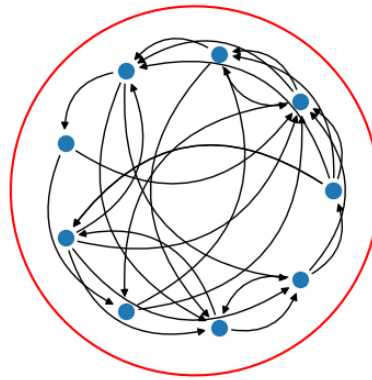


## Input layer

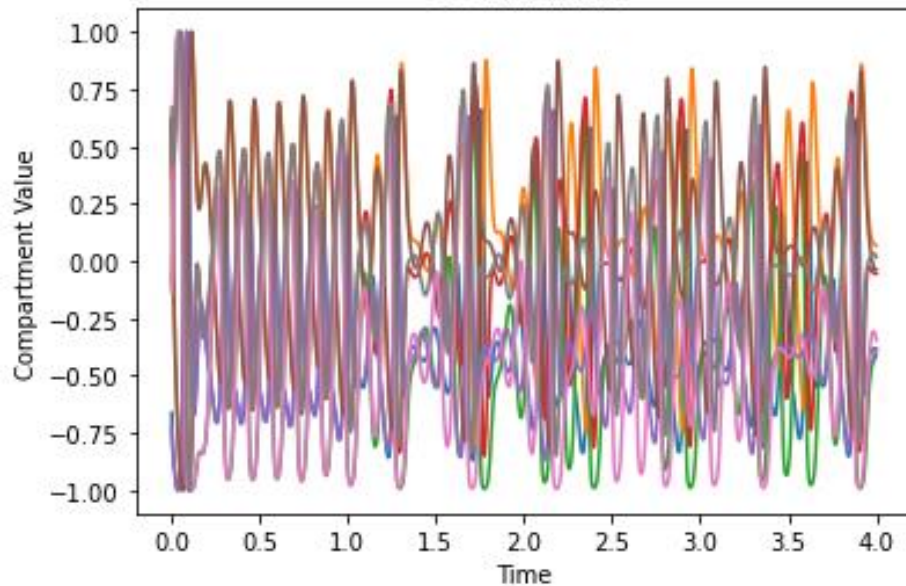
$X_1(t_0), \dots, X_1(t_{N_k})$   
 $X_2(t_0), \dots, X_2(t_{N_k})$   
 $X_3(t_0), \dots, X_3(t_{N_k})$   
 $X_4(t_0), \dots, X_4(t_{N_k})$   
 $Y_1(t_0), \dots, Y_1(t_{N_k})$   
 $Y_2(t_0), \dots, Y_2(t_{N_k})$   
 $Y_3(t_0), \dots, Y_3(t_{N_k})$   
 $Y_4(t_0), \dots, Y_4(t_{N_k})$



## Trained Reservoirs



Ground Truth

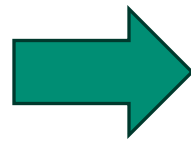


# A graph-based reservoir network is trained to predict two sets of Vano models side by side

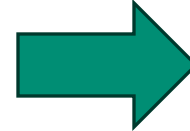
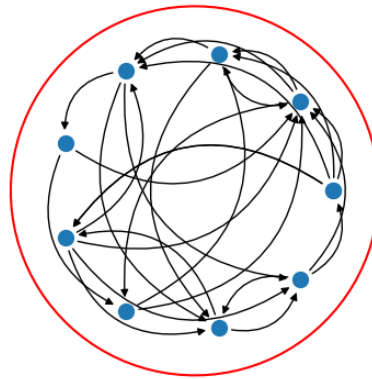


## Input layer

$X_1(t_0), \dots, X_1(t_{N_k})$   
 $X_2(t_0), \dots, X_2(t_{N_k})$   
 $X_3(t_0), \dots, X_3(t_{N_k})$   
 $X_4(t_0), \dots, X_4(t_{N_k})$   
 $Y_1(t_0), \dots, Y_1(t_{N_k})$   
 $Y_2(t_0), \dots, Y_2(t_{N_k})$   
 $Y_3(t_0), \dots, Y_3(t_{N_k})$   
 $Y_4(t_0), \dots, Y_4(t_{N_k})$



## Trained Reservoirs



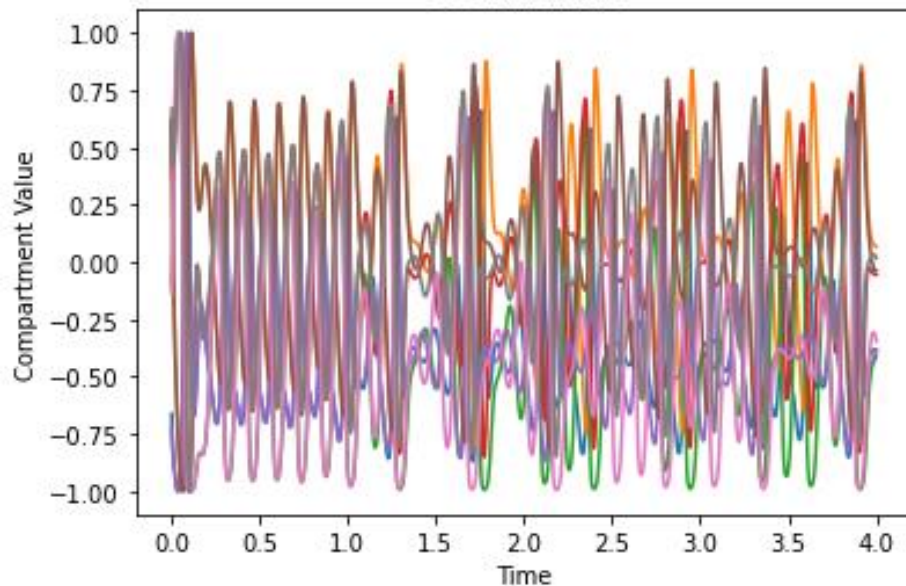
## Output layer

$X_1(t_{N_k+1}), \dots, X_1(t_{N_p})$   
 $X_2(t_{N_k+1}), \dots, X_2(t_{N_p})$   
 $X_3(t_{N_k+1}), \dots, X_3(t_{N_p})$   
 $X_4(t_{N_k+1}), \dots, X_4(t_{N_p})$   
 $Y_1(t_{N_k+1}), \dots, Y_1(t_{N_p})$   
 $Y_2(t_{N_k+1}), \dots, Y_2(t_{N_p})$   
 $Y_3(t_{N_k+1}), \dots, Y_3(t_{N_p})$   
 $Y_4(t_{N_k+1}), \dots, Y_4(t_{N_p})$

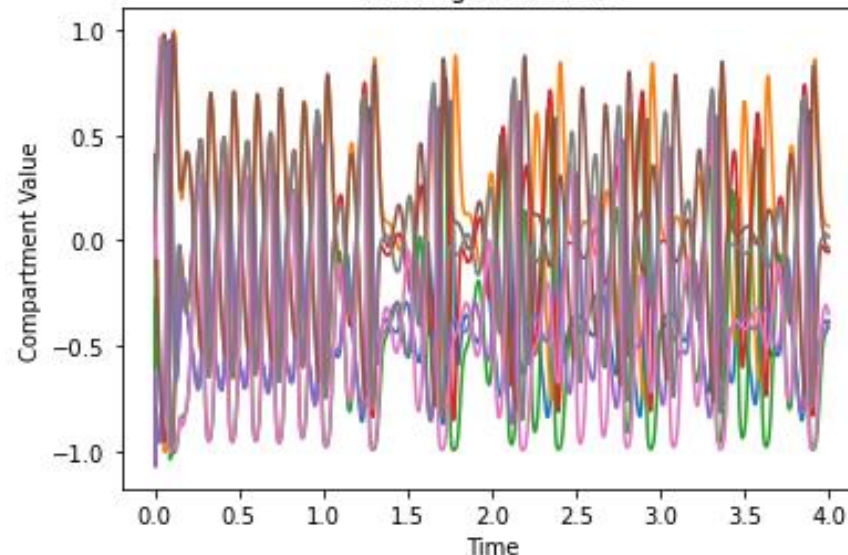
$g(t_{N_k+1}), \dots, g(t_{N_p})$

Mystery function

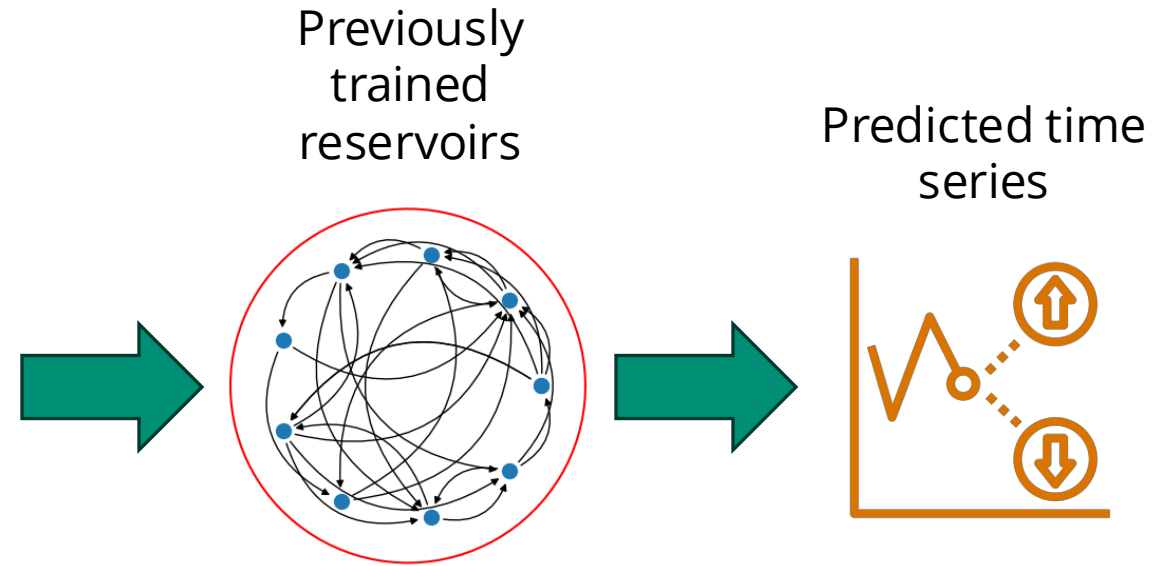
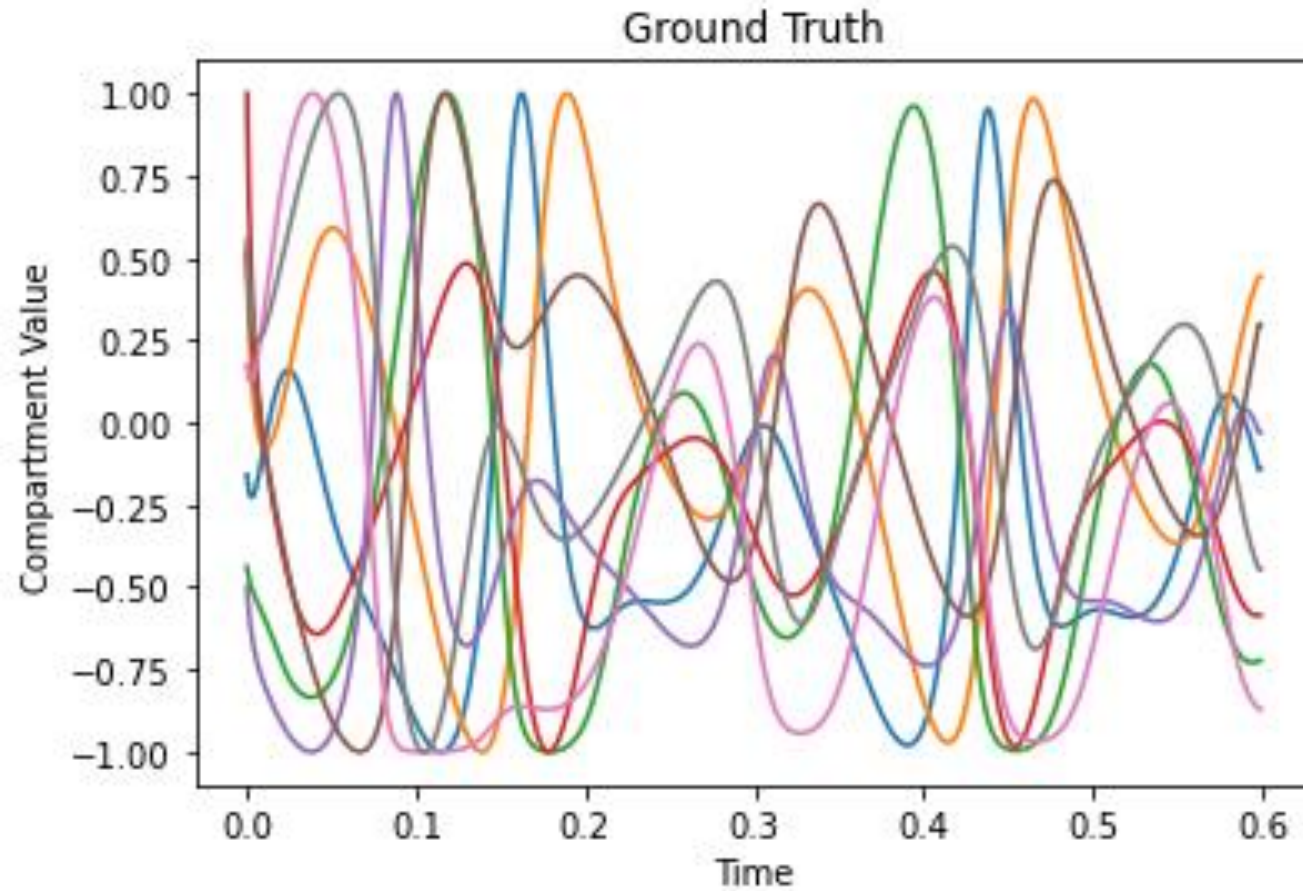
Ground Truth



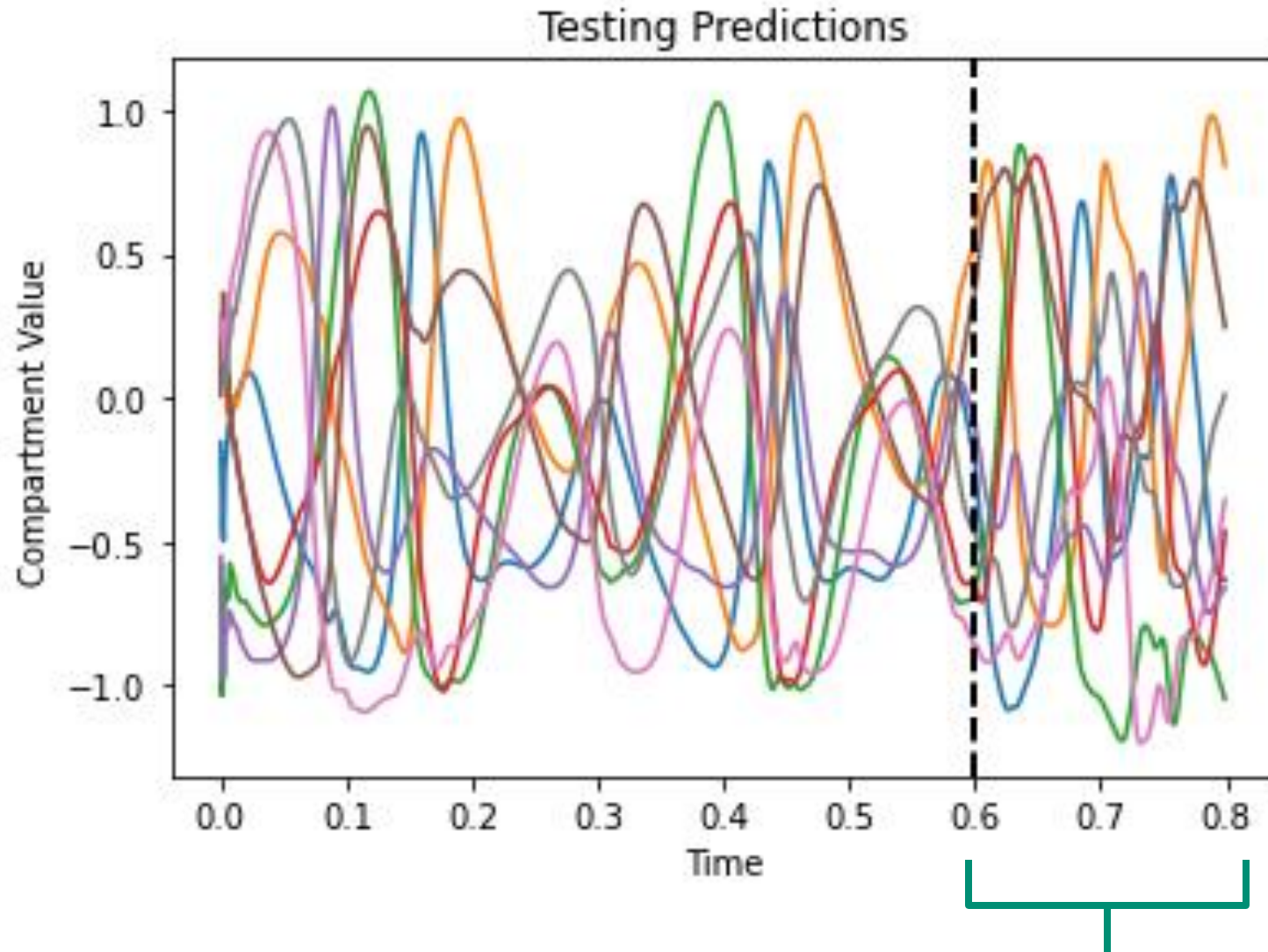
Training Predictions



# A new time series using perturbed initial conditions is generated to support prediction with trained reservoirs

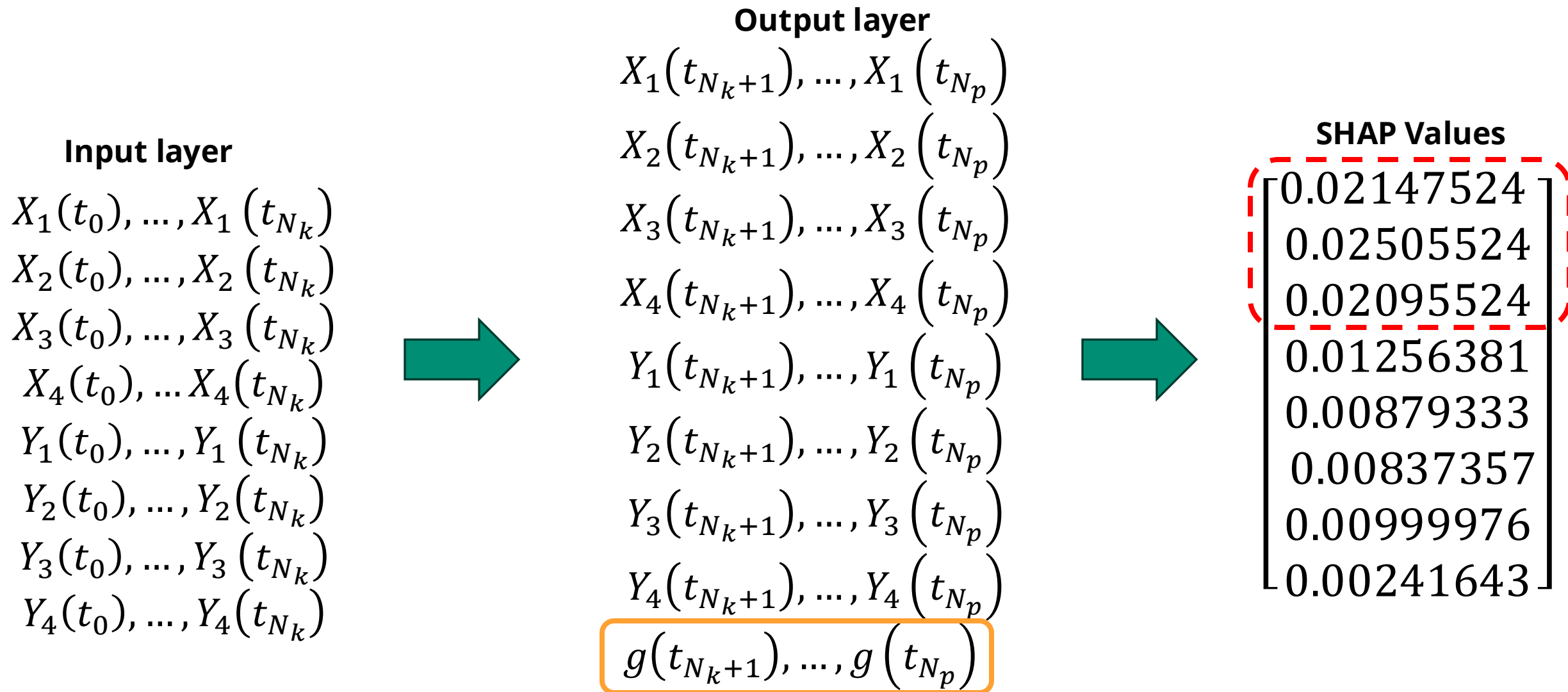


# Predicted time series using perturbed data and trained reservoirs with rollout





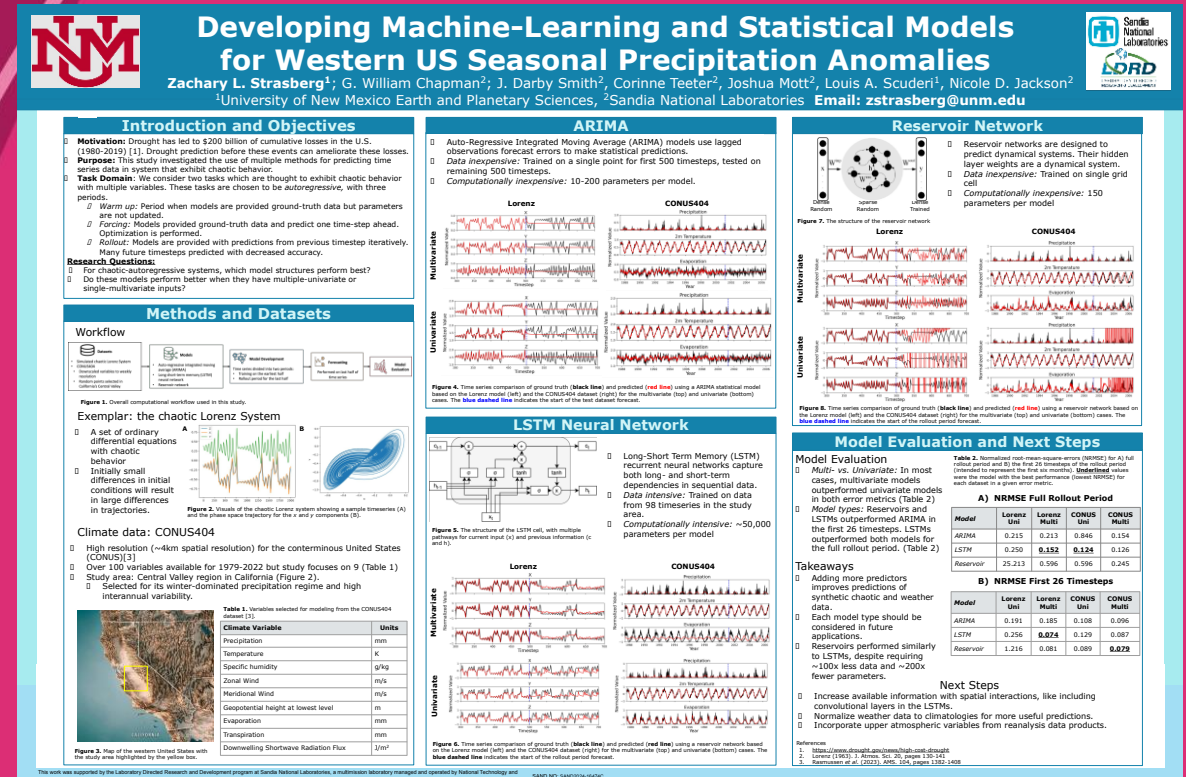
# Shapley Additive Explanation Values (SHAP) are used to determine influence of inputs on changes to outputs



# A51L-1838: Developing Machine-Learning and Statistical Models for Western US Seasonal Precipitation Anomalies

- Presenter: Zach Strasberg
- Friday, 13 December 2024
- 08:30 – 12:20
- Poster Halls B-C

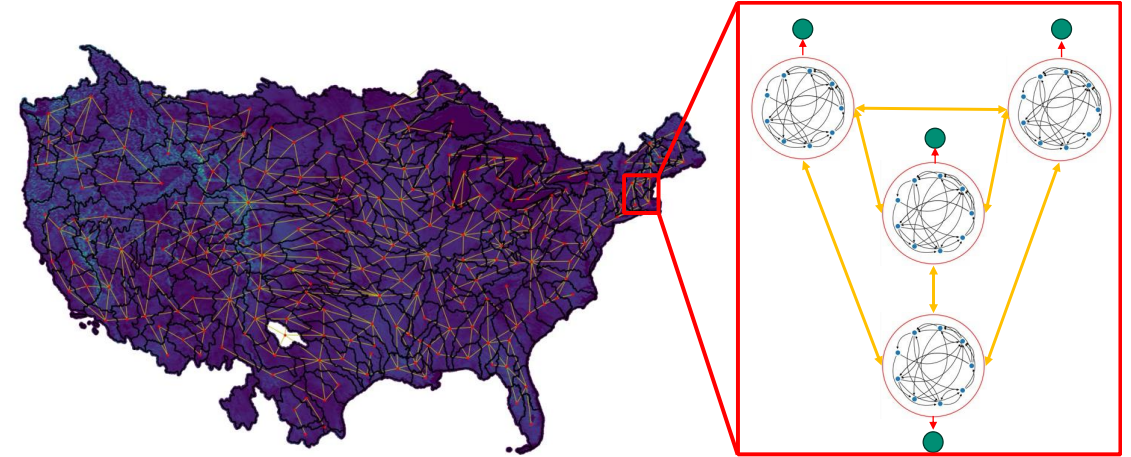
AGU24



# In conclusion, we have developed reservoir computing-based predictive time series models for chaotic, dynamic systems



- Graph reservoirs reduce error compared to single reservoirs
- Reservoir-based predictive model developed using the Vano system with chaotic behavior
- SHAP identified 3 key variables driving Vano model performance



## Future Work

- Increase variables and explainability techniques for the Vano model
- Consideration of multiple drought metrics (SPEI, SPI, etc.)
- Increase spatial extent of modeled watersheds

