Assessing the Influence of Soil Parameters in the Simulation of Soil Moisture in a CLM5 using EOF and SOM

Kachinga Silwimba, Alejandro N. Flores

Department of Geoscience, Boise State University

Introduction

This study looks at how different types of soil affect moisture predictions in a land surface model called the Community Land Model version 5 (CLM5) over the continental United States. We used two methods, Empirical Orthogonal Function (EOF) and Self-Organizing Maps (SOM), to figure out how soil characteristics relate to moisture levels. Our research found specific patterns of moisture based on the soil's texture and water-handling traits. By examining the results from CLM5, we gained a better understanding of how well the model can predict soil moisture in various places and weather situations. Our results show that using EOF and SOM can improve our knowledge of how environmental models represent the real world.

Empirical Orthogonal Functions (EOF) Analysis

- The EOF method uses the singular value decomposition techniques to compute EOF mode.
- Identify dominant patterns or modes of variation.
- SVD decomposes any $n \times m$ matrix Y_w of weighted gridded climate data into the form:

$$Y_w = \mathbf{U\Gamma V}^T \quad \mathbf{U} \in \mathbb{R}^{n\times n}, \mathbf{\Gamma} \in \mathbb{R}^{n\times m}, \mathbf{V} \in \mathbb{R}^{m\times m}$$

Weight of each EOF mode

Direction of the new axis (PC1, PC2 ....)

$$\begin{bmatrix} Y_w: \\ n\times m \\ matrix\end{bmatrix} = \begin{bmatrix} u_{11} & u_{12} & \cdots & u_{1p} \\ u_{21} & u_{22} & \cdots & u_{2p} \\ \vdots & \vdots & \ddots & \vdots \\ u_{n1} & u_{n2} & \cdots & u_{nn}\end{bmatrix}\begin{bmatrix}\gamma_{11} & 0 & \cdots & 0\\ 0 & \gamma_{22} & \cdots & 0 \\ \vdots&\vdots&\ddots&\vdots\\ 0&0&\cdots&\gamma_{nm}\end{bmatrix}\begin{bmatrix} v_{11}&v_{12}&\cdots&v_{1p}\\ v_{21}&v_{22}&\cdots&v_{2p}\\ \vdots&\vdots&\ddots&\vdots\\ v_{n1}&v_{n2}&\cdots&v_{mm}\end{bmatrix}$$

- To minimize the noise effect, singular value truncation is proposed
- To keep Γ largest eigenvalues and keep columns of U and V.

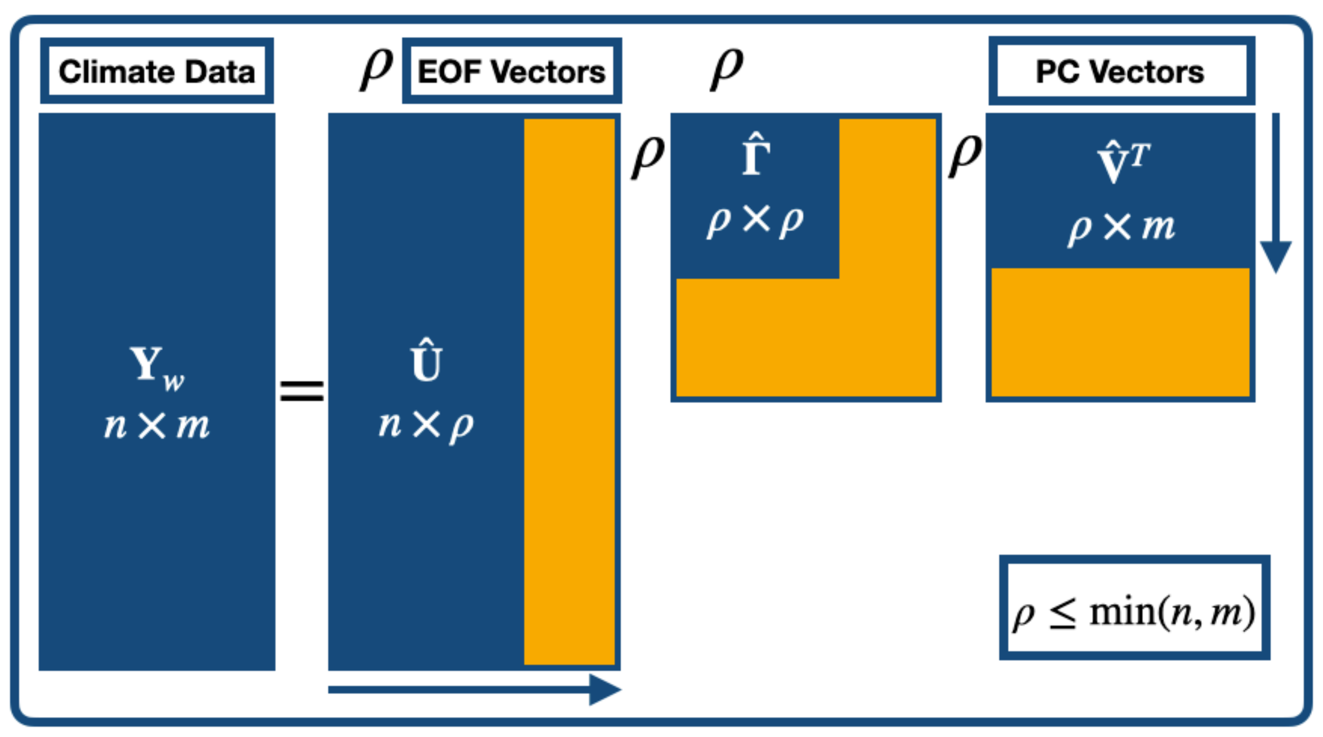


Fig.1: Illustration of Truncated Singular Value Decomposition on climate data. The data matrix Y_w with size $n \times m$ is simplified into a smaller set of EOF modes and principal components (PC) corresponding to the largest singular values.

Self-Organizing Map (SOM)

- Introduced by Prof. Teuvo Kohonen in 1982.
- Unsupervised neural network.
- Detects similarity and degrees of similarity.
- Clustering tool of high-dimensional and complex data.
- Training occurs via competition between the neurons.
- **Learning step**: the winning unit (and its neighbors) will update its weight vectors with:

$$w_i(t+1) = w_i(t) + \alpha(t) h_{i,\Omega(y)} \cdot (y - w_i(t))$$

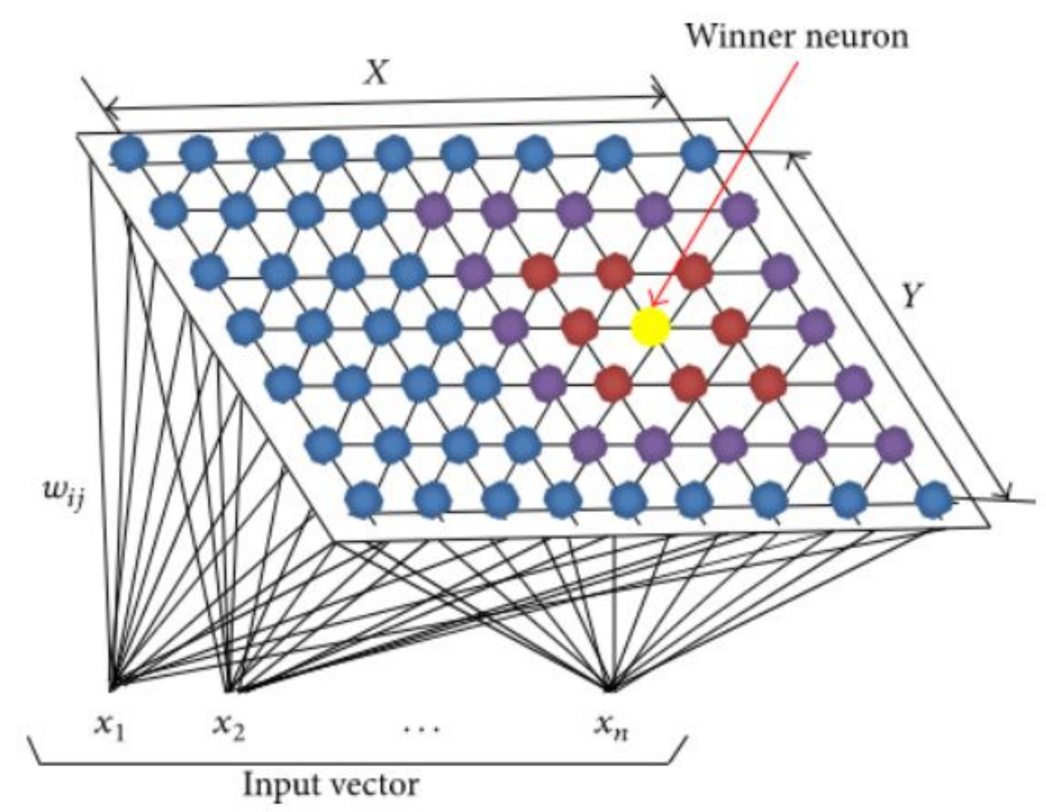


Fig.2: Visualization of a SOM. The network consists of input vectors mapped to a grid of neurons. Each neuron is connected to the input vector through weights w_{ij}. The yellow neuron represents the "winner" or Best Matching Unit (BMU) that has the closest weight vector to the input vector amidst the competing neurons (blue and purple) across the X and Y dimensions of the neuron grid.

Combination of EOF and SOM

- Cluster the dominant spatial patterns of Soil Moisture variations identified by EOF.
- Cluster EOF-derived patterns and recognize regions with similar soil moisture behaviors.

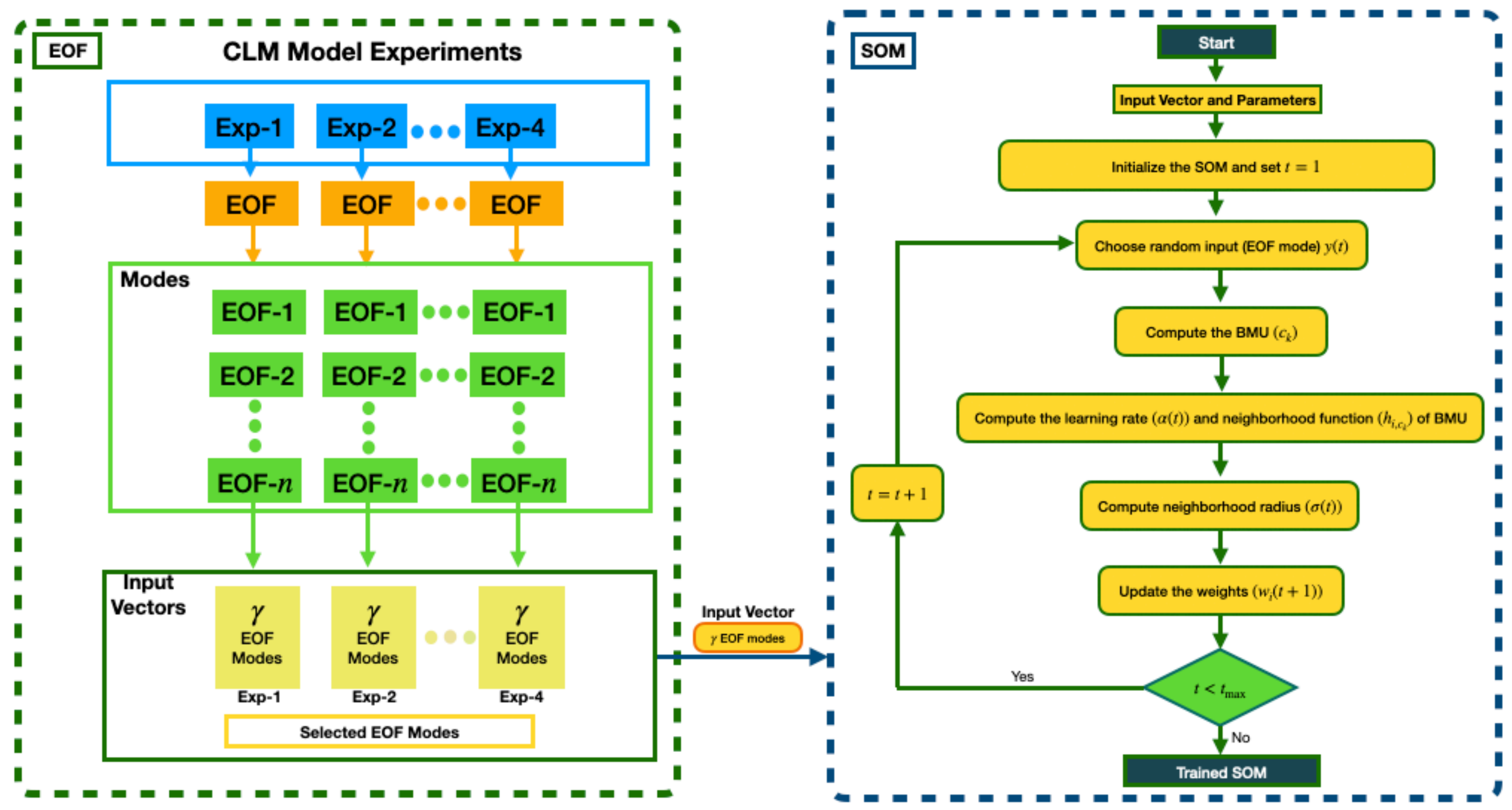
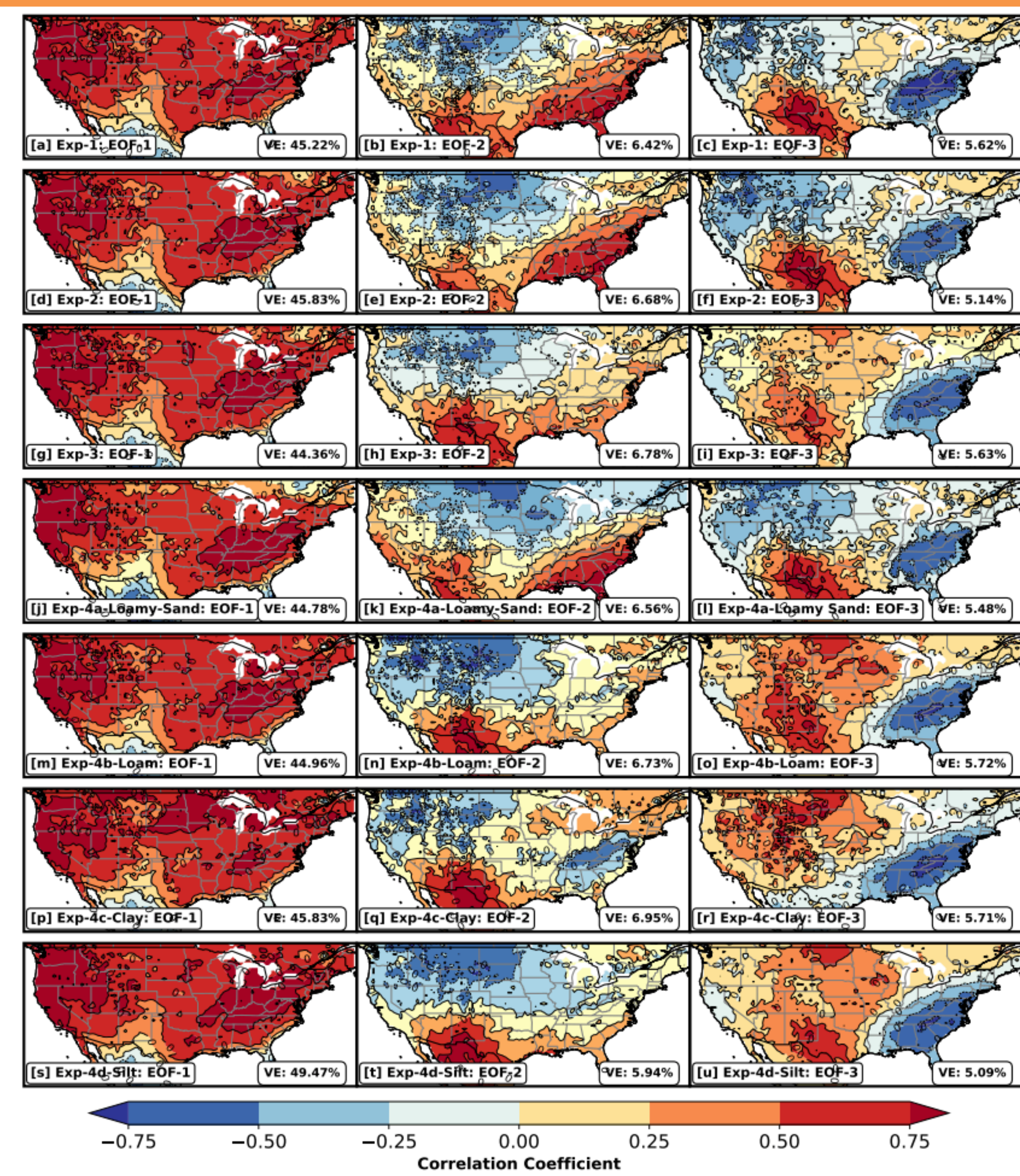
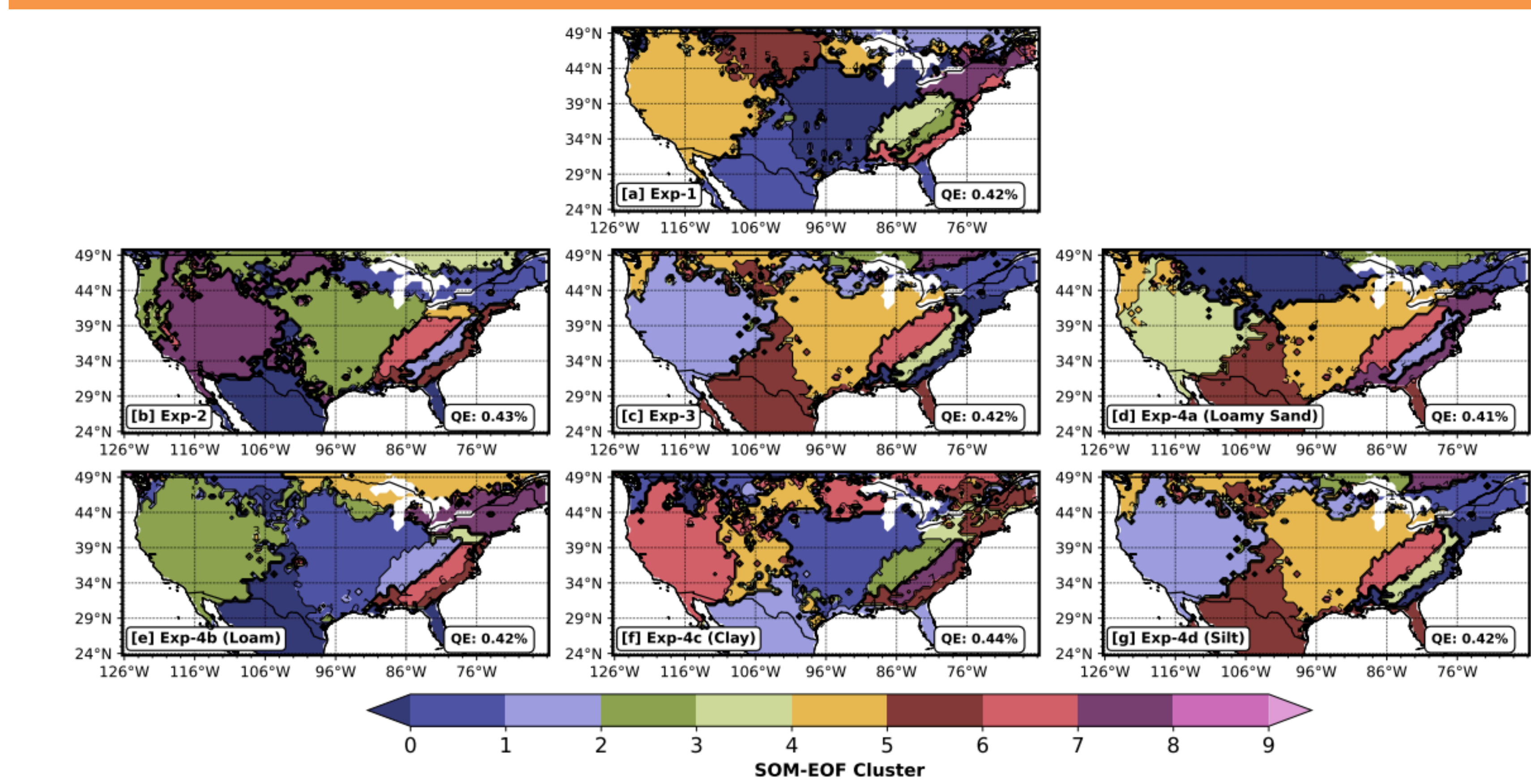


Fig.3. This flowchart shows the steps for analyzing climate experiment data. On the left, CLM5 experiments are processed to find patterns, which are then used as input for a SOM on the right. The SOM learns and organizes the patterns by updating its understanding over several iterations, helping to make sense of the climate data.

EOF Mode



Clustered EOF Modes



Conclusion

- Soil parameters effectively influence CLM5 simulations.
- Some regions are insensitive to soil parameter changes, while others are highly sensitive.
- Changes in SM patterns with different soil parameters highlight the need for accurate soil characterizations and model adjustments.

References

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2. Hannachi, A.: A primer for EOF analysis of climate data, Department of Meteorology, University of Reading, 1, 29, 2004. 185 Jawson, S. D. and Niemann, J. D.: Spatial patterns from EOF analysis of soil moisture at a large scale and their dependence on soil, land-use, and topographic properties, Advances in Water Resources, 30, 366–381, 2007.