Steven Naegele
CIRES / NOAA Global Systems Laboratory
Steven.Naegele@Colorado.edu / steven.naegele@noaa.gov

CIRES University of Colorado **Boulder** NOAA GSL

Investigating precipitation regimes using self-organizing maps

Why Is It Important?

Heavy precipitation can have major impacts on infrastructure, agriculture, and society, and different regions have different criteria for heavy precipitation. This therefore necessitates accurate background knowledge and forecasting of the weather regimes that can cause heavy precipitation for a given region, as well as common regimes that precede and follow them that can aid in forecasting. However, precipitation and other meteorological datasets can be large, making identification of important features difficult without the use of machine learning. In particular, self-organizing maps (SOMs) can train on large datasets and parse out the most common and most distinct patterns (Figure 1).

This investigation of precipitation regimes involves training SOMs on Multi-Radar Multi-Sensor (MRMS) observed precipitation data from January 2021 to December 2023. Six SOMs are trained on MRMS 1-h and 24-h quantitative precipitation estimate (QPE) data, with each SOM focused on one of six regions within CONUS to parse out storm types affecting each region. SOMs are able to cluster regimes with heavier precipitation, allowing investigation of where the heaviest precipitation falls for each region on average, when it is most likely to occur, how long it typically persists before transitioning to another regime, and regime-based numerical weather prediction (NWP) model forecast errors.

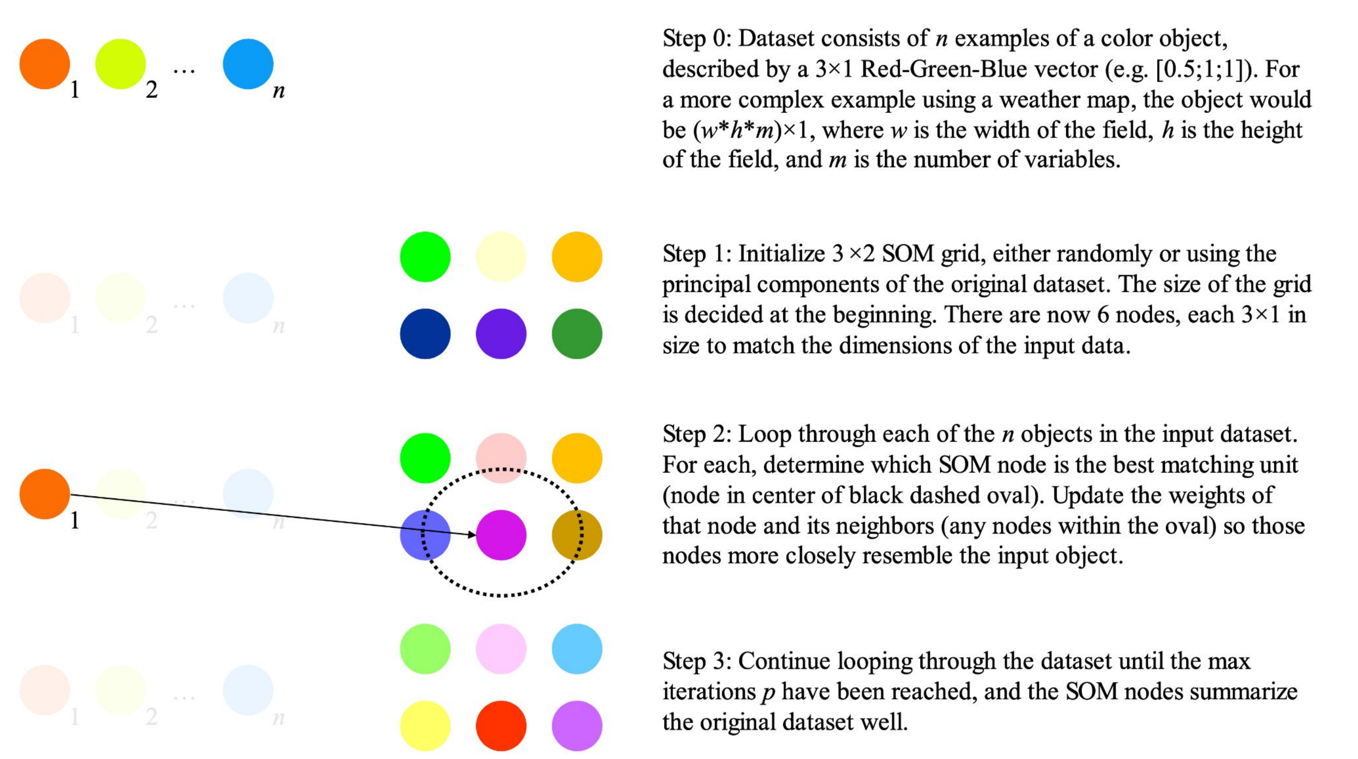


Figure 1. A diagram of how SOMs work using the example of identifying the most representative colors from a dataset of RGB values. (From Naegele et al. 2024)

Data and Methods

- Multi-Radar Multi-Sensor (MRMS; Zhang et al. 2016)
  - 1-hr & 24-h Quantitative Precipitation Estimate (QPE)
  - 6 sub-CONUS domains (here the focus is on South-Central)
  - Jan 2021 - Dec 2023
  - Data grid thinned by retaining every 10th grid point (10-km resolution) during training to save computational cost
- MiniSom (Vettigli 2018)
  - Hyperparameters (Table 1) resulted in lowest quantization and topographic errors

Grid Size	Learning Rate	Sigma	Epochs
5×5	0.25	1.75	500

Table 1. MiniSom Hyperparameters

References

Naegele, S. J. A. Lee, S. J. Greybush, G. S. Young, S. E. Haupt, 2024: Identifying wind regimes near Kuwait using self-organizing maps. *J. Renewable Sustainable Energy*, **16**, 026501, https://doi.org/10.1063/5.0152718.

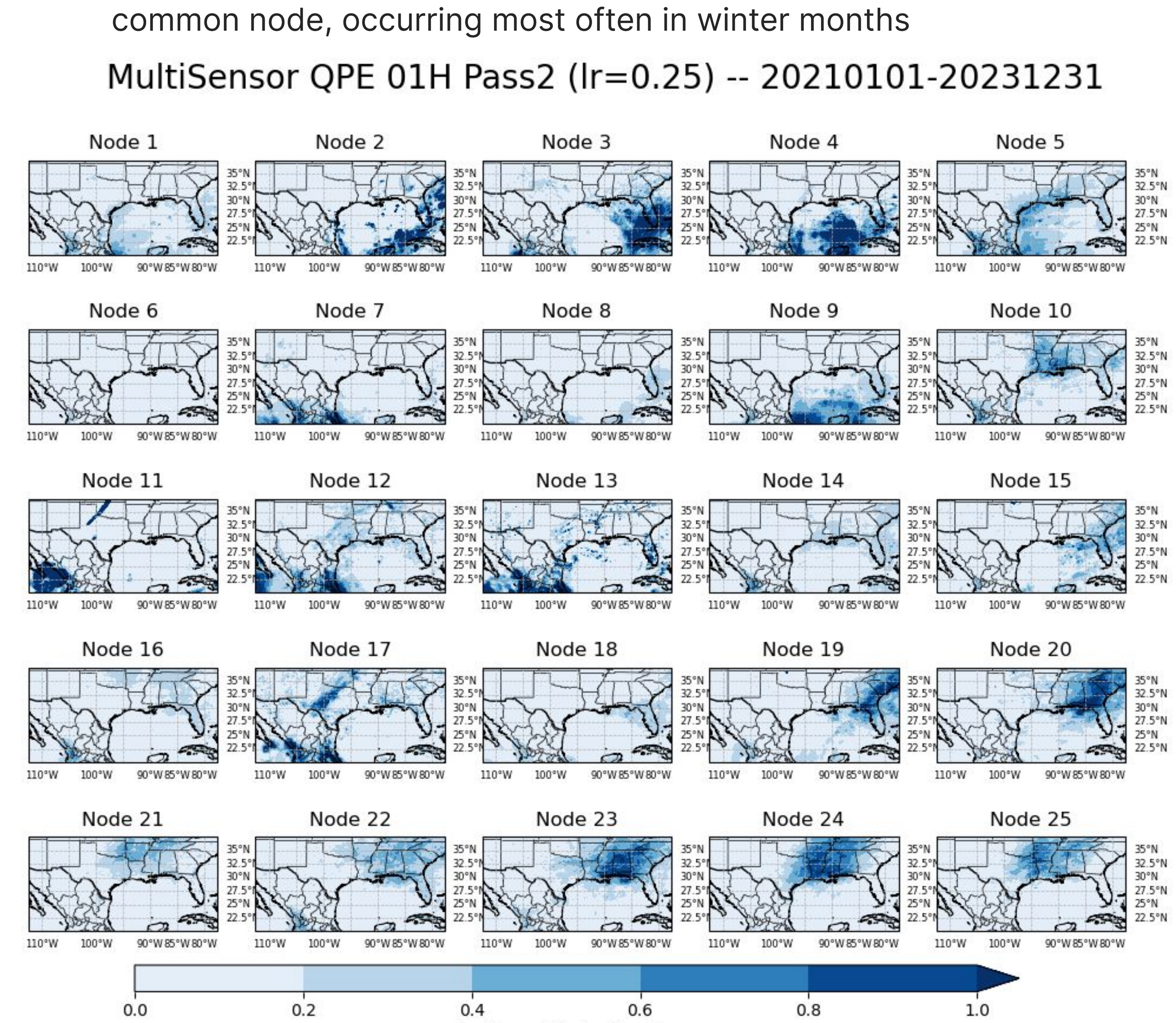
Vettigli, G., 2018: MiniSom: minimalistic and NumPy-based implementation of the Self Organizing Map. Available at https://github.com/JustGlowing/minisom/, accessed 03 Apr 2024.

Zhang, J., and Coauthors, 2016: Multi-Radar Multi-Sensor (MRMS) quantitative precipitation estimation: Initial operating capabilities. *Bull. Amer. Meteor. Soc.*, **97**, 621–638, https://doi.org/10.1175/BAMS-D-14-00174.1.

Spatial and Seasonal Patterns

- Several nodes represent heavier precipitation (Figure 2)
- Nodes 2, 3, 4, 11, 12, and 13 indicate average 1-hr quantitative precipitation estimate (QPE) > 1 mm and average 24-hr QPE > 25 mm somewhere in eastern Gulf of Mexico, Florida, and Caribbean (nodes 2, 3, and 4), as well as central Mexico (nodes 11, 12, and 13)
- Nodes 9, 10, 15, 17, and 19–25 represent more moderate-heavy 1-h and 24-h QPE, primarily over southeastern states
- The remaining nodes represent drier regimes with lighter mean QPE and lower node-based standard deviations of QPE

- Nodes with greatest QPE are generally the least common, but they tend to occur more frequently in summer and autumn months (Figure 3)
- The moderate-heavy QPE nodes are more common in spring-autumn
- Drier nodes can occur all year
  - Node 6 in particular has little to no QPE anywhere and is the most common node, occurring most often in winter months



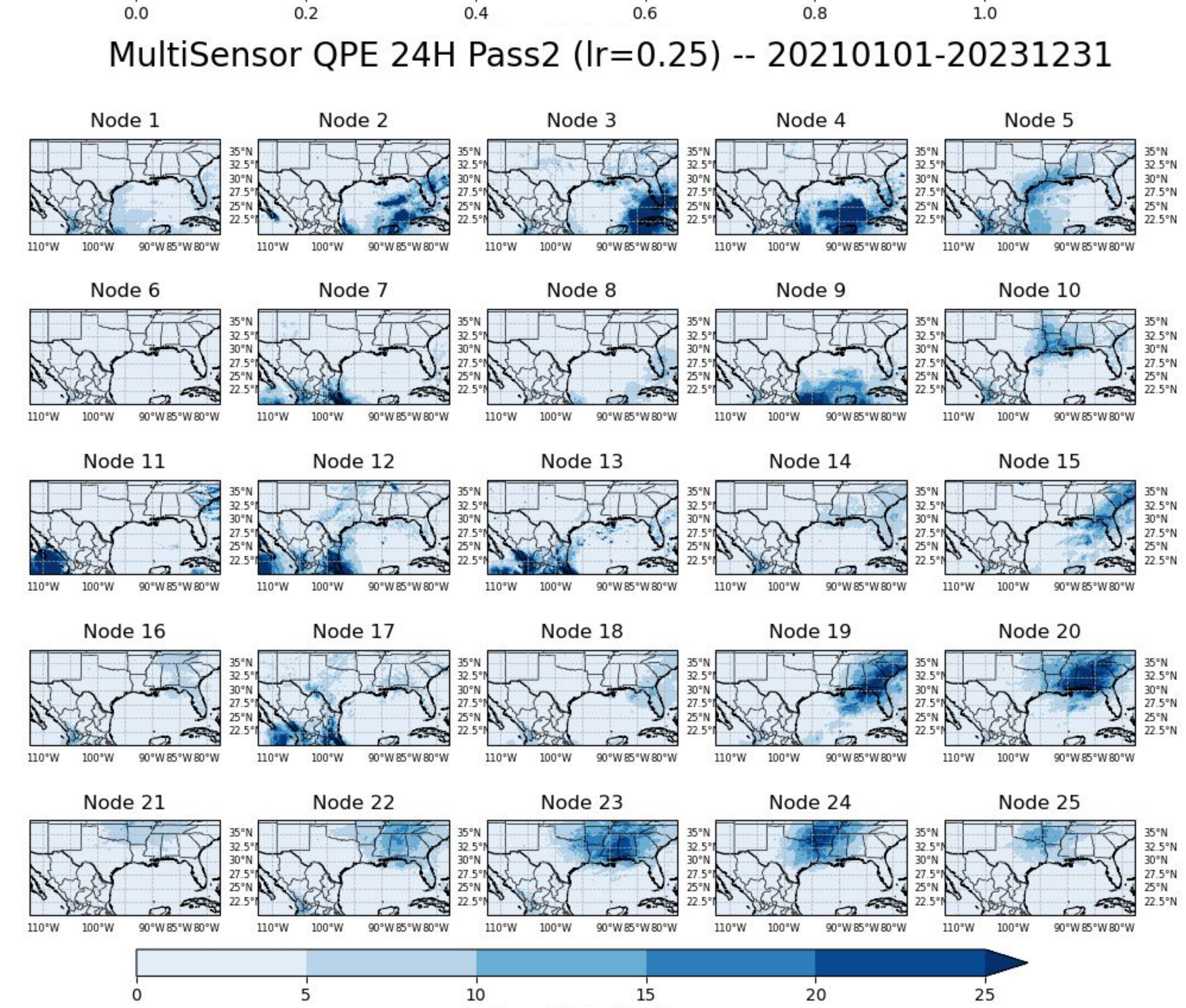


Figure 2. Prominent (top) 1-h and (bottom) 24-h QPE patterns for south-central CONUS from January 2021 to December 2023 after SOM training.

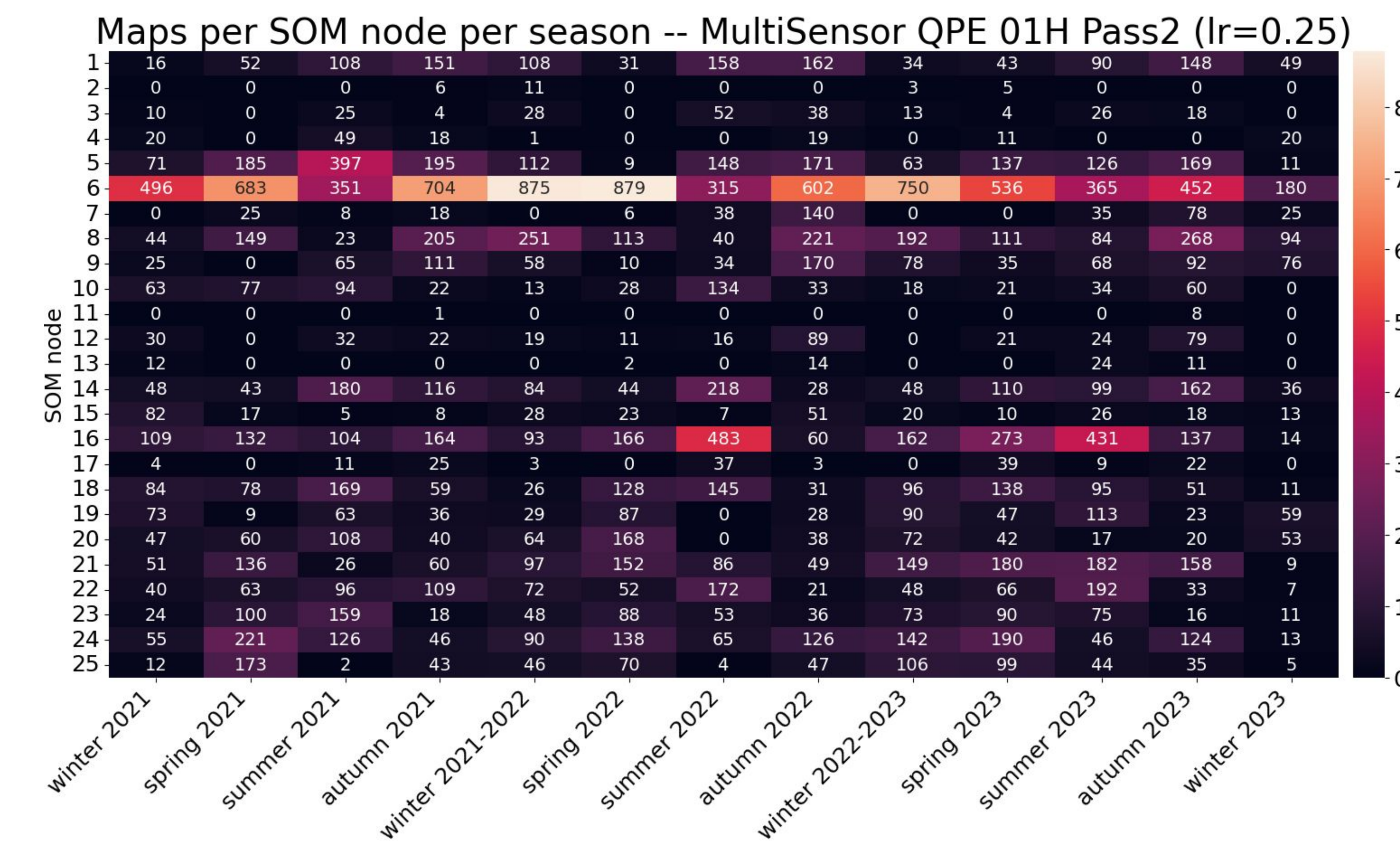


Figure 3. Number of hours within a given season represented by each SOM node.

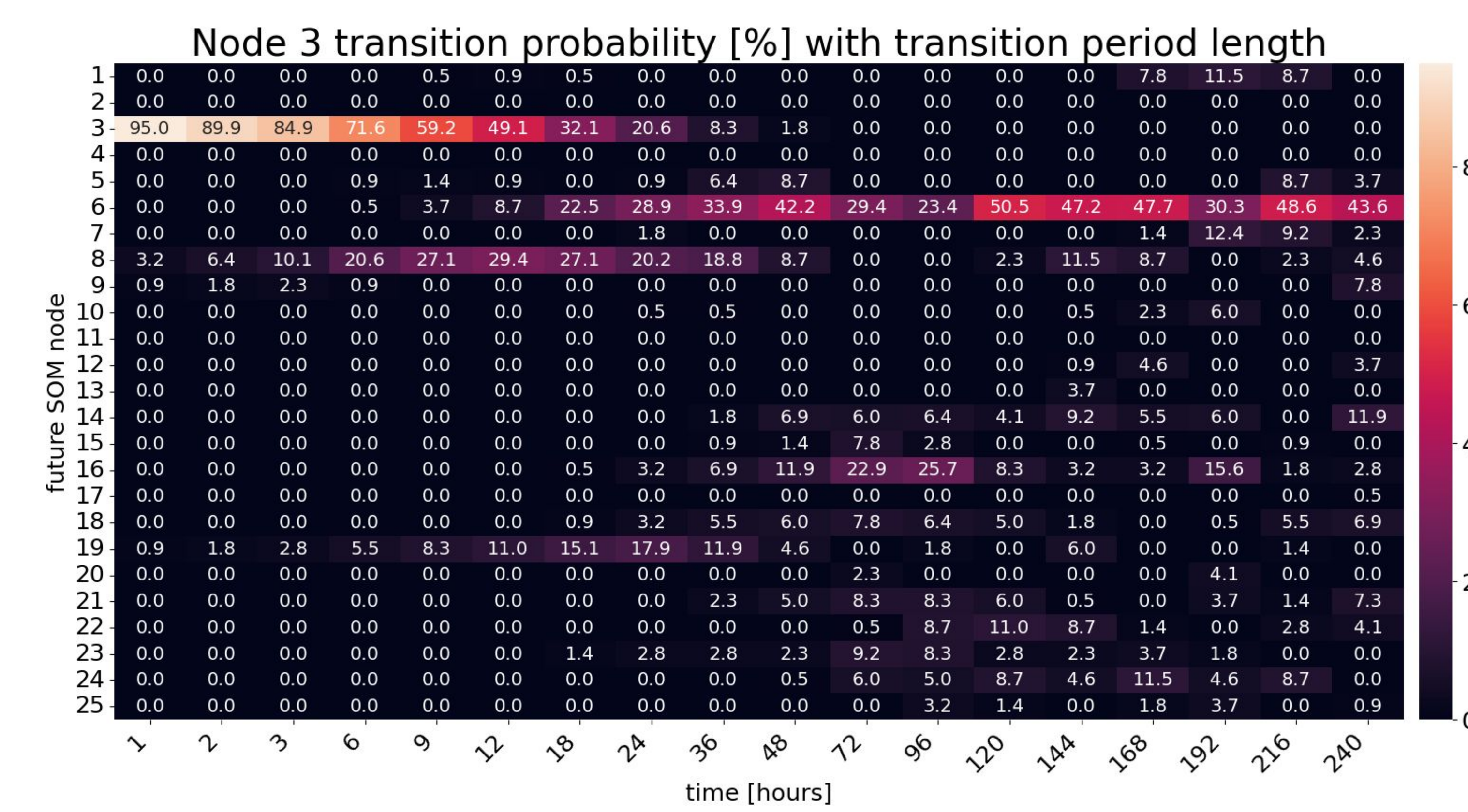


Figure 4. Probability (in %) of node 3 persisting or transitioning to another node after a given number of hours.

Node Transitions

- Focusing on node 3 (heavier average precipitation in south Florida) and calculating the probability of transitioning to another node over time
- Node 3 persists for about 6 hours before transitioning (Figure 4)
- The most common nodes node 3 transitions to are nodes 6, 8, and 19, followed by node 16 after 72–96 hours
  - Nodes 6, 8, and 16 represent nodes with little to no average precipitation, and thus a weakening of the storms present in node 3
  - Node 19 indicates a northward progression of mean precipitation

Future Work

- Filter data (ARI threshold) for more focus on regimes with precipitation
- Continue investigating other sub-CONUS domains
- Cluster NWP QPF using MRMS-trained SOM nodes and compare with MRMS to assess model forecast skill under difference precipitation regimes
- Add NWP model error as a training variable to further assess regime-based model performance

Acknowledgements

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