Upwelling along Complex Coastlines from Remotely Sensed Winds

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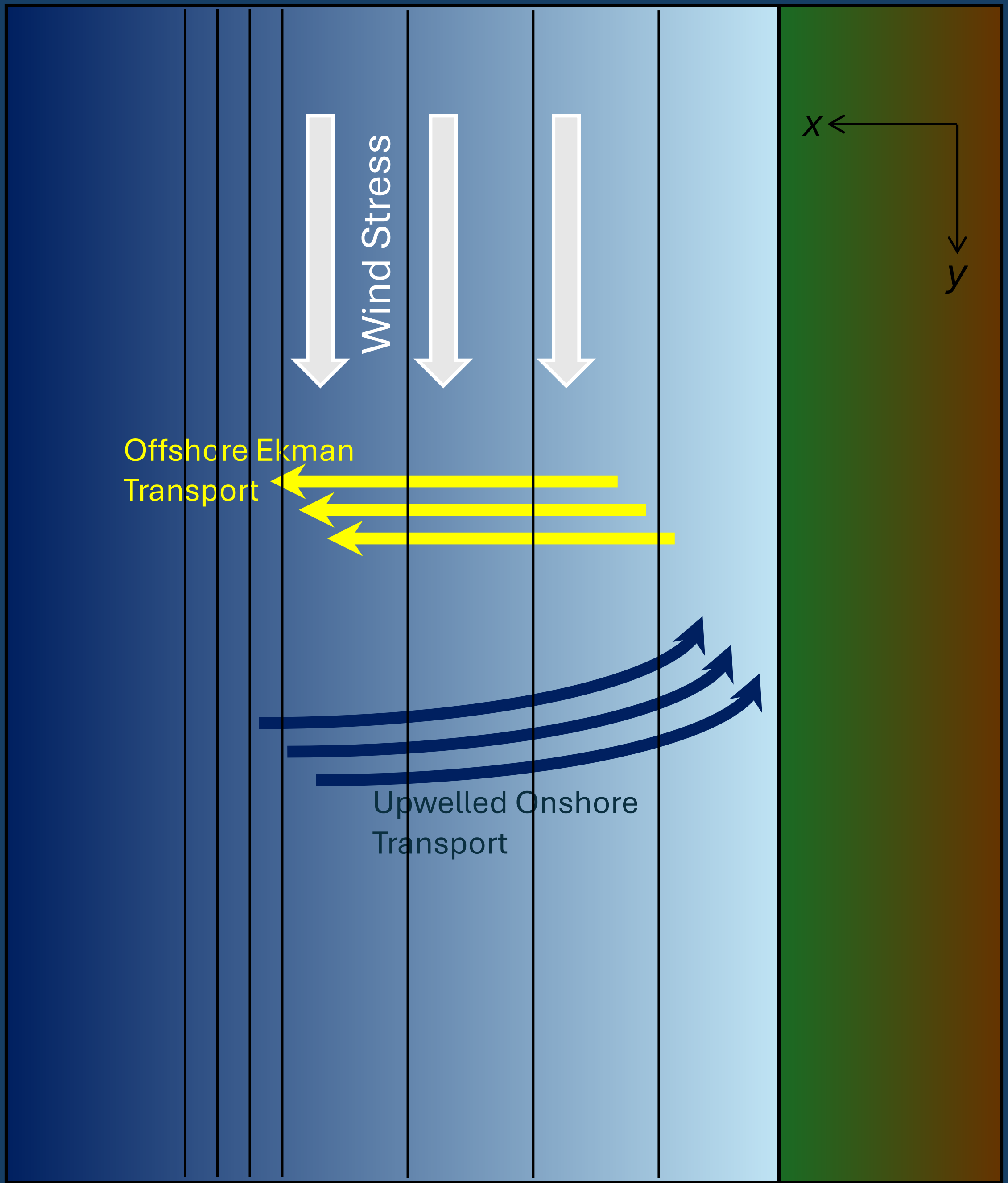
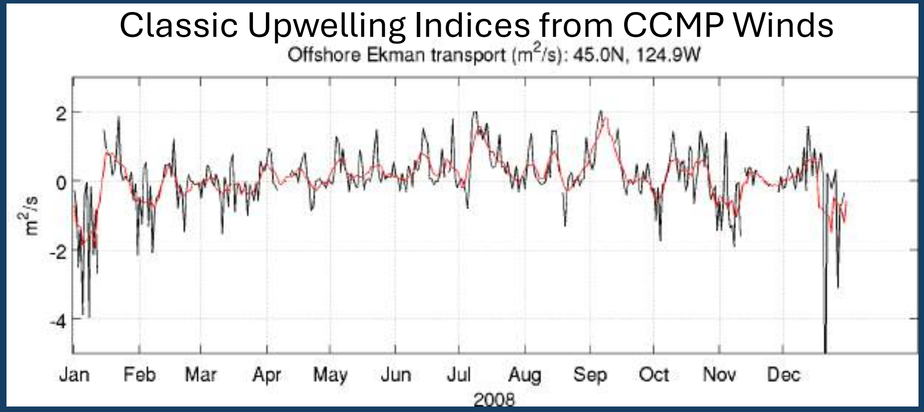
Idealized Coastal Upwelling



The offshore Ekman transport is

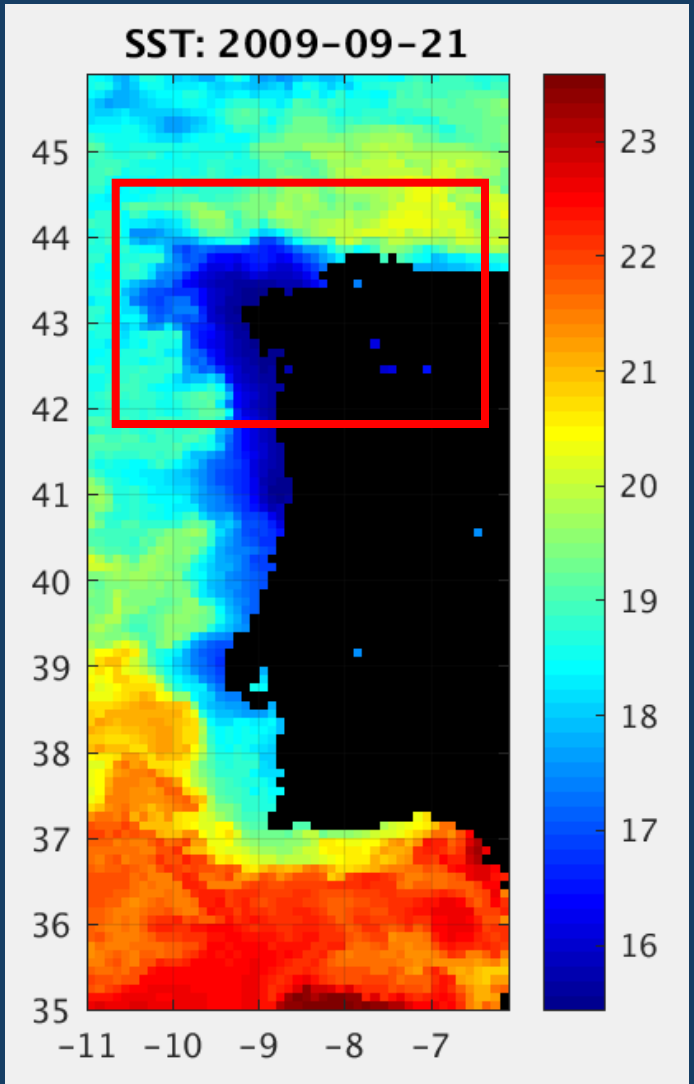
$$S_x = \frac{\tau_y}{\rho_0 f}$$

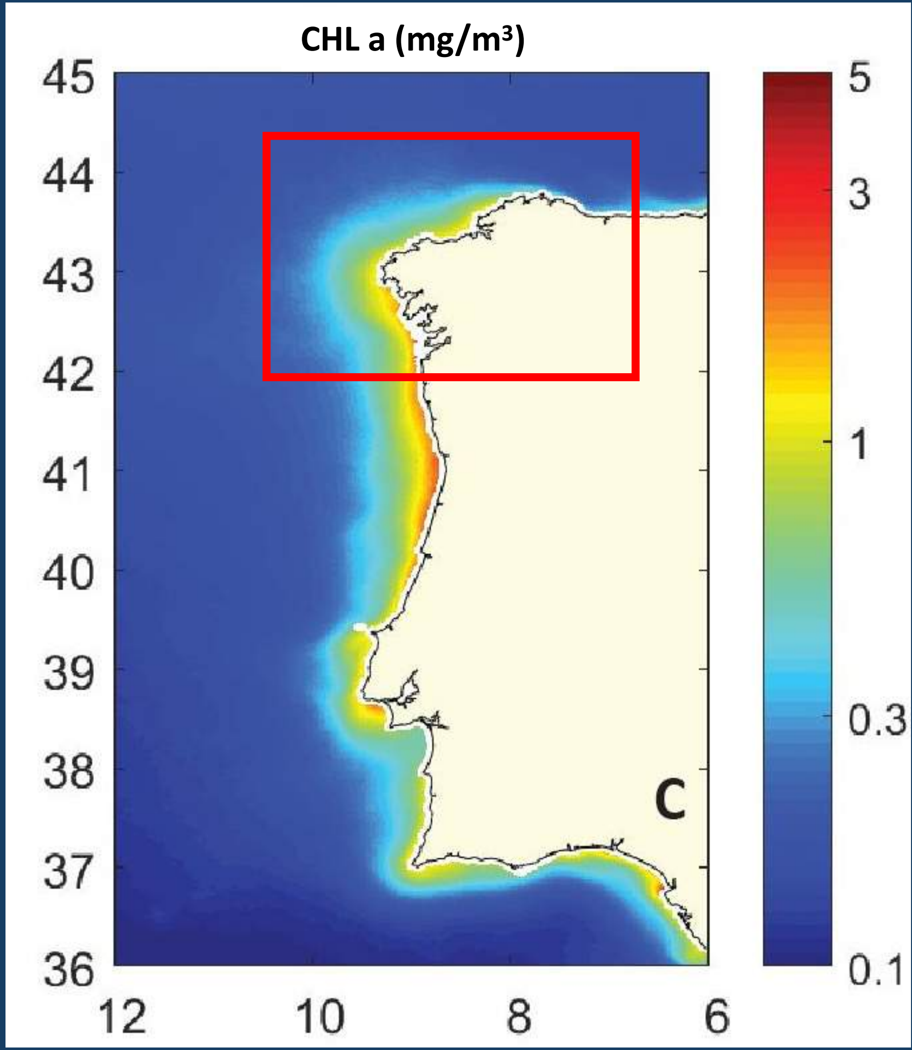
S_x is used as an upwelling Index



Based on assumption of no variations in the along-coast direction.

What about irregular coastlines?

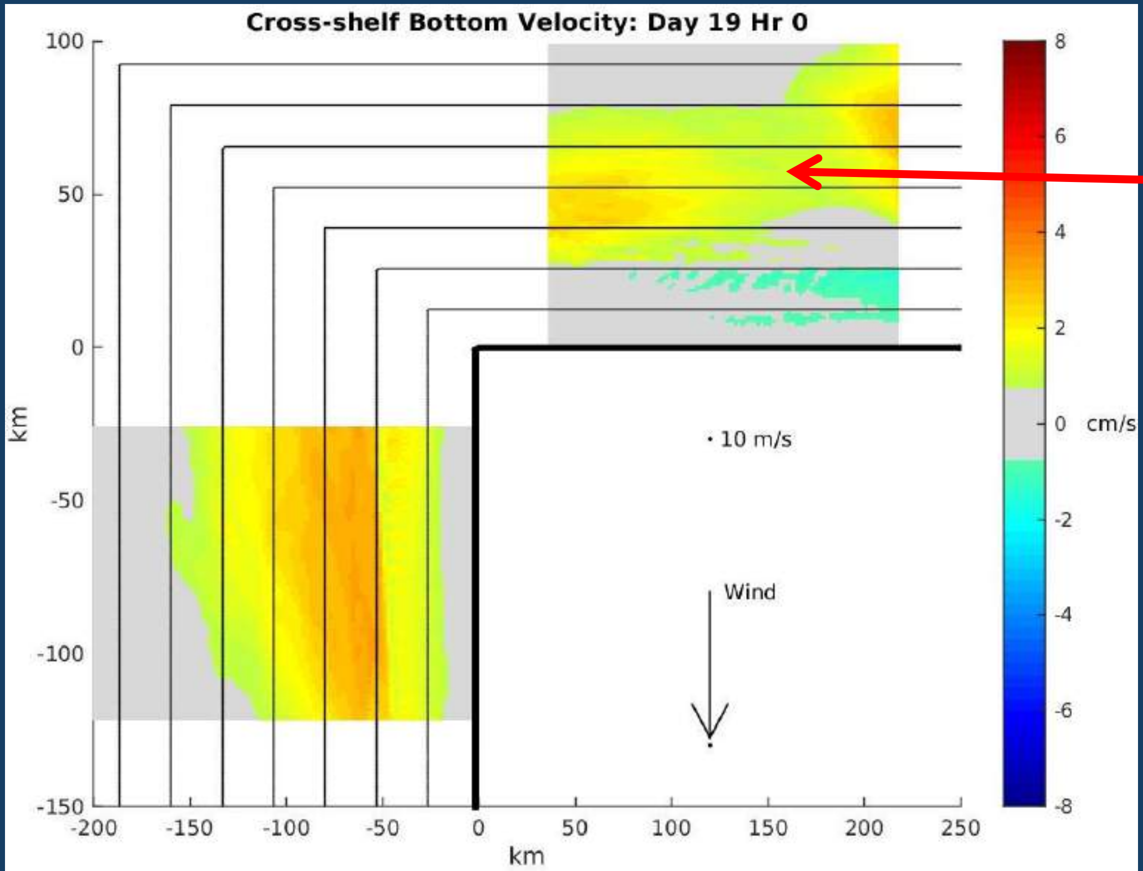




Average Summer satellite ocean color-derived chlorophyll-a (Ferreira et al., 2019)

Idealized Shelf Model

- Stratified water column
- Spatially uniform oscillating winds (5-day period)



Onshore winds (not alongshore) appear to be associated with an upwelling signal.

The downwelling and upwelling motions generated via Ekman transport on the western shelf propagate as a CTW to the northern shelf.

Previous work statistically analyzed time series of upwelling and local winds to determine directions of local winds most associated with upwelling.

This approach does not accurately account for remote impacts.

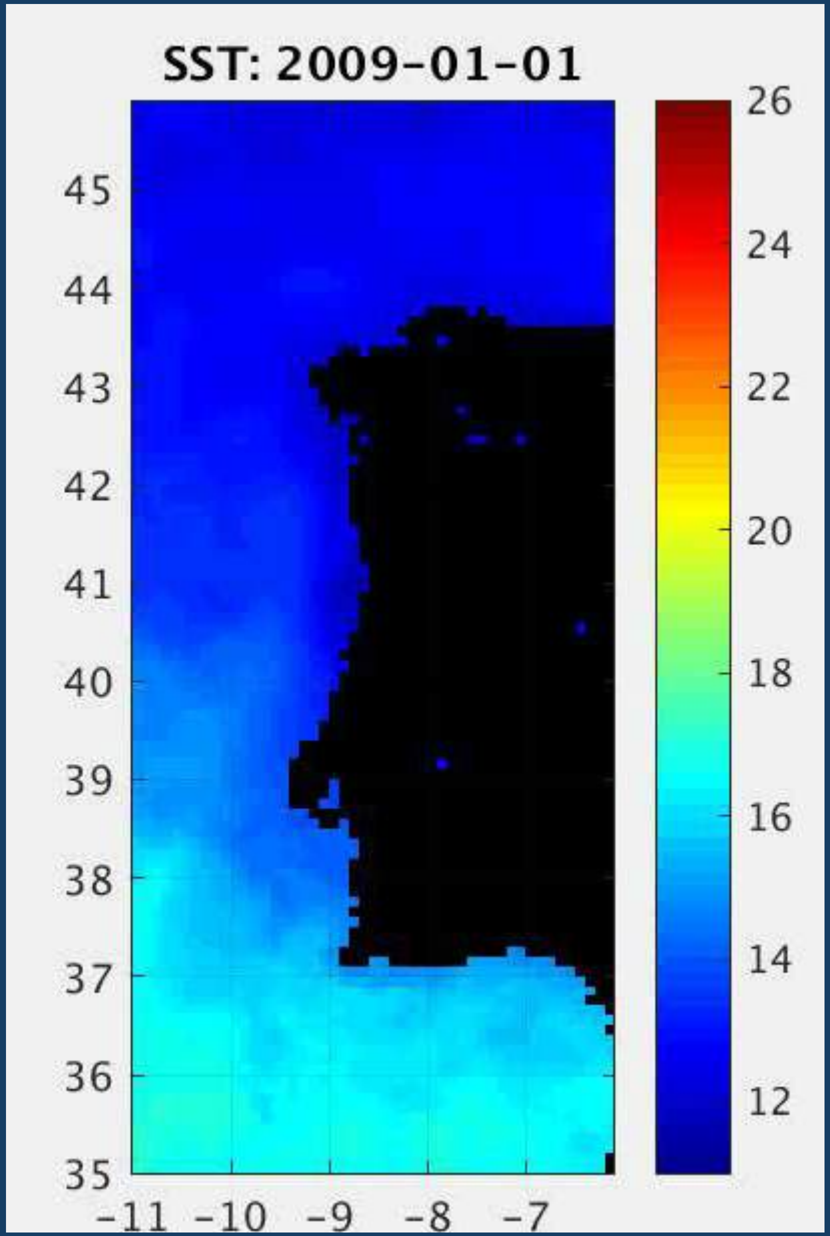
Here, wind fields over the region are analyzed to identify patterns associated with upwelling along irregular coastlines.

Application of the method to satellite wind measurements can aid studies of upwelling and coastal marine ecosystems in remote or inaccessible regions.

Upwelling has been well studied along west coast of Iberian Peninsula – due to prevalence of northerly winds.

Satellite SST reveals periods of upwelling along northern coast as well.

A machine learning technique, the Self-Organizing Map (SOM), is applied to identify characteristic wind patterns over the region associated with upwelling events on the northern coast of this complex coastline.



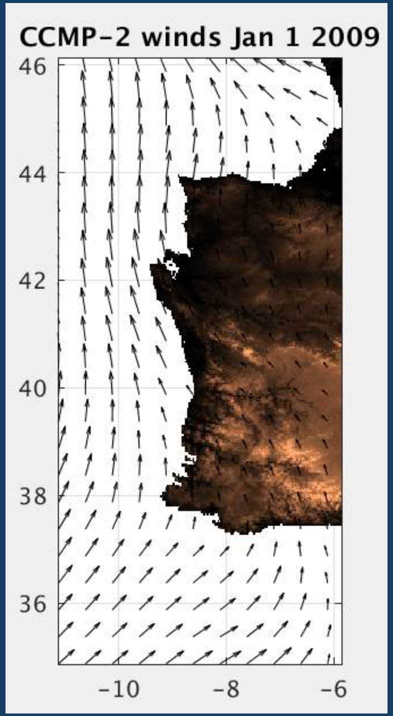
Self-organizing maps (SOM):

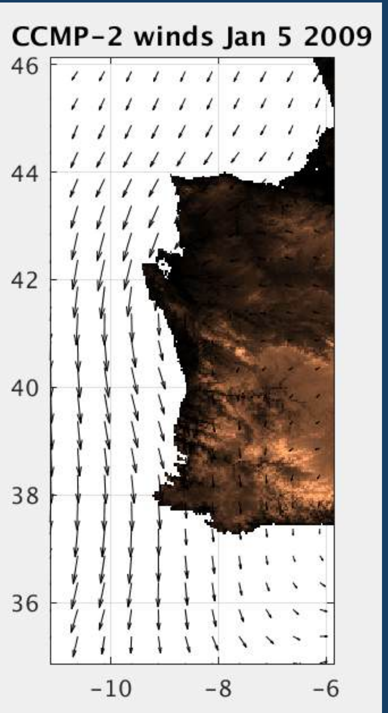
- Unsupervised machine learning technique
- Artificial neural network
- Reduces the input data (input space) to a lower dimensional representation (map space) by clustering the input vectors based on their similarity toward a set of neurons (nodes)
- Neuron that is closest to an input vector (in this case, a daily wind field), is called the Best Matching Unit (BMU).

Input data: CCMP2 daily wind fields (2009-2013)

Wind field grid size: 22 x 46 x 1826 (649 ocean points x 1826 days)

SOM Topology: 24 neurons (6x4)





SOM Methodology for wind fields:

Remap 3-dimensional vector input fields (lat x lon x time) into 2-dimensional scalar input array:

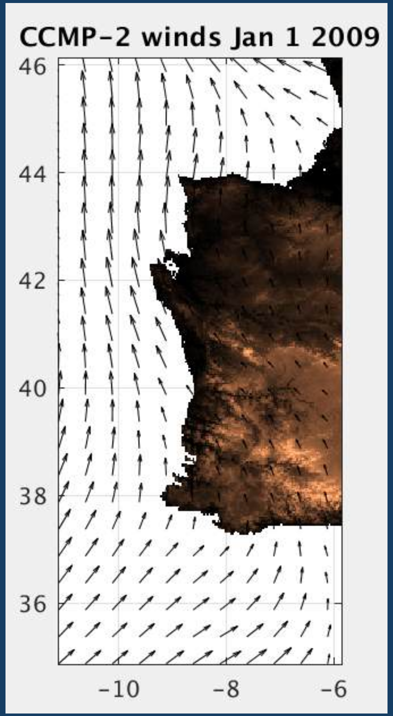
$\{u_{i,j,t}, v_{i,j,t}\} \rightarrow$
i=1..n
J=1..m
t=1..nT

$$\begin{bmatrix} u_{1,1,1}, u_{2,1,1} \dots u_{n,m,,1}, v_{1,1,1}, \dots v_{n,m,1} \\ u_{1,1,2}, u_{2,1,2} \dots u_{n,m,,2}, v_{1,1,2}, \dots v_{n,m,2} \\ . \\ . \\ . \\ u_{1,1,nT}, u_{2,1,nT} \dots u_{n,m,,nT}, v_{1,1,nT}, \dots v_{n,m,nT} \end{bmatrix}$$

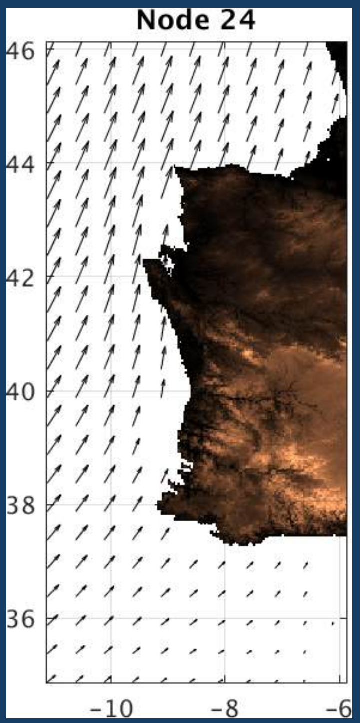
Perform SoM Training on input array

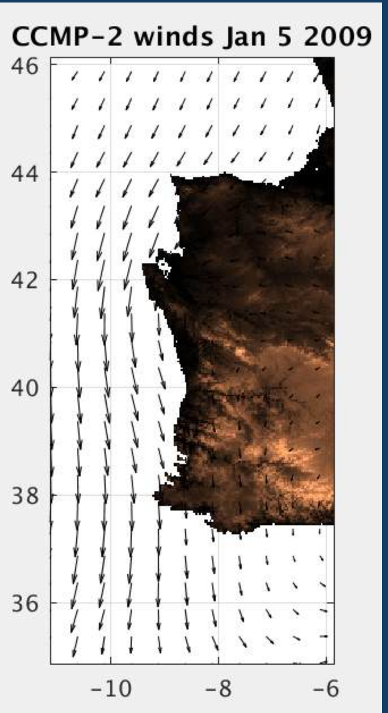
Remap neurons to wind fields

Determine BMUs for input wind fields

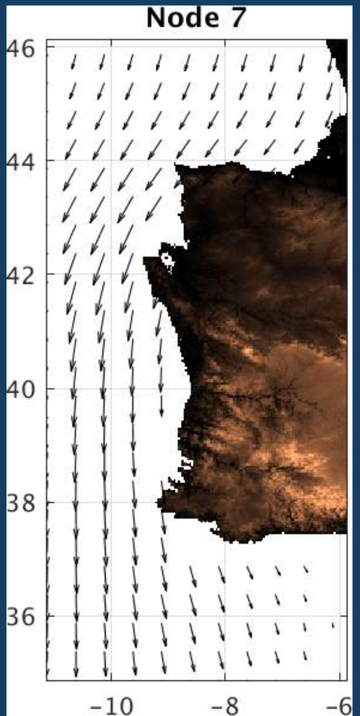


BMU=24

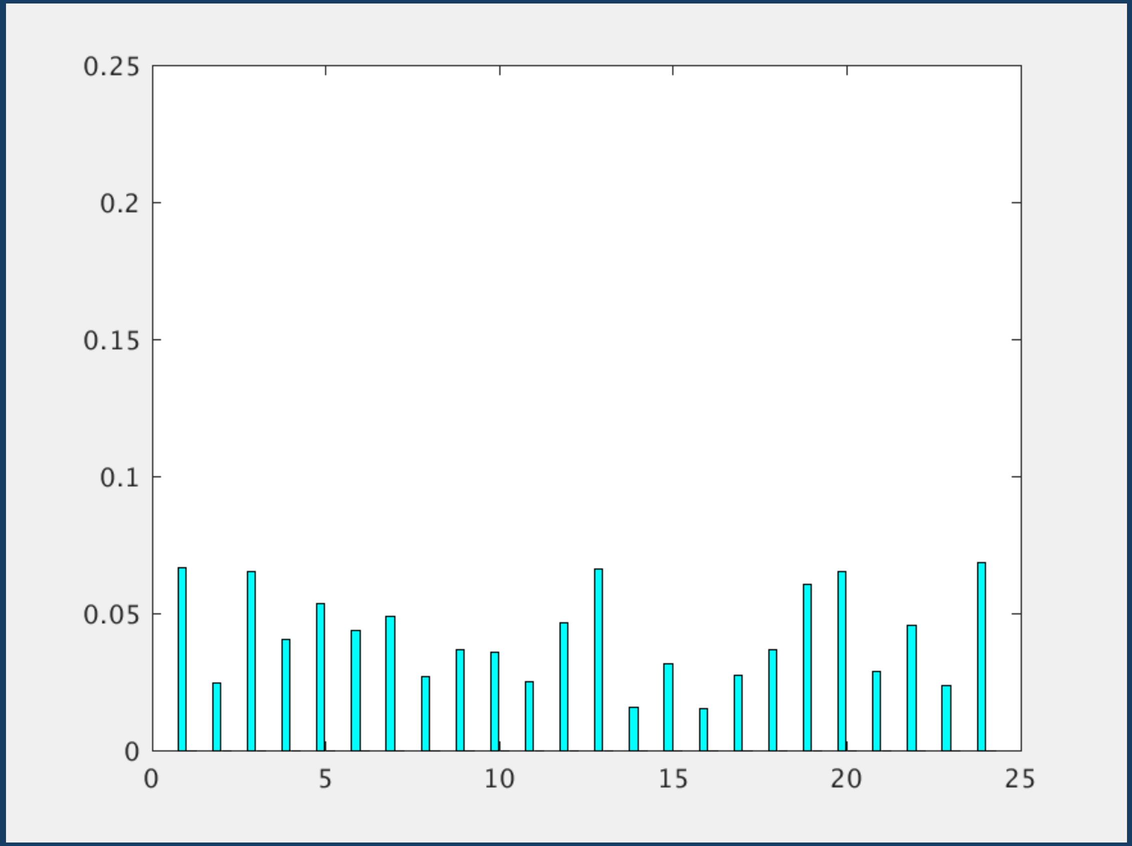




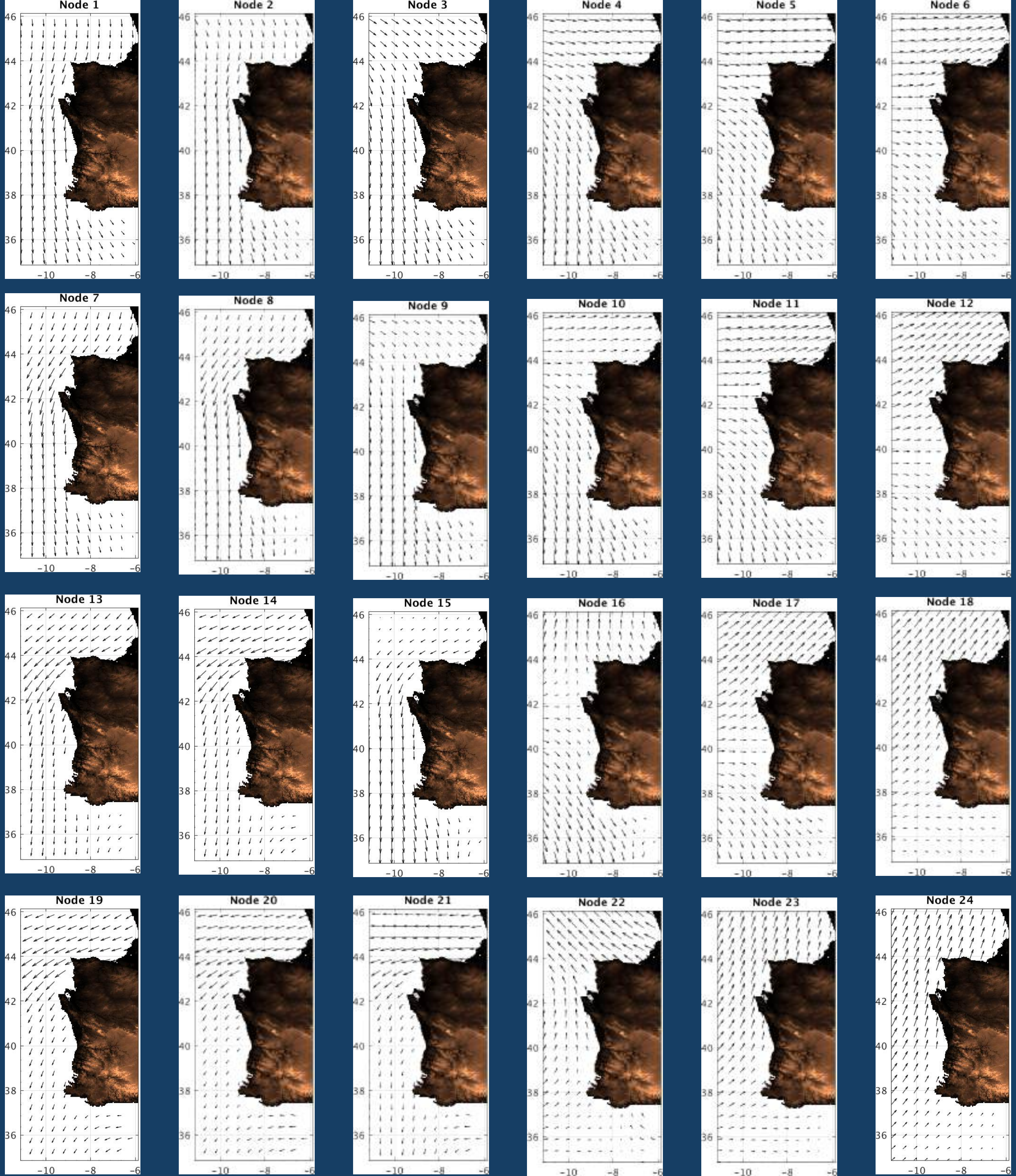
BMU=7



Frequency of Occurrence of each BMU

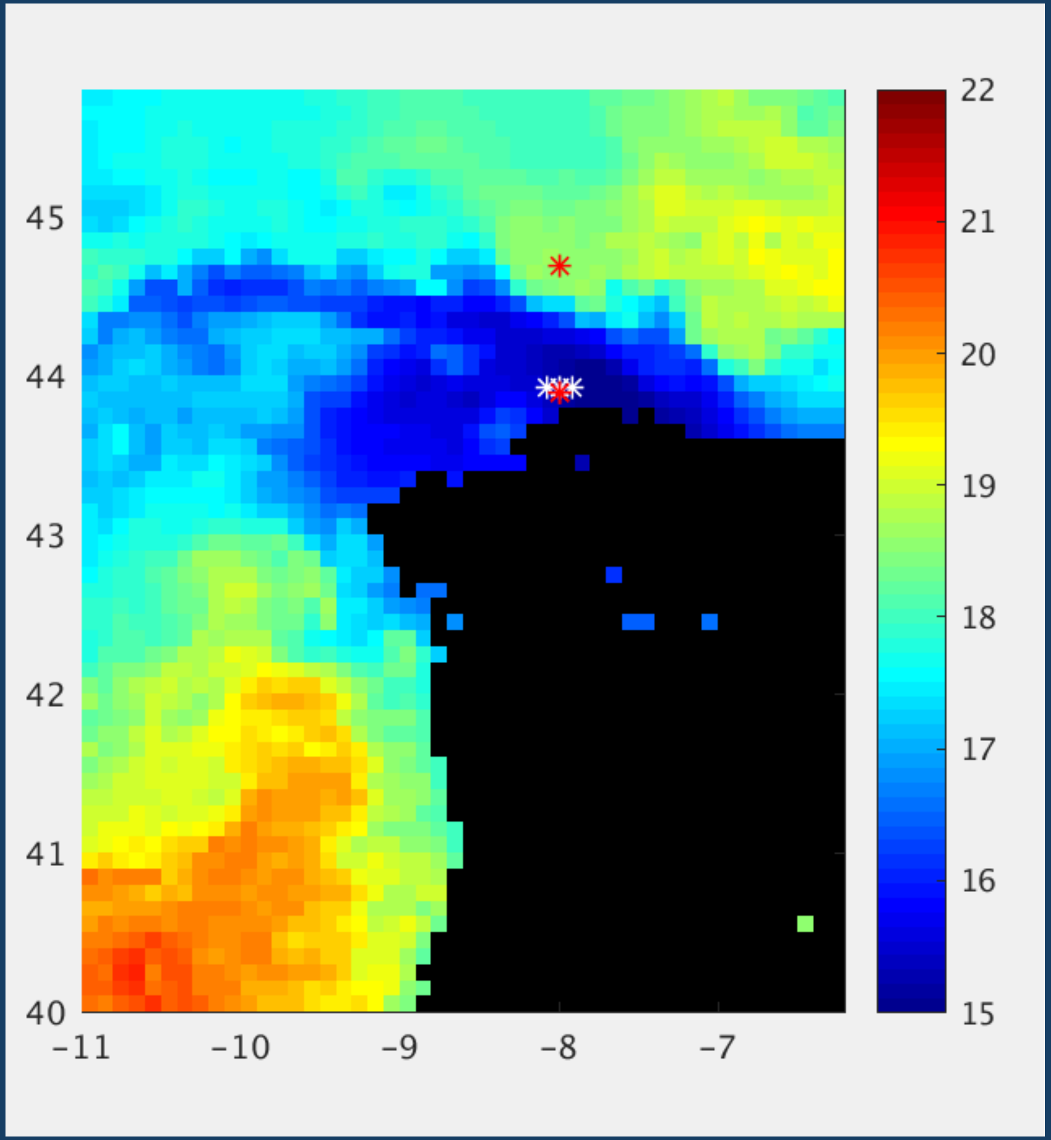


1,824 daily wind fields are clustered to 24 patterns (neurons or nodes)



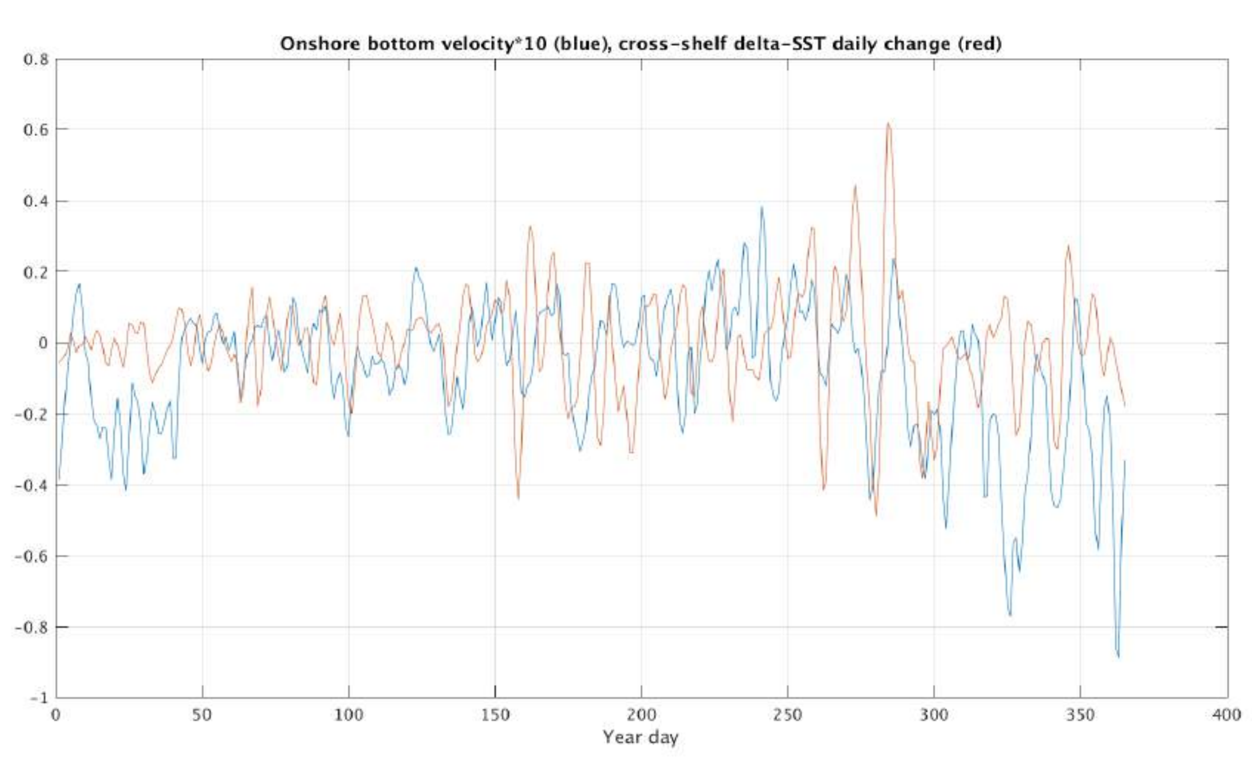
Upwelling proxies:

- Direct observations of upwelling are not common
- Upwelling evidenced by SST and ocean color signatures
- Ocean models can provide information about upwelling, but limited assessment of subsurface variability
- Two approaches used here for upwelling along 8W:
  - Daily change of Nearshore minus Offshore SST difference (GHRSST) – difference at red points
  - Onshore bottom velocity (HYCOM) – average of **white points**



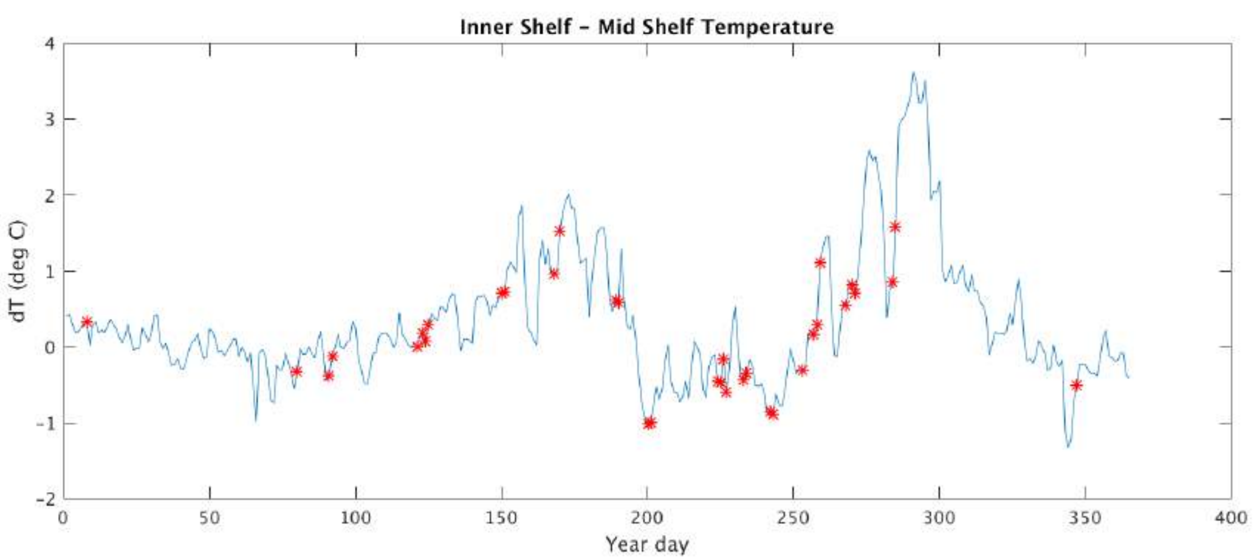
Modest correlation (0.3) between two upwelling proxy time series (delta SST filtered over 5 days)

- SST can be influenced by surface thermal fluxes
- Uncertainties in near-coastal currents in global model reanalysis



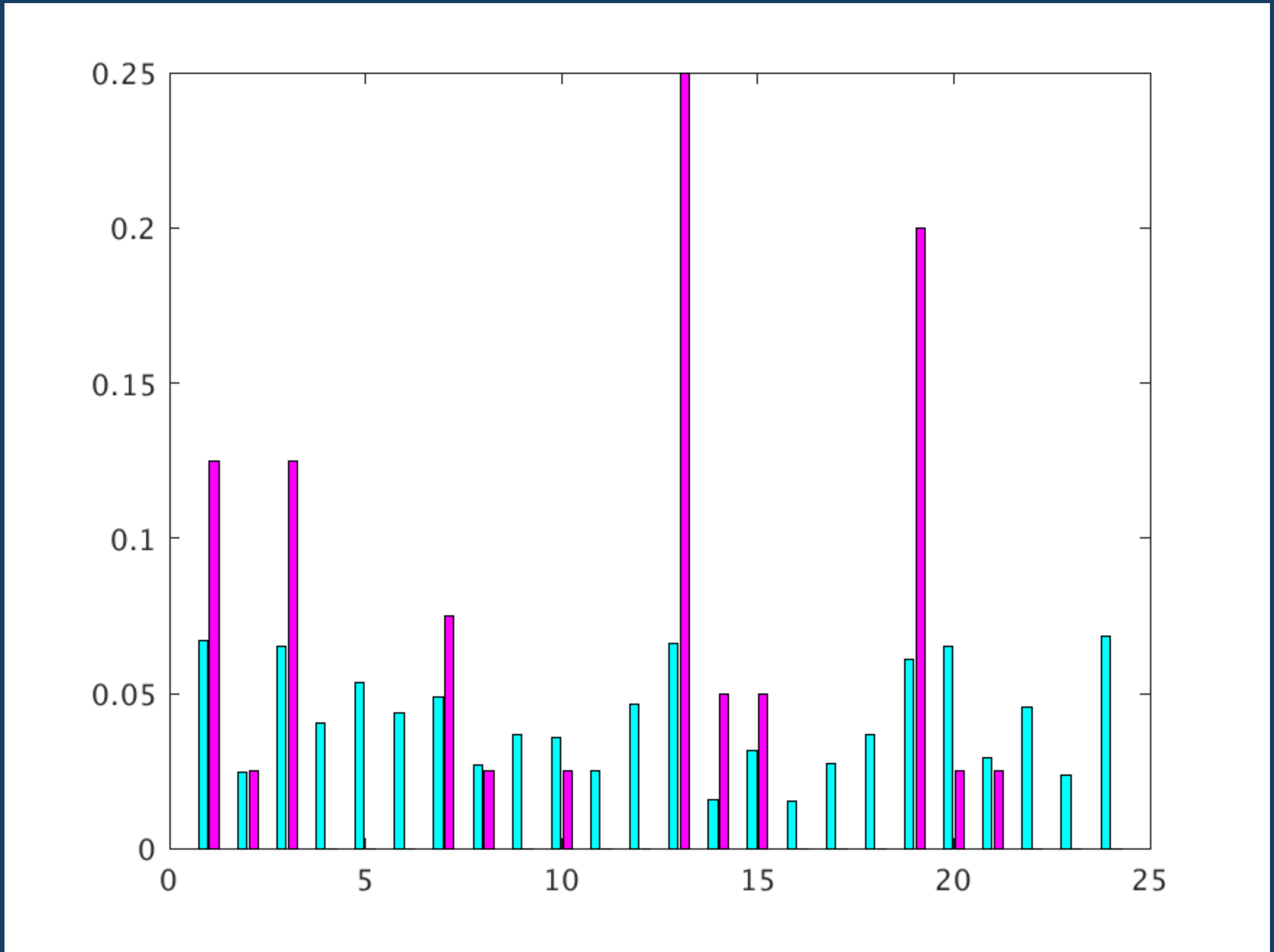
Define an upwelling period when:

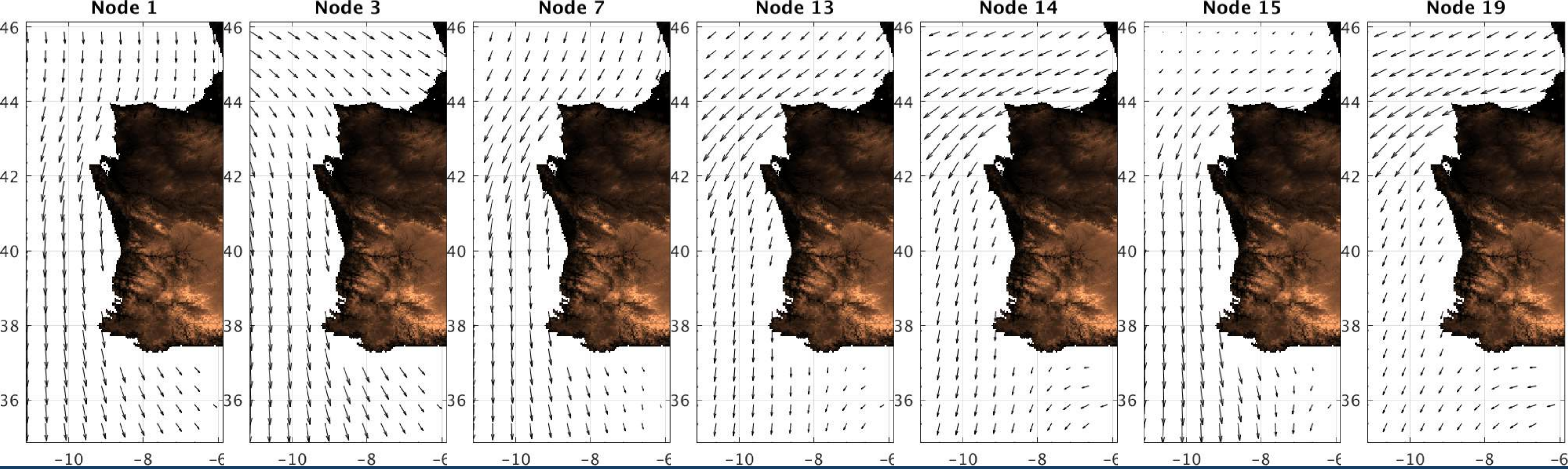
- **Daily averaged onshore bottom velocity > 1 cm/s**
  and
- **dSST change > 0.15°C per day**
  and one day before

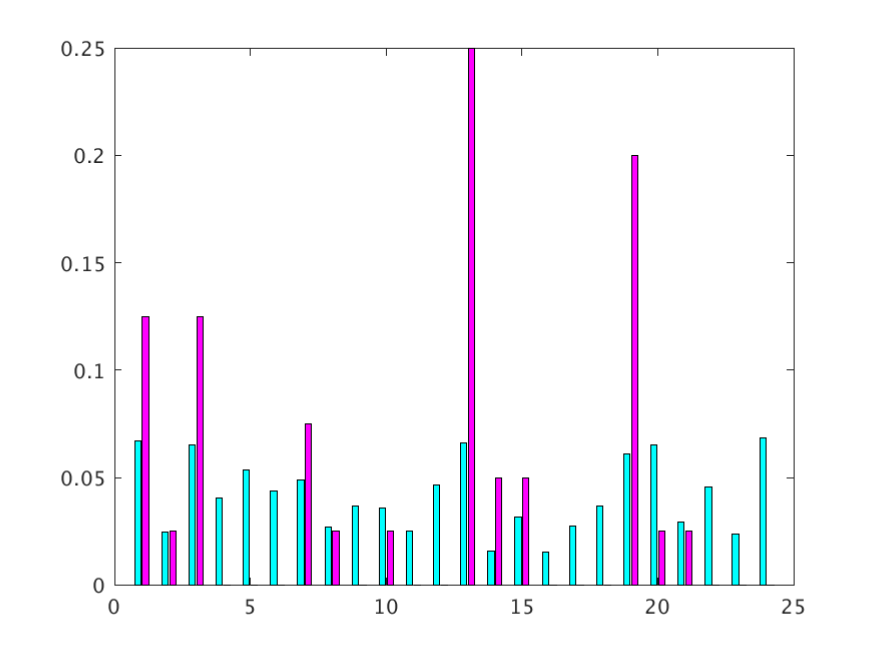


Comparison of histograms of BMUs for upwelling periods versus all time highlights neurons (characteristic wind fields) that are more likely to occur during upwelling periods

Frequency of Occurrence of each BMU







Nodes 1, 3, and 7 show largely onshore winds along northern coast with alongshore upwelling-favorable winds along western coast – consistent with propagation of remote upwelling signal from west to north coast versus local wind-driven upwelling.

Nodes 13, 14, 15, and 19 have winds with along-shore components on both north and west coasts – reinforcement of upwelling signal along propagation pathway. -- This wind pattern is strongly linked with upwelling along the northern coast (nodes 13 and 19).

Summary and Next Steps

- The SOM machine learning technique helps highlight spatial patterns in the wind fields that are associated with upwelling along coastlines that don’t match the assumptions for the classic coastal upwelling theory.

- Identification of BMUs for satellite-observed winds can aid in predicting or providing indices for coastal upwelling in such regions.

- Next steps will include:
  - Experiments with SOM parameters and topologies
  - Further development of multivariate upwelling proxies
  - Applications to other regions
  - Demonstration of BMU mapping from other wind data sets (e.g., NRT and swath products)