Machine Learning Approaches for Characterizing Upwelling-Favorable Winds along Complex Coastlines

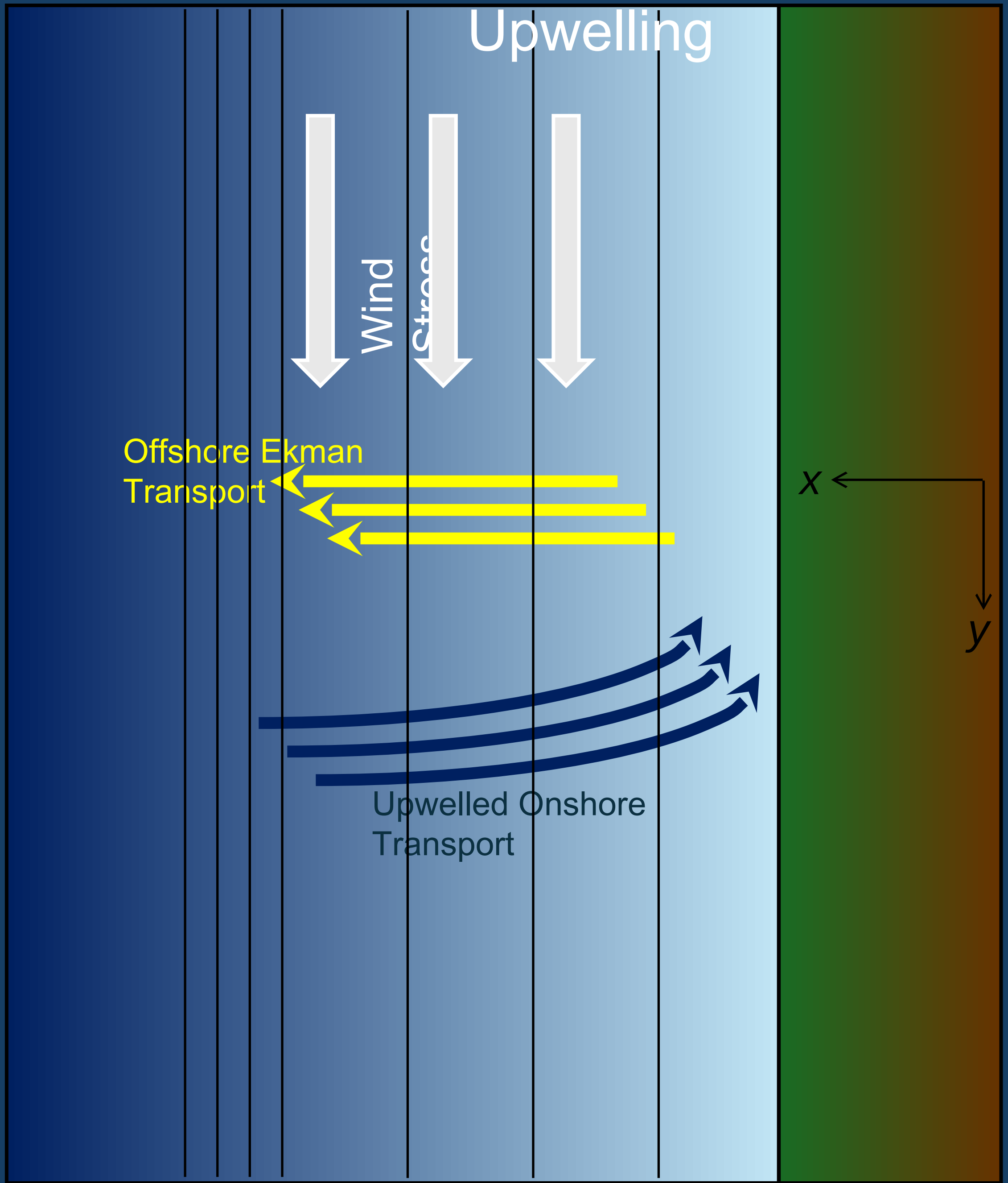
Steven Morey

Florida A&M University

NOAA Center for Coastal and Marine Ecosystems-II

Portions of this work have been funded by the NOAA Office of Education/ Educational Partnership Program award (NA16SEC4810009) to the Center for Coastal and Marine Ecosystems-II.

Idealized Coastal Upwelling



The offshore Ekman transport is

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

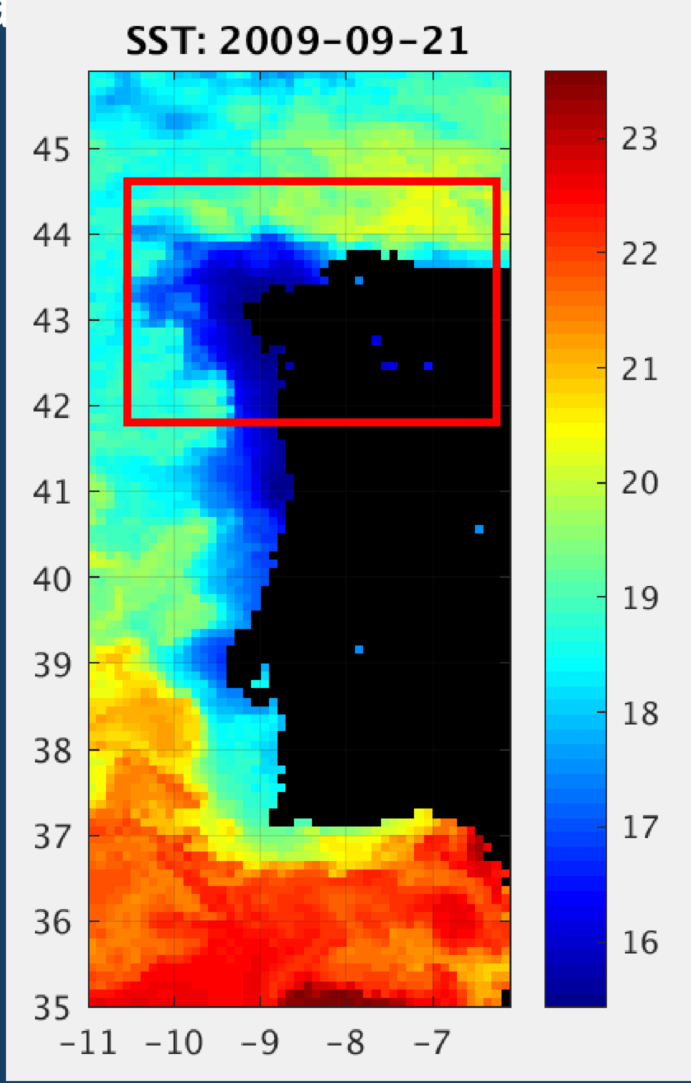
Based on assumption of no variations in the along-coast direction.

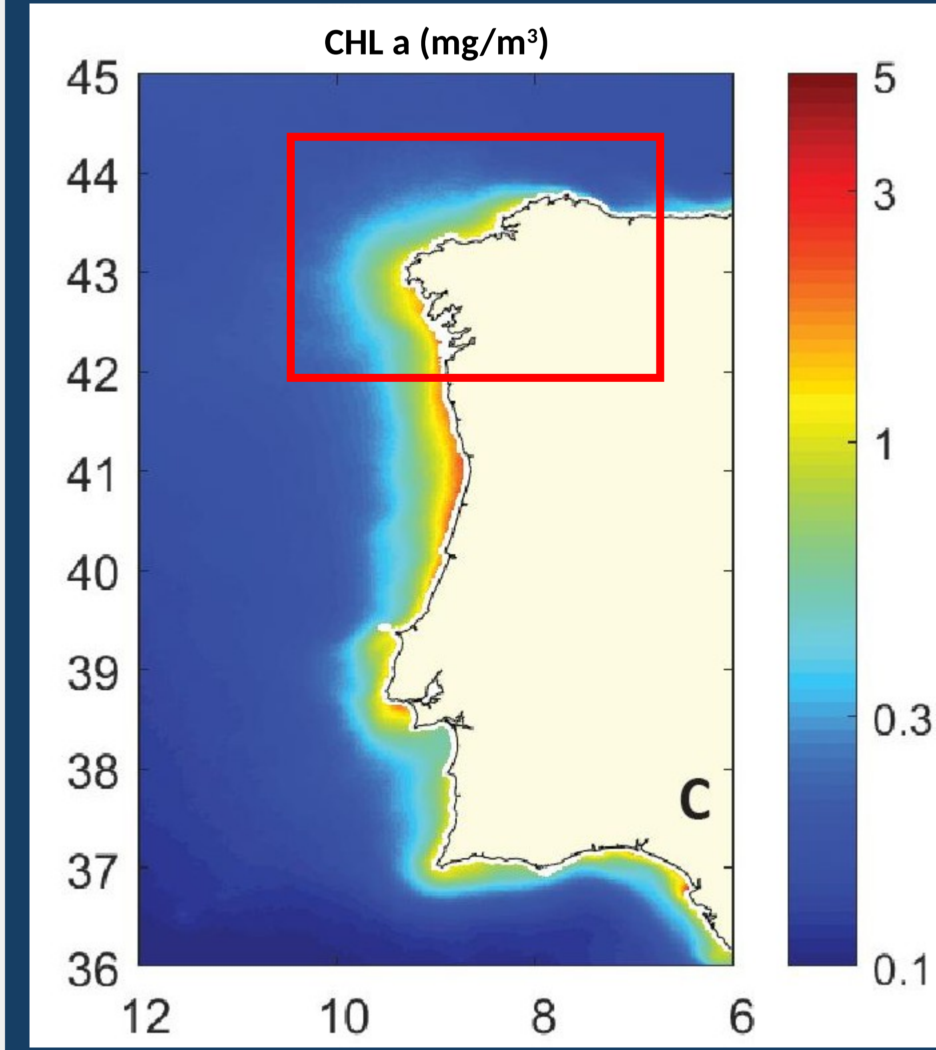
What about irregular coastlines?

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

Satellite SST reveals periods of upwelling along northern coast as well – not necessarily consistent with Ekman dynamics.

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





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

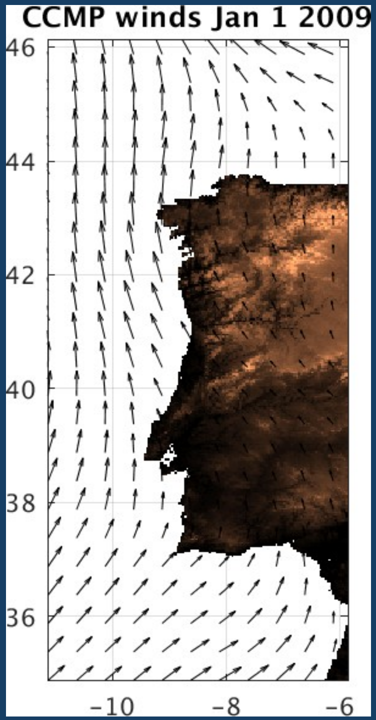
Self-organizing maps (SOM):

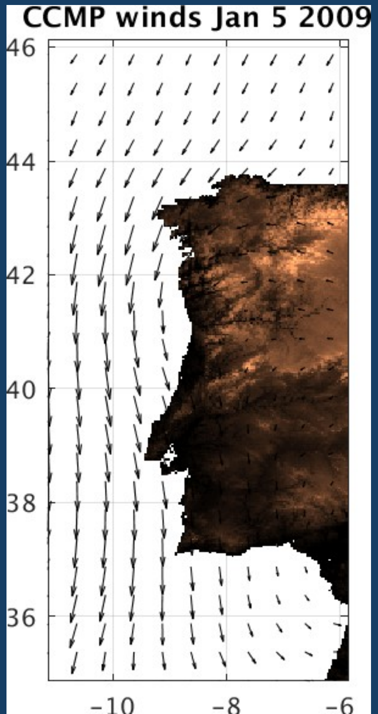
- Unsupervised machine learning technique
- Artificial neural network
- Reduces the input data (input space) to a lower dimensional representation (map space) by clustering the input vectors based on their similarity toward a set of neurons (nodes)
- Neuron that is closest to an input vector (in this 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

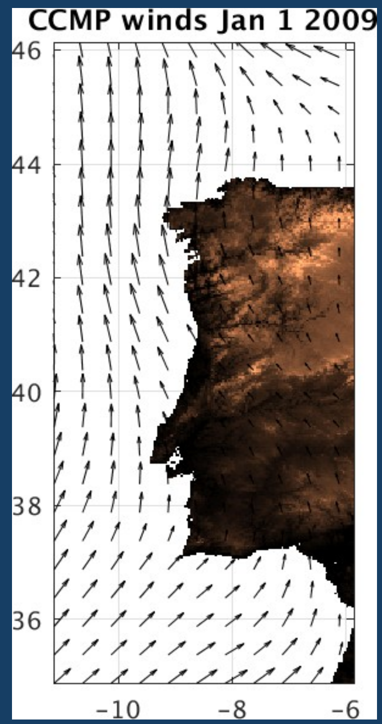
t=1..nT

$$\begin{bmatrix} u_{1,1,1}, u_2 \\ u_{1,1,2}, u_2 \\ \vdots \\ u_{1,1,nT}, u_{2,1,} \end{bmatrix}$$

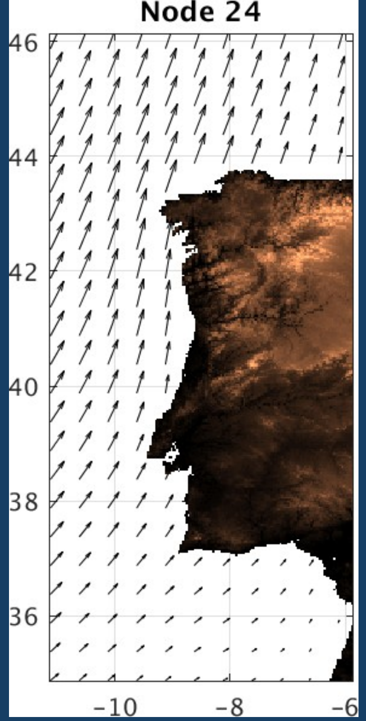
Perform SoM Training on input array

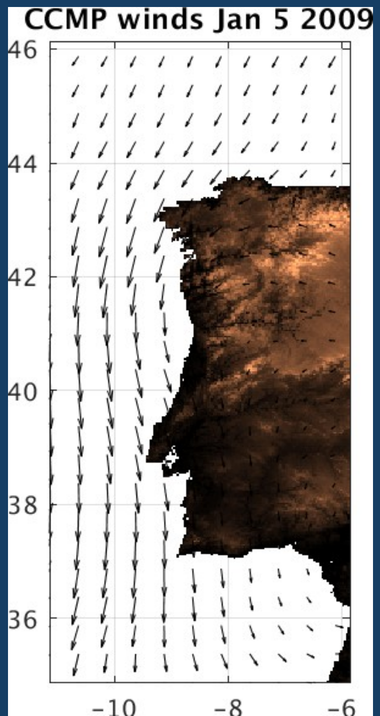
Remap neurons to wind fields

Determine BMUs for input wind fields

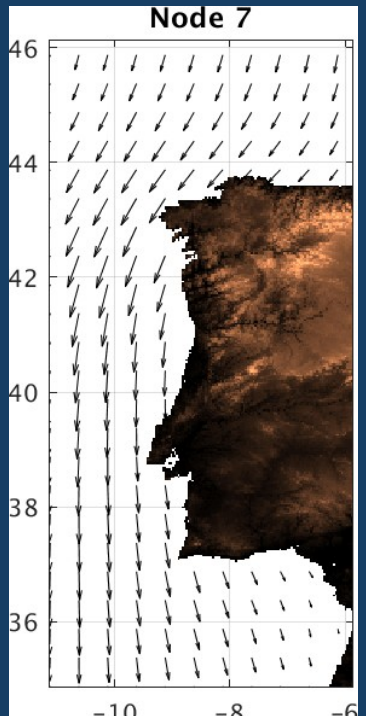


BMU=24

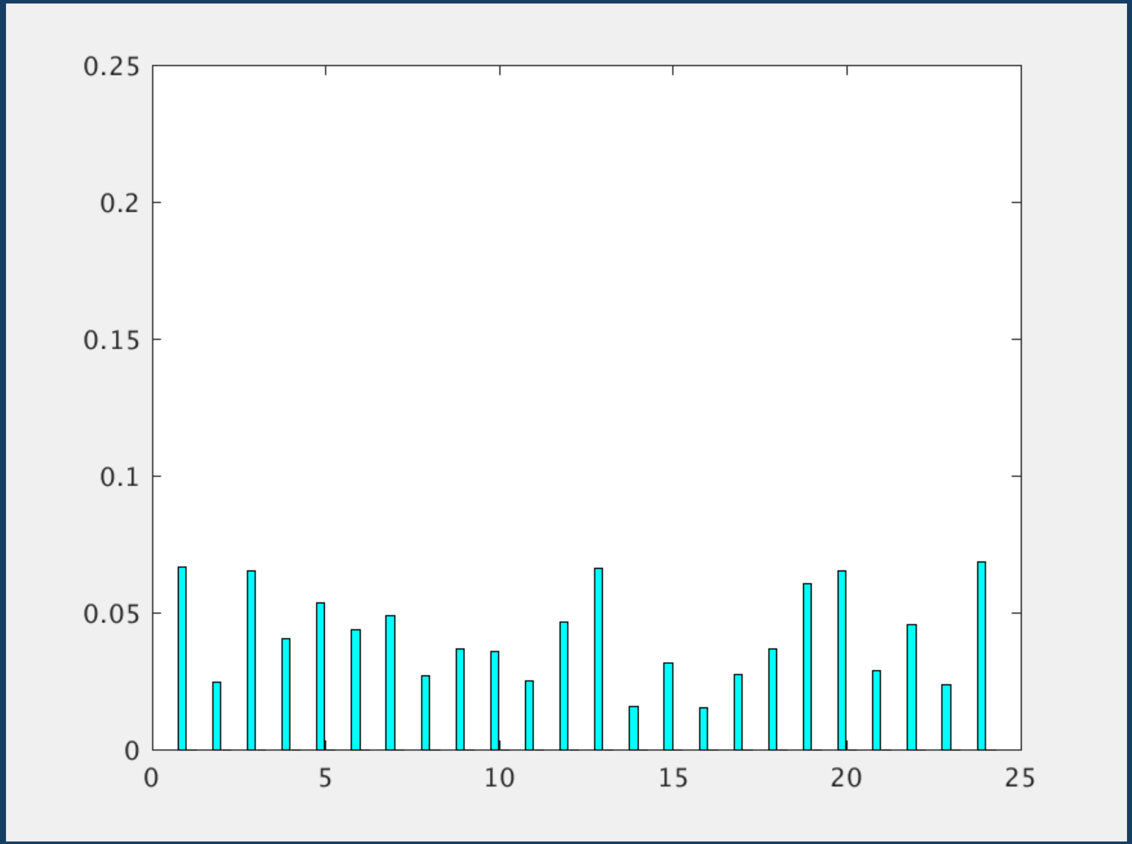




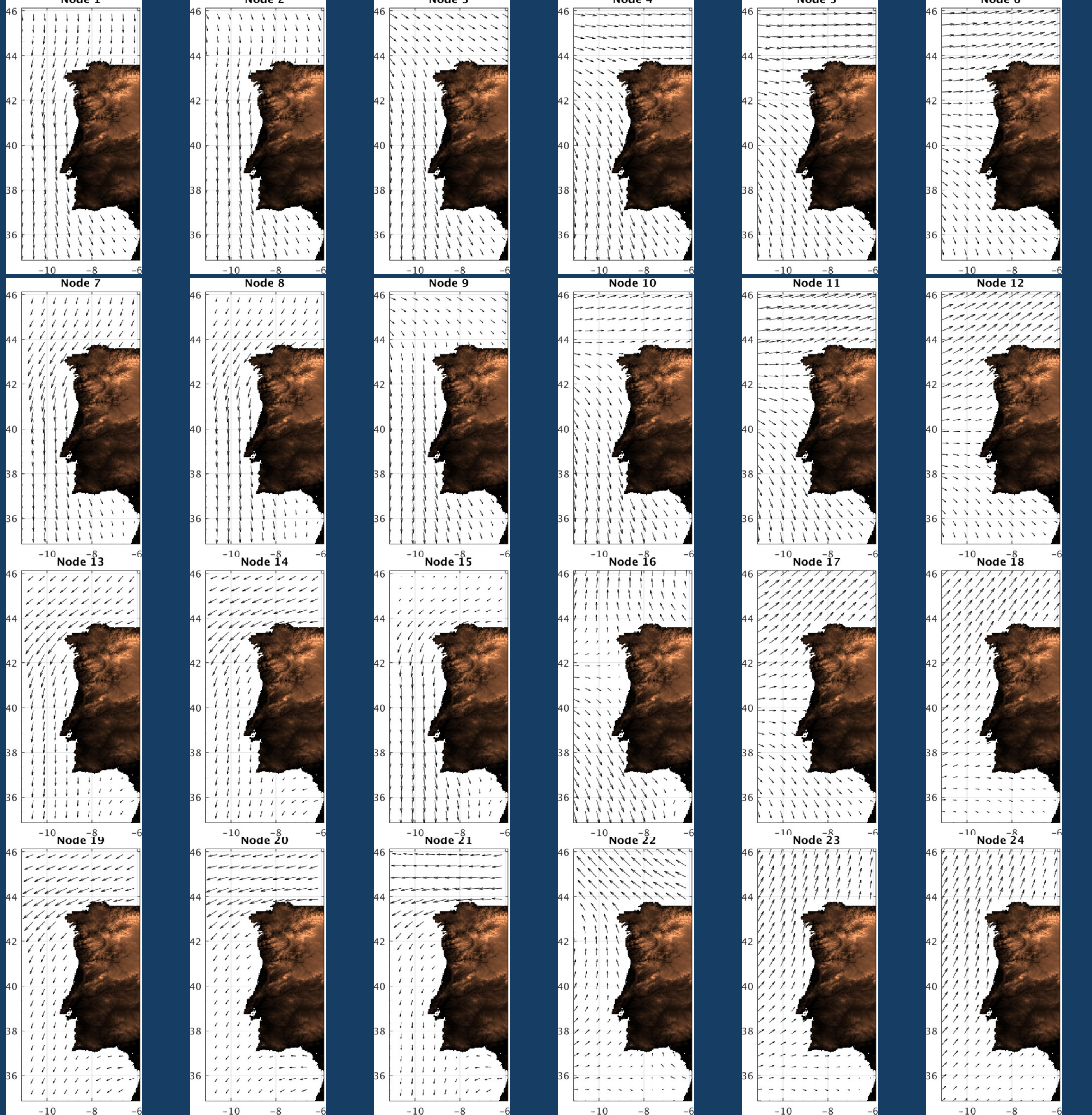
BMU=7



Frequency of Occurrence of each BMU



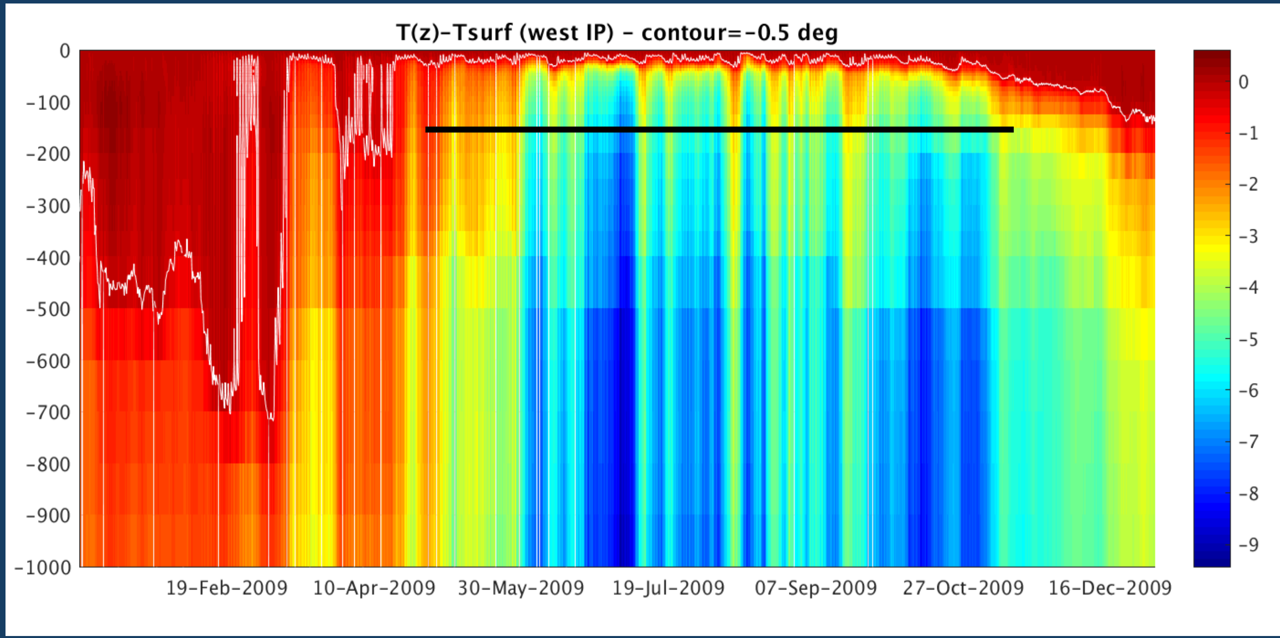
1,824 daily wind fields are clustered to 24 patterns (neurons or nodes)



Upwelling proxies:

- Direct observations of upwelling motions are not common
- Upwelling evidenced by SST and ocean color signatures
  - Difficult to conclusively link to upwelling because other processes impact SST and ocean color fields - surface thermal fluxes, mixed layer deepening, and terrestrial nutrient input
- Ocean models can provide information about upwelling
  - Onshore near-bottom velocity
  - **Temperature changes along the slope below the mixed layer**

Temperature change at depth relative to surface
Averaged over region offshore of western IP



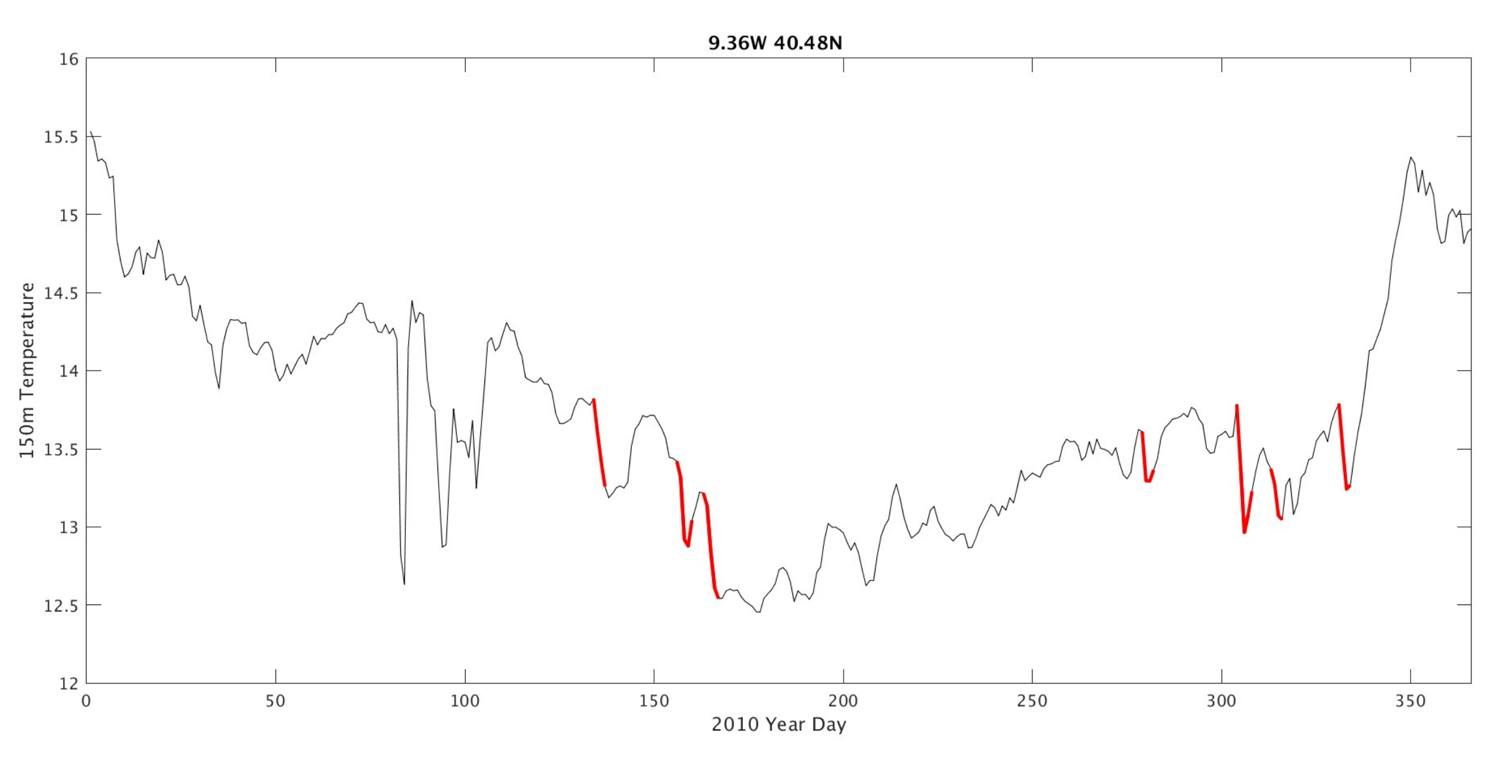
Upwelling signatures evident below 50m and distinct from mixed layer from May-Nov

Time series of near-bottom temperature along 150m isobath selected for analysis

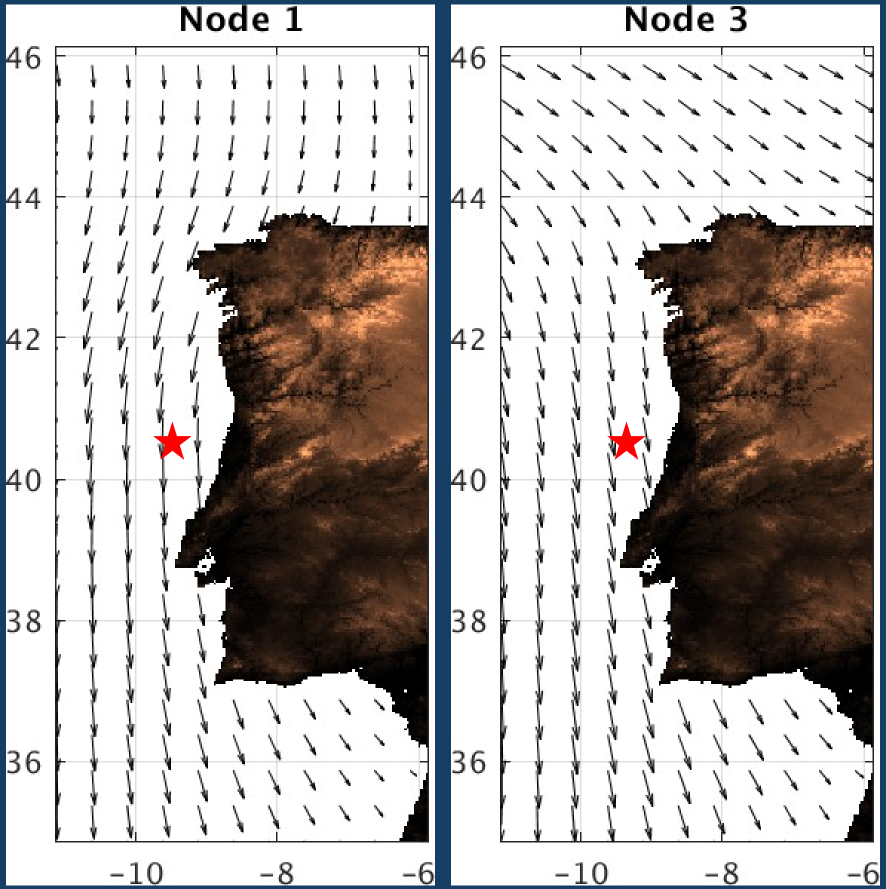
Define an upwelling period based on near-bottom temperature change (48-hour filtered) along 150m isobath.

- **dT/dt < -0.2°C / day**
- **Between May 1 and Nov 30 of each year (dominant upwelling season and removes impacts of mixed layer deepening/cooling)**

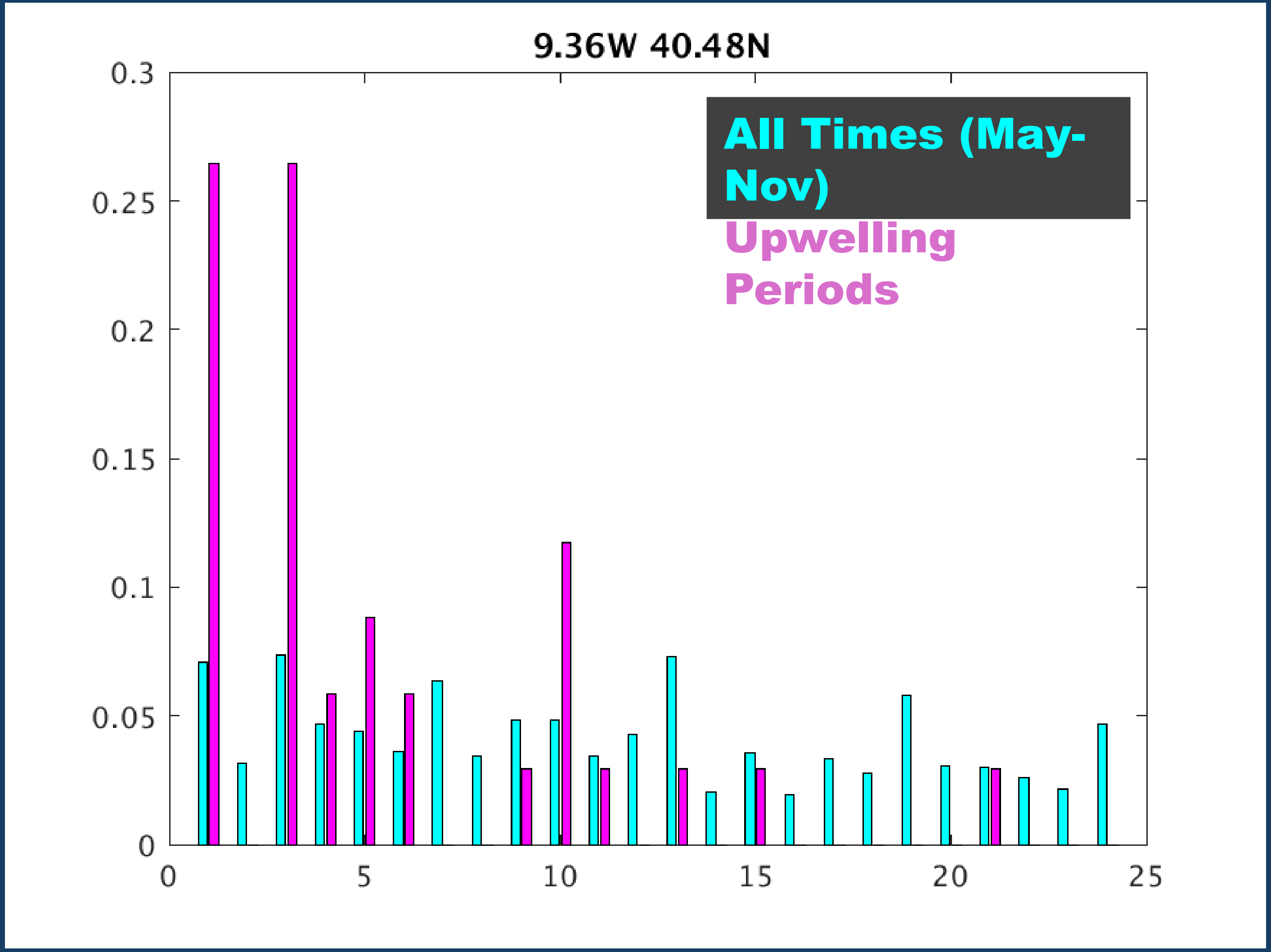
Near-bottom temperature along 150m isobath
Near Porto, Portugal

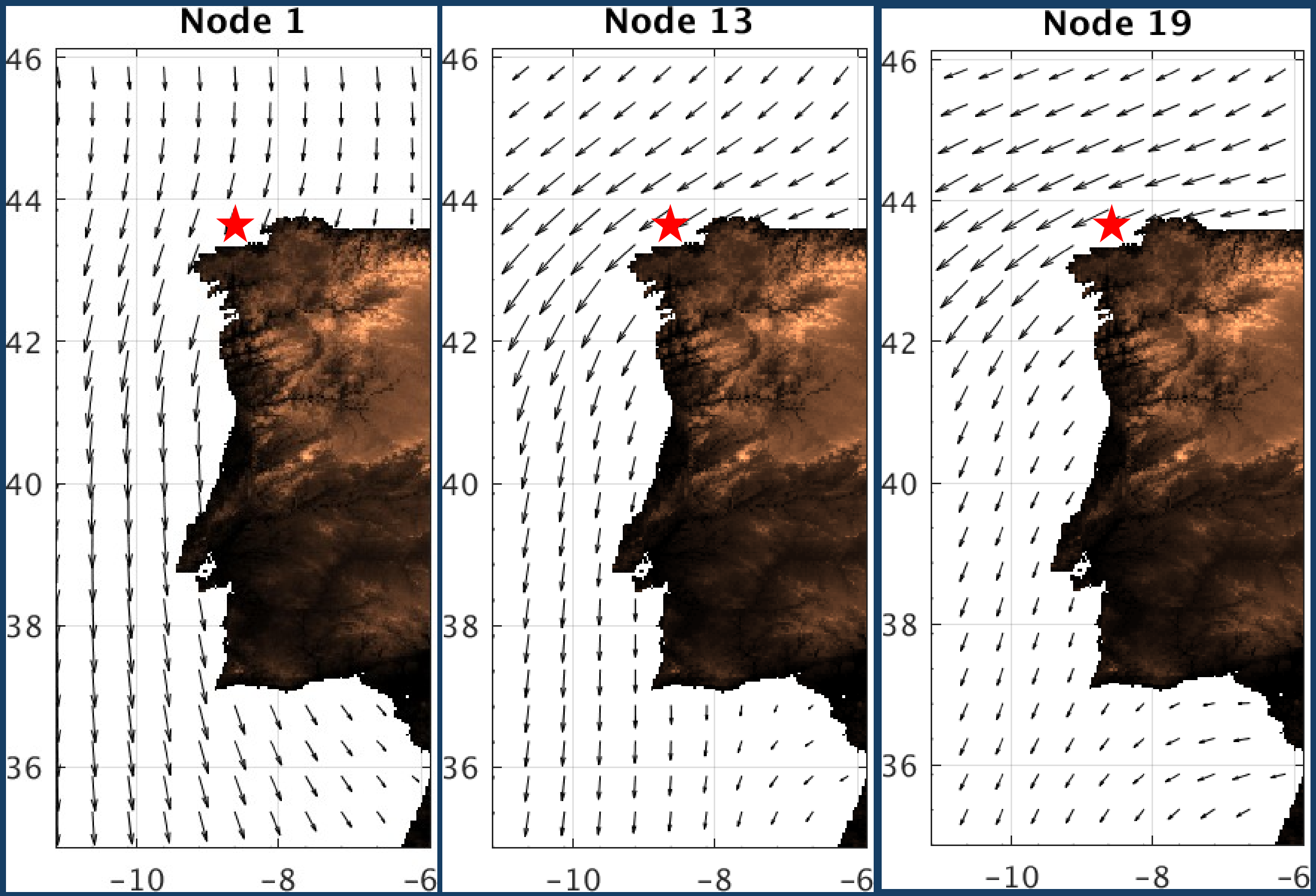


Comparison of histograms of BMUs for upwelling periods versus all time highlights neurons (characteristic wind fields) that are more likely to occur during upwelling periods

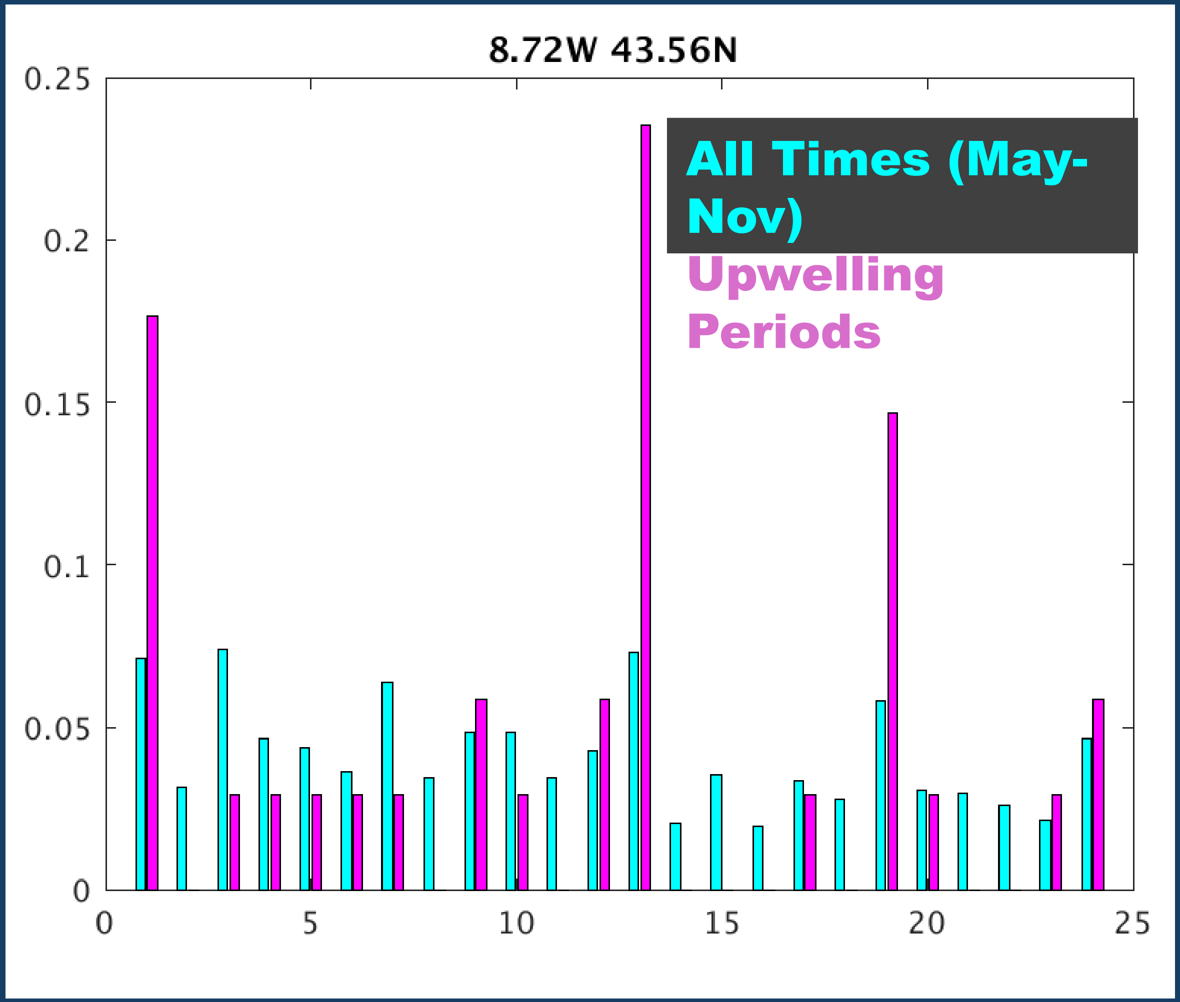


Frequency of Occurrence of each BMU





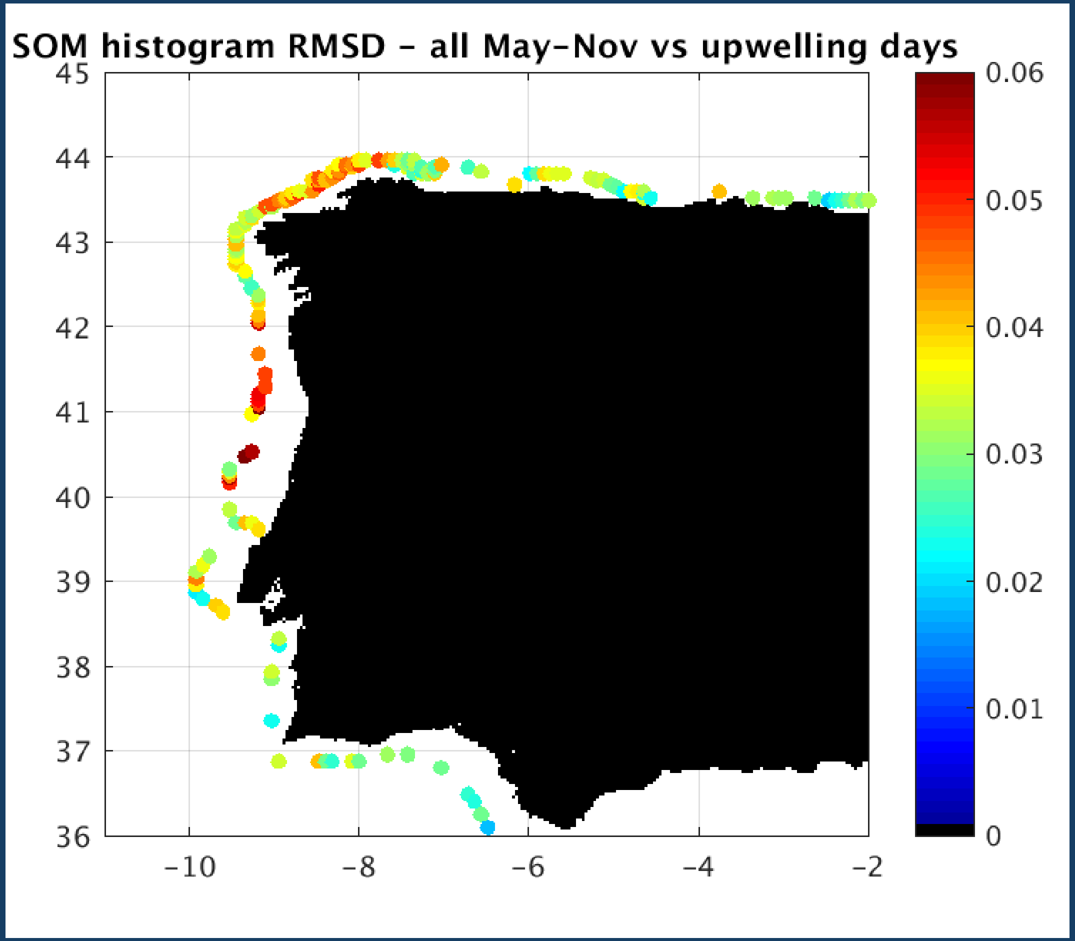
Frequency of Occurrence of each BMU

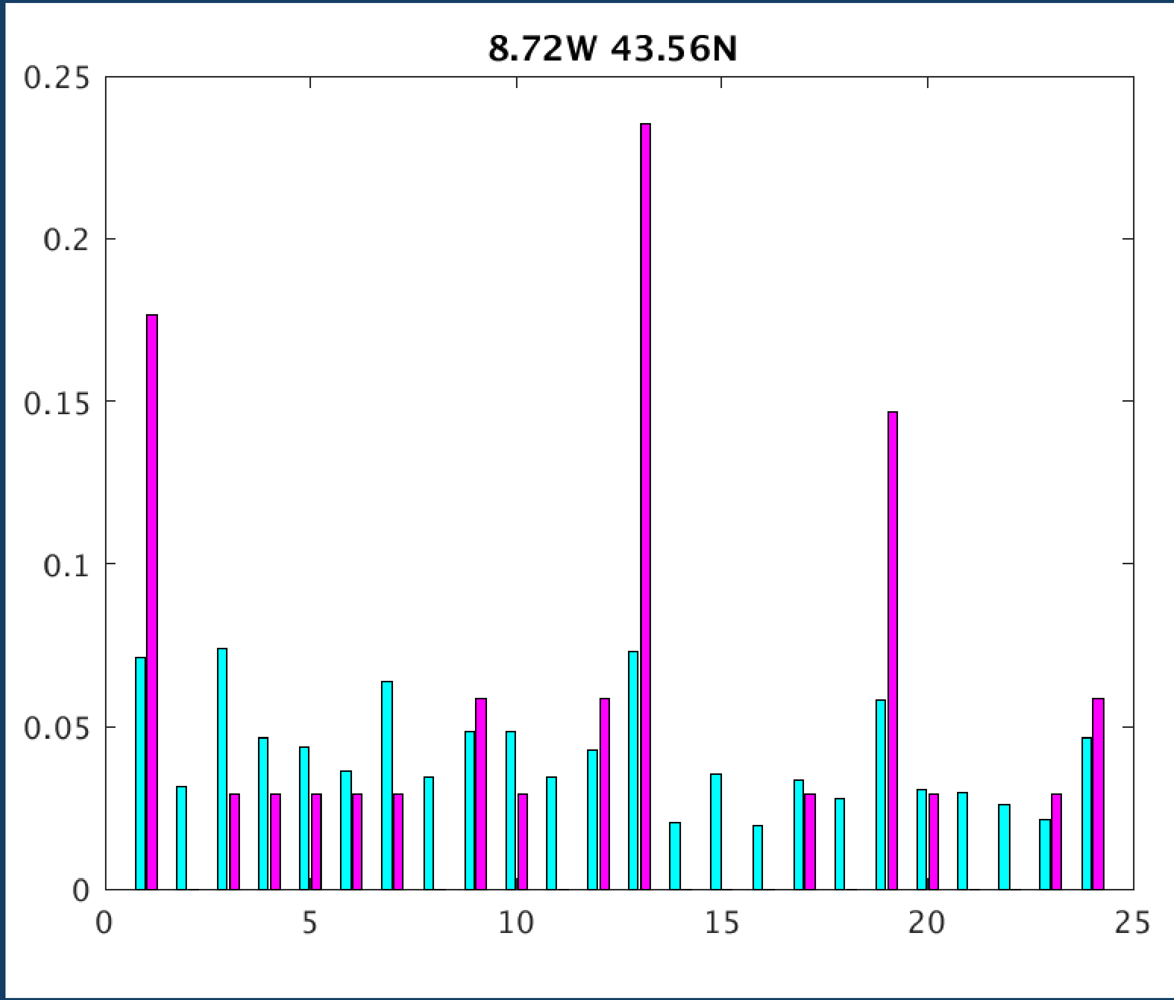


Local winds for BMU 1 pattern are nearly onshore – NOT consistent with local Ekman upwelling.

Northerly winds along the west coast force upwelling motions that propagate around to the north.

The RMS difference between the histograms of BMUs for all times and for upwelling times gives an indication of the association between the SOM and wind-driven upwelling motions.





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.

- Future plans :
  - Applications to other regions – Requires further development of upwelling proxies for training
  - Experiments with SOM parameters and topologies
  - Demonstration of BMU mapping from other wind data sets (e.g., NRT and swath products)