3 Stories

3 preliminaries

1. Ricardo as co-author - need approval plus plausible deniability for my side comments. Anything smart is his, anything smartass is mine
2. preliminary, on-going work, not a neat definite conclusion
3. Approved by no NOAA climate committee, or any NOAA org.

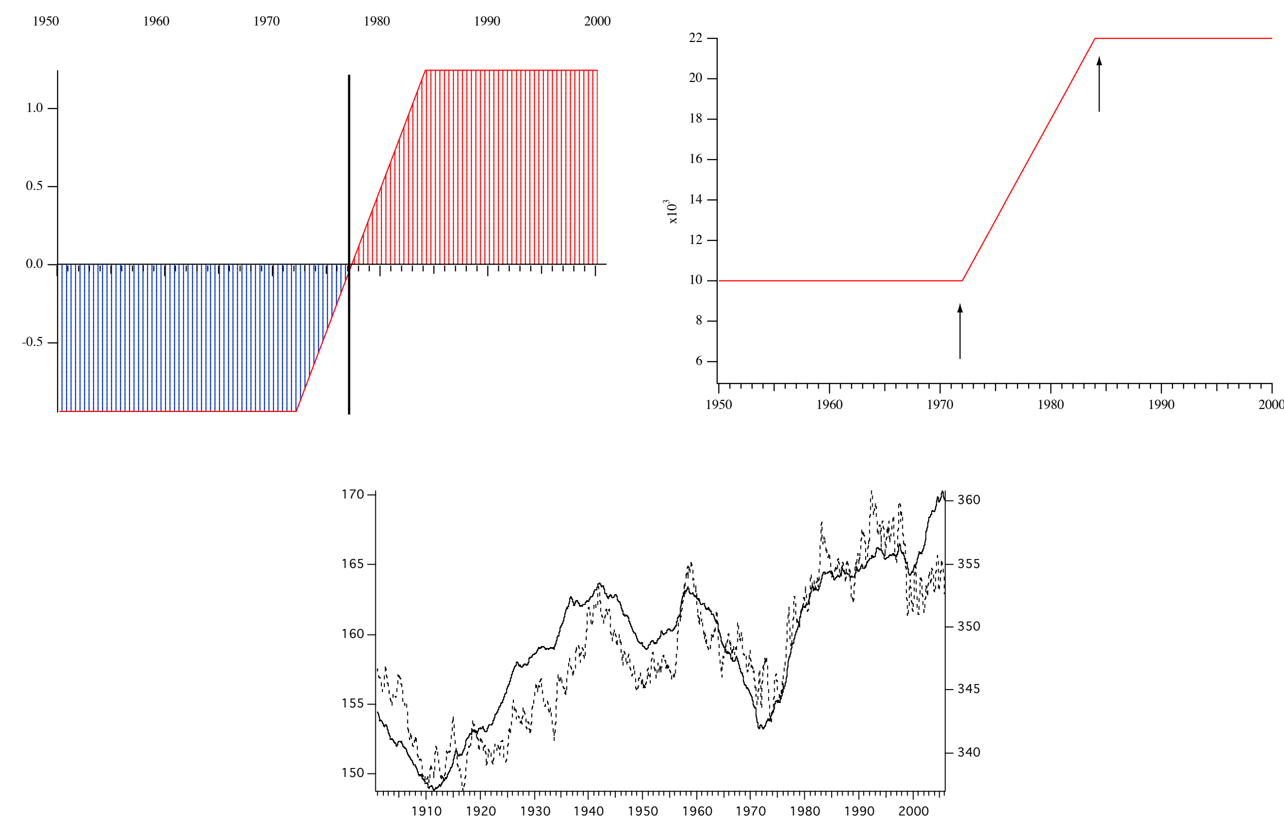
Weaving together 3 stories (if 3 are not enough, these go to 11) :

1 How you look at the data, whether you assume stationarity or not, level-crossing vs. dynamic change, matter.

2. Warming off the west coast 2006-2016, blobs everywhere

3. A new algorithm to do hi-resolution and multi-resolution space-time analysis on a laptop. Algorithm is intellectual property of Climate Corporation. Nothing here that isn't covered in a an approved talk at ISBA last summer.

Methods Influences Story



The Methods we choose to use can affect the story we tell from the data.

Story 1: The top left shows a level crossing as often presented, here saying the change was in 1976. The upper right shows the same series without all the coloring, and we see warming started in 1972 and ended in 1984. 1976 is the mid-point of that change, and has no physical meaning. Why other series don't line up with it - if the changed in 1972, different times to cross mean level, Bottom series shows real example.

Moreover, anomalies as usually calculated assume stationarity - a very crude seasonal filter. Can leave power in the seasonal frequencies (at best) or at worse leak into other frequencies. And a ton of parameters are being estimated (seasonal means at each location) which given the large amount of autocorrelation tend to be very unstable, and they are estimated without any sort of regularization.

Don't hear much about 1976 anymore. good example of this. it is not just about scoring statistical points. If we are trying to understand the processes, it matter greatly if we look at 1976, rather than 1972 and 1984, and more so because even if controlled by the same processes, different series will have mean crossings at different times.

Besides being lazy and re-using slide, there is a reason for using this particular example

Also pseudo replication

Pseudoreplication

filtered state = predicted state + gain*(predicted error)

gain approximately Process Noise/Measurement Noise

Last term roughly new information in the data point

Bartlett's Correction - $(1/n) * (1 + p^2)/(1-p^2)$
for $p = .8$, variance is 4.5 times bigger

Pseudoreplication clear to many people in spatial context - say but 50 sensors in my office to find out about temperature change over time - do not have 50 observations. If I took the ohs from one sensor and just duplicated them 50 times, people would cry foul, but not a lot different other than intent.
But same issues in time, though maybe not as obvious. In iid case, best that can be predicted is the mean, so the information value is MSE, but in non iid case, can be very little new info in the data point.

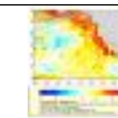
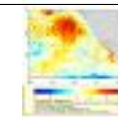
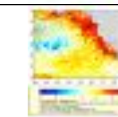
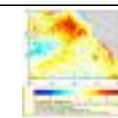
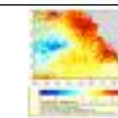
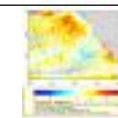
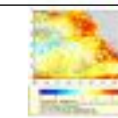
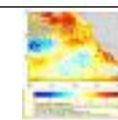
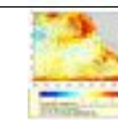
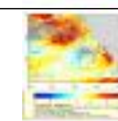
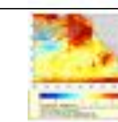
Many examples out there, that treat dependent data as iid. Maybe 30%-40% supposed explain variance in "fit", then used for prediction. The predictive accuracy is likely much much less. But it makes for pretty maps.

For the Bayesians out there (though the comments are true whether in Bayesian for Frequentist context), think of it as issues of shrinkage and regularization (see McElreath)

For, if we do not supplement the maximum likelihood method with some prior information about which hypotheses we shall consider reasonable, then it will always lead us inexorably to favor the 'sure thing' hypothesis HS, according to which every tiny detail of the data was inevitable; nothing else could possibly have happened.

Jaynes, E. T.. Probability Theory: The Logic of Science: Principles and Elementary Applications Vol 1 (p. 195). Cambridge University Press. Kindle Edition.

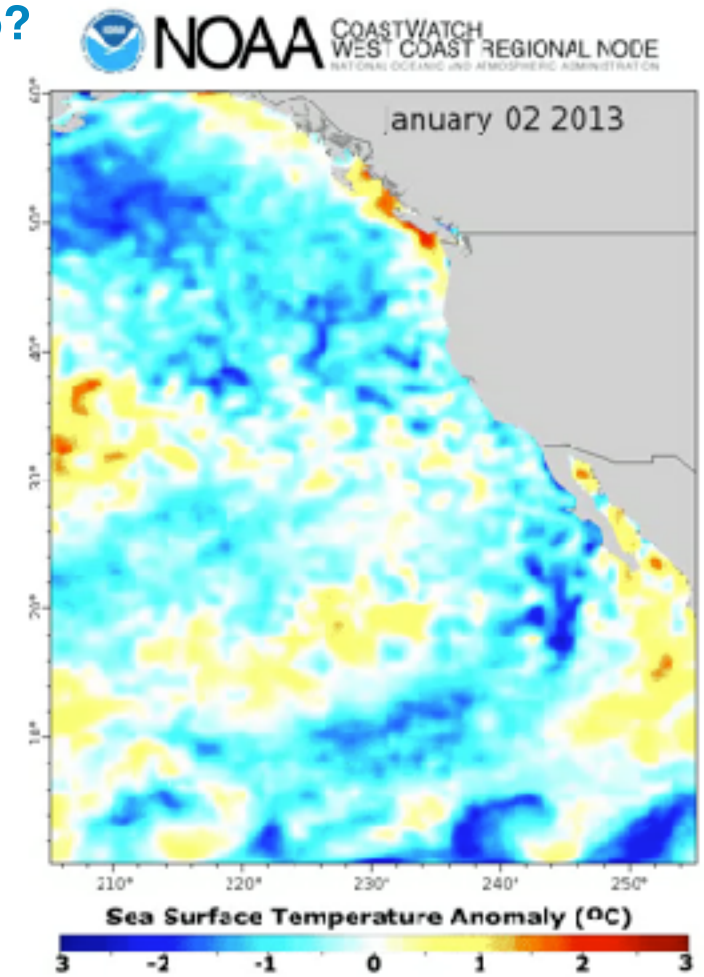
Where Did the Blob Go?

Month	2014	2015
January		
February		
March		
April		
May		
June		

Story 2. How can the blob disappear suddenly?

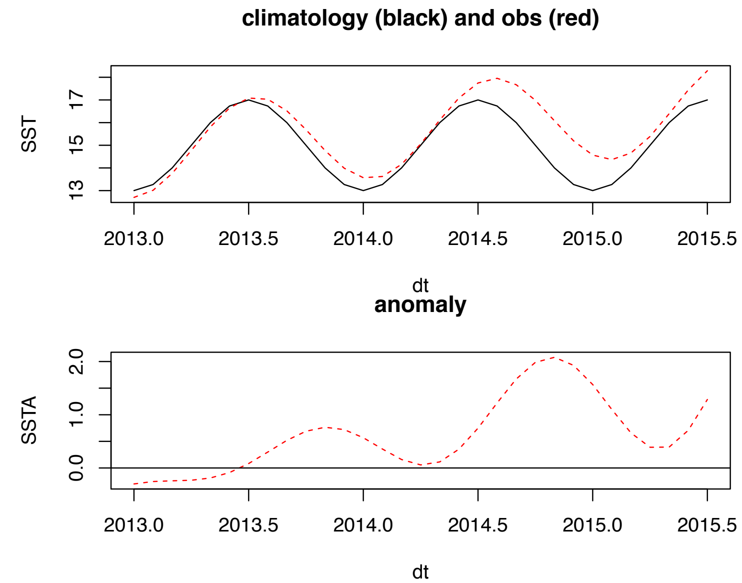
Sent by Skip Albertson, longtime data user. What is doing in April? Where did the blob go? Ask if bias in seasonal, or shift? Possible that big shift in warming in one month, but unlikely, but let's look at daily anomalies

Where Did the Blob Go?



We were worried we had done something wrong. Ryan Belcher and Dale Robinson of our group made a movie of the daily anomalies. A movie showing the daily MUR anomalies. We see the same behavior, on very short time scales. What can explain that?

Trend + Seasonal Phase Shift

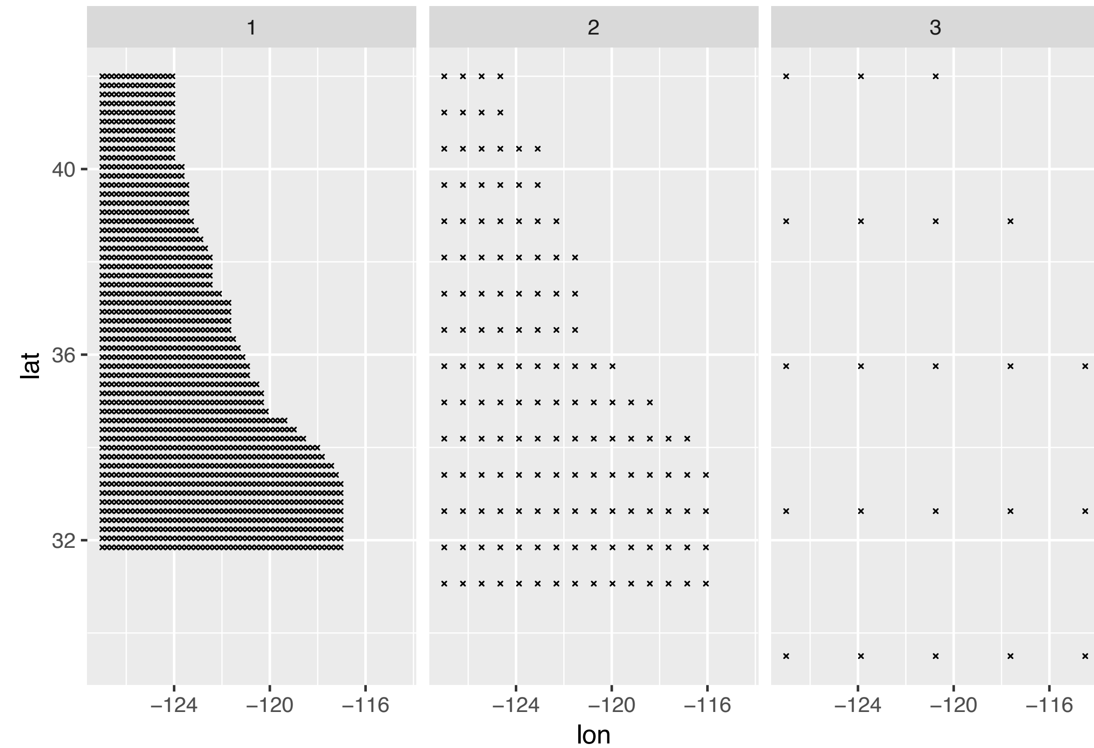


Start with cool 2013
Add warming trend (0.8C/yr)
Add slowly changing seasonal (0.5 months/yr)
Year-round positive anomalies by 2015

One possibility for what we are seeing is an overall warming trend, with a stronger change in the seasonality, particular in certain regions. Here the assumption is just that the phase of the seasonal shifts in time, but now imagine if the shape of the seasonal cycle is changing, so for some part of the season it is below the climatology and some part it is above.

We will come back to this.

Multiresolution Model



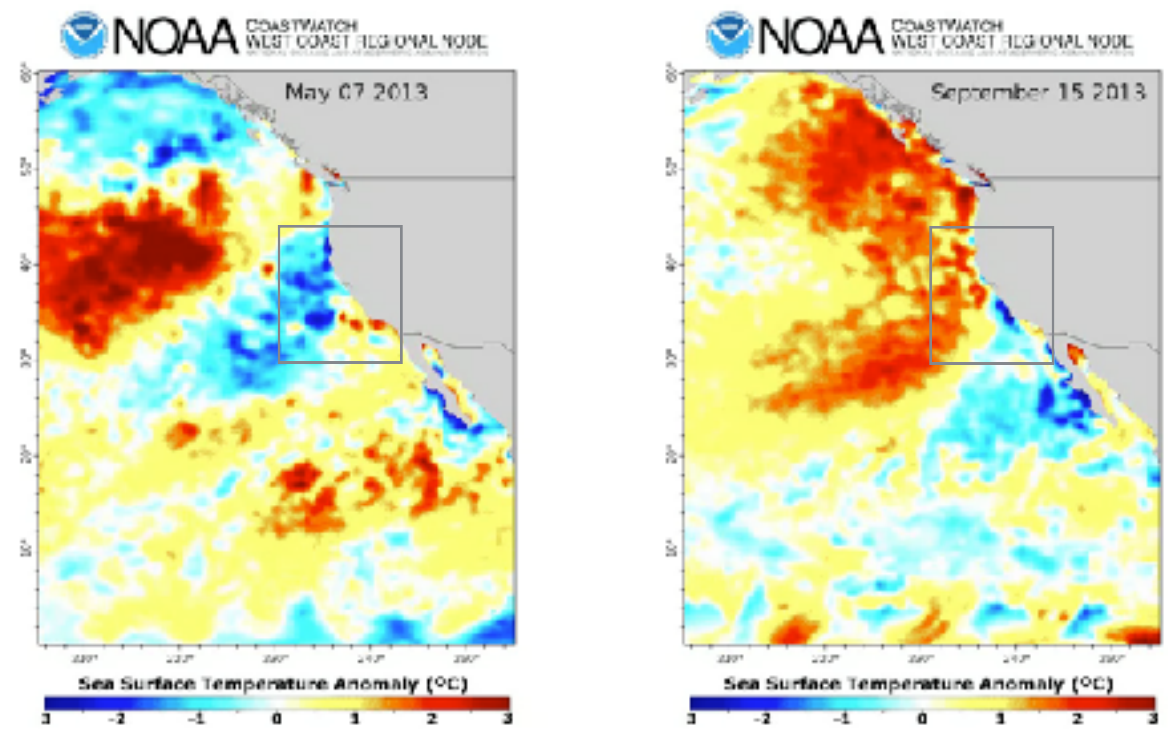
Story 3: Multi-resolution space-time analysis with seasonals that can vary in phase and amplitude

Many space-time analyses start by setting up a grid (like knots in 1d splines), putting a process at each knot, as well as a “convolution kernel” that describes the spatial influence of the process at that knot. The process at each knot, can have a changing mean, and seasonal components with changing phase and amplitude. But what resolution to use for the grid. Suppose we can do multiple resolutions at once, for very large datasets (say 1 million observation points), and can do Bayesian or frequentist analysis, and do so on a laptop? This is the basis of an algorithm by Ricardo deLemos. The algorithm is the intellectual property of The Climate Corporation, but we applied it to 10 years of daily MUR data (1km resolution) essentially on a 10-degree square.

Why multiresolution - process often occur at a given resolution, adding finer resolution just adds noise. For example, many algorithms for estimating fronts first do spatial smoothing, because fronts do not occur just at a fine-scale resolution, and the finer-scale behavior is “noise” in terms of identifying the front. For the Bayesians, you can see this as a regularization or shrinkage or partial pooling.

There is a paper on this algorithm, my name added on the end. May never see the light of day. Ricardo had some fundamental insights on how to do the calculations, I had some fundamental insight into how to choose smart colleagues.

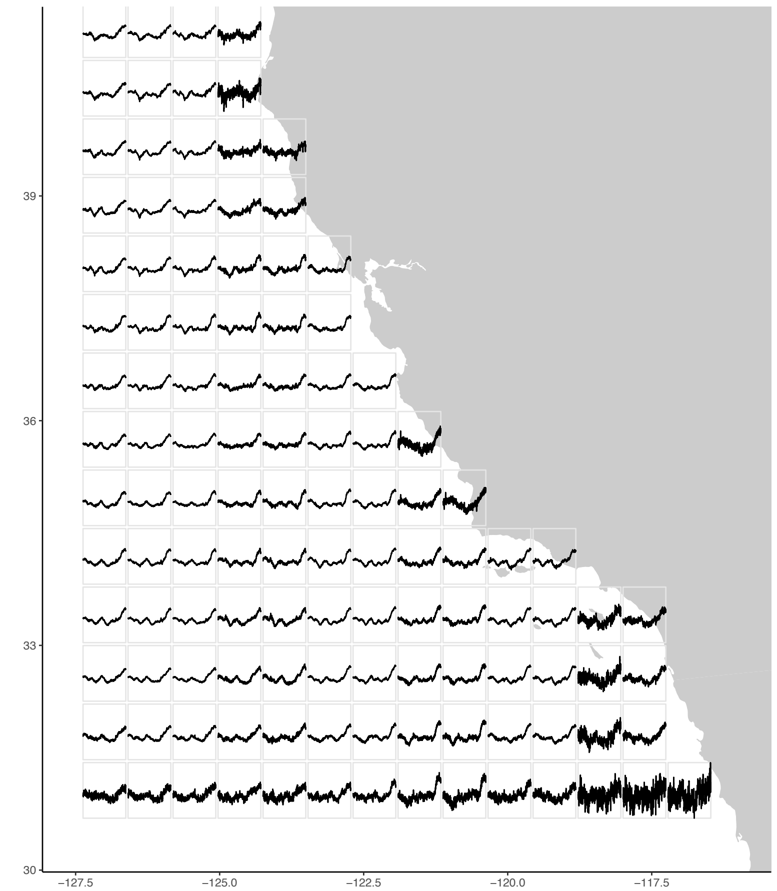
Right Location?



Area we initialed studied was not aimed at the blob,   more interested in upwelling and related processes. But given Skip's query, thought we would take a look to see what we could say about things going on in the NE Pacific.

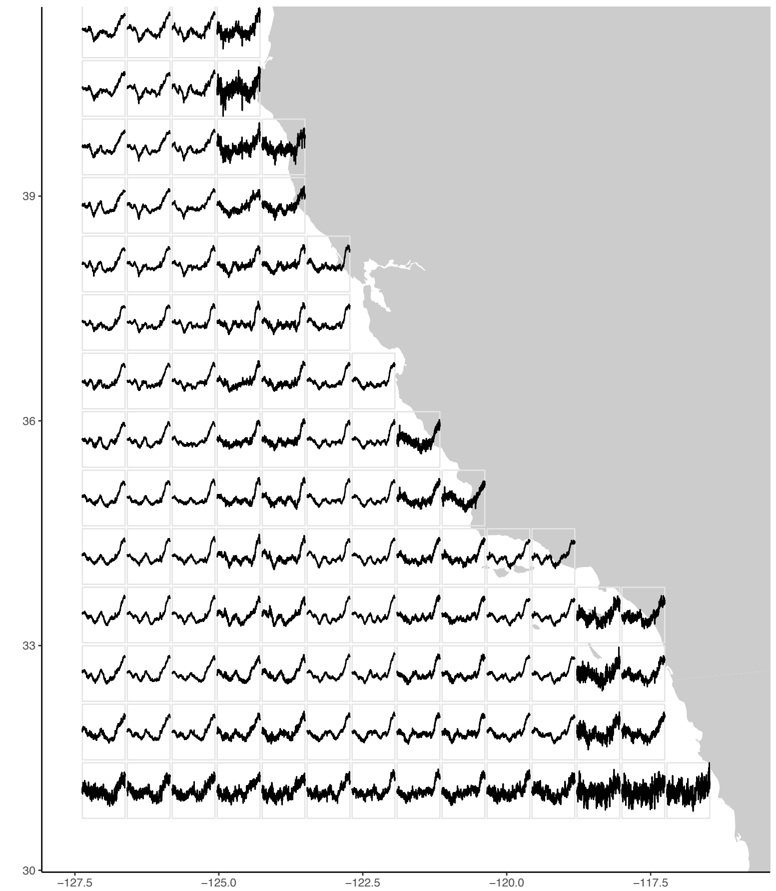
Is the area that we have studied actually catching the blob? Some periods yes, some periods no, so this should be a caveat to what will be shown. Recoding the algorithm and will go back and look at a wider area. Modeling was originally done for a different purpose, this came up after looking at the results and the inquiry from Skip.

Trend Posterior Mean



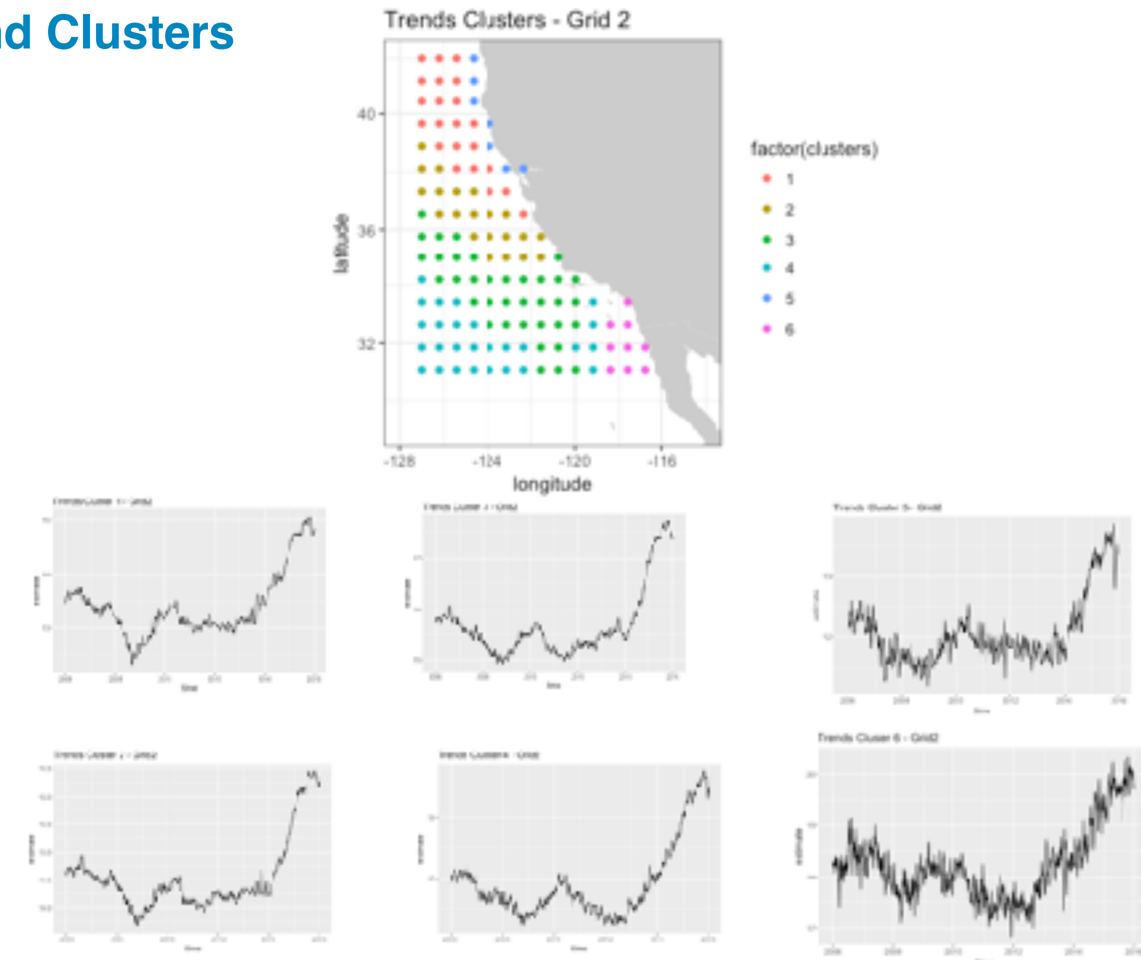
This shows the raw trends estimated from the model along a selected grid throughout the region. As we will see in more detail, starting around 2012 (maybe even earlier), there is warming everywhere, and at about the same amount. But the amount of change may be affected by the mean level.

Scaled Trend Posterior Mean



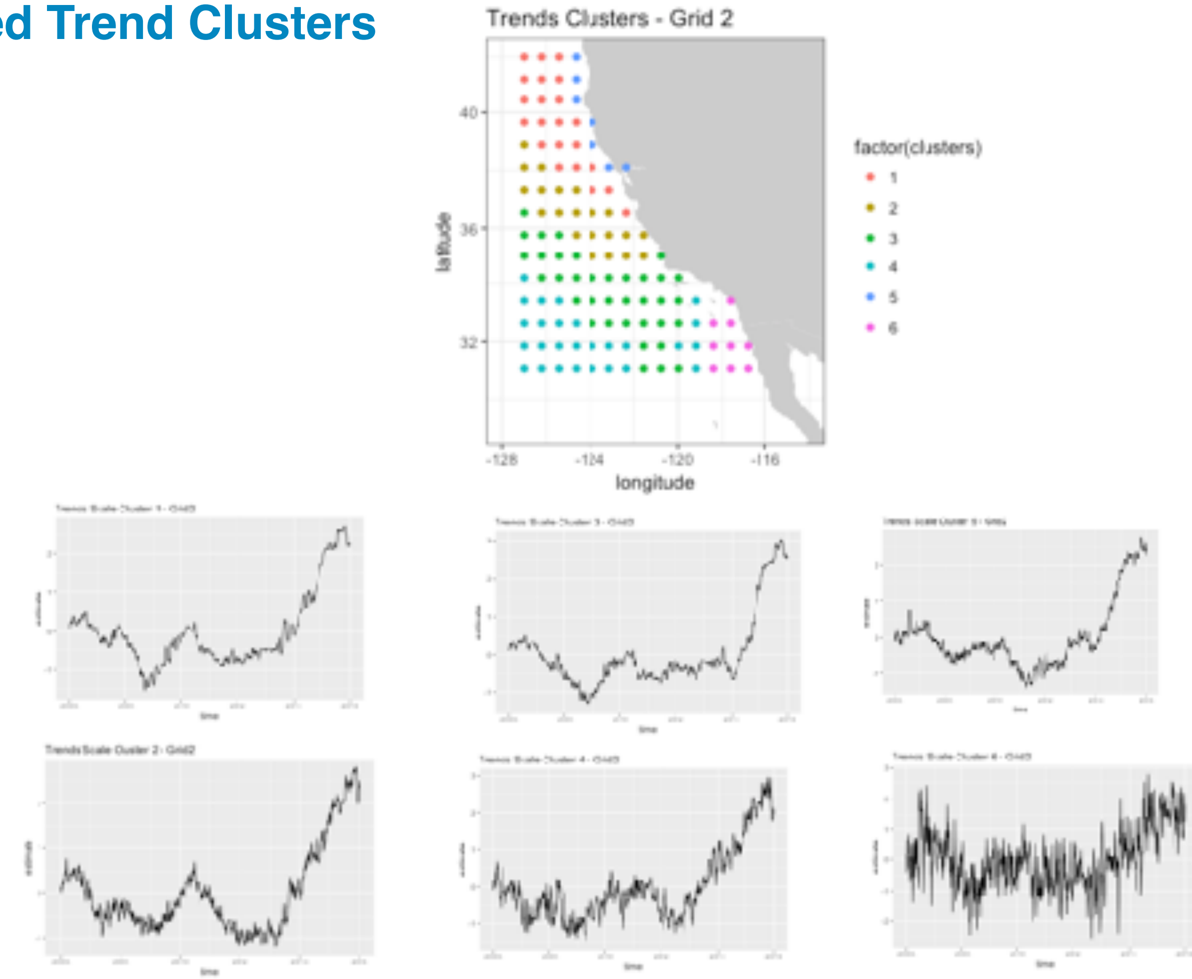
These are the scaled trends, so all series have mean zero and variance 1. The similarity of the upward trend is seen even more clearly.

Trend Clusters



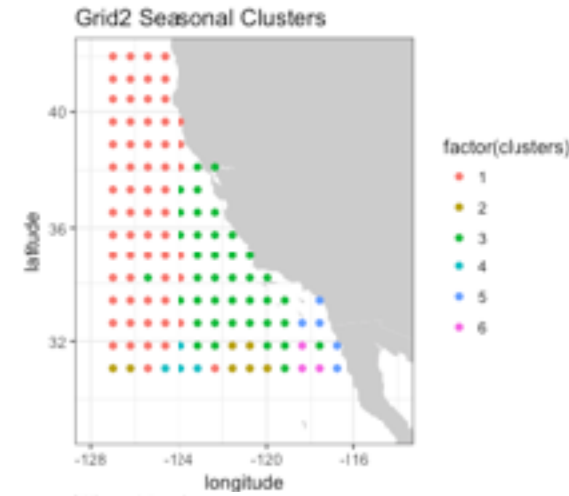
We can try to summarize the trends more by clustering the trends. Here we cluster using CORT as a measure of distance (which tries to capture both shape and shift) and pam for the clustering, with 6 clusters. The mean trend in each cluster is shown - not much difference in the critical period of blob.

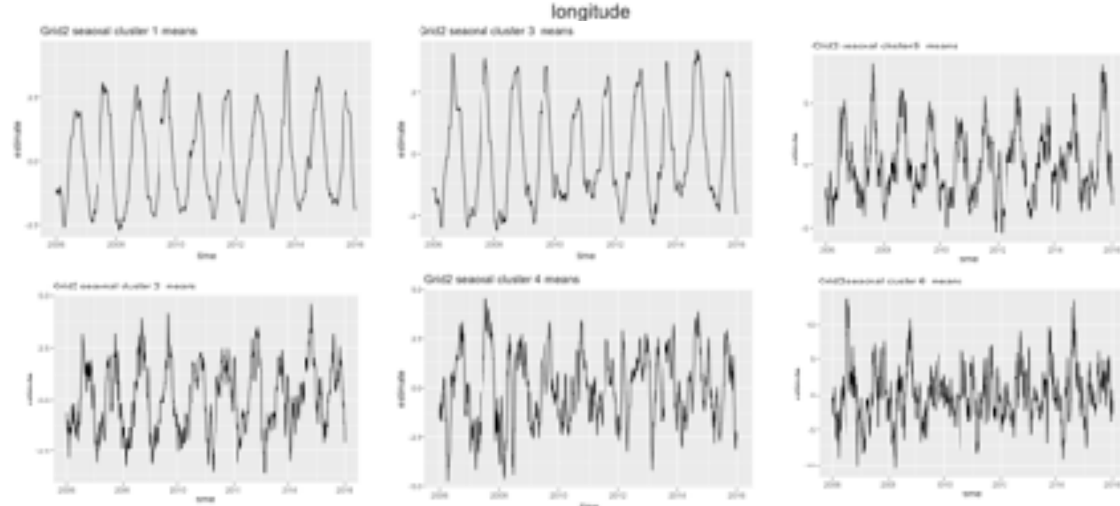
Scaled Trend Clusters



Here we do the same clustering on the scaled trends. Again the warming is region wide, and at about the same level.

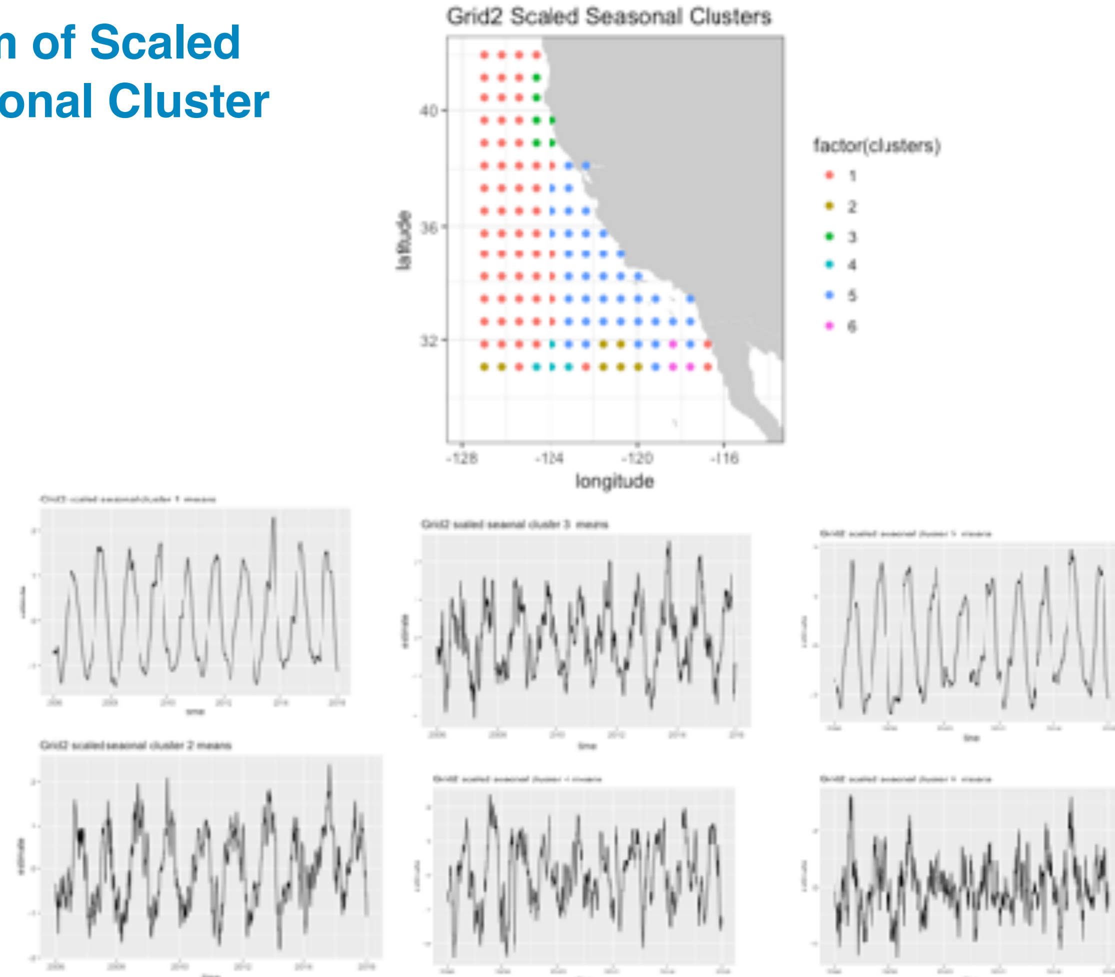
Sum of Seasonals Cluster





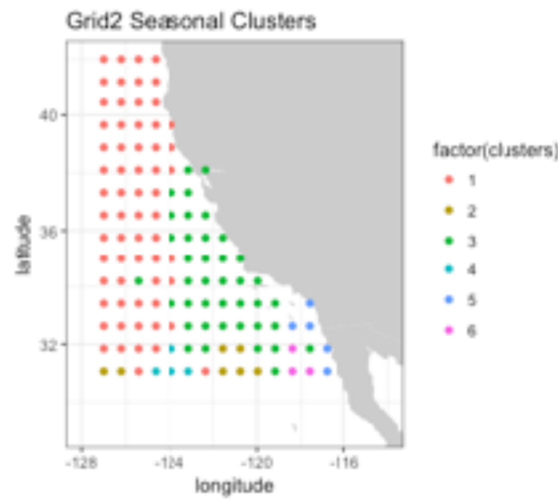
Here we clustering the sum of the seasonal components, there are significant differences in the region, and significant time dependent change. But unscaled seasonals can cluster together based on areas that have more variation in the seasonal, not the change in the seasonal

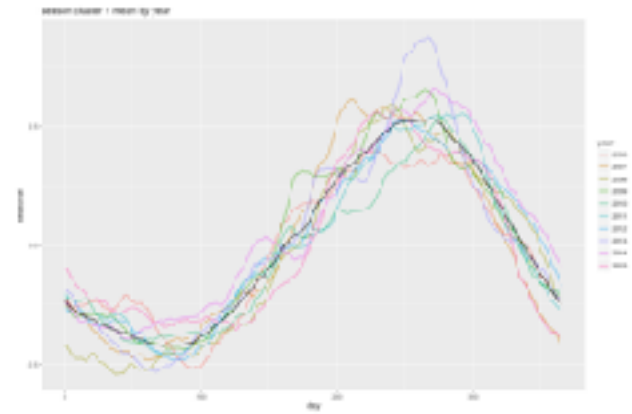
Sum of Scaled Seasonal Cluster

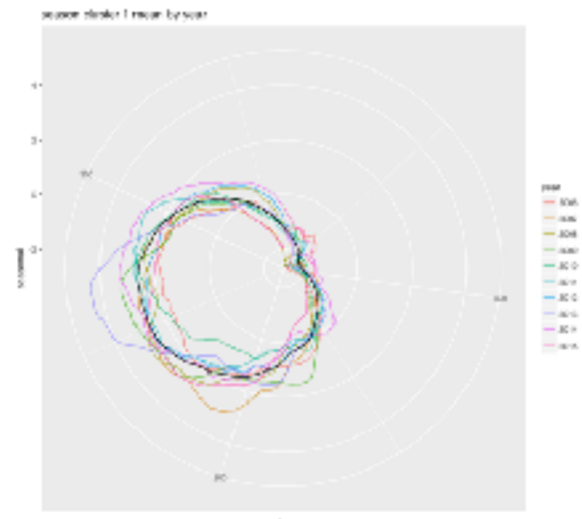


Here are the scaled seasonals, again showing significant temporal variability.

Seasonal Cluster 1
Yearly Pattern

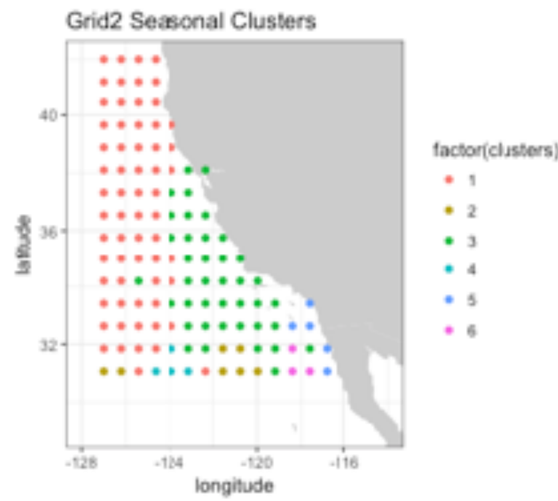


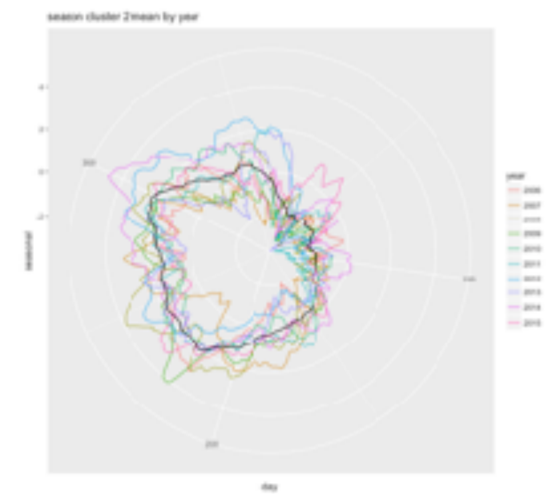




We look at the seasonals in each cluster in a manner that shows more clearly the shift in the year to year pattern.

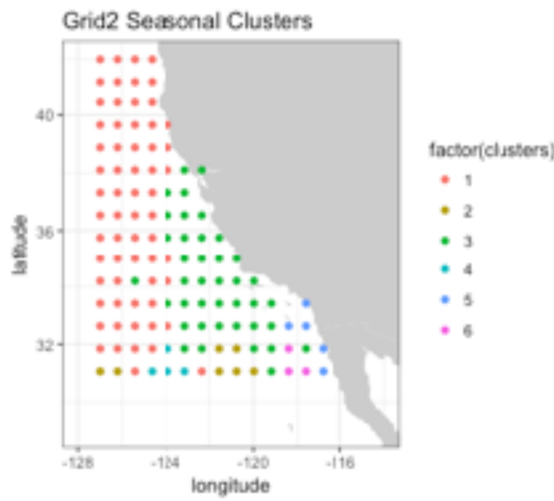
Seasonal Cluster 2
Yearly Pattern

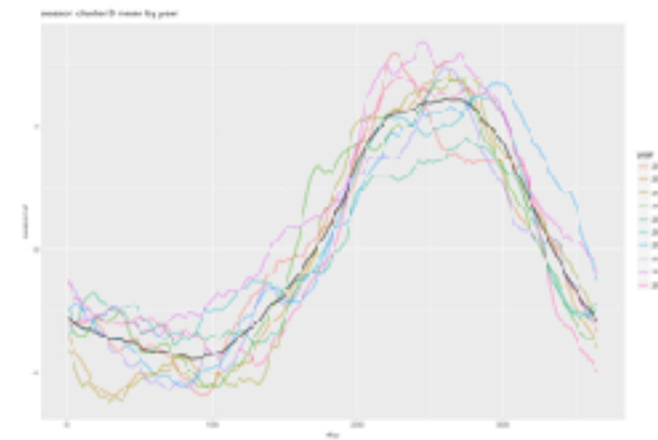


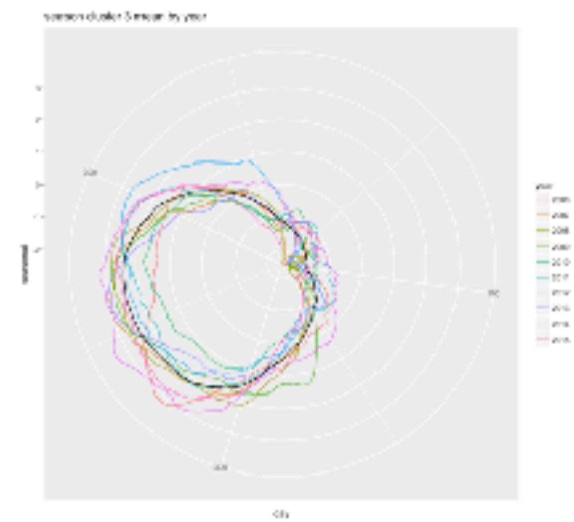


As before, but for cluster 2.

Seasonal Cluster 3
Yearly Pattern

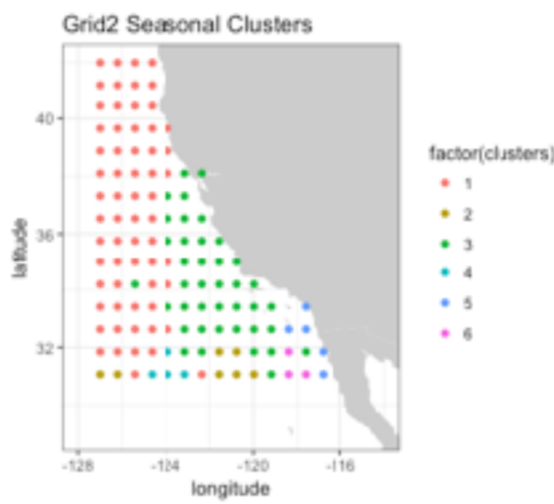


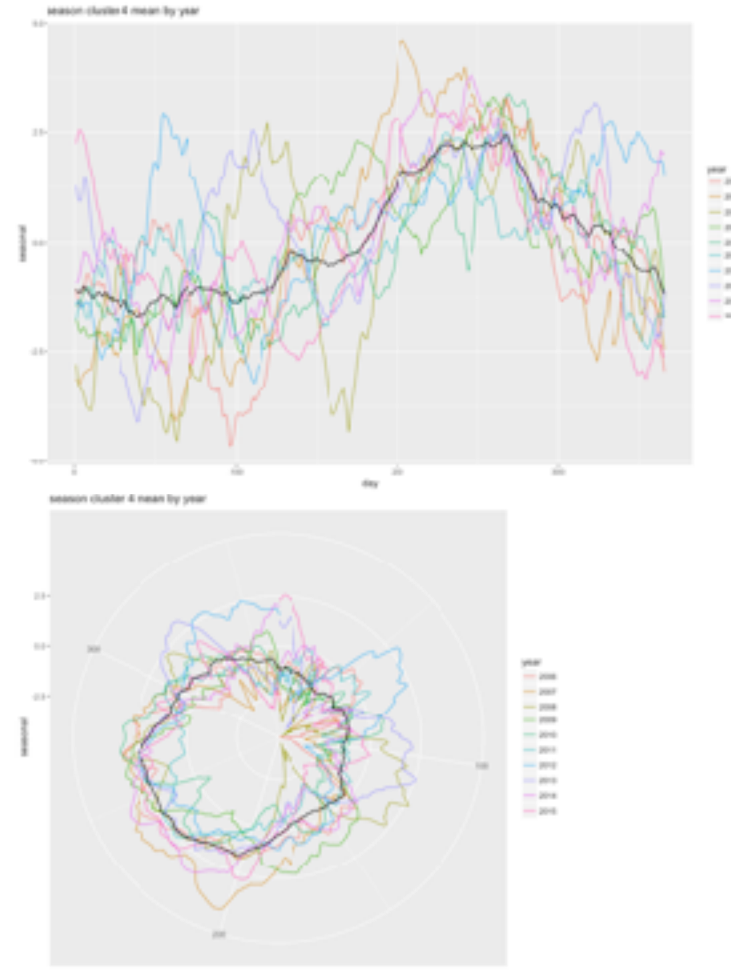




As before, but for cluster 3.

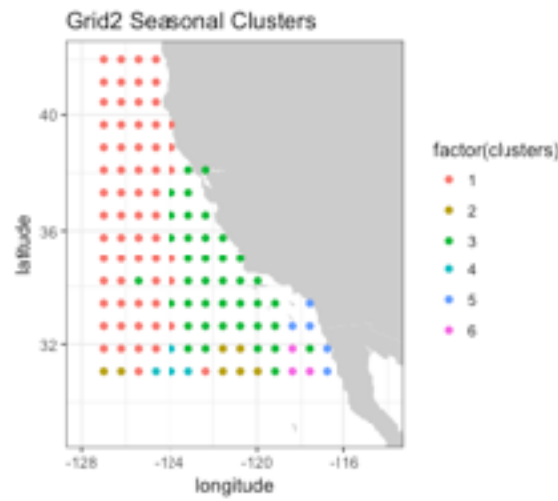
Seasonal Cluster 4
Yearly Pattern

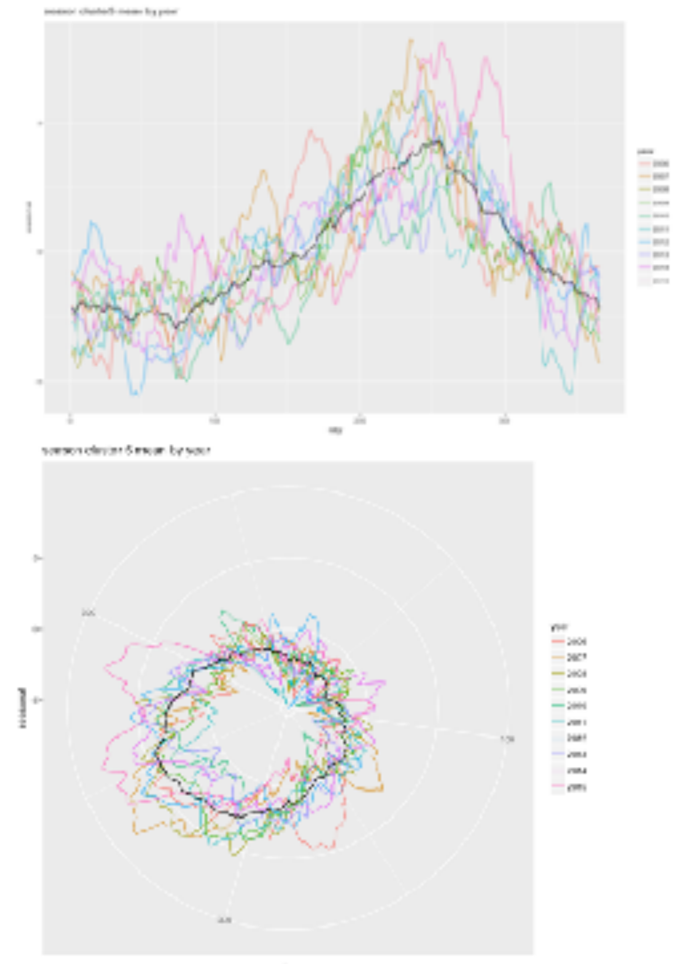




As before, but for cluster 4.

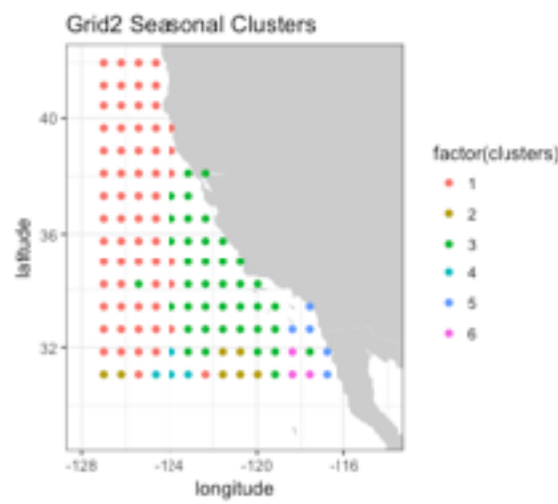
Seasonal Cluster 6
Yearly Pattern

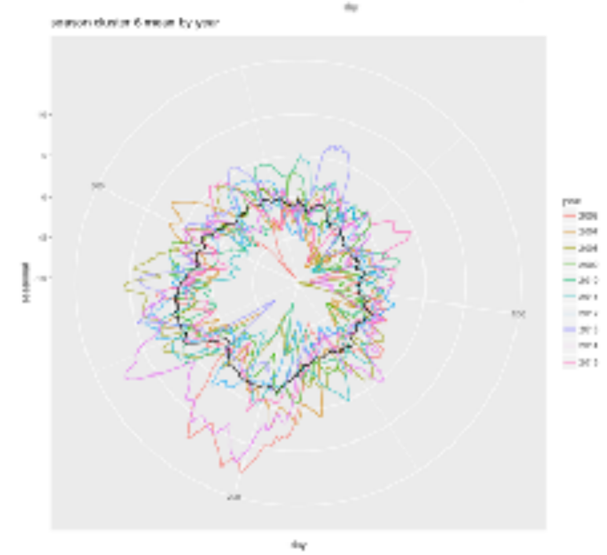




As before, but for cluster 5.

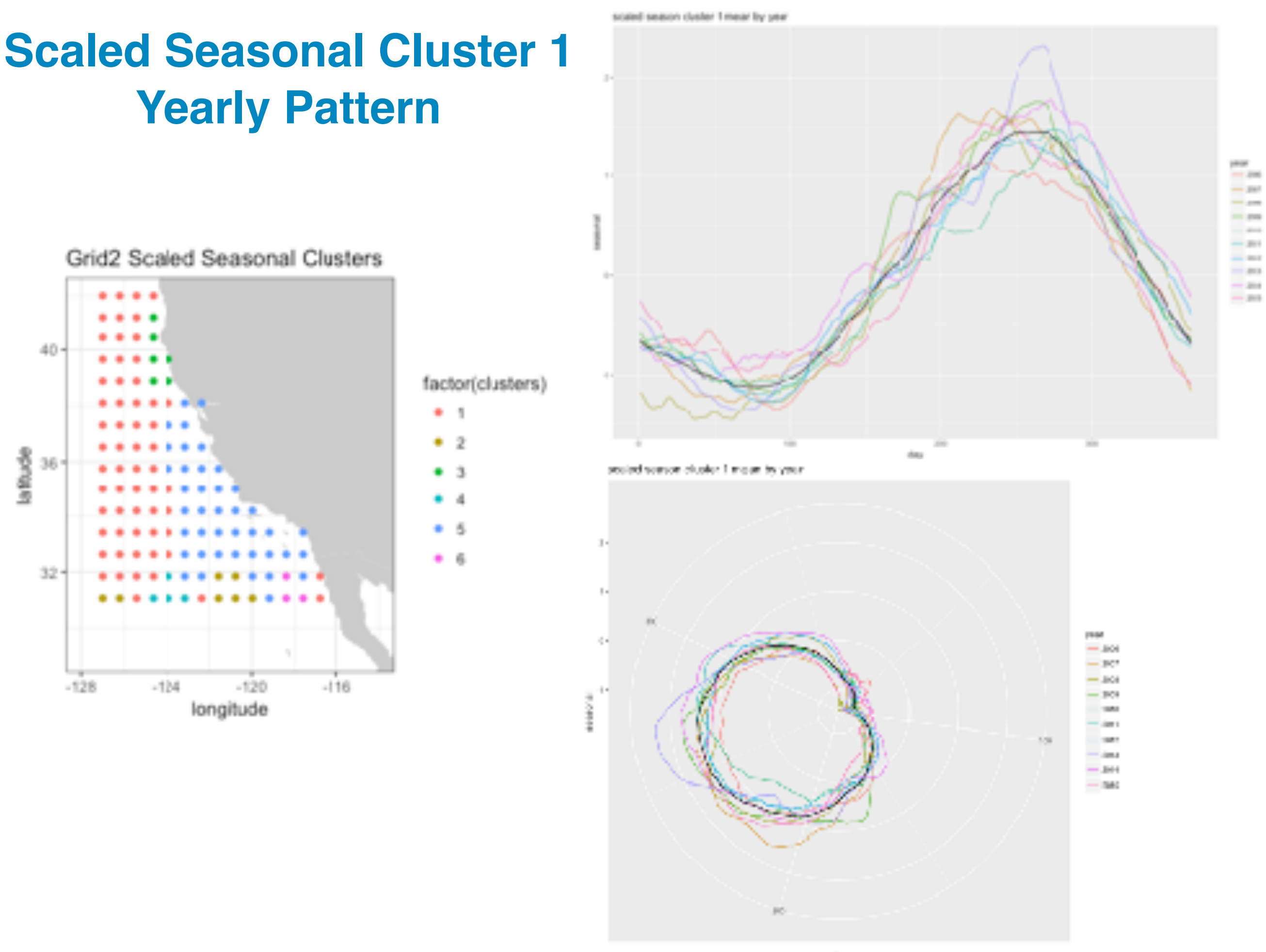
Seasonal Cluster 6
Yearly Pattern





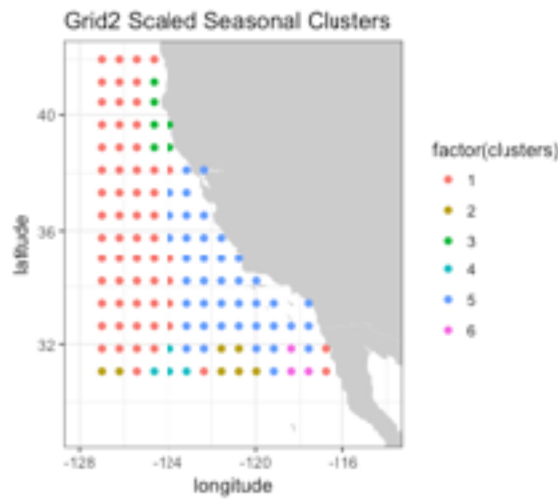
Cluster 6.

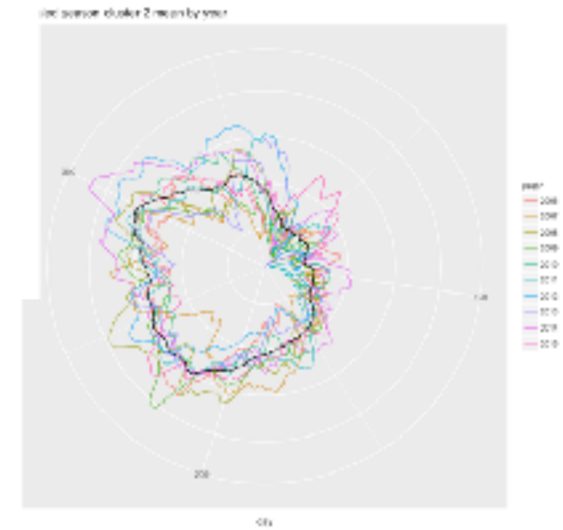
Scaled Seasonal Cluster 1 Yearly Pattern



Here we do the same for scaled seasonals. Cluster 1. The dark line is the mean behavior. The region of the blob is in this cluster.

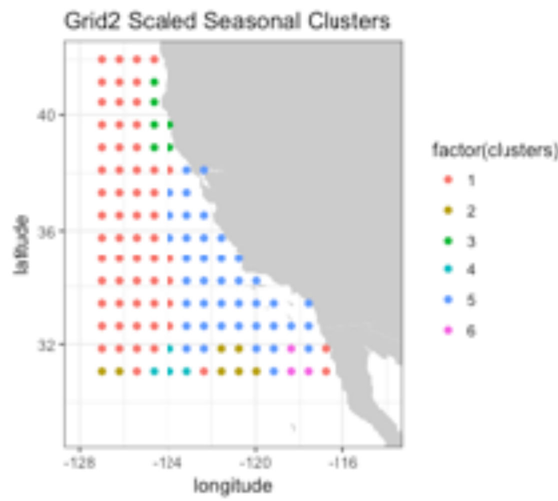
Scaled Seasonal Cluster 2 Yearly Pattern

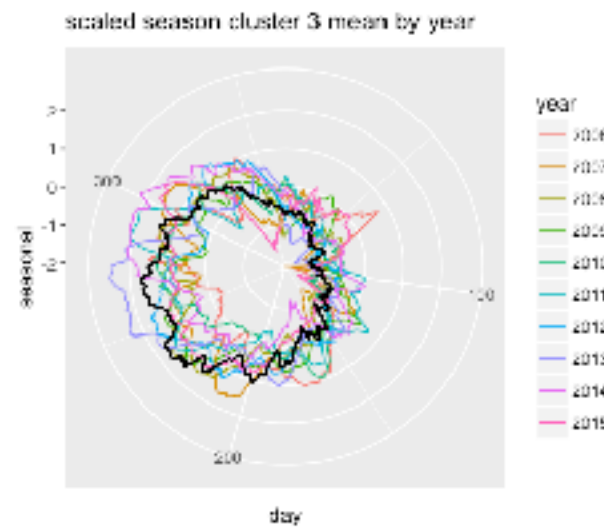




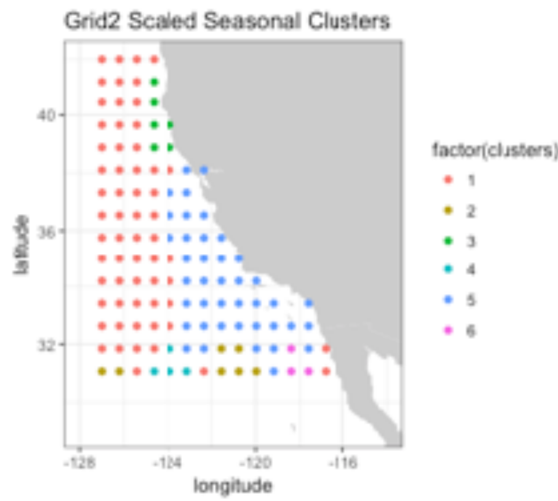
Cluster 2.

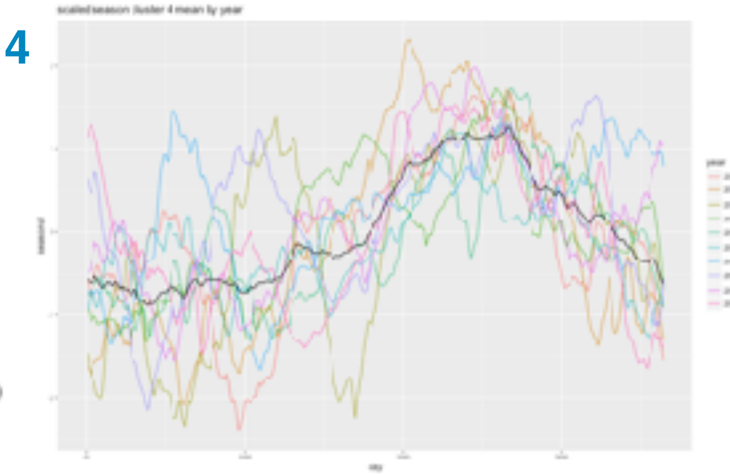
Scaled Seasonal Cluster 3 Yearly Pattern

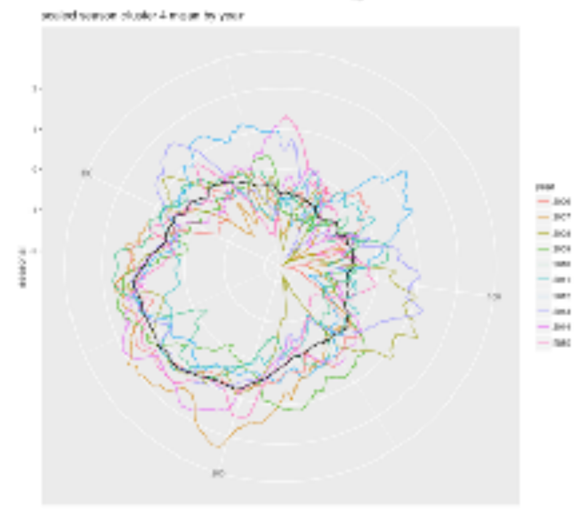




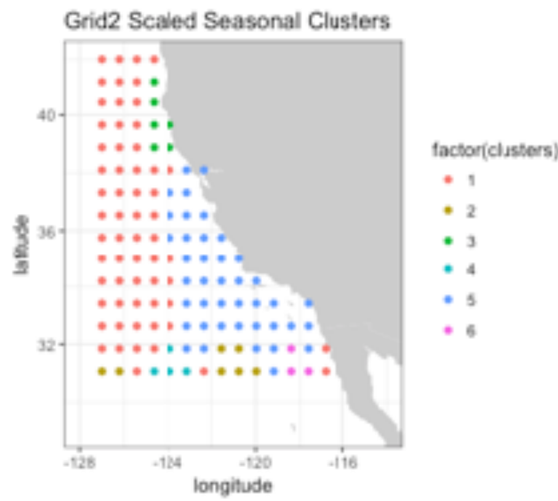
Scaled Seasonal Cluster 4 Yearly Pattern

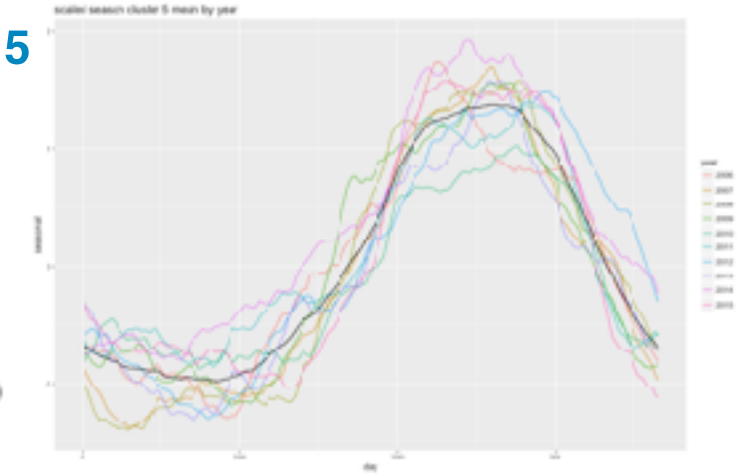


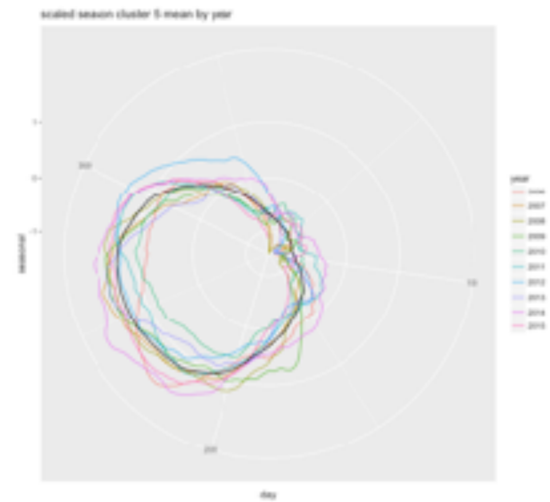




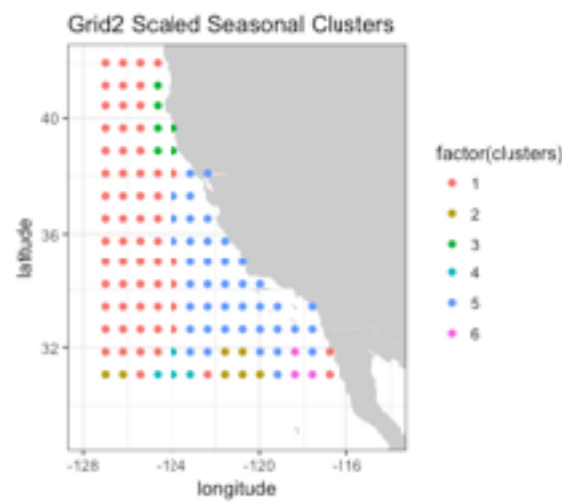
Scaled Seasonal Cluster 5 Yearly Pattern

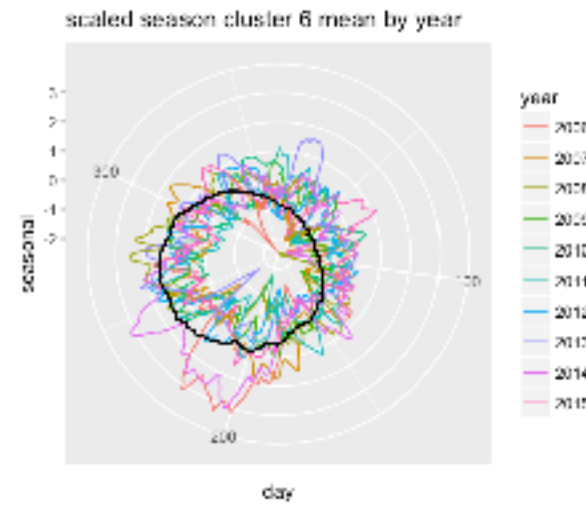


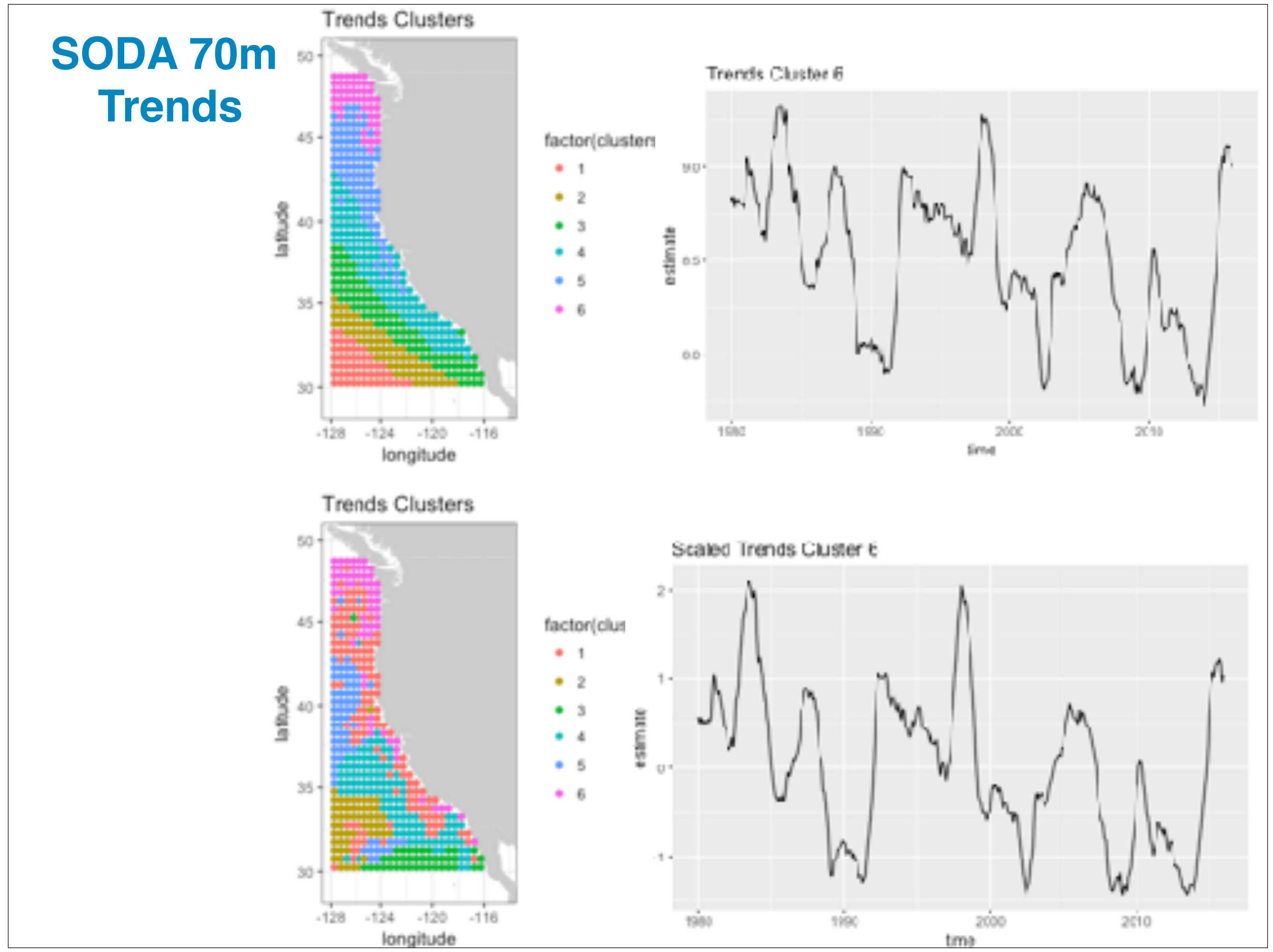




Scaled Seasonal Cluster 6 Yearly Pattern

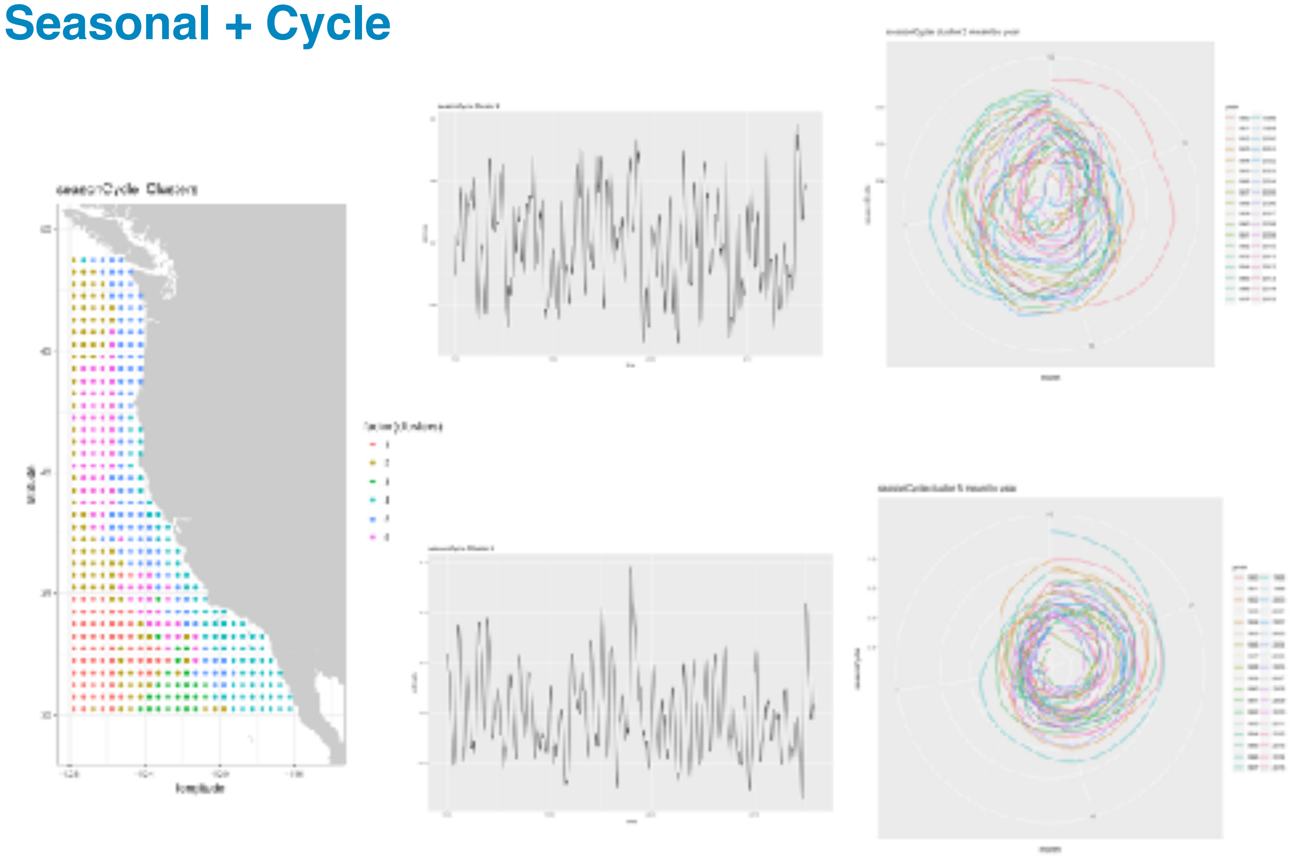






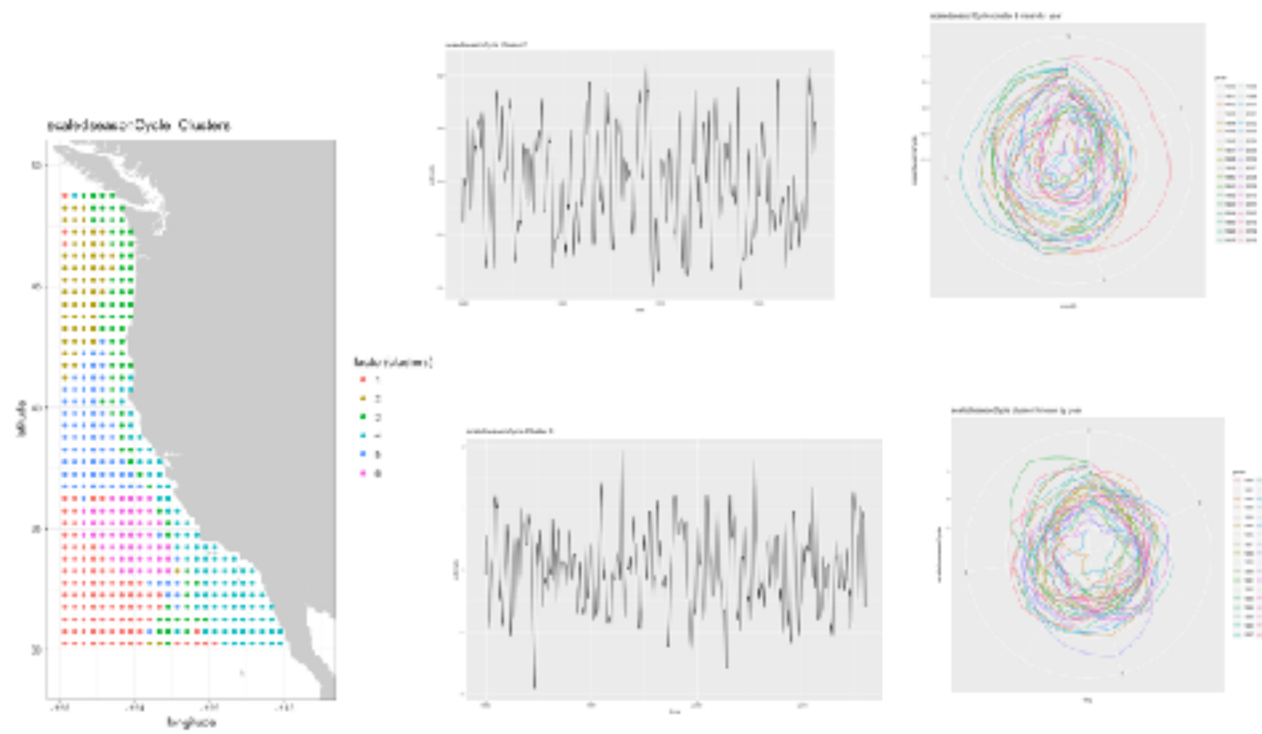
For the other variable to be looked at, the space-time model was not fit. Instead a state-space decomposition was fit to each area, and the resulting components clustered. Here monthly SODA temperature data at 75m depth, often close to the mix layer depth, The upscaled trend clusters clearly show the mean effect, the scaled ones not so clearly, but we see a warming period during the blob, but not anything out of line with previous values

SODA 70m
Seasonal + Cycle



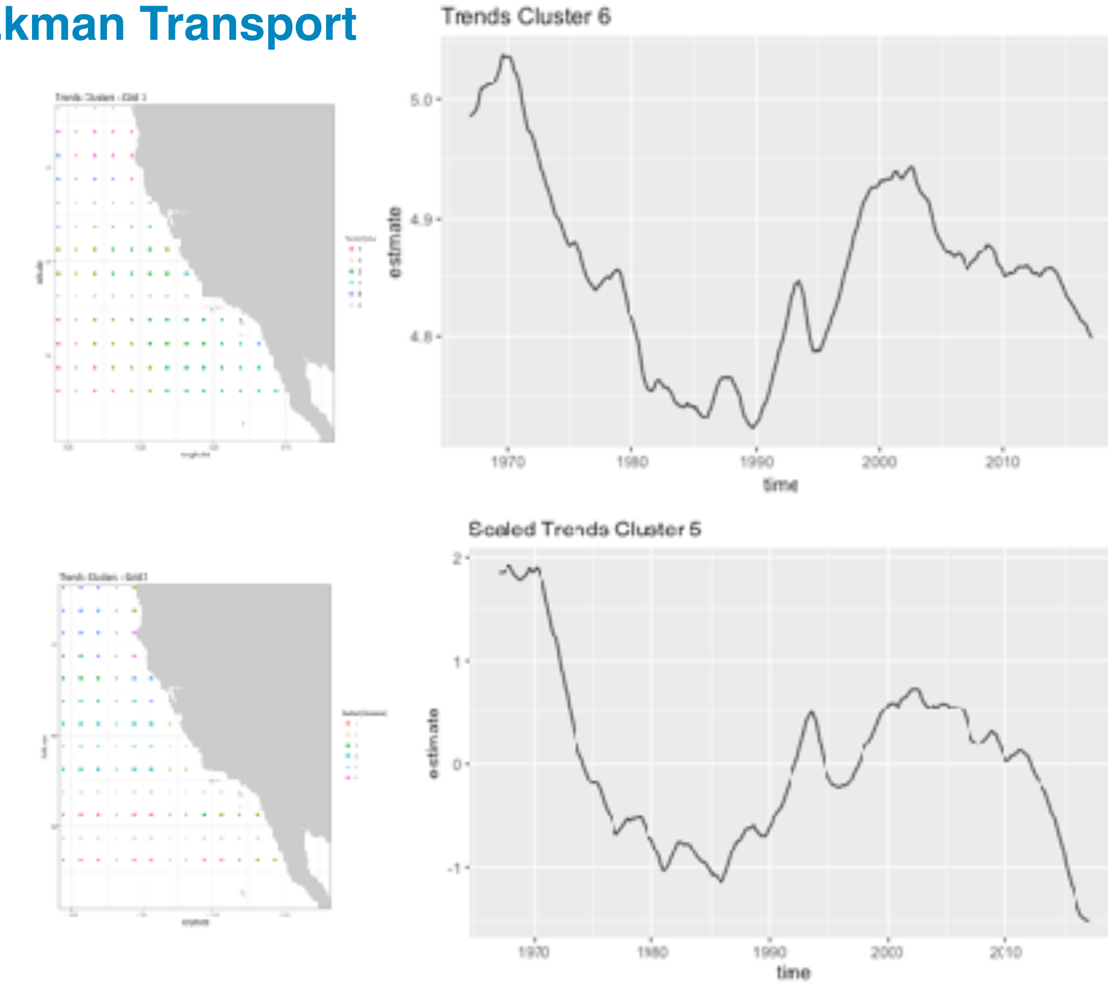
The season + cycle for the two northern clusters for SODA at 70m. Again, while a lot of variability, the main thing is a big outlier in the late years during the blob.

SODA 70m Scaled Seasonal + Cycle



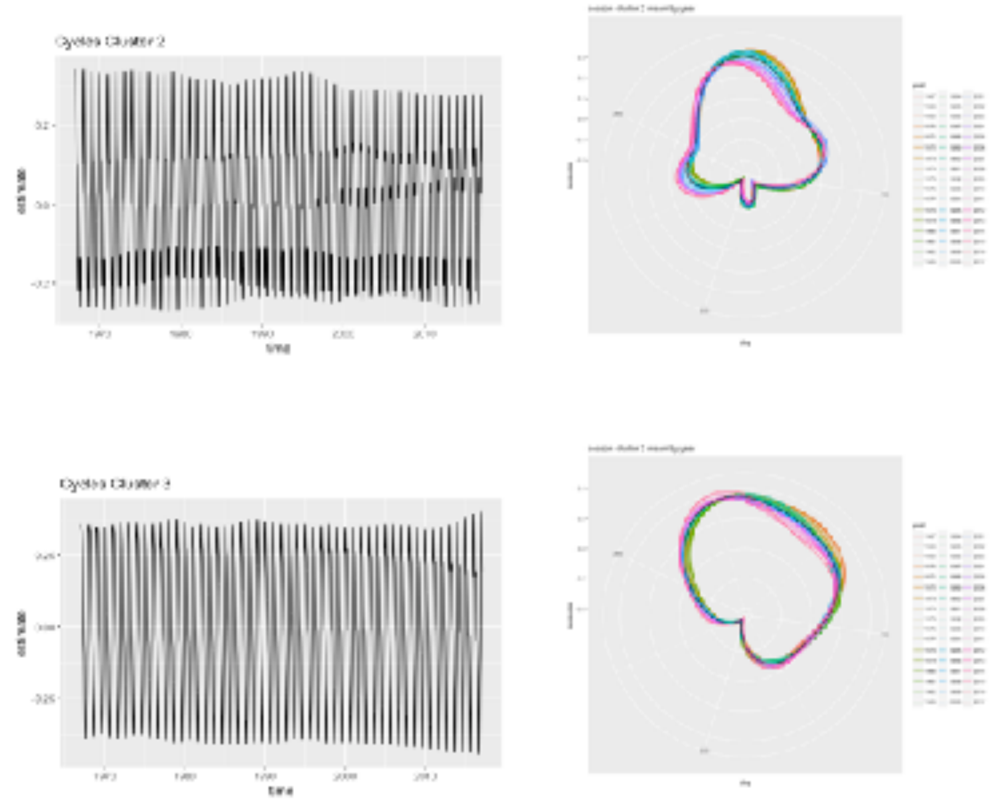
The scaled season + cycle for the two northern clusters for SODA at 70m

Ekman Transport



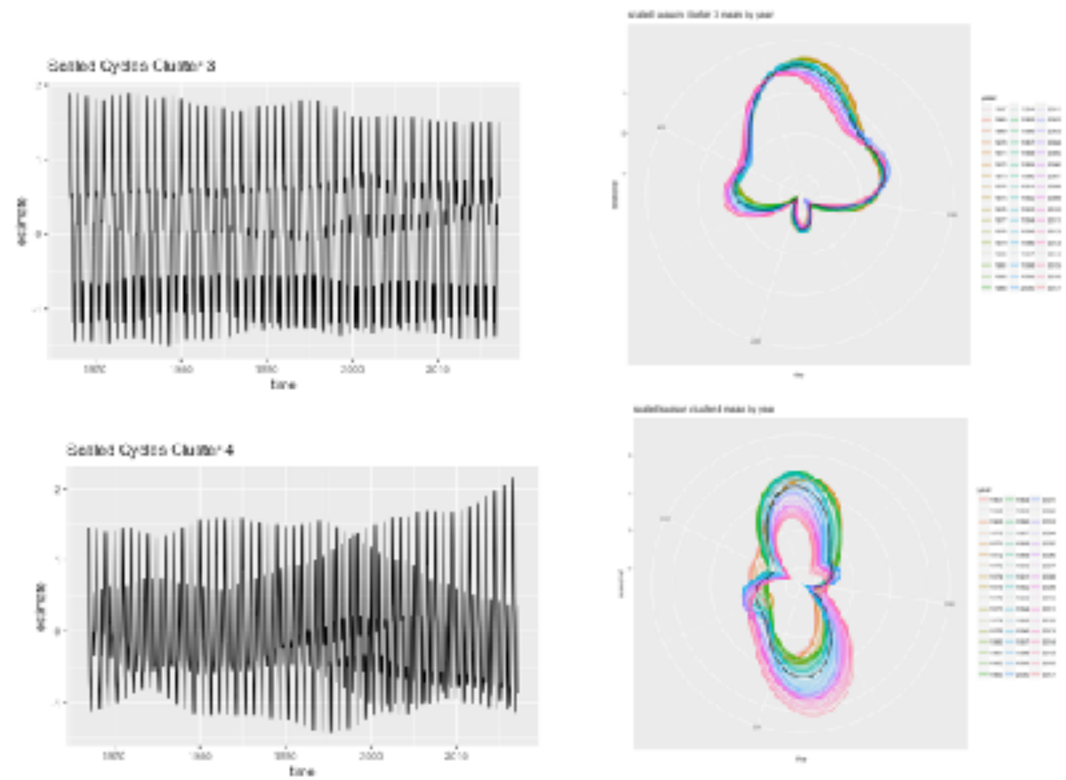
State-space decompositions were fit to daily estimates (averaged over 6-hourly data) of the y component of Ekman transport (in this region a pretty good measure of upwelling, given the coast angle). The region closest to the blob is in cluster 5, and not much in the trend would make 2012-2015 stand out, The is true for both the unscaled and scaled trends.

Ekman Transport
Seasonal + Cycle



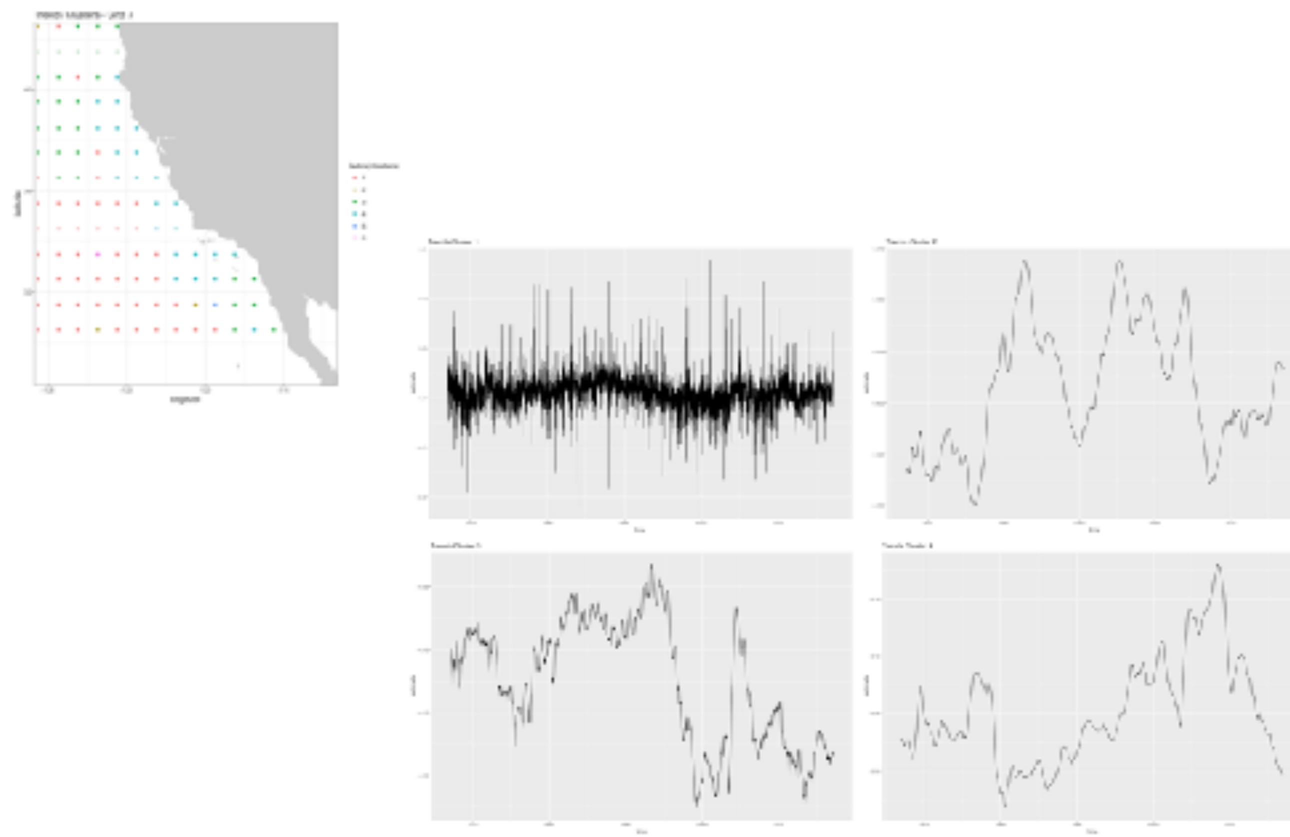
Here is the sum of the cyclic terms for Ekman transport which give the seasonal cycle. The onshore-offshore areas up north are in clusters 2 and 3, and while there is variability, nothing stands out for the period of the blob

Ekman Transport
Scaled Seasonal + Cycle



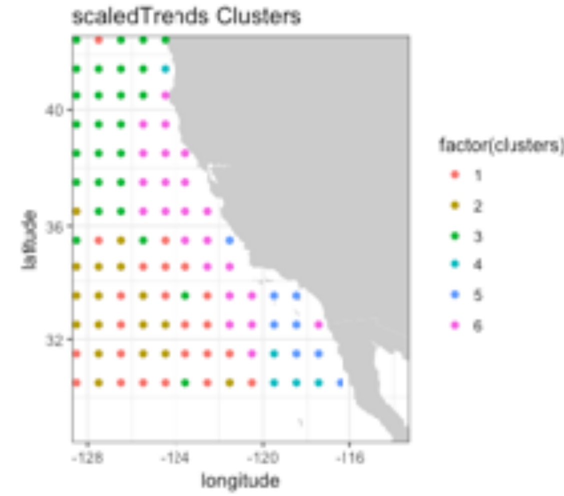
Here we look at the scaled seasonal for Ekman transport. The offshore region doesn’t have much, but the onshore region (cluster 5) shows a persistent increase during the early part of the year, and a decrease later in the year.

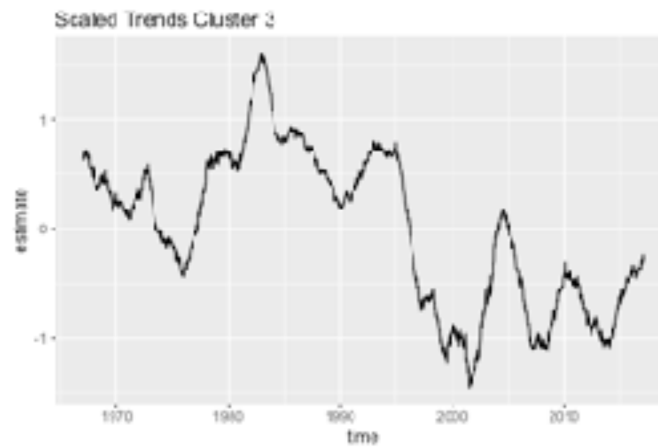
Wind Stress Curl Trends



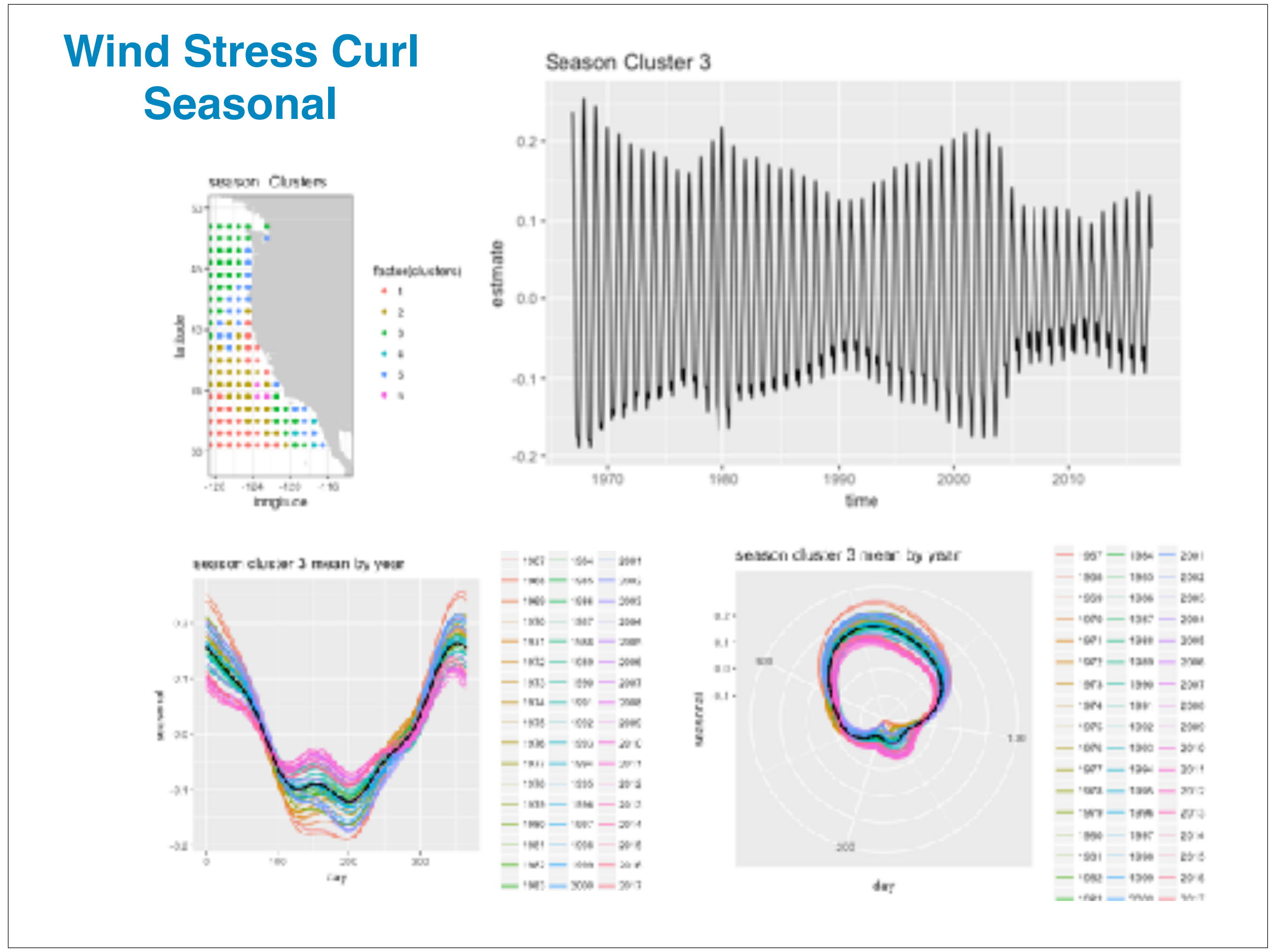
Cluster trends for Curl in the region

Wind Stress Curl Scaled Trends



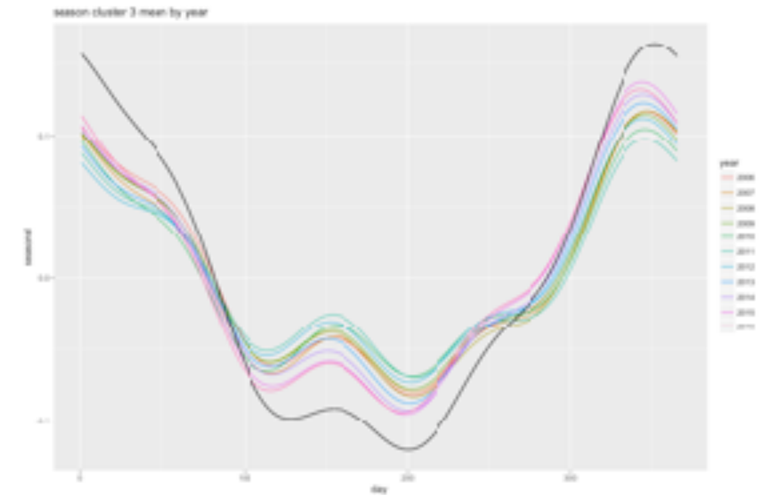


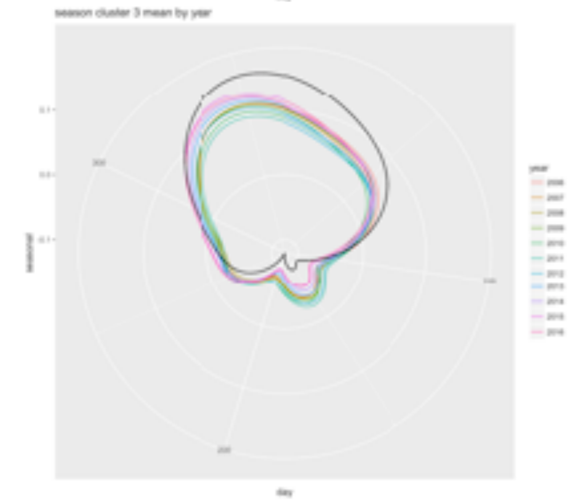
Scaled cluster trends in the region



Seasonal Cluster 3

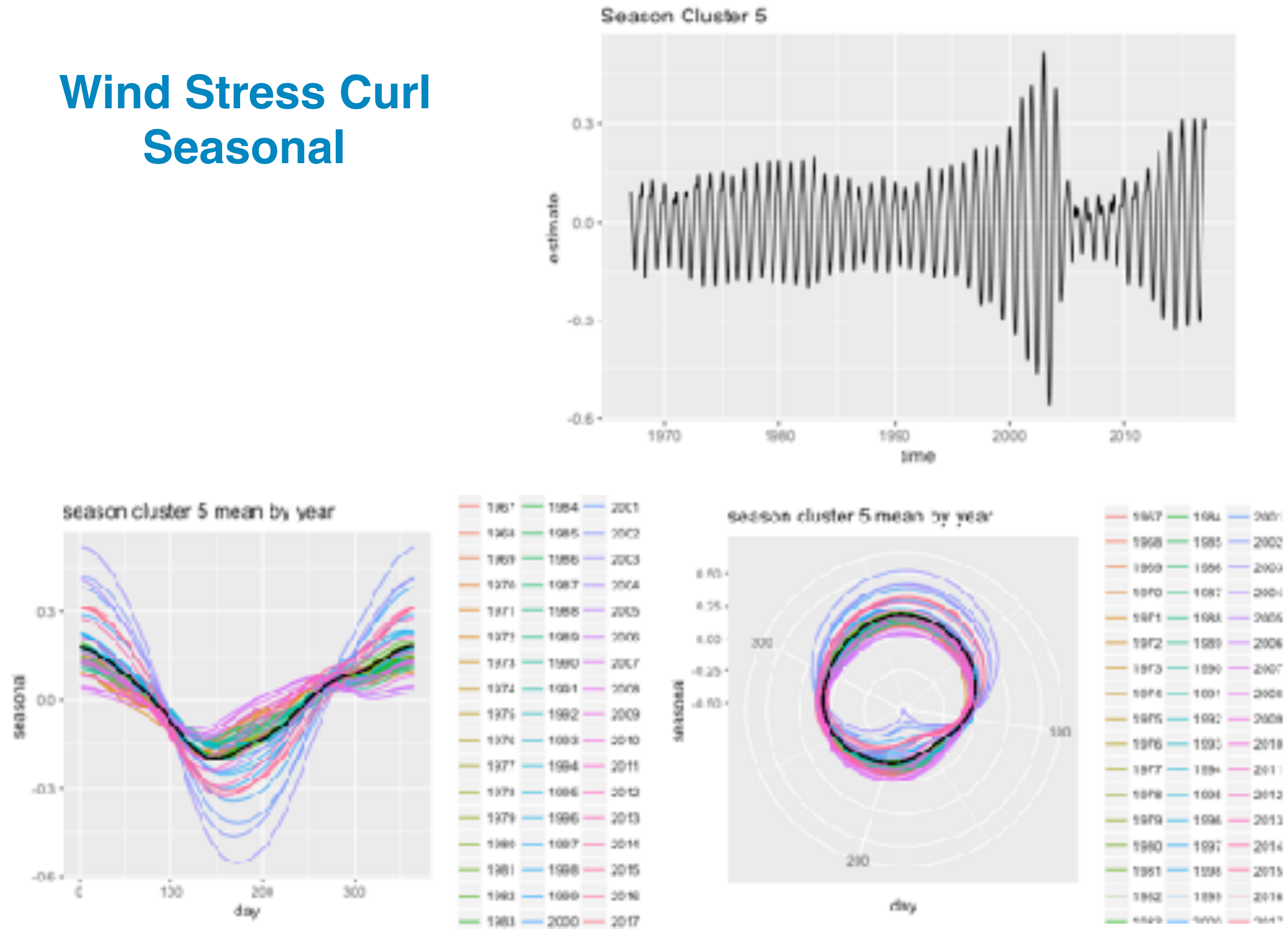
Wind Stress Curl Seasonal





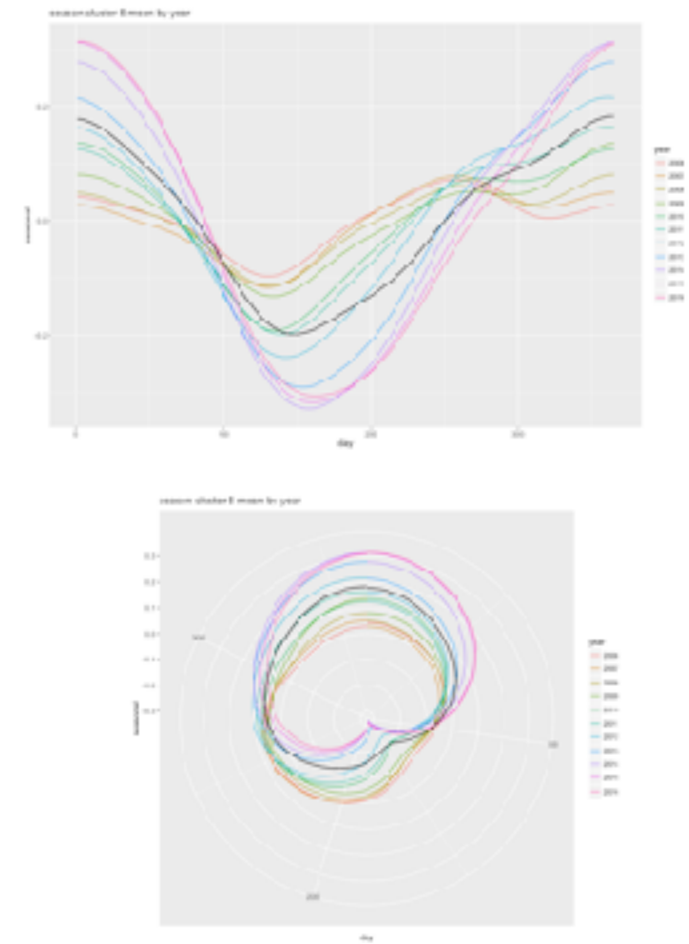
Zooming in on Curl Seasonal Cluster 3 for more recent years

Wind Stress Curl Seasonal



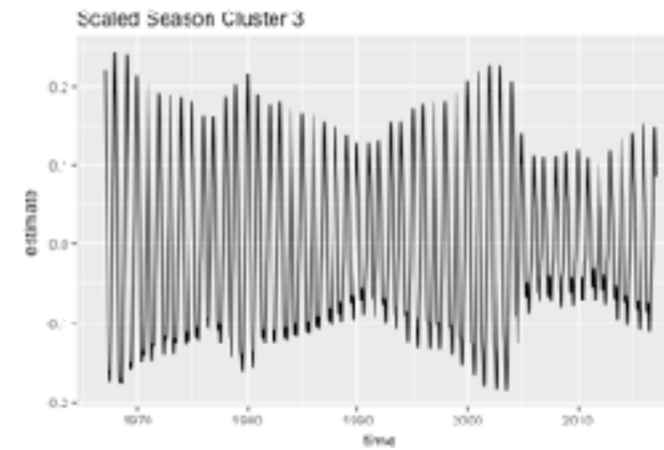
Curl Seasonal Cluster 5

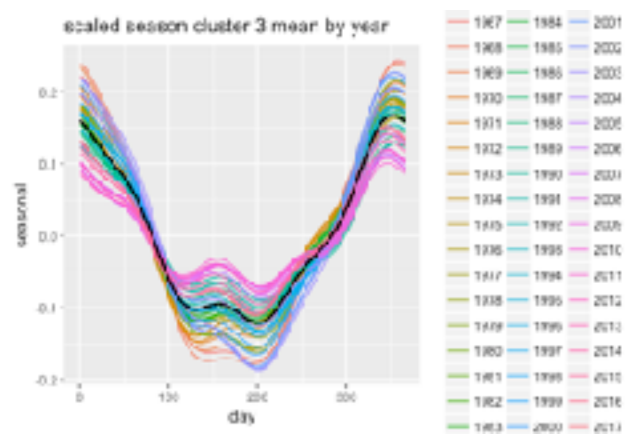
Wind Stress Curl Seasonal

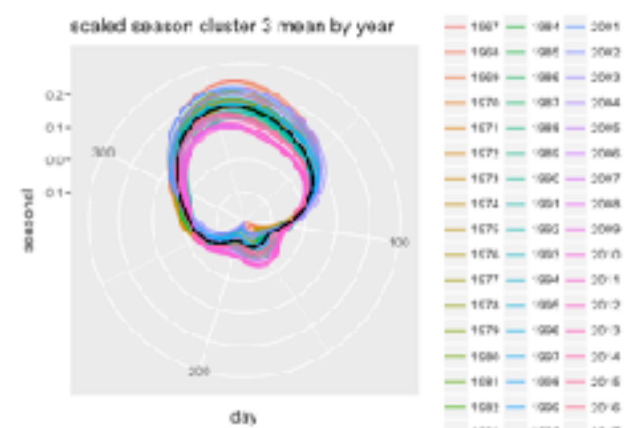


Zooming in on Curl cluster 5

Wind Stress Curl Scaled Seasonal

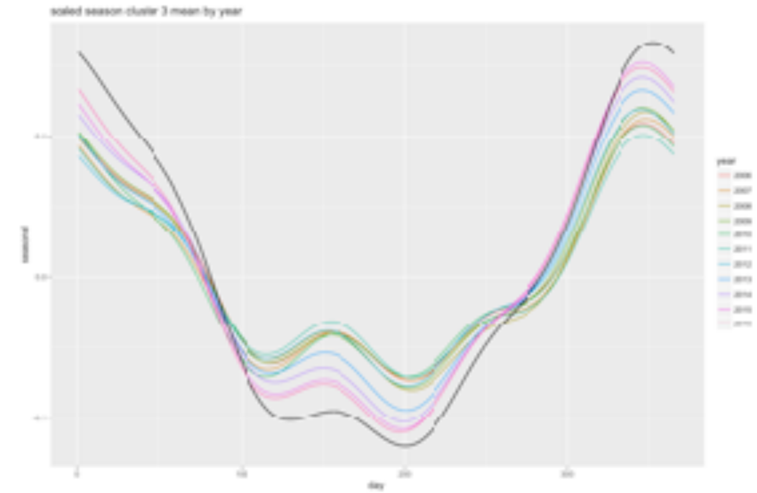


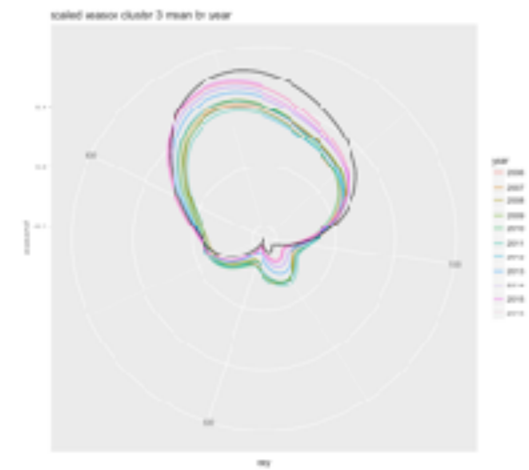




Scaled Curl Seasonal Cluster 3

Wind Stress Curl Scaled Seasonal





Zooming in on Scaled Curl Seasonal Cluster 3. The curl seasonal pattern change is consistent with our toy example

Prior to 1997-1998 a similar blob had been sitting offshore
From Schwing et al 2002

As seen throughout section 3.3, the recurring characteristic spatial relationship between atmospheric and oceanic anomalies in the CNP and NEP indicates that anomalous surface Ekman transports may have contributed to the development of oceanic anomalies. Anomalously positive (negative) wind stress curl should produce anomalous horizontal divergence (convergence) in surface Ekman transport and a shoaling (depression) of SSH and isopycnal surfaces via Ekman pumping. To test this idea, we compared the curl of the wind stress anomalies (shown as the anomaly of the mean of the daily curl fields) and SSHAs during key phases of the EN and LN events of 1995–2001.

Several previous studies have indicated that regional atmospheric forcing in the NEP is a major factor in producing oceanic anomalies during EN and LN events (e.g. Mysak, 1986; Simpson, 1992; Cayan, 1992; Miller et al., 1994). The characteristic spatial relationship between wind curl and SSH anomalies in the NEP (Fig. 14) and between anomalies in SLP, low-level winds, and upper ocean temperature (Figs. 6 and 8–13) indicate that anomalous Ekman transports may have been important factors in developing oceanic anomalies. Specifically, temperature advection resulting from vertical and horizontal Ekman transport appears to have contributed to upper ocean temperature anomalies in the CNP and NEP.

before the 1997-1998 El Nino, a similar blob of warm water had been sitting off-shore for a year or more. In progress of Oceanography, 2002, Schwing et al, commented on the possible role of wind stress curl in causing this.