

A wavelet based approach to climate biome clustering

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August 7, 2018

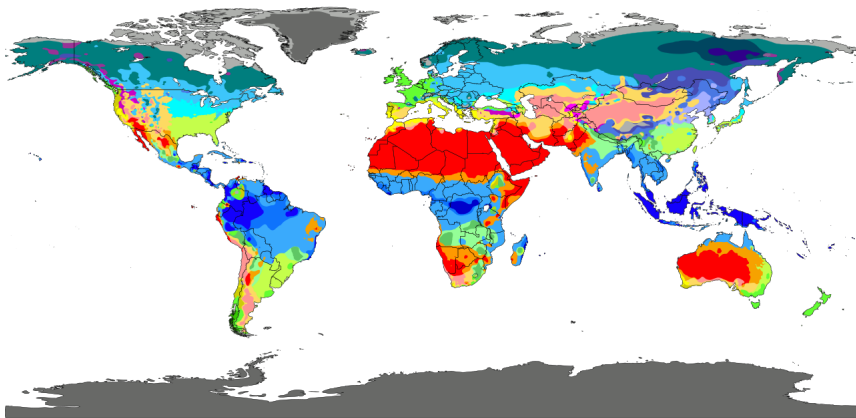
Type	Description	Criterion
A	Equatorial climates	$T_{\min} \geq +18\text{ }^{\circ}\text{C}$
Af	Equatorial rainforest, fully humid	$P_{\min} \geq 60\text{ mm}$
Am	Equatorial monsoon	$P_{\text{ann}} \geq 25(100 - P_{\min})$
As	Equatorial savannah with dry summer	$P_{\min} < 60\text{ mm in summer}$
Aw	Equatorial savannah with dry winter	$P_{\min} < 60\text{ mm in winter}$
B	Arid climates	$P_{\text{ann}} < 10 P_{\text{th}}$
BS	Steppe climate	$P_{\text{ann}} > 5 P_{\text{th}}$
BW	Desert climate	$P_{\text{ann}} \leq 5 P_{\text{th}}$
C	Warm temperate climates	$-3\text{ }^{\circ}\text{C} < T_{\min} < +18\text{ }^{\circ}\text{C}$
Cs	Warm temperate climate with dry summer	$P_{\text{smin}} < P_{\text{wmin}}, P_{\text{wmax}} > 3 P_{\text{smin}}$ and $P_{\text{smin}} < 40\text{ mm}$
Cw	Warm temperate climate with dry winter	$P_{\text{wmin}} < P_{\text{smin}}$ and $P_{\text{smax}} > 10 P_{\text{wmin}}$
Cf	Warm temperate climate, fully humid	neither Cs nor Cw
D	Snow climates	$T_{\min} \leq -3\text{ }^{\circ}\text{C}$
Ds	Snow climate with dry summer	$P_{\text{smin}} < P_{\text{wmin}}, P_{\text{wmax}} > 3 P_{\text{smin}}$ and $P_{\text{smin}} < 40\text{ mm}$
Dw	Snow climate with dry winter	$P_{\text{wmin}} < P_{\text{smin}}$ and $P_{\text{smax}} > 10 P_{\text{wmin}}$
Df	Snow climate, fully humid	neither Ds nor Dw
E	Polar climates	$T_{\text{max}} < +10\text{ }^{\circ}\text{C}$
ET	Tundra climate	$0\text{ }^{\circ}\text{C} \leq T_{\text{max}} < +10\text{ }^{\circ}\text{C}$
EF	Frost climate	$T_{\text{max}} < 0\text{ }^{\circ}\text{C}$

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└ Learning Climate Biomes

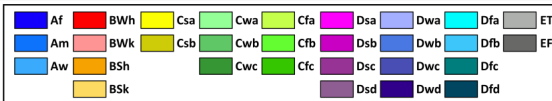
└ Köppen-Gieger Model

World map of Köppen-Geiger climate classification



Peel, M. C. and Finlayson, B. L.
and McMahon, T. A. (2007)
(University of Melbourne)

Vectorization by : Ali Zifan



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- *Detect where biomes are shifting*
- *Want a data driven model*

Supervised Learning: Discover salient features of data to separate into predetermined classes - Data comes with labels.

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- Data does **not** come with labels.

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Given an image of a leaf, determine which tree (from a predetermined list) it came from.

Unsupervised Learning: Discover classes hidden in the data
- Data does **not** come with labels.

Example

Given images of leaves, automatically sort images into bins based of features (not set or necessarily known).

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- *Generically speaking, supervised is “easier” than unsupervised*
- *Large scale unsupervised learning is notoriously difficult (AKA prohibitively expensive):*

$$K\text{-means} \sim \mathcal{O}(K * \text{number data} * \text{dim})$$

Example

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- *Taking DWT:*

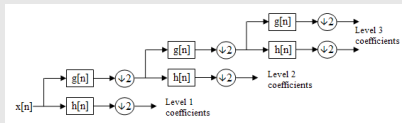
$$g_1 = [1, 2, 0.25, 0, 2]$$

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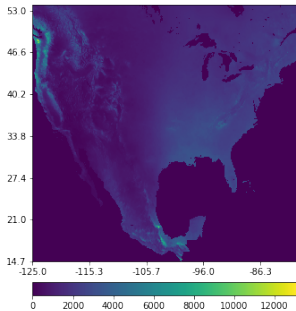
- Let $f = [1, 1, 2, 2, .5, 0, 0, 0, 3, 1]$.
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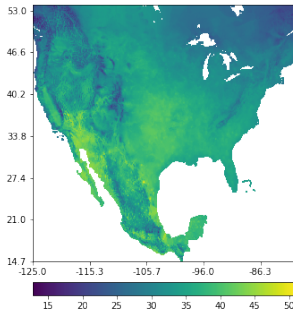


LOCA Data: 1950-1970

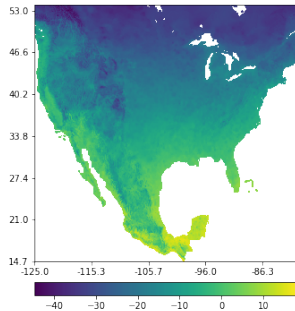
Prec Sum:



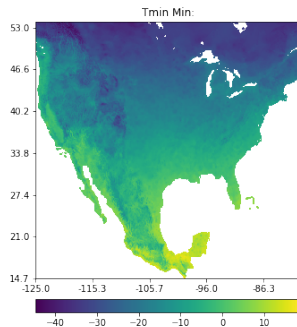
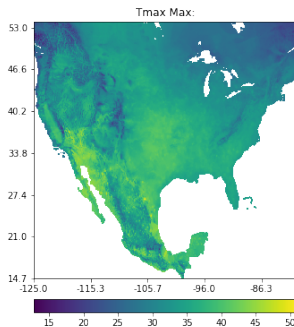
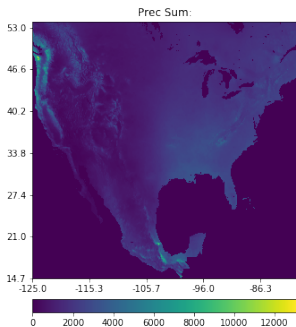
Tmax Max:



Tmin Min:



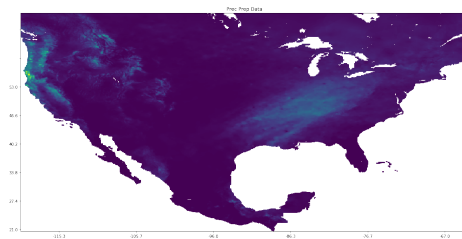
LOCA Data: 1950-1970



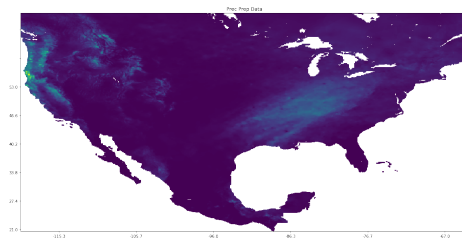
Choose wavelets:

- Space: Haar
- Time: db2

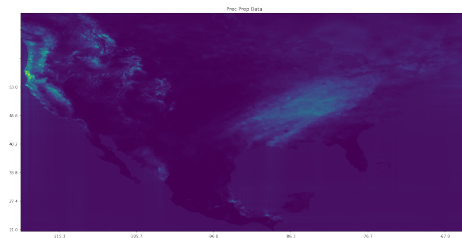
Prec Data: $t=0$



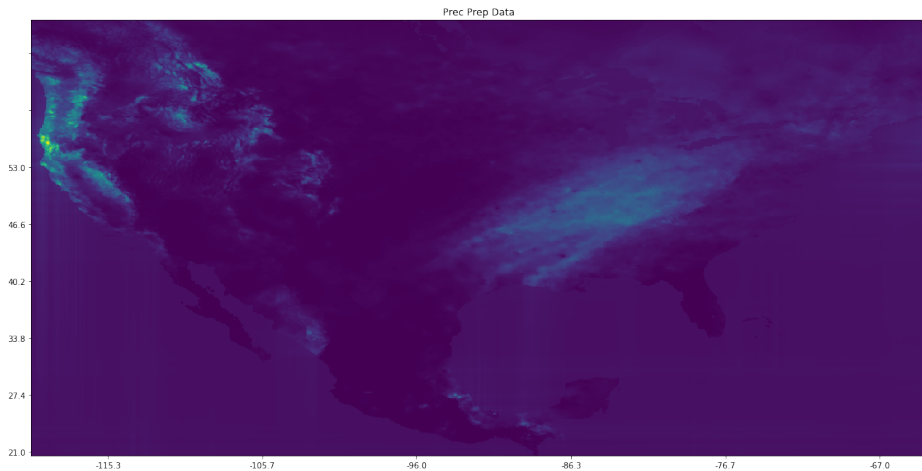
Prec Data: $t=0$



Interpolate Nan:

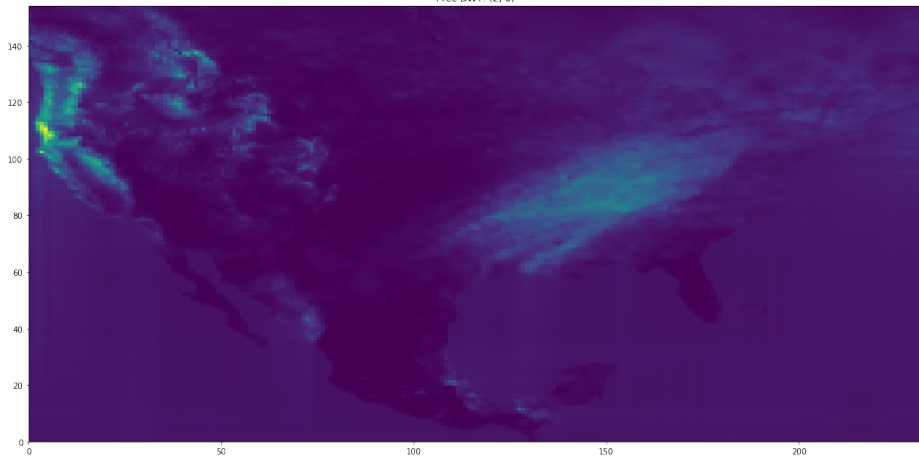


Interpolate Nan:



DWT: 2 space, 0 time

Prec DWT: (2, 0)

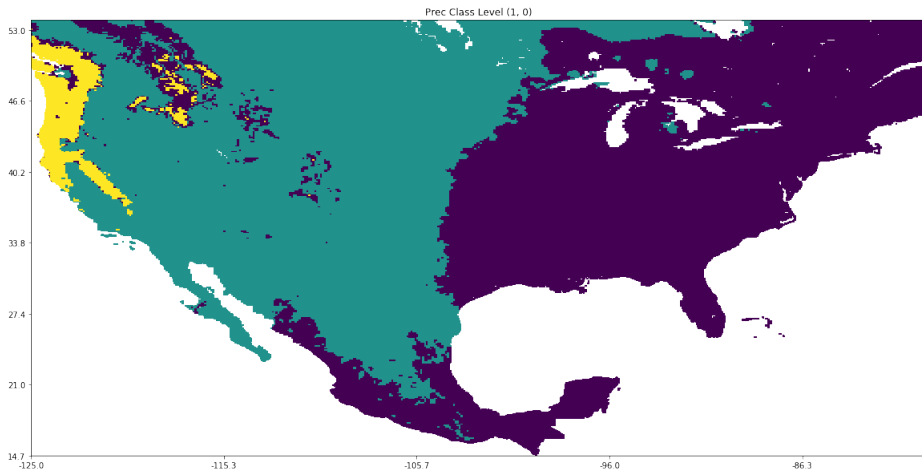


- Locate data values corresponding to non-NAN values (with ϵ boundary)

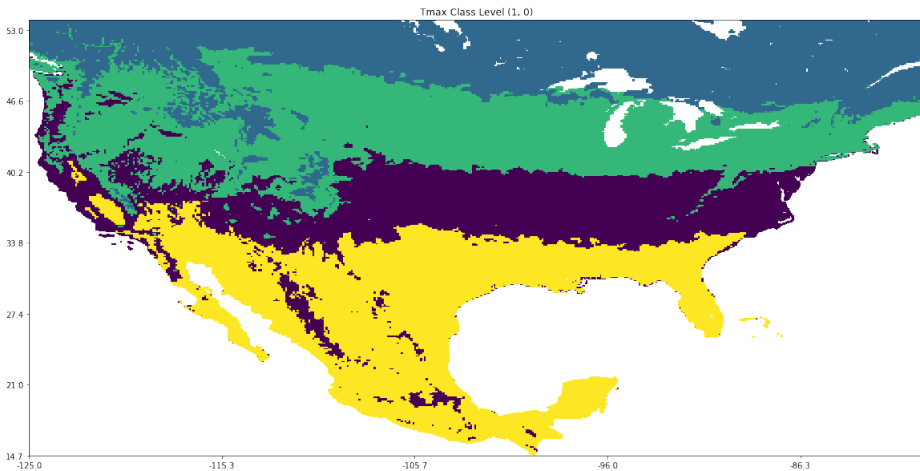
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- Cluster the approximation coefficients for each variable
 - Settled on K-means
 - Determined number of clusters using silhouette and Calinski Harabaz scores
 - Used 3 clusters for Prec, 4 clusters for Tmin and Tmax

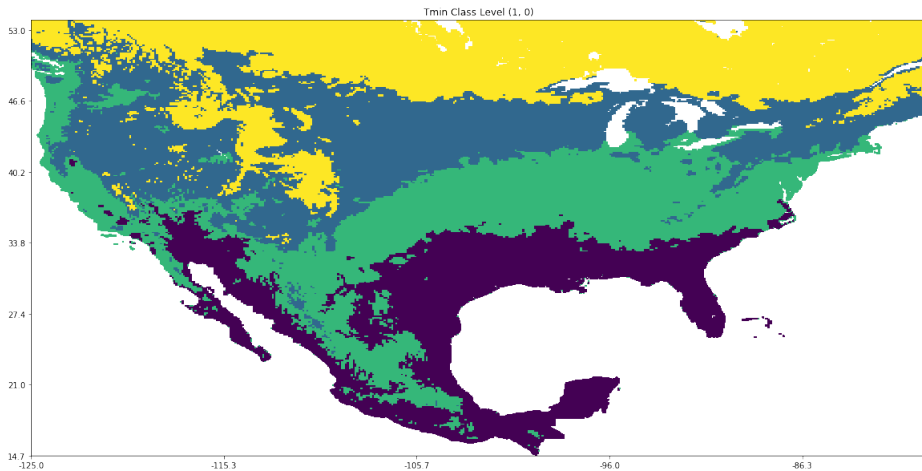
Data Clusters (1,0): 1950-1970



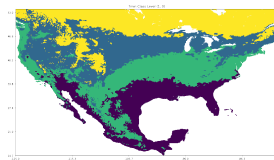
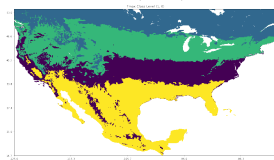
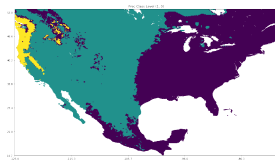
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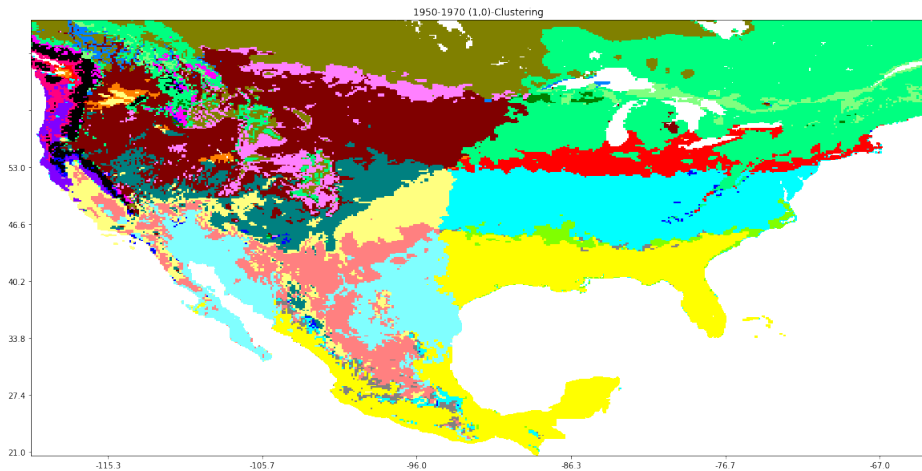
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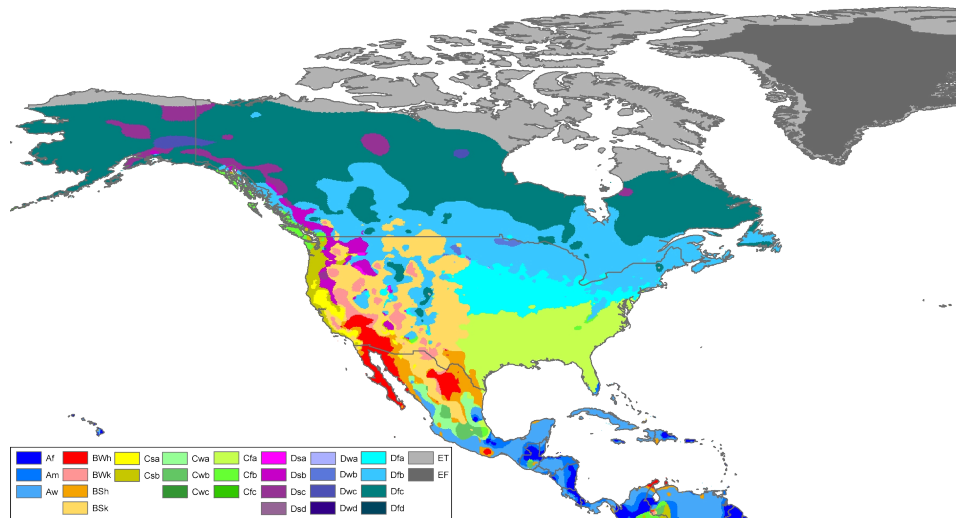
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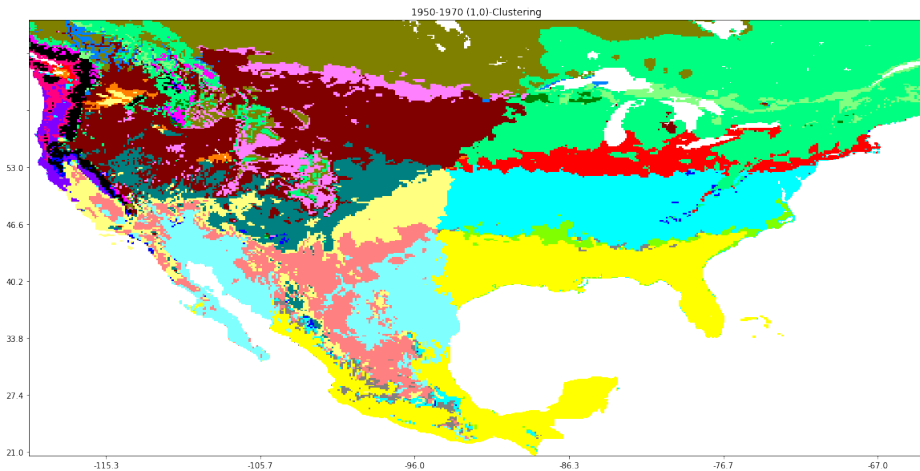
Combined Data Clusters (1,0): 1950-1970



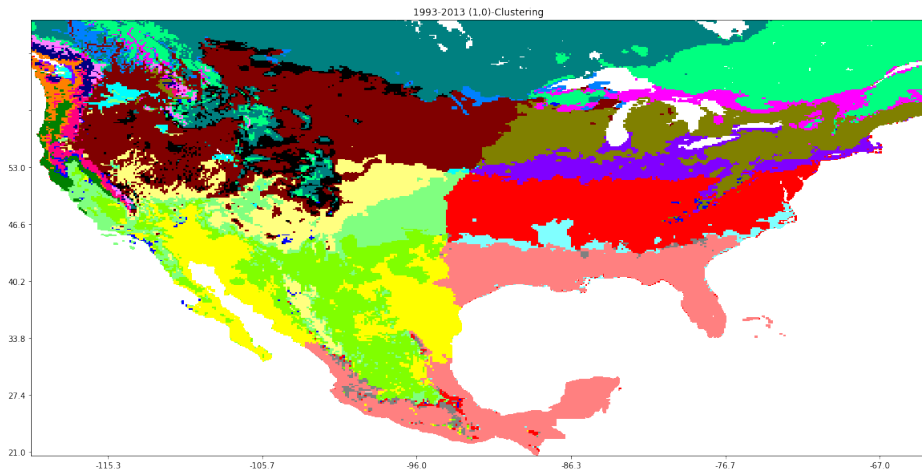
North America Köppen-Gieger Model



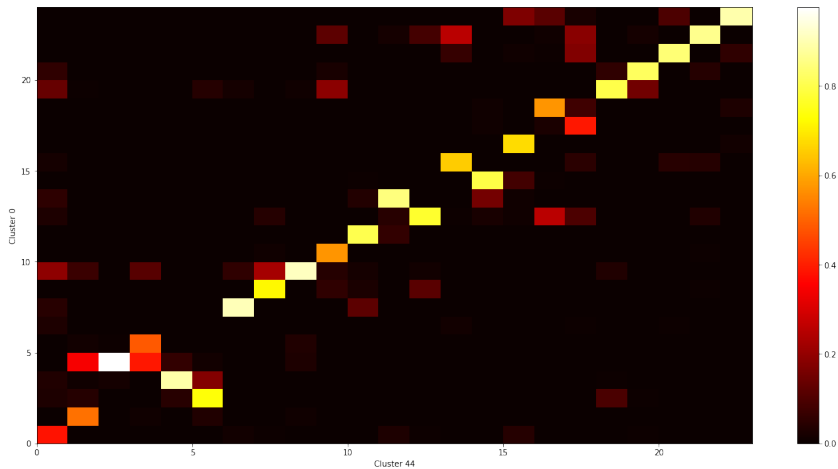
Combined Data Clusters (1,0): 1950-1970



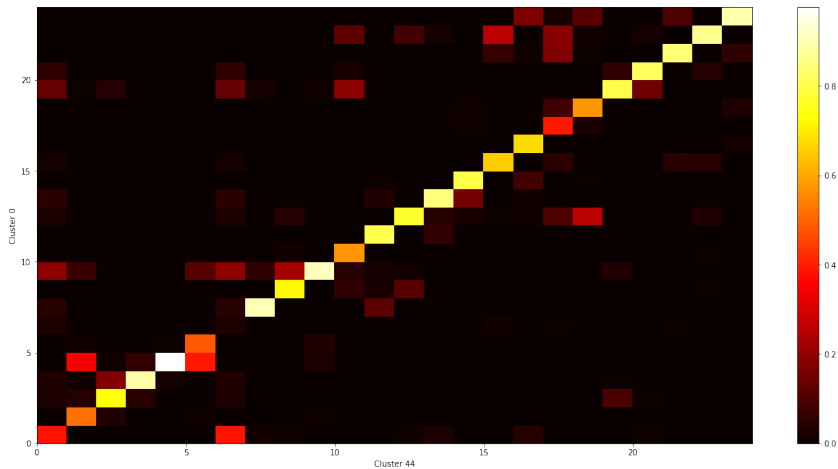
Combined Data Clusters (1,0): 1993-2013



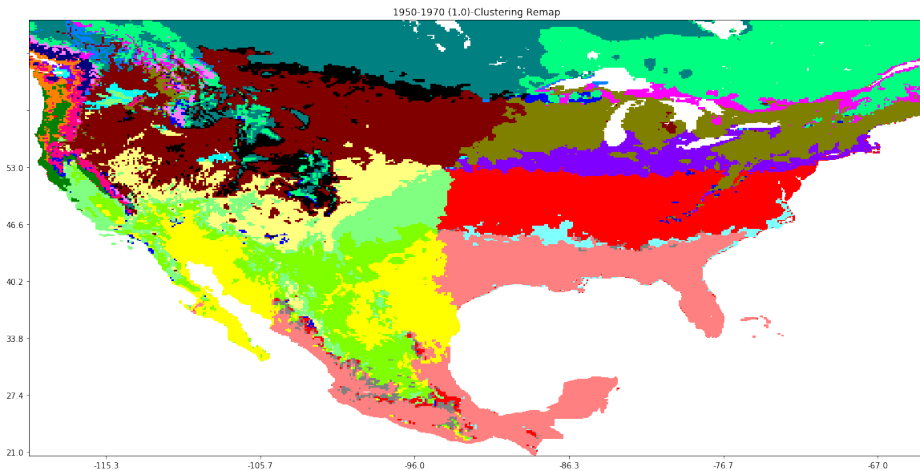
Correlation Between 1950-1970 Clusters and 1993-2013 Clusters



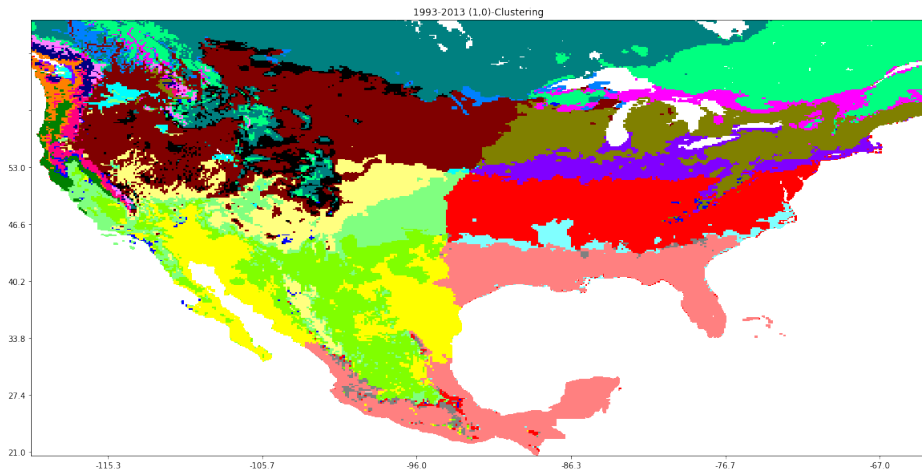
Sorted Correlation Between 1950-1970 Clusters and 1993-2013 Clusters



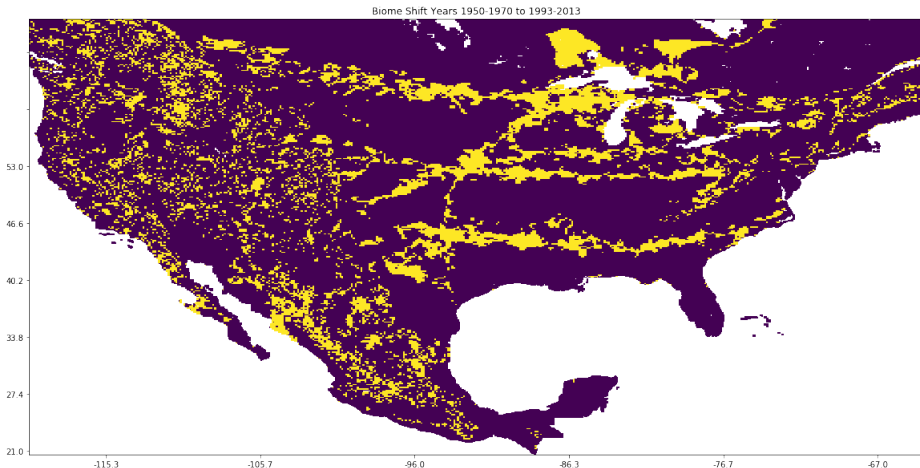
Reindex Combined Data Clusters (1,0): 1950-1970



Combined Data Clusters (1,0): 1993-2013



Difference Between 1950-1970 Clusters and 1993-2013 Clusters



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- 3 Perform an analytical comparison to the Köppen-Gieger Model
- 4 Apply this clustering method to the ocean data