# Robust and interpretable unsupervised machine learning techniques for analyzing the climate system

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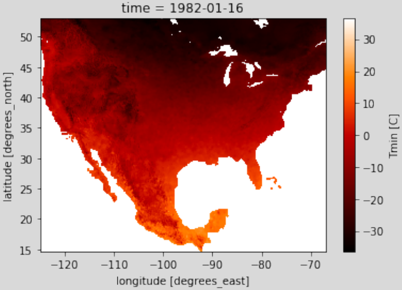
Figure: OpenAI CoastRunners misspecified reward function




- Gridded climate data set of North America.
- Grid cell is monthly data from 1950-2013, six kilometers across.
- Available variables used: precipitation, maximum temperature, minimum temperature.

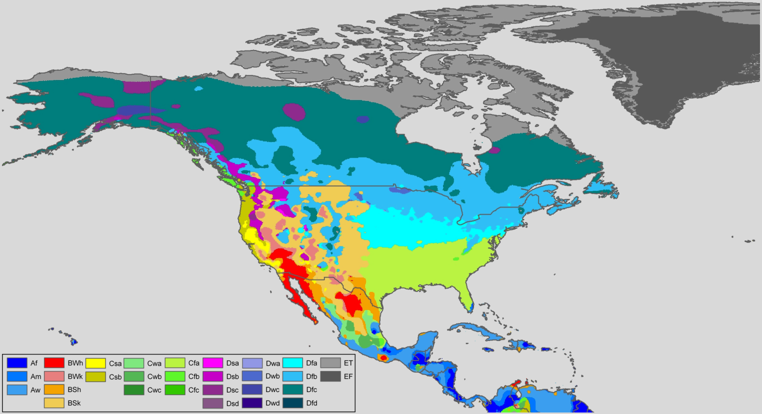



Figure: Köppen-Geiger map of North America (Peel et. al.)

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- The cut-offs in model are, to some extent, arbitrary.
- No universal agreement to how many classes there should be.

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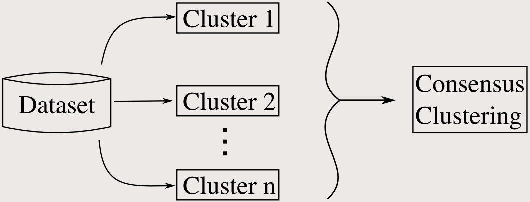


Figure: Many clusterings combined into a single **consensus clustering**.

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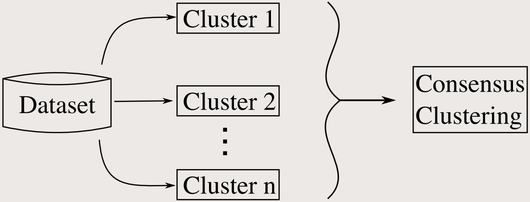


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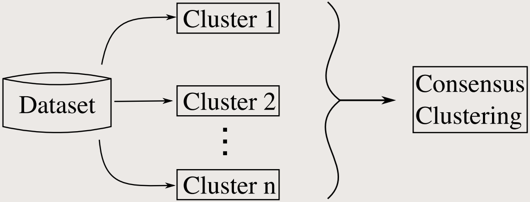


Figure: Many clusterings combined into a single **consensus clustering**.

- Clustering ill-posed - lack measurement of “trust”.
- Dependence on “hidden parameters” - **scale of data**.

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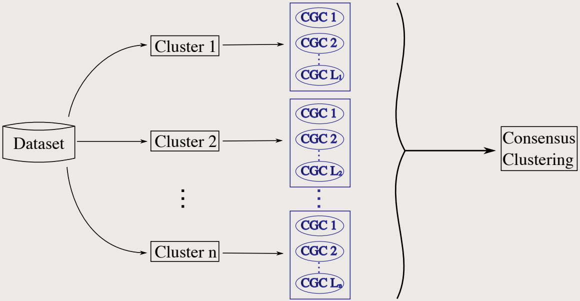

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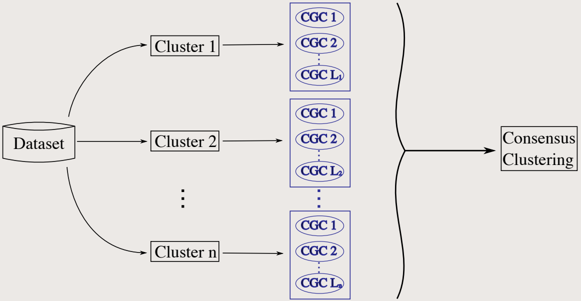


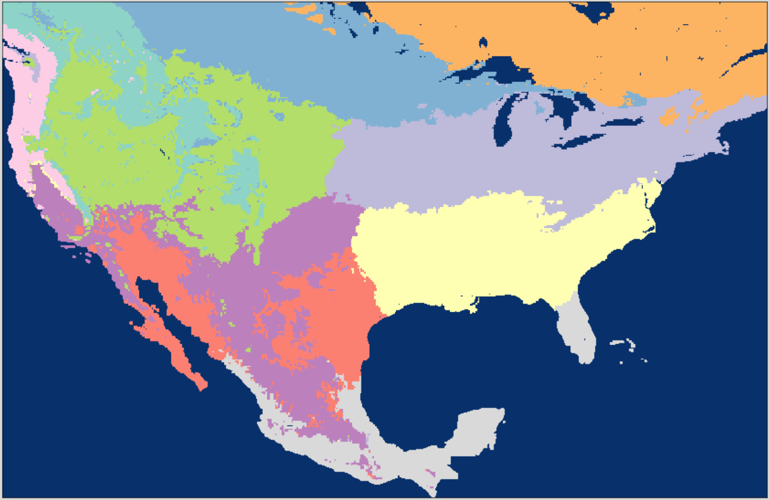


Figure: CGC: K-means $k = 10$, $(\ell_s, \ell_t) = (1, 1)$

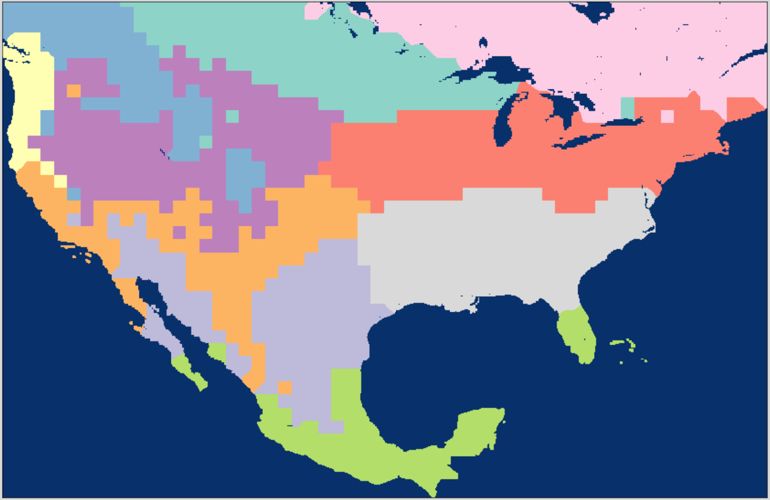
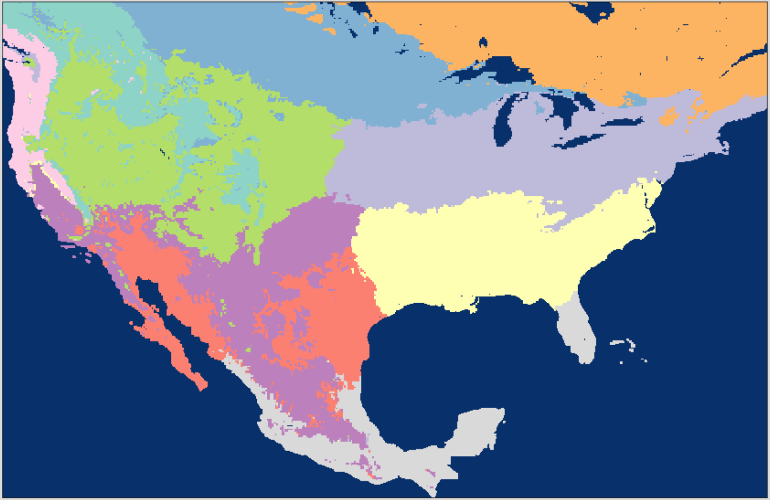


Figure: CGC: K-means $k = 10$, $(\ell_s, \ell_t) = (4, 1)$



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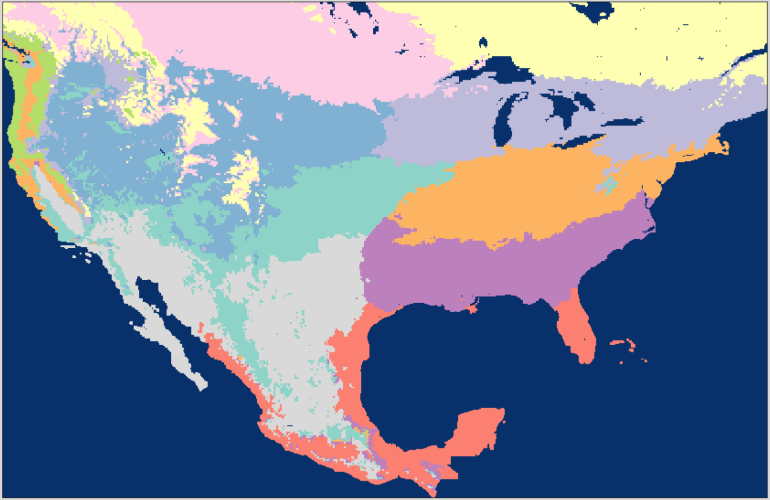
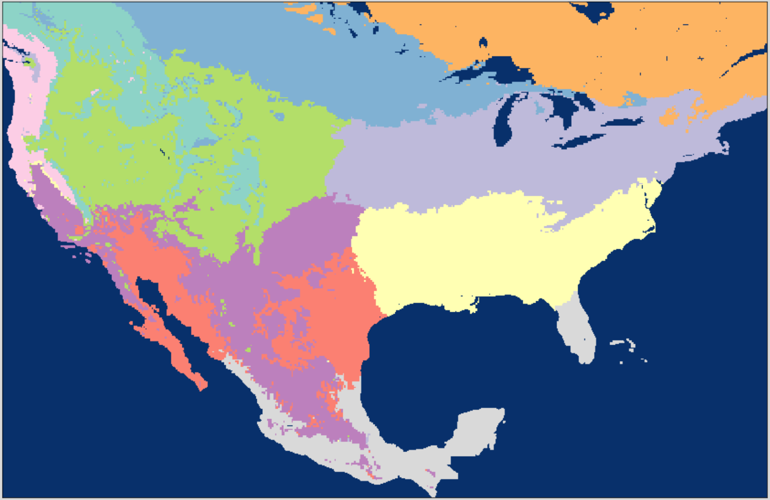


Figure: CGC: K-means $k = 10$, $(\ell_s, \ell_t) = (1, 6)$



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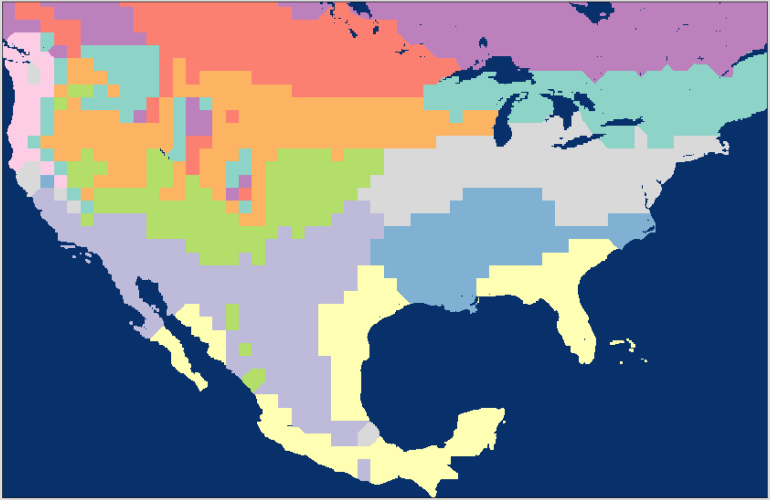

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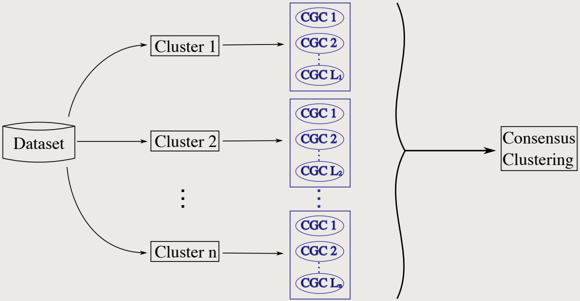

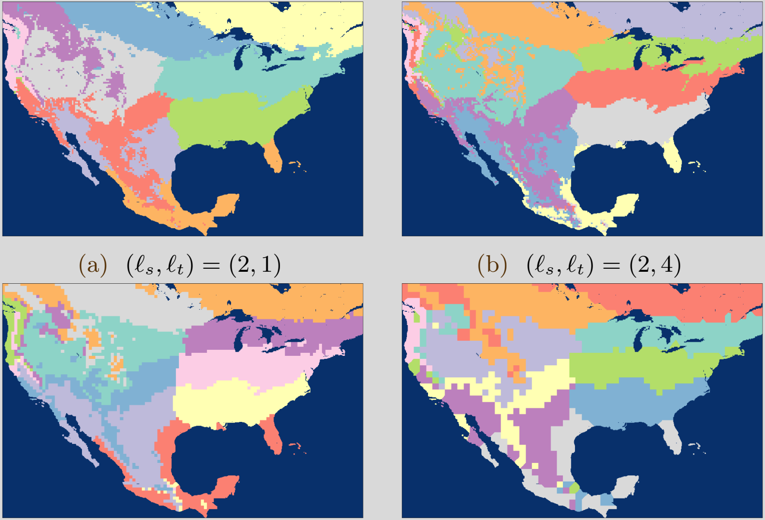

(a) $(\ell_s, \ell_t) = (2, 1)$

(b) $(\ell_s, \ell_t) = (2, 4)$

(c) $(\ell_s, \ell_t) = (3, 5)$

(d) $(\ell_s, \ell_t) = (4, 4)$

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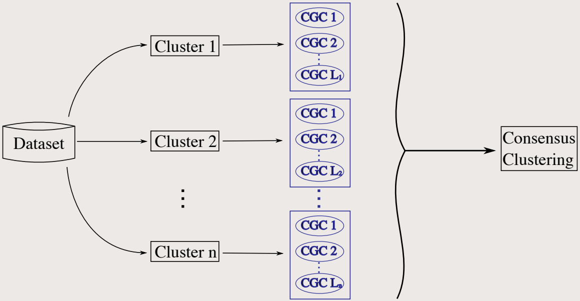


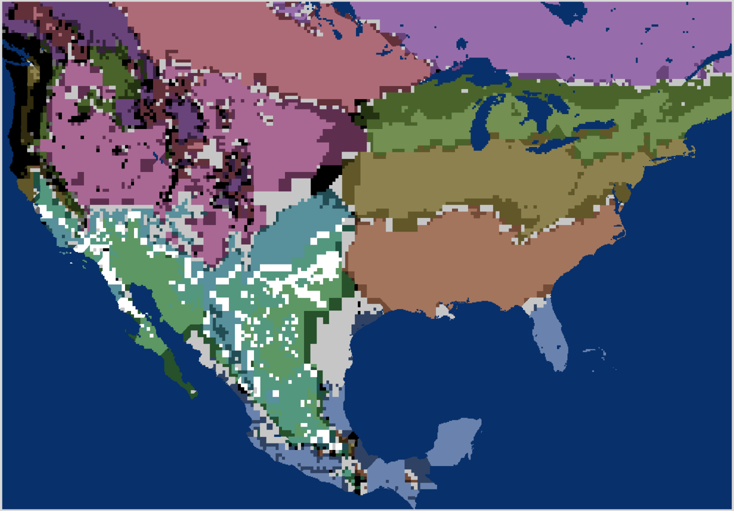
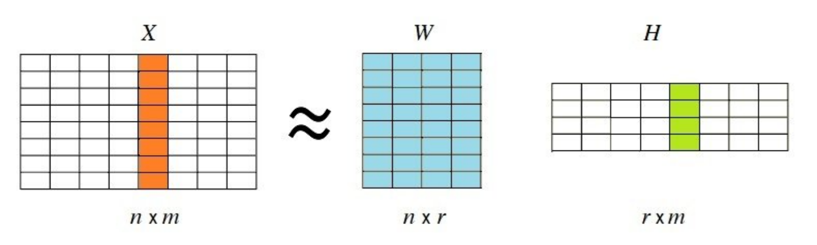


Figure: Consensus clustering from reduced ensemble of clusters for k=10, along with the trust. Grey = multi-class. Darker hue = lower trust.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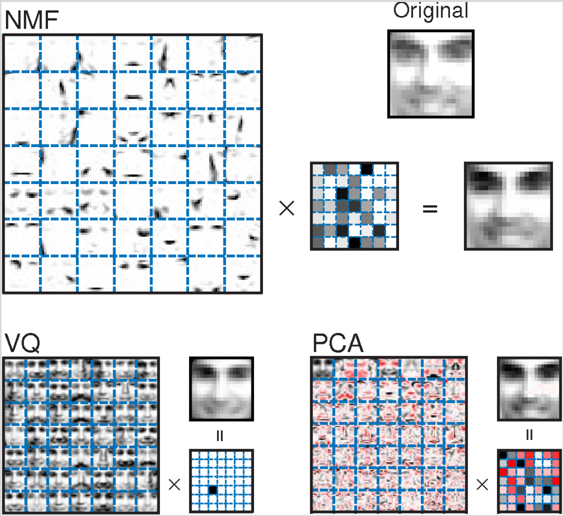
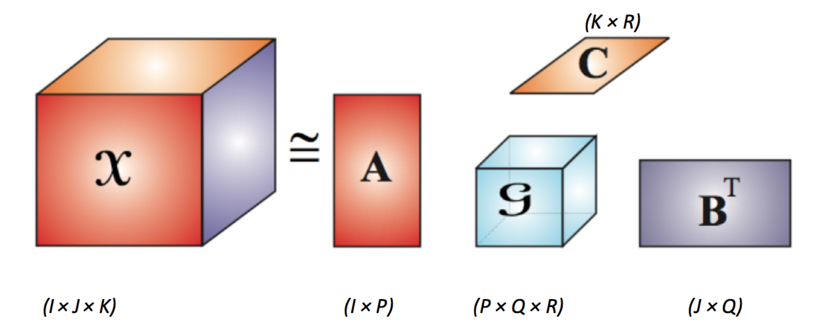



Figure: NMF versus other matrix decompositions (Lee, Seung)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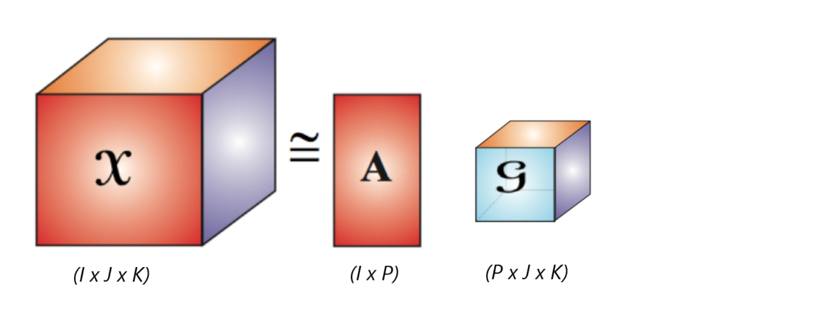
(I × J × K)
(I × P)
(P × Q × R)
(J × Q)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$\cong$
A
$\mathcal{G}$
(I x J x K)
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- At a certain point, one is fitting noise and not signal

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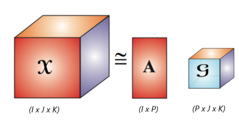
- NTF is finding interpretable climate signals



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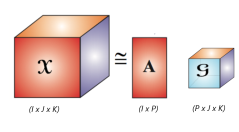


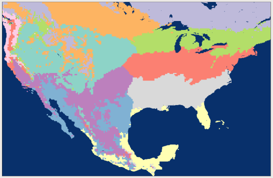

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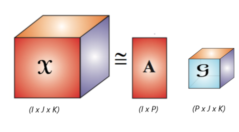


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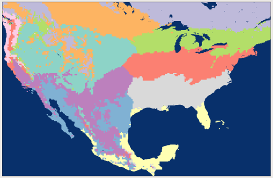
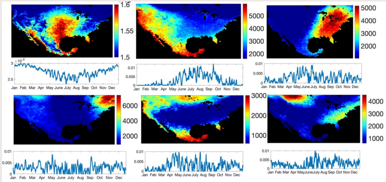


- Can we discover latent signatures of El Nino/La Nina?



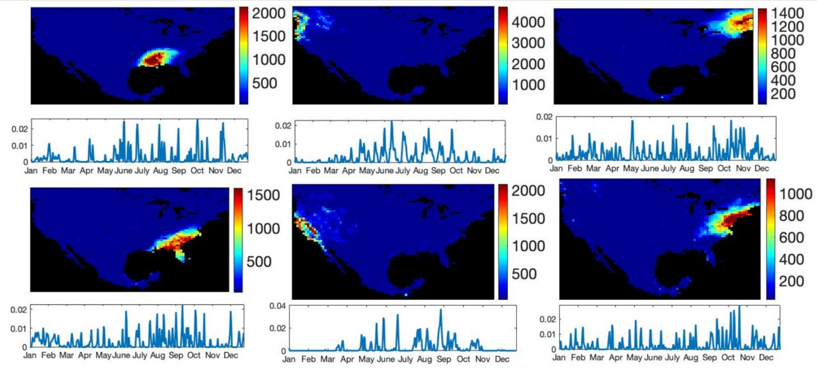
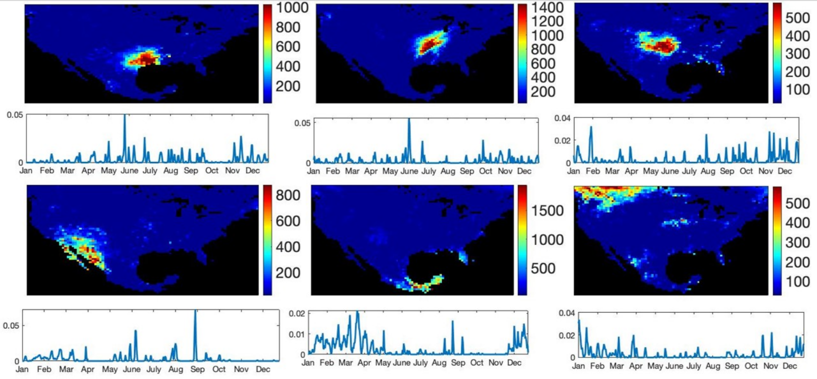



Figure: 1982 Precipitation Modes

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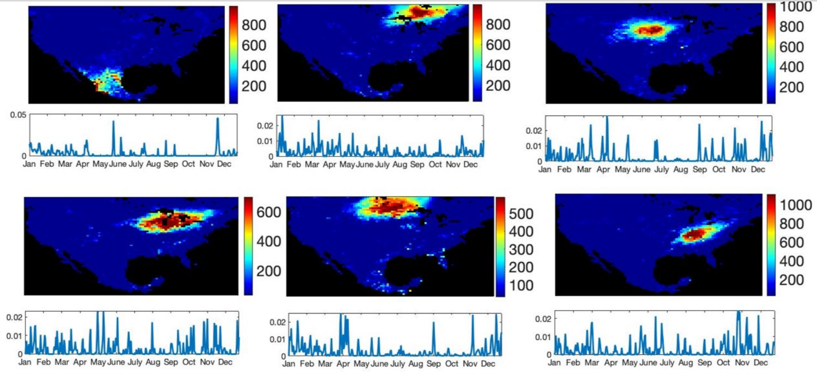


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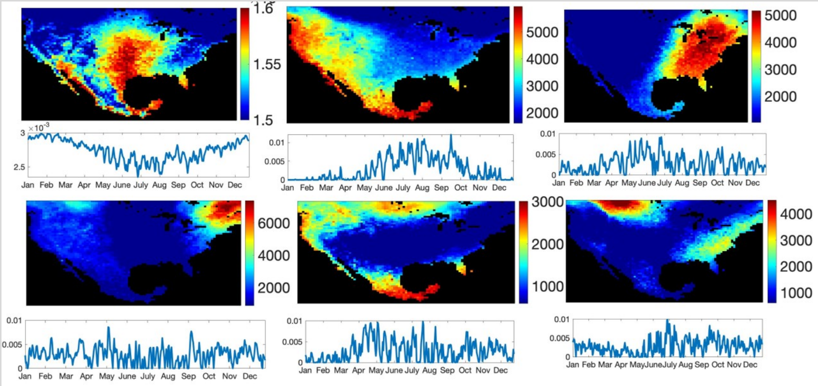


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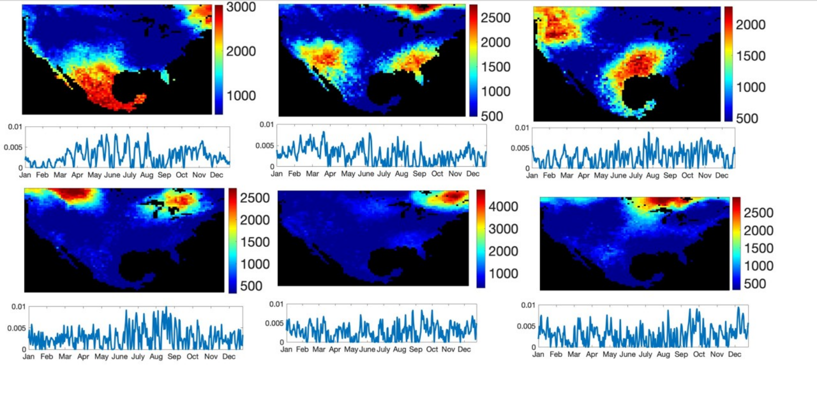
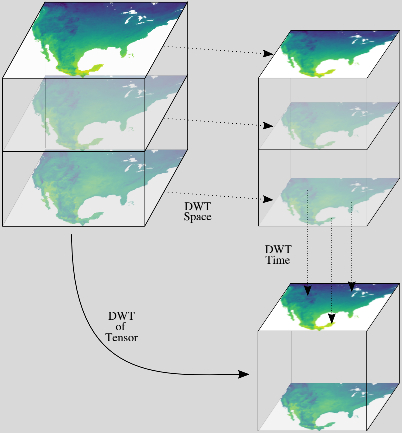



Figure: 1982 Temperature Modes

- The DWT splits a signal into high and low frequency
- Low temporal signal captures climatology (seasons, years, decades), while low spatial signal captures regional features(city, county, state).



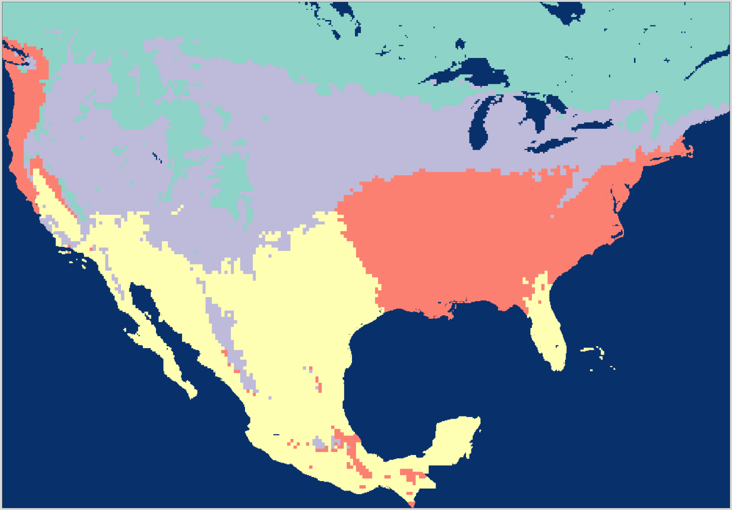


Figure: CGC: K-means $k = 4$, $(\ell_s, \ell_t) = (2, 3)$

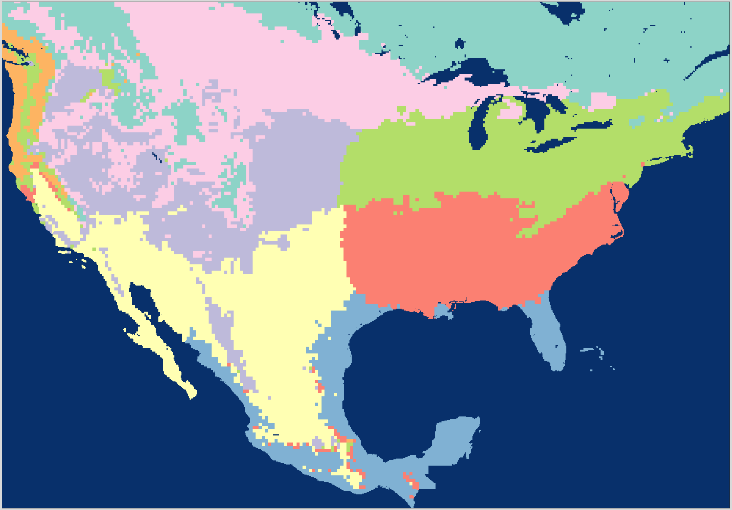


Figure: CGC: K-means $k = 8$, $(\ell_s, \ell_t) = (2, 3)$

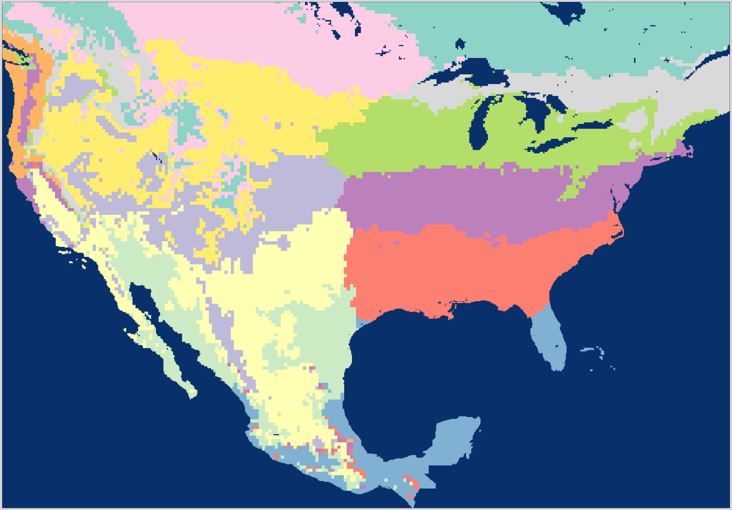


Figure: CGC: K-means $k = 12$, $(\ell_s, \ell_t) = (2, 3)$

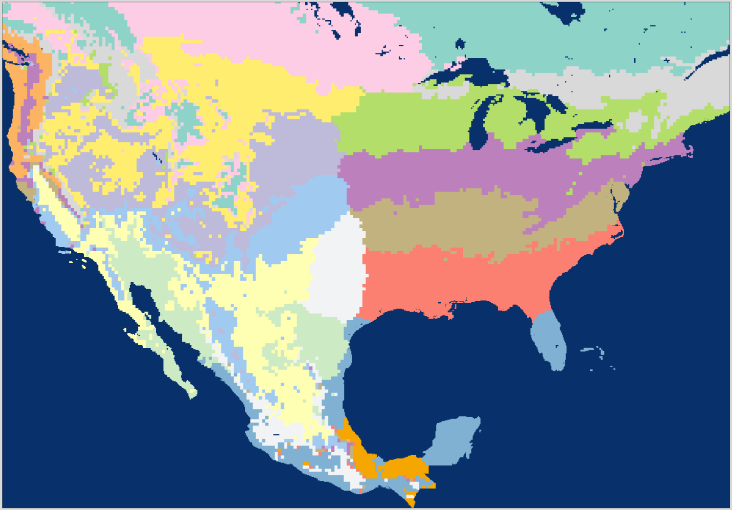


Figure: CGC: K-means $k = 16$, $(\ell_s, \ell_t) = (2, 3)$