Construction and Analysis of Climate Networks

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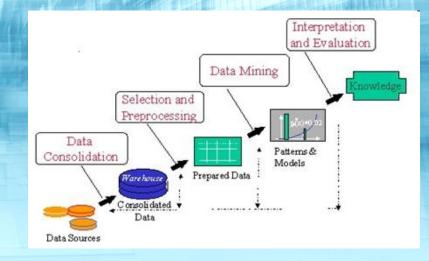
Workshop on Understanding Climate Change from Data Minneapolis, MN

August 15, 2011



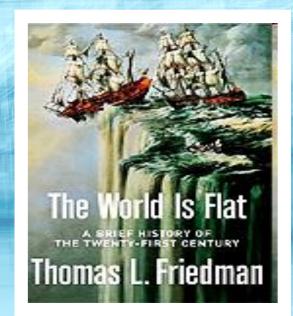
Working Definitions

- Knowledge Discovery is the process of identifying valid, novel, potentially useful, and ultimately understandable structure in data (source: ACM SIGKDD)
- Data Mining is the step in the knowledge discovery process concerned with identifying patterns in data and building models to represent those patterns



Mining Complex Data

- Complex spatio-temporal data pose unique challenges
- Tobler's First Law of Geography: "Everything is related, but near things more than distant."
 - But are all near things equally related?
 - Are there phenomena explained by interactions among distant things? (teleconnections)



Networks Primer

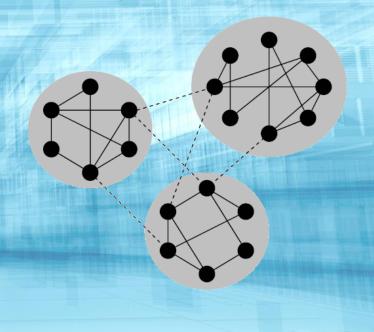
What is a Network?

- Oxford English Dictionary: network, n.: Any netlike or complex system or collection of interrelated things, as topographical features, lines of transportation, or telecommunications routes (esp. telephone lines).
- My working definition:
 Any set of items that are connected or related to each other.
 ("items" and "connections" can be concrete or abstract)

Networks Primer

Community Detection in Networks

- Identify groups of nodes that are relatively more tightly connected to each other than to other nodes in the network
- Computationally challenging problem for real-world networks



Climate + Networks?

- Networks are pervasive in social science, technology, and nature
- Many datasets explicitly • define network structure



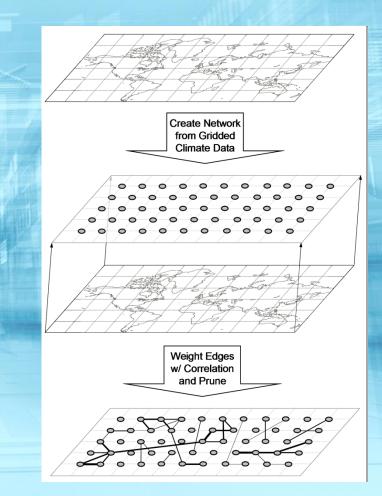
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But networks can also represent other types of data, • framework for identifying relationships, patterns, etc.

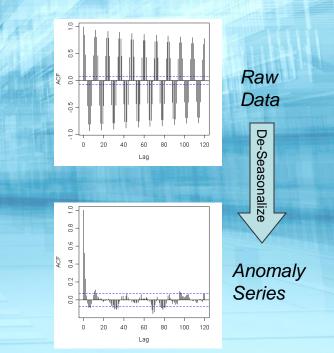
Network Construction

- View the global climate system as a collection of interacting oscillators [Tsonis & Roebber, 2004]
 - Vertices represent physical locations in space
 - Edges denote correlation in climate variability
- Link strength estimated by correlation, low-weight edges are pruned from the network



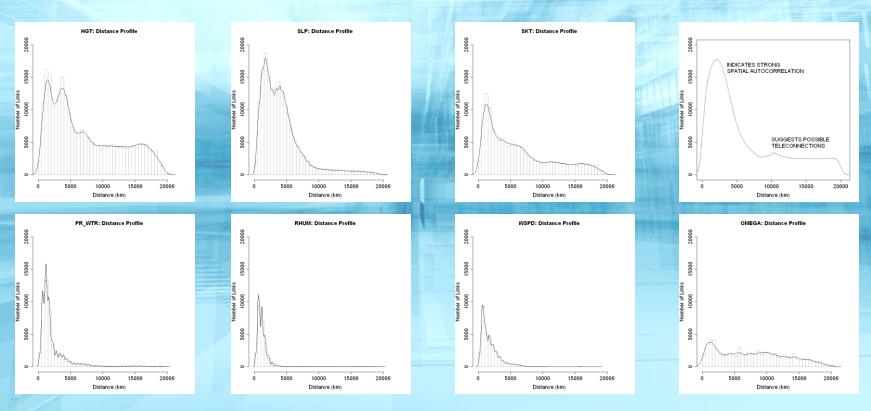
Example: Historical Data

- NCEP/NCAR Reanalysis (proxy for observation)
- Monthly for 60 years (1948-2007) on 5°x5° grid
- Seven variables:
 Sea surface temperature (SST)
 Sea level pressure (SLP)
 Geopotential height (GH)
 Precipitable water (PW)
 Relative Humidity (RH)
 Horizontal wind speed (HWS)
 Vertical wind speed (VWS)



Geographic Properties

• Examine network structure in spatial context (link lengths computed as great-circle distance)

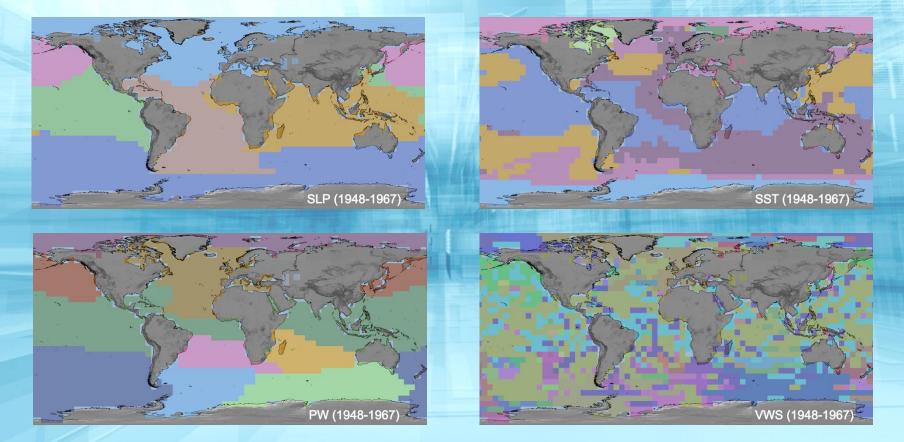


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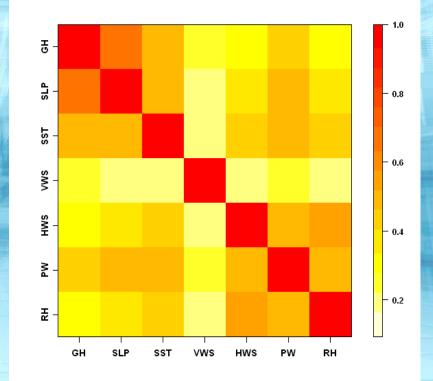
Clustering Climate Networks

Apply community detection to partition networks into "clusters"



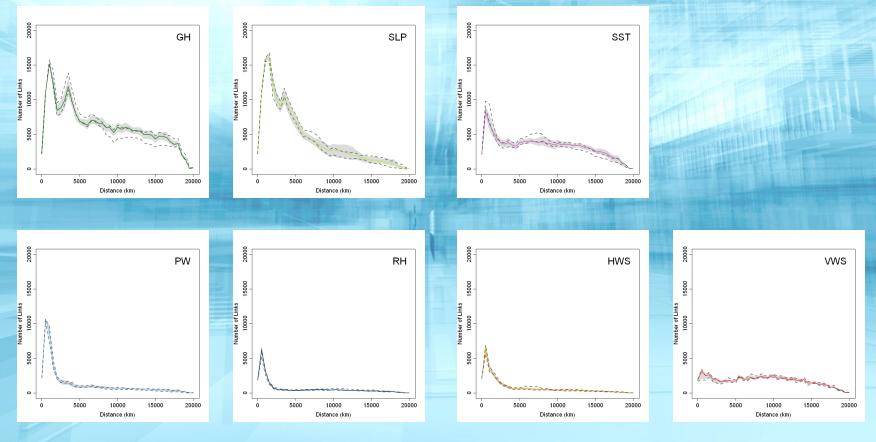
Cluster Similarity

- Compare cluster structure between different variables
 - Computed Adjusted
 Rand Index (ARI) to
 quantify similarity
 - Groupings correspond to those identified from the profiles



Stability over Time

Temporal evolution of profiles from sliding windows



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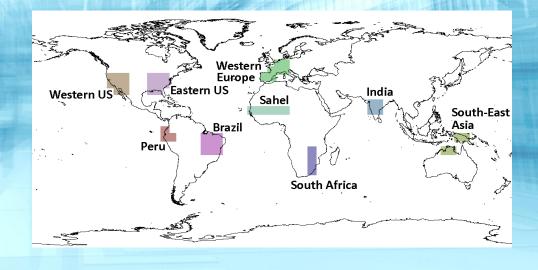
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Predictive Modeling

- Network representation is able to capture interactions, reveal patterns in climate
 - Validate existing assumptions / knowledge
 - Suggest potentially new insights or hypotheses for climate science
- Want to extract the relationships between atmospheric dynamics over ocean and land – i.e., "Learn" physical phenomena from the data

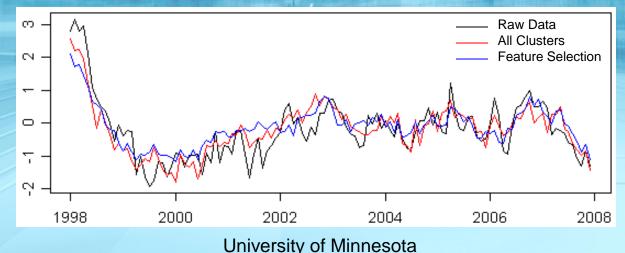
Predictive Modeling

- Use network clusters as candidate predictors
- Create response variables for target regions
- Build regression models relating ocean clusters to land climate



Illustrative Example

- Predictive model for air temperature in Peru
 - Long-term variability highly predictable due to well-documented relation to El Nino
- Small number of clusters have majority of skill
 - Feature selection (blue line) improves predictions



Results on Train/Test

	Region		Network Clusters		K-Means		
	Region	INELWORK Clusters		k = 5	k = 10	$k = k_n$	
Air Temperature	SE Asia		0.541		0.629	0.694	0.886
	Brazil		0.534		0.536	0.532	0.528
	India		0.649		0.784	1.052	0.791
	Peru		0.468		0.564	0.623	0.615
	Sahel		0.685		0.752	0.750	0.793
	S Africa		0.726		0.711	0.968	0.734
	East US		0.815		0.824	0.844	0.811
	West US		0.767		0.805	0.782	0.926
	W Europe		0.936		1.033	0.891	0.915
	Mean		0.680		0.737	0.793	0.778
	$\operatorname{Std}\operatorname{Dev}$		± 0.150		± 0.152	± 0.165	± 0.135
Precipitation	SE Asia		0.665		0.691	0.700	0.684
	Brazil		0.509		0.778	0.842	0.522
	India		0.672		0.813	0.823	0.998
	Peru		0.864		1.199	1.095	1.130
	Sahel		0.533		0.869	0.856	0.593
	S Africa		0.697		0.706	0.705	0.703
	East US		0.686		0.750	0.808	0.685
	West US		0.605		0.611	0.648	0.632
	W Europe		0.450		0.584	0.549	0.542
	Mean		0.631		0.778	0.781	0.721
	StdDev		± 0.124		± 0.182	± 0.156	± 0.207
Friedman Test ($\alpha = 0.05$)					\checkmark	\checkmark	\checkmark

Work-in-Progress

- More thoroughly incorporate multivariate relationships, nonlinearity, and temporal lags into network construction and predictive models
- Work with domain experts to integrate our (data-guided) predictive models with (physically-based computational) climate models
- Address computational issues arising from predictions at higher model resolution (both spatial and temporal), multiple variables, mean and extreme events, etc.

Upcoming Events

- First International Workshop on Climate Informatics, New York, NY, August 26, 2011 <u>http://www.nyas.org/climateinformatics</u>
- 2. NASA Conference on Intelligent Data Understanding (CIDU), Mountain View, CA, Oct 19-21, 2011 https://c3.ndc.nasa.gov/dashlink/projects/43/
- IEEE ICDM Workshop on Knowledge Discovery from Climate Data, Vancouver, Canada, December 10, 2011 http://www.nd.edu/~dial/climkd11/

Thanks & Questions

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