

NSF Expeditions in Computing

Understanding Climate Change: A Data Driven Approach

Vipin Kumar

University of Minnesota

kumar@cs.umn.edu

<http://climatechange.cs.umn.edu>



Expeditions Team



Vipin Kumar, UM



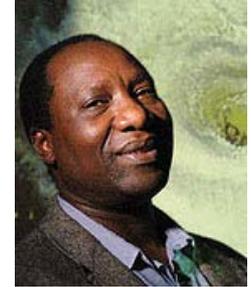
Auroop Ganguly, NEU



Nagiza Samatova, NCSU



Arindam Banerjee, UM



Fred Semazzi, NCSU



Joe Knight, UM



Shashi Shekhar, UM



Peter Snyder, UM



Jon Foley, UM



Alok Choudhary, NW



Ankit Agrawal, NW



Abdollah Homiafar
NCA&T



Michael Steinbach
UM



Singdhansu Chatterjee
UM



James Faghmous
UM



Stefan Liess
UM



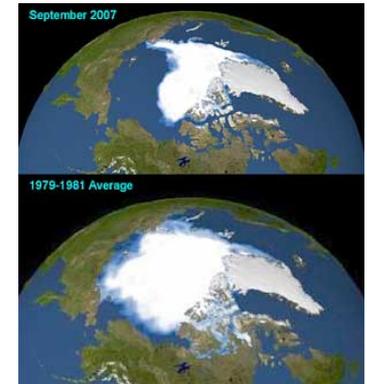
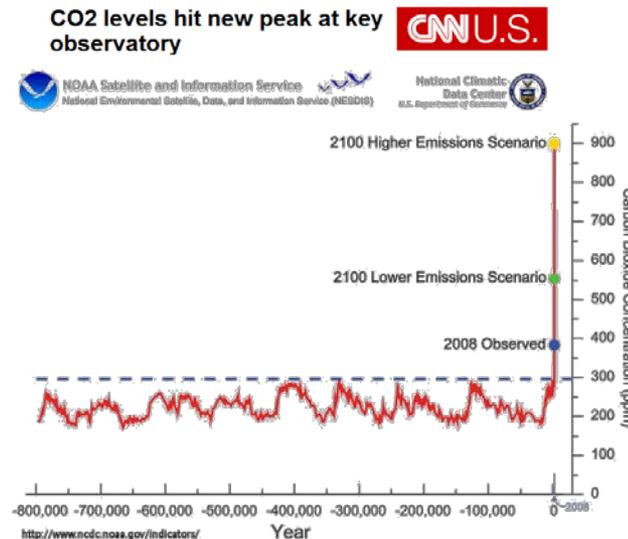
Shyam Boriah
UM

Understanding Climate Change - Motivation

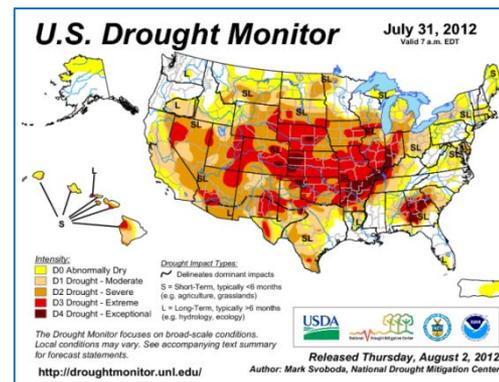
- **The planet is warming**
 - Multiple lines of evidence
 - Credible link to human GHG (green house gas) emissions
- **Consequences can be dire**
 - Extreme weather events
 - Regional climate and ecosystem shifts
- **There is an urgency to act**
 - Adaptation: “Manage the unavoidable”
 - Mitigation: “Avoid the unmanageable”
- **The societal cost of both action and inaction is large**

Key outstanding science challenge:

Actionable predictive insights to credibly inform policy



The Vanishing of the Arctic Ice cap
ecology.com, 2008



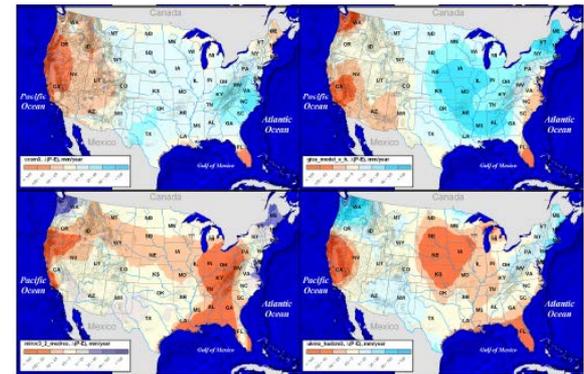
Russia Burns, Moscow Chokes
NATIONAL GEOGRAPHIC, 2010

Physics based models are essential but insufficient

- Relatively reliable predictions at global scale for ancillary variables such as temperature
- Least reliable predictions for variables that are crucial for impact assessment such as regional precipitation

“The sad truth of climate science is that the most crucial information is the least reliable”
(Nature, 2010)

Disagreement between IPCC models



Regional hydrology exhibits large variations among major IPCC model projections

Physics based models

Low uncertainty (High confidence)	High uncertainty (Low confidence)	Out of scope
Temperature	Precipitation	Forest fires
Pressure	Hurricanes	Malaria outbreaks
Large-scale wind	Extremes	Landslides

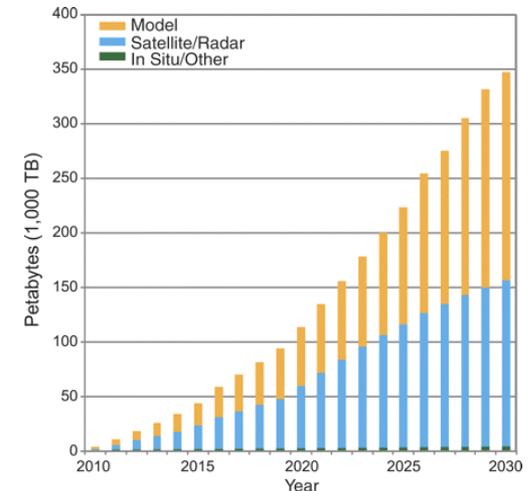
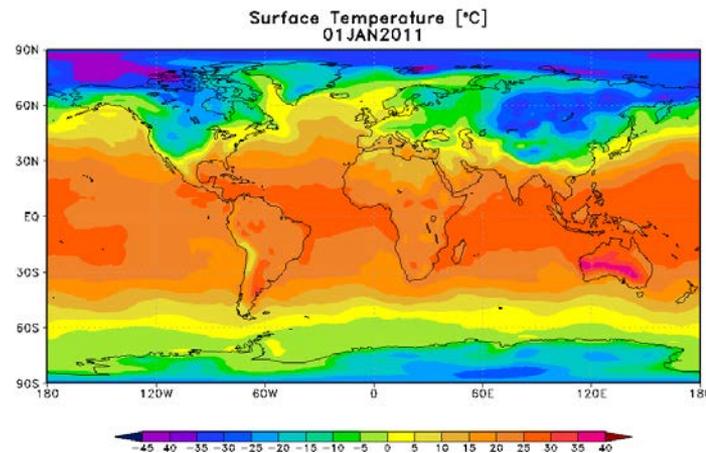
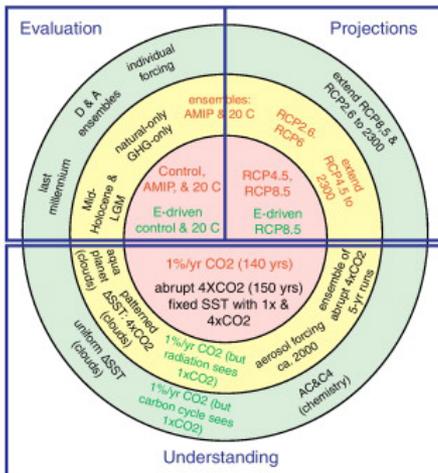
Big Data in Climate Science

Transformation from Data-Poor to Data-Rich

- Sensor Observations
- Reanalysis Data
- Model Simulations



Source: NASA



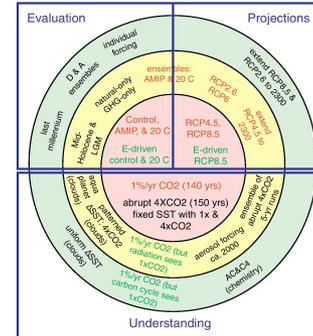
Source: Overpeck et al., *Science*, (2011)

August 4-5, 2015

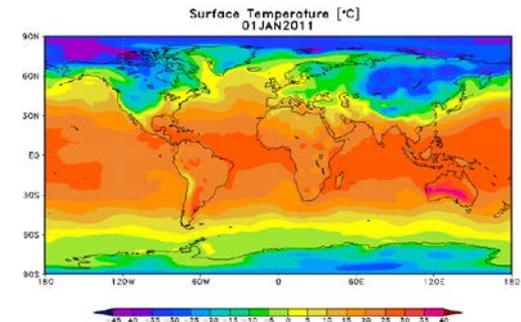
Big Data in Climate Science

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“Climate change research is now ‘big science,’ comparable in its magnitude, complexity, and societal importance to human genomics and bioinformatics.”
(Nature Climate Change, Oct 2012)



White House Brings Together Big Data & Climate Change

SCIENTIFIC
AMERICAN™

Can Big Data Help U.S. Cities Adapt to Climate Change?

March 20, 2014

CLIMATE  CENTRAL

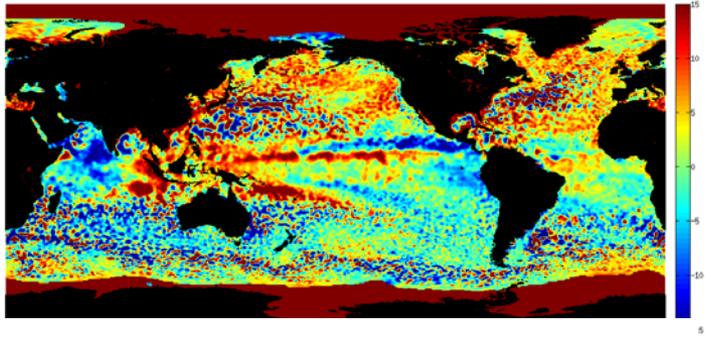
March 19, 2014

Project vision and scope

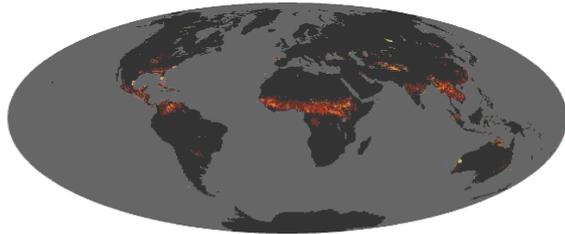
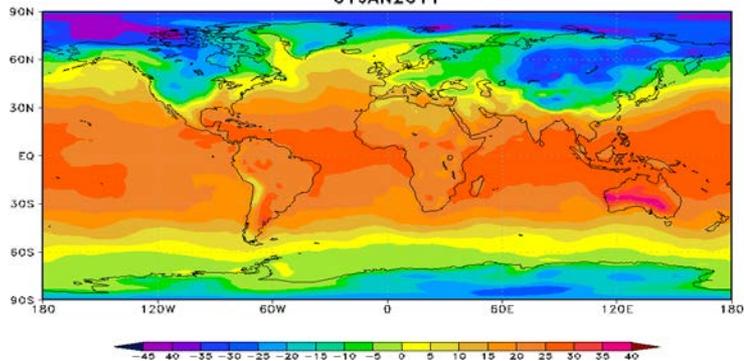
Transformative Computer Science Research Advancing Climate Change Science

Process Understanding	<p>Extreme Events</p> <ul style="list-style-type: none"> - Heat Waves - Rainfall Extremes - Droughts - Hurricanes <p>Model Evaluation</p> <p>Downscaling</p> <ul style="list-style-type: none"> - Statistical - Dynamical <p>Ocean-Atm.-Land Interactions</p>	<p>Change Detection</p> <ul style="list-style-type: none"> - Abrupt vs. Gradual - Point vs. Regions/Intervals - Change in Extremes <p>Spatio-Temporal Classification</p> <p>Sparse/High-Dim. Methods</p> <p>Causal Relationships</p> <p>Networks/Graphs</p> <p>HPC</p>	Computational Innovations
	Understanding Climate Change		

Challenges in data-driven analysis of climate data



Surface Temperature [°C]
01 JAN 2011



Active Fires
fire pixels / 1000 km² / day
March 2000

- Spatio-temporal auto- and cross-correlation
- Noisy, heterogeneous, and uncertain
- Evolutionary processes
- Multiple spatio-temporal scales
- Unknown, non-linear, and long-range dependency structure
- Variability
- Class imbalance
- Multivariate non-stationary
- Large unlabeled datasets
- Significance testing

Faghmous and Kumar (2013)

Computer

Theory-Guided Data Science for Climate Change

James H. Faghmous , Arindam Banerjee , Shashi Shekhar , Michael Steinbach Vipin Kumar, Auroop R. Ganguly Nagiza Samatova



Nonlinear Processes in Geophysics

An interactive open-access journal of the European Geosciences Union

Physics-driven data mining in climate change and weather extremes

Editor(s): A. Ganguly, V. Mishra, D. Wang, W. Hsieh, F. Hoffman, V. Kumar, and J. Kurths



A BIG DATA GUIDE TO UNDERSTANDING CLIMATE CHANGE:

The Case for Theory-Guided Data Science

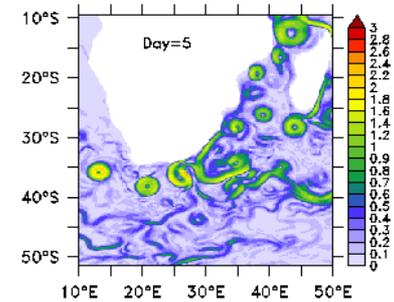
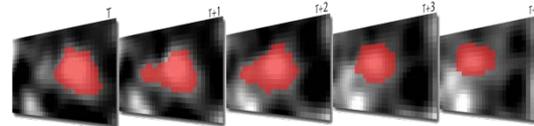
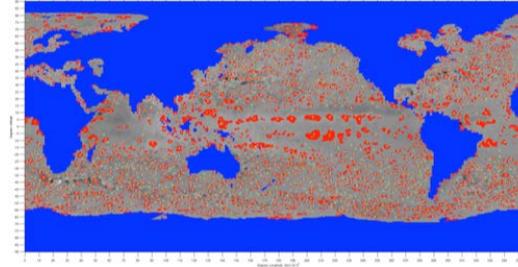
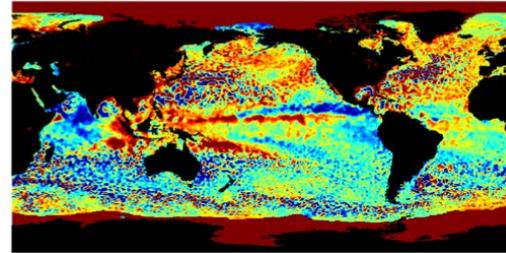
James H. Faghmous and Vipin Kumar

Highlights

- Highly inter-disciplinary research:
 - Computer science, hydrology, earth sciences, statistics, civil engineering
- ~ 150 publications (journals, conferences, and workshops) with authors from multiple disciplines
- A number of best paper and outstanding dissertation awards
- Public release of software & data products
- Advances in computer science driven by Earth science applications
- Advances in Earth sciences using computer science methods
- Development of physics-guided data mining paradigm
- Interdisciplinary community engagement: Computer science, engineering, physical sciences, and social or economic sciences

Pattern Mining: Ocean Eddies Monitoring

- Rotating coherent structures that are sources of intense physical and biological activity
- Identifying ocean eddies in satellite products is an active subject of research
- Used spatio-temporal context of the data to extract statistically significant features
- Open source data base of 20+ years of eddies and eddy tracks available for scientific applications
- Being used by oceanographers worldwide
- Enabled study of interactions between hurricanes and ocean eddies



Faghmous et al. *AAAI* (2012a)
Faghmous et al. *CIDU* (2012b) **Best student paper award**
Faghmous et al. *AAAI* (2013)

www.nature.com/scientificdata

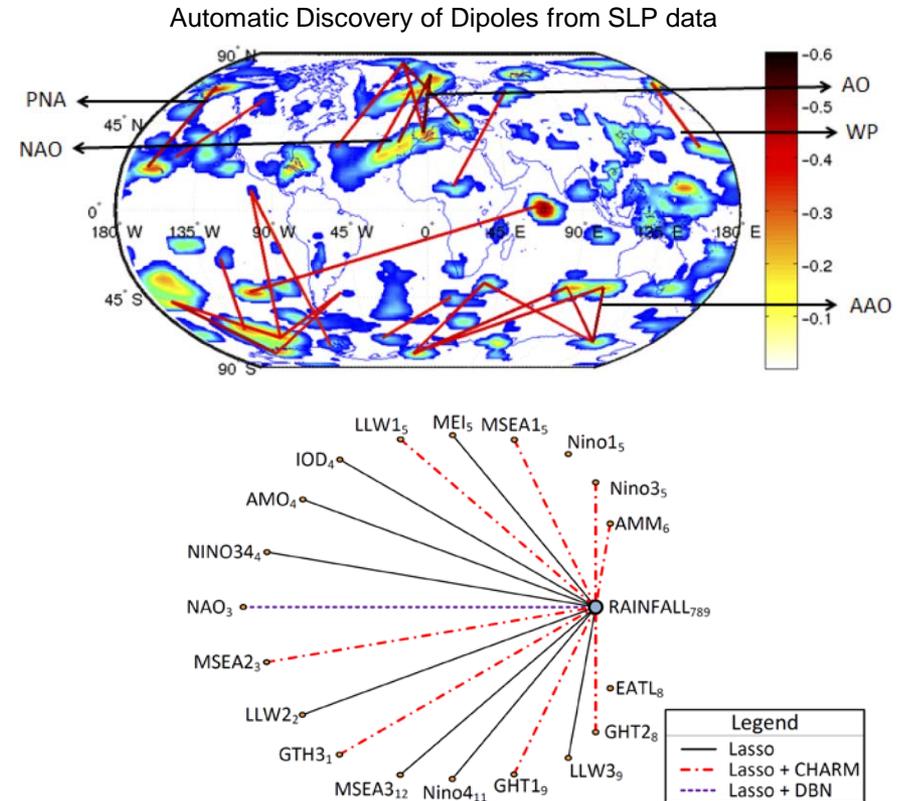
SCIENTIFIC DATA

OPEN A daily global mesoscale ocean eddy dataset from satellite altimetry

SUBJECT CATEGORIES
Physical oceanography
Climate and Earth system modelling

Network analysis: Climate teleconnections

- Large-scale long-range relationships play a crucial role in the atmosphere
- Discovering such relationships is laborious and imprecise
- Developed automated procedures to discover teleconnections in large climate data sets
- Technique discovered more robust relationships, new undiscovered relationships, and is a tool to evaluate climate models
- Data-driven Inference of modulatory networks in climate science



Kawale et al. *SDM*(2011a), *CIDU* (2011b) **Best student paper award, ACM SIGKDD** (2012)

Liess et al: *Journal of Climate* (2014)

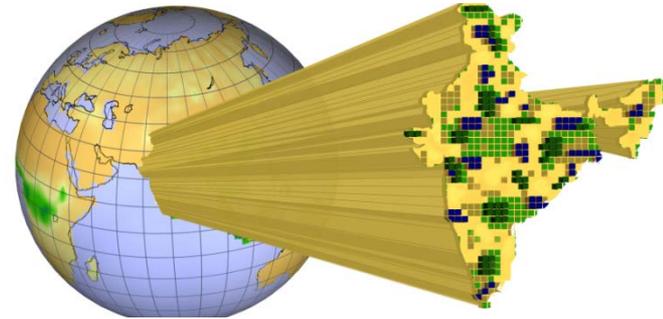
Lu et al: under review *Journal of Climate*)

González et al. *Nonlinear Processes in Geophysics Discussions*, 2015

Samatova et al. *SDM* 2012, *ICDM* 2013, *PKDD* 2015

Extremes and uncertainty: Heat waves, heavy rainfall, ...

- Climate change has been called “*global weirding*” owing to possible exacerbation of hydro-meteorological extremes and changes in regional weather patterns
- Understanding relevant dominant processes and discovering space-time dependence requires *physics-guided data mining* and *uncertainty quantification*
- Computational data and geospatial sciences can help translate insights from models and observations to metrics relevant for *adaptation and policy*
- Suite of methods developed new insights on climate extremes with uncertainty, and consequences for *critical infrastructures and key resources*



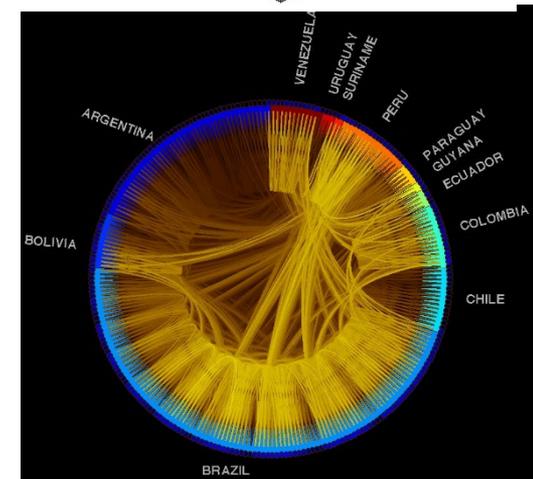
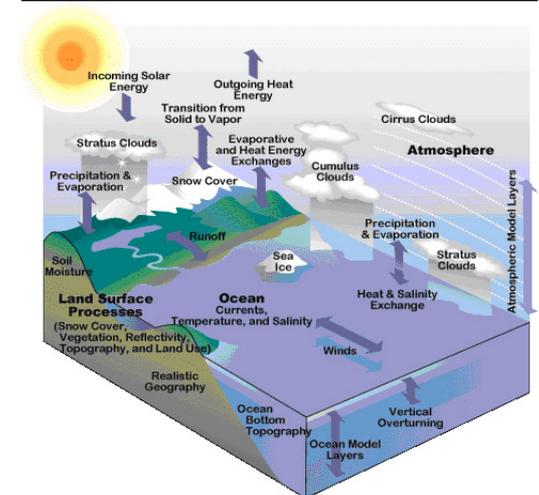
Ghosh *et al.* Nature Climate Change (2012)
Parish *et al.* Computers & Geosciences (2012)
Kodra *et al.* Environmental Research Letters (2012)
Ganguly *et al.* Climate Extremes & UQ: Book Chapter (2013)
Kodra *et al.* Scientific Reports, Nature (2014)
Kumar *et al.* Climate Dynamics (2014)

Predictive Modeling for Climate Data

- Regression for High dimensions, low sample setting
 - Statistical consistency using sparse hierarchical regularization
 - Examples: Sparse group lasso, Gaussian Markov random fields
- Multi-task learning with spatial smoothing
 - Combining outputs of multiple GCMs
 - Local regression with spatial smoothing
 - More accurate than local or global regression
- Inference using discrete graphical models (MRFs)
 - Mega-drought detection, trends over past 100-1000 years
 - Fast parallel algorithm: 10 mins on 20 cores, 30 secs on 500 cores
 - Detects all major droughts, model evaluation in progress
- Rare class prediction in the absence of ground truth
 - Used for mapping of forest fires globally
- Spatial Decision Tree (SDT) concept and SDT learning algorithms
 - Incorporates explicit Physics (e.g., continuity constraint)
 - Uses focal-feature based test and spatial-information-gain based objective functions.

SDM 2012, Best Student paper award
NIPS 2012
SDM 2013, Best Application paper award
ICML 2012
SDM 2012, 2013, 2014, 2015
UAI 2013
IJCAI 2015

Global Climate Models (GCMs)



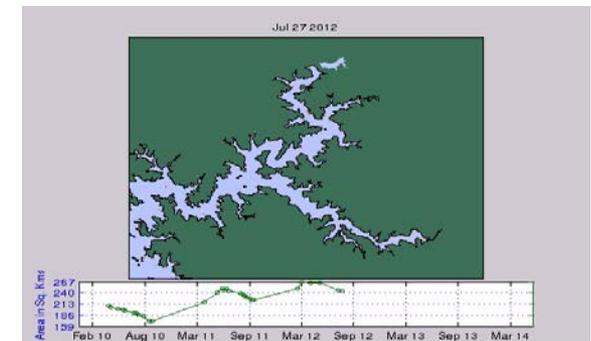
Temperature dependencies between Regions in South America

Change Detection

- The automatic detection of changes in large spatio-temporal datasets is important to monitoring and understanding the behavior of the global climate system.
- Abrupt Change Interval Miner (ACIM) and Sub-path Enumeration and Pruning (SEP)
 - Discovers interesting spatio-temporal sub-paths/intervals, such as those with abrupt changes.
 - These algorithms leverage explicit Physics (e.g., continuity violations)
- Detecting change points in non-stationary time series based on genetic algorithms
 - Can search for a global solution in the large search space of a non-convex constrained optimization.
 - Using information criteria methods, the optimal number of change points and clusters can be determined
- Robust scoring techniques for identifying diverse changes in spatio-temporal data
- Physics-guided approaches for global monitoring of changes in surface water bodies



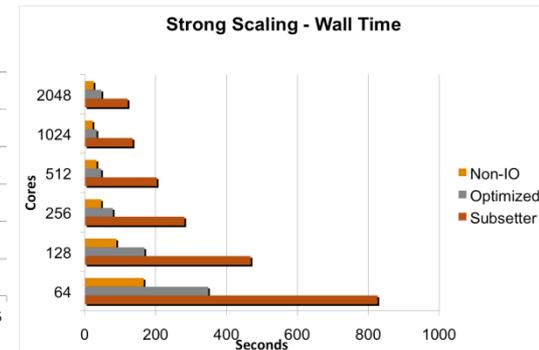
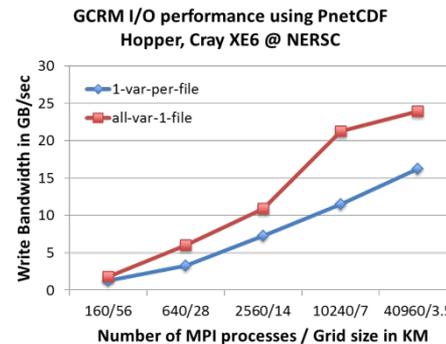
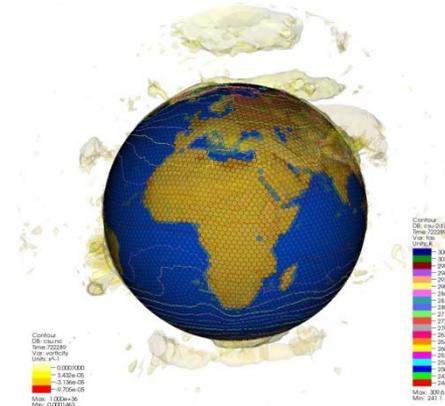
Land cover change detection



Monitoring the dynamics of surface water bodies

Scaling I/O and analytics: Global cloud resolving model

- Global Cloud Resolving Model (GCRM): simulates circulation associated with large convective clouds
- I/O was previously a major *bottleneck* for GCRM: **1.4 PB** data per simulation and **1.5 TB** per checkpoint
- Improved I/O throughput Using *Parallel NetCDF I/O library* optimizations, massive scalability
- Optimized memory utilization and process communication



Jin *et al.* EuroMPI (2011)
Patwary *et al.* SC (2012)
Hentrix *et al.* HPC (2012)
Kumar *et al.* IPDPS (2011)
Rangel *et al.* in review at journal (2013)
Jin *et al.* in review at journal (2013)

Sample of Education and Outreach Activities

Education

- Undergraduate and graduate courses/programs at the intersection of climate and data sciences
 - Graph Mining and Real-Time Data Stream Analytics
 - Climate Statistics
 - Coursera MOOC, “From GPS and Google Maps to Spatial Computing”, reached 21,844 across 182 countries
- Cross disciplinary training environment

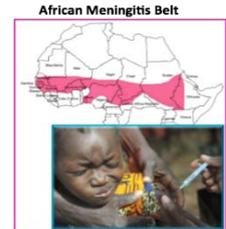
Professional Science Master’s degree program in Climate Change & Society



Engagement with UNEP, IPCC and World Economic Forum and wider climate science and impact community



FACES OF NSF RESEARCH
Future of Water Inspires Scientist to Develop Data-driven Models



Application to Climate: Meningitis Problem over West Africa



Breaking Story
Researchers Devise More Accurate Method For Predicting Hurricane Activity

Nurturing a “Climate Informatics” Community

“Climate change research is now ‘big science,’ comparable in its magnitude, complexity, and societal importance to human genomics and bioinformatics.” (Nature Climate Change, Oct 2012)

Workshops and sessions in climate & computer science venues



Special Issues

Nonlinear Processes in Geophysics

Physics Driven Data Mining

IEEE Computing in Science & Engineering Magazine

Computing in Climate: Challenges and Opportunities



Annual Workshop

Attended by 70-100 researchers from multiple disciplines