SDS Lab Overview
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Physics-guided statistical approach to uncertainty quantification from climate model ensembles

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Introduction: Auroop Ganguly

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Postdocs:
Poulomi Ganguli - drought characterization and prediction
Rachindra Mawagaledara - regional climate modeling
David Wang - oceanography

PhD Candidates:
Debasish Das - climate extremes data mining
Evan Kodra - extremes uncertainty quantification
Devashish Kumar - non linear dynamics and natural hazards
Saeed Zabet - Hydrological data analysis

Research Assistant:
Babak Fard - computer science

Professor:
Auroop Ganguly
Selected SDS Lab Members’ Research

2009

Increasing intensity and uncertainty in heatwaves

Ganguly et al. 2009

2011

Persistence of cold extremes under climate change

Kodra et al. 2011

2012

Increasing spatial variability in Indian rainfall extremes

Ghosh et al. 2012
Now: Putting a bunch of ideas together

Opportunity to use known physics, statistical models, and observed data to quantify (and reduce??) uncertainty in rainfall extremes

Tebaldi et al. 2004 & 2005

\[
E(\lambda|\{X_0, \ldots, X_9, Y_1, \ldots, Y_9\}) \approx \frac{a + 1}{b + \frac{1}{2}((X_i - \bar{X})^2 + \theta(Y_i - \bar{y} - \beta_e(X_i - \bar{X})))^2}.
\]

Pall et al. 2007

O’Gorman et al. 2009

Fasullo and Trenberth 2012

Hall and Qu 2006

Min et al. 2011
Physics Infused Statistical Uncertainty Quantification

What processes dictate rainfall extremes?

- Vertical wind velocity
- Horizontal moisture convergence
- Moist adiabatic temperature lapse rate
- Saturation vapor pressure \( \Rightarrow \) Local mean air temperature when extremes occur

- Idea: weight ESMs by which ones get the link between temperature and rainfall extremes right... let the unknown and unmeasured fall into uncertainty terms

Modeled and measured well
Modeled and measured less well
Physics Infused Statistical Uncertainty Quantification

Measuring ESM reliability: realism in portraying adherence to Clausius-Clapeyron Scaling

The original August-Roche-Magnus approximation to the CC...

A log transformation...

A (potentially generalized) linear regression relationship— with some unknown parameters— that can be mapped back to nonlinear deviations from CC scaling.

$$e_s(T) = 6.1094 \exp \left[ \frac{17.625 T}{T+243.04} \right]$$

$$\ln[e_s(T)] = \ln(6.1094) + \frac{17.625 T}{T+243.04}$$

A statistical mechanism to encapsulate a basic physical process— and the rest falling into an error term.

Example deviations from the August-Roche-Magnus, where h=1 is the original August-Roche-Magnus.
But will this link tell us anything useful?

We might want something like this...

- Which ESMs capture these patterns?
- And do they say something different about the future?

Hints that this approach *might* be useful in constraining uncertainty
  - Variability by region
  - Variability by season
  - Host of additional considerations...

In CONUS Observations: Processes that dictate rainfall extremes differ across seasons

Pearson's $\rho$ (seasonal maxima rainfall total, same day average temperature, 1915-2011)

% Change in Seasonal Maxima (1950-1999 $\rightarrow$ 2050-2099)

Spatial PDF Overlap [0,1]
Applying the idea in a UQ Framework

\[ \ln[H_r] \equiv \mu_r \approx \lambda_r + (\delta_r)X_r \]

\[ \ln[H_{j,r}] \equiv \mu_{j,r} \approx \lambda_r + (\delta_{j,r} + \delta_r)X_r \]

\[ \ln[P_{j,r} \mid H_{j,r}] \equiv \mu'_{j,r} \approx \lambda_r + \{(\delta'_{j,r} + \delta_r)Y_r - \beta[(\delta_{j,r} + \delta_r)X_r]\} \]

- GLMs for location parameters in a GEV or GPD model to be updated in a recursive MCMC algorithm
- Use concepts of skill and consensus (e.g. Tebaldi et al. 2004 and Smith et al. 2009)

Weight assignment:

\[ f(\delta_r, \delta_{j,r}, \delta'_{j,r}) \]

\[ \ln[R] = \ell + h \frac{17.625T}{T+243.04} + \varepsilon \]

Weights should decay as GCMs fall further from “true” nature of adherence to real CC scaling described by \( \delta_r \) (but not necessarily from theoretical CC scaling)
Thank you

PhD Committee

Auroop Ganguly (NEU) – Climate & Data Science

Snigdhansu Chatterjee (UMN) – Statistics

Albert-László Barabási (NEU) – Network Science

John Drake (UTK, previously lead climate modeler at ORNL) – Climate Modeling

Jerome Hajjar (NEU) – Structures

Ferdi Hellweger (NEU) - Hydrology


• Kodra, E., Ganguly, A.R., (2013), Asymmetric projected changes of hot versus cold temperature extremes under climate change. In review


2013: Model-data driven insights

**EVT and resampling: Statistical tools for hypothesis testing**

Almost unanimous that the global PDF will change asymmetrically – especially for winter and minimum temperature based extremes

CMIP5 model ensemble generally projects larger changes in the highest than the lowest statistics of temperature extremes

Covariates describing asymmetry:
season >> tail >> latitude band >> GCM variability