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

Evan Kodra

Introduction: Auroop Ganguly

08/2013

Professor
Auroop Ganguly

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

Postdocs:

Poulomi Ganguli - drought characterization and prediction

Rachindra Mawagaledara - regional climate modeling

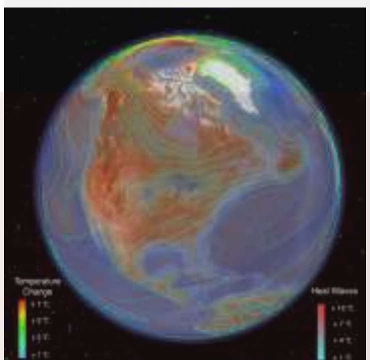
David Wang – oceanography and climate physics

Research Assistant
Babak Fard – computer science

Selected SDS Lab Members' Research

2009

Increasing intensity and uncertainty in heatwaves

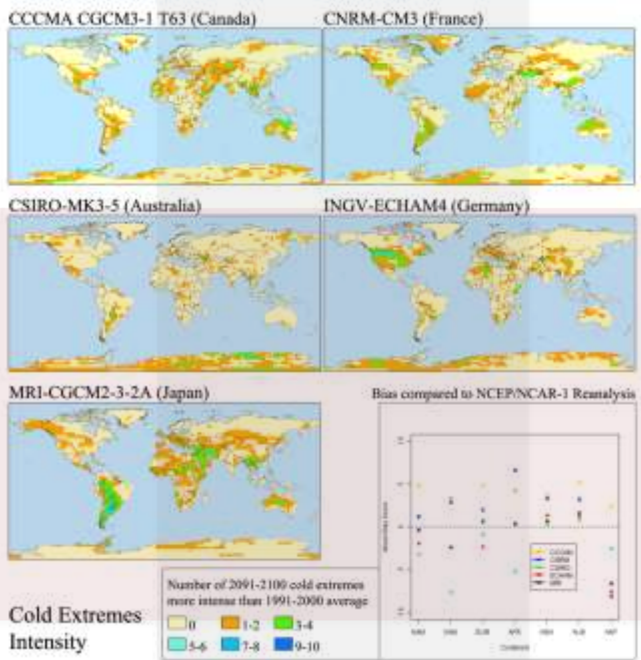


PNAS

Ganguly et al. 2009

2011

Persistence of cold extremes under climate change

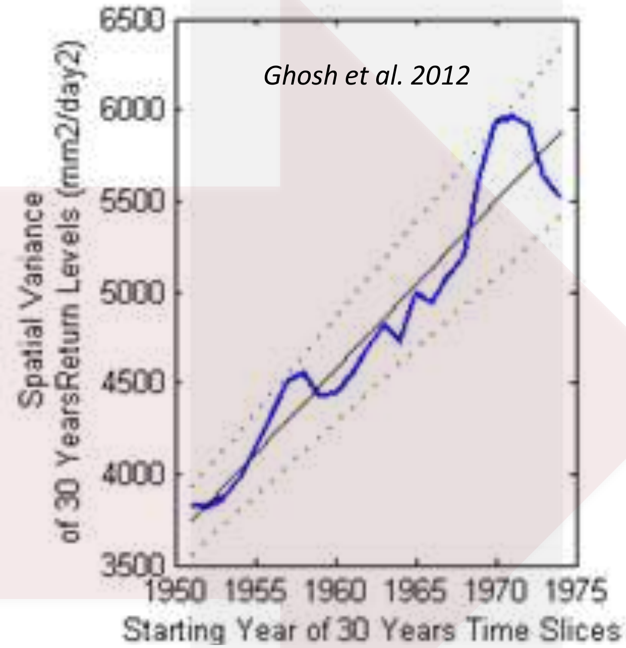


Kodra et al. 2011

GRL

2012

nature climate change

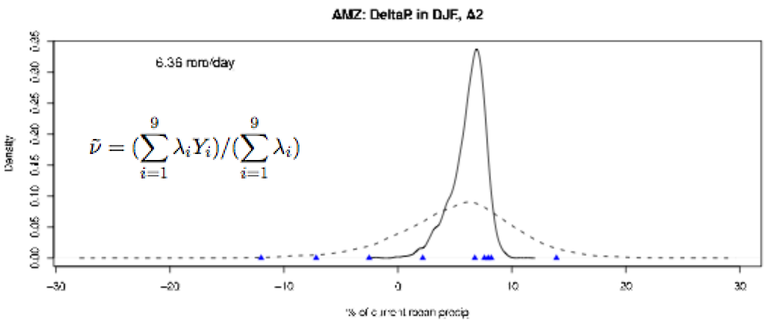


Increasing spatial variability in Indian rainfall extremes

Now: Putting a bunch of ideas together

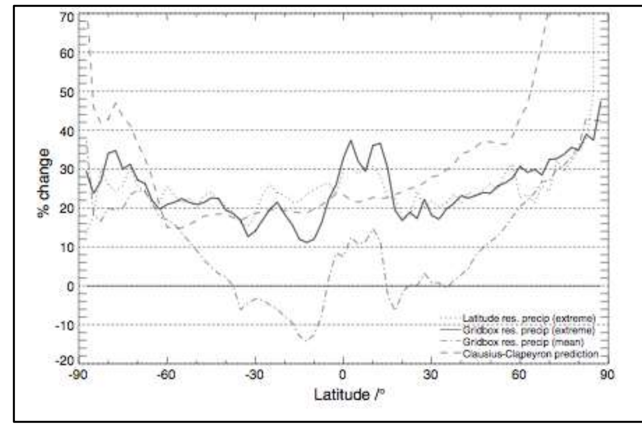
Opportunity to use known physics, statistical models, and observed data to quantify (and reduce??) uncertainty in rainfall extremes

Tebaldi et al. 2004 & 2005

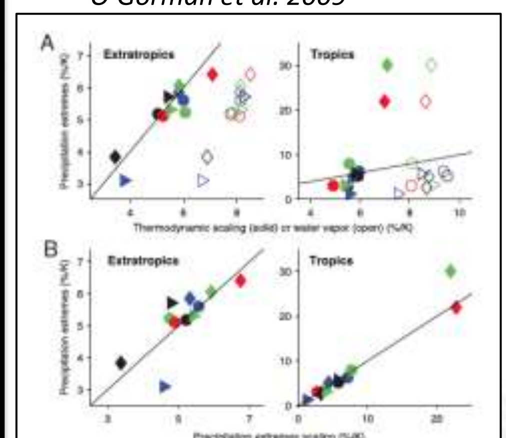


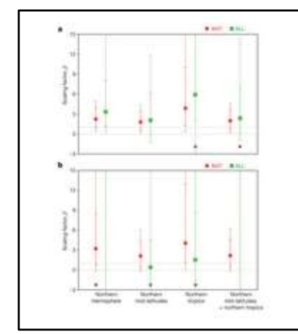
$$E(\lambda_i|\{X_0,\ldots,X_9,Y_1,\ldots,Y_9\}) \approx \frac{a+1}{b+\frac{1}{2}((X_i-\tilde{\mu})^2+\theta(Y_i-\tilde{\nu}-\beta_x(X_i-\tilde{\mu}))^2)}.$$

Pall et al. 2007



O'Gorman et al. 2009

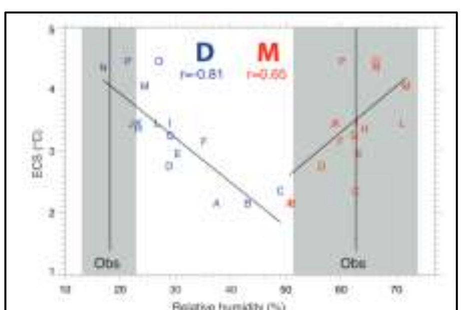




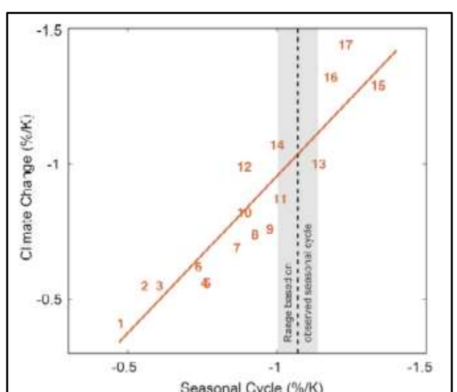
Min et al. 2011

$$P_e \sim -\left\{ \omega_e \left. \frac{dq_s}{dp} \right|_{\theta^*, T_e} \right\}$$

Fasullo and Trenberth 2012



Hall and Qu 2006



Physics Infused Statistical Uncertainty Quantification

What processes dictate rainfall extremes?

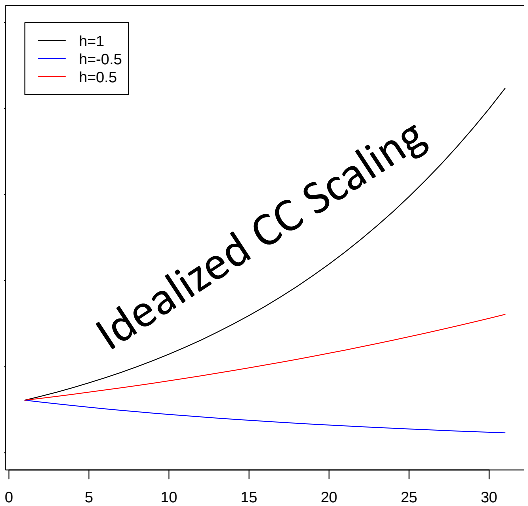
Modeled and measured well
Modeled and measured less well

- Vertical wind velocity
- Horizontal moisture convergence
- Moist adiabatic temperature lapse rate
- Saturation vapor pressure → 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

Physics Infused Statistical Uncertainty Quantification

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



Example deviations from the August-Roche-Magnus , where h=1 is the original August-Roche-Magnus .

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

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

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

A log transformation…

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

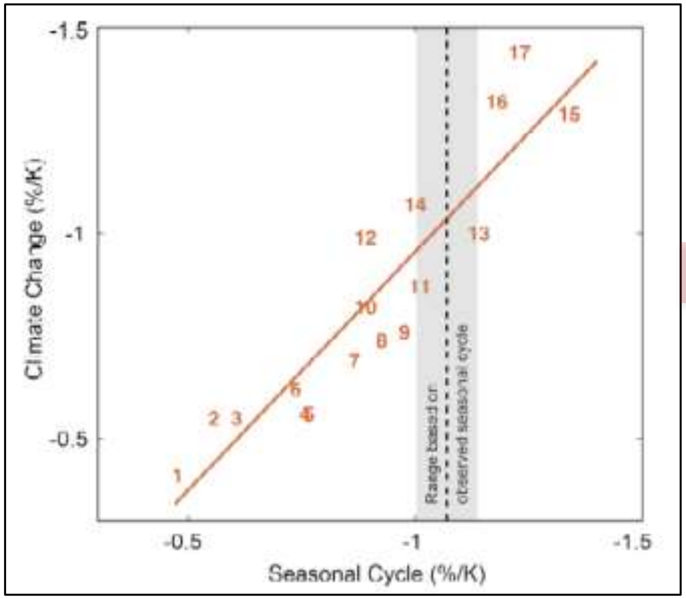
intercept slope error

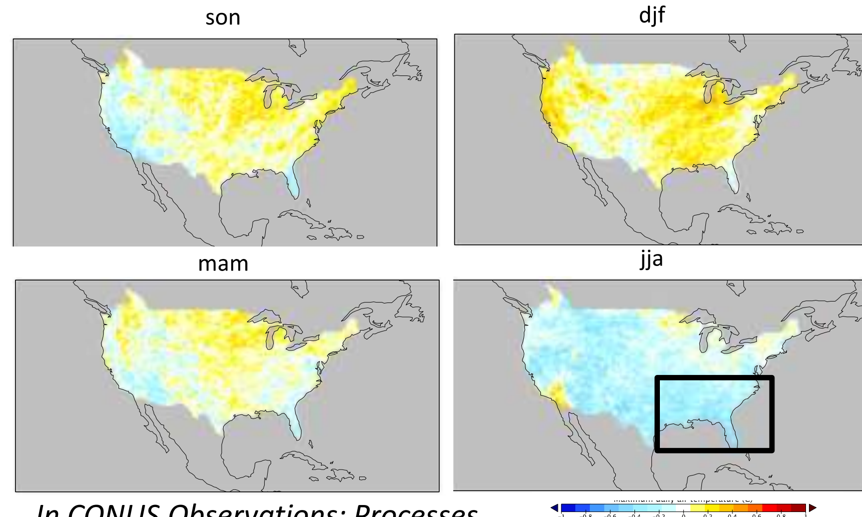
A (potentially generalized) linear regression relationship– with some unknown parameters – that can be mapped back to nonlinear deviations from CC scaling

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

But will this link tell us anything useful?

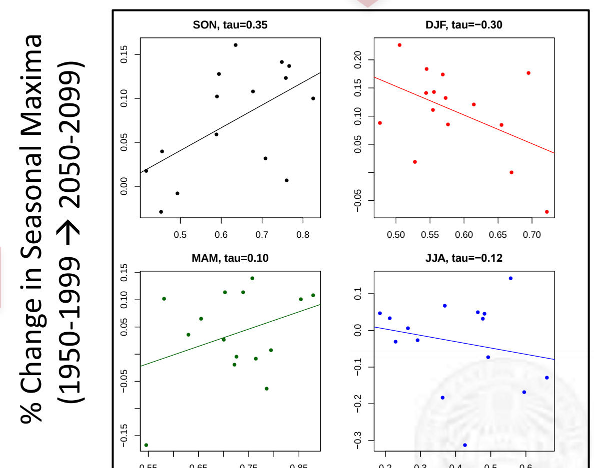
We might want something like this…





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

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



Spatial PDF Overlap [0,1]

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

Hints that this approach *might* be useful in constraining uncertainty

Variability by region

Variability by season

Host of additional considerations…

Applying the idea in a UQ Framework

$$\ln[H_r] \cong \mu_r \cong l_r + (\delta_r)X_r$$

$$\ln[H_{j,r}] \cong \mu_{j,r} \cong l_r + (\textcolor{blue}{\delta_{j,r}} + \delta_r)X_r$$

$$\ln[P_{j,r} \mid H_{j,r}] \cong \mu'_{j,r} \cong l_r + \{(\delta'_{j,r} + \textcolor{green}{\delta'_r})Y_r - \beta[(\delta_{j,r} + \delta_r)\, X_r]\}$$

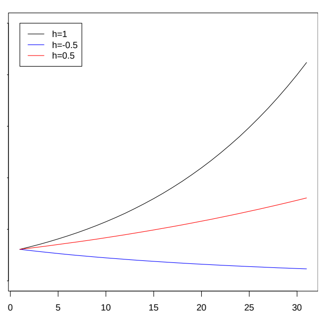
- ➔ GLMs for location parameters in a GEV or GPD model to be updated in a recursive MCMC algorithm
- ➔ Use concepts of skill and consensus (e.g. Tebaldi et al. 2004 and Smith et al. 2009)

$H_{k,r}$	Historical observation from dataset *k* at location *r*
$H_{j,r}$	Historical simulation from ESM *j* at location *r*
$P_{j,r} \mid H_{j,r}$	Projection from GCM *j* at location *r,* conditioned on GCM *j*'s historical simulation
X_r , Y_r	Historical temperature and future at location *r* (in reality uncertain)
δ	Regression coefficients relating X_r and Y_r to central tendency of log transformed rainfall extremes.

Weight assignment:

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

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



Weights should decay as GCMs fall further from "true" nature of adherence to real CC scaling described by δ_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

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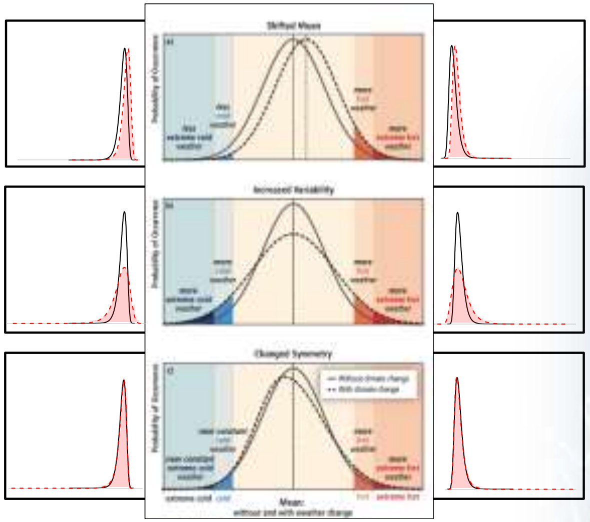
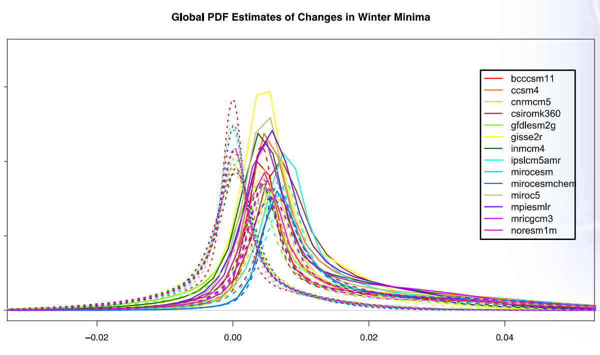
2013: Model-data driven insights

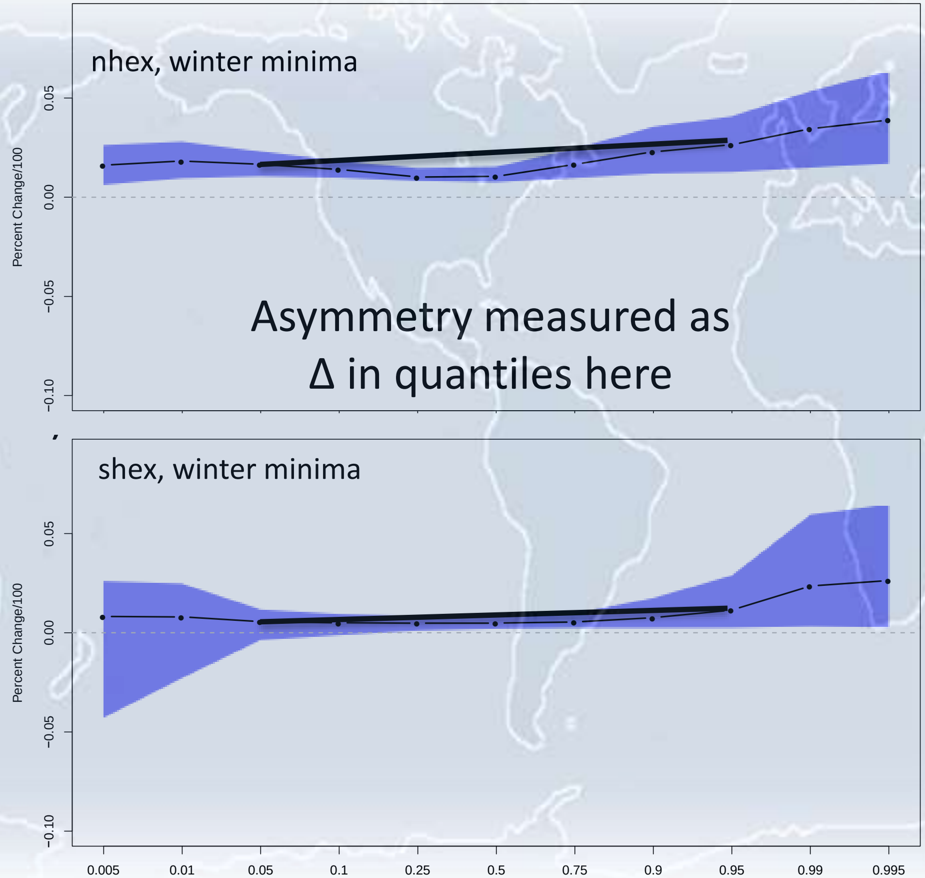


EVT and resampling: Statistical tools for hypothesis testing



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

Kodra et al. 2013



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