Lost Moments: The Effect of Pre-processing on Environmental Data

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w/ Hannah Director (Harvard -> LANL -> UW)

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Outline

A Look at Climate Data

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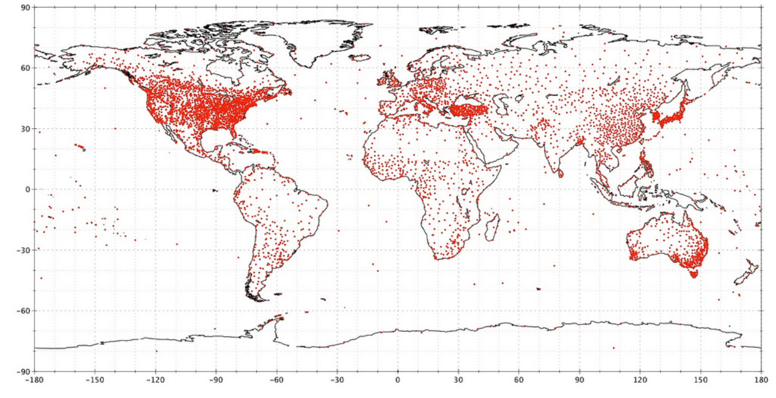
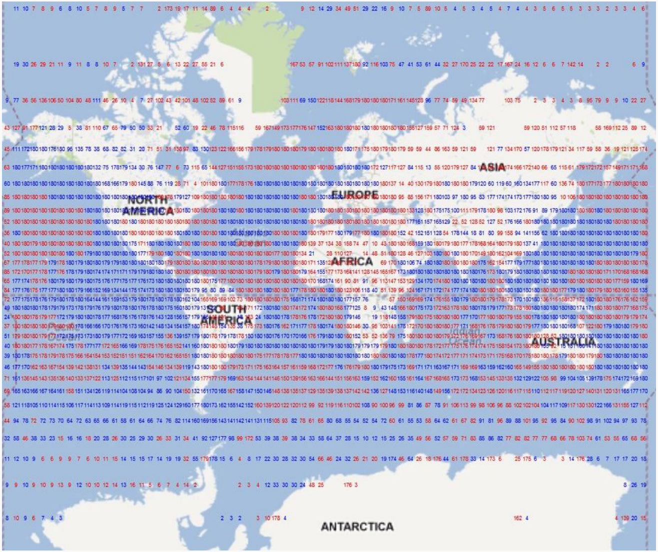
- While aggregation generally preserves the mean, the distribution of the raw measurements is drastically changed
- Failure to distinguish between raw/gridded data can significantly affect the scientific validity and real world impact of an analysis

Raw Climate Data



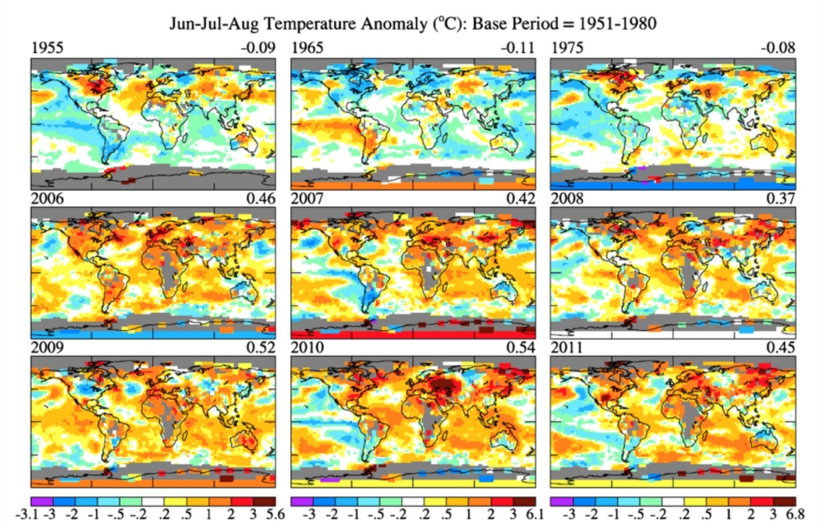
Source: http://employee.heartland.edu/rmuench/tempdata.htm

Gridded Climate Data



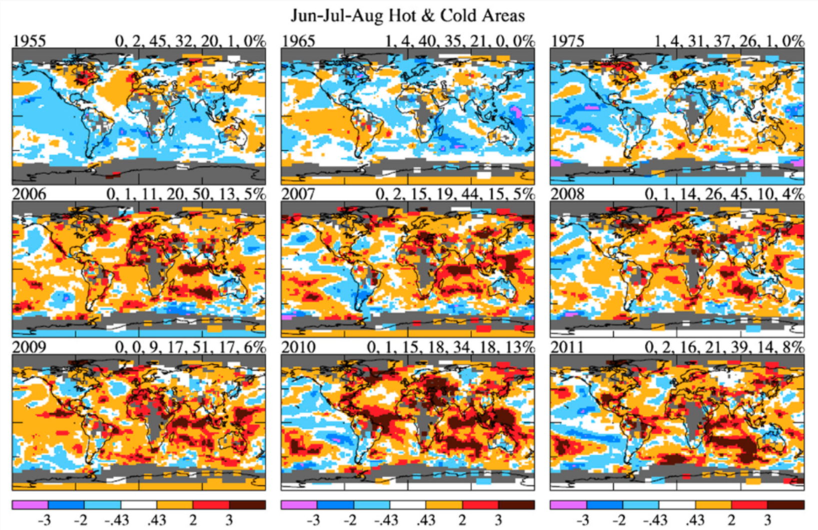
Source: https://sunshinehours.files.wordpress.com/2012/09/hadcrut3_gridded_180.jpg

An Example



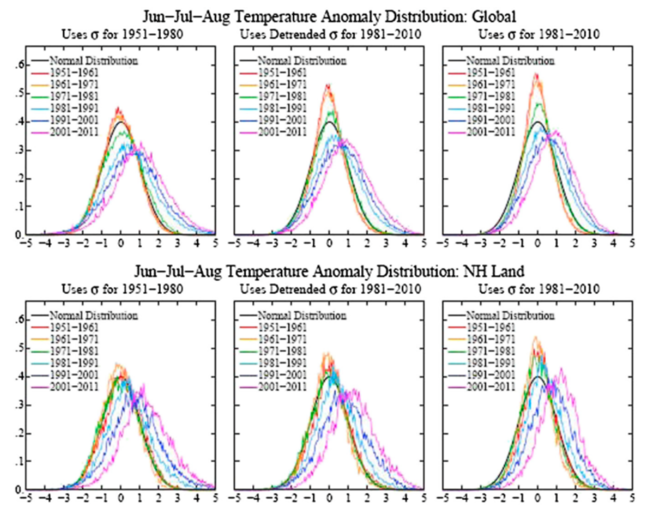
Hansen, Sato and Ruedy (PNAS 2012), Figure 1

An Example, continued



Hansen, Sato and Ruedy (PNAS 2012), Figure 3

An Example, continued



Hansen, Sato and Ruedy (PNAS 2012), Figure 4

An Example, continued

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  - reduction in surface station density
- Between 1951-1980 and 1981-2010, there is a 35% decrease in number of stations reporting monthly averages
- Rhines and Huybers (PNAS 2012) assume a $1\,^{\circ}\mathrm{C}$ variance within grid box, homogeneity, normality, and independence between stations
- Their conclusion is that after these adjustments, there is no obvious increase in variance

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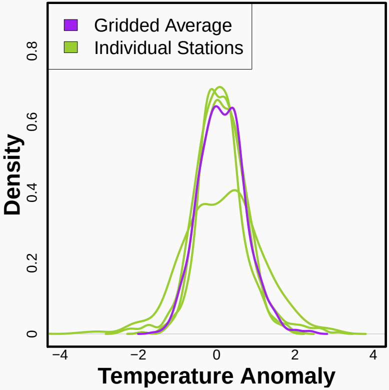
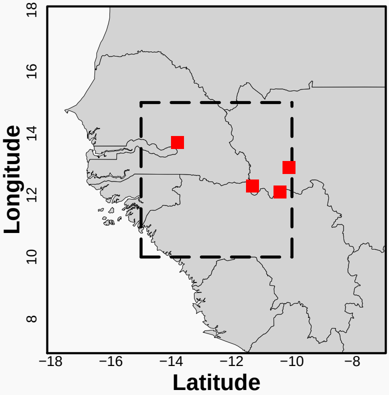
- Stations missing greater than 10% of measurements were omitted to ensure a relatively constant sample size

Gridding's Effect on Moments





Gridding's Effect on Moments

Table : *Mathematical definitions of the first four moments where X_i represents a single observation and $\overline{X}$ represents the mean of a group of observations and the relationships between these individual and averaged values.*

Moment	Def'n	Cumulant	Relationship
Mean (μ)	$\mathbb{E}(X)$	κ_1	$\mathbb{E}(\overline{X}) = \mathbb{E}(X_i)$
Variance (σ^2)	$\mathbb{E}[(X-\mu)^2]$	κ_2	$\mathbb{V}ar(\overline{X}) = \frac{1}{n}\mathbb{V}ar(X_i)$
Skewness (γ_1)	$\mathbb{E}[(\frac{X-\mu}{\sigma})^3]$	$\frac{\kappa_3}{\kappa_2^{3/2}}$	$\mathbb{S}kew(\overline{X}) = \frac{1}{\sqrt{n}}\mathbb{S}kew(X_i)$
Kurtosis (γ_2)	$\frac{\mathbb{E}[(X-\mu)^4]}{(\mathbb{E}[(X-\mu)^2])^2}$	$\frac{\kappa_4}{\kappa_2^2}$	$\mathbb{K}urt(\overline{X}) = \frac{1}{n}\mathbb{K}urt(X_i)$

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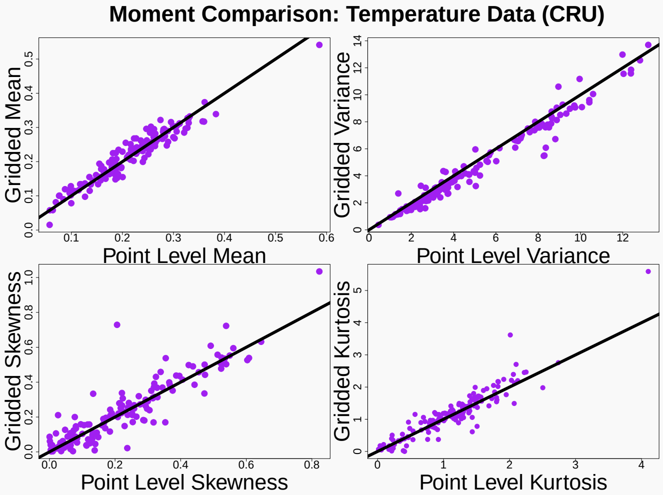

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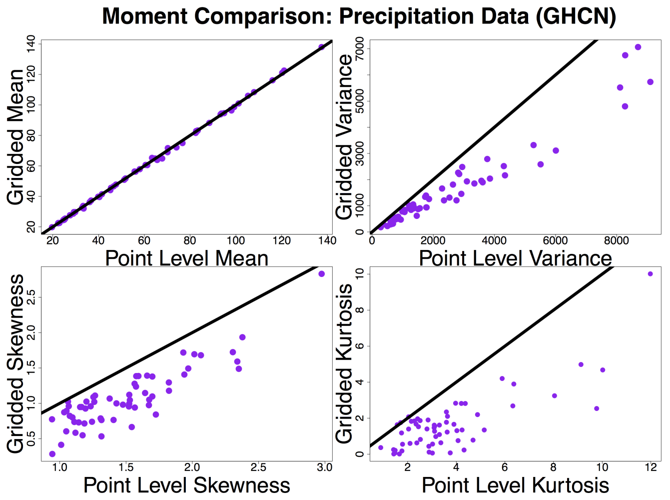

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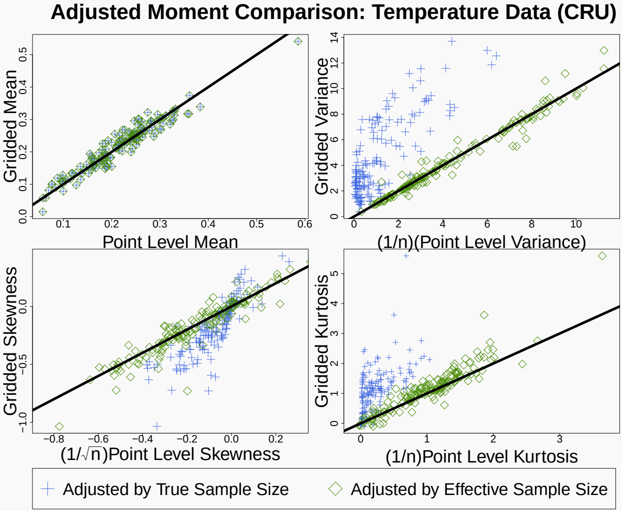
- Correlation can be estimated from historical data and previous research on what affects intra-site correlation

Thinking about Correlation 2



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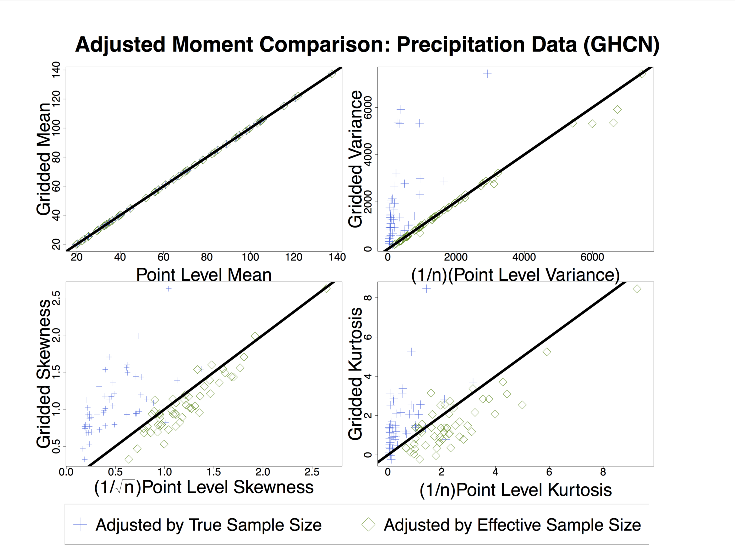

Extremes: A Simple Example

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- Extremes of the grid box average are not of practical interest, but estimates of extremes from individual station data are extremely noisy...
- So, we adjust the empirical moments of the gridded data to point-level using factors of the effective sample size
- These adjusted moments can be used to estimate the point-level distributional parameters and the corresponding distributions can be used to estimate what percent of the data is above or below extreme thresholds underlying data

Extremes: A Conservative Adjustment

CRU Temperature Data (Observed - Predicted)

Variance Adjustment	**Thresholds:** Lowest 2.5%	Lowest 5%	Highest 2.5%	Highest 5%
Unadjusted	0.60	0.33	0.27	0.16
Adj. by var/n	-13.42	-17.09	-14.63	-17.62
Adj. by var/n.eff	0.47	-0.01	0.10	-0.21

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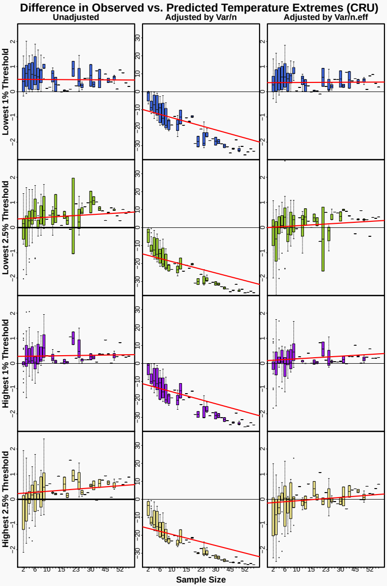

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GCHN Precipitation Data (Observed - Predicted)

Variance Adjustment	**Thresholds:** Highest 20%	Highest 10%	Highest 5%	Highest 2.5%
Unadjusted	1.48	2.00	1.62	1.11
Adj. by var/n	3.07	-1.96	-3.83	-4.22
Adj. by var/n.eff	0.38	0.16	0.17	0.21

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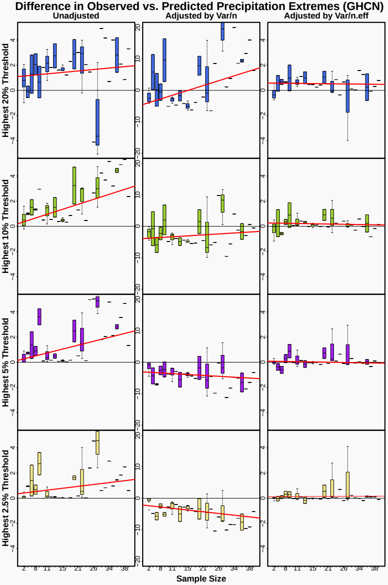

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- Reporting information on original sample sizes and intra-site correlation would make gridded products more interpretable and useful
- Similar issues likely exist for gridded climate model outputs and addressing them may be an area of future work