NCAR

Bursts and Cascades: Scaling Up Scientific Data Analysis

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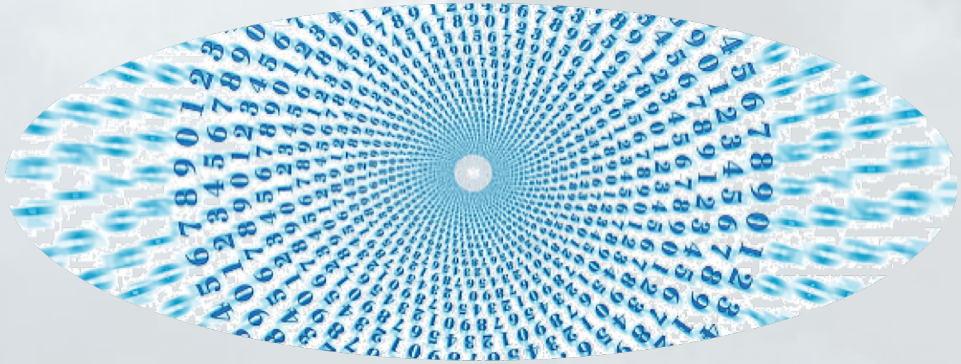
National Center for Atmospheric Research

What This Talk Is About

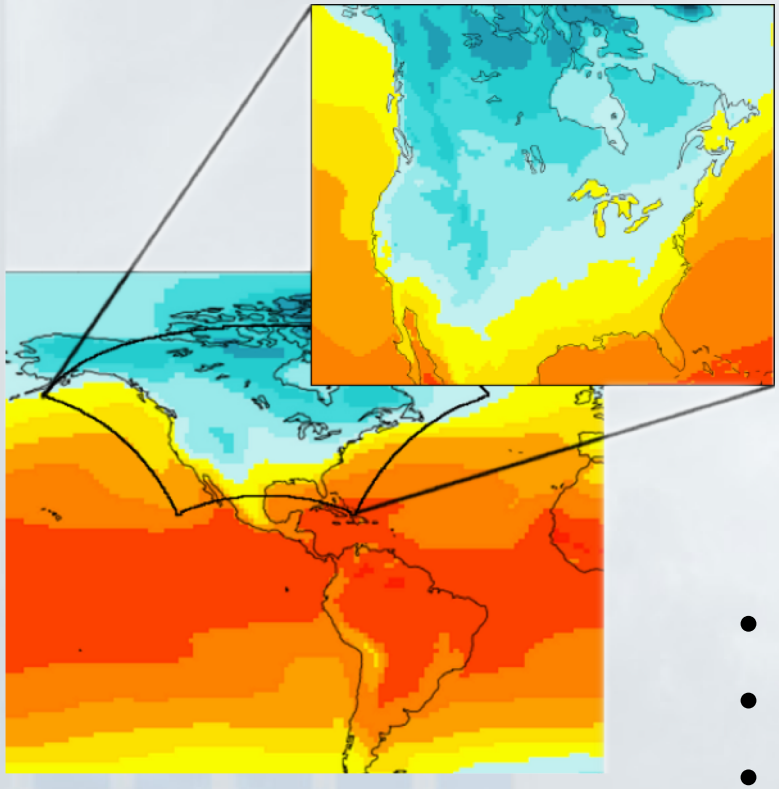
- Developing an analysis / derived data product:
  - Start with a test case you understand
  - Develop code
  - Apply it to the entire dataset
- Big Data happens when data volume (etc) is so large that normal approaches don't work
- Two successful approaches to scaling up:
  - Parallel burst
  - Hierarchical cascade



Parallel Burst:
Bias-Correcting NA-CORDEX

NA-CORDEX

Regional Climate Modeling in NA-CORDEX



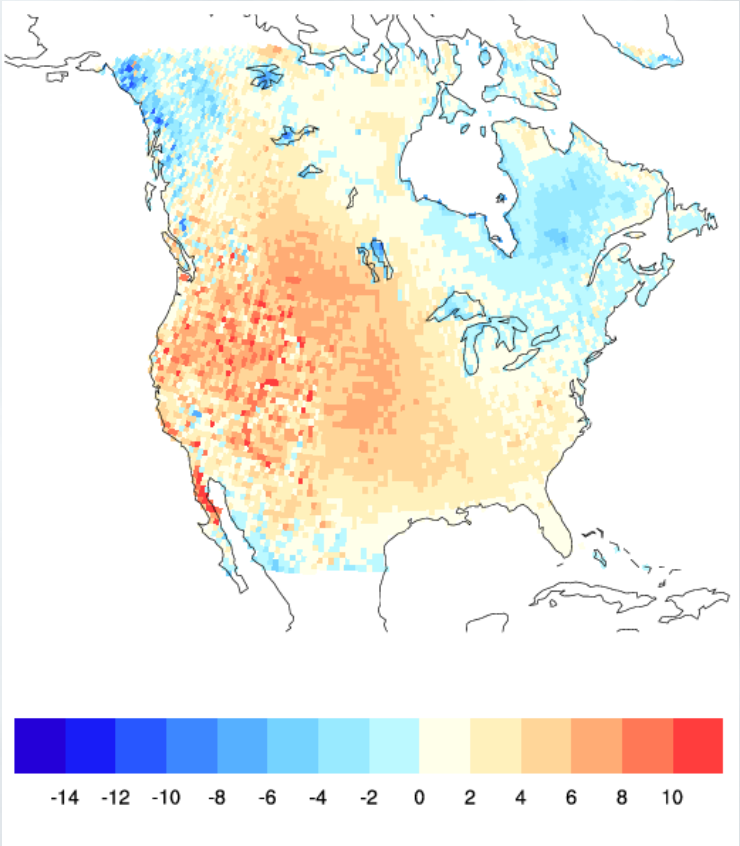
Nest high-resolution regional models (RCMs) inside coarser global models (GCMs) over North America

- Better mountains & coasts
- Better land surface detail
- Better convective processes
- Closer to impacts scale

Bias Correction

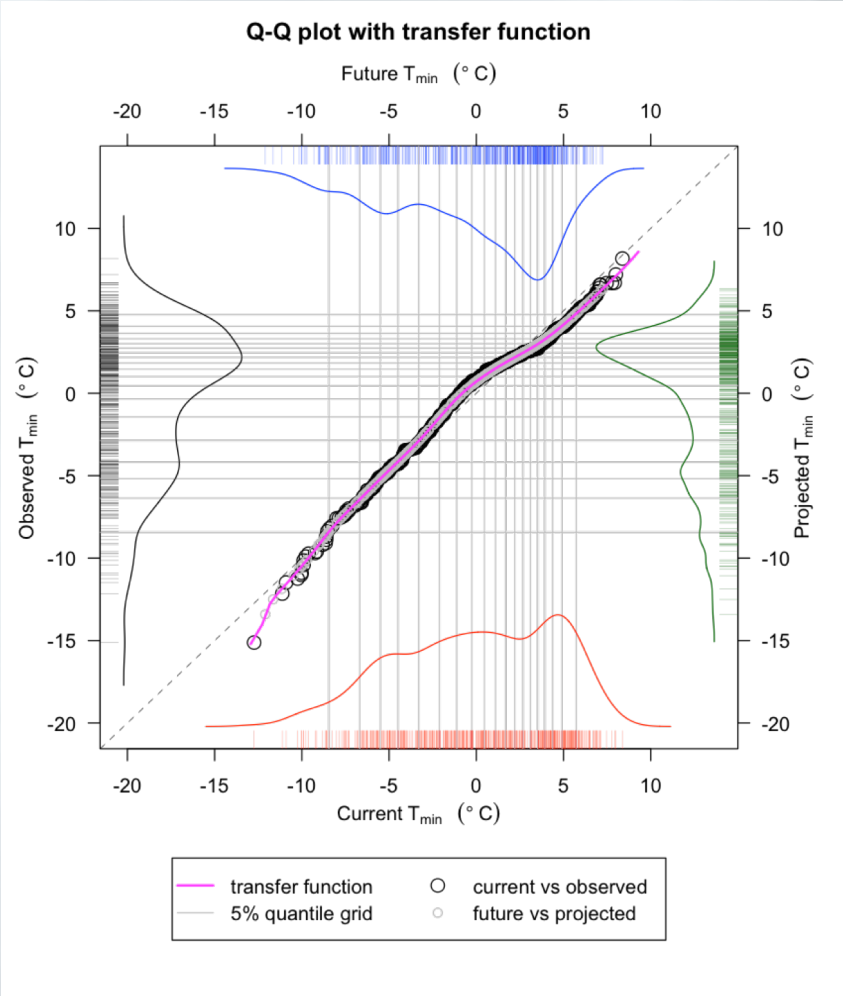
- RCMs & GCMs have systematic errors
  - Finite resolution
  - Parameterizations
  - Imperfect knowledge
- Correcting bias makes data more useable

Summer RCM Temperature Bias (°C)



BC Method: Distribution Mapping

- Adjust individual values so model PDF matches PDF of observations
- R script
- 20-25 seconds runtime
- 335-350 MB memory
- Reads 3 files (3.86 MB)
- Writes 2 files (3.1 MB)



Bias-Correcting (Part of)* the Dataset

*Full dataset is 5-10x bigger

3	variables
3	GCMs
2	RCMs
~~600 x 258~~	gridcells
232 x 154	(CONUS only)

x_____

643,104 timeseries

- 643k x 22 seconds
- = 14 million CPU-sec
- = 3,930 CPU-hours
- = 23+ weeks wallclock

- 2.36 TB in, 1.9 TB out

Conclusion: better run it in parallel!

Running in Parallel

GOOD

- Ridiculously parallel problem structure

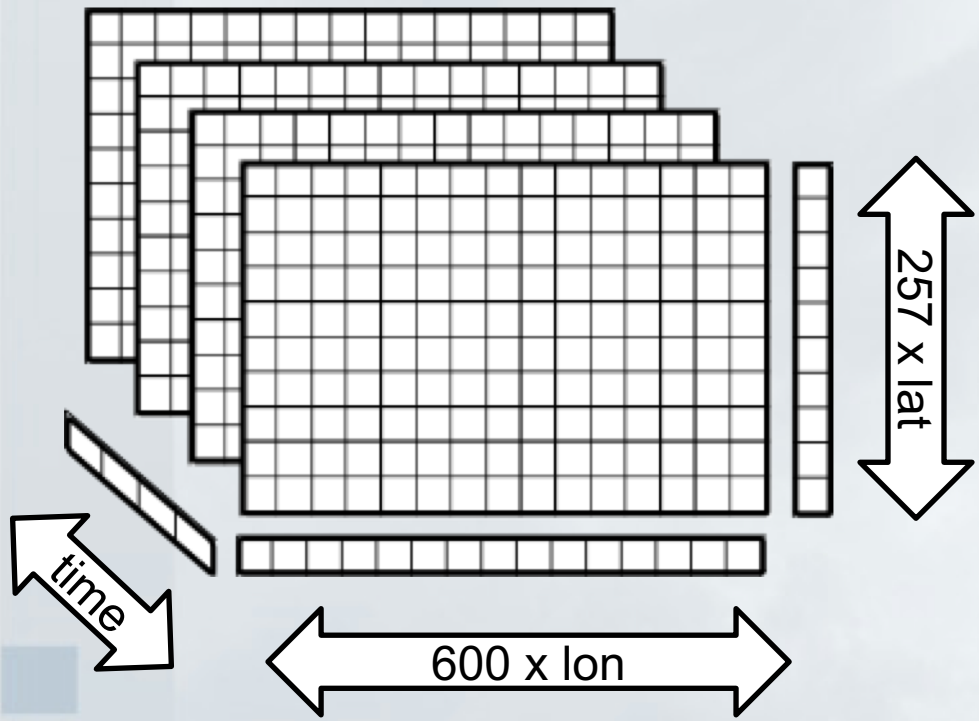
BAD

- No good tools for parallel I/O in R (esp. NetCDF)
- Can’t rewrite code in another language
  - No time; code uses R packages extensively

UGLY

- Rmpi package: version mismatch problems
- Supervisor process too big to fit on normal node
- Debugging parallel code is really hard

Solution (pt. 1): Disassemble NetCDF



- Data cube → data rods
- Components:
  - Global attributes
  - Ancillary (lat, lon, etc.)
  - Time coordinate
  - Main data variable
- Slice data by lon
- Slice each slice into rods (timeseries) by lat

Solution (pt. 2): MPMD Parallelism

- Use scheduler to distribute tasks from batch command file:
  - one task per line
  - one task per core
- Wrap commands in shell one-liner to capture output:

```
tcsh –c “Rscript --vanilla script.R arg1 arg2...”
```

- 1 job = 600 cores looping over 258 rods / slice

(This works so well I wrote a generic script for running batch files in parallel.)

Result: x2300 speedup with minimal code modifications

Lessons Learned

- Use generator scripts & templates to create batch files
- Parallelize disassembly / reassembly steps, too
- wallclock limit < 15 minutes + #cores < 1000
  = nigh-instant scheduling (backfilling empty holes)

➢ *Some problems don't show up until you try your code on the entire dataset*

➢ *Big error fixes can mean rerunning EVERYTHING*

  ➢ *I used up 20x extra CPU-hours getting it working correctly*

Moving to the Cloud?

- This problem is well-shaped for cloud
  - Burst demand
  - Highly parallel
  - Small task footprint
- AWS recommendation: Lambda service
  - Serverless computation triggered by file arrival
  - Est. cost: O($100s)

Complications

- In the cloud:
  file = immutable blob
  - ? File dis- / re-assembly
  - ? NetCDF → timeseries DB
  - ? transpose problem
- Data transfer in & out
  - 10s of TB is a lot
  - AWS "snowball" @$200?
- Only in Python

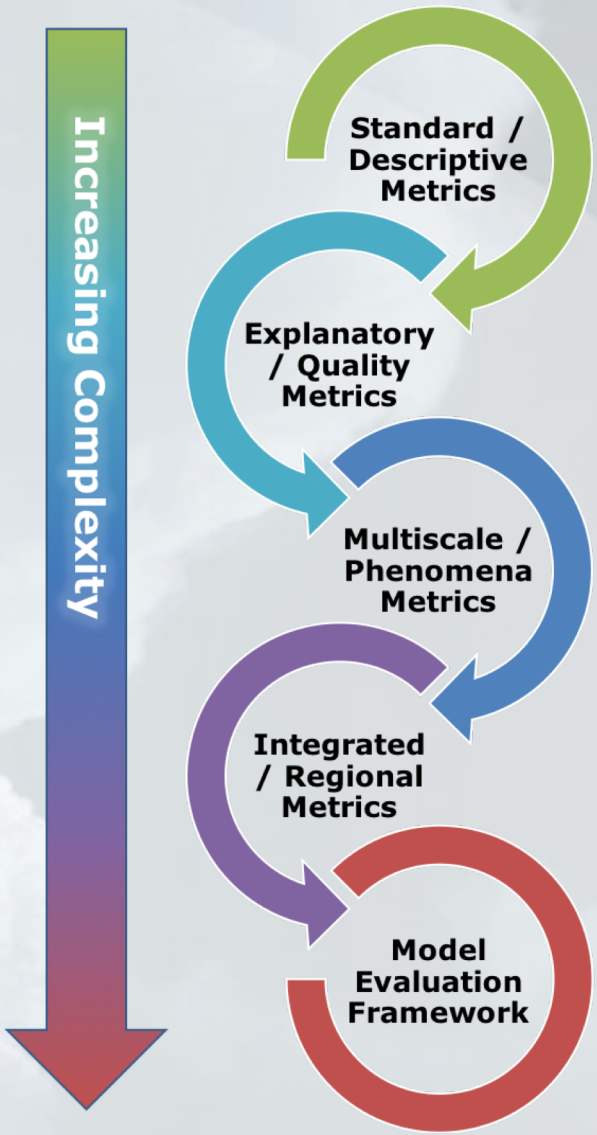
Hierarchical Cascade: Model Evaluation in FACETS

U.S. Department of Energy
FACETS
Framework for Assessing Climate's Energy-Water-Land Nexus using Targeted Simulations

Hierarchical Evaluation Framework: A Cascade of Metrics

1. Statistical Analysis
2. Process Analysis
3. Process Interaction Analysis
4. Credibility Analysis
5. Differential Credibility

Simpler analyses are distilled into quantitative metrics used to target more complex analysis

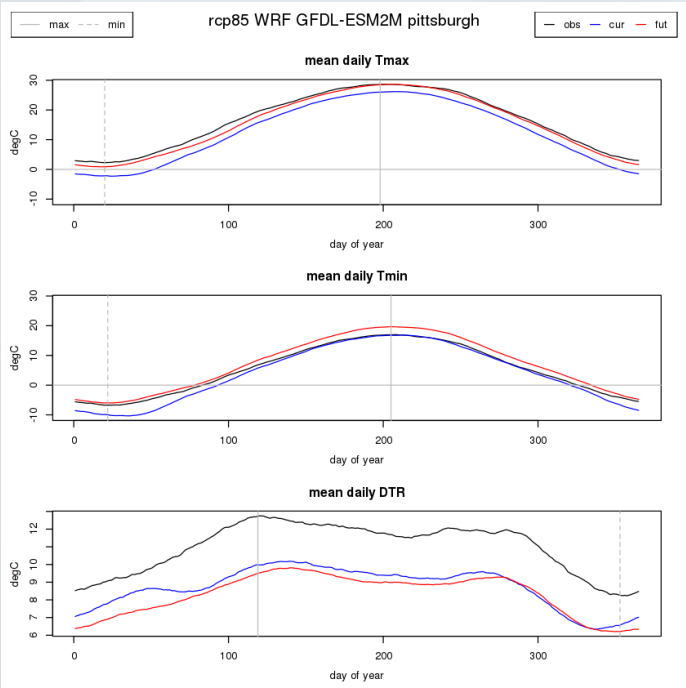


Evaluating NA-CORDEX RCMs

- 2 RCMs:
  - RegCM4 & WRF
- 3 CMIP5 GCMs
  - HadGEM2-ES
  - MPI-ESM-LR
  - GFDL-ESM2M
- Downscaling to 25 km
- Daily precip, Tmin, Tmax

10 test locations
with different climates
(1st stage of targeting)

Statistical Analysis → Numeric Metrics



period	GCM	RCM	tmaxcor	tmincor	dtrcor	tmaxmad	tminmad	dtrmad
hist	GFDL-ESM2M	RegCM4	0.995	0.998	0.515	7.86	5.6	1.99
hist	HadGEM2-ES	RegCM4	0.998	0.997	0.446	5.82	3.13	2.1
hist	MPI-ESM-LR	RegCM4	0.993	0.999	0.626	4.14	3.13	1.6
hist	GFDL-ESM2M	WRF	0.999	0.998	0.93	5.24	1.25	3.57
hist	HadGEM2-ES	WRF	0.998	0.996	0.724	2.68	3.02	3.06
hist	MPI-ESM-LR	WRF	0.999	0.996	0.572	6.77	3.33	3.32
rcp85	GFDL-ESM2M	RegCM4	0.994	0.999	0.743	5.13	2.29	1.37
rcp85	HadGEM2-ES	RegCM4	0.999	0.995	0.815	2.9	3.24	1.79
rcp85	MPI-ESM-LR	RegCM4	0.996	0.999	0.844	2.24	1.26	1.35
rcp85	GFDL-ESM2M	WRF	0.999	0.999	0.987	1.21	2.71	3.97
rcp85	HadGEM2-ES	WRF	0.998	0.997	0.919	2.99	6.41	3.76
rcp85	MPI-ESM-LR	WRF	0.999	0.996	0.785	3.03	5.04	2.86

“Low-Bar” Statistical Metrics

- Annual cycle (T, P)
- Monthly PDFs (T, P)
- Extreme value analysis of precipitation
- Seasonal precip intensity spectra
- Joint distribution of temp & precip

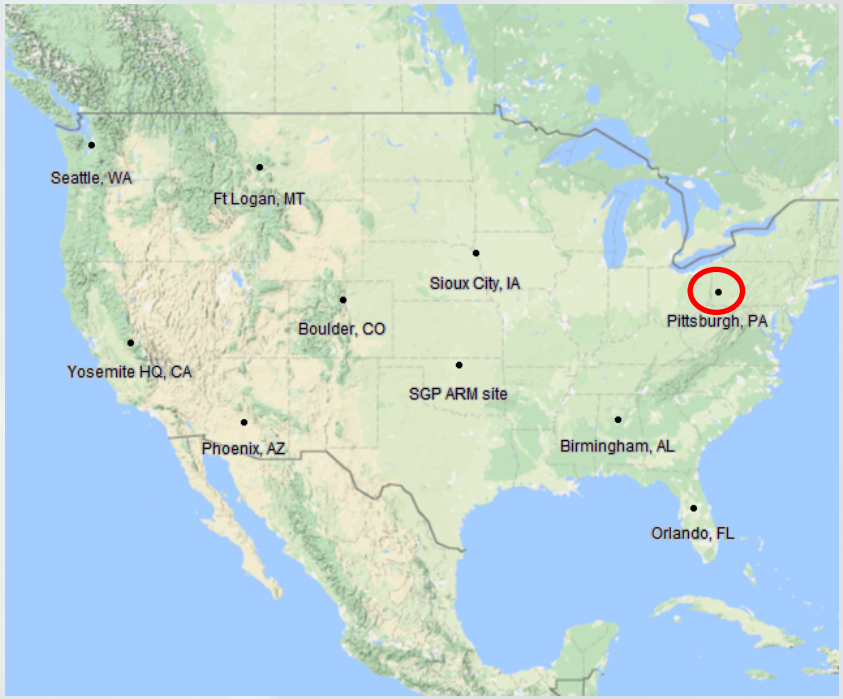
- Most informative: annual cycle of precipitation
  - Frequency
  - Intensity
  - Total
- Because everything affects precipitation

Pittsburgh, PA

- Simple precipitation cycle

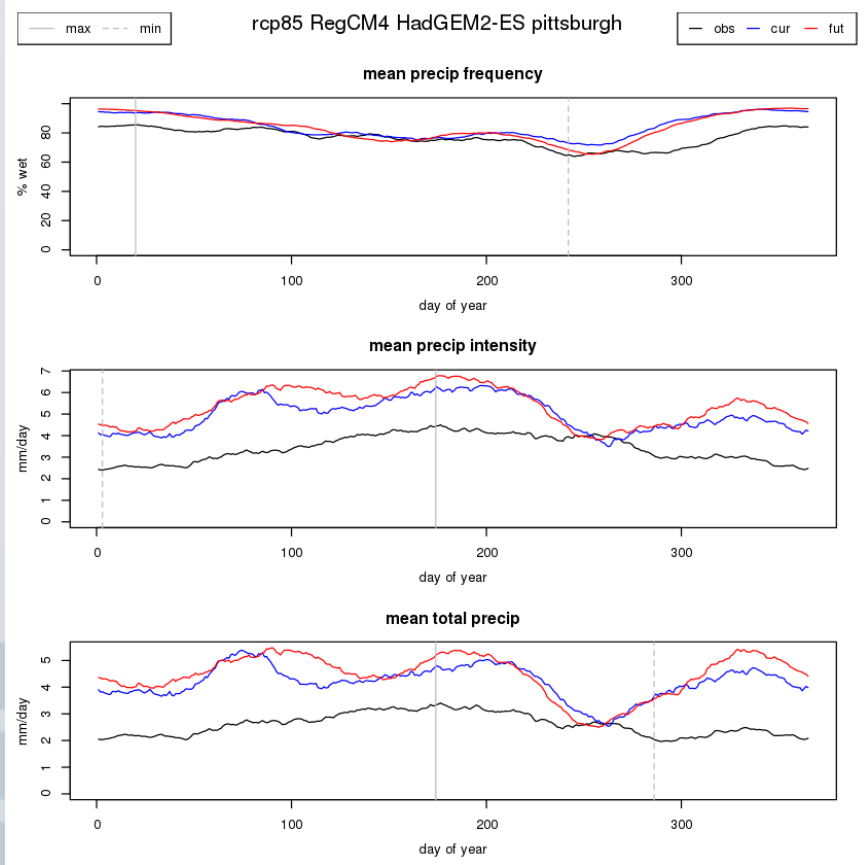
In general:

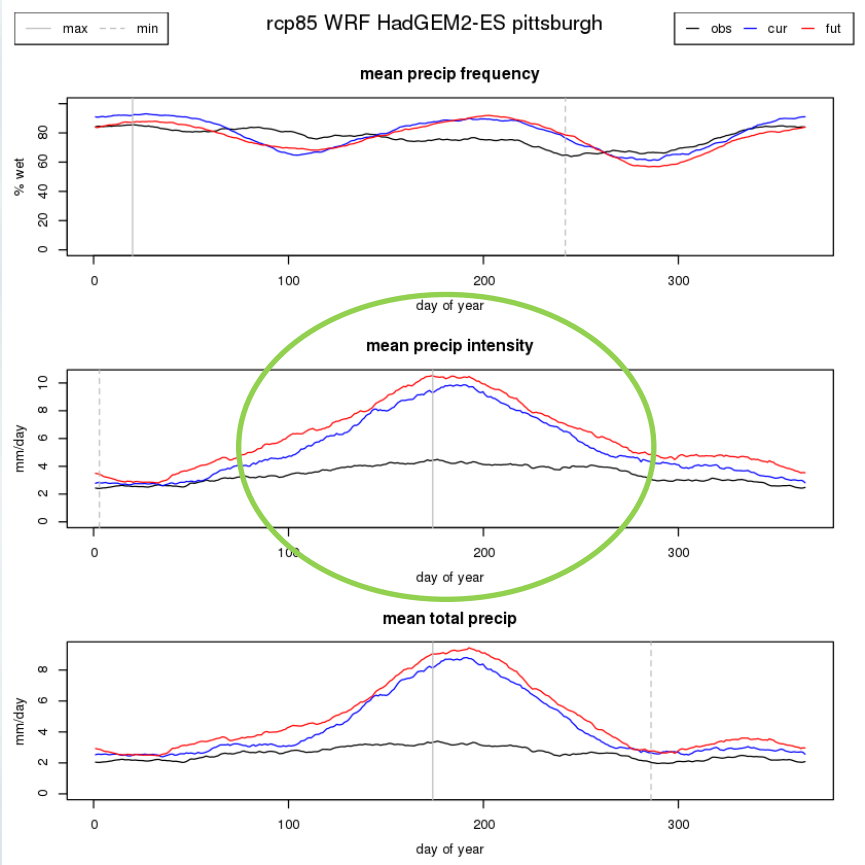
- Summer: mostly convective
- Winter: heavily forced
- Simulations with the same RCM look very similar



Pittsburgh: summer WRF bias

⇒ investigate convective parameterizations

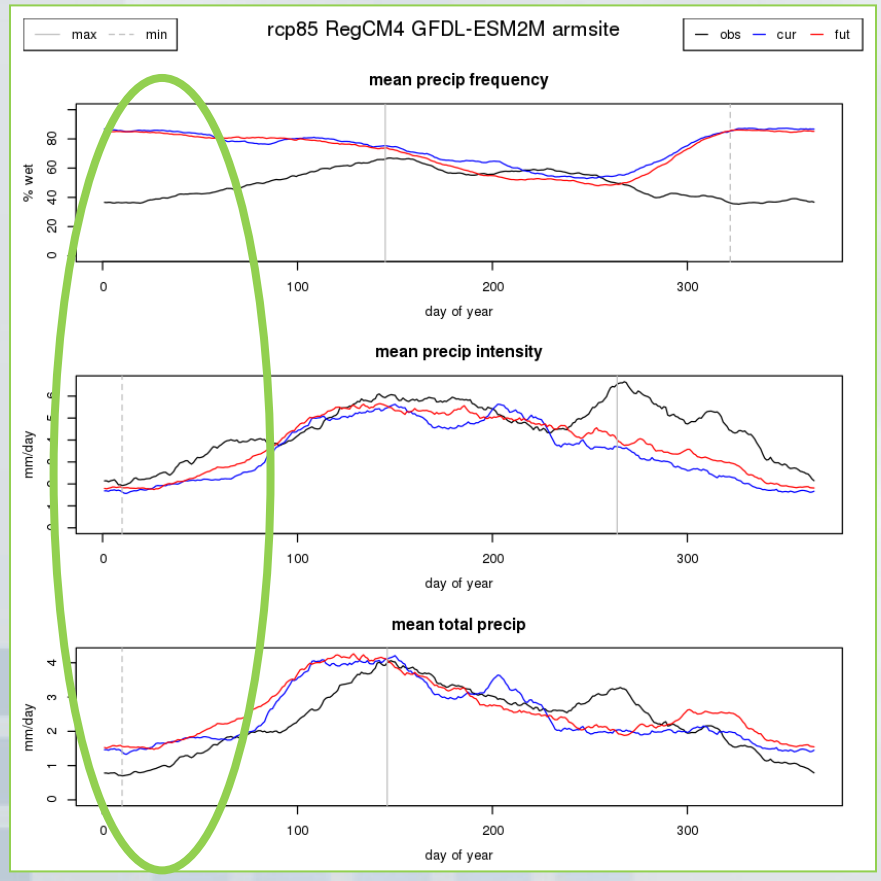


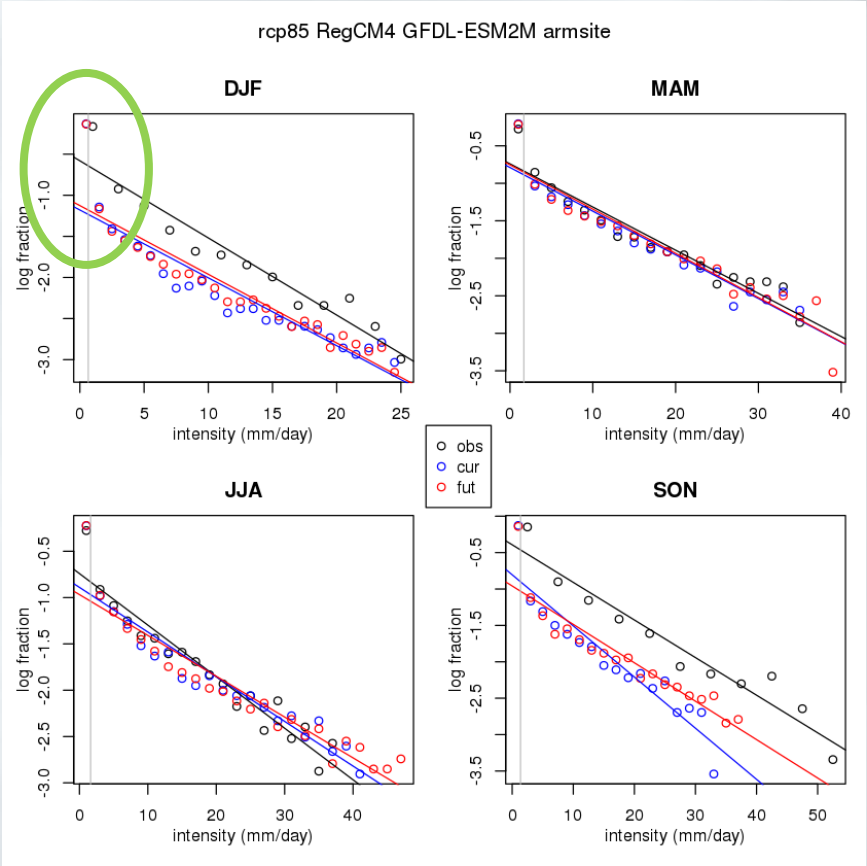


SGP ARM site, OK

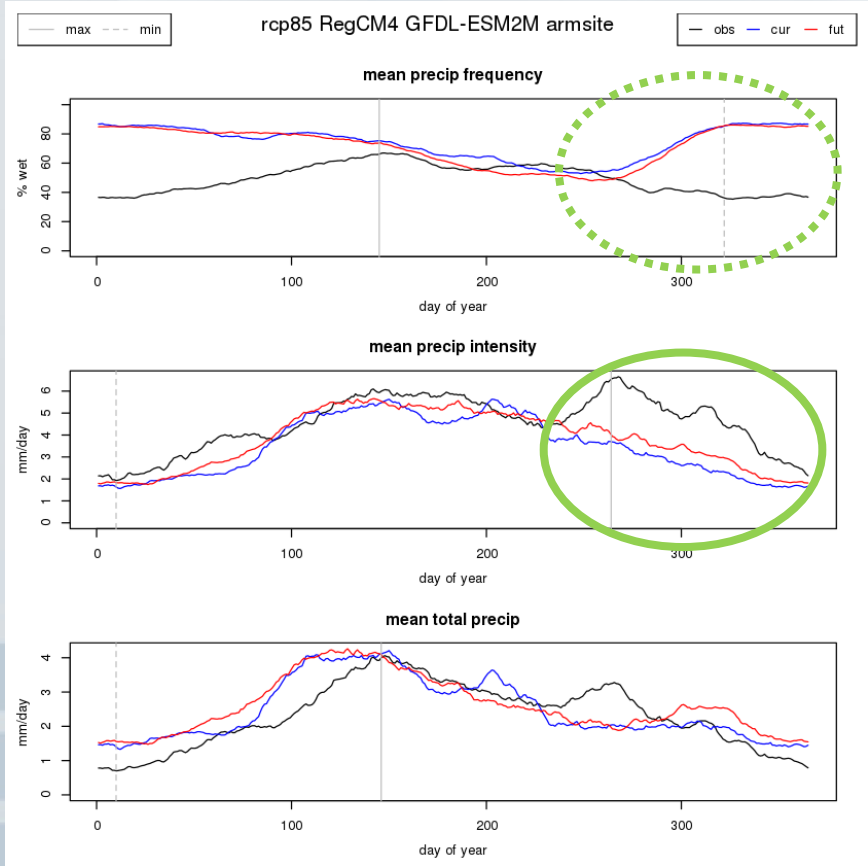
- DoE Climate Research Facility
- All WRF simulations look reasonable
- All RegCM4 simulations have similar problems

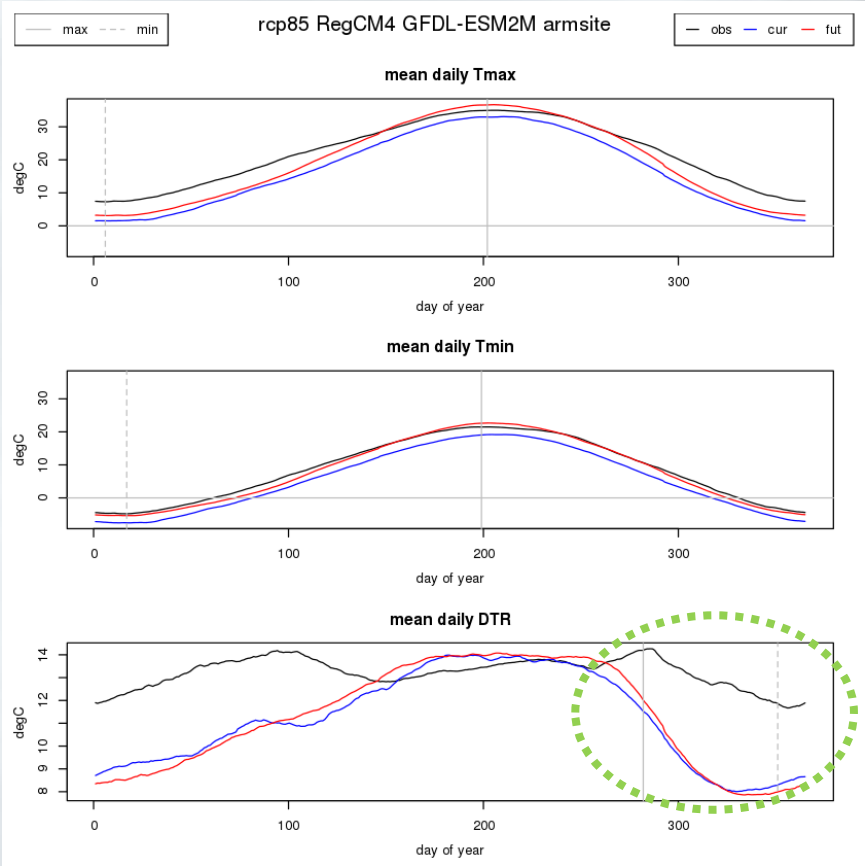
ARM site (1): Too much cold season drizzle in RegCM4 ⇔ no ice microphysics





ARM site (2): Missing cold-front convective lines
⇒ drizzle erodes instability in RegCM4





More complex analysis

⇕

More focused targets

- Basic climatology helps you pick test locations
- Differences in numeric metrics tell you which statistical analyses to examine
- Applying meteorological knowledge to the statistical analyses identifies candidates for process analysis
- Process analysis leads to region-specific phenomena-based metrics for use in interaction analysis
- Etc.

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Questions?