Interpreting Climate Model Projections of Extreme Weather Events

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University of Wisconsin-Madison

What information (about weather extremes) can be squeezed out of a collection of climate model projections?

-- **Focus of Study**: Daily extremes of heat, cold, and precipitation

-- **Domain**: Northeastern quadrant of U. S. with emphasis on Midwest

-- **Definitions**: Extreme heat = 90°F, Extreme cold = 0°F, Extreme precipitation = 2”

-- **Goal**: Strike a proper balance between comprehensive and simple statistical assessments

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Complex:

- Bayesian methods (Tebaldi et al., 2005)
- Hierarchical statistical models (Cressie and Wikle, 2011)
- Reliability Ensemble Averaging (Giorgi and Mearns, 2002)

Simple:

- Multi-model average
- Inter-model agreement on sign of change
- Inter-model spread (standard deviation, interquartile range)

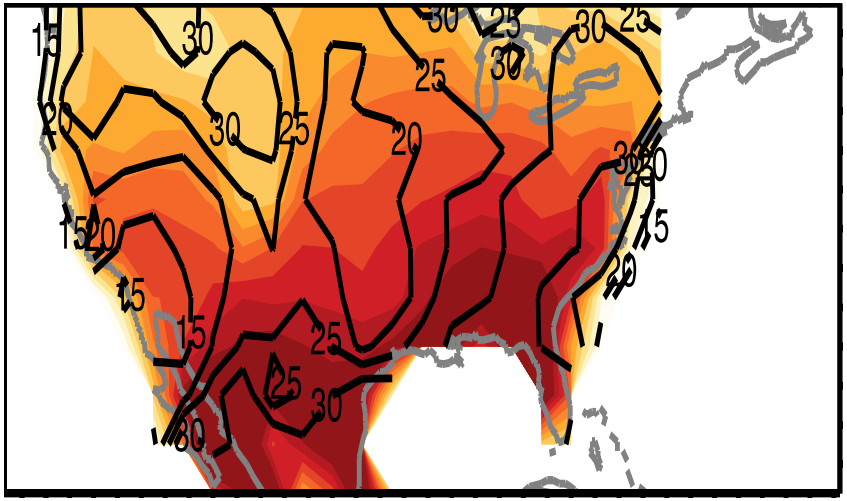
Proposed:

- Inter-model spread (coefficient of variation)
- Inter-model skewness
- Percentile ranges

Examples of Common Uncertainty Analyses

CMIP5 Model Agreement on Change in Summer Precipitation (Late 21st C)

CMIP5 Mean Change in 90°F Days and Intermodel Standard Deviation



Maloney et al. (2013)

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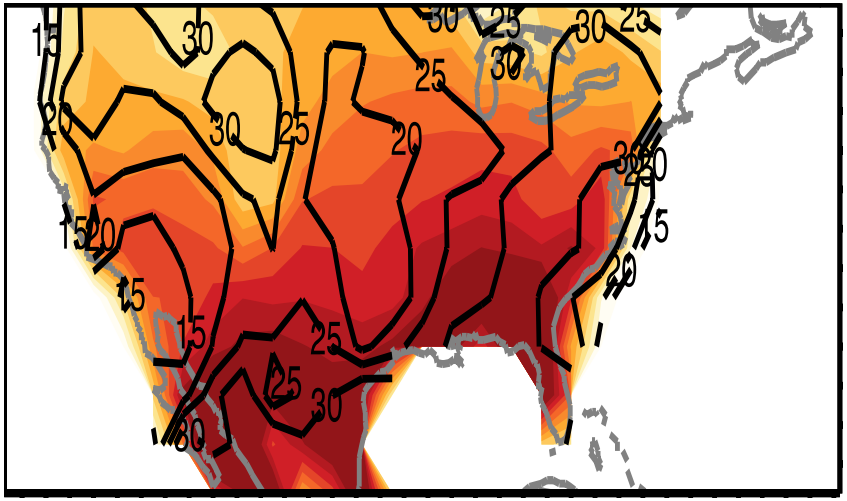


+ Better than simply considering the multi-model average
+ Accessible to non-technical audience

- Some important information is “left on the table”
- Not obvious how to use these results quantitatively

Maloney et al. (2013)

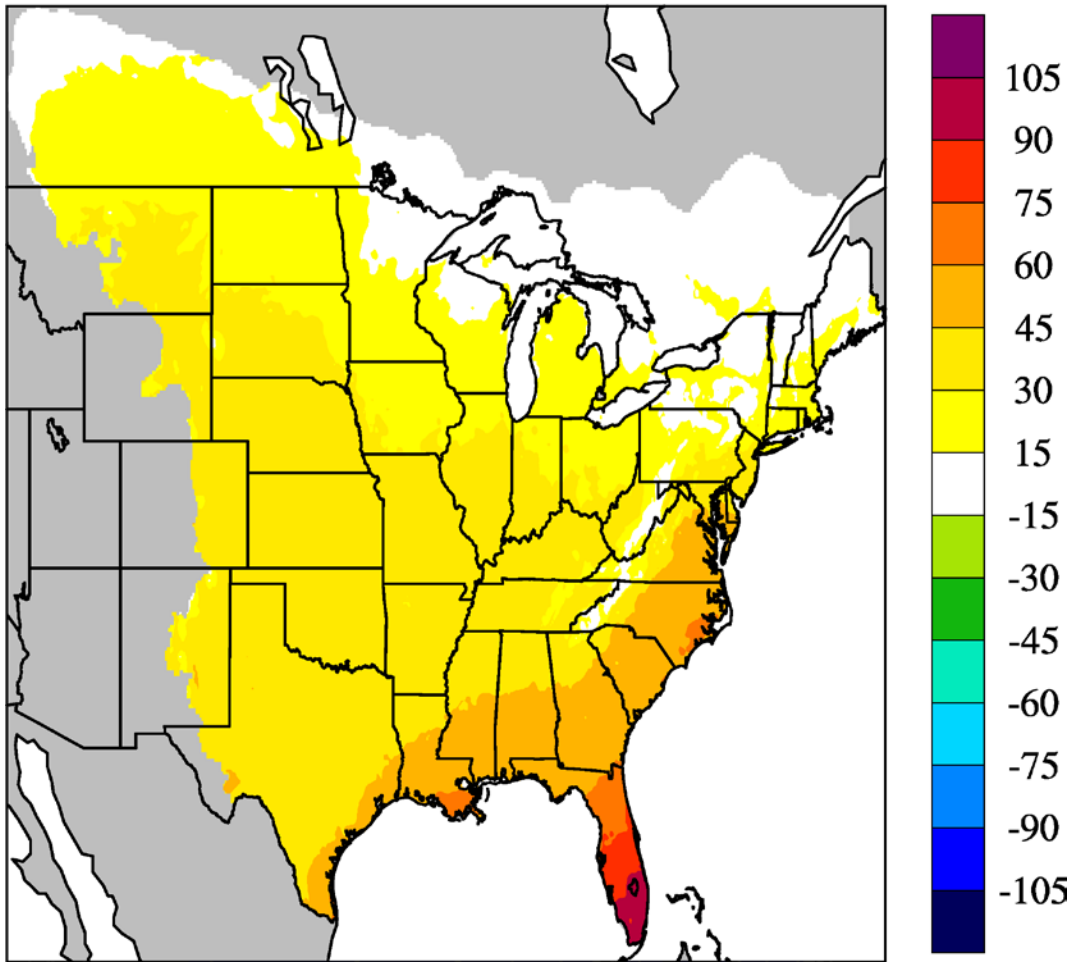
Statistical Downscaling Product

Source	13 CMIP3 / IPCC AR4 global climate models
Scenarios	A2, A1B, B1 A2 = High GHG emissions B1 = Lower emissions
Time Periods	1961-2000, 2046-2065, and 2081-2100
Temporal Resolution	Daily
Spatial Resolution	0.1° x 0.1°
Region	LCCs east of the Rockies
Variables	Maximum & Minimum temperature, Precipitation
Format	Cumulative Distribution Functions or Multiple Realizations
Data Type	Netcdf

** Models are bias-corrected to produce realistic 20th century output**

Change in Frequency of 90-degree Days per Year by Mid-Century "Middle-of-the-road" Emissions Scenario (A1B)

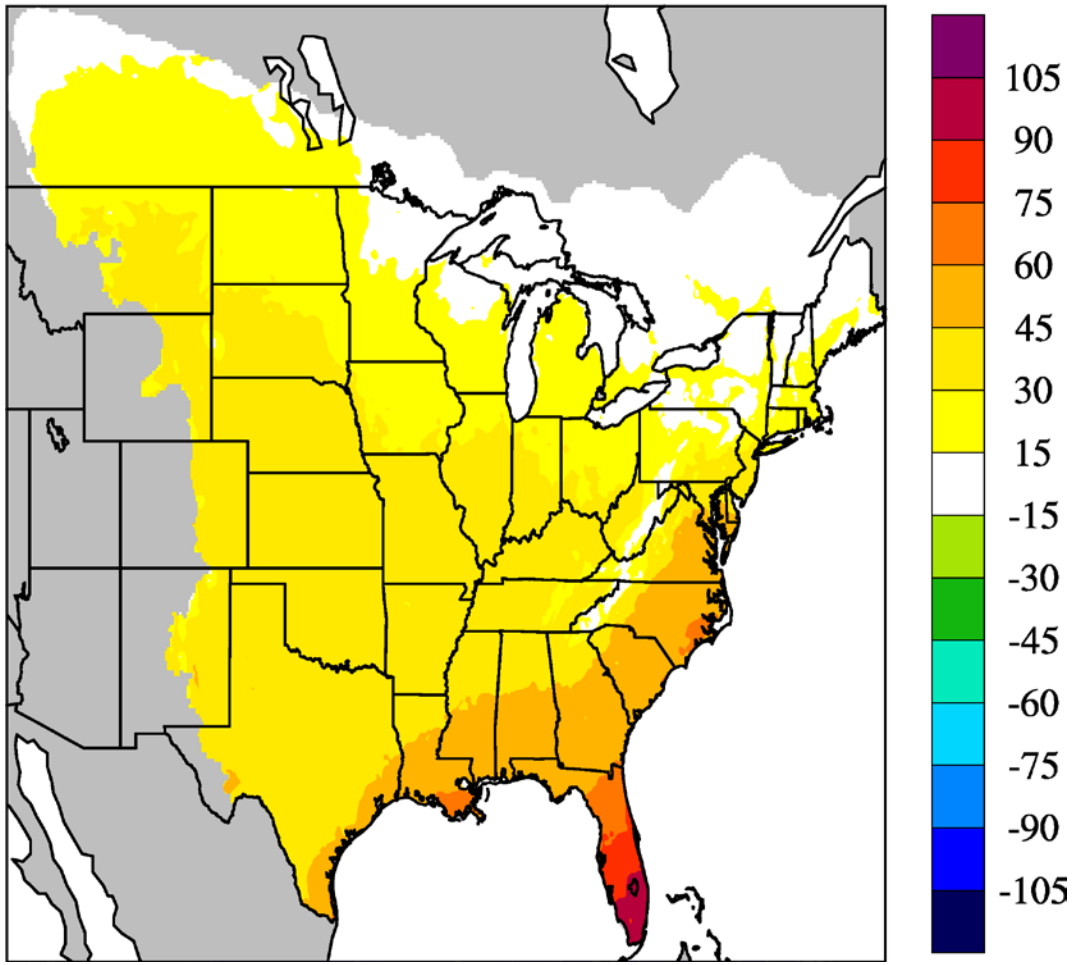
Average of 13 Climate Models



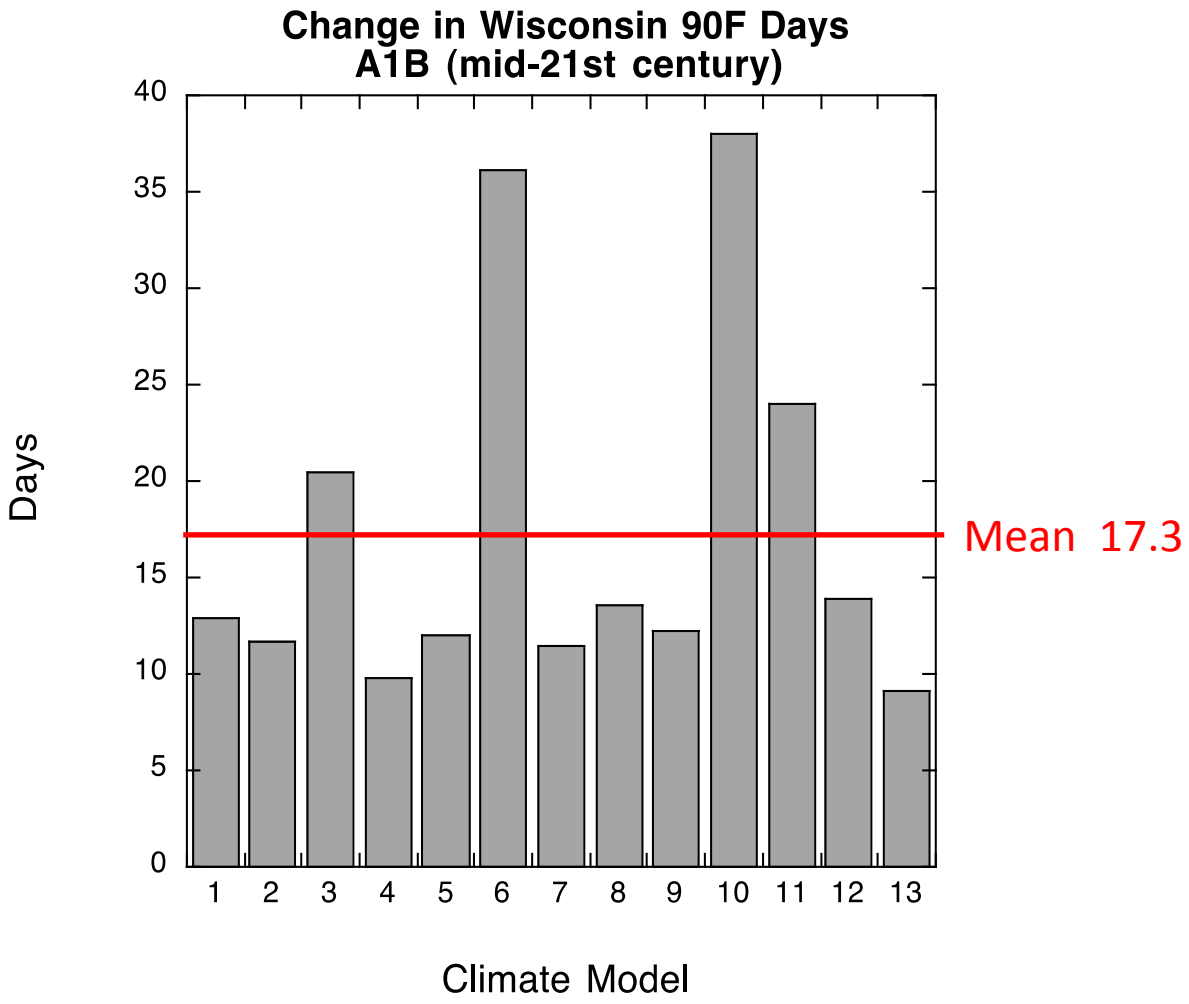
Change in Frequency of 90-degree Days per Year by Mid-Century "Middle-of-the-road" Emissions Scenario (A1B)

Average of 13 Climate Models

How can we do better?



Projected Change in Extreme Heat in Wisconsin



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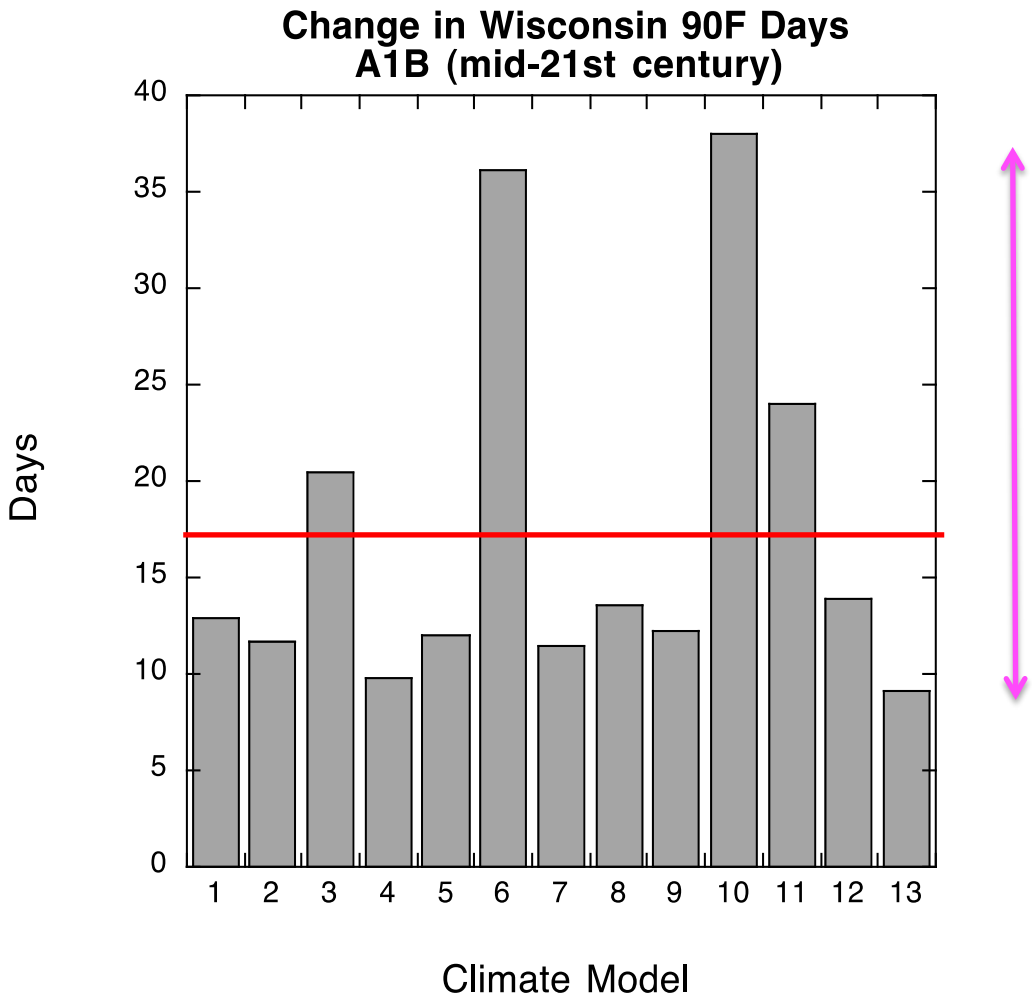

Amount of spread among model projections provides a confidence measure of the multi-model average

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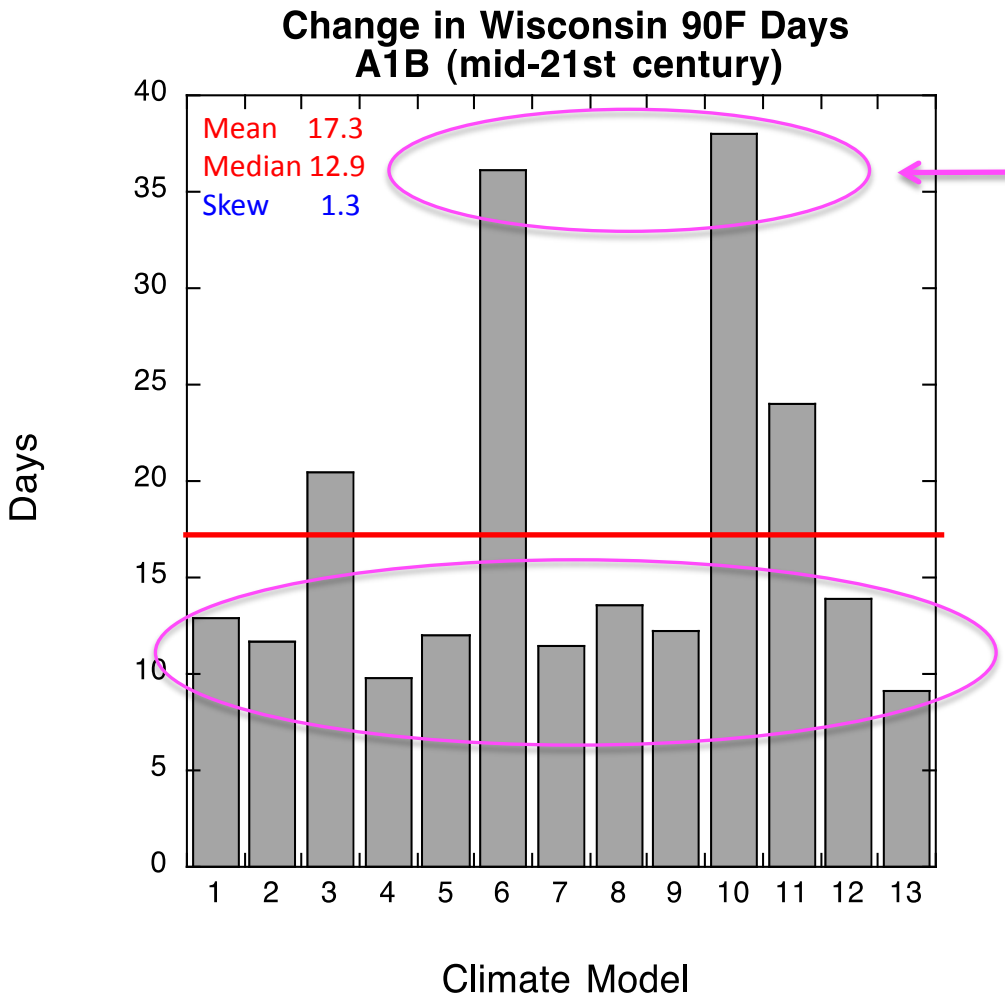

Two outlier models simulate large increases (> 35 days/year)

Most models simulate much smaller increases (9-14 days/year)

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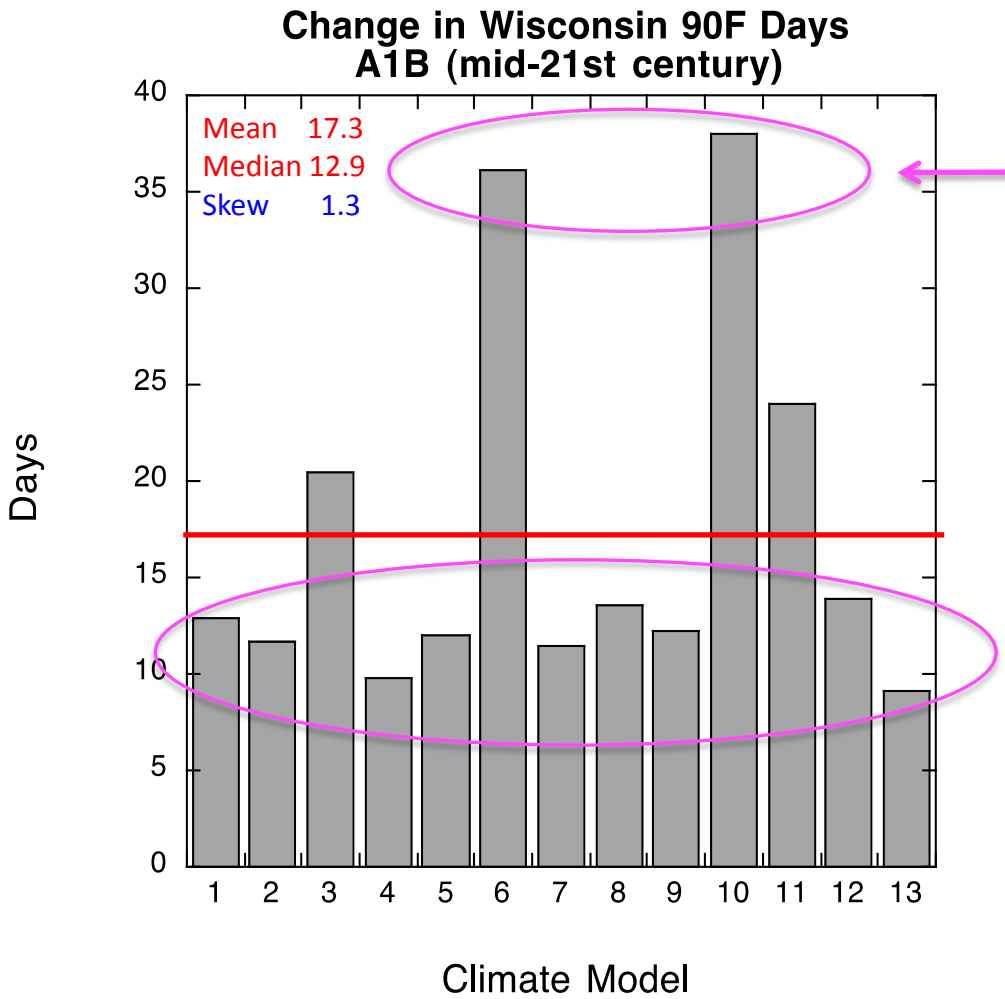


Two outlier models simulate large increases (> 35 days/year)

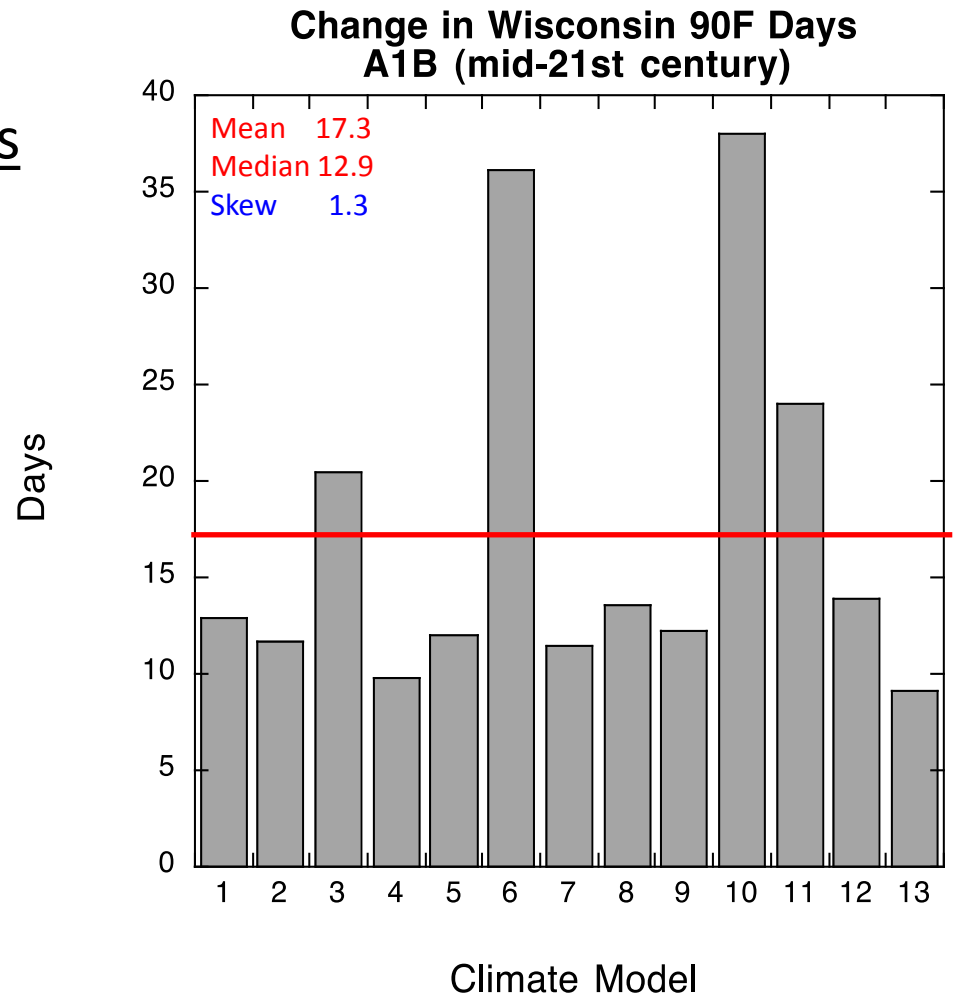
Most models simulate much smaller increases (9-14 days/year)

Skewness of projections provides confidence measure of low-end vs. high-end estimates

Projected Change in Extreme Heat in Wisconsin

Two Viable Assessment Strategies

1) Physical: evaluate the models to assign more weight to some projections and less to others

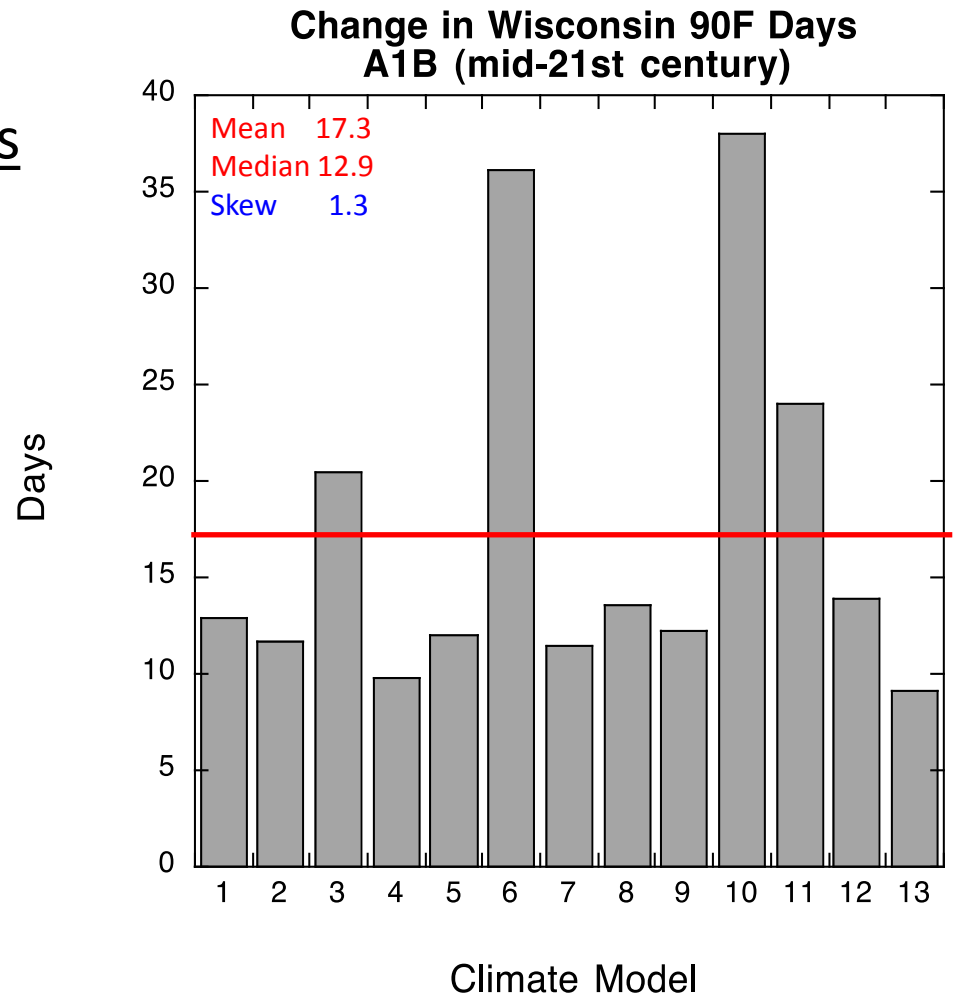


Projected Change in Extreme Heat in Wisconsin

Two Viable Assessment Strategies

1) Physical: evaluate the models to assign more weight to some projections and less to others

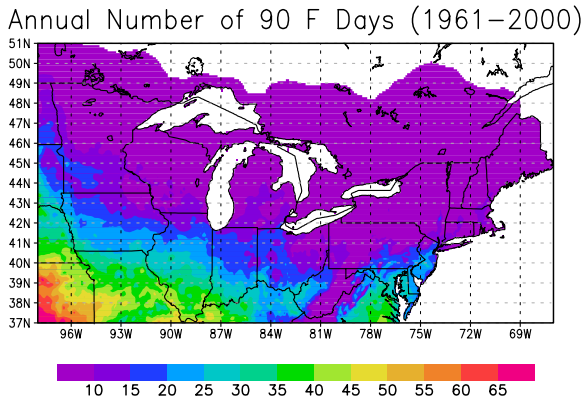
2) Statistical: apply "model democracy" by assuming that each model projection is equally valid



Climatology of Extremes, Late 20th Century, Intermodel Means (debiased)

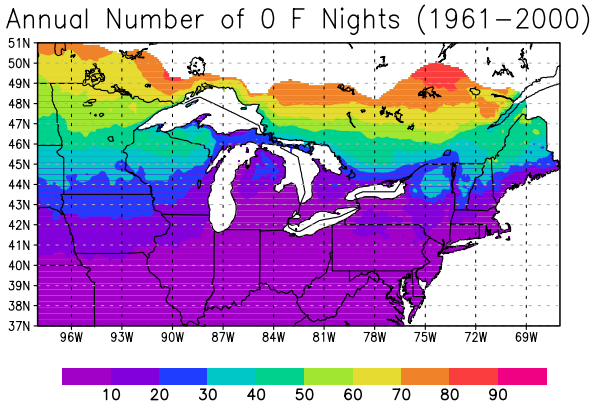
Range:

Extreme Heat



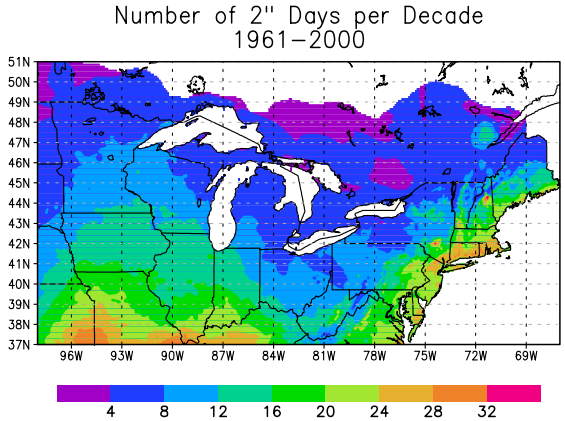
< 10 days to 65 days/year

Extreme Cold



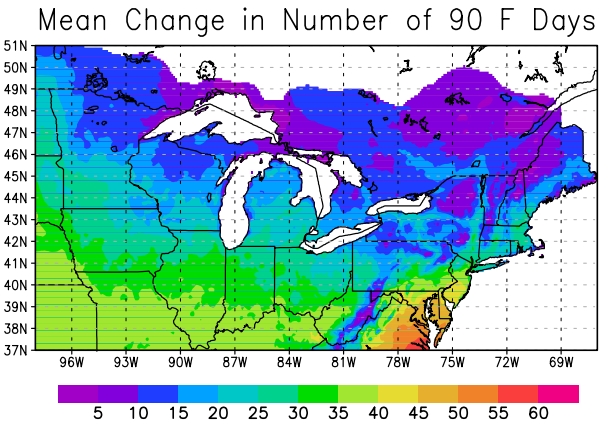
< 10 days to 90 days/year

Extreme Precipitation



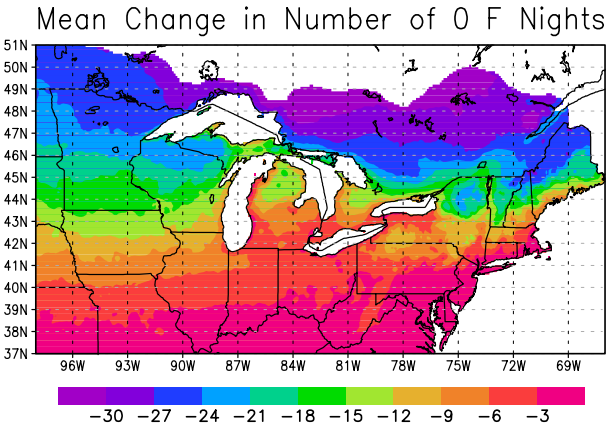
< 4 days to 32 days/decade

Changes in Extremes, mid-21st Century, A1B Scenario

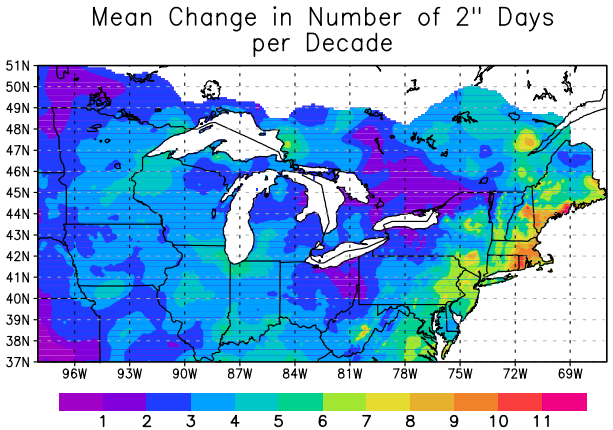


Range:

< 5 days to 60 days/year



< -3 days to -30 days/year



~1 day to 10 days/decade

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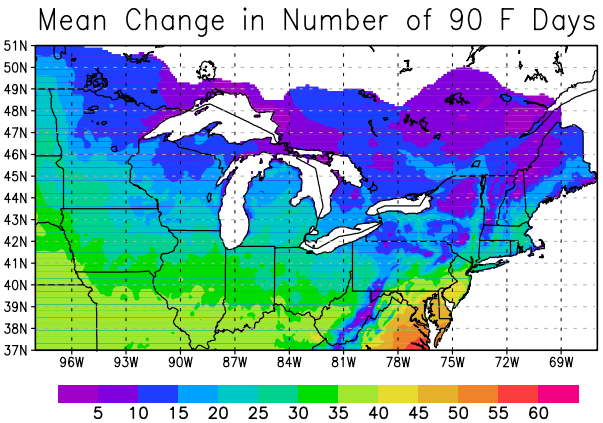
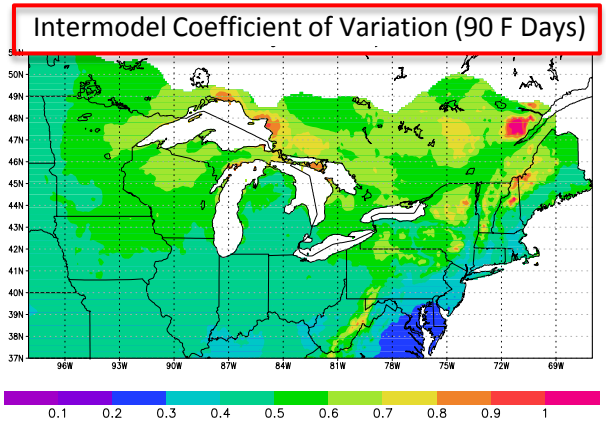
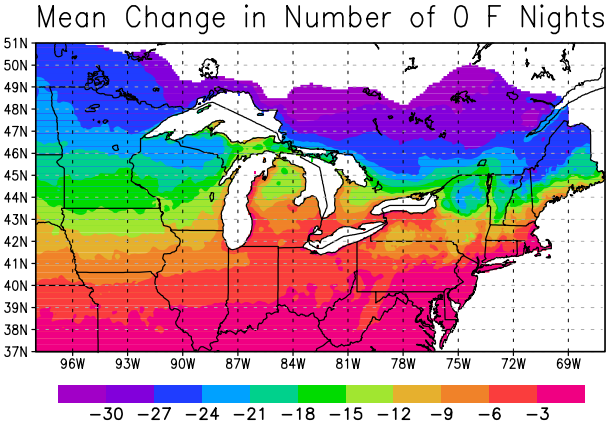
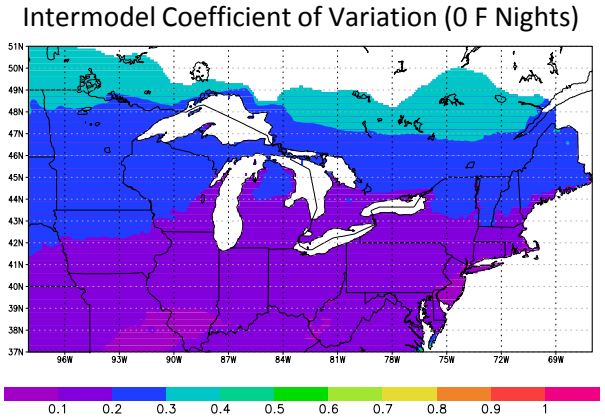




Range:

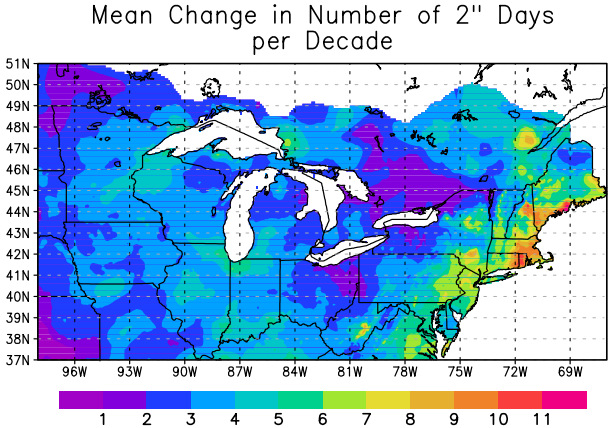
0.2 to 1

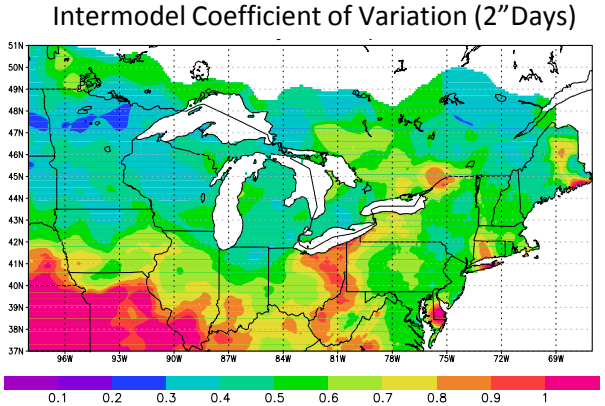




~0.1 to 0.4

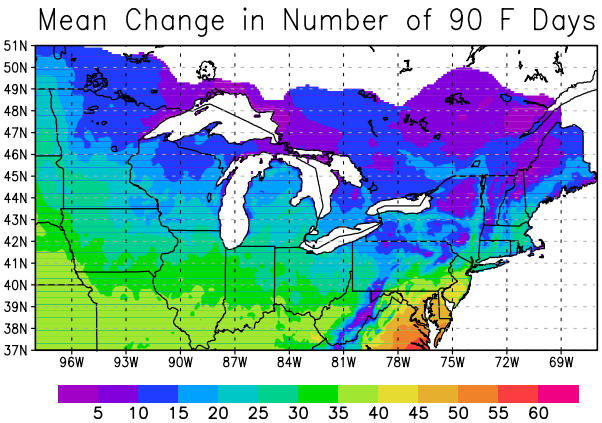
Higher and more uniform model agreement for extreme cold





0.2 to > 1

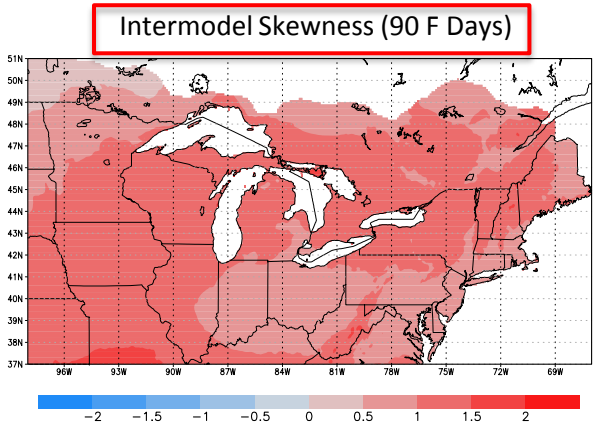
Changes in Extremes, mid-21st Century, A1B Scenario

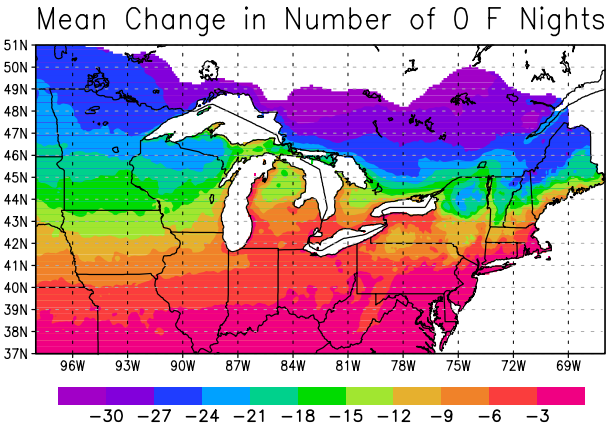


Outlier upper-end projections of extreme heat

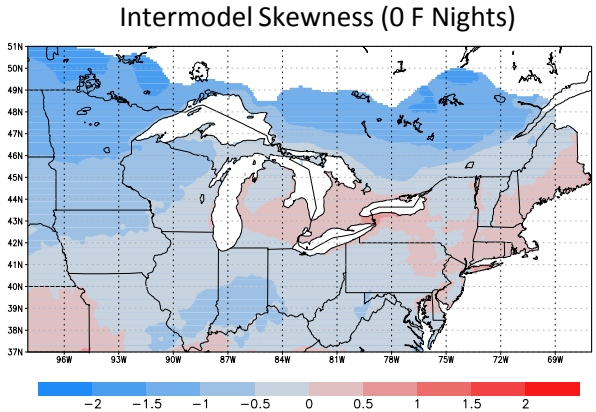
Range:

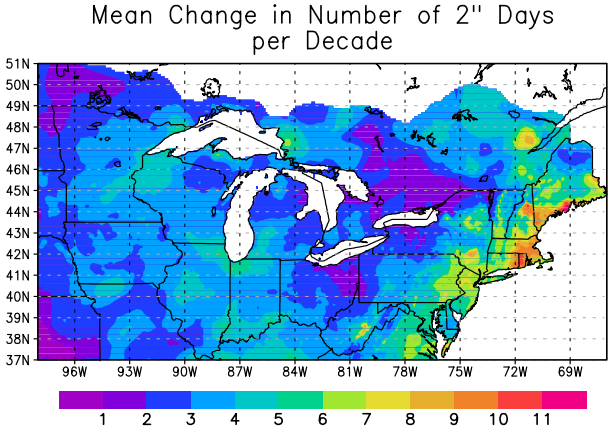
0.4 to 2



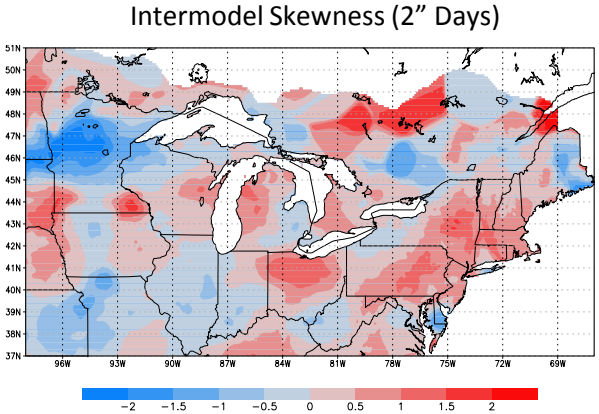


-2 to 0.5



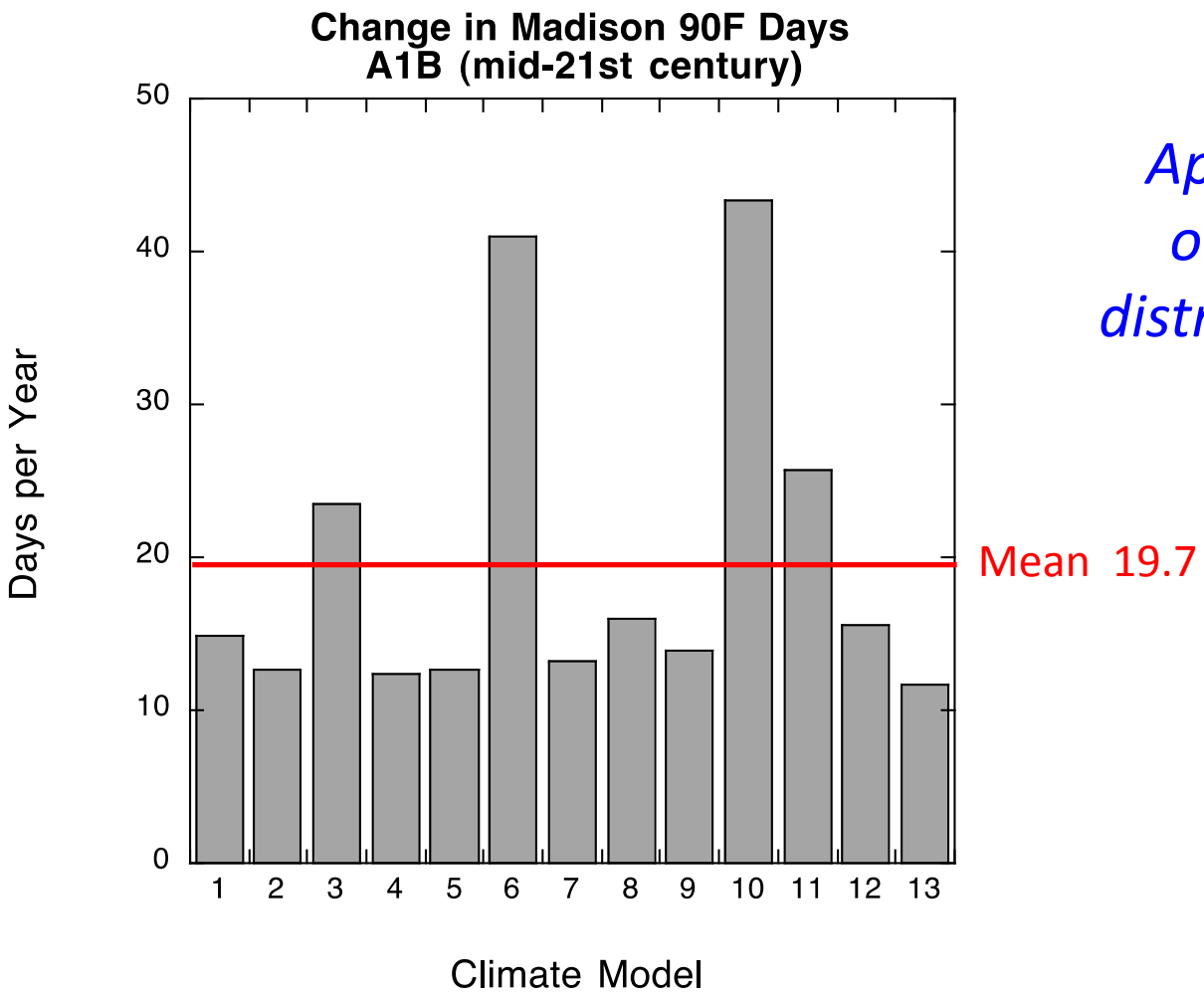


< -2 to > 2

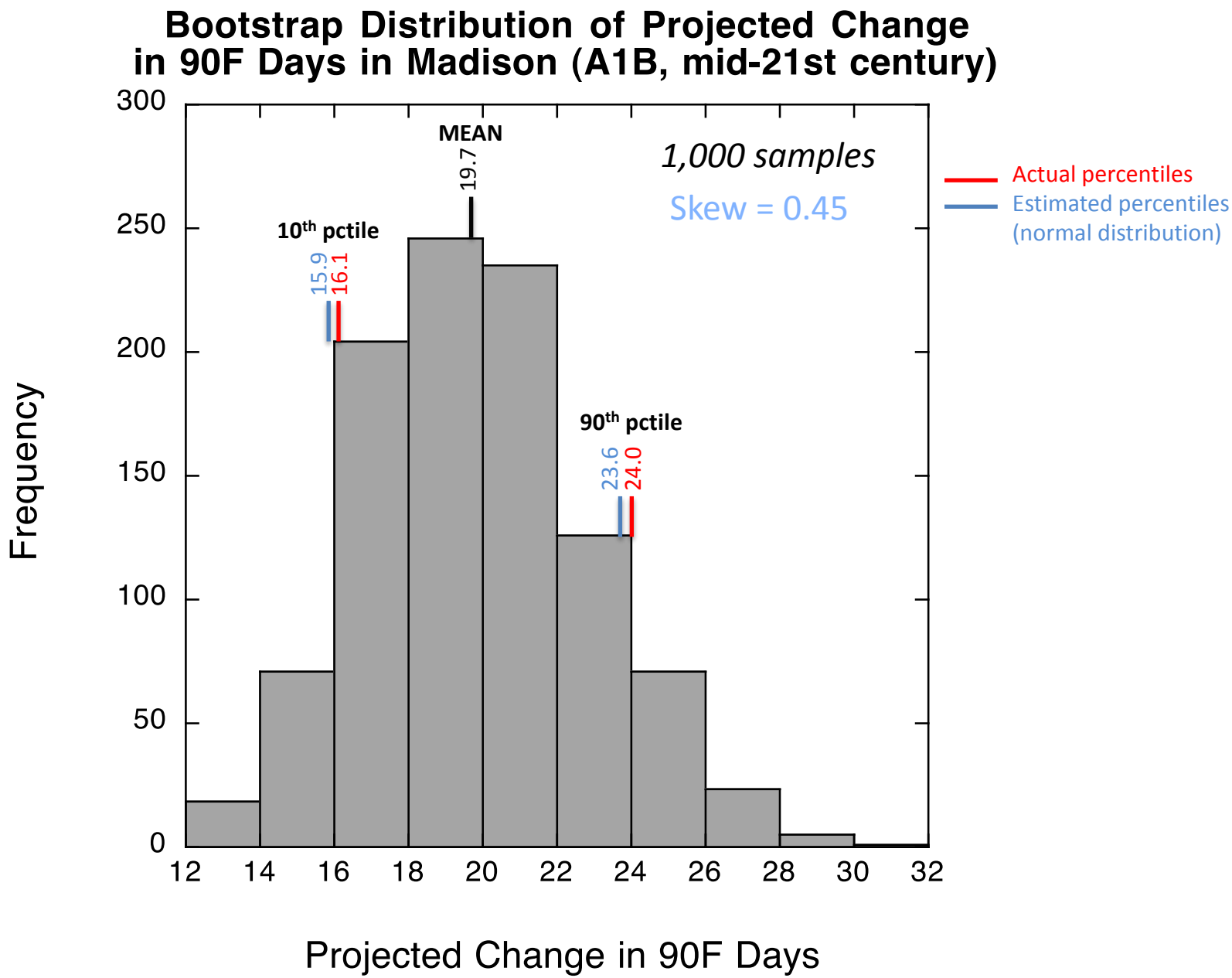


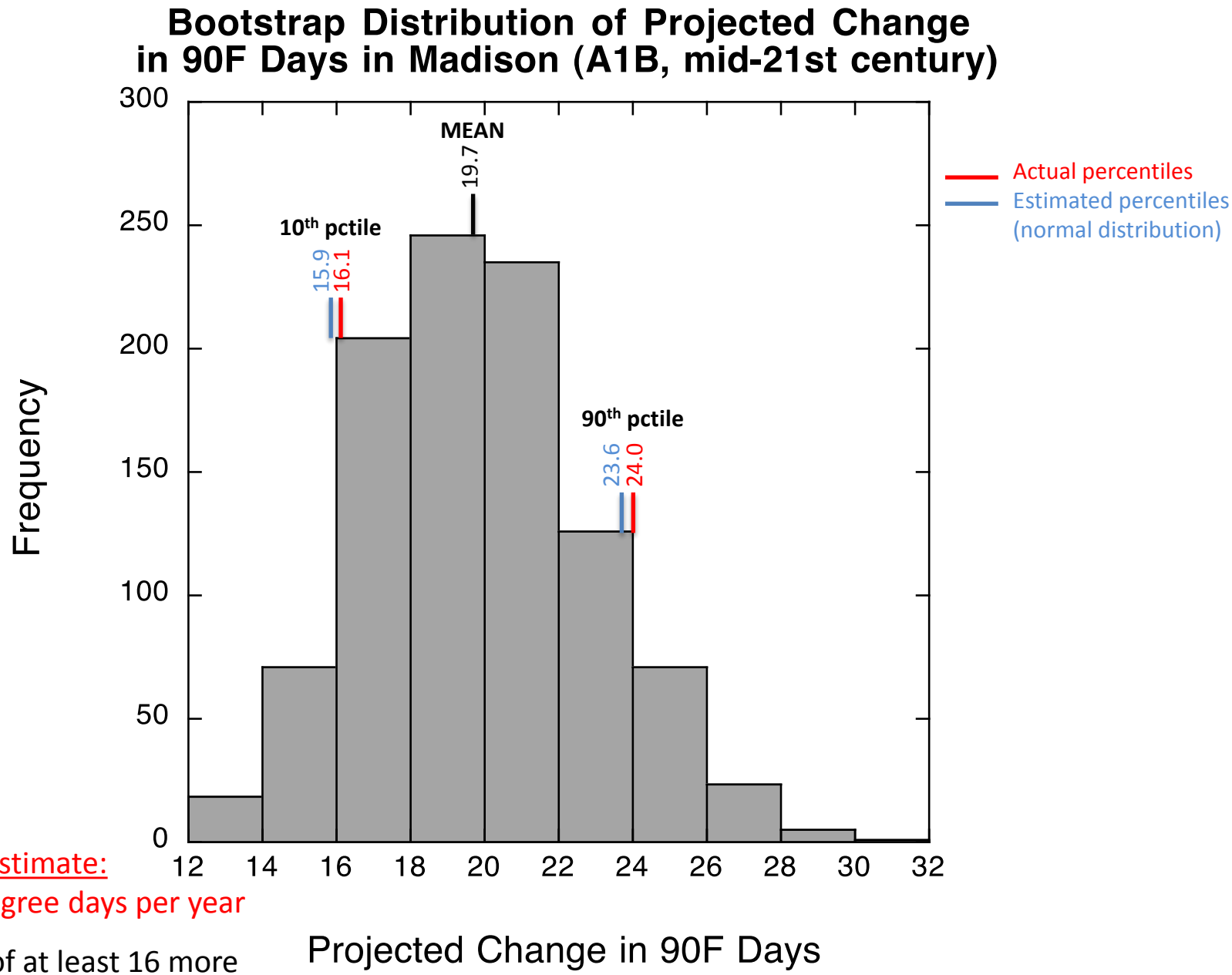
Obtaining Probabilistic Uncertainty Bounds

Projected Changes in Hot Days in Madison, WI



Apply bootstrapping to obtain many possible distributions of projections (Monte Carlo)


Bootstrap Distribution of Projected Change in 90F Days in Madison (A1B, mid-21st century)
1,000 samples
Skew = 0.45
MEAN
19.7
10th pctile
15.9
16.1
90th pctile
23.6
24.0
Actual percentiles
Estimated percentiles (normal distribution)
Frequency
Projected Change in 90F Days
0
50
100
150
200
250
300
12
14
16
18
20
22
24
26
28
30
32



Best Estimate:

19.7 more 90-degree days per year

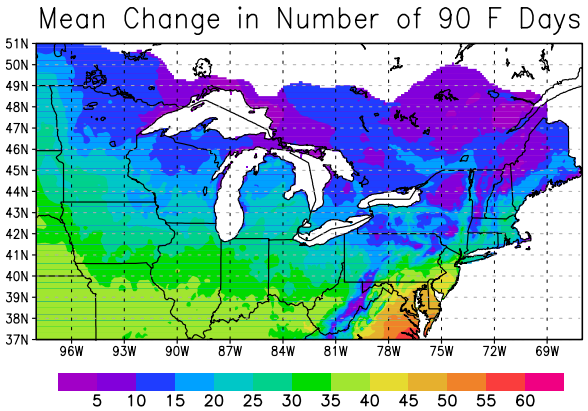
90% likelihood of at least 16 more

90% likelihood of no more than 24

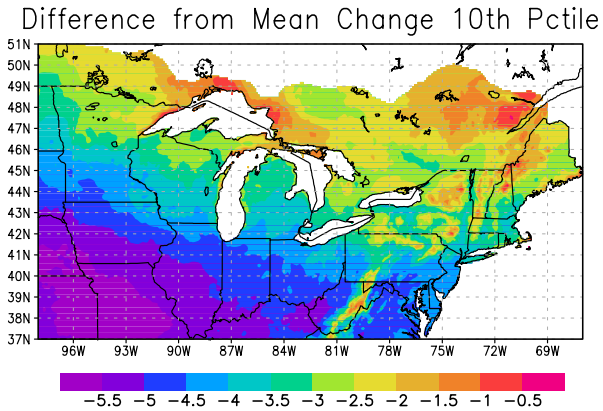
Spatial Patterns of Uncertainty Range <u>assuming Normal Distribution</u>

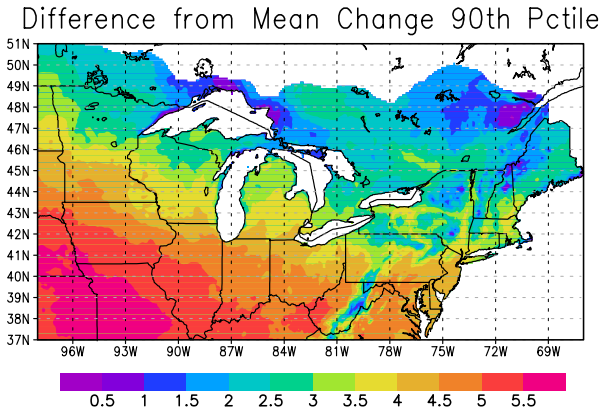
Projected Change in Hot Days

Multi-model Average



Uncertainty Range (10-90%)





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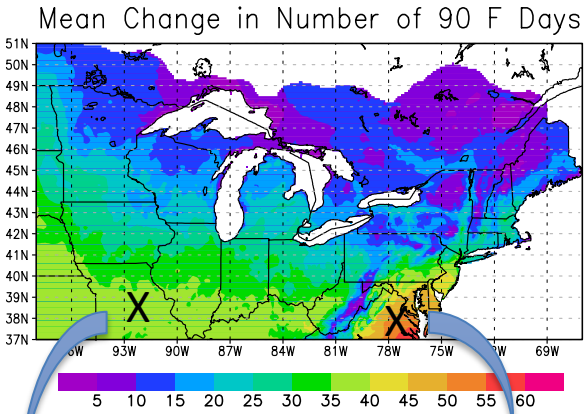

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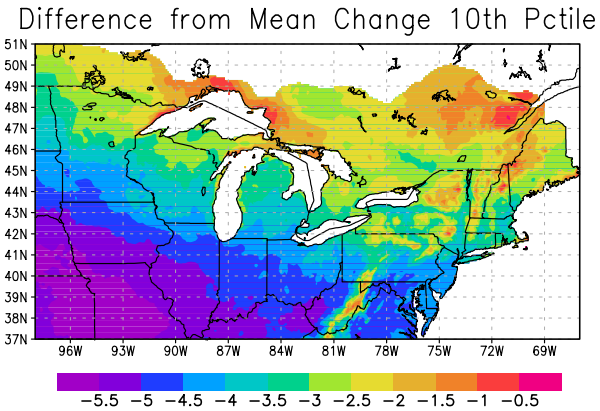

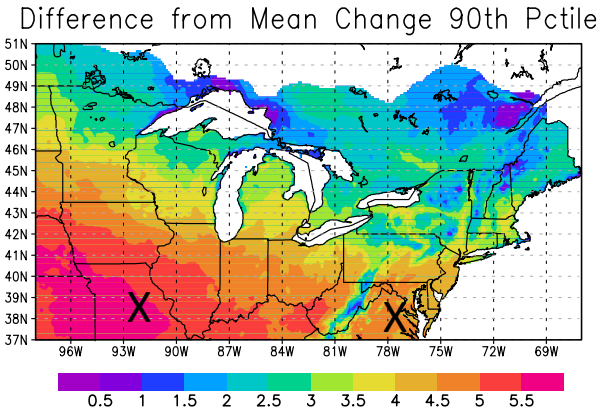

Richmond, VA: 53.4 +/- 4.5 days

Jefferson City: 36.4 +/- 5.7 days

Better intermodel agreement in southeast than southwest, despite stronger sensitivity

Summary

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  *-- Increases in **extreme heat** exhibit strong positive skewness among models*
  → More confidence in the majority of models that simulate smaller increases

  *-- Changes in **extreme cold** and **heavy precipitation** exhibit more symmetric distributions*
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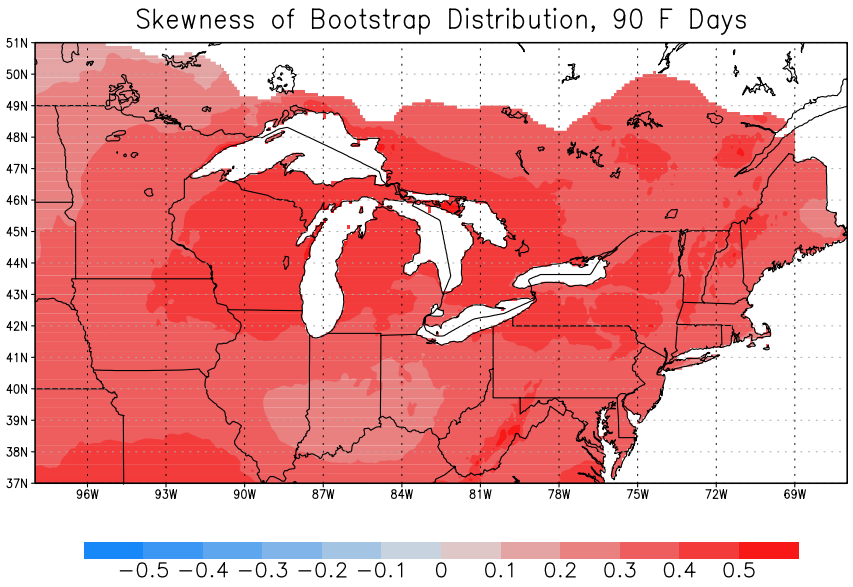
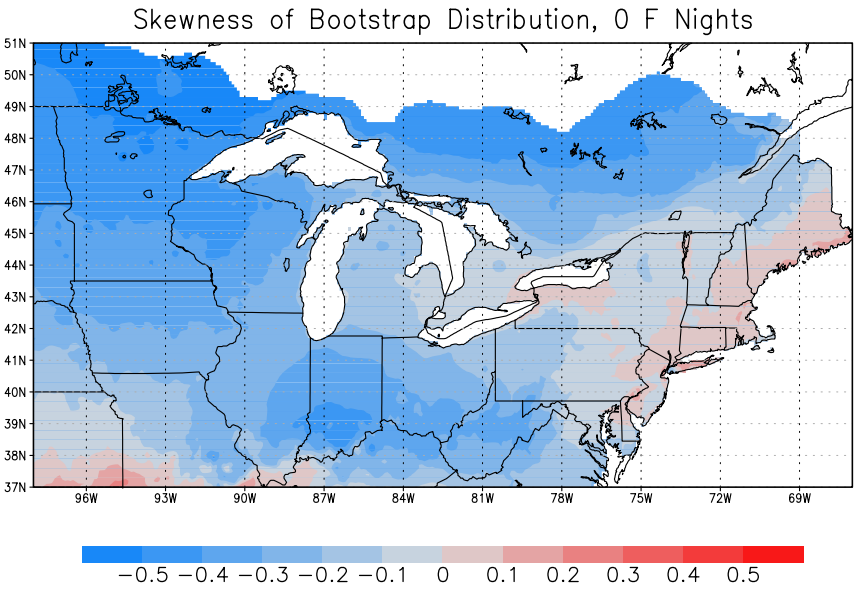
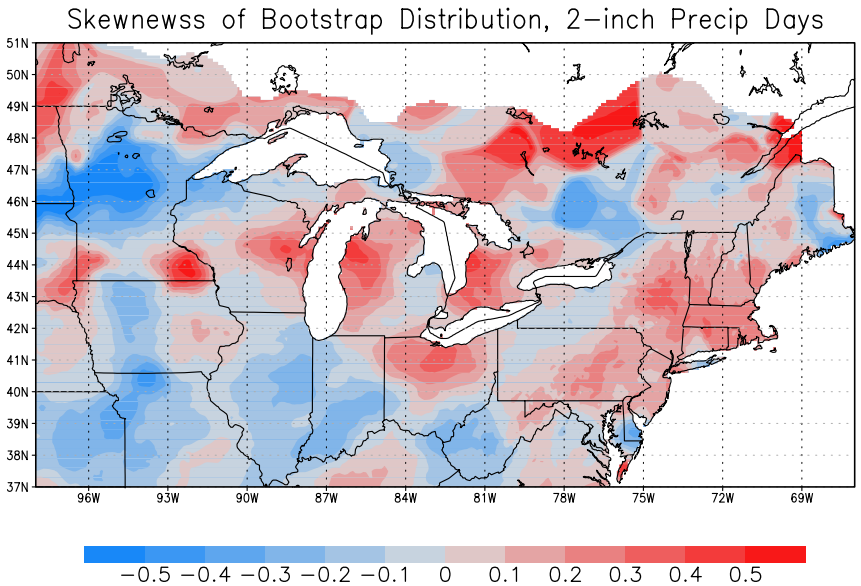
  -- May be an easy and useful tool for decision makers seeking specific uncertainty bounds

- Physically based assessments of model projections can and should be used to complement statistically based analysis

Skewness of Bootstrap Distributions

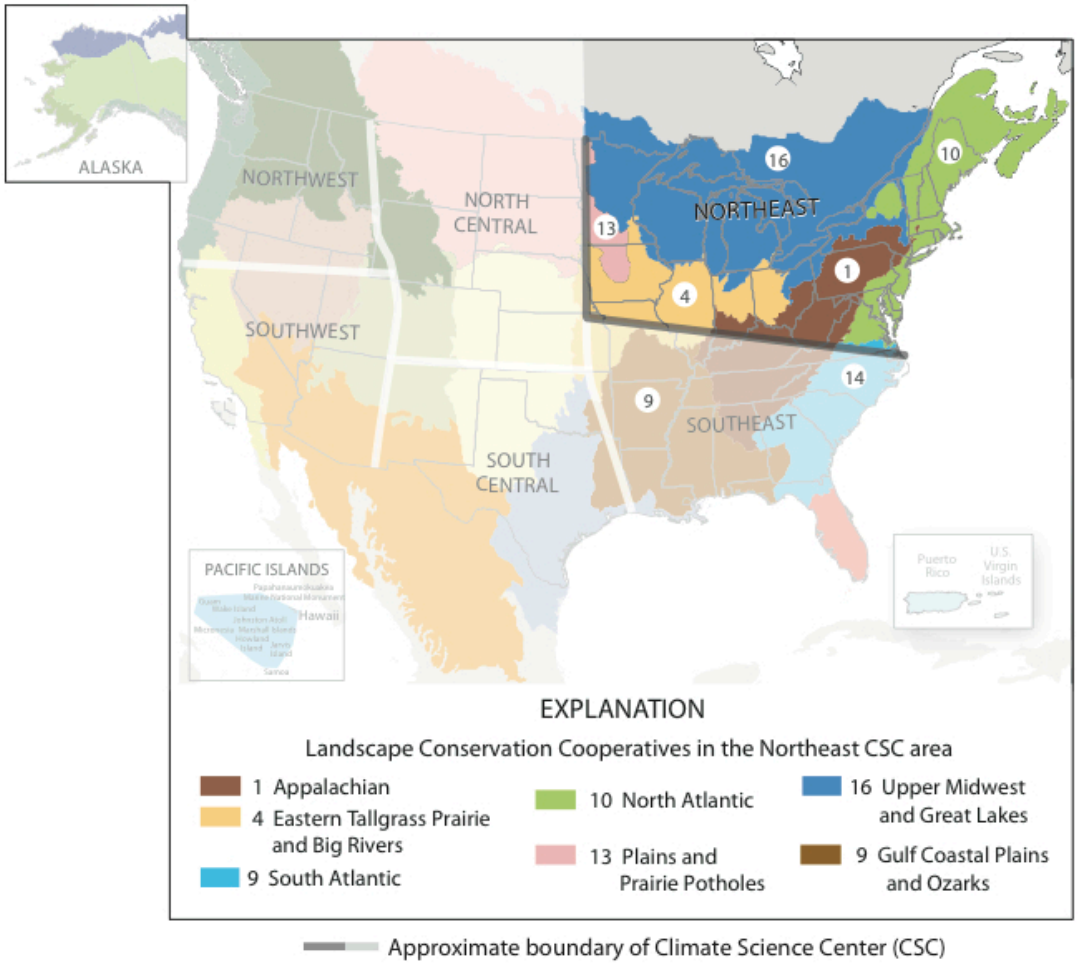






Fairly low skewnesses: < 0.5

Geographic Domains of Northeast Climate Science Center and Landscape Conservation Cooperatives



Approximate boundary of Climate Science Center (CSC)

Examples of Common Uncertainty Analyses

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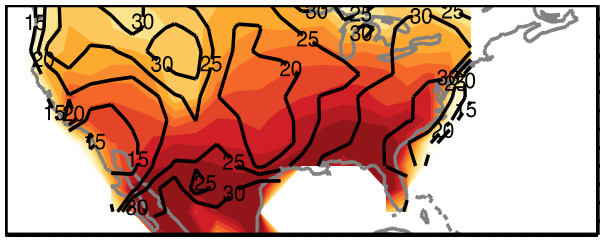


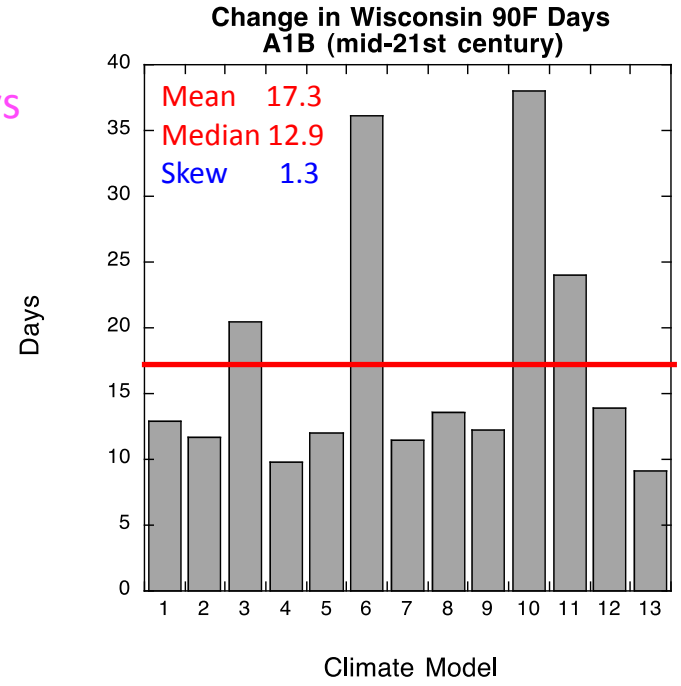
than individual models (for comparisons of significance tests, see Langenbrunner and Neelin 2013).

+ Better than simply considering the multi-model average
+ Accessible to non-technical audience

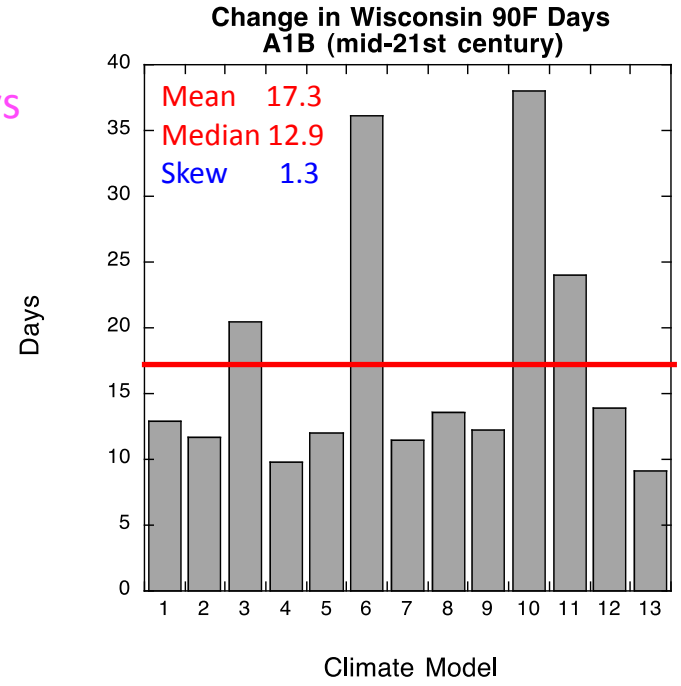
- Some important information is “left on the table”
- Not obvious how to use this quantifications

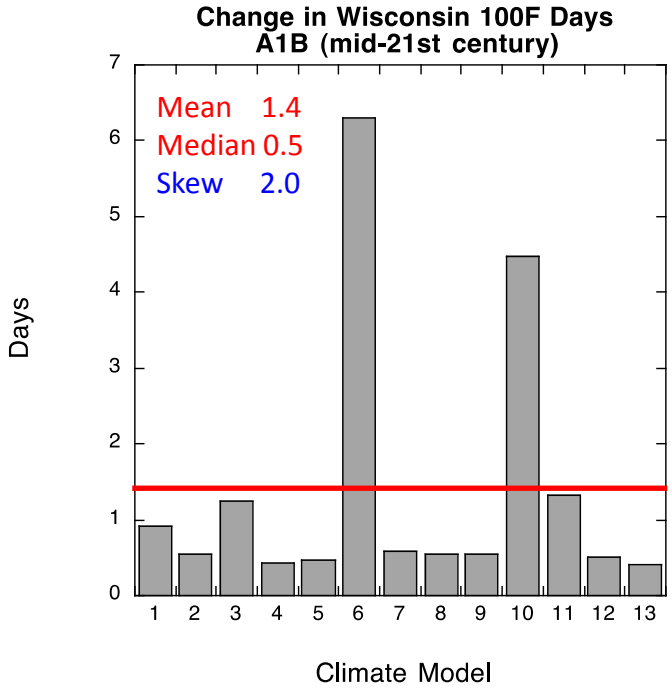
Maloney et al. (2013)

Hot Days


Change in Wisconsin 90F Days
A1B (mid-21st century)
Mean 17.3
Median 12.9
Skew 1.3
Days
0
5
10
15
20
25
30
35
40
1
2
3
4
5
6
7
8
9
10
11
12
13
Climate Model

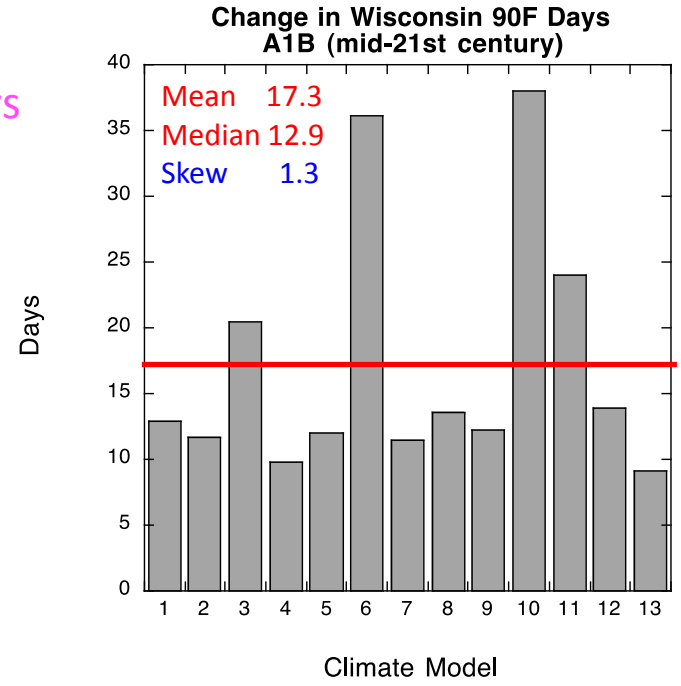
Hot Days

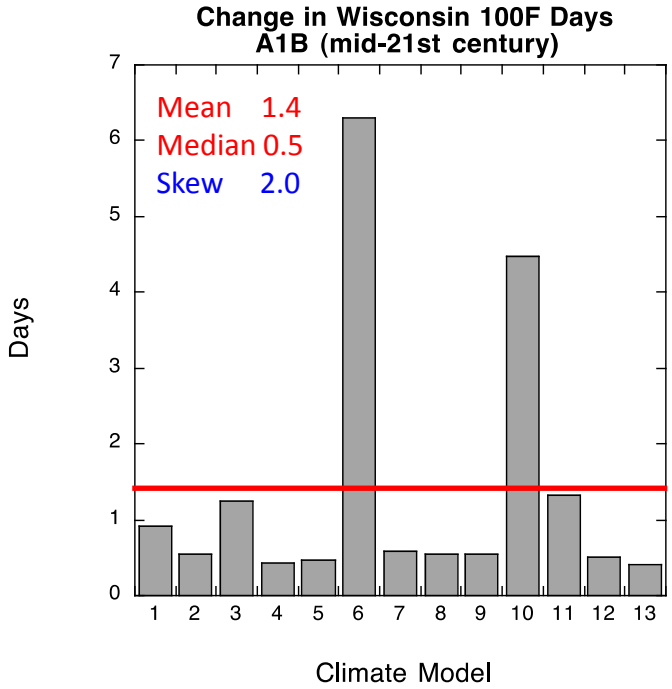




Very Hot Days (100°F)

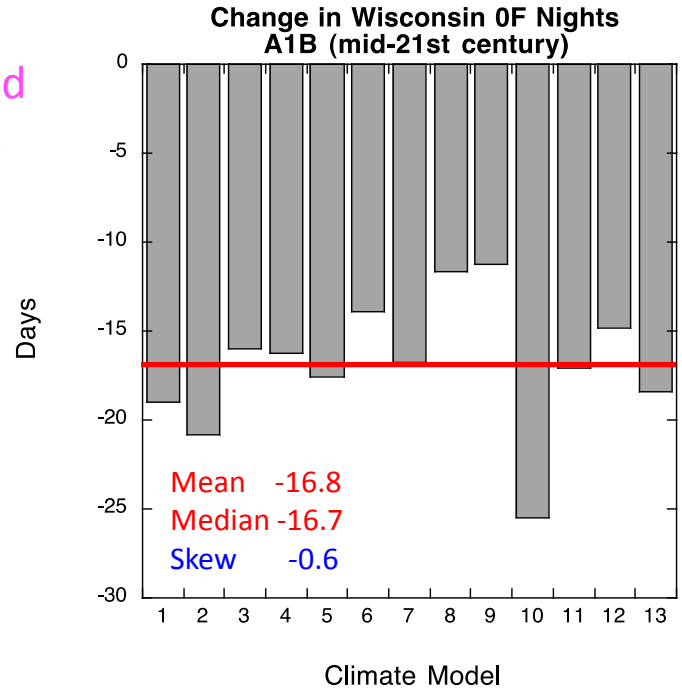
Hot Days



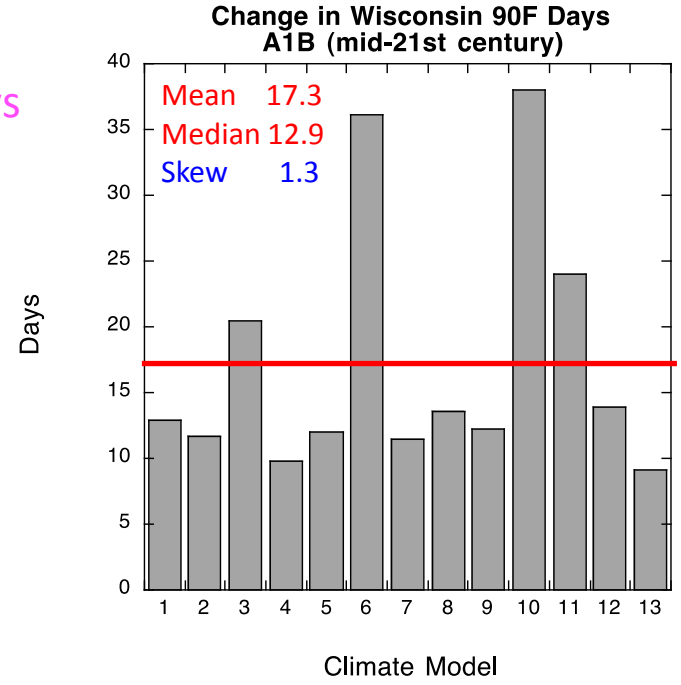


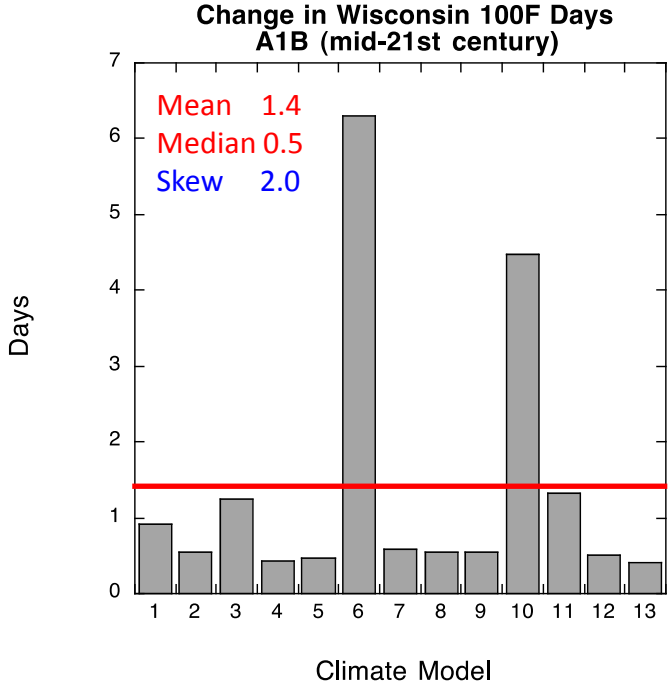
Very Hot Days

Very Cold Nights (0°F)



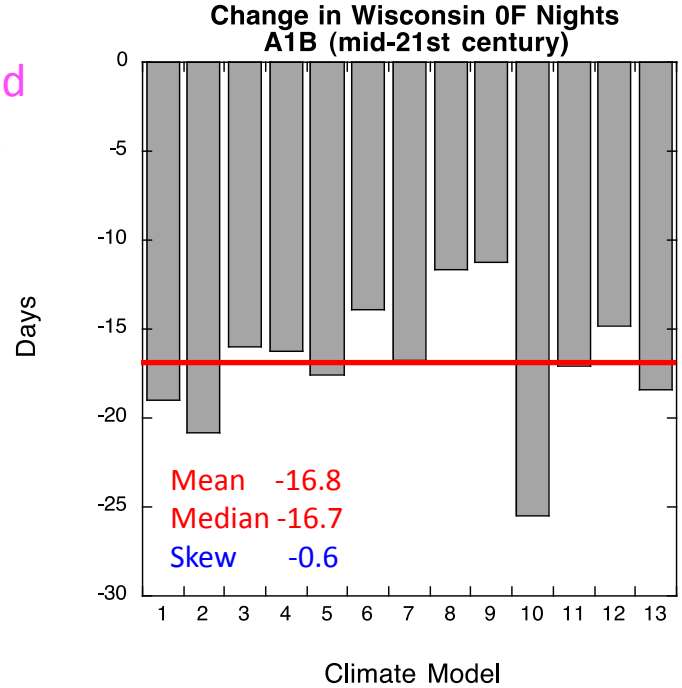
Hot Days

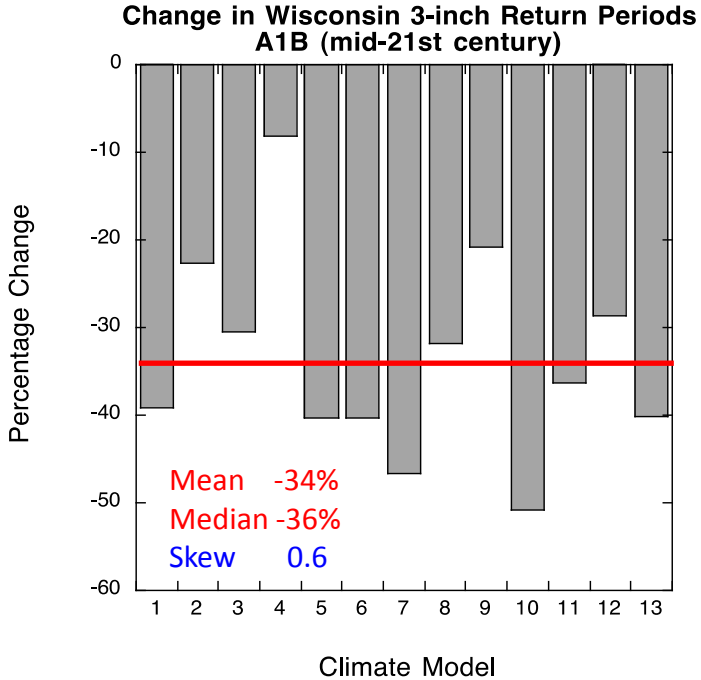




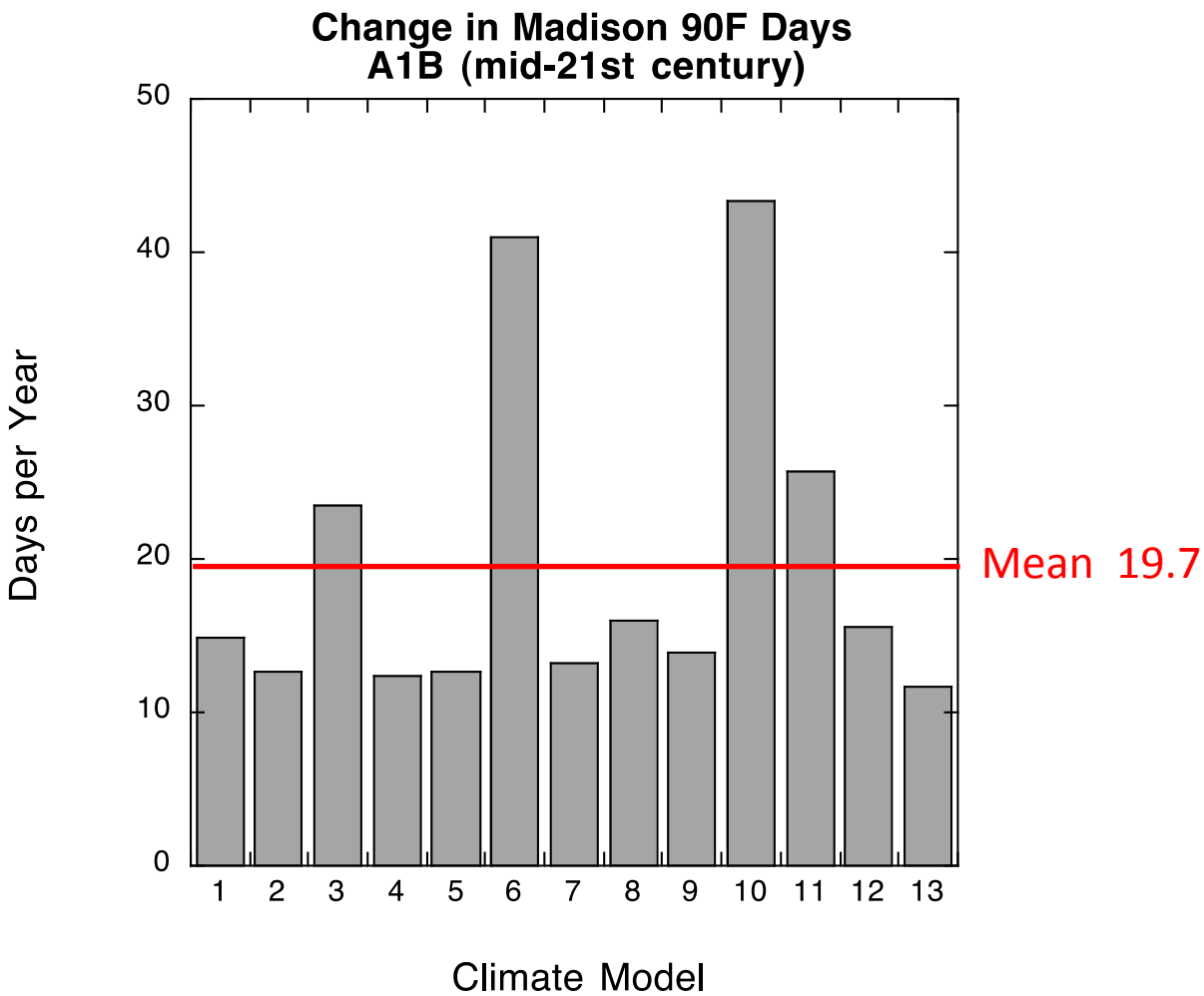
Very Hot Days

Very Cold Nights



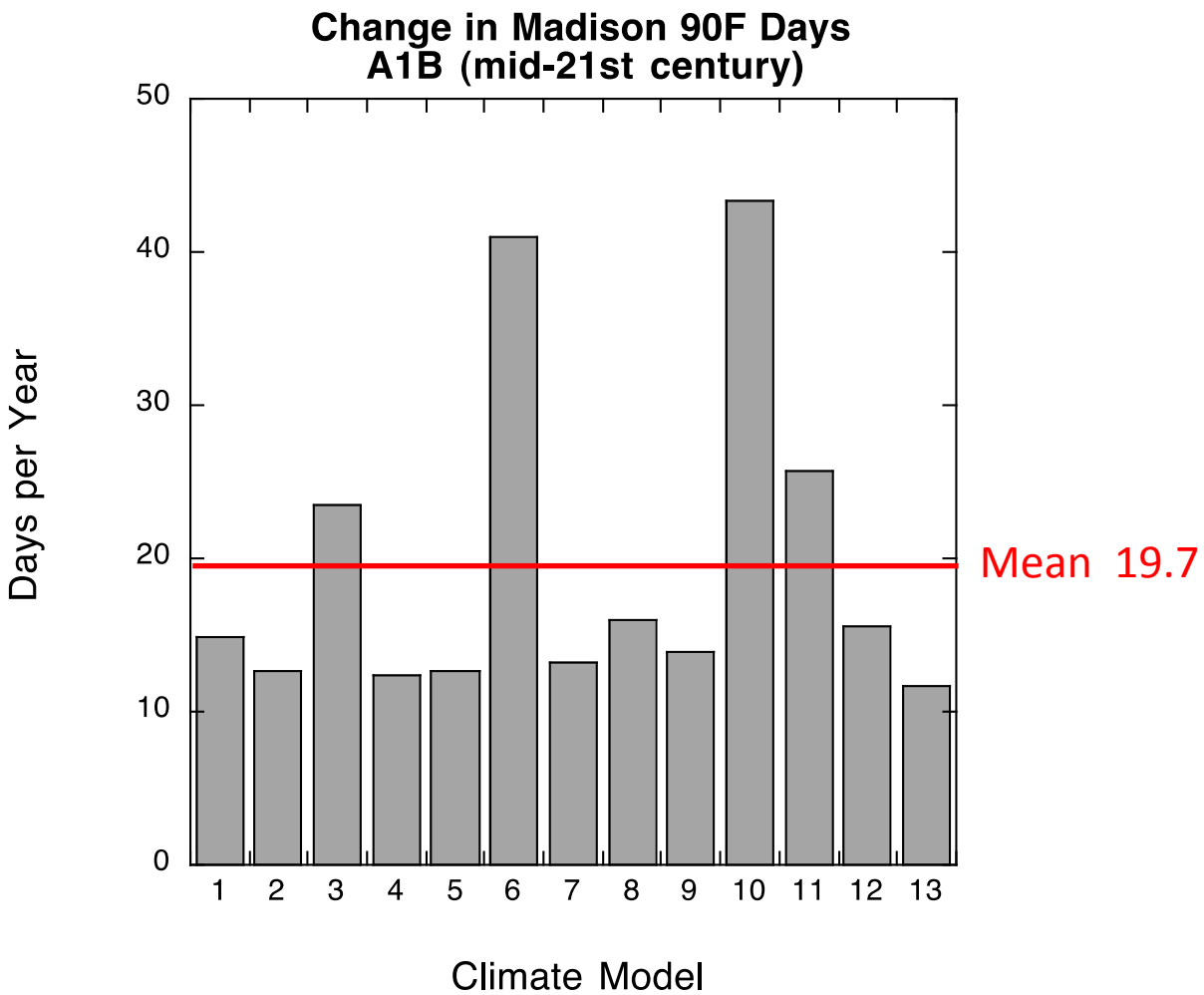


Very Wet Days (3-inch rainfalls)



Only one possible average out of many. Try resampling with a random combination of the 13 projections. Then another, and another. . .

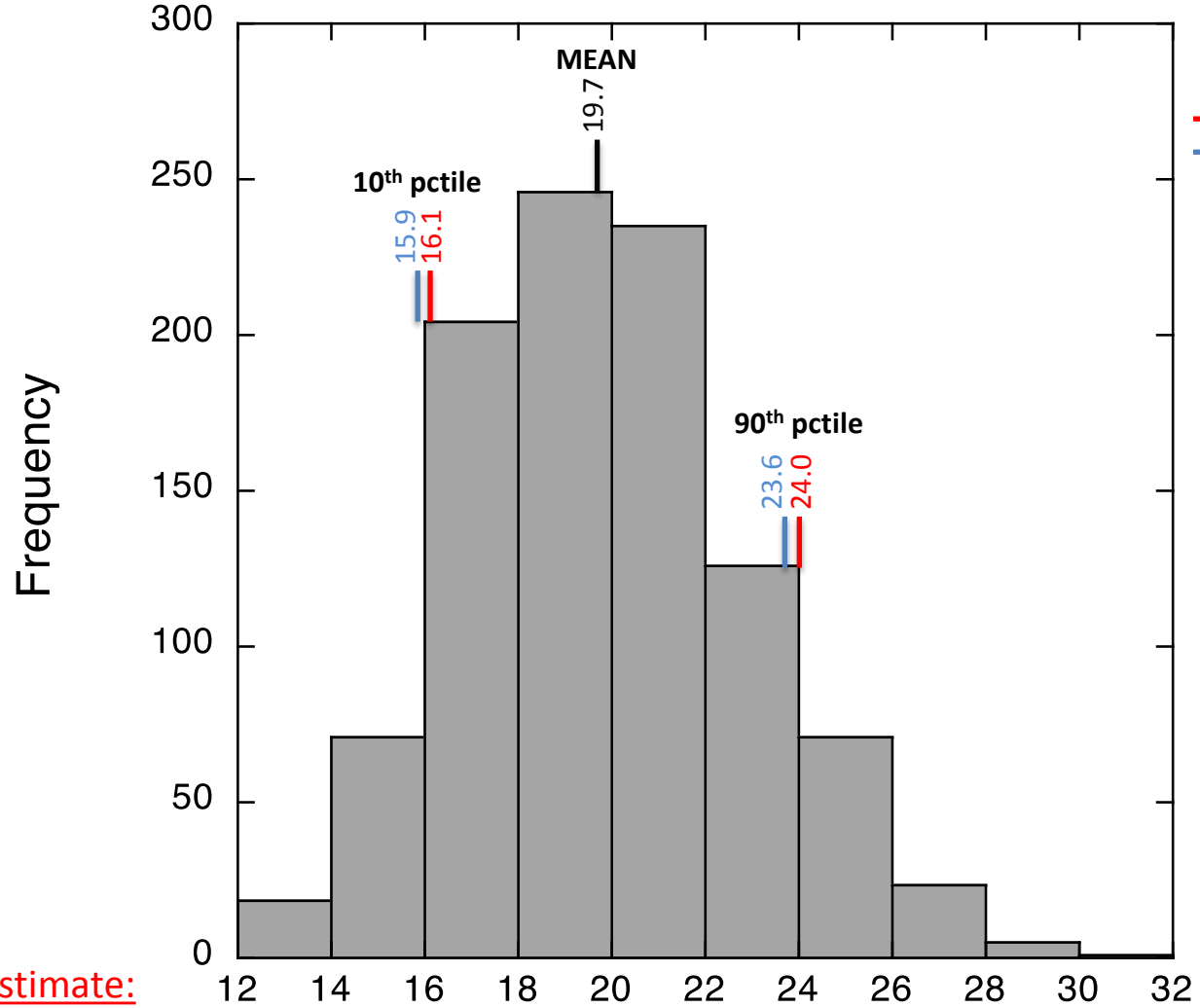
"Bootstrapping"



Other possible multi-model averages (Bootstrapping)

16.566
22.380
22.177
21.796
19.109
27.677
17.538
21.290
17.668
17.833
17.462
20.090
25.942
24.468
20.790
15.842
21.823
20.016
23.297
20.979
28.828

Bootstrap Distribution of Projected Change in 90F Days in Madison (A1B, mid-21st century)



Actual percentiles

Estimated percentiles (normal distribution)

Individual Models

11.7
12.3
12.7
12.7
13.2
13.8
14.8
15.5
16.0
23.5
25.8
41.0
43.4

10th pctile = 11.9
90th pctile = 42.4

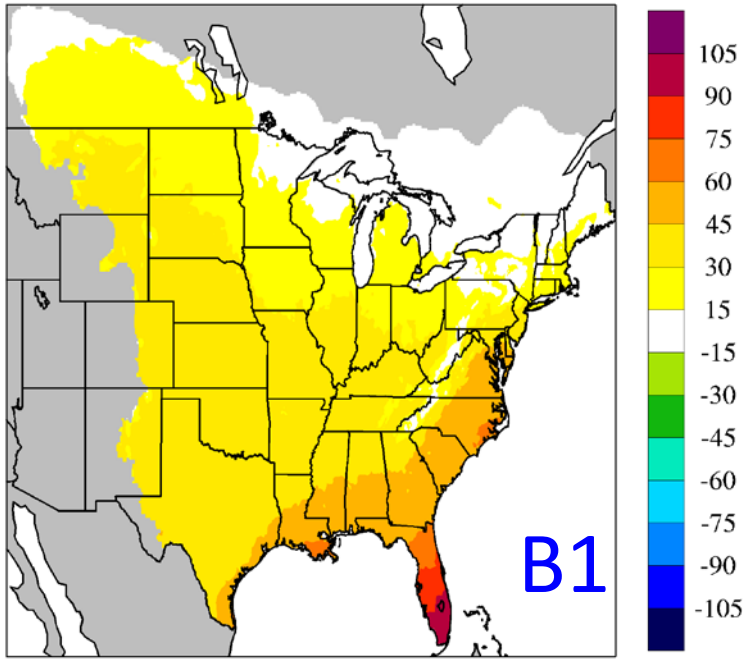
(based on raw data; no bootstrapping)

Best Estimate:

19.7 more 90-degree days per year

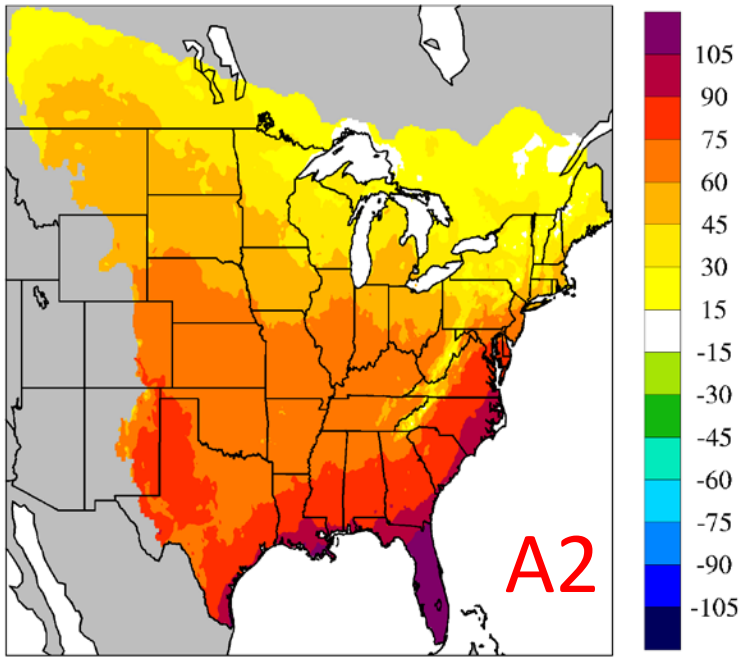
90% likelihood of at least 16 more

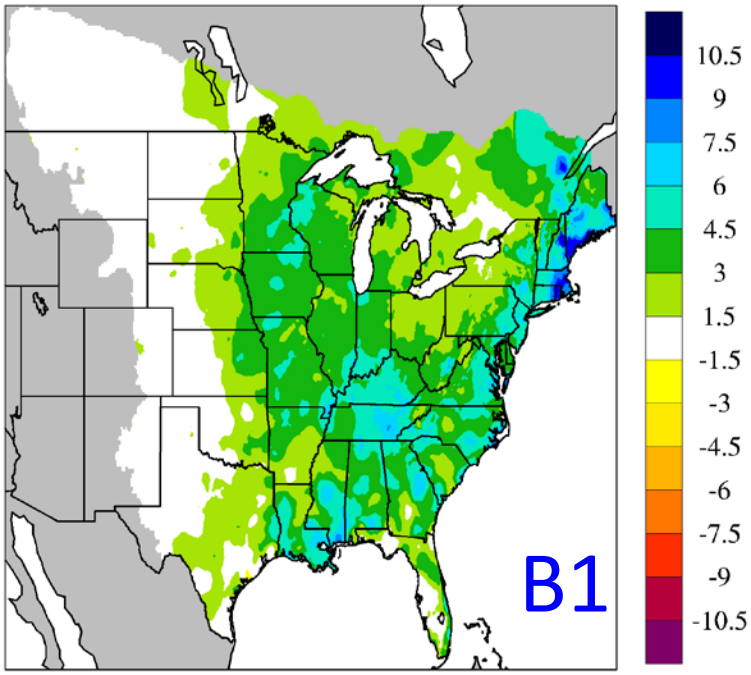
90% likelihood of no more than 24



Change in # 90°F+ Days Per Year

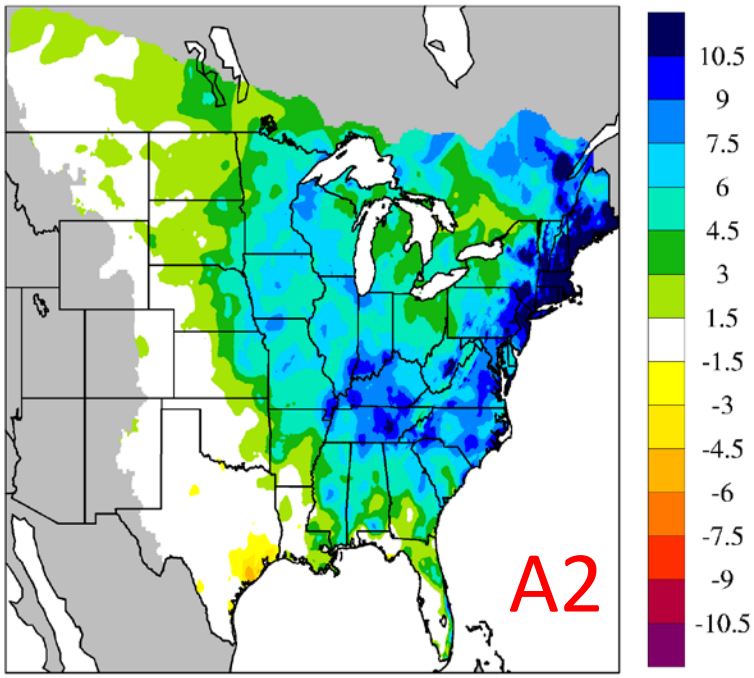
2081-2100 vs. 1961-2000





Change in # Days of 2”+ Precipitation Per Decade

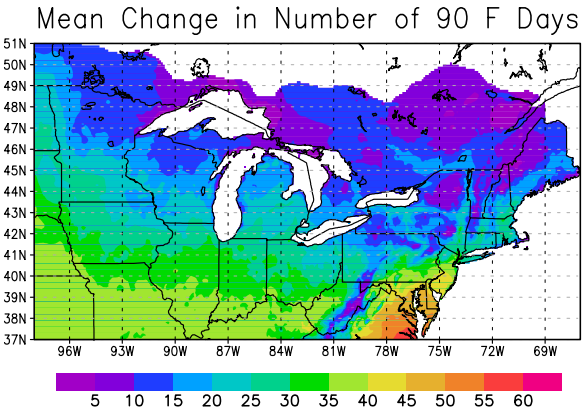
2081-2100 vs. 1961-2000

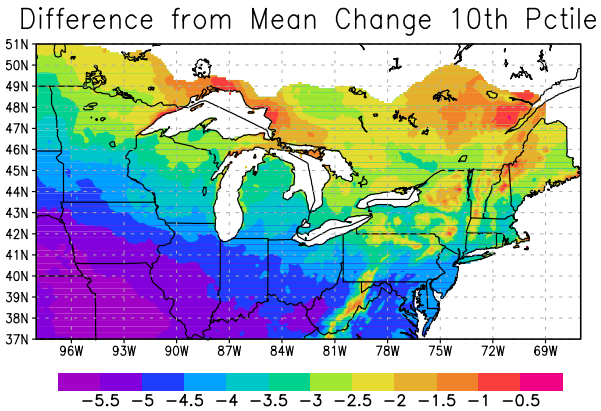


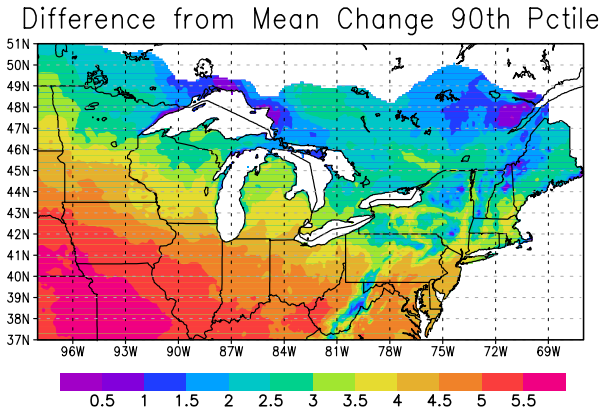
Spatial Patterns of Uncertainty Range assuming Normal Distribution

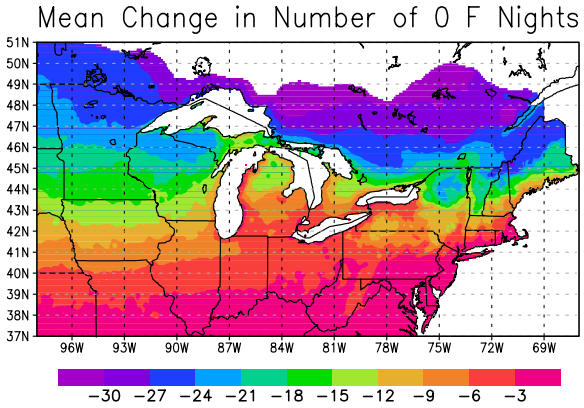
Multi-model Average

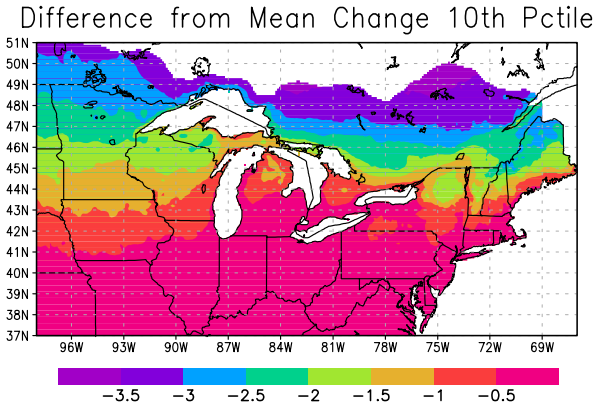
Uncertainty Range (10-90%)

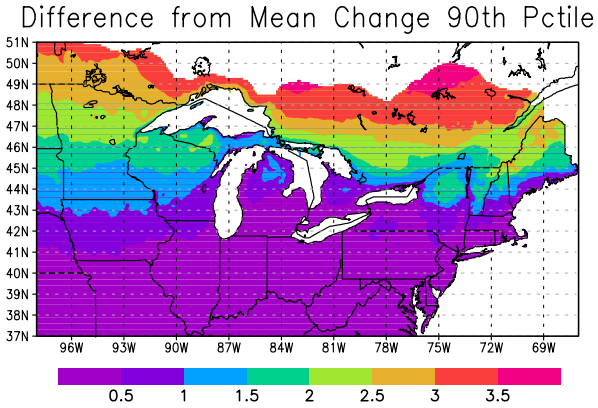




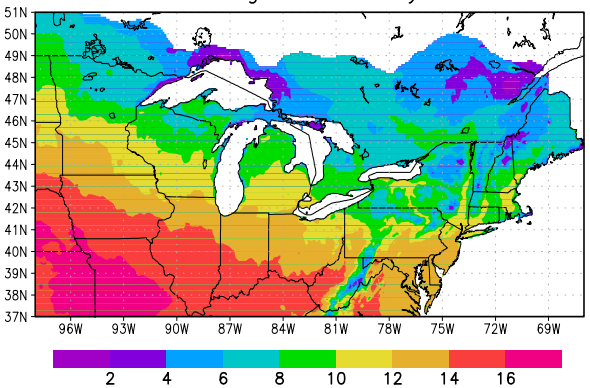




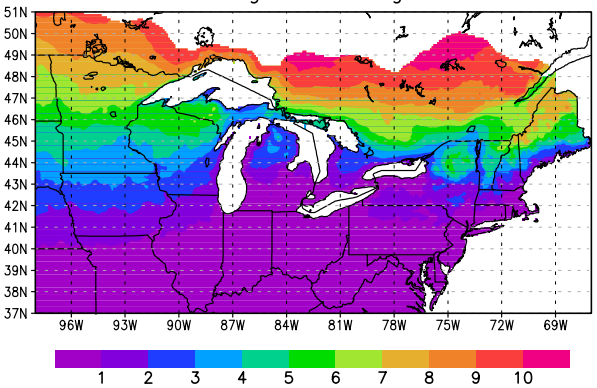




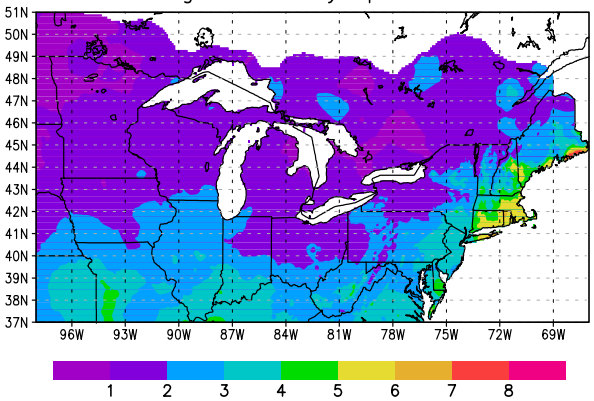
Intermodel Standard Deviation
Change in 90F Days



Intermodel Standard Deviation
Change in 0F Nights

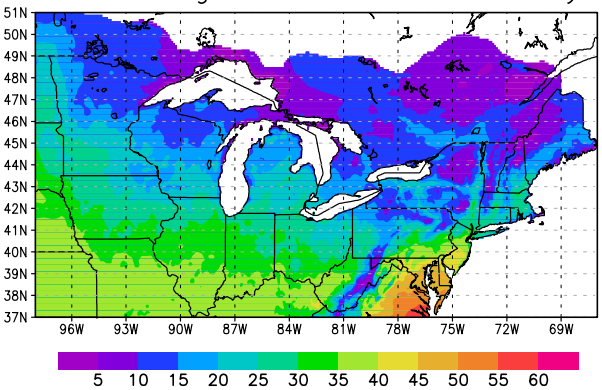


Intermodel Standard Deviation
Change in 2" Days per Decade

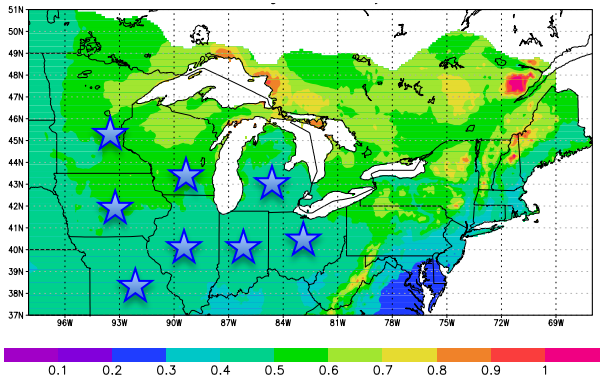


Changes in Extremes, mid-21st Century, A1B Scenario

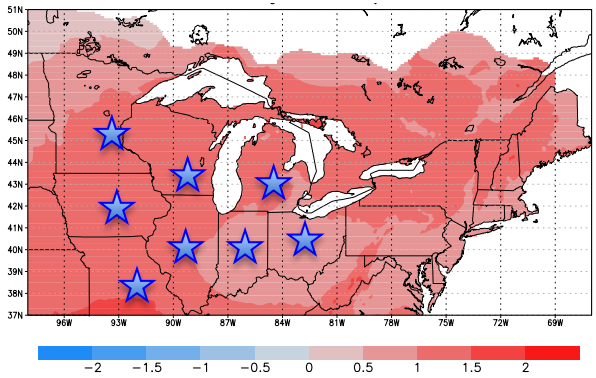
Mean Change in Number of 90 F Days



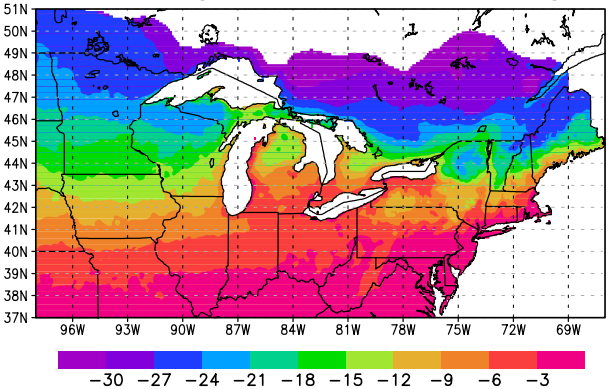
Intermodel Coefficient of Variation (90 F Days)



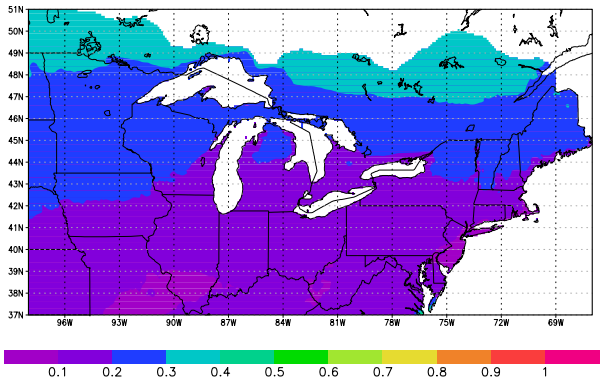
Intermodel Skewness (90 F Days)



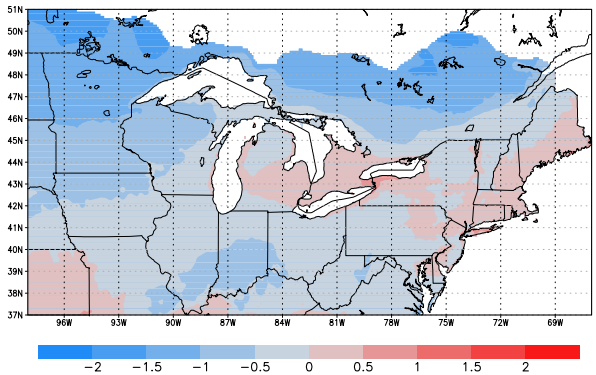
Mean Change in Number of 0 F Nights



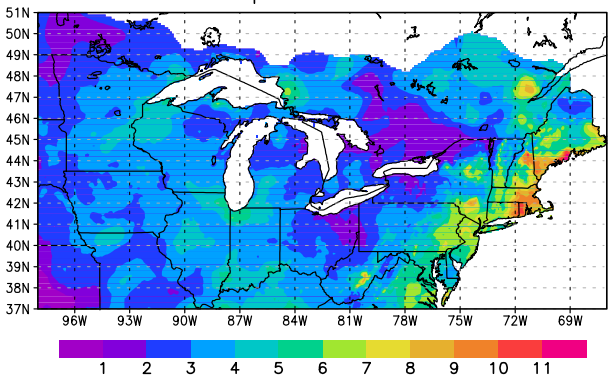
Intermodel Coefficient of Variation (0 F Nights)



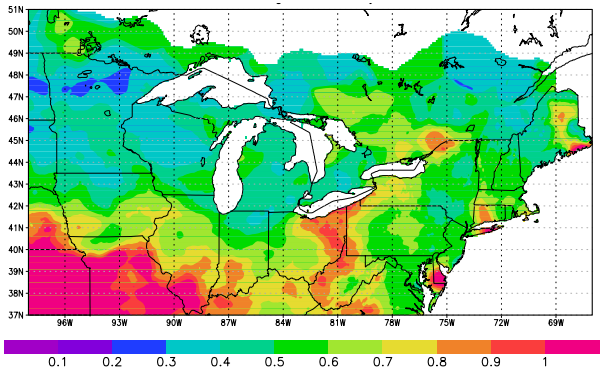
Intermodel Skewness (0 F Nights)



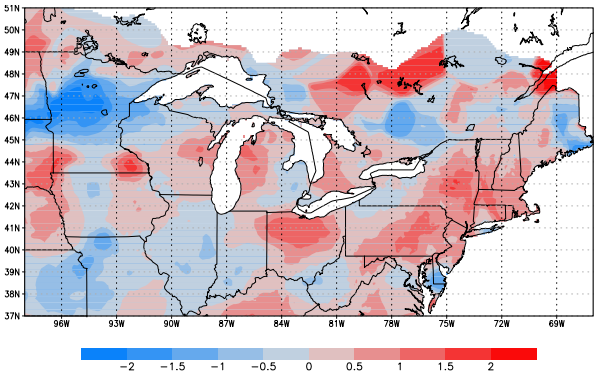
Mean Change in Number of 2" Days per Decade

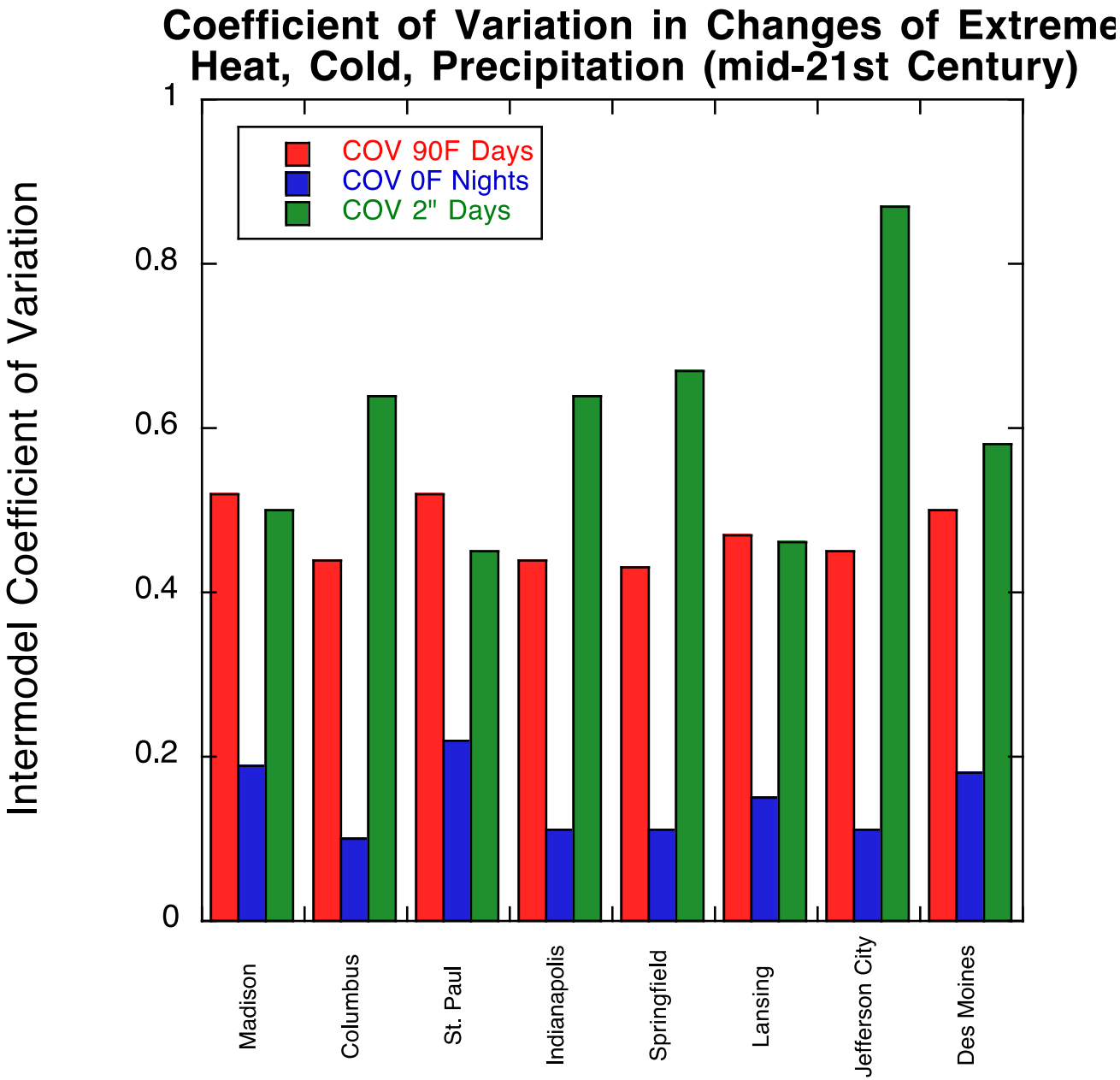


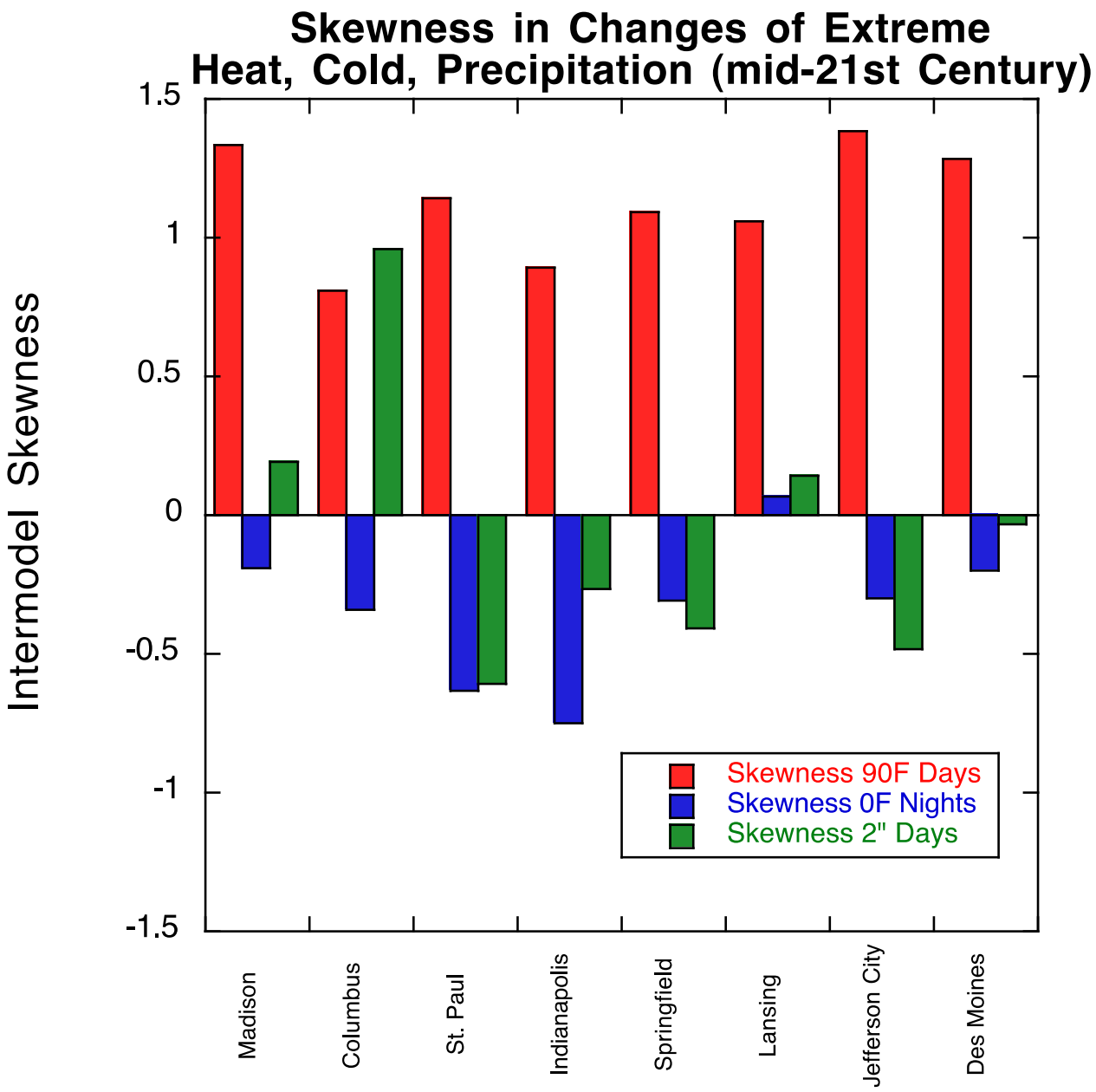
Intermodel Coefficient of Variation (2"Days)



Intermodel Skewness (2" Days)




Coefficient of Variation in Changes of Extreme
Heat, Cold, Precipitation (mid-21st Century)
Intermodel Coefficient of Variation
COV 90F Days
COV 0F Nights
COV 2" Days
1
0.8
0.6
0.4
0.2
0
Madison
Columbus
St. Paul
Indianapolis
Springfield
Lansing
Jefferson City
Des Moines


Skewness in Changes of Extreme
Heat, Cold, Precipitation (mid-21st Century)
Intermodel Skewness
1.5
1
0.5
0
-0.5
-1
-1.5
Skewness 90F Days
Skewness 0F Nights
Skewness 2" Days
Madison
Columbus
St. Paul
Indianapolis
Springfield
Lansing
Jefferson City
Des Moines