

Climate Downscaling for the National Climate Assessment: Practices and Challenges

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North Carolina State University (NCSSU), and
National Centers for Environmental Information (NCEI)



Acknowledgements

- Kenneth Kunkel, Laura Stevens, Jim Biard, and Sarah Champion (NCSU)
- David Easterling (NCEI)
- David Pierce and Daniel Cayan (UCSD)
- NA-CORDEX group
- Terence Thompson (Logistics Management Institute, VA)

Outline

- National Climate Assessment (NCA)
- Climate Downscaling for NCA
- Challenges and Paths Forward

National Climate Assessment (NCA)

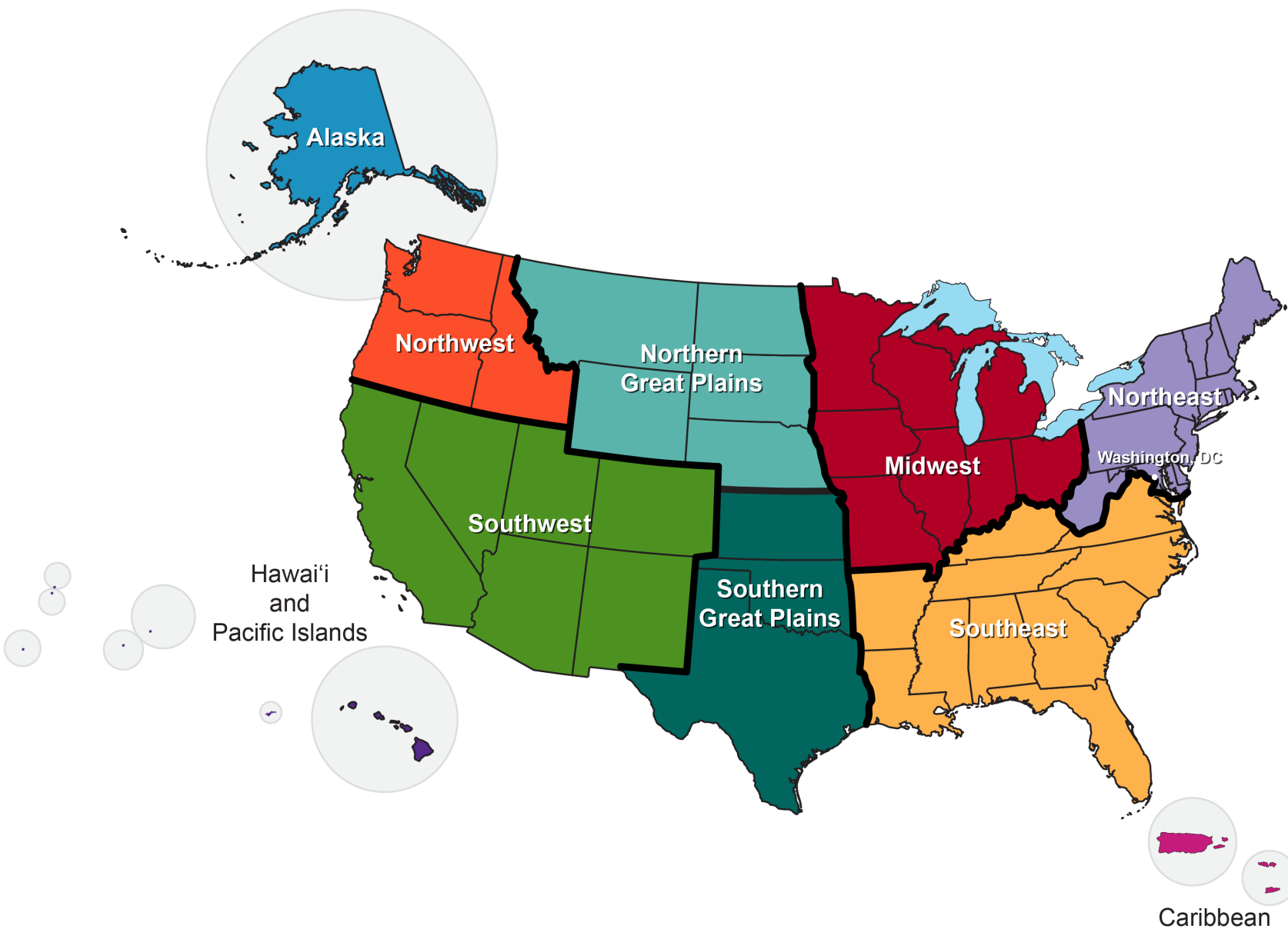
The NCA is an important resource for understanding and communicating climate change science and impacts in the United States. It informs the nation about already observed changes, the current status of the climate, and anticipated trends for the future. The NCA report process integrates scientific information from multiple sources and sectors to highlight key findings and significant gaps in our knowledge.

<http://www.globalchange.gov/>

<http://scenarios.globalchange.gov/scenarios/climate>

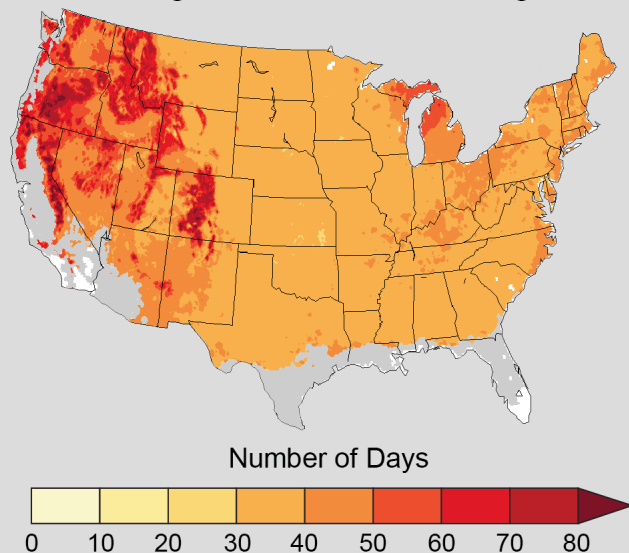
<http://nca2014.globalchange.gov/report>

NCA Regions

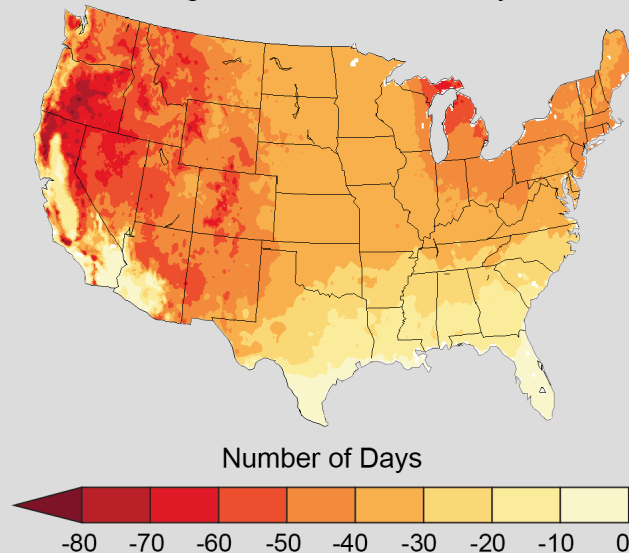


Projected Changes in Key Climate Variables Affecting Agricultural Productivity

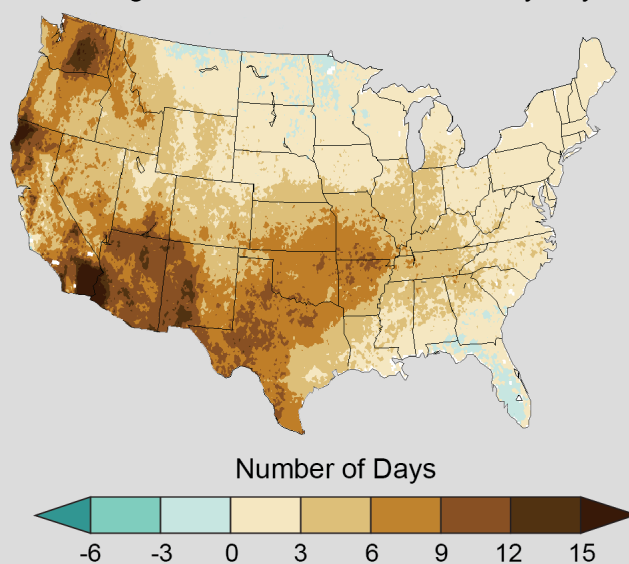
Change in Frost-free Season Length



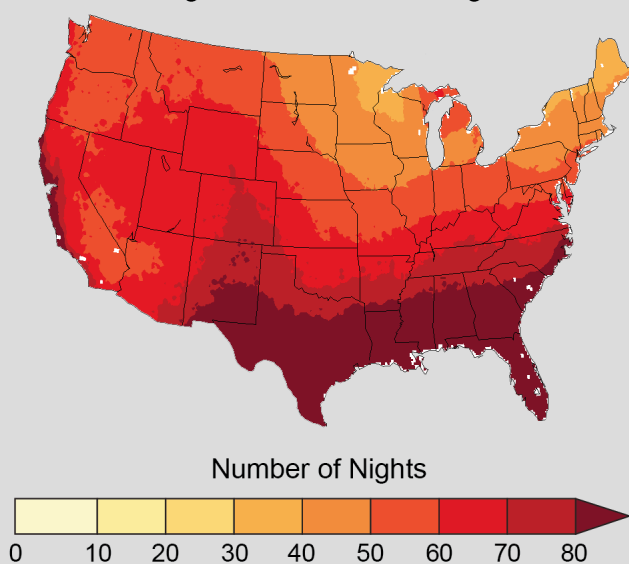
Change in Number of Frost Days



Change in Number of Consecutive Dry Days



Change in Number of Hot Nights



Climate Downscaling for NCA

Why Downscaling?

- **Actionable** regional/local climate information
- Climate assessment: **top-down** and **bottom-up** approaches
- Climate **extremes**

Derived Variables

Annual number of days > 86F	Annual number of icing ($T_{\max} < 32\text{F}$)days
Annual number of days > 90F	Annual number of frost ($T_{\min} < 32\text{F}$)days
Annual number of days > 95F	Annual highest 5-day maximum temperature
Annual number of days > 100F	Annual lowest 5-day minimum temperature
Annual number of days > 105F	Annual lowest 5-day minimum temperature
Annual number of days > 110F	Annual highest 1-day maximum temperature
Annual number of days > 115F	Annual lowest minimum temperature
Annual number of days $T_{\min} < 28\text{F}$	Annual lowest minimum temperature
Annual number of days $T_{\min} > 75\text{F}$	Cooling degree days
Annual number of days $T_{\min} > 80\text{F}$	Heating degree days
Annual number of days $T_{\min} > 85\text{F}$	Growing degree days, base 50 (F)
Annual number of days $T_{\min} > 90\text{F}$	Date of the first fall freeze
Annual number of days > 1 inch	Date of the last spring freeze
Annual number of days > 2 inches	Length of the frost-free season
Annual number of days > 3 inches	Length of the growing season (28F threshold)
Annual number of days > 4 inches	Length of the growing season (41F threshold)
Annual maximum number of consecutive dry days	
Annual maximum number of consecutive wet days	
Annual maximum 1-day precipitation	
Annual maximum 5-day precipitation	

Annual number of days with precipitation greater than the 99 th percentile
Annual total precipitation greater than the 99 th percentile
Annual number of days with maximum temperature lower than the 1 st percentile
Annual number of days with maximum temperature greater than the 99 th percentile
Annual number of days with minimum temperature lower than the 1 st percentile
Annual number of days with minimum temperature greater than the 99 th percentile

Climate Extremes

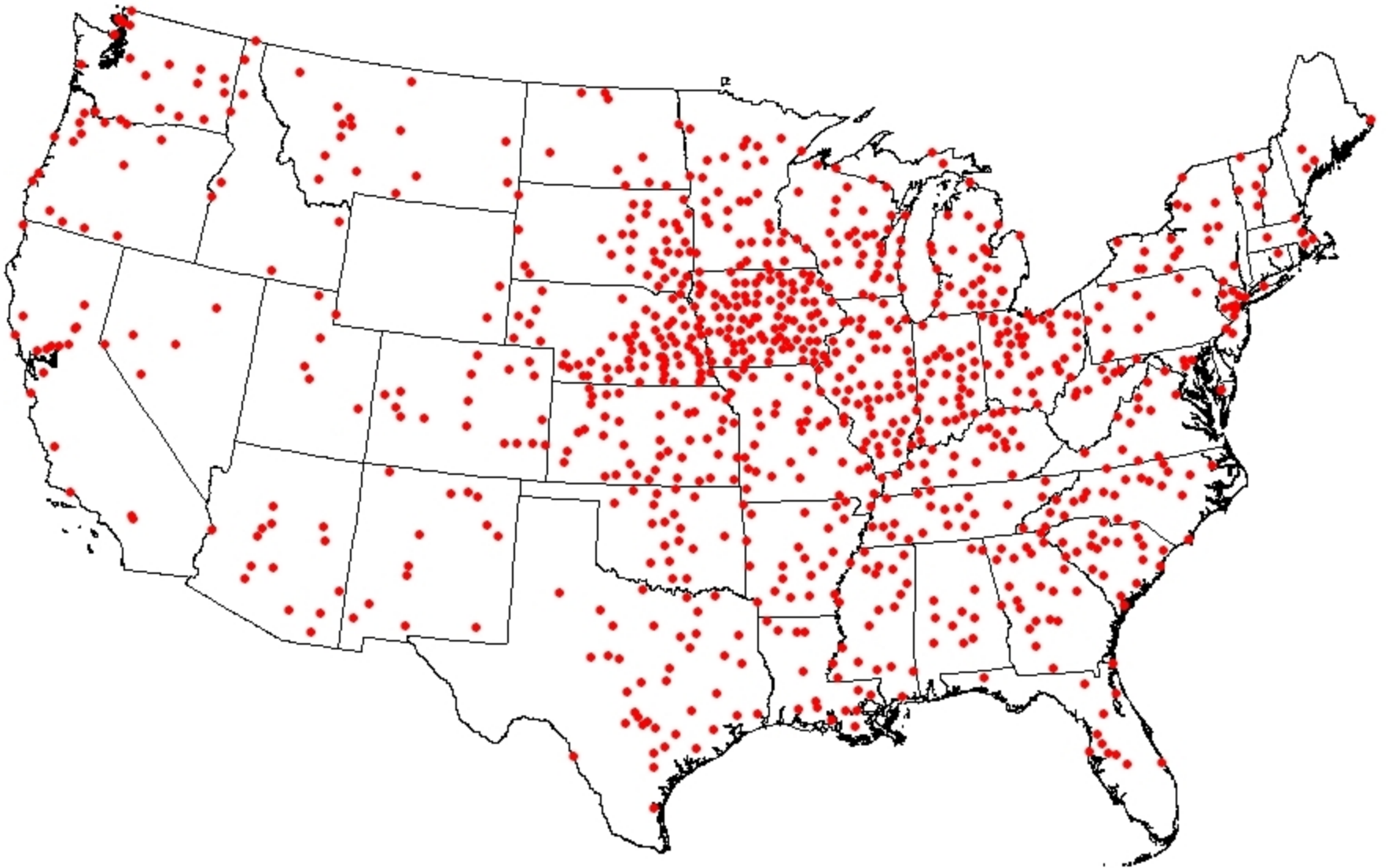
- projected changes for future 30-year periods, respect to the reference period of 1976-2005, using multi-model ensemble.

Climate Data

- National Weather Service's Cooperative Observer Network (COOP)
- NA-CORDEX
- LOCA

Long-term Precipitation Stations -

adequacy of data to detect and understand the past changes



NA-CORDEX Simulations

	CRCM5 (UQAM)	CRCM5 (OURANOS)	RCA4	RegCM4	WRF	CanRCM4	HIRHAM5		
ERA-Int	0.44° 0.22° 0.11°	0.44° †	0.44°	50km 25km	50km 25km	0.44° 0.22°	0.44°	RCP	ECS (°C)
HadGEM2- ES								4.5	4.6
				50km 25km	50km 25km			8.5	
CanESM2	0.44°		0.44°			0.44° 0.22°		4.5	3.7
	0.44°	0.22° †	0.44°			0.44° 0.22°		8.5	
MPI-ESM- LR	0.44°							4.5	3.6
	0.44° † 0.22° †	0.22° †		50km* 25km*	50km† 25km†			8.5	
MPI-ESM- MR								4.5	3.4
	0.44°							8.5	
EC-EARTH†			0.44°					2.6	~3.3
			0.44°				0.44°	4.5	
			0.44°				0.44°	8.5	
GFDL- ESM2M								4.5	2.4
		0.22° †		50km 25km	50km 25km			8.5	
Access	PoC	PoC	ESGF	PoC	PoC	CCCma	ESGF		
Institution	UQAM	OURANOS	SMHI	Iowa State *NCAR	U Arizona	CCCma	DMI		
Modeler	K. Winger	S. Biner	G. Nikulin	R. Arritt *M. Bukovsky	C. Castro, H-I Chang	J. Scinocca	O. Christensen		

Scripps Localized Constructed Analogs (LOCA) dataset

- 32 CMIP5 models
- Historical: 1950-2005. RCP 4.5 and RCP 8.5: 2006-2100 (2099 some models)
- Climatological period: 1950-99
- Interpolated model calendars to standard calendar w/leap days
- North America 24.5 N to 52.8 N at 1/16th degree resolution
- Daily Tmin, Tmax, Precip

ACCESS1-0
ACCESS1-3
CCSM4
CESM1-BGC
CESM1-CAM5
CMCC-CM
CMCC-CMS
CNRM-CM5
CSIRO-Mk3-6-0
CanESM2
EC-EARTH
FGOALS-g2
GFDL-CM3
GFDL-ESM2G
GFDL-ESM2M
GISS-E2-H
GISS-E2-R

HadGEM2-AO
HadGEM2-CC
HadGEM2-ES
IPSL-CM5A-LR
IPSL-CM5A-MR
MIROC-ESM
MIROC-ESM-CHEM
MIROC5
MPI-ESM-LR
MPI-ESM-MR
MRI-CGCM3
NorESM1-M
bcc-csm1-1
bcc-csm1-1-m
inmcm4

Slide from D. Pierce

Weighting Method

Weighting

- Independence Weights - Inter-model distances computed as simple root mean square differences are used to calculate independence weights
- Skill Weights - The RMSE distances between each model and the observations are used to calculate skill weights
- An overall weight is then computed as the product of the skill weight and the independence weight.

Variables

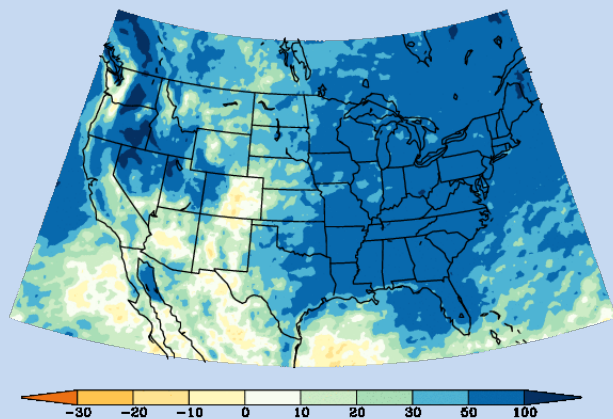
1. Surface Temperature (seasonal)
2. Mean Precipitation (seasonal)
3. TOA Shortwave Flux (seasonal)
4. TOA Longwave Flux (seasonal)
5. Vertical Temperature Profile (seasonal)
6. Vertical Humidity Profile (seasonal)
7. Surface Pressure (seasonal)
8. Coldest Night
9. Coldest Day
10. Warmest Night
11. Warmest day
12. Seasonal max. 5-day total precip.

Sanderson *et al.* 2016

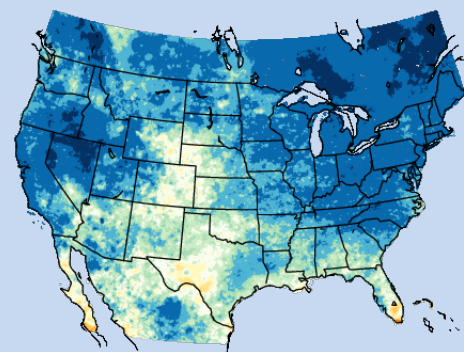
Change (%) in annual total precipitation greater than the 99th percentile

RCP8.5: 2070-2099 minus 1976-2005

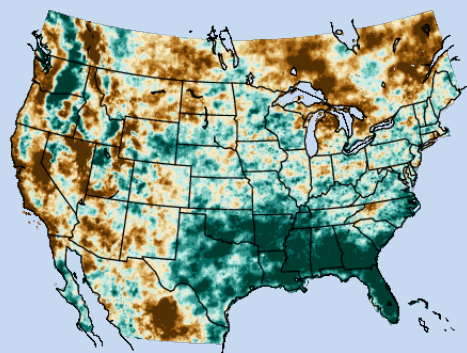
NA-CORDEX



LOCA



Difference

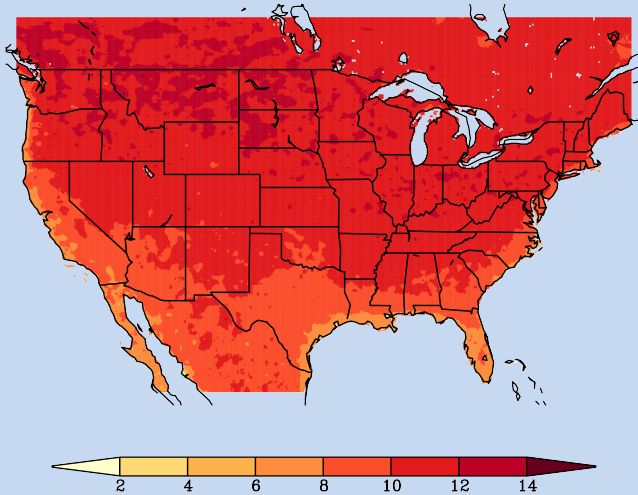


**National
Climate
Assessment**

U.S. Global Change Research Program

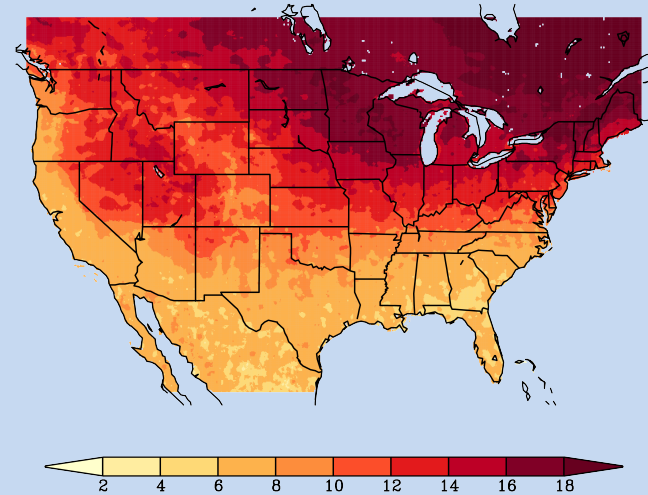
Annual highest 5-day maximum temperature

Change in annual highest 5-day Tmax by late 21st century, Deg F

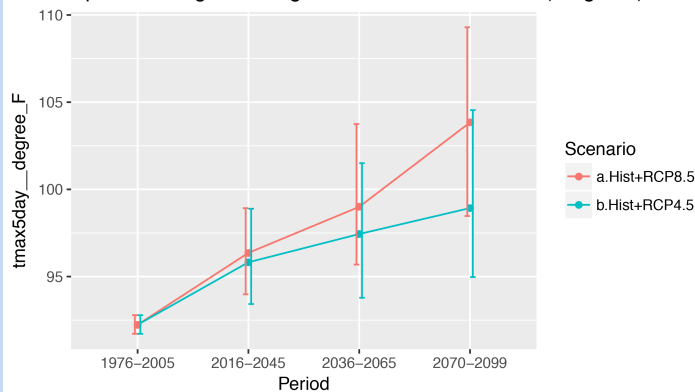


Annual lowest 5-day minimum temperature

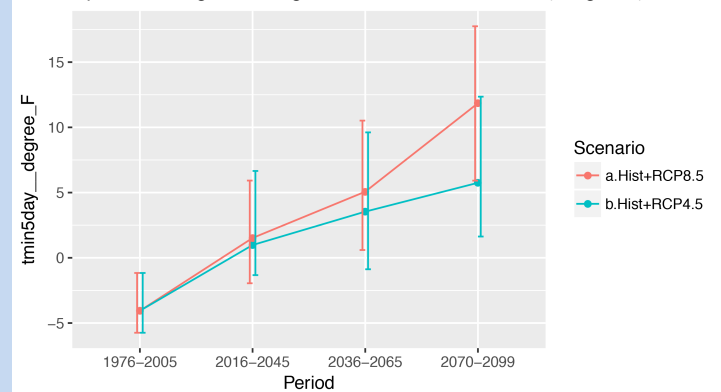
Change in annual lowest 5-day Tmin by late 21st century, Deg F



Chicago Metropolitan Statistical Area
Annual highest 5-day maximum temperature
Spatial average of 514 grid locations – 32 models (weighted)

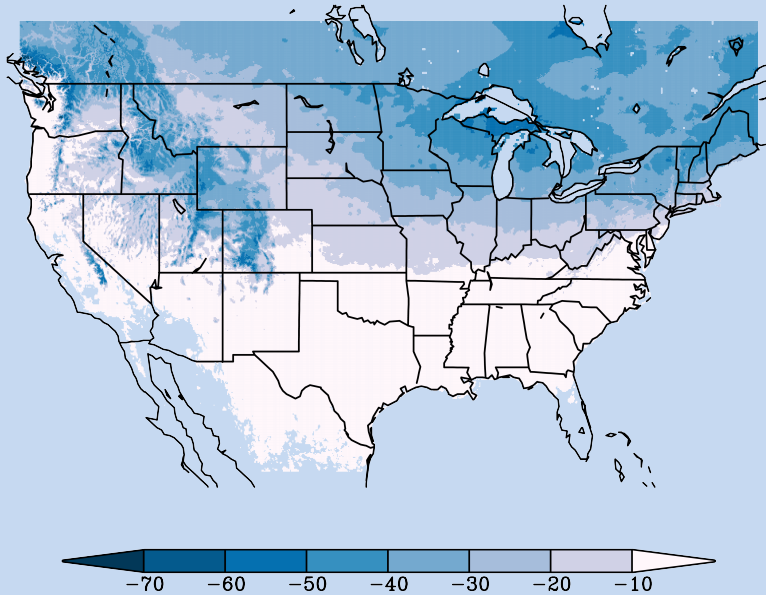


Chicago Metropolitan Statistical Area
Annual lowest 5-day minimum temperature
Spatial average of 514 grid locations – 32 models (weighted)

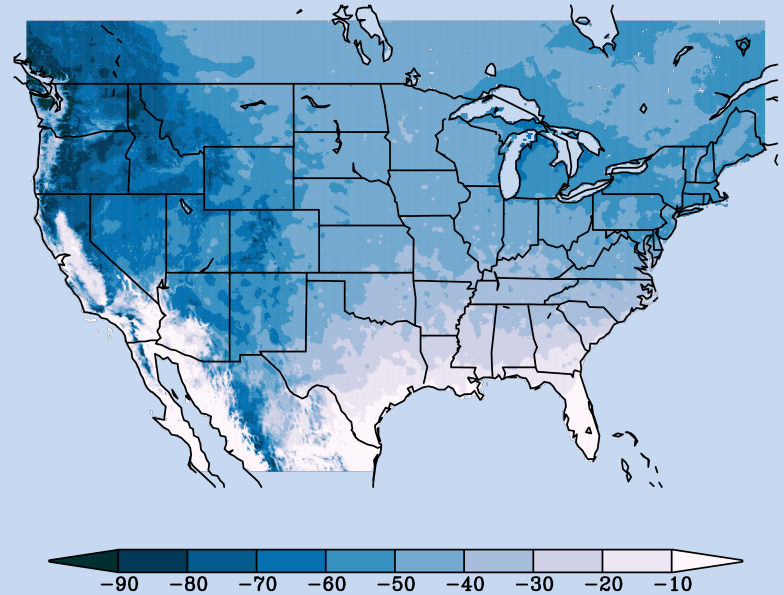


Annual number of icing/frost days

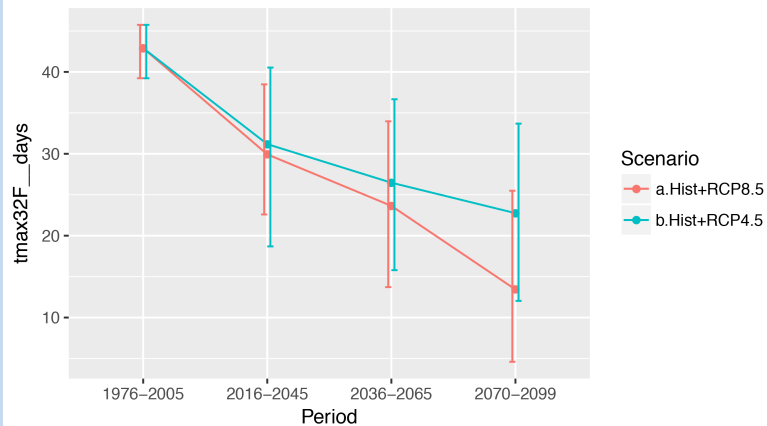
Change in annual # of icing days by late 21st century



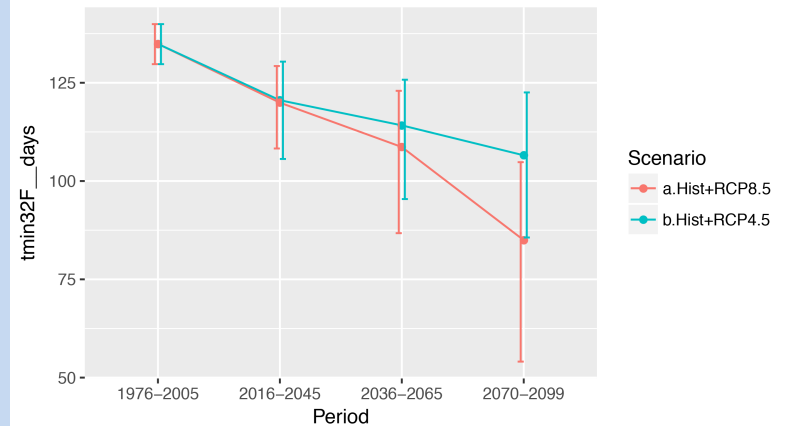
Change in annual # of frost days by late 21st century



Chicago Metropolitan Statistical Area
Annual number of icing days
Spatial average of 514 grid locations – 32 models (weighted)

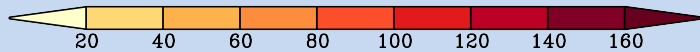
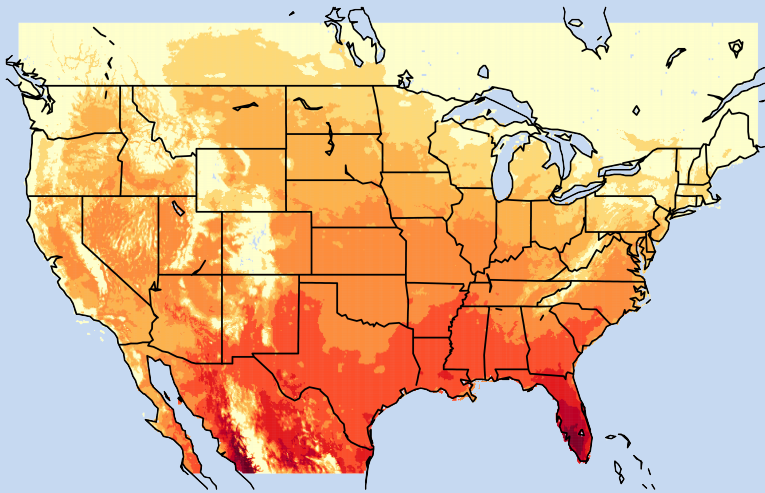


Chicago Metropolitan Statistical Area
Annual number of frost days
Spatial average of 514 grid locations – 32 models (weighted)



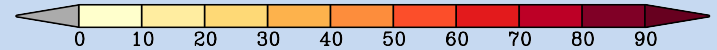
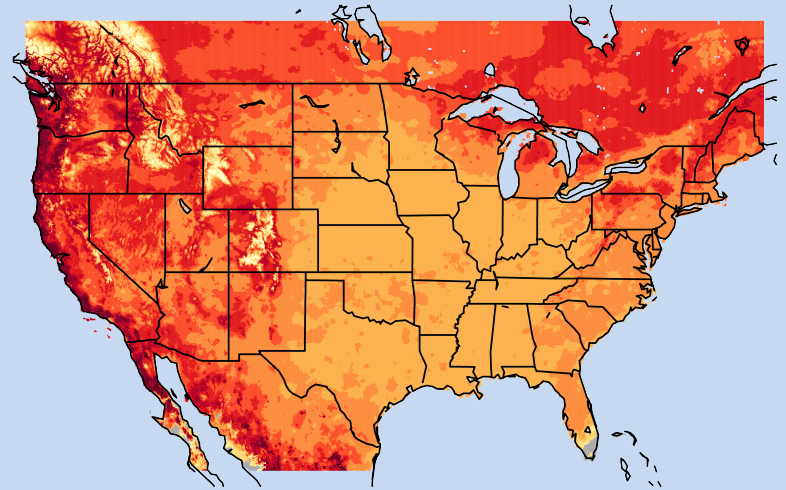
Annual number of days when max temperature $> 95^{\circ}\text{F}$

Change in annual #days $T_{\text{max}} > 95^{\circ}\text{F}$ by late 21st century



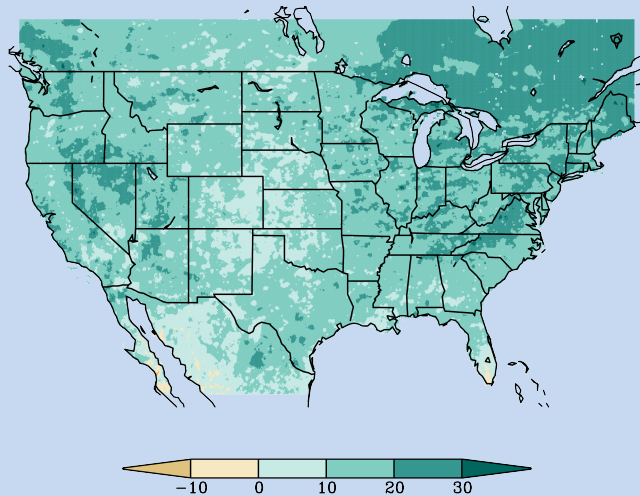
Length of the growing season (41°F threshold)

Change in length of the growing season (41°F threshold) by late 21st century, day



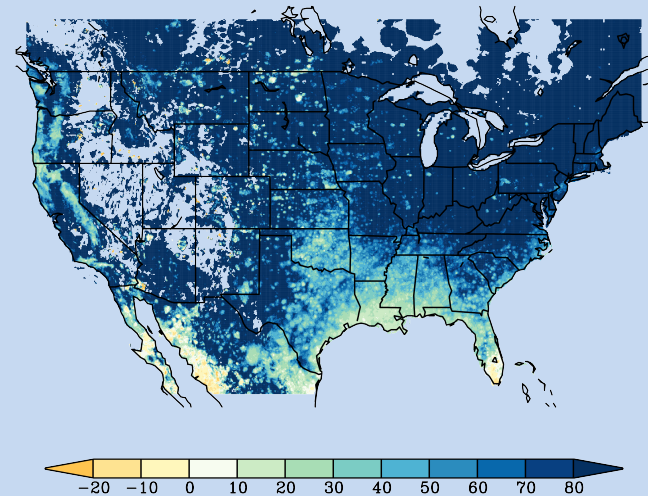
Annual Maximum 1-day precipitation (%)

Change (%) in annual max 1-day precip by late 21st century

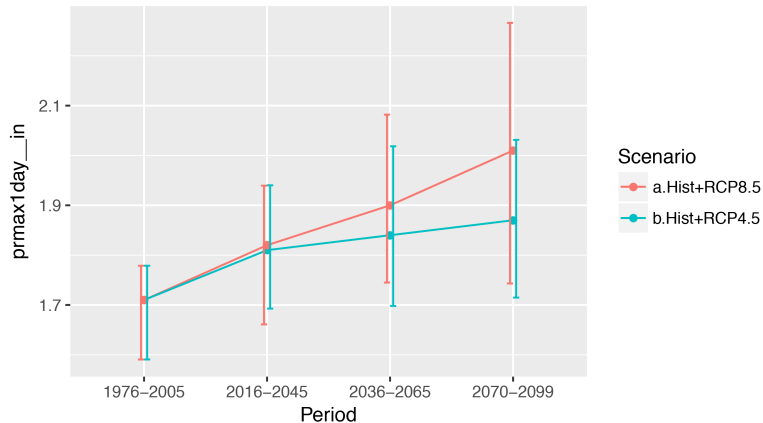


Annual number of Days > 2 inches

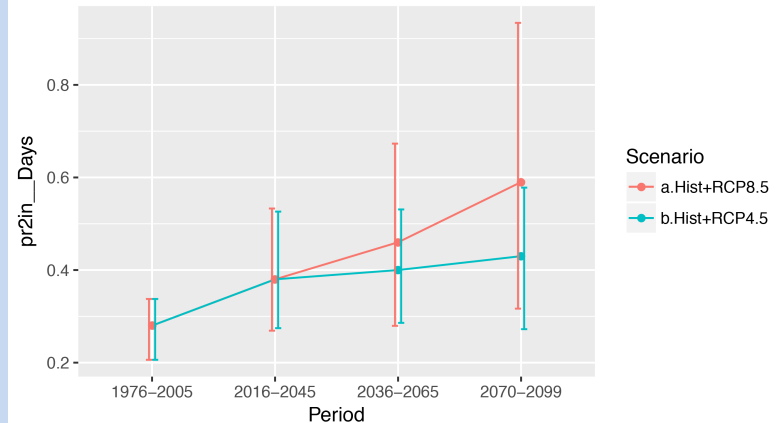
Change (%) in annual #days > 2 inches by late 21st century



Chicago Metropolitan Statistical Area
Annual maximum 1-day precipitation
Spatial average of 514 grid locations – 32 models (weighted)

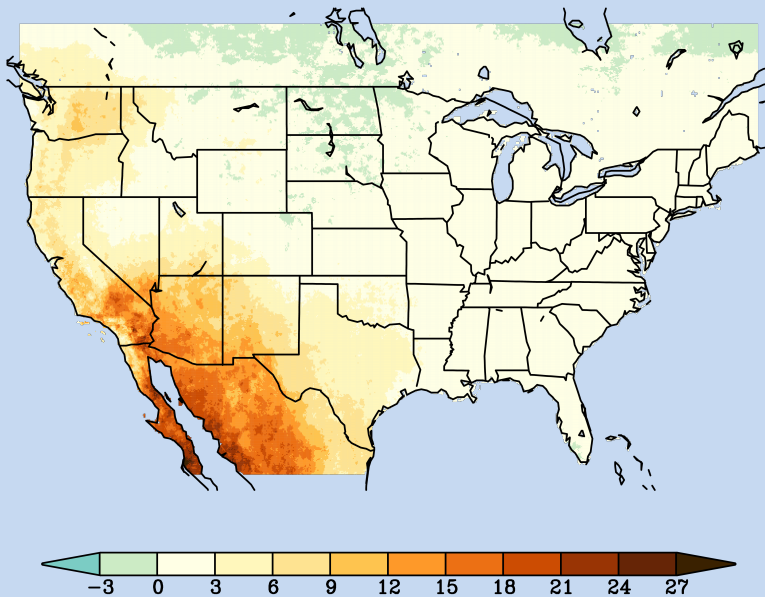


Chicago Metropolitan Statistical Area
Annual number of days > 2 inches
Spatial average of 514 grid locations – 32 models (weighted)

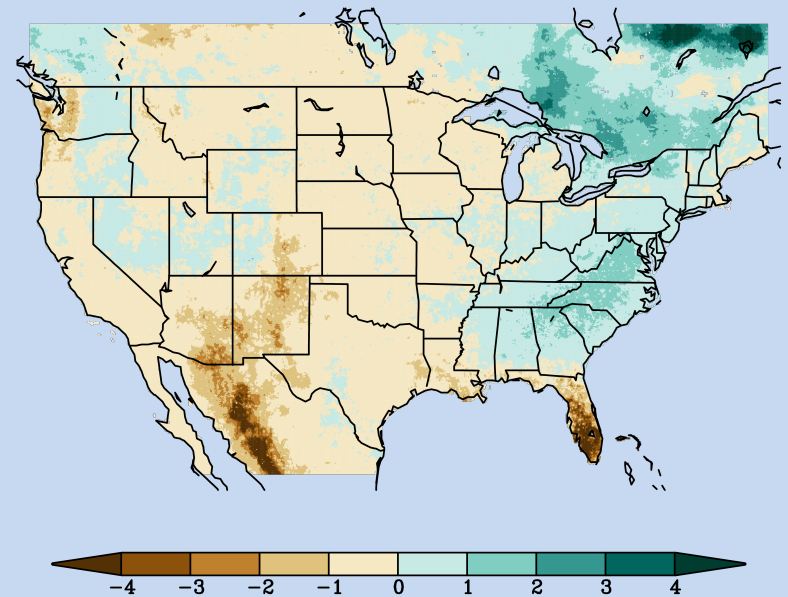


Annual Maximum Number of Consecutive Dry/Wet Days

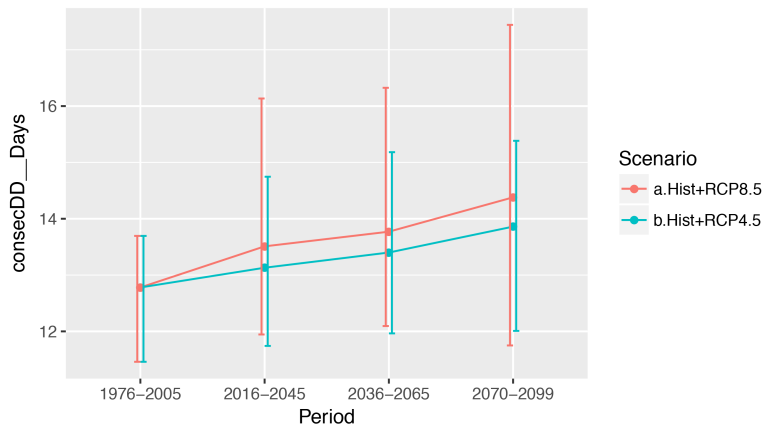
Change in annual max # of consecutive dry days by late 21st century



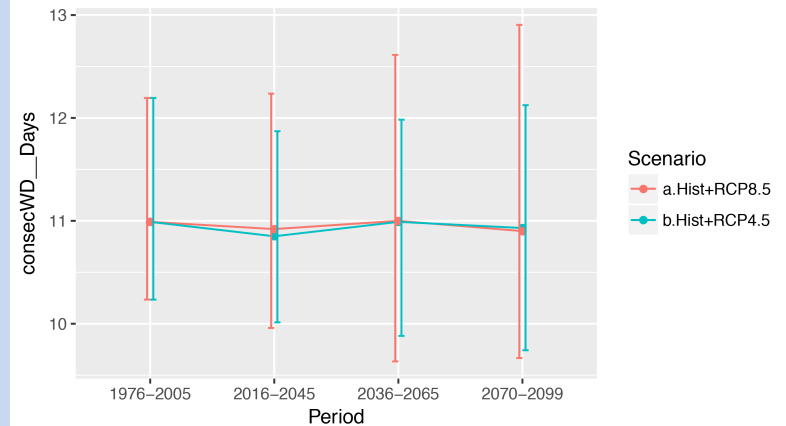
Change in annual max # of consecutive wet days by late 21st century



Chicago Metropolitan Statistical Area
Annual maximum number of consecutive dry days
Spatial average of 514 grid locations – 32 models (weighted)



Chicago Metropolitan Statistical Area
Annual maximum number of consecutive wet days
Spatial average of 514 grid locations – 32 models (weighted)

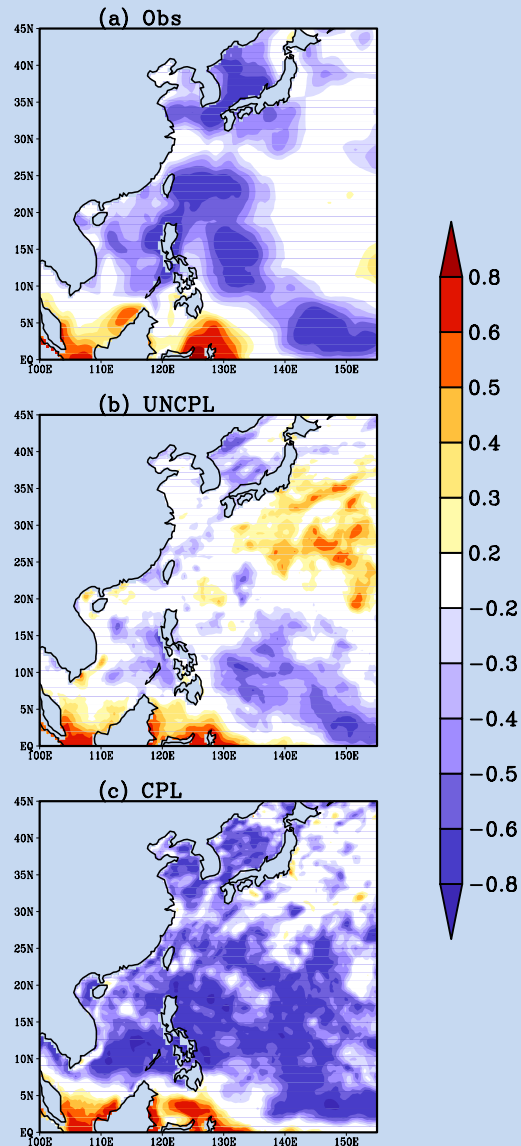


Challenges and Paths Forward

“Regional” focus of NCA imposes significant scientific and technical challenges.

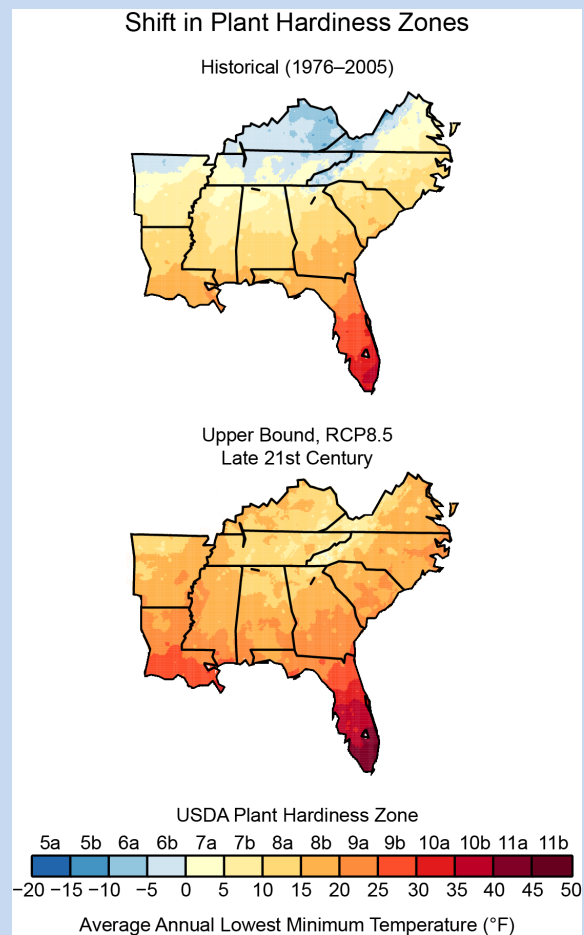
1. Right-scaling climate models – Downscaling tools should be thoroughly evaluated.
2. Matching model outputs to sectorial needs - Identifying appropriate climate data and climate information for vulnerability and impact assessments and impacts-related research.
3. Attribution of climate extremes – linking the extremes to weather systems
4. Uncertainty – Identifying the ensemble size for regional models
 - Ensemble size varies with the variables of interest

Correlation between SST and precipitation

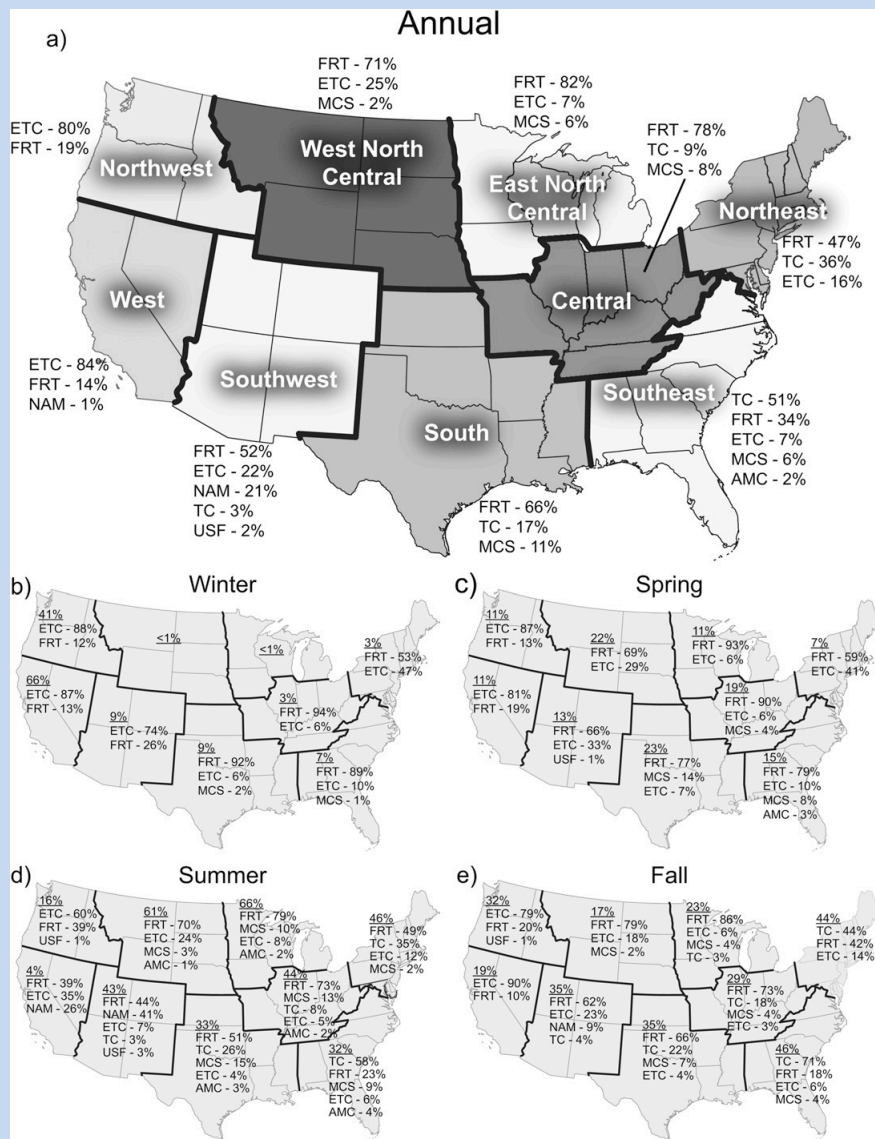


Li, Sun and Dai 2017

Plant hardiness Zones



Causes of major extreme precipitation events



Kunkel *et al.* 2012



**National
Climate
Assessment**

U.S. Global Change Research Program

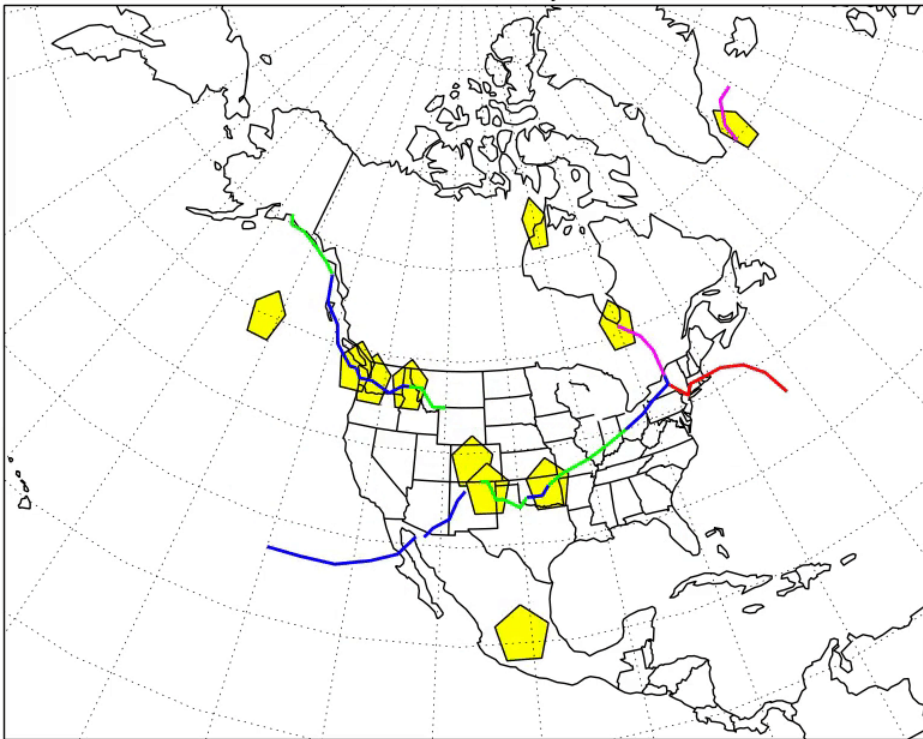
Fronts

- Deep learning neural network
- Inputs: surface values of
 - air pressure
 - air temperature
 - specific humidity
 - west-east and south-north wind velocity components
- Training dataset: 14-year set of fronts manually drawn by the National Weather Service and digitized into polylines
- Grid cell values of the probability of the presence of five types of frontal boundaries (cold, warm, stationary, occluded, and trough)

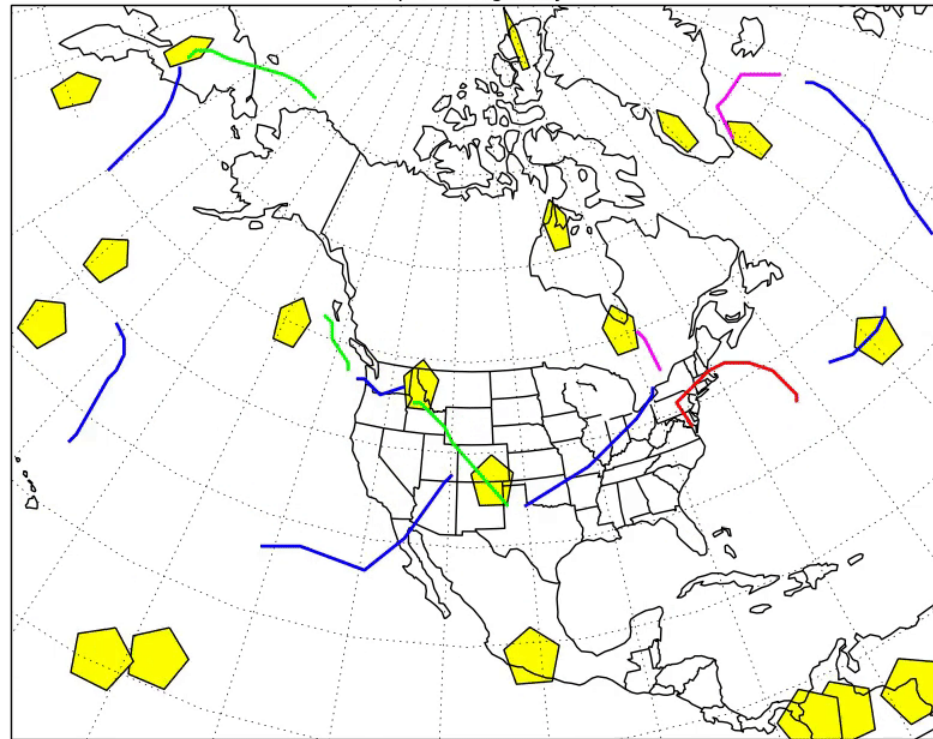
Front Identification Comparison Example

Front Identification Comparison

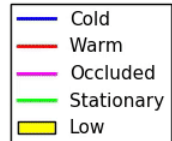
Human Surface Analysis



Deep Learning Analysis

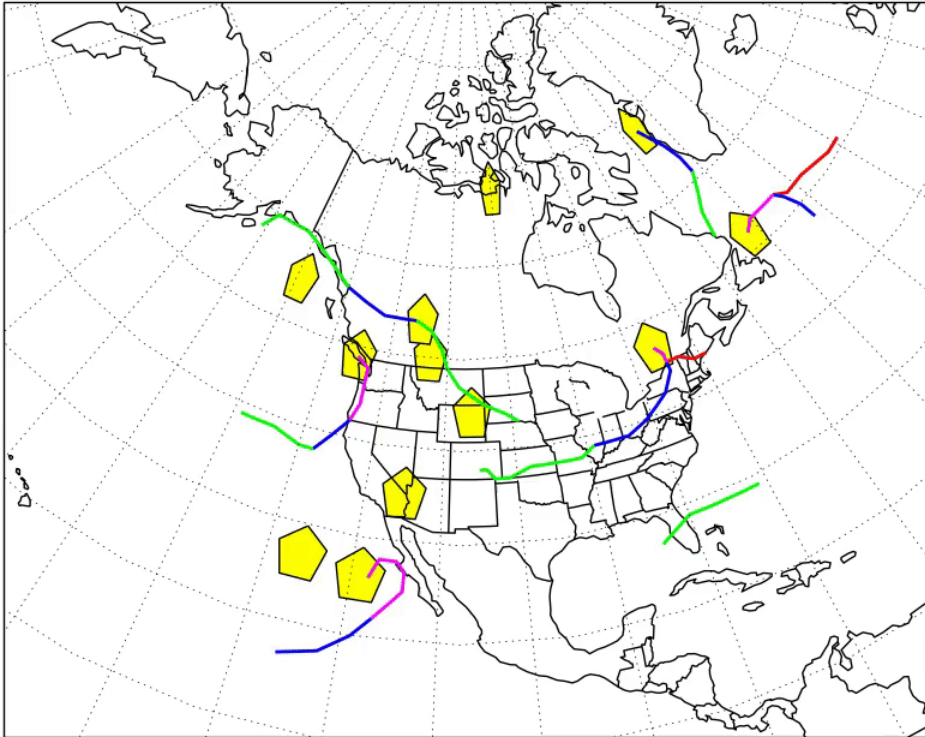


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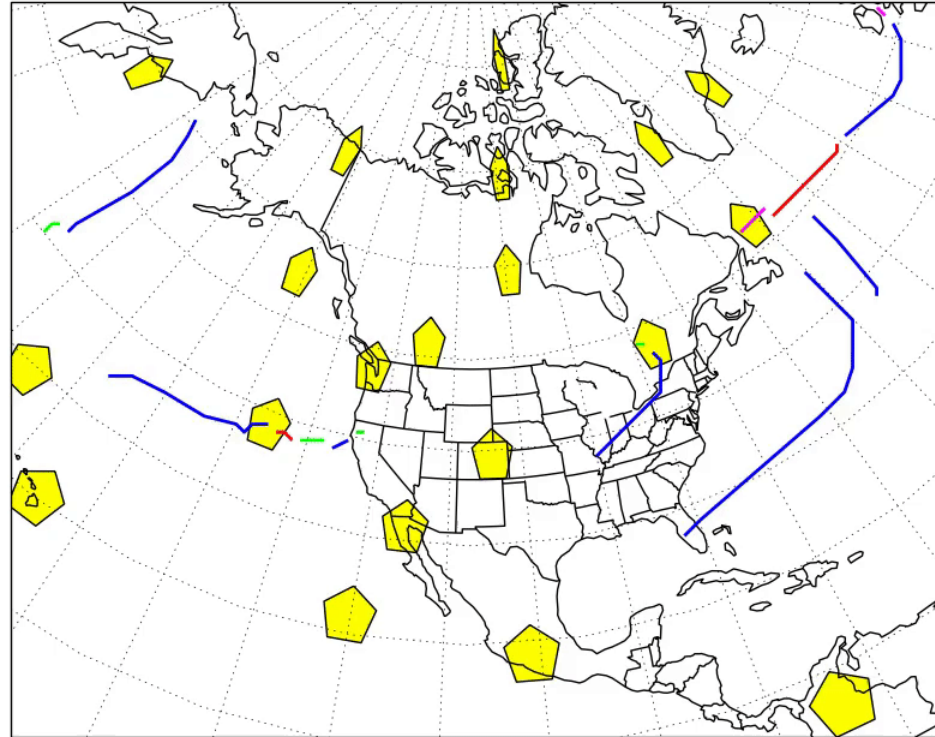


Front Identification Comparison

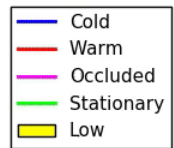
Human Surface Analysis



Deep Learning Analysis

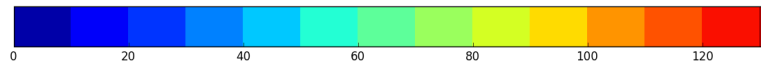
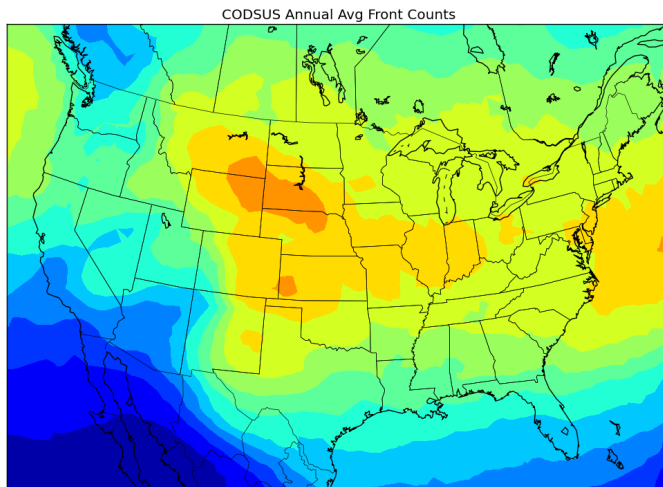


2004-01-01 00:00:00

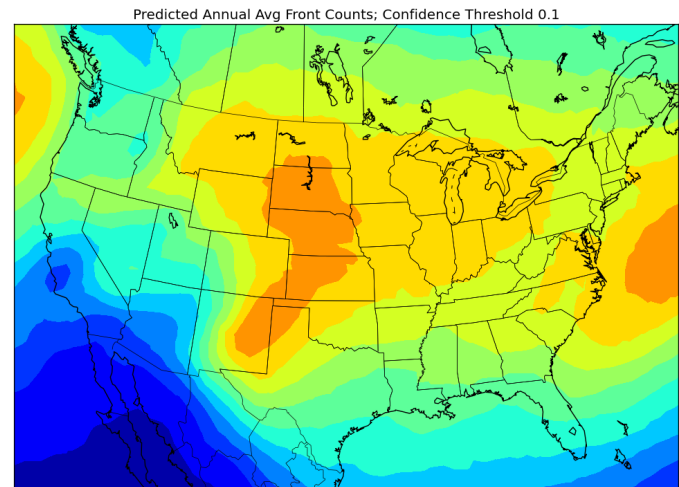


Cold Front Climatology (2003-2016)

**National Weather Service Manually
Analyzed Fronts (2004-2016)**

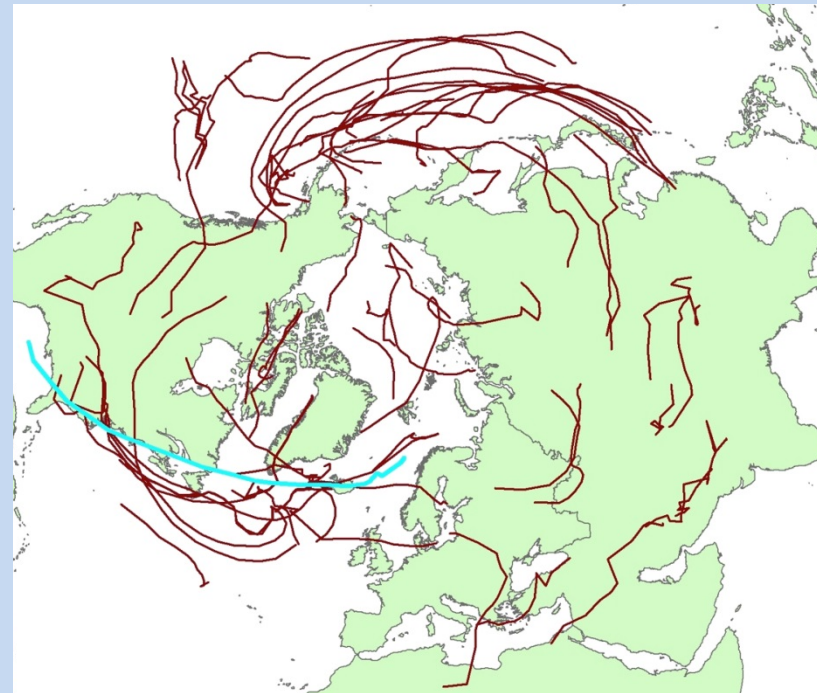


**Deep Learning Neural Network
automated front detection**



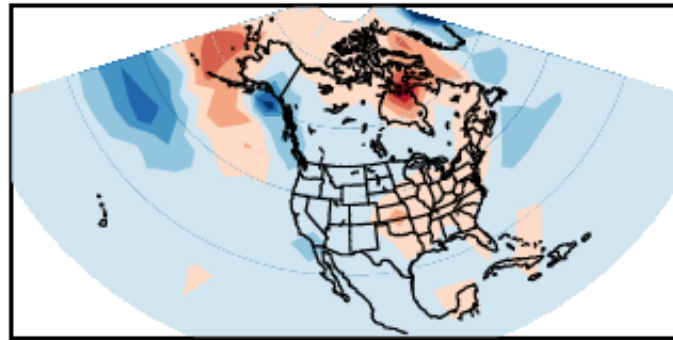
CMIP5 ETC analysis

Perform extensive analyses of CMIP5 model simulations, identifying the occurrence of ETCs causing heavy precipitation for historical and future simulations.

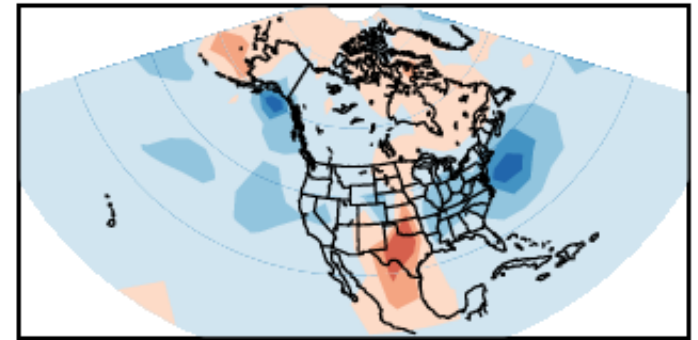


Extratropical Cyclone Future Change: 2070-2099

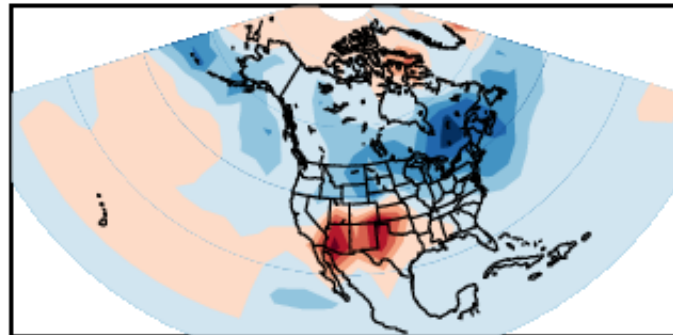
a) WINTER



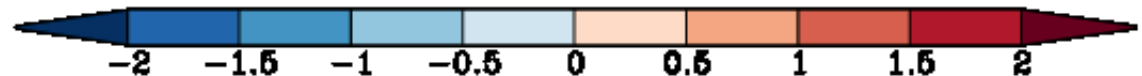
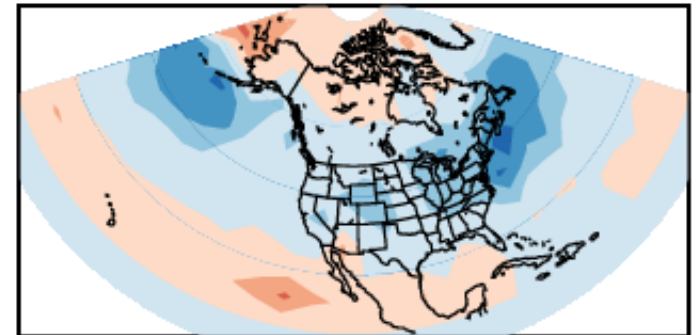
b) SPRING



c) SUMMER



d) FALL

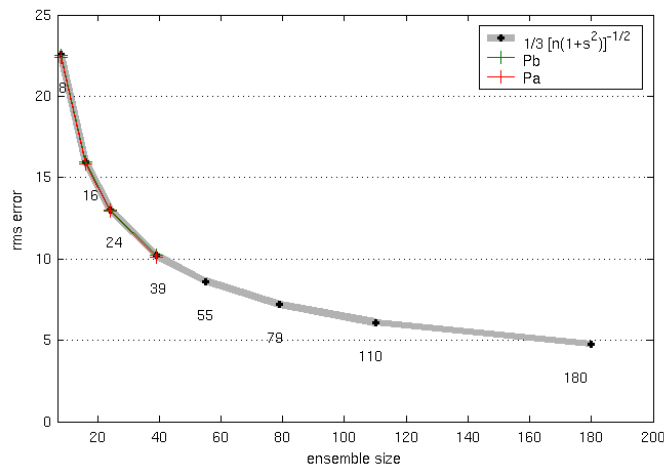
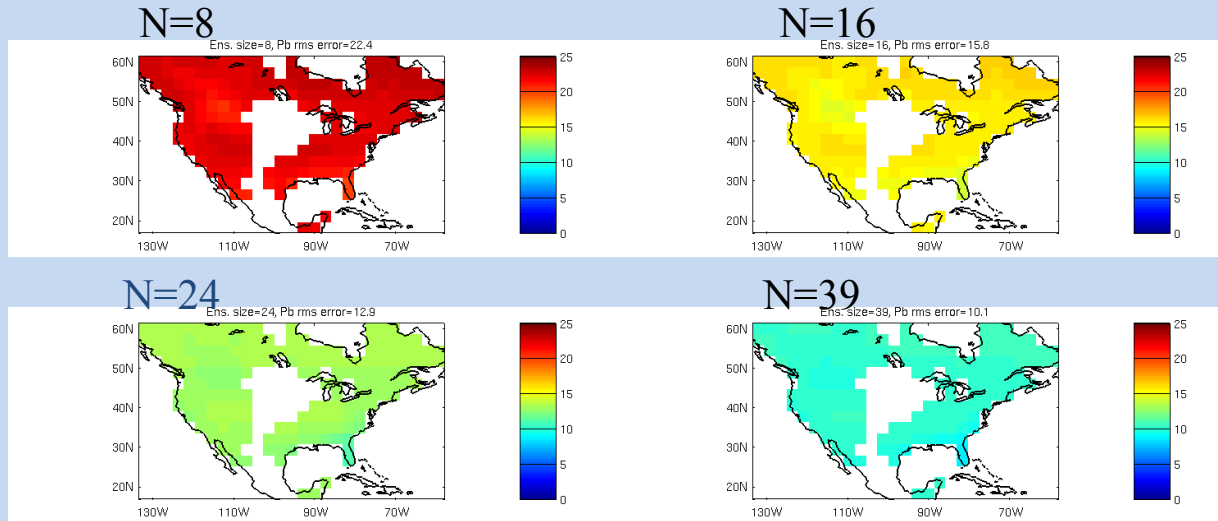


Increases in
eastern U.S. in
winter

Decreases in fall
everywhere

How to choose the number of ensembles?

SAMPLING ERRORS



Converges like

$$\frac{2}{3\sqrt{N}} \frac{1}{\sqrt{1+S^2}}$$

S = Signal-to-noise ratio

N = ensemble size

“True” rms divide by $\sqrt{2}$

M. Tippett

Summary

- Climate Downscaling has been extensively used in the National Climate Assessment.
 - 1) Temperature extremes are most directly affected by the climate change: heat waves are projected to increase in frequency, intensity, and duration, and cold snaps are projected to diminish in their frequency, but not necessarily in their intensity.
 - 2) Precipitation extremes are projected to become more frequent and more intense
 - 3) annual maximum number of consecutive wet days will significantly increase in the eastern U.S. and annual maximum consecutive dry days will significantly increase in the western U.S.

Summary (cont'd)

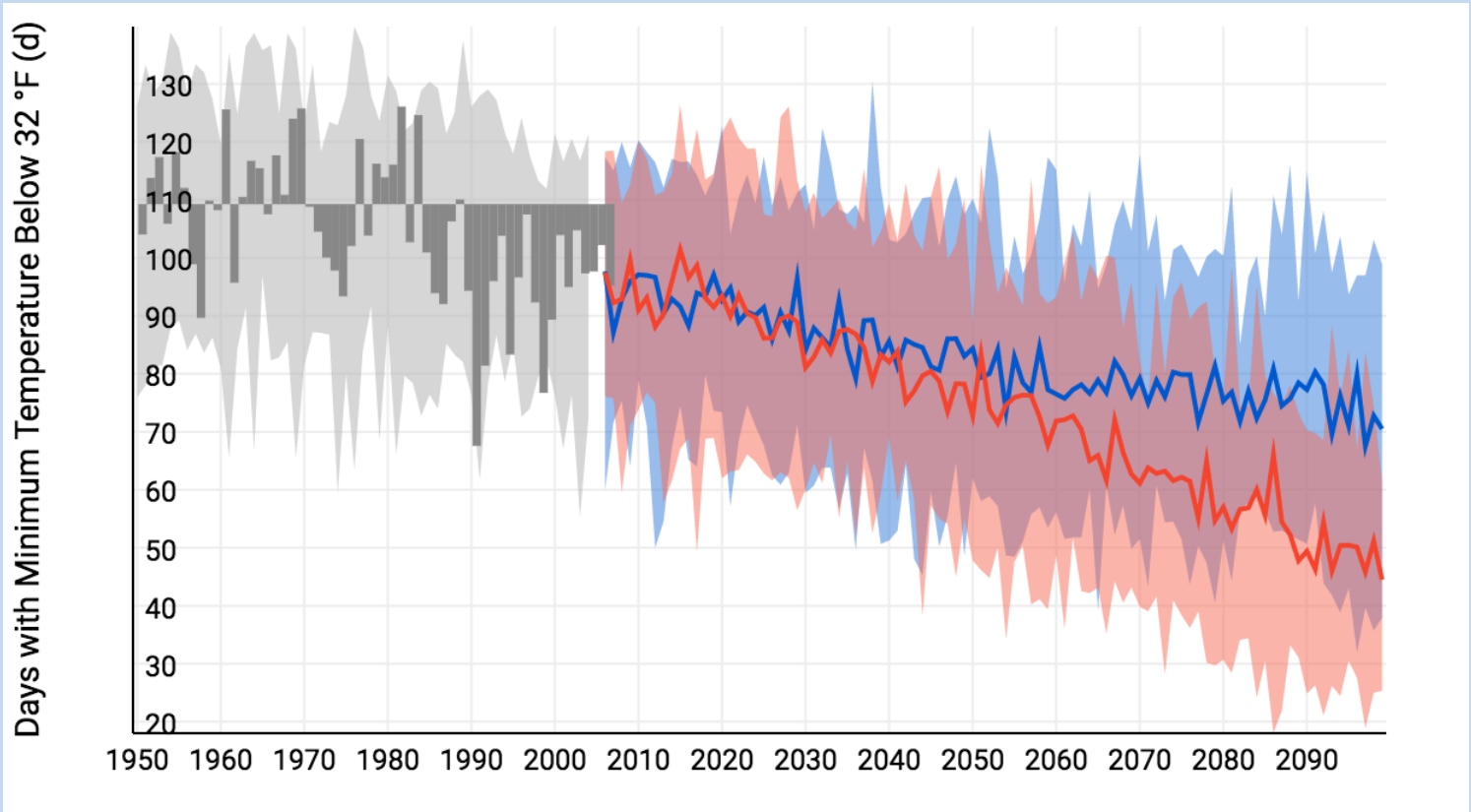
- The possibility exists to enhance climate information and increase our confidence in future climate change using dynamical downscaling
 - 1) Focus on climate variables that are both relevant and adding values by regional models. RCMs can resolve the topographic features and many physical processes such as convectively driven storms and monsoon-topography interaction at very high resolution. We do anticipate that RCMs will provide a realistic indication of how the characteristics of weather events will change in a warming world.
 - 2) Focus on the physical mechanisms of regional/local climate changes. The full set of dynamical fields available from RCMs will allow diagnostic investigation of these changes to complement the GCM projections.

Climate Explorer 2.0

- The Climate Explorer offers customizable graphs and maps of observed and projected temperature, precipitation, and related climate variables for every county in the contiguous United States.

<https://toolkit.climate.gov/climate-explorer2/>

Buncombe County



**National
Climate
Assessment**

U.S. Global Change Research Program

THANKS

ありがとう