Results from NCEP-driven RCMs

~ Overview ~

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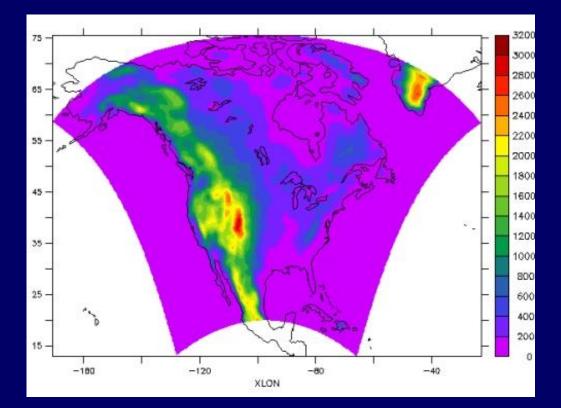
Simulations Analyzed



Domain

- Most of North America
- Period
 - 1979-2004
- Boundary Conditions

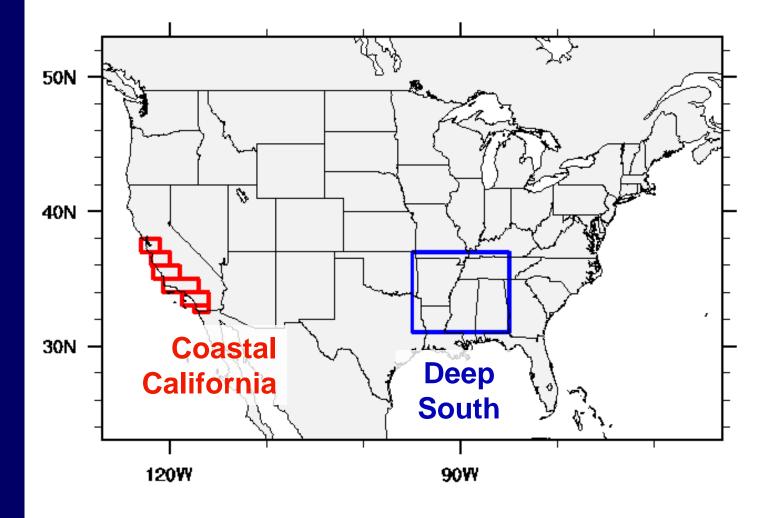
 NCEP/DOE reanalysis
- <u>Resolution</u>
 - 50 km



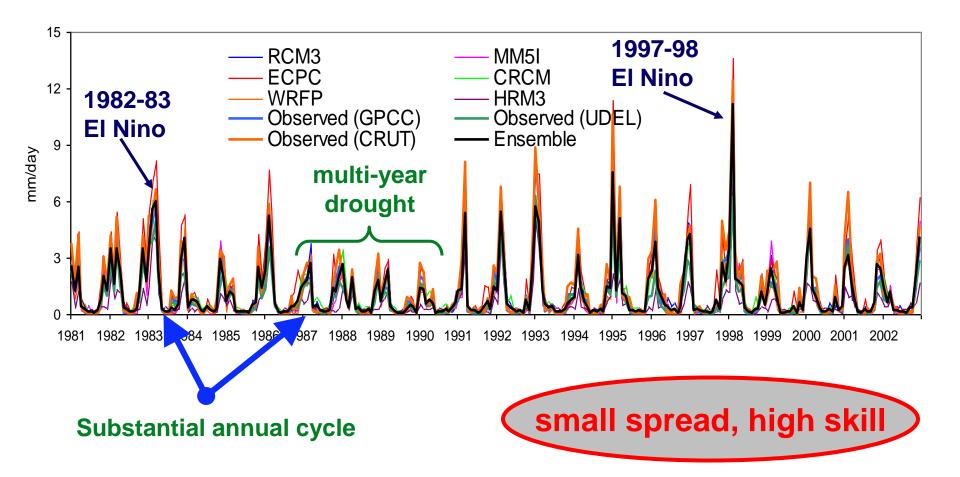
Part I: Interannual Variability

- Results shown for 1981-2002
- Comparison with 0.5° gridded precipitation analysis from the University of Delaware

Precipitation analysis for two regions



Monthly time series of precipitation in coastal California



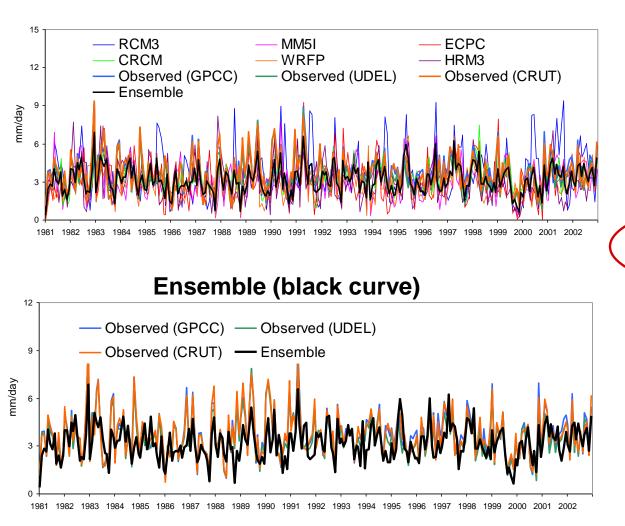
Correlation with Observed Precipitation - Coastal California

Ensemble	0.947
WRF	0.918
CRCM	0.946
RSM	0.945
MM5	0.925
RegCM3	0.916
HadRM3	0.857
Model	Correlation

All models have high correlations with observed **monthly time series** of precipitation.

Ensemble mean has a higher correlation than any model

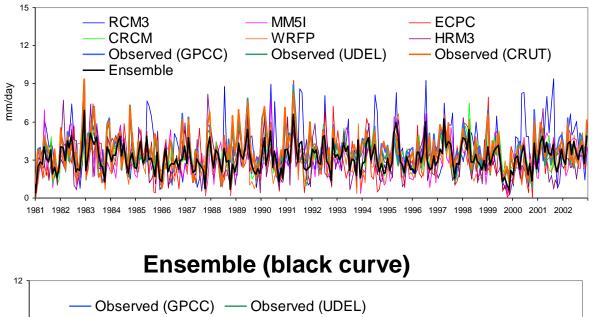
Monthly Time Series - Deep South



Model	Correlation
HadRM3	0.489
RegCM3	0.231
MM5	0.343
RSM	0.649
CRCM	0.649
WRF	0.513
Ensemble	0.640

Two models (RSM and CRCM) perform much better. These models inform the domain interior about the large scale.

Monthly Time Series - Deep South



		Observed (GPCC) Observed (UDEL)	
	9 -	— Observed (CRUT) — Ensemble	
mm/day	3 -		
	19	81 1982 1983 1984 1985 1986 1987 1988 1989 1990 1991 1992 1993 1994 1995 1996 1997 1998 1999 2000 2001 2002	

Model	Correlation
HadRM3	0.489
RegCM3	0.231
MM5	0.343
RSM	0.649
CRCM	0.649
WRF	0.513
Ensemble	0.640
RSM+CRCM	0.727

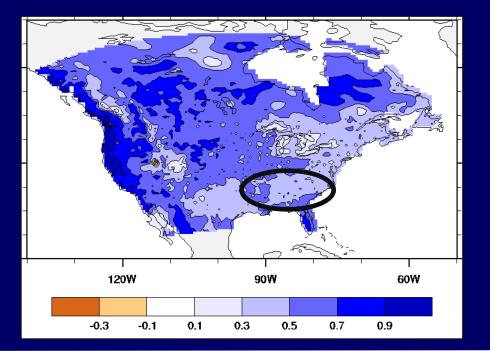
A "mini ensemble" of RSM and CRCM performs best in this region.

Correlation of Monthly Time Series

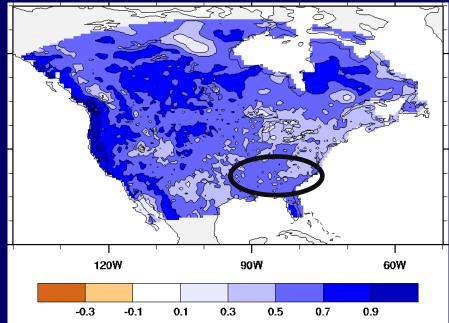
The "mini-ensemble" has better correlation than the full ensemble in the southern and eastern parts of the domain.

Other measures of forecast skill (such as bias) are not necessarily better.

Full ensemble



RSM + Canadian RCM

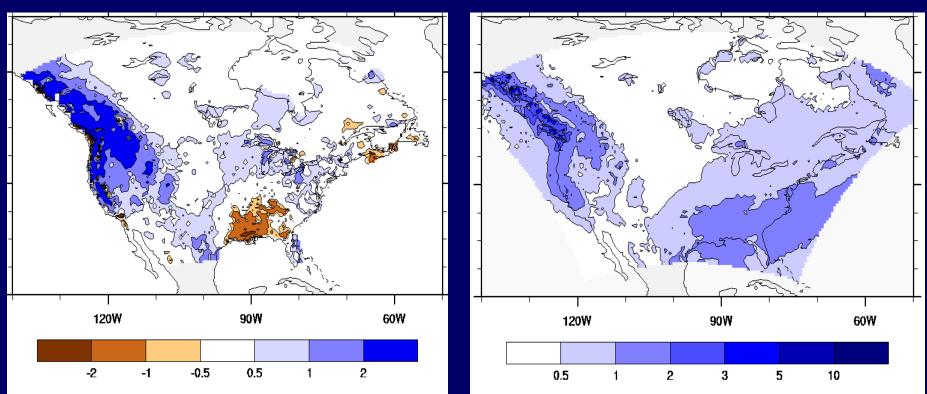


Ensemble error and spread (January)

There are hints of a spread-skill relation but it is not consistent.

Ensemble spread

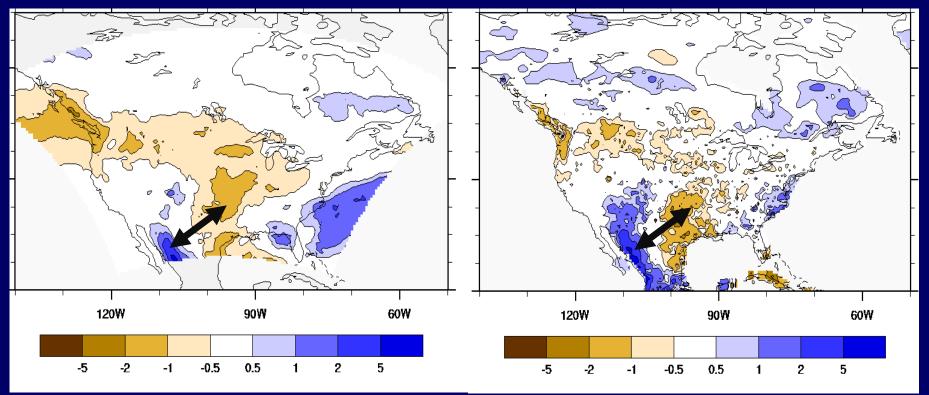
Bias



The ensemble reproduces the dipole of June-July precipitation change, but the monsoon does not extend as far north as observed.

ensemble July minus June

observed July minus June

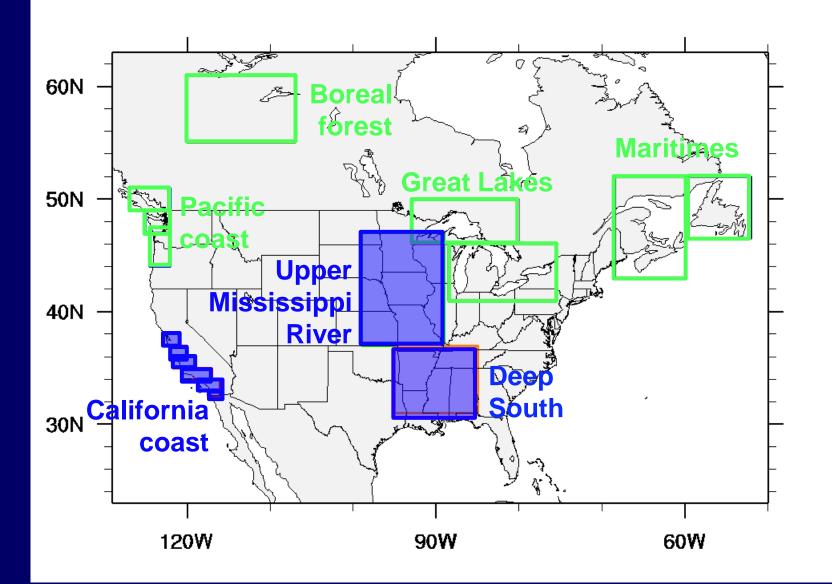


Part 2: Extreme Monthly Precipitation

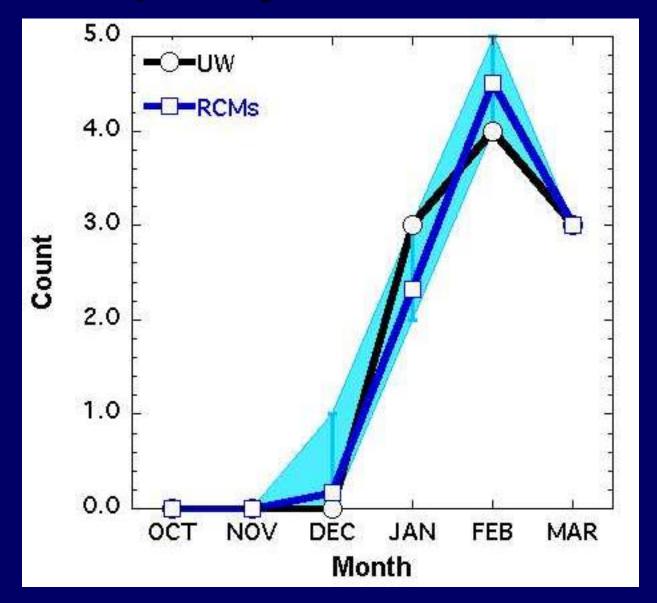
Observations

- ***** Precip: University of Washington VIC retrospective analysis
- ***** 500 hPa Heights: North American Regional Reanalysis
- <u>Comparison period: 1982 1999</u>
 - ***** 1979-1981 omitted spinup
 - ***** UW data end in mid-2000
- <u>Analysis</u>
 - * Cold season (Oct-Mar)
 - * 10 wettest months (top 10%)

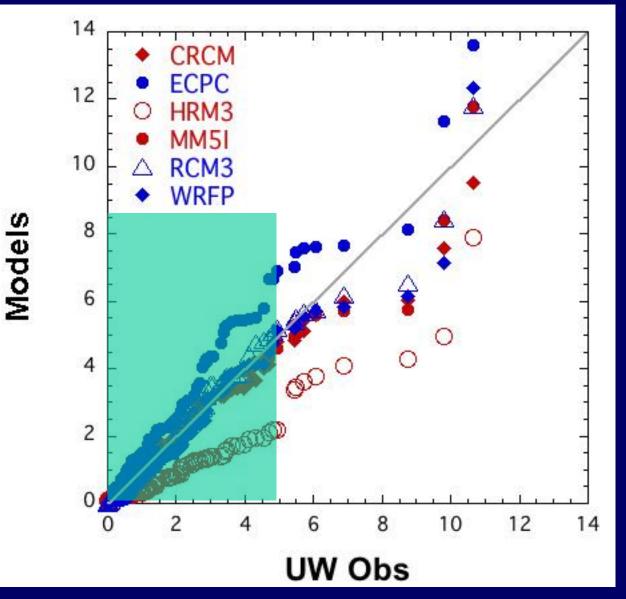
Regions Analyzed



Frequency – Coastal CA

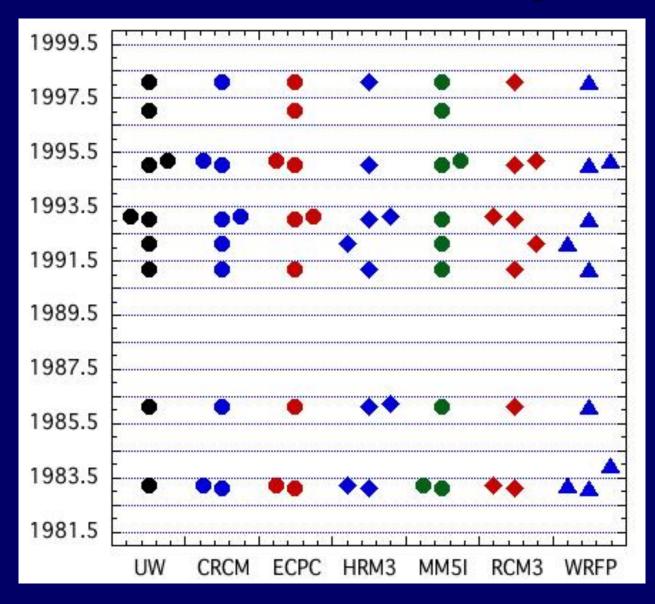


Ranked Precipitation – Coastal CA



Ensemble average of top 10 = 9 % smaller than UW

Interannual Variability – Coastal CA



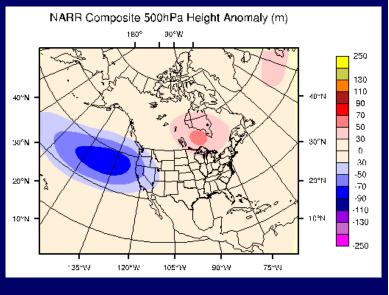
59 of 60 (98%) simulated extremes occur in cold seasons with an observed extreme.

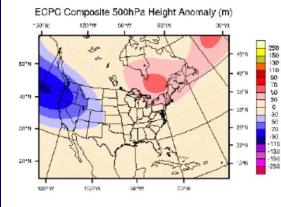
(random chance: 27)

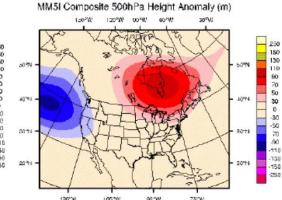
Composite 500 hPa Height Anomalies

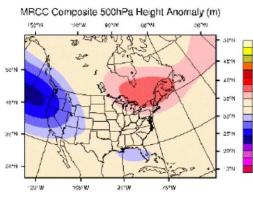
Top 10 Extremes

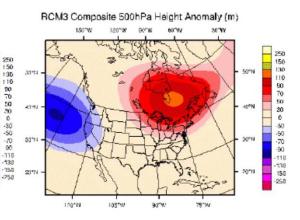
Coastal CA



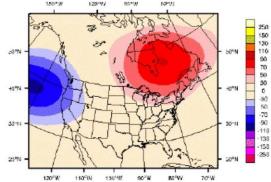




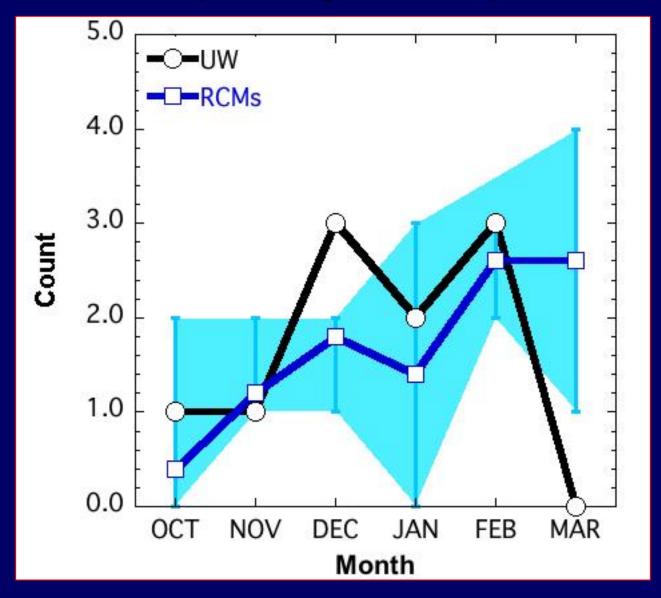




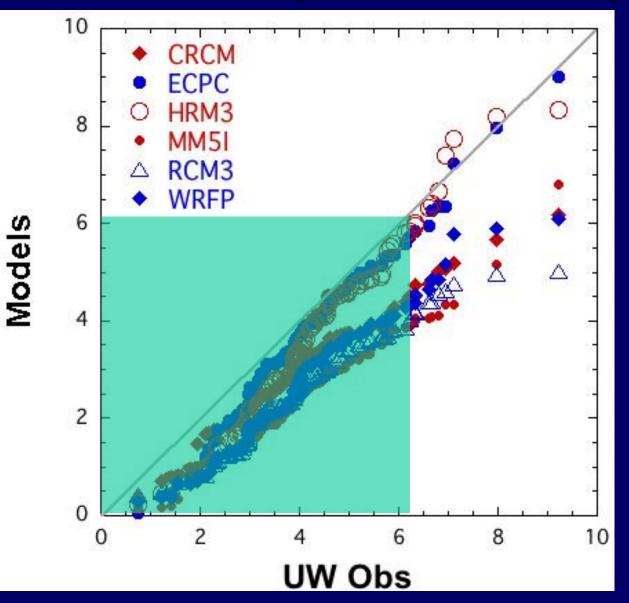
WRFP Composite 500hPa Height Anomaly (m)



Frequency – Deep South

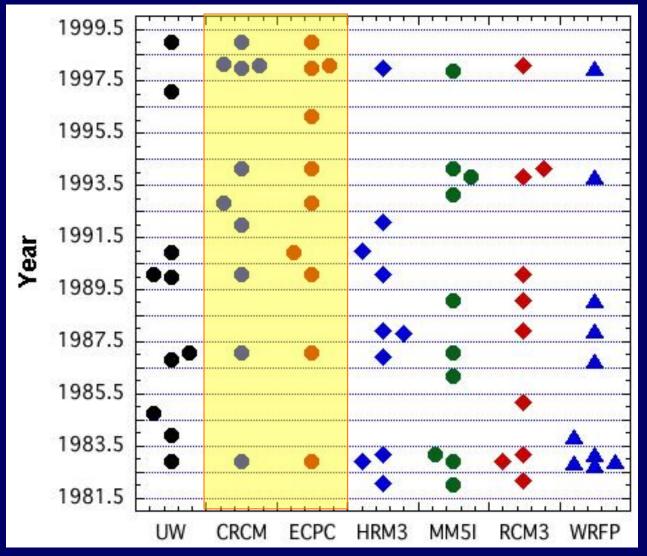


Ranked Precipitation – Deep South



Ensemble average of top 10 = 22 % smaller than UW

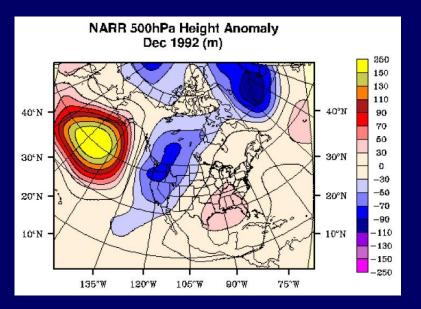
Interannual Variability – Deep South



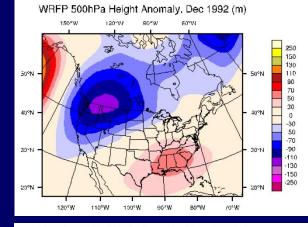
27 of 60 (45%) simulated extremes occur in cold seasons with an observed extreme.

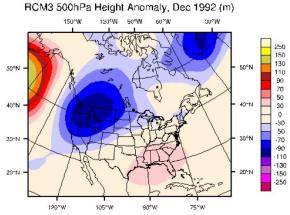
(random chance: 27)

500 hPa Height Anomalies – Deep South Extreme

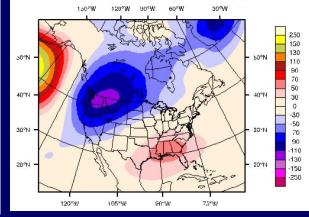


ECPC 500hPa Height Anomaly, Dec 1992 (m) 150°W 120°W 90°W 60°W 30 % 250 150 NOON 59N 130 110 90 40°N 70 50 40°N 30 35°N 0 -30 30°N -50 30°N 70 25°N -90 -110 -130 20°N -150 20°N -250 120 W 110°W 100°\V 80°W 80 W





MM5I 500hPa Height Anomaly, Dec 1992 (m)



Summary Monthly Precipitation

Where there is a substantial periodic cycle:
Models simulate well the interannual variability
Models simulate well monthly, regional extremes

Where there is no substantial periodic cycle:

- Models simulate poorly the interannual var. & extremes

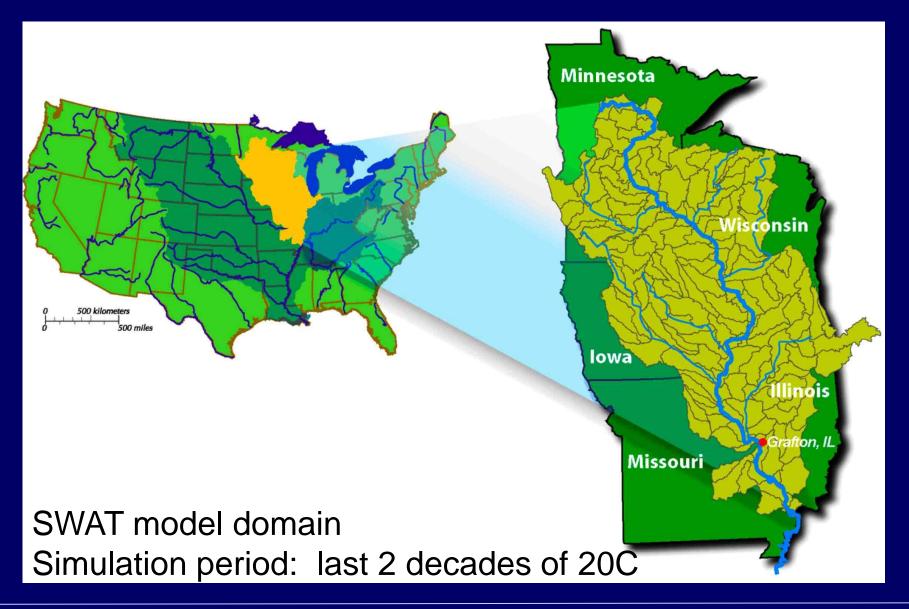
- Interior nudging improves interannual variability
- Interior nudging does not help extremes

Thank You!

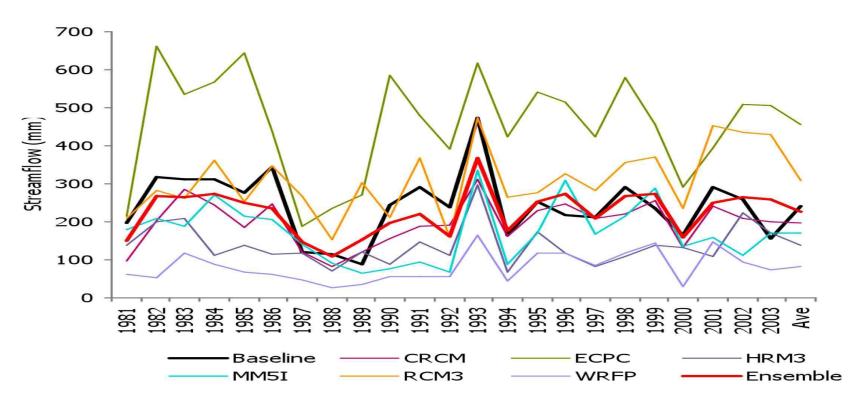


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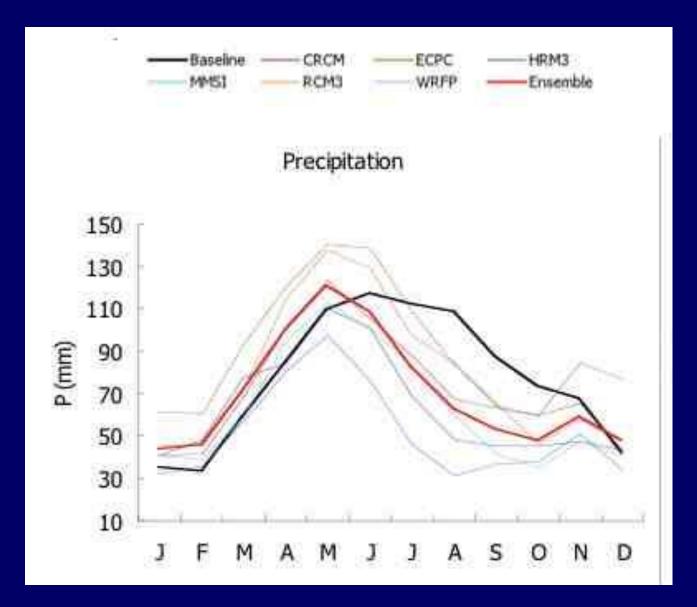
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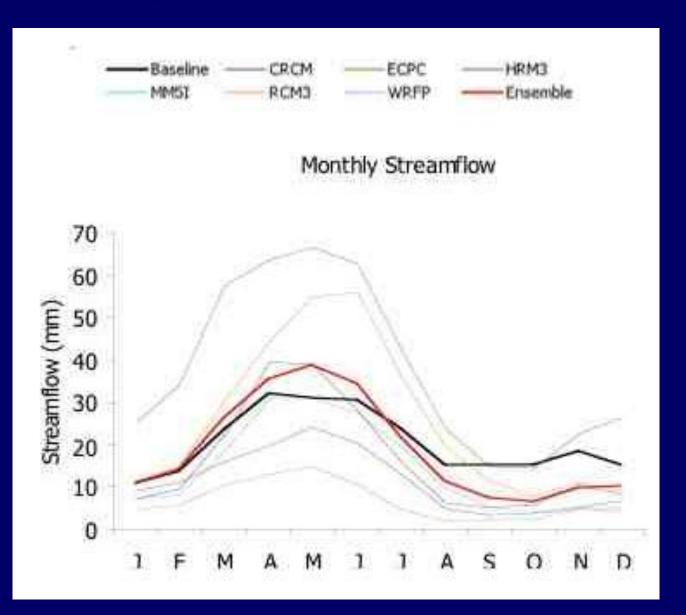


Streamflow Interannual Variability



Annual Streamflow





Summary

MONTHLY PRECIPITATION

Where there is a substantial periodic cycle:

- Models simulate well the interannual variability
- Models simulate well monthly, regional extremes

Where there is no substantial periodic cycle:

- Models simulate poorly the interannual var. & extremes
- Interior nudging improves interannual variability
- -Interior nudging does not help extremes

UPPER MISSISSIPPI STREAMFLOW

Ensemble replicates well the interannual variability Annual cycle simulated less well

Thank You!

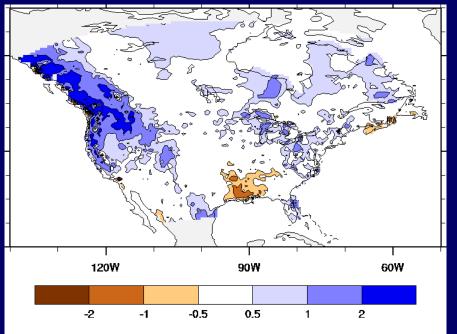


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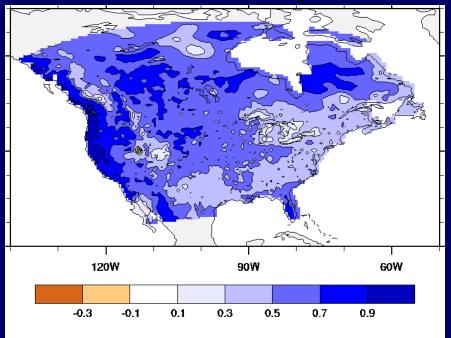
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Bias of the ensemble mean and correlation of ensemble monthly time series with observed time series.



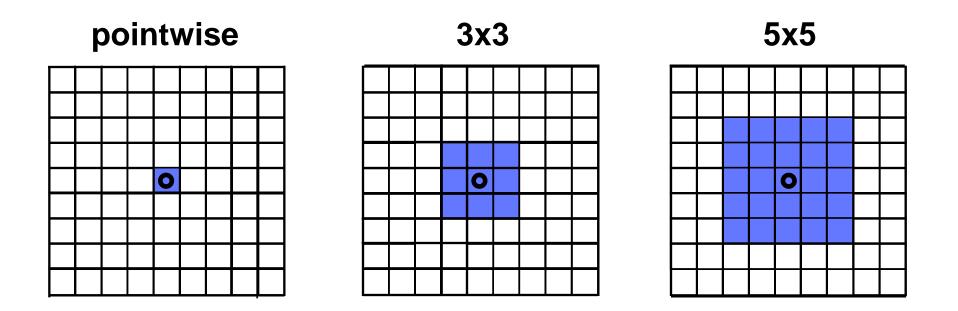


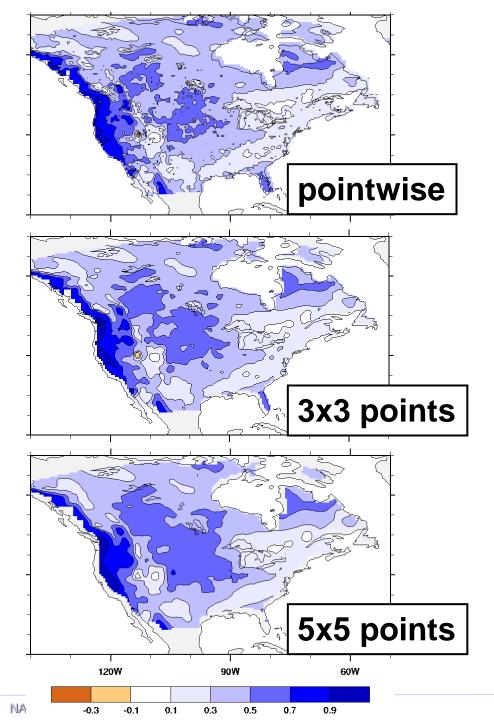
Correlation of monthly time series



How does spatial aggregation affect prediction skill?

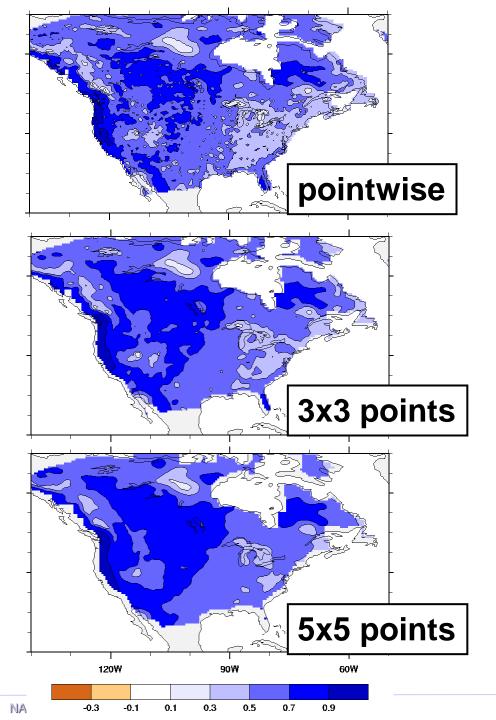
Average both model and observations onto 3x3 or 5x5 grid square areas.





Spatial aggregation tends to improve correlation, but effect differs across the domain.

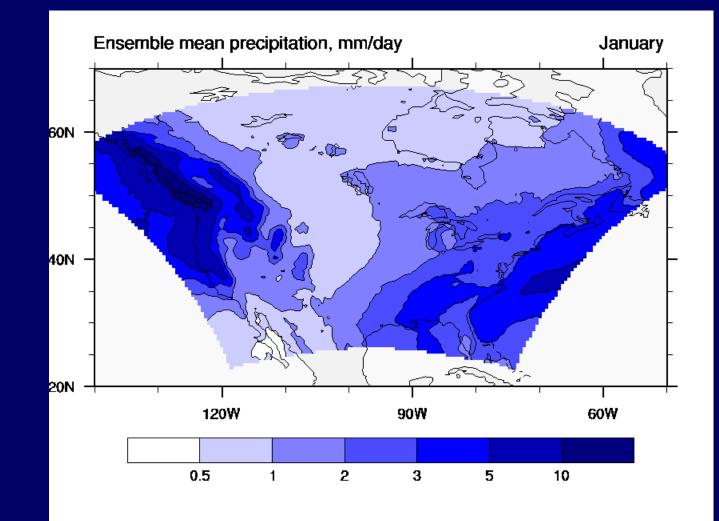
- Differs from model to model (MM5 shown here).
- Aggregation has more effect on individual models than on ensembles.
- Note improvement in central U.S. but not eastern U.S.



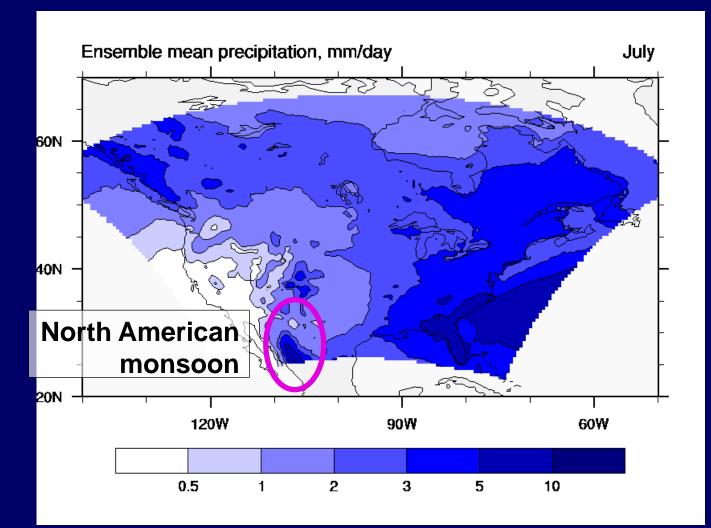
Aggregation has a greater effect on correlation in a model with spectral nudging.

- Canadian RCM shown here.
- Note improvement in eastern U.S.
- Hypothesis: Large scales are better represented in a model with spectral nudging, so smoothing out smallscale irregularities produces more improvement.

Ensemble mean precipitation: January



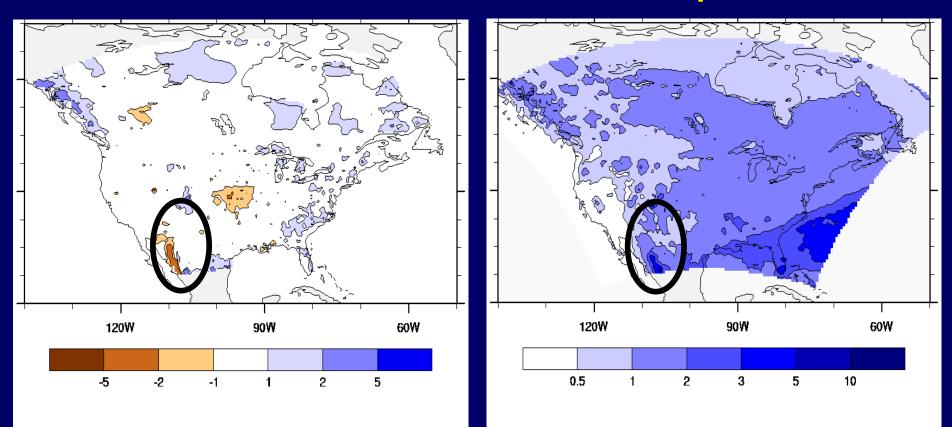
Process oriented evaluation: the North American monsoon



Ensemble error and spread (July)

Bias

Ensemble spread



Analysis of Extremes

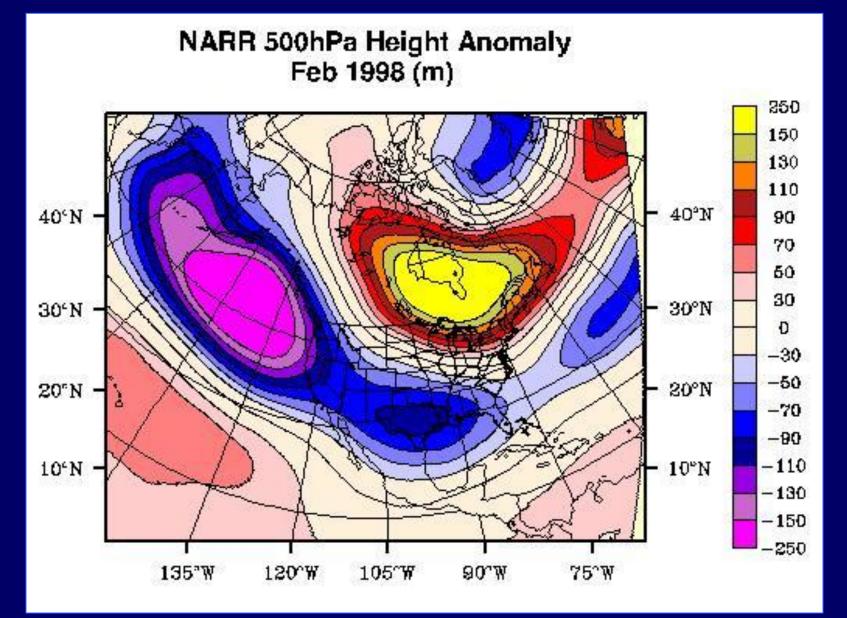
Societal importance, esp. for climate change

Key Question: Do climate models behave like observations?

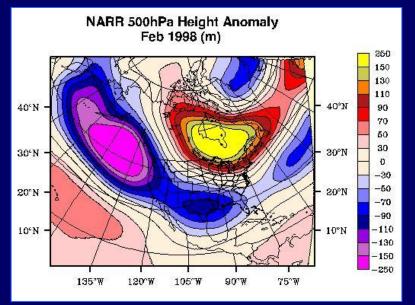
Diagnosis of physical mechanisms

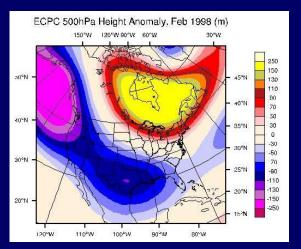
- Necessary for model vs. obs. comparison
- Basis for developing confidence in projections

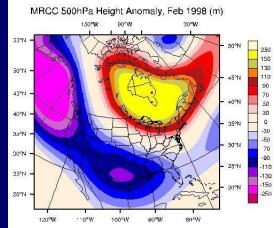
500 hPa Height Anomalies – Coastal CA Extreme



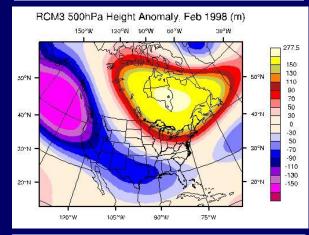
500 hPa Height Anomalies – Coastal CA Extreme

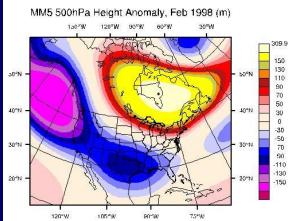






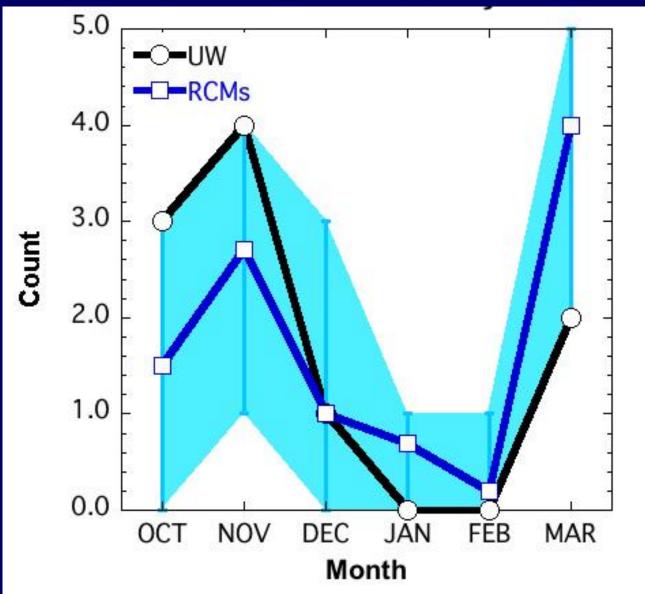
WRFP 500hPa Height Anomaly, Feb 1998 (m) 120114 SC"A 302.8 150 130 50°N SASN 110 90 70 50 30 40°N 0 -30 50 -70 -90 39*N -110 -130 -150 20°N BOWW 10°W 1200% 110°W 10098 962W



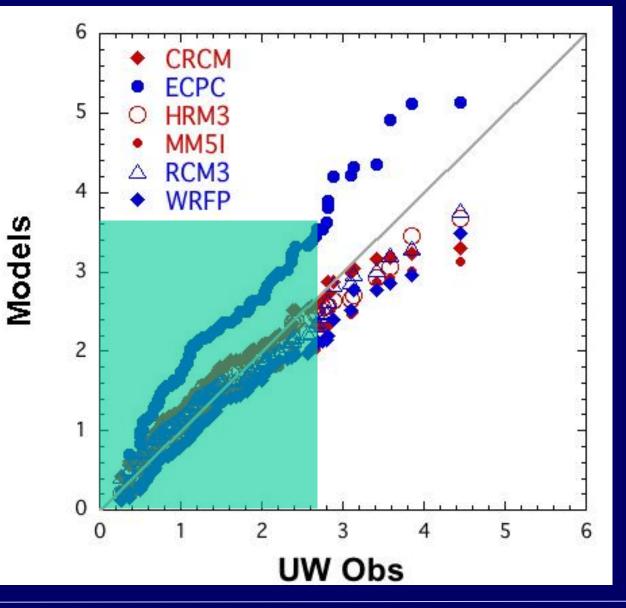


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Frequency – Upper MS

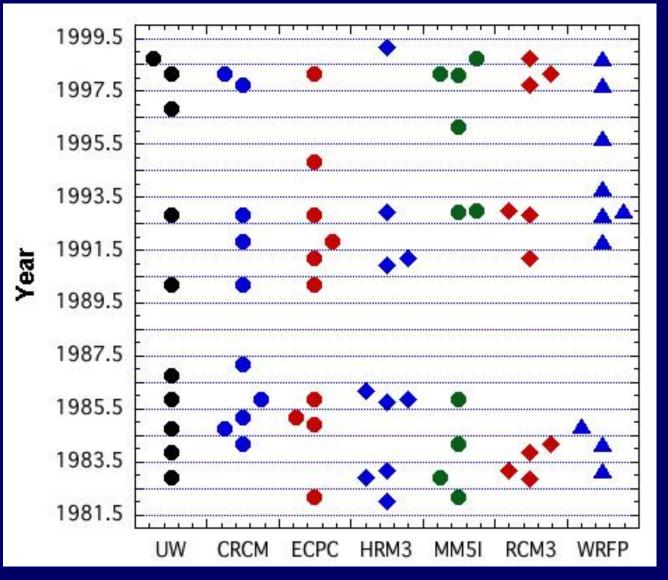


Ranked Precipitation – Upper MS



Ensemble average of top 10 = 6 % smaller than UW

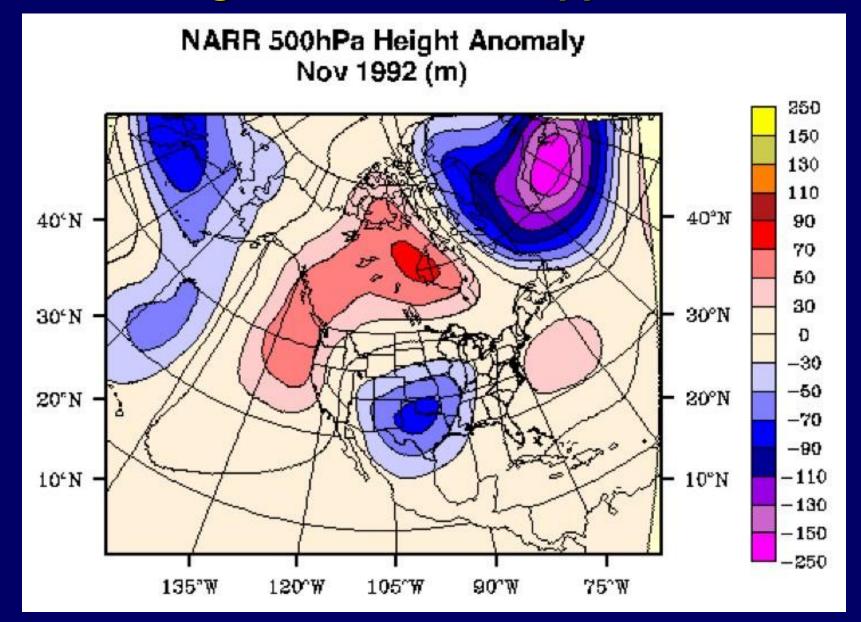
Interannual Variability – Upper MS



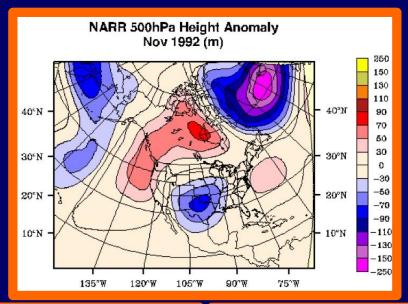
46 of 60 (77%) simulated extremes occur in cold seasons with an observed extreme.

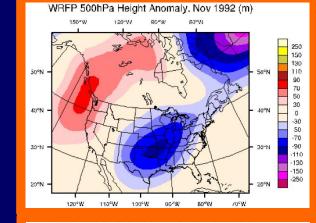
(random chance: 33)

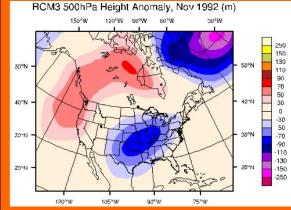
500 hPa Height Anomalies – Upper MS Extreme

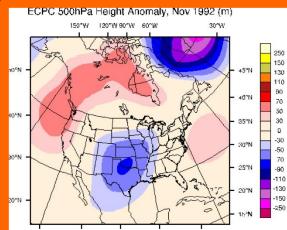


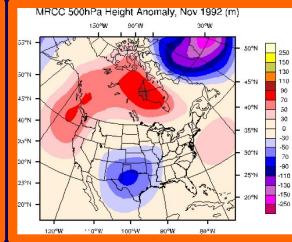
500 hPa Height Anomalies – Upper MS Extreme



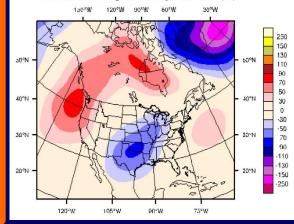








MM5I 500hPa Height Anomaly, Nov 1992 (m)

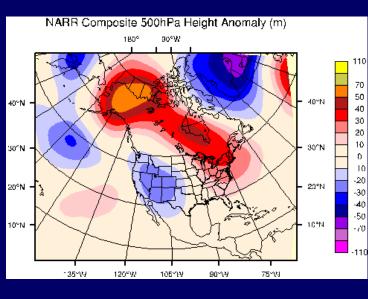


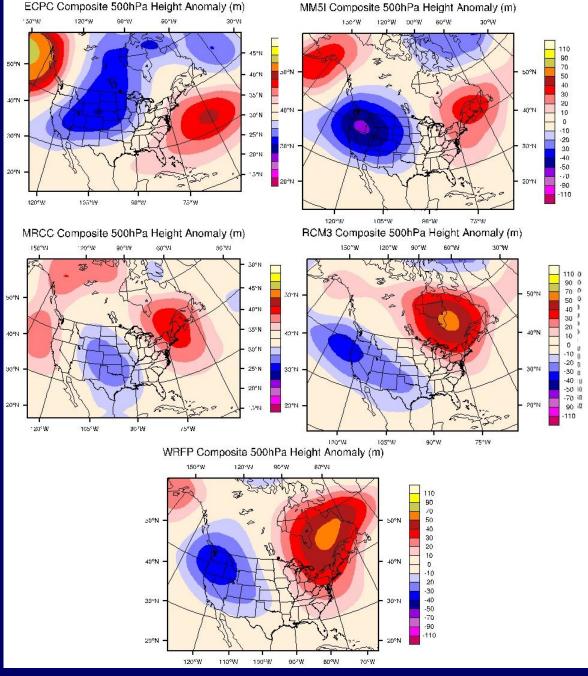
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Composite 500 hPa Height Anomalies

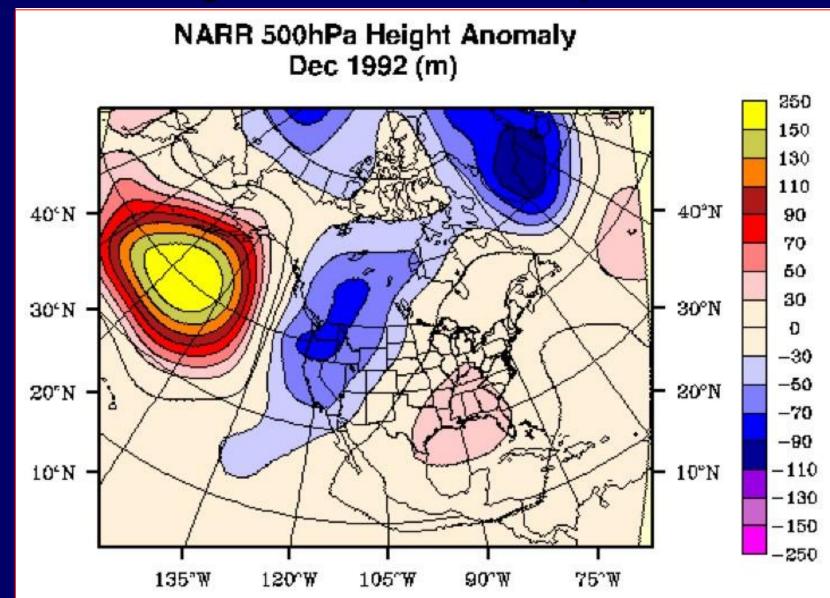
Top 10 Extremes

Upper MS





500 hPa Height Anomalies – Deep South Extreme



Correlation: Monthly Observations and Ensemble Mean

