DOWNSCALING GCMs TO PRODUCE METEOROLOGICAL VARIABLES AT LOCAL TO REGIONAL SCALES

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Special thanks to Phil Duffy for providing the high-resolution model results.

SUMMARY

- Future climate change – a probabilistic view
- Controlling factors for Californian climate
- Downscaling methods
- Choosing a driver AOGCM
- Examples … effects of increasing resolution
- Conclusions

FUTURE CLIMATE CHANGE – a probabilistic view

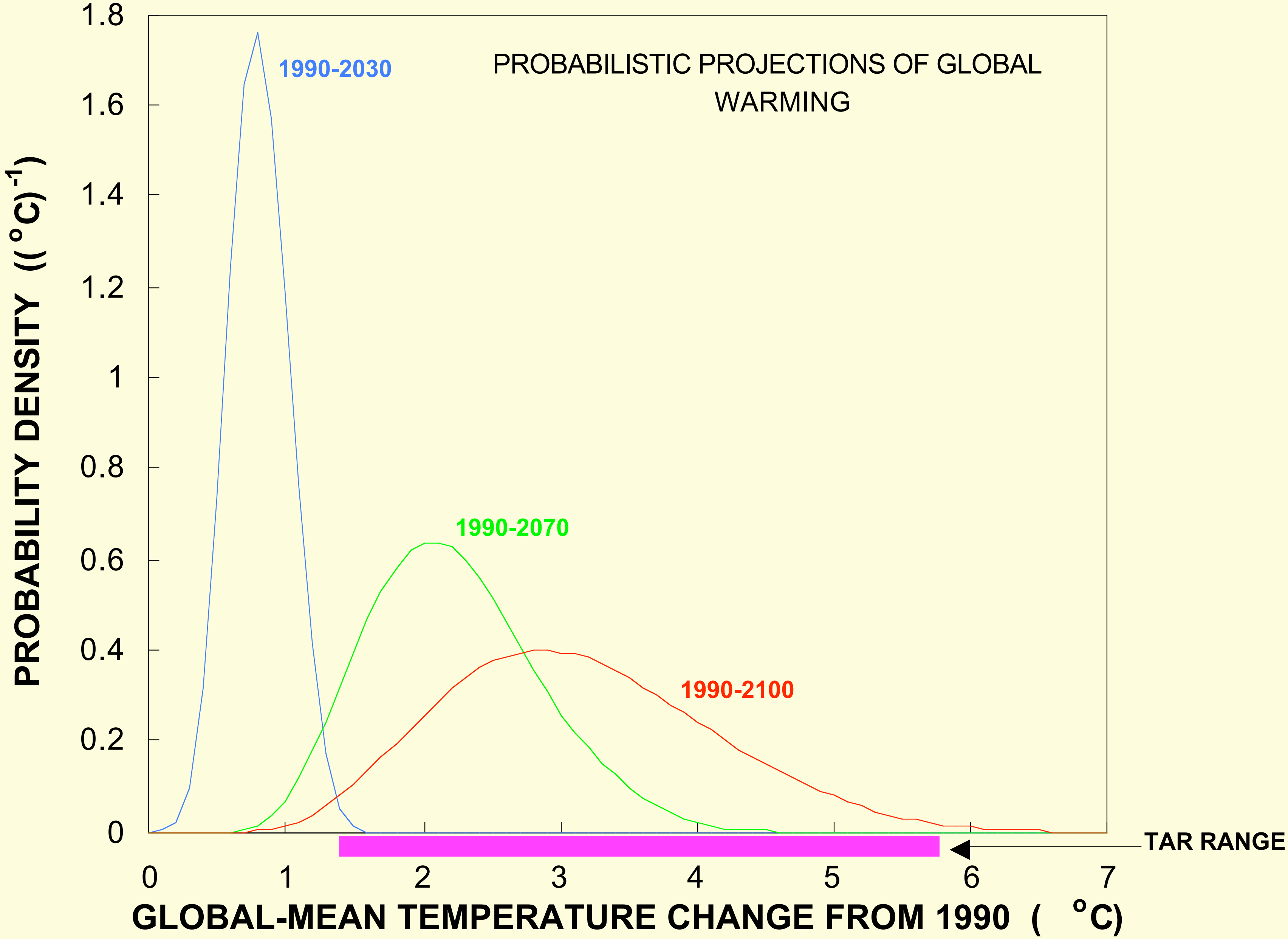
The principle used here is to separate out the global-mean temperature change and regional climate pattern aspects.

(1) Global temperature projections can be produced in probabilistic form (as time-dependent pdfs), accounting for uncertainties in emissions, climate sensitivity, etc.

(2) Patterns of change can be produced as normalized results; i.e., changes per 1^{o}C global-mean warming. In this way the effects of differing model sensitivities can be factored out and the pattern results are more easily compared

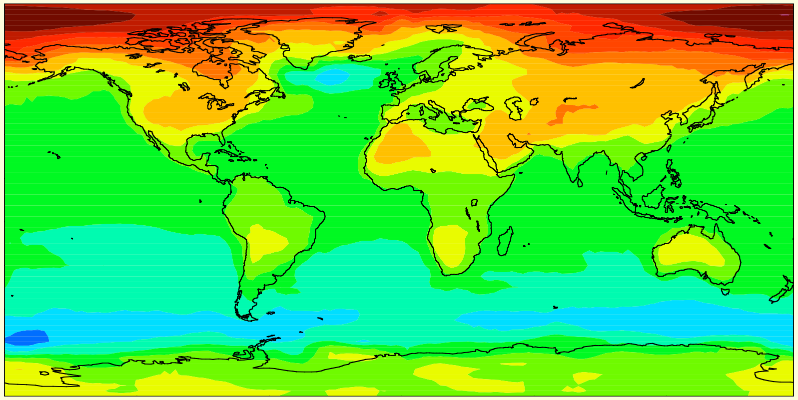
(3) Gridpoint normalized changes can be defined as pdfs by using the results of multiple models

(4) Global temperature pdfs and gridpoint pdfs for normalized data can then be combined to produce overall pdfs

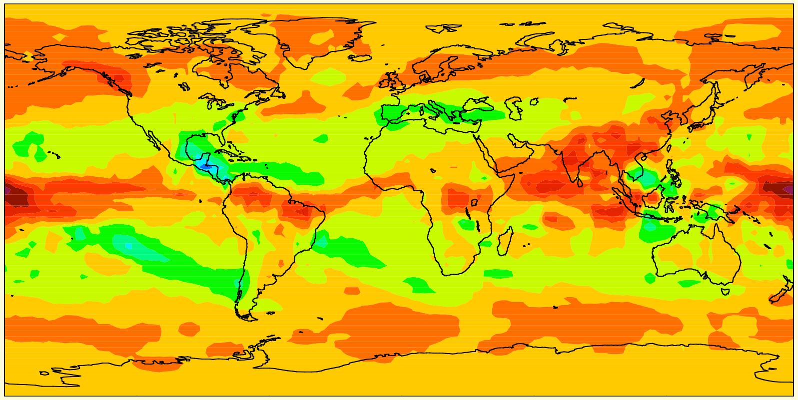

PROBABILISTIC PROJECTIONS OF GLOBAL WARMING
1990-2030
1990-2070
1990-2100
TAR RANGE
PROBABILITY DENSITY ((°C)$^{-1}$)
GLOBAL-MEAN TEMPERATURE CHANGE FROM 1990 (°C)
0
0.2
0.4
0.6
0.8
1
1.2
1.4
1.6
1.8
0
1
2
3
4
5
6
7

Normalized annual-mean temperature and precipitation changes in CMIP2 Greenhouse Warming Experiments (1%/year CO_2 increase)

Normalized temperature change



Normalized precipitation change



PROBABILISTIC GRIDPOINT INFORMATION FOR NORMALIZED CHANGES CAN BE DERIVED BY ASSUMING THAT ….

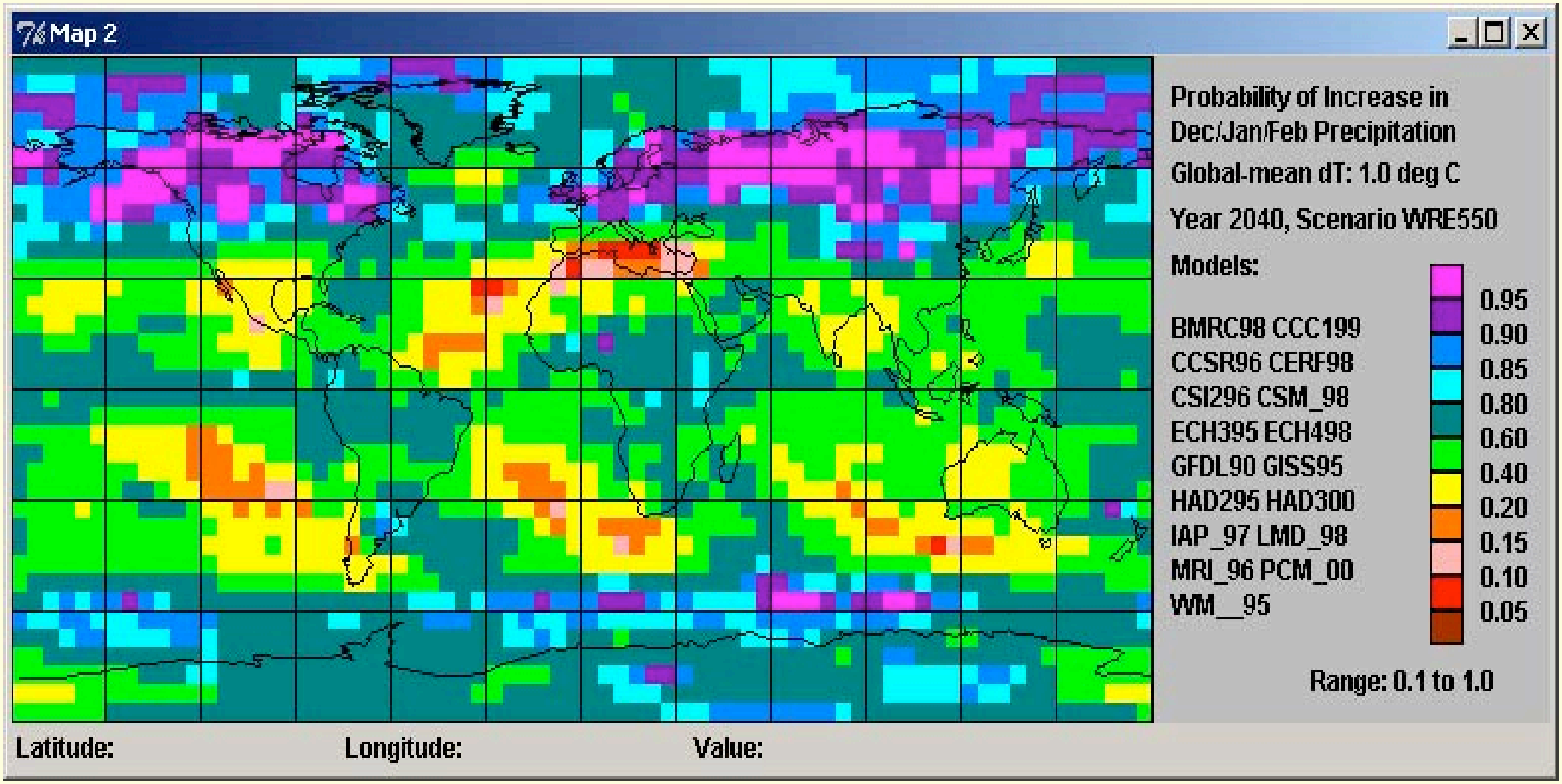
THE PDF IS GAUSSIAN WITH ….

MEAN EQUAL TO THE MEAN CHANGE OVER ALL MODELS

STANDARD DEVIATION EQUAL TO THE INTER-MODEL STANDARD DEVIATION

A SIMPLE OUTPUT FROM THIS IS TO DEFINE, FROM THESE PDFS, THE PROBABILITY OF A PRECIPITATION INCREASE …. AS IN THE FOLLOWING EXAMPLE ….

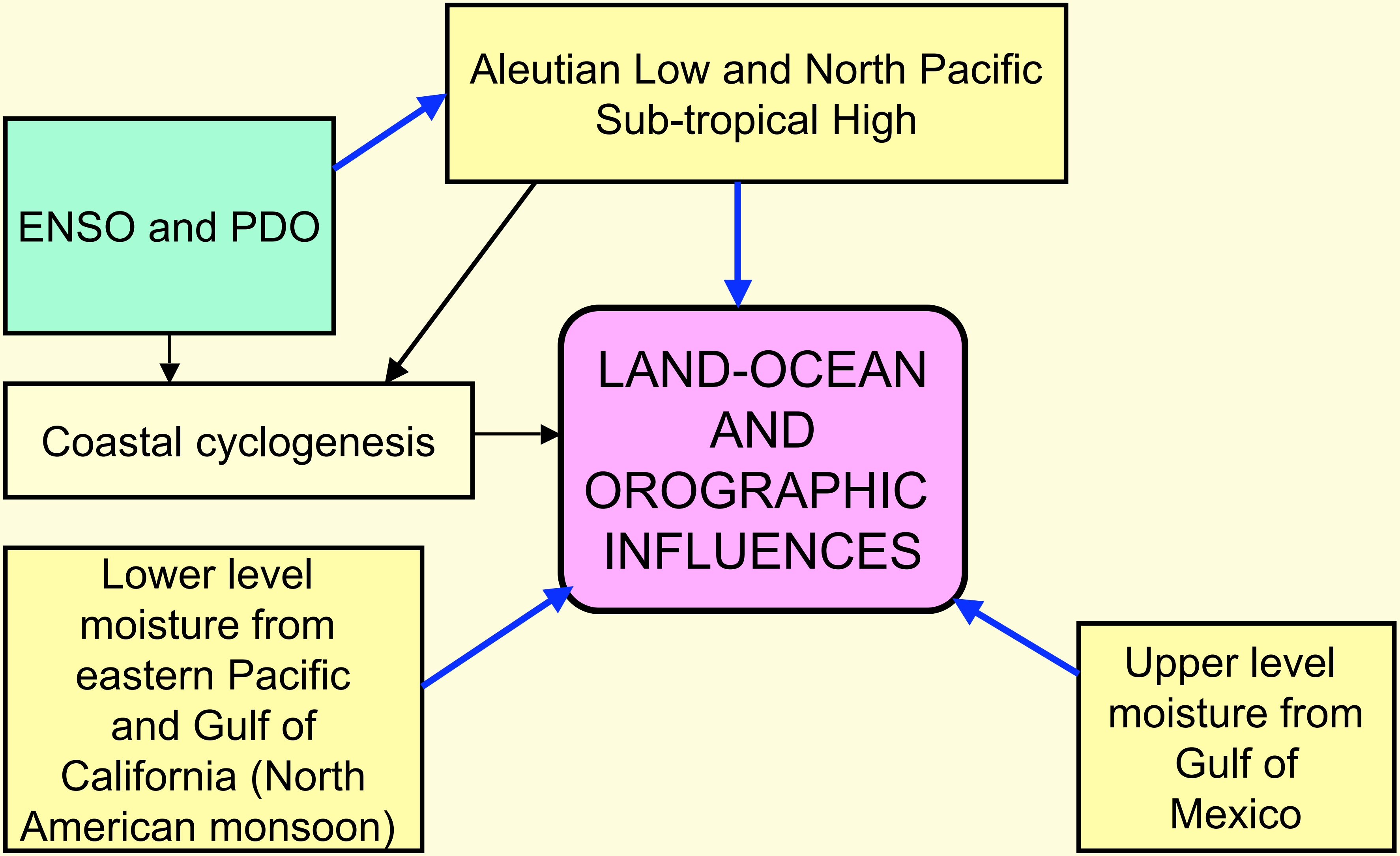
Probability of an increase in winter (DJF) precipitation



FACTORS INFLUENCING CALIFORNIAN CLIMATE

(Credible climate models should simulate these well)

FACTORS INFLUENCING CALIFORNIAN CLIMATE



DOWNSCALING

Primary Goal: To produce local to regional scale climate information, generally from coarse-resolution global-scale climate models

Secondary Goal: To improve the reliability of short timescale climate information

DOWNSCALING METHODS

Dynamical Downscaling: Uses physically-based models with finer spatial resolution than the original global model

Statistical Downscaling : Uses statistical relationships (usually some form of regression equation) where a fine-scale predictand is related to a set of course-resolution predictors

DYNAMICAL DOWNSCALING

METHOD	**DRIVERS** (time dependent)*
Nested RCM	Lateral and surface boundary conditions (state and fluxes) from AOGCM
Stretched-Grid AGCM	Surface boundary conditions from AOGCM
High-resolution AGCM	Surface boundary conditions from AOGCM
Hybrid method	AOGCM $\Rightarrow$ Hi-Res AGCM $\Rightarrow$ RCM

* All methods require specification of external forcings

STATISTICAL DOWNSCALING

ASSUMPTIONS:

(1) AOGCM projections for some variables (e.g. those characterizing circulation changes) – ΔX_i below – are more reliably projected than others (e.g. precipitation)

(2) These variables are the primary controls on sub-grid scale changes, ΔY below

(3) These controlling influences may be quantified using regression relationships of the form – $\Delta Y = \Sigma\ \Delta X_i$ + noise.

(4) Such regression relationships are stable in time (as they might be if they were determined by factors such as orography)

CHOOSING A DRIVER AOGCM

(1) AOGCM quality: which may be assessed by the model's validation performance [at global and regional scales, around the RCM boundary (especially fluxes), and for variability modes (such as ENSO)]

(2) Spanning the uncertainty range

(3) Availability of appropriate experiments (control and perturbation)

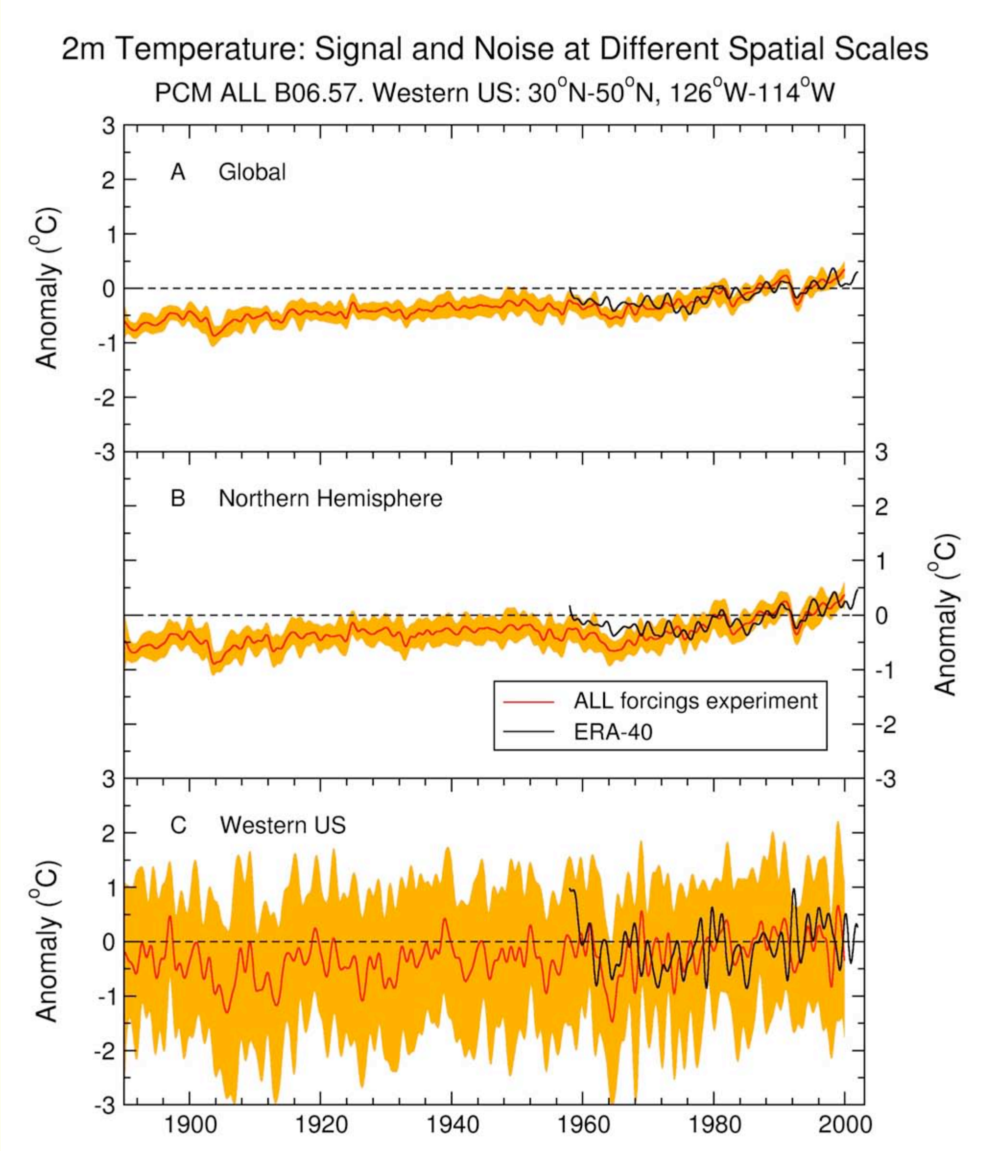
(4) AOGCM/RCM consistency (parameterizations, chemistry)

AOGCM VALIDATION

(Results for 17 AOGCMs from the CMIP data base)

(1) Simulating past variations
(2) Simulating present-day climate patterns
(3) Model biases
(4) Simulating present-day boundary fluxes
(5) Simulating natural models of variability (e.g. ENSO) and their teleconnection relationships

Surface temperature changes in PCM and ERA-40 show consistency even at sub-global spatial scales (results from Ben Santer)

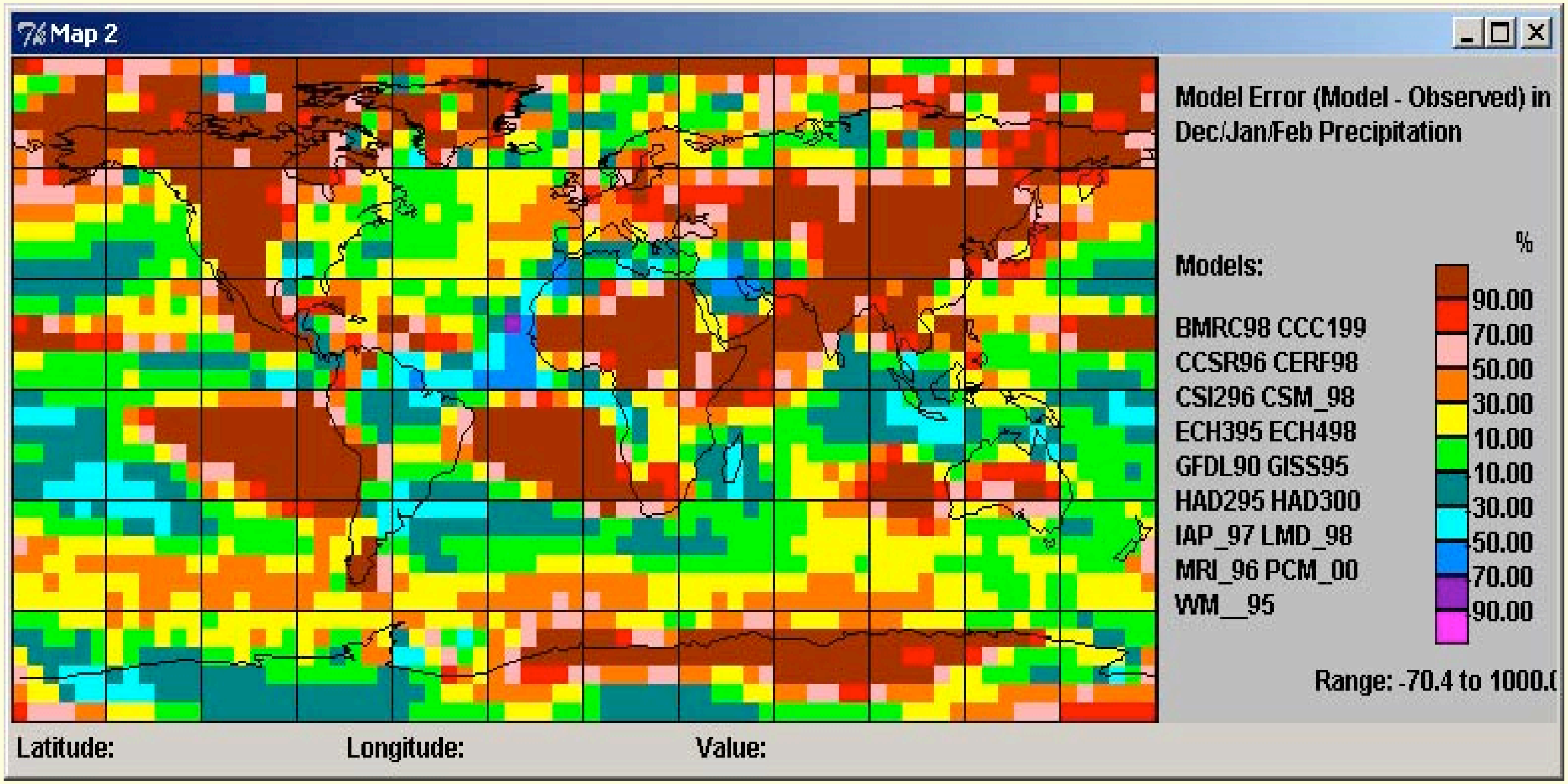


MODEL/OBS PATTERN CORRELATIONS FOR PRECIPITATION

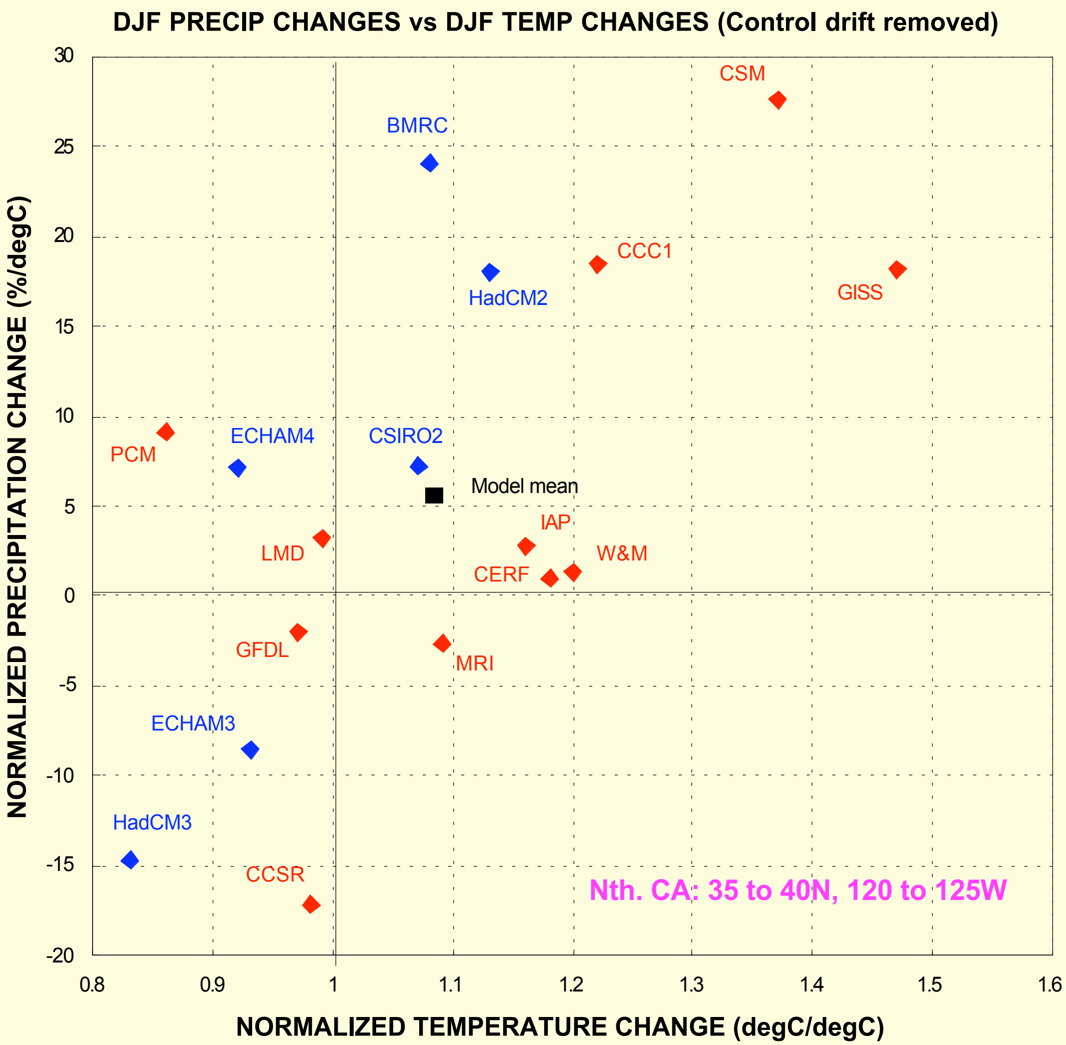
(W-USA = 25–50degN, 105–130degW)

MODEL	ANN: GLOBE	ANN: W-USA	DJF:GLOBE	DJF: W-USA
BMRC	0.721	**0.885**	0.741	**0.869**
CCC1	0.715	0.753	0.735	0.695
CCSR	0.744	0.570	0.769	0.644
CERF	0.802	0.737	0.792	0.785
CSIRO2	**0.864**	**0.801**	**0.850**	0.827
CSM	0.785	0.779	0.786	0.809
ECHAM3	**0.826**	0.775	**0.794**	0.707
ECHAM4	**0.908**	**0.879**	**0.885**	**0.921**
GFDL	0.736	0.536	0.786	0.540
GISS	0.729	0.595	0.708	0.597
HadCM2	**0.886**	**0.815**	**0.892**	**0.837**
HadCM3	**0.870**	**0.852**	**0.878**	0.827
IAP	0.660	0.730	0.698	0.681
LMD	0.686	0.632	0.620	**0.839**
MRI	0.697	0.742	0.697	0.695
PCM	0.670	0.735	0.706	**0.863**
W&M	0.678	0.179	0.691	0.044

Average model error for DJF precipitation : [100(Model – Obs)/Obs]



SPANNING THE RANGE OF POSSIBLE FUTURES
(blue = better models)



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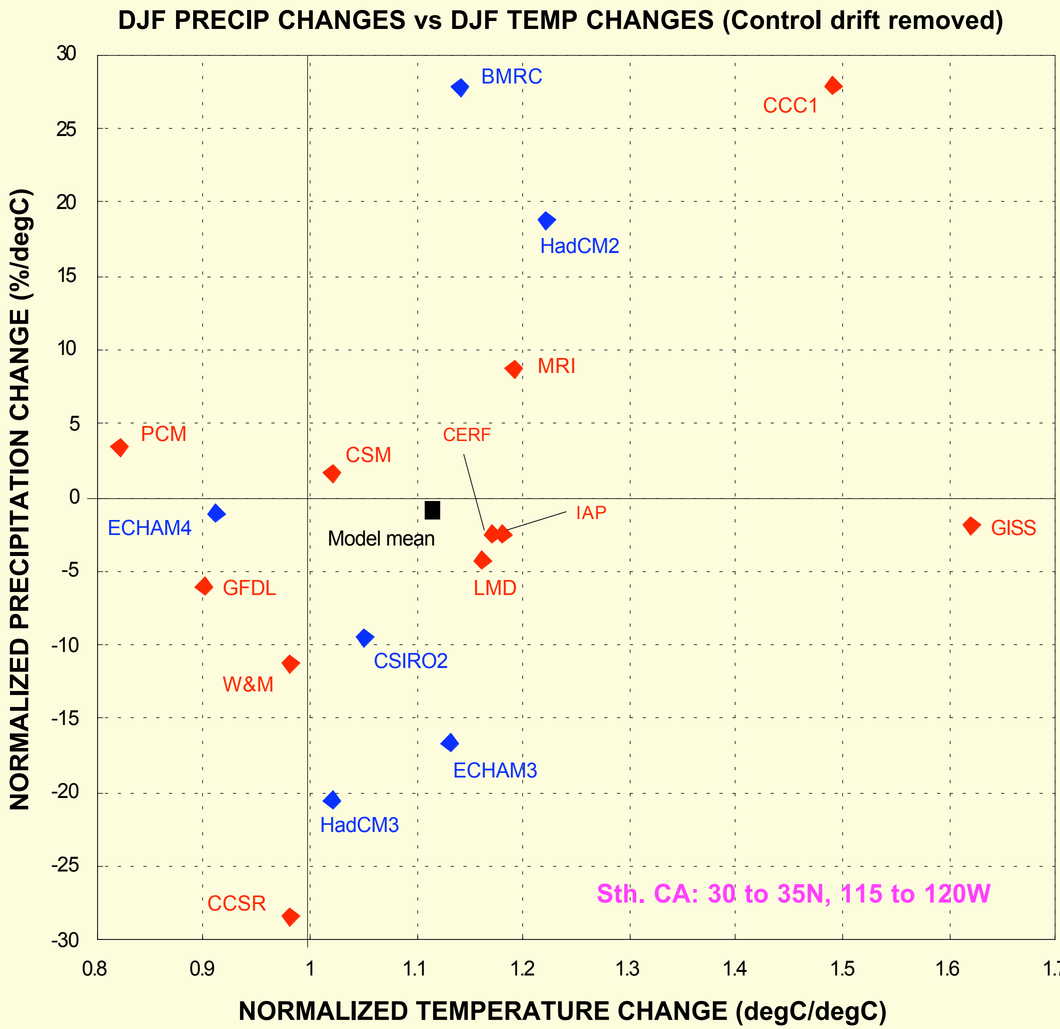


DOWNSCALING RESULTS

(from Phil Duffy)

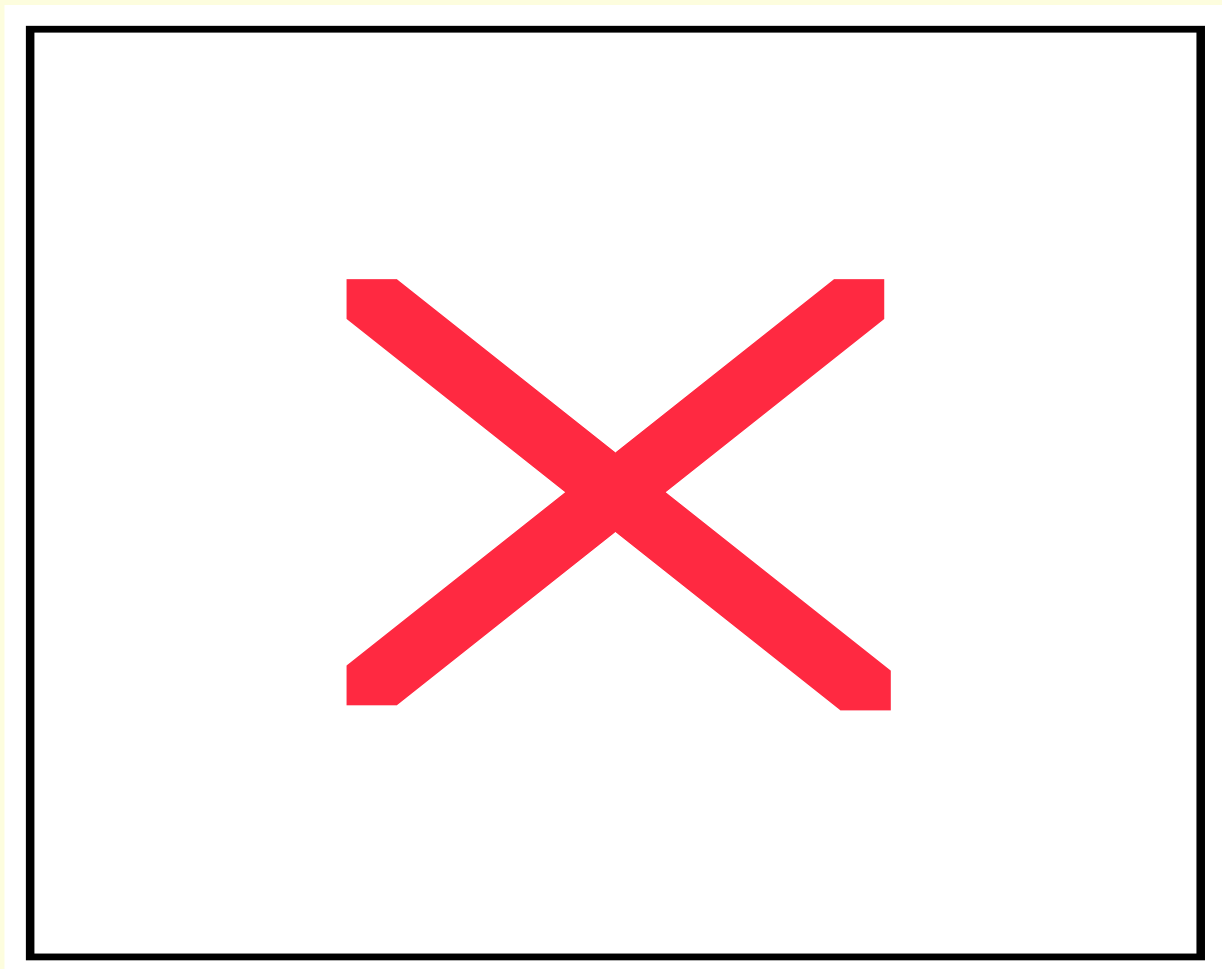
Effects of increasing spatial resolution on ….

precipitation patterns

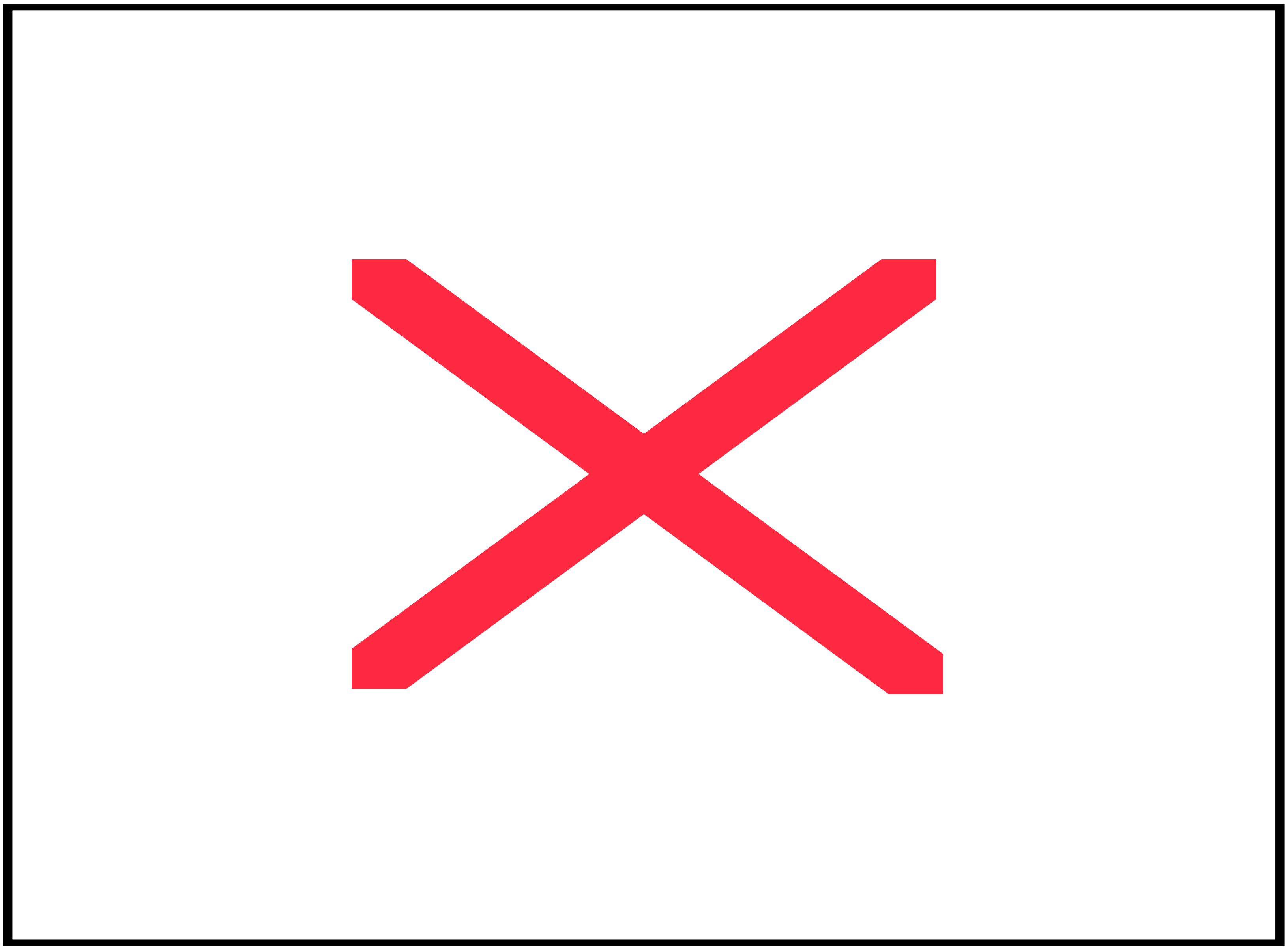
precipitation extremes

snow depth simulations

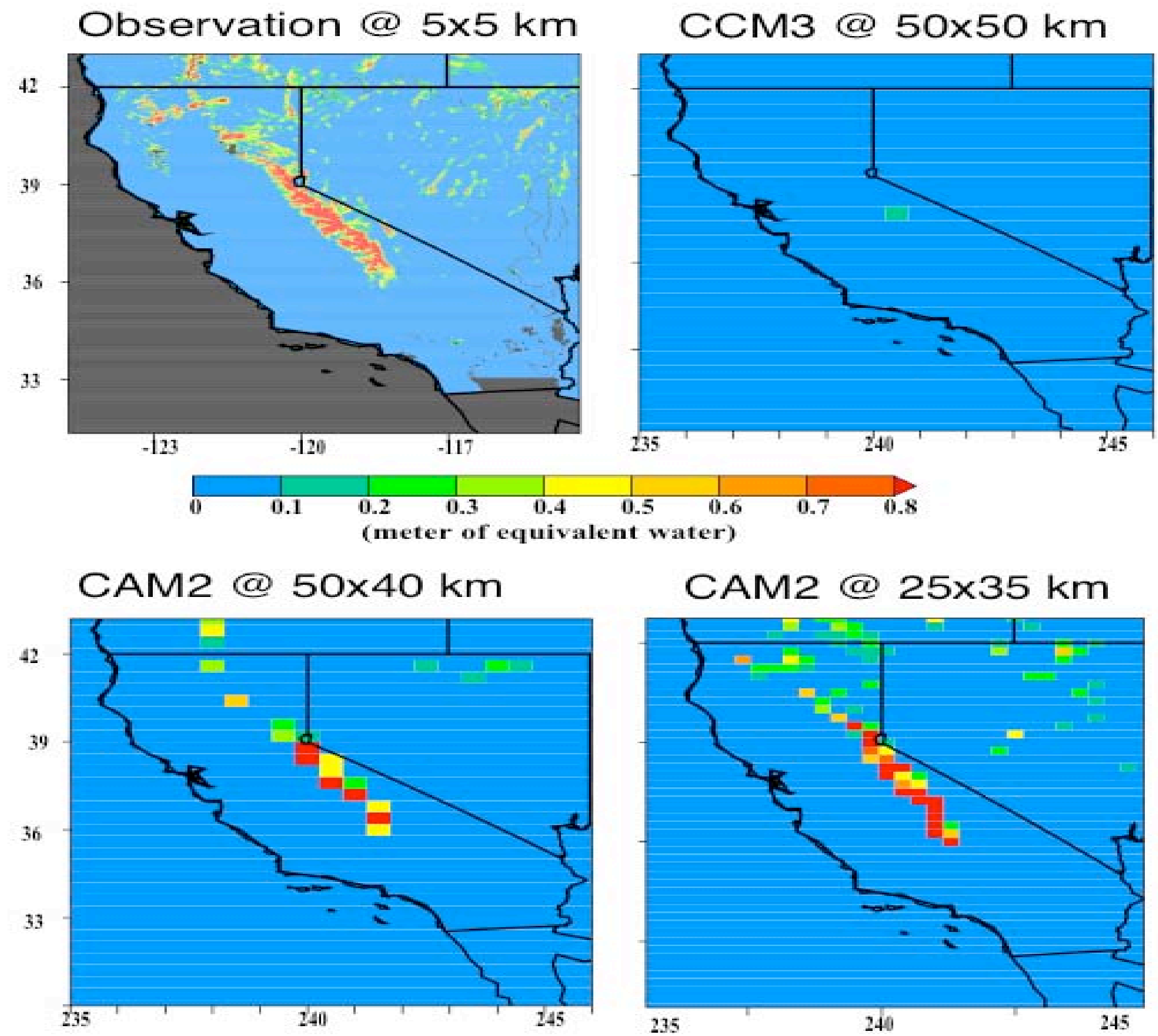
DJF precipitation. Upper and lower-left panels show results from CCM3 at increasingly fine spatial resolutions. Bottom middle panel uses a finite-volume dynamical core, which allows better representation of orography.



99th percentile daily precipitation amounts.



CA SNOW DEPTH IN MARCH



CONCLUSIONS

(1) AOGCMs give a wide range of future climates, all warmer, but with precipitation increases and decreases

(2) For downscaling, choosing a driver AOGCM requires new types of model validation studies (e.g., boundary fluxes; ENSO variability and ENSO/climate linkages)

(3) The following models have credible performance and reasonably span the range of normalized future climates: HadCM2, HadCM3, ECHAM4

(4) The following models have poorer performance and give a wider range of normalized future climates: CSM, PCM, MRI

(5) In addition, uncertainties in future emissions and climate sensitivity should be accounted for – although pattern scaling may circumvent this problem

(6) Although AOGCMs have serious precipitation biases, these appear to be largely related to inadequate spatial resolution and are much reduced by downscaling