Dynamical Downscaling: Assessment of model system dependent retained and added variability for two different regional climate models

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Presentation Outline

Motivation and background

Regional climate model experiments and methods

Results: Assessment of value retained and added by two RCMs

Conclusions and general implications for RCM experimental design

References

Castro, C.L, R.A. Pielke Sr., and G. Leoncini, Dynamical Downscaling: Assessment of value retained and added using the Regional Atmospheric Modeling System (RAMS), *J. Geophys Res*., **110**, D05108, doi:10.1029/2004JD004721, 2005.

Rockel, B., C.L. Castro, R.A. Pielke, Sr., H. von Storch, and G. Leoncini, Dynamical downscaling: Assessment of model system dependent retained and added variability for two different regional climate models . *J. Geophys. Res.,* **113**, D21107, doi:10.1029/2007JD009461, 2008.

Dynamical Downscaling Types

from *Castro et al.* (2005)

	Examples
TYPE 1: remembers real-world conditions through the initial and lateral boundary conditions	**Numerical weather prediction**
TYPE 2: initial conditions in the interior of the model are "forgotten" but the lateral boundary conditions feed real-world data into the regional model	**Retrospective sensitivity or process studies using global reanalyses**
TYPE 3: global model prediction is used to create lateral boundary conditions. The global model prediction includes real-world surface data	**Seasonal climate forecasting**
TYPE 4: Global model run with no prescribed internal forcings. Couplings among the ocean-land-continental ice-atmosphere are all predicted	**Climate change projection**

Definition of RCM:

Initial conditions in the interior of the model are “forgotten” but the lateral boundary conditions feed data into the regional model

Type 2 dynamical downscaling and above

Some a priori expectations for RCM dynamical downscaling (Type 2 and above)

A RCM should:

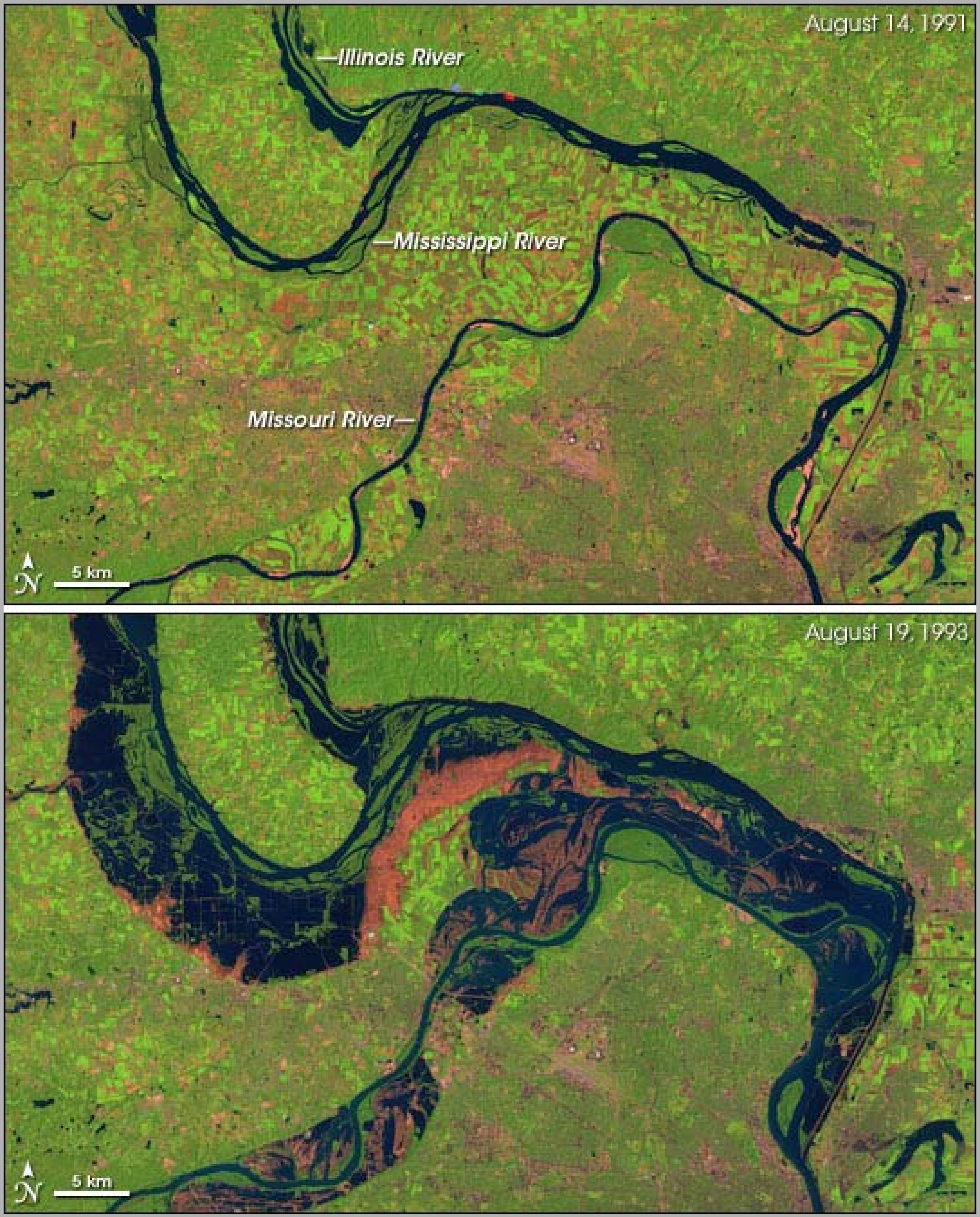
1. Retain or enhance variability of larger-scale features provided by the driving global model (i.e. those on the synoptic scale)

2. Add information on the smaller scale because of increase in grid spacing, finer spatial scale data (e.g. terrain, landscape) and possibly differences in model parameterized physics.

3. Add information that is actually of value, as demonstrated by comparing RCM results with independent metrics (e.g. observations for Type 2)

A good test case for a RCM… The Great Flood of 1993 in central U.S.

Our RCM experiments focused on the month of May…look at results after two weeks of integration.



Regional Climate Model Experiments and Methods

Castro et al. (2005)

Regional Atmospheric Modeling System (RAMS)

NCEP Reanalysis lateral boundary forcing.

Basic model experiments that investigated sensitivity to domain size and grid spacing with standard lateral boundary nudging only.

Follow on experiments that investigated sensitivity to 4DDA internal nudging.

Rockel et al. (2008)

CLM (or CCLM), climate version of German weather service COSMO model.

ECMWF ERA-40 Reanalysis lateral boundary forcing

Repeat basic model experiments of Castro et al. (2005)

Follow on experiments with spectral nudging.

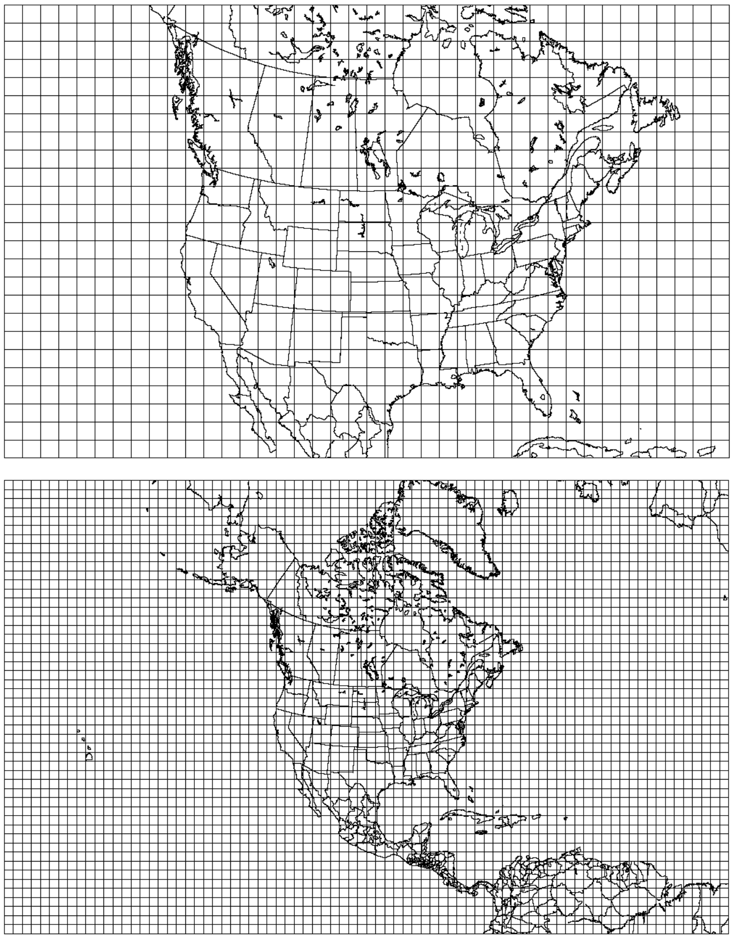


Figure 1. RAMS domains for model sensitivity experiments for Δx = 200 km.

Small Domain

Large Domain

3 nudging points used at lateral boundaries

Degradation of large-scale circulation features

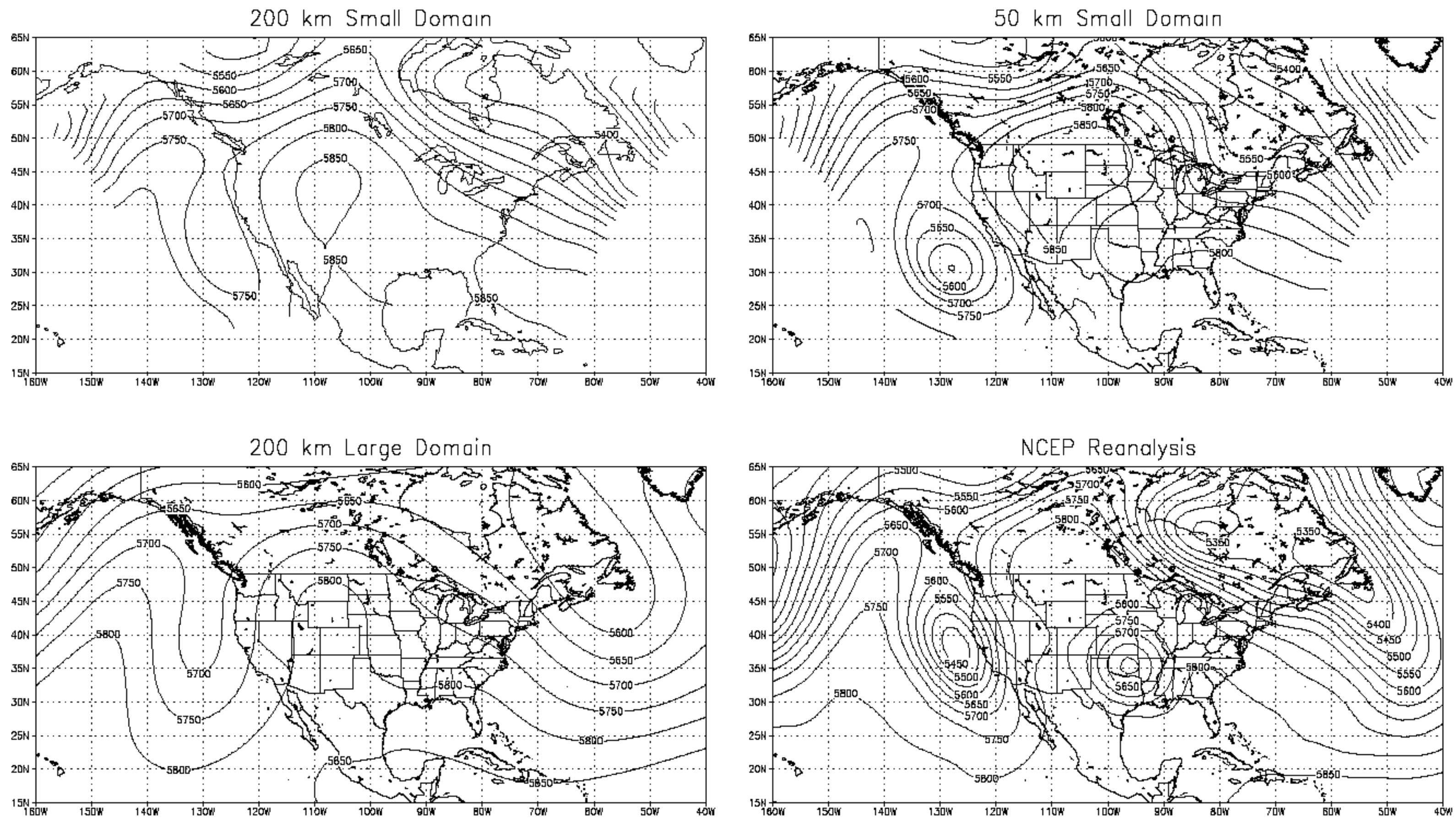
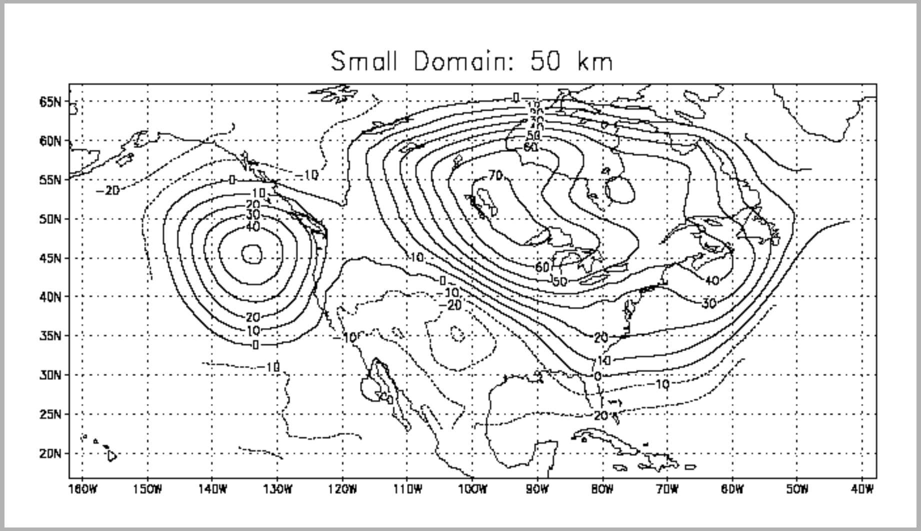


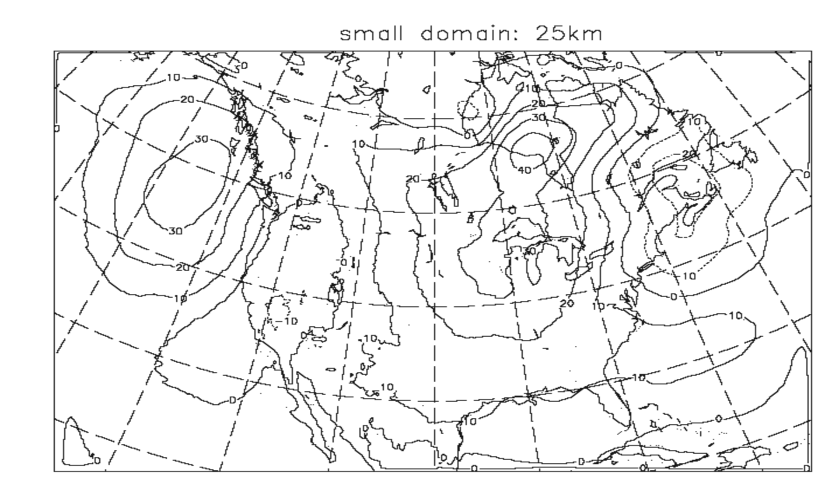
Figure 2. The 500-mbar height (m) on 0Z UTC, 12 May 1993, for indicated model basic experiments and NCEP Reanalysis.

Average 500-mb height difference (m) from driving reanalyses (last 15 days of simulation)

RAMS



CLM



Quantitative analysis of value retained by RCM at large scales

Compute 2-D power spectrum for a given model variable as a function of wavelength (Errico 1985). Do for both RCM and driving reanalysis.

Appropriate variable for large-scale: kinetic energy

Average power spectra of last 15 days of simulation.

Compute the ratio of average of the power spectra of RCM vs. driving reanalysis.

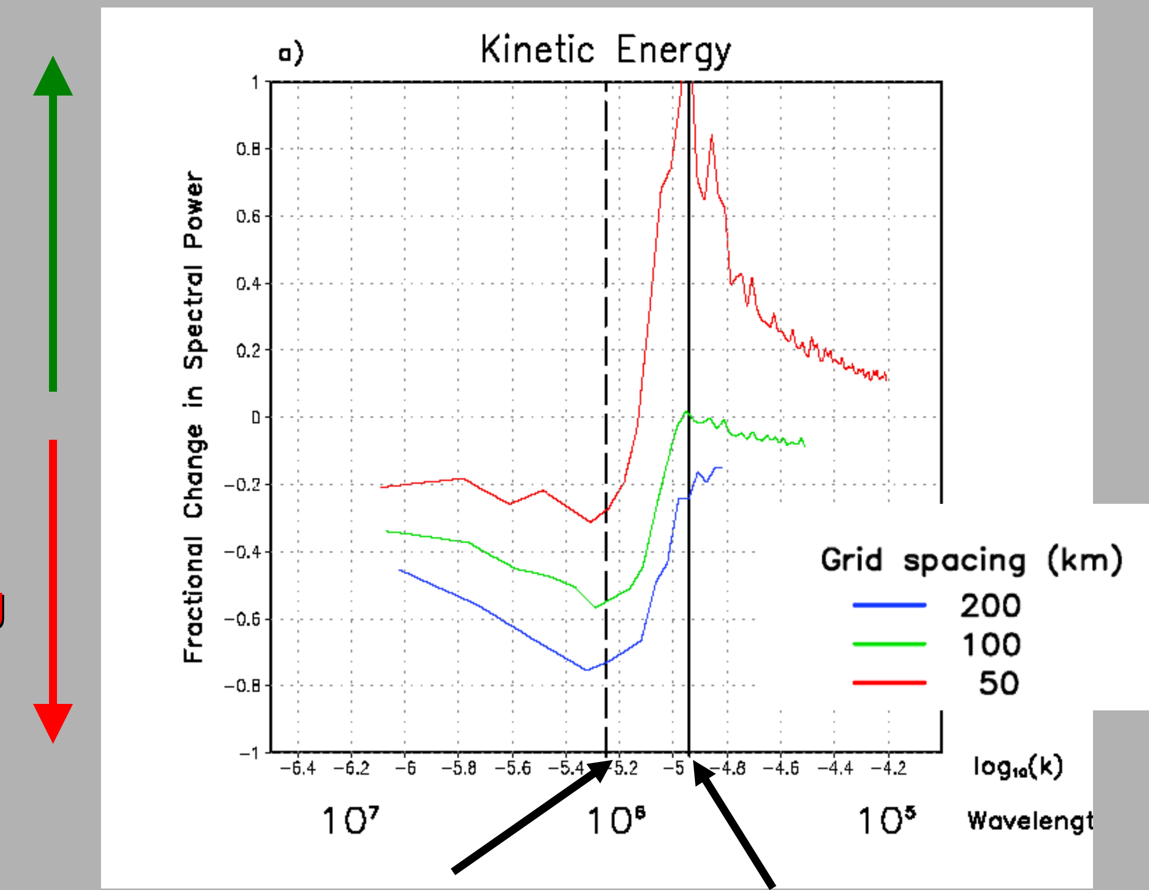
<u>Desired</u>: RCM retains or adds value at the largest scales where the driving GCM or reanalysis has information.

<u>Undesired</u>: RCM loses variability at the largest scales provided by the driving GCM or reanalysis.

Fractional change in spectral power of kinetic energy: RAMS Model

RCM variability MORE than driving reanalysis. VALUE RETAINED OR ADDED

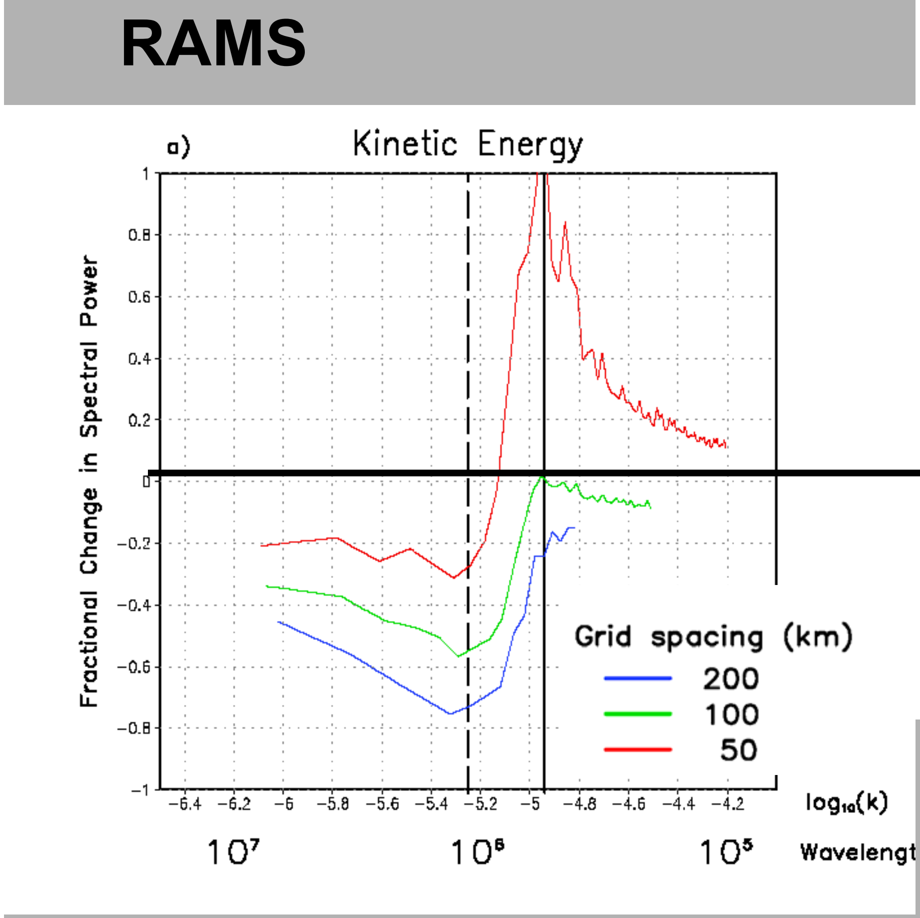
RCM variability LESS than driving reanalysis. VALUE LOST

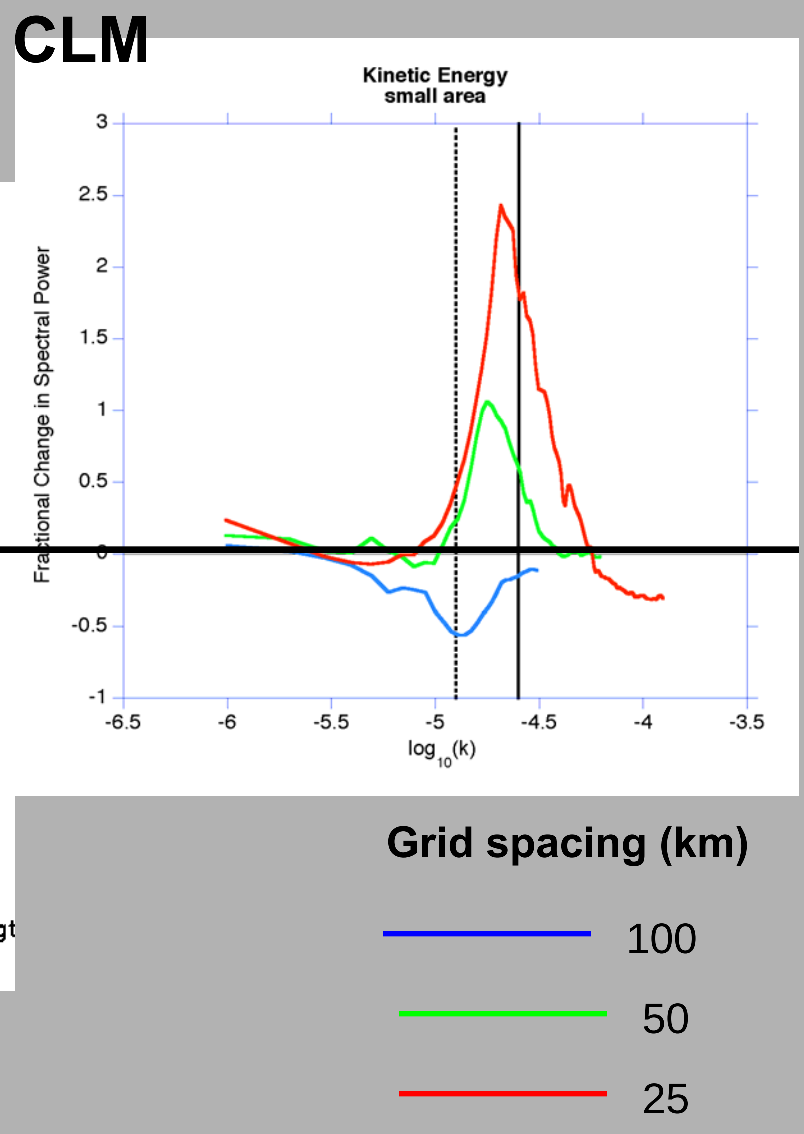


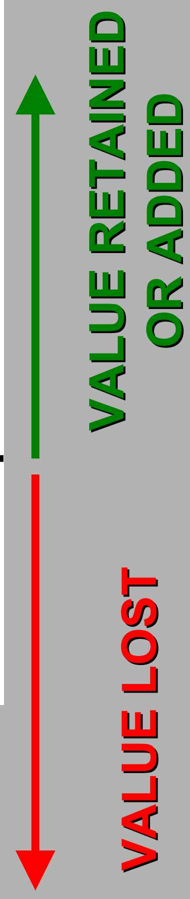
Shortest physically resolved wavelength in reanalysis (4Δx)

Nyquist frequency of reanalysis (2Δx)

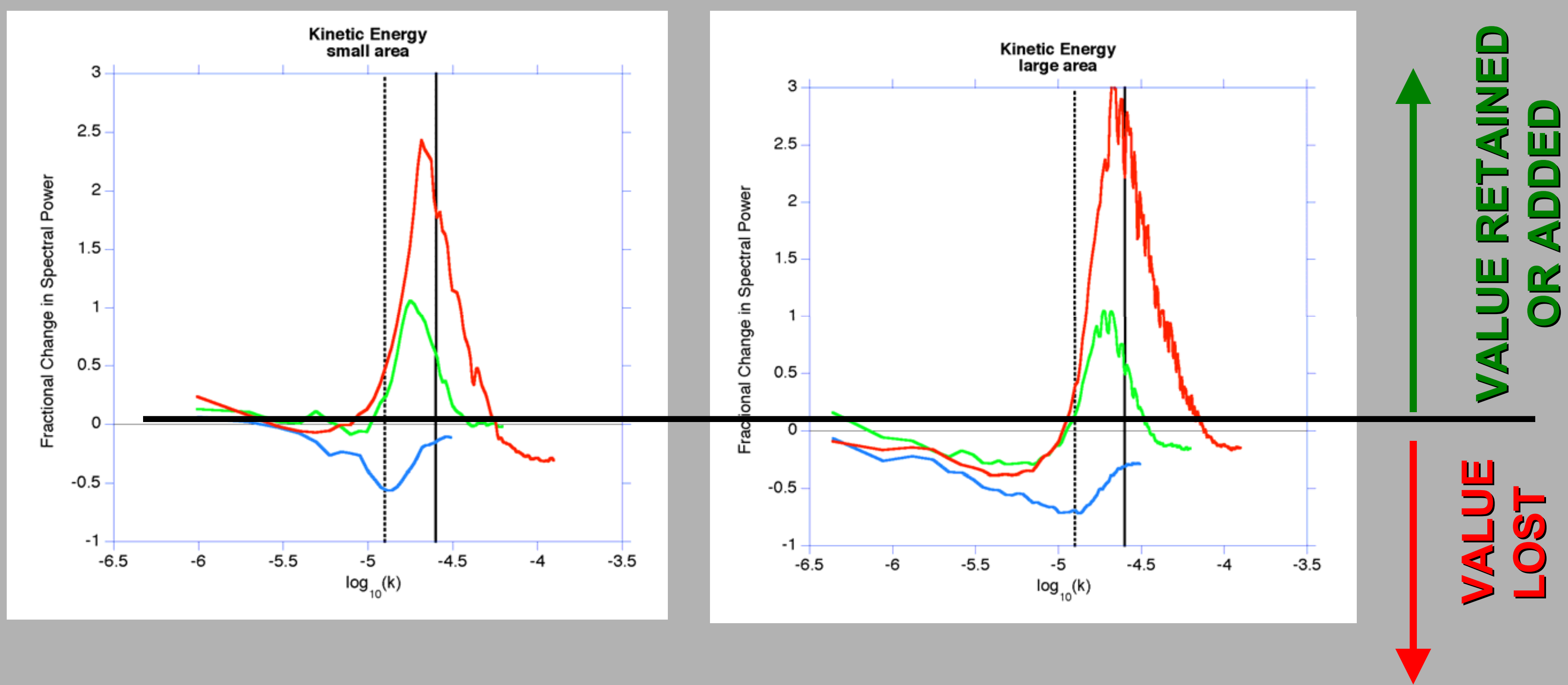
Is the same behavior present in CLM?







CLM: Small vs. Large Domains



Grid spacing (km)

100

50

25

Even greater loss of large-scale variability with a larger domain. RAMS generates identical result.

Quantitative analysis of value added by RCM at small scales

Compute 2-D power spectrum for a given model variable as a function of wavelength (Errico 1985). Do for RCM with and without interior nudging.

Appropriate variable for small-scale: moisture flux convergence

Average power spectra of last 15 days of simulation.

Compute the ratio of average of the power spectra of RCM with interior nudging vs. RCM with no interior nudging.

RAMS: Interior nudging at all wavelengths

CLM: Spectral nudging for largest wavelengths only

<u>Desired</u>: Interior nudging does not reduce variability at the smaller scales where the RCM is adding information.

<u>Undesired</u>: Interior nudging reduces variability at the smaller scales.

CLM Spectral nudging in brief

Applied at scales greater than 4Δx of driving global reanalysis for horizontal winds

Form of nudging coefficients for a given model variable in spectral domain:

$$\sum_{j=-J_a,k=-K_a}^{J_a,K_a} \eta_{j,k} \left(\alpha_{j,k}^{a}(t) - \alpha_{j,k}^{m}(t)\right) e^{ij\lambda/L_\lambda} e^{ik\phi/L_\phi}$$

$\alpha_{j,k}^{a}(t)$ **Fourier expansion coefficients of variable in driving larger-scale model (*a*)**

$\alpha_{j,k}^{m}(t)$ **Fourier expansion coefficients of variable in the regional model (*m*)**

$\eta_{j,k}$ **Nudging coefficient. Larger with increasing height.**

Change in spectral power of KE and MFC with internal nudging in RAMS

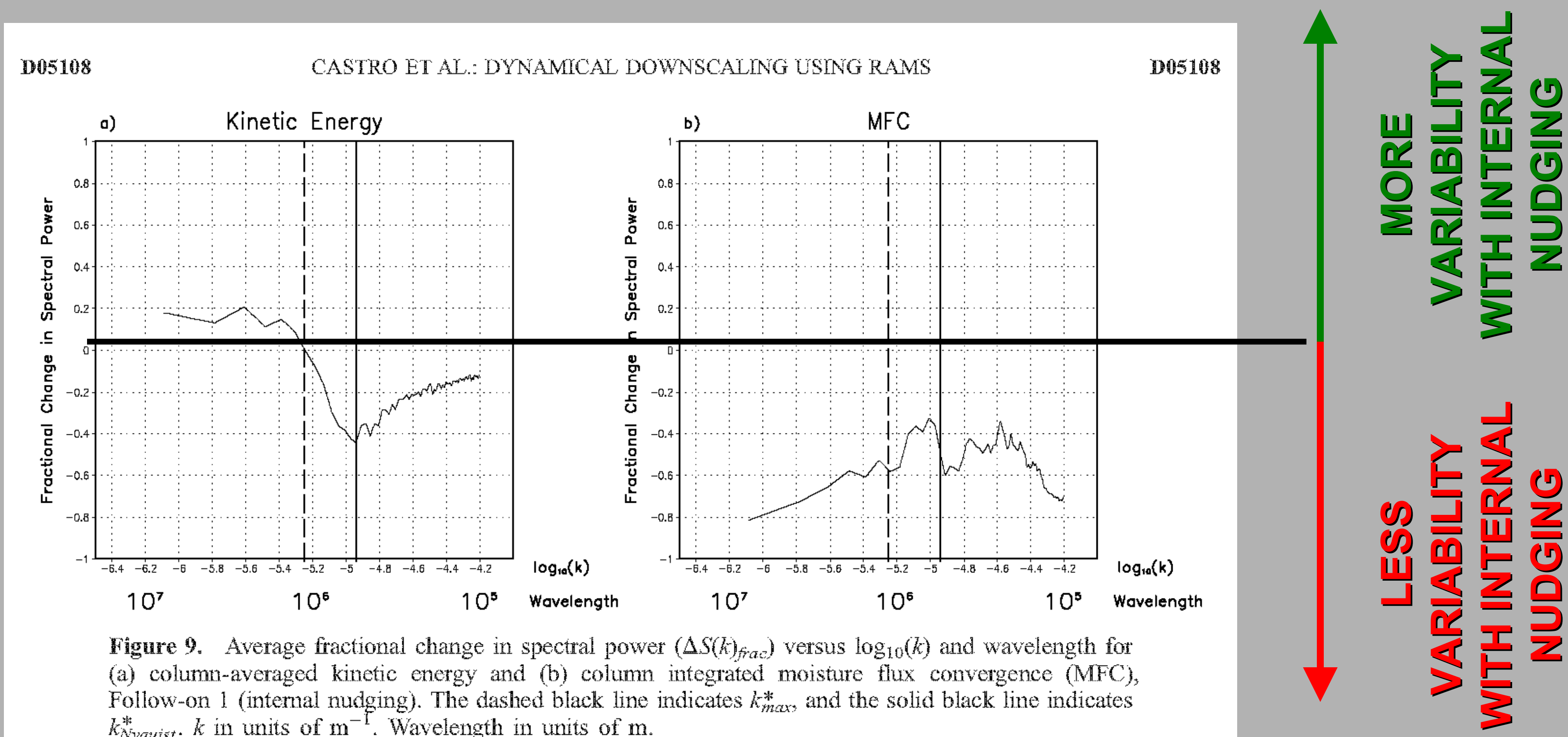
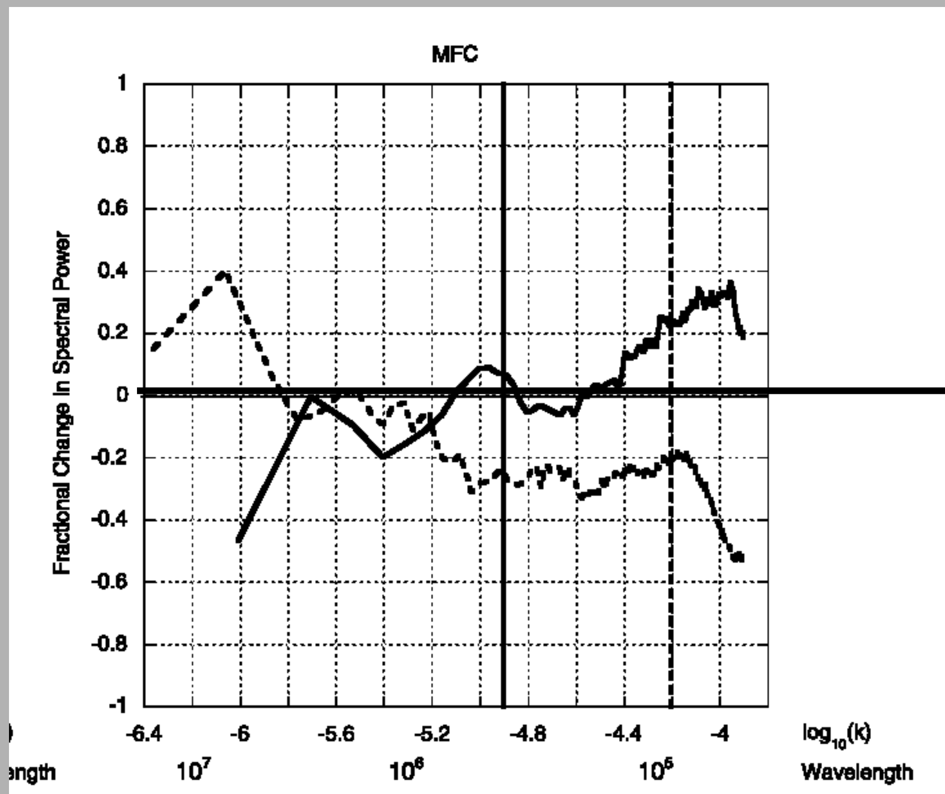


Figure 9. Average fractional change in spectral power ($\Delta S(k)_{frac}$) versus $\log_{10}(k)$ and wavelength for (a) column-averaged kinetic energy and (b) column integrated moisture flux convergence (MFC), Follow-on 1 (internal nudging). The dashed black line indicates k^*_{max}, and the solid black line indicates $k^*_{Nyquist}$. k in units of m^{-1}. Wavelength in units of m.

Tradeoff of internal nudging at all wavelengths: weaken variability at small scales where we want the regional model to add information.

Spectral nudging in CLM preserves the small-scale variability, so it's better!



MORE VARIABILITY WITH INTERNAL NUDGING

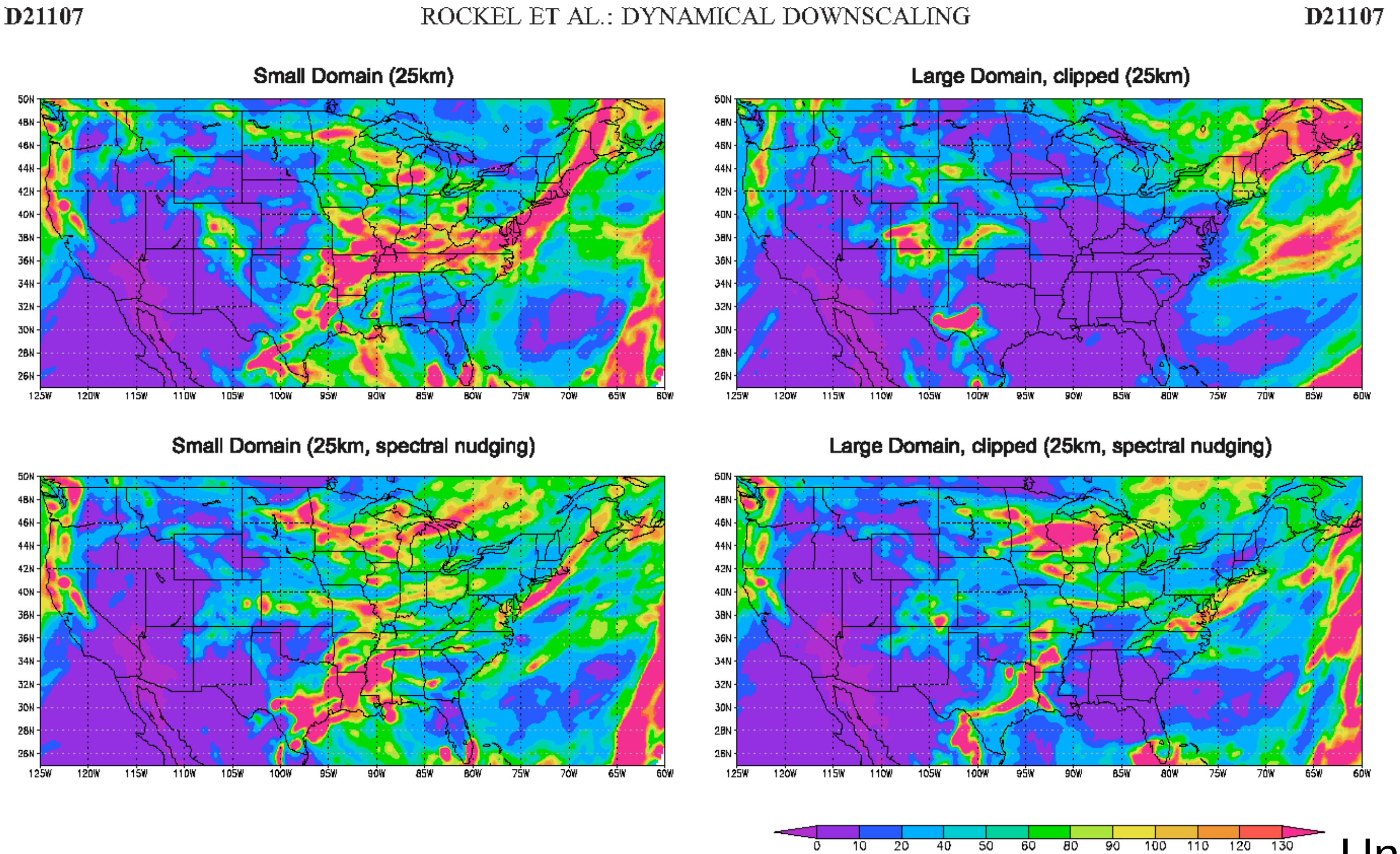
LESS VARIABILITY WITH INTERNAL NUDGING

Small domain

Large domain

$\Delta x = 25\text{km}$

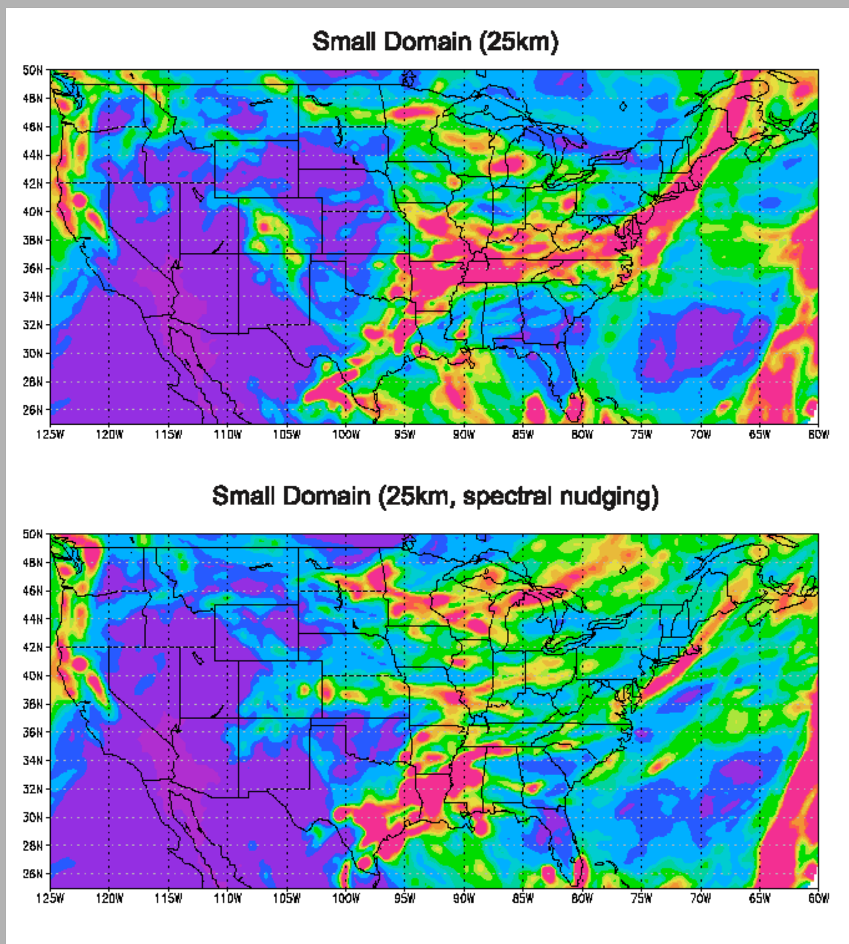
CLM Precipitation for various model configurations

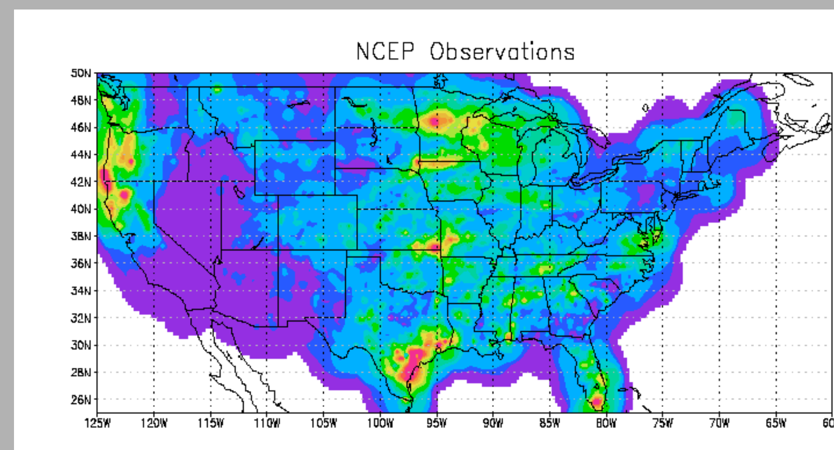


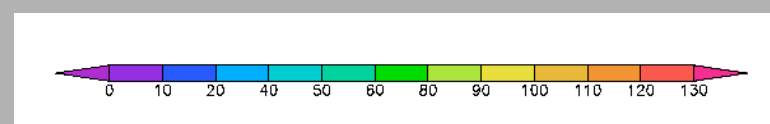
Units: mm

Figure 6. Precipitation results from CLM simulations for the second half of May 1993 without and with spectral nudging in the top and bottom rows, respectively.

CLM Precipitation comparison with observations for small domain







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Conclusions of our RCM studies

•The results for CLM reported in *Rockel et al.* (2008) are similar to those found in the RAMS study by *Castro et al.* (2005) for basic experiments using nudging only in a lateral boundary sponge zone. In both models, there is a loss of large-scale variability with increasing domain size and grid spacing.

•Internal nudging can alleviate loss of large-scale variability in both RCMs.

• Spectral nudging yields less reduction in added variability of the smaller scales than grid nudging and is therefore the preferred approach in RCM dynamic downscaling.

•Results suggest the effect to be largest for physical quantities in the lower troposphere (e.g. moisture flux convergence, rainfall)

General conclusions on utility of RCMs

- The utility of all regional models in downscaling primarily is not to add increased skill to the large-scale in the upper atmosphere, rather the value added is to resolve the smaller-scale features which have a greater dependence on the surface boundary.

- However, the realism of these smaller-scale features needs to be quantified, since they will be altered to the extent that they are influenced by inaccurate downscaling of the larger-scale features through the lateral boundary conditions and interior nudging or lack thereof.

- It should also be assessed if the dynamically downscaled information provides more accuracy than a corresponding statistical downscaling technique.