A New Metric to Quantify the Added Value of Regional Models

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Introduction

Added value by high resolution regional model has been a central interest by regional modelers.
e.g.,

Anthes et al, 1989; de Elía and Laprise, 2003; Castro, 2005; Feser, 2006; Rockel et al, 2008; Prömmel et al, 2009; Winterfeldt and Weisse, 2009

The central problem is how to quantify the "added value"

Measures of added value in the previous works

1. Realistic small scale.

    Subjective visual comparison. ➔Not quantitative. Poor measure.

2. Validation against observations.

    2.1. Fit of model simulations to station observations.

    Display individual station values.

    Display area average of station values.

    2.2. Fit of applied model products to station values

    Stream flow, water usage, energy usage, agricultural yield, etc.

    2.3. Spatial and temporal variability.

    Mostly done for idealized studies.

Limitation of the use of fit of model to observation.

--Error inherent with the model resolution --

Model error can be separated into two errors,

1. Model Error
2. Error inherent with model resolution, which is independent of model error.

These are explained in the next few slides.

Representativeness error (ε_R)

- The model grid point value is considered as a mean of the field represented by a grid point, which is a function of model grid size. Since the value is the most likely estimate at the grid, there is an error associated with it.
- This error may be named the representativeness error (ε_R), as it is commonly called in objective analysis.
- ε_R varies with model resolution as well as with the spatial variability of the field. For example, for near surface fields ε_R will be large over complex terrain and small over smooth land or over ocean. ε_R will be smaller for a smooth field, such as 500 hPa height, but larger for noisier vorticity, divergence and precipitation

Difference independent of model performance but due solely to resolution

$$F^{M}(x_{obs}) = [\, F^{T}(x_{grid}) + \varepsilon_M + \varepsilon_R \,]$$

F(xgrid) : field examined at grid points x_{grid},

ε^M : model error

[ ] : spatial interpolation operator.

Subscript 'obs' : observation at the observation location

Superscript 'T' : truth.

Superscript 'M' : model

The interpolation introduces an additional error ε_I from the interpolation of F^T(xgrid), ε_M and ε_R, leading to

$$F^{M}(x_{obs}) = [\, F^{T}(x_{grid}) \,] + [\varepsilon_M] + [\varepsilon_R] + \varepsilon_I$$

Eventually, we arrive at the following equation.

$$F^{M}(x_{obs})-F^{O}(x_{obs})= [\varepsilon_M] +[\varepsilon_R]+ \varepsilon_I+\varepsilon_{obs}$$

$[\varepsilon_M]$: Model error interpolated to station

$[\varepsilon_R]$: Model representativeness error interpolated to station.

ε_I : Model grid to observation interpolation error

ε_{obs} : Observation error (includes instrument, retrieval, representativeness and interpolation)

Estimation of [ε_R]

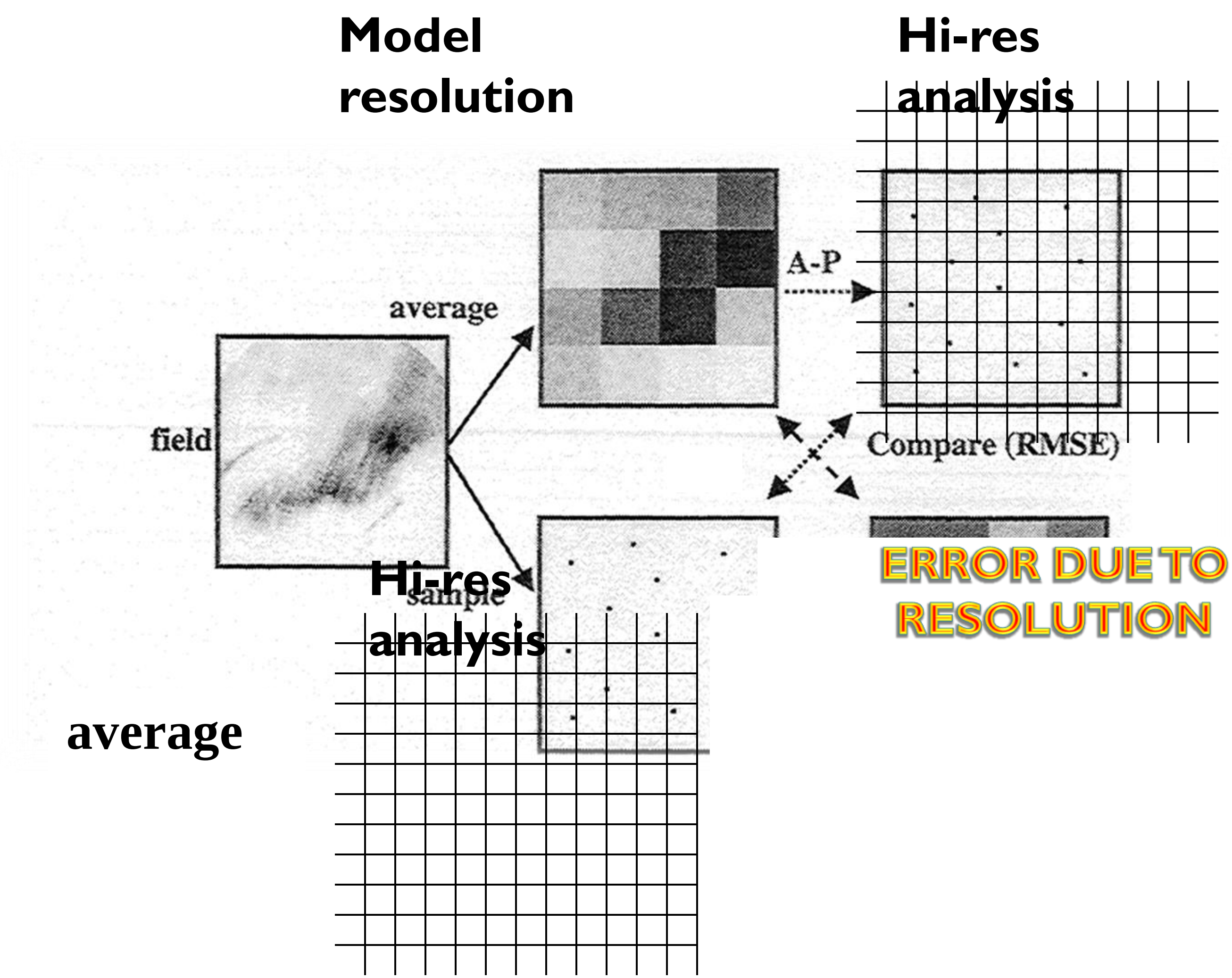
Tustison et al (2001)

Interpolates a field from a fine resolution analysis grid to a lower resolution model grid by area averaging (field A),

Then interpolating back to the analysis grid (field B).

The difference between the two (A-B) provides an estimate of the representativeness error

Estimation of [ε_R]



Representativeness error Example

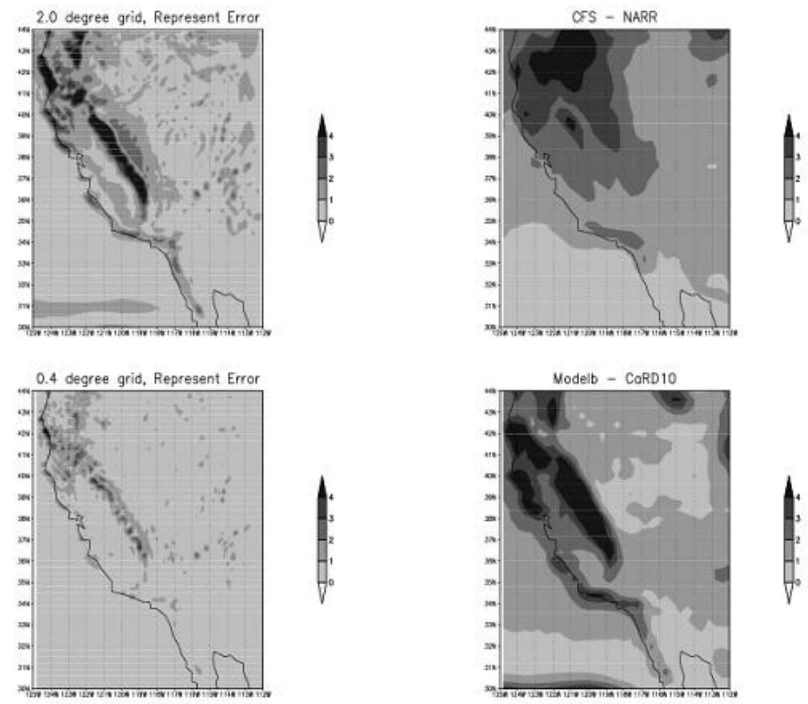


Figure 1. Model grid representativeness error (left panels) equivalent to CFS resolution (upper panel) and Model-b resolution (lower panel) compared with model error (left panels) for CFS (upper panel) and Model-b (lower panel). The variable is seasonally averaged precipitation root mean square error against NARR analysis.

Key points

- The key point of this argument is that when we discuss the added value of the regional model, conventional skill comparisons provide a combination of different types of errors, which makes it difficult to understand the true meaning of the "value added."
- For example, if the ε_M of the regional model is greater than that of the coarse resolution model, but ε_R is smaller due simply to the increased resolution, the fit to observations becomes better. Do we conclude that the regional model added value?
- For the model product users, the answer is probably yes, but for the modelers, the answer will probably be no. For the case of Figure 1, the magnitude of the fit of the simulations to analysis is about the same or slightly worse for Model-b, indicating that the high resolution model error is much larger than that of the coarse resolution CFS model.

Key points

- Recognizing the limitation of the simple fit of model grid point values to observation as noted above, there is an additional weakness in utilizing the improvement in skills, particularly their area average, as a measure of the value added.

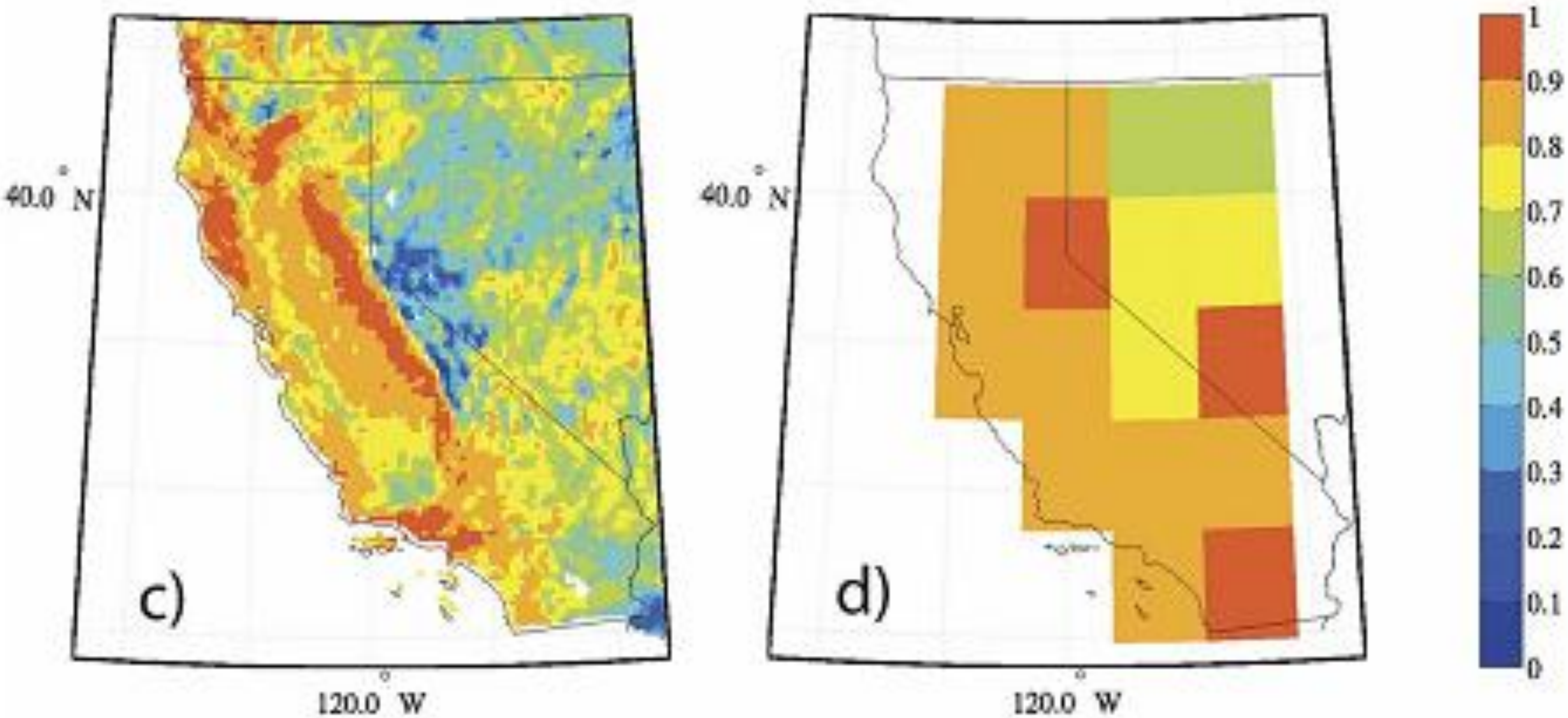


Figure 2. Correlation skill of January mean precipitation for CaRD10 (left) and NCEP/NCAR Reanalysis (right) verified against PRISM gridded observation. Computation is made using 1950-1997 data. Figure taken from Kanamitsu and Kanamaru (2007) Figure 10.

Introduction of new value added index

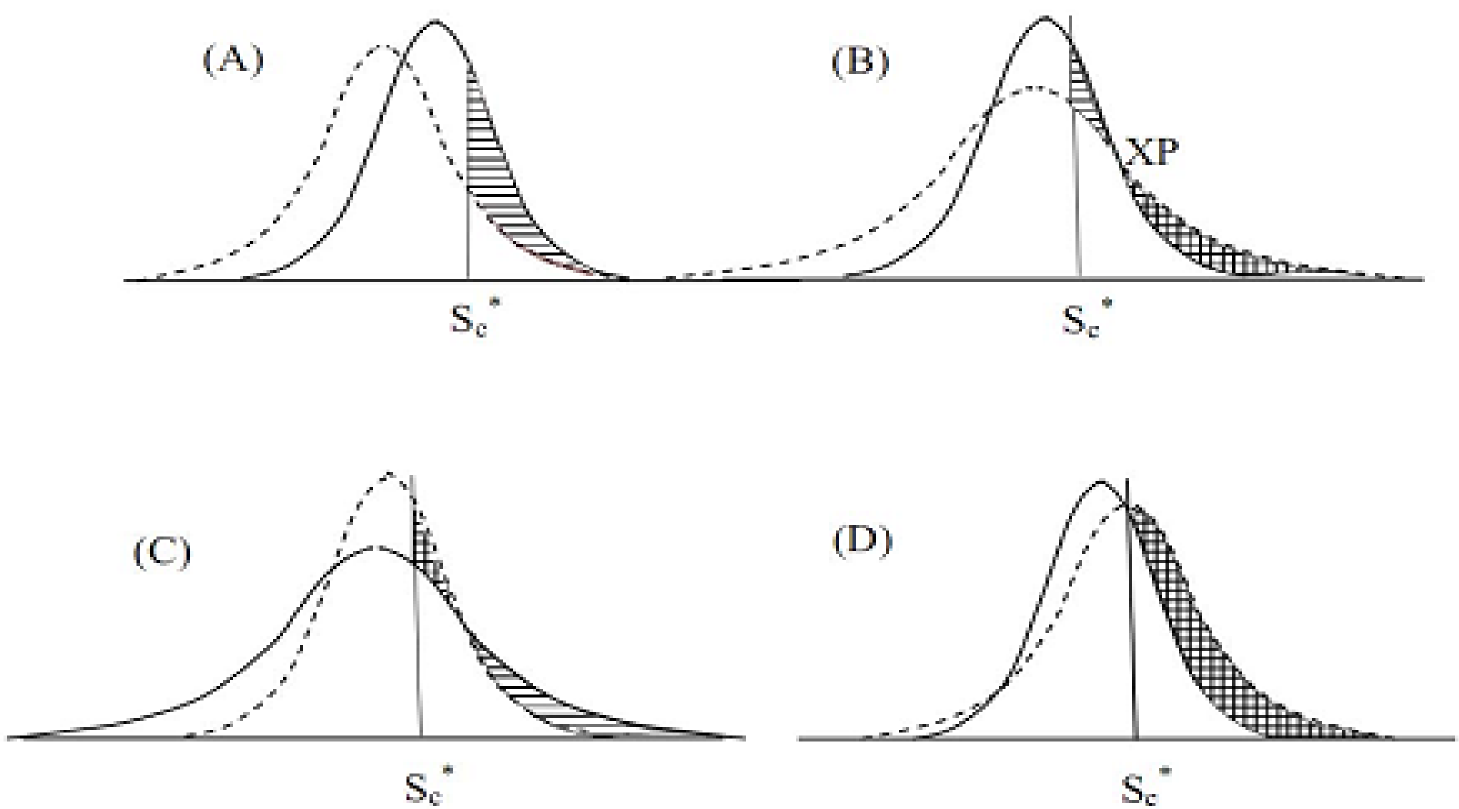


Figure 3. Idealized distribution functions of correlation skill over the model domain for two different models. See text for more detail. The hatched area with horizontal lines indicates where the dashed line model has lower skill, while cross hatched area indicates otherwise.

Some computational detail

How good the distribution of the temporal skill in space fit normal distribution?

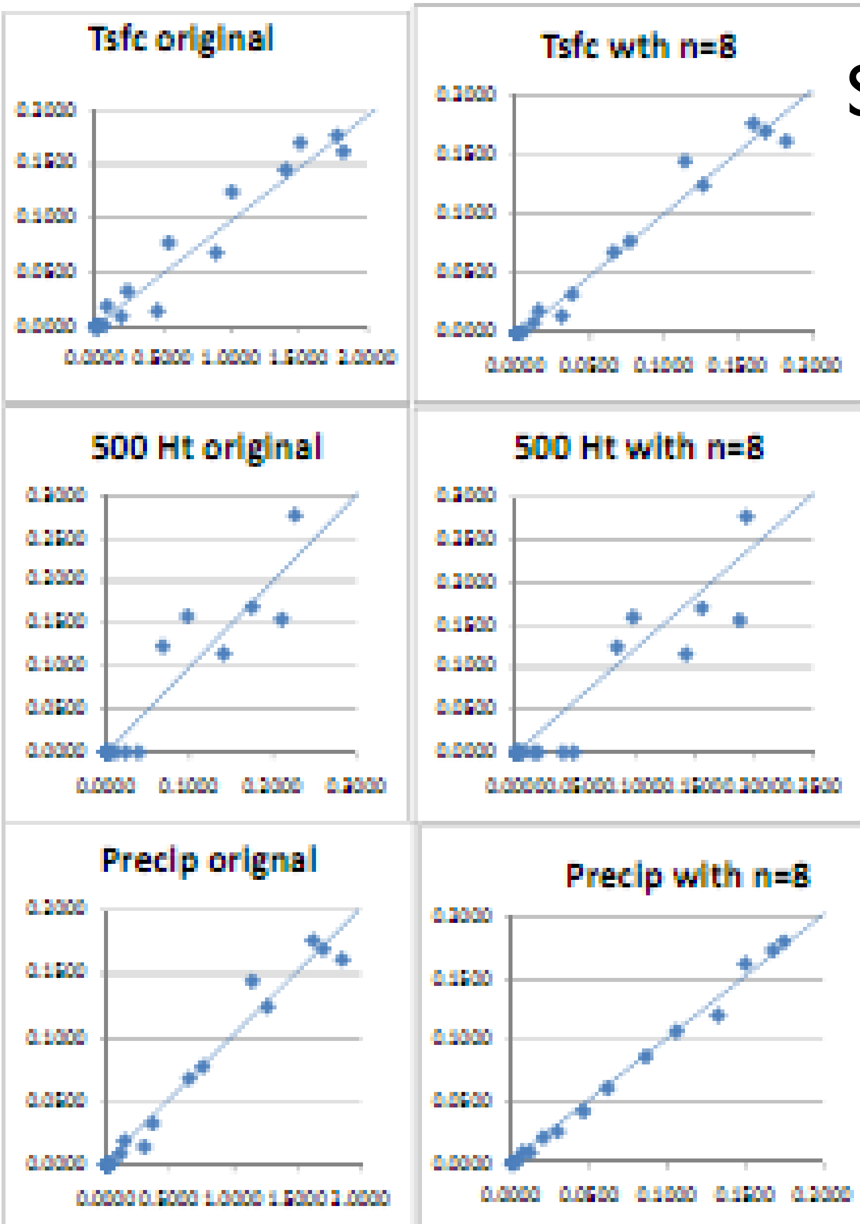


Figure 4. Normal test plot of near surface temperature (top), 500 hPa height (middle) and precipitation (bottom) with no transformation (left) and transformed with n=8 (right).

Fit of skill distribution to normal distribution.

	2m T	Precip.	500 hPa height
No scaling	0.987	0.970	0.963
n=4 scaling	1.090	1.147	1.240
n=8 scaling	0.997	0.997	1.077

(Closer to 1 fits better to normal distribution)

Example of AVI

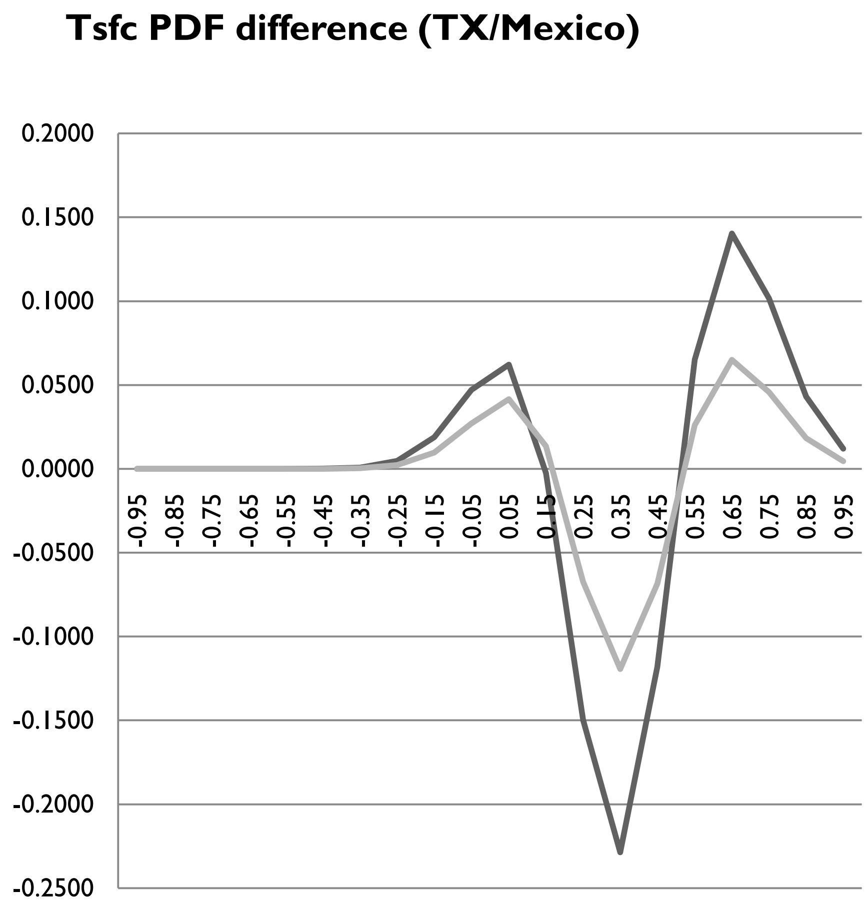


Figure 5. An example of the differences between Model-a and CFS (dark grey line) and Model-b and CFS (light grey line). Vertical axis is the normalized area (or number of grid points) and horizontal axis is skill.

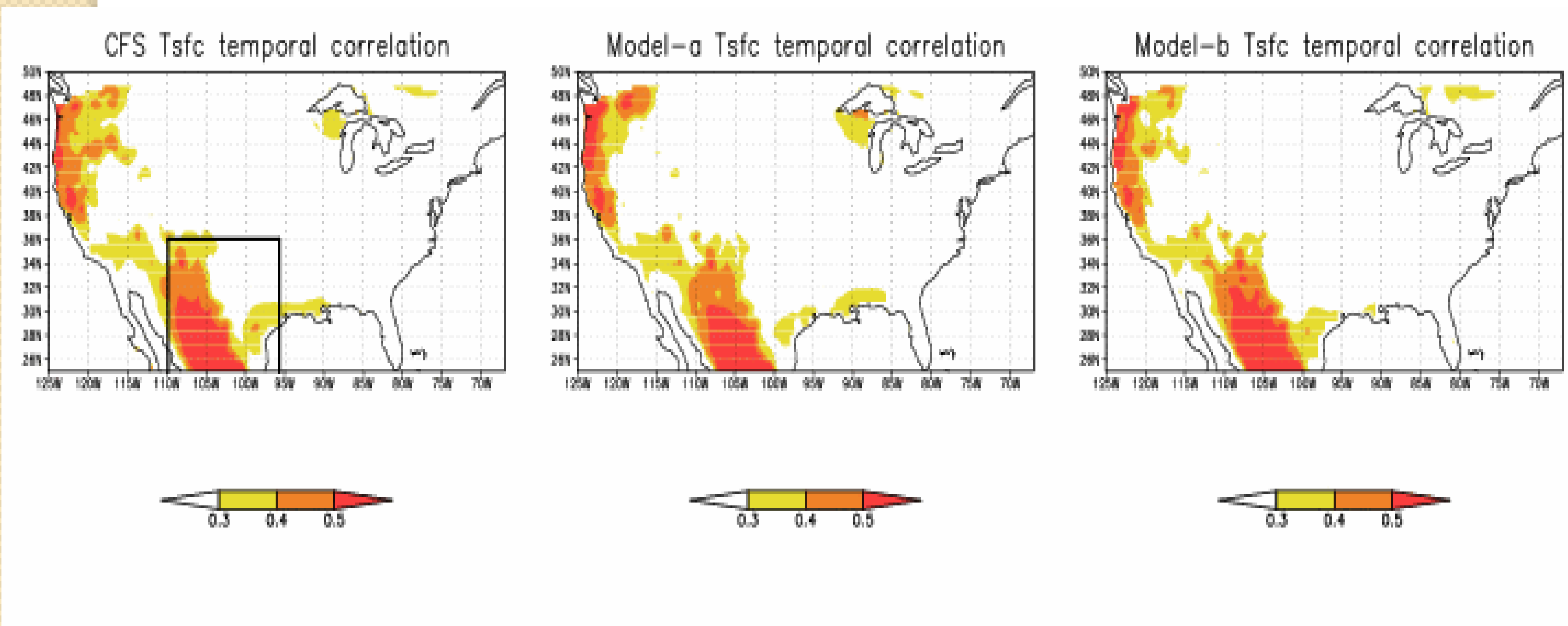


Figure 6. An example of the geographic distribution of near surface temperature skill for CFS (left), Model-a (middle), and Model-b (right).

scaled with x/(1-x^8)							
	Down Scale Mean	CFS Mean	X pt	Diff .3 to X pt	Diff > X pt	AVI	Added value
T2m TX/Mex Model-a	**0.35**	0.34	0.41	-0.03	0.03	0.03x	yes
T2m TX/Mex Model-b	**0.35**	0.34	0.49	-0.02	0.04	0.04x	yes
T2m US Model-a	**0.16**	0.14	No X	0.00	0.02	0.02	yes
T2m US Model-b	0.13	**0.14**	0.47	-0.01	0.01	0.01x	yes
Precip Tx/Mex Model-a	0.22	**0.23**	No X	0.00	-0.04	-0.04	no
Precip Tx/Mex Model-b	**0.24**	0.23	No X	0.02	0.02	0.02	yes
Precip US Model-a	0.18	**0.23**	No X	0.00	-0.07	-0.07	no
Precip US Model-b	**0.24**	0.23	No X	0.00	0.03	0.03	yes
Usfc TX/Mex Model-a	0.24	**0.27**	0.55	-0.06	0.02	0.02x	yes
Usfc TX/Mex Model-b	0.25	**0.27**	0.50	-0.07	0.06	0.06x	yes
Usfc US MODEL-a	0.32	**0.33**	0.33	0.00	-0.03	-0.03x	no
Usfc US Model-b	0.33	0.33	0.56	-0.03	0.02	0.02x	yes
Vsfc TX/Mex Model-a	0.07	**0.13**	No X	0.00	-0.07	-0.07	no
Vsfc TX/Mex Model-b	**0.22**	0.13	No X	0.00	0.16	0.16	yes
Vsfc US Model-a	0.10	**0.12**	No X	0.00	-0.05	-0.05	no
Vsfc US Model-b	**0.13**	0.12	No X	0.00	0.02	0.02	yes
500 ht Tx/Mex Model-a	0.63	**0.64**	0.65	0.04	-0.04	-0.04x	no
500 ht Tx/Mex Model-b	**0.65**	0.64	0.63	-0.08	0.08	0.08x	yes
500 ht US Model-a	0.38	0.38	0.51	-0.01	0.02	0.02x	yes
500 ht US Model-b	0.38	0.38	0.46	-0.01	0.02	0.02x	yes

Conclusions

1. A new metric to quantitatively measure the value added (AVI) by regional models was introduced. The proposed method focuses on the probability distribution of the geographical distribution of temporal correlation in the regional model domain or its sub-domain. AVI measures characteristic nature of the geographical distribution of skill.
2. This definition of the AVI was applied to several cases, and shown to satisfactorily characterize the advantage of regional model performance for different variables over different areas.

Future works

1. Apply the AVI to a large number of cases for many different models. ➔ MRED
2. Apply to a validation of short range forecasts.
3. Use normalized RMS to calculate AVI.
4. Extended the AVI to a time series of pattern correlations. In this case, the AVI indicates the high resolution model's ability to represent high time frequency phenomena, or occasional high skill cases.