Categorical predictability of regionalized surface temperature and precipitation over the southeast United States

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Coarsely resolved surface temperature and precipitation which are seasonally integrated using the FSU/COAPS GSM (Florida State University/Center for Ocean-Atmospheric Prediction Studies Global Spectral Model, ~1.8° lon.-lat. (T63)) for the period of 1994 to 2002 (March through September each year) are downscaled to local spatial scale of ~20 km for the southeast United States (Florida, Georgia, and Alabama) by applying both dynamical and statistical methods. This study is performed since 1) the individual local areas over the southeast United States frequently face extremely high temperature and the heavy rainfall with severe storms during summer, resulting in the devastating property damage and injuries. An accurate seasonal forecast with higher spatial resolution is essential to mitigate damage in advance. 2) This region is also noted for some of the largest areas of agricultural farms in the nation. Various kinds of crops and fruits (e.g., peach, tomato, corn, tangerine, peanut, citrus, and strawberry) are raised in these regions. Farmers and agricultural researchers need accurate climate forecasting to adapt management, increase profits, and reduce production risks.

Dynamical downscaling is conducted by running the FSU/COAPS Nested Regional Spectral Model (NRSM), which is nested into the domain of the FSU/COAPS GSM (GSM) (Shin et al. 2006; Cocke et al. 2007). A statistical downscaling is newly developed in this study. The rationale for this approach is that clearer separation of prominent local climate signals (e.g., seasonal cycle, dominant intraseasonal or interannual oscillations) in the observations and the GSM over the training period can facilitate the identification of the statistical relationship associated with climate variability between two datasets, which eventually leads to better prediction of local climate scenario from the large-scale simulations. The techniques primarily applied for statistical downscaling are Cyclostationary EOF (CSEOF) [*Kim and North*, 1997], multiple regressions, stochastic time series generation, and the cross-validation. Overall downscaling procedures are illustrated by the schematic diagram in Fig. 1.

Downscaled data are compared with the FSU/COAPS GSM fields and observations. Downscaled seasonal anomalies reasonably produce the local surface temperature and precipitation scenario from the coarsely resolved large-scale simulations. A series of evaluations including correlations, frequency of extreme events, and categorical predictability demonstrate the reliability of these downscaling models. As shown in Fig. 2 and 3 as examples, categorical predictability for seasonal maximum temperature anomaly (T_{max}) and rainy/dry periods reveals the correctness in percentage prevailing from 60 to 80 (T_{max}) and, from 50 to 70 (precipitation) by both downscaling methods, supporting that our downscalings yield the predictability perceptibly greater than random chance. The skill of this local forecast is comparable to or greater than predictability of large-scale NCEP climate seasonal forecasts [*Saha et al*., 2006]. Much lower incorrectness in percentage shown on the second and third column of figures, and the Heidke skill scores on the fourth column demonstrate the reliable skill of these downscaling approaches. Although there still remains a room for the improvement in predictive skill, these downscaled model results are reliable and can be used in many application models (e.g., crop model).

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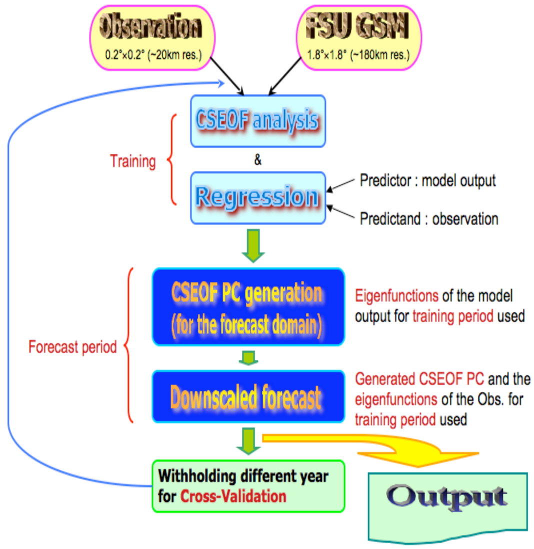

Figure 1. Schematic diagram of statistical downscaling procedure in the present study. Downscaling has been conducted using Cyclostationary EOF, multiple regression, and the time series generation techniques. Downscaled data are produced over 9 years (1994-2002) by repeatedly withholding a particular year and placing it on the prediction period under the cross-validation framwork.

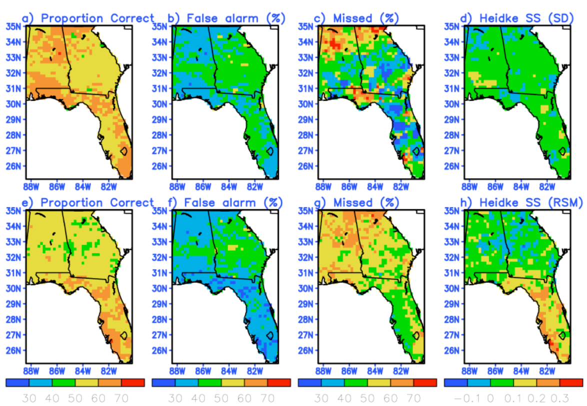

Figure 3. Same as Fig. 2 but for rainfall periods. The 5-day interval during which precipitation amount is greater than 5mm is classified into wet period otherwise the dry period (see table right).

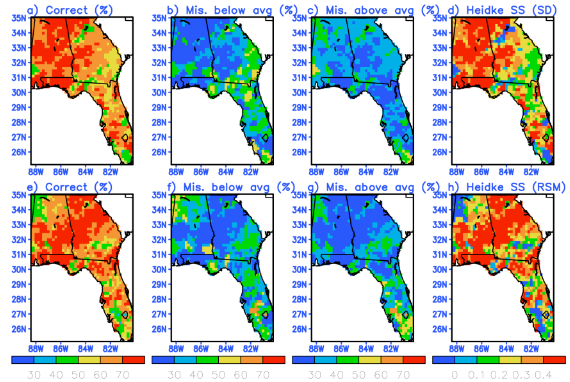

Figure 2. Categorical predictability in percentage (the left three columns) and Heidke Skill Score (right column) for the downscaled seasonal T_{max} anomaly. Two classes from categorization are 1) above climatological T_{max} and 2) below climatological T_{max}. Top panel depicts the result from the statistical downscaling whereas bottom panel the dynamical downscaling (the NRSM). The first three columns from the left illustrate the percentage of 1) correct prediction (the sign of downscaled anomaly & observed anomaly is same), 2) $\frac{P_{ab}}{P_{aa}+P_{ab}} \times 100$ (see the schematic probability table below), and 3) $\frac{P_{ba}}{P_{ba}+P_{bb}} \times 100$ (see table below).

Verifying analysis		Downscaled Forecast above average	Downscaled Forecast below average	
Obs.	Above	P_{aa}	P_{ba}	P_a^P
	Below	P_{ab}	P_{bb}	P_b^P
		P_a^F	P_b^F	1

Verifying analysis		Downscaled Forecast wet period	Downscaled Forecast dry period	
Obs.	wet period	P_{aa}	P_{ba}	P_a^P
	dry period	P_{ab}	P_{bb}	P_b^P
		P_a^F	P_b^F	1

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