7.14 MODEL UNCERTAINTIES CORRELATED WITH SPATIAL VARIABILITY OF PROGNOSTIC VARIABLES

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Abstract: The Coordinated Enhanced Observing Period (CEOP) project provides an integrated, globally covered dataset. The dataset obtained in CEOP buildup phase 1 includes in-situ data at 16 reference sites, model outputs at two numerical weather prediction centers as well as satellite products that cover the period from July to September, 2001. Based on this dataset at the reference sites, we indicate that gaps between prediction and observation are less for some variables (air temperature, humidity, and net radiation) than for other variables (shortwave radiation, and longwave radiation, sensible heat, latent heat). These gaps are not only caused by observing errors and modeling errors, but also by the footprint mismatching. Through the comparison, we suggest that downward shortwave radiation is generally overestimated, and downward longwave radiation is underestimated. However, the differences between observations and model output cannot be simply deemed as model errors in most cases. Instead, their differences may be related to the representativeness of in situ observations. Model intercomparisons suggest that the representative scales may be correlated with model uncertainties.

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1. INTRODUCTION

To achieve a more accurate determination of the water cycle in association with climate variability and change, as well as baseline data on the impacts of this variability on water resources, the Coordinated Enhanced Observing Period (CEOP) was launched on July 1, 2001. CEOP is seeking to achieve a database of common measurements from both in situ and satellite remote sensing measurements, as well as matching model output that includes Model Output Location Time Series (MOLTS) data along with four-dimensional data analyses (4DDA; including global and regional reanalysis) for each specified period (Koike, 2002; Koike, 2004). In this context, a number of carefully selected reference stations are linked closely with the existing network of observing sites involved in the GEWEX Continental Scale Experiments (CSE), which are distributed around the world (Fig. 1). CEOP has identified two scientific objectives, i.e., monsoon system studies, and water and energy simulation and prediction (Lau and Yasunari, 2002; Road and Marengo, 2002). CEOP is being developed and implemented within GEWEX of the World Climate Research Programme, and has also been endorsed by the Integrated Global Observing Strategy Partnership (IGOS-P) as the first element of the IGOS Water Cycle Theme (Bosilovich and Lawford, 2002).

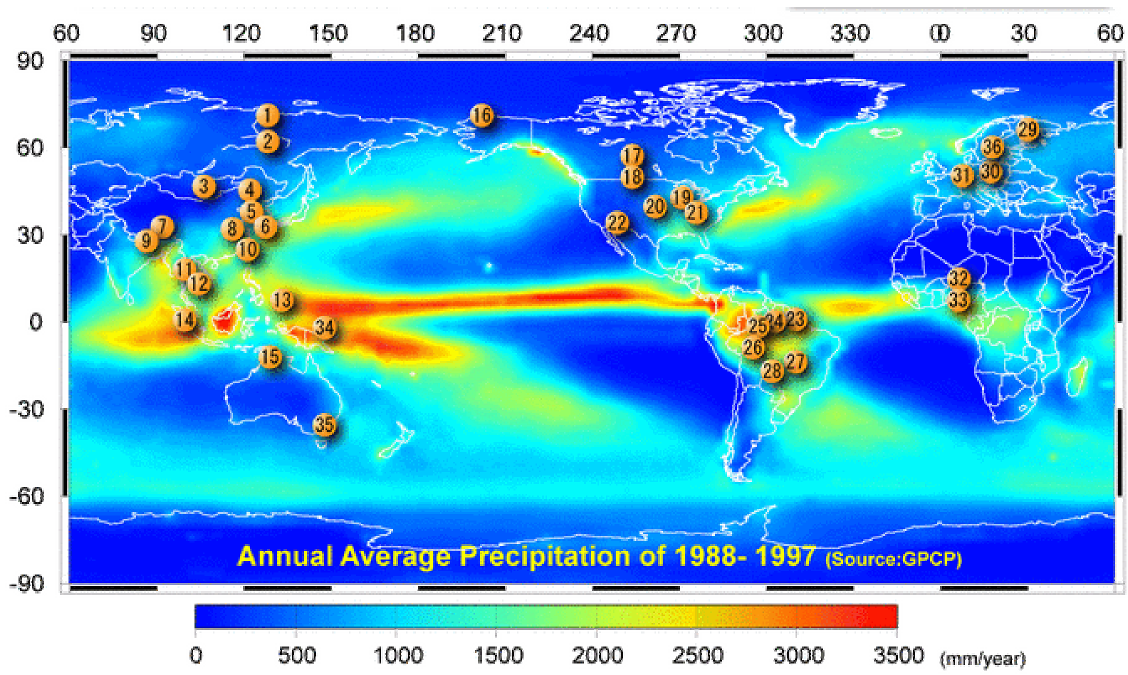


Figure 1 CEOP reference sites selected from GEWEX CSE sites. The attributes of each site are accessible via http://www.joss.ucar.edu/ghp/ceopdm/ref_site.html.

CEOP comprises a buildup phase from July 1 to September 31, 2001, and two annual cycle periods from October, 2002 to September, 2004. The dataset for the buildup phase (CEOP EOP1, 92 days) has documented in-situ data at 16 CSE sites, two hourly MOLTS products, respectively, from NASA Goddard Earth Observing system (GEOS3) and Global Land Data Assimilation System (GLDAS), and satellite products. These CSE sites are indicated in Fig.1 with number 3 (Mongolia), 9 (Himalayas), 10 (South China sea), 16 (North Slope of Alaska or NSA), 17 (Berms-spruce), 18 (Fort Peck or Ftpeck), 19 (Bondville), 20 (Southern Great Plains or SGP), 23 (Caxiuana), 25 (Manaus), 26 (Rondonia), 27 (Brasilia), 28 (Pantanal), 30 (Lindenberg), 31 (Cabauw), and 34 (Tropical Western Pacific-Manus or TWP-Manus). Site attributes are described in http://www.joss.ucar.edu/ghp/ceopdm/ref_site.html. Based on CEOP EOP 1 data, this study investigates model predictability by comparisons between in situ data and two model outputs and model uncertainties by model inter-comparisons, and explores possible relationships between model predictability, model uncertainties, and spatial scale of prognostic variables. In early studies, a lot of evaluations have been done through analyzing dense observed data (e.g., Bosilovich, 2002), sensitivities studies on parameters and schemes (e.g. Maynard and Royer, 2004), and various international projects of model comparisons (e.g., Global Soil Wetness Project (Dirmeyer et al., 1999), Project for Intercomparison of Land-surface Parametrization Schemes (Pitman et al., 1999), Atmospheric Model Intercomparison Project (Gates et al., 1999). However, CEOP provides a unique opportunity for verifying model, evaluating model uncertainties in the global climate variability.

2. ANALYSIS METHOD

The variables of interest are air temperature, air humidity, surface radiations, and surface heat fluxes. The high spatial variability of surface temperature and precipitation and their prediction difficulties have been widely known, so their comparison will not be shown in this study.

The 10-day mean value of each variable is applied to evaluating model performance. It may be calculated by either

$$\bar{x} = \sum_{i=1}^{24}\sum_{j=1}^{n_i} x_{i,j} \Big/ \sum_{i=1}^{24} n_i \,, \tag{1}$$

or

$$\bar{x} = \frac{1}{24}\sum_{i=1}^{24}\frac{1}{n_i}\sum_{j=1}^{n_i} x_{i,j} \,, \tag{2}$$

where i is the index of hour in a day and n_i is the number of available data of variable x at hour i in the 10 days of interest.

Eq. (1) and Eq. (2) give the same mean value if no data are missed. However, if some data are missed, the result from Eq. (1) can be sensitive to the number and the value of missed data. An example is the net radiation at Lindenberg site, where the observed net radiation was calculated from four radiation components. Because some observed data of shortwave radiation at noon were missed, some high values of net radiation were thus missed. As a result, the 10-day mean values of net radiation from Eq. (1) is unrealistically low (Fig. 2a), while the values from Eq. (2) are reasonably comparable to the NASA model outputs (Fig. 2b). Therefore, we adopt Eq. (2) to calculate 10-day mean values.

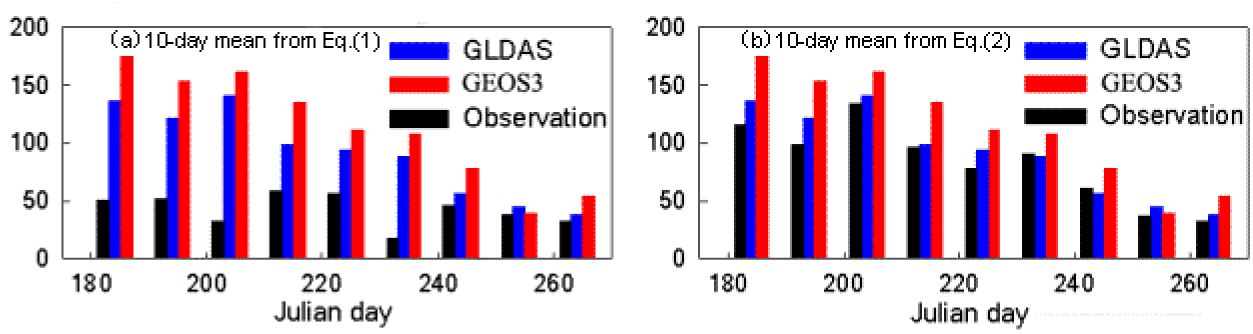


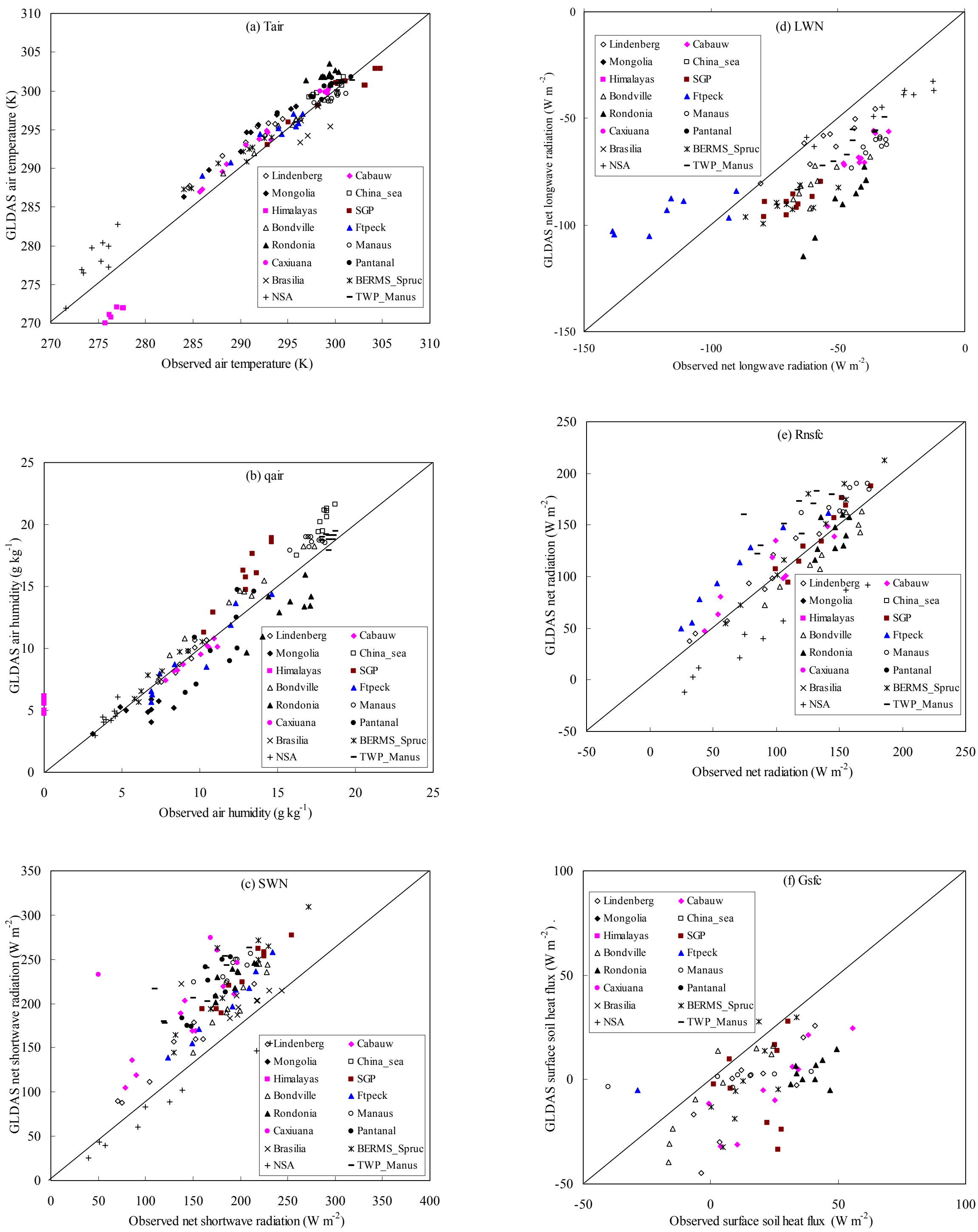
Figure 2 10-day mean net radiations from observation, NASA/GEOS3 and NASA/GLDAS at Lindenberg during CEOP EOP1

3. MODEL PREDICTABILITY

Fig. 3 shows the comparison of 10-day mean values of eight variables between GLDAS output and in-situ observations at the 16 CEOP reference sites. The result of comparison between GEOS3 and in-situ observations is similar to Fig.3 and thus it is not shown. A schematic figure of the relative deviations of model output from in situ observations is shown in Fig.4. In general, the comparisons show good agreements for air temperature (Tair), humidity (qair), and surface net radiation (Rnsfc), while worse for net shortwave radiation (SWN) (positive downward), net longwave radiation (LWN) (positive downward), surface sensible heat (Hsfc), surface latent heat (lEsfc), and soil heat flux (Gsfc). Therefore, the agreement between the model outputs and the observations significantly varies with the variables. The following gives a brief analysis on these results.

3.1 Observing errors

In general, air temperature, air humidity and net radiations can be measured with relatively high accuracy, whereas it is much more difficult to accurately measure surface heat fluxes. It has been widely reported that direct measurements of heat flux often result in the so-called energy unclosure problem (e.g., Yang et al. 2004). In addition, surface soil heat flux is usually not measured at the reference sites due to technique problems. The so-called “observed” soil heat flux in Fig. 3(f) was deduced from the energy budget equation using other measured energy fluxes, and therefore all the errors in the measured fluxes are overlapped to the “observed” soil heat flux, resulting in large “observation” error and large scattering in Fig. 3(f). We will visit Fig. 3(f) again in Section 3.3.



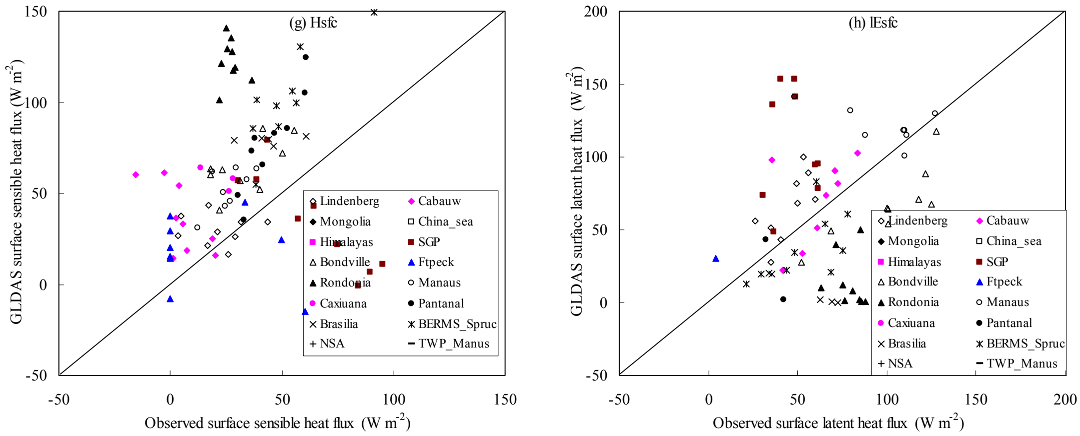


Figure 3 Comparison of 10-day mean values between GLDAS output and in-situ observations at 16 CEOP reference sites

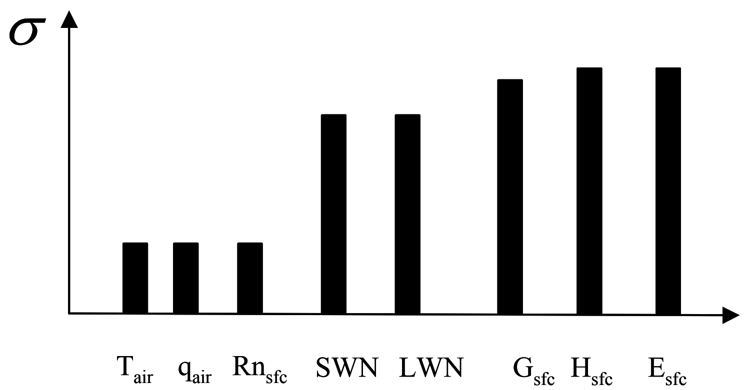


Figure 4 Schematic of deviation from in situ observations

3.2 Model errors

The complexities in meteorological modeling systems bring about a number of uncertainties in describing physical processes and specifying model parameters. Fig. 3(c) and 3(d) show that the modeled net shortwave radiation is systematically higher than in situ data while net longwave radiation is lower than in situ data. Although the spatial representativeness of in situ observations, which will be discussed in 3.3, may account for a part of these gaps, these global systematic deviations of model outputs from observations may be attributed to incorrect description of cloud optical properties or under-predicting cloud fraction in the model. In addition, the inconsistency of turbulent fluxes in Fig. 3(g) and 3(h) may partially be associated with the modeling errors of land surface processes.

3.3 Spatial representativeness of in situ observations

The model outputs represent an average over ~100km grids, but observations are usually carried out at a point-scale. If the specified land and vegetation parameters in the model grid differ from the ones at the observing site, then there is a so-called footprint mismatch problem. Such a problem occurs, more or less, at almost all the sites. For example, the Himalayas site is partially covered by vegetation and TWP-Manus is an island site, but they are specified as glacier and sea surface in GLDAS, respectively. Therefore, it is not surprising that the model outputs disagree with observations. Even though suffering the same footprint mismatch problem, we still notice the fact that some variables agree with observations while others do not, as shown in Fig. 3. This implies that the spatial representativeness of in situ observations may be different for each variable. In other words, each variable may have a different spatial variability or spatial scale. The following factors can significantly contribute to the spatial variability.

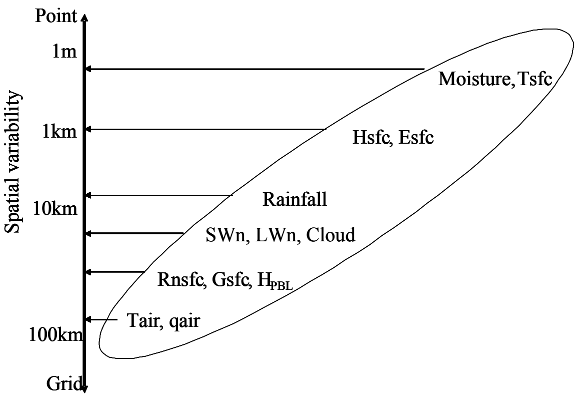


Figure 5 Spatial scale of each variable represented by in situ data.

(1) Surface heterogeneity (land cover, soil type and terrain variability). They are the major factors determining the spatial scale of the surface variables like surface temperature and soil moisture, surface wind, and energy budget.

(2) Spatial heterogeneity (convective cloud and rainfall). Their scales are strongly associated with the scale of shortwave radiation, longwave radiation, and rainfall event.

(3) Horizontal advection. If the wind is very weak, the surface air temperature and humidity would strongly determined by surface conditions; however, strong horizontal advection can play a dominant role in upscaling these variables, and makes them represent an average over an area much larger than other surface variables.

(4) Physical internal relationships. Shortwave radiation can be reduced by cloud while longwave radiation can be enhanced by cloud. As a result, the net radiation can represent a spatial scale larger than that for individual radiation components. Soil heat flux is affected by many factors such as soil thermal properties and soil moisture, but the dominant factor is the surface net radiation and thus has a scale close to the net radiation (Ma et al., 2003).

(5) Observing approach. Although surface energy budget has a spatial heterogeneity similar to surface temperature and soil moisture, heat fluxes measured by the eddy-correlation technique usually represent values averaged over the distance 100-200 times the sensor's reference height in the upwind direction, so the measured turbulent fluxes have a scale much larger than that for the surface temperature and the soil moisture.

Based on the above analysis, we propose a schematic interpretation of the spatial scale of each variable in Fig. 5. The air temperature (Tair), humidity (qair), surface net radiation (Rnsfc), and soil heat flux (Gsfc) can represent mean values over an area much larger than that for other variables, so the footprint mismatching problem can be alleviated to some extent for them, and thus their model outputs are closer to observations than other variables. The modeled Gsfc in Fig. 3(f) deviates far from the "observed" one because the "observed" Gsfc contains more significant errors than the simulated one. According to the scale analysis, Gsfc and Rnsfc have similar spatial scales, and hence their prediction should be of comparable accuracy, as shown in Fig. 3(e). On the other hand, the measurements of some variables like energy budget can only represent mean values over a patch-scale rather than mean values over a grid scale. Therefore, we cannot simply attribute their differences in Fig. 3 to model errors.

4. MODELING UNCERTAINTIES

Fig. 6 and Fig. 7 shows the comparisons between the outputs of two NASA models, respectively, for variables having a low and a high spatial variability. At Himalayas, NSA and TWP-manus sites, different land properties are set in the two models, so the comparisons at the three sites are removed. Because both models output grid-averaged values, their comparisons do not suffer a footprint mismatching problem. Fig. 6 clearly indicates that the model outputs give close values for the variables with a low spatial variability (Tair, qair, Rnsfc, Gsfc), suggesting small uncertainties. On the other hand, Fig. 7 shows the model outputs give quite different values for the variables with a high spatial variability (SWN, LWN, Hsfc, lEsfc). This contrast suggests that model uncertainties are associated with the spatial scale of each variable. In other words, high spatial variability would increase model uncertainties, probably because models may have distinct schemes to parameterize sub-grid-scale physical processes or have specified different parameters in conceptual models.

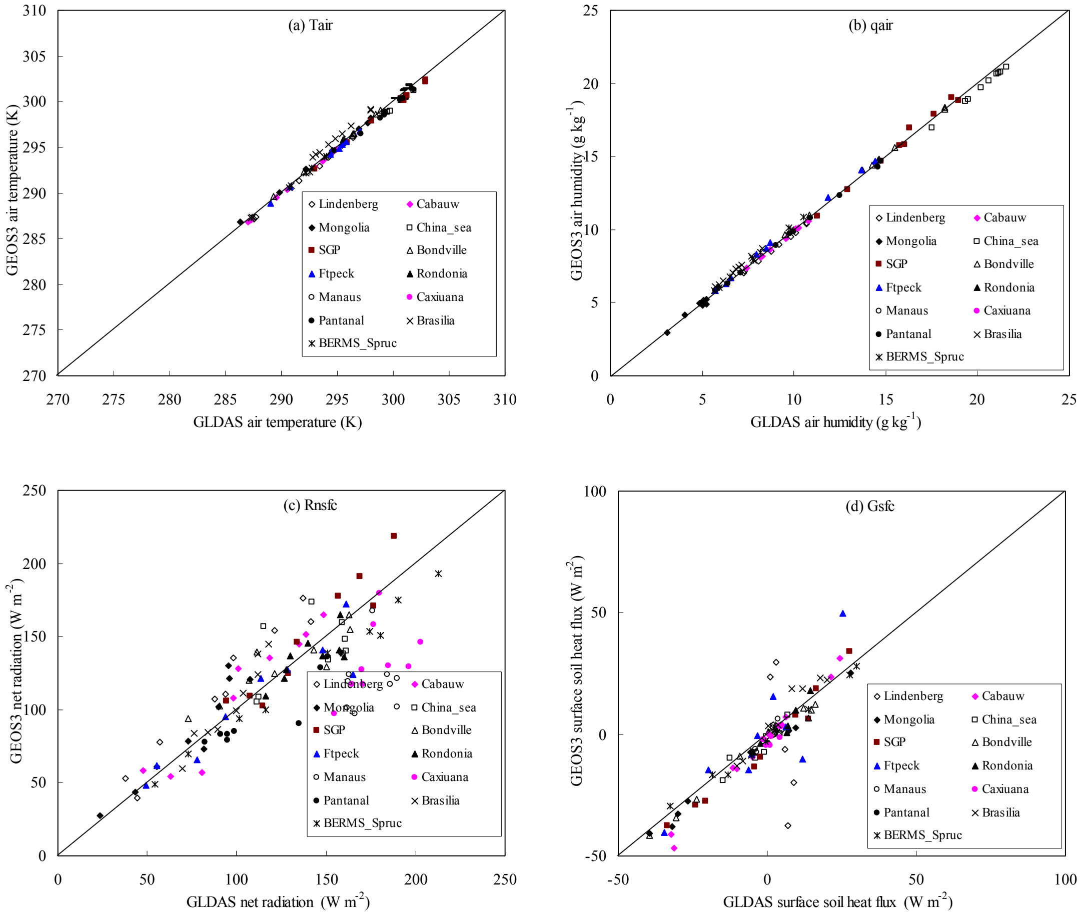


Figure 6 Comparison between GLDAS and GEOS3 at 13 CEOP reference sites for variables with a larger spatial scale

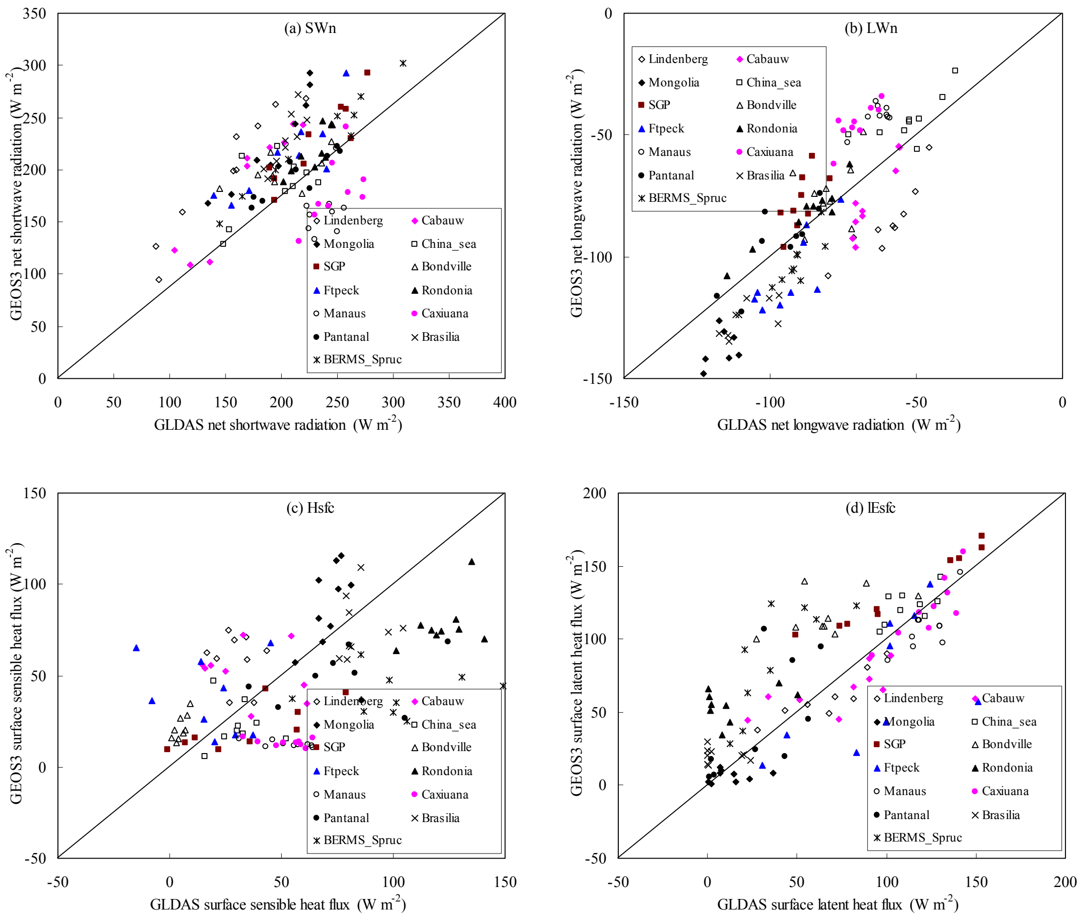


Figure 7 Comparison between GLDAS and GEOS3 at 13 CEOP reference sites for variables with a smaller spatial scale

5. Summary

Based on the analysis of CEOP EOP1 dataset, we investigated model predictability by comparing in situ data with two model outputs and model uncertainties by comparing two model outputs. Modeled values are generally consistent with in situ observations for surface air temperature, humidity, and net radiation, but not so for shortwave radiation, longwave radiation, sensible heat flux, and latent heat flux. It looks that the over-prediction of net shortwave radiation and under-prediction of downward longwave radiation are a global problem of numerical models. We suggest that the spatial scale is variable–dependent, and thus each variable observed in situ may represent a different scale. This scale-difference should be taken into account when evaluating model predictability. In other words, in situ ~ model differences cannot be simply interpreted as errors, because the scale represented by a variable can be much less than the model grid. Model inter-comparisons further indicate that model uncertainties also depend on spatial scales, and large modeling uncertainties may be related to small spatial scales of variables.

Because evaluating model predictability and uncertainties is complicated by the scale problem, an improved evaluation in the future needs upscaling point-observation to grid-average by incorporating satellite data, which have been obtained through CEOP project..

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