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Soil moisture initialization for climate prediction: Characterization of model and observation errors

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[1] While it has been shown that soil moisture data assimilation techniques can be used to constrain land surface model predictions with remotely sensed soil moisture observations to provide optimal climate model surface and root zone soil moisture initialization, a good understanding and quantification of both model and observation error are required. In this paper we therefore evaluate the catchment-based land surface model (CLSM) and scanning multichannel microwave radiometer (SMMR) soil moisture estimation errors using long-term in situ soil moisture measurements available for Eurasia. Generally, the CLSM surface and root zone soil moisture was found to be biased less than 0.08 vol/vol dry in dry climate and frozen soil areas and biased over 0.08 vol/vol (as high as 0.16 vol/vol) wet in wet climate areas. Moreover, the CLSM suffered from an underestimation in surface zone seasonal soil moisture variation. While the SMMR soil moisture estimates were also biased, less than 0.05 vol/vol dry in dry climate and over 0.10 vol/vol (as high as 0.2 vol/vol) wet in wet climate, they generally had accurate seasonal variations. This error characterization study is crucial for practical Eurasian data assimilation, as unbiased observations and model predictions, and reliable knowledge of relative observed and model predicted soil moisture errors are key data assimilation assumptions. This study therefore provides the error information required for data assimilation and emphasizes the need for careful bias representation when assimilating SMMR data into the CLSM. The potential deficiencies in this error assessment are acknowledged and discussed, including the disparate time-space representation of the various soil moisture sources.

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1. Introduction

[2] Accurate land surface moisture initialization in fully coupled climate system models is critical for seasonal-to-interannual climatological and hydrological prediction. *Koster and Suarez* [1995] and *Koster et al.* [2000a] have shown that the contribution of soil moisture to precipitation prediction outweighs ocean processes in transition zones between dry and humid climates. These studies have also shown that soil moisture persists on a seasonal timescale and that soil moisture anomalies often lead to precipitation anomalies a few months later. This modeled seasonal soil moisture persistence is in general agreement with long-term in situ soil moisture data [*Vinnikov et al.*, 1996; *Entin et al.*, 2000]. These studies are among many that indicate that accurate soil moisture initialization may lead to improved seasonal-to-interannual climate prediction.

[3] Many land surface process models have been developed to describe energy and moisture exchange between the land surface and atmosphere. While observed land surface forcing (such as precipitation and radiation) can be used in uncoupled land surface models to yield better soil moisture estimates than coupled models, soil moisture and flux predictions can still be poor due to poor initialization, forcing errors, simplified model physics, and uncertain model parameters [*Houser et al.*, 2001]. Constraining model states using remotely sensed observation assimilation may mitigate these errors and improve subsequent predictions.

[4] Satellite remote sensing can provide technically consistent global surface soil moisture estimates for use in climate model initialization that cannot be obtained through traditional in situ observation networks. Global 25-km resolution surface soil moisture has been estimated using

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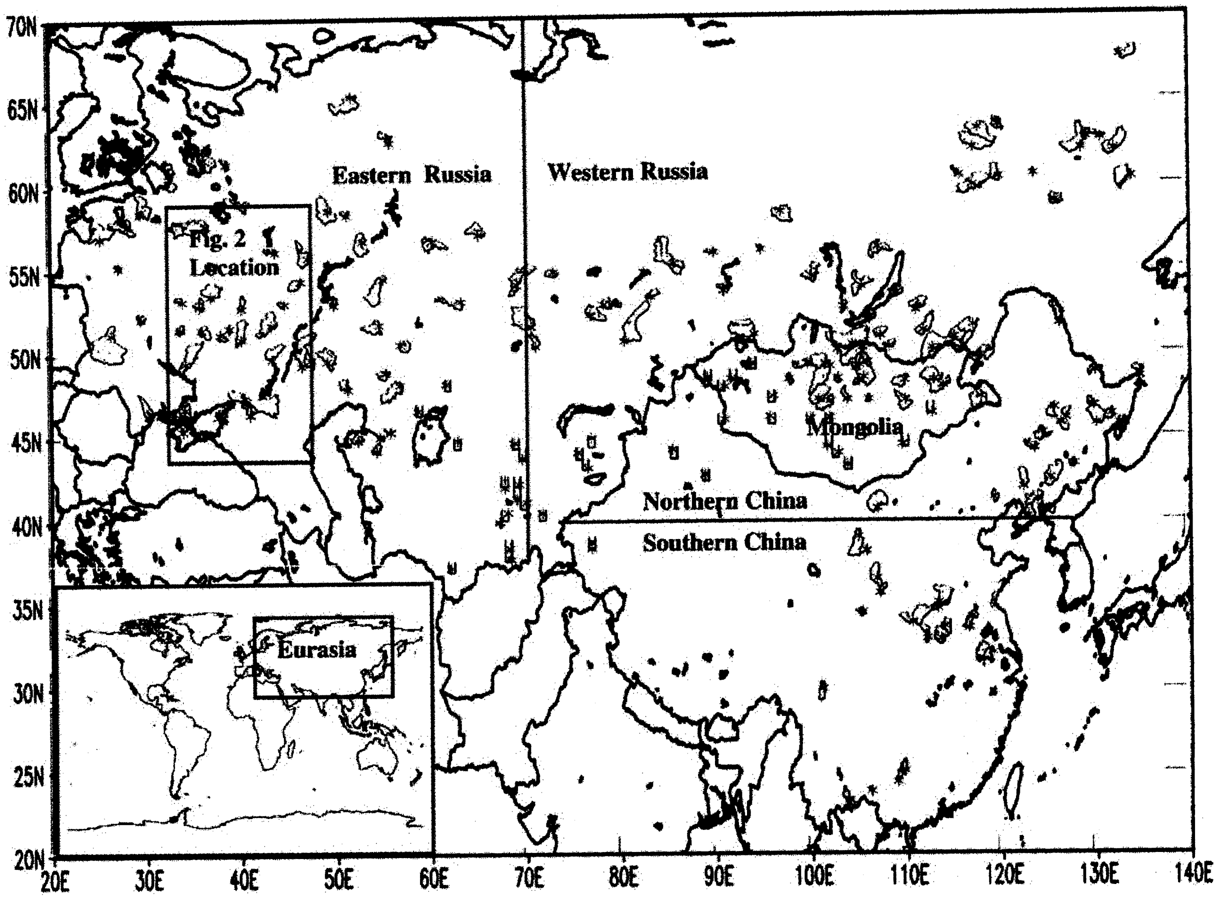

Figure 1. Distribution of Eurasian in situ observation stations and coinciding catchments used for comparison in this study. Two boundary lines to divide Russia into western Russia and eastern Russia, China into northern China and southern China, and the region with wilt level in situ measurements are also shown.

C-band passive microwave observations from the Nimbus 7 satellite scanning multichannel microwave radiometer (SMMR) for the 1979–1987 period [*Owe et al.*, 2001]. While no C-band passive microwave satellite measurements are available between SMMR and the 2001 launch of the Aqua satellite Advanced Microwave Scanning Radiometer for the Earth observing system (AMSR-E), low-latitude soil moisture has been estimated using Tropical Rainfall Measuring Mission (TRMM) X-band microwave observations [*Bindlish et al.*, 2003; *Gao et al.*, 2003] since 1998. These microwave-based soil moisture estimates are confined to the top few centimeters of soil and are subject to significant vegetation, soils, and roughness error sources. However, it has been widely demonstrated that assimilation of these surface soil moisture observations into land surface models should help mitigate model and observation errors and provide a more accurate root zone soil moisture estimate than modeling alone, which will be crucial for accurate climate prediction model initialization [*Walker and Houser*, 2001].

[5] The NASA Global Modeling and Assimilation Office (GMAO; formerly known as the Seasonal-to-Interannual Prediction Project, or NSIPP) aims to improve seasonal-to-interannual climate predictions using a global coupled Earth system model. To enhance climate prediction skill, innovative data assimilation algorithms are being developed to merge satellite data and model predictions. To this end, *Walker and Houser* [2001] included an extended Kalman filter (EKF) surface soil moisture data assimilation strategy in the GMAO's catchment-based land surface model (CLSM) [*Koster et al.*, 2000b]. This assimilation system was proved and refined using a synthetic twin experiment. *Walker and Houser* [2001] found that the unique CLSM physics are well suited for surface soil moisture assimilation, as the dominant prognostic moisture state variable (catchment deficit) has a significant correlation with surface soil moisture content except in very deep soils.

[6] The ensemble Kalman filter (EnKF) has also been implemented in the CLSM [*Reichle et al.*, 2002], being simply an alternative methodology for propagating the state covariance matrix that does not require model linearization. *Reichle et al.* [2002] evaluated the relative EnKF and EKF benefits using synthetic soil moisture observations. Their study demonstrated that both the EKF and EnKF produced

satisfactory soil moisture estimates, with the EnKF slightly outperforming the EKF when five or more ensemble members were used. However, the performance of both the EKF and EnKF is dependent on the assumption that model predictions and observations are unbiased and that reliable estimates of model and observation error are available. Therefore this study characterizes the CLSM and SMMR errors using the Eurasian in situ soil moisture observation network, which is the most extensive soil moisture data set available during the SMMR time period. This study differs from a similar CLSM, SMMR, in situ soil moisture comparison study by *Reichle et al.* [2004] for Eurasia undertaken in tandem with this study, in that they investigate only the correlation between the various data sets rather than the actual error magnitude in CLSM and SMMR data required for data assimilation.

2. Data Sets

[7] Figure 1 shows a map of the Eurasian in situ measurement station network and the corresponding CLSM catchments used in the evaluation. Details of the in situ, SMMR, and CLSM data sets are described in the following sections.

2.1. In Situ Observations

[8] Historical Eurasian soil moisture observations archived in the Soil Moisture Data Bank (SMDB) [*Robock et al.*, 2000] provide the validation data that underpin this paper's error analysis. The SMDB has 43 Chinese, 36 Mongolian, and 130 Russian soil moisture monitoring stations with 1981–1991, 1973–1997, and 1978–1985 periods of record, respectively. Most soil moisture monitoring sites were located in grass or crop fields, with each observation value being the average of four sample points across a plot area of 0.1–20 ha. Soil moisture profiles were measured biweekly over the top 1 m at 10-cm increments using the standard gravimetric technique. We define the surface zone soil moisture as the shallowest observation available, which for China is the top 5 cm and for Mongolia and Russia is the top 10 cm, and define root zone soil moisture as the top 1-m average.

[9] The SMDB includes a mix of plant available (Mongolia and Russia) and total (China) soil moisture, expressed as water volume divided by dry soil volume. Plant available soil moisture is the difference between the total soil moisture and the soil moisture at which vegetation begins to wilt. The plant available soil moisture observations for Mongolian and Russian sites were converted to total soil moisture to create a consistent data set and for comparison with model and remotely sensed soil moisture estimates, by adding the volumetric wilting point moisture content. As no wilting point observation data were available for Mongolia and Russia, the volumetric wilting point was estimated using a specified wilting point potential, soil properties (porosity, saturated soil suction, and Clapp and Hornberger *b* parameter) based on soil texture [*Reynolds et al.*, 2000], and the Clapp and Hornberger soil moisture retention curve relationship. Wilting point measurements for western Russia (not coincident with the soil moisture stations (K. Vinnikov and M. Mu, personal communication, 2003); see Figure 1 for the area) were then used to verify the wilting point

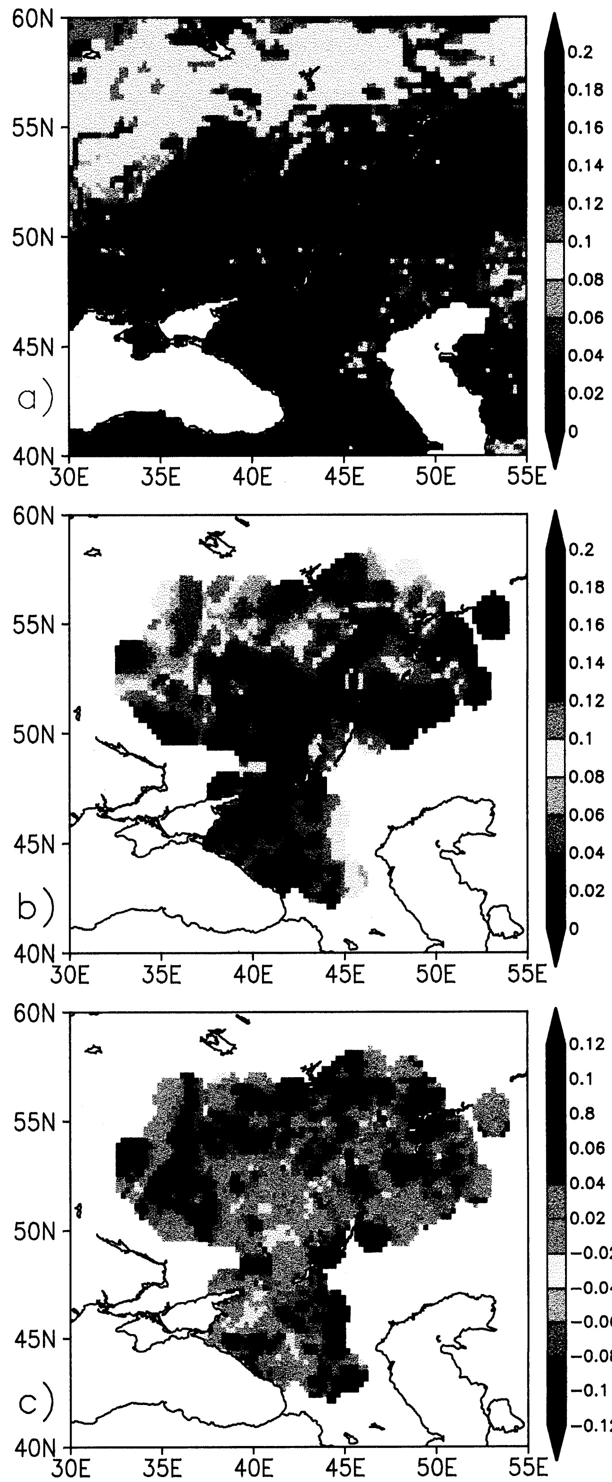

Figure 2. Comparison between (a) interpolated in situ wilting point measurements and (b) estimated wilting point based on soil texture properties (vol/vol). Figure 2c shows their difference.

estimates (Figure 2); wilting point was obtained by measuring soil moisture content at the time when plant wilting onset was observed. Overall, the interpolated wilting point observation field matched the estimated wilting point field well with a slight overestimation (0.05 vol/vol) in the north, giving confidence in the estimates at Mongolian and Russian stations. While the overestimation of wilting level may lead to slightly wet biased Russian and Mongolian observation soil moisture estimates, it does not affect the seasonal or interannual soil moisture change estimates.

[10] Figure 3 shows the SMDB surface and root zone total soil moisture seasonal variations (1979–1987 average). The four seasons are defined as winter (December through February), spring (March through May), summer (June through August), and fall (September through November). The SMDB Eurasian soil moisture patterns were found to generally follow the precipitation and vegetation patterns. China's monsoonal climate results in high soil moisture content along the coastline with a dry interior. The boundary between western China and eastern Russia near the Tibet Plateau is also wet, due to orographic precipitation. A division between wet and dry Russian and Mongolian regions is identified along latitude 50°–52°N. To the north, soil moisture content is generally above 0.25 vol/vol, while to the south soil moisture content is generally below 0.25 vol/vol. During summer this soil moisture division line shifts to the north, and during winter it shifts to the south. Vegetation reflects this soil moisture pattern with forest to the north and grasslands to the south.

[11] The largest soil moisture variations with depth are observed in China, with a surface zone that is much drier than the root zone. The Mongolian and Russian vertical soil moisture profiles are almost constant with depth. The larger vertical variation for Chinese stations may be related to China's monsoonal climate. Russia has the strongest seasonal soil moisture variation, having dry summers with wet winter and spring months, while the Chinese and Mongolian seasonal soil moisture variations are weak. The strong seasonal variation in Russia is directly related to snow accumulation and snowmelt.

2.2. Satellite Observations

[12] Surface zone (top 1 cm) soil moisture estimates at 25-km spatial resolution have been derived from the Nimbus 7 scanning multichannel microwave radiometer (SMMR) observations from 1979 to 1987 [*Owe et al.*, 2001]. The Nimbus 7 Sun-synchronous orbit resulted in two overpasses daily (noon and midnight), which have both been used in this analysis. The *Owe et al.* [2001] theoretical retrieval algorithm is distinctive from other approaches in its use of both the horizontal (H) and vertical (V) 6.6-GHz (C-band) polarizations together with temperature derived from the 37-GHz V data to solve for surface zone soil moisture and vegetation optical depth simultaneously. While the spatial resolution for SMMR data varies from 25 km at 37 GHz to 150 km at 6.6 GHz, due to oversampling, the 6.6-GHz SMMR observations were binned into 25-km global brightness temperature maps and the surface soil moisture was retrieved.

[13] The soil moisture algorithm has been validated using in situ soil moisture observations from Illinois [*Owe et al.*, 2001], Russia, Mongolia, and Turkmenistan [*De Jeu and Owe*, 2003]. The validation results indicated that soil moisture estimation accuracy was approximately 0.10 vol/vol and that the soil contribution to observed brightness temperature reduced to less than 25 percent for vegetation optical depths above 0.6. Hence soil moisture data for pixels with optical depth greater than 0.6 or soil moisture values greater than or equal to the soil porosity were omitted from our analysis. While the optical depth condition was used to screen soil moisture estimates in areas of dense vegetation, the soil porosity condition was used to screen unrealistic "wet" pixels found in the data set, believed to have resulted from divergence of the soil moisture retrieval algorithm.

[14] The SMMR-derived surface zone soil moisture seasonal climatology for pixels coincident with SMDB observations is shown in Figure 4. As remote sensing of soil moisture is impossible when the ground is snow covered, there are approximately half the summertime station comparisons during wintertime. The spring and fall SMMR soil moisture spatial patterns compare well with the SMDB in situ measurements shown in Figure 3 with wet in the north and dry in the south. For all seasons, SMMR shows a dry bias in western Russia and Mongolia and a wet bias in China. The dry bias shown in western Russian and Mongolian stations may be partially explained by the wet-biased in situ observations in these stations from the potentially overestimated wilting level used.

2.3. CLSM Predictions

[15] Novel CLSM features include its topographically defined catchments [*Koster et al.*, 2000b; *Ducharne et al.*, 2000], its explicit subgrid soil moisture variability treatment based on statistical topography induced heterogeneity, and its TOPMODEL [*Beven and Kirkby*, 1979] concept used to relate water table distribution to topography. This leads to the definition of three bulk moisture prognostic variables (catchment deficit, root zone excess, and surface excess) with specific moisture transfer between them. Using these three prognostic variables, the catchment is divided into stressed, unstressed, and saturated soil moisture regimes with separate evapotranspiration flux calculations for each, and the catchment average surface zone (top 2 cm), root zone (top 1 m), and profile (from 1 to approximately 3.5 m depending on total soil depth) soil moisture values calculated.

[16] The CLSM has been validated as part of the Project for Intercomparison of Land Surface Parameterization Schemes (PILPS)-2e [*Bowling et al.*, 2003] and the Rhone-Aggregation (Rhone-AGG) Soil-Vegetation-Atmosphere-Transfer (SVAT) model intercomparison project [*Boone et al.*, 2004]. While the CLSM reliably reproduced observed evaporation and runoff over large spatial scales, there has been no previous large-scale validation of its soil moisture prediction capability. The CLSM is still being actively refined and is currently in the process of being coupled with the GMAO's atmosphere and ocean models.

[17] The 13,236 Eurasian catchments and their associated CLSM parameters (soil properties, partitioning, base flow, timescale of moisture transfer between root zone and water table and between root zone excess and surface excess) were derived from the Hydro 1-k topographic data [*Verdin and Greenlee*, 1996] and a soil texture based estimation of soil hydraulic properties [*Cosby et al.*, 1984] using the FAO

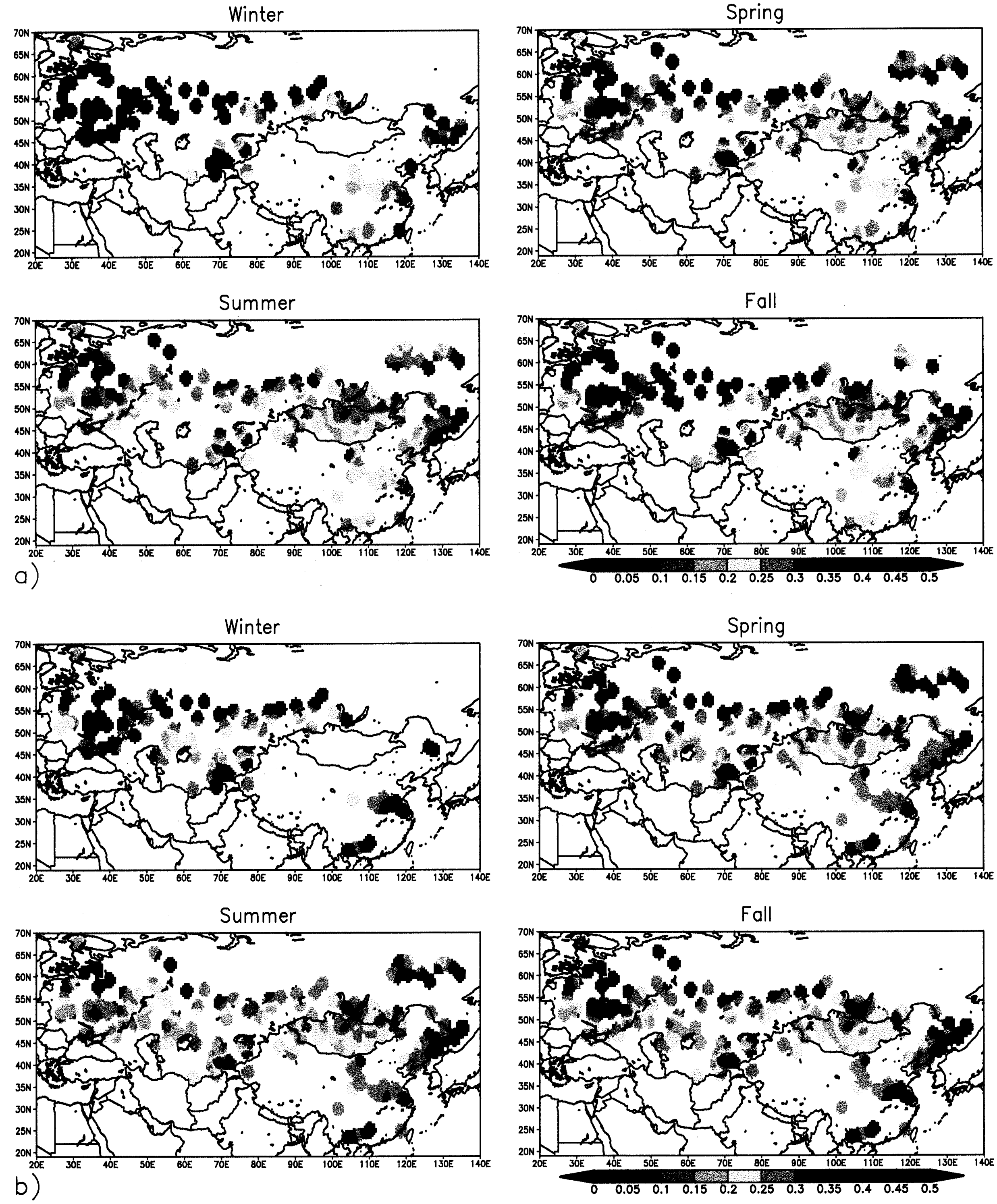

Figure 3. Eurasian in situ observed seasonal climatology of (a) surface (top 10 cm) and (b) root zone (top 1 m) soil moisture (vol/vol) using 1979–1987 data.

soil texture map of the world [*Reynolds et al.*, 2000]. Catchment vegetation parameters including vegetation type, Leaf Area Index (LAI), and greenness were taken from the ISLSCP Initiative I data set. Monthly values of greenness fraction and LAI were derived from advanced very high resolution radiometer (AVHRR) satellite data using the relationships of *Sellers et al.* [1996]. Additionally, half-degree 1979–1993 observationally corrected European

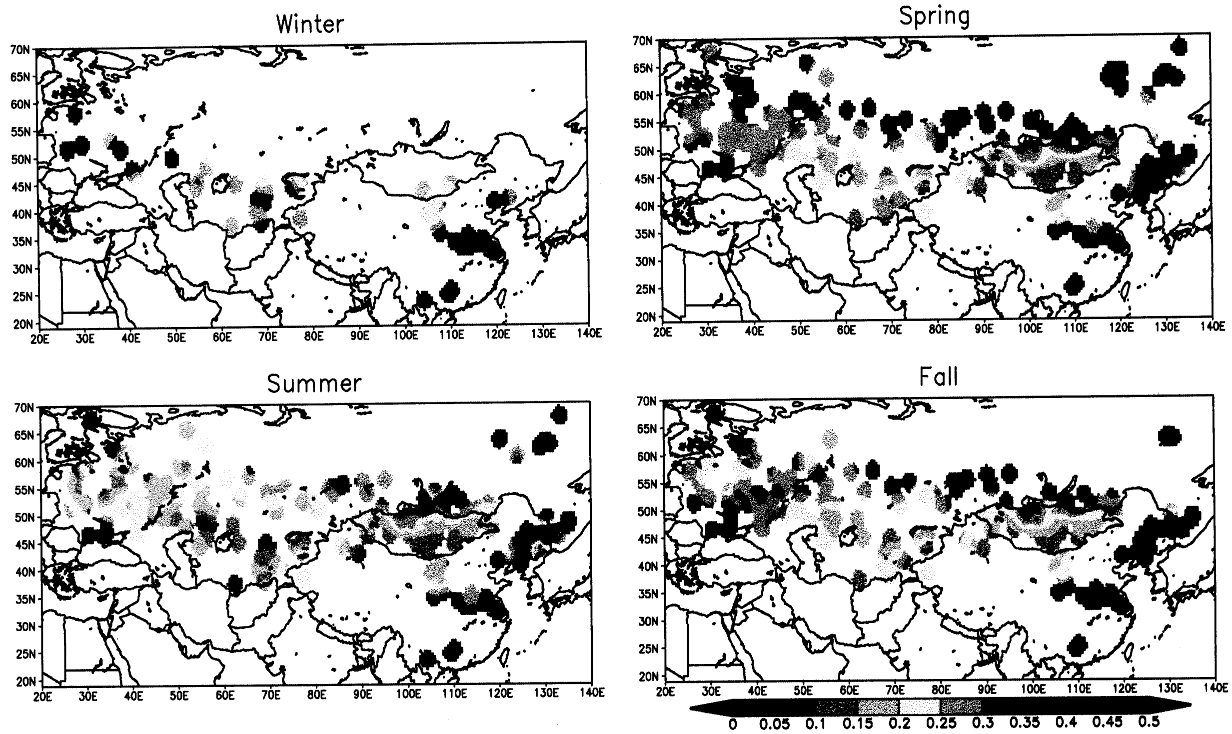

Figure 4. Eurasian SMMR-derived seasonal climatology of surface zone (top 1 cm) soil moisture (vol/vol) using 1979–1987 data. For comparison purposes, only SMMR observations coinciding with the in situ stations are shown.

Centre for Medium-Range Weather Forecasts (ECMWF) reanalysis data developed by *Berg et al.* [2003] were used to force the CLSM. This forcing data set has been shown to reduce forcing-induced soil moisture, runoff, and snow water equivalent simulation errors [*Berg et al.*, 2003]. The CLSM initial conditions were derived from model spin-up by repeated simulation of 1979 for 10 years.

[18] The CLSM seasonal climatology for Eurasian catchments coincident with SMDB observations is shown in Figure 5 for the surface (top 2 cm depth) and root zone (top 1 m depth) predictions. Both show similar surface and root zone spatial patterns with wet conditions in the north and dry in the south. Root zone soil moisture comparison demonstrates that model predictions match well with the in situ observations, but surface zone soil moisture comparison suggests a depressed seasonal variation in the model estimation, being too dry during the cold season, particularly in western Russia. This cold season surface zone soil moisture dry bias is a result of inadequate snowmelt model physics.

3. Results and Discussion

[19] While a qualitative assessment of the CLSM and SMMR error is given above, here we focus on a quantitative error characterization based on their comparison with the SMDB in situ observations. This is complicated by these three data sets having different sampling intervals and depths. For example, when the biweekly SMDB observations do not align with a satellite overpass, it is omitted from our comparison, resulting in only a fraction of the available SMMR data being used. Likewise, only CLSM output coinciding with the biweekly SMDB observations is used in the comparison. Further, each data set has a fundamentally different surface zone layer thickness; 1 cm for SMMR, 5–10 cm for in situ, and 2 cm for CLSM. Moreover, station measurements averaged over 0.1–20 ha areas are used to represent the areal average soil moisture over 625-km^2 SMMR pixels and up to 10,000-km^2 catchments.

3.1. In Situ, SMMR, and CLSM Soil Moisture Comparison

[20] To better understand the soil moisture seasonal cycle, the average monthly 1979–1987 CLSM, SMMR, and SMDB soil moisture data are compared for Russia, China, and Mongolia in Figure 6 with mean standard deviations of 0.06 vol/vol. For these purposes, Russia is divided into eastern and western regions along 70°E longitude and China is divided into southern and northern regions along 40°N latitude (see Figure 1).

[21] In Russia, both the SMMR and SMDB surface zone soil moisture data show a stronger seasonal cycle than the CLSM, with dry summers and wet winters. Moreover, the SMMR data in western Russia show a dry bias of 0.10 vol/vol in all seasons except for fall compared with the SMDB observations in western Russian. This dry bias may be partially, but not entirely, explained by the possibly wet-biased SMDB observations caused by too wet wilting level added. In addition to its smaller seasonal cycle, the CLSM surface zone soil moisture in western Russia shows a spring and fall dry bias. However, the western Russia CLSM root zone soil moisture is very close to the SMDB observations.

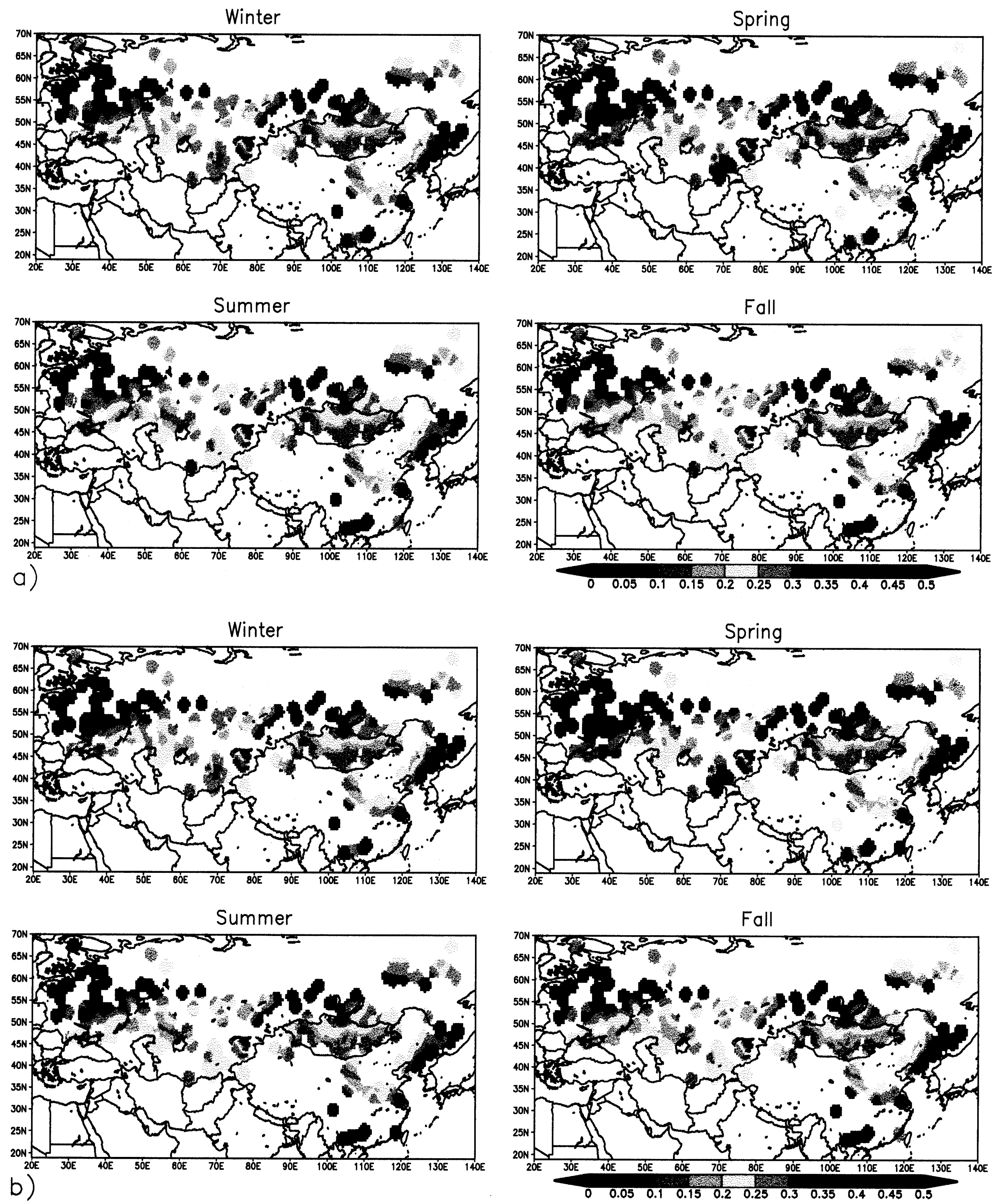

Figure 5. Eurasian model-derived seasonal climatology of (a) surface (top 2 cm) and (b) root zone (top 1 m) soil moisture (vol/vol) using 1979–1987 data. For comparison purposes, only model predictions coinciding with the in situ stations are shown.

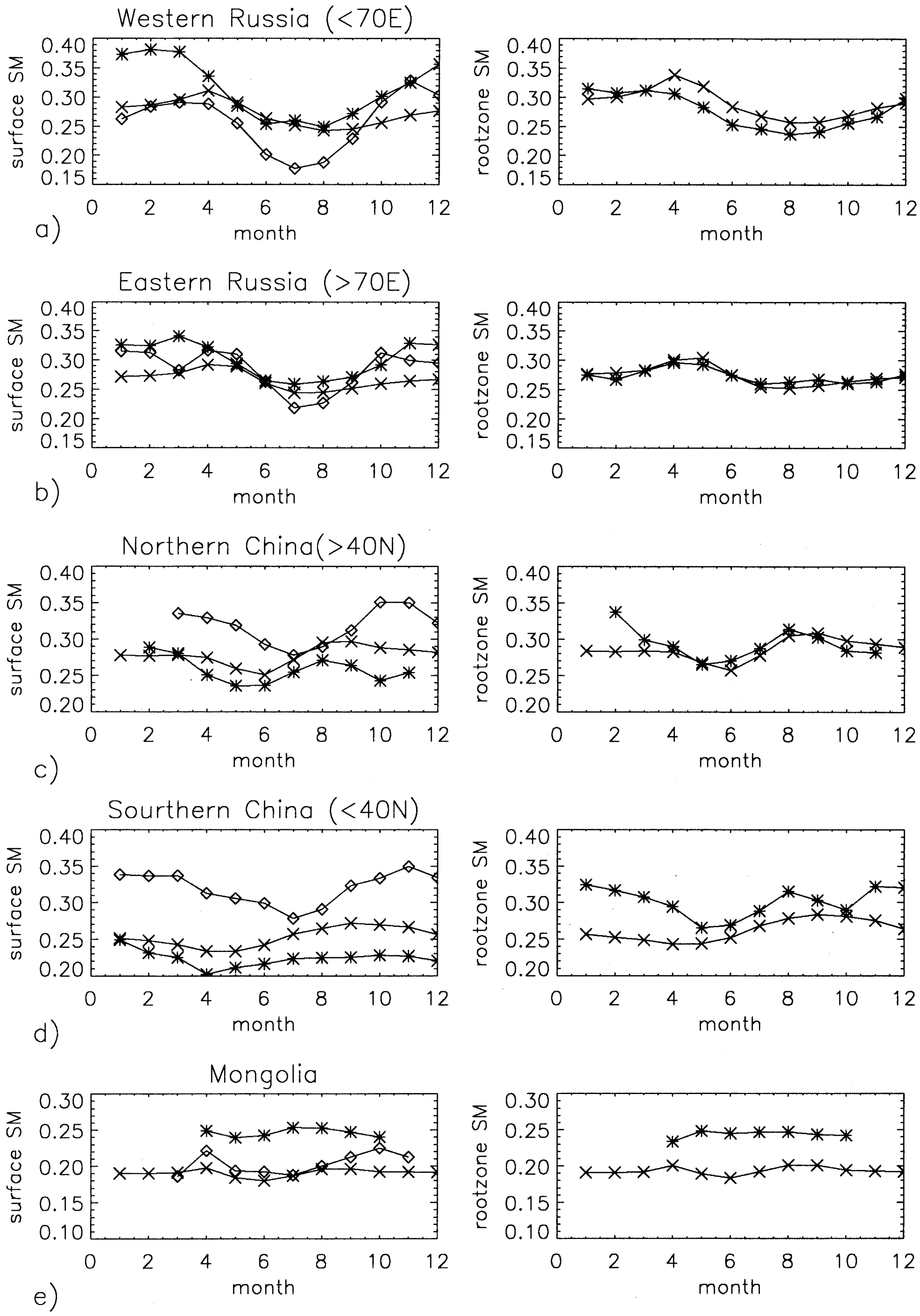

Figure 6. Comparison of Eurasian average monthly in situ (asterisks), SMMR (diamonds), and model (crosses) soil moisture (vol/vol) using 1979–1987 data. The left panels show surface zone soil moisture and the right panels show root zone soil moisture for (a) western Russia, (b) eastern Russia, (c) northern China, (d) southern China, and (e) Mongolia.

This dry bias in winter and fall and depressed seasonal variation in modeled surface zone soil moisture may be due to the strong surface and root zone soil moisture coupling in the catchment model, meaning that CLSM surface soil moisture estimates are unrealistic. Compared with western Russia, the soil moisture seasonality in eastern Russia is weak and the SMMR data are quite close to SMDB observations and the CLSM results still show a smaller seasonal cycle.

[22] In China, both the SMMR and CLSM surface zone soil moisture are wetter than the SMDB observations, with the SMMR overestimation being larger. However, the CLSM root zone soil moisture is drier than the SMDB observations, particularly in winter and in southern China. In northern China, the SMDB, CLSM, and SMMR seasonal variation is stronger than that in southern China.

[23] In Mongolia, both the CLSM and SMMR surface zone soil moisture are drier than the SMDB observations,

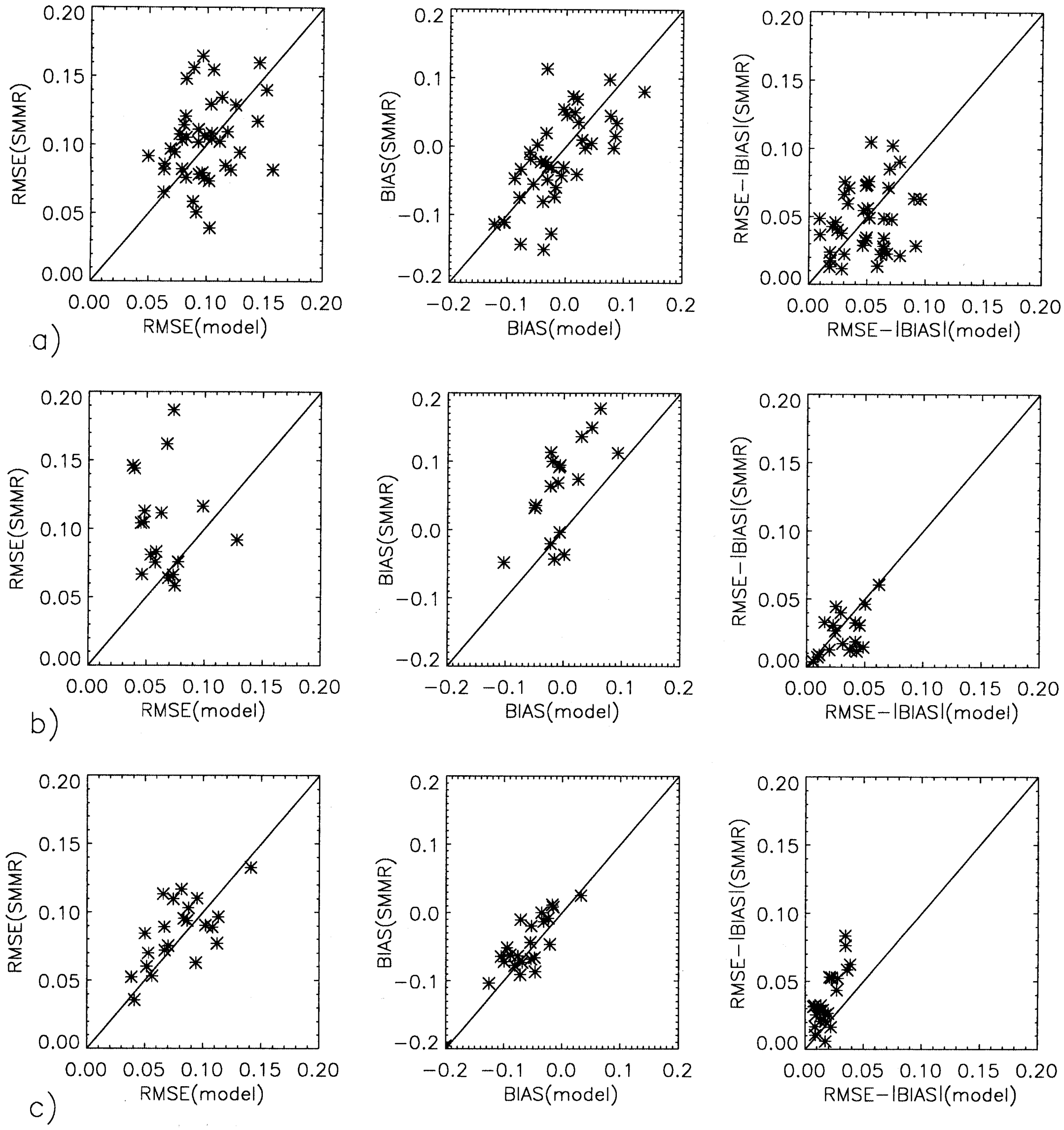

Figure 7. Comparison of SMMR and model surface zone soil moisture RMSE, bias, and their difference (vol/vol) for corresponding in situ observation stations in (a) Russia, (b) China, and (c) Mongolia.

with slightly less SMMR underestimation. This Mongolian dry bias may be due to inaccurate SMDB observations (A. Robock, personal communication, 2004), point measurements that poorly represent the areal average, or incorrect wilting point estimates leading to inflated SMDB total soil moisture observations.

3.2. SMMR and CLSM Soil Moisture RMSE and Bias

[24] Figure 7 shows scatterplots of the SMMR and CLSM soil moisture RMSE, bias, and their difference for SMDB in situ observations. The bias is defined as the long-term difference between SMMR or CLSM and the SMDB observations. To avoid error associated with incomplete time series, any SMDB time series with less than 20 observations per year were excluded. Moreover, CLSM and SMMR soil moisture error statistics were only calculated for coincident biweekly CLSM, SMMR, and SMDB data.

[25] The Russian CLSM and SMMR data have similar RMSE and bias magnitudes. About half the stations show a positive SMMR and CLSM bias, with bias contributing to more than half of the RMSE. The Chinese SMMR soil moisture RMSE and positive bias are larger than CLSM, with a large bias contribution to the RMSE. The Mongolian SMMR and CLSM soil moisture RMSE and bias are very similar, with most of the RMSE contribution from bias. Generally, both SMMR and CLSM are wetter than the SMDB observations. Figure 8 shows the CLSM and SMMR soil moisture RMSE and bias spatial distributions. Here it can be seen that the bias and RMSE have very similar spatial patterns, indicating that bias makes a significant contribution to the overall model and observa-

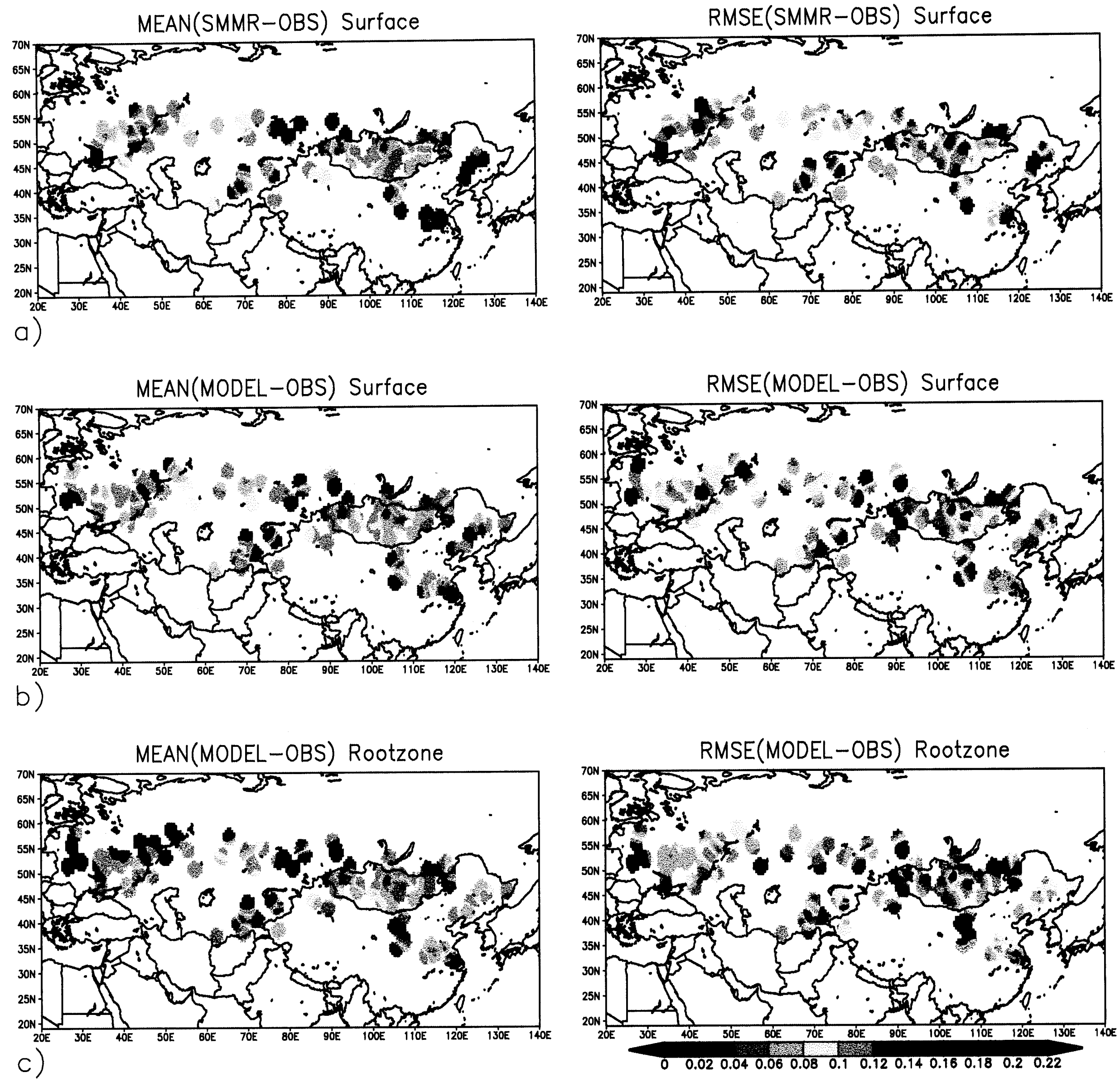

Figure 8. (left) Eurasian bias and (right) RMSE spatial distributions for (a) SMMR surface zone, (b) model surface zone, and (c) model root zone soil moisture (vol/vol).

tion errors. Bias analysis will be the focus of the remainder of the paper.

3.3. CLSM Soil Moisture Climatology Error

[26] Figure 9 shows the climatological (time series average) differences between the CLSM and SMDB surface zone and root zone soil moisture by season. The CLSM is biased dry in the already relatively dry Mongolian and southern Russian climate. Along the relatively wet Chinese east coast and the boundary between Mongolia and Russia, the CLSM shows wet-biased surface zone and root zone soil moisture. In northwestern Russia, the CLSM is biased very dry in the winter and fall, and biased wet in the spring and summer. This winter and fall dry bias may be partially related to the CLSM's simple soil freezing treatment and partially due to the fact that the modeled surface zone soil moisture is more tightly coupled with root zone soil moisture than other models. The spring and summer Chinese and Russian CLSM root zone soil moisture is biased wet with a dry bias during the winter and fall. Generally, the CLSM surface zone and root zone soil moisture are biased less than 0.08 vol/vol dry in dry climate and frozen soil areas, and are biased wet over 0.08 vol/vol (as high as 0.16 vol/vol) in wet climate areas.

[27] There are multiple possible sources of CLSM error. First, simplified CLSM physics can lead to systematic prediction error. For instance, the simple algorithm used to convert the CLSM's three soil moisture prognostic variables to surface zone soil moisture can lead to a misrepresentation of surface zone soil moisture. Moreover,

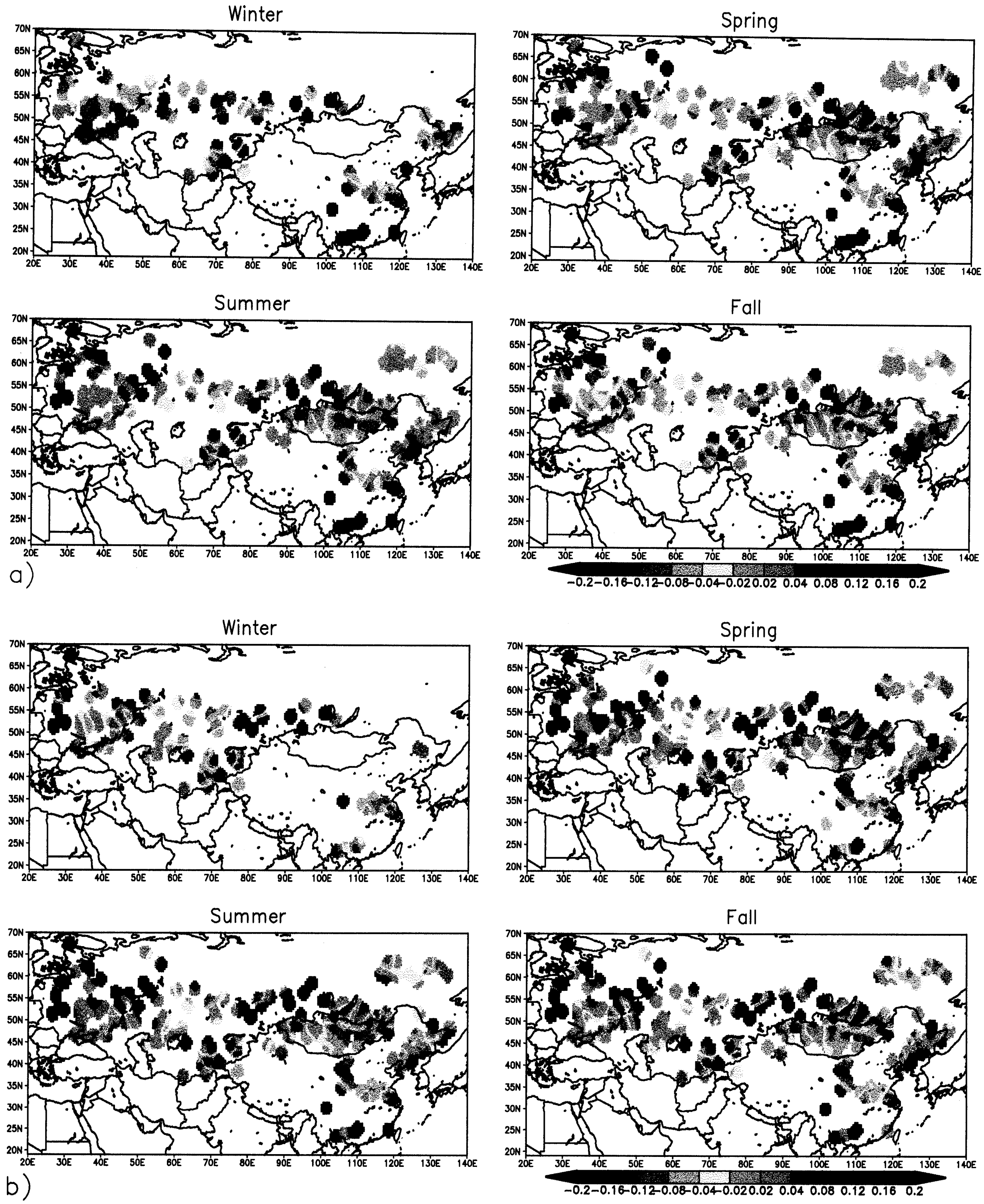

Figure 9. Differences in seasonal climatology between the model and in situ (a) surface and (b) root zone soil moisture (vol/vol).

the simple frozen ground treatment used by CLSM that prevents all soil water movement (including infiltration) when the soil temperature is below 0°C could lead to cold region dry biases. This point has been demonstrated by several studies where different models have given vastly different soil moisture estimates with the same inputs [e.g., *Koster and Milly*, 1997; *Entin et al.*, 1999]. Second, *Berg et al.* [2003] have shown that the CLSM soil moisture is very

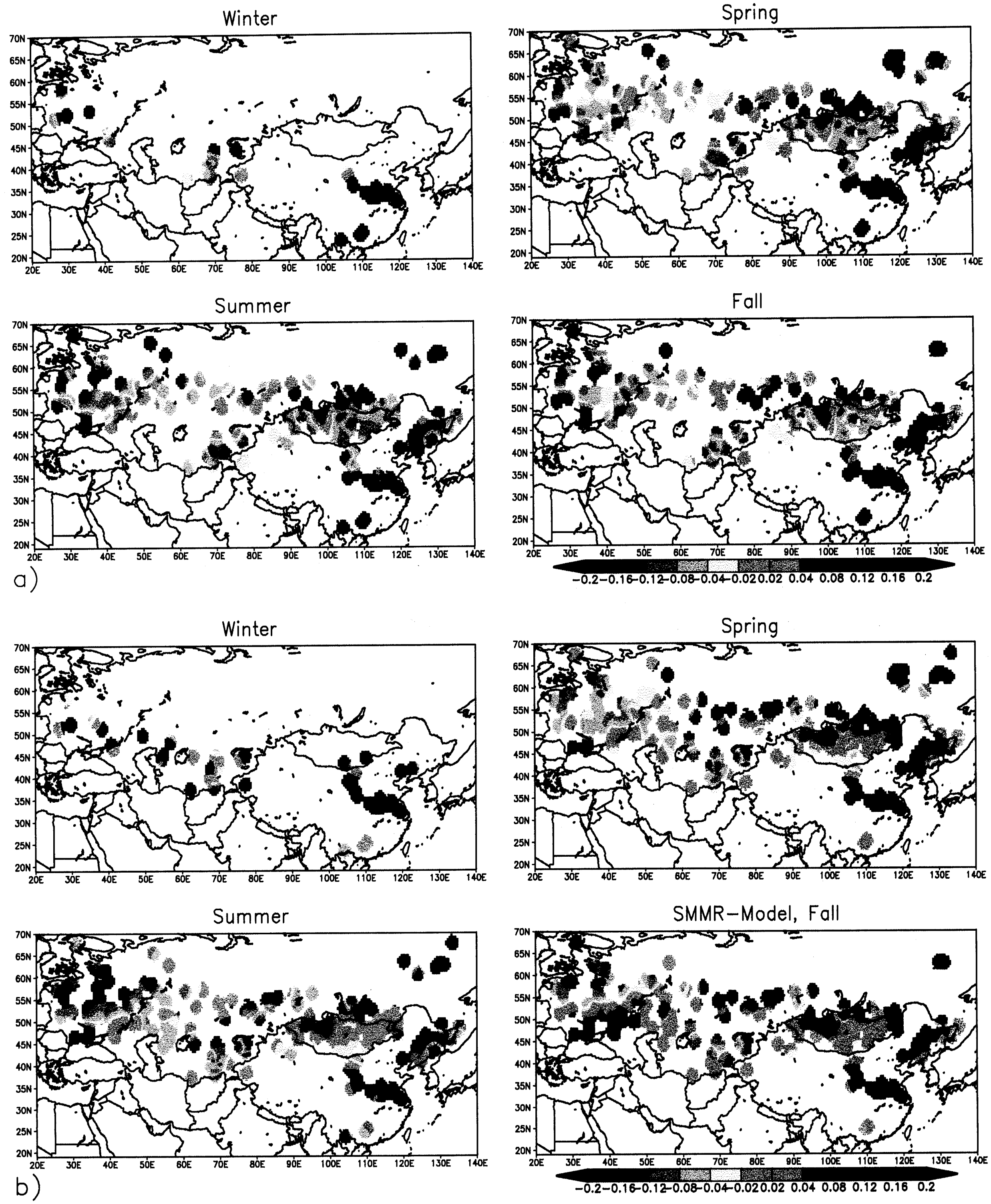

Figure 10. Differences in seasonal climatology between the (a) SMMR and (b) model surface zone soil moisture (vol/vol) and in situ measurements.

sensitive to forcing errors. Generally the global observation-corrected forcing improves the CLSM large-scale performance, but some local errors may still exist. Third, prediction errors can arise from incorrect CLSM vegetation and soil parameters.

[28] Although the gravimetric method is considered to be the most accurate way to estimate soil moisture, it can also have serious errors. Sample cores may contain roots, rocks, voids, and unique drainage characteristics that can lead to large differences between adjacent samples. Further, differ-

ences in sample extraction, compaction, handling, and processing can lead to error. Using field-average wilting point and bulk density can produce errors, or, as previously mentioned, there may be error related to using a potentially incorrect soil-type based wilting point for converting plant available soil moisture back to total soil moisture. We estimate that the Russian and Mongolia SMDB observations have a maximum 0.05 vol/vol wet bias due to errors in the estimated wilting level, as 0.05 vol/vol is the maximum wilting level estimate error observed.

[29] Finally, there are various errors of representation that must be considered. These errors are related to differing SMDB and CLSM averaging scales. The CLSM represents average soil moisture over a 1- to 10,000-km^2 mesoscale catchment, while in most cases only one in situ observation from four point measurements averaged over a less than 0.2-km^2 area is available. A single point soil moisture measurement cannot possibly represent the soil moisture of a large catchment, especially given the well-known large spatially heterogeneity of soil moisture. This issue is somewhat lessened by the multiple point sampling method, but the scale mismatch remains a concern. An additional representation error can be attributed to differing soil moisture depths. The CLSM represents surface zone soil moisture in the top 2 cm while the SMDB observations are averaged over the top 5–10 cm depending on location.

3.4. SMMR Soil Moisture Climatology Error

[30] Figure 10 shows the climatological differences between the SMMR, CLSM, and SMDB surface zone soil moisture by season. Mongolian and Russian SMMR surface zone soil moisture is drier than SMDB, except in the northeastern Russian wet climate. Conversely, the Chinese SMMR surface zone soil moisture is wetter for all seasons. The east Eurasian SMMR surface zone soil moisture is wetter than the CLSM, and drier in west Eurasia. Generally, SMMR is biased 0.05 vol/vol dry in dry climate and 0.1 vol/vol wet in wet climate regions, but with accurate seasonal variations. The largest SMMR bias was found in China and northeastern Russia, where precipitation and vegetation cover are also larger.

[31] Additional factors to consider when studying the discrepancy between SMMR and SMDB surface zone soil moisture include SMDB measurement error (reviewed earlier) and representation errors. The SMMR surface zone soil moisture estimate represents a 1-cm-deep average over a 625-km^2 area, whereas the 5- to 10-cm-deep surface zone SMDB observations represent the field scale at best. Influences from these factors likely affect the comparison between SMMR and SMDB but are not possible to quantify given the available data.

3.5. Toward Assimilation of Eurasian SMMR in the CLSM

[32] Our analysis indicates that the CLSM and SMMR surface zone soil moisture data contain both random and bias error as compared with our best available in situ observations. Therefore if SMMR is to be used to constrain the CLSM in a data assimilation procedure, then the predicted CLSM and SMMR errors to be used by the assimilation must be matched to the observed errors presented in this paper. Moreover, the significant CLSM and SMMR bias must be removed prior to assimilation, such that the observations are unbiased relative to the model. Bias must also be removed from the model's surface and root zone soil moisture output, such that the model is unbiased relative to observed soil moisture. An alternative approach may be to constrain CLSM changes in soil moisture rather than absolute values by using trends in SMMR observations, providing these trends are valid; Figure 6 shows that the SMMR soil moisture trend is similar to the SMDB trend. Using this soil moisture trend is a data assimilation challenge that we are currently investigating.

[33] The main objective of this study was to characterize the CLSM and SMMR error for data assimilation purposes. The study found that while on average the CLSM error was roughly the same magnitude as that for SMMR observations with an average of 0.1 vol/vol, this value had significant spatial and temporal variation, with times and locations when SMMR error was much less than CLSM error. It is at these times and locations that significant CLSM soil moisture prediction accuracy improvement is expected through assimilation of the SMMR observations. The challenge for data assimilation is to be able to accurately predict the complete spatial and temporal CLSM and SMMR soil moisture error variation determined by this study.

4. Conclusions

[34] The catchment-based land surface model (CLSM) and scanning multichannel microwave radiometer (SMMR) soil moisture estimation errors have been evaluated using long-term Soil Moisture Data Bank (SMDB) in situ soil moisture observations available for China (a strong monsoon climate), Mongolia (a dry climate), and Russia (a strong seasonal climate including heavy snow during winter). It was found that both the CLSM and SMMR observation errors have large spatial, temporal, and vertical variations. Generally, SMMR soil moisture estimates are biased but have accurate seasonal variations, while CLSM underestimates the seasonal soil moisture variation. In China, SMMR soil moisture estimates are wet biased while CLSM has limited vertical soil moisture variation. In Mongolia, both SMMR and CLSM soil moisture are dry biased, with the SMMR dry bias being smaller than the CLSM bias. There are many CLSM, SMMR, and SMDB soil moisture estimation deficiencies, including their disparate time and space representation, which may limit the application of these conclusions. Recently developed soil moisture data assimilation techniques can constrain land surface model predictions with remotely sensed soil moisture observations to give better surface and root zone soil moisture estimates. However, characterizing modeled and observed soil moisture errors is critical for data assimilation use in deriving climate prediction model initialization. This paper presents the errors in SMMR and CLSM soil moisture that need to be characterized by any assimilation scheme in order to produce accurate soil moisture estimates.

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