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Optimally Merging Precipitation to Minimize Land Surface Modeling Errors

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ABSTRACT

This paper introduces a new method to improve land surface model skill by merging different available precipitation datasets, given that an accurate land surface parameter ground truth is available. Precipitation datasets are merged with the objective of improving terrestrial water and energy cycle simulation skill, unlike most common methods in which the merging skills are evaluated by comparing the results with gauge data or selected reference data. The optimal merging method developed in this study minimizes the simulated land surface parameter (soil moisture, temperature, etc.) errors using the Noah land surface model with the Nelder–Mead (downhill simplex) method. In addition to improving the simulation skills, this method also impedes the adverse impacts of single-source precipitation data errors. Analysis has indicated that the results from the optimally merged precipitation product have fewer errors in other land surface states and fluxes such as evapotranspiration (ET), discharge R, and skin temperature T than do simulation results obtained by forcing the model using the precipitation products individually. It is also found that, using this method, the true knowledge of soil moisture information minimized land surface modeling errors better than the knowledge of other land surface parameters (ET, R, and T). Results have also shown that, although it does not have the true precipitation information, the method has associated heavier weights with the precipitation product that has intensity, amount, and frequency that are similar to those of the true precipitation.

1. Introduction

Precipitation and radiation are the most important input forcings driving land surface models (LSM), whereas land cover, soil properties, and topography are secondary effects that influence the partitioning of these forcings between canopy interception, soil layers, runoff, and atmosphere (Wei et al. 2008). Knowledge of temporal and spatial distributions of precipitation is crucial for producing realistic land surface simulations that enhance our understanding of hydrologic and atmospheric cycles. There are three main methods employed to acquire the precipitation information: ground observations (gauges and radars), numerical model simulations, and satellite-based techniques.

Gauges are regarded as the most reliable direct precipitation estimation method. However, they are unable to sample large-area spatial means because of sparse or nonexisting spatial coverage, are often subject to wind-induced undercatch, and have significant cold-season precipitation observation issues. In addition, gauges tend to be located at low elevation and in plain areas where precipitation is underestimated by missing the orographic-induced systems at higher elevations (Nijssen et al. 2001; Fekete et al. 2004).

Ground-based radar is a promising way to understand spatial precipitation characteristics, but the accuracy of radar-based precipitation estimates depends on numerous factors, including the radar reflectivity–rainfall rate relationship, terrain blockage, target distance from

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the radar, spurious echoes resulting from anomalous propagation of the radar beam, brightband contamination, and scatter from ground-clutter targets.

Precipitation forecasts by numerical models are not observed data, although they may assimilate observations such as radiosonde profiles, cloudiness, satellite temperatures, and so on. Numerical models may produce high-quality precipitation distributions in their analyses and short-range forecasts but less-skillful simulations over tropical areas (Arpe 1991; Mechoso et al. 2006). Dependent on the reality of the model physics, short-range forecasts may have some skill and smaller errors than satellite-based estimates during cool seasons at higher latitudes (Ebert et al. 2007); however, there are significant errors, particularly with convective precipitation (Dai 2006).

Satelliteborne precipitation estimates make use of the visible/infrared (VIS/IR) and microwave portion of the spectra with either active or passive instruments. VIS/IR-based observations, usually from geostationary platforms, have the frequent revisiting capability that measures the cloud-top temperature. However, VIS/IR-only-based precipitation products are biased significantly over areas with warm cloud top and over tropic and subtropic land areas where thick cirrus and multilayered clouds systems are still a challenge. Microwave-based products, from low-earth-orbiting (LEO) satellites, have limited temporal and spatial resolutions because of the technical inadequacy that hinders the deployment of microwave instruments on geostationary platforms. Microwave-based estimates are generated by using emitted or scattered radiation sourced from raindrops or the earth's surface, respectively. Emission- or scatter-based algorithms make use of emitted radiation by raindrops (land surface) over ocean (land) to estimate the precipitation amounts. Passive microwave-based products are good at detecting strong convective precipitation events but tend to miss shallow and warm rains (Tian et al. 2007).

However, owing to the unique ability to cover the globe, satellite-based precipitation products are highly desirable in hydrologic and atmospheric applications. Many LEO satellites have been launched over the last two decades, but not with optimal orbits, revisiting times, and/or spatial resolutions for monitoring precipitation at global scales. Many methods have been employed to merge satellite information into gridded precipitation products while taking advantage of their skills and minimizing their limitations: Climate Prediction Center Merged Analysis of Precipitation (CMAP; Xie and Arkin 1997); the Naval Research Laboratory (NRL) blended precipitation product (Turk and Miller 2005); Precipitation Estimation from Remotely Sensed Information using Artificial Neural Networks (PERSIANN; Sorooshian et al. 2000); Global Precipitation Climatology Project (GPCP) one-degree-daily precipitation estimates (1DD; Huffman et al. 2001); GPCP, version 2 (v2; Adler et al. 2003); Passive Microwave-Calibrated Infrared algorithm (PMIR; Kidd et al. 2003); GPCP Pentad (Xie et al. 2003); the Climate Prediction Center morphing method (CMORPH; Joyce et al. 2004); Tropical Rainfall Measuring Mission (TRMM) Multisatellite Precipitation Analysis (TMPA; Huffman et al. 2007); Global Satellite Mapping of Precipitation (GSMaP; Kubota et al. 2007); and Cooperative Institute for Climate Studies High-Resolution Optimally Interpolated Microwave Precipitation from Satellites (CHOMPS; Joseph et al. 2009).

Each of these datasets has its own advantages and disadvantages. To benefit from the strengths of each, it is crucial to delineate the weaknesses in terms of land modeling skill rather than comparison with limited gauge observations. There have been several studies focused on examining the error characteristics of precipitation products in terms of land surface modeling (Gottschalck et al. 2005; Tian et al. 2007; Turk et al. 2010). The need of methods to combine precipitation-related information from models, satellite, radars, and gauges is emphasized by Ebert et al. (2007). However, there has been no study that directly attempts to assign relative weights to different precipitation products with an autonomous procedure wherein a higher weight is given to products with more hydrologically relevant information.

This study has optimally merged different precipitation products and dynamically estimated the relative weights of each by minimizing the land surface modeling errors using the Nelder and Mead (1965) method with autonomous procedures. This study finds that optimally merging precipitation while simultaneously minimizing any surface parameter error [soil moisture (SM), temperature, runoff, or evapotranspiration (ET)] minimized errors in other LSM fluxes. Section 2 outlines the method, sections 3 and 4 present the results and discussion, and section 5 summarizes the conclusions.

2. Method

Different precipitation datasets have been optimally merged by assigning different weights at each time step to each product with an autonomous process using the National Centers for Environmental Prediction (NCEP)–Oregon State University–U.S. Air Force–National Weather Service Office of Hydrologic Development (or "Noah") LSM combined with the Nelder–Mead method to minimize modeling errors. The approach and method will be introduced in four sections: comparison of the merged precipitation products (section 2a), description of the study area and input model datasets (section 2b), the Nelder–Mead technique and optimization procedure (section 2c), and experiments performed to evaluate the capabilities of the method (section 2d).

a. Precipitation products

Precipitation products were initially intercompared to delineate the differences in the amount of rain each produced in time and space. The intercompared products included

1) TRMM 3B42, a microwave and infrared merged satellite-based product (Huffman et al. 2007),
2) PERSIANN, a geosynchronous satellite–based product using longwave IR imagery with an artificial neural network–based technique (Sorooshian et al. 2000),
3) NRL, a geosynchronous satellite–based product blended with passive microwave satellite data (Turk and Miller 2005),
4) NCEP Stage IV, a gauge-corrected radar product (Fulton et al. 1998),
5) the Rapid Update Cycle 20-km (RUC 20) model-based product (Benjamin et al. 2002), and
6) North American Land Data Assimilation System (NLDAS) precipitation dataset, a gauge-based radar-corrected product (Cosgrove et al. 2003).

Daily precipitation comparisons were done for 2006 using the following statistics: the annual cumulative precipitation, percentage of the precipitating bins (defined in this study as frequency), and the ratio of the annual cumulative precipitation amount to the percent of precipitating bins (a measure of intensity). In frequency estimations, events greater (smaller) than 0.1 mm day^{-1} precipitation were assumed to be precipitating (nonprecipitating). For rain-frequency estimation purposes, missing values are assumed to have a rain frequency that is consistent with the available data. However, this assumption does not present any problem unless there would be any information available that missing days rain characteristics that are significantly different than those of nonmissing data.

b. Study area and the model datasets

The Noah LSM simulations were performed from April to October 2006 over the well-studied Red–Arkansas basin area located from 107.0° to 91.0°W and from 32.0° to 40.0°N. All simulations in this study were forced by NLDAS data (temperature, wind, relative humidity, pressure, and radiation), where the precipitation data were the only input data that varied among different runs. NLDAS precipitation was used to force the control runs to obtain reference values (considered to be "ground truths" solely for the purpose of this optimization experiment) that were used to estimate the errors of individual simulations and merging simulations. The RUC 20, TRMM, PERSIANN, NRL, and Stage IV products were utilized for individual simulations, and the merged product of these five precipitation data was used for optimization simulations.

Initial conditions for all simulations were obtained after spinning up the model for 5 yr using NLDAS forcing (including the precipitation) data. For the simulations forced by the merged precipitation, in the case that any product had any missing data in any time window, that product was not included in the simulation for that particular time window. On the other hand, for the simulations forced by individual precipitation products, missing values were assumed to be 0. Ignoring the missing data creates an artificial dry bias in these simulations; however, this bias does not affect the conclusions of this study.

c. Nelder–Mead optimization process

At each time step, the objective was to find the n optimum weights corresponding to each precipitation product; the sum of weighted precipitations (the merged precipitation), along with the other NLDAS datasets, was used to force the Noah model to estimate surface flux/states. Errors were calculated by taking the absolute-value difference of these calculated surface parameters from the control-run surface parameters. The only known value at each time step is the resulting error of the merged precipitation, where n weights are the unknown values to be found. Thus, the error minimization at each time step involves more unknown variables than the known, which makes the system highly underdetermined. To make the system determined or overdetermined, the weights were kept constant over a time window and the total error over this interval was minimized.

The Nelder and Mead (1965) method was used to determine the optimum weights (Fig. 1). The weights are optimum in the sense that the weighted sum of precipitation values results in the smallest simulation error at each time window. To merge n different precipitation products, $2n + 1$ initial sets of weights were created, with the assumption that no one product was superior to the rest. Among these sets of weights, $n + 1$ sets were created randomly (from 0 to 1), and the remaining n sets were created by assigning 1 to each product separately and assigning 0 to the remaining products. Calculating the errors for each $2n + 1$ set of weights, the worst set (yielding the highest error) was replaced by a new set of weights. This replacement was performed by choosing α, β, and γ (reflection, contraction, and expansion) constants as 1.0, 0.5, and 2.0, respectively, as suggested by Nelder and Mead (1965). The replacement was repeated

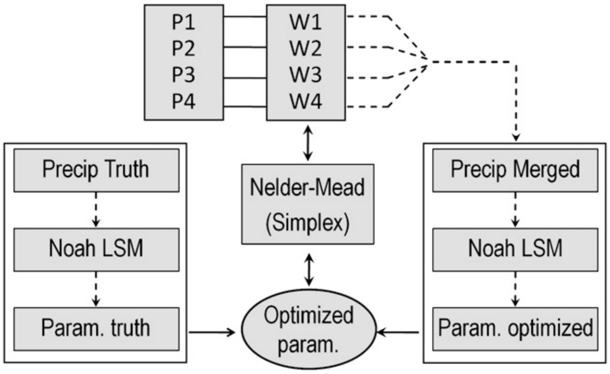

FIG. 1. Schematic representation of the method: P1, P2, and Pn are the first, second, and *n*th precipitation products to be merged, and W1, W2, and Wn are the associated precipitation weights that vary for each time window.

until either the desired accuracy (10^{-7}) was reached or the maximum number of iterations (100) was achieved. Considering that each initial random set of weights would result in separate minima, this initialization process was repeated 50 times. Among these iterations and initializations, the set with the minimum absolute error was chosen as the final weights. After obtaining these optimum weights that give the desired accuracy, the Noah model proceeds to the next time window, for which the same Nelder–Mead cycle is performed independent from the previous window.

The weights were constrained at any time window in which their sum cannot exceed 1 and individual weights cannot become negative. These constraints were imposed with the assumption that all precipitation products were not biased at the same time.

d. Experiments performed to evaluate the method

Using synthetic ground-truth data (i.e., the control simulation) provided more options for verification through additional variables. The performance of the method was evaluated for all land surface fluxes (total evapotranspiration, skin temperature *T*, surface runoff, and volumetric soil moisture content) for four different scenarios. This provided a complete analysis rather than comparisons with limited in situ ground measurements (e.g., soil moisture only), which in turn have inherent observational/sampling errors. In the first scenario, we have evaluated the performance change resulting from using different land surface parameters as truth. The second scenario assessed the benefit of adding more precipitation products. In the third scenario, the effect of time-window width was explored. The last scenario investigated the impact of using the merging method with noncalibrated models.

1) OPTIMIZATION VARIABLE EFFECT

In the first experiment, the optimization variable effect was explored with five separate sets of simulations constrained by top-layer soil moisture, total evapotranspiration, surface skin temperature, surface runoff, and multiobjective errors, where multiobjective minimization was chosen as the normalized summation of the soil moisture, evapotranspiration, and temperature errors. The normalization of units was performed to prevent any parameter error from dominating the cumulative error. Normalization constants were chosen by setting the magnitude of the normalized annual cumulative errors equal for these three parameters for a chosen subset of simulations. After running these simulations, these constants were chosen as 1000, 40, and 1 for soil moisture, temperature, and evapotranspiration errors, respectively. For all simulations, errors were summed over the time domain and averaged over the spatial domain.

2) MERGING BIASED PRECIPITATION PRODUCTS

In the second experiment, the effect of merging biased precipitation products on the method was explored. Two artificially created precipitation products using random numbers and climatological data also were merged along with the five precipitation products described in the first experiment. The rainfall frequency of the random precipitation product was taken from the NRL product, for which the magnitudes were assigned with absolute value of random numbers with normal distribution (0 mm h^{-1} mean and 10 mm h^{-1} variance). To avoid assigning artificial skill to the random product, the ratio of rainy days (defined in this study as frequency) was not taken from the truth (NLDAS) precipitation. Here, NRL was used; however, it could have been taken from any other product as well. A random product was then created by replacing the precipitation magnitude of NRL (for rainy days) with random numbers.

On the other hand, the climatological precipitation product had the same annual cumulative precipitation as the control (NLDAS) precipitation but was distributed equally over the entire year (~0.08 mm h^{-1}). The results of merging these seven precipitation products were compared with the optimization results obtained by merging five precipitation products.

3) EFFECT OF TIME-WINDOW WIDTH

In the third experiment, the effect of the time-window width was explored, where the precipitation weights are estimated by minimizing the errors over this window. The window width was altered from 5 to 72 h for 11 different scenarios to find the optimum interval with the

TABLE 1. Annual cumulative precipitation, precipitating pixel percentage (>0.10 mm h^{-1}), and precipitation intensity comparison for 2006 over the study area located from 107.0° to 91.0°W and from 32.0° to 40.0°N.

	RUC	TRMM	Stage IV	PERSIANN	NRL	NLDAS
Precipitation (mm yr^{-1})	630	610	682	1235	1007	722
Precipitation >0.1 (%)	15.9	5.7	11.4	9.1	9.6	18.9
Precipitation [mm yr^{-1} (%)$^{-1}$]	39	107	60	136	105	38

smallest errors. In all scenarios, soil moisture was selected as the parameter to constrain the simulations in which only five precipitation products were merged. The only difference between these 11 scenarios is the window width over which the precipitation products are optimally merged.

4) EFFECT OF MODEL CALIBRATION ON THE MERGING METHOD

In the fourth experiment, the effect of model calibration on the merging method was investigated by changing the soil-type parameterization of the model. The ground-truth data were obtained using soil type 2 (same as in previous scenarios), whereas the merging and individual precipitation simulations were performed using soil type 1. As in the previous experiments, the forcing data (except for the precipitation) were kept unchanged to assess the sensitivity of the total errors to model parameterization changes.

3. Results

Intensity comparisons were performed to determine the differences between precipitation products before merging (Table 1). The third row in Table 1 shows the average amount of precipitation each product would have captured with the assumption that it rained continuously 1% of the year (3.65 days) and that each product had identified the event as precipitation. Twofold–threefold intensity differences exist between the satellite-based products (TRMM, PERSIANN, and NRL) and the model/gauge- and radar-based products (Table 1). In general, satellite-based products had a tendency to relate similar events to more precipitation amounts than did the radar-based product, whereas the radar-based product related similar events to more precipitation amounts than did the model/gauge-based product.

Regardless of the optimization parameter, merging precipitation data with the above-described method gave simulation errors that are smaller than the errors forced by individual precipitation products. The errors were not only smallest in the optimized parameter field but also in the other fields (Table 2). There were two exceptions to this result:

1) The runoff simulation errors forced by RUC and TRMM products were smaller than the runoff errors of optimally merged simulations constrained by temperature.
2) The total precipitation error, when optimally merged simulations were constrained by runoff, was the highest among the simulations forced by individual precipitation products (Table 2).

The errors of evapotranspiration and temperature were lower when merged simulations were constrained by soil moisture than when constrained by evapotranspiration and temperature, respectively. Optimization simulations constrained by soil moisture yield the smallest errors (except runoff). As stated before and as expected, optimized simulations yielded better results for all parameters than did the set of simulations forced by individual precipitation sources. Runoff proved to be the most inefficient parameter to be optimized.

TABLE 2. Simulation errors of optimally merging simulation errors and run errors forced by individual precipitation products from 1 Apr to 31 Oct 2006. Note that merging simulations were constrained by surface runoff, ET, *T*, SM, and multiobjective parameter error, whereas individual simulations were forced by RUC, TRMM 3B42, PERSIANN, NRL, and Stage IV separately. Each column represents the errors of the simulation that were forced by either merged precipitation product or any of the individual precipitation products listed above.

	Merged precipitation optimization parameter					Individual precipitation sources				
Error parameter	Runoff	ET	*T*	SM	Multiobjective	RUC	TRMM	PERSIANN	NRL	Stage IV
Runoff (mm)	15	21	39	21	20	24	36	67	84	41
ET (W m^{-2})	30	24	29	16	20	39	40	47	45	38
T (°C)	0.63	0.49	0.49	0.26	0.40	0.74	0.84	0.93	0.90	0.78
SM (%)	0.036	0.030	0.036	0.013	0.022	0.05	0.051	0.06	0.057	0.049
Precipitation (mm)	278	185	133	99	154	212	228	267	264	202

TABLE 3. Simulation error comparison of optimally merging five precipitation products (Pnum5: merging RUC, TRMM, PERSIANN, NRL, and NCEP Stage IV), merging seven precipitation products [Pnum7: five products plus artificially created climatological data (''clim'') and random precipitation products (''ran'')], and seven simulations that were forced by individual precipitation products from 1 Apr to 31 Oct 2006.

	Merged precipitation product		Individual precipitations						
Error parameter	Pnum7	Pnum5	RUC	TRMM	PERSIANN	NRL	Stage IV	Clim	Ran
Runoff (mm)	20	21	24	36	67	84	41	19	274
ET (W m^{-2})	12	16	39	40	47	45	38	38	74
T (°C)	0.15	0.26	0.74	0.84	0.93	0.90	0.78	0.78	1.64
SM (%)	0.004	0.013	0.05	0.051	0.06	0.057	0.049	0.061	0.113
Precipitation (mm)	54	99	212	228	267	264	202	198	1082

Two artificially created precipitation (random number and climatological based) products were merged together with the five observed precipitation products. Merging these seven products not only resulted in smaller simulation errors than for any model runs forced by individual precipitation products, but it also improved the errors when compared with the simulations merging five products. Adding the artificial precipitation products improved the efficiency of the method in all fields that were tested (Table 3). This improvement can be explained by the ''stopped clock'' analogy that even a stopped clock shows the correct time twice per day. Artificially created products were omitted by the method by imposing 0 weights when they do not have any skill (which happens most of the time), and they slightly improved the results when they showed the truth just because of random chance (like the stopped clock). On the other hand, the runoff errors of the simulations forced by climatological precipitation were the smallest among all runs. One possible explanation for this artificial skill could be the hydrograph differences between climatological and other precipitation products. For any of the precipitation products, a temporally missed peak discharge would be counted twice (first for missing the actual peak and second for misguessing the peak), whereas the climatological product would have only a single peak error (not being penalized the second time for misguessing the peak).

Cumulative errors were minimized over a time window, where the total error depends also on the selected window width. Separate merging simulations constrained by soil moisture errors with various time-window widths were performed to determine the optimum temporal width that leads to the smallest annual cumulative error. Window widths of 5–8 h were found to generate the smallest LSM errors (Table 4), where in general the errors increased with an increase in the time-window width (Table 4).

The merging method with a perfect parameterization scenario was evaluated, where both simulations and reference (ground) truth were created using the same model parameters. To see the effects of the parameterization on the results, the soil type was changed to soil type 1 (coarse, loamy sand) in the merging simulations where the ground truth data were simulated by using soil type 2 (medium, silty clay loam). The soil-type change increased all the errors under this imperfect soil parameterization scenario (Table 5). The evapotranspiration, skin temperature, and soil moisture errors of the merging simulations remained smallest when compared with the errors of simulations with individual precipitation sources. On the other hand, the errors in runoff and cumulative precipitation fields of the merging simulations were not improved with respect to the errors of the simulations forced by individual precipitation products. The soil parameterization change also resulted in

TABLE 4. Simulation errors constrained by SM that the model runs were forced by precipitation obtained by merging five precipitation products at various window widths from 1 Apr to 31 Oct 2006. Note that the W values at the top of each column represent the temporal width of the time window in hours for which the errors were minimized.

	Time-window width (h)										
Error parameter	W5	W6	W7	W8	W9	W12	W18	W24	W36	W48	W72
Runoff (mm)	20.1	20.7	20.9	21.2	21.7	22.2	23.6	25.1	26.3	27.6	34.0
ET (W m^{-2})	15.6	16.0	16.2	16.5	16.7	17.2	18.2	18.5	19.3	20.4	23.8
T (°C)	0.25	0.26	0.27	0.27	0.28	0.29	0.32	0.32	0.35	0.37	0.43
SM (%)	0.013	0.013	0.013	0.014	0.014	0.015	0.017	0.018	0.019	0.021	0.027

TABLE 5. Simulation errors forced by different precipitation products, where the control simulations were run by assigning soil type as 2 and were forced by NLDAS precipitation. Merging-simulation errors were constrained by SM with merging five precipitation products. Note that the soil parameter for the bottom rows was changed to soil-type 1, whereas the parameter for the top rows was soil type 2.

	NLDAS	Merged	RUC	TRMM	PERSIANN	NRL	Stage IV
Soil 2							
Runoff (mm)	0.0	21	24	36	67	84	41
ET (W m^{-2})	0.0	15	39	40	47	45	38
T (°C)	0.0	0.26	0.74	0.84	0.93	0.90	0.78
SM (%)	0.0	0.013	0.05	0.051	0.06	0.057	0.049
Precipitation (mm)	0.0	99	212	228	267	264	202
Soil 1							
Runoff (mm)	15.4	20	19	21	26	29	22
ET (W m^{-2})	7	34	41	43	47	47	40
T (°C)	0.73	0.91	1.08	1.15	1.16	1.16	1.10
SM (%)	0.086	0.052	0.104	0.108	0.084	0.082	0.101
Precipitation (mm)	0.0	99	212	228	267	264	202

smaller soil moisture errors for merging runs than in the simulations with NLDAS precipitation (true precipitation), where the temperature, evapotranspiration, and runoff errors were still higher in the merging simulations.

Cumulative weights were estimated from simulations that merge five precipitation products by minimizing the soil moisture errors at each time window (Fig. 2). Overall, RUC data cumulative weights were heavier than the other precipitation products. The cumulative weight trends in Fig. 2 were similar for other merging simulations with different optimization constraints (figures not shown). In addition to this trend, cumulative weights also showed seasonality; in some seasons, some precipitation products were favored more than other products. For example, TRMM had the largest weights during April, May, and June, whereas RUC had the largest weight during July, August, September, and October.

4. Discussion

Similarities in precipitation characteristics among satellite-based products may not be obvious by looking only at the rainfall amount or only at the rainfall frequency. The intensity comparison analysis showed that satellite-based precipitation products have a tendency to assign heavier precipitation amounts on similar events than do radar- and model/gauge-based products (Table 1). This result 1) is consistent with Dai (2006), showing that models produce lighter precipitation than satellite data, 2) agrees with Sun et al. (2006) that models tend to precipitate too frequently even though they may have the same amounts, and 3) is consistent with Tian et al. (2007) that satellite-based measurements detect stronger events than do ground-based measurements. The intensity differences suggest that different platform (satellite, model, gauge/radar) precipitation products have unique characteristics, and their optimal merging could have a potential for a better modeling skill than any single product alone.

Simulations that are forced by optimally merged precipitation and constrained by various parameters resulted in smaller errors than did simulations forced by individual precipitation products. The knowledge of the true soil moisture information minimized errors better than other parameters. This could be due to soil moisture being more closely related to both water and energy balances with a land surface process memory than other parameters; that is, evapotranspiration and runoff are fluxes, they do not have any memory, and temperature is not as directly related to water balance as soil moisture.

Artificial precipitation products improved the land model simulations; merging seven precipitation products resulted in smaller errors than both merging five products and individual simulations in all fields. This improvement can be explained by the stopped clock analogy that even a stopped clock shows the correct time twice a day. Artificially created products were omitted

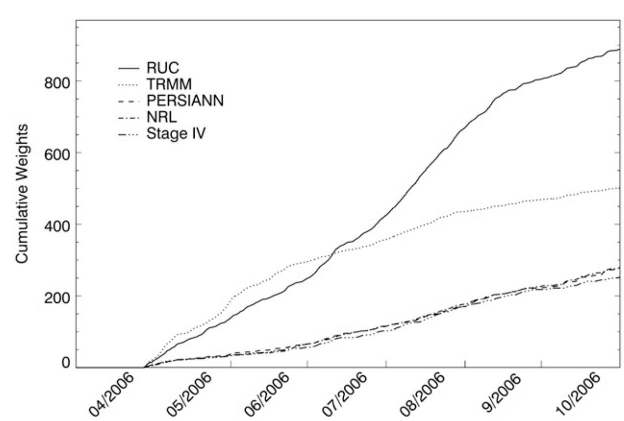

FIG. 2. Cumulative weights for five precipitation products merged by constraining the SM error.

by the methodology with imposing 0 weights when they do not have any skill (which happens most of the time), and they slightly improved the results when they showed the truth just because of random chance (like the stopped clock). The runoff errors of the simulations using climatology-based precipitation were an exception to this explanation (Table 3); they were the smallest among all runs. One possible explanation for this artificial skill could be the hydrograph differences between climatological and other precipitation products. For any of the precipitation products, a temporally missed peak discharge would be counted twice (first for missing the actual peak and second for misguessing the peak), whereas the climatological product would have only a single peak error (not being penalized the second time for misguessing the peak). Merging simulation errors increased as the window width was increased (Table 4). However, no clear threshold was found to conclude that there is a window-width limit at which the introduced merging algorithm skill would be diminished significantly. There is a trade-off between the number of precipitation products to be merged and the window width (number of time steps). Overall, merging more precipitation resulted in simulations with smaller errors (Table 3), whereas to keep the system from being overdetermined a wider time window is needed; however, this reduces the accuracy of the method. In addition, having the same precipitation values among the merged precipitation products can reduce the dimensionality and cause the system to be locally underdetermined. Hence, it is advised to have a greater window width (number of time steps) than the number of precipitation products to be merged. Error sensitivity studies are needed before identifying an optimum number of precipitation products and/or an optimum window width.

Imperfect land model parameterization greatly alters the merging algorithm skill and the resulting errors. In the absence of a good model parameterization, perfect observations still resulted in high errors (Table 5). Well-calibrated models are essential for this optimal precipitation-merging technique to be successful.

Using synthetic ground-truth data, merging simulations assigned heavier weights to RUC data (Fig. 2), perhaps because of the similarity between the RUC and the NLDAS (control) precipitation intensities (Table 1). Although the merging technique does not have the knowledge of the true precipitation, it had associated heavier weights with the precipitation product that has precipitation intensity, amount, and frequency that are similar to those of the truth run. The resulting cumulative weights showed seasonality (Fig. 2) in that TRMM had heavier weights in spring, whereas RUC had higher weights in summer and autumn. This analysis also enables further accuracy assessment of different precipitation products in time.

One of the limitations of this study is the model parameter saturation levels. Once the optimized parameter reaches the prescribed saturation level of the model, the assigned weights and the merged precipitation lose their meaning. For merging simulations that are constrained by soil moisture, this saturation happens frequently during the snowmelt period. Therefore, the simulations in this study were performed from April until October, when soil moisture saturation is not an issue.

To analyze whether the merged product can be used as a stand-alone precipitation product in hydrological models, further nonsynthetic simulations are needed. Nevertheless, using synthetic data, this study showed that any independent estimate of ground truth in any parameter can be translated into another flux/state by merging different precipitation data. It is important to stress here that the ground-truth information is a critical element in this method. Given the current and future availability of relatively routine observations of some relevant land surface parameters (such as remotely sensed soil moisture, land surface temperature, or evapotranspiration), the presented method can be adapted to constrain the land surface model so as to improve the terrestrial water and energy cycle simulation skills as well as to compare the ability of different precipitation products to help to improve the simulation skills in a land surface modeling framework.

5. Conclusions

Each precipitation dataset has its own advantages, limitations, and characteristic precipitation features (amount, frequency, and intensity). In this study, we have introduced a method to improve LSM water and energy balance skill by merging these independent precipitation estimates with the goal of preserving their advantages and minimizing their weaknesses with respect to LSM predictions. It has been found that optimally merging precipitation products minimized errors in all fields and resulted in smaller error than any individual product alone. Overall, minimizing the soil moisture errors improved LSM skills better than did other parameters. The knowledge of true soil moisture is more important than other land surface parameters to improve land water and energy balances.

The effect of imperfect model soil parameterization on LSM skills was also examined. The precipitation-merging method requires good model parameter calibrations to produce skillful simulations using observations. In the absence of good model parameterization, perfect observations still yield high errors.

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