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Research papers

A Monte Carlo-based multi-objective optimization approach to merge different precipitation estimates for land surface modeling

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ABSTRACT

Precipitation is a fundamental forcing variable in land surface modeling, controlling several hydrological and biogeochemical processes (e.g., runoff, carbon cycling, evaporation, transpiration, groundwater recharge, and soil moisture). However, precipitation estimates from rain gauges, ground-based radars, satellite sensors, and numerical models are affected by significant uncertainties, which can be amplified when exposed to highly non-linear land model physics. This work tests the hypothesis that precipitation data from different sources can be optimally merged to minimize the hydrologic response error in surface soil moisture simulations and maximize their correlation with ground observations (multi-objective optimization problem). This hypothesis is tested by merging three precipitation products (one satellite product, a ground-based dataset, and model-base estimates) that force a land surface model trained to minimize soil moisture anomalies. A Monte Carlo-based algorithm is developed to generate weights to linearly combine these precipitation datasets. Optimal combinations of weights are identified by minimizing the errors and maximizing the correlation between the model simulated soil moisture and the satellite-based SMOS soil moisture product. The proposed methodology has been tested over Oklahoma where high-quality, high-resolution (independent) ground-based soil moisture observations are available for validation purposes. Results show that there exist optimal combinations of these precipitation datasets that provide smaller errors and larger correlation coefficients between modeled soil moisture estimates and ground-based data with respect to forcing the land surface model with single precipitation datasets. Specifically, combining three precipitation products from different sources provides the largest correlation coefficient and the lowest root mean square error at several locations across Oklahoma.

1. Introduction

Precipitation is the most influential meteorological forcing variable for land surface modeling, providing moisture for processes such as runoff, biogeochemical cycling, evaporation, transpiration, groundwater recharge, and soil moisture. Knowledge of the precipitation characteristics and patterns is crucial for understanding the complicated interactions among small- and large-scale components within the water and energy cycles. The spatial and temporal variability of precipitation significantly impacts land surface state variables and fluxes (Gottschalck et al., 2005).

Accurate precipitation information at fine space and time scales has been shown to improve our ability to simulate land surface hydrological processes and states, including extreme events, such as floods and droughts (Scofield and Kuligowski, 2003). However, different types of precipitation estimates (ground-based estimates from rain gauges, weather radars, space-based estimates from satellite sensors, and numerical model-based estimates) might have variable accuracy and, thus, distinct hydrological utility in different regions (Maggioni and Massari, 2018).

Rain gauges are the only direct approach to measure precipitation. Although they provide high temporal resolutions, obtaining a spatially representative estimate requires a very dense network (Kidd et al., 2012). Weather radars overcome this issue, but their observational accuracy is affected by rain-path attenuation, lack of uniqueness in the reflectivity-to-rain rate relationship, calibration issues, contamination by ground returns, sub-resolution precipitation variability, and complex terrain effects (Borga et al., 2000; Krajewski et al., 2006; Marzano et al., 2004). Both rain gauges and radars require considerable financial and technological investment for operational and maintenance cost.

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Satellite precipitation products are available globally and are derived from a range of satellite sensor observations. Most algorithms combine infrared (IR) imagery with passive microwave (PMW) observations (e.g., Huffman et al., 2007, 2014; Joyce et al., 2004). On one hand, IR images are valuable because heavier rainfall is usually associated with larger and taller clouds with colder tops. On the other hand, emissions from raindrops cause an increase in the PMW radiation and the scattering due to precipitating ice particles produces a decrease in PMW radiation. The blending of complementary information from IR radiances and PMW observations has been proven successful in rainfall estimation (Turk et al., 1999). Nevertheless, satellite estimates can be affected by detection uncertainties, biases, and random errors, which depend on the accuracy of the remote sensor (retrieval error) and the lack of continuity in the coverage by low earth-orbiting satellites (sampling error; Bell et al., 2000). The performance of satellite precipitation products is influenced by seasonal precipitation patterns, storm type, and background surface (Ebert et al., 2007; Maggioni et al., 2016; Oliveira et al., 2016, 2018).

Numerical Weather Prediction (NWP) models represent a valid alternative to estimate global precipitation. NWPs are more accurate when predicting large-scale organized systems than more localized events, whose spatial and temporal variability cannot be explicitly captured by the model resolution. Moreover, model re-analysis precipitation products are the only available choice above 60° latitude and a valuable option above ~35° latitude, where they ingest a high number of ground observations. In summary, it is difficult to determine which precipitation product is optimal for a certain region and a certain season, due to inconsistency among different datasets. Moreover, obtaining precipitation information at the required accuracy level for hydrological applications and water resources management still remains a challenge.

There have been a number of attempts to improve the accuracy of precipitation products by merging surface gauge measurements with satellite-based estimates (Smith et al., 2006; Huffman et al., 2007; Tian et al., 2010; Tobin and Bennett, 2010). For instance, the recently developed Multi-Source Weighted-Ensemble Precipitation (MSWEP; Beck et al., 2017) is a global precipitation dataset that spans from 1979 to 2016 and has a 0.1°/3-hourly spatial/temporal resolution. MSWEP not only blends information from gauge and satellites, but also with model reanalysis and covers the entire globe, including the oceans. Similarly, other attempts successfully used high-resolution simulations from models, like the Weather Research and Forecasting Model (WRF), for removing satellite rainfall biases in mountainous areas, using a probability density function matching approach (Zhang et al., 2013, 2016; Nikolopoulos et al., 2015). More recently, Bhuiyan et al. (2018) proposed the use of a nonparametric, tree-based, quantile regression forest model to merge satellite and re-analysis precipitation products with an air temperature dataset, satellite soil moisture data, and a terrain elevation dataset. The merged product was used to force a hydrological model across the Iberian Peninsula and it was shown to reduce both systematic and random errors in streamflow simulations with respect to the individual precipitation products.

Most merging techniques have been calibrated and evaluated to a precipitation ground reference (e.g., rain gauge observations), but only a few studies calibrated the merging algorithm based on the hydrological response. For instance, Chiang et al. (2007) used the recurrent neural network method to merge satellite and rain gauge estimates to improve the accuracy of streamflow simulations for flash flooding modeling. Yilmaz et al. (2010) developed a merging method for multiple types of precipitation estimates by minimizing land surface modeling errors using the downhill simplex method. Their analyses have indicated that results from the optimally merged precipitation product present lower errors in land surface states and fluxes such as evapotranspiration, discharge, and skin temperature than do simulation results obtained by forcing the model using each precipitation product individually.

The main objective of this work is to develop an optimal precipitation dataset that combines the advantages of high-resolution products for improving land surface modeling skills. We focused here on improving a key land surface state – soil moisture – that determines the critical surface fluxes and water balance. Surface soil moisture controls the partitioning of available energy incident on the land surface, and, therefore, it is a fundamental variable in the water cycle that impacts local weather, such as cloud coverage and precipitation, and hydrological parameters, such as runoff and evapotranspiration (Betts and Ball, 1998).

Our hypothesis is that a combination of precipitation data from different sources optimized to minimize the hydrologic response error (soil moisture, runoff, evapotranspiration, etc.) has the potential to improve land surface model forecast skills. Ultimately, this solution will optimally merge a wide range of precipitation information from satellites, radars, gauges, and models trained to minimize errors in land model evaporation, runoff, and soil moisture response resulting in coupled forecast improvements in convection, clouds, precipitation, boundary layer processes, and atmospheric circulation. This will be possible if using the optimized land surface variables/fluxes to feed back into atmospheric models for improved meteorological forecasts. The hypothesis is tested here by merging three precipitation products (from satellite, ground-based, and models) trained to minimize satellite soil moisture (i.e., SMOS) anomalies. We conducted an uncoupled demonstration over Oklahoma where a high-quality, high-resolution, independent reference of ground-based soil moisture observations is available for validating the proposed methodology. The proposed methodology has been examined over Oklahoma where high-quality, high-resolution (independent) ground-based soil moisture observations are available for validation purposes. The next section describes all precipitation and soil moisture datasets, the land surface model, and the proposed methodological approach. Results are presented and discussed in Section 3, whereas Section 4 summarized the main conclusions, highlights the limitations of this work, and suggests future research directions.

2. Methodology

This work proposes a novel method to improve land surface model skills by optimally merging precipitation estimates from different data sources to minimize the land surface simulation errors (Fig. 1). Specifically, three precipitation estimates (from satellite, ground

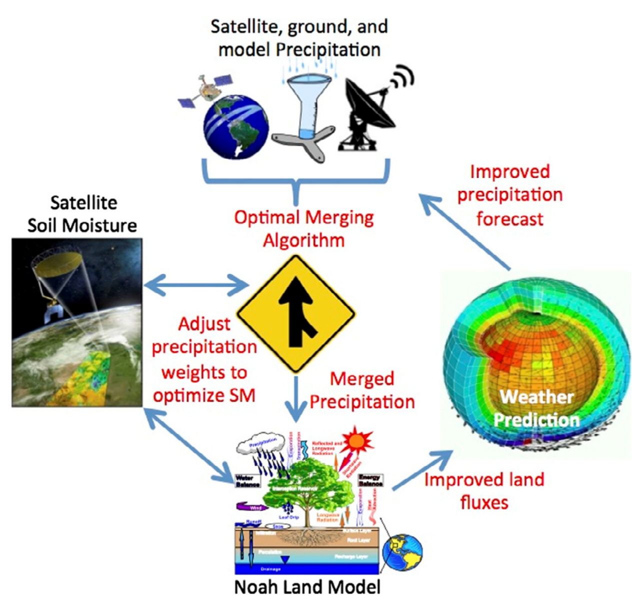

Fig. 1. The methodological approach.

Table 1
Dataset summary.

Dataset	Observation	Type	Spatial Resolution	Temporal Resolution
CMORPH	Precipitation	Satellite	8 km	30 min
NLDAS	Precipitation	Ground Radar + Model	12.5 km	1 h
NAM	Precipitation	Model	12 km	6 h
SMOS	Soil Moisture	Satellite	25 km	daily 3-days running mean
MESONET	Soil Moisture	Ground Observations	–	30 min

observations, and models) are merged to optimize surface soil moisture model estimates. The experiment is conducted over Oklahoma during 2014, using the Community Noah land surface model that integrates atmospheric forcings with land and vegetation parameters into a state-of-art land surface modeling system. Precipitation and soil moisture datasets (summarized in Table 1), the Noah land surface model, and the proposed approach adopted to achieve the above objectives are described next.

2.1. Precipitation dataset

Firstly, the National Oceanic and Atmospheric Administration (NOAA) Climate Prediction Center MORPHing (CMORPH; Joyce et al., 2004; Joyce and Xie, 2011) product was chosen as the satellite-based product in this study. The CMORPH algorithm integrates infrared observations from geostationary satellites with passive microwave data in two steps: 1) cloud system advections vectors from 30-minute intervals are generated; and 2) at each location a time-weighted linear interpolation is performed at consecutive times between the microwave sensor overpasses. CMORPH is available every half hour on a grid with a spacing of ~8 km.

Secondly, a ground-based precipitation estimate was considered. The multi-institutional North American Land Data Assimilation System (NLDAS) provides retrospective and real time atmospheric forcing estimates to support land surface modeling. Hourly precipitation data are derived from a combination of 1) daily National Center for Environmental Prediction Climate Prediction Center (CPC) gauge-based precipitation analyses and 2) hourly National Weather Service Doppler radar-based (WSR-88D) precipitation data, which are used to temporally disaggregate the daily CPC analyses (Cosgrove et al., 2003). This process exploits the accuracy of the rain gauge observations and the temporal and spatial resolution of a radar-based dataset and it is considered to be one of the highest quality precipitation products over CONUS.

Thirdly, the model based precipitation estimates are obtained from the North American Mesoscale Forecast System (NAM) project (Rogers et al., 2009). The NAM model is run four times daily and consists of two components: the NOAA Environmental Modeling System (NEMS) version of the Non-Hydrostatic Multi-scale Model in B-grid (NMMB) and the NCEP regional Grid-Point Statistical Interpolation (GSI) analysis. The NAM model is initialized with a 12-h run of the NAM Data Assimilation System, which runs a sequence of four GSI analyses and 3-h NEMS-NMMB forecasts using all available observations to provide a first guess to the NAM analysis. The NCEP High-Resolution Window Forecast System (HIRESW) consists of daily runs of the NEMS Non-hydrostatic Multiscale Model on B-grid and the NCAR Advanced Research WRF (ARW) at ~3–4 km resolution. Hereinafter we will refer to NAM as to indicate the NAM precipitation dataset.

Maps of 2014 means and standard deviations of the three precipitation products are shown in Fig. 2. Oklahoma is characterized by a wetter area in the southeastern region with a drying gradient moving towards the panhandle. The yearly precipitation variability is low across the study region, with higher standard deviations in the wetter area. The spatial distribution of rainfall is similar in the three dataset but, on average, NAM shows higher rainfall and higher variability compared to CMORPH and NLDAS, particularly in the wetter southeastern region. The differences in the three datasets prove the inherent different information that each one of them provides.

2.2. Soil moisture dataset

The Oklahoma Mesonet is an observational network of 115 meteorological stations across Oklahoma that collects, archives, and quality controls atmospheric, surface, and soil data in real time since 1994 (Brock et al., 1995). Although several variables are monitored at these stations, only soil moisture measurements are used here. Soil moisture (soil water potential) is recorded at four depths (5, 25, 60, and 75 cm) every 30 min. The high quality of this dataset has been proven in several applications, spanning from numerical weather predictions to fire monitoring (Carlson and Burgan, 2003) and estimation of downward longwave radiation (Sridhar and Elliott, 2002). The Mesonet stations used in this study are highlighted in Fig. 3. This ground-based soil moisture dataset is used as a benchmark for comparisons with model simulated soil moisture to evaluate the framework developed in this study.

However, the coverage of soil moisture ground observations is extremely limited. Satellite observations of microwave brightness temperature and backscatter can provide an estimate of soil moisture at large scales. Two recent satellite missions have the goal of measuring surface soil moisture globally. The NASA Soil Moisture Active Passive (SMAP) mission (Entekhabi et al., 2010), launched on January 31st, 2015, measures land surface brightness temperature, providing information on surface soil moisture (top 5 cm of the soil column). The usefulness of the SMAP-based soil moisture product is limited by its course resolutions (~36 km). The Soil Moisture and Ocean Salinity (SMOS; Kerr et al., 2010) is a European Space Agency (ESA) satellite launched in 2009 with the goal of monitoring surface soil moisture with an accuracy of 4% every three days. The calibration of the SMOS retrieval algorithm is based on in situ experiments and modeling activities that do not include the Mesonet network observations. A study by Kerr et al. (2012) compared area averaged SMOS soil moisture with independent ground-based soil moisture in the Little Washita watershed in Oklahoma and found a good agreement between the two.

The SMOS soil moisture product is used in this work at its native resolution of 25 km as the reference to minimize the error in the model simulations of soil moisture. The choice of a satellite-based product as reference is due to its global availability, making the proposed methodology applicable anywhere around the world. Maps of the 2014 mean and standard deviation of this product are shown in Fig. 3. A wetter area is observed in the eastern part of Oklahoma, which also presents the larger variability (higher standard deviation). This is consistent with the precipitation spatial distributions presented in Fig. 2 for the three rainfall products.

2.3. The Noah model

The Noah Land Surface Model (Noah-LSM) version 2.7.1 (Ek et al., 2003) in one dimension, sponsored by the NOAA Office of Global Programs (OGP), is adopted in this study. Noah-LSM was developed by the National Centers for Environmental Prediction (NCEP), Oregon State University (OSU), the Air Force, and the Hydrology Research Laboratory at the National Weather Service. Noah-LSM is updated with

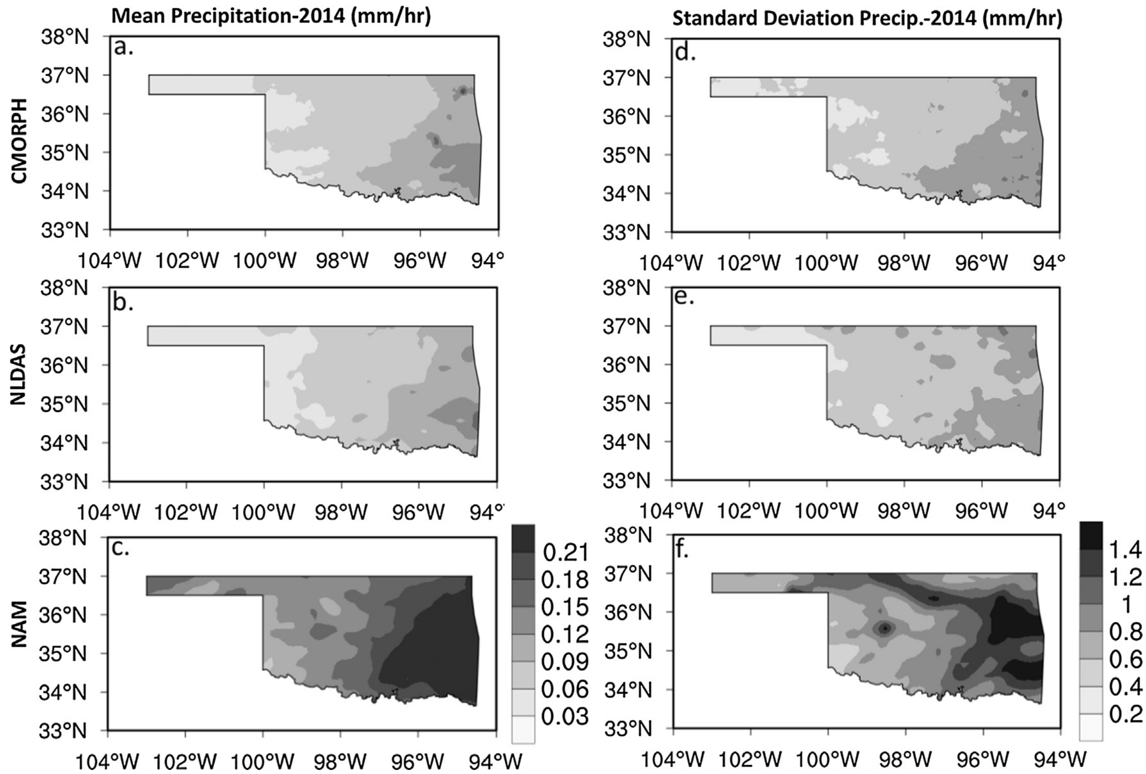

Fig. 2. Mean (a, b, c) and standard deviation of precipitation (d, e, f) over Oklahoma for CMORPH, NLDAS, and NAM during 2014.

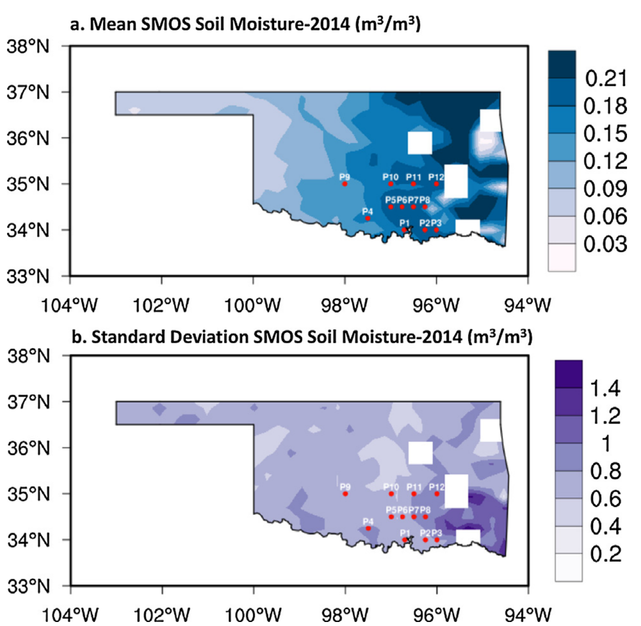

Fig. 3. Mean (a) and standard deviation (b) of soil moisture over Oklahoma for SMOS during 2014.

more advanced land physics compared to its ancestor Oregon State University (OSU) LSM, including four soil layers, snowpack and frozen soil physics (Koren et al., 1999), as well as snow cover–weighted surface fluxes, among others. It has been implemented in operational weather and climate models because of its moderate complexity and computational efficiency.

The meteorological forcing used for Noah-LSM are from Phase 2 of the North American Land Data Assimilation System, Phase 2 (NLDAS-2), which has been improved over the previous version of NLDAS (Cosgrove et al., 2003). The non-precipitation land-surface forcing fields for NLDAS-2 are derived from the NCEP North American Regional Reanalysis (NARR; Mesinger et al., 2006), while NLDAS used the ETA Data Assimilation System (EDAS; Rogers et al., 1996). NLDAS-2 has a spatial resolution of 1/8° and temporal resolution hourly for the period of 1979-present. Also, the parameterization used for vegetation type, Leaf Area Index (LAI), soil type, and elevation in Noah-LSM is the one from the NLDAS dataset.

2.4. The experimental approach

All precipitation and soil moisture products are rescaled and homogenized to the Noah-LSM spatial and temporal and resolution of 0.125°/1 h for the year of 2014. Then, the model is forced with each individual precipitation dataset, a combination of two of them, and a combination of all three products to obtain surface soil moisture simulations.

Precipitation products are linearly combined using a simple weighted average. Weights are randomly generated through Monte Carlo (MC) simulations. MC techniques are based on the idea of using randomness to solve problems that are difficult to solve analytically (like highly non-linear differential equations) and obtain numerical results thanks to repeated random sampling. A MC approach is used to generate 3000 different combinations of weights of the precipitation products to force Noah-LSM. First, weights are only applied to single precipitation products (i.e., weights equal to zero are assigned to the other two products), which corresponds to assuming that there exists a bias in the dataset and correcting for it. Then, a combination of two products is considered (i.e., a weight equal to zero is assigned to one out of the three products) and, finally, weights are applied to a combination of all three products (Fig. 4). Only positive weights are considered in this study as precipitation products are firstly tested individually with their corresponding weights, and only secondarily in combination with other products. In the first case, negative weights would translate into negative precipitation and have not therefore used for the sake of consistency. Moreover, weights are sampled independently for each

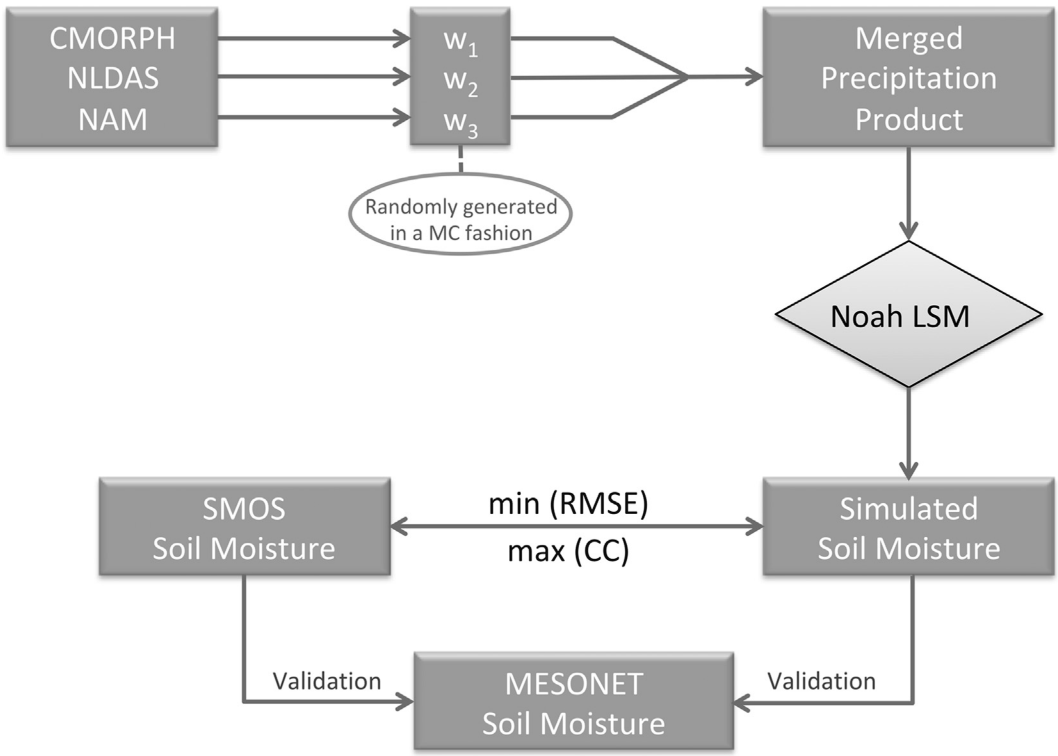

Fig. 4. The proposed methodological framework.

grid point so that the same exact procedure could be applied to any other region, since weights are not region dependent.

The performance of the merged precipitation estimates is then assessed in terms of two criteria: minimum root mean square error (RMSE) and maximum correlation coefficient (CC) between the model simulated soil moisture and the reference SMOS soil moisture product. However, the weight combination that minimizes the RMSE does not necessarily maximize the CC and researchers and/or end-users may be more inclined to use one criterion versus the other depending on the research and/or operational application. Therefore, we are looking at a multiple criteria decision-making problem where two objective functions are optimized simultaneously.

The Pareto efficiency definition is used to identify the optimal combination of weights. Specifically, a combination of weights is considered "optimal" (or "efficient", or "non-dominated") if there exist no other weight combination that improves one criterion (e.g., RMSE) without deteriorating the other criterion (e.g., CC). The Pareto frontier (PF) is the set of all Pareto efficient points (Marler and Arora, 2004). This concept was introduced in economics by Vilfredo Pareto (1848–1923), but it has further expanded to several other fields, such as engineering and science (Rubinstein and Osborne, 1994). The same framework could be easily applied to other or more criteria.

Building the PF is a purely mathematical process, in which the decision maker (DM) does not intervene. However, the question is: how to choose one weight combination from all the points that belong to the Pareto frontier? One option would be to either minimize the RMSE or to maximize the correlation, depending on the DM's interests, which would reduce the problem to a simple single-criterion decision. Another viable alternative is the Utopia point (U) method (Makowski, 2010). According to this technique, the DM picks the point on the PF that minimizes the distance from U, which is the point in the objective space that minimizes (or maximizes) all the objectives. All these three approaches (minimum RMSE, maximum correlation, and closer point to U) are considered and investigated in the next section.

3. Results and discussion

The performance of Noah-LSM forced with 3000 MC-generated combinations of weights for the three different precipitation products is initially assessed over a single grid-point (point P1 in Fig. 3). This study considers weights ranging between 0 and 1, as a preliminary analysis (shown in Fig. 5) demonstrated that increasing weights beyond 1 would not improve surface soil moisture simulations in terms of RMSE (which increases if weights greater than 1 are applied to the three precipitation products) and CC (which drops if weights greater than 1 are applied to CMORPH and NLDAS, whereas for NAM it is maximized if a weight of ~2 is applied). Since no a-priori knowledge on the bias in the precipitation products is assumed, the sum of the weights is not constrained to any value.

The 3-D plots in Fig. 6 show that there is no single combination of weights of the precipitation products that optimizes both criteria, but rather a region in the weight space that maximizes CC and minimizes RMSE. This proves that our problem is a two-objective (or two-criterion) problem. For P1, RMSE values range between 0.05 m^3/m^3 and 0.2 m^3/m^3, whereas CC values range between 0.43 and 0.68, showing overall satisfactory performance of Noah-LSM in modeling surface soil moisture at this location.

The Pareto frontiers are then constructed using the two objective functions defined above, one that minimizes the RMSE and the other that maximizes the CC. The CC is multiplied by −1 in order to minimize both objective functions for identifying the optimal combination of weights to be applied to the precipitation products. PFs are built for 12 Mesonet Oklahoma stations and the corresponding model grid cells. The optimization is performed independently for the 12 locations during 2014.

Fig. 7 shows PFs for each single precipitation product and for the combination of all three products. Since the goal is to minimize both objective functions, the closer to the axes, the more efficient the points are, according to the two identified criteria. Although at location P9 the combination of three different precipitation datasets does not produce any notable improvement in the soil moisture simulation (either in

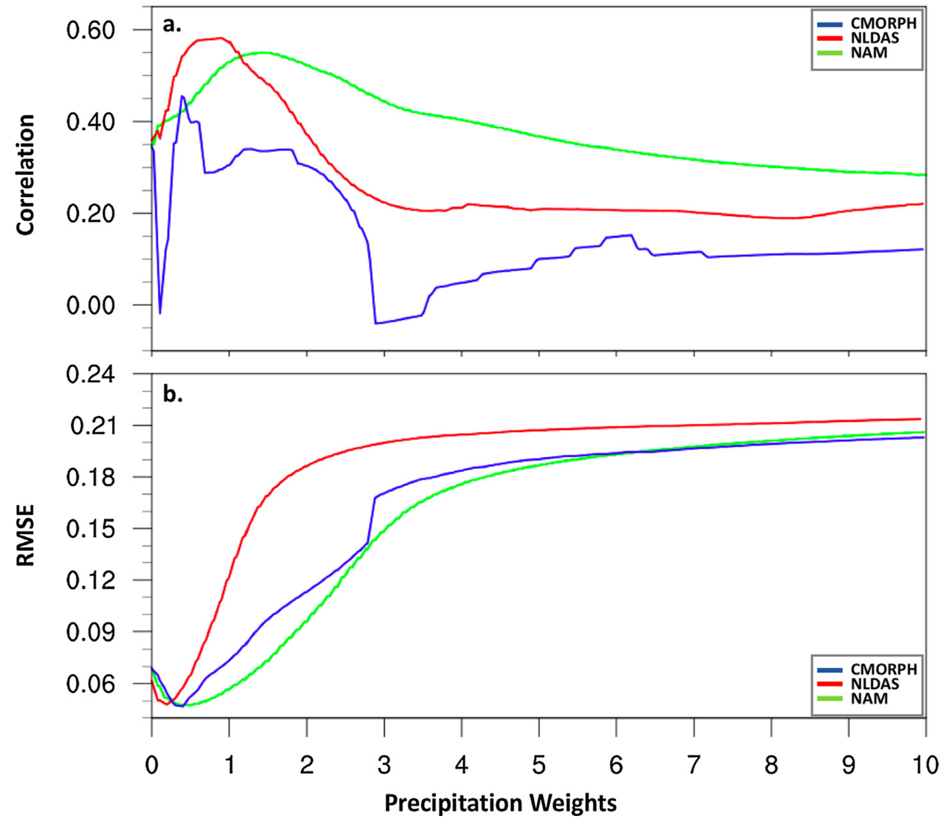

Fig. 5. Correlation (a) and RMSE (b) between SMOS soil moisture data and soil moisture simulated by Noah LSM forced with different weights of precipitation products.

RMSE or in CC), at all other locations the single precipitation product-forced simulation produces points that are dominated by the simulation forced with the combination of three precipitation products (blue line). In other words, the PFs obtained with the merged precipitation product dominate (i.e., are more efficient than) the PFs obtained with the single products, according to the RMSE and CC criteria. Overall, correlation coefficients range between 0.30 and 0.70, whereas RMSEs are as low as 0.05 m^3/m^3 and as high as 0.24 m^3/m^3. Combining three products is particularly useful for improving the correlation between simulated soil moisture and SMOS; as in most cases (9 locations out of 12) the PFs for the merged product (blue solid lines) reach to higher CC values than the single product-forced simulations (dashed lines).

Fig. 7 also shows that there is no single precipitation product that consistently performs better than the others. If only one dataset had to be chosen, NAM would be the one carrying the lowest RMSE and the highest CC in surface soil moisture simulations with respect to SMOS, followed by NLDAS and CMORPH. This suggests that overall both NLDAS and CMORPH are underestimating rainfall across the central southern part of Oklahoma and NAM produces precipitation estimates that better characterize the hydrological processes in the area. However, there are cases (like P1) where CMORPH performs better than NAM and NLDAS, and others (like P2) where NAM carries the lowest CCs and largest RMSEs. Therefore, the safest choice would be to merge all three products to guarantee an appropriate characterization of soil moisture dynamics in the region.

Similarly, Fig. 8 shows the PFs for the combination of two and three

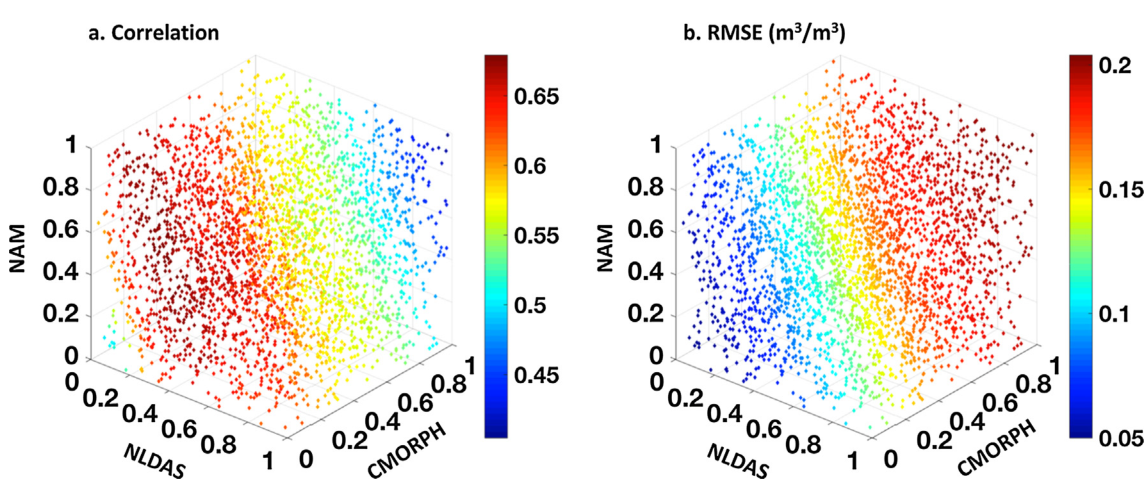

Fig. 6. Correlation coefficient (a) and RMSE (b) of simulated and SMOS soil moisture for the weighted combination of all three precipitation products (CMORPH-NLDAS-NAM) over the pixel centered in 96.5005 W, 34.0005 N (P1).

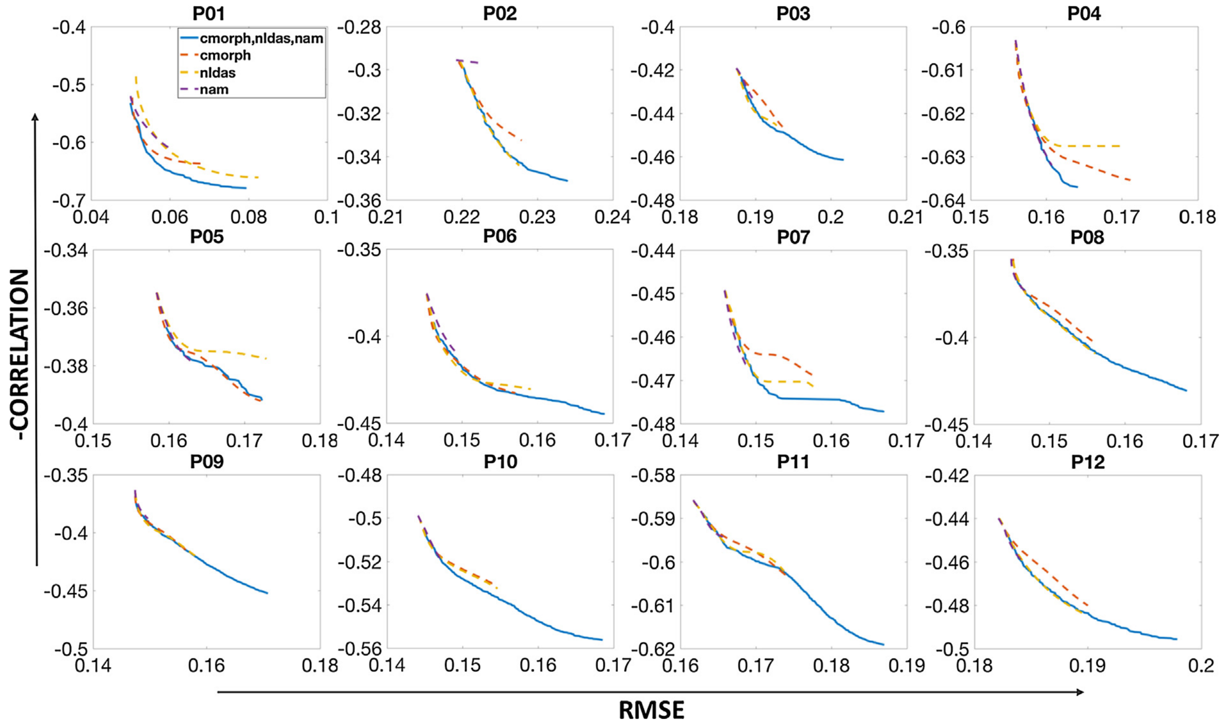

Fig. 7. Pareto Frontier points of simulated and SMOS soil moisture for single products and the combination of all three precipitation products, where Y-axis is correlation coefficient multiplied by (−1) and X-axis is RMSE, over the pixels shown in Fig. 2.

precipitation products to verify whether one of the three precipitation products could be neglected without deteriorating the model skill. Merging three products never worsens the performance of Noah-LSM in estimating soil moisture. At several locations, by merging only two products we obtain skill metrics that are comparable to the three-product combination. Nevertheless, no two-product combination is optimal for all locations. At four locations, the CMORPH + NAM combination yields the worst performance, at three locations CMORPH + NLDAS shows the poorest skill, at two locations NLDAS + NAM has the largest RMSEs and lowest CCs, and at the three remaining locations the skill of the four combinations is hardly discernible. This analysis corroborates that the three-precipitation product merging is recommended for soil moisture estimation in the region, as it consistently outperforms – or at the very least performs as well as – any other option.

The next step would be to identify one combination of weights among all the optimal points on the PF to estimate soil moisture time

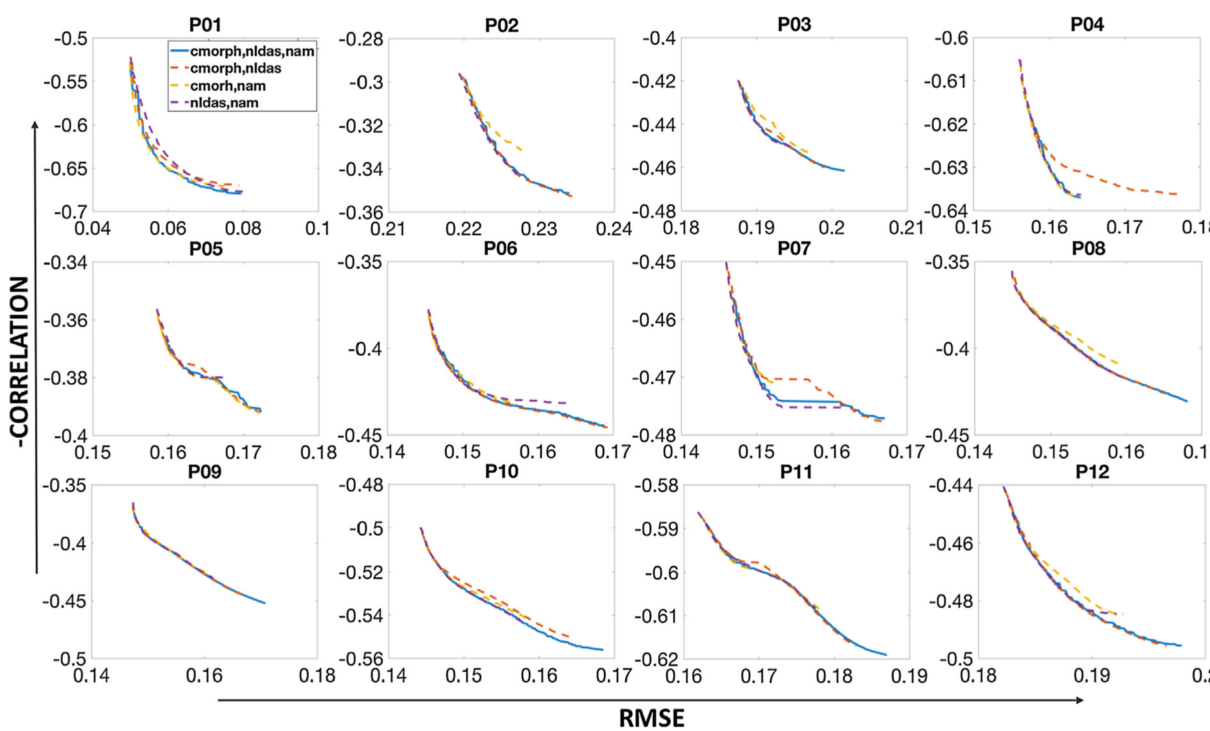

Fig. 8. Same as in Fig. 7 but for the combination of two and three precipitation products.

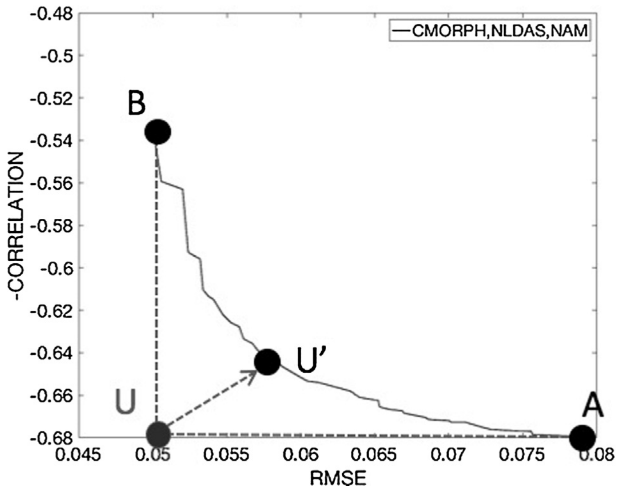

Fig. 9. Example of the Pareto frontier for the combination of all three precipitation products with three possible decision points: (A) maximum correlation; (B) minimum RMSE; and (U′) the closest PF point to the Utopia point (U).

series at the desired location. However, as discussed in the Methodology section, this is a political decision that the DMs will make based on their interest and applications. We here propose three possible methods to make that decision: i) maximum correlation regardless of RMSE (point A in Fig. 9); ii) minimum RMSE regardless of CC (point B in Fig. 9); and iii) the closest PF point to the Utopia point (point U' in Fig. 9). We would like to stress that the choice of any point on the PF is arbitrary.

We then performed a validation exercise using a high-quality, independent dataset, i.e., the Mesonet station observations. Specifically, the modeled soil moisture is compared to the top layer (5 cm) soil moisture collected at the 12 Mesonet stations highlighted in Fig. 3. The mean CC and RMSE between the Noah-LSM simulated soil moisture and the Mesonet soil moisture observations across the 12 stations are listed in Table 2 for all model simulations (with different combinations of precipitation inputs) at the three decision points identified in Fig. 9. Results in Table 2 show that the combination of three precipitation products carries the maximum mean CC and minimum mean RMSE for all the optimal points considered in the analysis (i.e., A, B and U). When only one product was used, CMORPH outperformed NLDAS that outperformed NAM when U' was considered as the decision point. When two products were combined, CMORPH + NAM outperformed CMORPH + NLDAS that outperformed NLDAS + NAM when U' was considered as the decision point. Although improvements are small, this study has demonstrated the hypothesis that a combination of precipitation data from different sources can be optimized to minimize the error in soil moisture simulations. Moreover, this framework can be applied to different datasets, different regions of the world, different criteria, and different land surface variables and fluxes.

4. Conclusions

This work aims to merge precipitation estimates from different sources including ground-based observations, satellites, and models to produce an estimate of precipitation that optimizes land surface model states and fluxes. Different sources of precipitation information (a satellite products, a ground-radar dataset, and model estimates) have been considered to improve the skills of the Noah land surface model in simulating surface soil moisture. We developed a Monte Carlo-based algorithm that generates weights to linearly and optimally combine these three precipitation datasets.

Results showed that there were optimal combinations of precipitation data that provided better soil moisture model estimates than forcing Noah-LSM with single precipitation datasets, in terms of both RMSE and correlation coefficient. Specifically, combining all three precipitation products from different sources provided the best correlations with ground observations and the lowest RMSEs at several locations across Oklahoma. However, no single linear combination of weights of the precipitation products was found that optimized both criteria, proving it to be a multi-objective problem.

The Pareto Frontier was adopted as a way to present all optimal combinations of weights that would improve one criterion, without deteriorating the other one. Then, a few options to pick one single weigh combination from all the Pareto efficient points were proposed, including maximizing one criterion alone (that being either CC or RMSE) and the closest PF point to the Utopia point, defined as the (unattainable) point in the objective space that optimizes all the objectives.

Results presented here are limited by the short time series and small study region. However, this work is intended to propose a methodology a methodological framework that should be tested in the future across larger and more heterogeneous areas (potentially at the global scale) and over longer time periods. Other criteria, such as relative bias and unbiased RMSE, could also be easily included in the framework, if of interest to the end-users. Another limitation is the comparison between volumetric soil moisture content from the model and observations, which may be problematic given the inherent biases in the model soil moisture climatology and satellite observations, as well as ground observation measurement representativeness errors. This issue could potentially be fixed by adopting a Cumulative Density Function (CDF)-matching technique (Reichle and Koster, 2004) to remove any existing bias in the soil moisture products prior to optimization. This may have the potential to improve errors in the modelled land surface fluxes and states. We would also like to point out that the Monte Carlo-based sampling can be relatively computationally inefficient, but it is unlikely to be confined within a local minimum. However, in the case of larger domains, algorithms such as the simplex, simplex-swarm, or a posteriori error estimator can be used to improve the framework computational efficiency.

This work developed a technique that could potentially be applied to any precipitation product, including the recent NASA Integrated Multi-satellitE Retrievals for GPM (Global Precipitation Measurement; Hou et al., 2008) product (IMERG; Huffman et al., 2014). Future work

Table 2
Mean correlation coefficient and RMSE between Mesonet observations and simulated soil moisture at the 12 locations shown in Fig. 3 for the three decision points identified in Fig. 9 (A/U′/B).

Noah LSM Precipitation Forcing	Correlation Coefficient (A/U′/B)	RMSE (A/U'/B)
CMORPH	0.708/0.713/0.716	0.095/0.087/0.082
NLDAS	0.725/0.711/0.701	0.083/0.099/0.107
NAM	0.696/0.697/0.696	0.112/0.111/0.111
CMORPH-NLDAS	0.705/0.719/0.705	0.101/0.088/0.098
CMORPH-NAM	0.718/0.721/0.715	0.084/0.084/0.087
NLDAS-NAM	0.715/0.715/0.707	0.090/0.089/0.095
CMORPH-NLDAS-NAM	0.730/0.729/0.719	0.080/0.079/0.084

should also investigate how performing a weighted combination of precipitation datasets may lead to extra days of precipitation – for instance in cases when only one product has nonzero precipitation. While this may improve soil moisture simulations, it could have significant impacts elsewhere (e.g., increased canopy evaporation, decreased runoff). When applying a similar method across a wider region, spatially correlated weights should also be considered within the sampling model using a spatial correlation function. Moreover, a similar approach that merges precipitation information from different sources could be easily adapted to optimize other land surface fluxes and variables, including runoff, evaporation, transpiration, and groundwater recharge. Although of higher complexity, a multi-variate optimization technique that simultaneously enhances two or more land surface model variables would ensure that the water budget was not altered to improve a model error.

Declaration of interests

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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