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Requirements of a global near-surface soil moisture satellite mission: accuracy, repeat time, and spatial resolution

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Abstract

Soil moisture satellite mission accuracy, repeat time and spatial resolution requirements are addressed through a numerical twin data assimilation study. Simulated soil moisture profile retrievals were made by assimilating near-surface soil moisture observations with various accuracy (0, 1, 2, 3, 4, 5 and 10%v/v standard deviation) repeat time (1, 2, 3, 5, 10, 15, 20 and 30 days), and spatial resolution (0.5, 6, 12 18, 30, 60 and 120 arc-min). This study found that near-surface soil moisture observation error must be less than the model forecast error required for a specific application when used as data assimilation input, else slight model forecast degradation may result. It also found that near-surface soil moisture observations must have an accuracy better than 5%v/v to positively impact soil moisture forecasts, and that daily near-surface soil moisture observations achieved the best soil moisture and evapotranspiration forecasts for the repeat times assessed, with 1–5 day repeat times having the greatest impact. Near-surface soil moisture observations with a spatial resolution finer than the land surface model resolution (~30 arc-min) produced the best results, with spatial resolutions coarser than the model resolution yielding only a slight degradation. Observations at half the land surface model spatial resolution were found to be appropriate for our application. Moreover, it was found that satisfying the spatial resolution and accuracy requirements was much more important than repeat time.

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Keywords: Soil moisture; Remote sensing; Mission requirements; Data assimilation; Modelling

1. Introduction

Data on land surface moisture is vital to understanding the earth system water, energy, and carbon cycles. Fluxes of these quantities over land are strongly influenced by a surface resistance that is largely soil moisture dependent. Soil moisture knowledge is critical in weather and climate prediction, where model initialization with hydrospheric state measurements has been shown to bring significant improvements in forecast accuracy and reliability [2,13,14]. Soil moisture observations will also benefit climate-sensitive socioeconomic activities, such as water management, agriculture, flood and drought monitoring, and policy planning, by extending the capability to predict regional water availability and seasonal climate. However, accurate land surface soil moisture observations are lacking, due to an inability to economically monitor spatial variation in soil moisture from traditional point measurement techniques. As a result, land surface models have been relied upon to provide an estimate of the spatial and temporal variation in land surface soil moisture. However, due to uncertainties in atmospheric forcing, land surface model parameters and land surface model physics, there is often a wide range of variation between different land surface model forecasts of soil moisture [16].

Over the past two-decades there have been numerous ground-based, air-borne and space-borne near-surface soil moisture (top 1–5 cm) remote sensing studies, using both thermal infrared and microwave (passive and active) electromagnetic radiation. Of these, passive microwave soil moisture measurement has been the most promising technique, due to its all weather capability, its direct relationship with soil moisture through

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the soil dielectric constant, and a reduced sensitivity to land surface roughness and vegetation cover [11]. However, to date there has been no dedicated space mission for the measurement of near-surface soil moisture. This is mainly due to the large antenna size (10's of meters) required for obtaining radiometric L-band observations at the desired spatial resolution (10's of km). As a result, scientists have resorted to making the best use of soil moisture information from non-optimal (i.e. C-band) sensors (e.g. [25]) and models [e.g. [20]).

Although current remote sensing technology can only provide a soil moisture measurement of the thin near-surface layer rather than the entire profile, there is a sizeable body of literature that has demonstrated an ability to retrieve the soil moisture content at much greater depths when this near-surface information is assimilated into a land surface model (e.g. [12,17,26–28,32–35]). Moreover, there is a great scientific demand for the soil moisture data that would be provided by such a mission [21].

While there is no current space-borne mission dedicated to soil moisture measurement, there are two missions in development stages. These are the European Space Agency passive L-band Soil Moisture and Ocean Salinity (SMOS) mission (2007 launch) and the U.S. National Aeronautics and Space Administration active/passive L-band HYDROSpheric states (HYDROS) mission (2009 launch).

Defensible global near-surface soil moisture measurement science and application requirements are vitally important for mission planning. In particular, mission planners need: (i) sensor polarization, wavelength and look angle requirements; and (ii) measurement accuracy, temporal resolution and spatial resolution requirements. (While satellite mission design must also consider the satellite overpass time, the main impact of this will be accuracy of the inferred near-surface soil moisture content, which will be a function of the specific remote sensing technique. Thus, we consider this as part of measurement accuracy.) The (i) requirements have been fairly well defined, with horizontally polarized <50° look angle [18,25] L-band [24] radiometer measurements, and horizontally polarized send and receive [31] C-band [8] 15° look angle radar measurements [30] yielding the greatest soil moisture sensitivities. However, the (ii) requirements have been less well defined. Apart from some "best guess" estimates by Engman [10] for spatial resolution (1–100 km), repeat time (1–10 days), measurement depth (top 5–10 cm) and accuracy levels (4–10%v/v) according to application, there are only the studies of Milly [22] and Hoeben and Troch [15], which recommend a daily repeat time, and Calvet and Noilhan [6], which recommends a 3 day repeat time. Finally, Jackson et al. [19] recommend without justification an accuracy of 4%v/v with a 10 km spatial resolution and 2–3 day repeat time.

Whilst L-band measurements are sensitive to a deeper layer of soil moisture near the earth's surface (≈1/10 to 1/4 of the wavelength, depending on soil moisture, wave polarization, look angle, etc) than say C-band, the requirement for passive L-band measurements is the reduced sensitivity due to soil moisture signal masking by vegetation, rather than sensing depth. Moreover, Walker et al. [33] have shown that in the context of data assimilation, the near-surface soil moisture observation depth is relatively unimportant, providing the actual measurement depth is known and this matches closely the model near-surface layer thickness.

This paper seeks to defensibly address the yet unresolved global near-surface soil moisture measurement accuracy, repeat time and spatial resolution requirements. Although the scientific community is calling for a 2–3 day repeat time and 10 km spatial resolution with better than 4%v/v accuracy in low vegetation areas [19], this may have little scientific basis. Rather than limit this paper's scope to a specific soil moisture remote sensing technique (such as the passive microwave brightness temperature), we consider the inferred space-borne near-surface soil moisture content measurement accuracy, repeat time and spatial resolution requirements, independent of the measurement technique.

It should be recognized that there may be complex interdependencies between the accuracy, repeat time, and spatial resolution soil moisture mission requirements, and that there may be other important criteria that are not examined here (i.e. observation depth, model structure,, model objective, spatial scale of the model, simulation error and its representation, etc.). Hence, this study examines the sensitivity of each observation requirement for a given objective, rather than finding the optimum requirement combination. In light of the near impossibility of completely defining the interdependency between all possible observation requirements and application objectives, this paper makes some important first steps towards quantifying some defensible targets. The authors hope that this paper will lead to a plethora of studies on this topic with different model structures, resolutions and objectives, using both synthetic and real data, so that firm recommendations on mission requirements can be made.

2. Methods

This paper addresses the near-surface soil moisture measurement mission requirements through a numerical "twin" (i.e. where a "control" model simulation is compared with a "treatment" model simulation) data assimilation study. First, a land surface model was used to generate a "truth" data set that provides the near-surface soil moisture "observations" to be assimilated, and the evaluation data against which the assimilation results are compared. The land surface forcing data and initial conditions were then degraded to simulate modeling uncertainties, and a second "open-loop" simulation (our best estimate of the truth from modeling without assimilation) performed. Finally, simulations were made where the observations with various accuracy, repeat time and spatial resolution are assimilated (using the extended Kalman filter) into the open-loop simulation.

There exists a continuum of possible twin synthetic data assimilation studies that are not only bounded by the choice of model physics (where the identical twin uses the same truth and open-loop model physics, and the fraternal twin uses different truth and open-loop model physics) but also by the choice of forcing, initial condition, observation, and error perturbations. While we can classify this study as an identical twin because it uses the same model physics for the truth and open-loop cases, our perturbation of open-loop simulation forcing fields prevent the open-loop simulation from identically replicating the truth, as in a true identical twin study. It is not possible or necessary for a single study to address the entire continuum of possible twin studies, so we present a logical first step in this research area.

2.1. Land surface model

This study used the catchment-based land surface model of Koster et al. [20]. It imposes a non-traditional land surface modeling framework that includes an explicit sub-grid soil moisture variability treatment that impacts both runoff and evaporation. A key catchment-based land surface model innovation is that the land surface element shape is defined by a hydrologic watershed, rather than an arbitrary grid.

This land surface model uses TOPMODEL [1] concepts to relate the water table distribution to the topography. Both water table distribution and non-equilibrium root zone conditions are considered, leading to the definition of three bulk moisture prognostic variables (catchment deficit, root zone excess and surface excess) and a special moisture transfer treatment between them. Using these three prognostic variables, the catchment may be divided into stressed, unstressed and saturated soil moisture regions. This land surface model framework provides a method for calculating the catchment fraction in each of these three regimes and their respective soil moisture content. Alternatively, the catchment average soil moisture content may be evaluated. As this model does not forecast near-surface soil moisture directly, as required for the assimilation, it must be diagnosed from the three moisture prognostic variables as outlined in Walker and Houser [32]. A complete model description is given by Koster et al. [20] and Ducharne et al. [9], and is summarized further by Walker and Houser [32]. The model has been evaluated against field data used by the PILPS-2c model intercomparison study in the Red-Arkansas Basin [9], PILPS-2e model intercomparison study in an arctic watershed [4], and the very large Rhone-AGG mid latitude watershed [3], with reasonable results.

2.2. Extended Kalman filter

The Kalman filter data assimilation algorithm tracks the statistically optimal conditional mean of a state vector and its covariance matrix, through a series of forecasting and update steps [5]. We have used a one-dimensional Kalman filter for updating the land surface model's soil moisture prognostic variables. A one-dimensional Kalman filter was used because of its computational efficiency and the fact that at the scale of catchments used (average catchment area of 4400 km^2), correlation between adjacent catchment soil moisture prognostic variables is only through the large-scale correlation of atmospheric forcing, soil properties and topographic attributes. Moreover, all land model soil moisture forecast calculations are independent of the adjacent catchment soil moisture content. The reader is referred to Walker and Houser [32] for a more detailed discussion of the Kalman filter, the Kalman filter equations and their catchment-based land surface model application.

For the initial covariance matrix, diagonal terms were specified to have a standard deviation of the maximum difference between the initial prognostic state value and the upper and lower limits. This represents a large initial soil moisture prognostic state uncertainty. Off-diagonal terms were specified as zero initially, suggesting no initial error correlation between the three soil moisture prognostic state variables. The forecast model error covariance matrix diagonal terms were taken to be the predefined values of 0.0025, 0.025 and 0.25 mm/min for surface excess, root zone excess and catchment deficit respectively, with the off-diagonal terms taken to be zero [32]. The assumption of error independence between the three soil moisture model prognostic variables is valid, as the physics used for forecasting these state variables are independent (i.e. different equations are used to represent the time evolution of surface excess, root zone excess and catchment deficit). This is unlike typical land surface models that vertically discretize the soil and apply the same soil moisture physics (i.e. Richards equation) for each of the soil layers.

3. Numerical experiments

To assess the global near-surface soil moisture measurement mission accuracy, repeat time and spatial resolution requirements, a set of numerical twin data assimilation experiments have been undertaken for the entire North American continent. While these most closely resemble identical twin experiments because they use identical model physics, we impose model error by perturbing the open-loop atmospheric forcing. We investigate the potential evapotranspiration and soil moisture forecast accuracy increase, when periodic near-surface soil moisture observations are assimilated into the land surface model, given typical atmospheric forcing and initial condition errors. By assimilating near-surface observations with different levels of error imposed, at different repeat times and from different spatial resolutions, the question of mission requirements is addressed. While there will be interaction between these three requirements, we deal with these individually so as to clearly demonstrate the individual impact that each of these will have on the assimilation of near-surface soil moisture observations. That is, we assimilate observations that are (i) perfect in spatial resolution at 3 day repeat (the proposed repeat time for SMOS and HYDROS) but with a range of accuracies—addresses the accuracy requirement, (ii) perfect in spatial resolution and accuracy at a range of temporal resolutions—addresses the temporal resolution requirement, and (iii) perfect accuracy at 3 day repeat with a range of spatial resolutions—addresses the spatial resolution requirement.

3.1. Model input data

This study uses atmospheric forcing data and soil and vegetation properties from the first International Satellite Land Surface Climatology Project (ISLSCP) initiative [29]. Such data include 2 m air temperature and humidity, 10 m wind speed, atmospheric pressure, precipitation, downward solar and longwave radiation, greenness, leaf area index, surface roughness length, surface snow-free albedo, zero plane displacement height, vegetation class, soil porosity, soil depth and texture. The land surface model was implemented with a 20 min time step, using 6 h atmospheric forcing data and monthly vegetation data. Soil properties in areas not defined by ISLSCP were assumed uniform with the values given by Walker and Houser [32]. The initial model states for 1 January 1987 were determined by "spin-up" through repeated simulation of 1987 until the model states reached equilibrium (i.e. the values at the end of the simulation period were the same for two successive simulations).

3.2. Truth simulation: observation and evaluation data

Using the Koster et al. [20] catchment-based land surface model, the initial spin-up conditions, and the model input data described above, the "true" soil moisture temporal and spatial variation across the North American continent was forecast for 1987. The near-surface (top 2 cm) soil moisture content forecasts were output once per day for each catchment to represent the soil moisture measurements that could be made by a space-borne remote sensing instrument. As such, these are error-free "observations", independent of spatial resolution, with a daily repeat time, and form the basis of the observation data to be assimilated. The evaluation data from this truth run also includes the root zone and profile soil moisture content, as well as evapotranspiration data.

To investigate soil moisture mission accuracy requirements, zero mean normally distributed perturbations were added to the error-free near-surface soil moisture observation data set described above. Standard deviations used for generating perturbations were 1, 2, 3, 4, 5 and 10%v/v. The repeat time requirement was investigated by sub-sampling the perfect observations to 1, 2, 3, 5, 10, 20 and 30 day repeat times.

In addressing the spatial resolution requirement, near surface soil moisture observations were derived at a range of spatial resolutions 0.5, 6, 12, 18, 30, 60 and 120 arc-min ($\approx$1–200 km). These were derived from the near-surface soil moisture catchment-based land surface model forecasts within the three soil moisture regimes (stressed, unstressed and saturated) and their respective fractions, rather than the catchment average used above. The three soil moisture spatial distribution regimes were mapped onto a grid with 30 arc-s resolution, using the compound topographic index [23] data from HYDRO1K. Using this approach, the saturated regime catchment fraction was assigned to that fraction of grid cells lying within the catchment boundary having the highest compound topographic index values, the stressed regime catchment fraction was assigned to the grid cell fraction having the lowest compound topographic index values, and the unstressed regime catchment fraction was assigned to the remaining grid cell fraction having intermediate compound topographic index values (Plate 1). This provided an error-free near-surface soil moisture observation data set at a resolution of 30 arc-s ($\approx$1 km), whose mean soil moisture content was the same as the original catchment average near-surface soil moisture output. This data set was then aggregated up to resolutions of 0.5, 6, 12, 18, 30, 60 and 120 arc-min, to represent near-surface soil moisture observations at different spatial resolutions by taking the average of the 0.5 arc-min soil moisture data for areas representing the appropriate resolution. These data sets were then transformed back to individual catchment average soil moisture observations (using an area weighting scheme) for assimilation.

3.3. Open-loop simulation

To represent the errors associated with any simulation due to initial condition and atmospheric forcing

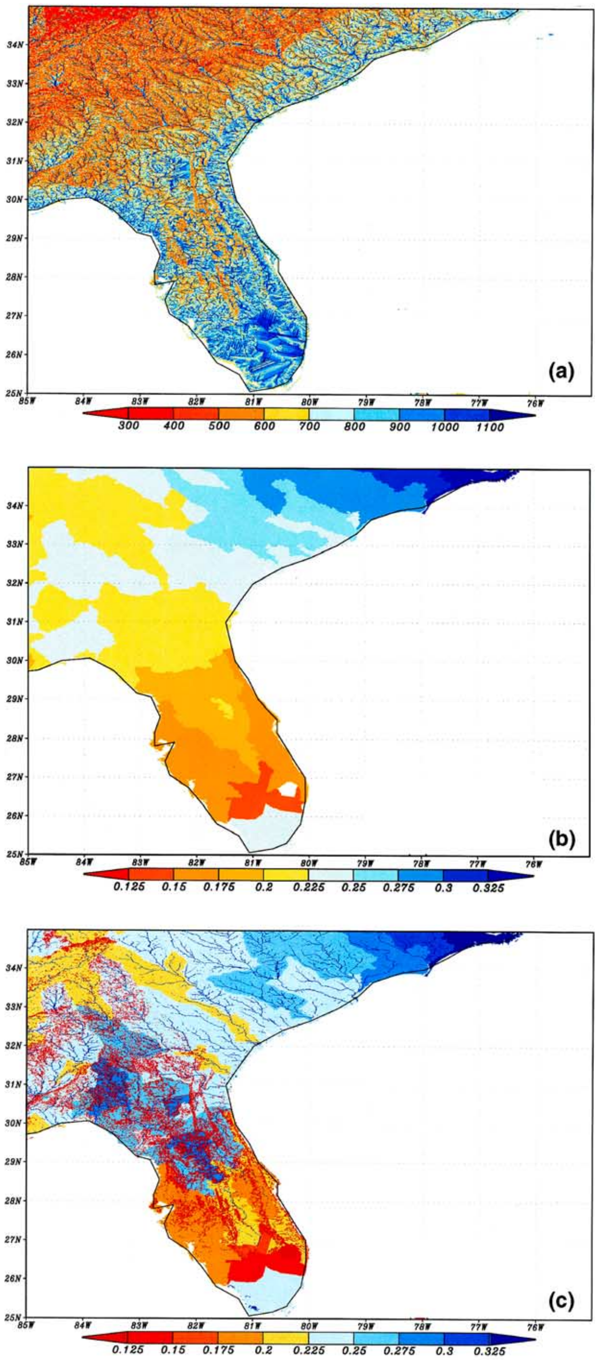

Plate 1. (a) Compound topographic index, (b) catchment average near-surface soil moisture for the entire profile (v/v) and (c) spatial variation of near-surface soil moisture within the catchments based on the compound topographic index (v/v).

error, the initial conditions and forcing data that were used in the truth run were degraded before input to the open-loop simulation. However, this does not account for model physics errors, as would be possible in a true fraternal twin experiment. Because this study assumed a perfect model, significant error in the open-loop simulation was ensured by initial condition and atmospheric forcing perturbations, namely precipitation.

The initial conditions were degraded by applying zero mean normally distributed random perturbations with the standard deviations given in Table 1 to the original three spun-up soil moisture prognostic variables. The forcing data were similarly degraded, using the Table 1 standard deviations to represent the uncertainty associated with atmospheric forcing measurement and interpolation error.

Applying precipitation perturbations was more difficult than other forcing parameters, as precipitation is an intermittent process. To account for the fact that precipitation could have occurred even when the data suggested there was none, a perturbation to precipitation was added whenever a normally distributed zero mean random number greater than three times its standard deviation was generated. To account for spatial variability, the precipitation record for each individual catchment was perturbed by a normally distributed zero mean random number with a standard deviation that is proportional to the average annual precipitation for that catchment. In this way, the perturbation standard deviation was taken as 1 mm h^{-1} multiplied by the ratio of catchment mean annual precipitation (55–4595 mm) to average North American catchment annual precipitation (595 mm).

As wind speed, downward radiation and precipitation cannot be negative, negative values after perturbation were truncated to zero; there was no attempt to maintain long-term averages. Fig. 1a shows a time series precipitation error histogram and Fig. 2a shows the resulting profile soil moisture forecast error. (The histogram plots show how the percentage number of catchments (indicated by variation in intensity) with a certain level of error (horizontal axis) varies through time (vertical axis) for a particular field (in this case precipitation).) It can be seen here that there is a wet open-loop simulation soil moisture bias due to a perturbed precipitation forcing wet bias. The open-loop precipitation forcing bias arises from truncation of random error perturbations that fall below zero. While this is undesirable from an assimilation perspective, such

Table 1
Standard deviations used for applying normally distributed random perturbations to the initial conditions and atmospheric forcing data

Surface excess	1 mm
Root zone excess	10 mm
Catchment deficit	100 mm
Convective precipitation	50% or 0.1–8 mm h^{-1}
Total precipitation	50% or 0.1–8 mm h^{-1}
2 m air temperature	5 °C
2 m dewpoint temperature	5 °C
Downward longwave radiation	25 W m^2
Downward shortwave radiation	50 W m^2
Surface pressure	1 kPa
10 m wind speed	1 m s^{-1}

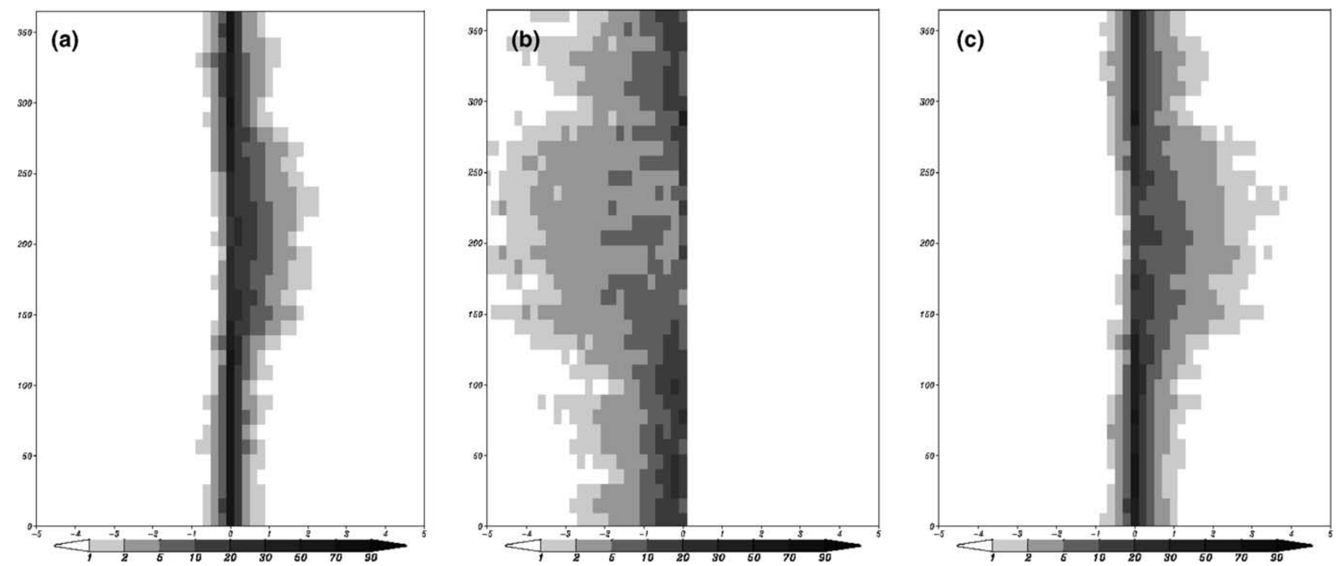

Fig. 1. Temporal precipitation error variation plotted as a time series (vertical axis—day of year) histogram (% of catchments) of errors in precipitation (horizontal axis—mm/day): (a) the original experimental design, (b) dry bias experiment and (c) wet bias experiment.

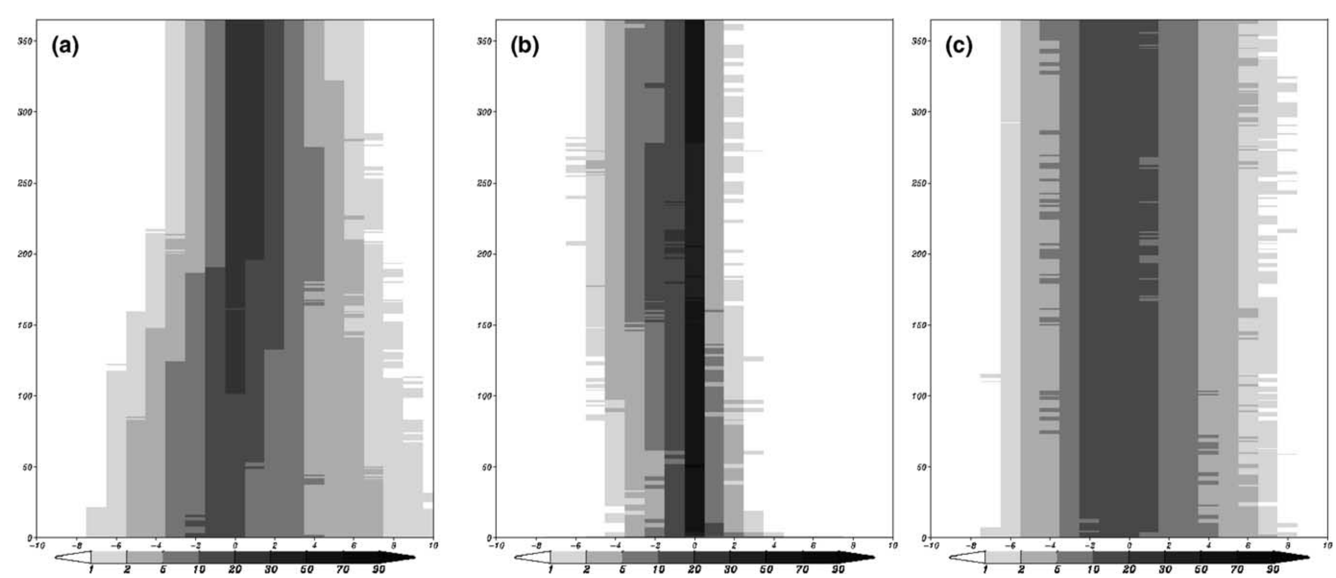

Fig. 2. Time series histogram of errors in soil moisture for the entire soil profile (%v/v) given the original experimental design: (a) no assimilation, (b) assimilation of perfect near-surface soil moisture observations and (c) assimilation of near-surface observations with 4%v/v standard error. Near-surface soil moisture observations are independent of spatial resolution with a 3-day repeat time.

biases are typical in atmospheric re-analysis data, so we decided to study the impact of this bias, rather than recreating an unbiased precipitation forcing perturbation.

It must be recognized that the perturbations applied to the open-loop simulation, and its subsequent forecast skill, is a critical assumption made in this study. Great care was taken to apply realistic atmospheric forcing errors to the open-loop simulation. While it would have been relatively easy to create an open-loop simulation with virtually no forecast skill by applying ridiculous forcing perturbations, that would result in unrealistically large skill increases when assimilation is performed.

3.4. Accuracy requirement

To investigate global near-surface soil moisture measurement mission accuracy requirements, individual simulations were made where the observation data, with various errors imposed, were assimilated into the open-loop simulation described above. The resulting soil moisture profile forecast error time series histogram with assimilation is given in Fig. 2b for error-free observations, and Fig. 2c for observations with 4%v/v error. The soil moisture forecast bias from the initial open-loop simulation (Fig. 2a) has been improved in both simulations, but the forecast error increased for the latter. Moreover, it should be noted that there is now a dry bias for the simulation with assimilation of perfect observations, most notably during the summer months. This is in direct contrast to the wet precipitation bias in the simulation without assimilation. This phenomenon is discussed in greater detail in the following section on bias considerations.

Fig. 3 shows the observation error effect on soil moisture profile forecasts when near-surface soil moisture measurements are assimilated. Here, both the spatially and temporally averaged root mean square (rms) error and mean error (or bias) in soil moisture and evapotranspiration forecasts from assimilation into the open-loop simulation are compared with that from the open-loop simulation without assimilation. This figure shows that both soil moisture and evapotranspiration forecast rms errors from simulations with the assimilation increased with observation error. Less than 3%v/v observation error was required for soil moisture forecasts to have less error than the original open-loop simulation. Provided the observation error was less than 5.5%v/v there was a mean error improvement.

A disconcerting result from these simulations was that, in some cases, the soil moisture forecast error with assimilation exceeded the soil moisture forecast error without assimilation; the basis for doing assimilation is to improve the soil moisture forecast error derived from imperfect initial conditions and atmospheric forcing, not exacerbate it. In the situation where one has ‘perfect’ forecast error covariance knowledge, this situation should not occur.

While this study had ‘perfect’ model physics, there were still errors in the model forecasts due to errors in the initial conditions and atmospheric forcing data. Moreover, the extended Kalman filter model covariance forecasts are at best a crude approximation of the true

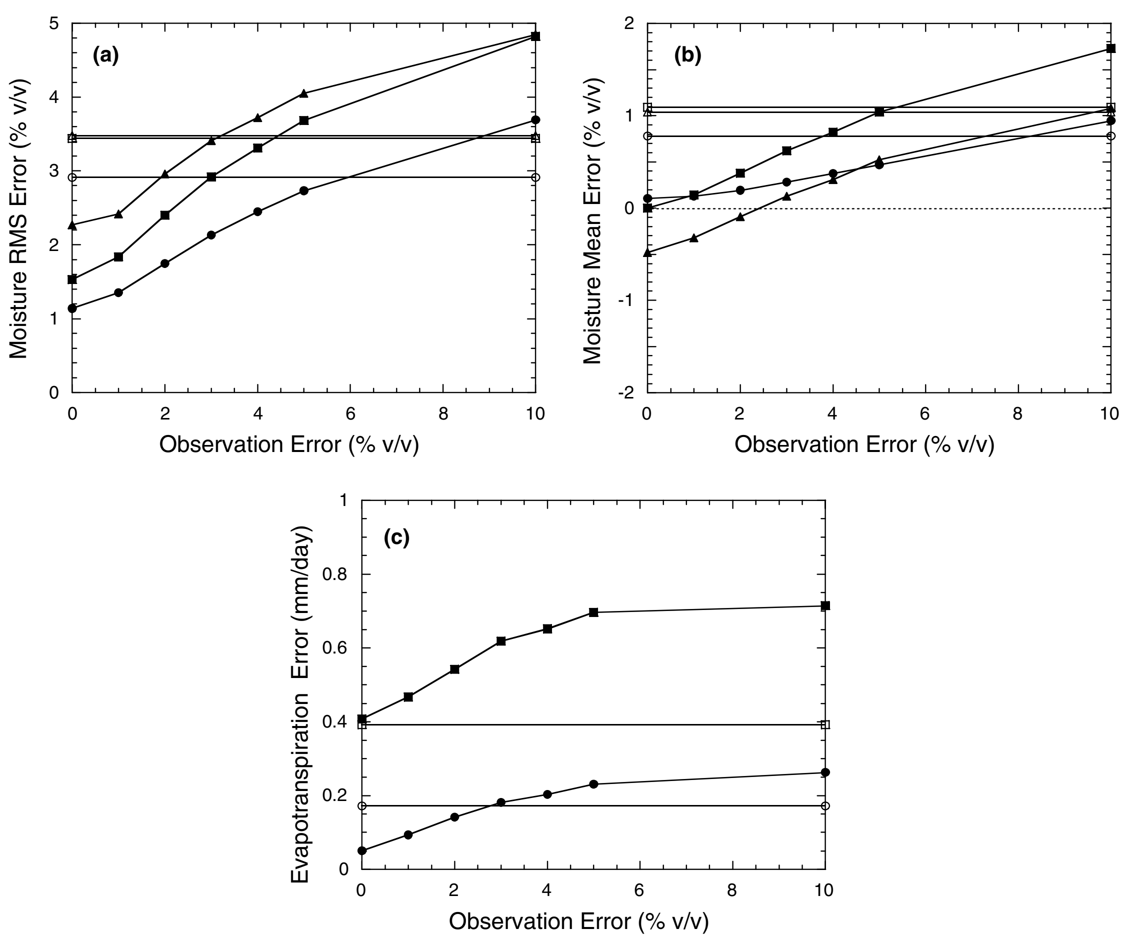

Fig. 3. Near-surface soil moisture observation error effects on: (a) surface (circle), root zone (square) and profile (triangle) soil moisture rms error; (b) surface (circle), root zone (square) and profile (triangle) soil moisture mean error; and (c) evapotranspiration rms (square) and mean (circle) error. Simulations with assimilation (solid symbols) are compared with the simulation without assimilation (open symbols). Near-surface soil moisture observations are independent of spatial resolution with a 3-day repeat time.

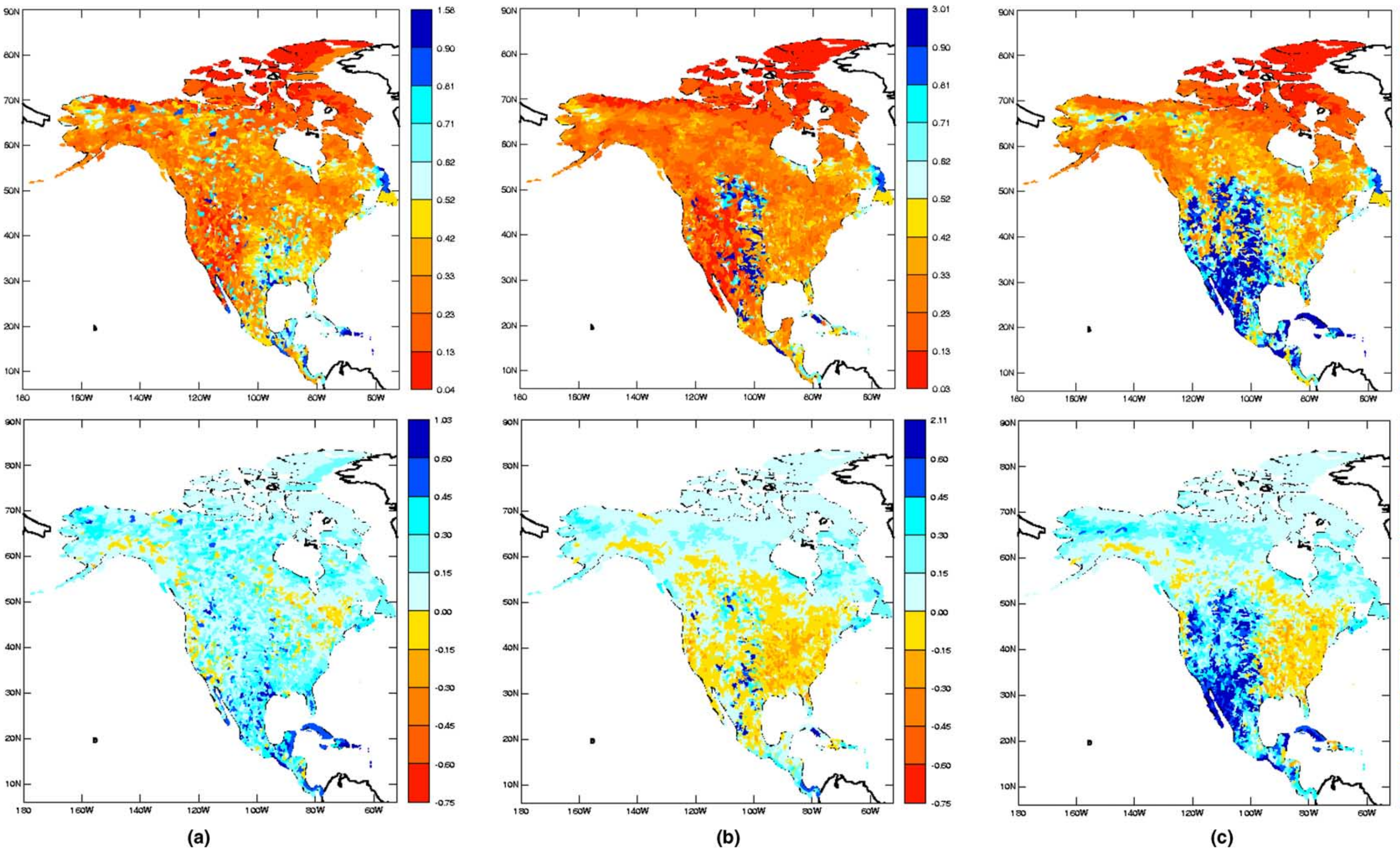

Plate 2. Temporally averaged evapotranspiration (mm/day) rms error (top row) and bias (bottom row) for (a) no assimilation, (b) assimilation of perfect near-surface soil moisture observations and (c) assimilation of near-surface soil moisture observation with 4%v/v standard error. Near-surface soil moisture observations are independent of spatial resolution with a 3-day repeat time.

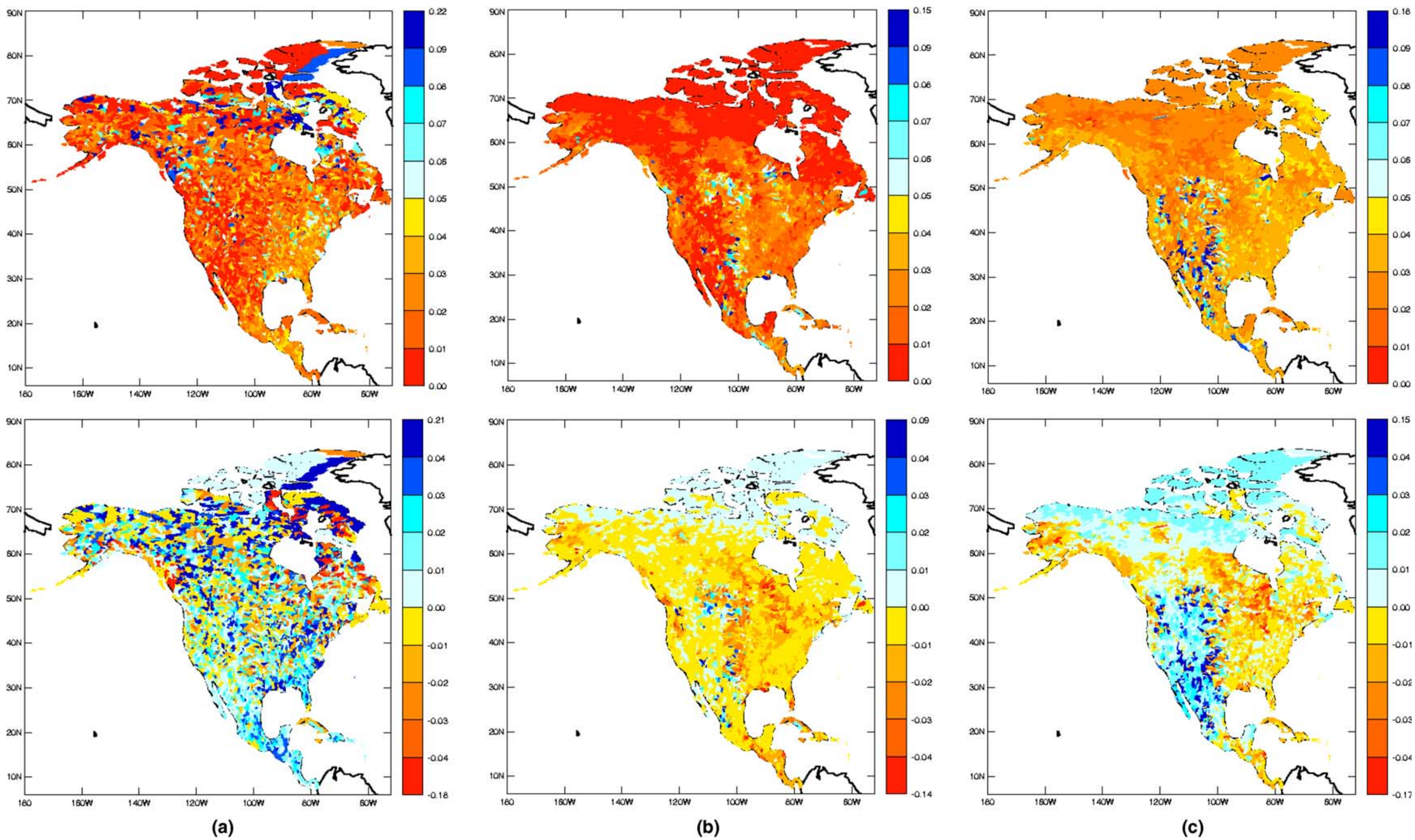

Plate 3. Temporally averaged soil moisture profile (v/v) rms error (top row) and bias (bottom row) for (a) no assimilation, (b) assimilation of perfect near-surface soil moisture observations and (c) assimilation of near-surface soil moisture observation with 4%v/v standard error. Near-surface soil moisture observations are independent of spatial resolution with a 3-day repeat time.

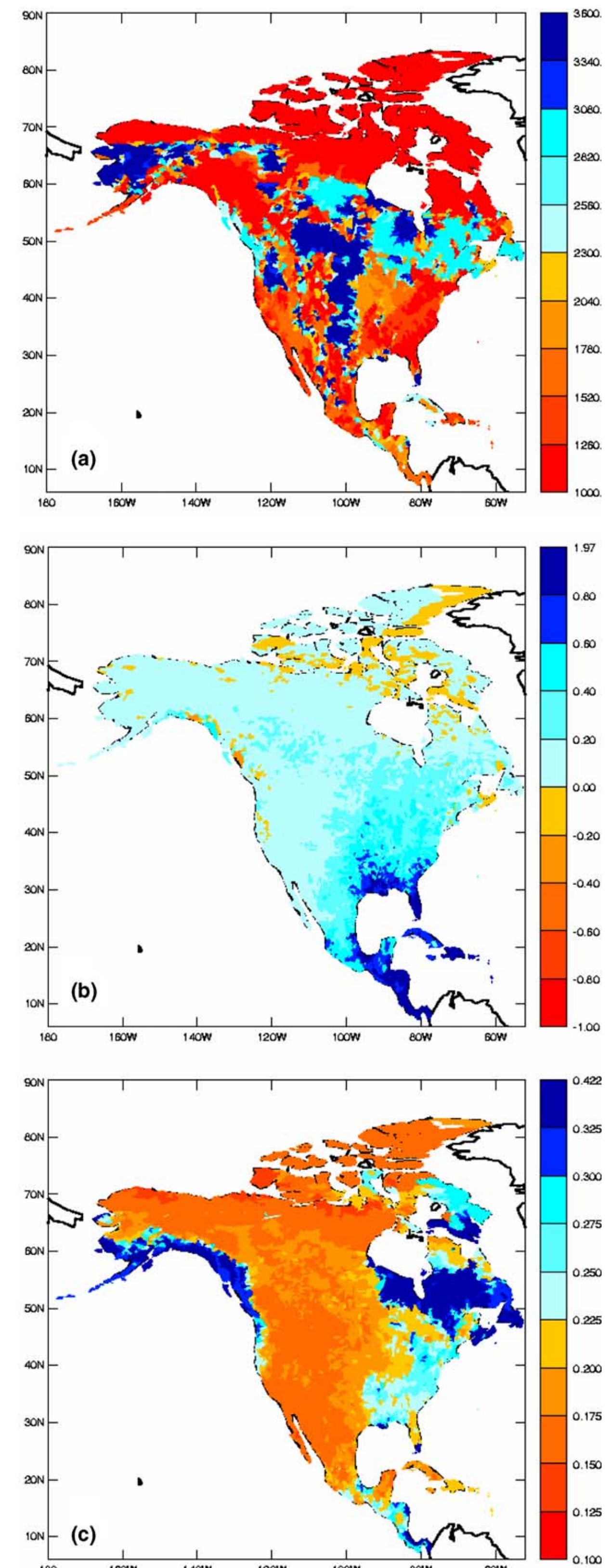

Plate 4. (a) Spatial variation in soil depth (mm), (b) temporally averaged spatial variation in precipitation bias (mm/day) and (c) yearly average soil moisture in the entire soil profile (v/v).

covariances (due to model linearization, assumptions about the model noise covariances, etc.). Using the ensemble Kalman filter in place of the extended Kalman filter [28] may overcome linearity assumptions, but it does not resolve the issue of model noise covariance specification. Correct knowledge of this model error covariance is essential if the correct weighting between model forecasts and observations is to be obtained. In this case it would seem that the estimated model uncertainty was too great in comparison to the observations, and hence the assimilation 'corrupted' the simulated soil moisture with the low quality observations. While the correct model error may have been calibrated in this application, that is not possible in the real world, and these problems are typical of what can be expected in the real world where we have even more limited forecast error covariance knowledge (see also [15]). Having said that, one still needs to be careful how the results from Fig. 3 are interpreted, as a great deal of information (5018 catchments by 365 days) is summarized into a single number, and it is likely that these values are being skewed by a few small catchments with large errors (see Plates 2 and 3).

Fig. 3 also shows that without assimilation, evapotranspiration forecasts from the open-loop simulation are positive biased. That is, open-loop simulation evapotranspiration forecasts are greater than truth simulation forecasts. This results from the wet open-loop soil moisture bias, which follows from the wet precipitation bias. However, provided the observation error was less than 3%v/v there was an evapotranspiration mean error improvement when near-surface soil moisture observations were assimilated, but the rms evapotranspiration forecast error was always greater than for the original open-loop simulation. Particularly interesting is the fact that the rms evapotranspiration error obtained for the assimilation run was always greater than for the open-loop simulation (only slightly for perfect observations). Plate 2 shows that for perfect observations, there are only few catchments (<5%) that have rms and mean errors significantly greater than for no assimilation. On the whole, there is a general rms and mean error improvement, with the bias switching from positive to negative for approximately 50% of the continent. However, for observations with 4%v/v accuracy, there is a much greater proportion with larger rms errors (20%) than for no assimilation, with distinct positive and negative bias zones. Moreover, there are some regions (most notable is Alaska) that show distinct rms and mean error similarities, both with and without the assimilation. This results from evapotranspiration being primarily controlled by factors other than soil moisture in that region. Also note that the rms error estimates have not been corrected for bias, and therefore reflect the mean error.

Plate 3 shows that apart from Alaska, there is a high correlation between both evapotranspiration and soil

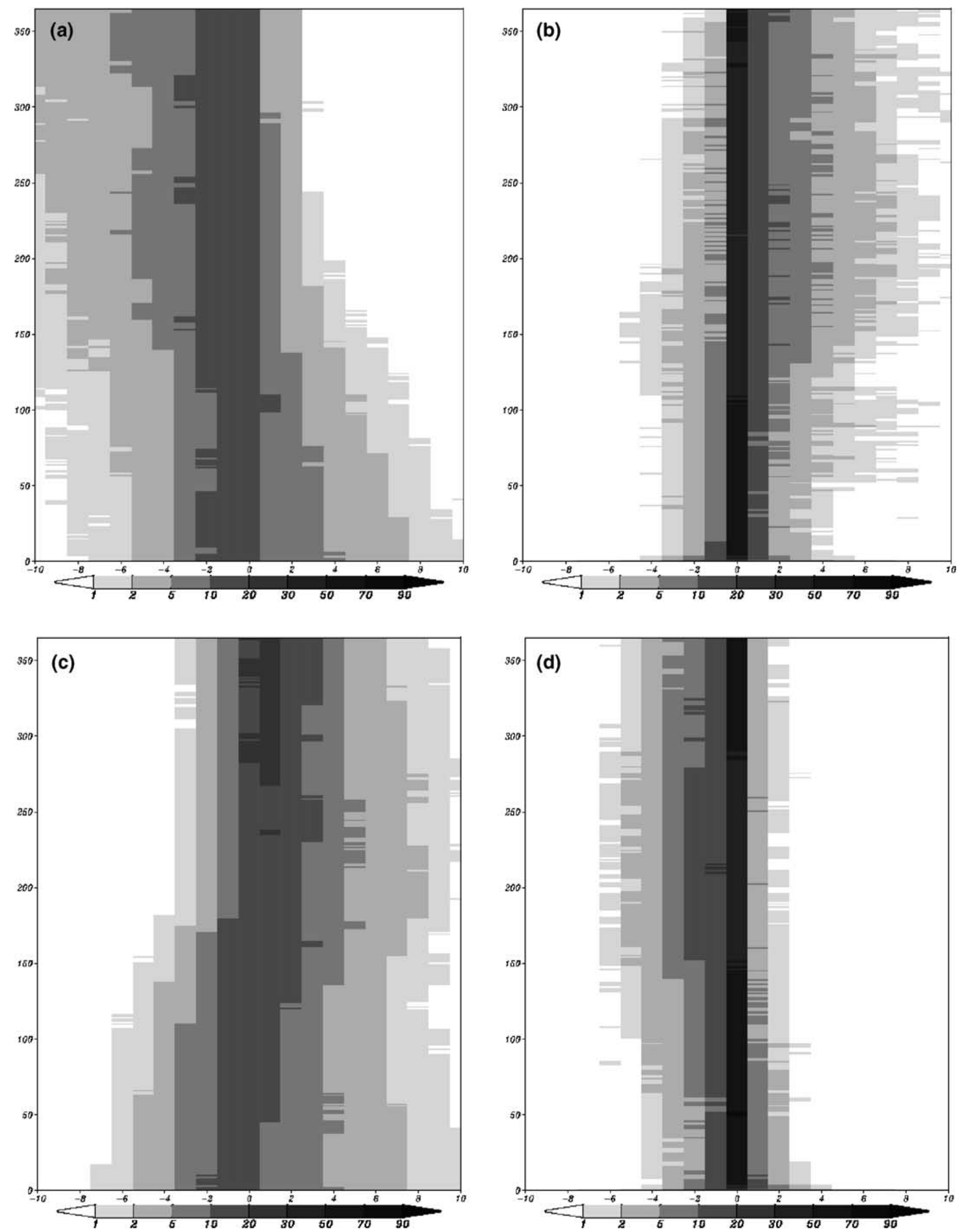

Fig. 4. Time series histogram of errors in soil moisture for the entire soil profile (v/v): (a) dry bias experiment with no assimilation, (b) dry bias experiment with assimilation of perfect observations, (c) wet bias experiment with no assimilation and (d) wet bias experiment with assimilation of perfect observations. Near-surface soil moisture observations are independent of spatial resolution with a 3-day repeat time.

moisture rms and mean errors. However, there is a much smaller continental fraction with large rms soil moisture errors as compared to the evapotranspiration. This would indicate the extent to which rms evapotranspiration errors are being influenced by the soil moisture bias. Moreover, it is this relatively small fraction of the continent that results in the high rms and mean error for larger observation errors in Fig. 3a and b, and as such it is only this small fraction that suffers greatly from imperfect error covariances, decoupling between the near-surface and deep soil moisture content in those regions with low soil moisture content [7] and soil depths greater than 3 m (see Plate 4). Of particular interest are the western wet bias and eastern dry bias (especially for 4%v/v observation errors), as also reflected by the evapotranspiration (this is discussed further in the

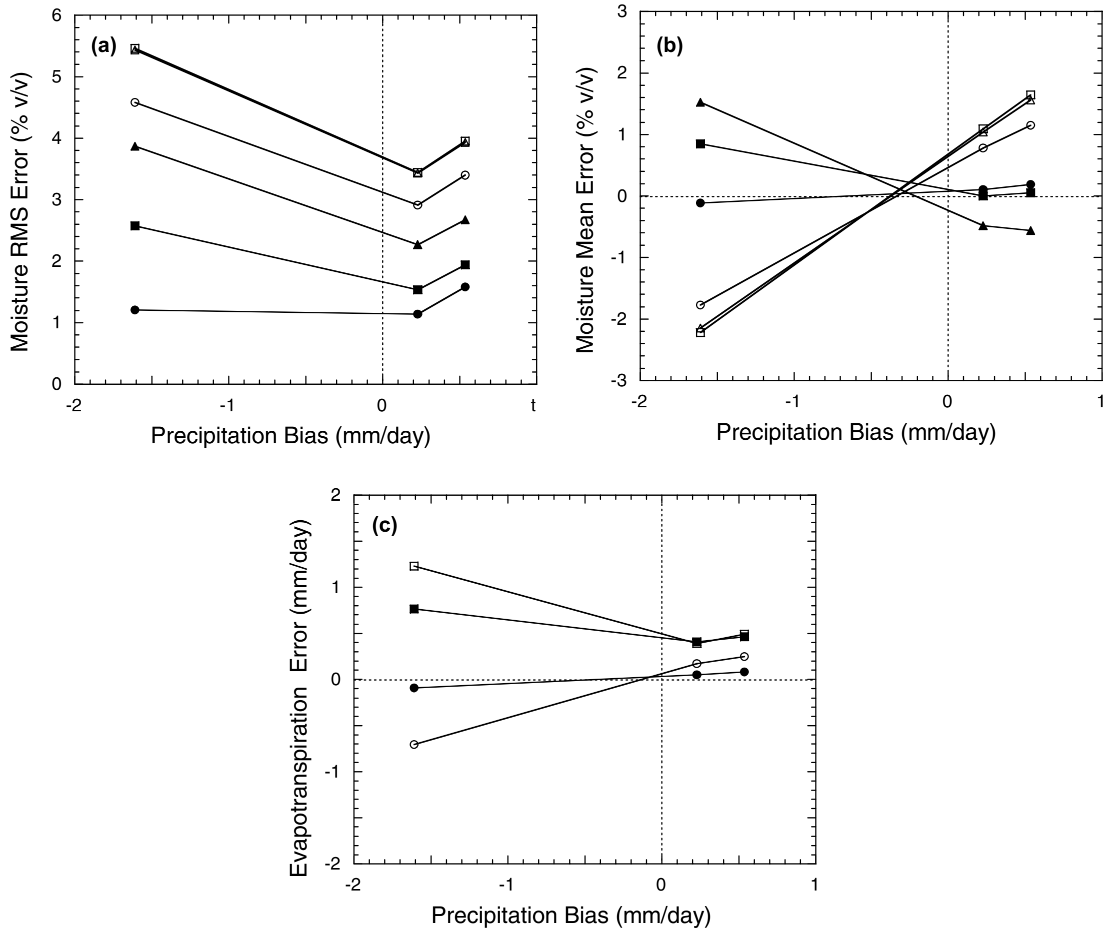

Fig. 5. Precipitation bias effect on: (a) surface (circle), root zone (square) and profile (triangle) soil moisture rms error; (b) surface (circle), root zone (square) and profile (triangle) soil moisture mean error; and (c) evapotranspiration rms (square) and mean (circle) error. Simulations with assimilation (solid symbols) are compared with the simulation without assimilation (open symbols). Near-surface soil moisture observations are free from error with a 3-day repeat time.

following section on bias considerations). It is this wet soil moisture forecast bias in a high evaporative demand area that leads to such a large positive evapotranspiration forecast bias.

The results from these simulations would suggest that to have a positive impact, assimilated near-surface soil moisture measurements should be no worse than 5%v/v accurate, but preferably better than 3%v/v. A degraded soil moisture simulation may result from assimilation of less accurate soil moisture observations (i.e. observations from areas with dense vegetation or other external influences), due to imperfect error covariance knowledge.

3.5. Bias considerations

Fig. 2 shows that a wet soil moisture bias, caused by a wet precipitation bias, results in a dry soil moisture bias when near-surface soil moisture observations are assimilated. Likewise, Plate 3 shows an eastern North America dry bias and a western North America wet bias when near-surface soil moisture observations are assimilated, with this wet bias being more pronounced as the near-surface soil moisture observation error increases.

The soil moisture profile forecast bias when near-surface soil moisture observations are assimilated results from violating a key Kalman filter assumption; that the continuous time error process is a zero mean Gaussian white noise stochastic process. Since the precipitation field was wet biased, the near-surface soil moisture forecast was always wet biased. The Kalman filter recognized (through the forecast covariance matrix) that the near-surface soil moisture had a strong correlation with the soil moisture profile, resulting in a soil moisture profile dry bias when the profile was corrected to counteract the near-surface wet bias (note that this model does not use traditional model layers but rather soil moisture storages from which soil moisture contents for various depths can be diagnosed). As the observation error was increased, the weight given to observations relative to model forecasts was decreased,

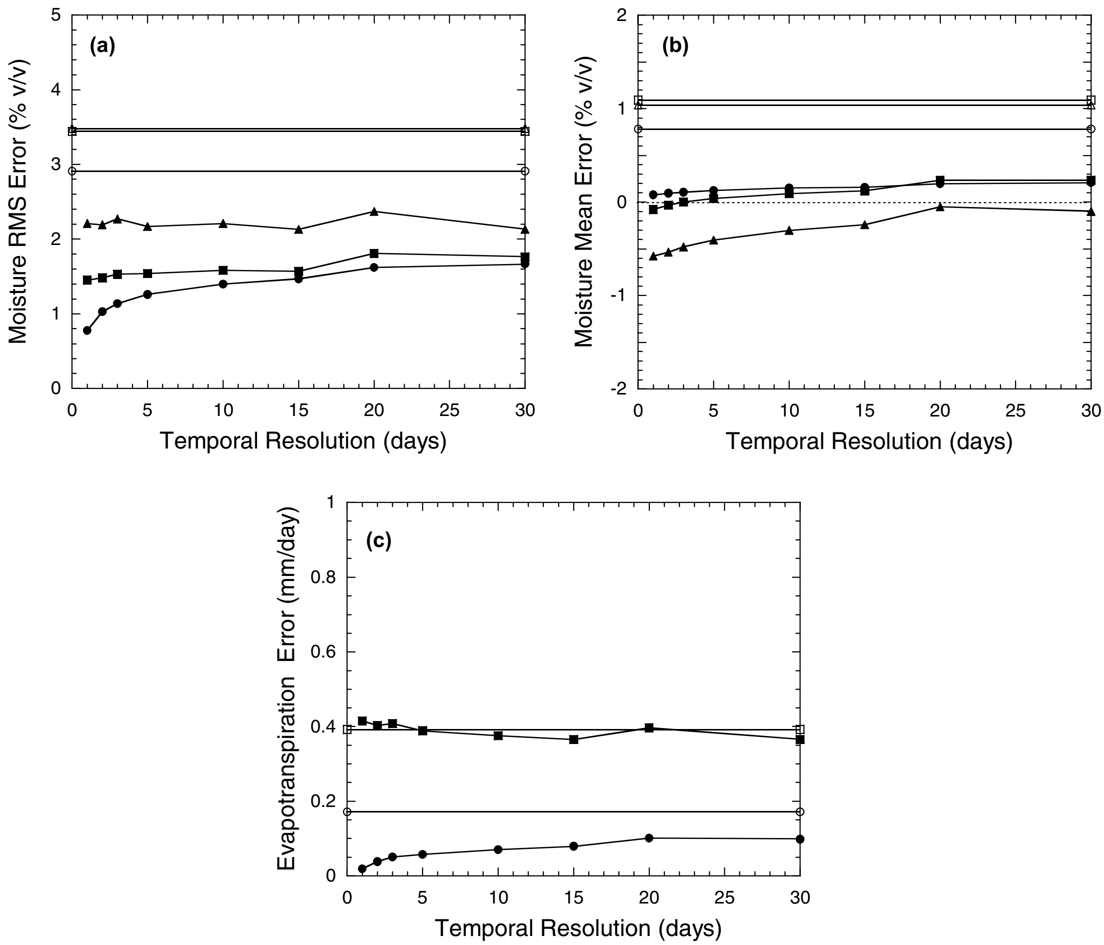

Fig. 6. Near-surface soil moisture observation repeat time effect on: (a) surface (circle), root zone (square) and profile (triangle) soil moisture rms error; (b) surface (circle), root zone (square) and profile (triangle) soil moisture mean error; and (c) evapotranspiration rms (square) and mean (circle) error. Simulations with assimilation (solid symbols) are compared with the simulation without assimilation (open symbols). Near-surface soil moisture observations are free from error.

producing less impact on the profile soil moisture content.

While this explains the dry soil moisture bias, it does not account for the wet bias. Plate 4b shows the spatial precipitation bias distribution, which is concentrated in the east, and hence explains why the dry soil moisture bias is most significant in the east (though there is a general wet precipitation bias for the entire continent). Moreover, Plate 4c alludes to the reason for the wet soil moisture bias in the west; the regions that display a wet bias in Plate 3 correspond with the regions that have the driest soil moisture content in Plate 4c. The reader should also note that this wet soil moisture bias only persists for the simulations with non-perfect near-surface soil moisture observations (see Plate 3). Thus, the reason for a wet soil moisture forecast bias is an effective wet near-surface soil moisture observation bias. When a perturbation makes the near-surface soil moisture observation wetter than the wilting point, there is the potential to make the total soil moisture wetter, but when the perturbation makes the near-surface soil moisture observation drier than the wilting point, the assimilation is unable to decrease the total soil moisture content below the wilting point due to model physical constraints. As such, this is equivalent to truncating the near-surface soil moisture observation to the wilting point, resulting in a wet biased surface soil moisture observation, which is more significant as the perturbation size (or amount of error) increases. This demonstrates that either model forcing or observation bias not accounted for in the assimilation scheme may cause adverse effects when near-surface soil moisture observations are assimilated.

To further demonstrate the forcing bias effect on soil moisture and evapotranspiration forecasts when near-surface soil moisture observations are assimilated, two additional simulations were made. The first assumed there was no precipitation (Fig. 1b), while the second assumed greater precipitation error, with a 100% standard deviation perturbation (Fig. 1c). Fig. 4 shows the

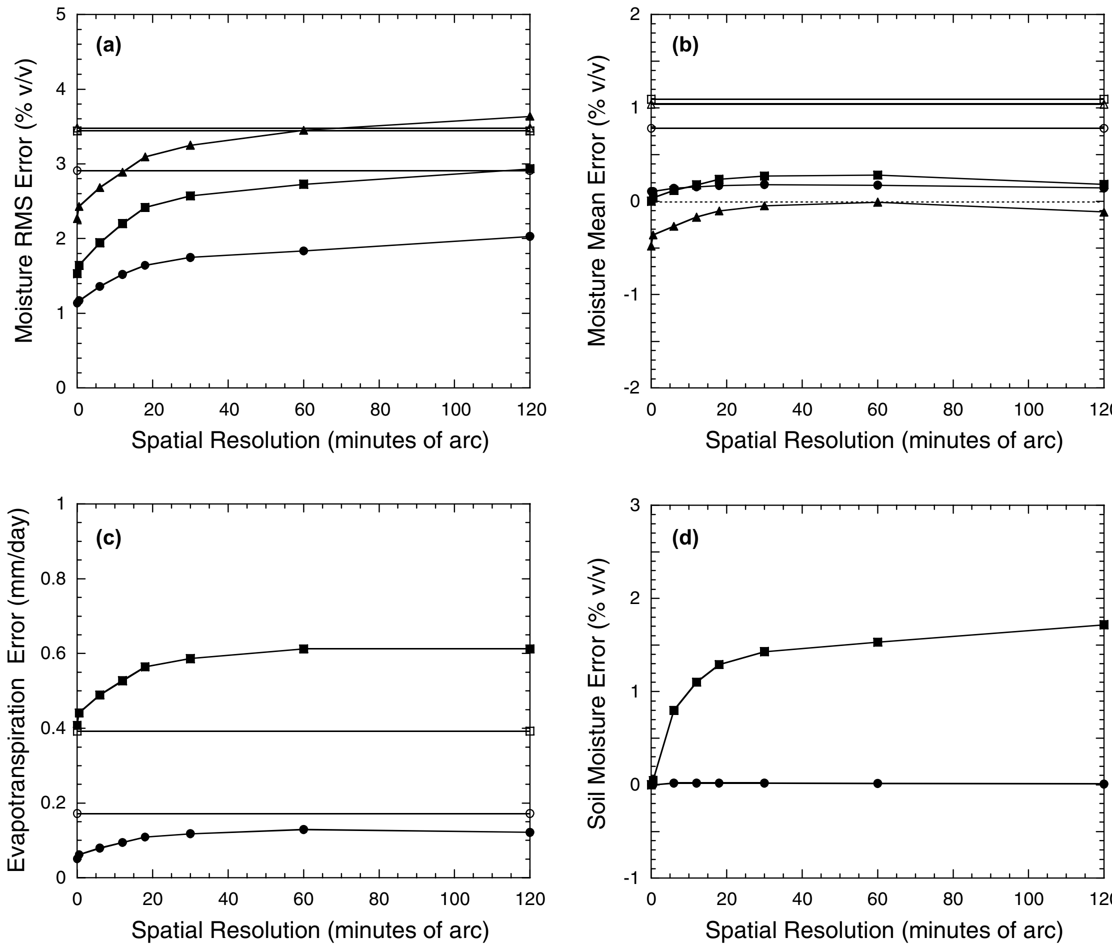

Fig. 7. Near-surface soil moisture observation spatial resolution effect on: (a) surface (circle), root zone (square) and profile (triangle) soil moisture rms error; (b) surface (circle), root zone (square) and profile (triangle) soil moisture mean error; and (c) evapotranspiration rms (square) and mean (circle) error. Simulations with assimilation (solid symbols) are compared with the simulation without assimilation (open symbols). Near-surface soil moisture observations, with a 3-day repeat time, are free from error apart from that introduced from spatial resolution; (d) rms (square) and mean (circle) error in observations.

profile soil moisture error time series histograms, with and without assimilation, where the assimilation both improves the soil moisture forecast and switches the direction of the bias. However, the soil moisture forecast bias for the simulation with no precipitation is worse than the simulation with precipitation, with the bias persisting for all months and not just during the summer.

The precipitation bias effect on soil moisture profile simulation with and without the near-surface soil moisture assimilation is shown in Fig. 5. Again, both the spatially and temporally averaged rms error and mean error in retrieved soil moisture and forecast evapotranspiration are compared with that from the open-loop simulation. This figure shows that modeled soil moisture and evapotranspiration rms errors are improved despite precipitation bias when perfect observations are assimilated. However, the best results were obtained when the precipitation bias was minimized. The resulting near-surface soil moisture and evapotranspiration forecast bias with assimilation was largely unaffected by the precipitation bias, but the root zone and profile soil moisture forecasts were heavily impacted. Moreover, these results would indicate that it is better to use poor precipitation information than to assume no precipitation occurred.

3.6. Repeat time requirement

To investigate the global near-surface soil moisture measurement mission repeat time requirement, individual simulations were made where the observation data, with various repeat times (1–30 days) and no error imposed, were assimilated into the open-loop simulation described above. The effect of repeat time on both soil moisture profile and evapotranspiration forecasts is shown in Fig. 6, where the spatially and temporally averaged rms and mean error from forecasts with near-surface soil moisture assimilation are compared with those without assimilation. This figure shows that the rms and mean soil moisture error is significantly improved when near-surface soil moisture observations are assimilated into the land surface model for all repeat times up to 30 days. However, a daily repeat time has the lowest rms soil moisture error, especially in the near-surface layer. This is to be expected, as this layer has the greatest interaction with the atmosphere; precipitation is the most dominant factor for near-surface soil moisture variations. We also note that decreasing the repeat time from one to two days has a significant near-surface soil moisture rms forecast error impact, with less impact for greater repeat times. However, the root zone and soil profile moisture contents are not similarly affected, as they have a much slower response to atmospheric forcing. Other reasons for the apparent lack of sensitivity to repeat time are: (i) the particular model used in this study has a very strong correlation between surface soil moisture and profile soil moisture content (i.e. catchment deficit), meaning that profile soil moisture retrieval occurs very quickly, as described by Walker and Houser [32]; and (ii) the analysis presented here is for the average across a continent and a year, meaning that the small time and space scale variations may be smoothed out. If the study were to be repeated for a different land surface model and/or a different analysis, then the results may well be different.

Fig. 6 also shows a significant mean evapotranspiration error decrease when near-surface soil moisture observations are assimilated, with little rms error impact. The mean error shows repeat time dependence similar to that for the near-surface soil moisture rms error.

This study suggests that the global near-surface soil moisture repeat time requirement for use in constraining land surface model states by assimilation is less than 5 days, with at least daily repeat time as the preferred interval. However, greater than 5 day repeat times (up to 30 days) have shown very little forecast degradation beyond those from a 5 day repeat time. Moreover, apart from near-surface soil moisture and evapotranspiration forecasts, repeat time has very little forecast performance impact.

3.7. Spatial resolution requirement

To investigate the global near-surface soil moisture spatial resolution requirement, individual simulations were made where the 3 day repeat time (no error imposed) soil moisture observations with various spatial resolutions (0.5–120 arc-min) were assimilated into the open-loop simulation. Fig. 7 shows the spatial resolution effect on both the soil moisture profile and evapotranspiration forecasts, where the spatially and temporally averaged rms and mean error from forecasts with near-surface soil moisture assimilation are compared with those without assimilation. This figure also shows the near-surface soil moisture observation error introduced due to interpolation from coarser resolution data. Here it can be seen that near-surface soil moisture observation rms error rose quickly from zero at the finest resolution to approximately 1.5%v/v at 30 arc-min (the average land surface model spatial resolution), and then increased only marginally for coarser resolutions (1.7%v/v).

These results suggest that the assimilated observation spatial resolution should be less than the land surface model resolution (the average catchment size in our application). This is because the interpolation of observations from a grid to an irregularly shaped catchment becomes more accurate as the spatial resolution of the observation data is decreased beyond the size of the catchment. As the observation spatial resolution becomes finer it more accurately maps the outline of the catchment, giving a more accurate average for the catchment. We suggest that while the highest spatial resolution data is desirable, a resolution of half the model resolution would be an appropriate trade-off between technical constraints and model requirements.

Fig. 7 shows consistent trends between the soil moisture forecast rms and mean error with assimilation, and the near-surface soil moisture observation rms error. This suggests that the near-surface soil moisture observation ability to accurately represent the near-surface soil moisture content at the appropriate scale is an important spatial resolution requirement consideration. As such, the accuracy requirement discussion would also apply here. This is most apparent when Fig. 7 is compared with Fig. 3c. Since the observation data error due to spatial resolution degradation was smaller than for accuracy degradation, the soil moisture errors decrease with the assimilation of observations from any spatial resolution. A comparison with Fig. 6 suggests that spatial (and hence accuracy) requirements are more important than repeat time requirements.

The results from this spatial resolution study do not take into account the additional information, such as stressed, unstressed and saturated soil moisture catchment fractions, which might be obtained from higher spatial resolution observations. This additional information may further constrain the assimilation by taking advantage of the unique catchment-based land surface model physics. Moreover, these results are applicable to a land surface model with approximately 30 arc-min spatial resolution; finer resolution land surface models may show stronger spatial resolution dependence.

These results suggest that the global near-surface soil moisture spatial resolution requirement is application specific; the flood forecasting and precision agriculture requirements will likely have different requirements than climate modeling and policy planning, as they operate at different spatial resolutions. We found that near-surface soil moisture measurements with a spatial resolution of approximately half the land surface model resolution were appropriate. However, this finding is dependent on the near-surface soil moisture measurement at a given resolution being an accurate near-surface soil moisture representation at the application resolution. Hence, 30 arc-min (50 km) near-surface soil moisture observations would be appropriate for climate modeling and policy planning applications.

4. Conclusions

This study has shown that the near-surface soil moisture observation error must be less than the required soil moisture forecast error, or slight model forecast degradation may result when used as data assimilation input. Typically, near-surface soil moisture observations must have an accuracy better than 5%v/v, but preferably better than 3%v/v. This study has also shown that assumptions in the assimilation framework lead to degraded forecasts when biased forcing and observations are used.

It was also found that for the temporal resolutions tested, daily near-surface soil moisture observations were required (further slight improvement would be expected from more frequent observations) to achieve the best soil moisture and evapotranspiration forecasts using a land surface model with 30 arc-min spatial resolution, particularly for near-surface (2 cm) soil moisture content and evapotranspiration. Longer repeat times between observations had only a minor root zone and total profile soil moisture forecast impact. The greatest repeat time impact was from 1 to 5 days, with longer times between observations having only a marginal degradation. These results conflict with Hoeben and Troch [15], who suggests that a repeat time greater than a day would be of little to no use in data assimilation. However, it must be noted that these two studies were undertaken for vastly different spatial scales.

Near-surface soil moisture observations with a spatial resolution finer than the model resolution were found to produce the best forecasts of soil moisture content and evapotranspiration. Observations with a spatial resolution coarser than the model resolution produced only slightly poorer results than observations at the model resolution. However, assimilating near-surface soil moisture observations at half the land surface model spatial resolution was a good compromise between model demands and technical constraints on making very high resolution measurements. Moreover, the results have shown that spatial resolution and accuracy are more important than observation repeat time.

While the above guidelines are a useful first step towards identifying some defensible targets for a global satellite soil moisture mission, it is not until a number of similar studies from a range of research groups are undertaken that firm recommendations can be made. Specifically, these studies should consider a range of model structures, spatial resolutions (from hillslope to global), and objectives (from climate modelling and weather prediction to flood forecasting), and should make use of both synthetic and real data (such as that from the SGP and SMEX experiments).

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References

[1] Beven KJ, Kirkby MJ. A physically based, variable contributing area model of basin hydrology. Hydrologic Sci—Bull 1979;24(1): 43–69.

[2] Betts AK, Ball JH, Viterbo P. Basin-scale surface water and energy budgets for the Mississippi from the ECMWF reanalysis. J Geophys Res 1999;104:19293–306.

[3] Boone A, Habets F, Noilhan J, Clark D, Dirmeyer P, Fox S, Gusev Y, Haddeland I, Koster R, Lohmann D, Mahanama S, Mitchell K, Nasonova O, Niu GY, Pitman A, Polcher J, Shmakin AB, Tanaka K, van den Hurk B, Verant S, Verseghy D, Viterbo P, Yang ZL. The Rhone-aggregation land surface scheme intercomparison project: an overview. J Climate 2003;17(1):187–208.

[4] Bowling LC, Lettenmaier DP, Nijssen B, Graham LP, Clark DB, El Maayar M, Essery R, Goers S, Gusev YM, Habets F, van den Hurk B, Jin JM, Kahan D, Lohmann D, Ma XY, Mahanama S, Mocko D, Nasonova O, Niu GY, Samuelsson P, Shmakin AB, Takata K, Verseghy D, Viterbo P, Xia YL, Xue YK, Yang ZL. Simulation of high latitude hydrological processes in the Torne-Kalix basin: PILPS Phase 2(e) 1: Experiment description and summary intercomparisons. J Global Planetary Change 2003; 38(1–2):1–30.

[5] Bras RL, Rodriguez-Iturbe I. Random functions and hydrology. Reading, MA: Addison Wesley; 1985. p. 559.

[6] Calvet JC, Noilhan J. From near-surface to root-zone soil moisture using year-round data. J Hydrometeorol 2000;1(5): 393–411.

[7] Capehart WJ, Carlson TN. Estimating near-surface soil moisture availability using a meteorologically driven soil-water profile model. J Hydrol 1994;160:1–20.

[8] Dobson MC, Ulaby FT. Active microwave soil moisture research. IEEE Trans Geosci Remote Sensing 1986;GE-24(1):23–36.

[9] Ducharne A, Koster RD, Suarez MJ, Stieglitz M, Kumar P. A catchment-based approach to modeling land surface processes in a GCM. Part 2: Parameter estimation and model demonstration. J Geophys Res 2000;105(D20):24823–38.

[10] Engman ET. Soil moisture needs in earth sciences. In: Proceedings of International Geoscience and Remoe Sensing Symposium (IGARSS). 1992. p. 477–9.

[11] Engman ET, Chauhan N. Status of microwave soil moisture measurements with remote sensing. Remote Sensing Environ 1995;51(1):189–98.

[12] Entekhabi D, Nakamura H, Njoku EG. Solving the inverse problem for soil moisture and temperature profiles by sequential assimilation of multifrequency remotely sensed observations. IEEE Trans Geosci Remote Sensing 1994;32(2):438–48.
[13] Fennessey MJ, Shukla J. Impact of initial soil wetness on seasonal atmospheric prediction. J Climate 1999;12:3167–80.
[14] Gallus Jr WA, Segal M. Sensitivity of forecasted rainfall in a Texas convective system to soil moisture and convective parameterization. Weather Forecast 2000;15:509–25.
[15] Hoeben R, Troch PA. Assimilation of active microwave observation data for soil moisture profile estimation. Water Resour Res 2000;36(10):2805–19.
[16] Henderson-Sellers A, Pitman AJ, Love PK, Irannejad P, Chen T. The project for intercomparison of land-surface parameterisation schemes (PILPS) phases 2 and 3. Bull Am Meteorol Soc 1995;76:489–503.
[17] Houser PR, Shuttleworth WJ, Famiglietti JS, Gupta HV, Syed KH, Goodrich DC. Integration of soil moisture remote sensing and hydrologic modeling using data assimilation. Water Resour Res 1998;34(12):3405–20.
[18] Jackson TJ, Schmugge TJ. Vegetation effects on the microwave emission of soils. Remote Sensing Environ 1991;36:203–12.
[19] Jackson TJ, Bras R, England A, Engman ET, Entekhabi D, Famiglietti J, et al. Soil moisture mission (EX-4) report, NASA land surface hydrology program post-2002 land surface hydrology planning workshop. Irvine, CA: April 12–14, 1999.
[20] Koster RD, Suarez MJ, Ducharne A, Stieglitz M, Kumar P. A catchment-based approach to modeling land surface processes in a GCM. Part 1: Model structure. J Geophys Res 2000;105(D20): 24809–22.
[21] Leese J, Jackson T, Pitman A, Dirmeyer P. Meeting summary: GEWEX/BAHC international workshop on soil moisture monitoring, analysis, and prediction for hydrometeorological and hydroclimatological applications. Bulletin of the American Meteorological Society. 2001. p. 1423–30.
[22] Milly PCD. Integrated remote sensing modeling of soil moisture: sampling frequency, response time and accuracy of estimates. In: Integrated design of hydrological networks (Proceedings of the Budapest Symposium), IAHS Publication No. 158. 1986. p. 201-11.
[23] Moore ID, Grayson RB, Ladson AR. Digital terrain modelling: a review of hydrological geomorphological and biological applications. Hydrol Process 1991:3–30.
[24] Njoku EG, Entekhabi D. Passive microwave remote sensing of soil moisture. J Hydrol 1996;184:101–29.
[25] Owe M, de Jeu R, Walker JP. A methodology for surface soil moisture and vegetation optical depth retrieval using the microwave polarization difference index. IEEE Trans Geosci Remote Sensing 2001;39(8):1643–54.
[26] Reichle RH, McLaughlin DB, Entekhabi D. Variational data assimilation of microwave radiobrightness observations for land surface hydrologic applications. IEEE Trans Geosci Remote Sensing 2001;39(8):1708–18.
[27] Reichle RH, McLaughlin DB, Entekhabi D. Hydrologic data assimilation with the ensemble Kalman filter. Monthly Weather Rev 2002;130(1):103–14.
[28] Reichle RH, Walker JP, Koster RD, Houser PR. Extended vs. ensemble Kalman filtering for land data assimilation. J Hydrometeorol 2002;3(6):728–40.
[29] Sellers P, Meeson BW, Closs J, Collatz J, Corprew F, Dazlich D, et al. The ISLSCP initiative i global data sets: surface boundary conditions and atmospheric forcings for land-atmosphere studies. Bull Am Meteorol Soc 1996;77:1987–2005.
[30] Ulaby FT, Batliva PP. Optimum radar parameters for mapping soil moisture. IEEE Trans Geosci Electron 1976;GE-14(2):81–93.
[31] Ulaby FT, Batliva PP, Dobson MC. Microwave backscatter dependence on surface roughness, soil moisture and soil texture. Part 1— Bare soil. IEEE Trans Geosci Electron 1978;GE-16(4):286–95.
[32] Walker JP, Houser PR. A methodology for initialising soil moisture in a global climate model: Assimilation of near-surface soil moisture observations. J Geophys Res—Atmospheres 2001;106(D11):11761–74.
[33] Walker JP, Willgoose GR, Kalma JD. One-dimensional soil moisture profile retrieval by assimilation of near-surface observations: a comparison of retrieval algorithms. Adv Water Resour 2001;24(6):631–50.
[34] Walker JP, Willgoose GR, Kalma JD. One-dimensional soil moisture profile retrieval by assimilation of near-surface measurements: a simplified soil moisture model and field application. J Hydrometeorol 2001;2(4):356–73.
[35] Walker JP, Willgoose GR, Kalma JD. Three-dimensional soil moisture profile retrieval by assimilation of near-surface measurements: simplified Kalman filter covariance forecasting and field application. Water Resour Res 2002;38(12):1301, doi:10.11029/2002/WRR001545.