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Operational assimilation of ASCAT surface soil wetness at the Met Office

I. Dharssi[1], **K. Bovis**[2], **B. Macpherson**[2], **and C. Jones**[2]

[1]Centre for Australian Weather and Climate Research, Australian Government Bureau of Meteorology, Melbourne, Australia
[2]Met Office, Exeter, UK

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Correspondence to: I. Dharssi (i.dharssi@bom.gov.au)

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Abstract

Currently, no extensive global soil moisture observation network exists. Therefore, the Met Office global soil moisture analysis scheme has instead used observations of screen temperature and humidity. A number of new space-borne remote sensing systems, operating at microwave frequencies, have been developed that provide a more direct retrieval of surface soil moisture. These systems are attractive since they provide global data coverage and the horizontal resolution is similar to weather forecasting models. Several studies show that measurements of normalised backscatter (surface soil wetness) from the Advanced Scatterometer (ASCAT) on the meteorological operational (MetOp) satellite contain good quality information about surface soil moisture. This note describes methods to convert ASCAT surface soil wetness measurements to volumetric surface soil moisture together with bias correction and quality control. A computationally efficient nudging scheme is used to assimilate the ASCAT volumetric surface soil moisture data into the Met Office global soil moisture analysis. This ASCAT nudging scheme works alongside a soil moisture nudging scheme that uses observations of screen temperature and humidity. Trials, using the Met Office global Unified Model, of the ASCAT nudging scheme show a positive impact on forecasts of screen temperature and humidity for the tropics, North America and Australia. A comparison with in-situ soil moisture measurements from the US also indicates that assimilation of ASCAT surface soil wetness improves the soil moisture analysis. Assimilation of ASCAT surface soil wetness measurements became operational during July 2010.

1 Introduction

Soil moisture can have a significant impact on near surface temperature and humidity, low clouds and precipitation by influencing the exchange of heat and water between the land surface and the atmosphere. Soil moisture can vary significantly over short distances so that measurements made at one location contain little information about

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neighbouring locations. The variability in soil moisture is due to the spatial distribution of rainfall and also the spatial variation of the soil texture, vegetation and topography. This is part of the reason that, currently, no extensive global soil moisture observation network exists. Some regional near real-time soil moisture observing networks do exist, such as the USDA: SCAN (US Department of Agriculture: soil climate analysis network). Famiglietti et al. (1999) examine the variability in soil moisture content of six fields with typical dimensions of 800 m × 800 m. In each field, soil moisture observations are made daily on a regular grid with 100 m spacing (49 sampling points per field). The standard deviations of the daily observations are found to be about 0.06 $m^3\ m^{-3}$.

Drusch and Viterbo (2007) have examined the performance of the ECMWF soil moisture nudging scheme that uses observations of screen temperature and humidity (they call it an optimal interpolation scheme) and concluded that soil moisture nudging significantly improves weather forecasts on large geographical domains. Temperature forecasts for the Northern Hemisphere were significantly improved for up to nine days and to a level of 700 hPa. However, by comparison with in-situ soil moisture observations from the Oklahoma mesonet they also conclude that soil moisture nudging fails to improve the analysis and forecasts of soil moisture itself. A number of new space-borne remote sensing systems, operating at microwave frequencies, have been developed that provide a more direct retrieval of surface soil moisture, e.g. ASCAT (Advanced Scatterometer, Bartalis et al., 2007) and SMOS (Soil Moisture and Ocean Salinity, Kerr et al., 2001). These systems are attractive since they provide global data coverage and the horizontal resolution is similar to numerical weather prediction (NWP) models. At microwave frequencies the dielectric constant of liquid water ($\simeq 70$) is much higher than that of the soil mineral particles (< 5) or ice. An increase in soil moisture leads to an increase in the dielectric constant of the soil which leads to a decrease in soil emissivity and an increase in soil reflectivity. Therefore, satellite based measurements of microwave brightness temperature (passive system) or backscatter (active system) can be used to derive estimates of surface soil moisture using a retrieval algorithm.

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However, using these additional sources of data is challenging since:

i. C-band (≃ 6 GHz) and L-band (1.4 GHz) microwave sensors only sense the top few cms of soil. NWP requires knowledge of soil moisture throughout the plant root zone, since plants extract soil water through their roots which then evaporates from their leaves. Many NWP centres are developing new land data assimilation (DA) schemes to correctly propagate the surface information down into the plant root zone (e.g. Draper et al., 2009a).

ii. Satellite microwave measurements can also be affected by numerous other factors such as vegetation water content and single scattering albedo, soil roughness, topography, soil texture, salinity and surface temperature. Consequently, retrieval algorithms can produce very biased estimates of surface soil moisture, Reichle et al. (2004). Using ground based observations of soil moisture from Australia, Draper et al. (2009b) have compared four different retrieval algorithms for the passive microwave Advanced Microwave Scanning Radiometer-Earth Observing System (AMSR-E) instrument and find large differences in the quality of the retrieval algorithms. Using ground based observations of soil moisture from France, Rudiger et al. (2009) compare two retrieval algorithms for AMSR-E and again find large differences in the quality of the retrieval algorithms. Therefore, the choice of retrieval algorithm is very important and more effort is required to develop better retrieval algorithms.

iii. NWP models may contain biases so that assimilating more accurate soil moisture data into the model may actually make the model surface fluxes of heat and moisture less accurate and hence cause weather forecasts to become worse. For example, Rooney and Claxton (2006) forced the Met Office land surface model MOSES with observed surface temperature and soil moisture and found that this made the MOSES estimated moisture flux worse. Therefore, improvements to the parameters and processes in land surface models are likely to be necessary before assimilation of satellite derived soil moisture shows significant benefit. The operational implementation of the Unified Model T/q soil moisture nudging scheme uncovered many deficiencies in the

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land surface model and prompted the work of Dharssi et al. (2009). This work resulted in large improvements to UM forecasts of screen temperature and humidity through better specification of the UM soil physical properties.

Most Met centres bias correct the retrieved satellite soil moisture. The available data (both ground based observations and model data) is insufficient to determine the true soil moisture climatology. Therefore, model soil moisture data is used for the bias correction and consequently the climatology of the bias corrected satellite soil moisture will agree quite closely with the climatology of the model soil moisture. This has the advantage that the bias corrected satellite soil moisture will be consistent with the assumptions made by the land surface model, such as assumptions about soil texture and vegetation parameters and the parametrisation of bare soil evaporation. Consequently, data assimilation of the bias corrected satellite soil moisture is more likely to improve model surface fluxes and lead to better weather forecasts. Many met centres use a bias correction technique called cumulative distribution function (CDF) matching (Reichle and Koster, 2004; Drusch et al., 2005) that requires a long time-series (at least one year) of satellite and model data. Any significant changes to the land surface model and/or satellite retrieval algorithm would necessitate a recalculation of the CDF matching parameters.

2 Met Office numerical weather prediction system

The Met Office uses the Unified Model (UM, Davies et al., 2005) for both numerical weather prediction and climate research. The version of the UM used in this work for the pre-operational trials has a horizontal resolution of about 40 km with 70 (or 50) vertical levels for the atmosphere and is based on the version of the global UM which became operational for NWP in March 2010. The 4DVAR data assimilation scheme is used for the atmosphere (Rawlins et al., 2007).

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2.1 Representation of land surface processes

The UM uses the MOSES 2 land surface scheme, Essery et al. (2001). The soil is discretised into four layers of 0.1, 0.25, 0.65 and 2 m thickness (from top to bottom). The soil hydrology is based on a finite difference form of the Richards equation and Darcy's law. The van Genuchten (1980) equations are used to describe the relationship of soil hydraulic conductivity and soil suction to the unfrozen volumetric soil moisture. The van Genuchten soil parameters depend on the soil texture (size distribution of the soil particles and the soil organic carbon content). Table 1 lists the van Genuchten soil parameters for the three UM soil textural types; coarse, medium and fine. The UM uses a new high resolution soil textures map that merges data from three separate sources; Harmonised World Soil Database (HWSD, FAO et al., 2008), State Soil Geographic Database (United States region, Miller and White, 1998) and point observations of soil sand, silt and clay fractions. The UM doesn't allow any vertical variation of soil texture, consequently data averaged over the 30 cm to 1 m depth of soil (subsoil) are used.

2.2 UM T/q soil moisture nudging scheme

The UM T/q soil moisture nudging scheme uses observations of screen temperature and humidity to analyse soil moisture (Best and Maisey, 2002). Because errors in the UM initial soil moisture field cause errors in forecasts of daytime screen temperature and humidity, knowledge of errors in forecasts of screen temperature and humidity can be used to slowly correct (nudge) the UM initial soil moisture. A reasonable simplification would be to state that the UM T/q soil moisture nudging scheme adjusts the model soil moisture to minimise the errors in six hour forecasts of daytime screen temperature and humidity. Errors in forecasts of screen temperature and humidity are due to many factors. Therefore, the UM T/q soil moisture nudging scheme seeks to identify and correct for those errors in screen temperature and humidity forecasts that are due to the model soil moisture. The UM T/q soil moisture nudging scheme is only active where there is evaporation, where the errors in screen temperature and humidity are

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of opposite sign (i.e. model boundary layer too warm and dry or model boundary layer too cold and moist), in unstable conditions (negative Richardson number) and where there is an absence of snow.

3 Scatterometer data

The advanced scatterometer (ASCAT) is an active C-band, 5.3 GHz microwave sensor on board the polar-orbiting satellite METOP, launched during October 2006. ASCAT is the successor system to the ERS-1 (1991 to 1996) and ERS-2 (launched 1996) C-band, 5.3 GHz microwave scatterometers. ASCAT measures microwave backscatter with two sets of three antennas on each side of the satellite ground track. At each spatial point, a set of three antennas make three nearly co-located backscatter measurements at incidence angles ranging between 25 to 65°. ASCAT covers two swaths of 550 km width each separated by a gap of about 360 km. Daily global coverage is 82% which is double that of the ERS-1/2 systems that use only one set of three antennas. The ASCAT descending and ascending equator crossings occur at about 09:30 and 21:30 mean LST. Backscatter products are delivered at two horizontal resolutions[1]. For this study the higher resolution product provided on a 12.5 km grid is used.

3.1 Conversion of ASCAT backscatter measurements to surface soil wetness

A time-series based, change detection algorithm (Wagner et al., 1999) is used to convert satellite backscatter measurements to a surface soil wetness $m_s(t)$. It is assumed that the surface volumetric soil moisture is linearly related to $m_s(t)$. First, a triplet of nearly co-located backscatter measurements are extrapolated to a reference angle of 40° ($\sigma(40^\circ, t)$) to eliminate any angular dependence. Soil roughness and topography are assumed to provide a time invariant contribution to $\sigma(40^\circ, t)$ while vegetation effects

[1]The products are actually sampled on a grid half of the footprint size (oversampled by a factor of 2).

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are assumed to vary seasonally. Therefore, the effects of soil roughness, topography and vegetation are removed by subtracting a dry reference function $\sigma_{dry}(40^{\circ}, t)$ that is annually periodic. $\sigma_{dry}(40^{\circ}, t)$ is estimated at each spatial grid point from the lowest recorded values of $\sigma(40^{\circ}, t)$ in a long time series (at least 10 years long) of measurements from ERS-1/2. A wet reference value $\sigma_{wet}(40^{\circ})$ that is time invariant, is estimated at each spatial grid point from the highest recorded value of $\sigma(40^{\circ}, t)$ in a long time-series of measurements. Thus the conversion of $\sigma(40^{\circ}, t)$ to $m_s(t)$ is given by:

$$m_s(t) = \frac{\sigma(40^{\circ}, t) - \sigma_{dry}(40^{\circ}, t)}{\sigma_{wet}(40^{\circ}) - \sigma_{dry}(40^{\circ}, t)}. \quad (1)$$

An exponential filter is used to estimate the profile soil water index (SWI) from a time series of surface soil wetness (m_s), see Table 5-2 of Scipal (2002) and Eq. (2) of Albergel et al. (2009). Scipal (2002) then uses an empirical relationship, developed for the Ukraine, to derive the volumetric soil moisture (θ) from the profile soil water index (SWI).

$$\theta = \theta_w + \mathrm{SWI} \times \left(\frac{\theta_{fc} + \theta_s}{2} - \theta_w \right), \quad (2)$$

where θ_w is the wilting point, θ_{fc} is the field capacity[2] and θ_s is the saturation point.

3.2 Comparison of ERS/ASCAT soil moisture products with ground based soil moisture observations

Albergel et al. (2009), Rudiger et al. (2009), Naeimi et al. (2009) and Scipal (2002) have found good agreement between ERS/ASCAT derived soil moisture and ground based soil moisture observations.

[2]For this report, we assume that field capacity is the volumetric soil moisture at a soil suction of 3.3 m.

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Albergel et al. (2009) compare ASCAT soil wetness with in-situ observation for South-Western France. Albergel et al. (2009) find that ASCAT observations are well correlated with the in-situ data ($r \simeq 0.56$) and no systematic dry or wet bias is observed. However, they do find interesting differences in the behaviour of the soil moisture in the topmost thin layer sampled by ASCAT ($\simeq$1 cm) and at 5 cm where the in-situ sensors are located. The soil moisture variations in the top $\simeq$1 cm are much more pronounced than at a soil depth of 5 cm. The topmost $\simeq$1 cm layer of the soil is subjected to much more rapid drying and wetting. They give an example of a rainfall event which leads to a rapid increase in the ASCAT soil moisture estimate. Whereas at a depth of 5 cm the increase in soil moisture only occurs a day after the rainfall event.

Naeimi et al. (2009) compare the scatterometer derived soil wetness with in-situ measurements at 5 cm from the Oklahoma Mesonet, for the three year period (2004–2006) and find high correlations between the derived soil wetness and in-situ measurements. Naeimi et al. (2009) also find high correlation between the scatterometer derived soil wetness and ERA-Interim reanalysis soil moisture data.

Scipal (2002) has compared ERS derived volumetric soil moisture with in-situ observations from China, Russia, Ukraine, Illinois and India. He finds that the ERS derived volumetric soil moisture has an accuracy of between 0.05 $m^3\,m^{-3}$ to 0.07 $m^3\,m^{-3}$, when the observed soil properties (θ_w, θ_{fc}, θ_s) are used in Eq. (2).

4 Conversion of surface soil wetness to surface volumetric soil moisture

The level 2 ASCAT soil moisture product is the surface soil wetness (m_s). The main level 3 product is the profile soil water index (SWI). We are primarily interested in the level 2 product since it is as close as possible to the satellite measurements and because we can use our land surface model (MOSES2, Essery et al., 2001) to propagate the satellite data to the deeper soil levels. Using MOSES2 should be more accurate than using an exponential filter to calculate SWI.

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Before the ASCAT surface soil wetness (m_s) can be assimilated, it must be converted to surface volumetric soil moisture (θ_{scat}). Following Scipal et al. (2008) a linear relationship is assumed,

$$\theta_{scat}(t) = a + b \times m_s(t). \quad (3)$$

From Eq. (3), the climatology of the ASCAT surface volumetric soil moisture is given by:

$$\overline{\theta_{scat}(t)} = a + b \times \overline{m_s(t)}, \quad (4)$$

where $\overline{m_s(t)}$ is the climatology of surface soil wetness. $\overline{m_s(t)}$ is derived from a long time-period of ERS-1/2 backscatter data and is provided by the ASCAT level 2 soil wetness BUFR product (bufr code 40003). In an analogous manner to CDF matching, we impose the condition that

$$\overline{\theta_{scat}(t)} = \overline{\theta_{UM}(t)}, \quad (5)$$

where $\overline{\theta_{UM}(t)}$ is the climatology of UM level 1 volumetric soil moisture that is derived by driving the UM off-line land surface model with observations based driving data (precipitation, short-wave and long-wave downward surface radiation, surface pressure, near surface air temperature, humidity and wind speed). The driving data is provided by the Global Soil Wetness Project 2 (GSWP2, Dirmeyer et al., 2006) and covers the period January 1986 to December 1995 at a spatial resolution of 1° latitude/longitude.

Combining Eqs. (3)–(5) then gives the equation used to convert ASCAT surface soil wetness to volumetric soil moisture:

$$\theta_{scat}(t) = \overline{\theta_{UM}(t)} + b \times \left(m_s(t) - \overline{m_s(t)} \right). \quad (6)$$

The parameter b varies spatially but is time invariant. From Eqs. (4) and (5), the parameter b can be estimated from the slope of the line of best fit through a scatter plot of $\overline{\theta_{UM}(t)}$ against $\overline{m_s(t)}$. Figure 1 shows example scatter plots with lines of best fit

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for three different regions. The scatter plots indicate that for regions with significant vegetation cover (such as the UK and Madagascar) the slope of the line of best fit is shallower and $b \simeq (\theta_s - \theta_w)$ while for regions with significant amounts of bare soil (such as SW Australia) the slope of the line of best fit is steeper and $b \simeq \theta_s$. Therefore, we assume

$$b = (\theta_s - v\theta_w), \tag{7}$$

where v is the fraction of vegetation cover.

Figure 2 compares histograms of the distribution of ASCAT surface soil wetness m_s with the distribution of UM level 1 soil wetness $\theta_{UM,1}/\theta_s$ for the NW Europe region ($\theta_{UM,1}$ is output from the UM T/q soil moisture nudging scheme of a control experiment). The shapes of the m_s and $\theta_{UM,1}/\theta_s$ distributions are significantly different. Also shown is the histogram of the distribution of converted ASCAT soil wetness θ_{scat}/θ_s. The histogram for θ_{scat}/θ_s is similar to the histogram for $\theta_{UM,1}/\theta_s$.

Note that we are not using CDF matching. The reason is that van Genuchten soil hydraulics was only introduced into the operational global UM during March 2010 and its introduction has a significant impact on the global UM soil moisture climatology. Consequently, we don't have a long enough period of model soil moisture data for the CDF matching. However, the constraint that $\overline{\theta_{scat}(t)} = \overline{\theta_{UM}(t)}$ ensures that $\theta_{scat}(t)$ will be consistent with the assumptions made by the UM land surface model and unbiased in a similar sense to CDF matching (CDF matching, in addition, allows the constraint of higher order moments such as variance, skewness and kurtosis).

5 Quality control of the ASCAT data

A quality control (QC) step is implemented to deal with missing data and to filter out measurements from regions with sea, snow cover, frost, mountains, dense vegetation, sand dunes, wetlands and open water. There is also a facility to reject data based on cross-track cell number. Once the ASCAT surface soil wetness measurements m_s have

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been converted to surface volumetric soil moisture θ_{scat}, a background quality control check is performed. If an observation is rejected by one QC check it is not tested by any other QC check, the QC checks are performed in the following order:

Snow. ASCAT data is rejected where the UM snow analysis (Pullen et al., 2008) indicates snow amounts greater than 0.05 kg m^2 .

Frost. ASCAT data is rejected where the UM screen temperature analysis has temperatures below 275.15 K.

Wetlands. ASCAT data is rejected where the inundation and wetland amount has a value greater than 15%. The data is derived from the Global Lakes and Wetlands Database level 3 product (Bartalis et al., 2008). The inundation and wetland amount is provided by the ASCAT level 2 soil wetness BUFR product (bufr code 40009).

Mountains. ASCAT data is rejected where the topographic complexity has a value greater than 20%. The topographic complexity is derived from the US Geological Survey GTOPO30 global digital elevation data. GTOPO30 has a horizontal resolution of 30 arc s ($\simeq$ 1 km). For each cell of the ASCAT global grid, the standard deviation of elevation is calculated and the result is normalised to values between 0 and 100% (Bartalis et al., 2008). The topographic complexity is provided by the ASCAT level 2 soil wetness BUFR product (bufr code 40010).

ASCAT estimated error. ASCAT data is rejected where the error in the ASCAT surface soil wetness is estimated to be greater than 7%. This check rejects ASCAT data from regions with dense vegetation (e.g. the Amazon) and sand dunes. The estimated error is provided by the ASCAT level 2 soil wetness BUFR product (bufr code 40002).

Cross track cell number. Figure 3 shows the error in the ASCAT surface soil wetness as a function of cross track cell number. To generate the figures, ASCAT data is extracted for a 3 day period, quality controlled and re-gridded onto a grid with $\simeq$ 25 km horizontal spacing. The root mean square difference between the quality controlled

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ASCAT measurements and the re-gridded data is then calculated for each cross track cell. Based on Fig. 3, ASCAT data is rejected for cells 1 to 4, 40 to 43 and 79 to 82[3].

Background quality control check. The background quality control check is performed after the ASCAT surface soil wetness measurements have been converted to volumetric soil moisture. For the quality control, we assume that the observation error $\sigma_o = 0.07\,m^3\,m^{-3}$, the background error $\sigma_b = 0.07\,m^3\,m^{-3}$, the prior probability of gross error $p(G) = 0.05$ and the observation is rejected if the posterior probability of gross error $p(G|o) > 0.5$. Following Lorenc and Hammon (1988),

$$p(G|o) = \frac{p(o|G)p(G)}{p(o)} = \frac{\kappa p(G)}{\kappa p(G) + N(y,\sigma^2)(1-p(G))} \tag{8}$$

where $\kappa = 1/\theta_s$, $y = \theta_{scat} - \theta_{ib,1}$, $\sigma^2 = \sigma_o^2 + \sigma_b^2$ and

$$N(y,\sigma^2) = \frac{1}{\sqrt{2\pi\sigma^2}} \exp\left(\frac{-y^2}{2\sigma^2}\right). \tag{9}$$

$\theta_{ib,1}$ is the UM intermediate soil moisture background for soil level 1 (see Fig. 4).

6 Regridding

The ASCAT surface volumetric soil moisture values θ_{scat} that have passed all the QC checks are gridded onto the UM grid. No thinning is performed, instead super-obing is used. The arithmetic mean of all θ_{scat} values that fall within the same model grid square is calculated and this mean value is then taken to be the observed value for that model grid square $\tilde{\theta}_{scat}$.

[3]For some early trials data was, unintentionally, only rejected from cells 32 to 41 and 77 to 82.

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7 Assimilation of ASCAT derived soil moisture

A simple nudging scheme is used to nudge the UM level 1 volumetric soil moisture (output by the UM T/q soil moisture nudging scheme) $\theta_{\mathrm{ib},1}$ towards the ASCAT derived super-ob value $\tilde{\theta}_{\mathrm{scat}}$. Such a scheme has been developed quickly and is computationally very cheap. The soil moisture analysis is given by

$$\theta_{a,l} = \begin{cases} \theta_{\mathrm{ib},1} + K(\tilde{\theta}_{\mathrm{scat}} - \theta_{\mathrm{ib},1}) & l = 1 \\ \theta_{\mathrm{ib},l} & l > 1 \end{cases}, \tag{10}$$

where l is the model soil level. The assimilation time window is six hours long and the soil moisture analysis is performed four times a day. See Fig. 4 for a schematic overview of the soil moisture analysis scheme.

K is a constant scalar value that is user specified and doesn't vary spatially or temporally. Some tuning will be required to determine the optimal value of K. Starting with Eq. (10) we can show that $\sigma_a^2 = \sigma_\mathrm{b}^2(1-K)^2 + \sigma_\mathrm{o}^2 K^2$, if the observation and background errors are uncorrelated. The value of K that minimises σ_a^2 is then given by $K = \sigma_\mathrm{b}^2/(\sigma_\mathrm{b}^2 + \sigma_\mathrm{o}^2)$. Unfortunately, we don't accurately know the values of σ_b^2 and σ_o^2. We might assume that $\sigma_\mathrm{b}^2 \simeq \sigma_\mathrm{o}^2$ which then gives $K \simeq 0.5$.

8 Trials of ASCAT soil wetness assimilation

Scipal et al. (2008), have examined the impact of assimilating ERS scatterometer derived soil moisture in the ECMWF NWP system. Three experiments were performed; a control (CTRL) where soil moisture is unconstrained and free-wheels, a test experiment (OI) with a soil moisture nudging scheme that uses observations of screen temperature and humidity and a second test experiment (NDG) that only uses ERS scatterometer derived soil moisture to nudge the model level 1 soil moisture. Scipal et al. (2008) find that the NDG experiment provides better forecasts of screen temperature and humidity than the CTRL but poorer forecasts than the OI experiment.

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Our trials differ from Scipal et al. (2008) in one crucial way; our test experiments use observations of screen temperature and humidity AND also ASCAT data to analyse the soil moisture. The UM T/q soil moisture nudging scheme that uses observations of screen temperature and humidity is applied first to correct the model soil moisture in all four soil layers. Next, ASCAT data is used to correct the model level 1 soil moisture (see Fig. 4).

8.1 Impact of assimilating ASCAT soil wetness on the global UM NWP index

Table 2 describes the trials performed and the impact on the global UM NWP Index. For trial 1 the UM forecasts start at 12Z each day, for the other trials UM forecasts start at 00Z and 12Z each day. The global UM NWP index is a convenient single value measure of forecast skill. The global UM NWP index primarily examines the forecast skill of extra-tropics mean sea level pressure, extra-tropics 500 hPa height and tropical wind. The impact of ASCAT soil wetness assimilation on the global UM NWP index is small and within the expected noise level for NWP trials of this duration (± 0.5). This result is unsurprising since soil moisture has only a small impact on the forecast parameters included in the global UM NWP index.

8.2 ASCAT minus UM background statistics

Figure 5 show that the land surface model is able to retain the information from the ASCAT soil wetness assimilation. Within a few weeks, the UM level 1 soil moisture $\theta_{\mathrm{ib},1}$ adjusts towards the ASCAT values $\tilde{\theta}_{\mathrm{scat}}$, such that the RMS values level off at about $0.05\,\mathrm{m}^3\,\mathrm{m}^{-3}$. This value is very similar to the expected accuracy of the ASCAT volumetric soil moisture. Figure 5 shows results from trial 1, the other trials also show similar results.

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8.3 ASCAT quality control statistics

Table 3 shows the percentage of ASCAT soil wetness measurements rejected in trial 1 by each quality control check. The quality control checks are applied in the order shown in Table 3. Apart from snow, there is no significant change in the percentage of observations rejected during the trial.

8.4 Soil moisture nudges

Figure 6 shows the RMS and mean size of soil moisture nudges (mm day^{-1}) from trial 1 for the July 2009 period. The RMS size of soil moisture nudges by both schemes is similar in trial 1 (where $K = 0.2$). At first sight, it may seem inconsistent to compare UM T/q soil moisture nudges in the top 1 m of soil with ASCAT nudges in the top 10 cm of soil. However, the UM T/q scheme adds water throughout the plant root zone and generally only adds a small amount of water to the top 10 cm of soil. Consequently, only comparing water added to the top 10 cm of soil would give the misleading impression that ASCAT nudges are much bigger than UM T/q soil moisture nudges. The ASCAT nudges in the top 1 m of soil are equal to the ASCAT nudges in the top 10 cm of soil. Therefore, there is no inconsistency in comparing ASCAT nudges in the top 10 cm of soil with UM T/q soil moisture nudges in the top 1 m of soil.

The mean size of soil moisture nudges (mm day^{-1}) from trial 1 for the July 2009 period show that in the Northern Hemisphere middle-latitude regions there is a general moistening of the soil by the UM T/q soil moisture nudging scheme. The ASCAT nudges do show a different pattern, in particular for North Africa and the Western United States (US) where the ASCAT nudging dries the soil.

For North Africa we can be confident that the moistening by the UM T/q soil moisture nudging scheme is erroneous and partly due to a bug in the model bare soil evaporation scheme. This recently discovered bug, switches off bare soil evaporation where the soil moisture in all four soil levels is below the wilting point. The correct model behaviour is

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that bare soil evaporation should only depend on UM level 1 soil moisture and that bare soil evaporation should switch off when the UM level 1 soil is completely dry. Correcting the bug causes a very similar drying of the UM North African soil as seen in Fig. 7.

Figure 7 shows the average difference in volumetric soil moisture ($m^3\,m^{-3}$) between the test and control experiments of trial 1 for the July 2009 period. The left panel shows differences for (the topmost) soil level 1, the right panel shows differences for soil level 2. The differences are biggest for soil level 1 and become progressively smaller for the deeper soil levels. In the trial, ASCAT nudging moistens the soil over much of the Southern Hemisphere, tropics and Eastern US. ASCAT nudging dries the soil over much of North Africa, Western US and Central Asia. ASCAT nudging has little impact on soil moisture for the European region.

8.5 Impact of assimilating ASCAT soil wetness on forecasts of screen temperature and humidity

Soil moisture influences the partitioning of net surface radiation into sensible, latent and ground heat fluxes. Consequently, soil moisture can have a significant impact on forecasts of screen temperature and humidity. Figures 8 and 9 show verification of UM screen temperature and screen relative humidity forecasts against observations for trial 1, which covers the May to July 2009 time period. These figures shows that ASCAT soil wetness assimilation has a positive impact in the tropics and Australia. For Europe (results not shown), North America and the Northern Hemisphere the impact is neutral. Mahfouf (2010) has assimilated ASCAT derived soil moisture using a simplified Extended Kalman Filter into a limited area NWP model covering Western Europe and finds a broadly neutral impact on forecasts.

Figure 10 shows screen verification results for trial 4. Trial 4 starts forecasts from both 00Z and 12Z as compared to trial 1 where forecasts are only started from 12Z. This is the reason that trial 4 screen verification doesn't show the zig-zag pattern seen in the trial 1 screen verification. Again ASCAT soil wetness assimilation gives a positive impact in the tropics and Australia. This time, there is also a positive impact for North

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America. Again, for Europe and the Northern Hemisphere the impact is neutral. Trials 2 and 3 show similar impact on screen verification as trial 4.

9 Comparison of model with in-situ soil moisture measurements

The US Department of Agriculture, Soil Climate Analysis Network (USDA SCAN) consists of about 100 automated sites, spread over the US that take soil moisture measurements hourly at soil depths of 5 cm, 10 cm, 20 cm, 50 cm and 100 cm. USDA SCAN sites use Stevens vitel hydra probes that measure the dielectric constant of the soil to determine soil moisture (Seyfried and Murdock, 2004; Seyfried et al., 2005). According to the user manual, the probes have an accuracy of 0.03 $m^3\,m^{-3}$. Since these are point measurements (and we are interested in the grid square average) they also contain errors of representativity of about 0.06 $m^3\,m^{-3}$ (based on the results of Famiglietti et al., 1999). This gives a total observation error of about 0.07 $m^3\,m^{-3}$.

A comparison has been made of the UM soil moisture, from trial 1, with USDA SCAN observations for the June to July 2009 period. 91 USDA SCAN stations have sufficient data for the June to July 2009 period for a comparison. Figure 11 shows the location of the USDA SCAN stations used for verification. For each station the UM level 1 soil moisture is compared with the mean of USDA SCAN 5 cm and 10 cm observations. For each station, the standard deviation (SD), RMS, Bias and Correlation between the UM and USDA SCAN observed soil moisture are calculated. The SD is a measure of the random error in the UM soil moisture while the RMS is a measure of both the random error and bias. Figure 13 show the results of the comparison for selected sites.

A simple quality control (QC) scheme has been implemented that rejects USDA SCAN stations where in either the TEST or CTRL experiment, the correlation is less than 0.3 or the SD is higher than 0.1 $m^3\,m^{-3}$ or the RMS is higher than 0.2 $m^3\,m^{-3}$. 60 USDA SCAN stations pass the QC (Fig. 12). Table 4 shows the verification statistics both with and without QC. The uncertainty in the verification statistics is also given using the 95% confidence intervals. For SD, RMS and Bias, the 95% confidence intervals

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are calculated as $\pm 1.96\sigma/\sqrt{n}$ where σ is the standard deviation of the SD_k, RMS_k or $Bias_k$ station values and n is the number of SCAN stations used ($n = 60$ with QC or $n = 91$ without QC). For correlation, the 95% confidence intervals are calculated as $\pm 1.96(1 - r^2)/\sqrt{N}$ (Jolliffe, 2007) where r is the correlation calculated using all the observations and N is the total number of observations used ($N = 3240$ with QC or $N = 4914$ without QC). The verification statistics suggest that assimilation of ASCAT surface soil wetness reduces the random error (SD) in the UM level 1 soil moisture (see also Fig. 11) and increases the correlation with ground based observations of soil moisture. The verification statistics also suggest that the UM level 1 soil moisture may have a slight moist bias in both the test and control experiments. Appendix A describes the equations used to calculate the verification statistics.

10 Operational implementation

Assimilation of ASCAT surface soil wetness has been implemented operationally in the global UM at Parallel Suite 24 (PS24) that started in May 2010 and became operational in July 2010. For operational use $K = 0.2$ in Eq. (10). As is usual, PS24 combines together a number of changes. In particular PS24 implemented a new cloud parameterisation scheme as well as changes to the radiation parameterisation and aerosol climatology. Since these changes will all have a significant impact on model performance, it is not possible to ascribe improvements at PS24 to any particular change.

11 Conclusions

We have developed a simple and computationally cheap method to assimilate ASCAT surface soil wetness measurements that has been implemented operationally. Trial results indicate that assimilation of ASCAT surface soil wetness has a positive benefit on forecasts of screen temperature and humidity for the tropics, North America and

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Australia. A comparison with ground based observations of soil moisture indicates that generally assimilation of ASCAT surface soil wetness improves the agreement between in-situ and model soil moisture. However, given the large errors of representativity in the point measurements it is unsurprising that the results are difficult to interpret and improvements are not seen at all measurement sites.

The comparison with ground-based soil moisture observations indicates that the UM level 1 soil may be slightly too moist. This might be because the UM doesn't allow any vertical variation of soil texture and uses texture data for the 30 cm to 1 m depth of soil. In general surface soils tend to be coarse (sandy) and become finer (higher clay content) in the deeper soil layers. Ignoring this vertical variation in soil texture would cause the model to over-estimate surface soil moisture. Rooney and Claxton (2006) find that reducing the soil saturated hydraulic conductivity K_s with soil depth improves the ability of the land surface model to simulate the correct soil moisture behaviour. Work is planned to quantify the importance of the vertical variation of soil texture.

Work is also underway at the Met Office on the development of a new land DA system based around the Met Office off-line land surface model and the Extended Kalman Filter (EKF). The new land DA system is expected to be able to make optimal use of a wide variety of observation types such as screen level observations and satellite data and to correctly propagate information from the surface into the deeper soil layers.

Appendix A

The notation $o_{k,t,z\mathrm{cm}}$ is used to describe an observation of volumetric soil moisture from USDA SCAN station k at time t and depth z. The average of SCAN observations at depths of 5 cm and 10 cm are used, thus we define

$$o_{k,t} = 0.5(o_{k,t,5\mathrm{cm}} + o_{k,t,10\mathrm{cm}}). \quad \text{(A1)}$$

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$m_{k,t}$ is UM level 1 volumetric soil moisture interpolated to observation space. The following equations are used to calculate the verification statistics for each station:

$$\mathrm{RMS}_k^2 = \frac{1}{T}\sum_{t=1}^{T}\left(m_{k,t} - o_{k,t}\right)^2, \tag{A2}$$

$$\mathrm{Bias}_k = \frac{1}{T}\sum_{t=1}^{T}\left(m_{k,t} - o_{k,t}\right) = \overline{m}_k - \overline{o}_k, \tag{A3}$$

where $\overline{m}_k = \frac{1}{T}\sum_{t=1}^{T} m_{k,t}$ and $\overline{o}_k = \frac{1}{T}\sum_{t=1}^{T} o_{k,t}$.

$$\begin{aligned}\mathrm{SD}_k^2 &= \frac{1}{T}\sum_{t=1}^{T}\left\{\left(m_{k,t} - \overline{m}_k\right) - \left(o_{k,t} - \overline{o}_k\right)\right\}^2 \\ &= \mathrm{RMS}_k^2 - (\mathrm{Bias}_k)^2 .\end{aligned} \tag{A4}$$

$T = 54$ is the verification time period in days. The overall verification statistics are given by equations:

$$\mathrm{RMS}^2 = \frac{1}{n}\sum_{k=1}^{n}\mathrm{RMS}_k^2, \tag{A5}$$

$$\mathrm{Bias} = \frac{1}{n}\sum_{k=1}^{n}\mathrm{Bias}_k, \tag{A6}$$

$$\mathrm{SD}^2 = \frac{1}{n}\sum_{k=1}^{n}\mathrm{SD}_k^2 = \mathrm{RMS}^2 - \frac{1}{n}\sum_{k=1}^{n}(\mathrm{Bias}_k)^2 . \tag{A7}$$

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Table 1. Unified Model van Genuchten soil parameters.

Parameter	Soil texture		
	Fine	Medium	Coarse
θ_s ($m^3\,m^{-3}$)	0.456	0.458	0.382
θ_r ($m^3\,m^{-3}$)	0.000	0.000	0.000
K_s ($mm\,s^{-1}$)	0.0015	0.0028	0.0195
$1/\alpha$ (m)	0.324	0.397	0.062
$1/(n-1)$	11.20	6.63	3.63

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Table 2. Impact on the global UM index of assimilating ASCAT soil wetness.

	Trial Period	Trial length (days)	UM vertical levels	K	NWP index vs. OBS	NWP index vs. ANAL
Trial 1	May to Jul 2009	79	70	0.2	+0.22	+0.06
Trial 2	Jun to Jul 2009	30	50	0.5	+0.19	−0.01
Trial 3	Aug to Sep 2009	38	50	0.5	−0.22	−0.31
Trial 4	Aug to Sep 2009	38	50	0.2	−0.25	−0.02
Trial 5	Dec to Jan 2010	24	70	0.2	+0.00	+0.13

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Table 3. Percentage of ASCAT soil wetness measurements rejected in trial 1 by each quality control check.

	End of Trial 12Z 24 Jul 2009 (%)	Mid Trial 12Z 24 Jun 2009 (%)	Start of Trial 12Z 5 May 2009 (%)
Sea points	68.4	65.3	66.3
Snow points	9.3	9.4	12.9
Frost points	1.1	0.6	0.7
Wetlands points	0.3	0.7	0.3
Mountain points	0.8	1.6	0.8
ASCAT estimated error	2.6	0.8	2.3
Cross track cell number	2.3	2.9	2.1
Background QC check	0.0	0.0	0.2

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Table 4. Verification statistics for trial 1 of UM level 1 soil moisture compared with USDA SCAN observations.

	TEST ASCAT assim.	CTRL No ASCAT assim.	Number of USDA SCAN stations Better	Same	Worse
With quality control of USDA SCAN stations					
SD ($m^3\,m^{-3}$)	0.041 ± 0.003	0.046 ± 0.003	45	1	14
RMS ($m^3\,m^{-3}$)	0.075 ± 0.007	0.082 ± 0.008	38	1	21
Correlation	0.79 ± 0.01	0.73 ± 0.02	25	5	30
Bias ($m^3\,m^{-3}$)	0.01 ± 0.02	0.01 ± 0.02	24	9	27
Without any quality control of USDA SCAN stations					
SD ($m^3\,m^{-3}$)	0.045 ± 0.003	0.051 ± 0.004	62	2	27
RMS ($m^3\,m^{-3}$)	0.108 ± 0.011	0.114 ± 0.011	55	2	34
Correlation	0.59 ± 0.02	0.52 ± 0.02	41	5	45
Bias ($m^3\,m^{-3}$)	0.03 ± 0.02	0.03 ± 0.02	41	15	35

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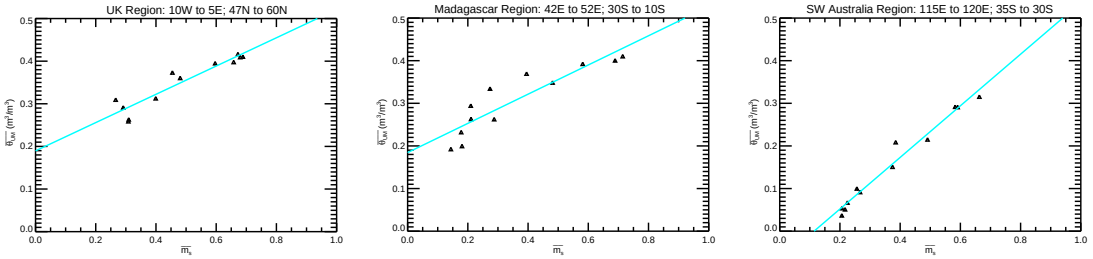

Fig. 1. Plots of UM level 1 volumetric soil moisture climatology $\overline{\theta_{\mathrm{UM}}}$ vs. the ASCAT surface soil wetness climatology $\overline{m_{\mathrm{s}}}$ for the UK region, Madagascar region and SW Australia region.

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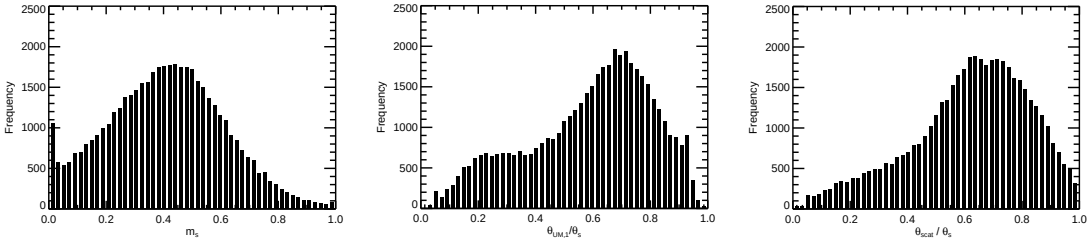

Fig. 2. Histograms of surface soil wetness m_s (left panel), UM level 1 soil wetness $\theta_{UM,1}/\theta_s$ (middle panel) and converted ASCAT soil wetness θ_{scat}/θ_s (right panel). Data is for the NW Europe region, 15° W to 15° E; 37° N to 60° N and time period May to July 2009.

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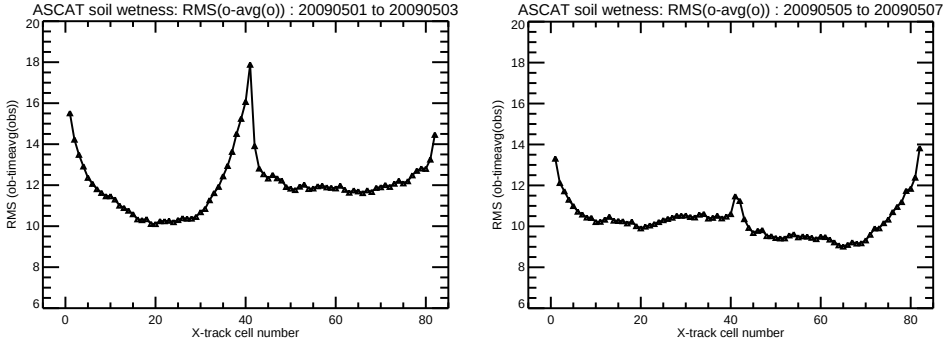

Fig. 3. Error in ASCAT surface soil wetness measurements as a function of cross track cell number. The left panel shows errors for the 3 day period; 1 May 2009 to 3 May 2009. On 4 May 2009, EUMETSAT implemented an operational improvement to the ASCAT bias correction. The right panel shows errors for the 3 day period; 5 May 2009 to 7 May 2009. The benefit of the improved bias correction is clearly visible, showing significantly smaller errors.

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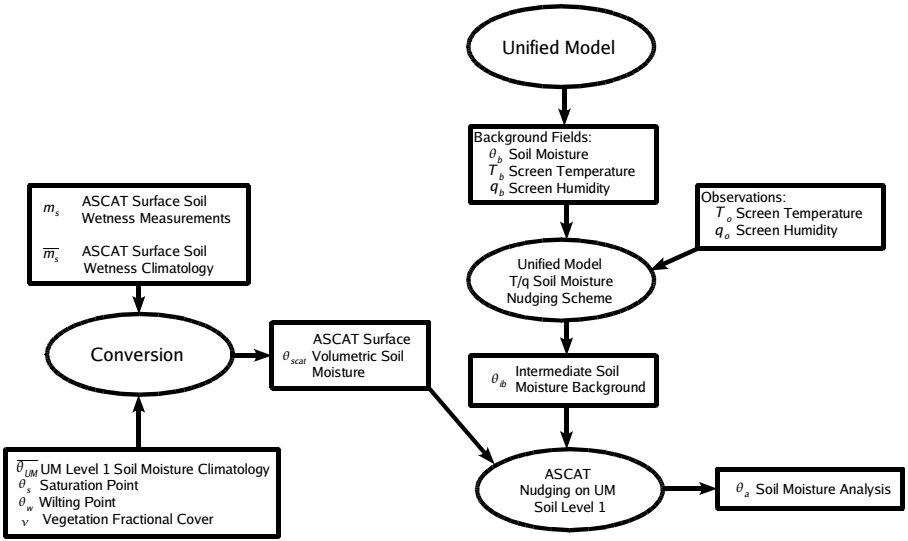

Fig. 4. Schematic view of the soil moisture analysis in the test experiments.

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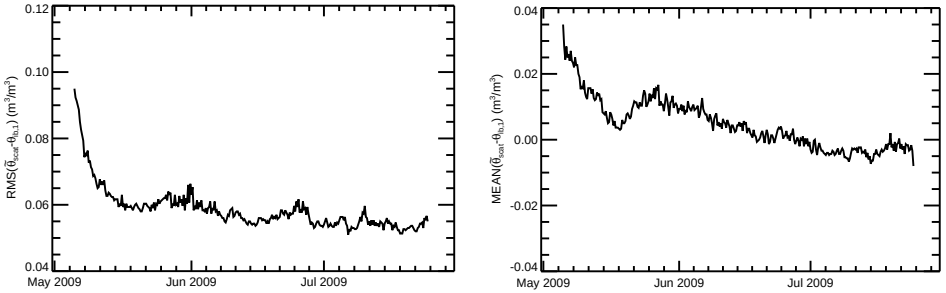

Fig. 5. Time series of RMS and MEAN differences between $\tilde{\theta}_{\mathrm{scat}}$ and the UM level 1 volumetric soil moisture $\theta_{\mathrm{lb},1}$, from the test experiment of trial 1.

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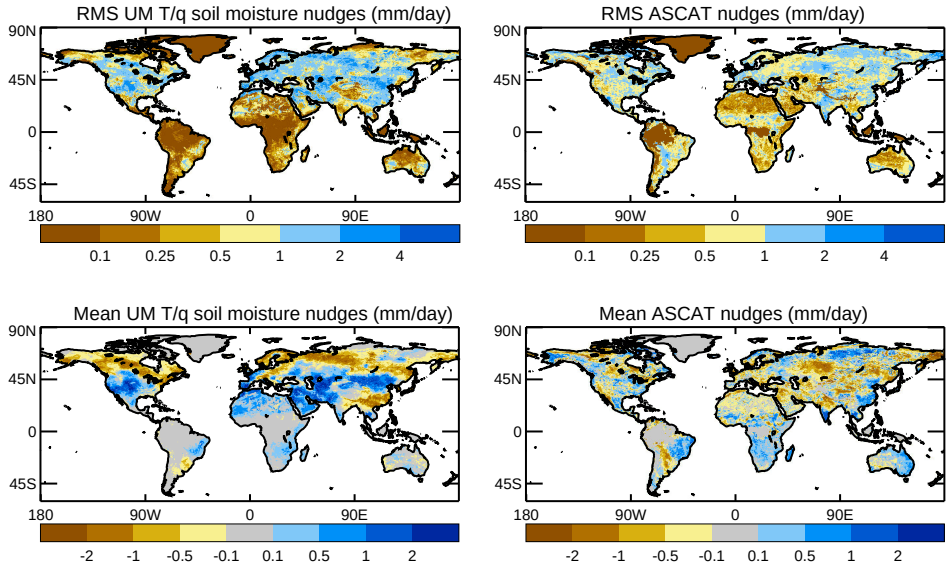

Fig. 6. RMS (top panels) and mean (lower panels) size of soil moisture nudges (mm day^{-1}) from trial 1 for the July 2009 period. The left panel shows nudges in the top 1 m of soil by the UM T/q soil moisture nudging scheme in the control experiment.The right panel shows nudges in the topmost UM soil level by the ASCAT nudging in the test experiment.

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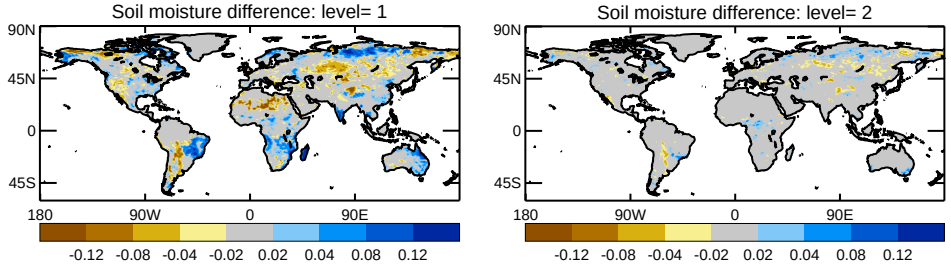

Fig. 7. Average difference in volumetric soil moisture ($m^3\,m^{-3}$) between the test and control experiments of trial 1 for the July 2009 period. The left panel shows differences for the topmost soil level, the right panel shows differences for soil level 2.

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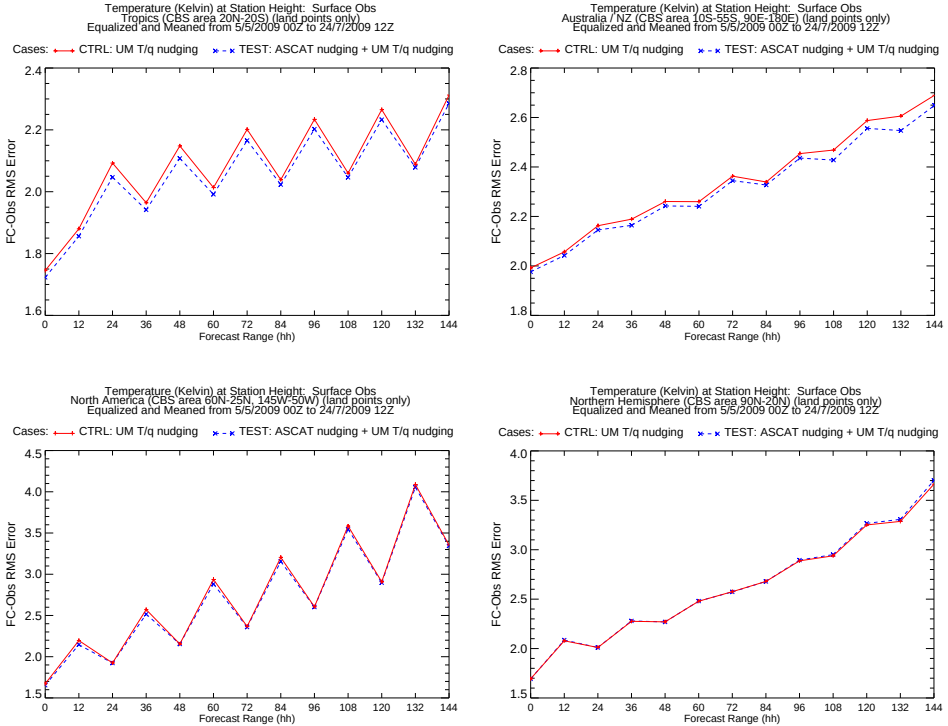

Fig. 8. Trial 1 verification of UM screen temperature forecasts against observations. The solid red lines (dashed blue lines) show RMS errors for the control experiment (test experiment that also assimilates ASCAT surface soil wetness measurements). Results are shown for the tropics, Australia, North America and Northern Hemisphere regions.

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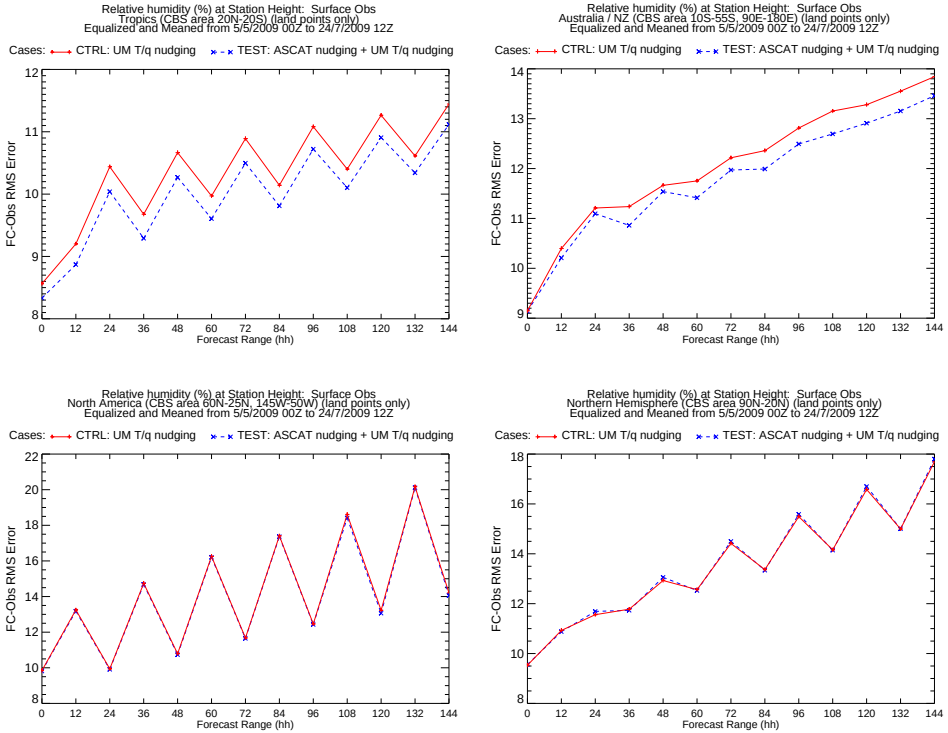

Fig. 9. Trial 1 verification of UM relative humidity forecasts against observations. The solid red lines (dashed blue lines) show RMS errors for the control experiment (test experiment that also assimilates ASCAT surface soil wetness measurements). Results are shown for the tropics, Australia, North America and Northern Hemisphere regions.

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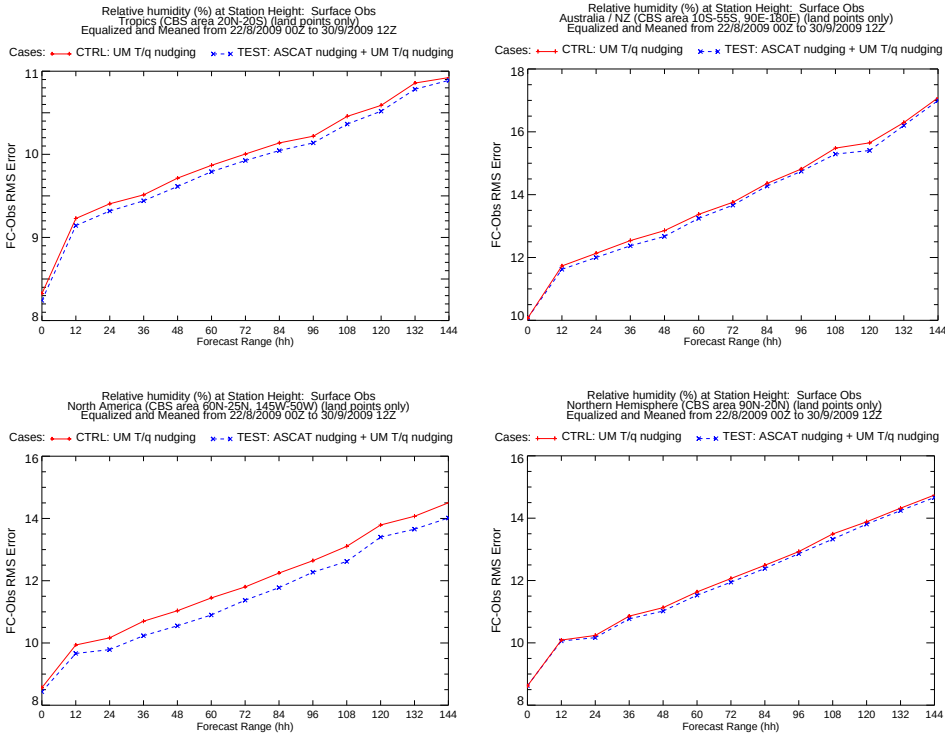

Fig. 10. Trial 4 verification of UM relative humidity forecasts against observations. The solid red lines (dashed blue lines) show RMS errors for the control experiment (test experiment that also assimilates ASCAT surface soil wetness measurements). Results are shown for the tropics, Australia, North America and Northern Hemisphere regions.

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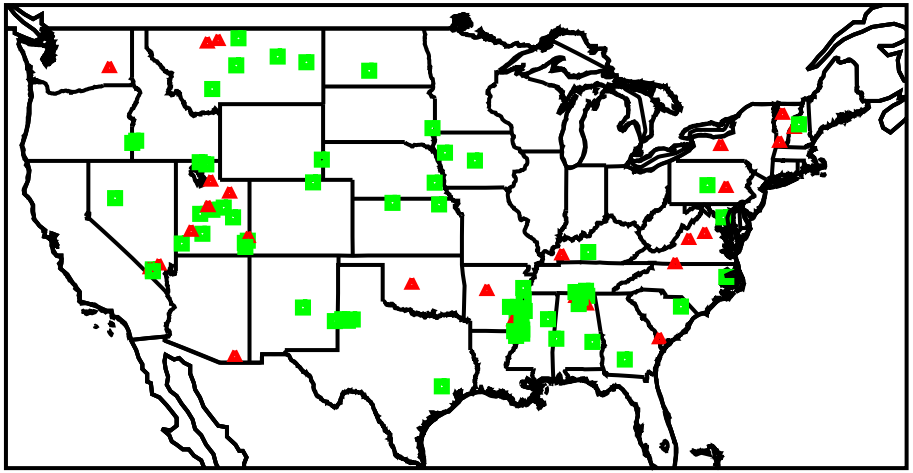

Fig. 11. Location of USDA SCAN stations. Green squares (red triangles) show stations where ASCAT surface soil wetness assimilation reduces (increases) the random error (SD) in UM level 1 soil moisture.

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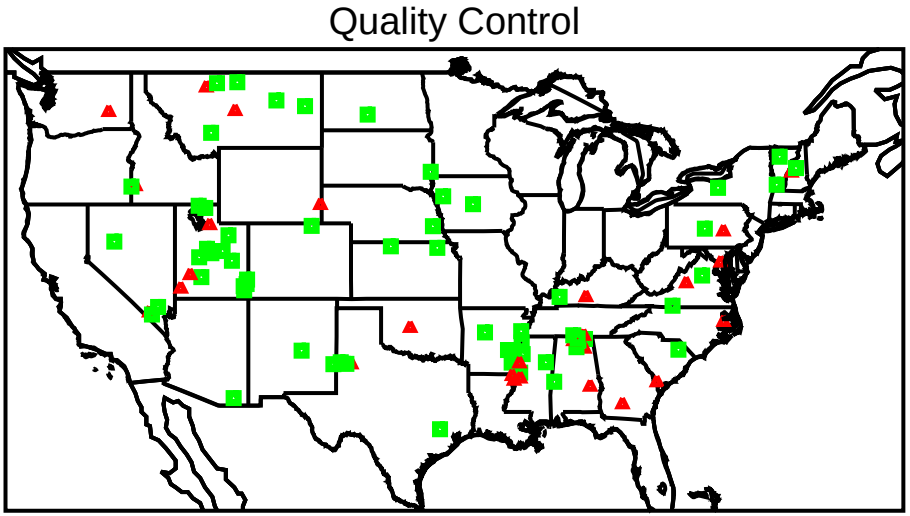

Fig. 12. Green squares (red triangles) show USDA SCAN stations passed (failed) by the quality control scheme.

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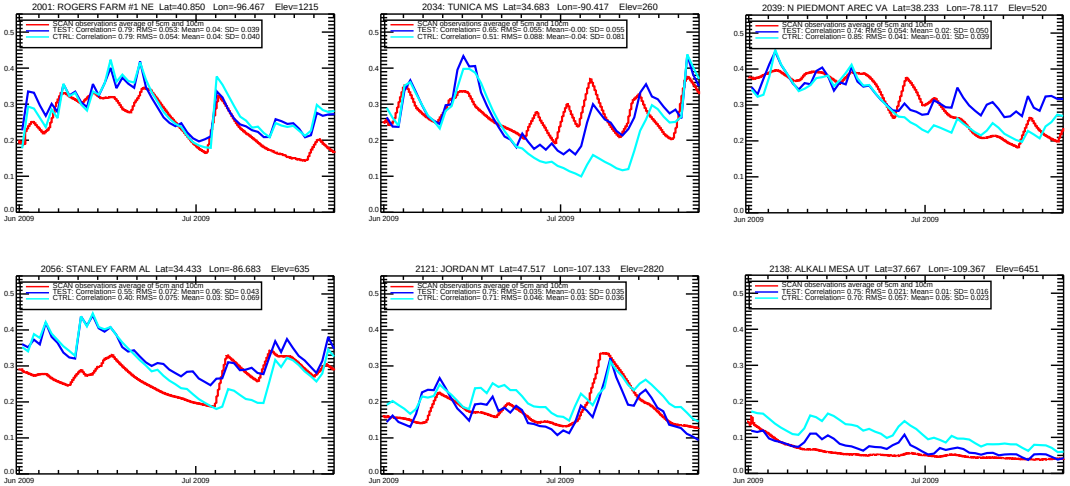

Fig. 13. Comparison of UM level 1 soil moisture with USDA SCAN measurements for six selected sites. The red curves shows the ground-based USDA SCAN soil moisture observations (mean of 5 cm and 10 cm measurements). The dark blue curves shows the UM level 1 soil moisture from the test experiment of trial 1 that assimilates ASCAT surface soil wetness. The light blue curves shows the UM level 1 soil moisture from the control of trial 1. The selected sites are in the the states of Nebraska (NE), Mississippi (MS), Virginia (VA), Alabama (AL), Montana (MT) and Utah (UT).

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