Towards the assimilation of scatterometer derived soil moisture in the ECMWF numerical weather prediction model

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Abstract

The European Centre for Medium-Range Weather Forecasts (ECMWF) currently prepares the assimilation of soil moisture data derived from advanced scatterometer (ASCAT) measurements. ASCAT is part of the METOP satellite payload launched in November 2006 and will assure the operational provision of soil moisture information until at least 2020. In several studies it has been shown that soil moisture derived from scatterometers contain skilful information. The objective of this paper is to evaluate the potential of ASCAT soil moisture data for numerical weather prediction. For this purpose scatterometer derived soil moisture will be compared to ERA-40 reanalysed soil moisture and a simple nudging experiment using ECMWF's Integrated Forecast System (IFS) will be carried out. The results of the assimilation experiment are compared to field observations from the Oklahoma Mesonet.

INTRODUCTION

In November 2006 EUMETSAT launched METOP-A the first out of three satellites of the polar system EPS. One of the instruments on-board the satellite is the advanced scatterometer (ASCAT), the successor instrument of the ERS scatterometers. Although designed to measure winds over the ocean there is increasing evidence that the configuration of the ERS and METOP scatterometers also facilitates the measurement of soil moisture over land. Currently an operational near real time soil moisture processor is implemented at EUMETSAT's central processing facility (Hasenauer et al. 2006). An initial soil moisture retrieval study indicated that the advanced sensor design and calibration provides even more accurate soil moisture data, providing an uninterrupted flow of high quality soil moisture information until at least 2020 (Bartalis et al. 2007).

In various fields of research soil moisture initial conditions have been found to be a crucial element in the performance of numerical models. In numerical weather prediction for example, predictability over land in mid-latitudes during spring/summer might be extend significantly in the monthly to seasonal ranges (e.g. Ferranti et al. 2006; Koster et al. 2004). Despite the important role of soil moisture, most NWP centres use very simple ways for initialising the land surface, ranging from nudging to climatology to optimum interpolation of proxy data. Hence, our knowledge about the assimilation of satellite derived soil moisture observations into regional to global NWP models is still limited. So far only one study reported on the assimilation of satellite derived soil moisture into an NWP model. Drusch (2007) used a simple nudging scheme to assimilate soil moisture derived from TMI satellite observations into ECMWF's NWP model over the United States. He concluded that the assimilation increased the accuracy of the surface fields while the impact on atmospheric variables was negative. In this study we will use a similar setting as described in Drusch (2007) to identify the potential of METOP scatterometer derived soil moisture to improve the skill of ECMWF's NWP model.

SCATTEROMETER DERIVED SOIL MOISTURE

In this study we used data from the WARP4 soil moisture archive maintained by the Vienna University of Technology (TUWien). Data of this archive is derived from backscatter measurements observed with the scatterometers on-board the ERS satellites. The ERS scatterometers are active microwave instruments operated in C-band at VV polarisation. The ERS-1 scatterometer regularly acquired data between August 1991 and May 1996, the ERS-2 scatterometer between March 1996 and January

2001, when due to a failure of a gyroscope all ERS-2 instruments were temporarily switched off. Since May 2004 ERS-2 data is again acquired and processed operationally, however only over selected regions of the world. WARP4 soil moisture observations are available on a Discrete Global Grid with a resolution of 50 km and are derived by applying the TUWien model (Wagner et al. 2003).

In the following a brief overview of the retrieval concept will be presented to afford a better understanding of the peculiarities of the soil moisture data. The challenge of soil moisture retrieval from scatterometer data is that also other factors -- surface roughness and vegetation structure -- influence the observed signal. To account for surface roughness and vegetation effects the TUWien model exploits the unique sensor design and the advantages of a change detection method. Technically, a reference backscatter value σ^0_{dry} representing backscatter from the vegetated land surface under dry soil conditions is subtracted from the actual σ^0 measurements to account for roughness and heterogeneous land cover. To account for the effects of plant growth and decay the vegetation sensitive signature of the multi-incidence angle σ^0 observations are exploited. As a result of the retrieval, a relative measure of soil moisture, m_S, in the surface layer (< 2 cm) is obtained which ranges between 0 and 1. Assuming that σ^0_{dry} represents a completely dry soil and σ^0_{wet} a saturated soil surface, m_S is equal to the degree of saturation, which is the soil moisture content expressed in percent of porosity. The reference values σ^0_{dry} and σ^0_{wet}, are estimated from the lowest and highest σ^0 values recorded during the period August 1991 to January 2001. By utilising data from a nine year period the reference values likely represent the respective soil conditions even in temporal sparsely sampled areas. In extreme climates such as deserts, were saturation is likely not observed a correction factor is applied to σ^0_{wet} in order to obtain spatially consistent soil moisture estimates.

To avoid the use of spurious observations, a rigorous data screening is implemented. Soil moisture can not be retrieved if the signal is dominated by scattering from dense vegetation (20-30 t/ha above-ground biomass), open water, rough topography or snow covered/frozen land-cover. Additionally, in the current implementation of the TUWien model the azimuthal viewing geometry of the ERS scatterometer is not correctly represented. Especially in regions characterised by surface patterns with distinct azimuthal orientation of the micro relief, as observed for example in sand deserts, this can lead to erroneous signals. Data screening is therefore based on the signal to noise ratio, the soil moisture sensitivity, the fraction of open water bodies and topography.

VALIDATION AND CALIBRATION

That scatterometer data contain skilful information about the soil moisture process has been shown in several validation studies (Dirmeyer et al. 2003; Crow et al. 2006; Pellarin et al. 2006). Recently the data has also been used successfully in first assimilation experiments (deWit et al. 2007) and in hydrological (Paraijka et al. 2006 and Scipal et al. 2005) and climate (Fontaine et al. 2007) studies. For successful data assimilation it is nevertheless important to characterise and correct for systematic differences that exist between the satellite observations and the corresponding model variables. We therefore compare scatterometer derived soil moisture to modelled soil moisture from the ECMWF ERA-40 reanalysis data. After that we discuss the necessity of data calibration and present a solution to correct for systematic differences in the data sets. To facilitate the comparison, scatterometer soil moisture was aggregated to the ERA-40 grid, a reduced Gaussian grid at approximately 125 km resolution, and pooled the data into 6 hourly files. The derived statistics are based on data from the period 1992-2000. Observations were masked if one of the data sets indicated missing observations or if the ERA-40 reanalysis indicated freezing conditions or snow cover.

Validation

We calculated the correlation coefficient for absolute observations, R_{ABS}, and for anomalies $R_{ANO.}$ Anomalies were calculated by removing the mean seasonal soil moisture cycle calculated from the 9 year period. Fig. 1 shows the correlation R_{ABS} and R_{ANO} between scatterometer derived and ERA-40 soil moisture. In general, R_{ABS} is positive over major parts of the land surface, with maximum values around 0.9. Over 85% of the observed land-surface R_{ABS} is significantly correlated, over 8% the correlation is not significant and over 7% the correlation is negative. For R_{ANO} these figures are similar. The spatial distribution of R_{ABS} clearly reflects zonal climate patterns. As has to be expected, R_{ABS} is high, with values around 0.9, in areas characterised by a distinct seasonal cycle of soil moisture such as in the Inter-tropical Convergence Zone (ITCZ). In this region R_{ANO} drops to values around 0.3. The low values of R_{ANO} in the ITCZ are noteworthy as they are consistently lower than values over regions like Europe or South East Asia. A possible explanation for these low values is a deficiency in the model, as low R_{ANO} values prevail in regions with a low number of synoptic stations. As screen level temperature and relative humidity is used to constrain the soil moisture analysis the observed relationship suggests that measurements from synoptic stations are important to sustain anomalies.

In climate zones with seasonally more equal distributed rainfall, R_{ABS} takes on values around 0.6. Over deserts R_{ABS} becomes negative. This problem can be attributed to a shortcoming in the satellite retrieval. Beside these general patterns, the maps also exhibit some unexpected features. For example over Europe, where soil moisture does not exhibit a clear seasonal cycle, R_{ABS} and R_{ANO} are comparably high. Similarly, R_{ABS} and R_{ANO} are high over South East China. South East China is characterised by a low sensitivity of the microwave signal to soil moisture due to the high amount of above ground biomass. In a similar study, using soil moisture data derived from the AMSR-E radiometer, which operates in the same microwave band, the area had to be masked as the observations did not contain skilful information (Reichle et al. 2007). On the other hand, R_{ABS} is low over the eastern parts of North America. The reason for these low correlations are not yet fully understood, but can possibly be related to higher amounts of above ground biomass and hence to a higher level of noise in the satellite soil moisture observations. Nevertheless there is large agreement between the modelled and observed soil moisture estimates and both data sets seem to capture the same processes.

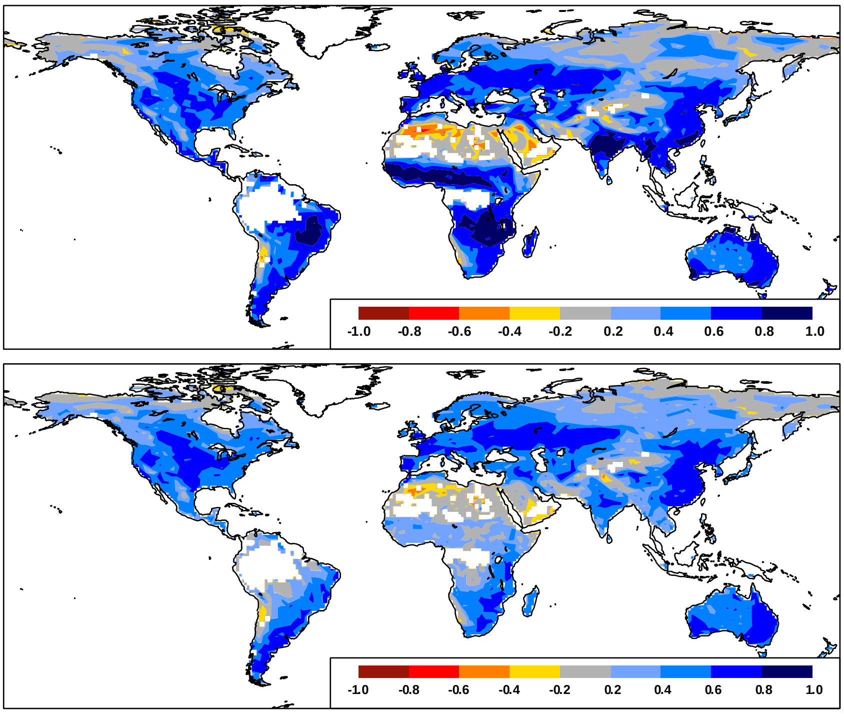

Fig 1: Correlation between ERA-40 and ERS scatterometer derived surface soil moisture for absolute values (top panel) and anomalies (bottom panel)

Calibration

The TUWien soil moisture retrieval provides an uncalibrated measure and can hence not be assimilated directly. Assuming that the scatterometer derived soil moisture corresponds to the degree of saturation, model equivalent volumetric soil moisture can be derived by a simple rescaling with the physical value of porosity. This approach looks attractive as porosity is a prescribed quantity in the model. However such a transformation does not account for idiosyncrasies of the model physics and the satellite retrieval method, which can result in large biases especially in the mean and dynamic range. Direct assimilation of these "biased" observations would prevent a statistically optimal analysis Dee (1998). We therefore need to calibrate the satellite observation with respect to the model climatology. The calibration is accomplished by scaling the scatterometer derived soil moisture to the model's climatology so that the cumulative distribution function (CDF) of satellite soil moisture and the model soil moisture match. The concept of CDF matching was used in similar studies (Drusch et al 2005; Drusch 2007) to effectively remove biases of TMI soil moisture observations. Strictly speaking this method does not allow deriving "correct" soil moisture; rather it removes differences between satellite observations and model data by ensuring statistical consistency. For this study we have simplified the CDF matching to a linear transform which effectively removes the differences in the first two moments (mean and variance). The disadvantage of neglecting differences in higher moments is compensated by the robustness of the method, especially in data sparse regions. In any case the impact of ignoring differences in higher order moments is small and scarcely reaches values above 0.01 m^3m^{-3}. From a technical viewpoint the linear approach is attractive as it can be fully parameterised by the mean and variance of both data sets (Eq.1). In Eq.1 Θ_C denotes the calibrated soil moisture, Θ_S the ASCAT/ERS level 2 soil moisture product and Θ_M the soil moisture of the model. VAR denotes the variance and the bar denotes the mean of the respective sample.

$$\Theta_C = a + b \cdot \Theta_S \qquad \textit{where} \;\; a = \overline{\Theta}_M - \overline{\Theta}_S \cdot \frac{VAR(\Theta_M)}{VAR(\Theta_S)} \qquad b = \frac{VAR(\Theta_M)}{VAR(\Theta_S)} \qquad (1)$$

ASSIMILATION EXPERIMENTS

We carried out three data assimilation experiments to evaluate the potential of scatterometer observations to improve the initialisation of soil moisture in ECMWF's Integrated Forecast System. Experiments are based on model cycle 31R2, which represents the operational model cycle from December 12th, 2006 to June 5th, 2007. For the sake of efficiency, the horizontal resolution was set to 125 km (spectral wavenumber cut-off at 159) and the vertical resolution was set to 91 layers with the lowest level at approximately 10 m. One experiment, which will be named CTRL hereafter, used the operational version of model cycle 31R2. In the operational version the soil moisture analysis is constrained by an optimum interpolation scheme of 2m temperature and 2m relative humidity. The second experiment, named OL, ran in an open loop setup were soil moisture was not constrained. The third experiment, NUDGE, used a nudging scheme instead of the optimum interpolation. All experiments were started from the same initial (operational) model state. Also the same forecast model was used. Therefore the only difference should be induced by the way how soil moisture is initialised. All experiments ran for the period May 1st to July 31st 2005.

ECMWF's Integrated Forecast System

ECMWF's Integrated Forecast System employs a 4D-Var data assimilation system that is run in two different analysis suites twice per day. One suite runs 4D-Var over a 12-hour window and produces analyses at 00 and 12 UTC, respectively. From these, short-range forecasts are generated that serve as model first-guess estimates of the atmospheric state for the second suite. The second suite runs again two analyses per day over 6-hour windows centred at 00 and 12 UTC, respectively. The second suite initialises the global medium-range forecasts (Hasler 2004). The IFS incorporates the land-surface scheme TESSEL (Viterbo et al 1995). In TESSEL the soil processes are calculated in four layers (0.07, 0.21, 0.72 and 1.68m). The heat transfer is described by the Fourier diffusion law. Vertical movement of water in the unsaturated zone is computed using the Richards equation and Darcy’s law. To keep the land surface model simple, currently a unique soil type with fixed soil hydraulic parameters is used globally. The land energy balance is solved for eight tiles separately (bare ground, low and high vegetation without snow, exposed snow, snow under high vegetation, interception reservoir, ocean/lakes and sea ice) with regard to skin temperature. Sensible and latent heat flux for each tile are parameterised by a resistance based formulation. The total energy is given as the sum of the tiled energy fluxes weighted by their area fractions. To constrain the soil moisture analysis, 2m temperature and 2m relative humidity observations are used in an optimum interpolation scheme (Douville et al 2000). The soil moisture analysis is carried out at 0600, 1200, 1800 and 0000 UTC. Soil moisture analysis increments are added throughout the root zone, i.e. the top three soil layers.

Soil moisture nudging

In the nudging experiment, differences between daily averages of calibrated scatterometer soil moisture and the modelled first guess are computed at 1200 UTC. The first guess comes from a 6-hour forecast from 0600 UTC base time. At 1200 UTC, one fourth of this difference is added to the first guess fields. Since the 1800 UTC first guess from 0600 UTC does not include the 1200 UTC increment, one half of the observation - first guess difference is added at 1800 UTC. The 12-hour forecast from 1800 UTC base time is initialised with the 1800 UTC soil moisture analysis and therefore contains the increments added at 1200 and 1800 UTC. Therefore at 0000 UTC, again one forth of the observation - first guess difference (as calculated at 1200 UTC) is added to the first guess fields and at 0600 UTC one half of the difference is added. Consequently, the full departures are added at 0600 UTC on the subsequent day. It has to be noted that the nudging scheme does not take any potential random errors in the satellite data into account. In addition, the nudging scheme is idealised since it uses the satellite information at 1200 UTC, although some parts of the observations were taken at later times.

RESULTS

To evaluate the use of scatterometer observations for initialising the model we compared the resulting fields to observations from the Oklahoma Mesonet. After that we analyse the increments. It has to be noted that during the analysis period, ERS-2 collected a substantial amount of observations only over North America, Europe and North-West Africa. The analysis of the result is hence limited to these regions.

Validation against in-situ observations

The Oklahoma Mesonet consists of over 110 automated stations measuring a variety of atmospheric and surface variables (Basara et al. 2000). During the analysis period, 89 stations reported soil moisture observations on a regular basis by heat dissipation sensors. The stations cover the area 33.8N to 37.0N and 102.9W to 94.6W.

For 82% of the stations the correlation between soil moisture from the NUDGE experiment and field observations increase substantially compared to the OL and CTRL experiment. The correlation coefficients are however low and show a large spread, with an average value of 0.46 ± 0.16 for the NUDGE, 0.36 ± 0.20 for the CTRL and 0.31 ± 0.21 for the OL experiment. The highest correlation was found between scatterometer and field observations, with a value of 0.56 ± 0.15. These low correlations partly reflect the scale mismatch between coarse resolution soil moisture and in-situ point observations. Similar values have been reported by Reichle et al. (2007) in an assimilation study using AMSR-E and SMMR soil moisture data. To account for the scaling problem we calculated a soil moisture “climatology” for Oklahoma by averaging model and field observations over all stations. The correlation coefficients for these climatologies are significantly higher with values of 0.73 for the NUDGE, 0.63 for the CTRL and 0.42 for the OL experiment. Again the highest correlation was found between scatterometer and field observations with a value of 0.82. These values are in line with Drusch (2007), who reported time series correlation coefficients of up to 0.8 between a TMI soil moisture based nudging scheme and Oklahoma Mesonet data.

Fig. 2 shows the time series of the averaged soil moisture data. Let us first compare soil moisture from the OL experiment (dark red line) and the in-situ observations (green line). As soil moisture in the OL experiment is not constraint, differences are only due to the sampling mismatch and model errors. The OL experiment follows the general soil moisture trend observed during MJJ only roughly. First of all we observe a significant dry bias of 0.05 m^3m^{-3}. Beside this the OL experiment also fails to capture a significant soil moisture increase in the first week of July and it tends to dry down to quickly after wetting up periods. The optimum interpolation scheme of the CTRL experiment partly compensate for these deficiencies by adding significant amounts of water to the system. This reduces the negative bias to a value of 0.025 m^3m^{-3}. The optimum interpolation scheme also compensates for the quick dry downs. During the dry down in the third week of May, for example this leads to more consistent soil moisture estimates. During the fourth week of June the optimum interpolation however overcompensates and adds to much water which leads to a too slow dry down. Nevertheless the soil moisture values are closer to real conditions. When we now move to the calibrated scatterometer observations (blue dots), we see that they follow the general trend more closely. Especially during the second half of the study period, the timing of soil moisture peaks, as well as dry down rates agree reasonably well with field observations. During the first half of the study period larger discrepancies are observed between the observations. Interestingly, apart from a few outliers, scatteromter observations are closer to the model during this period. Nevertheless, over the entire study period, the observed bias of 0.019 m^3m^{-3}, is lower than the values of the CTRL and OL experiments. Similarly, the standard deviation of the scatterometer observations is lower (0.014 m^3m^{-3}) compared to the respective values from the CTRL (0.019 m^3m^{-3}) and the OL (0.024 m^3m^{-3}) experiments. However the assimilation of these observations improves the analysis only slightly. Although the measurements force the model to a higher soil moisture level, the soil dries down rapidly after soil moisture has been added. Obviously the sampling frequency of the scatterometer is not sufficient to effectively constrain the model. Thus, when compared to the results of the CTRL experiment we observe a larger bias of 0.037 m^3m^{-3}. The standard deviation of 0.016 m^3m^{-3} is however significantly lower.

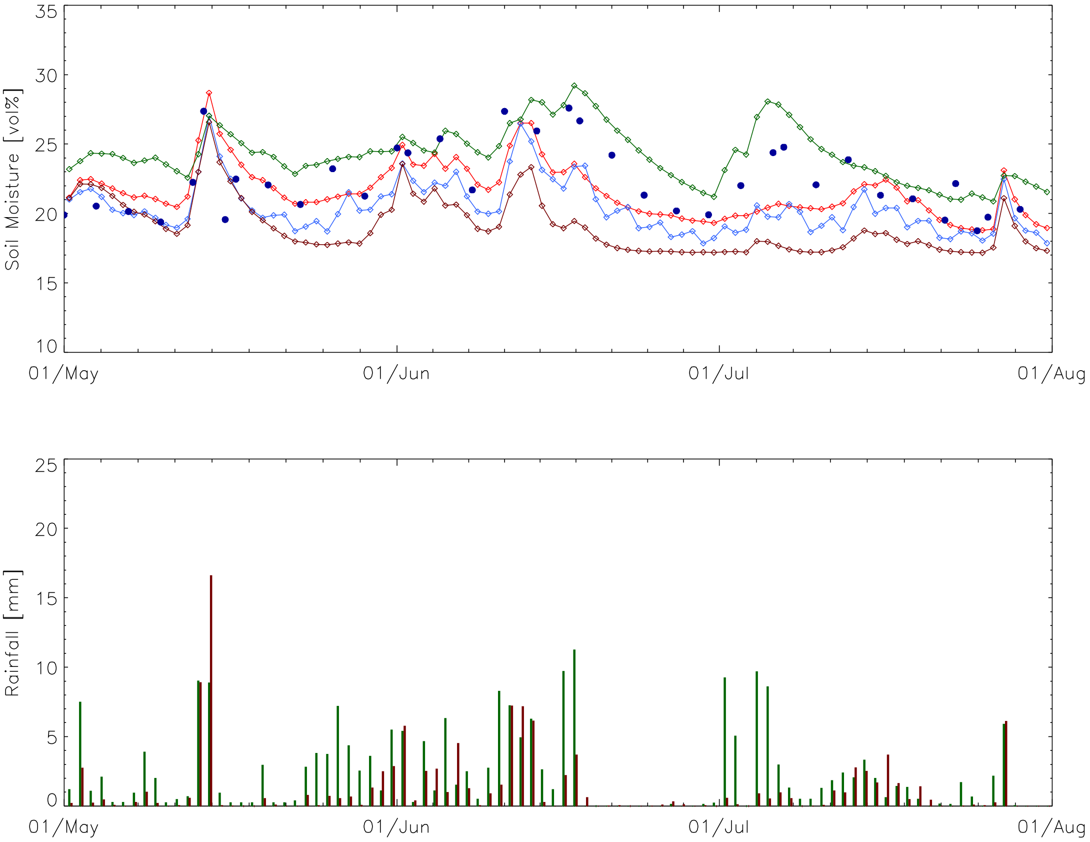

Fig 2: Upper panel: Time series of soil moisture from in-situ observations (green), the CTRL experiment (red), the OL experiment (dark red) and the NUDGE experiment (blue). Blue circle symbols display calibrated scatterometer soil moisture observations. Time series have been averaged over the entire network. Lower panel: Daily accumulated for the model (dark red) and the Oklahoma Mesonet (green).

Increments

Validation of soil moisture estimates with in-situ observations is limited to very few locations. An extended assessment of the performance of the assimilation algorithm can be obtained by examining the increments, defined as the analysis - first guess differences. We computed soil moisture increments for the entire root zone and accumulated them over the 3 month analysis period. As can be seen in Fig. 3 the optimum interpolation scheme of the CTRL experiment adds large amounts of water to the root zone. Maximum values, exceeding 250 mm, can be found in the South East of North America, in North West Africa and in Europe. In these regions the analysis adds 2.5 mm of water per day on average. Water is removed mainly over high latitudes but the amounts are much lower, scarcely reaching levels of 120 mm. To some extend these increments are an indication of the quality of the forecast system: Persistent analysis corrections are a clear sign of systematic model errors. The increments of the NUDGE experiment show a similar pattern as those from the CTRL experiment. Water is added/removed in the same regions. However the amount of water added/removed is much lower. Extreme values are around 120 mm in total, with 0.4 mm of water added per day on average. The lower amounts might be a result of the low sampling frequency of the ERS-2 scatterometer which is about once/twice a week. While the analysis of the CTRL experiment adds water in nearly every analysis step, the analysis of the NUDGE experiment adds water only if the satellite observes the respective region. The similar patterns nevertheless give clear evidence that the scatterometer observations can correct for systematic errors as introduced through an oversimplified land surface model and deficiencies in the soil hydrology.

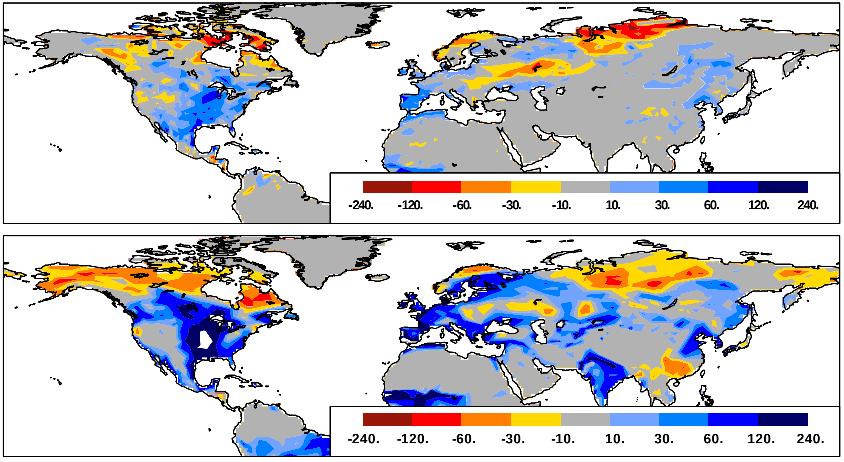

Fig 3: Soil moisture increments accumulated over MJJ 2005 for the NUDGE experiment (top) and the CTRL experiment (bottom). Red colour tones indicate that water is removed; blue colour tones indicate that water is added

CONCLUSIONS & OUTLOOK

The assimilation of ERS-2 scatterometer soil moisture into the ECMWF Integrated Forecast System was examined. It was shown that scatterometer derived soil moisture agrees well with modelled soil moisture. Differences in the data sets can be explained by either model or retrieval deficiencies. As scatterometer derived soil moisture represents a relative measure, a calibration procedure has been introduced which is based on the Cumulative Distribution Function matching approach. To evaluate the potential of scatterometer derived soil moisture to improve the skill of NWP models a simple nudging experiment was set up. Results of this nudging experiment suggest that the assimilation of ERS-2 scatterometer data produces small but significant improvements in the soil moisture analysis over large areas of the Oklahoma Mesonet even when a non-optimal nudging technique is used. The consistency of the analysis increments between the operational model and the nudging scheme further suggest that scatterometer derived soil moisture can be used to effectively correct for model simplifications. Significant improvements of the performance are expected from upcoming modifications. The availability of ASCAT soil moisture data will lead to an increase in stability of the system due to the higher observation frequency. The largest improvements are expected from the implementation of an Extended Kalman Filter for the land surface analysis. The extended Kalman filter is the optimum sequential data assimilation method for non-linear problems.

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