Impact of ASCAT Soil Moisture Assimilation on Regional Precipitation Forecasts: A Case Study for Austria

STEFAN SCHNEIDER AND YONG WANG
Zentralanstalt für Meteorologie und Geodynamik, Vienna, Austria

WOLFGANG WAGNER
Department of Geodesy and Geoinformation, Vienna University of Technology, Vienna, Austria

JEAN-FRANÇOIS MAHFOUF
Météo-France/CNRS, CNRM/GAME, Toulouse, France

(Manuscript received 18 October 2012, in final form 25 November 2013)

ABSTRACT

In this study, remotely sensed soil moisture data from the Advanced Scatterometer (ASCAT) on board the Meteorological Operational (MetOp) series of satellites are assimilated in the regional forecasting model, Aire Limitée Adaptation Dynamique Développement International (ALADIN-Austria), using a simplified extended Kalman filter. A pointwise bias correction method is applied to the ASCAT data as well as quality flags prepared by the data provider. The ASCAT assimilation case study is performed over central Europe during a 1-month period in July 2009. Forecasts of those assimilation experiments are compared to the control run provided by the operational ALADIN version of the Austrian Met Service, Zentralanstalt für Meteorologie und Geodynamik (ZAMG). Forecasts are furthermore verified versus in situ data. For a single-day case study the ability of the approach to improve precipitation forecast quality in the presence of high impact weather is demonstrated. Results show that 1) based on a one station in situ data evaluation, soil moisture analysis is improved, compared to the operational analysis, when ASCAT soil moisture data is assimilated; 2) pointwise bias correction of the satellite data is beneficial for forecast quality; 3) screen level parameter forecasts can be slightly improved as a result of this approach; and 4) convective precipitation forecast is improved over flatland for the investigation period while over mountainous regions the impact is neutral.

1. Introduction

Soil moisture can have a significant impact on near surface parameters like temperature and humidity, low clouds, and precipitation by influencing the exchange of heat and water between the soil and the lower atmosphere (Ferranti and Viterbo 2006; Dharssi et al. 2011). So, knowledge of soil moisture distribution is of crucial interest for numerical weather prediction (NWP; Seuffert et al. 2002) to ensure good forecast quality. Concerning precipitation, the feedback processes between increase of evapotranspiration and amplification of precipitation (Schär et al. 1999) are of major interest, as they are one of the precipitation key processes besides the forcing mechanisms leading to convection initiation. These processes are still neither recognized in detail nor adequately reproduced in weather forecast models, resulting in poor quantitative precipitation forecasting (Wulfmeyer et al. 2008). Nevertheless, only little has been done in investigating precipitation forecasts considering the use of additional soil moisture data, despite the fact that for example flash floods due to severe thunderstorms are frequent phenomena in large parts of Europe (Dotzek et al. 2009) and other regions in the world.

Nowadays, high-resolution models are resolving features such as synoptic forcing and local influences like orography and convergence zones which are predominant for thunderstorm initiation (Kaltenböck et al. 2009). Moreover, the need for proper soil moisture representation is well understood. Nevertheless, simplifications in the representation of modeled land surface processes in
NWP models are unavoidable. They are leading to systematic errors in the soil moisture field, which is degrading forecast quality (Drusch and Viterbo 2007).

Assimilation of measurements can help to overcome some of the weaknesses described. Unfortunately, there is no global and real-time in situ soil moisture measurement network providing useful data so far. This is due to the high variability of soil water content even over short distances especially during dry periods (Western et al. 1999). Although there is an initiative for such a network (Dorigo et al. 2011), satellite measurements are preferred for their global coverage, spatial representativeness and near-real-time availability. So the most recent dataset of Advanced Scatterometer (ASCAT) on a 25-km grid with a temporal resolution of less than 2 days is used here for assimilation experiments on a regional scale.

Although the assimilation of bias-corrected soil moisture measurements both with nudging (Scipal et al. 2008; Dharssi et al. 2011) and extended Kalman filter (de Rosnay et al. 2013) proved to be a meaningful approach for global models on average mainly in tropical regions, the impact on forecast quality over Europe is described as neutral for these investigations. On a regional scale, Mahfouf (2010) assimilated European Research Satellite (ERS)-calibrated and generally bias-corrected ASCAT data with a simplified extended Kalman filter (sEKF) and focused mainly on forecasts of 2-m temperature and humidity, showing some improvement for bias. Zhao et al. (2006) investigated the impact of ERS soil water index direct insertion in the fifth-generation Pennsylvania State University–National Center for Atmospheric Research (NCAR) Mesoscale Model (MM5) for precipitation forecasts in China and found some improvement with this simple approach.

The results presented here are among the first to focus mainly on the impact of ASCAT soil moisture assimilation on precipitation forecast quality in a limited-area model (LAM). This model is briefly described in section 2. Bias correction and data quality control are described in section 3. Experiments set up are presented in section 4. Results of the experiments are shown and discussed in section 5; section 6 includes the conclusions and outlook of this paper.

2. Forecasting model and verification tools

a. ALADIN-Austria

The regional model used for the assimilation experiments is Aire Limitée Adaptation Dynamique Développement International (ALADIN-Austria; Wang et al. 2006), the operational NWP system at the Austrian Met Service, Zentralanstalt für Meteorologie und Geodynamik (ZAMG). ALADIN-Austria is a hydrostatic, spectral LAM derived from the proposal of Bubnová et al. (1995). It includes a hybrid vertical coordinate and a spectral method with biperiodic extension of the domain using elliptical truncation of double-Fourier series. It uses a two-time-level semi-Lagrangian advection scheme, semi-implicit time-stepping, fourth-order horizontal diffusion, Davies–Kalberg-type relaxation and digital filter initialization (DFI; Wang et al. 2011). For moist physical processes, Modular Multiscale Microphysics and Transport (3MT) has been used (Gerard et al. 2009). Boundary conditions are provided by the global model, Action de Recherche Petite Echelle Grande Echelle (ARPEGE; Courtier and Geleyn 1988) with a 3-hourly coupling frequency. ARPEGE uses a four-dimensional variational data assimilation (4DVAR).

The model domain which is displayed in Fig. 1 has a horizontal grid spacing of 9.6 km and 60 vertical levels. Forecasts of the operational model run (called OPER in the following) have been used as reference to quantify improvements due to ASCAT assimilation. Neither atmospheric nor land surface data assimilation is applied in this operational setup of ALADIN.

b. Land surface and assimilation system

To take soil–atmosphere interaction into account, Surface Externalized (SURFEX; LeMoigne 2009) has been used in combination with the forecasting model. SURFEX is a stand-alone model for the representation of surface processes in NWP modeling. SURFEX includes a soil–vegetation–atmosphere transfer scheme called the Interaction between Soil Biosphere and Atmosphere (ISBA; Noilhan and Planton 1989; Noilhan and Mahfouf 1996) to simulate exchanges of water and energy between the surface and the atmosphere above and can be used offline (Mahfouf et al. 2009).

In the version used here, ISBA has two soil layers. The water transfers in the soil are described with two prognostic variables for the superficial soil layer water content $w_r$ (m$^3$ m$^{-3}$) with a depth of 1 cm and the deep reservoir water content $w_2$ (m$^3$ m$^{-3}$; Mahfouf 2010), in which depth is depending on the local soil type. The prognostic equations for these soil variables are based on the force–restore method (Deardorff 1977). For assimilating the ASCAT data, a simplified extended Kalman filter (Draper et al. 2009; Mahfouf 2010) included in SURFEX is used. In a first step, atmospheric input data from ALADIN-Austria from the lowest model level for each time step are provided. To initialize the system, they are taken from OPER. During the cycling experiment, the updated ALADIN atmospheric forecasts are used as input for the next assimilation. For each surface grid box, the near-surface air temperature, specific humidity, horizontal wind components, surface pressure, total
precipitation flux, and longwave and shortwave radiation fluxes from the NWP model are provided (Le Moigne 2009). Both \( w_g \) and \( w_2 \) form the state variable for the sEKF. The observation operator is the 6-h integration of ISBA. It has to be run once for each element of the state vector with perturbed prognostic variable, and once unperturbed. For a state vector with two variables as considered here, three runs are necessary for the linearization of the observation operator. The amplitude of the perturbation is chosen as \((1 \times 10^{-3}) \times (w_{fc} - w_{wil})\). Here \( w_{fc} \) is the volumetric field capacity and \( w_{wil} \) the wilting point at each grid point, depending on the soil type (Noilhan and Mahfouf 1996). The static background error covariance matrix \( B \) is defined by model error standard deviation, \( 0.6(w_{fc} - w_{wil}) \) for \( w_g \) and \( 0.3(w_{fc} - w_{wil}) \) for \( w_2 \). Measurements from ASCAT are applied at the beginning of the assimilation window. For a more detailed description of the sEKF see Draper et al. (2009).

c. Verification methods

Three different verification approaches are applied using (i) mean precipitation for the whole investigation period; (ii) a specific case study; and (iii) the object-oriented verification method SAL (Wernli et al. 2008), which contains three distinct components that consider aspects of the structure \( S \), amplitude \( A \), and location \( L \) of the precipitation field. SAL is used to verify the rainfall forecast quality in a predefined domain. The amplitude component \( A \) measures the relative deviation of the domain-average quantitative precipitation forecast from observations, where positive values indicate an overestimation of total precipitation. The structure component \( S \) is constructed in a way that it is positive for modeled precipitation structures too large and/or too flat. The location component \( L \) combines information about the displacement of the forecast precipitation center of mass to the observed center of mass and the error in the weighted-average distance of the precipitation objects from the total field’s center of mass. Both \( A \) and \( S \) can vary between \(-2\) and \(+2\), \( L \) can vary between \(0\) and \(+2\). A perfect forecast is characterized by a value of zero for all three components (Wernli et al. 2008).

For mean precipitation, analyses of the observed precipitation are provided by the high-resolution Integrated Nowcasting System (INCA; Haiden et al. 2011; Wittmann et al. 2010), run operationally at ZAMG. This system combines station measurements and radar data to provide an optimal spatiotemporal analysis of precipitation, which is defined as the best available representation of the true rainfall distribution for verification.

Modeled soil moisture fields are compared with in situ measurements provided by the Austrian Lebensministerium. The station is located in Schalladorf in northeastern Austria next to the Czech border (for exact location see...
Fig. 2), situated in hilly terrain and surrounded by agricultural area. Measurement depths are 35, 60, 90, 120, and 150 cm. Total soil depth at the nearest ALADIN model grid point is 2.06 m, and the superficial soil layer has a vertical depth of 1 cm. This means that there is no corresponding in situ measurement for the upper model layer, for the deep soil layer the weighted average of the measurement in five depths has been chosen for the comparison.

Forecast screen level parameters, mainly 2-m temperature and relative humidity, are verified against synoptic observation (SYNOP) stations. As large parts of the verification domain are covered by complex terrain, stations in low-elevation areas surrounding the Alps have been chosen to avoid effects due to topographic features not resolved by the model grid but influencing local measurements. Station data are quality controlled by the data provider and can be considered as reliable. To compare station data and model gridpoint output, model values are interpolated to the station location for two/three coordinates (longitude, latitude; altitude only in case of temperature) before the comparison. Classical statistical measures such as root-mean-square error (rmse) and bias are computed to evaluate the forecast skill.

3. ASCAT data

a. ASCAT

ASCAT is a C band (5.255 GHz) real aperture radar flown on the series of three Meteorological Operational (MetOp) satellites operated by the European Organization for the Exploitation of Meteorological Satellites (EUMETSAT). Even though it was designed for the retrieval of ocean surface winds, research with ASCAT and its predecessor, the scatterometer on board ERS-1 and ERS-2 has shown that it can also be used for retrieving soil moisture over land (Wagner et al. 2007). Given the importance of soil moisture for numerical weather prediction, hydrology, and many other applications (Koster et al. 2004; Seneviratne et al. 2010; Legates et al. 2011) it was thus decided to build an operational ASCAT soil moisture service at EUMETSAT (Bartalis et al. 2007). Since December 2008 this service has been providing ASCAT surface soil moisture maps in near–real time (130 min after sensing) at 25- and 50-km spatial scale (Wagner et al. 2010).

ASCAT has several technical characteristics that makes it attractive for soil moisture retrieval. First, it uses fan-beam antennas to cover two 550-km-wide swaths one on each side of the satellite ground track (Figa-Saldaña et al. 2002). For each swath, three antennas illuminate the ground surface, providing three independent backscatter measurements from different azimuth and incidence angles. For land applications this latter property of ASCAT is important because it allows the combined influences of soil moisture and vegetation on the backscattered signal to be separated (Wagner et al. 1999a). Another important feature of ASCAT is its excellent radiometric accuracy (Wilson et al. 2010). Even though C band has in general not been considered to be the optimum frequency for soil moisture retrieval (Kerr 2007), the very high radiometric accuracy of ASCAT means that even over vegetated areas, where the soil moisture signal is damped by the vegetation layer, soil moisture can be retrieved. Of
course, with increasing vegetation density the retrieval accuracy decreases and over dense forest areas the retrieval is not possible at all. Nonetheless, over regions predominantly covered by grasslands and agricultural fields the ASCAT soil moisture retrievals have in general been found to be of good quality (Albergel et al. 2009; Brocca et al. 2010; Sinclair and Pegram 2010). Recent comparisons of ASCAT with soil moisture products derived from the Soil Moisture and Ocean Salinity (SMOS) satellite (Kerr et al. 2010)—the first satellite especially designed for the purpose of soil moisture retrieval over land—show that the quality of the ASCAT soil moisture data is comparable, and in some regions such as western Europe even somewhat better than SMOS due to lower radio frequency interference (Albergel et al. 2012; Parrens et al. 2012). Also when compared to soil moisture products derived from passive multifrequency microwave radiometers such as the Advanced Microwave Scanning Radiometer for Earth Observing System (EOS) (AMSR-E), ASCAT usually gives very good results, particularly when short-term soil moisture fluctuations are being analyzed (Brocca et al. 2011; Draper et al. 2012).

b. Data preprocessing for assimilation

For the different experiments, reprocessed ASCAT data from the Technical University of Vienna (VUT), provided in June 2010, have been used. Before applying them for assimilation, they are preprocessed in the following three-step approach:

• Quality control

Backscatter measurements from the satellite are processed and converted to soil moisture index values (ranging between 0% and 100%) at EUMETSAT. During this procedure, several quality and processing flags are provided for each measurement (Scipal 2005). They are delivered with the data to guarantee the greatest possible transparency of the processing chain for the user. These flags are themselves uncertain, reflecting shortcomings in the current understanding of the retrieval algorithm and lack of suitable input data used to model these flags. Consequently, users are advised to investigate the best thresholds/masking criteria based on these flags.

Besides some technical quality flags, there are mainly four flags that are relevant for application due to lower reliability of the measurements in the cases of: frozen soil, snow cover, complex topography, and wetland. For all of these land cover categories, ASCAT measurements might not be as reliable as desired by the user, therefore, such data are usually withdrawn for the assimilation in NWP models (e.g., ALADIN; Mahfouf 2010), the Integrated Forecasting System (IFS; Scipal et al. 2008), and the Unified Model (UM; Dharssi et al. 2011). For the topographic flag, Mahfouf (2010) proposed to reject grid points with a topographic complexity of 15% or larger, while Draper et al. (2012) used a threshold of 10%. If quality flags are taken into account in the following experiments, this is the first step in the process chain. A quality check for unphysical values (below 0% or above 100% are rejected) in the original ASCAT dataset is performed for all experiments.

• Spatial interpolation

Irregularly distributed ASCAT measurements are interpolated to the ALADIN-Austria grid with an inverse distance weighting function (Shepard 1968), taking into account measurements within 25 km of the model grid point. ALADIN resolves scales of a few grid points, therefore, the scales of the modeled superficial soil moisture (mostly driven by the scales of the precipitation field) are between 20 and 40 km, thus corresponding to the ASCAT resolution. Only ASCAT measurements that passed the quality control are used for interpolation.

• Bias correction

To apply a bias correction on satellite measurements, model data are used. The advantage of this correction over a (usually not possible) bias correction against accurate measurements is the fact that model assumptions (e.g., soil type and vegetation distribution) are included in the satellite measurements after the correction procedure. Hence, bias correction is so far supposed to be crucial for assimilation of satellite data in NWP models. The approach for bias correction applied here is the cumulative distribution function (CDF) matching, proposed by Reichle and Koster (2004). CDF matching should be applied on a scale as localized as possible with a dataset as long as possible to gain best results (Draper et al. 2009). The pointwise approach is based on the idea that the retrieval algorithm for ASCAT is calculated independently for each grid point (Wagner et al. 1999b) without taking into account information from surrounding points. Hence, each of the ASCAT grid points should be compared separately to the corresponding ALADIN gridpoint forecasts. Besides this, model bias tends to have a spatial variability (Reichle et al. 2004), which has to be taken into account.

To investigate the impact of bias correction, both the pointwise approach and the general one proposed by Mahfouf (2010) are tested, comparing modeled soil moisture data (recalculated to relative values in percentage based on the model soil) and ASCAT satellite measurements. The fifth-order polynomial fit was chosen as it proved useful for matching ASCAT and ALADIN datasets (Mahfouf 2010).
For the comparison, data from 13 months in 2009 (June–December) and 2010 (January–June) have been used. It would be desirable to use longer time series of ASCAT and ALADIN for comparison, but because of updates in the ALADIN model version used at ZAMG, a longer homogenous model forecast dataset was not available. To obtain statistically significant results, only grid points with at least 100 available measurement–forecast data pairs were taken into account. Additionally, there need to be ASCAT measurements in the range of 3%–97% of soil moisture index during the investigated period. If the data range is smaller, the resulting regression equations would be not representative. Seasonal differences between ALADIN and ASCAT have not been considered in this approach. This is done although it is known that the a priori assumption of CDF matching about the temporal invariability of the difference between model and measurements is not true (Draper et al. 2009). Because of the small population at each grid point, a seasonal bias correction as proposed in Draper et al. (2009) was unfeasible. Because of the limitations described, for about 70% of all land grid points within the model domain, ASCAT data can be bias corrected and assimilated (see Fig. 1). Mainly Russia and the southwestern part of the domain, regions with a high sand fraction in the modeled soil tend to be dried the most (Sicily, the Netherlands, northern Germany, and Sweden).

Results of CDF matching are displayed in Fig. 3 for the (Fig. 3a) general and (Fig. 3b) pointwise approach. Although calculated with ERS-calibrated ASCAT data, the agreement of the general regression equation used in Mahfouf (2010) to the new one computed with the new dataset is quite good. Both are showing the same model behavior, which is not surprising as both use versions of the ALADIN-model: ALADIN is over (under) estimating soil moisture for dry (wet) soils, which can be explained by the model physics of the superficial soil layer. Below the wilting point, transpiration is nearly stopping so no further water loss is taking place and above field capacity water is taken out by gravitational drainage rapidly (Mahfouf 2010). Values above (below) the zero line indicate that the model is moister (drier) than the ASCAT measurement. Therefore, the measured ASCAT value will be increased (decreased) to better fit the model before assimilating the data.

For the pointwise approach, there is a large diversity in the regression equations, although they are also representing the model behavior of underestimating maxima and minima in the soil moisture distribution. Fifth-order polynomials for the CDF plotted in Fig. 3b are from grid points located at 41°–52°N, 15°E (pink line in Fig. 1). From the diversity of these few grid points it can be seen that local effects both in the model and in the satellite measurements have large influence on the results. Even on small regional scales, the differences in the regression equations can be large, while on the other hand there are regions with stronger similarities over larger distances.
4. Experimental setup

Several approaches have been tested to define the best strategy of using ASCAT data in regard to data quality and bias correction on the one hand and the balancing of background and observation error in sEKF on the other. Table 1 gives an overview of the five experiments presented in this paper (EXP1–EXP5).

For EXP1, all available satellite measurements have been assimilated and no quality flags and no bias correction have been applied at all during the whole experiment. This experiment is the reference to quantify the benefit of data preprocessing on forecast quality.

For EXP2, quality flags for topography, wetlands, snow, and frozen soil have been applied before the calculation of the regression equations. ASCAT measurements have been rejected if one or more of the four quality flags exceeded 5%. As this quality control is reducing the amount of available ASCAT measurements significantly especially over mountainous terrain (e.g., Austria), a general bias correction (Fig. 3a) was applied to the dataset.

For EXP3 and EXP4, the pointwise bias correction approach has been applied to the ASCAT data. Using the quality flag for topographic complexity would be reducing the amount of measurements for mountainous regions drastically, no matter how long the time series of data will be. Therefore, no quality flags have been applied for these two experiments to avoid large data-free regions within the model domain. It can be assumed that the retrieval errors made due to topography will be more or less constant with time and so CDF matching can be applied also to these lower-quality ASCAT measurements. It is also noted here that a recent validation study carried out by Brocca et al. (2013) suggests that the quality of the ASCAT soil moisture retrievals over alpine areas is better than assumed previously. It may, therefore, become necessary to revise the topographic complexity flag (i.e., the recommendation of which values are considered problematic or not). EXP3 and EXP4 are different in terms of the observation error used in the sEKF. The covariance of background errors is the same for all experiments; it is 0.6\((w_\text{fc} - w_\text{wilt})\) for \(w_\text{g}\) and 0.3\((w_\text{fc} - w_\text{wilt})\) for \(w_2\). For EXP4, the observational error standard deviation is chosen smaller than in EXP3 \(0.25(w_\text{fc} - w_\text{wilt})\) instead of \(0.6(w_\text{fc} - w_\text{wilt})\), so ASCAT measurements are supposed to be more reliable compared to the model background field. Thus, the sensitivity of the assimilation to the choice of background and observation error can be tested by comparing model output fields.

EXP5 is combining the quality control step in ASCAT data preprocessing (see EXP 2) with the pointwise bias correction. Besides the changes in soil moisture distribution due to assimilation, there are no differences in the model configurations for OPER and the five experiments.

July 2009 was characterized by numerous precipitation events in central Europe. So this month has been chosen as a test period, providing enough events for statistically meaningful results. For each experiment, forecasting runs starting at 0000 UTC with a forecast range of +48 h have been recalculated for all 31 days of the month, providing the dataset for verification. As the deep-layer water reservoir is just slowly responding to the assimilation of superficial soil moisture, a spinup period was chosen for all experiments. This period extends from 15 June to 30 June 2009. Forecasts from this period are not taken into account for verification.

5. Results

In this section, results from the different forecasting experiments are presented and validated. Mainly three components of the forecasting system are verified to quantify the success of the assimilation system: precipitation, soil moisture, and screen level parameters (2-m temperature and relative humidity).

a. Precipitation forecasts of OPER

The INCA analysis of accumulated precipitation for July 2009 (Fig. 4a) shows maximum values along the northern edge of the Alps from Lake Constance to Salzburg. Several local maxima can be found along the main alpine ridge, minima are located along the Danube and in eastern and northern Austria. Verifying the model forecasts against INCA, rainfall is overestimated along the main Alpine ridge and south of the domain and underestimated in southern Bavaria, along the northern slopes of the Alps and in southeast Austria (see Fig. 4b). The model overestimation of convective precipitation over the entire alpine region has been already described by Wittmann et al. (2010). The model is not able to reproduce the observed precipitation patterns, which are selective and clustered into specific regions and not as widespread as forecast by the model. This is especially true for low-precipitation events. These conclusions
are supported by the objective verification system SAL (Fig. 5). For this verification, both ALADIN precipitation forecasts and INCA analyses have been accumulated to 6-hourly sums for the whole INCA domain and eight subdomains within the INCA domain. Two characteristic domains ("easterly lowlands" and "western Austria") of them are displayed in Fig. 2. For 31 days in July 2009 and a forecast range of +48 h, 248 data pairs result. For each of these 6-hourly data pairs of ALADIN-Austria and INCA, scores are computed. Solely dates with precipitating events analyzed by the INCA system were taken into account and are displayed in Fig. 5. Scores are averaged for the whole verification period.

For all but one of the regions investigated, precipitation amount is overestimated ($A > 0$) by the model. The sole exception is the region easterly lowlands, where rainfall amount is slightly underestimated. This is in good agreement with the findings from Fig. 4b. If all 248 forecasting periods are averaged (including false alarms and missed hits by the model as well as events where no precipitation was forecast and measured), $A$ is slightly positive for easterly lowlands, too. This indicates that the model is providing more false alarms than missed hits. So the model is on the one hand overestimating the amount of precipitation events for this region but on the
other hand underestimating the rainfall amount in cases of hits. These findings are also true in an alleviated manner for other flatland regions investigated within the INCA domain. For the domains located along the main alpine ridge, values of $A$ are typically positive and large (see western Austria in Fig. 5) which is in correspondence with the overestimation of precipitation.

The $S$ score is larger than zero for all verification domains. This means that the forecast precipitation fields are too widespread and/or too flat compared to pattern analyzed with INCA.

The location score $L$ is quite similar for all regions, which is a typical behavior for this parameter when averaging it for several events (Wittmann et al. 2010). Therefore, this component is more useful for the investigation of single events. Nevertheless, the $L$ component is larger for the flatland regions than for the mountainous verification domains. This is in correspondence with the fact that convective precipitation in mountainous regions is higher correlated to topographic forcing and, therefore, to better-defined geographic regions than in flatlands. In lowlands, the distribution of precipitation pattern is more random, therefore, model performance is slightly worse for these regions.

**b. Precipitation forecasts of the assimilation experiments**

The main focus in the following discussion is on the different behavior of the model for precipitation forecasts in mountainous regions and flatland. SAL verifications for the domains easterly lowlands (EL) and western Austria (WA) are selected as representative domains. Figure 6 is displaying results for $A$ and $S$ for both domains and all experiments. The thresholds are referring to the averaged 6-hourly analyzed INCA precipitation within the subdomains. The forecast is supposed to be improved if it is more than 3% better (i.e., closer to zero) than the reference run.

For the rare strong events [$>10$ mm (6 h)$^{-1}$; three events during July 2009], forecasts in the lowlands can be improved by assimilation. The negative $A$ values are indicating that the amount of rain is significantly underestimated by the model for the hit events. The $A$ component is best (i.e., closest to zero) for EXP3 ($-0.94$), followed by EXP1 ($-1.14$) and worst for OPER ($-1.34$). All five experiments are improving forecast quality for $A$. The $L$ component for EL is improved for EXP3 and reduced by assimilation from $+0.32$ (OPER) to $+0.30/+0.30$ for the five experiments, respectively. For the $S$ component (Fig. 6b), forecast rainfall patterns are too small and/or intense for strong events, EXP3 ($-0.40$) is improving forecasts compared to OPER ($-0.54$), and EXP1 is degrading them.

For mountainous regions (WA), there are no clear differences from EXP1 to EXP5 and OPER for the $A$ component. This is also true for $L$, where the effect of assimilation during strong events is neutral ($+0.05$ for OPER and $+0.04/+0.04/+0.04$ for EXP1). For the $S$ component, forecast improvement can be detected for EXP3 ($-0.01$) and EXP4 ($-0.01$) compared to OPER ($-0.06$) for strong events.

Table 2 gives an overview of the averaged SAL components for all precipitation classes during July 2009 for both domains. It can be concluded that ASCAT soil moisture assimilation is mainly improving the $A$ component for this 1-month period. Including also false alarms ($A = +2$) and misses ($A = -2$) of the model to compute the $A$ component, the result is an $A$ value larger than zero for all experiments (not shown), indicating that there is an overestimation of forecast precipitation events in lowlands. For the $S$ component in flatlands, EXP3 provides on average the best results being closest to zero, followed by OPER and EXP2. For the $L$ component, EXP4 and OPER are best, and EXP1–3 and EXP5 are second best.

For all components, differences between different assimilation setups in mountainous terrain are insignificant. So different treatment in ASCAT preprocessing for the assimilation has a clear impact on the forecasts for flatlands, while in complex topography, the overall influence of the assimilation on the forecast quality is low. It is obvious from SAL that the soil moisture distribution is of minor importance for precipitation forecasts in mountainous regions; hence, assimilation has no clear positive impact here. Overall, verification results of SAL are leading to the conclusion that the combination of a pointwise bias correction and the use of almost all ASCAT soil moisture data (EXP3 and EXP4) is the preferred choice to improve forecasts during this 1-month testing period. The rejection of ASCAT measurements due to the quality control (EXP2 and EXP5) or the lack of a bias correction (EXP1) during preprocessing is degrading forecast quality.

So far, the results of SAL presented have been averaged over the whole forecasting period of 48 h. As convective precipitation has a pronounced diurnal cycle with a maximum in the afternoon and early evening and a weak secondary maximum in the morning hours (Dotzek 2001), Fig. 7 is displaying the forecasting behavior in dependency of the model lead time. The threshold is 0.0 mm, so all measured precipitating events are considered, the investigated domain is EL. A diurnal cycle of forecast quality is obvious for both $A$ and $S$. During daytime ($+12$ and $+36$ h), both scores are positive and precipitation is overestimated by the model for all experiments computed. During nighttime ($+24$ and $+48$ h), both the amount of precipitation and the upscale development
of convective systems in the evening and night hours is underestimated. This is indicating a problem in model physics to reproduce a realistic life cycle of convective cells, which is well known but not solved so far (Wulfmeyer et al. 2008). The overestimation of convective precipitation in the morning hours is even more pronounced for EXP1–5, leading to an undesired stronger overestimation of precipitation in the Alps for all experiments compared to OPER. However, precipitation forecasts during the nighttime can be improved especially for EXP3 and EXP4 and the increase in average precipitation improves forecasts for lowlands, especially along the northern side of the Alps.

c. Case study: 23 July 2009

A severe thunderstorm affected Austria north of the Alps on 23 July 2009. The synoptic situation was characterized by a high pressure system over southeast Europe, a low pressure system over England, and a cold front approaching Austria from the northwest. As a result of the high pressure system, conditions in Austria were sunny during the day and in combination with local effects caused by the complex topography, the prefrontal boundary layer was well pronounced and characterized by warm and humid air masses with high convective available potential energy. The southwesterly wind in
middle layers, which advected hot air from Alpine valleys, suppressed convection during the first half of the day. This caused an increase of the potential energy in the boundary layer. Convection was first triggered by a convergence line, connected to the cold front, at around 1400 UTC in Bavaria. Henceforward, several thunderstorm cells were developing in Bavaria and Austria along the northern slopes of the Alps, causing severe damages due to hail and downbursts over large regions (Pistotnik 2009).

While the potential for thunderstorms was well forecast for southern Bavaria and western Austria by OPER and also by other forecasting models, none of the models was able to forecast the correct thunderstorm tracks for eastern Austria. As in OPER (Fig. 8b), the most probable motion of the cells was from the northern side of the Alps northeastern toward the Czech Republic. Therefore, forecasts for eastern Austria gave a low degree of probability for thunderstorms. The INCA analysis (Fig. 8a) for the 24-hourly accumulated precipitation of 23 July 2009 is showing that large rainfall amounts were measured all along the northern side of the Alps; in addition, widespread hail was reported. Recalculating this case study with ASCAT data assimilation, the achieved forecast improvement is evident both in precipitation amounts (see Fig. 8c for the result of EXP3) and SAL verification (see Table 3). Verification scores are improved for all experimental settings over eastern Austria compared to OPER (not shown). Besides this positive result, two typical features of the forecasting system are the underestimation of precipitation in northern Bavaria and the overestimation of convection over the Alps (exemplarily displayed for OPER and EXP3 in Figs. 8b and 8c, respectively). For verification domain EL, mean areal precipitation for this event (INCA: 11.0 mm) was slightly overestimated by EXP3 but severely underestimated by OPER (see Table 3). Investigating the detailed SAL results, a slight temporal shifting of the event is detectable in EXP3 with a delay of about 2 h compared to INCA.

Nevertheless, the availability of the assimilation forecast run would have been of great help for the forecaster to improve the thunderstorm warnings for this day.

As described in Pistotnik (2009), the soil moisture distribution in eastern Austria was of major importance for this event. It influenced mesoscale features in the boundary layer, which resulted in favorable conditions for thunderstorm tracks from west to east instead of the northeast as suggested by OPER. So for this case study, the correct representation of soil conditions and therefore soil moisture data assimilation is mainly important for regions with several degrees of freedom for the storm track due to the lack of topographic forcing.

Increments of the superficial soil layer are displayed in Fig. 8d. Especially the moistening of the ground in eastern parts of Austria is expected to have a positive impact on forecast quality in this case. For precipitation, it can be concluded that in mountainous regions the influence of ASCAT assimilation is low. This will be mainly due to forcing mechanisms in complex topography, which are overlaying the slight modifications in soil moisture patterns due to the assimilation. So far, forecast quality is even degraded by soil moisture assimilation due to a further overestimation of the precipitation amounts. Forecasts can be improved for flatlands, where boundary conditions influenced by the soil moisture distribution have a larger impact on convective initiation and the movement of storm tracks. This effect is most evident for the assimilation runs using the pointwise bias correction.

d. Comparison of modeled and measured soil moisture

Because of the problems with forecasting correct precipitation patterns, it can be expected that also the modeled soil moisture distribution does not fit well to the reality. Furthermore, it cannot be easily determined just by investigating the analysis increments, which are in good agreement with the increments computed by Mahfouf (2010), if the assimilation is shifting the modeled soil moisture patterns toward a more realistic state. Therefore, the in situ measurement station Schalladorf in Austria is used to quantify the effect of the assimilation.

For the deep soil reservoir in Schalladorf, soil moisture in OPER is overestimated by 10% at the beginning of the period investigated. The difference between OPER and EXP3 at 1 July 2009 is due to the spinup phase of 16 days (see section 4). The RMSE of OPER compared to the in situ measurements for the whole month is 6.6%. Evidently, soil moisture forecast is sensitive to ASCAT soil moisture data assimilation (Fig. 9), as due to the assimilation, the modeled soil moisture of the deep layer can be significantly improved: the mean

### Table 2. Averaged SAL verification results for July 2009 for verification domains easterly lowlands and westerly Austria. Best results are in bold and results better or equal to OPER are in italic.

<table>
<thead>
<tr>
<th>Verification Domain</th>
<th>OPER</th>
<th>EXP1</th>
<th>EXP2</th>
<th>EXP3</th>
<th>EXP4</th>
<th>EXP5</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Easterly lowlands</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>S</td>
<td>-0.18</td>
<td>-0.24</td>
<td>-0.21</td>
<td><strong>-0.15</strong></td>
<td>-0.22</td>
<td>-0.22</td>
</tr>
<tr>
<td>A</td>
<td>-0.64</td>
<td>-0.59</td>
<td>-0.60</td>
<td><strong>-0.52</strong></td>
<td>-0.60</td>
<td>-0.59</td>
</tr>
<tr>
<td>L</td>
<td>0.29</td>
<td>0.30</td>
<td>0.30</td>
<td><strong>0.26</strong></td>
<td>0.28</td>
<td>0.29</td>
</tr>
<tr>
<td><strong>Westerly Austria</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>S</td>
<td><strong>0.06</strong></td>
<td>0.07</td>
<td>0.07</td>
<td>0.06</td>
<td><strong>0.06</strong></td>
<td>0.06</td>
</tr>
<tr>
<td>A</td>
<td>-0.16</td>
<td>-0.15</td>
<td>-0.14</td>
<td><strong>-0.14</strong></td>
<td>-0.14</td>
<td>-0.15</td>
</tr>
<tr>
<td>L</td>
<td><strong>0.19</strong></td>
<td>0.20</td>
<td>0.20</td>
<td>0.20</td>
<td>0.19</td>
<td>0.20</td>
</tr>
</tbody>
</table>
squared error can be reduced to 5.8% for EXP3, especially in the first half of the month it is quite clear that the assimilation run is improving the mean soil moisture, while for the second half of this case study, the drying of the soil is not captured correctly. Keeping in mind that this comparison is just valid for one single measurement point and therefore not representative of larger areas, it is nevertheless a promising result for the positive impact of soil moisture assimilation.

e. Screen level parameters

To investigate the influence of soil moisture assimilation on boundary conditions, screen level parameters have been verified for 36 low-elevation stations (elevation between 200 and 500 m) restricted to Austria so the results are geographically comparable to the precipitation evaluation. Verification is performed at the station locations; therefore, ALADIN forecasts have to be interpolated horizontally to these coordinates, taking into account differences in the height (for $T$) due to model orography. This simple interpolation algorithm is not taking into account differences in representativeness of the station measurements and the model forecasts, but the impact on the overall error made by the interpolation is equal for OPER and EXP1–5.

Forecasts of 2-m values are calculated using surface parameters and values from the lowest model level (on average 17 m above ground) using the approach of

![Fig. 7. (a) Amplitude and (b) structure component averaged for all 31 forecasting runs of OPER, EXP3 and EXP4 for the verification domain easterly lowlands depending on the model lead time in hours (abscissa).]
The way to treat this screen level diagnostic can have a large impact on the forecast quality, and the settings that are optimized for OPER have not been changed for EXP1–5. Despite this optimization, 0000 UTC runs for July 2009 with OPER have on average a warm and wet bias (see Table 4). Separating verification results for different daytimes, a pronounced diurnal cycle is evident (see Figs. 10 and 11). During the nighttime, there is a warm bias of about +1 K, averaged for all 36 stations. One reason for this behavior is the fact that shallow inversions originating due to emission of long-wave radiation during the nighttime are not well modeled by the interpolation algorithm. A detailed description for this effect can be found in Masson and Seity (2009). During the daytime, the temperature bias is slightly negative for OPER. Overall, the bias is drifting toward more positive values with an increasing lead time. For relative humidity (Fig. 11), there is a corresponding diurnal cycle with slight negative values during the nighttime and a large positive bias during the daytime. No vertical interpolation between model orography and station height was conducted for humidity. On average, bias of relative humidity is close to zero for OPER (see Table 4) due to the settings in the screen level diagnosis.

Assimilating ASCAT data are decreasing bias and root-mean-square error (RMSE) for temperature and RMSE for relative humidity for all experiments presented (Table 4) on average. Concerning the diurnal cycle, the positive bias during the nighttime is decreased. The negative temperature bias during the daytime is increased, which is explained by the changes in surface evaporation during the daytime due to the assimilation. The drift of the bias in OPER is reduced for all experiments (Fig. 10). While there is no change in the initial field for temperature due to assimilation, bias and RMSE can be reduced for relative humidity due to assimilation at the initial conditions. This positive impact lasts up to 6-hourly forecasts (Fig. 11); later on the overestimation of moisture near the ground during the daytime is even increased in the experimental runs.

It can be concluded that assimilation improves the quality of screen level parameters for the period of July 2009, verified with RMSE for low-elevation stations in Austria whereas the diurnal cycle of the bias is shifted toward cooler and wetter conditions with the use of ASCAT data.

<table>
<thead>
<tr>
<th></th>
<th>OPER</th>
<th>EXP3</th>
</tr>
</thead>
<tbody>
<tr>
<td>A</td>
<td>−0.53</td>
<td>−0.33</td>
</tr>
<tr>
<td>S</td>
<td>−0.10</td>
<td>−0.05</td>
</tr>
<tr>
<td>L</td>
<td>0.08</td>
<td>0.05</td>
</tr>
<tr>
<td>Mean areal precipitation (mm)</td>
<td>2.7</td>
<td>11.7</td>
</tr>
</tbody>
</table>
6. Conclusions and outlook

Data assimilation is a crucial ingredient for high-quality NWP forecasts. In recent years, several new data sources have been made available both by the remote sensing community and new satellite technologies. The one discussed here is the remotely sensed ASCAT superficial soil moisture product. It is provided almost worldwide (except in rain forests and deserts) and can be used in land data assimilation systems to improve the soil moisture pattern used in atmospheric NWP models. In this study, these data are assimilated in the regional forecasting model ALADIN-Austria by a simplified extended Kalman filter included in the soil analysis scheme SURFEX. These ASCAT data have been quality controlled using the quality flags prepared by the data provider (in some experimental setups) and bias corrected with a general and a pointwise approach using different setups to select the best one to deal with these satellite data. Land data assimilation experiments are performed for July 2009 over central Europe (with the atmospheric initial state prescribed from analyses). Already proven to be useful for global models especially in tropical regions, the study presented here shows the following:

- It is worth doing the pointwise bias correction as the diversity in the model domain is so large that a general correction flattens out spatial features that are important for forecasting performance.
- In mountainous regions where initiation of convection is significantly influenced by orography, the effect of soil moisture assimilation is neutral in verification although precipitation is even more overestimated on average.
- For flatlands, soil moisture assimilation is beneficial when focusing on precipitation forecasts. It can improve forecast quality for single events as well as the overall performance on average for the 1-month period investigated.
- Comparing modeled to measured soil moisture for a single site suggests that ASCAT soil moisture assimilation is beneficial for modeled soil moisture.
- Though not tuned for the additional use of ASCAT data so far, screen level parameters can be improved in terms of overall RMSE and BIAS reduction especially during the nighttime.

It is interesting that the use of quality flags is not necessarily leading to better forecasting results. It seems that the changes in the model soil due to the assimilation

<table>
<thead>
<tr>
<th>OPER</th>
<th>EXP1</th>
<th>EXP2</th>
<th>EXP3</th>
<th>EXP4</th>
<th>EXP5</th>
</tr>
</thead>
<tbody>
<tr>
<td>Bias T2M (K)</td>
<td>0.44</td>
<td>0.25</td>
<td>0.08</td>
<td>0.03</td>
<td>0.33</td>
</tr>
<tr>
<td>Bias RH2M (%)</td>
<td>0.47</td>
<td>2.68</td>
<td>4.08</td>
<td>4.31</td>
<td>1.70</td>
</tr>
<tr>
<td>RMSE T2M (K)</td>
<td>1.91</td>
<td>1.88</td>
<td>1.85</td>
<td>1.85</td>
<td>1.90</td>
</tr>
<tr>
<td>RMSE RH2M (%)</td>
<td>13.10</td>
<td>12.66</td>
<td>12.65</td>
<td>12.58</td>
<td>12.43</td>
</tr>
</tbody>
</table>

FIG. 9. Comparison for Schalladorf soil moisture index (%) between in situ measurements (dotted black line, right ordinate) and model forecasts of OPER (thick gray line, right ordinate) and EXP3 (thick black line, right ordinate) for the deep soil layer. Black triangles are the bias-corrected ASCAT measurements (left ordinate) at the nearest grid point to Schalladorf. The thin gray (black) line is the forecast superficial soil moisture from OPER (EXP3) (left ordinate).
cycle have a positive or at least neutral impact on the initial conditions used for the forecast. When comparing the different experimental setups, EXP3 with a point-wise bias correction and the use of almost all ASCAT data (minimal quality controls) provides the best overall results. By imposing rather strict quality controls on ASCAT data (as in EXP5), the number of assimilated observations is significantly reduced and the positive forecast impacts noticed in EXP3 are weakened. This point needs to be further examined in order to find a better compromise between the overall quality of the data and their number in the land data assimilation system.

The advanced screen level diagnostic of Masson and Seity (2009) should be used to further improve results in the future. Indeed, the time series of 13 months for the CDF matching is the shortest period possible to gain statistically meaningful results. Therefore, longer time
series should be investigated to account for the seasonal cycle in the differences between modeled and measured soil moisture values for an improved bias correction.

Another field of activity is the assimilation with an evolving $B$ matrix for a better background error representation instead of the static one used for the simplified EKF in this study. Other approaches like a coupled $(s)$EKF with an atmospheric 3DVAR system or an ensemble Kalman filter will also be of interest for future investigations. The detected impact of the ASCAT preprocessing on the output of the assimilation could be applied to address the uncertainties of the actual soil moisture conditions, thus leading to a more physical representation of errors in perturbed initial surface conditions as input for an ensemble prediction system.

**Acknowledgments.** We thank Christoph Wittmann and Alexander Jann from ZAMG for fruitful discussions and valuable contributions to the model runs, our colleagues from IPF for the help with ASCAT data and FFG, which partly funded these investigations in the ASAP project, Global Monitoring of Soil Moisture for Water Hazards Assessment (GMSM).

**REFERENCES**


——, J. Dong, and A. A. Berg, 2004: Global soil moisture from satellite observations, land surface models, and ground data: Implications for data assimilation. *J. Hydrometeor.*, 5, 430–442.


