

Downscaling of seasonal soil moisture forecasts using satellite data

S. Schneider¹, A. Jann¹, T. Gorgas¹

[1]{Central Institute for Meteorology and Geodynamics, Vienna, Austria}

Correspondence to: Stefan Schneider (stefan.schneider@zamg.ac.at)

Abstract

A new approach to downscale soil moisture forecasts from the seasonal ensemble prediction forecasting system of ECMWF (European Centre for Medium-Range Weather Forecasts) is presented in this study. Soil moisture forecasts from this system are rarely used nowadays though they could provide valuable information. Weaknesses of the model soil scheme in forecasting soil water content and the low spatial resolution of the seasonal forecasts are the main reason why soil water information is hardly used so far. The basic idea to overcome some of these problems is the application of additional information provided by two satellite sensors (ASCAT and ENVISAT ASAR) to improve the forecast quality, mainly to reduce model bias and increase the spatial resolution. Seasonal forecasts from 2011 and 2012 have been compared to in-situ measurements sites in Kenya to test this two-step approach. Results confirm that this downscaling is adding skill to the seasonal forecasts.

1 Introduction

Proper knowledge of soil water content and distribution is important for many applications in earth system sciences. Soil moisture has 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). Evapotranspiration, infiltration and runoff depend on soil wetness, as does the sensible heat flux from the surface and the heat stored in soils. Soils provide nutrients for the biosphere, and soil water is also important in biogeochemical cycles (Zreda et al., 2012).

1 Unfortunately, soil water content is both difficult to measure and forecast. This is due to the
2 high variability of soil water content both in time and space, even over short distances
3 (Western et al., 1999) which can hardly be captured by point measurements. Nevertheless,
4 ground-based methods can be applied over any depth, accurately calibrated, and logged at any
5 time scale (Western et al., 2002). Many of the globally available ground-based soil moisture
6 measurements are thus collected, harmonized, and made available to users through the ISMN
7 (International Soil Moisture Network; <http://ismn.geo.tuwien.ac.at>; Dorigo et al., 2013).
8 Remote sensing, on the other hand, provides excellent spatial coverage over large areas and
9 spatial representativeness, but the shallow measurement depth, confounding influence of
10 vegetation, indirect nature of the method, and relatively infrequent repeat cycles hamper the
11 use of the data (Western et al., 2002).

12 Due to the processes described above, the need for proper soil moisture characterisation in
13 modelling is well understood. Nevertheless, simplifications in the representation of modelled
14 land-surface processes in numerical models are unavoidable. They lead to systematic errors in
15 the soil moisture field which is degrading forecast quality (Drusch and Viterbo, 2007).
16 Furthermore, deficits in the short-range precipitation forecasts and representation of the
17 seasonal vegetation cycle (Balsamo et al., 2009) are intensifying the forecasting problems.
18 Thus, (seasonal) soil moisture forecasts are hardly used nowadays although it could be
19 valuable information. Especially in hydrological applications, including flood forecasting and
20 drought monitoring, one is interested in the root zone soil moisture at the catchment or finer
21 scales as its knowledge can significantly improve estimates (Wagner et al., 2007). This in turn
22 is necessary for agricultural and food security issues as well as disaster management. To
23 improve forecast representativeness and accuracy, a new method to downscale seasonal soil
24 moisture forecasts of the ECMWF ensemble forecasting system, providing high-resolution
25 soil water forecasts, is presented in this paper.

26 Data sources used for the investigation are described in section 2. Section 3 includes the
27 calibration and downscaling approach, and in section 4 the results are presented. Conclusions
28 are drawn in section 5, including an outlook on future work and applications.

29

30 **2 Data sources**

31 Seasonal forecasts as well as reference forecasts of soil moisture are generated at the
32 ECMWF. Soil moisture measurements are available from satellite platforms and in-situ

1 measurement sites in the testing region, located in Kenya. In the following subsections, the
2 data sources are described in detail.

3 **2.1 ASCAT soil moisture data**

4 The Advanced Scatterometer (ASCAT) is a C-band (5.255 GHz) real aperture radar operated
5 by EUMETSAT (European Organization for the Exploitation of Meteorological Satellites). It
6 is flown on the METOP satellites. Near-real-time (about 2 hours after sensing) ASCAT
7 surface soil moisture maps at 25 km and 50 km spatial scale are available operationally since
8 December 2008 (Wagner et al., 2010). ASCAT data used for this study have been provided by
9 Vienna Technical University. The backscattered measurements are used to estimate the
10 surface soil moisture content (Wagner et al., 2013; their Eq. 1), which is a number ranging
11 between 0 (dry limit) and 1 (moist limit), usually expressed in %. To convert it to volumetric
12 soil moisture content (being comparable to ECMWF model output), the soil porosity is
13 necessary (Wagner et al., 2013; their Eq. 2). There are no reliable porosity data for the target
14 region in Kenya, so this conversion is not possible without introducing an additional error
15 source, thus model output and COSMOS (COsmic-ray Soil Moisture Observing System)
16 measurements are converted to the index with values between 0 and 100% to make all data
17 sets comparable. ASCAT data are stored as time series for single grid points, so they were
18 interpolated to the ECMWF model grid (0.7° resolution) to be comparable. To do this, an
19 inverse distance weighting approach (Shepard, 1968) was used. ASCAT soil moisture is valid
20 for the surface soil layer with an approximate depth of 1-2 cm. Quality flags for wetlands,
21 snow cover, frozen soil and topographic complexity (Scipal, 2005) have been considered. For
22 the ASCAT grid points investigated over the target region, none of the flags had values which
23 would have made it necessary to reject measurements.

24 **2.2 Seasonal forecast data from ECMWF**

25 Seasonal forecasts used for this comparison are produced by the Seasonal Ensemble
26 Prediction System (EPS) of ECMWF. System 4 (Molteni et al., 2011), which was used in this
27 study, is in operational use since 2011. For the atmospheric part of the forecasting system,
28 ECMWFs Integrated Forecasting System (IFS) is used with a horizontal resolution of about
29 0.7° and 91 vertical levels with a model top at ~0.01hPa. Soil processes are modeled by H-
30 TESSEL (Hydrology-Tiled ECMWF Scheme for Surface Exchanges over Land; Balsamo et
31 al., 2009; Balsamo et al., 2011). Data output for soil moisture is provided daily for 4 vertical

1 soil levels: 0-7cm, 7-28cm, 28-100cm, 100-289cm. The seasonal forecasts include 51
2 ensemble members. Forecast runs are started at 00 UTC on the 1st of each calendar month
3 with a lead time of 215 days (5160 hours). Data have been extracted from the Meteorological
4 Archival and Retrieval System (ECMWF, 2013a) for 4x4 grid points in Kenya.

5 In order to compare ECMWF output and ASCAT data, the ECMWF data unit has to be
6 transformed from the original volumetric soil water [m^3m^{-3}] to an index with values between
7 0 and 100 (saturation fraction or soil water index (SWI)). H-TESSSEL distinguishes between
8 six different soil types. Using these soil types, for each of the grid points the SWI in % has
9 been calculated for the combined 1st and 2nd soil layer with

$$10 \quad SWI = \left(\frac{0.25SWL_1 + 0.75SWL_2}{SWL_{SAT}} \right) \cdot 100, \quad (1)$$

11 where SWL_{SAT} [m^3m^{-3}] is the saturation value for the grid point (solely depending on the soil
12 type); SWL_i [m^3m^{-3}] is the forecasted volumetric soil water of the i^{th} layer at the grid point.

13 **2.3 Reference forecasts from ECMWF**

14 The reference ensemble is created out of historical IFS analyses of the operational high
15 resolution forecasting system at ECMWF. This reference is used to find out if the seasonal
16 forecasting system has a prediction skill higher than a climatological forecast. Soil moisture
17 data from 00UTC runs for January 2001 to December 2012 from the two upper layers of the
18 H-TESSSEL soil scheme have been extracted from the MARS archive to ensure a model
19 climatology with sufficient robustness for comparison. As the resolution of the IFS
20 deterministic run (0.125°) is significantly higher than the seasonal EPS's one, the IFS grid
21 points with locations corresponding to the 16 EPS grid points in Kenya have been selected.

22 The analyses for all the years extracted have been combined, and as a result, a 12-member
23 poor-man ensemble for each of the sixteen model grid points is available as reference
24 forecast. Equation (1) has been applied to this data set, too.

25 **2.4 COSMOS station data**

26 To quantify the forecast quality of the ECMWF seasonal forecasts, two in-situ measurement
27 sites in Kenya have been used. They are part of COSMOS. The stationary cosmic-ray soil
28 moisture probe measures the neutrons that are generated by cosmic rays within air and soil

1 and other materials, moderated by mainly hydrogen atoms located primarily in soil water. The
2 neutrons are emitted to the atmosphere where they mix instantaneously at a scale of hundreds
3 of meters. Their density is inversely correlated with soil moisture (Zreda et al., 2012). Fig. 1
4 shows the location of the two probes which are operated by the University of Arizona. Data
5 are freely available on a web page (<http://cosmos.hwr.arizona.edu>) and have been downloaded
6 for the period 2011 to 2012. Measurements at the two stations are representative for a soil
7 layer of 15-30cm (depending on the current soil water content), so on average they are
8 representative for the same soil depth as the combined H-TESSEL layer 1 (0-7cm) and layer 2
9 (7-28cm) data calculated in Equation (1). COSMOS stations are measuring average soil water
10 content within a diameter of a few hectometers (Zreda et al., 2012). The correction to
11 atmospheric water vapor content described by Rosolem et al. (2013) has been applied to the
12 COSMOS level-3 (Zreda et al., 2012) soil moisture data, which are provided in volumetric
13 soil moisture [m^3m^{-3}]. Afterwards they were transformed to relative values between 0 and 100
14 by taking the lowest (highest) value in the measurements time series as 0 (100) and rescaling
15 all measurements between these two values.

16 Both COSMOS stations (KLEE: $36.867^\circ\text{E}/0.283^\circ\text{N}$, Mpala-North: $36.87^\circ\text{E}/0.486^\circ\text{N}$) are
17 within the same IFS grid cell (0.7° resolution of the seasonal EPS), but the nearest grid point
18 which is used for the comparison is different ($37.1^\circ\text{E}/0.0^\circ\text{N}$ vs. $37.1^\circ\text{E}/0.7^\circ\text{N}$). Unfortunately,
19 no other in-situ measurement sites are available within Eastern Africa where the satellite
20 downscaling parameters (see chapter 3) have been available for this investigation.

21

22 **3 The calibration and downscaling approach**

23 To downscale seasonal soil moisture forecasts from the global grid to a 1km resolution with
24 satellite data, a two-step approach is necessary. In a first step, the forecast climatology is
25 calibrated, meaning that it has to be shifted to the ASCAT climatology. This is done with a
26 CDF matching approach (Reichle and Koster, 2004). After this calibration, the relationship
27 between ASCAT and ENVISAT ASAR can be applied to the seasonal soil moisture forecasts
28 in a second step to gain results on a 1km grid.

29 **3.1 Step 1: Calibration with CDF matching**

30 To match ASCAT and ECMWF cumulative distribution functions, for each global model grid
31 point (within the selected domain) the daily IFS/EPS forecast values of each ensemble

1 member are compared to the available ASCAT measurements. As the forecasting model for
 2 each IFS/EPS member is the same, the number of ASCAT-IFS/EPS data pairs can be
 3 increased by the factor of 51 which makes the results more robust from the statistical point of
 4 view. Data from 7 consecutive seasonal runs (starting dates October 1st, 2011 to April 1st,
 5 2012) are compared. Based on these data pairs, a polynomial regression analysis is applied to
 6 the data set. Polynomials up to the ninth degree have been tested. It was found out that beside
 7 the linear regression all polynomials are reasonable for the bias correction. Comparing the
 8 mean of ASCAT with the means of IFS/EPS before and after the CDF matching, 4th order
 9 polynomials for the correction turned out to be the most proper one (i.e. the corrected
 10 IFS/EPS mean is fitting best to the ASCAT mean), followed by 8th and 3rd order polynomials.
 11 Thus it was decided to use 4th order polynomials as they are taking into account the most
 12 relevant statistical moments of expectation, variance, skewness and kurtosis. The CDF
 13 matching has been applied both to seasonal (EPS) and reference (IFS) forecasts.

14 **3.2 Step 2: Applying the ASCAT – ENVISAT ASAR relation**

15 For the disaggregation of coarse scale microwave measurements, finer resolution satellite data
 16 acquired e.g. by synthetic aperture radars (Das et al., 2011) are applied (Wagner et al., 2013).
 17 For 25km ASCAT soil moisture data, ASAR (Advanced Synthetic Aperture Radar) data
 18 acquired by the ENVISAT satellite are used. The method exploits the fact that the temporal
 19 dynamics of the soil moisture field is often very similar across a wide range of scales as they
 20 are often influenced by the same parameters (e.g. precipitation). This phenomenon is usually
 21 referred to as ‘temporal stability’ (Vachaud et al., 1985), meaning that the relationship
 22 between local scale and regional scale measurements may be approximated by a linear model.
 23 To estimate soil moisture at 1km scale from the 25km ASCAT soil moisture data,

$$24 \quad m_s^{1km}(t, x, y) = c_{ASAR}(x, y) + d_{ASAR}(x, y)m_s^{25km}(t), \quad (2)$$

25 is used (Wagner et al., 2013).

26 m_s^{1km} is the estimated surface soil moisture content over the 1km area centered at the
 27 coordinates (x, y) . m_s^{25km} is the calibrated ECMWF soil moisture at forecasting time t .
 28 Originally, m_s^{25km} is the ASCAT soil moisture retrieval at time t , but due to the calibration in
 29 step 1, this replacement with ECMWF model forecast data can be justified. The coefficients
 30 c_{ASAR} and d_{ASAR} are the two scaling parameters which are derived from long ASAR
 31 backscatter time series using the methods described in Wagner et al. (2008). So far, the

1 coefficients have been available solely for Europe and Australia. For the investigation
2 described herein, they have been calculated for Eastern Africa, too.

3 Tests with the disaggregated ASCAT-ASAR product show that it compares equally well to
4 in-situ measurements as the 25km ASCAT product (Albergel et al., 2010) but, overall, the
5 added value of this product is not yet very clear given that the downscaling parameters are
6 static, i.e. all information about the temporal behavior still comes from the original 25 km
7 ASCAT soil moisture product (Matgen et al., 2012). Nevertheless, the product facilitates data
8 handling and interpretation of the soil moisture information at much finer scales (through its
9 advisory flags), making it thus a valuable product from a practical point of view (Wagner et
10 al., 2013). This is likewise true for the ECMWF-ASAR product which is shown in the
11 following section. Comparing the measurements at station KLEE (36.7 on average) with the
12 closest ASCAT grid point (50.8) and the downscaled ASCAT soil moisture data at the four
13 1km grid points surrounding the in-situ station (50.3, 50.7, 50.0, 51.6) shows that the
14 downscaling changes the ASCAT measurements just slightly, improving 3 out of 4.

15

16 **4 Results**

17 For the verification of the forecast quality, weekly mean values have been calculated both for
18 COSMOS measurements and seasonal soil moisture forecasts. Each ensemble member has
19 been averaged separately. This approach was chosen for two reasons. First, possible outliers
20 and unpredictable scales in space and time are smoothed out due to this procedure. Second,
21 it is mainly the trend which is of interest while daily values of seasonal forecasts should not
22 be used anyway (Molteni et al., 2011). However, anomalous weather events can also be
23 suppressed with this averaging (ECMWF, 2013b).

24 To calculate statistical measures, the mean of the weekly values has been used for each of the
25 seven seasonal forecasting runs investigated (October 2011 to April 2012). The root mean
26 squared error (RMSE; Wilks, 2006) and the Pearson coefficient of linear correlation (PCC;
27 Wilks, 2006) have been chosen as statistical indices.

28 Fig. 2 shows the results for the seasonal forecast of February 2012 validated at the station
29 KLEE. The forecasting period is characterized by dry soils at the beginning of the period
30 followed by the rainy season starting in April. During the wet season, the spread of

1 measurements within a week is clearly higher than during dry periods. In the forecasting plots
2 (Fig. 2b-2g), the weekly mean value of the COSMOS station is marked with black dots.

3 The IFS climatological reference forecast (Fig. 2b) shows the typical behavior of the model
4 soil as H-TESSSEL is not able to reproduce very dry soils (Balsamo et al., 2009). So during the
5 dry season the soil moisture content is overestimated in the reference ensemble, and as a
6 consequence, the seasonal cycle is not pronounced enough. This leads to high values in
7 RMSE (24.1), so the climatology is not appropriate for forecast purposes in this case.

8 Due to the CDF matching (Fig. 2c) and downscaling (Fig. 2d), the tracing of the seasonal
9 cycle can be improved, but still soils are too wet in the model on average. Though the spread
10 is increased mainly due to the CDF matching, moisture is still overestimated by the model for
11 periods with dry soils. Both RMSE and PCC are improved after the downscaling.

12 The ensemble forecast of February 1st, 2012 (Fig. 2e) has the same problem as the reference
13 forecast with the soil being too wet during the dry season. The seasonal cycle of soil moisture
14 is captured much better in this case, resulting in a low RMSE (12.7) but also a low PCC
15 (0.31). CDF matching to the ASCAT climatology is improving the forecast (Fig. 2f), though
16 soil moisture is even underestimated at the beginning of the forecasting period. Due to this
17 underestimation, RMSE (12.9) is slightly worse compared to the raw EPS forecast, but the
18 seasonal cycle better fits the measurements (PCC=0.46). Downscaling to 1km improves the
19 forecast (Fig. 2g) for this case. The dry soil at the beginning of the forecasting period is still
20 underestimated, but the wet season is predicted much better with the downscaled forecast
21 product. The good forecast quality for months six and seven is still kept after this procedure.
22 Both RMSE (8.1) and PCC (0.73) can be clearly improved compared to the original EPS.

23 So it can be summarized for this example that both for the climatological forecast and the
24 seasonal forecast the downscaling approach improves the forecast quality.

25 The averaged results for all seven seasonal forecasts can be seen in Fig. 3. In terms of the grid
26 box size of the seasonal forecasting model, both stations are situated close together.
27 Nevertheless, the forecast quality is slightly different for KLEE and Mpala-North. Concerning
28 the PCC, downscaling is improving the score for Mpala-North both for climatology and EPS
29 forecasts. For the latter, the improvement (from 0.40 to 0.58) is significant. Significance was
30 tested with the Wilcoxon-Mann-Whitney test available in the statistical program R.
31 Furthermore, the EPS is better on average than the reference ensemble, but not significant
32 (0.44 vs. 0.40). As shown in Fig.2 for one case, the seasonal cycle is represented well by the

1 climatology for station KLEE, but with a large wet bias. Due to this, PCC for the climatology
2 is highly significant better at KLEE as the bias is neglected for computing the correlation. The
3 downscaling is improving PCC compared to the original grid both for climatology and EPS
4 on average, but not significant.

5 For the RMSE, the positive impact of the downscaling approach is even clearer. Climatology
6 is hard to beat at Mpala-North and the original seasonal forecast is significantly worse on
7 average than the reference forecast, but for both systems, the downscaled product is highly
8 significant better, reducing RMSE from 22.9 to 12.7 (for climatology) and from 26.2 to 19.1
9 (for seasonal EPS). This is also true for KLEE, whereas the EPS outperforms the reference
10 climatology for this station. RMSE can be highly significant reduced due to the downscaling
11 from 24.5 to 22.2 (for climatology) and from 15.6 to 11.9 (for seasonal EPS).

12

13 **5 Conclusions and outlook**

14 It can be concluded that the proposed downscaling approach with the included calibration is
15 working and provides useful results. This is demonstrated for two stations in Kenya. The
16 seasonal forecasting system (and also the reference ensemble made out of high-resolution
17 historical forecasts) has known problems in representing dry soils, thus leading to an
18 unrealistic seasonal cycle. Using the information contained in ASCAT soil moisture time
19 series, the described weakness can be partially overcome when calibrating the model
20 forecasts. This CDF matching is working well, even though the soil layers which are
21 compared are of different thickness (ASCAT: 1-2cm, ECMWF: 28cm), and has major
22 advantages over a calibration based on station measurements, as ASCAT satellite soil
23 moisture is available in sufficient quality almost everywhere over land (except rain forests,
24 deserts and polar regions). Furthermore, this approach is computationally simple.
25 Nevertheless, the polynomials have to be recalculated if changes in the model physics or the
26 satellite retrieval algorithm are taking place. The downscaling to a 1km grid with the ASCAT-
27 ENVISAT ASAR relation is also working well. Statistics is showing that the downscaling is
28 improving both climatology and seasonal forecasts, whereas results are highly significant for
29 RMSE. Concerning the forecast quality of the model, it can be stated that the climatology
30 created out of high-resolution analyses is an ambitious benchmark for the seasonal forecast
31 performance.

1 An application for this approach might be in the early warning of threats to food security in
2 dry regions around the world, thus this approach has been tested in Eastern Africa though the
3 data coverage of in-situ measurements is poor in this region. It would be especially interesting
4 to use the downscaled products in combination with crop models. Moreover it is relevant to
5 monitor soil moisture forecasts to detect weaknesses in forecast quality, as this parameter is
6 still not well captured by weather forecasting models nowadays though it is a relevant one,
7 especially for convective processes.

8 In a next step, it is planned to test the approach for other climate regions and more seasonal
9 forecast runs. Especially for dry climates, it would be interesting to combine the seasonal soil
10 moisture forecasts with drought indices. Furthermore, the variability on the 1km grid should
11 be investigated in detail for further improvement of this promising method.

12

13 **Acknowledgements**

14 We thank Trenton Franz (University of Nebraska-Lincoln) and Rafael Rosolem (University of
15 Bristol) for their support in the atmospheric water content correction of the COSMOS data
16 and two anonymous reviewers for their contributions. The downscaling parameters were
17 derived by the Photogrammetry and Remote Sensing group of the Vienna University of
18 Technology and provided in the frame project Hydrology-SAF, co-funded by EUMETSAT.
19 Work has been partly funded by FFG (Project FarmSupport under the Austrian Space
20 Applications Programme, FFG project number 833421) and ESA (Call AO/1-
21 6889/11/NL/CBi, Project GEOSAF).

22

1 **References**

- 2 Albergel, C., Calvet, J. C., de Rosnay, P., Balsamo, G., Wagner, W., Hasenauer, S., Naeimi,
3 V., Martin, E., Bazile, E., Bouyssel, F., and Mahfouf, J.-F.: Cross-evaluation of modelled and
4 remotely sensed surface soil moisture with in situ data in Southwestern France, *Hydrol. Earth*
5 *Sys. Sci.*, 14, 2177–2191, 2010.
- 6 Balsamo, G., Viterbo, P., Beljaars, A., van den Hurk, B., Hirschi, M., Betts, A.K., and Scipal,
7 K.: Revised Hydrology for the ECMWF Model: Verification from Field Site to Terrestrial
8 Water Storage and Impact in the Integrated Forecast System, *J. Hydrometeorol.*, 10, 623-643,
9 2009.
- 10 Balsamo, G., Pappenberger, F., Dutra, E., Viterbo, P., and van den Hurk, B.: A revised land
11 hydrology in the ECMWF model: a step towards daily water flux prediction in a fully-closed
12 water cycle, *Hydrological Processes*, 25(7), 1046-1054, doi: 10.1002/hyp.7808, 2011.
- 13 Das, N. N., Entekhabi, D., and Njoku, E.G.: An algorithm for merging SMAP radiometer and
14 radar data for high-resolution soil-moisture retrieval, *IEEE T. Geosci. Remote Sensing*, 49,
15 1504–1512, 2011.
- 16 Dharssi, I., Bovis, K.J., Macpherson, B., and Jones, C.P.: Operational assimilation of ASCAT
17 surface soil wetness at the Met Office, *Hydrol. Earth Syst. Sci.*, 15, 2729–2746,
18 doi:10.5194/hess-15-2729-2011, 2011.
- 19 Dorigo, W.A., Xaver, A., Vreugdenhil, M., Gruber, A., Hegyiová, A., Sanchis-Dufau, A.D.,
20 Wagner, W., and Drusch, M.: Global automated quality control of in-situ soil moisture data
21 from the International Soil Moisture Network. *Vadose Zone J.*, 12, 2013.
22 doi:10.2136/vzj2012.0097
- 23 Drusch, M., and Viterbo, P.: Assimilation of screen-level variables in ECMWF Integrated
24 Forecast System: A study on the impact on the forecast quality and analyzed soil moisture,
25 *Mon. Wea. Rev.*, 135, 300-314, 2007.
- 26 ECMWF: MARS User Guide, ECMWF Technical Notes, January 2013, 55 pp, 2013a.
- 27 ECMWF: User Guide to ECMWF forecast products, Version 1.1, July 2013, 129 pp,
28 <http://www.ecmwf.int/products/forecasts/guide/index.html> (13.11.2013), 2013b.
- 29 Ferranti, L., and Viterbo, P.: The European Summer of 2003: Sensitivity to Soil Water Initial
30 Conditions, *J. Climate*, 19, 3659-3680, 2006.

1 Matgen, P., Fenicia, F., Heitz, S., Plaza, D., De Keyser, R., Pauwels, V.R.N., Wagner, W.,
2 Savenije, H.: Can ASCAT-derived soil wetness indices reduce predictive uncertainty in well-
3 gauged areas? A comparison with in situ observed soil moisture in an assimilation
4 application, *Advan. Water Resour.*, 44, 49–65, 2012.

5 Molteni, F., Stockdale, T., Balmaseda, M., Balsamo, G., Buizza, R., Ferranti, L., Magnusson,
6 L., Mogensen, K., Palmer, T., and Vitard, F.: The new ECMWF seasonal forecasting system
7 (System 4), ECMWF Technical Memorandum (Technical Report) No. 656, 49 pp, 2011.

8 Reichle, R.H., and Koster, R.D.: Bias reduction in short records of satellite soil moisture,
9 *Geophys. Res. Lett.*, 31, L19501, doi: 10:1029/2004GL20938, 2004.

10 Rosolem, R., Shuttleworth, W.J., Zreda, M., Franz, T.E., Zeng, X., and Kurc, S.A.: The effect
11 of atmospheric water vapour on neutron count in the cosmic-ray soil moisture observing
12 system. *Journal of Hydrometeorology*, 14, 1659-1671, 2013. doi: 10.1175/JHM-D-12-0120.1.

13 Scipal, K.: Definition of Quality Flags, ASCAT Soil Moisture Report Series, 7, Institute of
14 Photogrammetry and Remote Sensing, Vienna University of Technology, Austria, 2005.

15 Shepard, D.: A two-dimensional interpolation function for irregularly spaced data, *Proc. 23rd*
16 *ACM Nat.Conf.*, Brandon/Systems Press, Princeton, NJ: 517-524, 1968.

17 Vachaud, G., Passerat de Silans, A., Balabanis, P., and Vauclin, M.: Temporal stability of
18 spatially measured soil water probability density function, *Soil Science Society of America*,
19 49, 822-828, 1985.

20 Wagner, W., Blöschl, G., Pampaloni, P., Calvet, J.-C., Bizzarri, B., Wigneron, J.-P., and Kerr,
21 Y.: Operational readiness of microwave remote sensing of soil moisture for hydrologic
22 applications, *Nordic Hydrology*, 38(1), 1-20, 2007.

23 Wagner, W., Pathe, C., Doubkova, M., Sabel, D., Bartsch, A., Hasenauer, S., Blöschl, G.,
24 Scipal, K., Martinez-Fernandez, J., Löw, A.: Temporal stability of soil moisture and radar
25 backscatter observed by the Advanced Synthetic Aperture Radar (ASAR), *Sensors*, 8, 1174–
26 1197, 2008.

27 Wagner, W., Bartalis, Z., Naeimi, V., Park, S.-E. , Figa-Saldana, J., and Bonekamp, H.: Status
28 of the METOP ASCAT soil moisture product. *IEEE International Geoscience and Remote*
29 *Sensing Symposium 2010 (IGARSS2010)*, Honolulu, Hawaii, USA, 276-279, 2010.

1 Wagner, W., Hahn, S., Kidd, R., Melzer, T., Bartalis, Z., Hasenauer, S., Figa, J., de Rosnay,
2 P., Jann, A., Schneider, S., Komma, J., Kubu, G., Brugger, K., Aubrecht, C., Züger, J.,
3 Gangkofner, U., Kienberger, S., Brocca, L., Wang, Y., Blöschl, G., Eitzinger, J., Steinnocher,
4 K., Zeil, P., Rubel, F.: The ASCAT Soil Moisture Product: A Review of its Specifications,
5 Validation Results, and Emerging Applications, *Met.Z.*, 22 (1), 5-33, 2013.

6 Western, A. W., Grayson, R. B., Blöschl, G., Willgoose, G. R., and McMahon, T. A.:
7 Observed spatial organization of soil moisture and its relation to terrain indices, *Water*
8 *Resour. Res.*, 35(3), 797–810, 1999. doi: 10.1029/1998WR900065

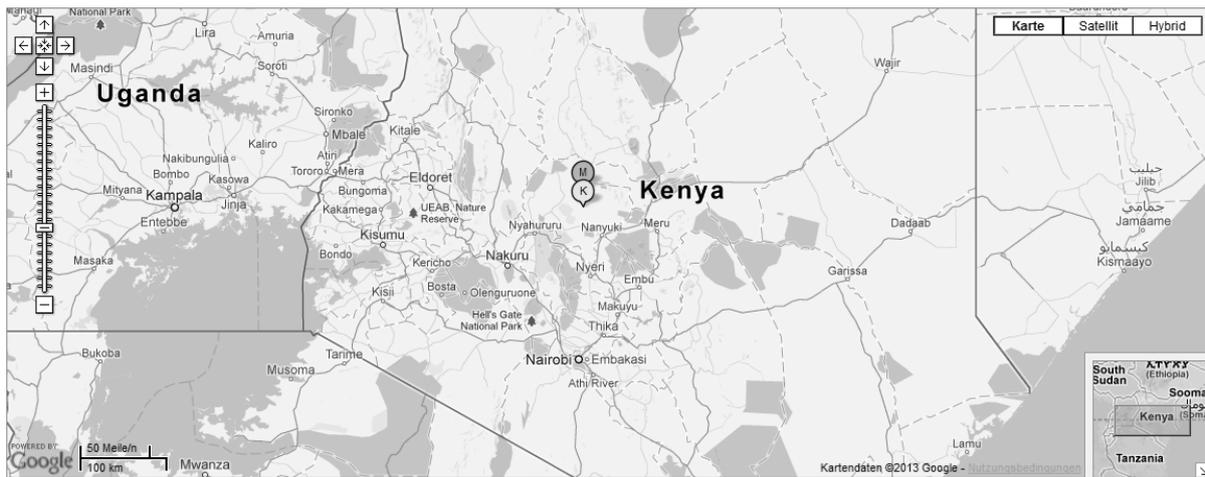
9 Western, A.W., Grayson, R.B., and Blöschl, G.: Scaling of soil moisture: a hydrologic
10 perspective. *Annu. Rev. Earth Planet. Sci.*, 30, 149-180, 2002. doi:
11 10.1146/annurev.earth.30.091201.140434

12 Wilks, D.S.: *Statistical Methods in the Atmospheric Sciences (Second Edition)*, International
13 *Geophysics Series*, 91, Academic Press, 2006.

14 Zreda, M., Shuttleworth, W.J., Zeng, X., Zweck, C., Desilets, D., Franz, T., and Rosolem, R.:
15 COSMOS: the COsmic-ray Soil Moisture Observing System, *Hydrol. Earth Syst. Sci.*, 16,
16 4079–4099, 2012.

17

1

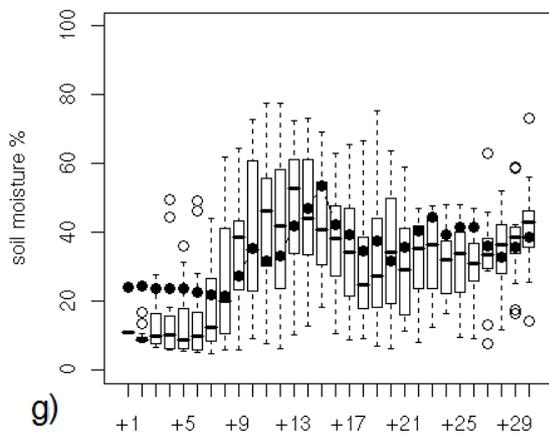
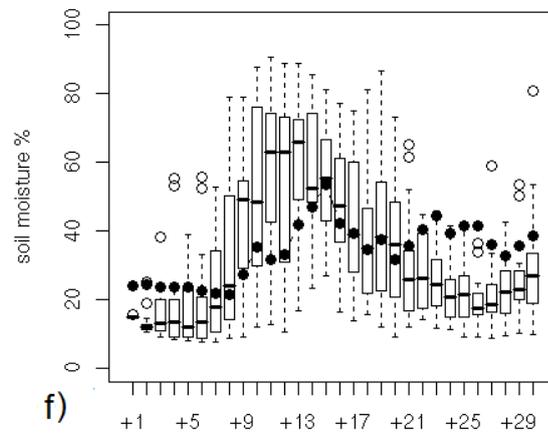
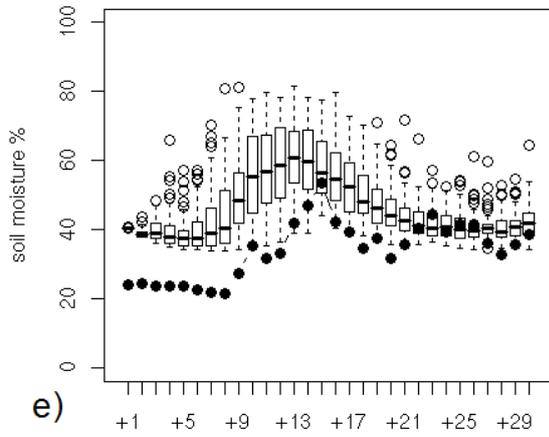
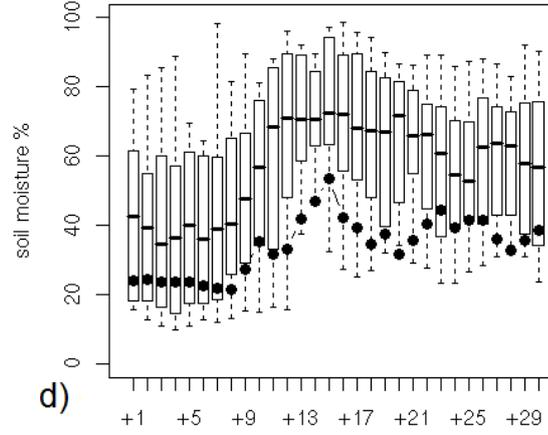
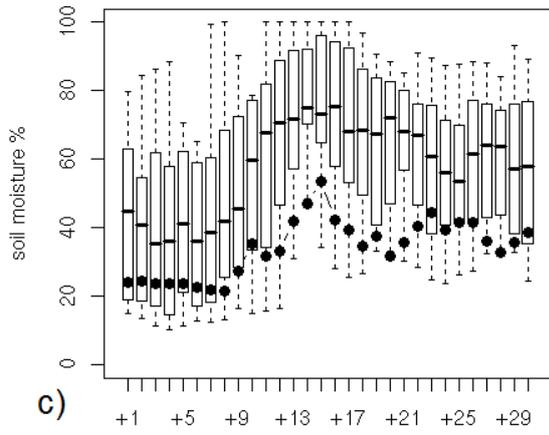
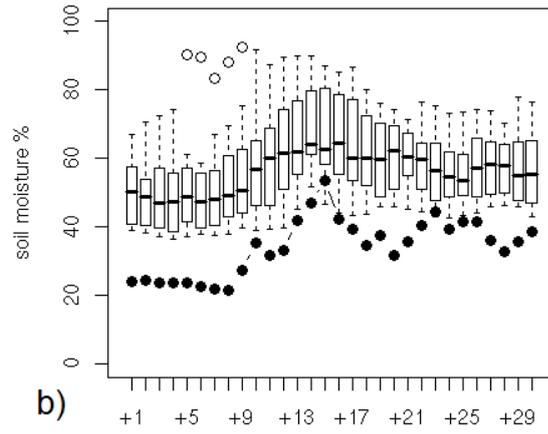
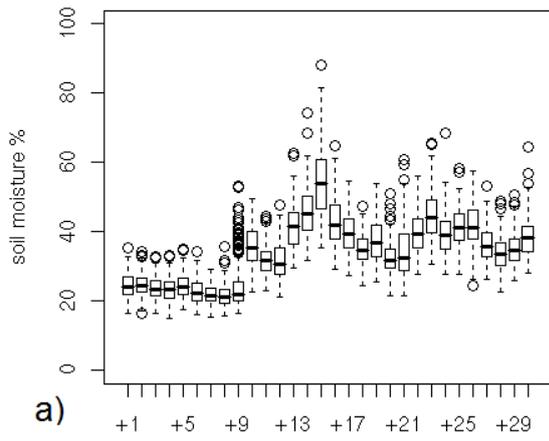


2

3 Figure 1. Location of the COSMOS in situ soil moisture measurements sites Mpala-North (M)

4 | and KLEE (K). (Picture from Google maps).

5



1

2 Figure 2. COSMOS soil moisture measurements (a) and forecasts (b-h) for the period
3 February to August 2012 for the station KLEE in Kenya. Numbers on the abscissa indicate
4 the number of weeks since February 1st, 2012. For the measurements (a), each boxplot
5 contains 168 values (24 hourly values * 7 days). For the forecasts, one column is representing
6 all ensemble members, whereas the forecasts of one week (one forecasted value every day)
7 are averaged for each member separately. b) is the IFS reference climatology, c) the CDF
8 matched IFS reference climatology, d) the CDF matched and downscaled IFS reference
9 climatology, e) is the EPS ensemble forecast, f) is the CDF matched EPS ensemble forecast
10 and g) is the CDF matched and downscaled EPS ensemble forecast. Black dots in b)-g) are
11 the mean values of the COSMOS station for the forecasting period.

1

	KLEE					MPALA				
	IFS CDF	IFS CDF 1	EPS	EPS CDF	EPS CDF 1	IFS CDF	IFS CDF 1	EPS	EPS CDF	EPS CDF 1
RMSE										
IFS	▲	▲	▲	▲	▲	▲	▲	▼	▲	↑
IFS CDF		↑	▲	▲	▲		↑	▼	↓	▼
IFS CDF 1			▲	▲	▲			▼	↓	▼
EPS				↓	▲				▲	▲
EPS CDF					▲					▼
PCC										
IFS	↓	↑	▼	▼	▼	↓	↑	↓	↑	↑
IFS CDF		↑	▼	▼	▼		↑	↑	▲	↑
IFS CDF 1			▼	▼	▼			↓	↑	↑
EPS				↑	↑				↑	▲
EPS CDF					↑					↑

2

3 Figure 3. Quality of the forecast expressed in RMSE (top block) and PCC (bottom block) for
4 stations KLEE (left) and Mpala-North (right). The arrow in a box is pointing upwards if the
5 forecast (top row) is better than the forecast (left column) on average for the 7 forecasting
6 runs. “↑” means that the improvement is not significant, “▲” significant (75-89.9) and “▲”
7 highly significant (90-100). IFS (EPS) is the reference climatology (seasonal forecast), IFS
8 (EPS) CDF is the bias corrected one and IFS (EPS) CDF 1 is the bias corrected and
9 downscaled climatology (forecast).

10

11

12

13

1
2
3
4
5
6
7