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Using soil moisture forecasts for sub-seasonal summer temperature predictions in Europe

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Abstract Soil moisture exhibits outstanding memory characteristics and plays a key role within the climate system. Especially through its impacts on the evapotranspiration of soils and plants, it may influence the land energy balance and therefore surface temperature. These attributes make soil moisture an important variable in the context of weather and climate forecasting. In this study we investigate the value of (initial) soil moisture information for sub-seasonal temperature forecasts. For this purpose we employ a simple water balance model to infer soil moisture from streamflow observations in 400 catchments across Europe. Running this model with forecasted atmospheric forcing, we derive soil moisture forecasts, which we then translate into temperature forecasts using simple linear relationships. The resulting temperature forecasts show skill beyond climatology up to 2 weeks in most of the considered catchments. Even if forecasting skills are rather small at longer lead times with significant skill only in some catchments at lead times of 3 and 4 weeks, this soil moisture-based approach shows local improvements compared to the monthly European Centre for Medium Range Weather Forecasting (ECMWF) temperature forecasts at these lead times. For both products (soil moisture-only forecast and ECMWF forecast), we find comparable or better forecast performance in the case of extreme events, especially at long lead times. Even though a product based on soil moisture information alone is not of practical relevance, our results indicate that soil moisture (memory) is a potentially valuable contributor to temperature forecast skill. Investigating the underlying soil moisture of the ECMWF forecasts we find good agreement with the simple model forecasts, especially at longer lead times. Analyzing the drivers of the temperature forecast skills we find that they are mainly controlled by the strengths of (1) the soil moisture-temperature coupling and (2) the soil moisture memory. We find a negative relationship between these controls that weakens the forecast skills, nevertheless there is a middle ground between both controls in several catchments, as shown by our results.

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1 Introduction

The remarkable persistence characteristics of soil moisture have been shown in many past and recent studies (Delworth and Manabe 1988; Entin et al. 2000; Koster and Suarez 2001; Seneviratne et al. 2006; Orth and Seneviratne 2012). Through its storage capacity, soil moisture can accumulate and integrate anomalies of the atmospheric forcing, such that consequently induced soil moisture anomalies may persist for weeks or even months in the case of extreme anomalies (see Seneviratne et al. 2010 for a review). These storage anomalies are (slowly) dissipated by the (mostly random) atmospheric forcing (Delworth and Manabe 1988; Seneviratne and Koster 2012). Soil moisture also affects runoff and evapotranspiration under certain conditions, leading to a strong coupling with these variables (Koster and Milly 1997; Koster et al. 2004b; Kirchner 2009; Teuling et al. 2009): A wet soil may lead to increased runoff and evapotranspiration, because a saturated soil moisture storage can hardly buffer precipitation and because soil and plants evaporate and transpire more, respectively, than under soil moisture-limited conditions.

On the other hand, a dry soil tends to reduce runoff and evapotranspiration because it can store a large fraction of the precipitation and imposes a moisture limitation to evaporation and transpiration of soils and plants, respectively. Even if atmospheric forcing and impacts of soil moisture on runoff and evapotranspiration tend to dissipate existing storage anomalies, the latter generally persist long enough to have substantial impacts on the atmosphere and land hydrology (Koster et al. 2010; Seneviratne et al. 2010; Orth and Seneviratne 2013a).

The persistence of soil moisture combined with its impact on the land water and energy balances makes soil moisture an important variable in the context of weather- and climate forecasting (Koster et al. 2004a; Balsamo et al. 2009; Douville 2010; Koster et al. 2011; van den Hurk et al. 2012). Especially temperature forecasts are impacted by soil moisture because of its impact on sensible heat flux, which results from its coupling with evapotranspiration (latent heat flux). Observational evidence has particularly highlighted links between spring surface moisture deficits and summer temperature extremes in many regions of the world (e.g. Hirschi et al. 2011; Mueller and Seneviratne 2012; Quesada et al. 2012).

In this study we aim to investigate the value of soil moisture forecasts for sub-seasonal temperature predictions using a mostly observation-driven approach, based on data introduced in Sect. 2. For this purpose we employ a conceptual simple water balance model (Koster and Mahanama 2012; Orth et al. 2013) to compute soil moisture in near-natural catchments across Europe, as described in Sect. 3.1. Section 3.2 explains how we use these estimates together with corresponding temperature observations to fit linear relationships between soil moisture and temperature anomalies. We also employ the water balance model to derive soil moisture forecasts, using atmospheric forcing forecasts issued from the European Centre for Medium Range Weather Forecasting (ECMWF). In Sect. 4, we then use the fitted soil moisture-temperature dependencies to translate the soil moisture forecasts into temperature forecasts, the skill of the resulting forecasts is compared to the skill of the respective ECMWF product for lead times ranging from 1 to 4 weeks.

2 Data

We use here a simple water balance model (Orth et al. 2013, see also Sect. 3.1) to infer soil moisture information from observations of streamflow which is used to calibrate the model. Additionally, precipitation, radiation, and temperature are used to force the model. Temperature is furthermore required to derive the linear dependencies with soil moisture and soil moisture-temperature coupling strengths (see Sects. 3.2.2 and 3.3). We use precipitation and temperature data from the E-OBS dataset (http://eca.knmi.nl [accessed on 25 March 2013]). The dataset was developed within the ENSEMBLES project (http://ensembles-eu.metoffice.com [accessed on 25 March 2013]) and is based on numerous stations across Europe, and the data is interpolated to a regular $0.5° \times 0.5°$ grid. Observed net radiation is obtained from a satellite-derived product from the NASA/GEWEX SRB project (http://eosweb.larc.nasa.gov/PRODOCS/srb/table_srb.html [accessed on 25 March 2013]), which has a resolution of $1° \times 2°$ in latitudes north of 45°N and $1° \times 1°$ south of 45°N.

Observed streamflow is used to fit the parameters of the simple water balance model for each catchment (see Sect. 3.1.1). As the employed streamflow data should be without or only minimal human impact we use a dataset compiled by Stahl et al. (2010) that contains respective measurements from >400 near-natural catchments across Europe. The data stems from the European water archive (http://grdc.bafg.de [accessed on 25 March 2013]), from national ministries and meteorological agencies, as well as from the WATCH project (http://www.eu-watch.org [accessed on 25 March 2013]). We use gridded forcing observations and forecasts from the grid cells where the centroid of a particular catchment is located.

We employ the simple water balance model to compute the soil moisture re-forecasts. To run the model during the forecasting period, we use forecasts of precipitation, net radiation and temperature from the European Centre for Medium-range Weather Forecasting (ECMWF). The temperature forecasts are moreover used as a benchmark for our soil moisture-based temperature forecasts. Additionally, we use the soil moisture from the ECMWF forecasts to compare these against the simple model soil moisture forecasts; for this purpose we sum up the soil moisture values from the 4 layers of the ECMWF model to yield total column soil moisture. The ECMWF forecasts are re-forecasts produced with the ensemble prediction system VarEPS (Vitart et al. 2008, http://www.ecmwf.int/products/changes/vareps/ [accessed on 25 March 2013]) with a consistent 2012 model version over our considered time period on a regular $0.5° \times 0.5°$ grid (ifs cycle 38r1). The forecasting system includes the HTESSEL land surface scheme (see Balsamo et al. 2011), and the initial soil moisture for the VarEPS forecasts is based on ERA-Land data (Balsamo et al. 2012) computed with the same scheme. The forecasts are initialized weekly, consist of five ensemble members, and have a maximum lead time of 32 days. Note that the low ensemble size of the ECMWF forecasts and consequently also of the simple model forecasts adds uncertainty to the skills scores computed in this study (e.g. Dqu 1997; Buizza and Palmer 1998; Ferro et al. 2008).

We compute soil moisture forecasts (and also soil moisture memory and the coupling with temperature) for the time period 1993–2007 using the simple water balance model forced with ECMWF forecasts of precipitation and radiation. To ensure that no temperature information of this period is reflected in the calibration parameters of the simple water balance model, we fit these parameters using observations from an earlier period (1984–1992).

2.1 Selection of catchments

This study focuses on the catchment scale, because the simple water balance model can only be applied on this scale. As the calibration of the simple water balance model does not work equally well in all catchments included in the Stahl et al. (2010) dataset, we leave out some catchments in this study. Their locations are displayed in Fig. 1, together with the locations of the considered catchments. The model parameters are fitted for each catchment to yield a maximum correlation between measured and modeled streamflow (see Sect. 3.1.1). This maximum correlation is used as a measure of suitability of the simple water balance model to be applied to a particular catchment. In this study, we ignore the 36 catchments with the lowest correlation values from the total of 436 catchments contained in the Stahl et al. (2010) dataset, as the model performs comparatively poorly in reproducing the hydrological variability in these catchments. Even if the corresponding cut-off value of the maximum correlation (0.666) and the resulting number of 400 considered catchments are arbitrary, the large number of catchments ensures a wide spatial coverage. Note that there is no clear spatial pattern of the model suitability as measured with the maximum correlation.

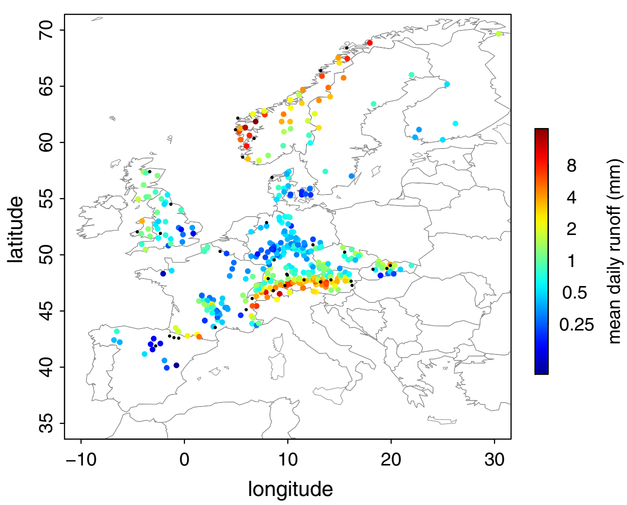

Fig. 1 Locations of catchments considered in this study shown through *colored dots*. The *color-coding* refers to the mean runoff. *Small black dots* denote the catchments of the Stahl et al. (2010) dataset not considered in this study

3 Methodology

3.1 Simple water-balance model

We use a conceptual simple water balance model introduced by Koster and Mahanama (2012) and adapted by Orth et al. (2013) to the daily time scale. The model relies on the water balance equation:

$$w_{n+\triangle t} = w_n + (P_n - E_n - Q_n)\triangle t \tag{1}$$

where w_n (in mm) refers to soil moisture at the beginning of day n, and P_n, E_n and Q_n (all in mm day^{-1}) denote the accumulated precipitation, evapotranspiration and runoff during time step $\triangle t$. We use a time step of $\triangle t = 1$ day in this study. In the model, normalized runoff and evapotranspiration (ET) are expressed as simple functions of soil moisture:

$$\frac{Q_n}{P_n} = \left(\frac{w_n}{c_s}\right)^{\alpha} \quad \textit{with } \alpha \geq 0 \tag{2}$$

$$\frac{\lambda \rho_w E_n}{R_n} = \beta_0 \left(\frac{w_n}{c_s}\right)^{\gamma} \quad \textit{with } \gamma > 0 \textit{ and } \beta_0 \leq 1 \tag{3}$$

where c_s, the water holding capacity of the soil expressed in mm, is used to scale soil moisture such that these functions cannot exceed 1. The unitless coefficient β_0 indicates the maximum fraction of net radiation (R_n) that may be transformed to latent heat flux ($\lambda \rho_w E_n$), thereby reflecting soil and vegetation characteristics. Such local attributes are also reflected by the unitless exponents α and γ that determine the character of the response of runoff to precipitation and of ET to net radiation. The latent heat of vaporization, λ, and the density of water ρ_w, are used to convert E_n into latent heat flux, to have the same units as R_n. The two functions (Eqs. 2, 3) are the main assumptions in the simple water-balance model; Orth et al. 2013 showed that the model is able to capture observed soil moisture dynamics despite this simple formulation.

Whereas the runoff Q_n responds immediately to precipitation, the model also computes streamflow, F_n, which is comparable with observed streamflow. It is computed from Q_n with an imposed delay to reflect the transport of runoff to the streambed and within the stream network:

$$F_n = \sum_{i=0}^{60} Q_{n-i\triangle t} \left(e^{-\frac{i\triangle t}{\tau}} - e^{-\frac{(i+1)\triangle t}{\tau}} \right) \tag{4}$$

where τ refers to the decay time scale of the runoff, and the exponential functions in (4) characterize the fraction of runoff at day $n - i$ that contributes to streamflow at day n. Considering 60 previous days ensures that the runoff is converted almost completely to streamflow.

Orth and Seneviratne (2013b) extended this simple water balance model to account for snow through a simple degree-day approach:

$$S_n = \begin{cases} max(S_{n-\Delta t} - f_m(T_n - 1), 0) & if\ T_n \geq 1°C \\ S_{n-\Delta t} + P_n & if\ T_n < 1°C \end{cases} \quad (5)$$

where S_n denotes the snow water equivalent (SWE), which is accumulated if precipitation occurs in combination with a mean daily temperature, T_n, below a threshold of 1 °C. If snow is present, and the temperature is above this threshold, melting takes place. The extent of the melting depends linearly on the temperature and is controlled by the degree-day melt factor f_m, which is constant over time and fitted for each catchment. Precipitation used in Eqs. (1) and (2) is modified according to snow accumulation or melting:

$$P_n = \begin{cases} P_n + f_m(T_n - 1) & if\ T_n \geq 1°C \\ 0 & if\ T_n < 1°C \end{cases} \quad (6)$$

3.1.1 Parameter fitting

The simple water balance model is based on a set of parameters, namely c_s, α, β_0, γ, τ, and f_m, which reflect characteristics of the soil, vegetation and climate. To fit these parameters, we run the model with observed precipitation, net radiation and temperature and compare modeled streamflow with observed streamflow. Note that this methodology requires that the model is applied at the catchment scale. We employ the optimization approach of Orth et al. (2013) in order to fit a set of parameters to each considered catchment that yields the highest correlation coefficient between modeled and observed streamflow. The simple water balance model enables us to extract information on soil moisture dynamics from streamflow observations (see Orth et al. 2013 for a detailed validation).

3.2 Forecasting approach

We compute forecasts of soil moisture over the time period 1993–2007 (see also Sect. 2), which we then translate into temperature forecasts using fitted linear dependencies. The forecasts are initialized weekly, like the ECMWF temperature forecasts. Note that all forecasts considered in this study are therefore re-forecasts. We focus on the month of July in the analyses, because we find overall the highest coupling strength between soil moisture and temperature in this month. The peak in the strength of land-atmosphere interactions is likely induced by the active vegetation and comparatively dry soils prevailing then. To match the characteristics of the ECMWF forecasts, the soil moisture forecasts are computed on the daily time scale with a lead time of up to 28 days. In the analysis, however, we compute weekly averages from forecast days 1–7, 8–14, 15–21 and 22–28 to (partly) exclude day-to-day variability.

3.2.1 Soil moisture forecasts

Reproducing the methodology of Orth and Seneviratne (2013b), we employ the simple water balance model to derive forecasts of soil moisture in each catchment. For this purpose, we use information on (1) modeled initial soil moisture (using the simple water balance model) and SWE values, and/or (2) forecasted atmospheric forcing from the ECMWF (see Sect. 2).

Until the forecast start date, we run the model using observed precipitation, net radiation and temperature to derive initial soil moisture and SWE. During the forecasting period we use either (1) the five members of the corresponding bias-corrected ECMWF forecasts (one control run and four perturbed forecasts) to force the model, or (2) the corresponding meteorological observations from 5 randomly selected years (excluding the year of the particular forecast). This yields soil moisture forecasts with five members which are either based on ECMWF forecasts or climatology.

Biases of the ECMWF forecasts are corrected by comparing their means with respective observations using daily data. In order to determine the bias in a particular year, we use the remaining 14 years to compute the bias correction, which ensures that the bias correction is independent of the particular forecasts. The bias is determined for each particular month, catchment and lead time through a comparison of mean observed and mean forecasted values. Radiation and temperature forecasts are calibrated by subtracting the bias, which we compute for each considered month and lead time; the same is done for precipitation forecasts but through multiplication with a constant correction factor.

3.2.2 Deriving temperature forecasts

As mentioned above, we translate the soil moisture forecasts into temperature forecasts using fitted linear relationships. Each of the members of a particular soil moisture forecast is translated into a temperature forecast such that these also consist of five members. As we aggregate the soil moisture forecasts to weekly averages (see above), we also use weekly averaged soil moisture and temperature data to derive these relationships. This helps to filter out (some of) the effects of synoptic weather variability, which allows us to better capture the link between soil moisture and temperature.

We derive the linear relationships from observed weekly-averaged catchment temperature anomalies and modeled catchment soil moisture anomalies using least-squares regression. Anomalies in a particular year are computed by subtracting the respective climatological value which we compute from temperature observations and modeled soil moisture of the remaining 14 years, as

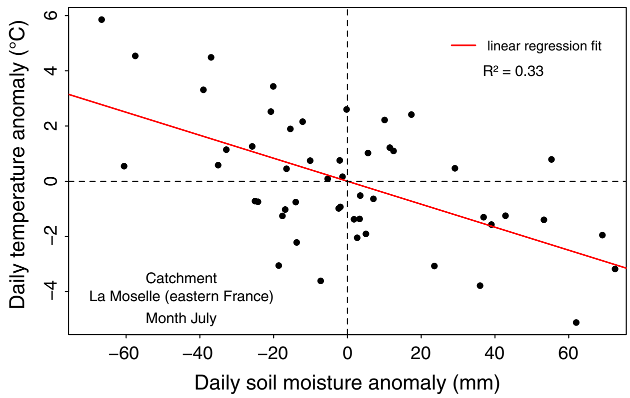

Fig. 2 Fitted least-squares regression between temperature and soil moisture in the La Moselle catchment

with the bias correction of the atmospheric forecasts. Again, this ensures that the anomaly computation is independent of the particular forecasts in each considered year.

The soil moisture forecasts in a particular year are translated using relationships computed with data from the previous 10 years (or 9 years in the case of the first year of the forecasting period, 1993, because soil moisture and temperature data are only available since 1984), such that no future information are used. We compute the relationships for July in each catchment based on 5 weeks × 14 years = 70 data pairs.

An example of a fitted linear relationship is displayed in Fig. 2. Note that the explained fraction of variance (R^2) is rather low for most catchments as there are many other controls of temperature anomalies (e.g. advection of air masses) beside soil moisture.

3.2.3 Determination of forecast skill

We compute the forecast skill as anomaly correlation coefficient for each considered catchment. For this purpose, we determine anomalies of the weekly-averaged ensemble mean forecasts (see above) and the corresponding weekly-averaged observations (as described in the previous subsection). This ensures that the forecast skill is computed beyond climatology. To compute the skill in the month of July we correlate the anomalies of all weekly-averaged forecasts that are least partly in this month with respective weekly-averaged observed anomalies, i.e. we use 5 (weeks per month) × 15 (years) = 75 data pairs.

To evaluate the forecasts also in a probabilistic sense, we compute the continuous ranked probability score (CRPS) as an alternative measure of forecast skill (e.g. Hersbach 2000). For this purpose we fit a normal distribution $f(x)$, where x represents temperature, to the forecasts of all five ensemble members using the maximum likelihood method. The CRPS is then computed as

$$CRPS = \int_{-\infty}^{\infty} (F(x) - F_0(x))^2 dx$$

where

$$F_0(x) = \begin{cases} 0 & \textit{if } y < \textit{observed value} \\ 1 & \textit{if } y \geq \textit{observed value} \end{cases}$$

To yield the skill of the forecast in a particular week and year (continuous ranked probability skill score, CRPSS), we compare the CRPS of the forecasted ensembles with the CRPS of the climatology (normal distribution fitted to observations from five other years of the forecast period):

$$CRPSS = 1 - \frac{CRPS_{forecast}}{CRPS_{climatology}}$$

The CRPSS ranges between $-\infty$ and 1, where 1 refers to a perfect forecast and values above zero indicate that the forecast is better than climatology. Given the above-mentioned 5 weeks of July and the forecasting period of 15 years, we yield 75 CRPS scores for each catchment. To express the skill in a particular catchment we use the median of these 75 scores, as well as the 90 %-quantile.

To avoid the impact of trends on the forecast skills, we apply a linear detrending to the observed temperature data, as well as to the modeled soil moisture data, before using the latter as initial condition in the soil moisture forecasts and before determining the linear relationship between soil moisture and temperature. We focus on each month separately (by masking the remaining months, respectively) in order to capture trends occurring only in particular times of the year. Linear trends were removed when statistically significant as indicated by a p value of less than 0.1 (two-sided t test).

To investigate the dependency of the forecast performances on initial soil moisture conditions, we compute the forecast skills (as anomaly correlations) for extreme conditions. For this purpose we select a subset of forecasts with especially dry or wet initial soil moisture conditions, instead of considering all 75 data pairs. In this selection we apply a threshold such that in the dry case we only consider forecasts with an initial soil moisture lying at least 0.67 standard deviations below the climatological mean, $w_n < \overline{w_n} - 0.67\sigma_{w_n}$, and in the wet case we select all forecasts with an initial soil moisture content lying at least 0.67 standard deviations above the climatological mean, $w_n > \overline{w_n} + 0.67\sigma_{w_n}$.

3.3 Soil moisture memory and soil moisture-temperature coupling

In order to analyze the forecast skills and their temporal and spatial variations, we compute the strength of the soil moisture memory and the strength of the soil moisture-temperature coupling in each catchment, as these are potential contributors of skill of our translated temperature forecasts. As in several other studies (Koster and Suarez 2001; Seneviratne and Koster 2012; Orth and Seneviratne 2012), we compute the soil moisture memory as an inter-annual correlation. To determine the memory at a lag of l weeks in a particular month (July in this study), we correlate the weekly-averaged soil moisture values of all weeks that are at least partly within this month of all available years with the respective values l weeks earlier. This means that we use 5 (weeks per month) $\times$ 15 (years) = 75 data pairs.

In the same way, but without time lag, we compute the soil moisture-temperature coupling strength as an inter-annual correlation between weekly-averaged soil moisture and corresponding weekly-averaged temperature observations, denoted hereafter as $\rho(w_n, T_n)$.

4 Results

In this section we compare the performance of the simple soil moisture-based temperature forecasts with the corresponding ECMWF product. We also investigate changes in the skill of the respective forecast products following extreme soil moisture anomalies. In the second part of the section we identify and investigate controls of the skill of the soil moisture-based temperature forecasts.

4.1 Comparing soil moisture-based versus ECMWF temperature forecasts

As described in Sect. 3.2.2 we translate weekly-averaged soil moisture forecasts into temperature forecasts using a linear relationship determined from observed temperature and modeled soil moisture. Figure 3 displays the temperature forecast skills of the soil moisture-based forecasts compared to corresponding forecasts from the ECMWF in all considered catchments (see Sect. 2). Note that the skills reported here are computed from anomalies, therefore even small correlations denote skill beyond climatology. We find very high skills of the ECMWF forecasts at short lead times (1–2 weeks), underlining the quality of this product. We also find that the soil moisture-based forecasts show significant skill in most catchments at short lead times as indicated by the large number of catchments with skills significantly greater than zero (evaluated from 95 %-level confidence intervals based on Fisher's Z-transform). Although the average skill across all catchments is clearly lower than that of the ECMWF forecasts at these short lead times, this confirms our assumption that information on sub-seasonal temperature evolution (beyond climatology) can be derived from soil moisture forecasts. Even if the underlying soil moisture forecasts are assumed to be very good at short lead times (Orth and Seneviratne 2013b), the skills of the inferred temperature forecasts are limited by the representation of the soil moisture-temperature coupling. The ECMWF forecasts on the other hand are expected to perform well as they are computed with a sophisticated weather model that considers other predictable processes such as temperature advection and atmospheric circulation patterns, which are clearly dominating the temperature predictability on short time scales. These forecasts tend to be slightly better in central Europe, whereas there is no clear geographical pattern of the forecast skills of the soil moisture-derived forecasts. At a lead time of 3 weeks, the soil moisture derived product yields better skills in 22 catchments (as denoted by black circles), mostly located across northern Europe. At the maximum lead time of 4 weeks the soil moisture-based product still shows significant temperature forecast skill in several catchments, whereas the ECMWF product displays significant skill in only few of the considered catchments. In 55 catchments the skill of the soil moisture-derived product is significantly higher than the respective ECMWF forecast skill. Note that this is clearly more than what would be expected by chance from the construction of the statistical test (5 % of 400 catchments equals 20 catchments). Also the average skill across all considered catchments at the maximum lead time is higher than in the ECMWF product. These results are of particular interest; the fact that our simple soil moisture-only based temperature forecast outperforms the ECMWF temperature forecast in a number of catchments at 3 and 4 weeks lead time highlights potential for further improvements of operational temperature forecasts through more efficient use of soil moisture information.

In Fig. 4 we present a comparison between the underlying soil moisture forecasts of the ECMWF product and from the simple model, at the beginning and at the end of the forecasts. The agreement between both products is expressed as a mean correlation computed from correlations between the soil moisture values in particular weeks. This methodology allows us to avoid impacts of the seasonal cycle, such that only soil moisture dynamics are compared. We find generally good agreement between the two soil moisture products at both lead times, except for mountainous areas. In these regions also the skill of the soil moisture-based forecast is low (see Fig. 3), therefore there might be a problem with the soil moisture dynamics of the simple model in these areas. Greater correlations at the end of the forecasts can be explained with the use of the same atmospheric forcing (ECMWF VarEPS forecasts) in both soil moisture products. However, this underlines the general similarity of the soil moisture dynamics in both

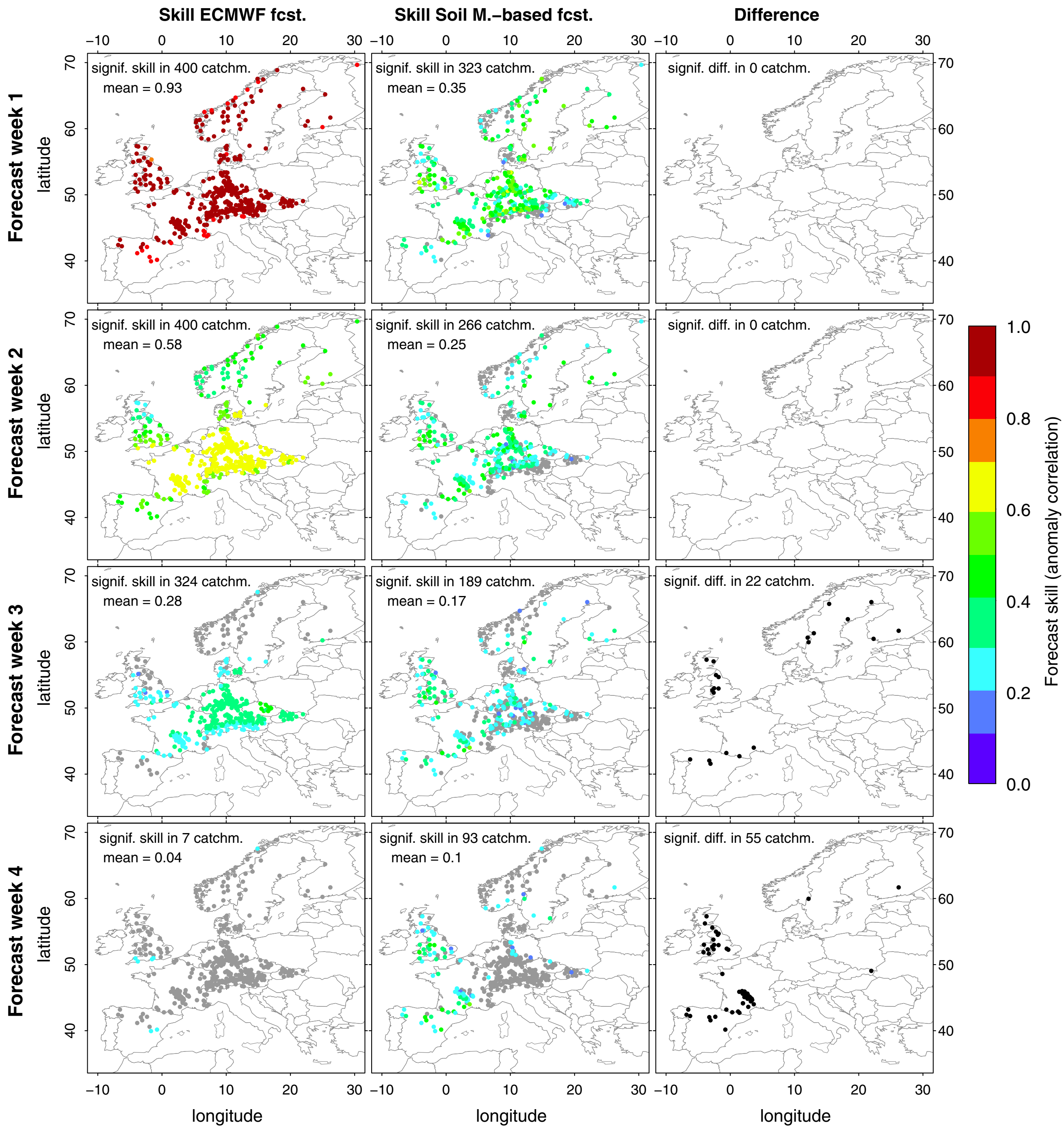

Fig. 3 Overview of temperature forecast skills of the ECMWF product (*left column*) and the simple soil moisture-based forecasts (*middle column*) in July. Shown for all considered catchments and lead times. *Grey dots* refer to insignificant skill on a 5 %-level (evaluated with confidence intervals based on Fisher's Z-transform). *Black dots* in the right column indicate significantly higher skill of the soil moisture-based product compared to the ECMWF product (evaluated on a 95 %-level with confidence intervals based on Fisher's Z-transform). Also indicated on the plots are the number of catchments with significant skill, the mean skill of all catchments (including insignificant skills), and the number of catchments with significantly higher skill in the soil moisture-derived product compared to the ECMWF product (*right column*)

schemes. Figure 4 shows high correlation at the end of the forecasting period especially in catchments in southern France and across Great Britain, however, in Fig. 3 we find significantly higher temperature forecasting skills in these regions at 4 weeks lead time in the simple model-based forecast. The fact that temperature forecast skill is lower in

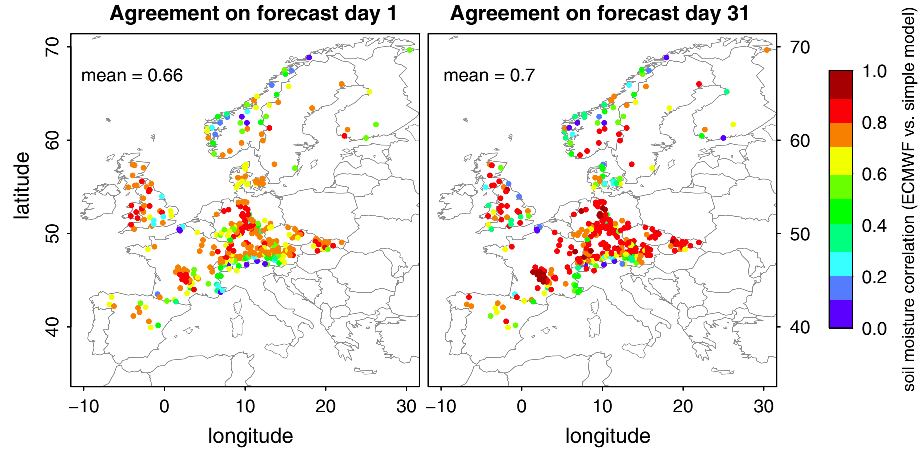

Fig. 4 Agreement between soil moisture in ECMWF forecasts and in simple model forecasts in summer (JJA) at lead times of 1 and 31 days, expressed as correlation (refer to text for details)

the ECMWF product even if the underlying soil moisture dynamics are similar suggests that more efficient use of soil moisture information for ECMWF temperature forecasts may be possible.

Figure 5 shows the median CRPS scores (see Sect. 3.2.3) of the two temperature forecast products. Note that these median scores are computed from 75 scores of all weeks that are in July in the considered 15 years. Comparing this probabilistic evaluation with Fig. 3, we find similar results for the ECMWF product, but clear differences for the soil moisture-based temperature forecasts. There is skill beyond climatology only in a few catchments, even at short lead times. At long lead times, the performance is not comparable to that of the ECMWF product. The reason for this difference is the low spread of the soil moisture-based forecasts, which is taken into account in the computation of the CPRSS in contrast to the anomaly correlation that uses the ensemble mean. Because of the soil moisture persistence, the ensembles of the underlying soil moisture forecasts are rather similar, especially at the beginning of the forecast as the initial soil moisture is the same. Consequently, also the derived temperature forecasts lack sufficient spread between the ensembles. However, if the forecasted temperature is close to the respective observation, the low spread becomes beneficial for the soil moisture-based forecasts, as shown in Fig. 6. Considering the 90 %-quantile of the CRPS scores instead of the median we find skill beyond climatology in the soil moisture-based forecasts in the majority of the catchments, and also better performance compared to the ECMWF product at long lead times.

Figure 7 displays the differences of the forecast skills expressed as anomaly correlation when considering only forecasts with extreme initial soil moisture conditions (see Sect. 3.2.3) in comparison to the results shown previously in Fig. 3. The skill of the soil moisture-derived forecasts increases on average at all lead times; at short lead times the skill improves in most regions across the continent, whereas at long lead times the improvement is limited to southern Europe and the UK. In the case of the ECMWF forecast, we find no skill change on average at short lead times, despite local changes. Towards longer lead times also the ECMWF forecasts are found to improve under extreme initial soil moisture conditions, especially at 3 weeks lead time in central Europe, whereas at 4 weeks lead time only few catchments show significant skill.

Figure 8 summarizes the results of Fig. 3 (in black) and compares them to the respective results computed from a subset of forecasts with extreme dry and wet initial conditions shown in Fig. 7 (in magenta). The performance of both forecasts (ECMWF and soil moisture-based) expressed by the average skill, improves under extreme conditions at long lead times. Probably the ECMWF forecasting model also captures the increased persistence of the atmospheric forcing which may coincide with extreme soil moisture anomalies (Orth and Seneviratne 2012). At short lead times, however, only the soil moisture-derived forecasts benefit from extreme initial soil moisture conditions. In contrast, the ECMWF forecast skills are not improved over these short lead times. The increased skill of the soil moisture-based forecasts found at all lead times highlights the added value of the initial soil moisture information in the case of extreme anomalies, in line with results of earlier studies (Koster et al. 2011; van den Hurk et al. 2012). Note that the number of catchments with significant skill may be smaller in the extreme cases; the lower number of forecasts considered to compute these skills consequently leads to a higher threshold for the skills to be significant at a 5 %-level. Focussing on forecast skills under dry and wet conditions separately, we find generally better performance under dry conditions at short lead times, whereas at long lead times there is no difference in the soil moisture-based product, and in the ECMWF product the skills are even higher in the wet case. As reported in Orth and Seneviratne (2012), high soil moisture memory under wet conditions is

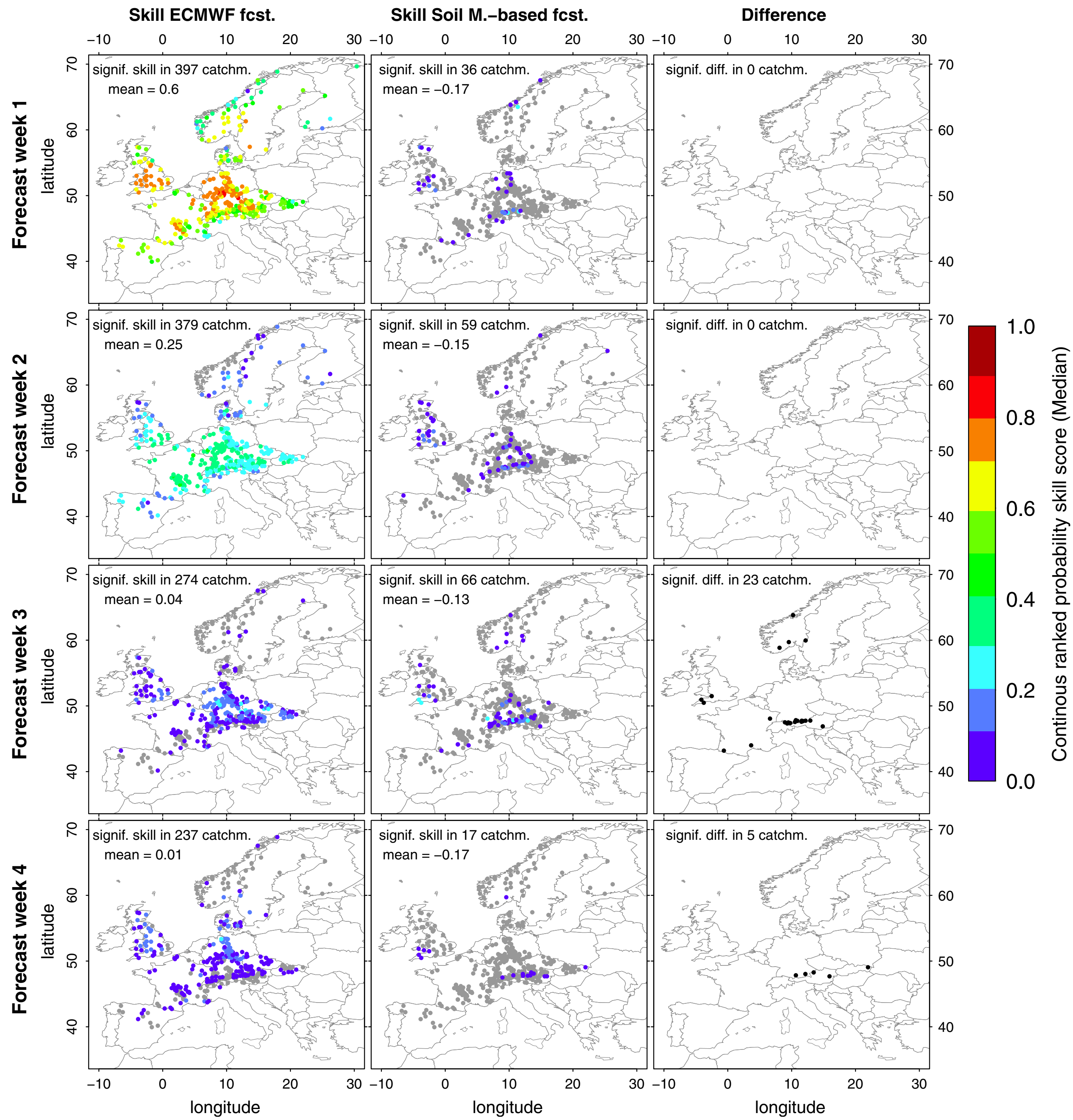

Fig. 5 Same as in Fig. 3, but with forecast skills expressed as the median of all continuous ranked probability skill scores (CRPSS) in July in each catchment. *Gray dots* refer to skill scores less than zero, meaning forecasts worse than climatology. *Black dots* in the right column indicate that the median CRPSS of the soil moisture-based product is at least 0.05 greater as the median CRPSS of the ECMWF product. As in Fig. 3, mean skills and the number of catchments with significant skill are indicated on the plots in the *left* and *middle column*, and the amount of catchments with significantly higher skill of the soil moisture-based forecasts is indicated on the plots in the *right column*

predominantly found in dry regions, and vice versa, because the corresponding anomalies can be larger and therefore last longer. The temperature forecasting skill of the soil moisture-based forecasts also depends (partly) on the underlying soil moisture memory (see next Section). The mean skill of the soil moisture-based forecasts at short lead times is dominated by high skills in Central Europe (see Fig. 3), therefore it increases stronger under dry

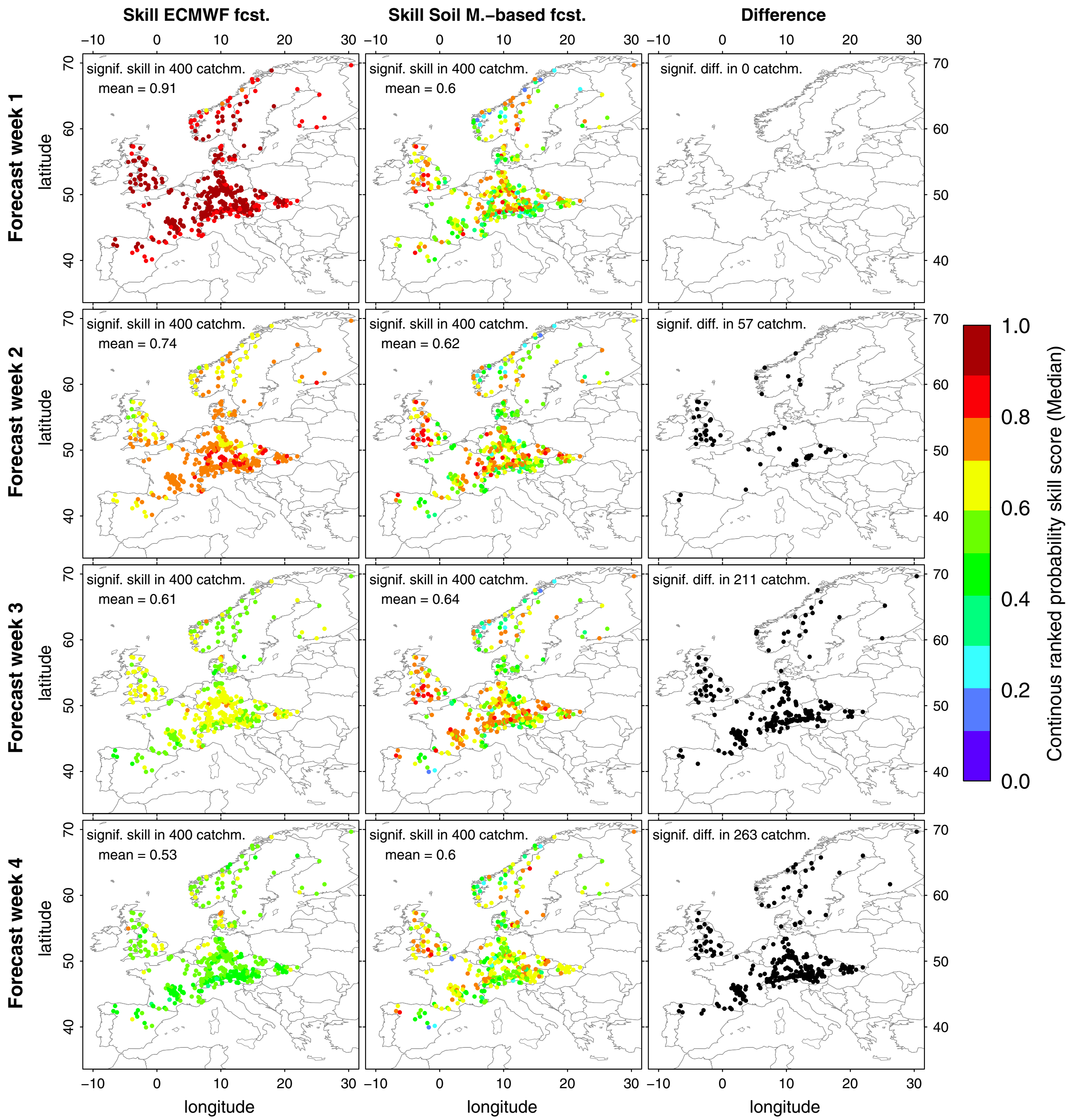

Fig. 6 Same as in Fig. 5, but with forecast skills expressed as the 90 %-quantile of all continuous ranked probability skill scores (CRPSS)

conditions. Catchments with high skill at long lead times, however, are located in Britain (wet) and southern Europe (dry), and consequently the average skills for wet and dry initial anomalies are similar.

Figure 8 illustrates moreover the impact of the initial soil moisture on the temperature forecast skill of the soil moisture-derived product versus the impact of the ECMWF forcing forecasts (see Sect. 3.2.1). At short lead times the skill is mostly based on the inital soil moisture, whereas at medium lead times of 2–3 weeks the contribution of the ECMWF forcing forecasts is at least comparable. Note that even if the ECMWF forcing forecasts have no or little skill at such lead times, their (positive) effect from short lead times is accumulated and delayed thanks to the soil moisture memory. However, this effect diminishes over time, such that the contribution of the ECMWF forcing forecasts to the temperature forecasting skill decreases towards longer lead times.

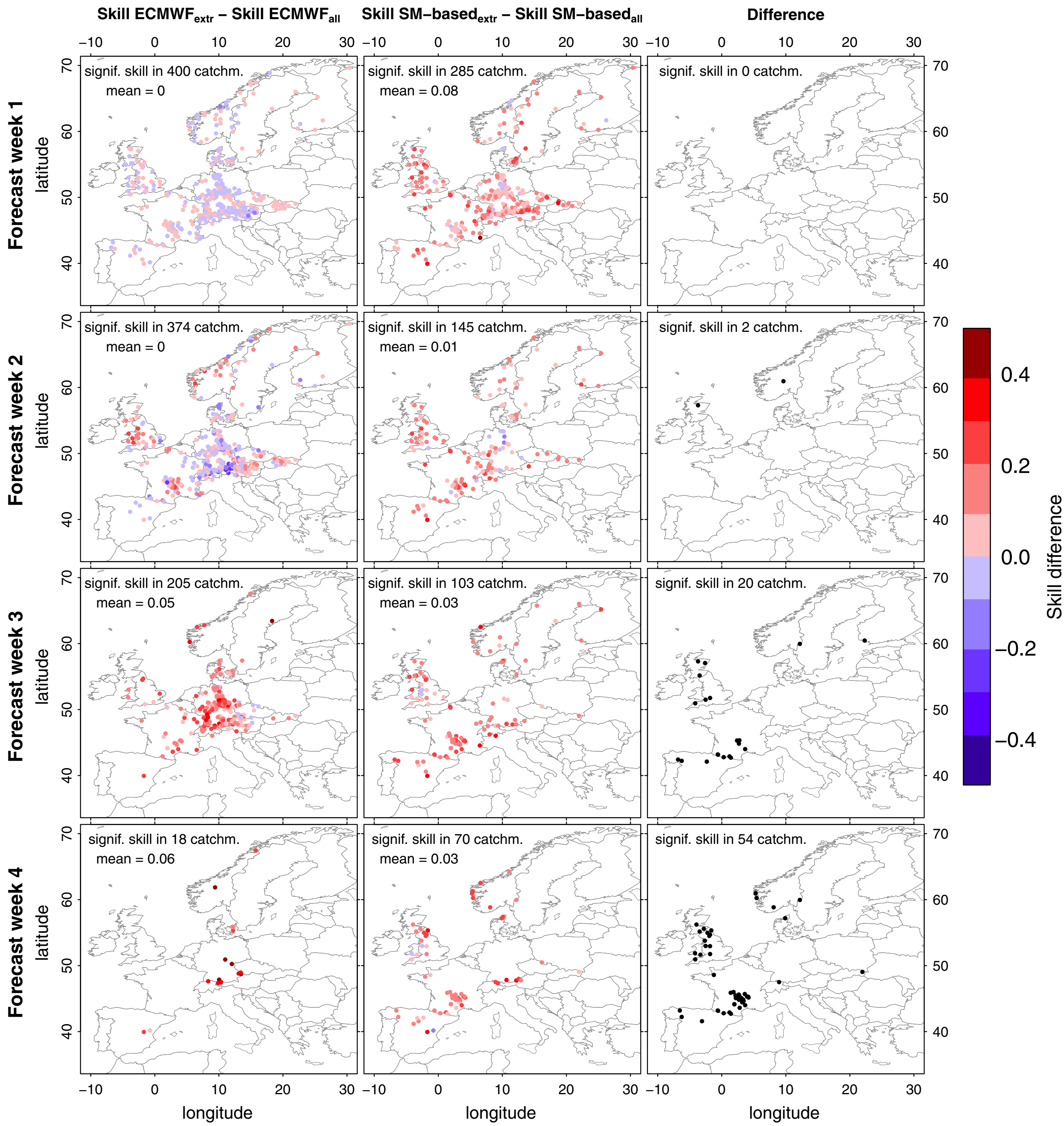

Fig. 7 Same as in Fig. 3, but displaying the difference between the skills in Fig. 3 and the skills derived when only considering forecasts with extreme dry and wet initial soil moisture (refer to text for details). Difference (*right column*) only displayed if forecast skill is significant

4.2 Controls of soil moisture-based temperature forecasts

The skill of the soil moisture-based temperature forecasts is, to first order, controlled by (1) the soil moisture-temperature coupling $\rho(w_n, T_n)$ which is reflected in the linear relationship used to translate the soil moisture forecasts, and (2) the soil moisture memory which allows a very good performance of soil moisture forecasts (Orth and Seneviratne 2013b).

The interplay between the forecast skill of the soil moisture-based temperature forecasts and its controls is illustrated in Fig. 9. The forecast skill is only high in catchments with a comparatively strong soil moisture-

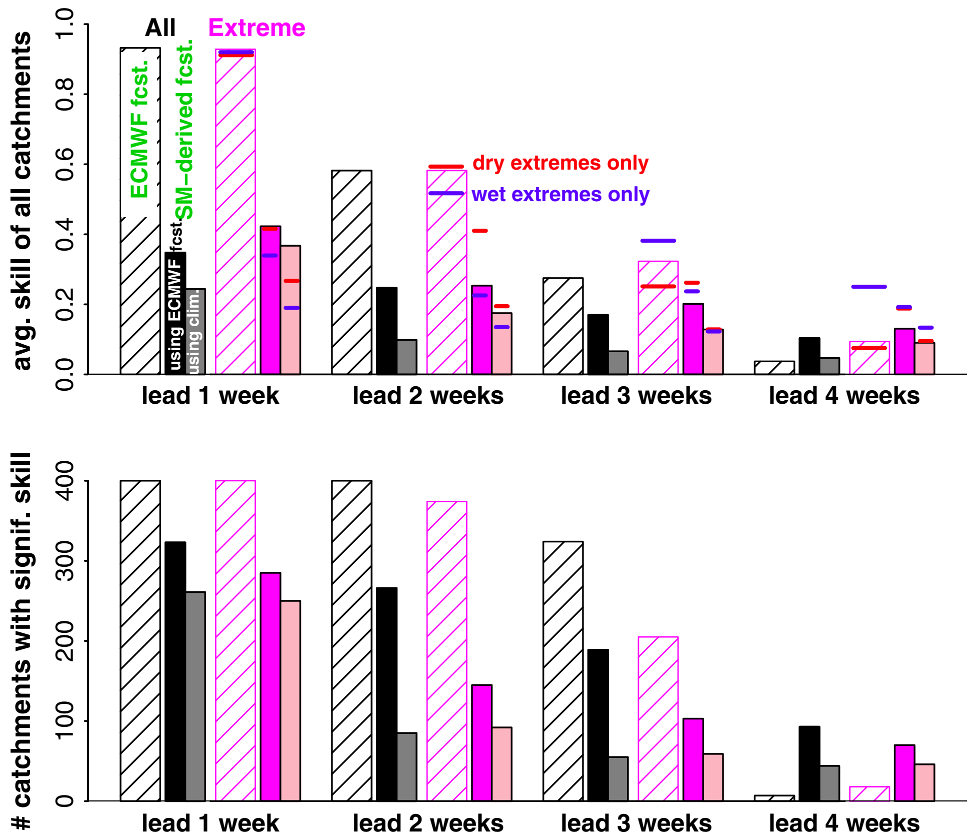

Fig. 8 Summary of performance of temperature forecasts. The *black bars* provide a summary of Fig. 3, the wide *striped black bars* indicate the skill of the ECMWF forecasts, and the *thin solid black bars* indicate the skill of the sm-only forecast model using the ECMWF forecast as atmospheric forcing. *Magenta bars* denote respective values computed from forecasts with extreme (dry and wet) initial soil moisture conditions (as shown in Fig. 7). The *red* and *blue horizontal lines* indicate respective values when considering dry and wet conditions only, respectively. The *thin gray* and *light magenta bars* denote respective values of soil moisture-derived forecasts that use climatological forcing instead of ECMWF forcing forecasts. The *upper row* displays average skills of all considered catchments at all lead times, and the *lower row* shows the number of catchments with significant skill at each lead time

temperature coupling *and* a comparatively strong soil moisture memory. At short lead times the coupling strength is the main control, as the memory is strong enough in almost all catchments. This changes at longer lead times at which there is zero forecast skill in many catchments with a strong coupling due to weak soil moisture memory. Note that therefore the catchments with the highest forecast skills at short lead times are not identical with those displaying the highest forecast skills at long lead times. Whereas the strong coupling supports the forecast skill at short lead times, it causes a weak memory at long lead times and therefore a low forecast skill. Additionally to the controls considered here, other controls such as the atmospheric forcing and its variability probably play a role as there are catchments with similar strength of coupling and memory but yet different forecast skills. Especially under extreme conditions when the soil is anomalously dry or wet, the prevailing atmospheric conditions may be changed, which also contributes to changes in forecasting skills under these conditions (Quesada et al. 2012).

There is a negative relationship between the memory of soil moisture and its coupling with temperature, which makes it difficult to achieve high forecast skills as it tends to prevent the concomitant occurrence of strong coupling and strong memory. This negative relationship can be understood from the fact that a strong coupling with temperature is caused by a strong link between soil moisture and evapotranspiration. Evapotranspiration tends to be high for wet soils and low for dry soils, therefore it tends to remove existing soil moisture anomalies and to consequently reduce its memory. Hence, a strong link between soil moisture and surface fluxes reduces the soil moisture memory (Koster and Suarez 2001; Seneviratne and Koster 2012). At short lead times this mechanism is of minor importance, as the memory is high enough in almost all catchments, but at long lead times the temperature forecast skill is only significant in a few catchments where there is a middle ground between strong memory and strong coupling.

Figure 10 displays the coupling strengths in all considered catchments. As expected from the impact of soil

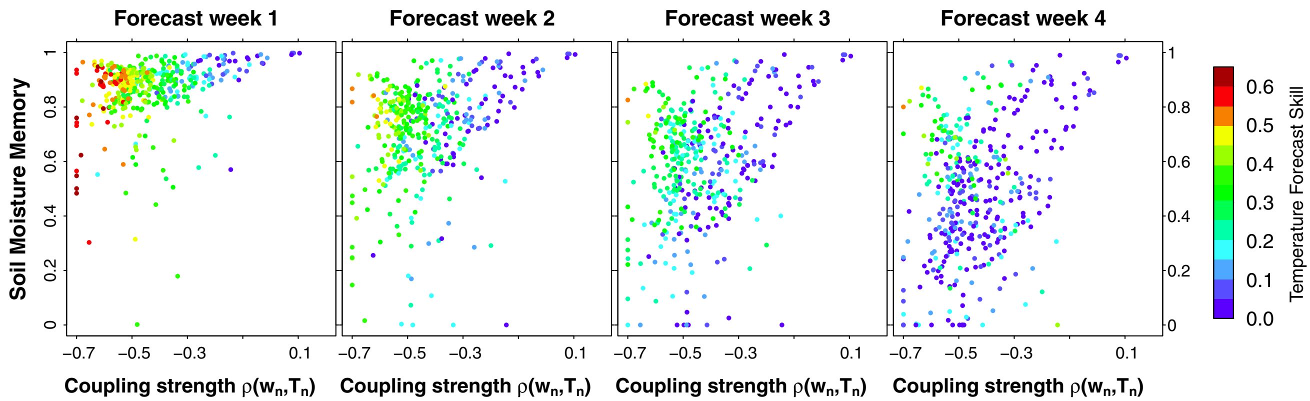

Fig. 9 Soil moisture memory plotted versus coupling strength $\rho(w_n, T_n)$ for all considered catchments at each considered lead time. The corresponding temperature forecast skill of the simple soil moisture-based forecast is indicated through *color coding*. Values from July used for all quantities

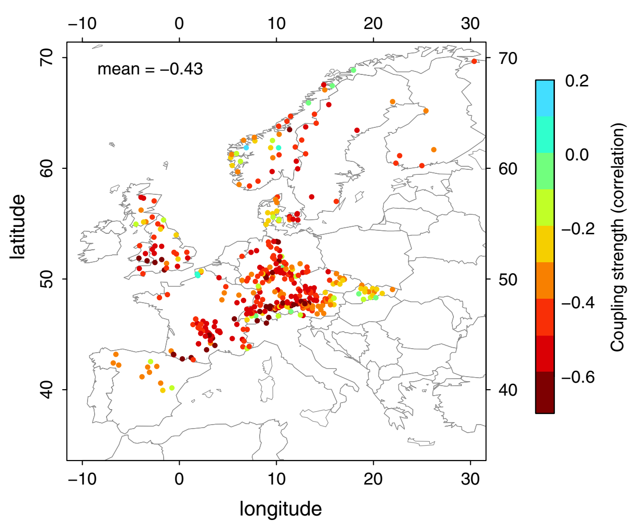

Fig. 10 Coupling strength between soil moisture and temperature in July expressed as inter-annual correlation $\rho(w_n, T_n)$ (see Sect. 3.3)

moisture on the land water and energy balances, in almost all catchments we detect a significant negative coupling between soil moisture and temperature. This coupling is strongest in central Europe, the southern UK, and in southern France; these regions correspond well with the regions of highest forecast skill at short lead times (where the coupling has most impact on the forecasts as described above) shown in Fig. 3. Note that there is almost no north–south gradient of the soil moisture-temperature coupling unlike what has been reported in other studies (e.g. Mueller and Seneviratne 2012). This can be explained by the fact that only few Mediterranean catchments are included in this study because the calibration of the simple water balance model requires that streamflow is present during the whole year. Furthermore, we only consider July and not the complete summer. In June and August the north–south gradient is more pronounced (not shown); but the average coupling strength across all catchments is weaker and consequently the skills of the soil moisture-derived forecasts are lower.

The soil moisture memory as a second control of the skill of the soil moisture-based temperature forecasts is shown in Fig. 11. The memory is very strong at short lead times across large parts of the continent, and even at maximum lead time there is considerable memory, which serves as a basis for the temperature skill we find at this lead time. Especially at long lead times, the memory tends to be strongest in southern Europe and in the southern UK; these regions coincide with the regions where we find highest forecast skill at long lead times in Fig. 3. Apart from these large-scale variations there are considerable small-scale variations highlighting the importance of local soil and vegetation characteristics.

5 Conclusions

In this study we assess the importance of soil moisture for weather prediction in general and for temperature forecasting in particular using a simple conceptual water-balance model and derived linear relationships between modeled soil moisture and observed temperature. We use these relationships to translate soil moisture forecasts into temperature forecasts. We focus on July as soil moisture-temperature coupling is strongest then. The skill of these forecasts is evaluated using the anomaly correlation coefficient and the CRPS. Note that with these measures of skill values greater than zero denote skill better than climatology.

At short lead times of 1–2 weeks these soil-moisture based temperature forecasts show significant skill beyond climatology in many catchments, therefore our simple concept of translating soil moisture forecasts is deemed

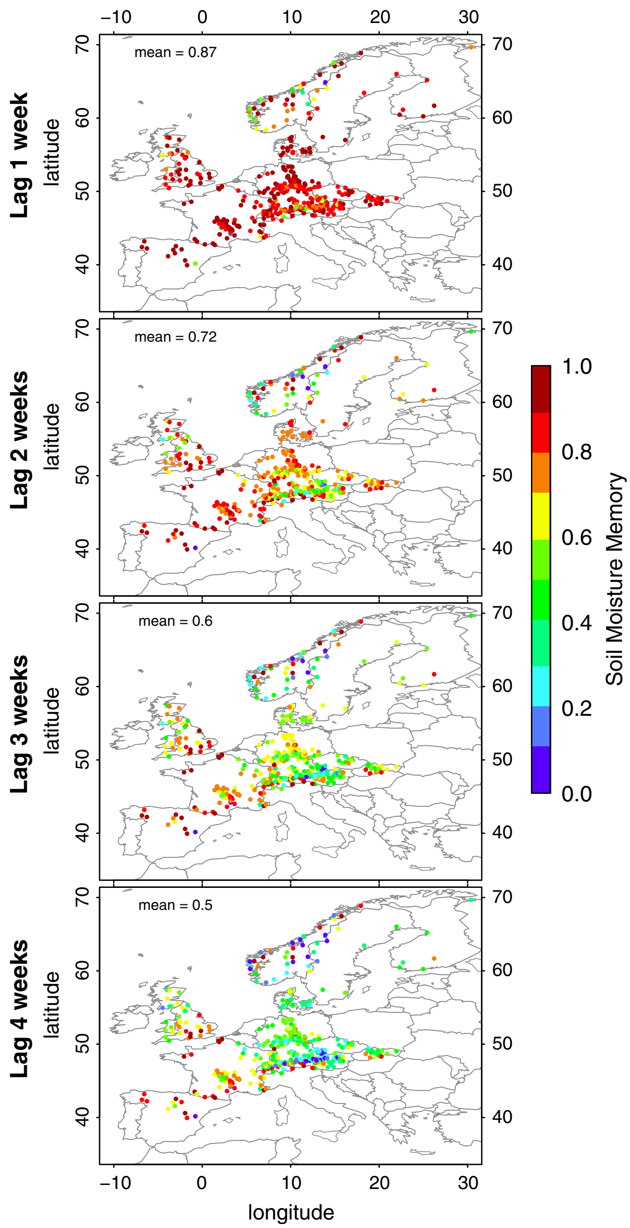

Fig. 11 Soil moisture memory in July expressed as inter-annual lag correlation (see Sect. 3.3) in all considered catchments

successful. At longer lead times of 3–4 weeks we find only some catchments with significant skill. Comparing the performance of the forecasts with a monthly temperature forecast issued by the ECMWF shows clearly lower skills at short lead times. This is expected as the skill of the soil moisture-based forecasts is limited to the information available from soil moisture-temperature coupling, while air advection and atmospheric circulation patterns clearly are the dominant source of predictability on these time scales (note that the soil moisture-only forecasts indirectly include some information on the latter through the forcing from the ECMWF forecasts, but only to the extent that this forcing leads to changes in temperature through effects on soil moisture-temperature feedbacks). However, at the longer lead times of 3 and 4 weeks, the soil moisture-based forecasts outperform the ECMWF product regionally as indicated by a significantly higher skill, thanks to the long-lasting soil moisture memory. At the maximum considered lead time of 4 weeks they show significant skill in more catchments, and also the average skill across all catchments is slightly higher. This result is noteworthy, since the applied approach solely uses information from soil moisture forecasts and their effects on temperature, while the ECMWF forecasts include further potential sources of skill in addition to a soil moisture model (Nonetheless the soil moisture-based forecasts also benefit from some additional information through the use of the ECMWF forcing forecasts to compute forecasted soil moisture). Note, however, that the discussed skills at long lead times are overall rather small, even if they are significantly better than climatology.

Comparing the underlying soil moisture forecasts of the simple model and the ECMWF system we find generally good agreement, suggesting similarity in the soil moisture dynamics of both models. The similarity even increases with lead time, therefore the fact that the ECMWF temperature forecasts perform overall slightly worse at long lead times suggests potential to improve the use of soil moisture information in the ECMWF system.

Evaluating the temperature forecast performances in a probabilistic framework, we find similar results for the ECMWF forecasts but worse performance of the soil moisture-based forecasts. This is because they lack spread in between the ensemble members due to the low spread of the underlying soil moisture forecasts caused by soil moisture persistence; consequently the majority of the CRPS scores is negative indicating less skill than climatology in these cases (low spread indicating overconfident forecasts is penalized by the CRPS). But some CRPS scores are very high, because in case the forecasted value is close to the respective observation the low spread increases the score.

Under extreme (initial soil moisture) conditions we find generally higher skills for both the soil moisture-derived forecasts and the ECMWF forecasts. Whereas the soil moisture-derived forecasts improve at all lead times, the ECMWF forecast skill increases only at longer lead times. This shows that information on initial soil moisture are increasingly valuable under more extreme conditions (see also Koster et al. 2011; Hirschi et al. 2011; van den Hurk et al. 2012; Mueller and Seneviratne 2012). Note that coinciding with such anomalies, the atmospheric circulation may be more persistent, thereby supporting soil moisture anomalies.

The comparatively good performance of the soil moisture-based temperature forecasts points out the potential value of soil moisture information for temperature forecasts.

However, the practical relevance of forecasts based solely on soil moisture is obviously low. Hence these results should be seen as a conceptual framework to assess soil moisture information as a potential source of forecast skill. Note furthermore that all skill scores computed in this study are based on an ensemble of 5 members only, and such a low ensemble size adds uncertainty to the resulting skill scores. Another source of uncertainty is the simple hydrological model used in this study, more sophisticated models may yield even better soil moisture forecasts and thus possibly improved soil moisture-based temperature forecasts.

Analyzing the soil moisture-based temperature forecasts, we identify two main controls of their skill: (1) the soil moisture-temperature coupling strength and (2) the soil moisture memory. High forecast skills are only found in catchments where the coupling and the memory are both concomitantly strong. This is the case only in a few catchments because the controls show a negative relationship with one another. This can be explained by the fact that soil moisture impacts temperature through its coupling to evapotranspiration, whereas this same coupling relationship tends to remove existing soil moisture anomalies, and thereby to reduce soil moisture memory.

In line with the results of earlier studies that used much more sophisticated modeling frameworks (Koster et al. 2010, 2011; van den Hurk et al. 2012), this study demonstrates the value of soil moisture information in the context of temperature forecasting. Especially on sub-seasonal time scales and in the case of extreme events such as droughts and heat waves, a realistic representation of (initial) soil moisture is thus crucial.

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