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Impact of soil moisture on extreme maximum temperatures in Europe

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ABSTRACT

Land-atmosphere interactions play an important role for hot temperature extremes in Europe. Dry soils may amplify such extremes through feedbacks with evapotranspiration. While previous observational studies generally focused on the relationship between precipitation deficits and the number of hot days, we investigate here the influence of soil moisture (*SM*) on summer monthly maximum temperatures (*TXx*) using water balance model-based *SM* estimates (driven with observations) and temperature observations. Generalized extreme value distributions are fitted to *TXx* using *SM* as a covariate. We identify a negative relationship between *SM* and *TXx*, whereby a 100 mm decrease in model-based *SM* is associated with a 1.6 °C increase in *TXx* in Southern-Central and Southeastern Europe. Dry *SM* conditions result in a 2–4 °C increase in the 20-year return value of *TXx* compared to wet conditions in these two regions. In contrast with *SM* impacts on the number of hot days (NHD), where low and high surface-moisture conditions lead to different variability, we find a mostly linear dependency of the 20-year return value on surface-moisture conditions. We attribute this difference to the non-linear relationship between *TXx* and NHD that stems from the threshold-based calculation of NHD. Furthermore the employed *SM* data and the Standardized Precipitation Index (SPI) are only weakly correlated in the investigated regions, highlighting the importance of evapotranspiration and runoff for resulting *SM*. Finally, in a case study for the hot 2003 summer we illustrate that if 2003 spring conditions in Southern-Central Europe had been as dry as in the more recent 2011 event, temperature extremes in summer would have been higher by about 1 °C, further enhancing the already extreme conditions which prevailed in that year.

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1. Introduction

It is well established that the state of the land surface influences atmospheric conditions, including impacts on near-surface temperatures, boundary layer development, and possibly rainfall generation. Soil moisture is a key variable controlling several of these interactions (Seneviratne et al., 2010). As such, the relationships between surface moisture and temperature means and extremes have been studied extensively using both observational and model derived products (e.g., Koster et al., 2006; Seneviratne et al., 2006; Fischer et al., 2007; Mueller and Seneviratne 2012; Miralles et al., 2014). Most of the inferred impacts of soil moisture on the climate system are mediated

by variations of evapotranspiration in soil moisture-limited regimes (Koster et al., 2004, Seneviratne et al., 2010), and these feedbacks also play an important role in the context of climate change, possibly leading to a shift in the location of hot spots of soil moisture-temperature coupling (Seneviratne et al., 2006).

Increases in climate extremes, due to changes in the mean, variance or shape of the distributions, can have larger impacts on ecosystems and society than changes in mean climate because it is often more difficult to adapt to changes in rare but high impact extreme events (e.g., IPCC, 2012; Reichstein et al., 2013). Several studies have shown that changes in the extremes do not always scale to changes in mean climate (see references in Seneviratne et al., 2012a). For instance, an extreme value analysis of the Central England daily mean temperature record has shown that hot summer extremes have evolved differently than mean summer temperature (Brabson and Palutikof, 2002). Furthermore, analyses of climate model projections also suggest that the warm tails of summer temperature

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distributions will warm more than mean temperatures in mid-latitude regions with substantial decreases in soil moisture content, in particular in Central Europe and the Mediterranean region (Orlowsky and Seneviratne, 2012). Accordingly, investigating the relationship between soil moisture anomalies and indices of temperature extremes in Europe is of high interest. Indices that have been developed to characterize temperature extremes (Zhang et al., 2011) include absolute indices (e.g., the hottest day of the year, season or month) and percentile indices that examine changes in the tails of the distribution (e.g., the number of days with maximum temperatures above the 90th percentile), among others. Many of these indices describe ‘moderate’ extremes with a re-occurrence time of one year (Seneviratne et al., 2012a).

Many studies have investigated the influence of land-atmosphere coupling on indices of extreme temperature. Antecedent surface moisture deficits estimated from the Standardized Precipitation Index (SPI) were related both to the number of hot days (i.e., the number of days with maximum temperatures above the 90th percentile) and the maximum heatwave duration (i.e., the maximum number of consecutive days with daily maximum temperature above the 90th percentile) in summer in Southeastern Europe (Hirschi et al., 2011). These results were confirmed in other studies for Europe (Quesada et al., 2012) and on the global scale (Mueller and Seneviratne, 2012), which identified other hot spots with a strong correlation between the number of hot days in the warm season and antecedent precipitation deficits. In these various studies, the relationship between antecedent moisture deficits and extreme temperature (assessed by the number of hot days) amplified for summers with a higher occurrence of hot days (Hirschi et al., 2011). On the other hand, the decreasing variability of hot extremes towards wetter conditions implies a higher predictability for the occurrence of hot days following wet rather than dry conditions. Indeed, wet spells are strictly followed by low numbers of hot days, but both high and low numbers of hot days can take place following dry conditions (Quesada et al., 2012; Mueller and Seneviratne, 2012). Hence, antecedent dry conditions were found to be a necessary but not sufficient condition for the occurrence of hot days. In addition, Quesada et al. (2012) considered the role of prevailing weather types in combination with spring moisture deficits in the occurrence of summer heat waves in Europe, identifying that both controls are important for the occurrence of hot days. The global analysis of Mueller and Seneviratne (2012) identified a relationship between precipitation deficits and the subsequent occurrence of hot extremes in a large fraction of the world, including many areas in North and South America, Europe, Australia and parts of China. In North America, these results are also consistent with previous findings of Durre et al. (2000), suggesting that the distribution of daily maximum temperature is shifted to higher values on days following low soil moisture anomalies (using soil moisture estimates from a water balance model), with the largest impacts at the warm end of the distribution.

In general, most studies of extremes examine changes or relationships in extreme indices (Vincent et al., 2005; Donat et al., 2013; McGree et al., 2013; Whan et al., 2013). Recently, however, more research uses extreme value theory to fit non-stationary generalized extreme value (GEV) distributions to precipitation and temperature data, with covariates used to explore relationships with large-scale climate drivers (e.g., Zhang et al., 2010; Sillmann et al., 2011; Photiadou et al., 2014). For instance, the relationship between hot spell duration, magnitude and frequency, and atmospheric blocking has been demonstrated for Europe using a non-stationary GEV model (Photiadou et al., 2014). A GEV analysis has the advantage of moving away from moderate extreme events and focusing on the far ends of the tails of the distributions. Robust predictions can even be made about the occurrence of rare events that have not (yet) been observed. To answer questions only related to extremes, it is preferable to fit

distributions only to the tails using an extreme value analysis rather than to model the whole distribution (Cooley, 2009).

One way of understanding the influence of soil moisture on (subsequent) temperature extremes is to study temperature differences on days with wet soil moisture compared with all days, i.e., using composites. Using such a method, Brabson et al. (2005) demonstrated that additional soil moisture is associated with more moderate return values (RVs) for both summer maximum and winter minimum temperatures in Britain. In addition, it was shown that future hot spells are longer when the analysis is restricted to low soil moisture days. That study fitted a stationary GEV distribution to a subset of days (i.e., wet soil moisture days) rather than using a non-stationary approach with an index of soil moisture as a covariate. Also Mueller and Seneviratne (2012) used composites to derive the distributions for the number of hot days following dry or wet conditions in Texas in a non-GEV application.

Despite the large body of research about the influence of land-atmosphere coupling on temperature, several questions remain. For instance, it is difficult to obtain continental scale observed soil moisture data sets (Koster et al., 2006; Seneviratne et al., 2010; Dorigo et al., 2013). Therefore, many observational studies use proxies for soil moisture (Hirschi et al., 2011; Mueller and Seneviratne, 2012; Zscheischler et al., 2014a) as data basis, while others used soil moisture derived from meteorological inputs to a water balance or land surface model (Durre et al., 2000; Orth and Seneviratne, 2014). A recent study alternatively used remote sensing estimates of soil moisture retrieved from microwave measurements, but also these data have some shortcomings, mostly because they only measure moisture in the top few centimetres of the soil (Hirschi et al., 2014). Hence, it is relevant to investigate how inferred relationships between surface moisture deficits and temperature extremes may depend on the use of the SPI compared to model-based soil moisture. The relationship between the number of hot days and the block maxima of maximum temperature also requires further analysis, because a direct translation from temperature extremes into the number of hot days cannot be expected. Finally, no previous research has examined the nature of soil moisture–extreme temperature relationship within a GEV framework.

In order to answer the above questions, we focus on the relationship between extreme temperature and a newly derived model-based soil moisture data set using an extreme value theory methodology. We concentrate on the summer months (June, July and August) and domains in Southeastern and Southern-Central Europe (SEE and SCE, respectively). These regions were chosen because SEE has been identified as a hot spot of soil moisture-temperature coupling (Hirschi et al., 2011; Mueller and Seneviratne, 2012) and because SCE was the main region affected by the 2003 heatwave (e.g., Schär et al., 2004; Fischer et al., 2007). The SCE domain is substantially different from the Central European domain considered in Hirschi et al. (2011), which only included Austria and the Czech Republic, while the SCE domain in the present study covers most of Southern France and Northern Italy (in addition to Austria and Southern Germany), and thus a large fraction of its area is located in a Mediterranean climate regime. The latter is expected to be associated with a soil moisture-limited evapotranspiration regime (Teuling et al., 2009) and thus a stronger impact of soil moisture availability on temperature on the interannual time scale (Seneviratne et al., 2010).

2. Data and methods

2.1. Study area and data sets

We focus our analysis on Europe (-9.75 to 49.75° E and 35.25 to 69.75° N) and the period 1984–2013 to coincide with the extent

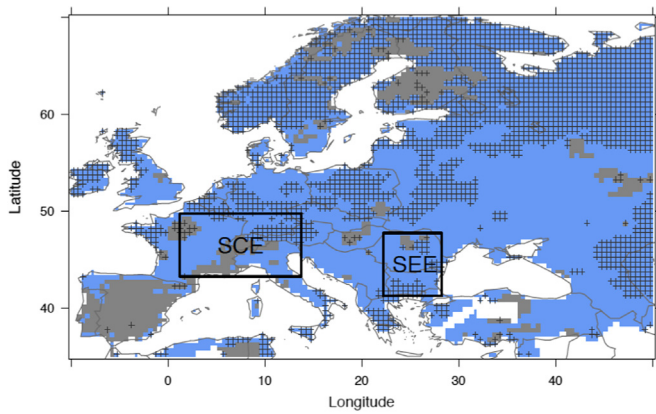


Fig. 1. Considered domains and fit of the GEV in Europe. Pixels where the GEV is a good fit for monthly summer TXx are colored blue, while locations that do not have a good fit are gray. Stippling indicates regions where inclusion of soil moisture as a covariate on the location parameter in M_{SM} does *not* significantly improve the fit. The Southern-Central European (SCE) and Southeastern European (SEE) domains are highlighted. The mask used in subsequent figures combines the results of these two tests and uses stippling where this map is gray or stippled.

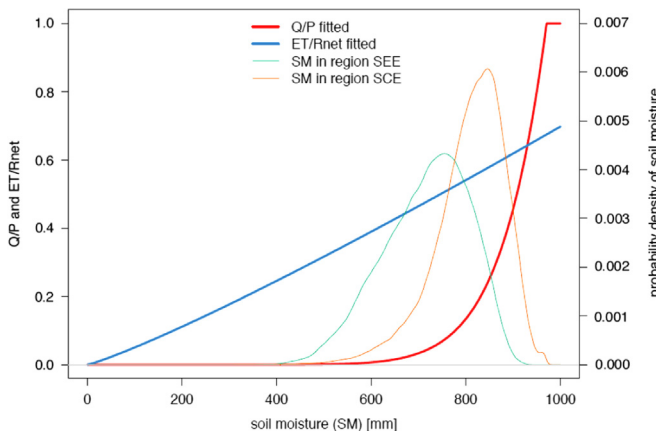


Fig. 2. The ratio of runoff to precipitation (Q/P , red) and evapotranspiration to net radiation ($ET/Rnet$, blue) used in the simple water balance model. Also shown are the empirical probability density functions of soil moisture (SM) over all days for the two regions, SEE (green) and SCE (orange). Soil moisture is bounded on the lower end by 5 mm (instead of zero, to ensure numerical stability) and on the higher end by 970.5 mm (field capacity). (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

of the gridded meteorological product (see description hereafter). The two mentioned regions, SEE and SCE (see above), are then selected for more detailed analysis (Fig. 1). The SEE domain (22.25 to 28.25°E and 41.75 to 47.75°N) was defined similarly to the corresponding domain considered in Hirschi et al. (2011). The SCE domain (1.25–13.75°E and 43.25–49.75°N) was selected focusing on the region most strongly affected by the 2003 heat wave (Schär et al., 2004).

The meteorological data is sourced from the E-OBS data set (Haylock et al., 2008, <http://www.ecad.eu/download/ensembles/download.php> [accessed 27.08.14]), over the period 1984–2013. From this data set, several indices are calculated to characterize extreme temperature and surface-moisture deficits. For the latter, we use the Standardized Precipitation Index (SPI). The SPI is a normalized index of monthly precipitation accumulated over the previous i months, where i is typically 1, 3, 6, 12, 24 or 48 months (McKee et al., 1993). While there is no standard definition of drought, the SPI has been widely used to characterize surface moisture deficits (e.g., Mishra and Singh, 2010; Hirschi et al., 2011), as soil moisture is tightly connected to precipitation forcing.

Nonetheless, evapotranspiration and runoff anomalies can be important for soil moisture evolution during drought events in Europe (e.g., Seneviratne et al., 2012b; Teuling et al., 2013). Hence it is relevant to consider the correspondence of SPI and soil moisture estimates as discussed in Section 3. Here we show results using SPI accumulated for $i=3$ months. However, sensitivity testing suggests that results are similar for the SPI calculated from the preceding 2, 3, 6-month periods, and weaker than presented here for $i=1$ month (not shown). Furthermore, the number of hot days (NHD) is calculated for each month by taking a count of days with the maximum temperature above the 90th percentile of the respective day of the year, as computed from all years (Hirschi et al., 2011; Mueller and Seneviratne, 2012).

Gridded soil moisture (SM) used in this study is inferred from precipitation, temperature and net radiation using a simple water balance model (see Orth et al., 2013 for a detailed description of the model, and Orth and Seneviratne, 2015 for a description of the data set). The model assumes power-law dependencies between soil moisture and respectively (i) evapotranspiration (normalized with net radiation) and (ii) runoff (normalized with precipitation). The model parameters determine the shape of these functions. Orth and Seneviratne (2015) optimized the model parameters using several state-of-the-art land surface data sets. Using the obtained parameters, which are constant across the entire continent, they introduced and validated a novel European land surface data set, which we employ in this study. Fig. 2 shows the resulting power-law functions, Q/P and $ET/Rnet$ as functions of soil moisture. Here Q is runoff, P is precipitation, ET is evapotranspiration, and $Rnet$ is net radiation. Additionally, empirical probability distributions of daily summer (JJA) SM values over the two focus regions SCE and SEE are shown. For comparison, we also use the reanalysis-based soil moisture data set from ERA-interim/land (Balsamo et al., 2013) to confirm our results over the period 1984–2010. ERA-interim/land is a single run from a land-surface model driven by ERA-interim (Dee et al., 2011) with rainfall corrected according to the Global Precipitation Climate Project data set (v2.1, Adler et al., 2003). The data set has been shown to compare reasonably well with observations from numerous stations across the world (Albergl et al., 2013).

2.2. Methods

The relationship between soil moisture at the first day of the month (SM) and maximum monthly temperature (TXx) was assessed using extreme value theory (e.g., Coles, 2001). The focus was on June, July, and August as the impacts of extreme temperature events are largest in summer and there is potential for interactions between extreme temperatures with dry soils. GEV distributions were fitted to the block maxima of daily maximum temperature (TXx) from each individual summer month with and without an index of surface-moisture availability as a covariate. Analysis is conducted in the R Statistical Computing environment (R Core Team, 2014), using the ‘extRemes’ package (Gilleland and Katz, 2011). Firstly, the stationary GEV model (M_{STAT}) was fitted to the block maxima of each summer month with no covariates (Eq. (1)):

$$G(x) = \exp \left\{ - \left[1 + \frac{\xi(x-\mu)}{\sigma} \right] \right\}. \quad (1)$$

The GEV distribution is described by three parameters: the location parameter (μ), which is similar to the mean of the distribution, the scale parameter (σ), which is a measure of the variability and, the shape parameter (ξ), that describes the type of distribution the data fits (i.e., Gumbel: $\xi=0$, Frechet: $\xi>0$, Weibull: $\xi<0$). Given that temperature extremes can be assumed to be finite (because of a finite amount of energy reaching the Earth’s surface) their scale parameter should be negative, i.e., they should follow a Weibull distribution. The shape parameter in M_{STAT} is between -0.05 and -0.50 , suggesting

that maximum temperature followed a Weibull distribution. The shape of the fitted distributions here are consistent with other studies that reported extreme temperatures with bounded tails (Andrade et al., 2012; Nogaj et al., 2006).

Secondly, non-stationary GEV models were fitted to TXx with an index of surface-moisture availability included as a covariate at each pixel. In this context, we used SM on the first day of each summer month from the simple water balance model (M_{SM}) and ERA-land (M_{ERA}), and monthly SPI (M_{SPI}), respectively, as a covariate on the location parameter (Eq. (2)), such that the location parameter is a linear function of the covariate, i.e.,

$$\mu(z) = \beta_0 + \beta_1 z, \quad (2)$$

with z denoting either SM or SPI and β_0 and β_1 denoting constants fitted to each location.

Two tests assessed the performance of the GEV fitted at each pixel. Firstly, a Kolmogorov–Smirnov goodness-of-fit test (K–S test, $p < 0.05$) was carried out on the stationary model (M_{STAT}) to assess whether the block maxima of each summer month follows a GEV distribution (Zhang et al., 2010). Secondly, the likelihood-ratio-test was conducted on the stationary (M_{STAT}) and non-stationary models (M_{SM} , M_{SPI} , M_{ERA}) to determine if the inclusion of the covariate resulted in a significant improvement of the model fit (Zhang et al., 2010). Locations where maximum temperature does not follow a GEV distribution are colored gray in Fig. 1, with most pixels that failed the K–S test located in the Iberian Peninsula. This latter feature is due to the negative skew of TXx , a lack of summer variability and a significant autocorrelation between years in the Iberian Peninsula (see Supplementary Information, Fig. S1 in the).

In addition, locations where soil moisture is not a significant covariate are stippled in Fig. 1. In later figures, these two masks are combined so that figures are stippled in pixels where either the GEV is not a good-fit or the covariate does not result in a significant improvement. Use of the summer block maxima of maximum temperature results in a better fit in the Iberian Peninsula, and more generally over the study domain, but with fewer pixels where the covariate (either SM or SPI) makes a significant improvement to the model. As such, the model we use was selected as a tradeoff between model fit and covariate significance. Previous work has compared the use of seasonal and monthly blocks in a GEV analysis. Decreasing block length, and thus increasing sample size, resulted in a smaller location parameter and larger scale parameter but had little impact on the magnitude of the return levels (Parey, 2008). In addition, the r -largest method has been widely used (Zhang et al., 2004, Zhang et al., 2010). This method fits the GEV to the r -largest values per block, where $r \geq 1$. The choice of r is a variance–bias tradeoff, with larger values of r likely violating the asymptotic support for the extreme value distributions (Zhang et al., 2010).

The influence of soil moisture regime on extreme temperature was quantified by comparison of return values when soil moisture was dry (10th percentile) and wet (90th percentile) in the non-stationary models (M_{SM} , M_{SPI} and M_{ERA}). As we use block maxima from each of the three summer months, the return values represent the values that are expected to occur once in T -summer-months, rather than once in T -years. As such we calculate the 60-summer-months return values as an approximation of the 20-year return value (RV20). Finally, the influence of soil moisture

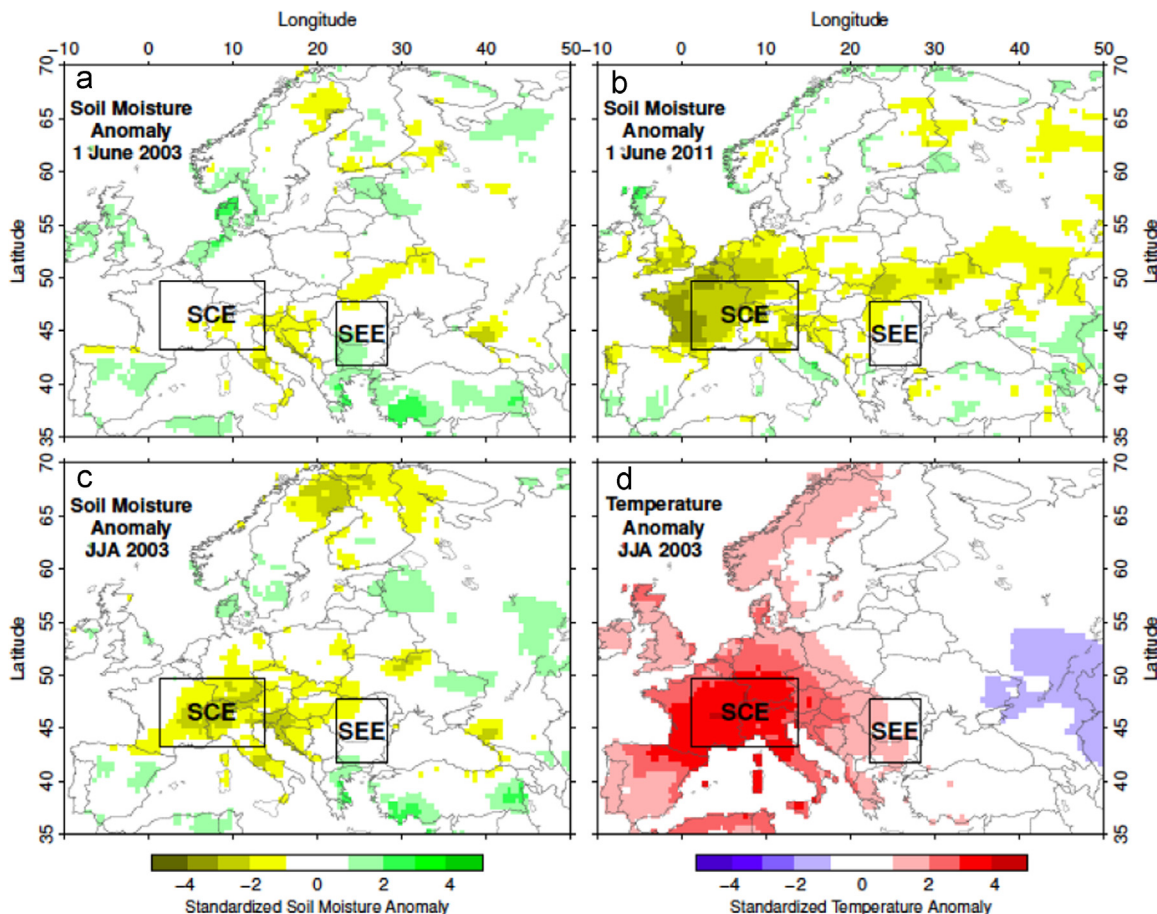


Fig. 3. Standardized soil moisture anomalies on the 1st June in (a) 2003 and (b) 2011. Mean summer anomalies of (c) soil moisture and (d) maximum temperature in 2003. The Southern-Central European (SCE) and Southeast European (SEE) regions are marked.

regime on the variability of extreme temperature was evaluated by comparing the spread of the confidence interval around the RV20 computed from temperature data during dry and wet soil moisture states, respectively. Confidence intervals are estimated using normal approximation (the delta method) in the 'extRemes' package (Coles, 2001; Gilleland and Katz, 2011; Gilleland, 2014). Comparing the width of the confidence intervals around the RV20 when soil moisture is dry and wet gives an indication of the uncertainty associated with each of the estimates. This information is relevant, as in the case of the NHD, higher variability of distributions (and thus higher uncertainty) was found after dry compared to wet conditions (e.g., Hirschi et al., 2011).

Next, quantile regression was conducted on the block maxima of monthly maximum temperature (TXx) and five-day mean soil moisture centered around the first day of the months of June, July, and August, within the time period 1984–2013 to assess their relationship throughout distribution at the 5th, 25th, 50th, 75th and 95th percentiles. Due to limitations in the availability of soil moisture data (see Section 1), previous research has used the SPI as a proxy for soil moisture. To evaluate this assumption, the relationship between SPI and model-based SM is assessed. In addition, previous work has found significant relationships between surface moisture deficits and the NHD, as such the relationship between the NHD and TXx is also discussed.

Finally, a case-study analysis was performed to assess the role of antecedent soil moisture conditions in the 2003 heat wave event, which was particularly extreme (e.g., Schär et al., 2004; Fischer et al., 2007; García-Herrera et al., 2010). In 2003, average May soil moisture conditions (-13 mm in SCE in the model-based SM , Fig. 3) were followed by a substantial decrease during summer due to dry and hot conditions in particular in the month of June (Seneviratne et al., 2012b). Despite late spring conditions with near-average soil moisture conditions, the 2003 summer was hot and dry leading to large-scale soil moisture deficits (Fig. 3c) and strong impacts on vegetation activity (e.g., Ciais et al., 2005). Conversely, in 2011, below average soil moisture in May (-70 mm in SCE in model-based SM , Fig. 3b) was followed by wetter conditions in summer (see Fig. 9a). To evaluate the role of antecedent soil moisture conditions on the 2003 heat wave, we combined the 2011 spring soil moisture levels with the meteorological forcing of summer 2003 and computed a soil moisture reconstruction given 2011 spring conditions and 2003 summer climate. We then evaluated the impact of the new (hypothetical) soil moisture conditions on temperature extremes by computing the corresponding change in the RV20 and the change in probability for reaching the RV20 of original 2003 under the new soil

moisture conditions. Daily soil moisture anomalies were standardized by dividing by the daily standard deviation of soil moisture.

3. Results

3.1. Extreme value analysis of summer temperature extremes with co-varying soil moisture

Summer maximum temperature extremes (TXx) follow an extreme value distribution in most regions of Europe (Fig. 1). The Iberian Peninsula and some areas in Southern Finland are an exception, there the distribution of temperature extremes of the summer months is narrow and negatively skewed, and thus does not follow an extreme value distribution (see Section 2.2 and Fig. S1). In most areas of Western Europe, Italy, Southeastern Europe and Eastern Europe, SM is a significant covariate (Fig. 1), i.e., including SM in the GEV model significantly improves the estimates of maximum temperature. This is in line with the expectation that in regions with an intermediate SM regime (not too dry and not too wet), SM significantly influences temperature (Seneviratne et al., 2010).

In areas where SM is a significant covariate, it is negatively related to temperature extremes, i.e., higher SM levels are associated with lower extreme temperatures (Fig. 4). Most areas show a decrease in monthly temperature maxima of about 1.5 °C for an increase in SM of 100 mm, with area averages of 1.8 °C and 1.6 °C in SCE and SEE, respectively. Corresponding with these results, lower SM levels lead to higher RV of temperature. We find that dry conditions (10th percentile of SM) lead to a 2 – 4 °C increase in 20-year RVs of temperature of compared to wet conditions (90th percentile of SM) in most regions (Fig. 5a). For SEE the difference in the 20-year RV between wet and dry soil moisture regimes is 2.3 °C, while for SCE it is 2.2 °C (Fig. 5a). The largest differences in 20-year RVs are found in Central France, Slovenia, Croatia, Bosnia and Herzegovina and Eastern Europe where hot extremes differ by almost 4 °C depending on the soil moisture content. In SCE and SEE there is no consistent change in the width of the confidence intervals around the 20-year RV for difference soil moisture regimes (Fig. 7).

To further investigate this relationship, we also compute quantile regression analyses (see e.g., Hirschi et al., 2011) of TXx as a function of SM for the two investigated regions (Fig. 6a and c). These results are consistent with an overall negative correlation between averaged TXx and SM levels for the two focus regions SCE and SEE, with regression coefficients of -0.04 and -0.02 , respectively (i.e., -4 and -2 °C/100 mm, Fig. 6a and c). However, the dependencies are

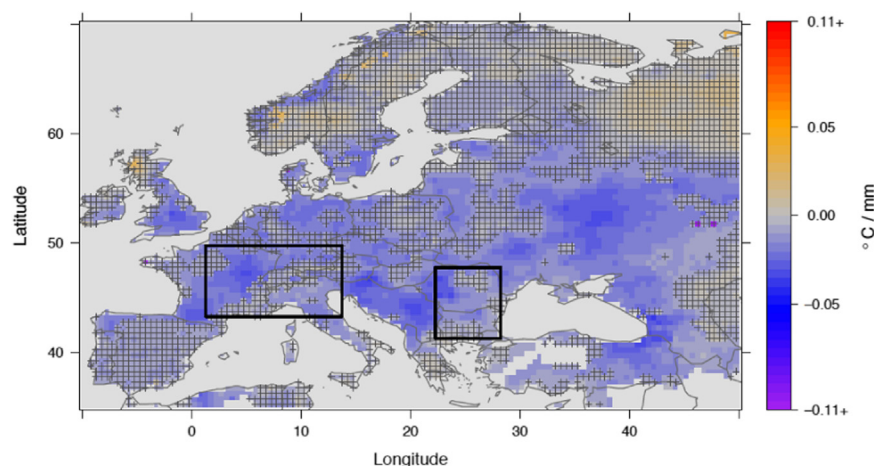


Fig. 4. The slope of the location parameter, β_1 , (°C/mm) in the non-stationary GEV model of extreme temperature with soil moisture as a covariate (M_{SM}). Stippling indicates regions where either the GEV is not a good fit for extreme temperature or soil moisture is not a significant covariate.

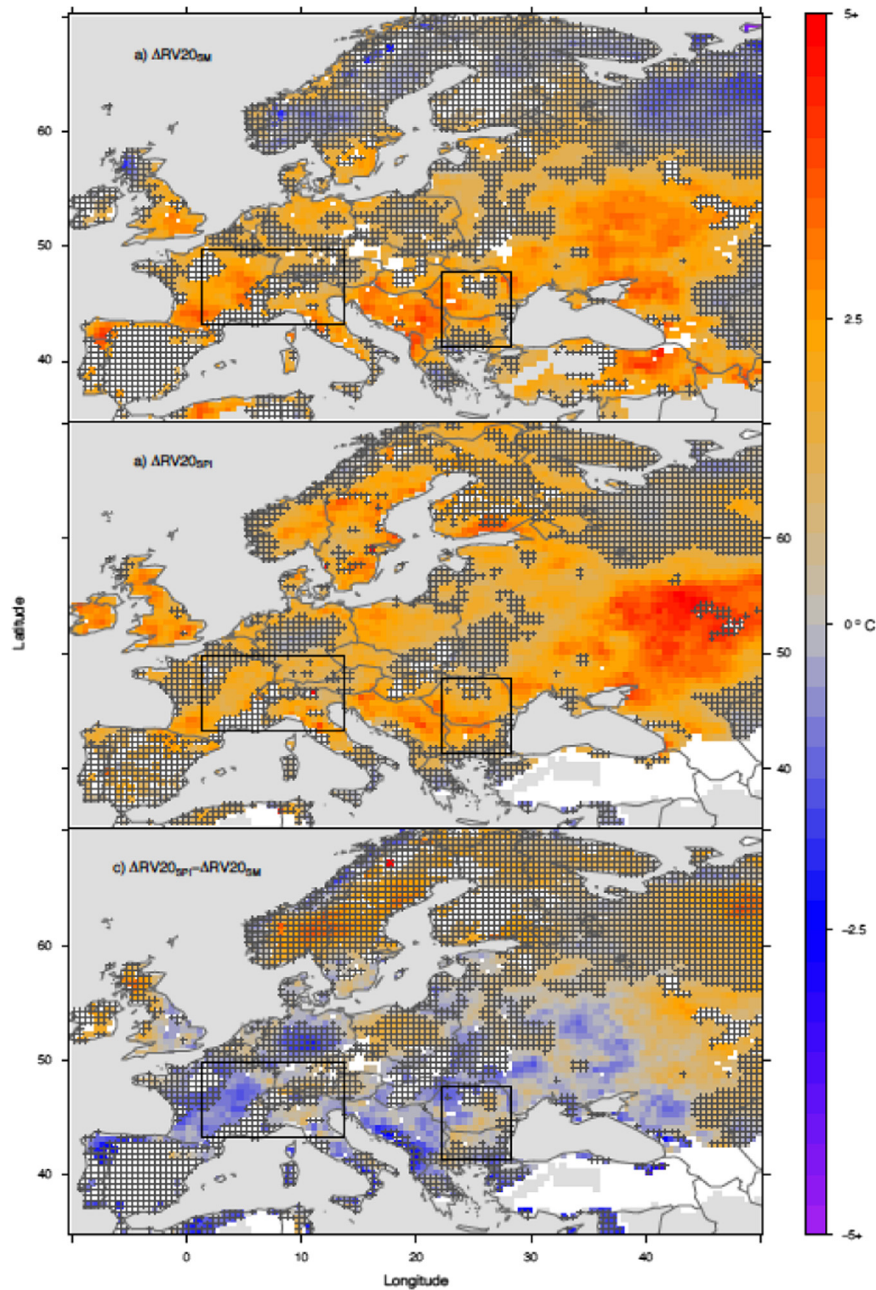


Fig. 5. ΔRV_{20} is the difference in the 20-year return value (RV_{20} , °C) between dry (10th percentile) and wet (90th percentile) regimes of the covariate. (a) ΔRV_{20} from M_{SM} . (b) ΔRV_{20} from M_{SPI} . (c) The difference between $\Delta RV_{20_{SPI}}$ and $\Delta RV_{20_{SM}}$. Stippling indicates regions where either the GEV is not a good fit for extreme temperature or in (a) and (b) SM or the SPI is not a significant covariate or in (c) either the SPI or SM are not significant covariates. White areas indicate pixels where the GEV could not be fit due to missing data.

qualitatively different from those for the relationship between NHD and SPI (Hirschi et al., 2011; Quesada et al., 2012; Mueller and Seneviratne, 2012), as can also be seen in Fig. 6b and d. Indeed the dependency of TX_x on soil moisture is found to be mostly linear with similar coefficients for different quantiles (Fig. 6a and c), while the dependency of NHD on SPI displays increasing slopes for higher quantiles and correspondingly higher spread of NHD for the dry conditions. Therefore, the confidence intervals for the GEV analysis do not show a systematic difference for dry vs. wet conditions in most areas, including SEE and SCE.

The differences in the results for the quantile regressions of TX_x with SM compared to NHD with SPI could be either due to differences in SPI and SM , or TX_x and NHD. Regressions of SPI on SM and NHD on TX_x (Fig. 8) suggest that both factors play a role. The other quantile

regression pairs (i.e., TX_x on SPI and NHD on SM , see Supplementary Information, Fig. S2) show that the different behavior of TX_x and NHD as a function of surface moisture (SM or SPI) deficits is linked to a threshold effect. If temperature maxima are low, and therefore below the threshold used to defined hot days, NHD is 0 (Fig. 8, left). This is the case for many of the smaller values of TX_x . Consequently, this results in smaller variability of NHD for wetter conditions and cooler temperatures, a feature not found for the dependency of TX_x on soil moisture. Moreover, the correlation between SM and SPI is not very strong (Fig. 8, right). SPI has often been used as a proxy for SM in previous studies (e.g., Hirschi et al., 2011; Mueller and Seneviratne, 2012; Zscheischler et al., 2014b). Yet, it is solely based on precipitation and neglects impacts of evapotranspiration (and runoff) on soil water content, which was shown to play an important role for drought

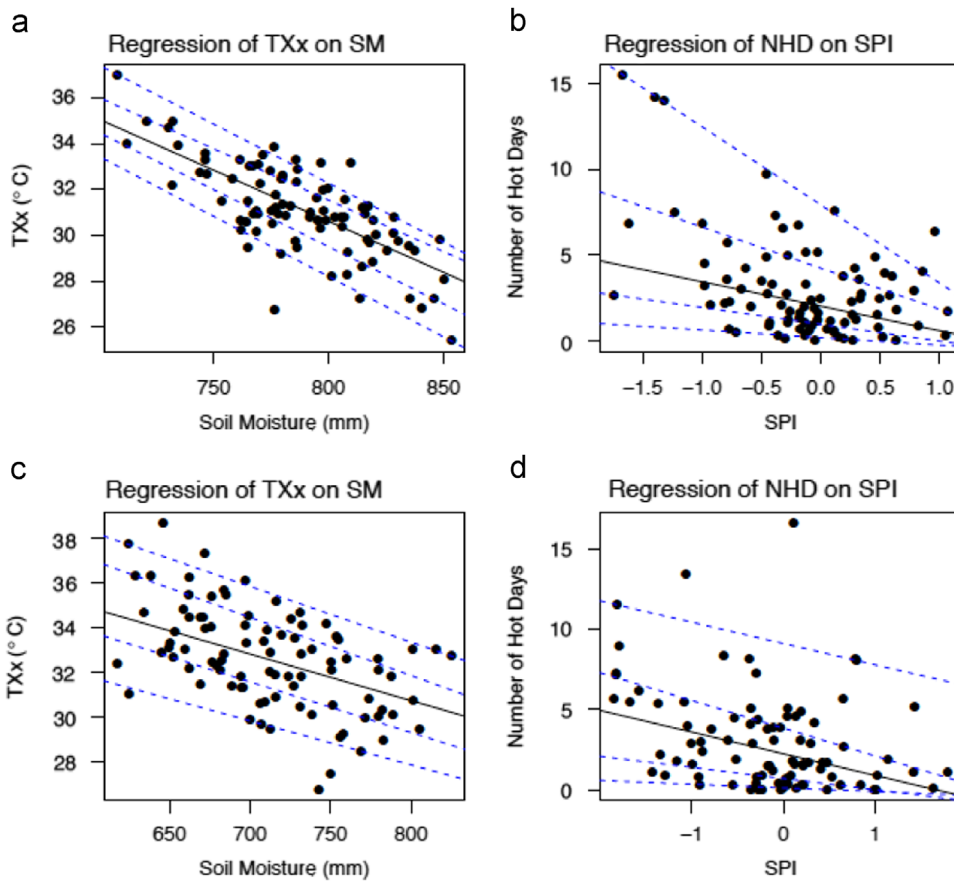


Fig. 6. The relationship between summer regionally averaged TXx with SM (a and c) and monthly NHD with monthly SPI-3 (i.e., accumulated over 3 months) (b and d). The regression lines for the 5th, 25th, 75th and 95th percentiles (dashed) and median (solid) are marked. The regions shown are Southern-Central Europe (SCE: a and b) and Southeastern Europe (SEE: c and d).

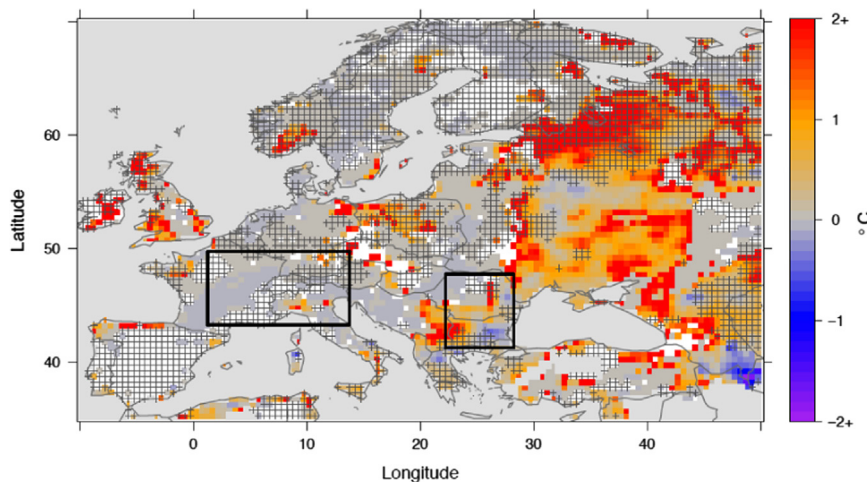


Fig. 7. The difference in the width of the confidence intervals ($^{\circ}C$) around the RV20 between dry (10th percentile) and wet (90th percentile) soil moisture regimes from M_{SM} . Stippling indicates regions where either the GEV is not a good fit for extreme temperature or soil moisture is not a significant covariate.

development in Central Europe (Seneviratne et al., 2012b; Teuling et al., 2013).

We further analyze if the different behavior of SPI and SM might impact the GEV analyses. To assess this, we fit a GEV distribution to TXx with SPI as covariate for the location parameter (M_{SPI}). Comparing the RV20 for dry and wet conditions corresponds well with the results for SM (Fig. 5b). Drier conditions in

the SPI lead to higher RV20 values. Compared to SM , using SPI as a covariate leads to a larger separation between dry and wet regimes in Eastern Europe (up to $2^{\circ}C$) and a smaller difference in Western Europe (between 1 and $2^{\circ}C$, Fig. 5c). Moreover, for large regions in Norway and Sweden, SPI is a significant covariate while SM is not (Fig. 5b). These differences are possibly related to the fact that SPI is a relative measure of moisture, which is

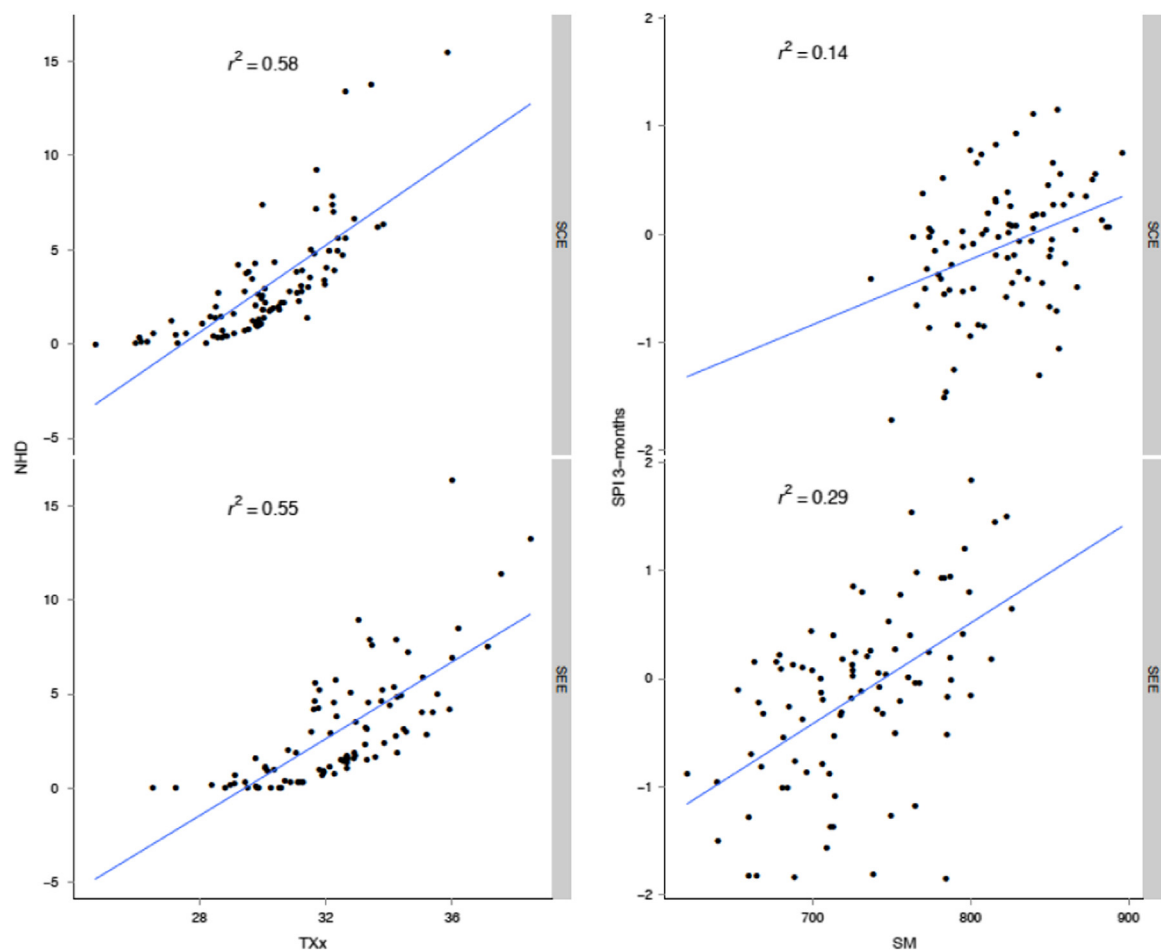


Fig. 8. The relationship between regionally averaged values of summer monthly NHD with TXx (left) and monthly SPI-3 (i.e., accumulated over 3 months) with SM (right). The linear regression and r^2 is indicated on each figure. The regions shown are Southern-Central Europe (SCE, top) and Southeastern Europe (SEE, bottom).

normally distributed for each location, whereas SM is an absolute measure. Consequently, SM is often close to saturation in higher latitudes and close to zero in dry areas.

To investigate the dependency of our results on the chosen SM data set, we repeated the analysis fitting the GEV distribution to TXx using soil moisture from ERA-land as a covariate (M_{ERA} , see Supplementary Information, Fig. S3). Results were similar when fit over the common period, although the influence of SM on TXx using the ERA-land SM is smaller than for the simple-model SM , with a 0.7 °C and 0.6 °C decrease per 100 mm of soil moisture in SCS and SEE, respectively. Spatially the influence of soil moisture regime on the RV20 is similar to M_{SM} , showing that our findings are robust independently of the employed soil moisture data set.

The use of a novel SM reconstruction and the consideration of impacts on absolute extreme maximum temperatures rather than the NHD enables us to re-examine the role of soil moisture-temperature relationships compared to previous assessments. The observational studies of Hirschi et al. (2011), Quesada et al. (2012), and Mueller and Seneviratne (2012) focused on relationships between precipitation deficits estimated with SPI and impacts on NHD as an indicator for extreme temperatures. These previous results indicated a strong impact of surface moisture deficit on hot extremes, a finding also confirmed by our study. Our results furthermore suggest, however, that contrary to the results obtained with NHD data, the relationship is not markedly different for dry vs. wet conditions. Indeed, results based on the NHD displayed a higher variability after dry vs. wet conditions (e.g., Hirschi et al., 2011), a finding due in large part to a threshold

effect, i.e., the fact that NHD is 0 as long as a temperature threshold is not exceeded and thus NHD generally shows much lower variability when temperatures are low (a similar effect would also be expected in the case of exceedance temperatures). Overall, our findings imply a mostly linear impact of soil moisture on temperature maxima in summer months (consistent with results from climate models, e.g., Seneviratne et al., 2013).

3.2. The impact of spring SM conditions on the summer 2003 heat wave

In 2003, Europe was struck by an unprecedented summer heat wave and serious drought (Schär et al., 2004; Andersen et al., 2005; Fischer et al., 2007). Around 40,000 deaths were registered in Europe during the heat wave, which affected mostly elderly people (García-Herrera et al., 2010). Nonetheless, recent results have suggested that the spring of 2003 was not anomalously dry (e.g., Seneviratne et al., 2012b; Wetter et al., 2014), with the exception of the conditions in June. Two main heatwave periods occurred, one in June and another one in August. The August heatwave was particularly extreme (leading to a mortality rise of 60% in France, Fouillet et al., 2006; García-Herrera et al., 2010), and was strongly exacerbated by dry conditions in that month (Fischer et al., 2007). The meteorological conditions of the heatwave also included an extremely persistent blocking and the intense negative soil moisture anomaly in central Europe and the resulting feedback mechanism (García-Herrera et al., 2010). Conversely, spring 2011 was dry but the meteorological conditions became

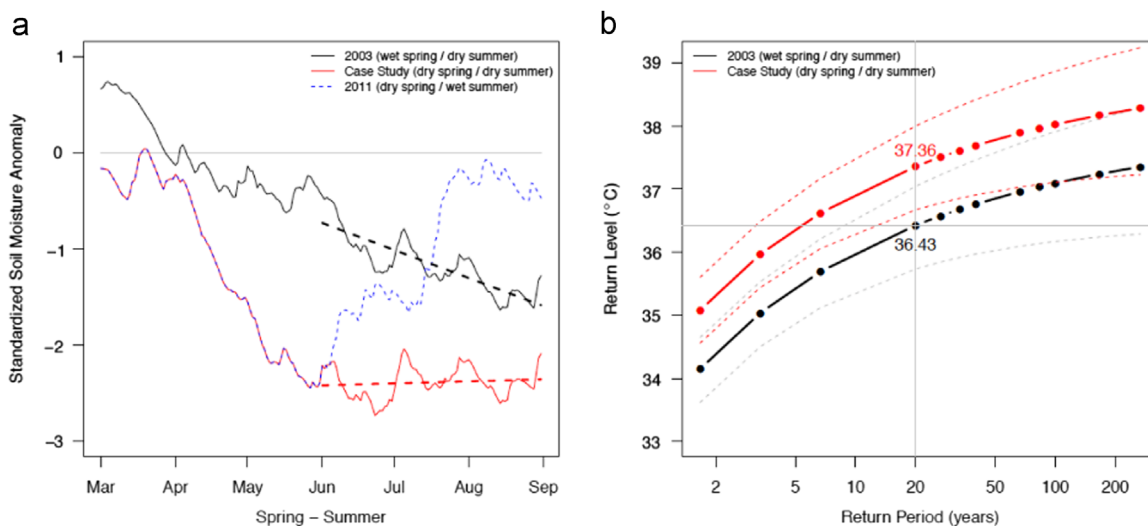


Fig. 9. (a) Standardized daily soil moisture anomalies from Southern-Central Europe for spring and summer in 2003 (black, solid), in the case study where dry soil moisture conditions of 2011 are combined with the meteorological forcing from 2003 (red, solid) and 2011 (blue, dashed). The line of best fit over the summer period is marked for 2003 and the case study year. (b) Southern-Central European return values for 2003 (black) and the case study year (red) with 95% confidence intervals marked in dashed lines. RV20 is marked and the 2003 RV20 is highlighted with gray solid lines. The return values are calculated from the non-stationary model with the mean summer soil moisture of each year used as the covariate. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

wetter in June, and the summer temperatures were not particularly high. Using the derived GEV model, we assess here what could have been the temperature conditions in the summer 2003 if the spring had been drier than in that year, i.e., like in 2011.

For this purpose we replace the *SM* at the beginning of the summer 2003 with the much drier corresponding value of 2011 (Fig. 9a). Starting with *SM* of June 1st 2011, we use the summer climate of 2003 to drive the *SM* reconstruction, and to compute the (hypothetical) soil moisture evolution that would have occurred with much drier initial soil moisture conditions. Note that this experiment does not include any soil moisture–atmosphere feedbacks (e.g., the influence of soil moisture on precipitation or circulation is not taken into account), which could enhance the impact of soil moisture on temperature in case of positive soil moisture–precipitation feedbacks (e.g., Guillod et al., 2015). Summer temperature anomalies were largest in the SCE domain (Fig. 3d); hence we focus our analysis on that region. The actual *SM* anomaly in summer 2003 was -47 mm in SCE (this corresponds to approximately 1.2 standard deviations (SD)). If the summer of 2003 had started with the *SM* levels of 2011, the summer *SM* anomaly would have been -95 mm (or 2.4 SD) according to the employed model. In the case study year, *SM* reaches the mean summer deficit in mid-June and changes little throughout the summer, while in 2003 *SM* levels decrease until the end of summer (Fig. 9a). Given our findings in the previous sub-section this might have had severe impacts on hot temperature extremes. Indeed, the change in *SM* conditions leads to an increase of the 20-year RV of summer temperature extremes by about 1 °C, from 36.43 °C to 37.36 °C (Fig. 9b). Put in different words, exchanging the initial *SM* conditions leads to a $4 \times$ increase in probability of reaching 36.43 °C across the whole summer, from 1.7% to 7% (the probability of a 1-in-60-summer-months or 1-in-20-years event is 0.017). The importance of soil-temperature feedback for the emergence of mega-heatwaves was shown for several European events, including the 2003 SCE heatwave and the 2010 Russian heatwave (Fischer et al., 2007; Miralles et al., 2014). However, once the soil is dried out, a continued precipitation deficit cannot further lower the soil moisture, and hence the soil moisture-temperature feedback is not further amplified. This may also explain the low inter-annual temperature variability across the Iberian Peninsula (see Section 2.2).

4. Discussion and conclusions

In this study we applied for the first time extreme value theory onto temperature extremes using soil moisture as a covariate. With this approach we could quantify the impact of initial soil moisture on extreme hot temperatures, which is particularly relevant in areas with intermediate soil moisture regime. While it is known that hot temperatures in summer are impacted by precipitation deficits in spring in many areas (e.g., Mueller and Seneviratne, 2012), our study extended this insight and provided an estimate of the degree to which soil moisture influences the magnitude of the temperature extremes. This was possible, because, in contrast to previous studies, we used monthly temperature extremes instead of the number of hot days per month as primary variable. Consistent with previous work, we found high variability in the NHD at low *SM* and *SPI* values, with a narrowing in the NHD distribution under wetter conditions. In contrast, the distribution of *TXx* showed no such change for wet and dry *SM* and *SPI* regimes. Furthermore, the differences in confidence intervals surrounding the 20-year return value of *TXx* between dry and wet soil moisture regimes were small in Southern-Central and southeast Europe, underlining the limited impact of soil moisture on hot temperature variability. It is important to understand how soil moisture and other drivers of extreme heat are associated with changes in both the intensity of extreme temperature and the duration of events, as both can increase risk of mortality as well as common health problems. For example, in North America, heat wave mortality risk increased by 2.5 % for each 0.56 °C increase in heat wave intensity, and by 0.4 % for each 1-day increase in length (Anderson and Bell, 2011). Increased understanding of the relationship between absolute maximum temperature extremes and soil moisture could have value in forecasting applications for heat extremes.

Another feature setting this study apart from previous work is the use of soil moisture data derived from a simple water balance model (Orth and Seneviratne, 2015). We showed a moderate positive correlation between *SM* and the *SPI* (accumulated between 2 and 6 months), which, combined with the agreement between results obtained from *SPI*- and *SM*-based analyses, indicates that *SM* can be approximated by the *SPI*. A previous analysis in North Carolina found a stronger correlation between normalized *SM* and the *SPI* on a shorter biweekly timescale (Sims and Raman, 2002). The weaker relationship we find may be associated with differences in evapotranspiration or

runoff between locations, or the shorter time scale of the previous study. Many previous studies using the SPI as a proxy for soil moisture have added valuable insights as to the nature of the relationship between precipitation deficits and extreme temperature (e.g., Hirschi et al., 2011; Mueller and Seneviratne, 2012). However, while precipitation is the main driver of SM levels, we show that there is not a perfect relationship between the SPI and employed SM dataset. It is preferable to use SM directly, where possible, rather than relying on a proxy measure that does not account for processes such as evapotranspiration or runoff. This is even more important under changed future climate conditions where precipitation, evapotranspiration and runoff may change in different ways, further altering the relationship between SM and the SPI. Nonetheless, we note that the used SM data is a model-based product and could have some limitations as well, although results with an alternative model-based data set (ERA-land) were found to be similar.

In a case study we focused on the summer climate of 2003 with different initial soil moisture conditions. We showed that the temperatures of 2003 could have been much higher if spring soil moisture levels had not been as close to climatology as they were. This demonstrates the importance of antecedent soil moisture conditions on summer heat wave events. Mean summer precipitation is projected to decrease in Central Europe by the middle of the 21st century, while winter and spring rainfall is projected to increase (Seneviratne et al., 2012a; Jacob et al., 2014). The GEV analysis shows that a decrease in summer precipitation, and thus surface moisture, could result in increases in the magnitude of extreme heat events (consistent with obtained modeling results, e.g., Seneviratne et al. 2006, 2013). The case study demonstrates the influence of spring SM conditions on summer SM conditions and hence on summer extreme temperatures, as lower SM levels at the beginning and during the summer 2003 are associated with a 1 °C increase in the 20-year RV. This result emphasizes the importance of understanding seasonal changes in the hydrological cycle in addition to annual changes.

This framework can be extended to other regions where there is a relationship between SM and temperature, such as North America. Regions where this method is appropriate can be determined by the fit of the GEV and the significance of the covariate. However, fitting a GEV distribution using all summer months may not be the most appropriate approach in regions with low temperature variability and high autocorrelation, such as on the Iberian Peninsula. Hence, for such regions, if longer data sets are available (> 30 years), we suggest fitting the GEV distribution to annual maxima. If the model fit is significant (i.e., the fit passes the goodness-of-fit and likelihood-ratio tests), this framework is able to answer outstanding questions related to the size of the impact SM has on the magnitude of temperature extremes. The availability of a global model-based SM data set, albeit covering a short time frame, would increase the transferability to this type of analysis. This would make this approach applicable in other regions, in order to complement research using the SPI and to better understand relationships between the land-surface and temperature extremes

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Appendix A. Supporting information

Supplementary data associated with this article can be found in the online version at <http://dx.doi.org/10.1016/j.wace.2015.05.001>.

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