Clim Dyn (2009) 32:75–93
DOI 10.1007/s00382-008-0375-9

Contribution of realistic soil moisture initial conditions to boreal summer climate predictability

S. Conil · H. Douville · S. Tyteca

Received: 27 September 2007 / Accepted: 17 January 2008 / Published online: 5 February 2008

Abstract Seasonal climate forecasts mainly rely on the atmospheric sensitivity to its lower boundary conditions and on their own predictability. Besides sea surface temperature (SST), soil moisture (SM) may be an additional source of climate predictability particularly during boreal summer in the mid-latitudes. In this work, we investigate the role of SM initial conditions on near-surface climate predictability during ten boreal summer seasons using three complementary ensembles of AMIP-type simulations performed with the Arpège-Climat atmospheric general circulation model. First we have conducted an assessment of the SM predictability itself through a comparison of simple empirical SM models with Arpège-Climat. The statistical and dynamical models reveal similar SM prediction skill patterns but the Arpège-Climat reaches higher scores suggesting that it is at least suitable to explore the influence of SM initialization on atmospheric predictability. Then we evaluate the relationships between SM predictability and some near surface atmospheric predictability. While SM initialization obviously improves the predictability of land surface evaporation, it has no systematic influence on the precipitation and near surface temperature skills. Nevertheless, the summer hindcast skill is clearly improved during specific years and over certain regions (mainly north America and eastern Europe in the Arpège-Climat model), when and where the SM forcing is sufficiently widespread and strong. In this case, a significant impact is also found on the occurrence of heat waves and heavy rains, whose predictability at the seasonal timescale is a crucial challenge for years to come.

Keywords Soil Moisture predictability · Land–atmosphere interactions · Boreal summer predictability · Severe climate events

S. Conil (✉)
LPAT-GEOL, Département de Physique, UFR SEN, Université des Antilles et de la Guyane, Campus de Fouillole, 97157 Pointe-à-Pitre Cedex, Guadeloupe, France
e-mail: sebastien.conil@univ-ag.fr; sebastien.conil@gmail.com

H. Douville · S. Tyteca
CNRM/GMGEC/UDC, Météo France, Toulouse, France

1 Introduction

Internal dynamical and physical processes as well as external factors induced by other climate key components both contribute to the seasonal atmospheric variability. The recognition of the atmospheric sensitivity to its initial conditions and the further development of observational and assimilation systems was a key contribution to the improvement of numerical weather prediction model. Such models are routinely used to predict atmospheric anomalies within the few next days (less than 10) even with an imperfect knowledge of the actual and future boundary conditions (mainly ocean surface and soil states). The use of ensembles provides a measure of the reliability of the forecasts but also helps to quantify the probability of occurrence of extreme events.

At monthly to seasonal time-scales, the atmosphere interactions with the other climate components such as the ocean and land surface become of primary importance. Furthermore, the deterministic prediction skill being limited, long-range forecasting aims at predicting the risks of anomalous situations and extreme events.

Seasonal climate predictability can arise in two distinct ways. Predictability of the first kind focuses on the initial value problem. To first order, it is the specification of the initial ocean state that is here crucial since it provides the main "memory" of the climate system. Yet, other factors such as variations in land hydrology are potentially relevant (Douville 2004) and their effective contribution to seasonal predictability must be now quantified. This is the subject of the present study. Predictability of the second kind focuses on the boundary value problem. How predictable changes in the atmospheric boundary conditions can provide predictive power? A common-class of second-kind predictability studies are the AMIP-type experiments where atmospheric models are forced with observed sea surface temperatures (SSTs). Similar experiments have been driven by prescribed soil moisture (SM) fields and have also suggested that land is potentially an additional source of climate predictability at monthly to seasonal timescales (Conil et al. 2007).

Nevertheless, the effective contribution of boundary conditions to seasonal predictability relies not only on the atmospheric sensitivity to the boundary forcings, but also on the predictability of the boundary forcings themselves. The development of seasonal climate forecasting system has been nurtured by the increasing knowledge of the El Niño Southern Oscillation (ENSO) and its remote impacts on inter-annual climate variability through the atmospheric teleconnections. While the climate predictability of some key tropical and extratropical regions has been linked to ENSO, in many other regions and/or when the ENSO forcing is weak, climate predictability seems to be low and it is important to look for other potential sources of relevant climate memory. A striking example is the long hot and dry summer experienced in European countries in 2003 with dramatic socio-economical consequences. The predictability of this recent European heat wave (and of other similar events) is still unclear and discussed (Rodwell and Doblas-Reyes 2006; Ferranti and Viterbo 2006; Black and Sutton 2007; Della-Marta et al. 2007). Given the major impacts of such events, their poor prediction by the current seasonal forecasting systems (Rodwell and Doblas-Reyes 2006), the apparent relationship between winter precipitation and summer heatwaves (Vautard et al. 2007) and the fact that the anthropogenic climate change may favour their occurrence (Schar et al. 2004; Seneviratne et al. 2006a, b; Gershunov and Douville 2007), a robust assessment of the long-range predictability associated with land memory seems urgently needed.

SM anomalies can contribute to seasonal climate predictability only if they are themselves predictable and if the atmospheric response to the SM forcing is strong enough (compared to SST-forced and internal variability). Koster and Suarez (2001) have shown that SM memory is controlled by the seasonality of the atmospheric state, the dependence of evaporation on SM, the variation of runoff with SM and by the coupling between SM and the atmosphere. SM memory is short within the Tropics, increases with latitude and varies with season but is relatively longer in arid regions (Manabe and Delworth 1990; Wu and Dickinson 2004). Furthermore, SM memory can be much longer in dry conditions than in wet cases in warm climates. In the Kanamitsu et al. (2003) experiments, SM predictability was found to be high in the arid/semiarid regions and smaller over rainy temperate zones and tropical monsoon regions. Previous studies have shown that SM persistence could be translated to atmospheric persistence in a small number of regions (Schlosser and Milly 2002). Koster et al. (2000, 2002) have suggested that atmospheric variability in transition zones between dry and humid areas may be particularly affected by land surface forcings. Using a statistical approach, Alfaro et al. (2006) showed significant contributions from antecedent soil moisture conditions to seasonal summer temperature predictability, including the frequency of extreme daily temperature. They specifically showed that this predictability is due to the influence of soil moisture on maximum rather than minimum temperatures. Gershunov and Douville (2007) explicitly identified the central and eastern US as a region with strong soil moisture–temperature coupling, a region where winter and spring precipitation anomalies pre-condition the likelihood of extreme summer heat. Recently, the follow-up GLACE inter-comparison project (Koster et al. 2004a, b) has investigated the land–atmosphere feedbacks and their contributions to intraseasonal atmospheric predictability in a perfect model framework. While the same "hot spots" of strong land–atmosphere interaction were identified, the GLACE study also revealed a large range of coupling strengths in the participating models.

Other previous studies have been devoted to the impacts of land surface initialization on seasonal forecast skill. Beljaars et al. (1996) highlighted the contribution of SM to the anomalous wet 1993 summer over the USA. Fennessy and Shukla (1999) suggested that the influence of realistic initial SM was mainly local and dependent on several factors including the area extent and magnitude of the initial SM anomaly, its persistence but also the mean climate of the region. While they emphasized the mismatch between observed and simulated SM, Zhang and Frederiksen (2003) indicated that realistic relative SM anomalies may contain a useful information for improving the simulated climate variability mostly locally.

In most sensitivity studies, realistic initialization of SM; however, led to mixed results concerning the skill of precipitation or temperature forecast as in Koster and Suarez (2003b) or Dirmeyer (2003). Based on observations and modelling results, Gershunov and Douville (2007) suggested that an abatement of long-standing wet conditions in the central and eastern US will lead to increased heat wave activity over that region.

The role of soil moisture in triggering atmospheric predictability at the monthly to seasonal timescale has been investigated for many years at CNRM. Using a 2-year SM climatology derived from the first phase of the Global Soil Wetness Project (GSWP, Entin et al. 1999), Douville and Chauvin (2000) showed that perfectly anticipated SM boundary conditions could strongly increase the predictability of the 1987 versus 1988 mid-latitude northern hemisphere summer climate anomalies in the Arpège-Climat atmospheric GCM. When only initialized from GSWP at the end of May; however, SM had a much weaker impact thereby suggesting that springtime SM anomalies are not necessarily sufficiently persistent to be a source of climate predictability at the seasonal timescale. Douville (2003) assessed the influence of interactive versus climatological SM boundary conditions on the variability and predictability of boreal summer climate. SM variability was shown to have a significant impact on the near-surface atmospheric variability in keeping with the results of Fennessy and Shukla (1999). The study also revealed that the design of the sensitivity experiments (relaxed versus prescribed fast and/or slow land surface variables) could affect the atmospheric response to the imposed land surface forcing. Douville (2004) carried on the assessment of SM role in climate variability and contrasted the influence of climatological versus reanalysed SM initial conditions, suggesting again the limited global impact of SM initialization but its significant contribution to the mid-latitude summer potential predictability in those years when widespread and large SM anomalies are found at the end of the spring season.

This conclusion was recently confirmed by Conil et al. (2007) who revisited the experimental design of Douville and Chauvin (2000), but using the 10-year SM climatology derived from GSWP-2 over the 1986–1995 period (Guo and Dirmeyer 2006). A combination of realistic SST and SM forcings has been used to highlight their respective contributions to climate predictability in different ensemble hindcast simulations of 1986–1995. While in the Tropics SST anomalies clearly maintain a potential predictability throughout the annual cycle, in the mid-latitudes the SST forced variability is only dominant in winter and SM plays a leading role in summer. We have shown that the prescribed realistic SM is essential to maintain near surface climate anomalies, at the same time reproducible (with a good signal to noise ratio) and effectively predictable (with a good hindcast score). Focusing on the north American and European regions, we have demonstrated the role of SM in the generation and maintenance of monthly to seasonal climate signals, particularly on their spatial structure, their time evolution and their amplitude.

In this companion paper, we address two main limitations of the study by Conil et al. (2007). First, a new set of experiments has been designed to assess the role of realistic initial SM conditions on the boreal summer predictability. A realistic initialization of SM and a proper representation of the land–atmosphere feedbacks seem necessary to improve state-of-the-art dynamical seasonal predictions, but will be actually efficient only in the areas where SM anomalies are themselves predictable at the monthly to seasonal timescale (since remote effects of SM are probably much more limited than SST teleconnections). Our previous study has revealed that ''perfect'' SM boundary conditions can in theory contribute to near-surface climate predictability at the seasonal timescale. Here, we investigate the practical contribution of as realistic as possible SM initialization. Secondly, we go beyond the simple analysis of seasonal means in assessing the atmospheric predictability, looking also at daily model outputs and giving a special attention to severe climate events (heatwaves, droughts, heavy precipitation). In practice, forecasting such "unusual" events is probably more relevant than the prediction of seasonal anomalies. Surprisingly, few studies have explored this possibility and it is here proposed to provide a preliminary assessment of the "skill" (using prescribed SST) of the Arpège-Climat AGCM in this respect and of its sensitivity to SM boundary/initial conditions.

Section 2 is dedicated to the presentation of the experiments and to a brief evaluation of the SM memory itself. The global hindcast skill of near-surface climate is evaluated and discussed in Sect. 3. The temperature and precipitation severe events prediction are presented in Sect. 4. Section 5 focuses on two case studies of the boreal summer mi-latitudes. A summary and discussion of the results is given in Sect. 6.

2 Ensemble simulations and soil moisture persistence

The Arpège-Climat AGCM has first been used to perform global seasonal (4 months) summer (JJAS) hindcasts in which SM is either fully interactive or relaxed toward the monthly GSWP-2 analysis (Conil et al. 2007). GSWP-2 has offered us the opportunity to produce a global land surface reanalysis over the 10-year period from 1986 to 1995, by driving the ISBA land surface model with a state-of-the-art $1° \times 1°$ atmospheric forcing. The resulting SM climatology is therefore fully consistent with the Arpège-Climat model.

Three AMIP type-experiments driven by observed monthly SSTs and composed of ten members have been performed over the 10 boreal summer seasons over the period 1986–1995.

In the first ensemble FF, SM is fully interactive (control experiment). In the second ensemble GG, SM is relaxed toward GSWP-2 (as in Conil et al. 2007). In the last ensemble GF, SM is fully interactive as in FF, but is initialized from the GG outputs at the end of May. None of these experiments deals with the impact of atmospheric initialization, which; however, could be important during the first month of the integration.

In the FF ensemble, the Arpège model has been run continuously with interactive SM from September 1985 to the end of 1995 using initial SM and atmospheric conditions taken from ten September days (first of the month for ten consecutive years) of a previous AMIP simulation. It is basically a "random" initialization and the first 4 months of each member are discarded since the results are analysed over the 1986–1995 period. For the GG ensemble, the atmospheric initial conditions are the same, but SM is nudged towards the GSWP-2 land surface reanalysis obtained with the ISBA land surface model. Finally, in the GF experiment, the SM and atmospheric initial conditions are taken on June 1st from each member of GG, but the nudging is then removed. All ensembles are driven by observed monthly mean SST boundary conditions.A global evaluation of the FF and GG experiments is available in a companion study by Conil et al. (2007).

Experiment's name	SST	SM
FF	Observed (AMIP)	Fully interactive
GG	Observed (AMIP)	Relaxed toward GSWP-2
GF	Observed (AMIP)	Initialized by GSWP-2 and fully interactive

As emphasized by Dirmeyer (2005), the potential benefit of SM initialization can be lost very rapidly if there is a significant drift in the coupled land–atmosphere model. For this reason, one might be interested in evaluating the predictability of SM itself and in comparing the skill of the coupled land–atmosphere model with simple statistical persistence model. Similar persistence model were used to forecast SST in the early dynamical seasonal prediction systems (Colman and Davey 2003). SM anomalies have shown a certain amount of persistence in the observational datasets as well as in numerical simulations, depending mainly on the geographic location and on the season. Observational as well as simulated datasets consistently indicate that SM variations in time correspond to a red noise process. Delworth and Manabe (1988) introduced a first order Markov process driven by chaotic/random precipitation to describe SM memory. Koster and Suarez (2001) addressed the two main limitations of the Markowian framework (the meteorological forcing is stationnary and has no persistence) and introduced a more complete framework, taking into account the seasonality of the forcing and its persistence. SM memory in the GLACE simulations has been evaluated in this perspective by Seneviratne et al. (2006a).

Here simple statistical model are used to predict SM and to compare with the dynamical SM prediction made by the ISBA-Arpège coupled model. Three "persistence" models of increasing complexities were introduced. First a crude persistence model is used in which the initial SM anomalies in May are kept constant troughout the summer (JJAS). The second model is a damped persistence model (consistent with an AR1-process but without any stochastic forcing) varying throughout the annual cycle $SM(t+1) = \alpha_1 {*} SM(t)$. The parameter α_1 is the observed lag-1 autocorrelation [correlation between $SM(t+1)$ and $SM(t)$] and is estimated for each month of the summer season, June to September. The third model is another damped persistence model consistent with an AR-2 process (without any stochastic forcing) changing along the annual cycle: $SM(t+1) = \beta_1 {*} SM(t) + \beta_2 {*} SM(t-1)$. The parameters β are derived from the lag-1 and lag-2 SM autocorrelation using the Yule–Walker equations (Von Storch and Zwiers 1999). These parameters are fitted on a month by month basis as the autocorrelation coefficients are season dependent. Finally these two AR-1 type and AR-2 type models have been fitted on the ISBA and Multi-Model GSWP-2 SM anomalies to test their robustness.

Unless specified otherwise, the GSWP-2 analysis refers to the land surface simulation produced by the Arpège-Climat configuration of the ISBA land surface model, in contrast with the multi-model GSWP-2 reanalysis which refers to the ensemble mean climatology derived from all participating land surface models (including a three-layer ISBA hydrology not yet used in the Arpège-Climat AGCM).

May (and April) SM anomalies for each year (1986–1995) of the GSWP-2 analysis have been used to predict SM for the following summer, from June to September. Each model skill has been also evaluated against the GSWP-2 climatology. Figures 1 and 2 compare the skill score in terms of anomaly correlation coefficient (ACC) and root mean square error (RMSE) between each grid point predicted and analysed SM anomalies. The patterns are very similar, showing regions where SM can be predicted by statistical or dynamical models and regions where the prediction potential is weak. The distribution of skill is very close to the SM 2-months lagged correlation shown in Conil et al. (2007). In contrast with equatorial and monsoon regions, the subtropics show high level of predictability and of SM persistence. The mid-latitudes continental regions show a mix of high and low skill score

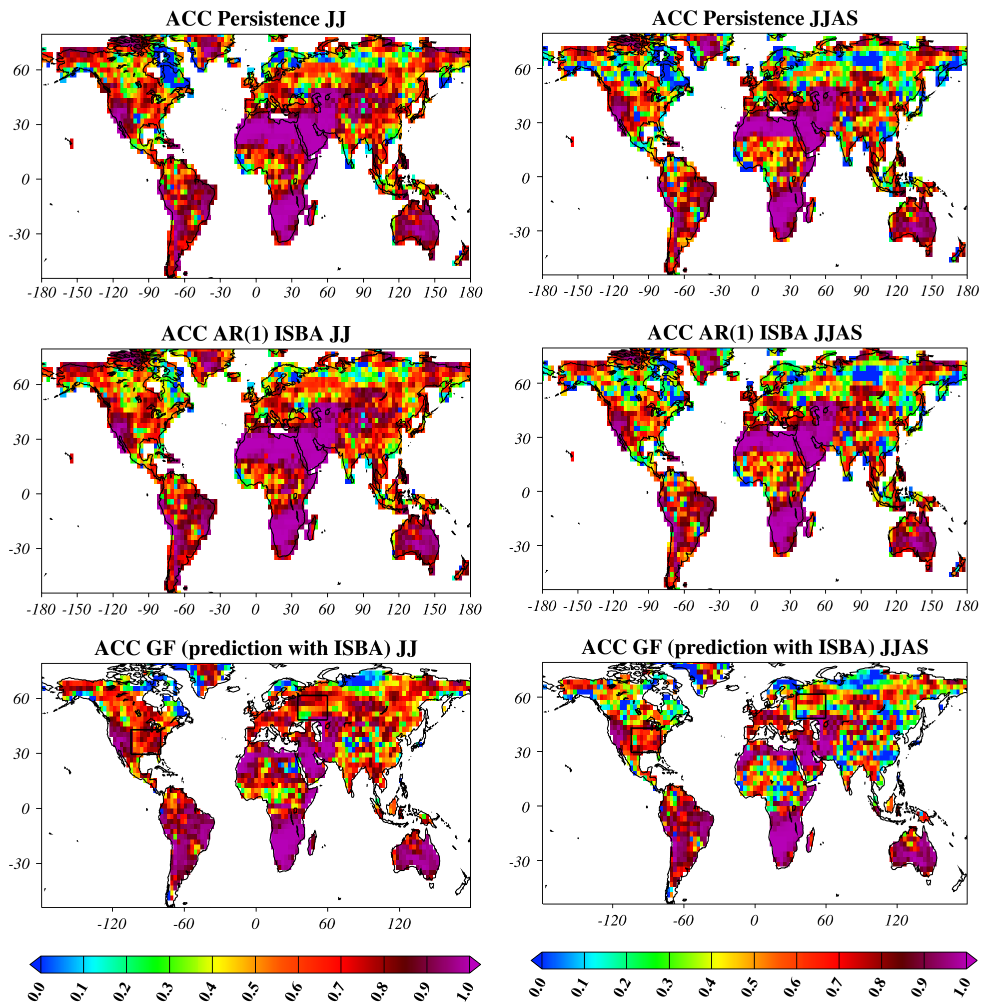

Fig. 1 Spatial maps of anomaly correlation coefficient (ACC) between monthly predicted and Isba-GSWP2 reanalysed Soil Moisture for the early season, June July (*JJ, left panels*) and for the summer season JJAS (*right panels*), for the persistence model (*upper panels*), the AR1-Isba model (*middle*) and the Isba LSM (*lower panels*). The *black boxes* in the lower panels are showing the north American (34N–49N/105W–80W) and eastern European (55N–70N/35E–60E) regions used later in the analysis

patches. This overall pattern of SM predictability and SM persistence is very close to the one drawn by Seneviratne et al. (2006a) based on an ensemble of perfect model simulations, in the GLACE framework. The equatorial and monsoonal regions experience a large increase in their mean SM from May to August, following the rapid increase of the rainfall rate during the onset of the monsoon. But in the northern mid-latitudes, SM decreases mostly because of the large potential evapotranspiration and net surface radiation during the summer. These opposite SM seasonal evolutions may partly explain why SM predictability is lower in the rainy equatorial and monsoon regions and higher in some continental mid-latitudes. Soil depth through its influence on the water holding capacity also plays a critical role in the SM predictability. Seneviratne et al. (2006a) have shown, in the GLACE multi-model ensemble, that while SM memory intermodel differences are as large as regional differences, water holding capacity is the most important factor for such intermodel differences.

The statistical and dynamical predictions are giving similar pattern of SM skill, but the dynamical coupled land–atmosphere model is globally showing the best results. For indication, Fig. 3 shows for each grid points the best model in terms of ACC and RMSE for June and the overall JJAS season. We have to caution that these ACC and RMSE scores were computed with only ten summers and thus the differences between the statistical and dynamical models may not be significant on a grid point by grid point basis. Given the pattern shown in Fig. 3 it seems; however, obvious that, at least for the first 2 months (June and July), the ISBA-Arpège coupled model outperforms the statistical models. We must recognize that these SM statistical models are relatively crude and could be improved, for example by taking into account the large-scale pattern of SM variability (Colman and Davey 2003; Entin et al. 2000) but our results suggest that the ability of the Arpège-Climat model to predict SM anomalies at the monthly to seasonal timescale is at least sufficient to explore the influence of SM initialization on atmospheric predictability.

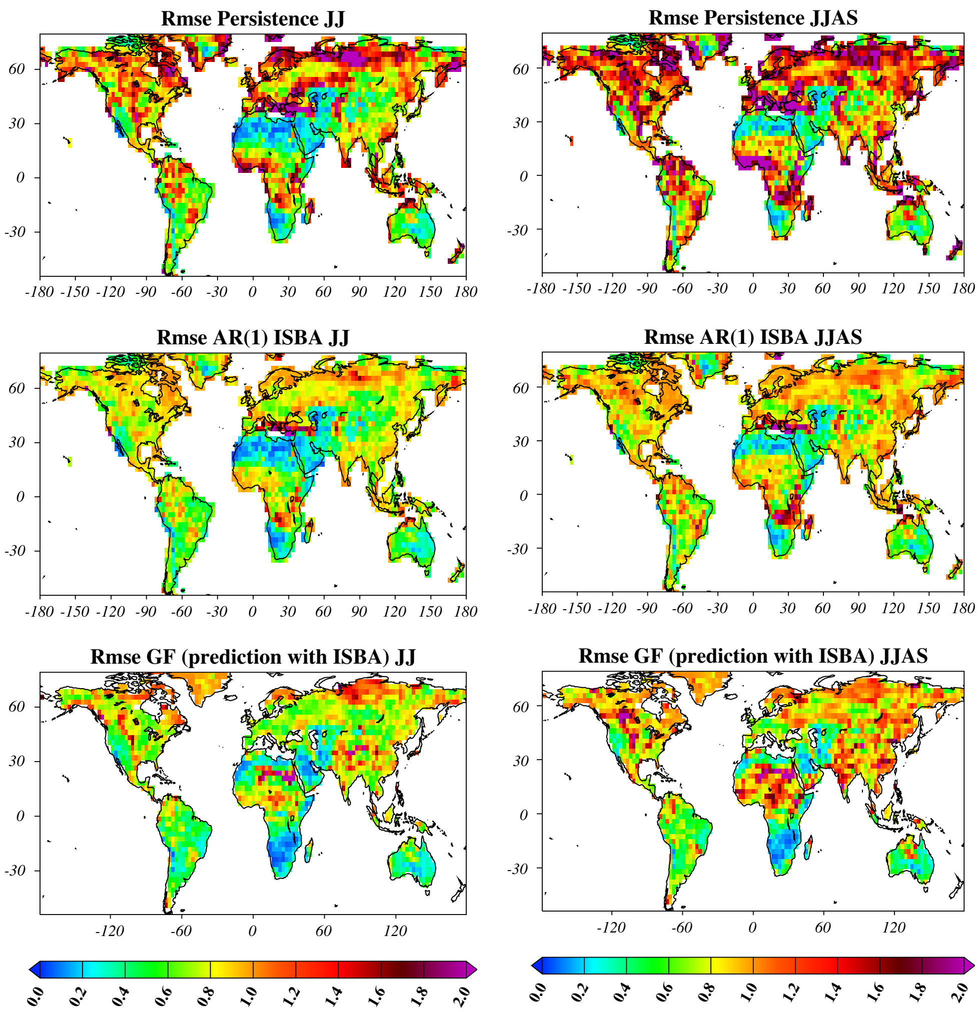

Fig. 2 Spatial maps of normalized root mean squared error (*RMSE*) between monthly predicted and Isba-GSWP2 reanalysed Soil Moisture for the early season, June July (*JJ, left panels*) and the summer season JJAS (*right panels*) for the persistence model (*upper panels*), the AR1-Isba model (*middle*) and the Isba LSM (*lower panels*)

Figure 4 shows the evolution of the performance of each model with the lead time. As mentioned, the ISBA-Arpège model gives the best scores in all months but its performance is higher at the beginning and decreases as the lead-time increases. When considering the entire boreal summer season, it shows the best skill score in almost 40% of the land grid points.

The spatial averages of the ACC and RMSE for two different regions, north America (34N–49N/105W–80W) and eastern Europe (55N–70N/35E–60E), where there is some predictability (excluding desert areas) at least during the first month are shown in Fig. 5. Over the two regions characterized by a drying of the land surface during the boreal summer, the skill of each model decreases with the increase of the lead time. Each model (statistical and dynamical) shows a very similar level of skill but the ISBA-Arpège coupled model seems to be the best model (even if the correlation coefficient differences might not be significantly different on a one by one basis). Over the entire season (considering monthly means or seasonal means) the skill level is higher in the tropics (not shown) where the SM decreases during the JJAS season and is not affected by poorly predictable precipitation variations.

3 Evaporation, 2 m temperature and precipitation global skill

In the following the emphasis will be put on the relationships between the SM anomalies and the atmospheric state, trying to relate the SM predictability to some atmospheric/climate predictability. First we will focus on three key variables: evaporation, near surface temperature and precipitation over land. Figure 6 shows the global distribution of the ensemble mean ACC computed between the predicted and the analysed monthly anomalies over the ten JJAS seasons in the FF, GF and GG experiments. In the following, simulated evaporation, temperature and precipitation are compared to "observational estimates", the GSWP-2 evaporation, CRU temperature and the GPCP precipitation.

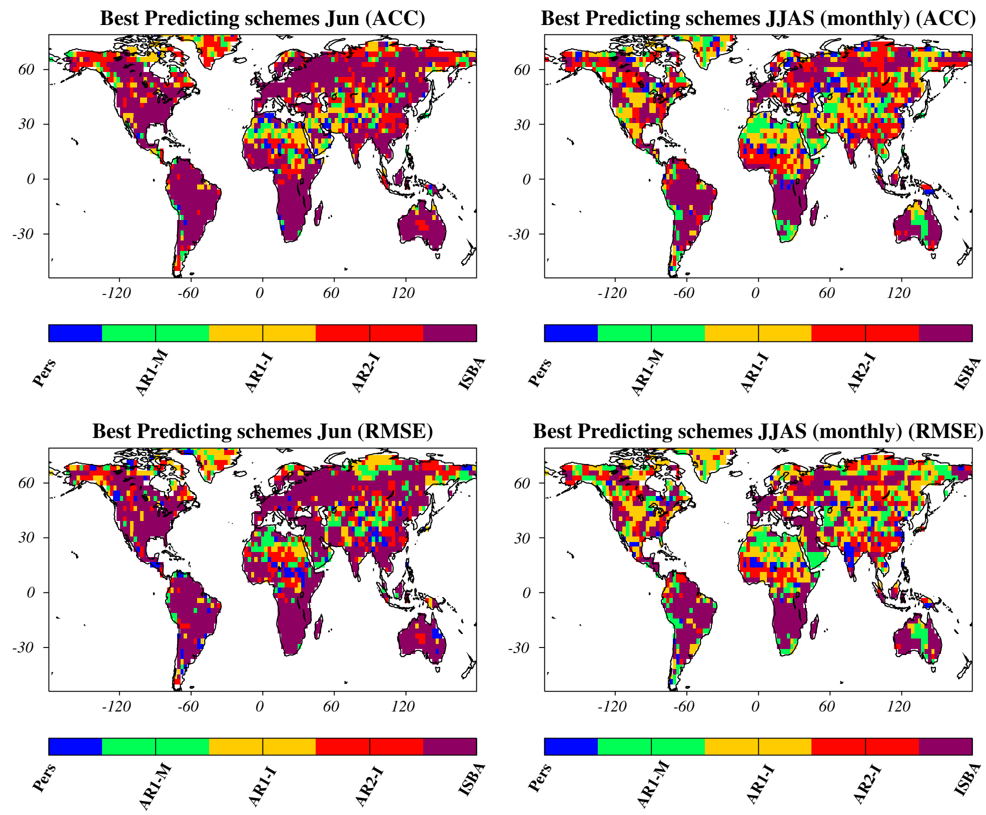

Fig. 3 Spatial maps of the best predicting schemes evaluated at each grid point for the first month June (*left panel*) and the overall season JJAS (*right panel*). For each grid point, the best predicting scheme is the SM prediction model having the higher ACC (*upper panels*) and lower RMSE (*lower panels*). In the legend, *Pers* stands for the Persistence model, *AR1-M* for the AR1 model fitted on the multi-model GSWP2 SM anomalies, *AR1-I* for the AR1model fitted on the Isba GSWP2 SM anomalies, *AR2-I* for the AR2model fitted on the Isba GSWP2 SM anomalies, *ISBA* for the SM anomalies predicted by the ISBA-Arpege coupled model (GF ensemble mean)

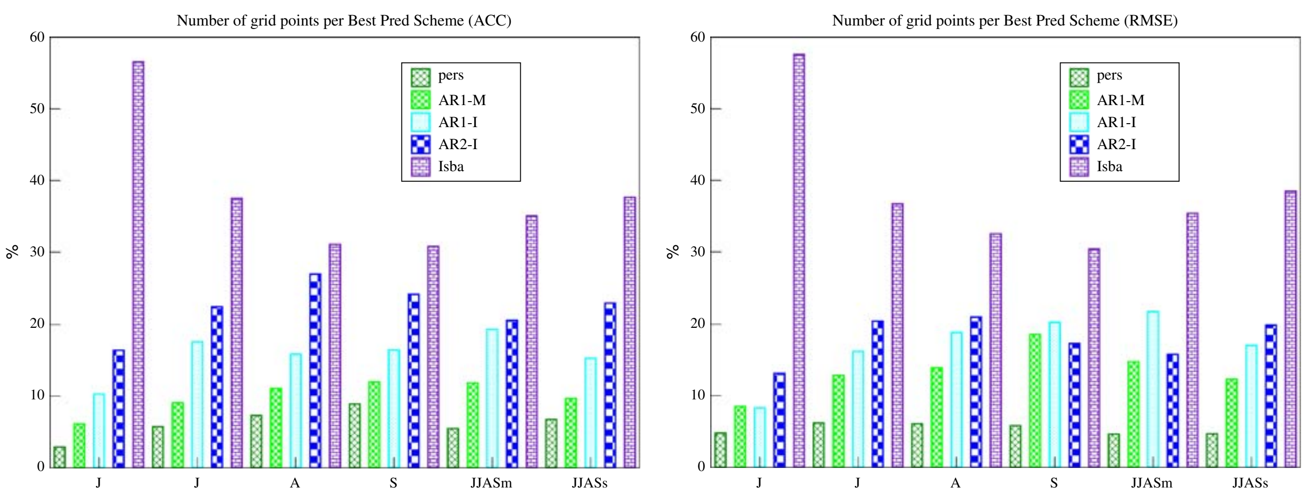

Fig. 4 Number of grid points where each SM prediction model appears to be the best predicting scheme (Fraction of the total land grid points). The fraction of points where each model is the best is evaluated for each month June, July, August and September, showing the evolution with the lead-time but also for the overall season using monthly means (*JJASm*) and seasonal means (*JJASs*). The best prediction model has been estimated using the ACC (maximum ACC, *left*) and the RMSE (minimum RMSE, *right*). In the legend, *Pers* stands for the Persistence model, *AR1-M* for the AR1 model fitted on the multi-model GSWP2 SM anomalies, *AR1-I* for the AR1 model fitted on the Isba GSWP2 SM anomalies, *AR2-I* for the AR2 model fitted on the Isba GSWP2 SM anomalies, *ISBA* for the SM anomalies predicted by the ISBA-Arpege coupled model (GF ensemble mean)

The hindcast of evaporation clearly benefit from the realistic initialization over most of the continental areas. In some tropical regions and in northern midlatitudes, the SST conditions are able to maintain well-correlated anomalies but the SM initialization still gives a further improvement of the average skill. In the monsoon regions (in central America, western Africa, India and east Asia) the onset of the monsoons and the following subsequent rainfall, with

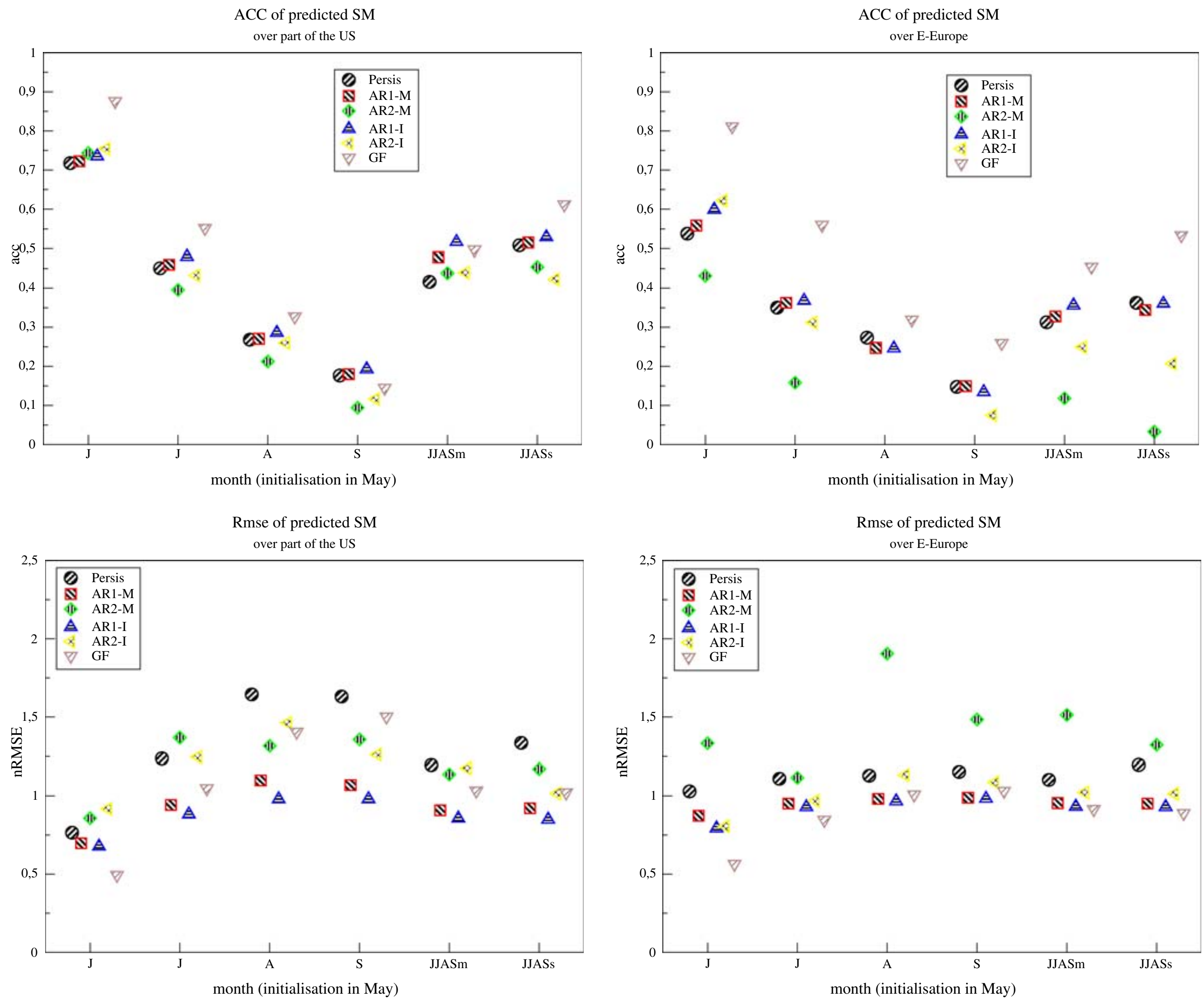

Fig. 5 Average ACC (*upper panels*) and normalized RMSE (*lower panels*) of each SM prediction model over 2 different regions: North American (*left panels*) and Eastern Europe (*right panels*). For each region, the average skill is shown for each month, June, July, August and September, showing the evolution with the lead-time but also for the overall season using monthly means (*JJASm*) and seasonal means (*JJASs*). In the legend, *Pers* stands for the Persistence model, *AR1-M* for the AR1 model fitted on the multi-model GSWP2 SM anomalies, *AR2-M* for the AR2 model fitted on the Multi-Model GSWP2 SM anomalies, *AR1-I* for the AR1 model fitted on the Isba GSWP2 SM anomalies, *AR2-I* for the AR2 model fitted on the Isba GSWP2 SM anomalies, *GF* for the GF ensemble mean SM anomalies predicted by the Arpege-Climat land–atmosphere coupled model

large spatio-temporal variability and a poor predictability, lead to an increase of the average SM associated with a lost of SM memory and a low skill in SM and evaporation.

While major differences are seen between the ensemble mean SM and evaporation summer hindcast skills, the near surface temperature and precipitations summer skills in GF and FF are much closer. It seems to be an indication that SST boundary conditions have a much stronger influence than SM initialization on the evolution of temperature and precipitation. It could also be caused by the biased modelled precipitation that forces SM to drift from its initial realistic state toward an unrealistic state close to "FF". Not surprisingly, the hindcast skill of near surface temperature is much higher than the skill of precipitation. The intrinsic predictability of temperature exceeds that of precipitation in magnitude and in spatial extent as also revealed by our previous study (Conil et al. 2007) and by Koster et al. (2004a, b) on a sub-seasonal timescale.

This first assessment of the contribution of SM initial condition to the seasonal forecasting skill is limited by the short period of the GSWP-2 analysis of SM, implying that only ten summers can be simulated. Nevertheless the temporal ACC's of SM, evaporation, near surface temperature and precipitation presented here give a first

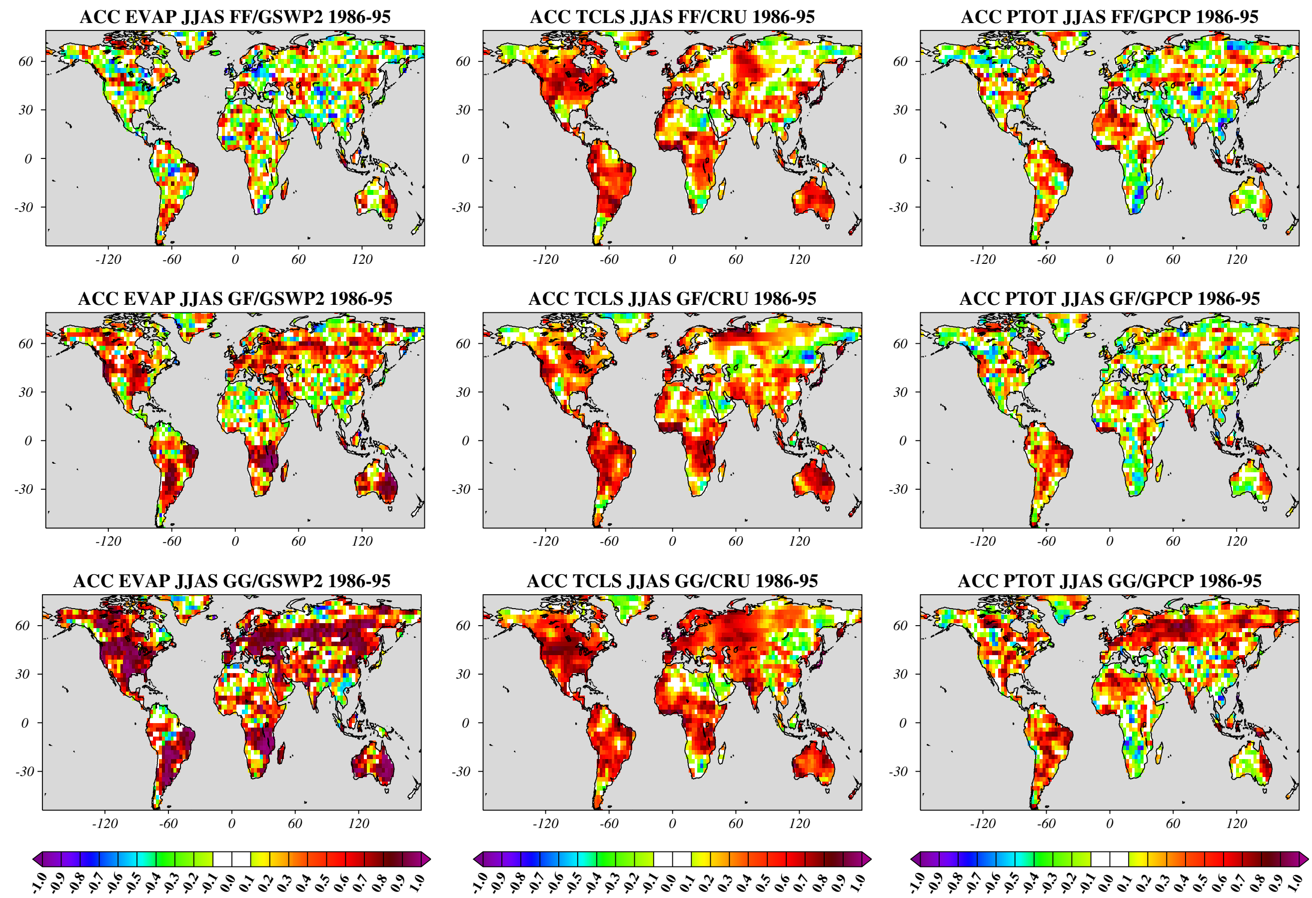

Fig. 6 Summer (*JJAS*) skills (correlation coefficient of the ensemble mean anomalies with the CRU 2 m temperature and GPCP precipitation) of the ensemble mean evaporation (*left*), 2 m temperature (*middle*) and precipitation (*right panels*) in the two ensembles FF (*upper panels*), GF (*middle panels*) and GG (*lower panels*)

indication on the skill of the hindcast systems to reproduce climate anomalies. It is an integrated estimation of the skill made on a grid point by grid point basis, in each of the hindcast ensembles.

We have also looked at the simulated spatial patterns of the anomalies and assess their accuracy as a function of the year considered. We believe that SM initialization might be useful and might improve the summer hindcast during some particular year (say for example when SST forcings are weak) but might have no or only weak influence on the summer climate during other seasons. Spatial ACC (SACC) of evaporation, near surface temperature and precipitation have been computed for each ensemble members and for the ensemble mean over different regions (not shown).

When considering the evaporation, the GF average SACC stands between the GG SACC (in which realistic SM are “prescribed” all along the simulations) and the FF average SACC. On average the FF hindcasts show almost no skill while the GG hindcasts reach a significant skill level (0.68). The GF hindcast still benefit from the realistic SM initial conditions and reach on average 0.37. It is interesting to notice that the spread level is the same in the FF and GF experiments and is about twice the spread in GG. Having a fully interactive SM thus strongly increases the internal variability of evaporation (by a factor of 2 for this particular metric).

Looking at the summer to summer variability, the GG evaporation SACC for the NH extratropics and the north American continent are quite stable but the GF and FF SACC’s are much more variable. Over the north American region, while during some years like 1988, 1993 and 1995, the SM initialization helps the GF ensemble mean SACC to reach high level (almost as high as GG), in some others the skill is much lower (1994 for example). Now considering near surface temperature and precipitation SACC’s, the GG results outperform the FF and GF results, which are nearly the same. Furthermore the average spread level is very similar in all experiments. The realistic SM initialization thus has a weaker effect on near-surface temperature and precipitation than on evaporation. The individual summer SACCs are also varying from year to year. It should be noticed that a low SACC might reveal either a weak forced signal, implying a weak predictability, or a strong but poor response of the Arpège-Climat model.

While the FF and GG performance are not month-dependent, the evolution of GF SACC of soil moisture and precipitation with the lead time (in months, not shown) reveals that the skills decrease with the lead-time. The GF simulations of SM anomalies outperform the FF simulations in each month even if its score is much lower at the end of the season. Considering evaporation, the GF scores reach the GG level in the first month, June, but then decrease to be around the FF score between August and September. For temperature and precipitation, the three experiments SACC's are close to each other and are not lead-time dependent. While the GF experiment clearly outperforms the FF experiment for soil moisture and evaporation, there's no significant difference between the two when one considers temperature and precipitation.

4 Temperature and precipitation severe events

SM initial and boundary conditions help to reproduce realistic mean summer near-surface climate anomalies as shown in the previous section. While mean temperature and precipitation summer anomalies are certainly of interest, extreme hot/dry events may have disastrous socio-economical consequences (like the 1988 US drought and the 2003 European heat waves) and could be more relevant than mean climate for potential end-users of seasonal forecasts. In this section, we assess the influence of SM conditions on the forecasting skill of simple "severe" temperature and precipitation indices. Dealing with extremes or severe events in climate simulations implies making assumptions regarding what is termed "severe". Extremes such as the annual maximum daily precipitation or summer maximum daily maximum temperature (Tmax) have been studied with different extreme value distributions. In the climate framework the extreme indices used have a much broader context. In practice, it is as important but much easier to consider less extreme events (events that are located far from the mean climate but more likely to occur) that may thus be qualified as severe events. The STARDEX project dedicated to the evaluation of downscaling methodologies for extremes and the CLIVAR expert team for climate change detection monitoring and indices (ETCCDMI) have coordinated effort and research for the development of a suite of climate extreme indices derived from daily temperature and precipitation data, such as percentiles, growing season length and wet/dry day duration.

In the present work, we use some of these indices that are related to summer hot and/or dry events. For each summer season we have analysed a number of indices including: maximum Tmax, number of hot days (Tmax anomalies above 3 or 5° fixed and the 90th percentile thresholds, heat wave duration (maximum number of consecutive hot days using the three different thresholds, in intervals of at least 3 or 6 days), number of rainy days (days when precipitation >1 mm/day), number of heavy rain days (days when precipitation >10 mm/day), dry spell length (max number of consecutive dry days). These severe indices were computed from daily values and anomalies of near-surface temperature and precipitation. The anomalies have been defined with respect to a smooth annual cycle computed over the summers 1986–1995. We do not present any percentile based indices because the estimation of long-term 10th or 90th percentile would not be necessarily robust given the only 10-year period of the simulation ensembles.

In this section, we present the ability of the model to reproduce some severe indices and the influence of SM conditions on model skill. To assess model skill we have used daily near-surface maximum temperature from the quasi-global gridded dataset covering the 1946–2000 period and compiled by the Met Office Hadley Centre for Climate Prediction and Research (Caesar et al. 2006). To evaluate the precipitation indices we have made use of two complementary datasets, the first being the GTS gauge-based analyses of daily precipitation over global land areas interpolated within the ISLSCP Initiative II framework. The second is a subset of over ten thousand available station records of daily rainfall distributed across Canada (Vincent and Gullett 1999), USA (Groisman et al. 2004) and Mexico (Miranda 2003) all quality controlled and homogenized at the National Climatic Data Center (NCDC). We have computed the severe indices with the same methodologies in these three datasets.

Figure 7 shows the global distribution of the ensemble mean ACC computed between the predicted and the analysed monthly anomalies of number of hot days, heat wave duration, and number of rainy days over the ten JJAS seasons in the FF, GF and GG experiments. First of all, we have to notice that our definition of hot days, e.g. days where Tmax anomalies is at least 3° above the climatology, implies that there are very few hot days in the tropics, where day-to-day temperature variability is lower. In general, there's a very similar level of skill in the FF and GF experiments but much higher skill scores in the GG experiment, looking both at the temperature and precipitation severe indices. The SM realistic boundary conditions thus also help to generate realistic level of severe events at least over the mid-latitude continents. But realistic initial SM conditions are not enough to improve the simulations

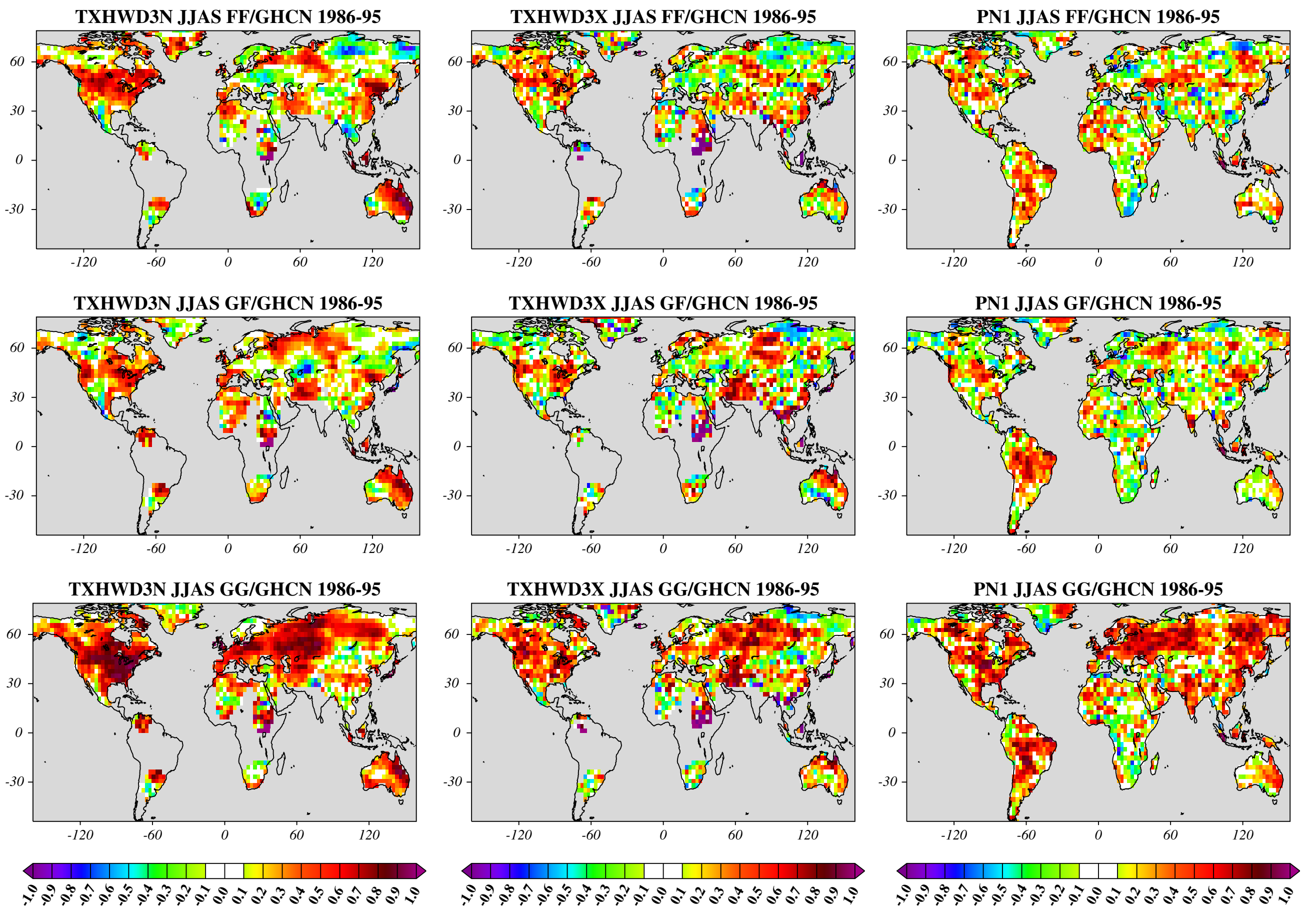

Fig. 7 Summer (*JJAS*) skills (correlation coefficient of the ensemble mean anomalies with the HadGHCN daily temperatures and with the GTS daily precipitation) of the ensemble mean number of hot days (*left panels*), longest heat wave (*center*) and number of rainy day (*right panels*) in the three ensembles FF (*upper panels*), GF (*middle*) and GG (*lower panels*)

of temperature and rainfall severe events. The hindcast skill score of the dry spell length is much lower than that of the number of rainy days or that of heat wave duration. Further work will be required to explain this difference and understand if it is because heat wave and dry spell are maintained by different processes (and that may be related to poor predictability of the processes responsible for precipitation) or if it is due to the intrinsic limitations of our study or to statistical artefact.

We have shown that realistic SM initial and boundary conditions may improve climate simulations and seasonal forecasting, during boreal summer. Over the ten summers analysed previously, the influence of land-surface conditions seems to be dependent of the climate regime, varies from one region to another, but may also varies from one summer to another. It is therefore a major issue to identify regions and times where SM may play a role in seasonal climate forecasting. It is beyond the scope of this paper to implement a comprehensive and original method to distinguish situations where and when SM conditions are critical to seasonal climate forecasting. In the next section, we simply illustrate that land surface conditions (as exemplified here with SM) may influence climate at monthly to seasonal time-scales under certain conditions. We will now focus on the European and north American regions where evidence of some skill has been given previously.

5 European and North American summers

Figures 8 and 9 show the 10 year-evolution of regional mean anomalies of evaporation, temperature and precipitation and number of hot days, heat wave duration and number of rainy days in the central US (34N–49N/105W–80W) and north eastern Europe (55N–70N/35E–60E) regions. The ensemble mean anomalies are marked by a symbol. The error bars surrounding the symbol are showing the spread of the ensemble (one standard deviation). Several useful statistics are added in the legend. The *a*

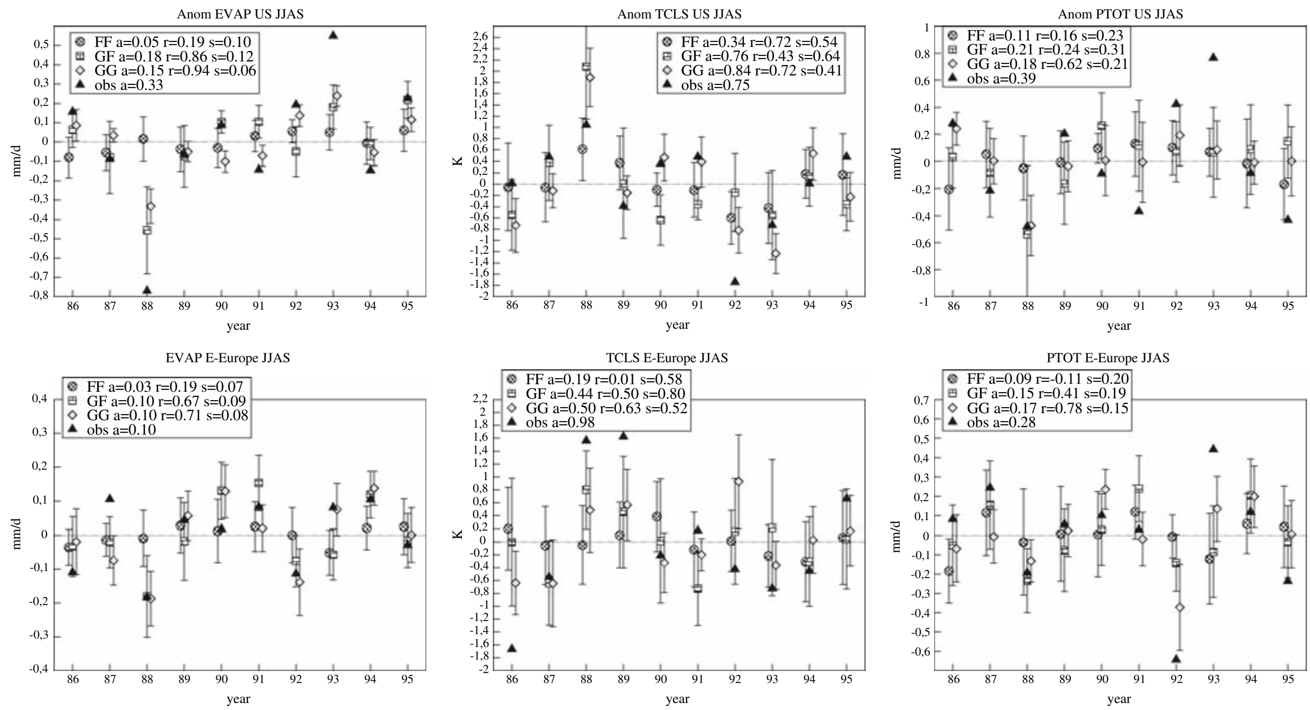

Fig. 8 Regional average of summer (*JJAS*) evaporation (*left panels*), 2 m temperature (*middle panels*) and precipitation (*right panels*) anomalies. The region covering part of the USA (Eastern Europe) (see Fig. 1 for the exact definition) is shown in the *upper (lower) panels*. The *boxes* shown in Fig. 1 are defining the two regions. The ensemble mean anomalies are plotted with a symbol and error bars represent the standard deviation of the anomalies within the ensemble. In the legend the *a* value is the standard deviation (amplitude) of the ensemble means and of the reanalysis. The *r* value is the correlation of the ensemble mean anomalies with the reanalysis. The *s* value is the average standard deviation within the ensemble. Units: mm d^{-1} and K

value gives the mean amplitude of the ensemble mean time series, the *r* value gives the correlation coefficient of the ensemble mean and the observed time series, e.g. the skill score, the *s* value is the average spread for the given ensemble, e.g. the average standard deviation within an ensemble.

From these statistics, the introduction of realistic SM initial and boundary conditions increases the magnitude of the anomalies. In the FF experiment, the ensemble mean anomalies have a much weaker magnitude than in the GF and GG experiments. The skill of evaporation is increased significantly but the change of temperature and precipitation skill is much smaller (and in the American region the FF temperature hindcast is even better than the GF one). In the north American region the SST forcing contributes to the maintenance of climate anomalies while in the eastern Europe the SST contribution is much weaker. The climate effect of SM anomalies will thus appear differently in the two regions, as it will interfere with the SST forced signal.

We now compare the spread (a qualitative estimation of the internal variability) in the control (FF), initialized (GF) and fully relaxed (GG) experiments. As expected, the spread decreases in GG given the lack of intra-ensemble SM variability. More surprisingly, it increases in GF where SM is fully interactive but each simulation has the same initial conditions. This increase cannot be explained by a systematic drift (we do not find any evidence of a systematic drift of the SM or evaporation). It is not observed in every region and it might not be significant.

From these statistics, the use of realistic SM initial conditions thus helps maintain larger ensemble mean anomalies and increases their skill compared to observations. Looking at the summer to summer climate variations we notice that the northern American and European regions have experience some years with contrasted wet/cool and dry/hot summers. During those summer large anomalies of evaporation, temperature and precipitation are noticeable, while during the others the climate anomalies are weaker.

At last, we concentrate on two contrasted situations, wet/cool and dry/hot summers, when some predictability is seen, in two mid-latitudes region, the north American continents and the European regions. Evaporation, temperature and precipitation anomalies for the summers 1992/1987 over Europe and summers 1988/1993 over north America are presented in Figs. 10 and 12. Number of hot days, heat wave duration and number of rainy days are shown in Figs. 11 and 13. Spatial correlation coefficient between ensemble mean anomalies and observed anomalies are given on each panel. Compositing dry vs. wet summers results in a rainfall deficiency, a decrease of

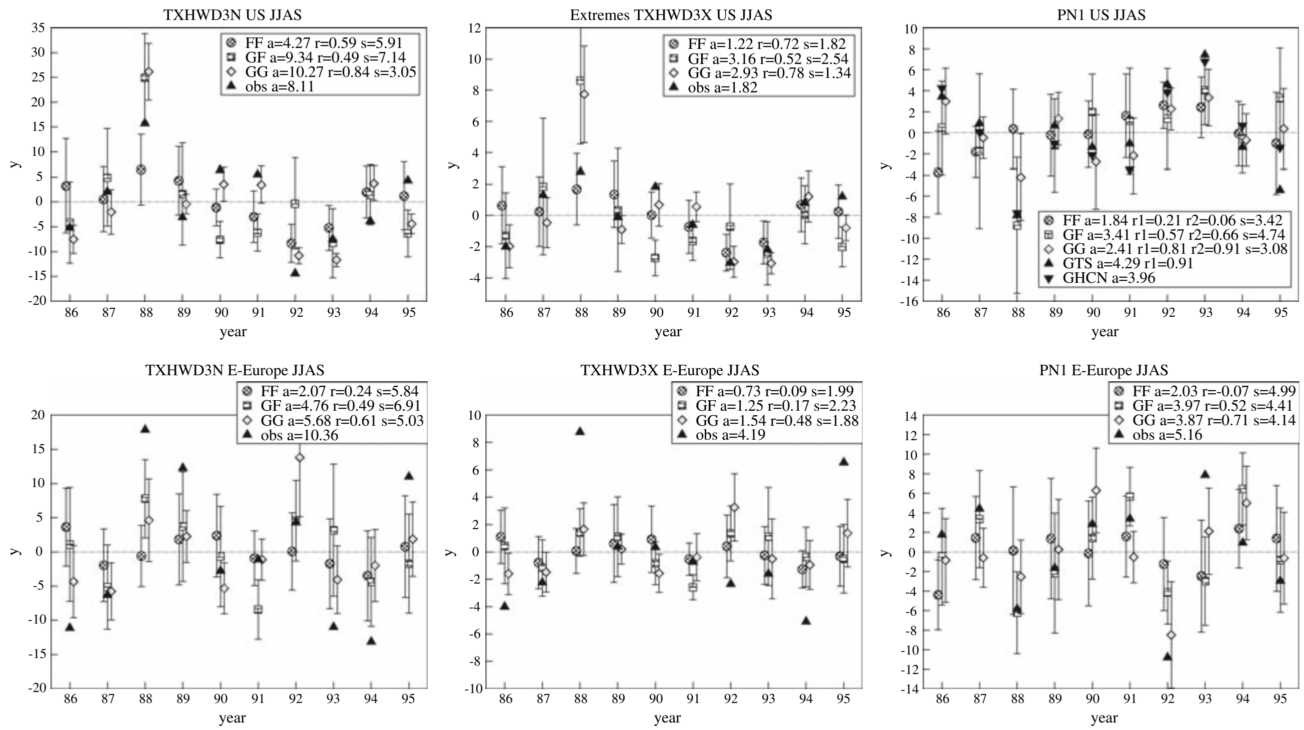

Fig. 9 Regional average of summer (*JJAS*) number of hot days (*left panels*), longest heat wave duration (*middle panels*) and number of rainy days (*right panels*) anomalies. The ensemble mean anomalies are plotted with a *symbol and error bars* represent the standard deviation of the anomalies within the ensemble. In the legend the *a* value is the standard deviation (amplitude) of the ensemble means and of the reanalysis. The *r* value is the correlation of the ensemble mean anomalies with the reanalysis. The s value is the average standard deviation within the ensemble

evaporation and an increase in near surface temperature as shown over north America and western Europe. It also results in more hot days, an extension of heat wave and fewer rainy days.

Looking at the SACC the FF ensemble mean performs reasonably well for temperature but not for evaporation and precipitation (Figs. 10, 12). The FF ensemble also shows a good SACC for the severe temperature events but not for precipitation (Figs. 11, 13). In the GG experiment, the use of realistic SM boundary conditions offered an opportunity to produce hindcasted anomalies of evaporation, temperature and precipitation with realistic spatial structure. The GF ensemble mean anomalies revealed that realistic SM initial conditions helped to improve the realism of the spatial pattern of hindcast anomalies that almost reach the GG level. Furthermore the GF ensemble mean and the GG ensemble mean anomalies are of the same magnitude but the FF anomalies are much weaker.

For these two different regions, considering two contrasted summers, the use of realistic SM anomalies significantly improve the climate simulations. The magnitude and the spatial distribution of the ensemble mean evaporation, temperature and precipitation anomalies (Figs. 10, 12) are much better hindcasted in the GF experiment than in FF. It is also remarkable that the GF system performs almost as well as the GG system. The use of realistic SM initial conditions in these two particular summers help us to make reliable hindcasts of the climate state and of soil moisture. The realistic SM initial and/or boundary conditions seem necessary to maintain temperature and precipitation anomalies with realistic spatial pattern and magnitude (Figs. 10, 12). They also contribute to the maintenance of severe temperature and precipitation anomalies, and thus seem also necessary to simulate realistic heat wave or drought durations (Figs. 11, 13). Nevertheless it should be remembered that this apparently “positive” result is case-dependent, and probably model-dependent as well.

6 Summary and discussion

Dynamical monthly to seasonal forecasting systems based on coupled land–atmosphere–ocean models rely on advanced assimilation techniques for providing realistic ocean and atmospheric initial conditions. In contrast, land surface initialization has received less attention in operational seasonal prediction systems and has been mostly

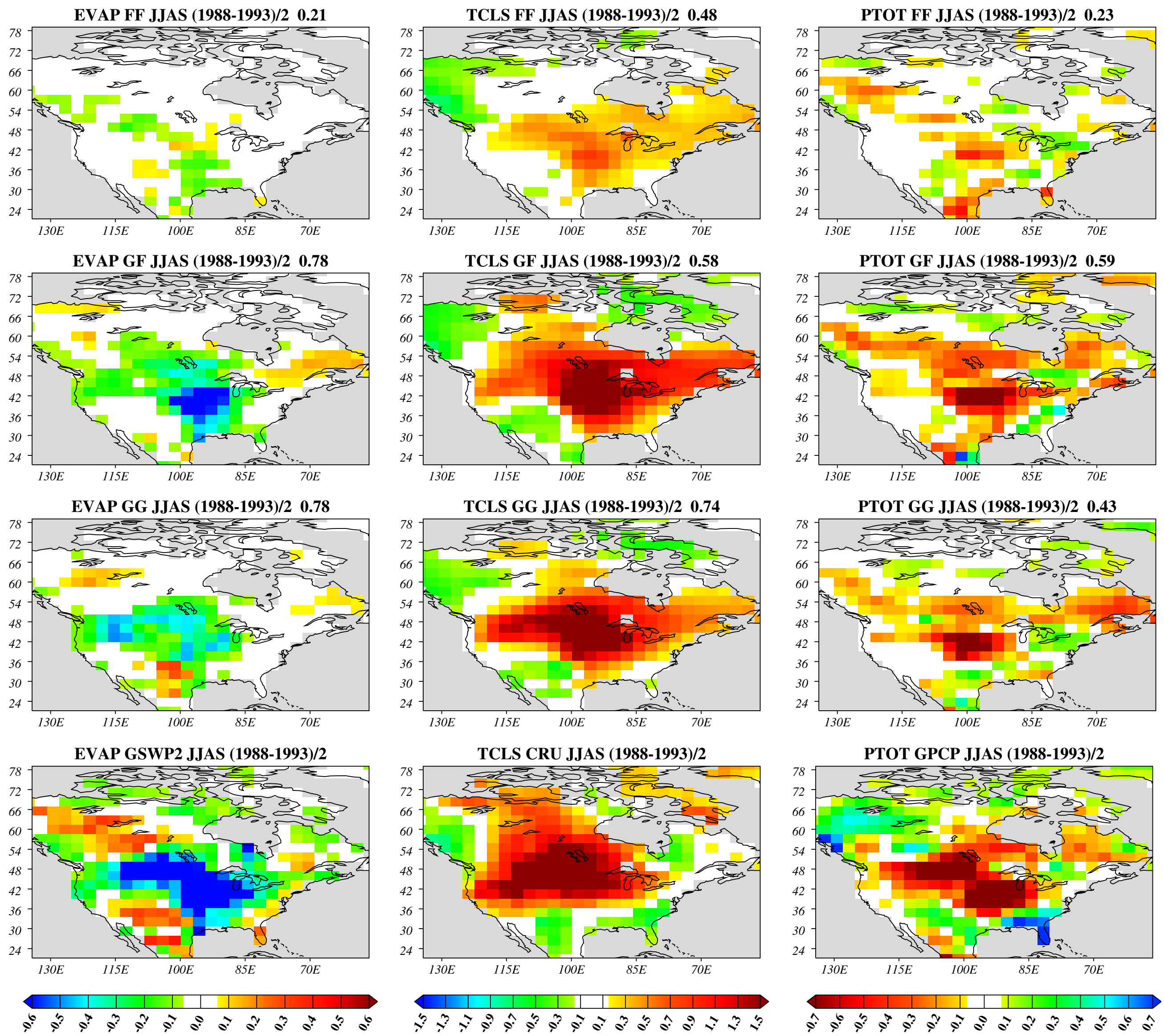

Fig. 10 Difference between the summer 1988 and 1993 anomalies of evaporation (*left panels*), 2 m temperature (*middle panels*) and precipitation (*right panels*). The ensemble mean anomalies in the experiments are shown in the three upper panels (FF, GF and GG from top to bottom). The Isba GSWP2 (evaporation), GPCP (precipitation) and CRU (2 m temperature) anomalies are presented in the lower panels. The spatial anomaly correlation coefficient (SACC) between the ensemble mean and "observed" anomalies is given in the title of each plot. Units: mm d^{-1} and K

explored in hindcast mode given the difficulty to produce reliable land surface analyses in real time (Drusch and Viterbo 2007).

In a recent paper the relative contributions of SST and SM to atmospheric variability were assessed using ensembles of AMIP type experiments (Conil et al. 2007). The role of SM in the near-surface atmospheric variability was highlighted, particularly for the boreal summer mid-latitude continents. The use of realistic SM conditions refined the simulation of interannual climate variability but this positive impact was mainly local and confined to the low troposphere as also pointed out by Fennessy and Shukla (1999).

In the present paper, we investigate the contribution of realistic SM initial conditions to the forecast skill during boreal summer. No particular attention has been given to atmospheric initialization despite its obvious impact during the first month (Rodwell and Doblas-Reyes 2006; Koster et al. 2004a, b) and the focus here is mainly on the seasonal timescale.

In the first part of the paper, SM prediction by the ISBA-Arpège land–atmosphere model has been evaluated against

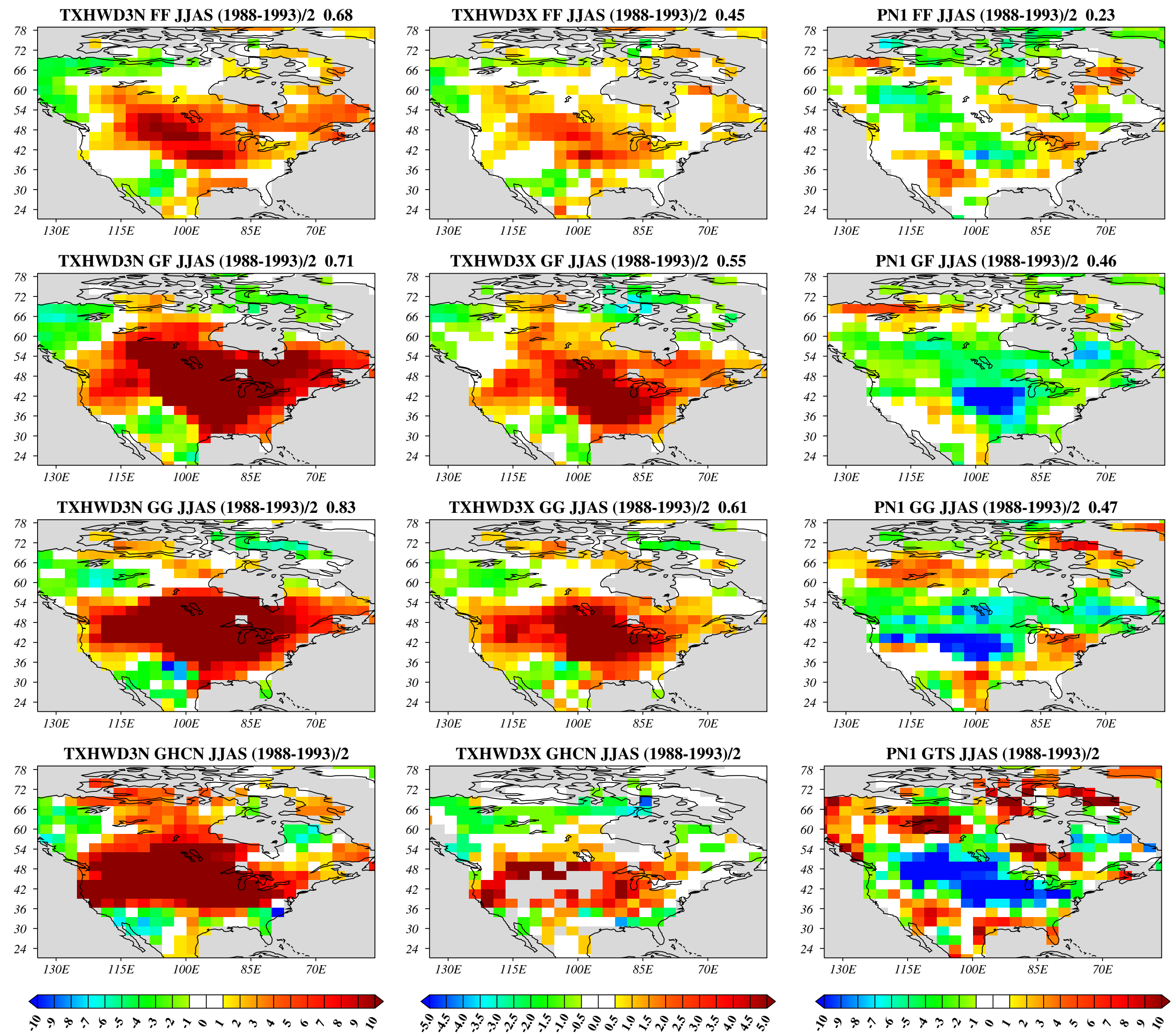

Fig. 11 Difference between the summer 1988 and 1993 anomalies of numbers of hot days (*left panels*) (total heat wave duration), longest heat wave duration (*middle panels*) and number of rainy days (*right panels*). The ensemble mean anomalies in the experiments are shown in the three upper panels (FF, GF and GG from top to bottom). The HadGHCN and GTS daily data are presented in the lower panels. The spatial anomaly correlation coefficient (SACC) between the ensemble mean and reanalysis anomalies is given in the title of each plot

simple statistical SM prediction models such as persistence or auto-regressive models. The results revealed that the ISBA-Arpège model yields better (or at least similar) SM hindcast skill. It is thus reasonable to use this model to explore the relevance of SM initialization in seasonal hindcast experiments driven by observed SSTs. Three ensembles of AMIP-type boreal summer (JJAS) simulations covering the 1986–1995 period have been compared. In the first ensemble, FF, the ISBA land surface model is fully coupled to the Arpège atmospheric model and SM is interactive. In the GG ensemble, SM conditions are relaxed toward the GSWP-2 reanalyses, whereas in the GF experiment they are again interactive but initialized using the GG SM outputs at the end of May.

While major differences are obtained between the ensemble mean SM and evaporation summer hindcast skills, the near surface temperature and precipitation summer skills in GF and FF are much closer. These results suggest that, on average, SST boundary conditions have a much stronger influence than SM initialization on the seasonal predictability of temperature and precipitation in the Arpège-Climat AGCM. It will be the aim of the second phase of the GLACE intercomparison project to evaluate the robustness of this conclusion. Besides the use of

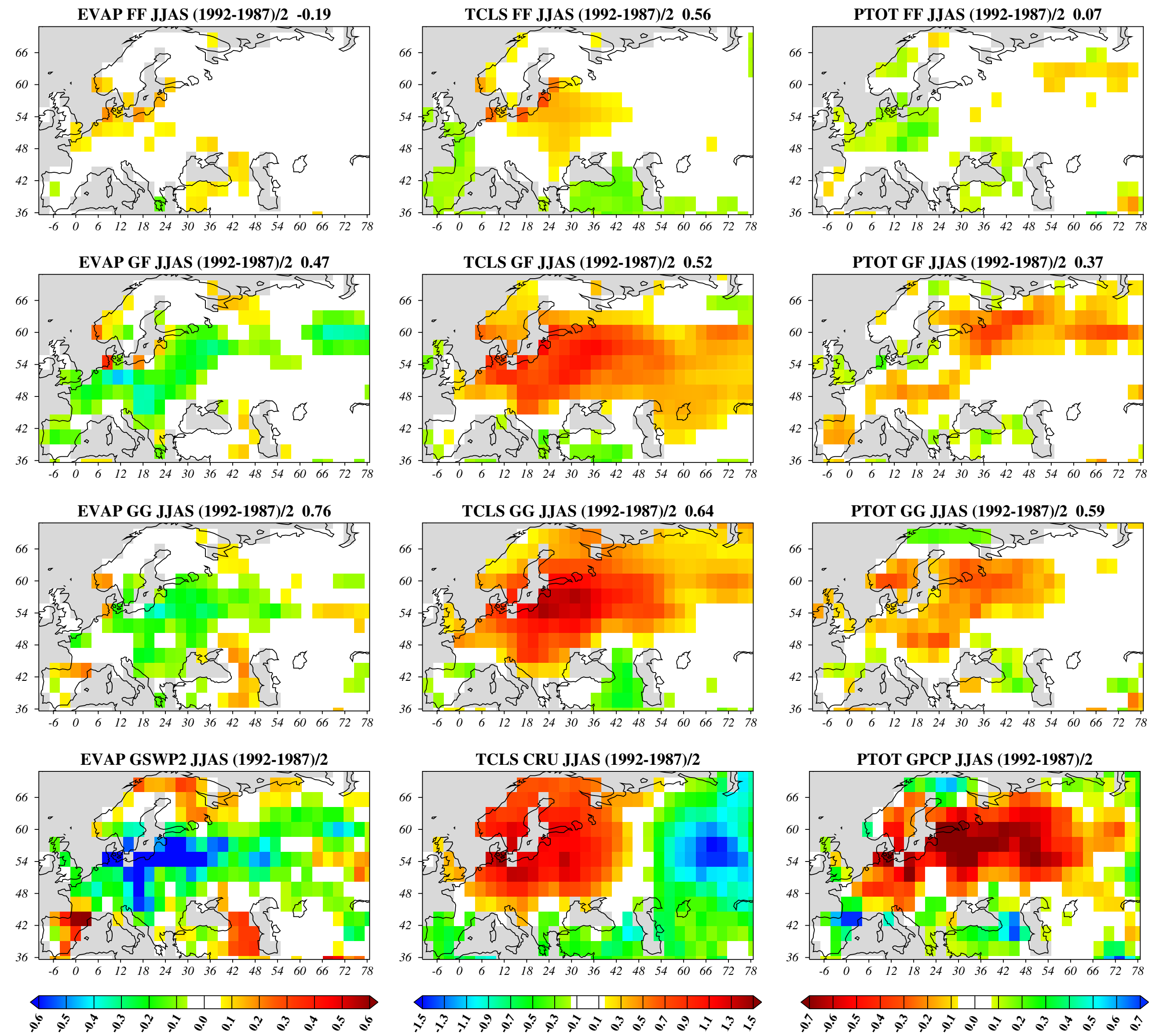

Fig. 12 Difference between the summer 1992 and 1987 anomalies of evaporation (*left panels*), 2 m temperature (*middle panels*) and precipitation (*right panels*). The ensemble mean anomalies in the experiments are shown in the three upper panels (FF, GF and GG from top to bottom). The Isba GSWP2 (evaporation), GPCP (precipitation) and CRU (2 m temperature) anomalies are presented in the lower panels. The spatial anomaly correlation coefficient (SACC) between the ensemble mean and reanalysis anomalies is given in the title of each plot. Units: mm d^{-1}, and K

different GCMs, GLACE 2 should also include seasonal hindcasts with predicted rather than perfect SST boundary conditions, which could also modulate the relative influence of SM and SST on seasonal predictability.

In our study, the intrinsic predictability of temperature exceeds that of precipitation in magnitude and in spatial extent as also revealed by (Conil et al. 2007). The benefit of a realistic land surface initialization appears when widespread and strong SM anomalies are observed at the beginning of the summer season. Thus three main factors seem to play a role in the local impact of SM initialization on the forecast: the size and magnitude of SM anomalies, the sensitivity of evaporation to SM and the sensitivity of temperature and precipitation to evaporation (Koster and Suarez 2003a). From our experiments we conclude that evaporation is highly sensitive to (though not fully constrained by) SM in many areas but temperature and precipitation show contrasted regional sensitivities.

SM predictability itself is region-specific, mainly because it depends on the soil depth (and water holding capacity) and on the main climate state and its seasonality. It is also a function of the summer considered as it depends

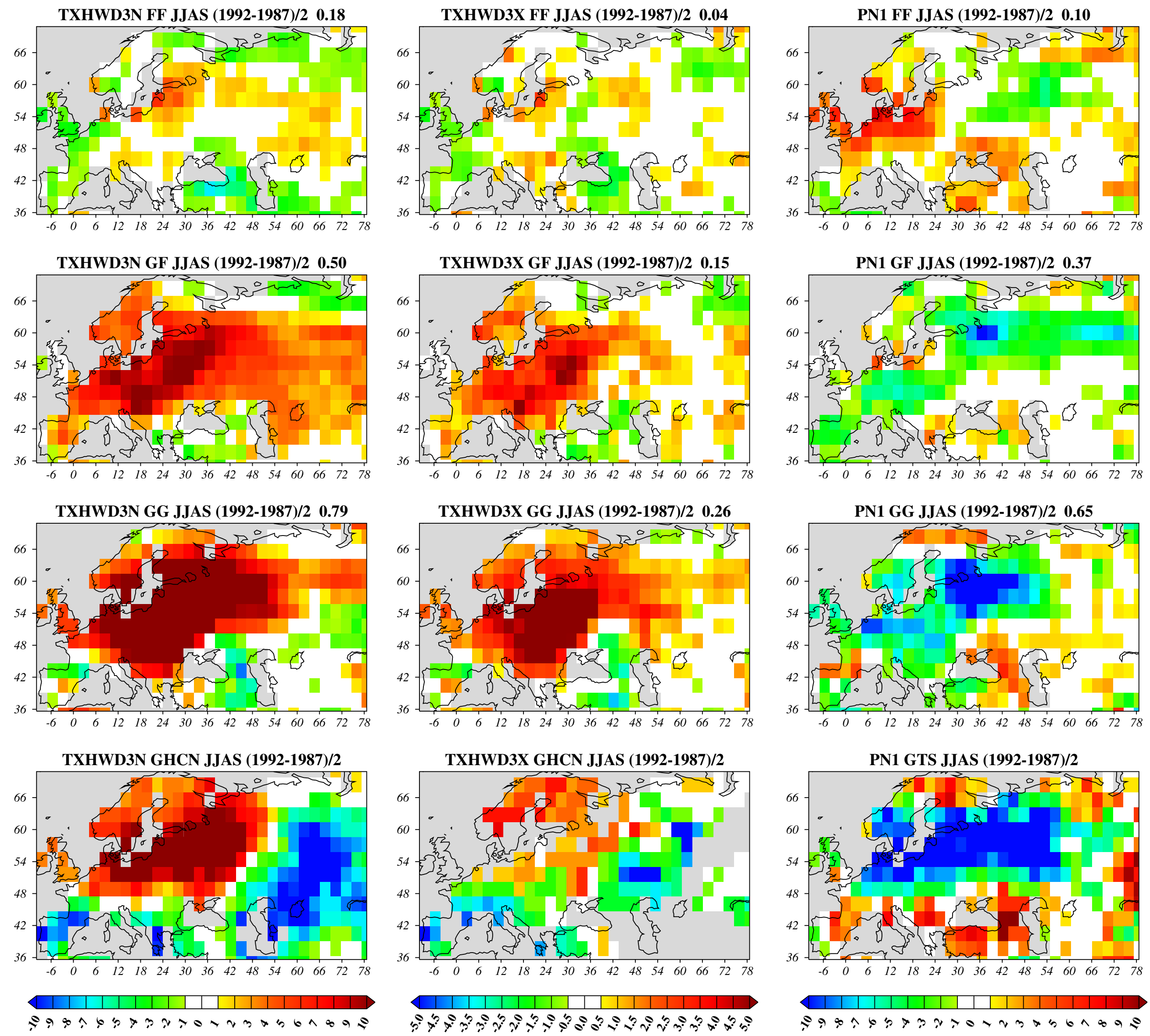

Fig. 13 Difference between the summer 1988 and 1993 anomalies of numbers of hot days (*left panels*) (total heat wave duration), longest heat wave duration (*middle panels*) and number of rainy days (*right panels*). The ensemble mean anomalies in the experiments are shown in the three *upper panels* (FF, GF and GG from *top to bottom*). The HadGHCN and GTS daily data are presented in the *lower panels*. The spatial anomaly correlation coefficient (*SACC*) between the ensemble mean and reanalysis anomalies is given in the title of each plot

on the SM initial anomalies and on the following land–atmosphere interactions. Large-scale atmospheric circulation also plays a key role in modulating land–atmosphere interactions. It has been recognized that SM persistence and its possible positive effects on the overlying atmosphere are greater in the transition zones between wet and dry climates. We argue that while these transition areas might have an average location and extension, they might also evolve in time and thus SM persistence and land–atmosphere coupling strength may be case-dependent. As shown recently in the GLACE framework, simulated SM persistence is also modulated by the simulated mean climate and land surface state. In a different framework, Koster et al. (2004a, b) have already suggested that some summers may be easier to forecast than others. They have also pointed out the mid-western US drought of 1988 as a particularly highly predictable case.

Future work should be dedicated to the investigation of the favourable and/or unfavourable factors for the boreal summer seasonal forecast. We will focus particularly on the relationship between SM conditions and the following atmospheric circulation regimes. Furthermore our study did not explore the use of realistic atmospheric initialization, which could help sustain the predictability of SM during the first month of the seasonal hindcasts. Future work should thus be devoted to the assessment of the relative roles of SM and atmospheric initial conditions on genuine seasonal hindcasts, with particular attention given to their possible synergy.

While seasonal climate anomaly forecasts are certainly of interest, seasonal prediction of the occurrence of extreme (or at least severe) meteorological events such as heat waves and droughts are critical for broad socio-economic concerns. The necessity to improve reliability of severe event forecasts has been particularly illustrated by the recent European heat wave of 2003 and its poor prediction. Furthermore a number of recent studies have revealed that while mean climate may change in the future due to anthropogenic forcings, climate variability change may be even sharper as it is rather difficult to adapt to extremes.

Many physical processes and factors contribute to the generation and maintenance of mid-latitude heat wave and drought. Cassou et al. (2005) have shown that European heat waves, over the period 1950–2003, have been associated with two specific atmospheric regimes. In 2003 anomalous tropical Atlantic heating related to wet conditions over the Caribbean and Sahelian regions seems to have favoured their occurrence. Black and Sutton (2007) added that Mediterranean and Indian Ocean SST anomalies may have contributed to the maintenance of the early and late summer heat waves, respectively, that occurred over Europe in 2003. While oceanic forcings have certainly played a key role in the occurrence of specific atmospheric anomalies that have favoured the heat wave, land–atmosphere interactions have also probably contributed to its generation and intensification. Extreme summer events are frequently preceded by large precipitation deficit and positive SW radiation anomalies at the surface. Ferranti and Viterbo (2006) have shown that initial dry soil anomalies may influence the atmosphere for up to 3 months and with greater impact than SST forcings. Using a regional model, Fischer et al. (2007) indicated that SM anomalies were a major contributor to the 2003 summer heat wave intensity. They have also shown that SM anomalies are critical in the evolution of European heat waves. Vautard et al. (2007) illustrated the apparent relationship between winter Mediterranean precipitation deficit and subsequent European hot summers through anomalous northward transport of warm and dry air.

In summary, the results obtained in this study confirm that realistic SM boundary conditions are necessary to capture seasonal climate anomalies over the mid-latitude continents during summer and particularly over Europe. While the period 1986–1995 is too short to conclude definitively, our study also reveals that severe heat wave and drought occurrence and intensity are influenced by SM anomalies. Furthermore we have shown that SM initialization has a positive effect on the mean seasonal forecast skill as well as on the prediction of severe events. These results need to be confirmed with other models, as is planned in the GLACE-2 intercomparison project that will be also based on the 10-year GSWP-2 soil moisture reanalysis. Longer SM climatologies will be necessary to provide a more robust assessment of what can be expected from improved SM initialization as well as improvement in the SM reanalysis datasets themselves, the uncertainty of global SM data sets derived from different land surface models being still quite large as shown by Guo and Dirmeyer (2006). Nevertheless, given the poor skill of state-of-the-art seasonal prediction systems in the summer mid-latitudes and the growing body of evidence that land hydrology is a significant source of predictability, it is now urgent to develop efficient real-time land surface data assimilation systems in synergy with the numerical weather prediction community. Finally, future work should also be dedicated to evaluating the impacts of SM initialization and land–atmosphere interactions on high-frequency atmospheric variability and the predictability of severe climate events.

Acknowledgments The authors would like to thank A. Gershunov for preparing the north American precipitation using various original data sources and for his careful reading of the paper.

References

Alfaro E, Gershunov A, Cayan DR (2006) Prediction of summer maximum and minimum temperature over the Central and Western United States: the role of soil moisture and sea surface temperature. J Clim 19:1407–1421

Beljaars A, Viterbo P, Miller M, Betts A (1996) The anomalous rainfall over the United States during July 1993: sensitivity to land surface parameterization and soil moisture anomalies. Mon Wea Rev 124:362–383

Black E, Sutton R (2007) The influence of oceanic conditions on the hot European summer of 2003. Clim Dyn 28:53–66

Caesar J, Alexander L, Vose R (2006) Large-scale changes in observed daily maximum and minimum temperatures—creation and analysis of a new gridded dataset. J Geophys Res 111:D05101

Cassou C, Terray L, Phillips AS (2005) Tropical Atlantic influence on European heat waves. J Clim 18:2805–2811

Colman AW, Davey MK (2003) Statistical prediction of global sea-surface temperature anomalies. Int J Climatol 23:1677–1697

Conil S, Douville H, Tyteca S (2007) The relative influence of soil moisture and SST in climate predictability explored within ensembles of AMIP type experiments. Clim Dyn 28:125–145

Della-Marta PM, Luterbacher J, von Weissenfluh H, Xoplaki E, Brunet M, Wanner H (2007) Summer heat waves over western Europe 1880–2003, their relationship to large-scale forcings and predictability. Clim Dyn 29:251–275

Delworth T, Manabe S (1988) Influence of potential evaporation on the variabilities of simulated soil wetness and climate. J Clim 1:523–547

Dirmeyer P (2003) The role of the land surface background state in climate predictability. J Hydrometeorol 4:599–610

Dirmeyer P (2005) The land surface contribution to the potential predictability of boreal summer season climate. J Hydrometeorol 6:618–632

Douville H (2003) Assessing the influence of soil moisture on seasonal climate variability with AGCMs. J Hydrometeorol 4:1044–1066

Douville H (2004) Relevance of soil moisture for seasonal atmospheric predictions: is it an initial value problem. Clim Dyn 22:429–446

Douville H, Chauvin F (2000) Relevance of soil moisture for seasonal climate predictions: a preliminary study. Clim Dyn 16:719–736

Drusch M, Viterbo P (2007) Assimilation of screen-level variables in ECMWF's integrated forecast system: a study on the impact on the forecast quality and analyzed soil moisture. Mon Wea Rev 135:300–314

Entin J, Robock A, Vinnikov K, Zabelin V, Liu S, Namkhai A (1999) Evaluation of Global Soil Wetness Project soil moisture simulations. J Meteor Soc Japan 77:183–198

Entin J, Robock A, Vinnikov K, Hollinger S, Liu S, Namkhai A (2000) Temporal and spatial scales of observed soil moisture variations in the extratropics. J Geophys Res 105:865–877

Fennessy M, Shukla J (1999) Impact of initial soil wetness on seasonal atmospheric prediction. J Clim 12:3167–3180

Ferranti L, Viterbo P (2006) The European summer of 2003: sensitivity to soil water initial conditions. J Clim 19:3659–3680

Fischer E, Seneviratne S, Vidale P, Luthi D, Schar C (2007) Soil moisture–atmosphere interactions during the 2003 European summer heatwave. J Clim 20:5081–5099

Gershunov A, Douville H (2007) Extensive summer hot and cold extremes under current and possible future climatic conditions: Europe and north America. In: Diaz H, Murnane R (eds) Climate extremes and society. Cambridge University Press, Cambridge (in press)

Groisman PYa, Knight RW, Karl TR, Easterling DR, Sun B, Lawrimore JM (2004) Contemporary changes of the hydrological cycle over the contiguous United States: trends derived from in-situ observations. J Hydrometeorol 5:64–85

Guo Z-C, Dirmeyer PA (2006) Evaluation of GSWP-2 soil moisture simulations, Part 1: inter-model comparison. J Geophys Res 111:D22S02

Kanamitsu M, Lu C, Schemm J, Ebisuzaki W (2003) The predictability of soil moisture and near-surface temperature in hindcasts of the NCEP seasonal forecast model. J Clim 16:510–521

Koster R, Dirmeyer P, Hahmann A, Ijpelaar R, Tyahla L, Cox C, Suarez M (2002) Comparing the degree of land–atmosphere interaction in four atmospheric general circulation models. J Hydrometeorol 3:363–375

Koster R, Suarez M (2001) Soil moisture memory in climate models. J Hydrometeorol 2:558–570

Koster R, Suarez M (2003a) Suggestions in the observational record of land–atmosphere feedback operating at seasonal time scales. J Hydrometeorol 5:567–572

Koster R, Suarez M (2003b) Impact of land surface initialization on seasonal precipitation and temperature prediction. J Hydrometeorol 1:408–423

Koster R, Suarez M, Heiser M (2000) Variability and predictability of precipitation at seasonal to interannual timescales. J Hydrometeorol 1:26–46

Koster R, Suarez M, Liu P, Jambor U, Berg A, Kistler M, Reichle R, Rodell R, Famiglietti J (2004) Realistic initialization of land surface states: impacts on subseasonal forecast skill. J Hydrometeorol 5:1049–1063

Koster R et al (2004) Regions of strong coupling between soil moisture and precipitation. Science 305:1138–1140

Manabe S, Delworth T (1990) The temporal variability of soil wetness and its impact on climate. Clim Change 16:185–192

Miranda S (2003) Actualizacion de la base de datos ERIC II. Final report of the project TH-0226, IMTA internal reports

Rodwell M, Doblas-Reyes F (2006) Medium-range, monthly, and seasonal prediction for Europe and the use of forecast information. J Clim 19:6025–6046

Schar C, Vidale PL, Luthi D, Frei C, Haberli C, Liniger MA, Appenzeller C (2004) The role of increasing temperature variability in European summer heatwaves. Nature 427:332–336

Schlosser C, Milly P (2002) A model-based investigation of soil moisture predictability and associated climate predictability. J Hydrometeorol 3:483–501

Seneviratne S, Koster R, Guo Z, Dirmeyer P, Kowalczyk E, Lawrence D, Liu P, Lu C-H, Mocko D, Oleson K, Verseghy D (2006a) Soil moisture memory in AGCM simulations: analysis of global land–atmosphere coupling experiment (GLACE) data. J Hydrometeorol 7:1090–1112

Seneviratne SI, Luthi D, Litschi M, Schar C (2006b) Land–atmosphere coupling and climate change in Europe. Nature 443:205–209

Vautard R, Yiou P, D'Andrea F, de Noblet N, Viovy N, Cassou C, Polcher J, Ciais P, Kageyama M, Fan Y (2007) Summertime European heat and drought waves induced by wintertime Mediterranean rainfall deficit. Geophys Res Lett 34:L07711

Vincent LA, Gullett DW (1999) Canadian historical and homogeneous temperature datasets for climate change analyses. Int J Climatol 19:1375–1388

Von Storch H, Zwiers F (1999) Statistical analysis in climate research. Cambridge University Press, Cambridge

Wu W, Dickinson R (2004) Time scales of layered soil moisture memory in the context of land–atmosphere interaction. J Clim 17:2752–2764

Zhang H, Frederiksen C (2003) Local and nonlocal impacts of soil moisture initialization on AGCM seasonal forecasts: a model sensitivity study. J Clim 16:2117–2137