Dear Editor

Here below is the response to your own suggestions. All our replies to the suggestions by the reviewers are added as comments to the documents with their suggestions.

References

I updated the literature by adding sentences referring to the work by Arnal et al. (2018), Harrigan et al. (2018), Meissner et al. (2017) and Bazile et al. (2017).

Paper length:

Reviewer 2 put forward three suggestions for shortening the paper. We believe that the evaluation of skill in evapotranspiration is important, as argued in the beginning of Section 3.3, and fits very well into the present paper. So, we did not remove it.

The second suggestion was to cut on Section 3.4. This section was added to the paper of the second submission is response to suggestions by reviewer 1, e.g. his main point 2:

please consider either arguing more thoroughly why you have decided to take a different approach from the standard ESP and reverse-ESP or changing the experiment designs.

And in response to suggestions by the editor, e.g.

Please clarify or repeat the experiment, or even clearly state in the objectives and conclusions the different aims of your approach in relevance to the original ESP/revESP.

Perhaps, we somewhat overreacted, so Section 3.4 became too long. I shortened the section considerably (from 870 to 664 words) and moved the figure to the supplementary material.

We followed the third suggestion of Reviewer 3 and removed Figure B2. It is now in the supplementary material).

In total, we removed 2.5 figures, namely Figure 13, Figure B2 and half of Figure 4. I also shortened the paper by removing words, sentences and paragraphs. I removed a paragraph from the introduction and two paragraphs from Section 4.4 (Towards an operational system)

Reliability

We acknowledge that reliability is an important property of forecasts and that it is hence valuable to publish an analysis of the reliability of the hindcasts. However, the topic of the present paper is an **explanation of the skill**, and not the reliability, of our hindcasts. So, the reliability evaluation that we added in an appendix is only vaguely related to the contents of the paper and **would seriously break the flow of the paper** if it was included in the main text. In the companion paper, however, **skill was analysed**. Hence, analysis of reliability would have well fitted in the first paper but we are obviously too late to do so. We see two reasonable solutions: 1) publish an addenda to the companion paper or 2) leave the evaluation of reliability in the appendix of the current paper, and summarise the analysis and refer to the appendix in the main text. In the new version we have implemented the last option, with the following text in the introduction of the paper:

To extend the evaluation of the system, its reliability was analysed. The main finding is that during the two first lead months the system is not far from being perfectly reliable but that with progressing lead time reliability is reduced. We also found that discrimination skill and reliability have similar characteristics, e.g. for longer lead times the highest values of reliability are found in some regions with considerable amounts of discrimination skill. Details of this analysis are provided in Appendix A.

Review of “Seasonal streamflow forecasts for Europe – II. Sources of skill” by Wouter Greuell et al.

This paper looks at the sources of skill in the WUSHP model-based seasonal hydrological forecasting system, producing hydrological forecasts for up to seven months of lead time over Europe. To this end, the authors first analysed the skill of the meteorological forcings of WUSHP (ECMWF’s System 4 seasonal meteorological hindcasts). They also produced several hindcast datasets, based on which they carried out a complete investigation of the sources of skill (i.e. initial conditions of soil moisture and snow and meteorological forcings) in the seasonal runoff, discharge and evapotranspiration hindcasts.

The results presented in this paper are based on a thorough and original analysis and provide a great contribution to the field’s existing literature. Furthermore, this paper is overall coherently written and I recommend it to be accepted after minor revisions. Below, a few comments which should hopefully guide the authors in revising this paper for publication.

Main comments:

- Since the last version of this paper, the authors do not seem to have updated their references list with the latest literature within the field, more specifically the papers published in the same HESS special issue on “Sub-seasonal to seasonal hydrological forecasting”. This is for instance apparent on P26 L841-844, where the authors mention that to their knowledge, only two other studies looked at the sources of skill in seasonal hydrological forecasts produced by a similar system, over Europe. There are several papers in the same special issue which look at the skill of (System 4-driven) seasonal hydrological forecasts over the globe, Europe, or parts of Europe. These papers all benchmark the skill of the state-of-the-art seasonal hydrological forecasts to forecasts such as the ESP. I would highly recommend for the authors to update their references with this latest literature.

- This paper is very rich in results and figures. I would recommend for the authors to present the results in a more concise manner when possible and to remove non-essential figures from the main body. This would help highlight the key results of this paper (in my opinion and according to the paper’s title, the analysis of the origins of skill in the runoff hindcasts) and keep the readers’ focus throughout the paper. I have made below a few more specific comments about this.

- The legend is too small for most of the sub-figures.

Title: in my opinion, the title doesn’t fully reflect the content of the paper. Firstly, this paper looks at runoff and discharge and the word “streamflow” is not used much in the paper. Furthermore, this paper presents much more than just a streamflow analysis. I would therefore recommend changing the title to something more representative of the content of the paper, for example: “Seasonal hydro-meteorological forecasts for Europe: sources of skill”.

Abstract: the abstract is overall too long and dives into the results in great detail before explaining the methods used. I would recommend laying out the methods used more clearly before mentioning the results. The results’ paragraph should be much shorter and highlight the key results of the paper, leaving the details for the main body. You use the word “streamflow” here and on a few occasions in the paper (e.g. P30 L973) while the rest of the time the words “runoff” or “discharge” are used. Please consider removing the word “streamflow” from the paper or clarifying what it refers to.

P4 L95-96: please specify here which variables this analysis is based on.

P4 L109-110: you need to explain here what the ESP is for readers not yet familiar with it.

P4 L109-116: it would be good to explain more clearly here that the hindcasts you produced for this paper are inspired from the conventional ESP and reverse-ESP, but that they differ in their set up and why that is (with regards to the overall aim of the paper).

P4 L118: could you please reference here one or multiple papers that have looked at the effect of evapotranspiration on runoff, more specifically on seasonal timescales.

P5 L165-166: "a length of seven months" is ambiguous. Using the word lead time would be clearer.

P6 L195-196: do the observations you mention here refer to the pseudo-observations?

P7 L235-236: this explanation of the target month number is slightly confusing and not necessarily needed. You could simply say that the target month refers to the month for which the forecast is made. I also find jumping between the terms "lead month" and "lead time" throughout the paper a bit confusing.

P7 L245-251: please remind the reader that in this paper you use alternative methods to the standard ESP and reverse-ESP (widely used in the literature) because you want to keep these hindcasts as close as possible to the FullSH for the aim of this paper.

P8 L252-271: I like the experiments' new names (after the first revision of the paper). Does snow conditions refer to the snow cover?

P8 L274: do you mean "random" instead of "uneven"?

P9 L308: please clarify what you mean by "most important input variables". Most important for what?

3.1: did you look at the effect of trends in the System 4 precipitation hindcasts?

Figure 1: in the caption, it says that "yellow cells have insignificant skill". There are however multiple shades of yellow on the map. You could instead say that the lightest yellow colour shows insignificant skill. P10 L328-329: for which lead months?

P12 L372-373: the lead month 0 line for the un-detrended hindcasts looks very close to the line for the detrended hindcasts, except for April, June and November.

P12 L373-374: it however doesn't drop as quickly as for precipitation

P12 L395-396: I agree with this observation for JJA, while for the other months it is not so evident

P13 L415: why was lead month 5 selected to illustrate this point? Do the other lead months show (dis)similar results?

P13 L421-423: for the sake of conciseness, I would maybe remove these results.

P13 L428-429: could this be due to some trend or predictor that takes shape in autumn and affects temperatures in Europe in winter? I wouldn't dismiss it as spurious.

P14 L472-474: the difference is however not very significant, except in late summer-autumn.

Figure 4: I would suggest moving the bottom two sub-figures to the supplementary material as it won't affect the main storyline of the results.

Figure 5: green and red should never be used together on a plot. A more colourblind friendly palette should be used instead (same for Figure 13). Since you mention the FullSH in the results that correspond to this figure it would make sense to add a line for the FullSH here as well.

P17 L537-547: these are great results!

P17 L549-550: could that be because the snowpack is at its maximum around February in Europe?

P17 L565-569: I wouldn't mention these results here unless you explain what the differences could be due to.

Figure 6: is this figure essential in the main body? You only discuss the additivity of skill from the initial soil moisture and snow conditions, which Figure 5 already shows as an average over Europe. In my opinion, the text is sufficient here.

P18 L583-585: this sentence is slightly confusing.

P19-20 L619-620: could this be rather due to the groundwater initialisation?

Figure 8: this figure is not necessary and a few sentences are sufficient to raise this point.

P20-21 L637-653: couldn't this be due to the fact that we can expect most of the snow in Europe (except for high mountain ranges) to have melted already by May? Knowing the snow cover at the start of May is therefore of not much added value for forecasting future runoff compared to knowing what it is earlier in the year, in April for example (when more snow is still present and available for runoff).

3.3: this part is too long and steals the spotlight from the runoff section, which should be the highlight of the paper according to the title. I would therefore suggest to summarise the text corresponding to Figures 10 and 11 in just a few lines and remove these figures from the main body.

P22 L695-698: I would describe what is observed on sub-figure 9b before comparing those results to the ones obtained for runoff.

P22 L700-703: please mention that these results correspond to the FullSH.

P26 L819-822: many studies (published in the same special issue) found higher skill in the ESP (compared to a state-of-the-art seasonal hydrological forecasting system) beyond the first or second month of lead time over Europe or for specific basins/regions of Europe and are worth mentioning here.

P29 L935: I am not sure to understand what is meant by "inter-member variability".

P29 L942-944: one further difference is that the initial conditions in the reverse-ESP are the full range (or ensemble) of historical initial conditions, instead of a single value (i.e. climatological average).

P30 L953-954: this is a repetition of what was said in the previous paragraph.

P31 L1007-1013: this is a very good point!

P33 L1080-1081: I would remove this example from the conclusions

Technical corrections:

- P14 L445: lead month 1 instead of 0?

- P16 L524: “run-off” is used instead of “runoff” (comes up again after)

- P22 L686: the “o” is missing in “MeteoSH”

- P27 L879: “taken from” instead of “taking from”.

Report[GW1] #2

Submitted on 22 Oct 2018
Anonymous Referee #2

Anonymous during peer-review: Yes No

Anonymous in acknowledgements of published article: Yes No

Recommendation to the Editor

1) Scientific Significance Does the manuscript represent a substantial contribution to scientific progress within the scope of this journal (substantial new concepts, ideas, methods, or data)?	Excellent **Good** Fair Poor
2) Scientific Quality Are the scientific approach and applied methods valid? Are the results discussed in an appropriate and balanced way (consideration of related work, including appropriate references)?	Excellent Good **Fair** Poor
3) Presentation Quality Are the scientific results and conclusions presented in a clear, concise, and well structured way (number and quality of figures/tables, appropriate use of English language)?	Excellent **Good** Fair Poor

For final publication, the manuscript should be

accepted as is

accepted subject to **technical corrections**

accepted subject to minor revisions

reconsidered after **major revisions**

I am willing to review the revised paper.

I am **not** willing to review the revised paper.

rejected

Suggestions for revision or reasons for rejection (will be published if the paper is accepted for final publication)

Major comments[GW2]

This is a resubmitted version of a study describing the sources of skill in a Europe wide streamflow forecasting system. It's my second review of the paper. As I noted last time, dynamical continental scale ensemble prediction systems are at the cutting edge of seasonal streamflow forecasting, the paper is reasonably well presented, and it is well within the scope of HESS. In addition, the authors **have addressed several of my concerns, including improving the description of their analyses of forecast skill and trends, and peforming analyses of reliability.** They have also added some interesting analyses of sources of skill in **Figure 12**. I commend them on their efforts. **There are still some outstanding issues**, however. Some are repetitions of my statements last time, others have arisen from the revision. They are as follows:

1) **Reliability**: the authors have expended considerable effort on investigating reliability with attributes diagrams. Unfortunately, they have placed all this effort in an **Appendix**, and have not referred to that appendix at all in the body of the paper. As I stated previously: reliability is a crucial attribute of ensemble forecasting systems, and merits discussion. This is particularly true when the main analyses used in this paper reduces the ensemble to a deterministic forecast (i.e., correlations rather than the use of probabilistic scores). I recommend at least some of this analysis be moved into the body of the paper. The reliability results are not particularly strong - the ensembles appear strongly overconfident at longer lead times - but I think this is an avenue

for future improvement. (NB - see also my suggestions for shortening the paper, below.)

2) Paper Length: the addition of analyses and discussion has resulted in a **paper** that is, in my view**, too long**. I offer three possible ways to shorten the paper:
i) I reiterate my recommendation from my previous review that the **analyses of evapotranspiration forecasts** be removed from this paper, and given its own paper.
ii) Figure 13, and its accompanying discussion, is superficial and could easily be removed. One of the major benefits of ESP forcings is that they offer a reliable estimate of uncertainty. This is distinct from the authors' InitSH experiment, which samples from Sys4 (resulting in an ensemble that is likley to be overconfident). This of course does not show up in correlations calculated on the median ensemble member. **The authors could simply state something like "The use of InitSH produced very similar correlations to ESP (not shown for brevity)."** If the authors feel strongly that Fig 13 should be included, they could put it in as another panel in Figure 5 (and reduce the discussion of it to a sentence or two), but I think this is unnecessary.
iii) The **analysis of reliability of actual streamflow forecasts (Figure B2) is probably unnecessary**, as the remainder of the paper verifies against pseudo observations. It could be removed.

Specific (minor) comments

L101 "specific hindcasts" - would 'experiments' perhaps be a better term[GW3]?

L125-132 Arnal et al. 2018 has done this comprehensively over Europe recently, and is worth mentioning, both here and in the discussion of your results[GW4].

L175 "To spin up discharge, each 7-month hindcast was preceded by a one month simulation" The companion paper implies that the hydrological states at the start of the 1-month spin-up are taken from a long-run simulation (if I've interpreted this correctly). This is important information (!) and should be included. At present, it reads as though only a single month is used to spin-up hydrological model states, which is nowhere near enough[GW5].

L196 "from the observations themselves" Should this be 'pseudo-observations[GW6]'?

L252-274 This information is perhaps better presented in a table, for easy reference[GW7].

L256-257 "More specifically, we selected member 1 from the 1981 hindcasts, member 2 from the 1983 hindcasts, etc. By using identical meteorological forcing for all of the years of the hindcasts, skill due to skill in the forcing is eliminated." Does this effectively mean that an ensemble member is drawn randomly from each year[GW8]?

L270-271 "skill due to initial conditions is eliminated" Should that be "skill due to initial hydrological conditions is eliminated[GW9]"?

L274 "15 uneven years[GW10] 1981-2009" I take it this means the years {1981, 1983, ..., 2007, 2009}(?) Does this mean the exact (perfect) rainfall forecast is included in the ensemble when assessing odd years? I.e., if you are evaluating forecasts for the year 2009, the observed rainfall for that year is included in the forecast ensemble[GW11]?

L288-289 "Thus, like the FullSH, all specific hindcasts for a single starting date consist of 15 members, which is important since ensemble size affects skill metrics". Of far greater concern is strict cross-validation of forecasts. Including a 'perfect' rainfall forecast in an ensemble of 15 is likely to have a much greater impact on skill scores than ensemble size. I don't think this is defensible. (Though as I recommend removing the ESP figures/experiment, above, it does not need to be addressed[GW12].)

L401-420 I think the additons to this explanation of what you're trying to show with your analysis of temperature trends has improved it considerably - it's much clearer to me (and hopefully others) now. There are a few instances later in the paper where phrases such as[GW13]
"

L500 "The InitSH forcing is the same for each year, so its interannual variation does not contain a signal nor noise." The 'signal' depends on observations, which vary from year to year. So you can't say there is no 'noise' - the accuracy of InitSH changes each year, because the observations vary. Rather than centering this discussion on signal and noise, it would be easier to simply talk about forecast accuracy. I think the main conclusion to draw from Fig 4 is that when the WHUSP forecasts are reduced to the median, at longer lead times the meteorological forecasts from FullSH are less accurate than the randomly drawn met forecasts in InitSH. This is possible, of course, and a reason why a number of studies choose calibration methods rather than simple bias-corrections to process meteorological forecasts (see Zhao et al. 2017) (and also one of the reasons why ESP forecasting systems are difficult to beat[GW14]).

L645-646 "However, there is compensation for this direct effect by an indirect effect through soil moisture." Is it possible that this is an artefact of breaking correlations between states? i.e., SnInitSH has averaged soil moisture states at lead 0 - could running the model induce more correctly correlated soil moisture states at lead 1? In other words, could this be an artefact of your choice to average states, rather than using an ensemble of model states as standard revESP experiments do? If so, I think this should be acknowledged somewhere[GW15].

L542-L543 "Skill in the precipitation forcing of the first lead month leads to skill in the states of soil moisture and snow at the end of that month." I would guess skillful forecasts occur at long lead times in at least some catchments where there is no skill in precipitation in the first month. Correctly initialised hydrological models can produce skillful streamflow forecasts for a number of months, even with completely uninformative forcings[GW16].

L817-819 "This result is counter-intuitive but, as we discussed, a logical consequence of forcing with interannual variation
that has no or insufficient skill, such as the S4 forcing[GW17]." This doesn't sound logical to me at all. InitSH has, by design, zero meteorological forecast skill - so you cannot explain the poor S4 performance by saying it S4 has no meteorological forcing skill. (If this were so, it should perform similarly to InitSH, not worse than it.) I think the explanations possible are: 1)there are actual flaws in the forecast S4 forcings; this might be because of bias (though this is unlikely, as I'm sure the quantile mapping takes care of this) or that the S4 forecasts are negatively skillful (i.e., less accurate than and ESP forecast - this looks the most likely candidae) at longer lead times. 2) the way you've assessed the forecast insn't sufficiently sensitive to determine

L821-822 "have identical meteorological forcing for each year". I think I commented on this in the past revision: ESP forecasts are frequently not identical for each year, because they are often cross-validated. So they are similar, but not identical. They are similar to InitSH in that they are (or should be) uninformative, but give a reliable uncertainty spread[GW18].

L841 "To our knowledge, two other studies analysed" as noted previously, Arnal et al. 2018 have done very similar work to that presented here, and with the same forcing[GW19].

L859 "In any case, that contribution depends and will depend on the climate model used (e.g. S4 or GloSea5)." It can also very much depend on the method used to process climate forecasts. Calibration removes bias, but also ensures consistently inaccurate forecasts (i.e., negatively skillful forecasts, in the sense that they perform worse than climatological reference forecasts) return to something like a climatology forecast. This allows skill at short lead times in meteorological forecasts to propagagate through to long lead times in streamflow predictions. Quantile mapping only removes bias[GW20].

L879 "taking" should be "taken[GW21]"

L883 Figure 12 - headings say 'as lead' when they should say 'at lead[GW22]'

l1031 "this is not the case for practical applications" - well, it probably says that if you are choosing a benchmark/reference forecast, climatology is probably not good enough; it would be more stringent to use a benchmark of climatology+trend[GW23][GW24].

L1174 Figure B1 - This is a nice figure, but wouldn't it have been better to look at forecasts exceeding the median, to make it more consistent with the calculation of correlations (which are calculated on the median ensemble member[GW25])?

Typos/Grammar

L145 "So, the objective" Delete "So, " [GW26]

L205 "and to be available" should be "and are available[GW27]"

L675 Delete the first 'because[GW28]'.

References

Arnal L, Cloke HL, Stephens E, Wetterhall F, Prudhomme C, Neumann J, Krzeminski B, Pappenberger F. 2017. Skilful seasonal forecasts of streamflow over Europe? Hydrol. Earth Syst. Sci. Discuss. 2017: 1-27. DOI: 10.5194/hess-2017-610.

Zhao T, Bennett JC, Wang QJ, Schepen A, Wood AW, Robertson DE, Ramos M-H. 2017. How suitable is quantile mapping for post-processing GCM precipitation forecasts? Journal of Climate 30: 3185-3196. DOI: 10.1175/jcli-d-16-0652.1.

Seasonal ~~streamflow~~ hydro-meteorological forecasts for Europe: ~~— II.~~ s~~S~~ources of skill

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Abstract

This paper uses hindcasts (1981-2010) to investigate ~~which~~the -sources of~~cause~~ ~~the~~ skill in seasonal hydrological forecasts for Europe. ~~, as identified in the companion paper (ref)~~The hindcasts were produced with WUSHP (Wageningen University Seamless Hydrological Prediction system). Skill was identified in a companion paper. In WUSHP, hydrological processes are simulated by running the Variable Infiltration Capacity (VIC) hydrological model forced with an ensemble of bias-corrected output from ECMWF's Seasonal Forecasting System 4 (S4). We first analysed the meteorological forcing. The precipitation forecasts contain considerable skill for the first lead month but hardly any significant skill at longer lead times. Seasonal forecasts of temperature have more skill. Skill in summer temperature is related to climate change and more or less independent of lead time. Skill in February and March is unrelated to climate change. Different sources of skill in hydro-meteorological variables were isolated with a suite of specific hydrological hindcasts akin to Ensemble Steamflow Prediction (ESP). These hindcasts show that in Europe initial conditions of soil moisture form the dominant source of skill in runoff. From April to July, initial conditions of snow contribute significantly to the skill. Some remarkable skill features are due to indirect effects, i.e. skill due to forcing or initial conditions of snow and soil moisture at an earlier stage is stored in the hydrological state (snow and/or soil moisture) of a later stage, which then contributes to persistence of skill. Skill in evapotranspiration originates mostly in the meteorological forcing. For runoff we also compared the full hindcasts (with S4 forcing) with two types of ESP (like) hindcasts (with identical forcing for all years). Beyond the second lead month, the full hindcasts are less skilful than the ESP (like) hindcasts because interannual variations in the S4 forcing ~~at long blead times~~ consist mainly of noise which enhances degradation of the skill.

~~Abstract~~

~~Seasonal forecasts can be exploited to optimize hydropower energy generation, navigability of rivers and irrigation management to decrease crop yield losses. This paper is the second of two papers dealing with a model-based system built to produce seasonal hydrological forecasts (WUSHP: Wageningen University Seamless Hydrological Prediction system), applied here to Europe. In WUSHP, hydrology is simulated by running the Variable Infiltration Capacity (VIC) hydrological model with meteorological forcing from bias-corrected output of ECMWF's Seasonal Forecasting System 4 (S4). WUSHP is probabilistic. For the assessment of skill, hindcasts (1981-2010) were generated. Whereas the first paper presented the development and the skill evaluation of the system, this paper provides explanations for the skill.~~

~~To that purpose, we first analysed the forcing and found considerable skill in the precipitation forecasts for the first lead month but hardly any significant skill for subsequent lead months. Seasonal forecasts of temperature have more skill. Skill in summer temperature is related to climate change and more or less independent of lead time. Skill in February and March is unrelated to climate change. Sources of skill in runoff were isolated with a suite of specific hindcasts. These revealed that, beyond the second lead month, streamflow hindcasts with meteorological forcing that is identical for all years (InitSH) have more skill in runoff than the streamflow hindcasts forced with S4 output (FullSH). This occurs because interannual variability of the S4 forcing has hardly any skill while it adds noise. Other specific hindcasts show that in Europe initial conditions of soil moisture form the dominant source of skill in runoff. From April to July, at the end of the melt season, initial conditions of snow contribute significantly to the skill, provided forecasts do not start earlier than in February. Some remarkable skill features are due to indirect effects, i.e. skill due to forcing or initial conditions of snow and soil moisture at an earlier stage is stored in the hydrological state (snow and/or soil moisture) of a later stage, which then contributes to persistence of skill. Finally, predictability of evapotranspiration was analysed in some detail, leading among others to the conclusion that its skill originates mostly in the meteorological forcing.~~

1 Introduction

Society may benefit from seasonal hydrological forecasts (Viel et al., 2016; Soares and Dessai, 2016; Crochemore et al., 2016), i.e. hydrological forecasts for future time periods from more than two weeks up to about a year (Doblas-Reyes et al., 2013). Such predictions can be exploited to optimize e.g. hydropower energy generation (Hamlet et al. 2002), navigability of rivers in low flow conditions (Li, et al., 2008) and irrigation management (Ghile and Schulze 2008; Mushtaq et al. 2012) to decrease crop yield losses.

This is the second paper about seasonal hydrological forecasts for Europe produced with WUSHP (Wageningen University Seamless Hydrological Prediction system), a dynamical (i.e. model-based) system. In summary, the forecasts of WUSHP are made with the Variable Infiltration Capacity (VIC) hydrological model, which uses bias-corrected output of forecasts from ECMWF's Seasonal Forecast System 4 (S4) as meteorological forcing. The system is probabilistic.

In the present and in the companion paper (Greuell et al. 2018), WUSHP is used as a research tool for purposes of academic interest. In the companion paper, the set-up of WUSHP has been described and spatial and temporal variations of skill, or lack thereof, in runoff and discharge in Europe have been established by means of hindcasts. Significant skill was found for many regions, varying by initialisation and target months. For lead month 2, hot spots of significant skill in runoff are situated in Fennoscandia (for target months from January to October), the southern part of the Mediterranean (from June to August), Poland, Northern Germany, Romania and Bulgaria (mainly from November to January) and Western France (from December to May). In general, the spatial pattern of significant skill in runoff was found to be fixed in space while the skill decreased in magnitude with increasing lead time. Some significant skill remained even at the end of the hindcasts (7 months).

To extend the evaluation of the system, its reliability was analysed. The main finding is that during the two first lead months the system is not far from being perfectly reliable but that with progressing lead time reliability is reduced. We also found that discrimination skill and reliability have similar characteristics, e.g. for longer lead times the highest values of reliability are found in some regions with considerable amounts of discrimination skill. Details of this analysis are provided in Appendix A.

The current paper aims to identify the sources of the skill in WUSHP and is structured in two main parts. In the first part, an analysis of the skill in the most important meteorological forcing variables (precipitation, two-meter temperature and incoming short-wave radiation from S4) is presented. For S4, this was done earlier by Kim et al.

(2012) for the boreal winter months (DJF) with initialisation on the first of November. For that case, they found that in Europe S4 has no skill in the precipitation forecasts and some skill in the temperature forecasts for Southern Sweden, Southern Finland, the region south-east of Saint Petersburg and Northern Germany. Scaife et al. (2014) analysed the skill for the same target months and starting date but with another prediction system, namely the Met Office Global Seasonal forecast System 5 (GloSea5). ~~Scaife et al. (2014)~~They found that, while the GloSea5 temperature forecasts for Europe contain hardly any significant skill, the ~~but that~~ GloSea5 forecasts of the North Atlantic Oscillation are correlated significantly with observed temperatures in northern and southern Europe. This means that there is untapped predictability in the GloSea5 temperature forecasts. We will analyse predictability of the mentioned output variables of S4 for the whole continent and will consider all combinations of lead and target months.

The second line of analysis aims to investigate the reasons for presence or absence of skill in hydro-meteorological variables by means of a series of specific hindcast ~~experiment~~s that isolate potential sources of skill, namely meteorological forcing, the initial conditions of soil moisture and the initial conditions of snow. ~~Then, a suite of specific hindcasts is carried out and evaluated,~~ Such an approach was explored earlier by Wood et al. (2005), Bierkens and Van Beek (2009) and Koster et al. (2010). ~~The 30 years of standard hindcasts produced by WUSHP, analysed in the companion paper and referred to as Full Streamflow Hindcasts (FullSH; climate-model-based hindcasts" according to Yuan et al., 2015) constitute the starting point.~~ ~~Then, a suite of specific hindcasts is carried out and evaluated, an approach explored earlier by Wood et al. (2005), Bierkens and Van Beek (2009) and Koster et al. (2010).~~ Each specific hindcast is ~~largely~~ basically identical to the standard hindcasts that we analysed in the companion paper, named~~the~~ Full Streamflow Hindcasts (FullSH; climate-model-based hindcasts" according to Yuan et al., 2015). ~~FullSH but~~However, in the specific hindcasts one or two of the sources of predictability are isolated by eliminating the effect of all of the other sources through removal of their interannual variation. In the ensuing analysis the skills in ~~runoff~~ hydro-meteorological variables found in the different specific hindcasts will then be compared among themselves and with the skill from the FullSH.

These specific hindcasts[RH1] are ~~related and~~ similar in structure to~~,~~ ~~to~~ and inspired by the conventional Ensemble Streamflow Prediction (ESP) technique (e.g. Wood and Lettenmaier, 2008, Shukla and Lettenmaier, 2011, Singla et al., 2012~~1~~), which ~~are~~can~~can~~, like our specific hindcasts, be ~~be~~ used to isolate sources of skill. ~~However, in~~The main difference between the specific hindcasts of this study and the ESP technique is that in ESP and its variant reverse-ESP the meteorological forcing is taken from data based on observations, ~~and not~~while in the present study the forcing is taken from meteorological hindcasts~~, as in the present study~~. In fact, we also produced ESPs. In Sect. 4.3 we will compare these with one of the other specific hindcasts and more generally discuss the relation between our specific hindcasts and the ESP suite.

Though this paper focusses on runoff, the analysis is complemented with an analysis of the skill in evapotranspiration s~~S~~ince this variable ~~evapotranspiration~~ has a large effect on runoff (see Willmott et al., 1985)~~, the analysis is complemented with an analysis of the skill in this variable~~. Predictions of evapotranspiration also have independent value because they are useful for planning of water level control in polders and for planning of water use for irrigation and fertiliser application. As for runoff, we will exploit the specific hindcasts to isolate the different sources of predictability in evapotranspiration forecasts.

~~Bierkens and van Beek (2009) investigated the sources of runoff skill for seasonal hydrological forecasting over Europe. They found that in winter initial conditions constitute the dominant source while in summer meteorological forcing and initial conditions are equally important. Singla et al. (2011) assessed the skill of hydrological predictions for France and concluded that over most plains the predictability of hydrological variables primarily depended on forcing, whereas it mainly depended on snow cover over high mountains. The Seine catchment area was an exception as the skill mainly came from the initial state of its large and complex aquifers.~~

The version of VIC that we used was only crudely calibrated (by Nijssen et al., 2001). Hence, ~~streamflow~~ discharge computed by the present version of the system may be expected to deviate substantially from observations, both in terms of the mean and in terms of the spread of the ensemble of forecasts. Also, within WUSHP no post-processing of discharge is carried out to correct for such deficiencies. This makes the system unsuitable to issue forecasts of absolute amounts of discharge but the system can be used to provide information on how likely it is that in a coming month or season discharge will be above or below normal. Consequently, the most important criteria for the selection of skill metrics (see Sect. 2.2) are their ability of discrimination, and their insensitivity to biases and to the spread of the forecasts.

~~The~~ The objective of the present paper is to analyse, at a pan-European and at regional scale, the sources of probabilistic skill of seasonal hydrological forecasts produced by WUSHP. The next section (Sect. 2) will describe the seasonal prediction system itself, the analysis approach as well as details of the various specific hindcast performed. We will present the skill in ~~three variables of~~ the meteorological forcing (Sect. 3.1), ~~followed by~~isolate the skill in runoff ~~found in the various specific hindcasts, which allows attribution~~due to either forcing or different types of initial conditions (Sect. 3.2), and finally ~~an~~ analyse the~~is of~~ skill in evapotranspiration (Sect. 3.3). We conclude with a discussion (Sect. 4) and conclusions (Sect. 5).

2 System and methods

2.1 The forecast system

The forecasts of WUSHP combine three elements, namely meteorological forcing from ECMWF's Seasonal Forecast System 4 (Molteni et al., 2011), bias correction of the meteorological forcing with the quantile mapping method of Themeßl et al. (2011) and simulations with the Variable Infiltration Capacity (VIC) hydrological model (Liang at al., 1994). The skill of the system was assessed with hindcasts. These cover the period 1981-2010, were initialised on the first day of each month and ~~have a length of~~extend to a lead time of seven months. The system is probabilistic (15 members), so each set of hindcasts consists a total of 5400 runs (30 years * 12 months * 15 members). In addition a single reference simulation was performed, in which VIC was run with a gridded data set of model-assimilated meteorological observations, namely the WATCH Forcing Data Era-Interim (WFDEI; Weedon et al., 2014). The reference simulation has a dual aim. The first aim is to create initialisation states for the hindcasts. Secondly, the output of the reference simulation, e.g. ~~discharge~~runoff, is used for verification of the hindcasts. This output will be named "pseudo-observations" here.

Due to the set-up of the routing module of VIC, the state of discharge could not be saved and loaded. Hence t~~T~~o spin up discharge, each 7-month hindcast was preceded by a one month simulation with WFDEI forcing, which in turn was initialised with the model states generated in the reference simulation and zero discharge. All hindcasts and simulations were performed on a 0.5° x 0.5° grid in natural flow mode, i.e. river regulation, irrigation and other anthropogenic influences were not considered. VIC is run with a time step of 3 hours. More details about the set-up of the system and the hindcasts can be found in the companion paper (Greuell et al., 2018).

2.2 Methods of analysis and observations

In this paper we analyse hindcasts of runoff, discharge and evapotranspiration. Runoff is defined as the amount of water leaving the model soil either along the surface or at the bottom, while we define discharge as the flow of water through the largest river in each grid cell.

Discrimination skill (briefly skill from now on) is measured in terms of the correlation coefficient between the median of the hindcasts and the (pseudo-)observations (R). We will designate R-values as significant for p-values less than 0.05. We also considered metrics designed for the evaluation of categorical forecasts (terciles), namely the Relative Operating Characteristics area (ROC area)~~ area~~ and the Ranked Probability Skill Score (RPSS). The thresholds used for assigning individual (pseudo-)observations ~~observations~~ to terciles were determined from the (pseudo-)observations~~observations~~ themselves. Similarly hindcasts were assigned to terciles by reference to themselves. Due to this strategy metrics are unaffected by biases, a desired property (see Sect. 1). In the companion paper skills in terms of the considered metrics were compared and it was found that for all combinations of target and lead month the skill patterns in the maps were similar to a high degree. For that reason we selected only one of them (R) for this paper.

Unless mentioned otherwise, prediction skill of the hydrological variables is determined against the pseudo-observations (see Sect. 2.1). These have the advantages of being complete in the spatial and the temporal domain and ~~to be~~of being available for all model variables. We will refer to this type of skill as “theoretical skill”. In the companion paper theoretical skill for discharge was compared to “actual skill”, which is the skill assessed with real observations. ~~It was concluded that, in terms of R and on average across all target months and for lead month 2, the ratio of actual to theoretical skill was 0.67 for "large basins" and 0.54 for "small basins". These two categories were defined on the basis of the observations of discharge, which were acquired from the Global Runoff Data Centre, 56068 Koblenz, Germany (GRDC) and gridded onto the 0.5° x 0.5° model grid. Large basins are catchments upwards from the monitoring station larger than 9900 km^2 and small basins are catchments upwards from the station with an area smaller than that of the corresponding grid cell.~~

For the determination of the skill of the meteorological forcing we used the WFDEI data.

To investigate the possible contribution of trends to skill, skill in the meteorological forcing and in runoff was determined both before and after removing the trend from both the (pseudo-) observations and the hindcasts. Data were detrended by first constructing time series (1981-2010) for each variable, target month, lead month and grid cell (30 values). We then removed the trend from each time series by first fitting a least-squares regression line to the ~~original ~~time series and then subtracting the time series corresponding to the line from the original data. For the hindcasts, time series were constructed for the mean of the ensembles and the resulting best fit was subtracted from each member individually.

Like in the companion paper, skill was analysed on a monthly and not on a seasonal basis with the aim of achieving a relatively high temporal resolution in the skill analysis. Attention was confined to consistent skill, which we define as skill that persists during at least two consecutive target or lead months. In accordance with Hagedorn et al. (2005), we designated the first month of the hindcasts as lead month zero~~, so target month number is equal to the number of the month of initialisation plus the lead month number.~~.

In most result sections, we will first analyse and explain skill at the level of the entire domain. We will then take out the most noteworthy details of the summary plots and seek an explanation for them.

2.3 Isolation of sources of skill and surface water initialisation

As already pointed out in the introduction, a number of specific hindcasts were carried out with the aim of isolating the contributions of different sources to skill. The Full Streamflow Hindcasts (FullSH), in which skill is due to both meteorological forcing and initial conditions, constitute the starting point. The specific hindcasts can be seen as restricted, in the sense of limiting the types of sources of skill, versions of the FullSH. The following five sets of specific hindcasts, each consisting of 5400 computer runs, were produced:

1) The *InitSH* isolate the skill due to both types of initial conditions considered here (soil moisture and snow). Like in the FullSH, the annually varying initial conditions are taken from the reference simulation while for each year the meteorological forcing is identical and consists of an ensemble of fifteen S4 hindcasts. More specifically, we selected member 1 from the 1981 hindcasts, member 2 from the 1983 hindcasts, etc. By using identical meteorological forcing for all of the years of the hindcasts, skill in hydro-meteorological variables due to skill in the forcing is eliminated.
2) The *SMInitSH* isolate the skill due to the initial conditions of soil moisture only. SMInitSH is identical to InitSH but in all SMInitSH snow initial conditions are taken as the 30 year average of the snow conditions in the reference simulation.
3) The *SnInitSH* isolate the skill due to the initial conditions of ~~snow~~ snow contained in the snow cover~~only~~. SnInitSH is identical to InitSH but in all SnInitSH soil moisture initial conditions are taken as the 30 year average of the soil moisture conditions in the reference simulation.
4) The *MeteoSH* isolate the skill due the meteorological forcing and as such are the full complement of the InitSH. Like in the FullSH, the annually varying forcing is taken from the probabilistic S4 hindcasts while for each year the initial soil moisture and snow conditions are identical and equal to the 30 year average of the soil moisture and snow conditions in the reference simulation. By taking identical initial

conditions for all of the years of the hindcasts, skill due to the initial conditions of soil moisture and snow is eliminated.

5) The *ESP* are identical to the InitSH, both in terms of their construction and in terms of their purpose. However, in the ESP the forcing is not taken from the S4 hindcasts but from the WFDEI data by selecting the 15 ~~uneven~~ odd years from 1981 to 2009.

Forcings and initial conditions of all of these hindcasts differ among the calendar months, so that the annual cycle is conserved. Hence, in the list above:

- "Identical for all years" means that the forcings (or the initial conditions) for all hindcasts starting in ~~January~~ e.g. May are identical.
- "30 year average" means that the initial conditions for all hindcasts starting in ~~January~~ e.g. May are averaged over all of the ~~January~~ May 1st ~~conditions~~ model states in the reference simulation.
- "Annually varying" means that the forcings (or the initial conditions) for all hindcasts starting in ~~January~~ e.g. May vary from year to year.

These statements also hold for the other calendar months.

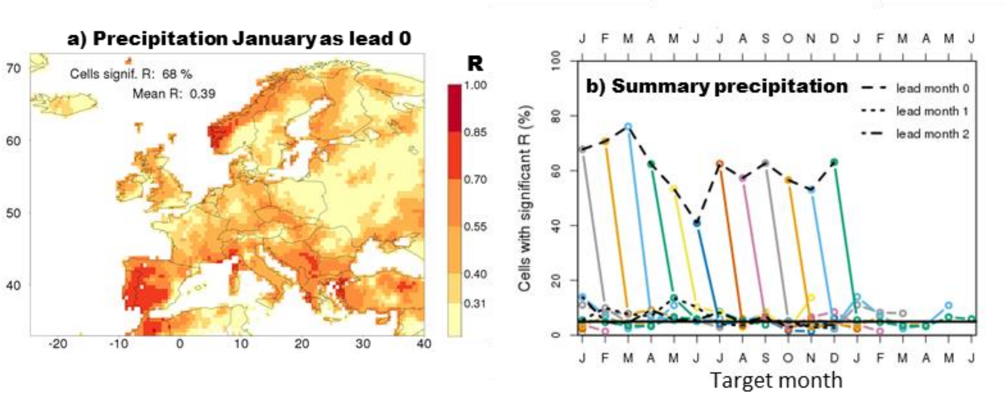
Thus, like the FullSH, all specific hindcasts for a single starting date consist of 15 members, which is important since ensemble size affects skill metrics (Richardson, 2001). Also, in all hindcasts the probabilistic character is exclusively due to the 15 members of the meteorological forcing while initial conditions are deterministic. This consistency is important since the main aim of the various specific hindcasts is to compare them with each other. A disadvantage of the small ensemble size ~~of the forcing~~ is the sampling uncertainty, see Sect. 4.2 of the companion paper.

~~All of the hindcasts were preceded by a one month run with reference forcing (WFDEI) with the single aim of initialising the amount of discharge in the rivers. So,~~ D~~d~~ischarge initialisation, a potential source of skill, is not considered. This has no effect on most of the analyses of the paper, since these are made in terms of runoff. Where discharge is analysed the effect of discharge initialisation is, due to the limited residence time of water in the rivers, restricted to the first lead month of the hindcasts (see Yuan, 2016).

3 Explanations of skill in hydrological variables

3.1 Skill in the meteorological forcing after bias correction

In this sub-section, the skill of the meteorological forcing will be analysed. Attention will be limited to the three ~~most important~~ input variables of VIC that have the largest effect on runoff and evapotranspiration, namely precipitation, two-meter temperature and incoming short-wave radiation. The WFDEI data are used as a reference. Here the data after bias correction are considered. In Appendix ~~A~~ B we will discuss the skill of the raw S4 data, which is the meteorological forcing before bias correction. Differences in skill between the bias-corrected and the uncorrected data are negligible for temperature and short-wave radiation and small for precipitation.



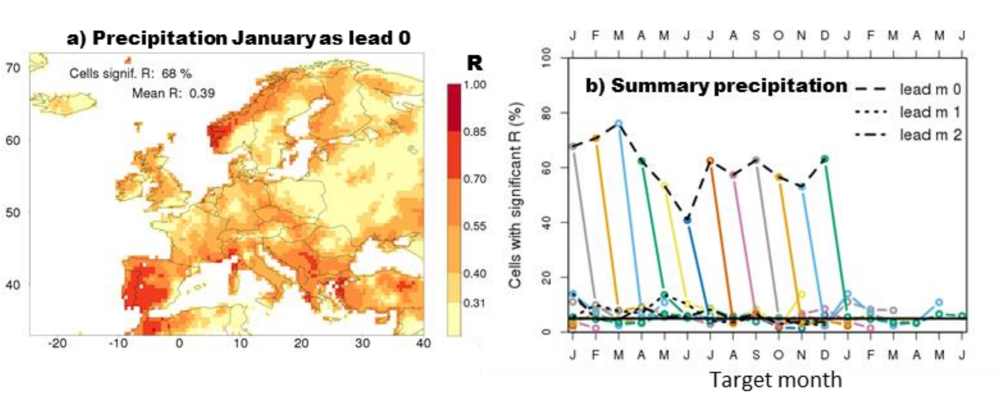
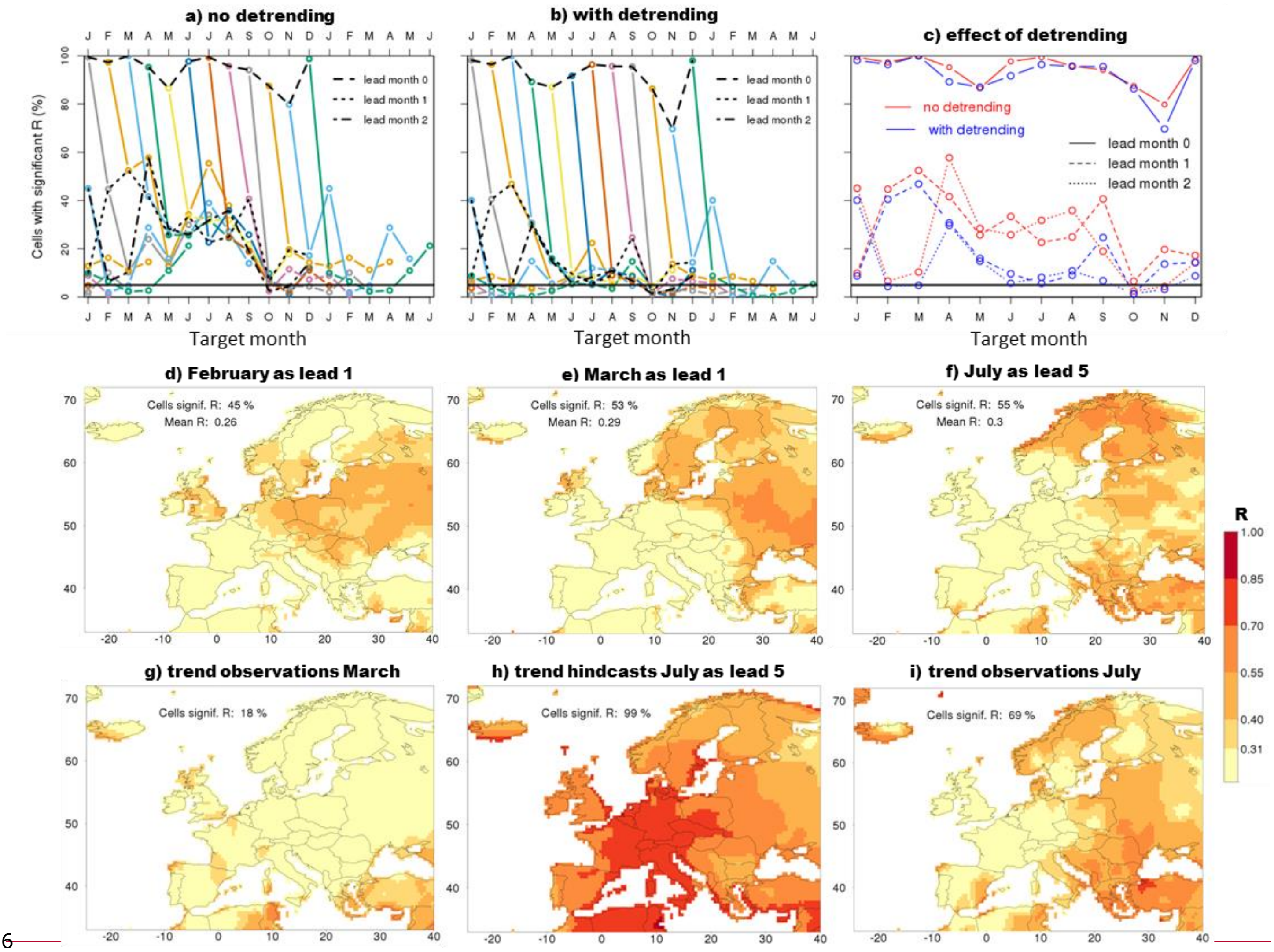


Figure 1: Skill of the precipitation hindcasts after bias correction. Fig. 1a shows a map of the correlation coefficient between the observations and the median of the hindcasts (R), for target month January as lead month 0. The threshold of significant skill lies at 0.31, so ~~yellow~~ cells with the lightest yellow colour have insignificant skill and g~~. G~~rid cells with other colours have significant skill~~, with the amount of skill increasing with darkening colours~~. The legend provides the percentage of cells with significant values of R and the domain-averaged value of R. Fig. 1b depicts the percentage of cells with significant

skill in terms of R, as a function of the target and lead month. Each coloured curve represents the hindcasts starting in a single month of the year and has a length of 7 (lead) months. For better visualisation the parts of the curves that end in the next year are shown twice, namely at the left hand and the right hand side of the graph. Black lines ~~(dashed, dotted and dashed-dotted)~~ connect the results for identical lead times, which are specified in the legend (lead m = lead month). The horizontal line gives the expected fraction of cells with significant skill due to chance in the case that the hindcasts have no skill at all (5%).

Fig. 1 shows results of the skill analysis of the precipitation forcing. Fig. 1a provides an example of the skill for a single target and lead month (January as lead month 0). A summary of the skill in the precipitation hindcasts is given in Fig. 1b, which plots the fraction of all cells within the domain with statistically significant R values. So, Fig. 1a condenses into a single point in Fig. 1b. During the entire year, there is considerable skill for lead month 0 (on average in 61% of the domain) but skill declines very rapidly to 6% for lead months 1 and 2, just 1% more than the percentage of cells in the case of no true skill at all. Hence, from lead month 1 on, skill is almost negligible. Regarding lead month 0, there is more skill in January, February and March than during the other months. For the ~~same~~ lead month 0, hot spots of consistent skill, i.e. with a duration of significant skill of at least three target months, are situated on the Iberian Peninsula from November to March, in Western Norway from January to April, in Greece and Western Turkey from December to February and in Scotland from December to March. All these occurrences of consistent skill are restricted to the winter half of the year and mostly to coastal regions (see Fig. 1a), suggesting them to be linked to the initial state of the sea surface temperature.


a) no detrending
b) with detrending
c) effect of detrending
J F M A M J J A S O N D J F M A M J
Cells with significant R (%)
0
20
40
60
80
100
lead month 0
lead month 1
lead month 2
no detrending
with detrending
Target month
d) February as lead 1
Cells signif. R: 45 %
Mean R: 0.26
e) March as lead 1
Cells signif. R: 53 %
Mean R: 0.29
f) July as lead 5
Cells signif. R: 55 %
Mean R: 0.3
g) trend observations March
Cells signif. R: 18 %
h) trend hindcasts July as lead 5
Cells signif. R: 99 %
i) trend observations July
Cells signif. R: 69 %
R
1.00
0.85
0.70
0.55
0.40
0.31
-20
-10
0
10
20
30
40
70
60
50
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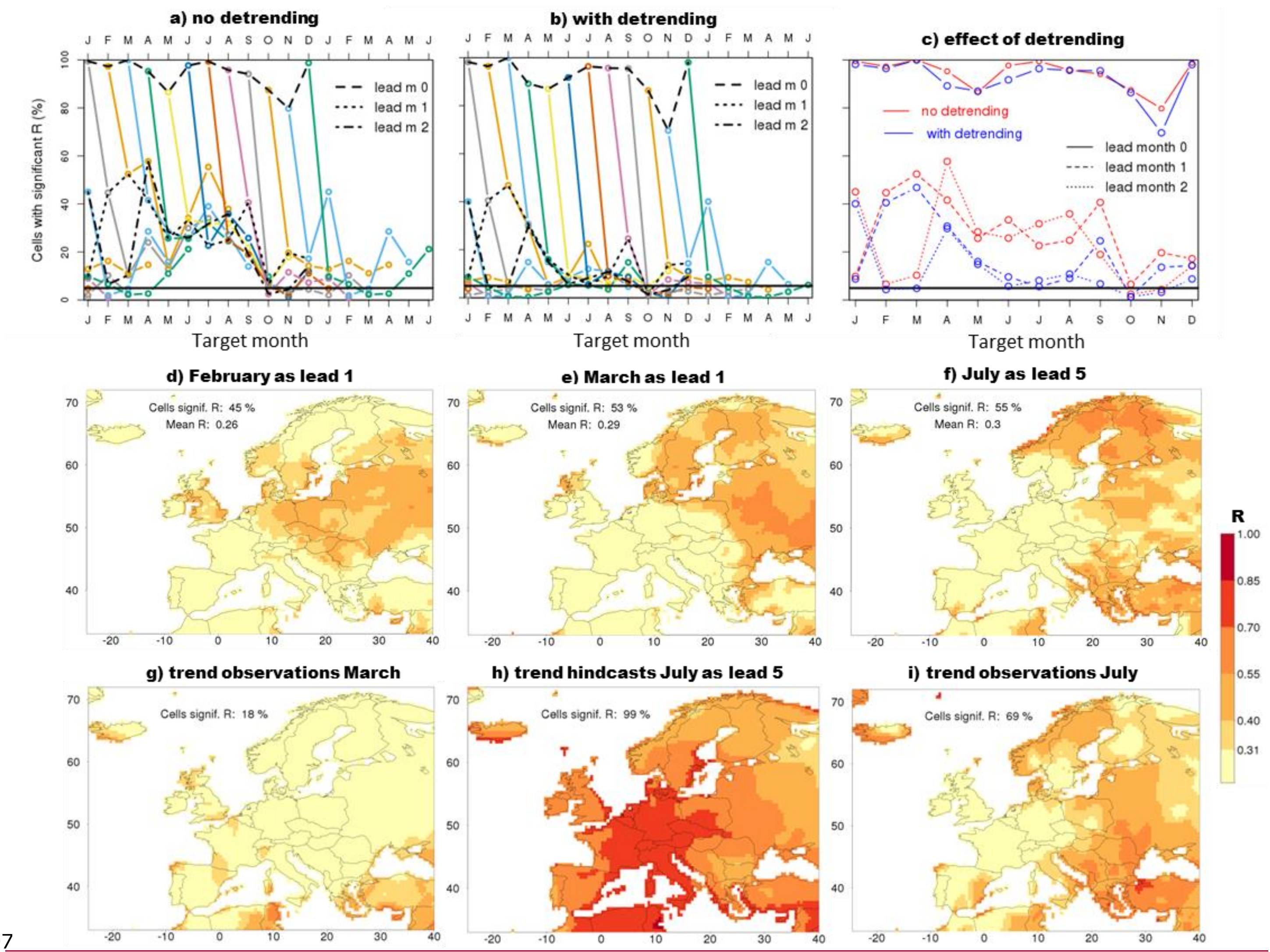


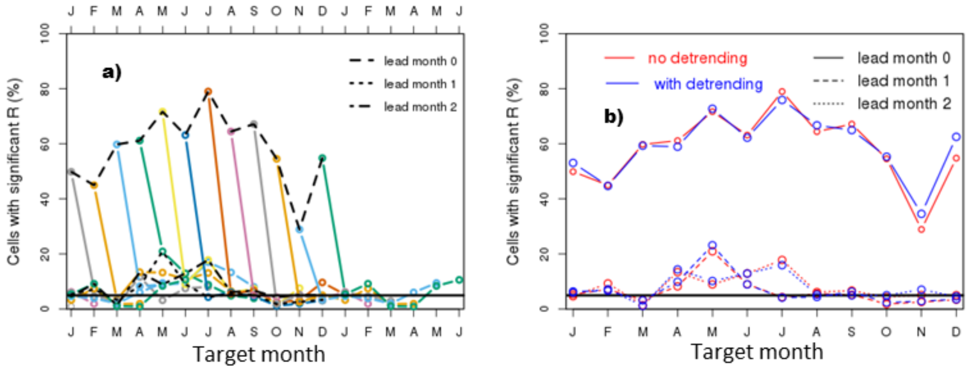
Figure 2: Skill of the two-meter temperature hindcasts after bias correction. Figures 2a and 2b give the percentage of cells with significant values of R for the un-detrended (a) and the detrended (b) temperature hindcasts (see Fig. 1b for further explanation). Fig. 2c compares annual cycles of skill of un-detrended and detrended data for the first three lead months. The three panels in the middle row show maps of R for the un-detrended temperature hindcasts for target months February (Fig. 2d) and March (Fig. 2e) as lead month 1 and July as lead month 5 (Fig. 2f). The bottom three panels depict the correlation coefficient of the trend (not the trend itself) of the observed monthly mean temperature for March (Fig. 2g) and July (Fig. 2i), and ~~of the trend in the median~~mean of the hindcasted temperature for July as lead month 5 (Fig. 2h).

Figure 2 shows important aspects of skill in the two-meter temperature hindcasts. One aspect is the possible contribution of a 30-year trend, which could be related to greenhouse warming, to the skill. Figure 2a and 2b provide summaries of the skill of the un-detrended and the detrended data, respectively, whereas Fig.~~ure~~ 2c compares these two types of data. For lead month 0, the ~~un-detrended~~ hindcasts have significant skill in the largest part of the domain (Figs. 2a and 2b) and d~~.~~etrending has a small effect (Fig. 2c). At longer lead times, the percentage of cells with significant skill quickly drops towards the theoretical no skill limit (5%) but there are a few exceptions, namely:

- For lead month 1, February and March temperatures are predicted with significant skill in a considerable part of the domain (44% in February; 53% in March). In both months the region with skill is more or less contiguous and comprises the Russian part of the domain, the Ukraine and the regions bordering the southern part of the Baltic Sea (Figs. 2d and 2e). In February the region of skill extends towards Central Europe. In March it also comprises northern Fennoscandia. This skill hardly diminishes by detrending the data (Figs. 2b and 2c), suggesting that the skill is not related to climate change. Indeed, in February and March the observed trend (in the WFDEI data set) is insignificant across most of the domain (11% of the domain in February and 18% in March) and, more importantly here, it is insignificant in the regions with significant skill in the temperature hindcasts (Fig. 2g demonstrates this for March). We conclude that the temperature skill in February and March as lead month 1 must be due to initial conditions of the climate model (see also the discussion on Fig. 10).
- The three summer months (JJA) exhibit significant skill at all lead times in much more than 5% of the domain (a range from 22 to 56% for all combinations of the three summer months and all lead months beyond lead month 0), see Fig. 2a. In this case the fraction of cells with significant skill is not a function of lead time, which is the type of behaviour that Yuan (2016) also found for the Yellow River basin. Since Figs. 2b and 2c demonstrate that the skill for JJA more or less vanishes when the temperature hindcasts and observations are detrended, we conclude that the~~is~~ skill for these months is due to trends in the data and hence probably related to greenhouse warming. Another conclusion is that skill that hardly varies with lead time ~~that skill might~~may be related to climate change~~, if the magnitude of the skill does not or hardly varies with lead time~~.

It should be noted here that trends can only cause correlation between hindcasts and observations, and hence skill in the hindcasts, if they are present in both time series. A random time series of hindcasts is not correlated with a time series of observations with a trend and vice versa. Indeed, time series of both hindcasts and observations have a maximum in significant trends in summer, when trends form the prime source of skill according to our analyses. In the hindcasts and on average over all lead times beyond the first month, the summer months exhibit significant trends in almost the entire domain (95%), versus 79% of the domain in the other months of the year, on average. Similarly, observed trends are significant during the three summer months in 67% of the domain, versus only 24% of the domain in the other months of the year, on average. These percentages also show that significant trends occur in a larger part of the domain in the hindcasts than in the observations. So, the observations, and not the hindcasts, are mostly limiting the occurrence of trend-related skill in the temperature hindcasts. This point is illustrated by the example of July as lead month 5 in Figs. 2f, h and i~~g-i~~ but a similar illustration could have been provided for the other summer months and different lead months. Figure 2h shows that the trends of the hindcasts for July ~~as lead month 5~~ are significant across almost the entire domain (99% of the domain). However, according to Fig. 2i only 69% of the domain has a significant trends in the observed July temperatures. Indeed, the patterns of significance of Fig. 2f (skill in the temperature hindcasts) and Fig. 2i (significance of observed trends) agree to a large extent.

- April, May and September combine the behaviour of February and March, which have skill due to initial conditions of the climate model, with the skill of the summer months, which show skill related to trends (Fig. 2c).
- January has a considerable amount of significant skill but only for lead month 2 (42% across the domain). This skill occurs in a stroke of land reaching from England to Russia, which vaguely coincides with the region in which Kim et al. (2012) found skill in the S4 temperature hindcasts for the three winter months. However, as this skill is not found in adjacent lead and target months and thus not consistent, we speculate that this skill is spurious.



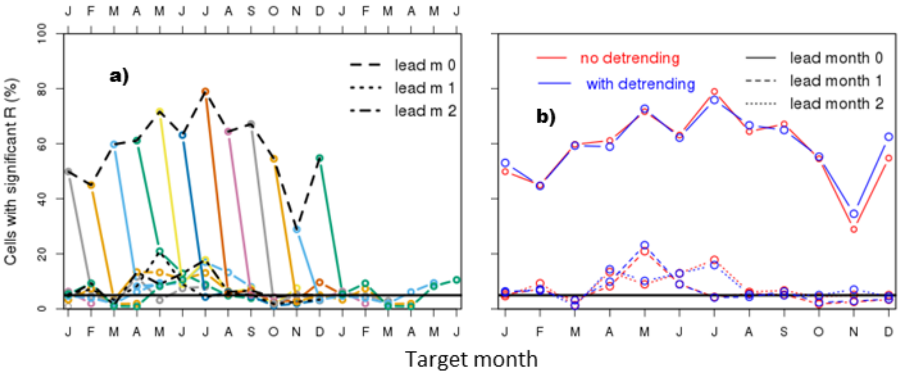


Figure 3: Skill of the incoming short-wave radiation hindcasts after bias correction. Figure 3a gives the percentage of cells with significant values of R (see Fig. 1b for further explanation). Fig. 3b compares annual cycles of skill of un-detrended and detrended data for the first three lead months (see Fig. 2c for further explanation).

Since short-wave incoming radiation is important for evapotranspiration, we finalise this sub-section with a short analysis of its predictability (Fig. 3). In terms of R, skill is considerable during the first lead month with 58% of the cells having significant skill, on average over the year. Months ~~There tends to be more skill~~ from March to September tend to have more skill than ~~during~~ the ~~remaining~~ other months of the year. Beyond lead month 0 skill settles around the no skill line, except from April to July, but the fraction of cells with significant skill never exceeds 21% (in May as lead month ~~0~~1). Trends in the data hardly affect skill (Fig. 3b).

3.2 Sources of skill in runoff and discharge

~~While Sect. 3.1 dealt with predictability of the meteorological forcing,~~In this sub-section analyses the effects of ~~skill in the~~the meteorological forcing and ~~in~~ the initial conditions on the predictability of runoff and discharge (discharge is only considered in Fig. 4) are isolated. We first address the question of how much of the skill in the runoff hindcasts ~~could be~~is linked to trends ~~trends that are possibly related to climate change~~. To examine this question, the pseudo-observations and the hindcasts of runoff were detrended and the skill was compared to that of the un-detrended data sets. We found that for lead month 2 and averaged over all months of the year, the fraction of cells with a significant R decreased from 58.7 to 57.4% due to detrending, a difference of 1.3%. This difference is much smaller than the decrease for temperature (11.8%). We conclude that trends contribute very little to skill in runoff. All analyses of this sub-section hereafter pertain to un-detrended data. ~~Unless indicated otherwise, the pseudo-observations are used for verification.~~

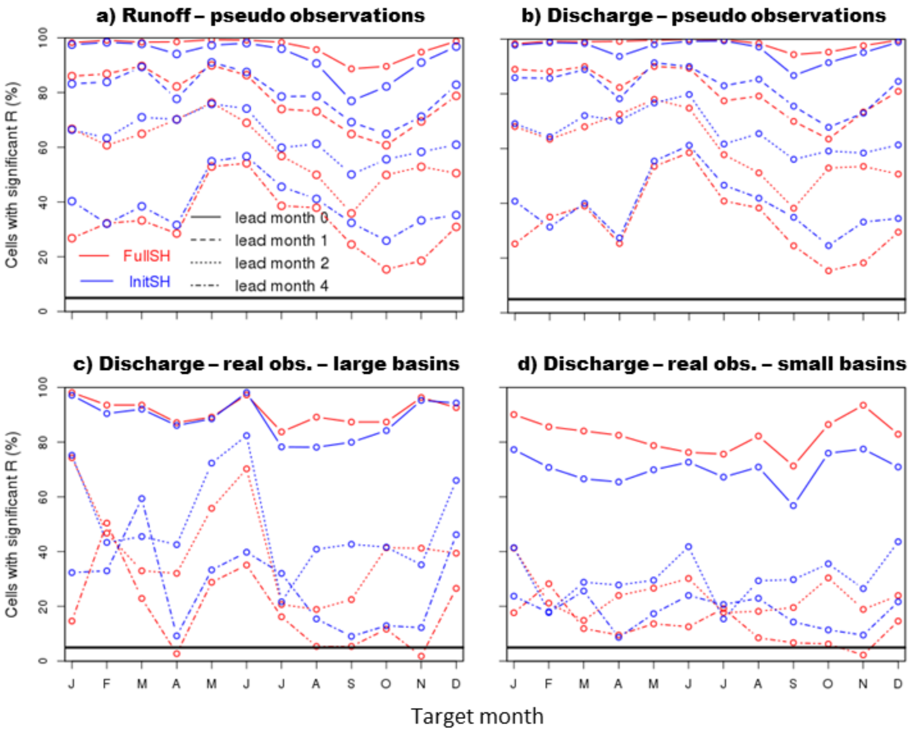
3.2.1 The relative importance of initial hydrological conditions

Figure 4 compares the InitSH with the FullSH in terms of the fraction of cells with a significant R~~. Figs. 4a and 4b show the result~~ for runoff (Fig. 4a) and discharge (Fig. 4b). ~~, respectively, using the pseudo-observations, so calculations for all cells of the domain contribute to the result.~~ While the lumped results hardly differ between runoff and discharge (the companion paper discusses small differences in skill between these two variables), systematic differences in skill between the FullSH and InitSH are revealed. ~~In~~ For lead month 0, skill is higher in the FullSH than in the InitSH for all target months of the year, though the difference becomes very small when the fraction of the domain with significant skill approaches 100% and hence becomes unsuitable to discriminate between the two~~different~~ cases. ~~.~~Beyond lead month 1, the reverse occurs for most target months. Lead month 1 is transitional with the order of skill depending on the time of the year. We produced figures similar to Fig. 4, all shown in the supplementary material, for skill evaluation:

1) ~~o~~Of discharge with real, instead of pseudo-, observations, both for large basins (Fig. S1a) and small catchments (Fig. S1b), and for a sub-set~~lection~~ of the large catchments with relatively little human impact (Fig. S2).
2) O~~o~~f runoff ~~with all of the considered metrics~~ in terms of the fraction of the domain with significant skill for the other metrics considered (RPSS, ROC AN, ROC BN; Figs. S3-S5) and in terms of the domain-mean value of R (Fig. S6).

In all of these cases, the reversal of skill around lead month 1 was found. So, the reversal is a robust feature and not an artifact due to the type of observations, nor due to human impacts on~~f~~ river flow, nor an artefact of the metric used in the verification procedure. ~~Figs. 4c (for large catchments) and 4d (for small catchments) compare actual discharge skill, i.e. skill determined with real discharge observations, of the FullSH with that of the InitSH. As discussed in the companion paper, domain-average actual skill is less than domain-average theoretical skill but, more importantly here, the reversal of skill after~~

~~lead month 1 found with the pseudo-observations is confirmed with real observations, both for large and for small basins. While Fig. 4c is based on the data for all 111 large catchments, a similar graph was produced for a selection of the large catchments with relatively little human impact (about half of the 111 basins; Fig. S1 in the supplementary material; see the companion paper for a description of the selection procedure). Again the reversal occurs after lead month 1, so this phenomenon is also confirmed by real observations from relatively pristine basins. Figures similar to Fig. 4 (Figs. S2-S5) illustrate that the skill reversal is found for all of the metrics considered in this study and also for the domain-mean of R.~~



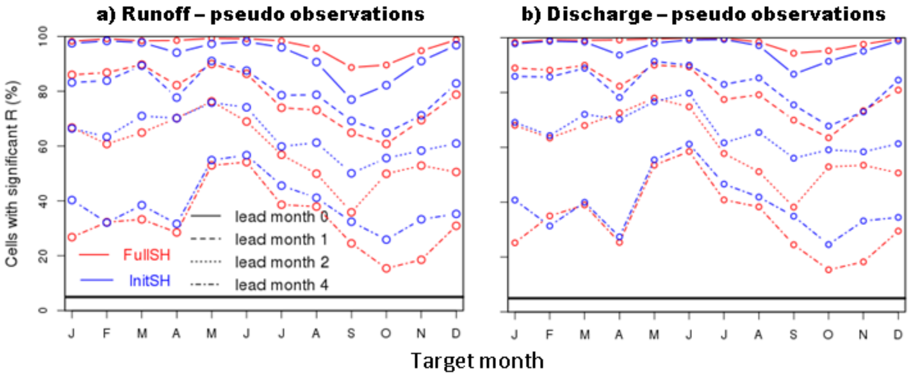


Figure 4: Comparison of the annual cycles of skill of the InitSH (blue) and the FullSH (red). The ~~top~~ two panels show theoretical skill obtained with the pseudo-observations for runoff (Fig. 4a) and discharge (Fig. 4b) at four different lead times. ~~The bottom two panels compare actual skill of discharge for large (Fig. 4c) and for small (Fig. 4d) basins at three different lead times (months 0, 2 and 4).~~

The explanation of the reversal deals with the ranking of the runoff in different years since our metrics largely measure ranking. We will argue that while the InitSH forcing has a neutral effect on the ranking of the runoff forecasts and hence on their skill, FullSH forcing without skill has a negative effect on the ranking of the runoff forecasts and hence on their skill. The InitSH forcing is, by construction, identical for all years. Using this forcing, interannual differences in forecasted runoff diminish with increasing lead time and approach zero when the effect of the initial conditions vanishes. However, to a good approximation rankings of forecasted runoff for different years remains the same as at t=0. So, the forcing has a neutral effect on the ranking and hence on skill. Contrary to the InitSH, the FullSH forcing differs from year to year. This changes the ranking of different years of the runoff forecasts. If the FullSH forcings contains skill, these changes in ranking tend to bring, statistically, the forecasts towards the observations, so skill is added to the runoff forecasts. This is what happens at short lead times. At longer leads, the FullSH can be considered as having no skill. This tends to randomly shuffle the ranking of the runoff forecasts and hence diminishes their skill. Of course, the ranking of the (pseudo-)observations of different years also changes during the course of the forecasts, which generally has a negative effect on runoff skill unless forcing is perfect. This “observation argument” complicates the whole argument but it has no consequences for the argument above since it affects the skill of the FullSH and the InitSH in the same way.

~~wouldwould observationsand increasingly so with increasing lead time, increasingly However, i these forecast-observation deviationsexhibit FullSH , while by design they are identical each year in the InitSH forcing. This leads to an extra degradation of skill with FullSH forcing that is absent with InitSH forcing.~~ [RH2]~~The neither , nor theforcing eforcing which the forcing is free of, and this the higher of the latter compared to timeWe hypothesize that the reason for the reversal lies in the signal-to-noise ratio of the meteorological forcing. The InitSH forcing is the same for each year, so its interannual variation does not contain a signal nor noise. However, the forcing of the FullSH varies from year to year. During the first lead month this forcing has considerable skill (see Sect. 3.1), so the signal-to-noise ratio of the forcing is relatively high. This enhances skill in the FullSH with respect to InitSH. At longer lead times the interannual variation in the forcing hardly contains a signal, with the exception of some limited skill in the~~

~~temperature hindcasts (see Sect. 3.1), so the signal-to-noise ratio is low. Noise in the meteorological hindcasts reduces skill in the FullSH with respect to InitSH. Figure 4 demonstrates that averaged across the domain, the reversal between skill enhancement due to the signal in the forcing of the FullSH and skill reduction due to noise in the forcing of the FullSH occurs at some time between the first and the third lead month, with the exact timing of the reversal depending on the target month.~~

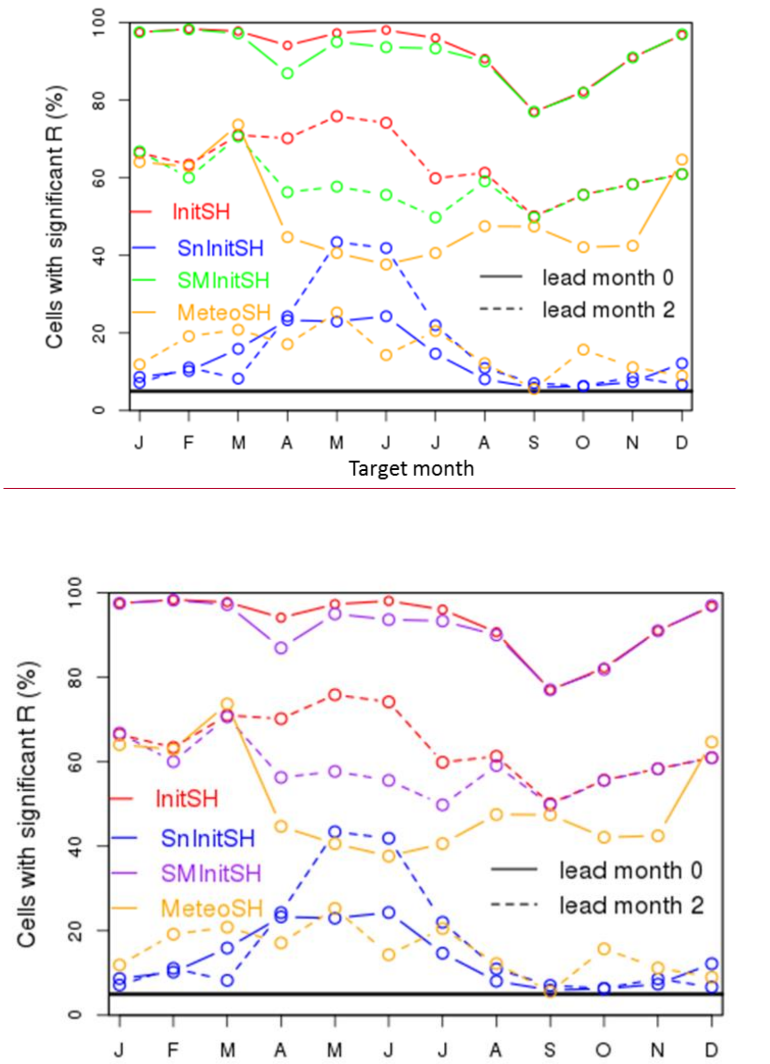


Figure 5: Comparison of the annual cycles of the skill in the runoff hindcasts of four specific hindcasts for lead months 0 and 2. Different colours correspond to different specific hindcasts and different line types to different lead months.

3.2.2 The relative contributions of soil moisture and snow initial conditions, and of meteorological forcing

Figure 5 compares the skill in ~~run-off~~runoff of the specific hindcasts (except ESP) for two lead months (0 and 2). At both lead times and for all target months, initialisation of soil moisture is the dominant source of skill in Europe. Initialisation of snow and meteorological forcing are less important. This is true for all lead times (not shown here).

Meteorological forcing does not only have a relatively small contribution to the domain-averaged skill of Fig. 5 but also to regional skill. We searched for combinations of a region and target months where the MeteoSH produce consistently equal or more skill than the SMInitSH but we did not find any combination where this clearly was the case. On average across the domain and for all target months, d~~D~~uring the first lead month there is more skill due to the forcing (MeteoSH) than due to snow initial conditions (SnInitSH). For later lead months this order depends on the target month, mainly because skill due to snow initial conditions varies strongly during the year. Although skill in ~~run-off~~runoff due to meteorological forcing (in the MeteoSH) is relatively small, it does exceed the skill in the forcing variable to which runoff is most sensitive, precipitation (compare Fig. 5 with Fig. 1). Whereas predictability of precipitation is almost limited to the first lead month, significant skill in runoff due to forcing is more widespread for lead months 1 and 2 (on average over the year in 23 and 15 % of the domain, respectively). We explain the enhanced skill in runoff mainly by an indirect effect. Skill in the precipitation forcing of the first lead month leads to skill in the states of soil moisture and snow at the end of that month. These model states then serve as the source of skill during the next lead months, when the precipitation forcing has no skill at all. In addition to this indirect effect of precipitation, the skill in the hindcasts of temperature (Fig. 2) contributes to ~~the~~ skill in runoff in the MeteoSH.

From April to July, a considerable part of Europe has significant skill derived from snow initialisation provided initialisation does not occur earlier than in February, probably because in all parts of Europe with significant snow fall this process does not stop before February 1.~~.~~ Skill due to snow initialisation reaches a maximum in May and June, resulting in a maximum in skill in the InitSH-hindcasts ~~and the FullSH~~ for these months and for most lead times. When snow contributes considerably to predictability (from April to July), the skill in the InitSH exceeds the skill in the SMInitSH. Because for target months from August to March snow contributes little to predictability, the percentages of cells with significant skill in InitSH and SMInitSH are almost identical for these months. The rapid rise in skill due to snow initialisation at the transition from April to May explains a remarkable feature that we noticed in the companion paper, namely an increase in runoff skill with lead time at this time of year. Another noticeable feature is that the skill due to snow initialisation for lead month 2 exceeds skill due to snow initialisation for lead month 0. This occurs for target months from May to August and will be explained in the text corresponding to Fig. 8.

Figures similar to Fig. 5 but for all metrics of the present study are included in the supplementary material (Fig. S7~~6~~). The graphs for the ROC areas for the Above Normal (AN) and Below Normal (BN) terciles are qualitatively similar to the graph for R. This also holds for the RPSS though fractions of the domain with significant RPSS are almost always lower than for the other metrics, probably because the RPSS is a summary metric for all three terciles including the middle one, which generally has much lower ROC areas than the other two terciles.~~. An exception is the relatively large amount of significant skill in the SnInitSH when RPSS is used as metric.~~

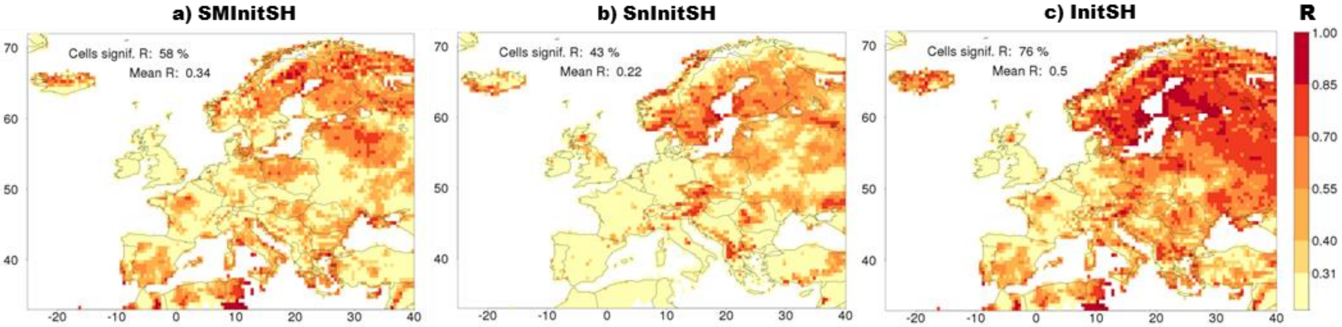


Figure 6: Example that compares the skill in runoff of three specific hindcasts (SMInitSH (a), SnInitSH (b) and InitSH (c)), for target month May as lead month 2. For more explanation, see Fig. 1a. White, terrestrial cells correspond to cells where observations or hindcasts consist for more than one third of zeros or one sixth of ties.

Figure 6 compares skill maps for the three specific hindcasts that isolate skill due to initial conditions (InitSH, SMInitSH and SnInitSH). It illustrates that skill~~at~~ due to snow and soil moisture initialisation are not only more or less additive at the scale of the entire domain (Fig. 5) but also at regional scale~~ skill due to snow and soil moisture initialisation are more or less additive~~. ~~Copies of the~~The patterns of skill due to soil moisture initialisation e.g. in Africa, on the Iberian Peninsula and in Western France (Fig. 5a) are also found in the map of skill due to ~~both soil moisture and snow~~ both components of initialisation (Fig. 5c). Small regions with considerable skill due to snow initialisation (Fig. 5b) like those near Stockholm, in South-east Czechia and South-east Austria also stick out as foci of skill on the map of skill due to both soil moisture and snow initialisation (Fig. 5c). Where both soil moisture and snow initialisation cause moderate skill, e.g. in Southern Finland, the combined specific hindcast exhibits more significant skill. ~~The additive behaviour of skill in the two initialisation components is also visible in Fig. 5.~~

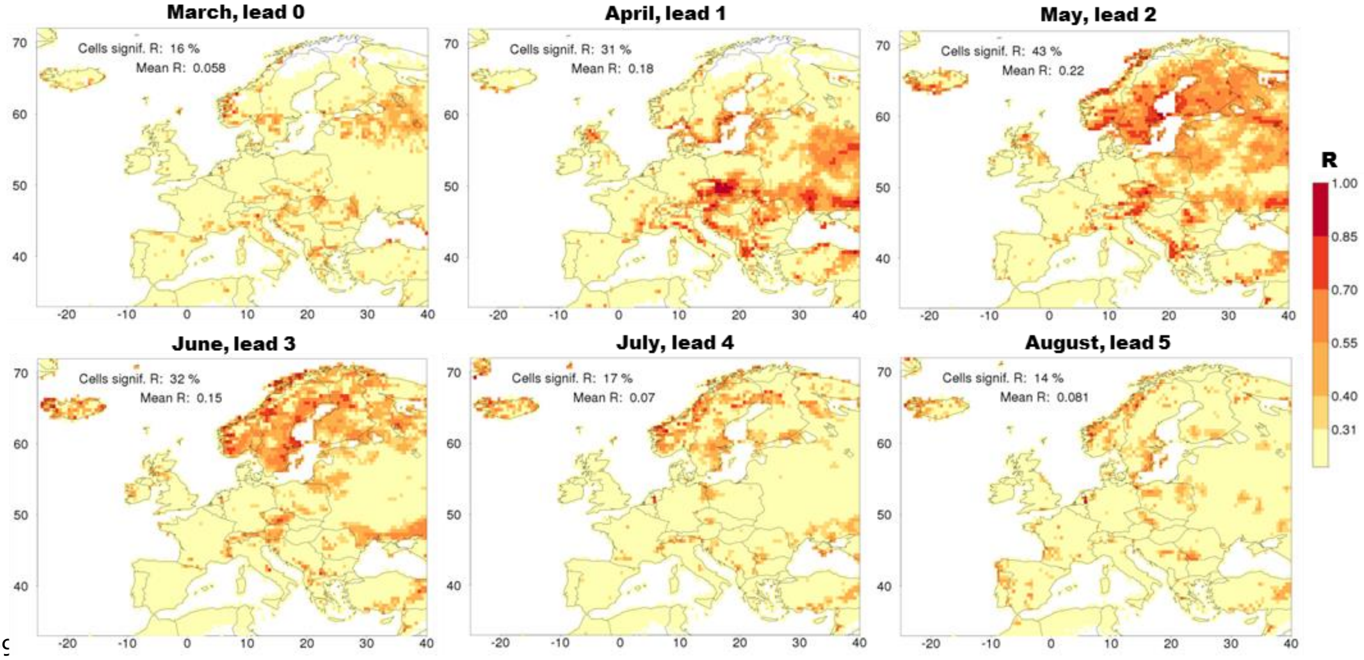


Figure 7: Example showing the variation of skill in runoff as a function of lead time in the SnInitSH, for initialisation on March 1. For more explanation, see Figs. 1a and 6.

Figure 7 zooms in on the specific hindcast that isolates skill due to snow initialisation (SnInitSH), giving the example of a time series of skill as a function of lead time, after initialisation on March 1st. One observation is that skill does not gradually decrease with time but has a maximum during the snow melt season. We like to note that locally skill is hardly generated during the part of the melt season when a snow pack covers the surface in each year. The reason is that in VIC the rate of snow melt is almost insensitive to snow pack thickness (Sun et al., 1999). Hence, as long as the surface is covered by snow in each year, inter-annual variation in snow melt is absent or negligible. Skill is only generated towards the end of the melt season, when snow melt differs from year to year because snow stops to be available for melt at different dates due to different initial amounts of snow. So, the initial snow conditions cause skill because of interannual variation in the duration of the period that it takes to melt the snow present at the time of initialisation and not because of interannual variation in the melt rate. Of course, the timing of the end of the melt season differs regionally and with elevation, which largely explains the patterns of skill visible in the maps of Fig. 7. A good example is Scandinavia, where the earliest skill (in April; lead month 1) occurs at low elevations near the coasts of Southern Norway and Sweden, at the end of the local snow season. The latest skill (in July; lead month 4) occurs in the Norwegian mountains, again at the end of the local snow season (we ascribe the skill in South-east Sweden in July and August to chance). It is also relevant to note that the skill patterns in the maps of Fig. 7 are influenced by the fact that VIC has higher vertical resolution than its horizontal resolution may suggest, by performing simulations in multiple elevation bands within each grid cell, accounting for sub-grid variations in topography. Therefore, sub-grid topography leads to spreading of the snow skill signal of individual cells over longer periods of time.

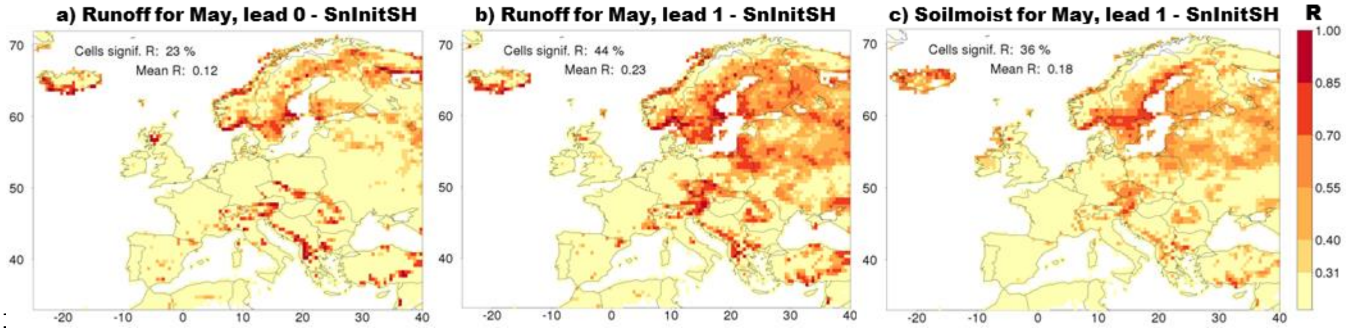


Figure 8: Example illustrating that skill in runoff for a target month may increase with lead time, namely for runoff in May as target month 0 (a) and 1 (b) in the SnInitSH. Skill in ~~the hindcast of~~ soil moisture in the SnInitSH for May as lead month 1 is shown (c) because it provides ~~an~~ part of the explanation for the mechanism causing the increase in skill with lead time. For more explanation, see Figs. 1a and 6.

To finish the analysis of the SnInitSH, Fig. 8 analyses a ~~remarkable~~ noticeable feature. In SnInitSH, hindcasts for May have less skill when the hindcasts are initialised on May 1 (Fig. 8a) compared to initialisation during preceding months (February, March or April, Fig. 8b is for initialisation on April 1). Similar ~~counterintuitive~~ results are found for June and July as target months. This result is ~~counterintuitive~~noteworthy because in hindcasts with initialisation on May 1 there is, due to the use of pseudo-observations for verification, perfect knowledge about snow conditions on that date. With initialisation on April 1, snow conditions on May 1 differ from those of the pseudo-observations, which by itself must lead to less skill in May runoff. The simple explanation is that on April 1 more grid cells have a snow cover than a month later on May 1 but then the question arises why those grid cells that lose their snow cover in April still exhibit significant skill in runoff during the month of May. The answer lies in an indirect effect. Interannual variations in the amount of snow at April 1 lead to predictable interannual variations in soil moisture on May 1 (Fig. 8c), when the snow cover has melted, which then by itself acts as an additional source of skill in runoff in May.

~~This result is counterintuitive because in hindcasts with initialisation on May 1 there is, due to the use of pseudo-observations for verification, perfect knowledge about snow conditions on that date. With initialisation on April 1, snow conditions on May 1 differ from those of the pseudo-observations, which by itself must lead to less skill in May runoff. However, there is compensation for this direct effect by an indirect effect through soil moisture. In SnInitSH, soil moisture has no skill on the date of initialisation, e.g. May 1 in the hindcasts starting on that date. However, in the hindcasts starting on April 1 the perfect knowledge of the snow conditions on that date leads via skill in snow melt in April to some skill in soil moisture on May 1 (Fig. 8c), which then leads indirectly to skill in runoff in May. Since we find more skill in May runoff after snow initialisation on April 1 than after snow initialisation on May 1, the gain of skill in the runs starting on April 1 due to the indirect effect overcompensates for the loss of skill in the same runs due to the direct effect.~~

To finalise this section, the specific hindcasts were exploited to attribute the hotspots of significant skill in runoff for lead month 2, listed in the companion paper, to the different potential sources of skill. This was done for each of the hotspots by~~ an~~ inspection of the maps of skill (like those of e.g. Fig. 6) for three specific hindcasts that isolate the different sources of skill (SMInitSH, SnInitSH and MeteoSH). If the hotspot was present in e.g. SMInitSH, soil moisture initialisation is one of the sources of skill. Results are summarised in Table 1. Almost all of the significant skill in the hotspot regions is due to the initial conditions of soil moisture. Exceptions are formed by the target months from April to July when skill is caused by a mix of the initial conditions of snow and soil moisture in regions with significant snow melt~~ skill~~. In these cases the relative contributions of the two sources varies in time and space but soil moisture is more important than snow, except in Fennoscandia where in June snow dominates and in July both sources are of about equal importance. In none of the hotspots of skill, meteorological forcing contributed significantly to this.

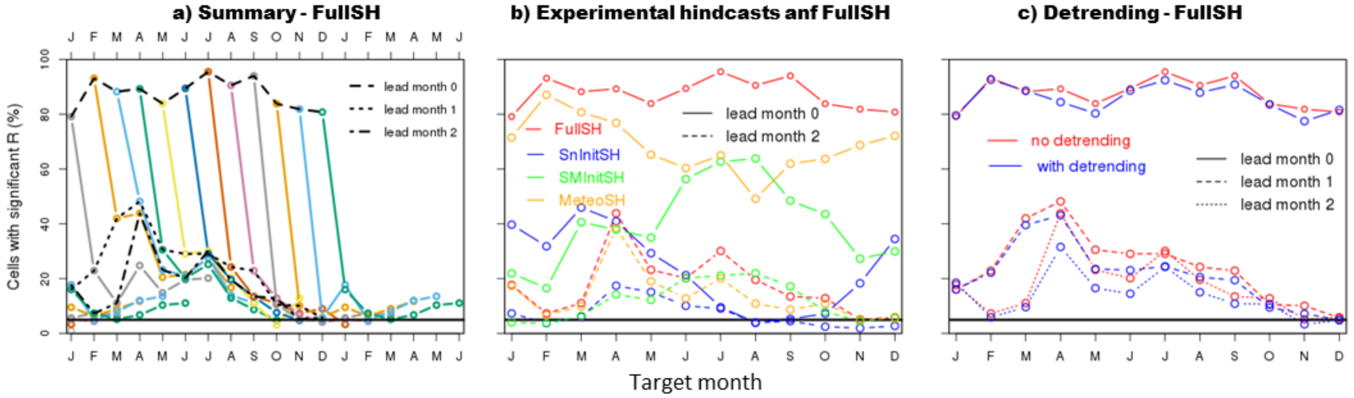
Table 1 Sources of skill for hotspot regions and periods of skill. SM is soil moisture.

Region	**period**	**source of skill**
Fennoscandia	Jan - Mar	SM
	Apr - Jul	SM and snow
	Aug - Oct	SM
Poland and Northern Germany	Oct - Mar	SM

	Apr - May	SM and snow
Western France	Dec - May	SM
Romania and Bulgaria	Oct - Mar	SM
	Apr - May	SM and snow
southern Mediterranean	Jun - Aug	SM

3.3 Skill and source of skill in evapotranspiration

This section analyses skill in the hindcasts of evapotranspiration, b~~B~~ecause hindcasts of evapotranspiration are useful in themselves, because evapotranspiration affects runoff (see Sect. 1)~~,~~ and in order to demonstrate the rich possibilities of the pseudo-observations, ~~and~~ the specific hindcasts and the detrending to unravel the various sources of skill. ~~, this section analyses skill in the hindcasts of evapotranspiration.~~ In VIC evapotranspiration is computed with the Penman-Monteith method (see Shuttleworth, 1993).



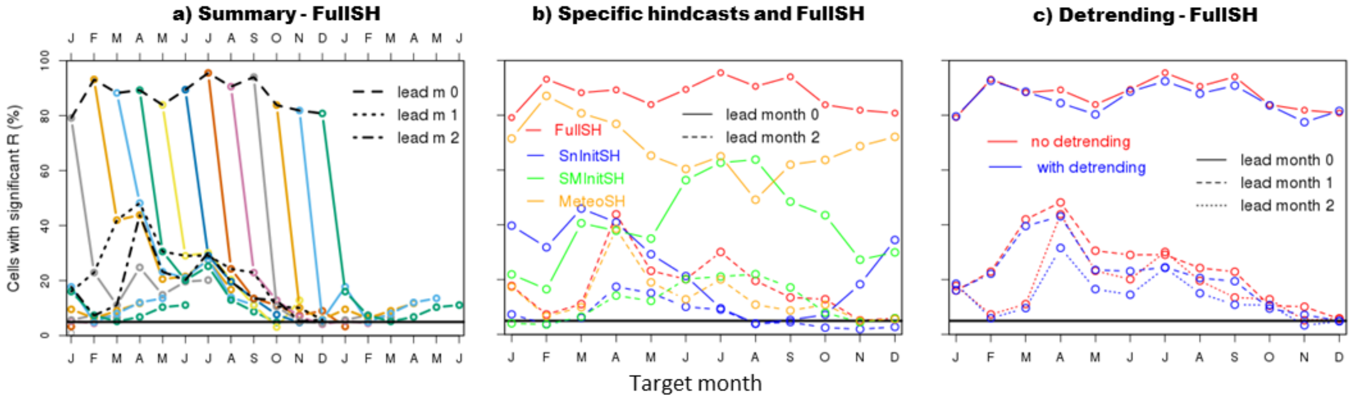


Figure 9: Summary plots of the skill of the hindcasts of evapotranspiration. Figure 9a summarises the FullSH (for more explanation, see Fig. 1b), Fig. 9b depicts the annual cycles of skill for the FullSH and three specific hindcasts (SnInitSH, SMInitSH and MeteoSH) for lead months 0 and 2, and Fig. 9c compares the annual cycles of skill of the un-detrended and the detrended FullSH for the first three lead months.

Figure 9a summarizes skill in evapotranspiration in the FullSH. Levels of predictability are higher than for precipitation (Fig. 1), similar to those for temperature (Fig. 2) and lower than those for runoff (Fig. 4a). Figure 9b isolates the diverse contributions to skill for lead months 0 and 2 by showing the skill for the FullSH and three specific hindcasts. ~~(SMInitSH, SnInitSH and MeteoSH).~~ Averaged over the year, meteorological forcing (MeteoSH) contributes more to predictability in evapotranspiration than the initial conditions, among which soil moisture (SMInitSH) causes more skill than snow (SnInitSH). Hence, comparing skill in runoff with skill in evapotranspiration, the most important source of skill shifts from the initial conditions of soil moisture to meteorological forcing.

~~more and initial soil moisture less to predictability in evapotranspiration than to predictability in runoff. Initial snow is the least important of the three sources of skill.~~

~~F~~In the FullSH (Fig. 9b) and focusing on lead month 2, there is hardly any skill in the evaporation hindcasts from November to March (9% of the domain, on average over these months), with the exception of January (18%) when the region of skill (Germany and Benelux) is part of a larger region of skill in the temperature hindcasts for the same target and lead month. We blame the winter minimum of skill in evapotranspiration to the low levels of evapotranspiration and the low levels of skill in the temperature forecasts for the same period. The next month (April) exhibits the highest level of skill of all months (44% of the domain), which is mainly due to meteorological forcing ~~(MeteoSH)~~ and ~~with~~ has smaller contributions by the initial conditions of soil moisture ~~(SMInitSH)~~ and snow ~~(SnInitSH)~~. From May to September there is some significant skill (23% of the domain, on average over these months). Whereas in May forcing is still the most important contributor to skill, initial conditions of soil moisture form the main contributor from June to October. We speculate that this shift in the order of importance between forcing and soil moisture is due to the amount of variability in soil moisture. In Europe in spring (April, May), soil moisture variations are relatively small and hence hardly contribute to variations in evapotranspiration. Later in the year (June to September), soil moisture is often available in limited amounts, so variations are larger and hence contribute more to variations in evapotranspiration. Snow initial conditions contribute to skill only during the snow melt season from April to July.

The contribution of trends to predictability of evapotranspiration is summarised in Fig. 9c, for lead months 0, 1 and 2. For lead month 2 and averaged over all target months of the year, detrending leads to a decrease in the fraction of cells with a significant R from 17.6 to 13.8%, a difference of 3.8%. The contribution of trends to skill in evapotranspiration is less than its contribution to skill in temperature (a difference of 11.8%) but larger than its contribution to skill in runoff (a difference of 1.3%). Trends contribute to skill in evapotranspiration during the part of the year when they also contribute to skill in atmospheric temperature (Fig. 2c), namely from April to September and in November (for lead month 0). However, whereas during the three summer months the skill in the temperature hindcasts is almost exclusively linked to climate change, a considerable part of the domain still exhibits skill in evapotranspiration after detrending.

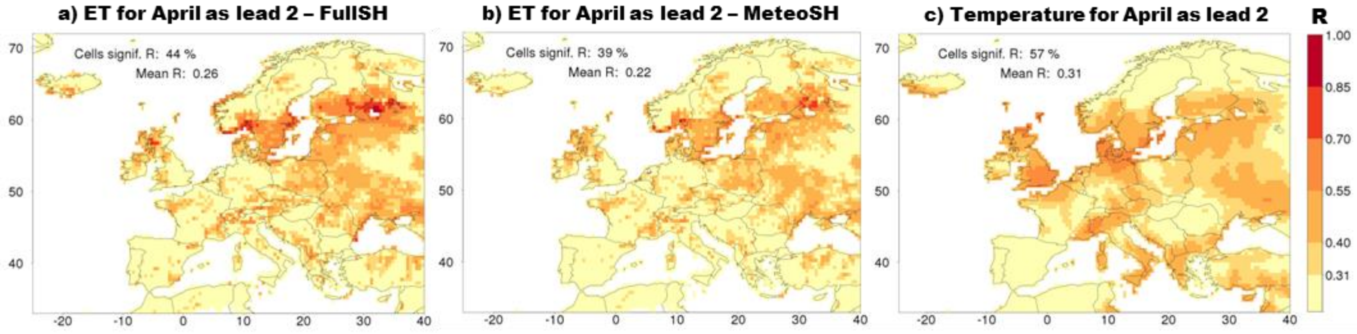


Figure 10: Explanation of the skill in the hindcasts of evapotranspiration for target month April as lead month 2. The panels map the skill in evapotranspiration of the FullSH (a), of the MeteoSH (b) and of the hindcasts of temperature (c). For more explanation, see Fig. 1a.

To provide a deeper understanding of the skill in evapotranspiration, the skill in April and July is analysed in some detail. Figure~~.~~ 10 deals with April as lead month 2, showing the skill in evapotranspiration from the FullSH in Fig. 10a and from the MeteoSH in Fig. 10b. Regions of skill, mainly a stroke of land from southern Fennoscandia to the Black Sea, are the same in the FullSH and in the MeteoSH though skill is somewhat degraded in the MeteoSH. This indicates that meteorological forcing causes most, though not all, of the skill. Indeed, Fig. 2e (March) and 10c (April) ~~(skill in temperature for March as lead month 1) and Fig. 10c (skill in temperature for April as lead month 2)~~ show that the temperature forecasts for these two months after initialisation on February 1~~of the preceding lead month and the lead month considered~~ contain skill in the ~~same~~ mentioned region~~s~~. We conclude that much of the skill in evapotranspiration is due to skill in the temperature hindcasts. The remaining part of the skill is due to initial hydrological conditions. While ~~(~~Fig. 9b shows this for the entire domain~~).~~, we also~~We~~ found limited amounts of skill in the SnInitSH and the SMInitSH for April in the ~~same~~ stroke of land from southern Fennoscandia to the Black Sea (not shown here). This means that in that region initial conditions of the hydrological model on February 1 provide some skill to the hindcasts of evapotranspiration for April. We like to note that this could be consistent with the conclusion in Sect. 3.1 that the skill in the temperature hindcasts of February and March in this same region are due to the initial conditions of the climate model. These initial conditions could e.g. be sea surface temperatures but also the local state of snow and/or soil conditions. In the latter case, the two types of predictability in the mentioned regions would have the same or a similar source. Initial conditions of snow and/or soil conditions in S4 would lead to skill in the temperature hindcasts of S4 while initial conditions of snow and soil moisture in VIC lead to skill in the evapotranspiration hindcasts of VIC.

During the summer months and for all lead times, skill in evapotranspiration occurs in two regions, namely the southern part of the Mediterranean, and Western and Northern Norway. Fig. 11 shows target month July as lead month 5, as an example. Whereas Fig. 11a is for the FullSH, Figs. 11b-d depict the maps for three specific hindcasts (SnInitSH, SMInitSH and MeteoSH) and Fig. 11e shows skill for the FullSH after detrending. Since the SnInitSH and the MeteoSH exhibit hardly any skill while SMInitSH has considerable skill in the Mediterranean (Figs. 11b-d), it can be concluded that the skill in this region is due to soil moisture initial conditions. So, in this particular case, knowledge of soil moisture conditions on February 1 still yields skill in evapotranspiration in July. This skill in the Mediterranean is not affected by detrending (compare Figs. 11a and 11e), so it does not have a climate change component.

The skill in Norway has a more complicated origin. The three specific hindcasts show that it is due to a mix of initial snow conditions (Fig. 11c) and meteorological forcing (Fig. 11d). The effect of the initial snow conditions (on February 1) can be understood with the help of the analysis of runoff skill in the SnInitSH (Fig. 7), which led to the conclusion that runoff skill caused by snow initialisation occurs at the end of the melt season, which is July in much of Norway. Therefore, in this country and in July the timing of the disappearance of snow cover varies from year to year. This then has a considerable effect on evapotranspiration since bare soil has, compared to snow, higher surface temperatures and hence more evapotranspiration in summer. The contribution to skill by forcing (Fig. 11d) fades with but is not removed by detrending (not shown here), so it has a part that is related to climate change and a part that is unrelated to climate change. The climate-change-related skill due to forcing resides in the temperature hindcasts, which have significant skill in this region at all lead times (Fig. 2f). The non-climate change related skill in the MeteoSH for July is likely an indirect effect of the skill in the forcing (especially precipitation) ~~in~~ during the first lead month (February). This leads to skill in snow water equivalent towards the end of February, which fades but has not disappeared completely on July 1 (Fig. 11f) and then causes skill in evapotranspiration at the end of the melt season.

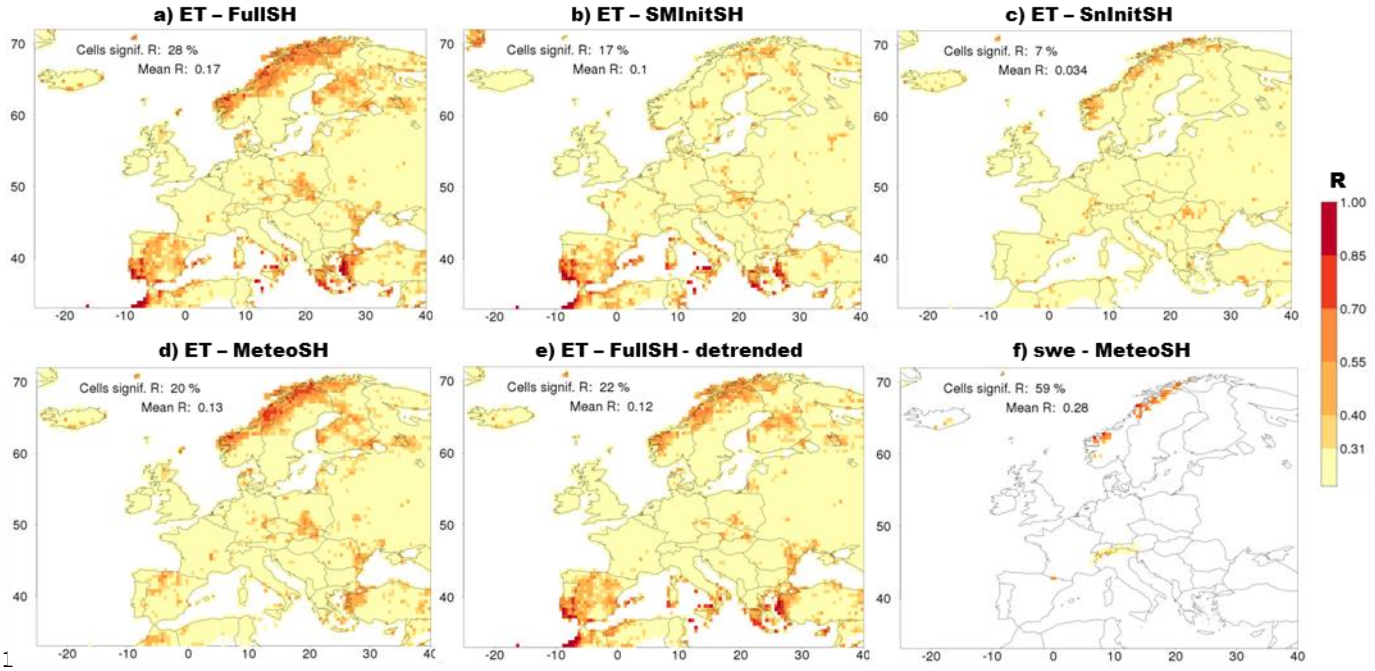


Figure 11: Explanation of the skill in the hindcasts of evapotranspiration (ET) for July by taking lead month 5 as an example. The panels map the skill in evapotranspiration of the FullSH (Fig. 11a), SMInitSH (Fig. 11b), SnInitSH (Fig. 11c), MeteoSH (Fig. 11d) and the FullSH after detrending (Fig. 11e). Figure 11f depicts skill of the hindcasts of snow water equivalent (swe) in the MeteoSH. For more explanation, see Fig. 1a. Note that statistics in the legends of the panels refer only to that part of the domain for which R was computed, which consists of all coloured cells.

4 Discussion

4.1 Comparison of skill with previous studies

A remarkable result of our work is the reduction of the skill in runoff beyond lead month 1, when annually varying S4 forcing is used (FullSH) instead of meteorological forcing that is identical for all years (InitSH), see Fig. 4. This result is counter-intuitive but, as we discussed, a logical consequence of forcing with interannual variation that has no or insufficient skill, such as the S4 forcing. Other studies compared FullSH (also called climate-model based hindcasts) with ESP hindcasts, which are slightly different from our InitSH (see Sect. 4.3) but like the InitSH have ~~identical~~ uninformative meteorological forcing for each year. Some of these studies (e.g. Singla et al., 2012~~1~~, and Mackay et al., 2015) found little overall difference in skill between the FullSH and ESP hindcasts. However, Bazile et al. (2017) in a study of Canadian catchments broadly confirms our finding that beyond the first lead month ESP is superior to FullSH while the reverse holds for the first lead month. Arnal et al. (2018) compared FullSH with ESP hindcasts and found that in Europe ESP has more discrimination skill (“potential usefulness”) than FullSH, although there are exceptions both spatially and seasonally. These authors, however, do not mention any trend with lead time in the difference between FullSH with ESP. ~~However, in~~In contrast with our results, skill is enhanced when using meteorological hindcasts, also at longer leads, in the studies of Yuan et al. (2013), Thober et al. (2015), ~~and~~ Yuan (2016) and Meiβner et al. (2017). This contrast might be explained by more skill in the meteorological hindcasts of the mentioned studies than in the present study, which could be due to the type of meteorological hindcasts (~~none~~ only Meiβner et al., 2017, used S4) or the investigated region (in the mentioned studies US, Europe, ~~and~~ China and Germany, respectively). ~~Indeed,~~ Europe is a region with relatively little skill in meteorological hindcasts (Kim et al., 2012, Scaife et al., 2014, and Baehr et al., 2015). Effects of regional differences in the skill of the forcing on the relative skill of ~~full~~ FullSH and ESP ~~hindcasts~~ are mentioned by Wood et al. (2005), who reported that ~~full hindcasts~~FullSH for the Western United States have practically no skill improvement over the ESP, except for some regions and seasons with predictability of the forcing originating in ENSO teleconnections.

The specific hindcasts of this study show that in Europe initial conditions of soil moisture are the largest source of skill in the seasonal ~~run-off~~runoff forecasts produced with WUSHP. ~~In terms of domain averages, this is true for all lead and target months.~~ Contributions to skill by the initial conditions of snow and by the meteorological forcing are mostly much smaller. To our knowledge, two other studies analysed sources of skill of hydrological seasonal forecasts for Europe with dynamical systems similar to those of the present study, namely Bierkens and Van Beek (2009) and Singla et al. (2012~~1~~). Comparing our results with those of Bierkens and van Beek (2009), both studies agree that initial conditions form the dominant source of skill. However, compared to the present study, Bierkens and van Beek (2009) find a larger contribution to skill by the meteorological forcing, at least in summer. This difference might be due to the quality of the forcing. Bierkens and van Beek (2009) developed an analogue events method to select, on the basis of annual SST anomalies in the North Atlantic, annual ERA40 meteorological forcings, which they used as forcing for their hydrological model. One might speculate that in Europe their semi-statistical forcing is more skilful than the S4 forcing used in WUSHP. This suggests that there is room for improvement of climate model seasonal forecasts, so if and when this improvement is realised, the relative contribution of the meteorological forcing to skill in hydrological variables would increase. As to the second study of the sources of skill, ~~In any case, that contribution depends and will depend on the climate model used (e.g. S4 or GloSea5).~~ ~~Results of these two studies were summarised in the introduction. However, the~~ conclusions of Singla et al. (2012~~1~~) are not directly comparable with those of the present study as they used ESP and reverse-ESP (see Sect. 4.3).

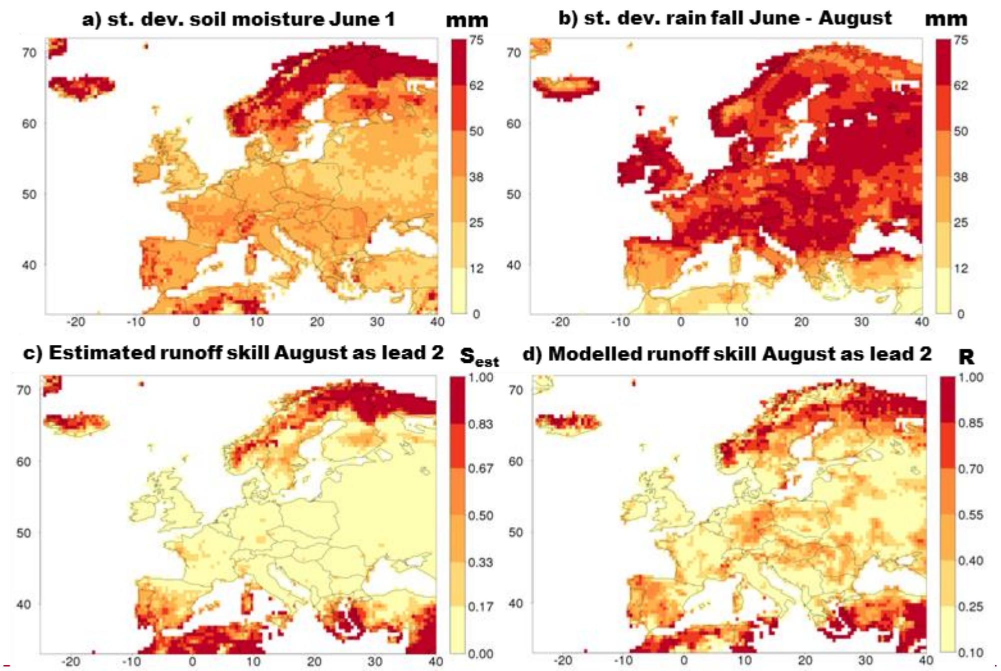
~~Comparing our results with those of Bierkens and van Beek (2009), both studies agree that initial conditions form the dominant source of skill. However, compared to the present study, Bierkens and van Beek (2009) find a larger contribution to skill by the meteorological forcing, at least in summer. This difference might be due to the quality of the forcing. Bierkens and van Beek (2009) developed an analogue events method to select, on the basis of annual SST anomalies in the North Atlantic, annual ERA40 meteorological forcings, which they used as forcing for their hydrological model. One might speculate that in Europe their semi-statistical forcing is more skilful than the S4 forcing used in WUSHP. This suggests that there is room for improvement of climate model seasonal forecasts, so if and when this improvement is realised, the relative contribution of the meteorological forcing to skill in hydrological variables would increase. In any case, that contribution depends and will depend on the climate model used (e.g. S4 or GloSea5).~~

4.2 Understanding the skill due to initial soil moisture

The dominance of soil moisture initial conditions in terms of domain-lumped skill also extends to the hotspot regions and periods of skill (Table 1). The understanding of the skill linked to soil moisture can be deepened by another level as in Shukla and Lettenmaier (2011). The underlying idea is that this type of skill increases with the interannual variability of soil moisture at the date of initialisation and that this skill is gradually eliminated during the course of the hindcasts by interannual variability in processes like rain fall and snow melt. The question is to what extent hotspots of skill (see

Table 1) linked to soil moisture initialisation are due to the cause of the skill and to what extent they are due to a lack of interannual variability in the processes that eliminate the skill? Figure 12 helps answering this question for the skill found in the runoff hindcasts of August as lead month 2 with a simple method of analysis. Figure 12a shows the standard deviation of total modelled soil moisture (σ_{SM}) on the day of initialisation (June 1), taken from the reference simulation. Figure 12b depicts the standard deviation of total rain fall (σ_{RF}) during the course of the hindcast (June – August), taken~~ing~~ from the WFDEI data set, which is the investigated skill-eliminating factor. These two quantities were combined into an estimate of the skill ($\mathrm{S}_{\mathrm{est}}$):

$$S_{est} = \exp\left(-\frac{{\sigma_{RF}}^2}{{\sigma_{SM}}^2}\right) \quad (1)$$


a) st. dev. soil moisture June 1
mm
b) st. dev. rain fall June - August
mm
75
62
50
38
25
12
0
70
60
50
40
-20
-10
0
10
20
30
40
c) Estimated runoff skill August as lead 2
S_{est}
d) Modelled runoff skill August as lead 2
R
1.00
0.83
0.67
0.50
0.33
0.17
0.00
1.00
0.85
0.70
0.55
0.40
0.25
0.10

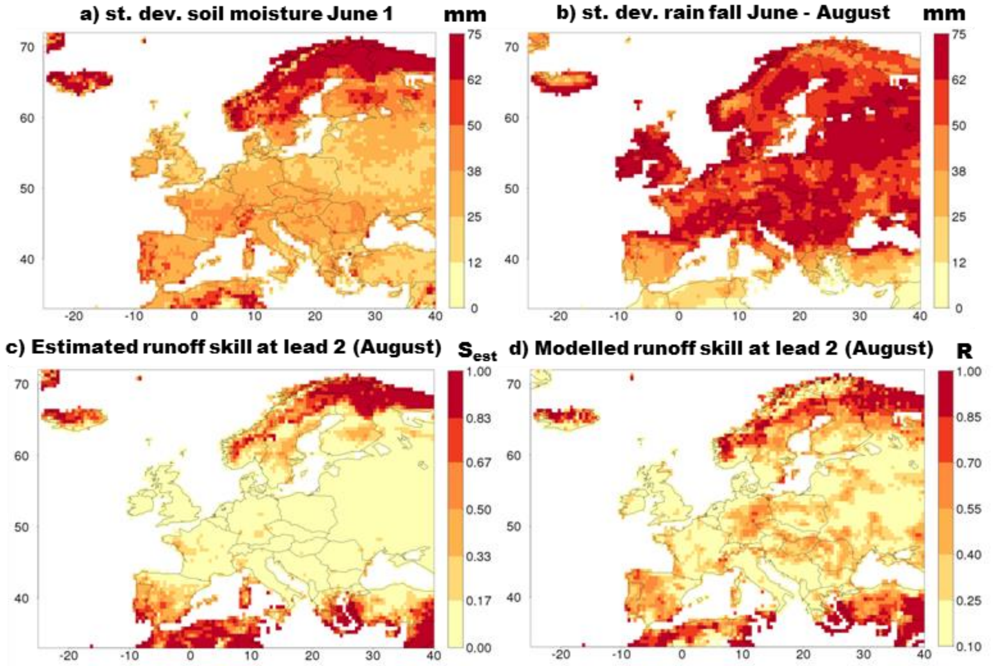

a) st. dev. soil moisture June 1
mm
b) st. dev. rain fall June - August
mm
75
62
50
38
25
12
0
70
60
50
40
-20
-10
0
10
20
30
40
c) Estimated runoff skill at lead 2 (August)
S_{est}
d) Modelled runoff skill at lead 2 (August)
R
1.00
0.83
0.67
0.50
0.33
0.17
0.00
1.00
0.85
0.70
0.55
0.40
0.25
0.10

Figure 12: Illustration of a simple method that partly explains skill in runoff due to initial soil moisture, exemplified for target month August as lead month 2. Figure 12a is a map of the standard deviation in soil moisture at the date of initialisation (June 1). Similarly, Fig. 12b maps the standard deviation of observed rain fall during the course of the hindcasts (June-August). These two standard deviations are combined into an estimate of the skill (Eq. 1) in Fig. 12c, which is compared with the skill of the FullSH (Fig. 12d). Note that the

colour scales of Figs. 12c and 12d differ from each other and differ from scales of other figures (e.g. Fig. 1a).

This estimate (Fig. 12~~-~~c) needs to be compared with the skill of the hindcasts, mapped in Fig. 12d in terms of R. The two maps are not expected to be exactly equal, not only because of the simplicity of the estimation method but also because S_{est} is not a correlation coefficient. However, in the limits S_{est} has the desired properties. It is equal to zero for the cases of constant initial amounts of soil moisture or infinite variability in rain fall. It is equal to one for the cases of infinite variability in soil moisture or constant rain fall. The correlation coefficient between the patterns in Figs. 12c and d is highly significant (0.67) and the hotspot regions of skill are the same in both panels, namely the northern part of Fennoscandia and the southern part of the Mediterranean. So, in the case of August as lead month 2 the estimation method is reasonably successful in computing the pattern of skill in the hindcasts with the simple means of the WFDEI data set and model calculations from the reference simulation. The ~~additional~~ merit of the estimation method is the deeper understanding of the cause of the skill in the two hotspot regions. Northern Fennoscandia is a hotspot because the amount of interannual variability in initial soil moisture is larger than elsewhere (Fig. 12a). The southern part of the Mediterranean is a hotspot because the amount of interannual variability in rainfall is lower than elsewhere (Fig. 12b).

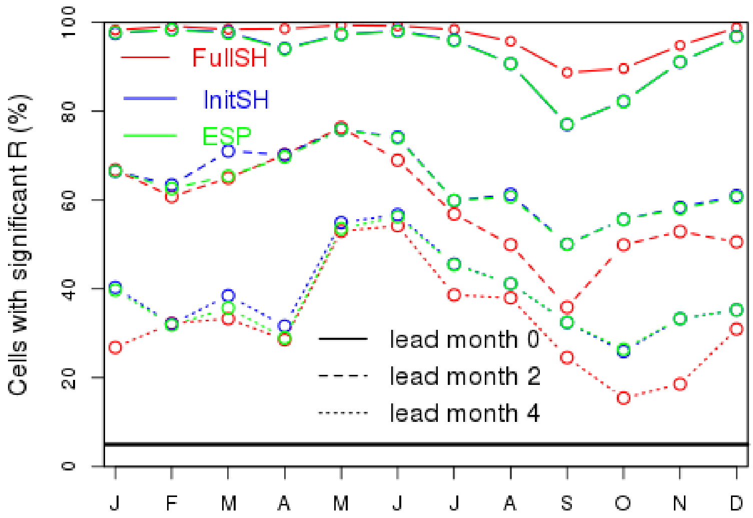
This simple method of analysis helped to bring the understanding of the skill in northern Fennoscandia and the southern Mediterranean to a deeper level but it was less successful for the other hotspots. A more thorough analysis along these lines and a deeper understanding of skill in the hindcasts is left for future work.

4.3 Relation of the present specific hindcasts with conventional ESP

The specific hindcasts of this study are related to the well-known Ensemble Streamflow Predictions (ESP) (e.g. Wood and Lettenmaier, 2008, Shukla and Lettenmaier, 2011, Singla et al., 2012~~1~~, ~~and~~ Van Dijk et al., 2013, and Harrigan et al., 2018). ESP are not only used as an experimental tool in science but are also widely used to produce forecasts in operational mode (Day, 1985). ESP used for scientific purposes can be subdivided into ESP proper (called ESP from now on) and reverse-ESP.

ESP (hindcasts) are similar to the InitSH of this study. In both types of hindcasts the initial conditions vary from year to year and are quasi-perfect, i.e. they are taken from a simulation like our reference simulation, while the meteorological forcing is uninformative, e.g. by being the same for all years (in the InitSH and e.g. in the ESP of~~does not vary~~ Shukla and Lettenmaier, 2011), or by varying~~-~~ randomly from year to year (e.g. in the ESP of Singla et al., 2012)~~from year to year~~. This eliminates skill due to the meteorological forcing, so skill can only be due to the initial conditions. However, while in ESP the forcing is selected from historic observations, it is selected from the S4 hindcasts in InitSH in order to retain an inter-member variability and other statistical characteristics of the time series similar to that in the FullSH. An advantage of ESP is that its production is relatively cheap because no climate model forecasts are needed.

Similarly, reverse-ESP (see Wood and Lettenmaier, 2008) resemble the MeteoSH of this study. In both types of hindcasts the meteorological forcing varies from year to year while the initial conditions are identical for each year. This eliminates skill due to the initial conditions, so skill can only be due to the forcing. However, while in reverse-ESP the forcing of each year is made up of the observations of that year, it is made up of the S4 hindcasts in the MeteoSH. Moreover, in reverse-ESP ensembles are built by using differing initial conditions, whereas they are built by using differing meteorological forcings in the MeteoSH.



~~Figure 13 Comparison of the annual cycles of skill of the FullSH (red), the InitSH (blue) and the ESP (green) for three different lead times. Where blue or green symbols seem to be missing, they coincide.~~

~~So, both in ESP and in the InitSH the meteorological forcing is identical for all years of the hindcasts with the aim of eliminating the skill due to the forcing.~~ If indeed in ESP and in the InitSH all skill due to the meteorological forcing is removed, the remaining skill, which is due to the annually varying initial conditions, should logically be the same in ~~ESP and InitSH~~both types of hindcasts since the initial conditions ~~in both types of hindcasts~~ are the same. To test this expectation we produced ESP and compared their skill ~~with the skills of the FullSH and~~with that of the InitSH. Indeed, skill from these two types of hindcasts is almost identical as demonstrated in the supplementary material (Fig. S8). We conclude that skill produced with specific hindcasts with a forcing that does not vary from year to year is not sensitive to the choice of that forcing, perhaps with the exception of forcings that deviate strongly from being realistic. We like to note here that in odd years one of the ESP ensemble members is identical to the pseudo-observation used for verification. This is a concern but we deemed this less important than the requirement of identical forcing for all years, which is crucial for the explanation of the skill reversal (Sect. 3.2.1).

~~Figure 13 shows results for three different lead times. In the graph most of the points for the ESP are indistinguishable from their counterparts for the InitSH. So, all conclusions that were drawn from Fig. 4 and especially the reversal with lead time of the ranking of predictability for the FullSH and the InitSH, are equally true for the ranking of the FullSH and the ESP. We also conclude that, though forcings in the InitSH and the ESP differ, skills from both types of specific hindcasts are, as expected, virtually identical, which can be ascribed to the fact that the forcings do not vary from year to year. We speculate that this result would also hold for other plausible forcings that do not vary from year to year.~~

This ~~behaviour~~ similarity of the InitSH and ESP is in sharp contrast with the skill resulting from reverse-ESP and MeteoSH, which are expected to be totally different. Keeping in mind that in both types of hindcasts skill is caused only by skill of the meteorological forcing, this is the skill of the S4 hindcasts in the MeteoSH. The present study showed that in Europe there is a small contribution to skill in the ~~streamflow~~ runoff hindcasts by the forcing and that this contribution tends to decrease with time. This differs from reverse-ESP, in which skill is small at the beginning and then increases with lead time to reach perfect skill at very long leads (see Wood and Lettenmaier, 2008) because the meteorological forcing is quasi-perfect (i.e. identical to the forcing in the reference simulation) while the influence of the initial conditions, which are non-informative in reverse-ESP ~~eliminate skill~~, decreases with time.

~~In summary, amounts of skill are almost the same for ESP and InitSH, and totally different for reverse-ESP and MeteoSH. Also, interpretations of reverse-ESP and MeteoSH differ. MeteoSH can be used to assess skill in the streamflow hindcasts due exclusively to skill in the meteorological hindcasts. Reverse-ESP can be used to quantify skill due to prescribing meteorological observations, i.e. the skill if we had perfect~~

~~knowledge about the meteorological forcing during the forecast period and no knowledge about the initial conditions. Such a specific hindcast would not fit into the present study. In fact, ESP, reverse-ESP and a reference simulation were produced by Wood and Lettenmaier (2008) and Shukla and Lettenmaier (2011) for purposes that differ from those of the present study. Their aim was to quantify what can be gained if the meteorological forcing (in ESP) or the initial conditions (in reverse-ESP) are improved from containing climatological information to being quasi-perfect, i.e. when they are equal to the meteorological observations and the initial state of the reference simulation. Wood et al. (2016) extended this type of analysis by determining sensitivities of the streamflow to changes in the information of the meteorological forcing and the initial conditions.~~

4.4 Towards an operational system

We plan to launch an operational version of WUSHP. That version might include a post-processing procedure with the aims of removing biases in discharge and making the system more reliable. This could perhaps be done with statistical calibration (e.g. Gneiting et al., 2005, and Schepen et al., 2014), a technique that, contrary to quantile mapping, considers information that is available from correlations between hindcasts and observations (see Wood and Schaake, 2008, and Madadgar et al., 2014).

The superiority of the InitSH (and the ESP) with respect to the FullSH for hindcasts beyond the first two lead months raises the question whether one should, in an operational version of WUSHP and for these lead months, issue forecasts like the InitSH (or ESP) and not forecasts like the FullSH. The logical answer is “yes” but such a strategy should then be reconsidered when the meteorological forcing is taken from a new, possibly improved version of the climate model, or from another, possibly better type of climate model.

The applied methods of analysis are not suitable for giving quantitative advice on what would be the best investment for increasing the amount of skill of WUSHP. However, since initial soil moisture is the dominant source of predictability, a large gain of skill could possibly be made by assimilation of soil moisture observations into the modelled state of soil moisture (see e.g. Draper and Reichle, 2015). In addition, observations of snow water equivalent could be assimilated into the modelled state of snow (see e.g. Griessinger et al., 2016). Improving the calibration of VIC would be another obvious road towards improvement of the seasonal predictions discussed in this paper. This should lead to higher actual skill but not necessarily to more theoretical skill, see the discussion section of the companion paper.

~~In this study we analysed the effect of trends on predictability by comparing skill for un-detrended and detrended observations and hindcasts. The effect of trends was almost negligible for runoff, considerable and in summer even dominant for atmospheric temperature and of intermediate magnitude for evapotranspiration. While for academic purposes the distinction between climate-change related and non-climate change related skill contributes to a better understanding of the skill, this is not the case for practical applications. To our knowledge, operational forecast systems issue their predictions without considering trends, i.e. predictions are issued by taking a historic period covered by observations or hindcasts as reference.~~

~~This study demonstrates the power of using pseudo-observations for verification. These data cover all cells of the entire domain and they are available for all hydrological model variables, e.g. runoff and evapotranspiration, which have no equivalent (runoff) or are sparse (evapotranspiration) in the realm of real observations. Many features of skill would not have been detectable with real observations. At the same time, we like to stress that actual skill obtained with real observations is generally less than theoretical skill obtained with pseudo-observations, as discussed extensively in the companion paper.~~

5 Conclusions

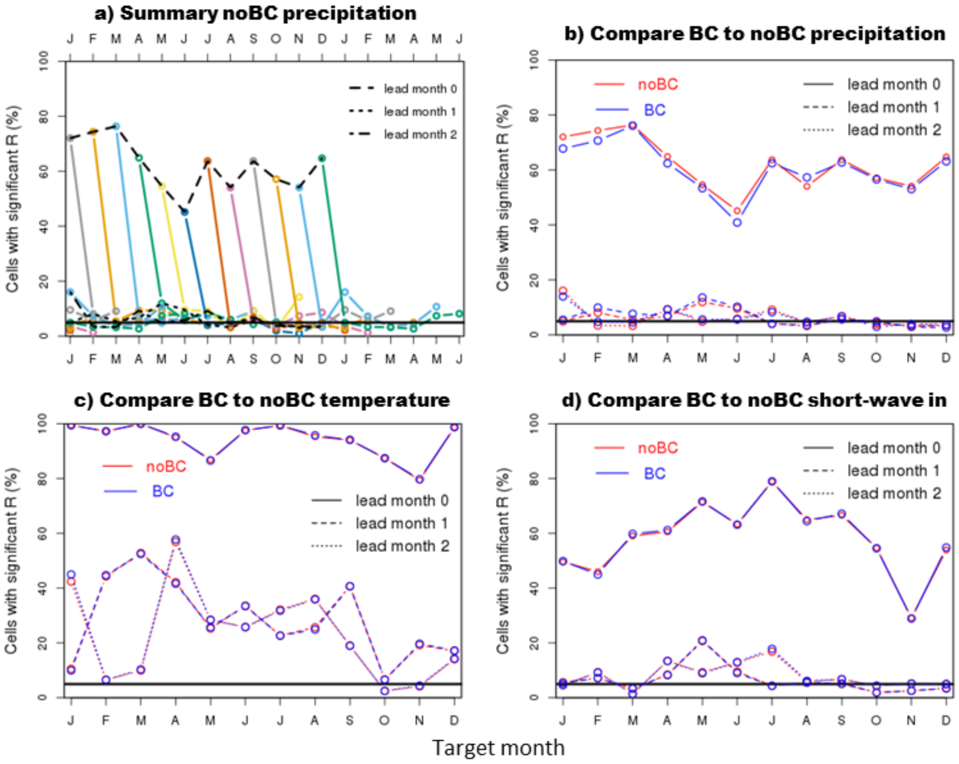
The present paper explains skill in the hindcasts of WUSHP, a seasonal hydrological forecast system, applied to Europe. We first analysed the meteorological forcing, which consists of bias-corrected output from a climate model (S4), and found considerable skill in the precipitation forecasts of the first lead month but negligible skill for later lead times. Seasonal forecasts for temperature have more skill. Skill in summer temperature was found to be related to climate change occurring in both the observations and the hindcasts, and to be more or less independent of lead time. Skill in North-East Europe in February and March is unrelated to climate change and must hence be due to initial conditions of the climate model.

Sources of skill in runoff were isolated with specific hindcasts, namely SMInitSH (soil moisture initialisation), SnInitSH (snow initialisation), InitSH (a combination of soil moisture and snow initialisation) and MeteoSH (meteorological forcing). These hindcasts revealed that, beyond the second lead month, hindcasts with forcing that is identical for all years but with “perfect” initial conditions (InitSH) produce, averaged across the model domain, more skill in runoff than the hindcasts forced with S4 output (FullSH). This occurs because interannual variability of the S4 forcing adds noise while it has hardly any skill. The other specific hindcasts showed that in Europe initial conditions of soil moisture form the dominant source of skill in runoff. For target months from April to July, initial conditions of snow contribute significantly, with a domain-mean maximum in May and June. The timing of that maximum varies spatially and coincides with the end of the melt season, when snow melt differs from year to year because snow stops to be available for melt at different dates. All regional and temporal hotspots of skill in runoff found in the companion paper are due to initial conditions of soil moisture, with smaller or larger contributions by the initial conditions of snow for target months from April to July in hotspot regions with snow fall in earlier months. We further showed that skill due to snow and soil moisture initialisation is more or less additive.

Some remarkable skill features are due to indirect effects, i.e. skill due to forcing or initial conditions of snow and/or soil moisture is, during the course of the model simulation, stored in the hydrological state (snow and/or soil moisture), which then by itself acts as a source of skill. ~~Examples occur in the skill of run-off for target months from May to July in the SnInitSH and in the skill of run-off in the MeteoSH.~~

Predictability of evapotranspiration was analysed in some detail. Levels of predictability and the annual cycle of skill are similar to those for temperature. For most combinations of target and lead months, forcing forms the most important contributor to skill but for lead month 2 initial conditions of soil moisture dominate from June to October. ~~The sources of some regional and temporal hotspots of skill in evapotranspiration were analysed with the specific hindcasts.~~

~~Appendix A Skill in the meteorological forcing before bias correction~~



~~Figure A1 Skill, in terms of the percentage of cells with significant values of R, for three components of the raw S4 forcing. Figure A1a shows precipitation skill, as a function of target and lead month. The other three panels compare the skill of the raw S4 output (noBC) with its bias-corrected version (BC) as a function of the target month and for the first three lead months. Precipitation is plotted in Fig. A1b, temperature in Fig. A1c and incoming short-wave radiation in Fig. A1d.~~

~~Sect. 3.1 is an analysis of the skill of the meteorological forcing after bias correction. Because predictability of the meteorological forcing is an interesting topic by itself, we here present an analysis of the skill of the meteorological forcing before bias correction, i.e. of the raw S4 output, limiting attention again to the three variables considered in Sect. 3.1. Fig. A1a summarizes the skill of the raw precipitation hindcasts, which should be compared with the summary for the bias-corrected hindcasts precipitation in Fig. 1b. Such a comparison is made for lead months 0, 1 and 2 in Fig. A1b. Similar comparisons are made for the two-meter temperature and incoming short-wave radiation in Figs. A1c and A1d, respectively. At this level of summarizing the differences in skill between the~~

~~two types of data, differences are small for precipitation and negligible for temperature and short-wave radiation. Also, patterns of skill for all three variables, such as those shown in the maps of Figs. 1 and 2, are almost identical for the bias-corrected and the raw data. The fact that differences are small is not surprising because the bias corrections hardly change the ranking of the values while the value of the correlation coefficient largely depends on the ranking of the hindcasts relative to the ranking of the observations. Results, in terms of differences in skill between raw and bias-corrected meteorological forcing, are essentially the same for the other metrics used (ROCarea and RPSS).~~

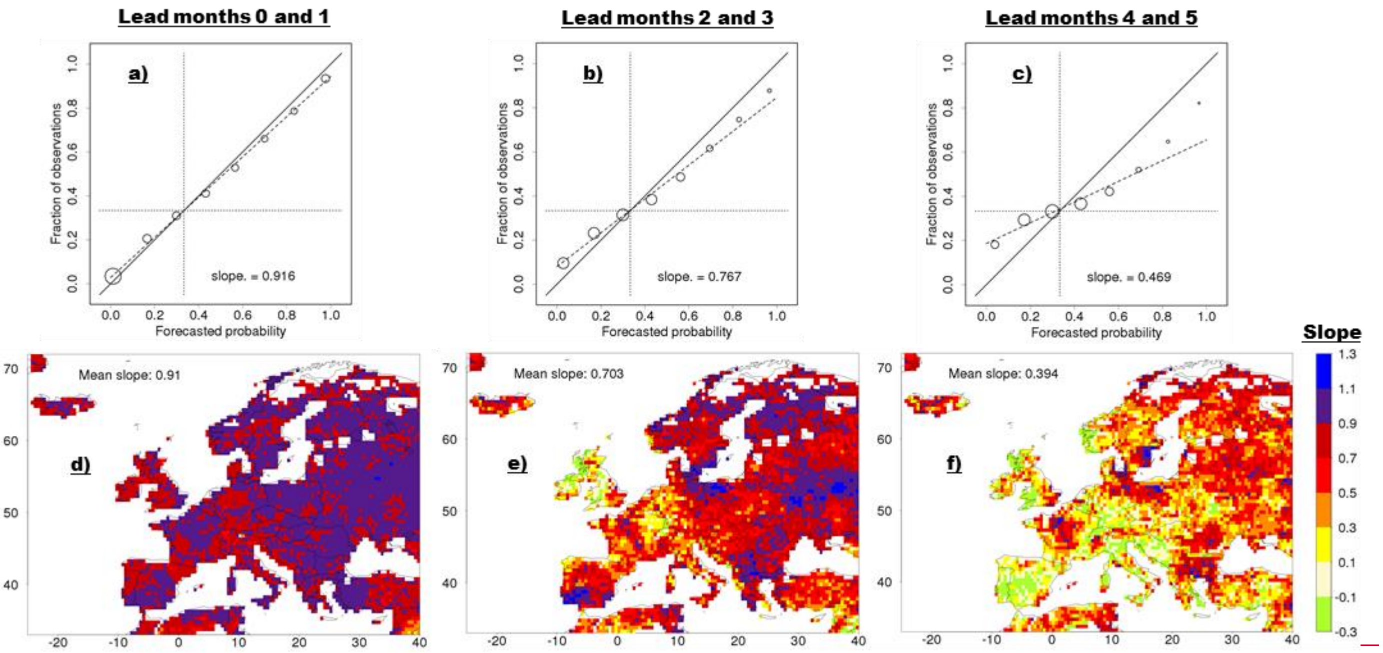
Appendix A~~B~~ Reliability of the hindcasts

To complement the analysis of discrimination skill of WUSHP published in the companion paper, this appendix presents a short evaluation of the reliability of the system. Per definition forecasts are considered “reliable” when the forecast probability is an accurate estimation of the relative frequency of the predicted outcome (Mason and Stephenson, 2008). We assessed the reliability of the discharge hindcasts of the FullSH by means of so-called reliability diagrams (see Mason and Stephenson, 2008), which we produced and evaluated as follows:

- For each grid cell and combination of a category (or tercile; AN, NN and BN), lead month and target month we proceeded as follows:
    - Divide the 30 (number of years) observations into terciles and give them a binary number (1 if the event falls in the considered category, 0 otherwise).
    - Divide the 450 (number of years x number of ensemble members) forecasts into terciles.
    - Determine for each of the 30 years the forecast probability of the event occurring (forecast falling in the considered tercile).
    - Pair the binary observations with the forecast probabilities.
    - Sort the paired data into eight bins stratified by the forecast probabilities of the event.
    - Compute bin averages of the forecast probability and of the binary observations.
- Pool the results for two consecutive lead months and the three target months of the same season.
- The results were further processed as follows:
    - They were aggregated for the entire domain and then plotted. Examples for the BN tercile and the spring months (MAM) as target are shown in Figs. B1a-c ~~and B2a-c~~ with lead month number increasing from left to

right. In each diagram a linear regression is applied to the data points, weighing individual points by the number of data pairs in the bins. Because tercile thresholds are set independently for observations and forecasts, the resulting line always goes through the climatological intersection (one-third in our case; see Weisheimer and Palmer, 2013) and ~~it is~~results are insensitive to biases. As in Weisheimer and Palmer (2013) we use the slope of the line as a measure of reliability. A slope equal to 1 corresponds to perfect reliability and a slope equal to 0 indicates no reliability at all.

- Reliability diagrams similar to those in Figs. A~~B~~1a-c ~~and B2a-c~~ were produced for each terrestrial grid cell, and best-fit lines and their slopes were computed. The slopes were plotted in maps, of which examples for the BN tercile and the spring months (MAM) as target are shown in Figs. A~~B~~1d-f and A~~B~~2d-f.



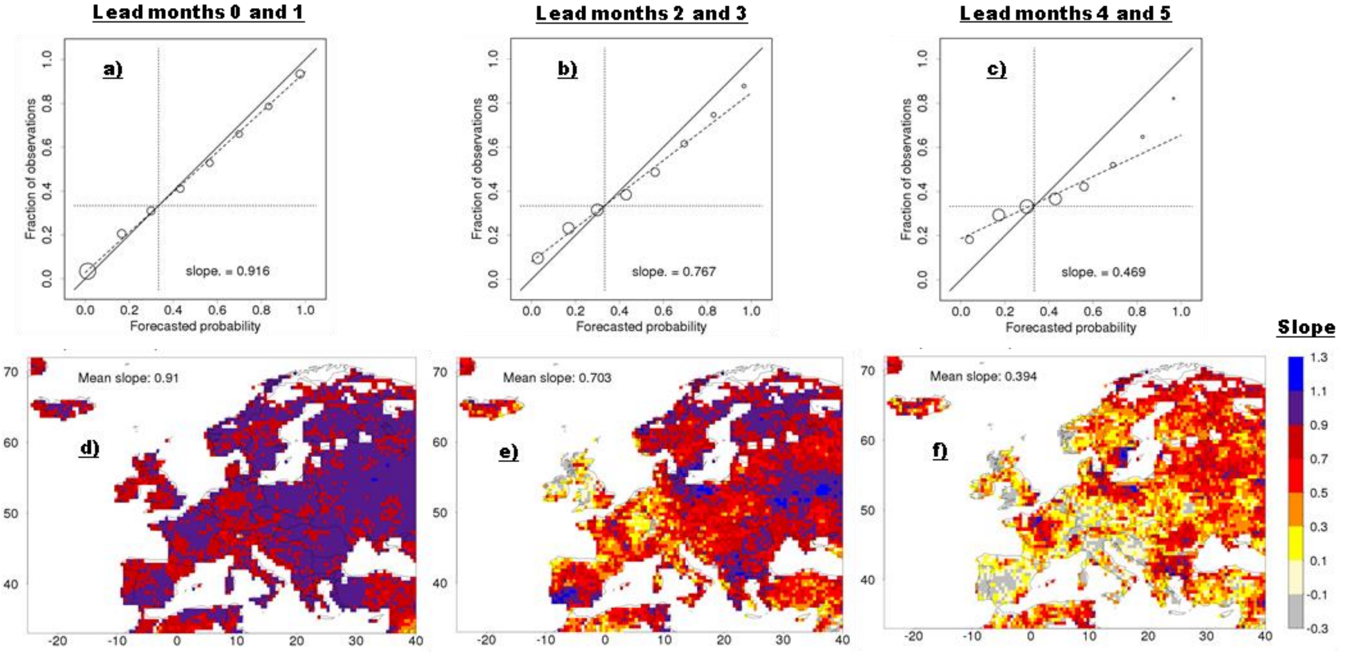
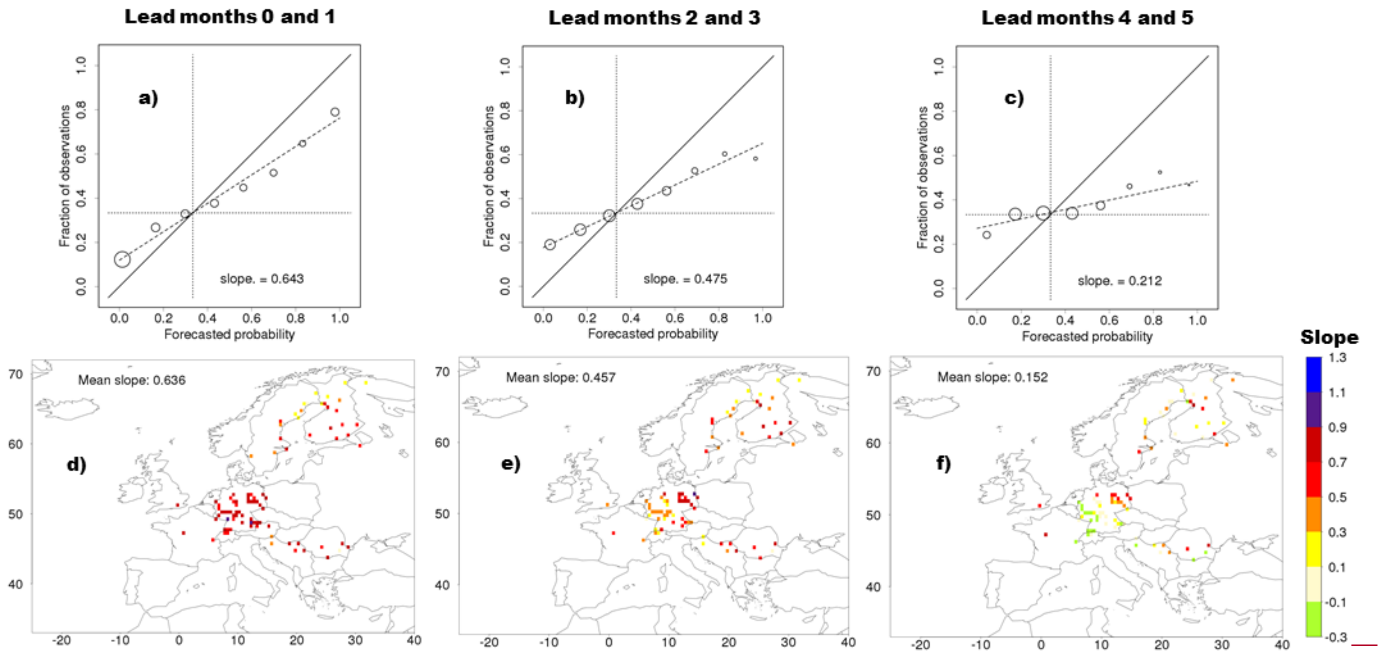


Figure A~~B~~1 Reliability of the FullSH discharge hindcasts for the BN tercile in spring (target months MAM). Pseudo-observations were used for verification. Lead time increases from left to right. Figures A~~B~~1a-c depict aggregated reliability diagrams for the full domain. The forecasted probabilities of BN discharge (horizontal axis) are collected in eight bins. The vertical co-ordinate is the relative frequency of BN discharge observations for all of the forecasts in a specific bin. The solid line is the 1:1 line. The dashed line shows the best fit to the eight data points, each weighted by the number of observations contributing to the bin (N_{bin}). The area of the symbols is proportional to N_{bin}. The dotted lines are the averages of the variables along the two axes (one-third). Similar reliability diagrams were made for all grid cells individually and the slopes of the best-fit lines are plotted in Figs. A~~B~~1d-f.

For the analysis it is helpful to first consider the value of the slope in two extreme cases. If pseudo-observations are used for verification and lead time approaches zero, all members of the hindcasts for a specific year approach the pseudo-observation of that year. Hence, all hindcasts fall in the same category as the observation, so the reliability diagram condenses to two points at the coordinates [0,0] and [1,1], which represent, respectively, two-third and one-third of all contributing data. In this case the hindcasts are utterly reliable and utterly sharp. The second case is when the hindcasts have no discrimination skill at all, i.e. forecast probabilities of an event are randomly paired with the outcome (whether the event occurs or not). In this case, the slope of the fitted line is equal to zero, so the hindcasts are not reliable at all, and sharpness is minimal, i.e. forecast probabilities tend to approach one-third for each of the terciles.

In Fig. A~~B~~1 reliability is evaluated for the case of verification with pseudo-observations. For the first two lead months, the slope of the line in the diagram of the aggregated data (Fig. A~~B~~1a) is 0.916. Hence, during these two lead months the system is not far from being perfectly reliable and it is rather sharp with relative maxima in forecast probability in the lowest and the highest bin. Then, with progressing lead time, reliability is reduced, i.e. the slope of the aggregated data decreases to 0.767 (for lead months 2 and 3; Fig. A~~B~~1b) and 0.469 (for lead months 4 and 5; Fig. A~~B~~1c). Moreover, with increasing lead time sharpness is reduced, with gradually more ensemble forecasts approaching the climatological forecast, i.e. a probability of one-third for each of the terciles.

The maps of Figs. A~~B~~1d-f show the geographical distribution of the slope from the reliability diagrams. For the first two lead months most values of the slope for individual grid cells lie between 0.7 and 1.1 (Fig. A~~B~~1d) and the domain-averaged slope is 0.910. At longer leads, the highest values are found in some regions with considerable amounts of discrimination skill, such as Poland and Northern Germany, Western France, and Romania and Bulgaria (see Table 1). Reliability also tends to increase towards the northeast of the continent. Domain mean values of the grid level slope are generally somewhat lower than the slope of the aggregated data. This can, at least partly, be ascribed to more scatter of individual points around the best-fit line because of the much smaller sample size for individual grid cells.



~~Figure B2 Reliability of the FullSH discharge hindcasts for the BN tercile in spring (target month MAM). Real observations for large basins were used for verification. See Figure B1 for more explanation.~~

~~Figure B2 is analogous to Fig. B1 but instead of using the pseudo-observations, the real observations for large basins (Sect. 2.2) are taken for verification. Compared to verification with pseudo-observations, slopes are closer to zero and therefore the forecasts seem to be less reliable and more overconfident. Independent of the type of verification data, R~~Reliability for the AN tercile is almost equal to that for the BN tercile while slopes are much closer to ~~one~~ zero for the NN tercile (not shown here). ~~Finally~~Also, levels of reliability show little variation during the year, except for the autumn (SON), when slopes are smaller (not shown here). Finally, Fig. S9 in the supplement shows that for verification real instead of pseudo-observations, slopes are closer to zero, so forecasts seem to be less reliable and more overconfident.

Strikingly, discrimination skill and reliability have similar characteristics. Both decrease with increasing lead time, differences between the AN and BN terciles are relatively small while scores for the NN tercile are clearly inferior to those for the two outer terciles. Also, regional maxima in discrimination skill and reliability tend to coincide, and scores of discrimination skill and reliability are smallest in autumn~~ and higher for verification with pseudo-observations than for verification with real observations~~.

Appendix B Skill in the meteorological forcing before bias correction

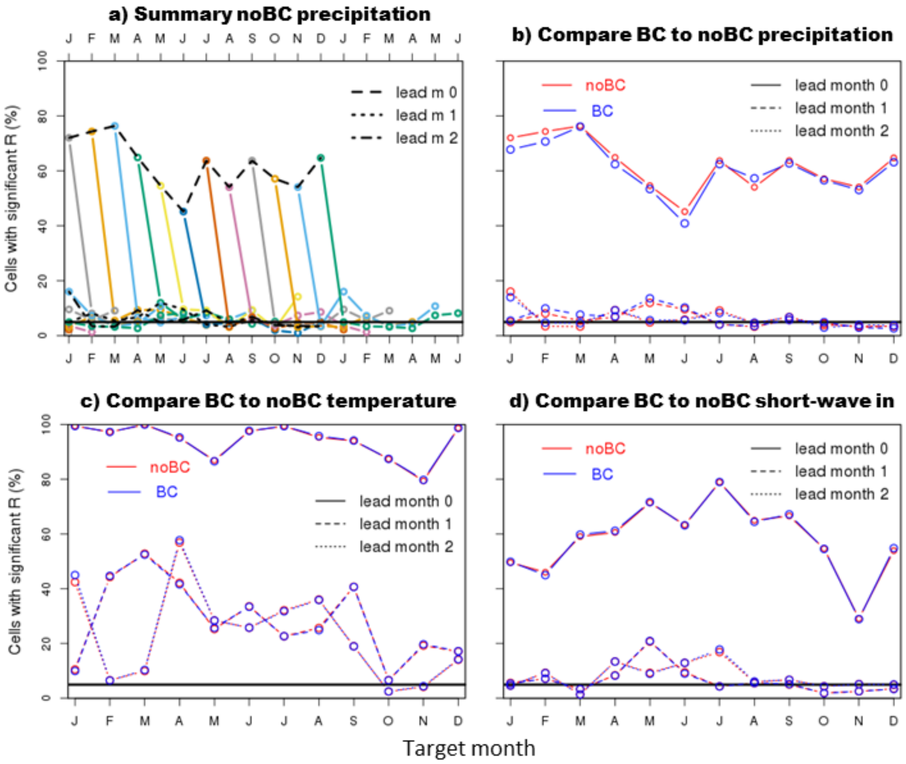


Figure B1 Skill, in terms of the percentage of cells with significant values of R, for three components of the raw S4 forcing. Figure B1a shows precipitation skill, as a function of target and lead month. The other three panels compare the skill of the raw S4 output (noBC) with its bias-corrected version (BC) as a function of the target month and for the first three lead months. Precipitation is plotted in Fig. B1b, temperature in Fig. B1c and incoming short-wave radiation in Fig. B1d.

Section 3.1 contains an analysis of the skill of the meteorological forcing after bias correction. Because predictability of the meteorological forcing is an interesting topic by itself, we here present an analysis of the skill of the meteorological forcing before bias correction, i.e. of the raw S4 output, limiting attention again to the three variables considered in Sect. 3.1. Figure B1a summarizes the skill of the raw precipitation hindcasts, which should be compared with the summary for the bias-corrected hindcasts of precipitation in Fig. 1b. Such a comparison is made for lead months 0, 1 and 2 in Fig.

B1b. Similar comparisons are made for the two-meter temperature and incoming short-wave radiation in Figs. B1c and B1d, respectively. At this level of summarizing the differences in skill between the two types of data, differences are small for precipitation and negligible for temperature and short-wave radiation. Also, patterns of skill for all three variables, such as those shown in the maps of Figs. 1 and 2, are almost identical for the bias-corrected and the raw data. The fact that differences are small is not surprising because the bias corrections hardly change the ranking of the values while the value of the correlation coefficient largely depends on the ranking of the hindcasts relative to the ranking of the observations. Results, in terms of differences in skill between raw and bias-corrected meteorological forcing, are essentially the same for the other metrics used (ROC area and RPSS).

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