Hierarchy of climate and hydrological uncertainties in transient low flow projections

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Author's Response

Dear Editor,

We believe most of the referees' comments have been addressed in the revised manuscript. Apart from the numerous changes following specific comments – which appear in the marked-up version –, three main changes have been made:

- Several elements have been transferred from discussion to methods, and from results to discussion,
- A new subsection dedicated to the advantages and limitations of the QE-ANOVA approach has been added to the discussion,
- A supplementary material including additional verification graphs has been appended to the manuscript.

Best regards.

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Hydrology and Earth System Sciences
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Discussions

Interactive comment on "Hierarchy of climate and hydrological uncertainties in transient low flow projections" *by* J.-P. Vidal et al.

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The referee comments are recalled in italics and followed by the authors' responses.

The paper proposes a methodology to estimate a transient probability distribution of yearly hydrological variables conditional to ensemble projections. Specifically, yearly anomalies and rolling means over 30 years of anomalies of MAM7 are analysed. The projections are derived from a model chain involving GCMs, statistical downscaling methods and hydrological models and the contribution of each model chain member to total uncertainty is quantified using quasi-ergodic analysis of variance.

General comments

The authors investigate the relevant topic of future changes to low flow behavior and

makes use of transient projections which is important for water management for specific years. The paper is generally well written and provides relevant and timely references. It also presents clear figures to support their statements.

The authors would like to thank the referee for this positive evaluation of the manuscript.

However, I see some points that need to be addressed before I feel confident in recommending final publication:

1. *Since projections are used on hydrological models I miss the description on how these models were tested on robustness. If a hydrological model is not robust - in this case particularly targeting low flow-, I do not trust indications that are made with projections, i.e. in changed conditions. See for instance the simple recommendations made by Klemes (1986).*

   We understand this point of view, and this comment calls for different elements of response.

   First, as mentioned P12657L11, ORCHIDEE has not been calibrated and incidentally shows a very low performance on various low flow metrics. Moreover, only manual sensitivity tests have been performed to select J2000 parameters.

   Second, for GR5J, MORDOR, CEQUEAU and CLSM, tests of robustness have been run by following the approaches recommended by Klemeš (1986): split-sample tests have been performed over two consecutive periods P1 (1980-1994) and P2 (1994-2009). Results on different metrics (including low flow metrics) are summarized by Sauquet et al. (2015, p. 63-69). They show that all models tend to have difficulty in simulating low flows. Moreover, as mentioned in the manuscript P12671L1-7, differential split sample tests have been performed by considering 5-year subperiods with contrasted climatic conditions: 1983-1988 (cold and snowy), 1988-1993 (dry and quite cold), 1993-1998 (wet and snowy), 1999-2004 (wet and warm) and 2004-2009 (dry and warm). The results for all these tests on different metrics (including low flow metrics) are summarized by Sauquet et al. (2015, p. 70-72). They show that all calibrated models seem equally robust with regard to their low flow simulations. Other differential split sample tests have been performed with CLSM and are summarized by Magand et al. (2015). The results from all these tests prompted us to comment in the manuscript on the necessity to include parameter uncertainty in future uncertainty assessments (see P12670L25 to P12671L12). As mentioned in the manuscript P12671L5-7, detailed results of split-sample tests will be presented in a follow-up paper.

Third, and most importantly, this manuscript focuses on the decomposition of uncertainties, independently of the quality of the models, be they GCMs (Global Climate Models), SDMs (Statistical Downscaling Methods) or HMs (Hydrological Models). To this aim, only anomalies with respect to the REF period (1980-2009) are considered throughout the manuscript, in order to remove the effect of potential biases in low flow indicators. What may be relevant to the present paper is an assessment of how the models are able to simulate the observed interannual variability of low flow anomalies. All models show a very good interannual variability of MAM7 anomalies, except for the low-elevation catchment (Verdon@Sainte-Croix) in summer where their performance is a bit lower. The above statement are however not valid for ORCHIDEE which shows only a fair performance.

Some of the above comments will be added to Section 5.3.

2. *The paper reads nicely and logic until the discussion starts. Here there are many parts that actually would belong to the Methods and Results sections. Please, restructure for better readability of the entire paper. (See also Specific comments)*

   We will restructure the manuscript to (1) integrate the analysis of the origins of divergence of low flow responses from different HMs (Sect. 5.2) in the Methods section, keeping only the comparison to findings from other studies, (2) move specific comparisons to other studies currently in the Results section to a ded-

icated subsection of the Discussion section. For the sake of readability of this document, specific comments corresponding to this main comment will not be recalled below.

3. *The authors introduce convincingly the benefit of transient projections. Hence, I would expect a discussion on this benefit underlined with the results that are presented as well as concrete examples for application. Particularly, the time of emergence and related uncertainties are not discussed (see also Specific comments).*

   Some comments will be added to the revised manuscript to discuss the benefit of a transient decomposition of uncertainties, for example for assessing the time of emergence of the change signal on low flows for an individual year or for 30-year time slice averages. Such comments will be included on a subsection discussing the advantages and the limitations of the QE-ANOVA approach. See also responses to specific comments below.

Specific comments

- *12652L20 Does the reference present the low number or does it propose alternatives? (not clear from its placement); name these alternatives briefly*

  Peel et al. (2015) actually proposes an alternative to circumvent the low number of GCM runs, by stochastically generating time series based on resampled GCM projections. This will be made explicit in the revised manuscript.

- *12653L5 why is it called comprehensive, briefly state why*

  All possible combinations of the available GCMs / GCM runs / SDMs / SDM realizations / HMs are considered in this dataset. To hopefully be even clearer, each run of each GCM has been downscaled with each SDM, and each realization of this downscaled climate projection dataset has served as forcing for each of the HMs.

- *12654L17 does the higher elevated catchment contain glacierized parts?*

  The Durance@Serre-Ponçon indeed contains some glacierized parts mainly located in the Écrins massif, accounting for around 20ḱm^2 in 2006-2009 (Gardent, 2014, p. 181) and shrinking (Gardent et al., 2014). These parts represent only 0.5% of the catchment surface area and glacier melt has therefore little influence on the low flows at Serre-Ponçon.

- *12654L21-L25 I wonder if these reconstitutions and their related uncertainties could influence the outcomes of the uncertainty contribution partitioning. Please, clarify.*

  Reconstituting natural streamflow is a prerequisite of any climate change effect on hydrology in regulated catchments like the Durance one, in order to remove anthropogenic influence from reservoir operations that may vary from year to year. Such reconstitutions – that of course carry some uncertainties – are here only used to calibrate the hydrological models to hopefully simulate the natural component of the catchment hydrology. In the present study, these models are only used with forcings from the downscaled GCM projections. We therefore hardly see how these reconstitutions may influence the uncertainty contribution partitioning as they were used in a similar way by all calibrated hydrological models.

- *12655L16ff the basic principle is introduced, but since three different SDMs are used it would be good to briefly introduce the specific differences among them, or earlier refer to Table2*

  An earlier reference to Table 2 and previous references (which both contain additional information and differences between SDMs) will be made in the revised manuscript.

- *12656l12-17 How often and how much was the temperature corrected? -> possible impacts on results? And impacts on the interpretation in 12668L2 "identical"?*

  The temperature correction (occurrence and amount) is highly dependent on the SDM considered. For example, few and generally small corrections are required for d2gen which include the large-scale temperature at 700hPa above the catchment, corrections are higher for dsclim that includes the large-scale T2m above France as a predictor, and again higher for analog that does not include any temperature-related predictor. Such a correction may therefore contribute to reduce the difference in downscaled projections from the different SDMs, at least for the temperature at the scale of the whole Durance basin, the spatial aspects being unchanged. It may therefore contribute to reduce the SDM uncertainty part in the overall uncertainty. This discussion will be added to the revised manuscript. Concerning the second point of this comment, there is no impact on the interpretation of the sentence P12669L2: when a specific combination (GCM / GCM run / SDM / SDM realization) is considered, meteorological forcings (downscaled gridded projections) are indeed identical for all HMs.

- *12657L13 what are the consequences of this initially coupled mode if any?*

  There is no direct consequence as they are here used here in a forced mode. This sentence was simply intended to highlight the initial purpose of such models – which is different from the one of rainfall-runoff hydrological models – and therefore the potentially lower adequacy to such catchment-scale modelling. It will be clarified in the revised text.

- *12657L14 Here I miss the description on how the hydrological models were tested on robustness (Klemeš 1986)*

  See response to main comment #1.

- *12657L19 is there a practical motivation for choosing the MAM7 and not any other low flow metric?*

The choice of the MAM7 was guided by the requirement for (1) an annual indicator, and (2) an indicator commonly used internationally for operational purposes. This will be clarified in the revised text.

- *12658L5 is there snowfall already before November in the higher catchment?*

  Based on data from the 1980-2009 period, snowfall may happen in late October in the Durance@Serre-Ponçon but in limited amounts.

- *12665L26 -12666L2 Methods not Results – also I find this Time of Emergence very appealing and would appreciate more details and thoughts on applicability on it*

  See response to main comment #3. The concept of Time of Emergence (ToE) has been introduced by Giorgi and Bi (2009) and popularized by Hawkins and Sutton (2012). The only requirement for applying this concept is an estimate of the multimodel signal of change and an estimate of the natural/internal variability. Some discussion will be added to the revised manuscript.

- *12669L26-28 actually, less snow pack can have two natural reasons related to precipitation: 1) less precipitation fell in general or 2) precipitation fell as rain; these two would have different effects and would not necessarily result in more water for winter low flow*

  The referee is right. But the fact that precipitation totals are identical for all HMs (for a specific GCM / GCM run / SDM / SDM realization) makes reason 1) not relevant here. What is left is therefore reason 2), hence our difficulty on interpreting this result. We would be happy to have more external insights on this particular point, as mentioned in the manuscript.

- *12671L13 I would appreciate a discussion on the time of Emergence and its relevance for application respectively the limitations that are related to this metric; could it be influenced by the initial calibration for instance?*

  See response to main comment #3. We do not believe the ToE metric could be influenced by the calibration processes, but some additional analysis may confirm this. What is true, however, is that the ToE is intrinsically linked to the choice of the reference period chosen for calculating the anomalies (see Hawkins and Sutton, 2016, for some relevant comments on that issue). It is also highly linked to the quality of the estimates for both the multimodel mean signal and the internal variability. The time series approach used here makes this estimation rather robust. This would have not been the case with other uncertainty estimation approaches such as the one proposed by Yip et al. (2011) as the contribution of internal variability to total uncertainty variance is here very high.

- *12671L25- 12672L4 the benefit of transient quantification of uncertainties should be discussed before appearing in the conclusions - potentially comparing to other studies that used other than low flow variables and then leading to applicability particularly for the water management with the focus on low flow as pointed at in the conclusions 12672L24f*

  Some discussion on this point will be added to the revised manuscript. See also the response to main comment #3 and responses to specific comments on the Time of Emergence (ToE). Benefits for the water manager will be discussed, and notably how such results may inform robust adaptation strategies and how they may change the focus of such strategies compared to previous studies that looked only at changes in 30-year average quantities.

- *12689 I like this Figure very much!*

  Thank you.

- *12692 Figure4 Durance@Serre-Ponçon makes me wonder how suitable GCMs in higher Alpine catchments are. ECHAM5 and CNCM33 show opposite signals over the entire period (winter). Could the authors add some words on the suitability of GCMs in high Alpine catchments?*

The performance of GCMs in higher Alpine catchment is actually not really relevant here. Indeed, the downscaling step makes use of GCM predictors not necessarily located above the specific catchment. Geopotential height predictors used by all 3 SDMs are for example considered over a large spatial domain covering a large part of France.

Technical comments

- *12650L8 and L9 "of" ->"for"?*

  We believe the appropriate use of "to take account" is with "of".

- *12650L12 "possible transient futures" rephrase!*

  We may replace it by "transient possible futures" if required.

- *12650L16 "most elevated", only two catchments are studied -> change*

  This will be replaced by "more elevated".

- *12650L19-21 Unclear, rephrase*

  This will be replaced by "The time of emergence of the change signal is however detected for low-flow averages over 30-year time slices starting as early as 2020."

- *12651L20 either "paragraphs propose" or "paragraph proposes" (I guess the latter?)*

  This will be replaced by: "The following paragraphs propose...".

- *12652L25f reformulate for better understanding*

  This will be replaced by: "Lastly, the majority of hydrological change studies so far mainly focused on uncertainties in the streamflow regime."

- *12652L26 when -> while*

  The sentence will be modified as: "Some of them [...], but relatively few..."

- *12653L1 "possible futures", please change to "future possibilities" or similar*

  We would like to keep the wording as “possible futures” as we believe it conveys the appropriate concept.

- *12653L5 move 1980-2065 after hydrological projections*

  We will rephrase the sentence as: "[...] transient hydrological projections over the 1980-2065 period..."

- *12653L12 verb missing after critically*

  We don’t think any verb is missing, as the sentence draws a parallel between "relative contributions of model uncertainty...." and "[relative contributions] of both large-scale and local-scale components of internal variability". We may add numbers in brackets to make it more explicit.

- *12655L7 add "the" before year*

  The sentence will be modified accordingly.

- *12655L9 that -> these GCM runs*

  We unfortunately don’t understand the modification proposed by the referee.

- *12655L10 runs -> is*

  We believe using the verb "to run" is valid here.

- *12656L1 predictors*

  The plural is indeed appropriate here.

- *12659L5 NFS would mean N* F* S mathematically speaking, please change to S N F or similar throughout*

  There is obviously a misunderstanding over "NFS". NFS refers to Noise-Free Signal, an abbreviation already used by Hingray and Saïd (2014). It will be made more explicit and defined earlier on in the revised manuscript to remove any possible confusion with mathematic notations.

- *12661L16 did Hingray and Saïd do the same of did they overfit - not clear from this sentence*

  The sentence is indeed unclear and will be rephrased. Hingray and Saïd (2014) also used a linear trend not to overfit interannual fluctuations.

- *12668L13 "snowpack building" rephrase*

  We propose to replace it by "snowpack accumulation and snowpack melt".

- *12671L27 change "account of" into "into account" and place after "variability"*

  We believe the two formulations are equally valid, but we may use the proposed one in the revised manuscript.

- *12692 correct to "catchments" in the caption*

  This typo will be corrected.

- *12701 add "the" before year 2065*

  The sentence will be modified accordingly.

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Hydrology and Earth System Sciences Discussions

Interactive comment on "Hierarchy of climate and hydrological uncertainties in transient low flow projections" *by* J.-P. Vidal et al.

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The referee comments are recalled in italics and followed by the authors' responses.

The article presents a transient decomposition of uncertainties in low flow changes in two Alpine catchments. The decomposition is done for 30-year as well as for yearly statistics. As a method for the decomposition, the quasi-ergodic ANOVA method proposed by Hingray and Saïd (2014) is used. It is shown that in the ensemble mean, the low flows generally decrease. The largest fraction of uncertainty comes from internal variability. Hydrological models also contribute substantially to the total uncertainty, which is discussed to be due to differences in snow and evapotranspiration routines between the different hydrological models. Also, a comparison to a standard

ANOVA method is presented. It shows that the quasi-ergodic ANOVA method results in a smoother transient uncertainty decomposition than the standard ANOVA.

General comments

The discussion paper studies a relevant topic and applies state-of-the art methods to look at low-flows in a climate-impact study. It is well written and has a high scientific quality including a sound literature discussion. Also, the mathematical details of the applied method are given in a conclusive way. I recommend publication after my comments below have been taken into account.

The authors would like to thank the referee for this positive evaluation of the manuscript and for the insightful comments on the QE-ANOVA method.

Major comments

The paper very much relies on the statistical method of the quasi-ergodic ANOVA introduced by Hingray and Saïd (2014) and consequently, other aspects in the impact modeling chain are less well detailed. I do not mind that and in fact would like to see even more discussion of the QE-ANOVA. There are many assumptions made in the QE-ANOVA and some of them could be verified. For example, the stationarity of the variance has not been proved, something which is even more relevant since the authors use yearly anomalies with a higher degree of variability. If there is a considerable degree of non-stationarity in the variability, I would like this to be included in the discussion of the QE-ANOVA results.

Assuming a constant coefficient of variation of the variable studied with respect to the inter-realization dispersion (for SSIV) and with respect to the inter-run dispersion (for LSIV) is indeed a central hypothesis in the QE-ANOVA method. We will try to avoid here using the term of stationarity which is subject to much discussion in the recent literature.

It is indeed possible to relax this hypothesis and compute yearly empirical values of the variance terms in Equation (A1) for SSIV. In Equation (A1), the empirical variance Vark[Y(m,r,k,t)/ŷ(m,t)] may be calculated for any (m,r) at any time horizon t of the simulation period. SSIV(t) may then be calculated without the quasi-ergodic assumption. Figure 1 below compares the temporal evolution of SSIV with the quasi-ergodic (QE) assumption – as in the manuscript – and without it, as defined above. It shows that the hypothesis is quite reasonable and allows removing some noise without altering the overall temporal evolution.

Similarly, it is also possible to relax this hypothesis for LSIV, even if in a degraded mode because of the different numbers of runs from each GCM, and because of the fact that 2 of them (out of 4) only have one run. In equation (A3), the temporal evolution of Varr[Y(m,r,•,t)/ŷ(m,t)] may therefore be calculated for any m where r>1 (i.e. for model chains that include either IPCM4 and ECHAM5). Figure 2 below shows here again that the quasi-ergodic hypothesis is quite reasonable. The above comments will be included in the discussion section and figures provided as a supplementary material or in annex.

Over all, I would also like to see a more critical discussion of the results, not only highlighting the advantages but also the limitations of the QE-ANOVA results. It has to be clear for a Non-ANOVA specialist what they can expect from the method, since many impact modelers would probably like to use the QE-ANOVA approach. For example, the QE-ANOVA approach would not be suitable to study changes of extreme precipitation for which other studies have shown that the variability can increase even in case of decreasing mean.

In addition to the response to the above comment, the revised manuscript will also include a dedicated subsection of the discussion on the advantages and limitations of the QE-ANOVA method, including the central issue of extracting the signal with a relevant shape. This issue necessarily leads to overestimate LSIV (see Hingray and Saïd, 2014). As a complement to the response of the previous comment, the hypothesis of a constant coefficient of variation over the whole period may actually be thus relaxed by

using only a limited number of time steps around the target time horizon for calculating LSIV. In such a local QE-ANOVA approach, the estimation can next be applied in turn for each target time horizon, allowing the LSIV to depend on the target time. This approach leads to quite interesting results for synthetic data with various response to uncertainty ratios, as shown by Hingray et al. (submitted).

Also, although the literature review is generally good, it would be good to include a part about other ANOVA methods. In particular, the study by Northrop and Chandler (2014) could be cited to refer to another method that is able to deal with an unbalanced design.

We agree that a number of other ANOVA methods have been presented and applied in the recent years. The main focus on our work was however not to present a new ANOVA method but rather to explore the hierarchy of uncertainty sources in a specific hydrological issue using (and adapting in a way) an already existing ANOVA method. Of course the results of the uncertainty analysis may significantly depend on the method. We recently explored this issue from synthetic experiments (Hingray et al., submitted). We will acknowledge this point in the discussion and mention the possibility / interest to apply other methods such as the one of Northrop and Chandler (2014) pointed out here, which seems indeed interesting to explore especially the robustness of uncertainty estimates.

I have tried to give as detailed comments as possible below. I am looking forward to the author's response and would also be happy to discuss certain aspects if necessary.

Detailed comments

- *Title: The term "Hierarchy" is a bit misleading, as there is no dominating hierarchy but the contributions of the different uncertainty sources are changing over time. To me, hierarchy is something structurally inherent. Also, the term might lead to confusions with the use of hierarchical ANOVA models, which are not used in this* *study.*

We would prefer to keep the current title as the work indeed attempts at finding the hierarchy of climate and hydrological uncertainties in hydrological projections. The fact that such a hierarchy depends on the target time horizon will be specified in the revised abstract and conclusions in order to remove any ambiguity. Moreover, we do not think confusions may arise with hierarchical ANOVA models as we never use the term in the manuscript (abstract included).

- *Section 2.2.1: Which variables were used from the GCMs?*

  The GCM variables used as statistical downscaling predictors depend on the SDM. More information on predictors can be found in Lafaysse et al. (2014), but SDM versions used here slightly differ. A complete description of versions used here may be found in Hingray et al. (2013, p. 24). With their notations, the versions used here are: analog20, d2gen22 and dsclim11. In short, all 3 SDMs use some sort of geopotential fields (either sea level pressure or geopotential height at 700 or 1000 hPa), and for d2gen and dsclim, some large-scale indicator of temperature (either at the surface or at 700 hPa), and additional predictors like for example humidity (relative, specific or flux at 700hPa) or geostrophic wind components at 700 hPa.

- *And what do the different runs in Tab. 1 stand for? Of course, the introduction gives some hints, but it should be clearly stated in this section, too.*

  The different runs correspond to different free simulations of a GCM differing only by their initial conditions (here in 1850), and thus provide an estimate of the GCM internal variability. This will be reminded in this section.

- *Also, has the data since the end of ENSEMBLES been published publicly? If so, please indicate the data source.*

  ENSEMBLES data are publicly available through the project website http://ensembles-eu.metoffice.com. This data source will be added to the revised manuscript.

- *Page 12656, lines 18-29: It is unclear which parameters that are used for the subsampling. Was it changes in mean annual temperature and precipitation or anything else? Please specify.*

  The conditioning variables used for the subsampling have indeed not been specified in the manuscript. They are changes between 2 periods (1980-2009 and 2036-2065), on summer and winter precipitation and temperature, and on inter-annual variability of annual precipitation and temperature, all of them on basin-average (whole Durance basin) variables. They have been carefully chosen based on their relevance for water management. This will be added to the revised manuscript.

- *Also, what are the properties of LHS regarding the joint properties of the sub-sampled distributions?*

  Conditioned LHS critically seeks to preserve the joint properties of the multivariate distributions (see e.g., Christierson et al., 2012).

- *Section 2.2.3 and Table 3: A list of required input variables for each hydrological model should be given. Furthermore, since the evapotranspiration process description is mentioned later on to be a potential reason for differences in low flow projections, a short description of the evapotranspiration routines should be included in Table 3 in a similar manner as the snow routines have been listed.*

  We agree with the referee. We opted in the first place not to mention these descriptions, but we now understand it may bring some relevant information. Roughly, two types of evapotranspiration modelling approaches may be identified: computation of actual evapotranspiration from energy balance models in

CLSM and ORCHIDEE, and use of Penman-Monteith potential evapotranspiration (Allen et al., 1998) for the other HMs. This information will be added to Table 3.

- *Section 3.1: Please indicate in the text and caption of Fig. 2 that the regimes were estimated based on reconstructed streamflows and not observations.*

  We will specify that naturalised streamflow time series have been used for estimating natural regimes.

- *Page 12660, lines 19-20: This is only true if the trend model is correctly separating the LSIV from the NFS for any given lead time. In general and given the linear trend model, it is likely that LSIV and the SSIV are overestimated (see also discussion in Raisänen 2001 and Hingray and Saïd (2014). Please discuss this limitation here and at other text passages where the partitioning between NFS and variability is presented.*

  As mentioned in a response above, this will be commented in the "QE-ANOVA advantages and limitations" subsection of the Discussion.

- *Page 12660, line 20-22: I understand that the SSIV is generated using the stochastic SDM realizations which in turn use the GCM data as input. Thus, there might be some sort of interaction between the LSIV and SSIV. For e.g., the SDM might generate a different variability for a GCM that is at the high end of the range with respect to one that is at the low end of the range of projected changes. It would be good if the authors could comment on that and discuss this either here or later in the article. Is there a reason why not to construct a 2-way-ANOVA for the variability part of the data? Such an ANOVA could take interactions into account. The design is unbalanced, but this should not affect your sum of squares estimation in a more severe way as what you do in Eq. A3 and A4 where all available runs of a particular GCM are taken thereby giving more weight to the GCMs with more runs.*

  Unfortunately, it is not possible to use a standard 2-way ANOVA to disentangle the two internal variability components. Indeed, for a given chain GCM-SDM, SDM realization#1 of, say, GCM run#1, does not correspond to realization#1 of run#2, due to the stochastic nature of SDM realizations. No ANOVA with only fixed effects can therefore be applied here. Mixed-effects ANOVA models may be tested, but they cannot provide an assessment of possible interactions. Considering the comment on the number of runs, Equations (A3) and (A4) use an average over all available runs for a given model chain. There is therefore no larger weight given to GCMs with more runs.

  On the other hand, we agree that the SSIV value could in principle depend on the GCM. Figure 3 below shows the QE-ANOVA estimates of the SSIV for groups of hydrometeorological chains associated with each GCM. No clear dependence of SSIV to GCMs emerges from this figure: discrepancies between GCMs do exist but they may vary over time.

- *Page 12662, line 6: It is unclear how the time slice averages are calculated. Do you use some fixed time slices or a moving 30 year approach? Please clarify at some stage in the manuscript. I have noticed that this comes later in 4.2 but I would have expected it to be defined earlier.*

  Thank you for pointing out this possible source of confusion. We actually use a moving 30-yr approach. This will be clarified in the revised manuscript.

- *Section 4.2, subsection title: Same comment as for the title. Hierarchy is arguably not the best term here.*

  As mentioned above, we would prefer to keep this term here for supporting the message that hydrological uncertainty is qualitatively and quantitatively as important as climate uncertainty.

- *Page 12663, line 21: Although I agree that internal variability often is larger than* *other sources of uncertainty, the manuscript has up to this point not given a reason why this had to be expected.*

We will add some supporting information earlier in the manuscript to support the fact that this results was expected, notably by including results from other studies (Hawkins and Sutton, 2011, etc.), but also by referring to Figure 3 where internal variability components are both very high compared to the change signal from this particular hydrometeorological modeling chain, but also from the grand ensemble change signal.

- *Page 12663, line 27: "previous studies". References are needed to point the reader to the previous studies.*

  They actually refer to the studies referenced in the previous sentence (Lafaysse et al. 2014; Hingray et al, 2014). This will be clarified.

- *Page 12664, lines 2-4: Interesting to see that the same set of SDMs leads to different degrees of uncertainty distributions when mean streamflow or low flows are analysed. I would ask the authors to also include a short discussion on the relation to other uncertainty sources. Without knowing the details about the employed SDMs, it seems to me that all make use of a similar concept (analogues) and represent only a small part of all available SDMs. If more diverse SDMs would have been used, the SDMs might have contributed more to the total uncertainty.*

  The representativity of the set of SDMs applied here within the large superpopulation of possible SDMs (with reasonable skill) is an interesting question, which could be also posed for GCMs and HMs. It has to be noted that even if the three SDMs rely on the same basic idea of analogue resampling, the concepts for selecting analogue situations are quite different (see Table 2 and detailed description in Lafaysse et al., 2014). Moreover, Lafaysse et al. (2014) found large differences between different versions of a given SDM using slightly different sets

of predictors. It is therefore unclear whether more diverse SDMs (or a larger number of versions from the SDMs used) would contribute more to the total uncertainty. To come back to the different effects on different streamflow indicators, it has to be noted that low flows are much more dependent on catchment processes than annual streamflow, therefore reducing the impact of different SDMs. These comments will be added to Section 5.3.

- *Page 12664, lines 25-27: The authors use a lognormal distribution to transfer the estimated variances into confidence bounds. I think this cannot be done straightforwardly since the variance parameter in QE-ANOVA is estimated based on non-logarithmized data. In other words, from the QE-ANOVA you get an effect with is normally distributed with zero mean and some variance, but those parameters are not directly portable to a lognormal distribution, which can be seen by, for e.g., the fact that a lognormal distribution never has zero mean. Anyway, judging from the results in Fig. 10 that look fairly ok, I assume that the authors have taken this into account and there is just a need for more clarification in the text on how the estimated variance and mean parameters are transferred so that a lognormal distribution can be used.*

  The relevant transformations of mean and variance from a normal distribution to the ones of a log-normal distribution have indeed been used. This will be clarified in the revised manuscript.

- *Page 12665, lines 9: The authors should state that also here, the decrease in internal variability for the 30-year time averages is due to the decrease in the ensemble mean.*

  We agree. See also responses to previous comments on this topic.

- *Page 12665, lines 10-14: A discussion of the decrease in the internal variability is necessary. A link to the relevant equations in the appendix might be helpful* *for the interested reader. It should also be stated that this decrease is a direct consequence of the quasi-ergodic assumption and could be an artefact.*

This is right, and this issue will be added to the new "QE-ANOVA advantages and limitations" subsection of the Discussion, as detailed in the response to previous comments.

- *Page 12665, line 21: "...in 2033-2039, that is for 30 year time-slices starting before 2015." Unclear as both 2033-15 and 2039-15 are not less or equal than 2015.*

  The sentence indeed contains a typo. It should read: "... starting around 2020".

- *Page 12666, lines 13-17: Unclear sentence. I understand it in a way that you are discussing the time of emergence for the results based on yearly anomalies, however, I cannot see that the lines in Fig. 11 exceed the 95*

  The sentence is indeed unclear. It actually comments the differences between actual modelling chains and perfect ones. It notably states that with a perfect modelling chain, one may be able to detect the change signal one decade earlier for both catchments in summer. We will rephrase it accordingly in the revised manuscript.

- *Section 5.1: I would suggest including a discussion of the relation between hydrological model uncertainty and the performance of the hydrological models with respect to the analyzed variable - here low flows. The two LSMs (ORCHIDEE and CLSM) used are behaving quite differently from the rest of the hydrological models. If those two were excluded from the analysis, the hydrological model uncertainty would probably be quite a bit smaller. And I would also expect those two HMs to have a worse performance in the reference period than the remaining ensemble - of course due to their main goal to be a LSM rather than a catchment model.*

  The relation between a present-day performance and a climate change signal is being highly discussed in the literature for GCMs. And indeed, a similar reasoning may of course be followed for HMs. However, this study uses anomalies from a reference period as a target variable in order to remove any present-day bias, and to hopefully reduce such a relationship if it actually exists. See also the response to comments to referee #1 on this particular topic. About the specific HMs ORCHIDEE and CLSM now: while present-day performance of ORCHIDEE on the interannual variability of low flows is indeed low, CLSM performance is actually generally in the middle range of other models. This result thus does not corroborate a simple relation between present-day performance and future changes. A sensitivity test of the uncertainty decomposition results on the subset of HMs retained would therefore be interesting (and similarly on subsets of GCMs or SDMs) but out of the scope of the present study. However, the above comments will be added to the discussion in Section 5.3, together with corresponding answers to comments from referee #1. It has to be noted that a similar experiment on HM uncertainty evolution following removal of CLSM has been performed on another multimodel study on the Seine catchment by Habets et al. (2013).

- *Section 5.1, first paragraph: I would argue that also the common way how HMs are calibrated leads to larger uncertainties for low flows. If, for e.g., NSE is maximized, the model is fitted better to high values than low values as the squared deviations give more weight to high values.*

  Actually, each HM has been calibrated in a specific way, as this has been left to the discretion of each R2D2-2050 project partner. The following table summarizes the objective function used for each model and provides some additional comments.

  This table will be added to the Table 3 of the manuscript. The general guidelines for the R2D2-2050 project were aiming at having HMs able to correctly simulate the whole range of flows, and not specifically high flows. However, the ref-

Table 1. Hydrological model calibration details. KGE refers to the Kling-Gupta Efficiency (Gupta et al., 2009).

Acronym	Calibration approach	Objective function
GR5J	Optimisation	KGE on $\sqrt{Q}$
MORDOR	Optimisation	KGE on Q
CEQUEAU	Semi-distributed optimisation	multicriteria
J2000	Manual sensitivity analysis	–
CLSM	Manual calibration	KGE on Q plus bias
ORCHIDEE	–	–

eree is right when stipulating that different calibration approaches may lead to an increase in HM uncertainty in low flow changes. This also goes along the lines discussed in the manuscript P12670L25-P12671L12 about the uncertainty in hydrological parameters. Some comments on the different possible objective functions across HMs will be added to Section 5.3.

- *Page 12667, lines 17-19: Isn't this to be expected since HM's fraction of variance is estimated based on the linear trend fit as well as the internal variability is very much smoothed due to the quasi-ergodic assumption, therefore removing a large part of the variability in time? The authors should discuss that the smoothness comes at the cost that one relies on the assumptions made.*

  This is right of course, and it indeed directly follows the assumptions made in the QE-ANOVA method. The underlying hypotheses behind this method are that both the Noise-Free Signal (NFS) and the internal variability evolve in a smooth way over time. These hypotheses appear quite reasonable as they ensue from a global gradual phenomenon – the increase in greenhouse gas concentrations – whose consequences are themselves gradual, at least within the time frame considered in this study. What can be discussed is how these hypotheses are implemented here in the uncertainty decomposition method, i.e. through (1) the

choice of a linear trend for estimating NFSs and (2) the choice of a constant coefficient of variation of internal variability over time. The above comments will be added to the discussion on the advantages and limitations of the QE-ANOVA method.

- *Figure 1: The coordinate system is not defined here. Preferably, the coordinates should be converted to Lat/Lon or at least the projection specifications for the lambert projection should be indicated.*

  We prefer sticking to the projection most commonly used in France. This is a Lambert conformal conic projection called "Lambert II étendu" with parameters specified in this document for example: http://www.ign.fr/sites/all/files/geodesie_projections.pdf. This reference will be added to the figure caption.

Technical comments

- *Page 12653, line 3: Should be "water manager's"*

  This will be corrected.

- *Page 12666, line 9: "an unchanged ..." instead of "a unchanged..."*

  This will be corrected.

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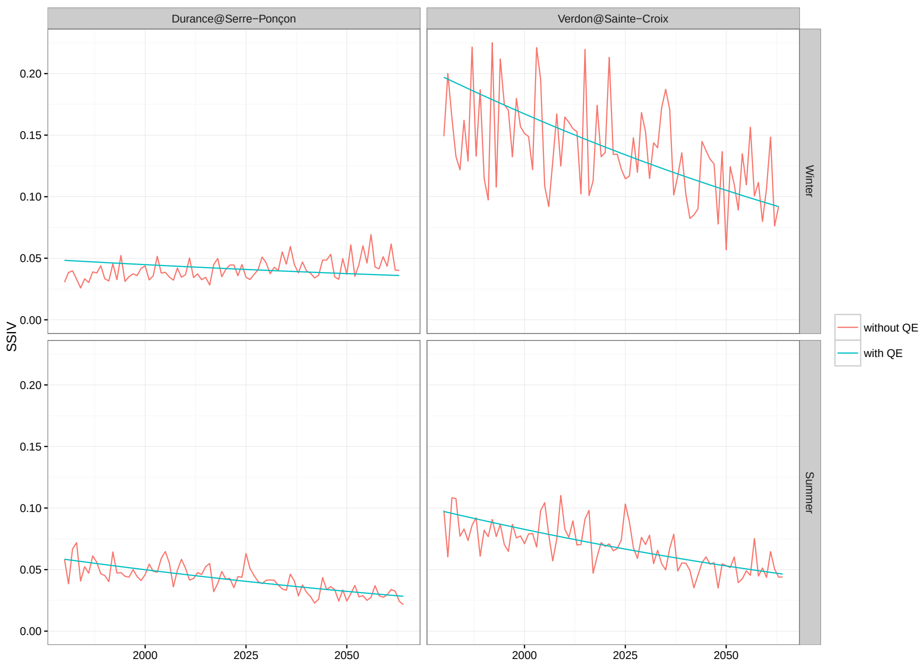

Fig. 1. Temporal evolution of SSIV with and without the quasi-ergodic (QE) assumption.

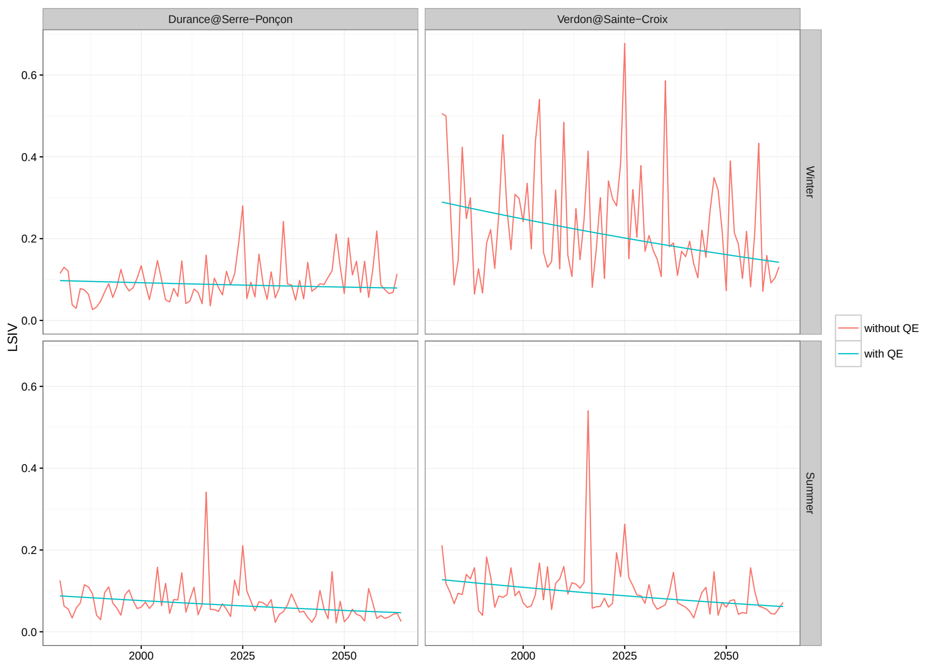

Fig. 2. Temporal evolution of LSIV with and without the quasi-ergodic (QE) assumption.

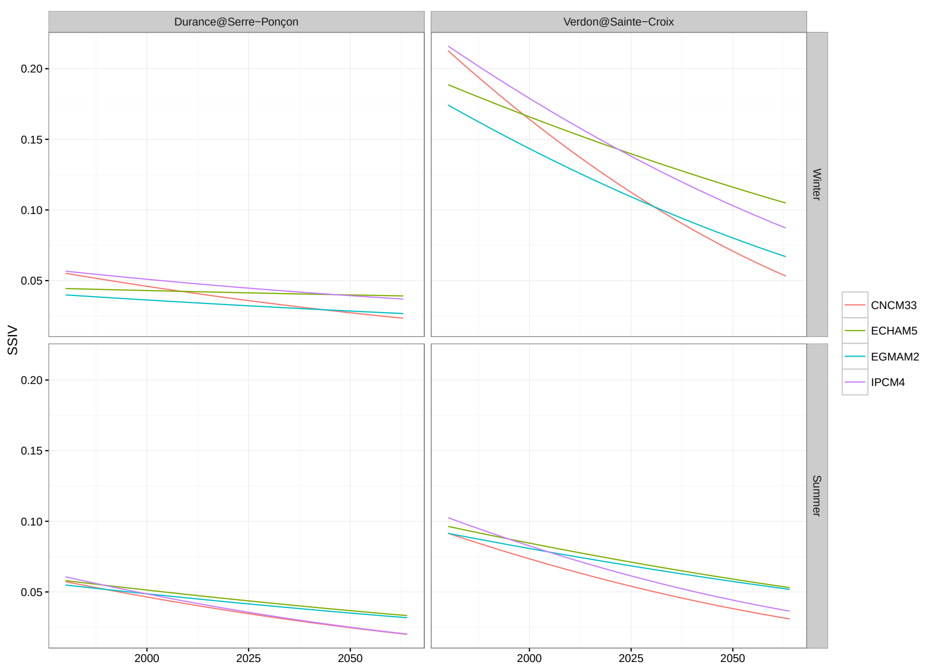

Fig. 3. Temporal evolution of SSIV computed for groups of hydrometeorological chains associated with each GCM.

Hierarchy of climate and hydrological uncertainties in transient low flow projections

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Abstract. This paper proposes a methodology for estimating the transient probability distribution of yearly hydrological variables conditional to an ensemble of projections built from multiple general circulation models (GCMs), multiple statistical downscaling methods (SDMs) and multiple hydrological models (HMs). The methodology is based on the quasi-ergodic analysis of variance (QE-ANOVA) framework that allows quantifying the contributions of the different sources of total uncertainty, by critically taking account of large-scale internal variability stemming from the transient evolution of multiple GCM runs, and of small-scale internal variability derived from multiple realizations of stochastic SDMs. ~~The QE-ANOVA framework~~ This framework thus allows deriving a hierarchy of climate and hydrological uncertainties that depends on the time horizon considered. It was initially developed for long-term climate averages and is here extended jointly to (1) yearly anomalies and (2) low flow variables. It is applied to better understand possible transient futures of both winter and summer low flows for two snow-influenced catchments in the southern French Alps. The analysis takes advantage of a very large dataset of transient hydrological projections that combines in a comprehensive way 11 runs from 4 different GCMs, 3 SDMs with 10 stochastic realizations each, as well as 6 diverse HMs. The change signal is a decrease in yearly low flows of around $-20\,\%$ in 2065, except for the ~~most~~ more elevated catchment in winter where low flows barely decrease. This signal is largely masked by both large- and small-scale internal variability, even in 2065. The time of emergence of the change signal ~~on 30year~~ is however detected for low-flow ~~averages is however around 2035, i.e. for~~ averages over 30-year time slices starting ~~in~~ as early as 2020. The most striking result is that a large part of the total uncertainty – and a higher one than that due to the GCMs – stems from the difference in HM responses. An analysis of the origin of this substantial divergence in HM responses for both catchments and in both seasons suggests that both evapotranspiration and snowpack components of HMs should be carefully checked for their robustness in a changed climate in order to provide reliable outputs for informing water resource adaptation strategies.

1 Introduction

Incorporating global change in long-term water resource planning, water management and water governance is a ~~-~~major issue water managers currently have to face (see e.g. Clarvis et al., 2014; Bréthaut and Hill Clarvis, 2015). Indeed, hydrological impacts of climate change may significantly alter amounts and timing of both the water demand and the water availability. Future water availability informing water resource adaptation strategies are usually assessed based on hydrological modelling with forcings from General Circulation Model (GCM) projections for specific catchments and/or at the national scale (see e.g. Christierson et al., 2012; Chauveau et al., 2013). In this context, a water manager with some degree of awareness in potential climate change impact studies is entitled to ask the following question, particularly relevant for long-term planning: for a given year in the future, what will be the probability of having a low flow value lower than a given baseline? Note that a very similar question has been recently addressed by Sexton and Harris (2015) on the probability of a seasonal temperature/precipitation average for a given year being lower or higher than a present-day baseline. In order to answer the water manager question, one should address four different scientific issues: (1) computing future hydrological changes, (2) generating a transient evolution of those changes, (3) disentangling hydrological change signal from effects of natural/internal climate variability, and (4) focusing on the lower part of the streamflow distribution. The following paragraphs ~~proposes a~~ propose a brief review of how ~~such~~ the issues listed above have been tackled in the literature.

The first issue has been largely addressed in the literature over the last decades, through the use of hydrometerological modelling chains composed of GCMs, downscaling techniques – either regional climate models or statistical downscaling ~~techniques~~ methods (SDMs) – and hydrological models (HMs). Such hydrometerological chains provide a quantification of the hydrological change signal, but also an estimate of the uncertainty associated to each level of the modelling chain, provided of course that they include multiple models at each level (Wilby and Dessai, 2010). There is a growing body of literature on the quantification of the contribution of each level of the hydrometeorological chain to the overall modelling uncertainty in hydrological changes (Dobler et al., 2012; Finger et al., 2012; Bosshard et al., 2013; Hagemann et al., 2013; Addor et al., 2014; Lafaysse et al., 2014; Schewe et al., 2014; Giuntoli et al., 2015; Vetter et al., 2015). In most cases, contributions from the different sources of uncertainty are derived through more or less formal analysis of variance (ANOVA) techniques which recently became a common tool in climate studies (Yip et al., 2011; Sansom et al., 2013).

These projections are however historically and still generally derived for specific time slices in the future, and only few studies engaged in deriving transient hydrological projections (Lafaysse et al., 2014; Barria et al., 2015).

The issue of quantifying internal climate variability and its additional contribution to modelling uncertainty has retained much attention from the climate community over the last few years (Hawkins and Sutton, 2009, 2011; Deser et al., 2012). The quantification of global climate variability has been recently propagated downstream the modelling cascade in some hydrological studies (Lafaysse et al., 2014; Seiller and Anctil, 2014; Gelfan et al., 2015; Peel et al., 2015; van Pelt et al., 2015). When internal variability is estimated from the analysis of multiple runs from a GCM in most studies, alternatives have been proposed to circumvent the often low number of available runs which prevent simple robust estimations ~~(see e.g. Peel et al., 2015)~~ (see e.g. Peel et al., 2015, for an example alternative approach). Another type of internal variability has moreover been taken into account in a few regional studies: the variability of small-scale meteorological features given a signal from GCMs, estimated from stochastic downscaling methods (either perfect-prog methods or weather generators) (Lafaysse et al., 2014; Fatichi et al., 2015; Peel et al., 2015).

Lastly, the ~~first objective of the~~ majority of hydrological ~~changes~~ change studies so far ~~was on~~ mainly focused on uncertainties in the streamflow regime. ~~When some~~ Some of them explored changes in the entire flow duration curve (Dobler et al., 2012; Bosshard et al., 2013; Fatichi et al., 2015), but relatively few focused on the lower end of the hydrological spectrum (see e.g. Wilby and Harris, 2006; Giuntoli et al., 2015; Vetter et al., 2015).

The objective of this work is to deliver relevant information on possible futures of low flows for informing water resource adaptation strategies. To this aim, it attempts to answer the water manager's question by addressing all four issues listed above for two specific snow-influenced Alpine catchments with high stakes on water resources. This work takes advantage of a ~~-~~very large dataset of transient ~~1980–2065 hydrological projections that combines in a comprehensive way~~ hydrological projections over the 1980–2065 period, that gathers all possible combinations of hydrometeorological modelling chains built from 11 runs from 4 different GCMs, 3 SDMs with 10 stochastic realizations each, as well as 6 diverse HMs. Time series of mean annual minimum flow over 7 days are first derived separately for winter and summer for both catchments and for each of the 1980 hydrological projections. The quasi-ergodic analysis of variance (QE-ANOVA) framework developed by Hingray and Saïd (2014) is applied on this low flow dataset to quantify the relative contributions of (1) model uncertainty due to GCMs, SDMs and HMs, but also critically of (2) both large-scale and local-scale components of internal variability. This framework is here extended to analyse not only changes in time-slice averages, but also yearly anomalies, in order to take account of the year-to-year variability that is of much interest for operational water management.

Section 2 introduces the two case study catchments and describes the hydrological projection dataset used. Section 3 presents the selected low flow indicator for two separate seasons and details the QE-ANOVA approach and its adaptation and extension to yearly anomalies of low flows. Results are given in Sect. 4 and discussed in Sect. 5.

2 Data

2.1 Case study catchments

The Durance basin is located in the Southern French Alps, and water flows into the Rhône river. This basin has a total area of 14 000 km^2 and an altitude range of 4000 m. It carries high stakes for water resources as it produces 10 % of French hydropower and supplies drinking water to approximately 3 million people (Warner, 2013). It is moreover exposed to various climatic influences, from Alpine climate in the upper northern part to Mediterranean climate in the lower southern part. Water resources are already under high pressure due to substantial abstractions within and out of the river basin, and global change will question the sustainability of the current rules for water allocation among the different uses, among all other governance challenges (Bréthaut and Hill Clarvis, 2015). The R2D2-2050 project addressed this issue by building projections of future water availability, prospective scenarios of water demand, as well as prospective scenarios of future water management (Sauquet et al., 2014).

Two case study catchments are considered here: the Durance@Serre-Ponçon and the Verdon@Sainte-Croix (see Fig. 1). They have been selected here for two main reasons: first, they are located upstream the two largest reservoirs in the Durance catchment, the Serre-Ponçon reservoir being actually the second largest in Europe. The management of these

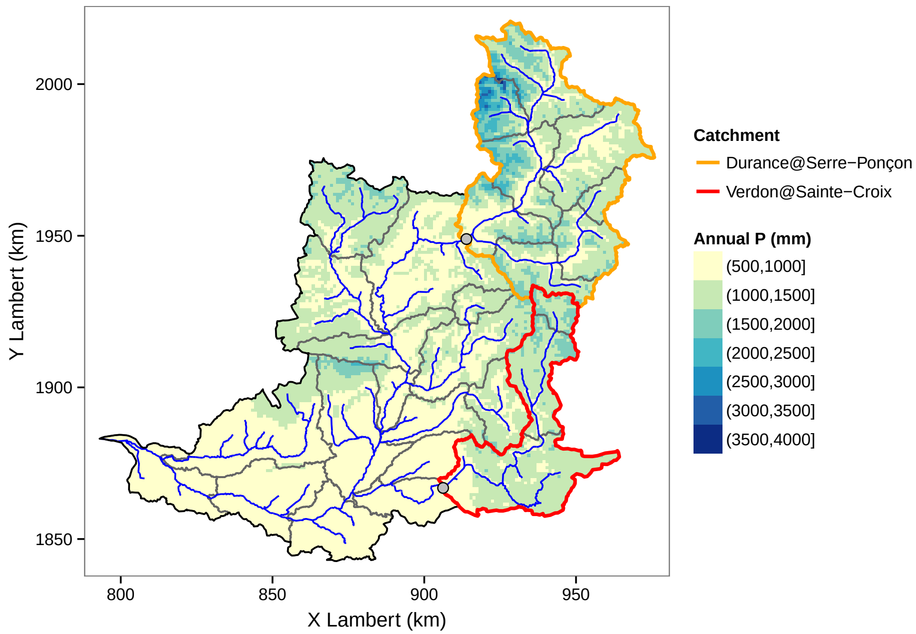

Figure 1. Delineation of the Durance basin and the two case study catchments drawn on the gridded map of the 1980–2009 mean annual precipitation from the SPAZM reanalysis (Gottardi et al., 2012) . The coordinate system is the Lambert II Étendu conformal conic projection (http://www.ign.fr/sites/all/files/geodesie_projections.pdf).

reservoirs is coordinated to fulfil water demands from various uses. Second, their hydrological regime is largely influenced by snowpack/snowmelt processes, with differences stemming from their altitude range and geographical location. The Durance@Serre-Ponçon (3580 km^2) is located in the heart of the French Alps and more than half of its area is above 2500 m~~,~~ ~~whereas the~~ . It contains a small glacierized part (0.5 % of the catchment area, Gardent et al., 2014) that may contribute to late summer streamflow in some specific upper subcatchments (Lafaysse et al., 2011) , but much less so for the whole catchment. The Verdon@Sainte-Croix (1620 km^2) is located on the southern Mediterranean edge of the Alpine range, with a maximum altitude of 2500 m.

Reconstitutions of natural streamflow for both stations were provided by the EDF power company which manages both Serre-Ponçon and Sainte-Croix reservoirs. Reconstructed streamflow were derived prior to the R2D2-2050 project from outflows and stored volumes in the two reservoirs, and corrected from the influence of other upstream hydropower reservoir operations. In this study, these reconstructed streamflow time series were only used to calibrate some of the hydrological models as detailed in Sect. 2.2.3.

Table 1. Global model runs under the A1B emissions scenario. Different runs from a given GCM correspond to simulations differing only from their initial conditions (see Johns et al., 2011)

Acronym	Institute	GCM name	Number of runs	Reference
CNCM33	CNRM (France)	CNRM-CM3.3	1	Salas-Mélia et al. (2005)
EGMAM2	FUB (Germany)	EGMAM+	1	Huebener et al. (2007)
IPCM4	IPSL (France)	IPSL-CM4_v2	3	Marti et al. (2010)
ECHAM5	DMI (Denmark) & MPI (Germany)	ECHAM5-C	6	Roeckner et al. (2006)

2.2 Hydrological projection dataset

2.2.1 Global climate projections

Climate projections over the Durance basin are based on global projections from the ENSEMBLES project (van der Linden and Mitchell, 2009), and more specifically from the STREAM2 simulations using more recent versions of the GCMs (Johns et al., 2011). The simulations used here are forced by 20C3M forcings (historical forcing by greenhouse gases and aerosols) until the year 2000, and emissions from the A1B scenario afterwards (Nakićenović et al., 2000). Table 1 lists the GCM runs used in this study, for which appropriate variables for downscaling were available ~~and that were used in this study~~from the ENSEMBLES project website[1]. The specific period considered here runs from 1 August 1958 to 31 July 2065.

2.2.2 Downscaled climate projections

The spatial resolution of the global projections is not adapted to hydrological modelling over small areas like the Durance basin. A downscaling step has therefore been performed within a previous project on this basin (RIWER2030, Hingray et al., 2013). Three statistical downscaling methods (SDMs) have been applied here (see Table 2), all of them primarily based on the analogue principle introduced by Lorenz (1969). This principle ~~is based~~ relies on the assumption that similar large-scale atmospheric circulation patterns lead to similar local-scale values of near-surface meteorological variables. SDMs build statistical relationships between an archive for predictors and an archive for predictands. For each GCM run, each SDM provides 100 stochastic realizations of meteorological time series in order to generate a probabilistic output of the downscaling step (see Lafaysse et al., 2014, for details on the stochastic generation process). All three methods have been extensively used in previous climate change impact studies (see e.g. Bourqui et al., 2011; Vidal et al., 2012; Chauveau et al., 2013; Lafaysse et al., 2014), and their main characteristics are given in Table 2. Further details on the SDMs are given by ~~Hingray and Saïd (2014)~~ Hingray et al. (2013, p. 24: with their notations, the versions used here are analog20, d2gen22 and dsclim11) , Hingray and Saïd (2014) , and Lafaysse et al. (2014).

The archive for ~~predictor~~ predictors is the NCEP/NCAR global reanalysis (Kalnay et al., 1996) and the archive for predictands is the DuO near-surface reanalysis (Magand et al., 2014) built as a hybrid between the SPAZM (Gottardi et al.,

[1]http://ensembles-eu.metoffice.com

Table 2. Statistical downscaling methods.

Acronym	Institute	Method name	Description	Reference
analog	EDF/LTHE	analog20	Analogues	Obled et al. (2002)
dsclim	CERFACS	dsclim11a2	Weather types + transfer functions	Boé et al. (2006)
d2gen	LTHE	d2gen22	Transfer functions + analogues	Mezghani and Hingray (2009)

2012) and Safran (Vidal et al., 2010) reanalyses. DuO combines the higher spatial resolution of SPAZM ($1\,\mathrm{km}^2$) – relevant for example for high-altitude precipitation – and the higher temporal resolution (hourly) and the additional variables (including wind and radiation) of Safran that are required inputs for land surface models. The period considered as an archive for analogue dates runs from 1 August 1980 to 31 July 2005 (Hingray et al., 2013). Local-scale variables for target dates are taken as the ones from each analogue date. The Penman–Monteith reference evapotranspiration (ET0, Allen et al., 1998) required as an input by conceptual models is additionally computed from meteorological variables. An additional correction on the temperature of the analogue date is moreover potentially applied to ensure the consistency with large-scale regional temperature from the GCM (Mezghani and Hingray, 2009; Boé et al., 2009; Hingray et al., 2013). When such a ~~-~~correction is applied, related meteorological variables like infrared radiation or specific humidity from the analogue date are also corrected for ensuring inter-variable consistency following Etchevers et al. (2002).

The downscaling process thus led to 3300 (11 GCM runs $\times$ 3 SDMs $\times$ 100 realizations) hourly/daily gridded climate projections over the Durance catchment for the period 1 August 1958 to 31 July 2065. A subsampling of 10 realizations out of 100 from each combination of SDM and GCM run has next been applied to reduce the number of different forcings for the impact models and therefore lighten the computational burden by an order of magnitude. This subsampling was made through a ~~-~~Latin Hypercube Sampling (LHS) approach, which allows to subsample a multidimensional distribution while preserving its marginal properties (McKay et al., 1979; Minasny and McBratney, 2006). This approach has been recently used by Christierson et al. (2012) and Green and Weatherhead (2014) to sample the UKCP09 probabilistic climate projections (Murphy et al., 2009). The conditioning variables used for the LHS have been carefully chosen based on their relevance for water resource management: they are changes – between 1980-2009 and 2035-2065 at the scale of the whole Durance basin – on summer and winter precipitation and temperature, and on interannual variability of annual precipitation and temperature.

2.2.3 Hydrological projections

Six hydrological models have been run by different R2D2-2050 project partners over up to 26 catchments in the Durance basin during the project. Only simulations with GCM-driven forcings described above at the two selected catchments described in Sect. 2.1 are considered ~~In~~ in the present work. The main characteristics of the 6 models as well as the calibration approaches against the reference period 1980–2009 – called REF in the following – are shown in Table 3. ~~Most of them~~ All conceptual models use a degree-day approach for modelling the snowpack evolution, while physically-based models rely on their energy balance models (3-layer snow model for CLSM and 1-layer model with constant properties for ORCHIDEE). All conceptual

Table 3. Hydrological model characteristics. KGE refers to the Kling-Gupta Efficiency (Gupta et al., 2009)

Acronym	Project partner	Type / Distributed	Calibration	Reference
GR5J	Irstea HBAN	Conceptual / No	Optimisation on KGE$(\sqrt{Q})$	Pushpalatha et al. (2011)
MORDOR	EDF DTG	Conceptual / No	Optimisation on KGE(Q)	Garçon (1999)
CEQUEAU	EDF R&D	Conceptual / Yes	Semi-distributed optimisation on multiple criteria	Hendrickx (2001)
J2000	Irstea HHLY	Conceptual / Yes	Manual sensitivity analysis	Krause (2002)
CLSM	UMR METIS	Physically-based / Yes	Manual calibration on KGE(Q) and bias	Ducharne et al. (2000)
ORCHIDEE	UMR METIS	Physically-based / Yes	No calibration	Krinner et al. (2005)

models use Penman-Monteith ET0 while physically-based ones compute actual evapotranspiration from their water and energy balance models. Most of these models have been extensively used in previous climate change impact and adaptation studies in other French catchments, often in multimodel contexts (see e.g. Paiva et al., 2010; Moatar et al., 2010; Bourqui et al., 2011; Chauveau et al., 2013; Habets et al., 2013). ~~Hydrological models have been calibrated against naturalized streamflow data over the reference period 1980–2009 – called REF in the following – except for ORCHIDEE for which default parameters were used. It has to be noted that CLSM and ORCHIDEE are land surface models initially built for running in a coupled mode with GCMs.~~

The hydrological modelling step thus led to 1980 ~~daily streamflow time series from 1980~~ transient hydrological projections – 330 downscaled climate projections times 6 HMs – for the period 1 August 1958 to ~~2009 for each of the two~~ 31 July 2065. They include daily streamflow, actual evapotranspiration and snow water equivalent for the 2 catchment case studies.

3 Methods

3.1 Low flow indicator

The low flow indicator chosen here is the Mean Annual Minimum flow over 7 days (MAM7) (WMO, 2008). This choice was guided by the requirement for (1) an annual indicator and (2) an indicator commonly used internationally for operational purposes. In Alpine catchments influenced by snowpack/snowmelt processes, two distinct low flow periods can be identified with different underlying physical processes (see, e.g. Laaha and Blöschl, 2006a, b; Laaha et al., 2013). Summer low flows occur as a consequence of persistent dry and warm weather periods when evaporation exceeds precipitation. Winter low flows occur when precipitation is temporarily stored in the snow cover causing runoff recession. Two distinct seasons are therefore considered for computing the MAM7: summer (1 June–31 October) and winter (1 November–31 May). Figure 2 shows these two ~~low flow~~ low-flow seasons and the observed daily interannual regime over the REF period for the two catchment case studies. ~~Low flow~~ Low-flow seasons are less well marked for the low elevation Verdon@Sainte-Croix which experiences a higher interannual variability of autumn flows due to potentially heavy rainfall events.

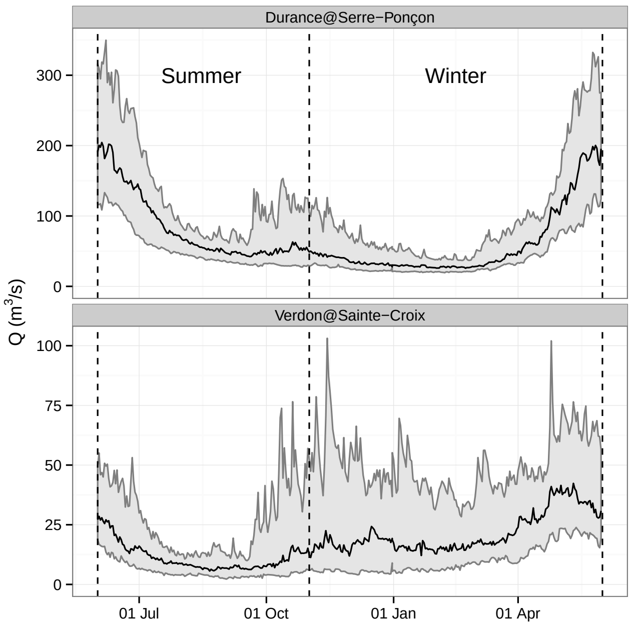

Figure 2. Daily interannual regime of naturalised streamflow over the REF period for the two catchment case studies, and season boundaries for low flow analysis. Grey ribbons frame the first and last deciles and the black line shows the median value.

3.2 The Quasi-Ergodic ANOVA framework

3.2.1 General principles

The partitioning of uncertainties in hydrological projections is performed in the framework of the quasi-ergodic analysis of variance (QE-ANOVA) framework developed by Hingray and Saïd (2014). This framework allows disentangling model uncertainty from internal variability in any unbalanced multimember multimodel ensemble, as the one available here. Model uncertainty components are estimated from the noise-free change signals (NFSs) of the different modeling chains using a classic analysis of variance framework. Internal climate variability components are then estimated based on the residuals from the NFSs, relying on the quasi-ergodic assumption for transient climate simulations. The paragraph below describes briefly the QE-ANOVA framework and the reader is referred to Hingray and Saïd (2014) for more details on the methodology, and to Lafaysse et al. (2014) for an application to hydrological variables.

Previous applications of the QE-ANOVA framework focused on changes in time-slice averages of the raw data y. In the following equations, the variable studied is noted Y and represents such a time-slice average. Equation (2) defines the relative change of the variable studied Y with respect to a baseline Y_0, for any prediction lead time t:

$$\Delta(g,s,h,r,k,t) = \frac{Y(g,s,h,r,k,t)}{Y_0} - 1 \quad (1)$$

where g, s and h are indices over GCMs, SDMs and HMs, respectively, r is an index over runs from a given GCM, and k an index of stochastic realizations from a given SDM. In the following, m will denote a GCM-SDM-HM modelling chain as a short for ~~(g,s,h)~~ (g,s,h). The relative change Δ may be written as:

$$\Delta(m,r,k,t) = \text{NFS}(m,t) + \eta(m,r,k,t) \tag{2}$$

where $\text{NFS}(m,t)$ is the ~~noise-free signal~~ Noise-Free Signal (NFS) of the change variable for chain m, i.e. the estimated response of the modelling chain, and $\eta(m,r,k,t)$ are the residuals of stochastic realization k of SDM s for the run r of GCM g. The total uncertainty of Δ corresponds to the sum of variances of both terms on the right hand side of Eq. (2). They correspond respectively to the model uncertainty and to the internal variability of Δ for the modelling chains. Their different components are estimated as follows.

3.2.2 Deriving noise-free change signals (NFSs)

NFSs are estimated by first fitting trend models to the raw data y for each of the modelling chains, considering all available GCM runs and all SDM stochastic realizations available for this specific chain. NFSs are then obtained by considering relative changes of these trend models with respect to the baseline Y_0:

$$\text{NFS}(m,t) = \frac{\hat{y}(m,t)}{Y_0} - 1 \tag{3}$$

where $\hat{y}$ is the trend model output. In the present work, Y_0 is taken as the average of the trend model over the reference period for a given modelling chain:

$$Y_0(m) = \overline{\hat{y}(m,t)}\,|_{t\in\text{REF}} \tag{4}$$

This choice has also been made by Bracegirdle et al. (2014) and is similar to the approach of Charlton-Perez et al. (2010) who considered changes with respect to a fitted trend value for a given reference year.

3.2.3 Partitioning model uncertainty

NFSs can be partitioned into GCM, SDM and HM contributions through a 3-way ANOVA according to the following equation:

$$\text{NFS}(m,t) = \mu(t) + \alpha(g,t) + \beta(s,t) + \gamma(h,t) + \epsilon(m,t) \tag{5}$$

where $\mu(t)$ is the overall climate response representing the grand ensemble mean of all projections at time t, $\alpha(g,t)$, $\beta(s,t)$ and $\gamma(h,t)$ are the main effects of GCM g, SDM s and HM h, respectively, and ϵ is the residual that may partly be due to model interactions. The empirical variances associated to these different effects correspond to the different components of model uncertainty – namely GCM, SDM, and HM uncertainty – and of residual/model interaction uncertainty, noted RMI in the following. The 3-way ANOVA on NFSs moreover allows identifying individual *model effects*, i.e. average deviations of the NFSs from the grand ensemble mean μ due to a given model, be it a GCM, a SDM or a HM.

3.2.4 Partitioning internal variability

The internal climate variability variable η in Eq. (2) can be partitioned into a ~~large scale and a small scale~~ large-scale and a small-scale component. The first one originates from the internal/natural fluctuations of the climate and the latter results from the variability in local meteorological situations observed given a ~~large scale~~ large-scale atmospheric configuration. In the present multimember multimodel ensemble, the ~~large scale~~ large-scale internal variability (LSIV) stems from GCM internal variability. For a modeling chain driven by a given GCM, the LSIV leads to the fluctuations around the long term trend simulated with that chain. It also corresponds for any prediction lead time to the dispersion between projections obtained or that would be obtained for different runs of this GCM. The ~~small scale~~ small-scale internal variability (SSIV) originating here from a stochastic SDM is expressed as the ~~deviations~~ dispersion of the different stochastic realizations of a SDM for a given lead time.

For the present ensemble of projections, estimates of both internal variability components are derived with the quasi-ergodic assumption of transient climate simulations for relative change variables, following Appendix B of Hingray and Saïd (2014). This assumes that the variance of the studied variable – or more precisely the coefficient of variation – is constant over the whole simulation period. In the present study, and conversely to the previous work, the baseline used for the estimation of the change variable is a constant $Y_0(m)$ that depends only on the modelling chain m. The expressions of SSIV(t) and LSIV(t) given by Hingray and Saïd (2014) thus simplify. They are given in Appendix A.

3.3 Application of the QE-ANOVA framework to low flows

3.3.1 Choice of NFS

Simple linear trend models are used to fit MAM7 projections of the whole period considered (1980–2065), on the contrary to Hingray and Saïd (2014) who considered piecewise NFSs composed of a constant value over a control period and a linear or polynomial trend over a transient period separated by a pivot year. The choice of a unique trend model is motivated by the shorter and wholly transient period considered here. Indeed, the pivot year has been estimated as 1950 and 1980 for temperature and precipitation respectively for the Durance@Serre-Ponçon by Hingray and Saïd (2014). The choice of a ~~linear trend~~ linear trend – following Hingray and Saïd (2014) for precipitation – was made not to overfit large interannual fluctuations of the low flow indicator~~, as done by Hingray and Saïd (2014) for precipitation. The NFS are computed from~~ .

72 ~~fitted~~ linear trend models were fitted, one for each modelling chain, e.g. for each combination of GCM, SDM and ~~hydrological model. Each NFS~~ HM. The NFS of each modelling chain is then obtained by considering relative changes with respect to the average of the trend model for the associated chain over the 1980–2009 REF period following Eq. (4).

Figure 3 shows an example of winter low flow NFS for the Durance@Serre-Ponçon, for the IPCM4 GCM, the d2gen SDM, and the CLSM ~~hydrological model~~HM. This specific NFS is a decrease reaching around $-25\,\%$ in 2065 when the grand ensemble mean shows a much smaller decrease. This figure also exemplifies the prominent contribution of internal variability components – within panel for SSIV and across panels for LSIV – compared to the change signal from this particular modelling chain, but also compared to the grand ensemble change signal.

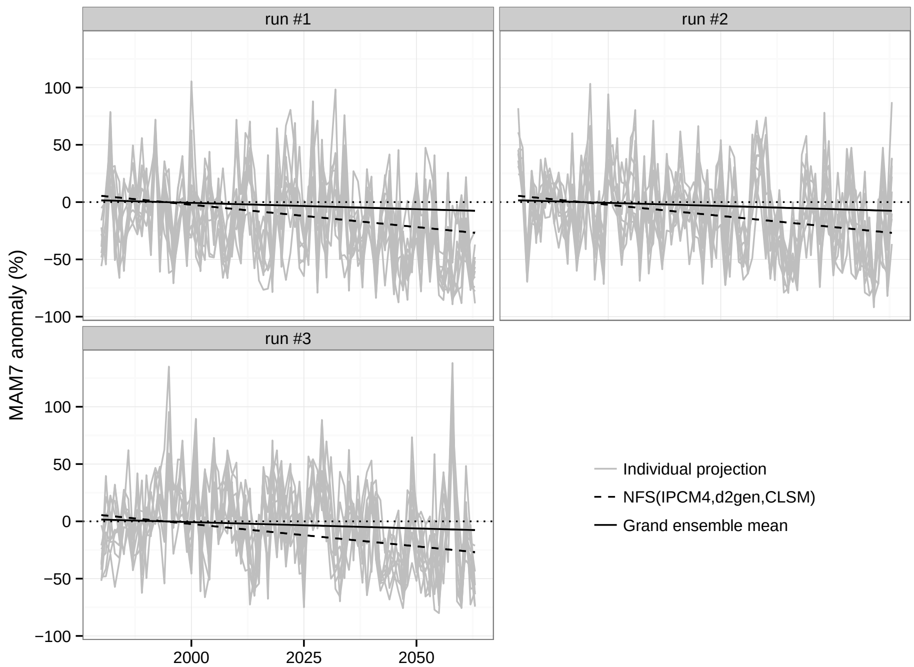

Figure 3. Winter low flow NFS($g = $ IPCM4, $s = $ d2gen, $h = $ CLSM) for the Durance@Serre-Ponçon, fitted to all 30 projections available as combinations of the IPCM4 GCM (3 runs), the d2gen SDM (10 realizations) and the CLSM hydrological model. Each panel shows 10 d2gen realizations from a given IPCM4 run as well as the common NFS and the grand ensemble mean.

3.3.2 ~~Extension of~~ Extending the framework to uncertainties in yearly anomalies

In this study, the QE-ANOVA framework is extended for partitioning the uncertainties not only on changes in time-slice averages as in the previous applications, but also on yearly anomalies of the raw values, in order to capture the effects of year-to-year variability in the uncertainty quantification. The studied variable Y in Eq. (2) is therefore taken as either y – the raw yearly variable – or $\overline{y}$ – a rolling 30 year ~~time-slice~~ average. Uncertainty analyses on both yearly values and time-slice averages will be presented in parallel in the next section. It has to be noted that in both cases, NFSs are fitted to the yearly data, resulting in a similar decomposition of model ~~uncertainties~~ uncertainty sources through the 3-way ANOVA.

4 ~~Results~~

3.1 ~~Identification of individual model effects~~

3.0.1 Deriving transient low-flow confidence bounds

The ~~3-way ANOVA on NFSs (cf. Eq. 5)allows identifying individual model effects~~total variance and grand ensemble mean computed through the QE-ANOVA approach allows deriving transient confidence bounds for the evolution of low flows, provided that an assumption is made on the shape of the distribution. Following previous uncertainty decomposition work on decadal averages, a normal distribution is selected for 30-year low-flow averages (see, e.g. Hawkins and Sutton, 2009; Charlton-Perez et al., 2010; Hawkins and Sutton, 2011) . A lognormal distribution is selected here for yearly values in order to take account of the skewed and bounded distribution of low flows, and appropriate lognormal distribution parameters have been derived from the grand ensemble mean and the total variance (see Appendix B). Additionally, the confidence range may be partitioned into the different sources of uncertainty identified by the QE-ANOVA approach in order to provide a transient evolution of these uncertainties.

3.0.2 Detecting the Time of Emergence of a low-flow change signal

Having transient probabilistic projections further allows detecting the Time of Emergence (ToE) of a change signal in low flows, i.e. ~~average deviations of the NFSs from~~ the time when this signal emerges from the underlying variability and uncertainty noise (Giorgi and Bi, 2009) . We define here the ToE as the first time when the 95% confidence interval of low-flow anomalies – either yearly or 30-year rolling averages – does not include the zero change. This ToE is therefore determined in a transient way, more on the line with the approach of Hawkins and Sutton (2012) than with the few recent hydrological applications in which it is only resolved at the 20- to 30-year time scale (see e.g. Köplin et al., 2014) .

The ToE analysis described above is also applied to perfect hydrometeorological chains, i.e. chains with no GCM, SDM, or HM uncertainty. The total variance is in this case estimated from internal variability components and residuals only, and the grand ensemble mean ~~μ due to a given model, be it a GCM, a SDM or a HM~~ is retained from the analysis with actual modelling chains. Note that the latter assumption requires adopting a thruth-centered paradigm (see e.g. Knutti et al., 2010) for all model types, which is yet controversial for GCMs (see e.g. Sanderson and Knutti, 2012) . The corresponding confidence interval thus allows to assess the potential to detect as early as possible the ToE when considering only the irreducible part of the future uncertainty, following the framework developed by Hawkins and Sutton (2009, 2011) .

3.1 Investigating HM contribution to uncertainty in low-flow changes

A specific issue of interest in this study is the dependence of the low-flow evolution on the HM used, all other things being equal. The fraction of variance due to the HMs in the whole ensemble of hydrological projections as given through the QE-ANOVA approach described above is checked against a simple single-time ANOVA decomposition approach proposed by von Storch and Zwiers (1999, chap. 9) and recently applied by Christierson et al. (2012) for a similar hydrology-climate partitioning purpose. The fraction of variance due to the HMs is estimated for each prediction lead time based on only data for that lead time, conversely to the time series approach of QE-ANOVA. It is computed as:

$$R_a^2 = \frac{\mathrm{SSA} - \frac{p-1}{p(n-1)}\mathrm{SSE}}{\mathrm{SST}} \tag{6}$$

where SSA is the treatment sum of squares, SSE the error sum of squares, SST the total sum of squares, p the number of HMs (6), and n the number of different climate projections used to force each HM (330).

Potential sources for the HM contribution to the total uncertainty are further investigated through the evolution of selected HM state variables potentially relevant for explaining the evolution of summer and/or winter low flows. Computed summer low flows in snow-influenced catchments depend on two main factors other than external meteorological forcings: evapotranspiration and previous winter snowpack. More precisely, both Godsey et al. (2014) and Jenicek et al. (2016) suggested maximum Snow Water Equivalent as a relevant predictor for summer minimum low flows. Drivers of computed winter low flows are a bit harder to identify. Three hydrological drought types identified by Van Loon et al. (2015) for cold climates are relevant for assessing winter absolute low flows. On one hand, the "Cold snow season drought" and the "Warm snow season drought" are closely related to the timing of snowpack accumulation/melt, indicators of which are difficult to extract from time series (see e.g. Whitfield, 2013) . On the other hand, the "Rain-to-snow-season drought" describes the continuation of preceding water deficit into winter (see also Van Loon et al., 2010) . All external meteorological forcings like total precipitation being equal, only differences in modelled evapotranspiration can be in this case retained as a potential source of HM contribution in winter low-flow uncertainty. The two selected HM state variables for both seasons are therefore the mean annual Actual Evapotranspiration (AET) and the maximum Snow Water Equivalent (maxSWE). AET and maxSWE output time series are extracted for all 1980 hydrological projections. Noise-free signals are extracted from these series in the same way than for low flows (see Sect. 3.2.2), and HM effects are derived from these NFSs (see Sect. 3.2.3). Comparing HM effects on low flow changes with HM effects on AET/maxSWE may confirm possible drivers of the divergence, even if no causal relationship can be actually drawn.

4 Results

4.1 Individual model effects on low-flow changes

Figure 4 shows individual GCM effects around the grand ensemble mean. Looking first at this grand ensemble mean, low flows are projected to decrease in both catchments and in both seasons. However, when the decrease in 2065 is around only -7 % of the 1980–2009 average for the Durance in winter, it reaches -25 % in summer for both catchments and even exceeds -30 % in winter for the Verdon. The dispersion between GCM effects around the grand ensemble mean is quite large in winter, leading to changes ranging for example from -20 to $+2$ % for the Durance in 2065. The range of GCM effects is more limited in summer, but still higher than 10 % in 2065. CNCM33 (resp. ECHAM5) tends to systematically give a larger (resp. lower) decrease than the grand ensemble mean. IPCM4 (resp. EGMAM2) also gives a larger (resp. lower) decrease, but only in summer.

Figure 5 shows individual SDM effects around the grand ensemble mean. Individual SDM effects are not homogeneous over catchments and seasons, with analog for example generating a stronger decrease for the Durance in winter and a smaller one for the Verdon in summer. In the other two situations, the dispersion between SDM effects is hardly noticeable.

Figure 6 shows individual ~~hydrological model~~ HM effects around the grand ensemble mean. The dispersion is here generally very large, with ranges of more than 30 % for the Durance in winter and for the Verdon in summer. The dispersion is more limited for the Verdon in winter. Looking into more details at individual models, ORCHIDEE stands as an outlier for the Durance in winter with a projected decrease of -28 % in 2065. Similarly, CLSM projects a much more severe decrease than

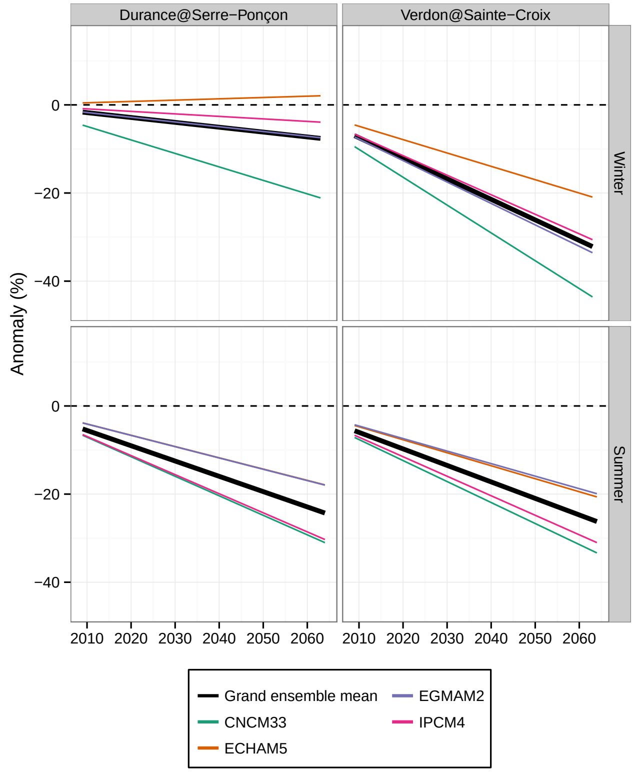

Figure 4. GCM effects on low flow changes around the grand ensemble mean for both catchments and both seasons.

other models in summer for both catchments. J2000 contrarily tends to generate a ~~smaller decrease~~ smaller decrease than the grand ensemble mean in all four cases.

4.2 ~~Hierarchy~~ Time-dependent hierarchy of the different sources of uncertainty

The contribution of each source of uncertainty quantified by the QE-ANOVA approach can be expressed as a fraction of the total variance for each lead time t (see, e.g. Hawkins and Sutton, 2011). Figure 7 shows this decomposition of total variance for rolling ~~30year average low flow~~ 30-year average low-flow changes in both catchments and both seasons. As ~~expected~~shown in many previous studies (see e.g. Hawkins and Sutton, 2011) , internal variability components contribute for the most part of the total variance for short lead times. They remain generally above 20 % in 2065~~–~~, and around 45 % for the Verdon in winter~~, which is consistent with the analyses performed for the Durance by Hingray and Saïd (2014) on mean annual precipitation, and by Lafaysse et al. (2014) on mean annual streamflow~~. Large-scale internal variability accounts for around three quarters of the total internal variability~~, which is also consistent with previous studies~~. The decomposition of model uncertainty into GCM, SDM and HM contributions reveals interesting features: first, GCMs accounts for 15 to 25 % of the total variance at the

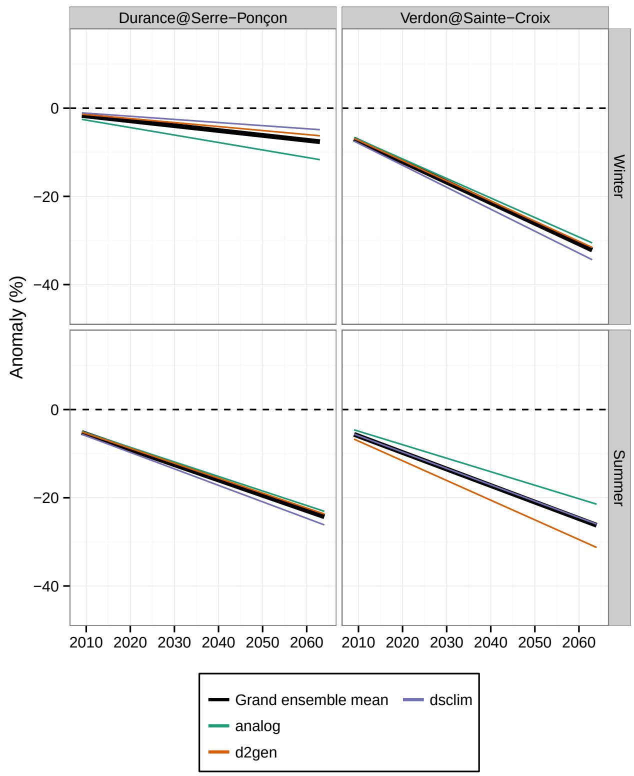

Figure 5. As for Fig. 4, but for SDM effects.

end of the period, and SDMs for less than 6 %, with even negligible contributions for the Verdon in winter and for the Durance in summer. ~~The SDM contribution is thus much smaller than for the mean annual streamflow (see Lafaysse et al., 2014) .~~

HM contribution to total variance is however largely non negligible. Values in 2065 reach 35 % in summer for both catchments and even 43 % for the Durance in winter. The Verdon in winter is the only case where values remain around 10 %. Lastly, residuals and model interactions generally account for 10 to 20 % of total variance.

Figure 8 shows a similar decomposition of total variance in both catchments and both seasons, but for yearly low flow anomalies. The most striking point is the very large contribution of internal variability components in all cases and for all lead times, up to more than 80 % in 2065, and even 94 % for the Verdon in winter. Such a prominence of internal variability is clearly visible in individual time series plots ~~, even in~~ like Fig. 3, where the change signal of the considered NFS is yet rather high. Small-scale internal variability generally accounts here for one third of the total internal variability uncertainty. By construction of the NFSs, the remaining part of variance due to model uncertainties divides up into GCM, SDM, HM and residuals (RMI) in the same way as for time-slice averages in Fig. 7.

4.3 ~~Projected evolution and associated confidence bounds~~

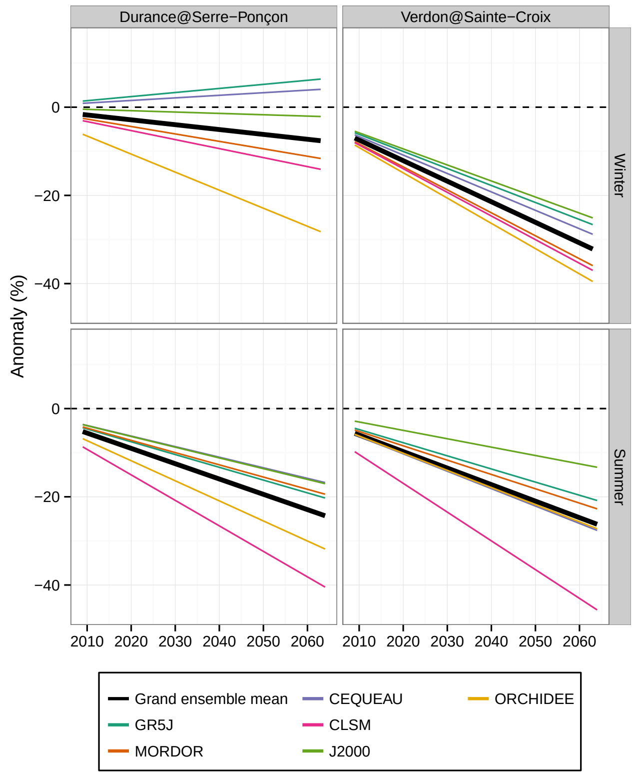

Figure 6. As for Fig. 4, but for HM effects.

~~The total variance and grand ensemble mean computed through the QE-ANOVA approach allows deriving transient confidence bounds for the evolution of low flows, provided that an assumption is made on the shape of the distribution. Following previous uncertainty decomposition work on decadal averages, a normal distribution is selected for 30year low flow averages (see, e.g. Hawkins and Sutton, 2009; Charlton-Perez et al., 2010; Hawkins and Sutton, 2011) . A lognormal distribution is selected here for yearly values in order to take account of the skewed and bounded distribution of low flows. Additionally, confidence range may be partitioned into the different sources of uncertainty identified by the QE-ANOVA approach in order to provide a transient evolution of these uncertainties.~~

4.3 Projected evolution and associated confidence bounds

Figure 9 shows the evolution of ~~30year~~ 30-year average changes in low flows and associated confidence bounds for both catchments and for both seasons. The total uncertainty ~~increase~~ increases with lead time in all cases and by a factor of 2.5 between 2009 and 2065 in summer, more than 3.5 for the Durance in winter, and only 1.3 for the Verdon in winter. The main contributor to this increase is HM uncertainty followed by GCM uncertainty. For the Verdon in winter, a decrease in both internal variability components nearly offsets this increase in model uncertainty.

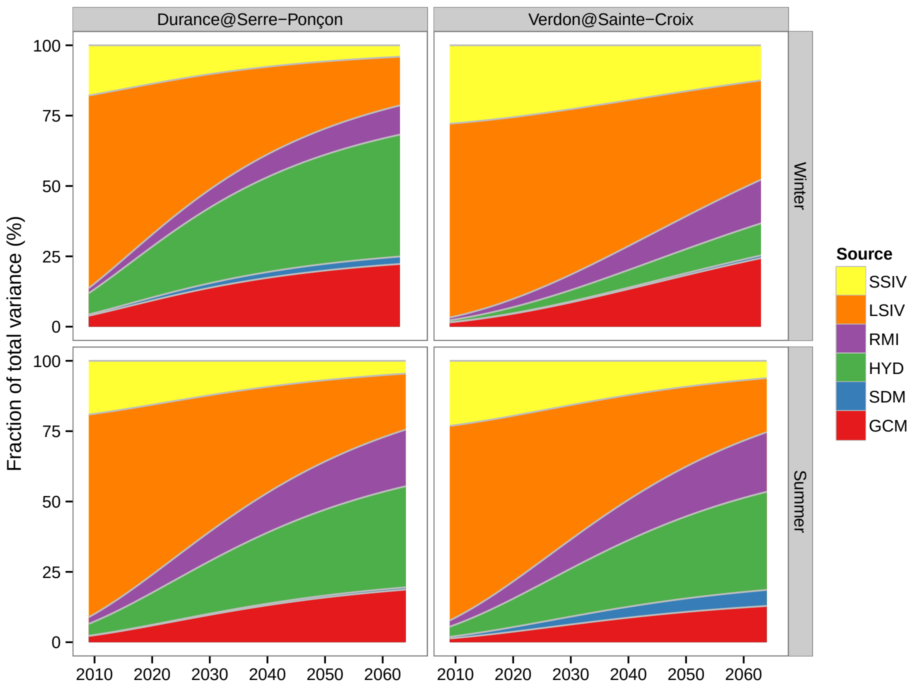

Figure 7. Fraction of total variance explained by each source of uncertainty for rolling 30 year time-slice averages of low flow changes with respect to the REF period average. Values are plotted in the middle of each time slice.

Figure 10 plots the evolution of ~~low flow~~ low-flow yearly anomalies. The difference with respect to Fig. 9 lies in the amplitude of internal variability components. They moreover both tend to decrease with lead time as a consequence of the decrease in the grand ensemble mean. Their evolution counterbalances the increase in model uncertainties, leading to a reduction in total uncertainty in all cases except the Durance in winter.

4.4 ~~Probability~~ Time of Emergence of a low flow decrease and potential to reduce uncertainty

Figure 9 ~~suggests~~ above suggested that the probability of a ~~30year~~ 30-year average low flow lower than the REF period average could be very close to 1 after 2050, except for the Durance in winter. Blue curves in Fig. 11 show the evolution of this probability along the period considered. Except for the Durance in winter where the change signal is too weak compared to uncertainties, the probability of a negative change between the REF period and a future period reaches 95 % in 2033–2039, that is for ~~30year~~ 30-year time-slices starting ~~before 2015.~~ around 2020.

Red curves in Fig. 11 show the probability of a low flow for a given year being lower than the REF average. This second probability remains below 90 % even at the end of the period in all cases. It thus prevents to draw any definitive conclusion on the sign of the yearly anomaly with respect to the REF period average for any given lead time up to the end of the studied period.

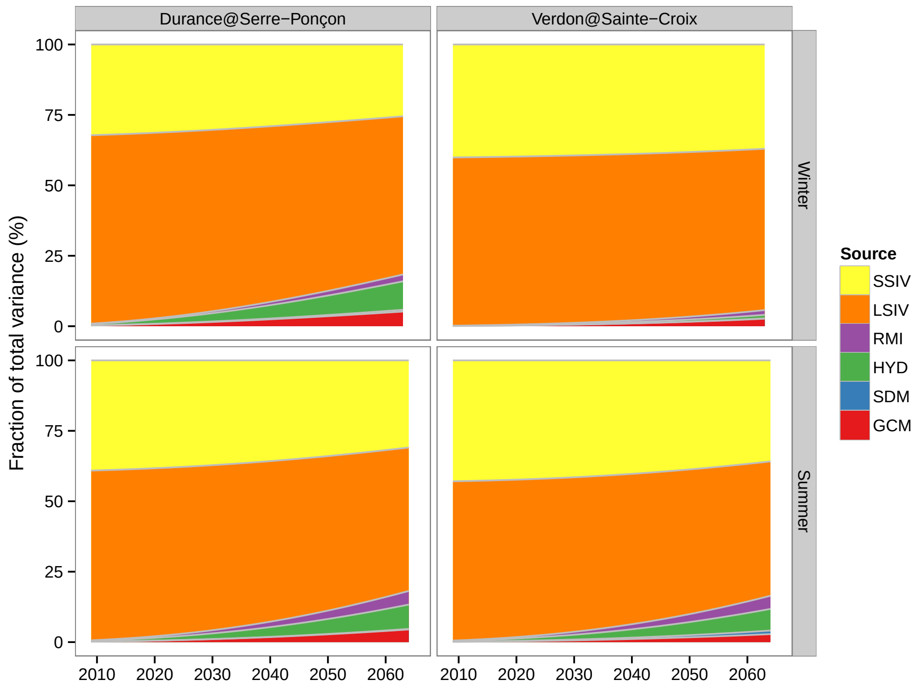

Figure 8. As for Fig. 7, but for yearly low flow anomaly with respect to the REF period average.

~~The Time of Emergence (ToE) of the signal of change in average low flows is here determined in a transient way, more on the line with the approach of Hawkins and Sutton (2012) than with recent hydrological applications in which it is only resolved at the 20 to 30year time scale (see e.g. Köplin et al., 2014) .~~

Figure 11 also shows the potential to reduce the uncertainty in low flow projections and more specifically its effect on the estimation of the probability of a ~~low flow decrease. The potential to reduce uncertainty in projections is the part of total uncertainty due to models, i.e. the reducible part of this uncertainty (see Hawkins and Sutton, 2009, 2011) .~~ low-flow decrease. Dashed lines in Fig. 11 denote results that would be obtained with a perfect hydrometeorological model chain~~, by considering only uncertainties due to internal variability components and residuals, and assuming a unchanged grand ensemble mean response. Note that the latter assumption requires adopting a thruth-centered paradigm (see e.g. Knutti et al., 2010) for all model types, which is yet controversial for GCMs (see e.g. Sanderson and Knutti, 2012)~~. The probability of a ~~low flow~~ low-flow decrease is of course higher in all cases. ~~If little improvement is noted for yearly anomaliesbecause of~~ For yearly anomalies, due to the large contribution of internal variability components, ~~the time of emergence of the signal~~ using a perfect modelling chain still does not allow to detect the ToE within the time horizon considered. However, for 30-year rolling averages, the ToE at the 95~~confidence level occurs around a~~ % confidence level can be detected around a decade earlier for both catchments in summer, and can be estimated at 2070 for the Durance in winter, where the signal is not expected to emerge ~~with actual models~~within the considered time horizon using the actual modelling chains.

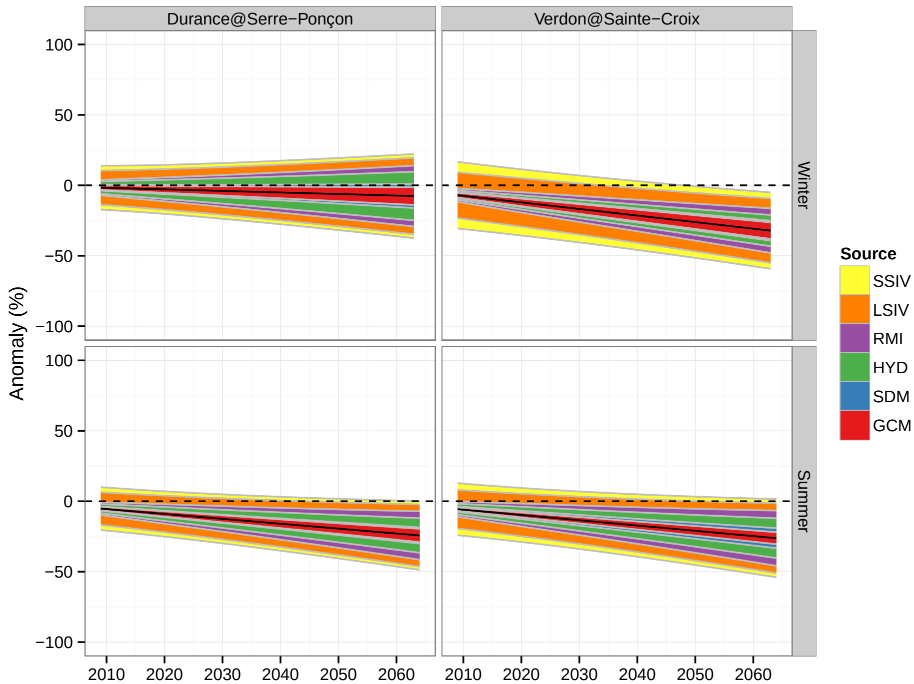

Figure 9. Projected changes in 30-year averages of low flow for both stations and seasons, together with a partitioning of the 90 % confidence interval into the different uncertainty sources. See text for details. Values are plotted in the middle of each time slice. The fraction of the confidence interval for a given source of uncertainty is proportional to the standard deviation of its contribution to the total standard deviation, following Hawkins and Sutton (2011) and Hingray and Saïd (2014) .

5 ~~Discussion~~

4.1 ~~On~~ Further analysis on HM contribution to the ~~hydrological model~~ total uncertainty

Figure 7 highlighted the large and growing part of total uncertainty due to hydrological models on low flow projections in summer for both catchments, and in winter for the Durance. ~~This part of uncertainty is higher than values obtained in other studies for other hydrological indicators like monthly flows (see e.g. Christierson et al., 2012; Bosshard et al., 2013) . However, it is consistent with recent findings that HM uncertainty is higher than GCM uncertainty in snow-dominated catchments (see e.g. Giuntoli et al., 2015) . Indeed, low flows are strongly linked to catchment processes that may be represented differently in different hydrological models. It is therefore understandable that the contribution of HMs to the total uncertainty is higher than, say, for annual flood peak projections.~~

~~The fraction of variance due to the HMs in the whole ensemble of hydrological projections is checked against a simple single-time ANOVA decomposition approach proposed by von Storch and Zwiers (1999, chap. 9) and recently applied by Christierson et al. (2012) for a similar hydrology-climate partitioning purpose. The fraction of variance due to the HMs is estimated for each prediction lead time based on only data for that lead time, conversely to the time series approach of~~

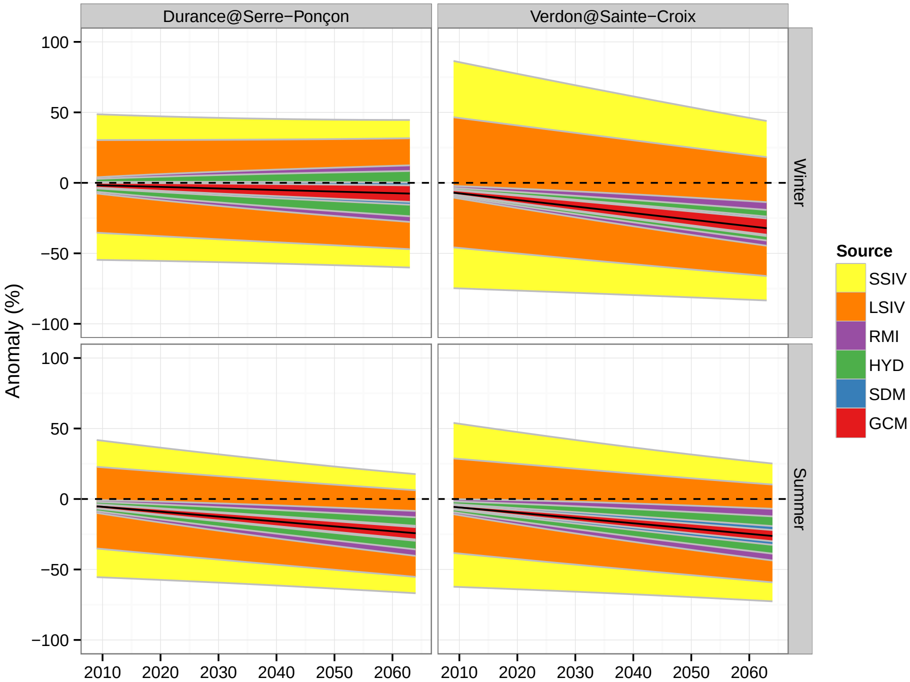

Figure 10. As for Fig. 9, but for yearly anomalies.

~~QE-ANOVA. It is computed as:~~

$$R_a^2 = \frac{\mathrm{SSA} - \frac{p-1}{p(n-1)}\mathrm{SSE}}{\mathrm{SST}}$$

~~where SSA is the treatment sum of squares, SSE the error sum of squares, SST the total sum of squares, p the number of HMs (6), and n the number of different climate projections used to force each HM (330).~~ Figure 12 now compares QE-ANOVA to the simpler approach for computing the fraction of variance explained by HMs~~for yearly low flow anomalies~~. Due to internal variability, estimates from the single-time approach for yearly low flow anomalies are very noisy from one year to the next. QE-ANOVA results are quite consistent with this simpler approach and interestingly propose a smoother and more robust version of it. Figure 12 also shows a similar comparison for ~~30year~~ 30-year rolling averages and proposes similar conclusions, except that the noise in the simple approach estimates occur at the multidecadal time scale.

4.2 ~~Origins of divergence in low flow responses from different hydrological models~~

~~After noticing this divergence in low flow responses to climate change from different hydrological models, one may ask about its origins in terms of physical processes. Recall that for a given GCM-SDM chain – and a given run and stochastic realization of this chain – meteorological forcings are identical for all HMs. The only differences in hydrological effects thus originate from the physical parametrization of the HMs.~~ The effects from individual models shown in Fig. 6 show that ~~this divergence~~

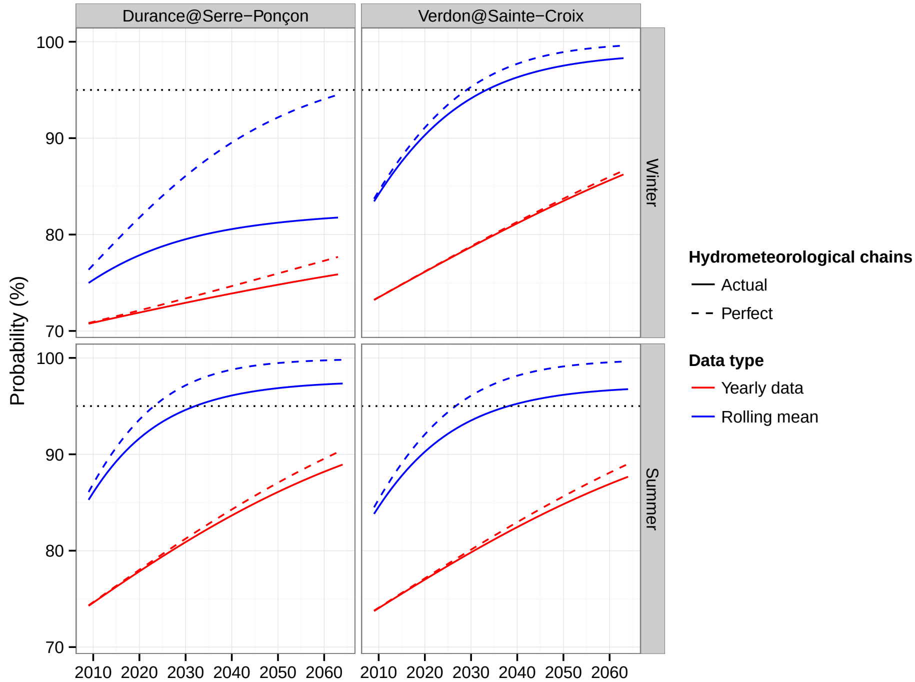

Figure 11. Evolution of the probability of a low flow below the REF period average, for yearly anomalies and 30-year rolling time-slice averages, with the hydrometeorological model chains used here and with a perfect hydrometeorological model. See text for details.

the HM divergence in low flow changes emerges from hydrological processes evolving differently in different models under a ~~-~~changed climate, all climate forcings being equal.

~~Computed summer~~ Figure 13 first shows that HM effects on AET are negatively correlated with HM effects on low flows in ~~snow-influenced catchments depend on two main factors other than external meteorological forcings: evapotranspiration and previous winter snowpack. More precisely, both Godsey et al. (2014) and **?** suggested maximum Snow Water Equivalent~~ both catchments and both seasons. Otherwise said, hydrological models showing a stronger increase in evaporation tend to simulate a stronger decrease in low flows. It is important to note that this somewhat reasonable relation is however not significant for summer flows at the 90 % confidence level. In summer, and for the Durance only, effects on low flows are significantly correlated with effects on the other potential driver (maxSWE)~~as a relevant predictor for summer minimum low flows~~. The slope of the relationship correspond to around 20 % of reduction in low flows for each 10 % reduction in maxSWE. The relation between effects on low flows and effects on maxSWE for the Verdon in summer is not significant and has a gentler slope.

~~Drivers of computed winter low flowsare a bit harder to identify: indeed, winter low flowsdepend on the first hand on the timing of the snowpack building and melting~~

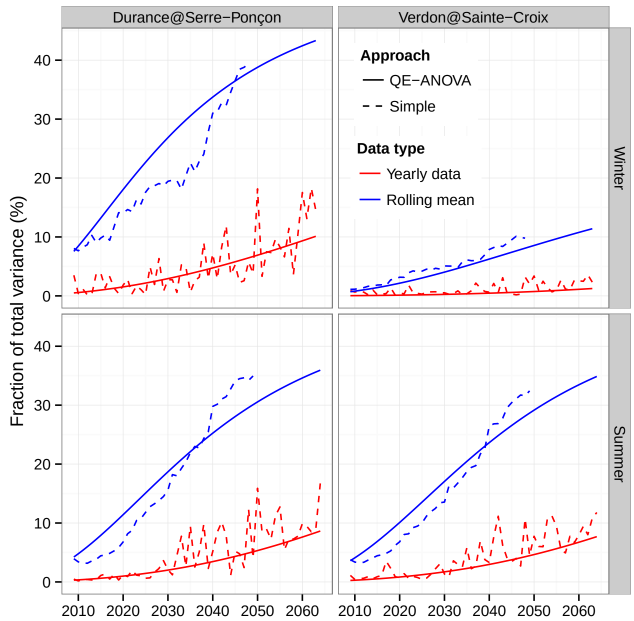

Figure 12. Fraction of total uncertainty due to hydrological models computed from the QE-ANOVA and a simpler approach (see text for details), for both yearly anomalies and changes in 30 year rolling averages.

5 Discussion

5.1 On QE-ANOVA advantages and limitations for future low-flow analysis

The approach used here provides a transient evaluation of uncertainties in yearly values or time-slice rolling averages in future low flows. It notably allows to estimate the ToE of a decrease signal in low flows. The time series approach at the heart of the QE-ANOVA framework makes this estimation rather robust. This would not have been the case with other uncertainty estimation approaches such as the one proposed by Yip et al. (2011) , due to the high year-to-year variability in the low-flow indicator (and more generally on any catchment-scale hydrological indicator). Smoothing out such variability may allow the water manager mentioned in the introduction having a clear view on the probability of crossing any management-relevant threshold for any year in the future, and therefore ~~on rain/snow transition threshold and snowmelt parameters. On the other hand, they also depend on baseflow and therefore on evapotranspiration processes over the preceding months. Existing drought typologies as proposed by ? and Van Loon et al. (2015) may help in identifying potential drivers. Indeed, one way to consider a hydrological model leading to a higher than average low flow decrease is through its tendency to simulate more – with respect to the grand ensemble mean – hydrological droughts during one of the two low flow seasons in a changed climate.We use here the word hydrological drought for a streamflow deficit with respect to a daily variable threshold level as in ? . In that specific sense, a drought is not necessarily associated with a severe low flow. Out of the 5 hydrological drought types identified by Van Loon et al. (2015) for cold climates, only 3 are therefore relevant for assessing winter low~~

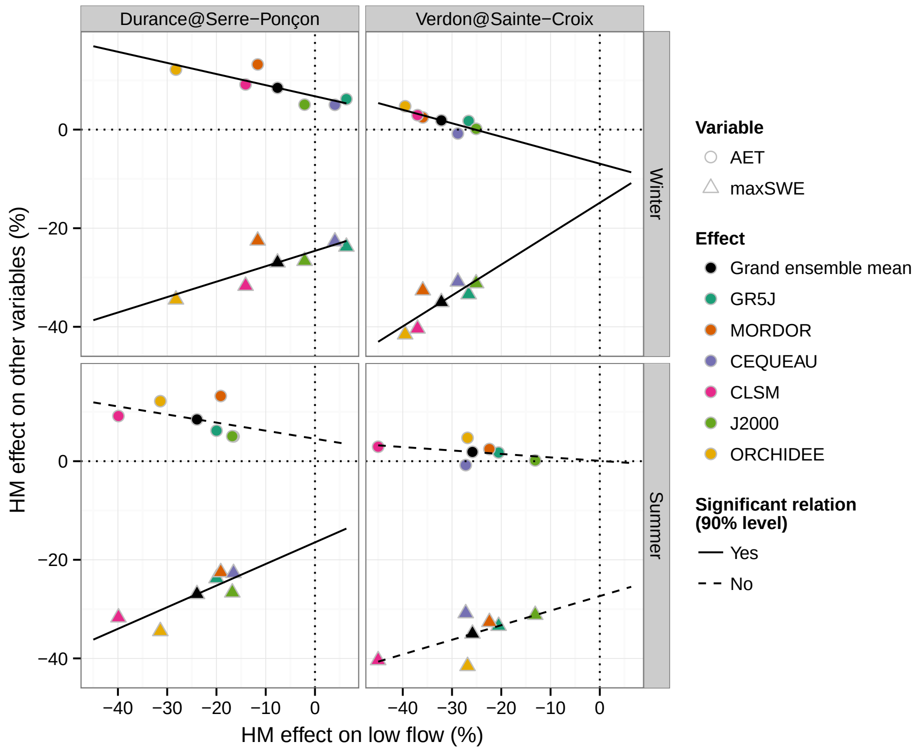

Figure 13. Relations between HM effects on low flow anomaly and HM effects on AET/maxSWE anomaly for the year 2065. Significant relations at the 90 % confidence level are shown with solid lines.

~~flows. On one hand, the Cold snow season drought~~anticipating when such probabilities will not be compatible any more with current management options, facilities and regulations. Moreover, water management rules rely on long-term average water available during the low-flow season, but also on thresholds related to individual low-flow values reached for a given year. The two time scales studied here may thus contribute to build more robust adaptation strategies than the ones based solely on changes in 30-year time-slice averaged quantities, which has been the focus of many studies until now. It has to be noted that such ToE estimates are intrinsically linked to the choice of the reference period chosen for calculating the anomalies (see Hawkins and Sutton, 2016, for relevant comments on this issue) .

More generally, all above statements rely on the assumptions of both the QE-ANOVA framework described in Sect. 3.2 and the further choices made for this specific application to yearly low-flow indicators (see Sect. 3.3). Four points are discussed below. First, the QE-ANOVA framework was retained for studying this complex uncertainty design partly because it critically allows to disentangle large-scale and ~~Warm snow season droughtare closely~~ local-scale variability, which is not the case with other recently published ANOVA methods (see, e.g. Northrop and Chandler, 2014) . Second, the simple linear trend model adopted likely overestimates both the LSIV and the SSIV (see Raïsänen, 2001; Hingray and Saïd, 2014, for discussions on this issue) . However, this is clearly the most reasonable choice when dealing with indicators with a high interannual variability. Third, the slight decrease in internal variability components that can be spotted in Fig. 9 is related to the ~~timing of snowpack building/melting, indicators of which are difficult to extract from time series (see e.g. Whitfield, 2013) . On the other hand, Rain-to-sow-season droughtdescribes the continuation of preceding water deficit into winter (see also Van Loon et al., 2010) . This deficit may be due to either a lack of precipitation – but this feature is not relevant here as total precipitation is a common forcing for all HMs – or to a strong evapotranspiration.~~

~~Based on all the above considerations, we selected two potential drivers of divergence in hydrological model responses: mean annual actual evapotranspiration (AET) and the maxSWE. We extracted AET and maxSWE output time series for all 1980 hydrological runs used in the low flow analysis above. Noise-free signals were extracted from these series in the same way than for low flows (see Sect. 3.2.2), and HM effects derived from these NFSs. Comparing HM effects on low flow changes with HM effects on AET/maxSWE may confirm possible drivers of the divergence, even if no causal relationship could be actually drawn~~quasi-ergodic assumption of a constant coefficient of variation in the low-flow indicator and the fact that the grand ensemble mean actually decreases. Fourth, this assumption may be relaxed for SSIV by computing yearly empirical values of the variance terms over stochastic downscaling realizations in Equ. A1. Comparing the temporal evolution of SSIV with and without the quasi-ergodic assumption shows that this assumption is quite reasonable (See Supplementary Material). Similarly, it is also possible to relax this assumption for LSIV, even if in degraded mode (1) because of the different numbers of runs from each GCM, and (2) more importantly because of the fact that 2 out of 4 GCMs only have one run. The temporal evolution of the variance terms in Equ. A3 may indeed be computed empirically for any m where $r > 1$. The quasi-ergodic assumption is again confirmed by comparing the temporal evolution of LSIV with and without this assumption, using the 2 GCMs with multiple runs (See Supplementary Material).

~~Figure 13 first shows that effects on AET are negatively correlated with effects on low flows in both catchments and both seasons. Otherwise said, hydrological models showing a stronger increase in evaporation tend to simulate a stronger decrease in low flows~~

5.2 On HM contribution

The HM contribution to total uncertainty shown in Fig. 12 is higher than values obtained in other studies for other hydrological indicators like monthly flows (see e.g. Christierson et al., 2012; Bosshard et al., 2013) . However, it is consistent with recent findings that HM uncertainty in low-flow changes is higher than GCM uncertainty in snow-dominated catchments (see e.g. Giuntoli et al., 2015) . Indeed, low flows are strongly linked to catchment processes that may be represented differently in different hydrological models. It is ~~important to note that this somewhat reasonable relation is however not significant for summer flows at the 90confidence level. In summer , and for the Durance only, effects on low flowsare significantly correlated with effects on the other potential driver (maxSWE). The~~ therefore understandable that the contribution of HMs to the total uncertainty is higher than, say, for annual flood peak projections.

Possible drivers of the divergence in HM responses has been explored through the analysis of changes in model state variables AET and maxSWE. Figure 13 highlighted the evapotranspiration component as a probable driver of HM divergence in both summer and winter low flows. Moreover, the slope of the relationship ~~correspond to around 20of decrease in low flows for each 10decrease in maxSWE , which~~ between HM effects on summer low flows and HM effects on maxSWE in the Durance is quite consistent with findings from Godsey et al. (2014) on historical data in the Sierra Nevada (California). The ~~relation between effects on low flows and effects on maxSWE~~ less marked relationship obtained for the Verdon ~~in summer is not significant and has a gentler slope. This last result~~ is again consistent with findings of ~~?~~ Jenicek et al. (2016) who found a lower sensitivity of summer low flows to snow accumulation for less elevated catchments.

~~The interpretation of~~ Interpreting the positive (and significant) relation between HM effects on winter lows flows and HM effects on maxSWE is much more difficult. One would indeed expect on the contrary that storing less water in the snowpack would leave more water to sustain winter low flows. As mentioned above, winter low flows may originate from various and complex processes and some compensations may occur. Godsey et al. (2014) indeed found that under a changed climate, a reduction in maxSWE may be offset by increased storage in autumn or winter and by shifts in the timing of maximum evapotranspiration. Moreover, both Magand et al. (2014) and Lafaysse et al. (2014) showed that a reduction in snow cover area leads to a higher evaporation on the Durance catchment. Further studies aiming at explaining the precise processes leading to a ~~divergence in hydrological model~~ divergence in HM responses on winter low flows should therefore explore these leads.

A way forward to disentangle the origins of the divergence in low flow responses from different hydrological models in general would be to make use of the Framework for Understanding Structural errors ~~(FUSE Clark et al., 2008)~~ (FUSE, Clark et al., 2008) , which has already has been applied by Staudinger et al. (2011) to assess the performance on ~~low flow~~ low-flow indicators of a variety of model structures. Assessing the robustness of such structures in a climate change context would perhaps lead to improvements of existing model ~~structure~~ structures as those used in the present work.

Finally, this study is based on the assumption that low-flow projections derived from all individual HMs – but also from all individual GCMs and SDMs – are equally valid. No simple relation could be found between present-day performance in simulating interannual variability in low-flow anomalies and HM effects. The robustness of the uncertainty decomposition results may therefore be tested with subsets of HMs, as well as subsets of GCMs and SDMs. It has to be noted that an experiment on HM uncertainty evolution following removal of an outlier model has been recently performed by Habets et al. (2013) .

5.3 ~~Integrating additional~~ On sources of uncertainty

The hydrological projection dataset explored in this work includes a fairly comprehensive list of uncertainty types compared to most of previous studies (see Dobler et al., 2012; Addor et al., 2014, for recent hydrological studies with multiple uncertainty sources). ~~However,~~ The contribution of internal variability components is consistent with the analyses performed for the Durance by Hingray and Saïd (2014) on mean annual precipitation, and by Lafaysse et al. (2014) on mean annual streamflow.

The hierarchy of model uncertainties is however different from other hydrological indicators. For changes in the mean annual streamflow of the Durance catchment, SDM uncertainty was found to be larger than GCM uncertainty (Lafaysse et al. 2014). It is here much lower for low flows, probably due to the lower inter-SDM spread in dry/wet states than in precipitation amounts. However, one cannot exclude the possibility of the SDM contribution being underestimated, in two possible ways. First, one cannot guarantee that the sample of SDMs – but also GCMs and HMs – is representative from the unknown superpopulations. Indeed, no dynamical downscaling with Regional Climate Model has been for example considered here on top of the 3 SDMs. Moreover the latter all belong to the single family of Perfect Prognosis methods (Maraun et al., 2010) . Nevertheless, it has to be noted that the concepts for selecting analogue situations with the 3 SDMs used are quite different (see Sect. 2 and Lafaysse et al., 2014) . Morever, Lafaysse et al. (2014) found large differences between different versions of a given SDM using slightly different sets of predictors. It is therefore unclear whether more diverse SDMs – or a larger number of versions from the SDMs used – would contribute more to the total uncertainty. A second possible origin of the low SDM uncertainty contribution may be the shared adjustment of regional average temperature to the one of the driving GCM (see Sect. 2.2.2).

Additionally, some other potential sources of uncertainty were not considered. First, this dataset is conditional on the single A1B emissions scenario, which should not be detrimental to results presented above given the relatively close time horizon considered. Adding the scenario uncertainty in the QE-ANOVA framework would be relatively straightforward as it would take the form of an additional fixed effect alongside GCMs, SDMs and HMs.

~~Another potentially important contribution to the overall hydrological uncertainty would be the uncertainty in hydrological model parameters. The~~ The uncertainty related to the temporal transferability of parameters – whether from SDMs or HMs – has not been considered either in this study. The hydrological uncertainty was found to be high when compared to that of SDMs and GCMs, but it was also likely underestimated. Indeed, the time transferability of ~~model~~ HM parameters in a climate change context and its contribution to overall uncertainties has recently been explored by some studies ~~(see e.g. Finger et al., 2012; Dobler et al., 2012)~~ (see e.g. Finger et al., 2012; Dobler et al., 2012; Parajka et al., 2016) . One way to incorporate this source of uncertainty into the QE-ANOVA framework and combine it with hydrological model structure uncertainty would be to devise a calibration protocol common to all HMs that would split the calibration period into distinct subperiods showing climatic contrasts, as proposed and applied by Thirel et al. (2015). Such a protocol has actually already been applied in the R2D2-2050 project ~~(see Sauquet et al., 2014) for a~~ (see Sauquet et al., 2014, p. 70-72) for a subset of hydrological model structures and ~~the analysis of results~~ results show that all calibrated models seem equally robust with regard to their low-flow simulations. This will be the subject of a follow-up paper. ~~Results~~ When moving to future conditions, results based on CLSM for a small upstream Durance subcatchment showed that hydrological projections may be highly sensitive to the calibration period through some specific parameterized processes (Magand et al., 2015). Using such a calibration protocol may then allow computing the hydrological model parameter contribution in a way similar to internal climate variability components in the QE-ANOVA framework.

6 Conclusions

This paper proposes a methodology for estimating the transient probability distribution of yearly hydrological variables conditional to an ensemble of projections built from multiple general circulation models (GCMs), multiple statistical downscaling methods (SDMs) and multiple hydrological models (HMs). The methodology is based on the quasi-ergodic analysis of variance (QE-ANOVA) framework that allows quantifying the contributions of the different sources of total uncertainty, by critically taking account of (1) large-scale internal variability stemming from the transient evolution of multiple GCM runs, and of (2) small-scale internal variability derived from multiple realizations of stochastic SDMs. ~~The QE-ANOVA framework~~ This framework thus allows deriving a hierarchy of climate and hydrological uncertainties that depends on the time horizon considered. It was initially developed for long-term climate averages and is here extended to include year-to-year climate variability in probabilistic hydrological projections, thereby following the recommendations of Sexton and Harris (2015). Indeed, results from climate impact and adaptation projects usually focus on time-slice changes, and therefore underestimate the role of climate variability. Taking ~~account of~~ the year-to-year variability – which is large for hydrological variables in general ~~–~~ and for low flows in particular – into account is therefore especially relevant for better informing water resource adaptation strategies. To the authors' knowledge, it is the first time that a transient quantification of low flow uncertainties (including internal variability) is proposed.

The QE-ANOVA framework is applied to better understand possible transient futures of both winter and summer low flows for two snow-influenced catchments in the southern French Alps. The analysis takes advantage of a very large dataset of daily transient hydrological projections over the 1981–2065 period, that combines in a comprehensive way 11 runs from 4 different GCMs, 3 SDMs with 10 stochastic realizations each, as well as 6 diverse HMs. Results from the extended QE-ANOVA approach may be summarized into three points. First, the change signal is a decrease in yearly low flows of around −20 % in 2065 with respect to the 1980–2009 reference, except for the most elevated catchment in winter where low flows barely decrease. Second, this change signal of yearly low flow anomalies is largely masked by both large- and small-scale internal variability, even in 2065 at the end of the period considered. The time of emergence of the change signal on ~~30year~~ 30-year low-flow averages is however around 2035, i.e. for time slices starting in 2020. ~~But the most striking result is that a~~ Third, a large part of the total uncertainty – up to 40 % in 2065 for ~~30~~30-,year averages compared to less than 25 % due to the GCMs – stems from the difference in ~~hydrological model~~ HM responses.

Two main conclusions can be drawn from the above analysis, leading to corresponding lessons for future actions. First, internal variability brings by far the largest part of the uncertainty in low flows for an individual year in the future, even when the change signal is relatively large. ~~From the water manager point of view, the best way to adapt to climate change would therefore be to adapt to~~ Increasing the robustness and resilience of water systems to future climate conditions urges therefore water resources managers to first account for the internal climate variability. The scientific focus should then be on providing robust estimates of this ~~internal climate~~ variability by for example looking more and further into the past to identify benchmark situations and events that would serve as training sets for testing adaptation strategies, e.g. through historical hydrometerological reconstructions (see, e.g., Caillouet et al., 2016) .

Second, low flow responses from different hydrological models diverge in a changing climate, presumably due to differences in both evapotranspiration and snowpack components resulting from the large range of approaches implemented in the 6 ~~hydrological~~ models used here. Hydrological models should therefore be carefully checked for their robustness in a changed climate in order to increase the confidence in hydrological projections. In particular, efforts should be put on validating the robustness of all components of hydrological models with specific analyses and relevant datasets, notably for evapotranspiration and snowpack evolution.

Appendix A: Expressions of internal variability components

A1 Small scale internal variability

When a single GCM run is available for a given modelling chain m, the small-scale internal variability component of the relative change Δ for m (see Equ. 2) can be estimated for any future prediction lead time t from the empirical inter-realization variance of Δ for t (Eq. B2 in Hingray and Saïd, 2014). In the present work, the reference used for the estimation of the change variable is a constant (namely $Y_0(m)$). The expression thus simplifies as:

$$\mathrm{Var}_k(\Delta) \approx \left(\frac{\hat{y}(m,t)}{Y_0\,(m)}\right)^2 \cdot \mathrm{Var}_k\left[\frac{Y\,(m,r,k,t)}{\hat{y}(m,t)}\right] \tag{A1}$$

where Var_k is the empirical variance over stochastic realizations.

The variance in Eq. (A1) is equivalent to a coefficient of variation of Y with respect to the inter-realization variance. Assuming this coefficient of variation as roughly constant over the whole simulation period, the SSIV of chain m may be thus estimated from the temporal mean of this coefficient for this specific chain. When multiple runs are available for m, the SSIV of Δ for m is estimated from the multirun mean of their temporal mean. The SSIV component for the whole projection ensemble is finally derived for each lead time t as the multichain mean of these chain-specific estimates:

$$\mathrm{SSIV}(t) \approx \frac{1}{N_g N_s N_h} \sum_{g=1}^{N_g} \sum_{s=1}^{N_s} \sum_{h=1}^{N_h} \frac{1}{T N_{g,r}} \left(\frac{\hat{y}(m,t)}{Y_0(m)}\right)^2 \cdot \sum_{r=1}^{N_{g,r}} \sum_{t=1}^{T} \mathrm{Var}_k\left[\frac{Y\,(m,r,k,t)}{\hat{y}(m,t)}\right] \tag{A2}$$

where T is the total number of time steps covered by the simulation period and $N_{g,r}$ is the number of runs for GCM g. Note that the SSIV is a function of time via the signal terms $\hat{y}(m,t)$ in Eqs. (A1) and (A2).

A2 Large scale internal variability

The large scale internal variability component for any given chain m has the same expression as that of SSIV in Eq. (A1) but, due to the limited number of runs available, the inter-run variance (or equivalently the coefficient of variation) cannot be estimated in a robust way. Following the quasi-ergodic assumption for transient climate projections, the LSIV for Y with respect to the inter-run dispersion is assumed to be, in terms of coefficient of variation, constant over the whole simulation period. It follows that for any time t and any chain m:

$$\mathrm{Var}_r\left(\frac{Y\,(m,r,\bullet,t)}{\hat{y}(m,t)}\right) \approx \mathrm{Var}_T\left(\frac{Y\,(m,r,\bullet,t)}{\hat{y}(m,t)}\right). \tag{A3}$$

where Var_r is the empirical variance over runs, Var_T is the empirical variance over time, and $Y\,(m,r,\bullet,t)$ denotes the average over all stochastic realizations from SDM s.

When multiple runs are available for a chain, this variance component is estimated from all runs. The LSIV component of Δ is finally estimated from the multimodel mean of the temporal and inter-run variance of $\cancel{Y(m,r,\bullet,t)}$ $Y(m,r,\bullet,t)$ (Eq. B6 in Hingray and Saïd, 2014). Again, as the reference used here for estimating relative changes is a constant, the expression simplifies as:

$$\mathrm{LSIV}(t) = \frac{1}{N_g N_s N_h} \sum_{g=1}^{N_g} \sum_{s=1}^{N_s} \sum_{h=1}^{N_h} \left(\frac{\hat{y}(m,t)}{Y_0(m)} \right)^2 \cdot \mathrm{Var}_{T,N_{g,r}} \left(\frac{Y(m,r,\bullet,t)}{\hat{y}(m,t)} \frac{Y(m,r,\bullet,t)}{\hat{y}(m,t)} \right) \tag{A4}$$

Appendix B: Transferring normal distribution parameters to lognormal distribution parameters

Let m_n and v_n be the mean and variance of a normal distribution. Let M_l and V_l be the mean and variance from the corresponding lognormal distribution. M_l and V_l can be expressed as:

$$M_l = e^{\left(m_n + \frac{v_n}{2}\right)} \tag{B1}$$

$$V_l = \left(e^{(v_n)} - 1\right) \cdot e^{(2 \cdot m_n + v_n)} \tag{B2}$$

This formulation is used to derive the distribution – and associated confidence bounds – of yearly low-flow indicators based on the grand ensemble μ and the total variance obtained from the QE-ANOVA decomposition.

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~~Fraction of total uncertainty due to hydrological models computed from the QE-ANOVA and a simpler approach (see text for details), for both yearly anomalies and changes in 30year rolling averages.~~ ~~Relations between HM effects on low flow anomaly and HM effects on AET/maxSWE anomaly for year 2065. Significant relations at the 90confidence level are shown with solid lines.~~