Dear Kerstin,

We thank the editor and three referees for their assessment of our manuscript. Please find our detailed responses below. We believe we have addressed all points raised by the reviewers carefully and modified the manuscript accordingly.

Kind regards,

Gregor Laaha

# Response to the comment of C. Luce (Referee)

We would like to thank the reviewer for his frank assessment of the manuscript. Below is our response to the issues raised in the review. The original comment is printed in plain font, our response is printed in italics.

This was a challenging paper to review. It leaps firmly into the midst of a swirling field of debate about how to use trends, projections, and sensitivities to inform estimates of potential futures, a valuable and necessary discussion for the community. It seems to do so, though, with little sensitivity to some of the tensions in that field of work, perhaps intentionally (?). Given the potential value in engendering further discussion on this debate and more openly explaining and exploring the logic embedded in alternative methods. I will bite on the offered bait. Readers find in this manuscript, on the one hand, a very interesting, even engaging, introduction written by some of the luminaries in hydrology about one of the principle challenges in the field. On the other hand, part way through the manuscript, the narrative becomes enmeshed in speculation. While some of the speculative leanings were hinted at in the introduction, they were overt in the synthesis and following sections. Specifically, the authors postulate that concordance and discordance among the three approaches can directly inform decisions on which are correct or incorrect. They do so without support of evidence from this analysis or citation of previous evidence that conclusions about projections derived from concordance are correct. Although these issues make the current manuscript difficult to follow, a reframing of the argument may be able to use much of the same information in a more constructive context. That context would be asking whether they can do what they did. There is greater value in discussing myriad reasons why there might be disagreement among these methods rather than attempting to resolve those disagreements through, as yet, unvetted assumptions.

The reviewer states that "the authors postulate that concordance and discordance among the three approaches can directly inform decisions on which are correct or incorrect." We would state this slightly differently in saying that we postulate that concordance and discordance among the three approaches are indicators of the confidence one can have in the projection.

# The Good:

There was much to appreciate about this paper. It offers a discussion of the challenges facing us in estimating effects and consequences of climate change and the importance of correct estimates for water resources management. They open with a general discussion of how trend information has been applied in contrast to more strictly mechanistic reasoning. I appreciate the opportunity in that for learning about other work in this area, as well. There are also some good lessons and warnings about different reasoning approaches, for example a concise description of concerns about the "upward" approach based on uncertain precipitation. I particularly appreciated several examples wherein logic, deductive, and inductive reasoning were noted as useful tools for interpretation, and then summarized in the first paragraph at the top of page 13072.

The paper also works with a large dataset condensed to a few representative examples. This assisted in taking in the information from a humanly-comprehensible set of time series while providing a sense of both the spatial diversity (and spatial correlation) and temporal diversity to ensure that patterns are not emergent from a few preselected sites or times. In short, it was rich in both spatial and temporal diversity without overwhelming. In this it was aided by well-constructed graphics. A few questions remain, but on the net, substantial information was made readily available to the readers to evaluate claims.

# The Concerns:

Ultimately, the paper raises many questions about alternative methods for projecting the future, which is of great value. In this case they do so by applying those alternative methods and comparing results. In doing so they ride roughshod over a number of potential objections related to each method (though enumerating a few as they did). If the intended purpose were to explore where the various objections or errors in logic lead each method potentially astray, so as to offer a reference or catalog on how we can, and do, go wrong in our projections, I could see much value. Instead, the authors venture in the introduction that the three different methods can be reconciled by expert judgment, and reveal in the synthesis section that they evaluate differences primarily (or maybe just initially) on agreement between alternative methods, stating, "The confidence one has in the projection will depend on how strongly the pillars agree, and on their individual uncertainties," and "The confidence bounds of the individual projections are a starting point for assessing the credibility of each pillar," and (in the conclusion) "In all cases, the confidence in the combined projection will depend on how closely the pillars agree, and on the individual uncertainties." I am aware of no studies (and they cite none) demonstrating the truth of these statements, and they do not test them in this manuscript.

The main concern of the reviewer seems to be the premise of the paper that agreement between results of alternative methods is an indicator of the credibility while variation between the results is an indicator of the uncertainty of the projections. We apologise for not explicitly providing supporting evidence for this statement which we are doing now. The IPPC Good Practice Guidance Paper on Assessing and Combining Multi Model Climate Projections (Knutti et al., 2010, p. 2), for example, has: "Ensemble: A group of comparable model simulations. The ensemble can be used to gain a more accurate estimate of a model property through the provision of a larger sample size, e.g., of a climatological mean of the frequency of some rare event. Variation of the results across the ensemble members gives an estimate of uncertainty." This is exactly what we are doing in this paper. The premise underlying this paper is exactly the one underlying all IPCC (and most other) ensemble projections. The Good Practice Guidance paper further has "Ensembles made with the same model but different initial conditions only characterise the uncertainty associated with internal climate variability, whereas multi-model ensembles including simulations by several models also include the impact of model differences. Nevertheless, the multi-model ensemble is not designed to sample uncertainties in a systematic way and can be considered an ensemble of opportunity." We are doing multi-model ensembles which are not a systematic sampling but do provide insight into uncertainty and credibility, at least according to the IPCC point of view. We agree that this premise involves assumptions but it certainly is good practice. In the revised manuscript we make the basis of the premise more explicit and give full justification.

Knutti, R., G. Abramowitz, M. Collins, V. Eyring, P.J. Gleckler, B. Hewitson, and L. Mearns, 2010: Good Practice Guidance Paper on Assessing and Combining Multi Model Climate Projections. In: Meeting Report of the Intergovernmental Panel on Climate Change Expert Meeting on Assessing and Combining Multi Model Climate Projections [Stocker, T.F., D. Qin, G.-K. Plattner, M. Tignor, and P.M. Midgley (eds.)]. IPCC Working Group I Technical Support Unit, University of Bern, Bern, Switzerland.

I acknowledge their sentence saying, "here, the analysis aims at understanding the reasons for the disagreement, by checking the credibility of each projections based on the data used and the assumptions made." This is a wonderful sentiment. I also acknowledge examples of physical reasoning provided in the following section (7.2). However, the examples provided were brief and simplified in their analysis and subject to alternative physical reasoning to that offered by the authors. There were also no systematic rules or principles beyond "consistency" offered for evaluating the alternatives, no generalization beyond each case study analyzed by the experts. Rather than highlight the complexity and potentially the equivocal nature of the comparisons, they indicate that the correct answer is most likely where there is consensus among multiple potentially untenable lines of logic.

Probably at the heart of my questions is that the first and third approaches use trend extrapolation in a fairly direct way, either of the phenomenon of interest directly (low flow) or the precipitation and temperature driving that behavior. These are offered as nominally equivalent replacements for climate projections from GCMs without reasonable (or any) consideration of the various low-frequency climate contributions to those trends. I've certainly heard the name Hurst brought up any time I even present an historical trend, and I know this group has previously published on the subject. I don't know of any circumstance where historically derived trends are accepted unquestioningly as an expectation for an ongoing rate of change. It would seem that I would need to accept raw extrapolation of a 30-year trend as a reasonable estimate in order to accept the reasoning of this paper. In essence, there are multiple layers of assumption – linearity in trend and process, causality by time or temperature alone as a basis for extrapolation – necessary to allow us to hold all pillars in equal stead, itself a seeming assumption for the proposed reconciliation process.

Again, we were probably not clear on the role of the trend extrapolation methods. We fully agree that historically derived trends should not be accepted unquestioningly as an expectation for an ongoing rate of change and already say so a number of times in the paper. More importantly, we intend to paint on a broader canvas. The trend extrapolation methods are examples of projection approaches that differ from the usual GCM based scenarios. The aim of the paper is not to promote the extrapolation of trends but to illustrate the value of using different methods based on different data. Another model type that could be equally well used within the same framework would be "trading space for time" (see, e.g. Perdigão and Blöschl, 2014). Yes, there are multiple layers of assumptions but the paper does not hinge on them. Rather the paper hinges (as pointed out by the reviewer) on the premise that consistency/inconsistency between different methods is an indicator of certainty/uncertainty. In the revised manuscript we highlight the broader perspective and explicitly state that the trend extrapolation is an example rather than a recommended method.

Perdigão, R. A. P., and G. Blöschl (2014) Spatiotemporal flood sensitivity to annual precipitation: Evidence for landscape-climate coevolution, Water Resour. Res., 50, 5492-5509, doi:10.1002/2014WR015365.

We can shorthand the "three pillars" in concise terms as: 1. Direct extrapolation of a trend in flow 2. Calculation of flow from GCM-projected climates using a model 3. Calculation of flow from trend-extrapolated climates using the same model (P.S. A table – perhaps not quite this perfunctory – might be a useful way to summarize and contrast the pillars.) "Flow" need not be the variable of interest, and we can conceptually generalize to other hydrologic outcomes, some of which have nonlinear relationships with climate forcings at varying time scales. On the basis of this alone, why might we expect the 1st and 3rd "pillars" to match in all but the trivial 0-trend case? We know that the mean of a non-linear process is not the same as the non-linear process operating on the means of the inputs. The presentation of the third alternative also seems to offer eerily stationary variance in projections (perhaps I misinterpret the red-lines in the plots?) that contradicts some well recognized expectations (e.g. Field et al, 2012). These points are entirely aside from the fact that the trends in climate for the third is based on 1948-2010, while that for the first is 1976-2008. If the first and third pillars are not

really rigorously framed, they come across as "strawmen" proposals in contrast to the more conventional GCM-based approach. At the same time, generous criticism is offered for GCM precipitation projections in the introduction (probably well deserved), which lends a certain frailty to that pillar as well. Are the authors trying to warn us that the three pillars of hydrologic projection are made of straw; that we should be watching for the big bad wolf? It does not seem to be their intent, but it is a difficult feeling to escape.

As noted above, the aim of the paper is not to promote the extrapolation of trends but to illustrate the value of using different methods based on different data. We are now making this clearer in the revised paper.

Perhaps the disconnect for me in reading this paper is related to my own slow work about reconciling GCM projections against trends (See Luce and Holden, 2009 and Luce et al., 2013 for instance). It seems that there should be utility in contrasting trends in climate and flow with GCM and hydrologic model retrospectives. It is important to question and hone our precipitation expectations, which seem so deeply uncertain from GCMs. But challenging the GCM projections with raw extrapolations of flow or climate seems like a weak challenge, particularly given that we know there are other periodical trends potentially superimposed. I fear that without demonstrated rigor in the trend analysis, the kind of effort the authors offer will be dismissed by our partners in the climate and atmospheric sciences community.

The reviewer seems to imply here that the trend analysis in the paper lacks rigor, while the methods used in Luce and Holden (2009) and Luce et al. (2013) do provide the necessary rigor. May be we are missing the point here, but it seems to us that Luce and Holden (2009) and the present manuscript are very similar with respect to the trend estimation and its interpretation. Luce and Holden (2009) estimate trends in the distribution of annual runoff at 43 gages and interpret the detected trends in the context of snow melt and climate indices, not unlike the interpretations of this paper. They also make the implicit assumption that the trend will continue into the future when they make management recommendations (which is obviously about the future), e.g. "Water allocation will become increasingly difficult with increasingly low annual streamflows" (p. 4). We therefore cannot see why the Luce and Holden (2013) provide more process detail on the comparison between GCM results and trend analyses. We do take the point that more quantitative process detail would strengthen the paper. We have therefore added, where appropriate, quantitative support of the process interpretations in the spirit of Luce et al. (2013).

On a more technical level, their method did not assume a Gaussian distribution of residuals around the trend line while the method used in this paper does. To adopt more rigor, we therefore compared the trend estimates with those using a nonparametric approach based on bootstrapping to estimate distribution-free confidence intervals. The results are given in supplement A of this response. The bootstrap distributions of predicted values turn out to be very close to Gaussian so the results change very little. The expected changes never differ by more than 4% from those of the method used in this paper, and their 95% confidence bounds never differ by more than 21% (period 2021-2050) and 33% (period 2051-2080) from those of this paper. However, we do see the value of the nonparametric approach and have adopted it therefore in this paper, replacing the Gaussian approach in the original manuscript.

I perceive the scientific community already taking on permutations of these three "pillars" through a range of scientific methods examining the sensitivity and consistency aspects through careful dissecting of trends of different time scales and variability from a range of climate processes. I acknowledge that these examinations are commonly of limited spatial scope and perhaps tediously meticulous, but do we have to abandon our sense of caution to effectively make a challenge? Have the various local efforts at incremental progress become too diffuse in their effect? Do we need to consider alternatives that have a touch of the outrageous? Perhaps so, and I'm open to the manuscript doing so; it just seems like a

position that requires some justification given the other excellent ongoing work in the community, only a small portion of which is cited.

As mentioned above we now give more detailed justification of the approach adopted.

# A Suggestion:

It seems the paper would most benefit from a more questioning stance; asking whether they can do what they would like to do – unless they are able to cite someone else who has it successfully. It would be wonderful and useful if they (or presumably in the future, "we") could apply their approach of comparing among the three pillars. If section 7.1 were framed more in the context of developing a hypothesis about how the three approaches (perhaps with slight refinements for 1 and 3 to acknowledge the potential need for anthropogenic attribution) could frame a genuinely systematic approach to reconciliation, the manuscript would come across more constructively. Then section 7.2 would presumably demonstrate that, in fact, the projections in agreement are more likely to occur. At the very least I would expect it would generate an excellent discussion on potential futuring practices that is informed by some thorough analysis of a large data set.

We take the reviewer's point of adopting a more questioning stance. We have condensed the manuscript by 30% and changed the perspective throughout the paper to better highlight the causes of the differences between the methods.

# A Perspective?

This final question is not intended to require modification of the manuscript or response by the authors. It is just here as a point of consideration or perspective relative to the overall framing offered by the current manuscript, which may or may not be helpful to briefly ponder. An underlying conceptualization of all three pillars is in determining the rate of change. One lesson from the various climate modeling exercises is a monotonic trend in temperature. If we do not societally change our fossil energy consumption practices, it is not a question of "if" we will reach 3, 4, or 6 C increases, just "when". If we resolve our temperature uncertainty to instead be a temporal uncertainty, we can recast our questions to be about the sensitivity to temperature and a plausible range of precipitation. Is the timing question so important that we should prioritize that as our fundamental question in hydrology over assuring that we can adequately describe the hydrological system response to a generalized "warming" of 2 to 6 C? Should our three pillars have a heavy weight on timing, or by accepting the eventuality, focus on hydrologic process or sensitivity?

Sincerely, Charles Luce

# References:

Field, C. B., Barros, V., Stocker, T. F., Qin, D., Dokken, D. J., Ebi, K. L., Mastrandrea, M. D., Mach, K. J., Plattner, G.-K., Allen, S. K., Tignor, M., and Midgley, P. M.: Managing the Risks of Extreme Events and Disasters to Advance Climate Change Adaptation (SREX). A Special Report of Working Groups I and II of the Intergovernmental Panel on Climate Change Cambridge University Press, Cambridge, UK, and New York, NY, USA, 582 pp., 2012.

Luce, C. H., and Holden, Z. A.: Declining annual streamflow distributions in the Pacific Northwest United States, 1948-2006, Geophys. Res. Lett., 36, L16401, doi:10.1029/2009GL039407, 2009.

Luce, C. H., Abatzoglou, J. T., and Holden, Z. A.: The Missing Mountain Water: Slower Westerlies Decrease Orographic Enhancement in the Pacific Northwest USA, Science, 342, 1360-1364, DOI: 10.1126/science.1242335, 2013.

# Response to the comment of L. Samaniego (Referee)

We would like to thank the reviewer for his positive and insightful comments on the manuscript. Below is our response to the issues raised in the review. The original comment is printed in plain font, our response is printed in italics.

This manuscript is based on the presumption that the combination of statistical analysis, process-based modeling using climate and stochastic projections as well as expert judgement is the best way to assess climate impacts on low flows. Without any further analysis, one could dare say that this premise should be true considering that this approach has much more information than any single analysis and thus should have less chance of not finding an answer that is closer to the true one. The authors strive to demonstrate the advantages of the proposed approach and the validity of this premise with a regional study conducted in four Austrian river basins. The manuscript is well written although it is a bit too long in my opinion. The topic of the study is relevant for HESS but the manuscript requires a substantial revision before publication. Below, I provide a number of issues to be clarified before publication.

We would rephrase the above statements in saying that the three pillar approach is a plausible way to assess climate impacts (not necessarily the best as we do not compare it with other approaches) and that we strive to demonstrate the usefulness of the premise rather than its validity, as validity can never be demonstrated for the future. We have now removed Figure 1 which may have been suggestive of the claim of a "best method".

• My first remark refers to the terminology chosen for this manuscript. My impression after reading the abstract and the introduction is that the names given to the various methods and the proposed "three-pillar" approach can be considerably simplified without diminishing the message that the authors try to convey. On the contrary, it will help the reader. I wonder, for example, what a data-based method has to do with a downward approach (downward refers to "toward a lower place, point, or level")... and conversely a mechanistic one with an upward approach ... I know that these terms have been used in current literature, but in my opinion, these buzzwords can be replaced by method A and B without changing the meaning of the sentences. I suggest either to justify the meaning of "downward" and "upward" in the present context or even better, to simplify the text. In my opinion, the so-called "downward approach" is a classical statistic method, so I wonder why not calling it simply like that.

The terminology of upward and downward approaches (Sivapalan et al., 2003) reflects the alternative avenues towards obtaining understanding of how a system operates which is unrelated to whether the methods are statistical or deterministic. The upward or mechanistic approach is based on a preconceived model structure that puts conceptual components such as runoff generation together (hence upward), while the downward approach infers the catchment functioning from an interpretation of the observed response at the catchment scale (fingering down to smaller scales, hence downward). We realise there are subtleties involved and the terminology is not essential for the paper, so we have removed it.

• In this study, old IPCC nomenclature for emission scenarios (A1B, B1, A2 etc) are still used instead of the newer RCPs proposed by the IPCC. Newer climate projections (e.g., CMIP5) are readily available for quite some time. Please explain why.

Jacob et al. (2015) showed that the most recent regional climate simulations over Europe, accomplished by the EURO-CORDEX initiative (RCPs, Moss et al., 2010), are rather similar to the older ENSEMBLES simulations with respect to the climate change signal and the spatial patterns of change. For consistency with related studies in Austria (e.g. Parajka et al., 2016) we have therefore chosen the older emission scenarios. We are now noting this in the manuscript.

Moss, R. H., Edmonds, J. A., Hibbard, K. A., Manning, M. R., Rose, S. K., van Vuuren, D. P., Carter, T. R., Emori, S., Kainuma, M., Kram, T., Meehl, G. A., Mitchell, J. F. B., Nakicenovic, N., Riahi, K., Smith, S. J., Stouffer, R. J., Thomson, A. M., Weyant, J. P., and Wilbanks, T. J.: The next generation of scenarios for climate change research and assessment, Nature, 463, 747–756, 2010.

Jacob, D., Petersen, J., Eggert, B., Alias, A., Christensen, O. B., Bouwer, L., Braun, A., Colette, A., Déqué, M., Georgievski, G., Georgopoulou, E., Gobiet, A., Menut, L., Nikulin, G., Haensler, A., Hempelmann, N., Jones, C., Keuler, K., Kovats, S., Kröner, N., Kotlarski, S., Kriegsmann, A., Martin, E., Meijgaard, E., Moseley, C., Pfeifer, S., Preuschmann, S., Radermacher, C., Radtke, K., Rechid, D., Rounsevell, M., Samuelsson, P., Somot, S., Soussana, J.- F., Teichmann, C., Valentini, R., Vautard, R., Weber, B., and Yiou, P.: EURO-CORDEX: new high-resolution climate change projections for European impact research, Reg. Environ. Change, 14, 563–578, doi:10.1007/s10113-013-0499-2, 2014.

• Authors do not formulate in the introduction a research hypothesis to be tested. I guess, the authors intend to test that the "Three-pillar approach" is superior than any of the single ones, but failed both to explicitly mention this hypothesis and to present statistic evidence that corroborates this assertion.

Actually, we are not intending to test a hypothesis in this paper. The aim of the paper is to present an approach to assess climate impacts on low flows from different sources of information. The objective is twofold, to present the concept and to illustrate the viability of the approach. A hypothesis that the three pillar approach is superior to any of the single methods would be testable in a synthetic world (where the future is generated and assumed to be perfectly known) but this would probably be a rather trivial exercise. The real world is more complex, so we confine ourselves to illustrating the feasibility of the approach very much in the spirit of ensemble predictions. We are now making the underpinning philosophy of ensemble predictions more explicit in the paper.

• L19, P9. If a hydrologic model is used in this study, I do not understand why a runoff index is not used instead of a meteorological drought index like SPEI. Streamflow, and thus low flow characteristics, are the outcome of the whole hydrologic system that is represented by a hydrological model. Moreover, it is well documented in the literature that atmospheric drought indices are quite transient whereas those related to soil moisture, groundwater, and runoff are not (Samaniego et al JHM 2013 and sources therein). Thus, the stochastic dependence of SPI or SPEI with any low-flow index is, in general, not significative (Kumar et al. 2016 HESSD). It should also explained why a Gaussian transformation (perhaps due to a long tradition...) should be applied a variable than is definitely non-Gaussian (i.e., P EP). L14 P9. A more reliable approach to "check the realism" of the ensemble climate simulations would be to estimate a runoff index over a historial period in which reanalysis (or hindcasts) and historial meteorological forcings are available. This is probably the best way to know whether a RCM or a Numeric Weather Prediction Model output can explain observed low-flow spells or other kinds of drought events as proposed by Thober et al. 2015.

We agree that a number of methods can be used for testing the realism of ensemble climate simulations (and we find the methods suggested by the reviewer useful), but the jury is probably still out on what is the most suitable method in a particular hydro-climatological setting. Kumar et al. analyse groundwater anomalies rather than low flows, so their results are not fully applicable to the present case, while Haslinger et al.. (2014) did find significant links between SPEI and low flows in the study area. The SPEI has been adopted here for its simplicity and because it can be calculated from the HISTALP data (Auer et al., 2007) back to the year 1800. Given this is a side issue in the paper, in our opinion, comparing different methods would go beyond the scope of this paper. The hydrological modelling later in the paper allows a more detailed comparison in the spirit of the references suggested by the reviewer. We now give an explicit justification of the use of SPEI.

• L18 P.5 It is not clear to me why the "first and second pillars" do not use local information used in the third pillar. After all, trends are based on local meteorological observations and any rainfall-runoff model, to my knowledge, uses local observations of rainfall, temperature, and discharge. Please elaborate why they have to be different (L22)?

We appreciate the comment as the wording has indeed been lacking clarity. The first two pillars do not use observed changes in the stochastic rainfall characteristics while the third pillar (stochastic extrapolation) does. We have reworded the sentence for clarity.

• L17 ff, P5. I guess authors demand too much from downscaled GCM-RCM forcings. GCM and RCM are climate models describing the evolution of physical processes in the atmosphere, ocean, cryosphere and land surface at large temporal and spatial scales (about 2.5\_). They are not intended to describe transient states, consequently one can not say that they are reliable or not. They do not have all the process necessary to describe rainfall generation at smaller scales like high resolution numerical weather models have if they are run at 1 km to 2 km spatial resolution. RCMs at 1/4 resolution and larger would be hardly able to estimate convective precipitation over mountainous areas like Austria. For GCMs, this is almost an imposible job. If this is known, I wonder why the hydrology comuntiny insist on getting "reliable" daily precipitation (say from RCMs inreanalysis mode) from these models so that low-flow statistics can be estimated ... Dynamic and stochastic downscaling may help a bit but many studies have shown, for example, that very few RCMs from the ENSEMBLES project are even able to get extreme statistics of the observed rainfall fields at monthly time scales (see e.g., Soares et al. 2012 JGR in Portugal, and Thober & Samaniego JGR, 2014 in Germany). As a consequence, low-flow statistics and its variability (e.g., Q95) obtained from reanalysis (e.g., WATCH) should be evaluated as expectations over reasonable periods (e.g., over decades). Likely yearly statistics are too short a period. See for example Schewe, J. et al. as an alternative.

We fully agree with the remark that RCM outputs should be assessed at time scales longer than a year and we did not intend to convey the impression that individual years should be taken at face value. In the discussion we are now making it clearer that the focus is on decadal rather than yearly scales and this is how the figures should be interpreted.

• L13 p8. The area of the river basins and the sampling size used in this study are probably too small to derive conclusive results. Authors should consider that the area of a GCM grid cell like ECHAM5 is at least 9 \_ 104 km2 and that of a RCMs used in Reclip:century is approximately 1 \_ 102 km2 (based on the project report). As a rule of thumb, due to the Courant–Friedrichs–Lewy condition, it is not recomendable to use prognostic values of state variables or fluxes obtained by numeric integration for areas less than four times the area of a typical grid cell. This implies that the minimun area to be consider in this case is a basin with at least 4 \_ 102 km2. Three of the study areas do not fulfill this condition. As a result, the uncertainty of the numerical model plus that of the downscaling techniques would increase dramatically which, in turn, would negatively affect the impact analysis. I recommend to test this approach in large basins that fulfill this condition and to enlarge the sample size considerably.

Yes, the spatial scales of applicability of RCM simulations is on the order of hundreds of km<sup>2</sup>. This is exactly the reason why we put the smaller catchments into a regional context (Figure 3, now Figure 2). This was acknowledged by reviewer #1: "the paper also works with a large dataset condensed to a few representative examples ... that ensure that patterns are not emergent from a few preselected sites or times." As suggested by the reviewer we are now making the scale considerations of the climate simulations more explicit in the manuscript with respect to Figure 3, now Figure 2.

• L15 P11, I suggest to use a non-parametric test to estimate confidence bounds considering that the underlaying variable is certainly non-Gaussian. In this case, parametric t-Student estimations for confidence bounds do not apply.

This is a good point. We therefore reanalysed the data by a nonparametric approach based on bootstrapping to estimate distribution-free confidence intervals. The results are given in supplement A of this response. The bootstrap distributions of predicted values turn out to be very close to Gaussian so the results change very little. The expected changes never differ by more than 4% from those of the method used in this paper, and their 95% confidence bounds never differ by more than 21% (period 2021-2050) and 33% (period 2051-2080) from those of this paper. However, we do see the value of the nonparametric approach and have adopted it therefore in this paper, replacing the Gaussian approach in the original manuscript.

• The structure of the manuscript is cumbersome in some sections. I suggest that methods and results from every approach is presented separately to easereading. The number of sections is quite large for a research paper in my opinion. This manuscript is a bit long too. *In response to this comment we have reorganised the paper, merging the methods sections into one chapter and condensing the entire manuscript by about 30%.* 

• L31, p19. Authors do not attempt to estimate "how strongly the pillars agree". It will be very enlightening to see a statistical analysis in this respect.

We appreciate the idea and have added a figure (now Fig. 11) showing the probability density functions (pdfs) of the low flow projections from the three methods for the period 2021-2051. We have tested the consistency of the pdfs by a two-sample Kolmogorov-Smirnov test which, however, gives lack of significant agreement for most cases which does not provide a lot of insight. We have therefore chosen to limit the quantitative comparison to the new figure.

• L2 ff p 26 As I said earlier, I have no doubt of this statement. In general, more information should lead to more reliable results. I do not see novelty on this statement. This can be inferred, for example, from simple parametric statistical tests by gradually changing the sampling size and estimating the effect on the confidence bounds for a given statistic. L29 ff is a consequence of this. Authors should present results and make statistical tests that demonstrate with large degree of certainty that adding information gradually leads to better results in this case. I have, however, reservations, on how soft data (e.g. historical reports), or subjective impressions can be used in a formal statistical analysis to "correct" confidence bound.

We agree that, to some degree, more information leading to more reliable results is an obvious statement. On the other hand, this is exactly the basis of multi-model ensemble projections. We have now changed the tone of the presentation in order not to imply that the use of more information is novel, rather the particular implementation in the context of low flow projections. Of course this can be formalised, for example by Bayesian methods that can handle subjective information (eg. Viglione et al., 2013) but this would go beyond the scope of this paper.

• Fig 11 is quite dense. It is supposed to be a synthesis, but I hardy can understand it. Sorry. In my opinion, this manuscript could become a nice contribution to the field if these issues are addressed before publication.

While reviewer Luce did note that the graphics of the paper are well constructed we can see the point here. To assist in the interpretation we have added a new figure (now Fig. 11) which is simpler and more clearly demonstrates the similarities and differences of the pillar projections.

Luis Samaniego

# References

Schewe, J., Heinke, J., Gerten, D., Haddeland, I., Arnell, N. W., Clark, D. B., et al. (2014). Multimodel assessment of water scarcity under climate change. Proceedings of the National Academy of Sciences of the United States of America, 111(9), 3245–3250. <u>http://doi.org/10.1073/pnas.1222460110</u>

Thober, S., & Samaniego, L. (2014). Robust ensemble selection by multivariate evaluation of extreme precipitation and temperature characteristics. Journal of Geophysical Research-Atmospheres. <u>http://doi.org/10.1002/(ISSN)2169-8996</u>

Soares, P. M. M., R. M. Cardoso, P. M. A. Miranda, P. Viterbo, and M. Belo-Pereira (2012), Assessment of the ENSEMBLES Regional Cli- mate Models in the representation of precipitation variability and extremes over Portugal, J. Geophys. Res., 117(D7), D07114, doi:10.1029/2011JD016768.

Samaniego, L., Kumar, R., & Zink, M. (2013). Implications of Parameter Uncertainty on Soil Moisture Drought Analysis in Germany. Journal of Hydrometeorology, 14(1), 47–68. http://doi.org/10.1175/JHM-D-12-075.1

Thober, S., Kumar, R., Sheffield, J., Mai, J., Schäfer, D., Samaniego, L. (2015). Seasonal Soil Moisture Drought Prediction over Europe Using the North American Multi-Model Ensemble (NMME). Journal of Hydrometeorology, 16(6), 2329–2344. http://doi.org/10.1175/JHM-D-15-0053.1

R. Kumar, J. L. Musuuza, A. F. Van Loon, A. J. Teuling, R. Barthel, J. Ten Broek, J. Mai1, L. Samaniego, and S. Attinger, (2016). Multiscale evaluation of the standardized precipitation index as a groundwater drought indicator, HESSD. http://www.hydrolearth-syst-sci-discuss.net/12/7405/2015/hessd-12-7405-2015.pdf

# Response to the comment of Referee #3

We would like to thank the reviewer for her/his positive and insightful comments on the manuscript. Below is our response to the issues raised in the review. The original comment is printed in plain font, our response is printed in italics.

This is a paper that is worthy of publication in HESS. The authors do an excellent job synthesizing existing literature on modeling low streamflow hydrology, and provide an interesting approach to assessing the impact of climate change on low streamflow prediction. Low streamflow prediction is inherently a challenging problem, and combining and assessing multiple approaches to forecasting low flows given potential climate change helps develop more holistic approach to low streamflow prediction. As such, I strongly recommend this paper be published in HESS, as it provides information useful to a wide variety of readers. Regardless, I do have a number of comments and suggestions that the authors might consider when revising this manuscript.

1) The three-pillar approach presented in this paper is not necessarily restricted to low streamflow estimation (i.e. it could just as easily be applied to flood flows or other hydrologic statistics). This should be made clear to the reader.

We agree that the overall approach is useful for a wider range of applications. We are now making this clearer in the discussion section of the paper.

2) One reason that low streamflow estimation is challenging is that they are typically driven by groundwater discharge processes (both recharge and discharge). These processes are difficult to understand and model due to their heterogeneous nature, and often these processes are overly simplified in rainfall runoff models (whose focus is typically flood or average streamflow prediction). Some discussion of this is warranted, as well as how these processes and their drivers are impacted by changes in climate.

We fully agree, groundwater processes controlling streamflow are often of a local nature modulated by the local hydrogeology, and the runoff model used is indeed a very simple representation of these processes. We are now acknowledging this in the discussion section of the paper and discuss potential effects of the simplification.

3) [NOTE: The following comment was written prior to this reviewer reading the entire manuscript. I am aware that this is discussed at the end of the paper (page 13096 line 13), but perhaps is should be discussed earlier since I continued to question this assumption throughout the paper.] An assumption of a linear trend in Q95 is made (equation (1)). Some discussion of the merit of this assumption is warranted. The authors could refer to Figure 5 in this discussion. While the Hoalp catchment's Q95 trend appears to be linear, in the Buwe catchment the trend seems to be driven by a regime shift in the last 10 years of the record (most likely creating a trend in the residuals). The implication of this assumption should be discussed. For instance, are the error bounds associated with these projections impacted by this assumption? Is there is a regime shift and not a linear trend, might you under-predict future low flows at this catchment?

We have added a note regarding the assumption earlier in the paper (where the linear trend model first appears), and we now address this point in the discussion section (referring to Figure 5), in particular the different shapes of the low flow changes in Hoalp and Buwe (trend vs regime shift). Regime shift is indeed a possibility and has now been given more prominence in the paper.

4) I believe the significance codes in Table 1 are incorrect. I think the symbols should either be switched in the table or in the table footnote.

Many thanks for pointing this out. The formatting error has been corrected.

5) A brief explanation of how groundwater discharge is modeled in the TUVmodel is warranted, as well as what parameters are calibrated in the SCE-UA routine. *A brief explanation has been added.* 

6) The results in Table 3 seem deceptive to me, since they are for model prediction across the entire streamflow regime. While the weights are changed to assess the impact of higher and lower streamflow prediction on Zq, it's difficult to understand how these are important to this analysis. In addition, even though Table 3 says that this model does poorly at Buwe, the Q95 predictions in Figure 5 seem quite good. You might consider explaining this. *An explanation has been added.* 

7) There are a number of small typographic errors:

a) Page 13084 line 25. "(" before "Ceola" should be removed.

b) Page 13086 line 1. The "Q" in "ZQ" should be a subscript.

c) Page 13094 line 1. "on" should be "one".

d) Page 13097 line 7. "cam" should be "can".

e) Page 13099 line 16. "for Hundecha and Merz (2012)." should be "for (Hundecha and Merz, 2012)."

All these typos have been corrected.

# SUPPLEMENT A

# ## Original CI

Table #2 Trend projections FOR MID OF PROJECTION PERIOD <u>2035</u> for (2021-2050) and <u>2065</u> for (2051-2080)

	Hoalp	Muhlv	Gurk	Buwe
Predicted discharge 2050 (m <sup>3</sup> /s)	0.28 m³/s (0.19, 0.38) m³/s	0.67 m³/s (0.36, 0.97) m³/s	1.17 m³/s (0.48, 1.87) m³/s	0.02 m³/s (-0.10, 0.14) m³/s
Change 2050 (%)	+42% (-5, +88)	-10% (-51, +32)	-36% (-74, +1)	-89% (-156, -21)
Predicted discharge 2080 (m <sup>3</sup> /s)	0.35 m³/s (0.20, 0.51) m³/s	0.58 m³/s (0.07, 1.09) m³/s	0.74 m³/s (-0.42, 1.90) m³/s	-0.08 m <sup>3</sup> /s (-0.29, 0.12) m <sup>3</sup> /s
Change 2080 (%)	+78% (1, 156)	-21% (-91, +48)	-60% (-123, +3)	-145% (-258, -33)

# ## BOOTSTRAPED CI (5000 replications)

Table A.2 Trend projections FOR MID OF PROJECTION PERIOD <u>2035</u> for (2021-2050) and <u>2065</u> for (2051-2080)

Table 2

	Hoalp	Muhlv	Gurk	Buwe
Predicted discharge 2050 (m <sup>3</sup> /s)	0.28 m³/s (0.19, 0.37) m³/s	0.68 m³/s (0.45, 1.02) m³/s	1.19 m³/s (0.58, 2.00) m³/s	0.02 m³/s (-0.14, 0.14) m³/s
Change 2050 (%)	+39% (-7, +71)	-8% (-41, +34)	-36% (-7 <mark>2, -1</mark> )	-90% (-177, -22)
Predicted discharge 2080 (m <sup>3</sup> /s)	0.35 m³/s (0.22, 0.45) m³/s	0.60 m³/s (0.15, 1.14) m³/s	0.74 m³/s (-0.23, 2.01) m³/s	-0.08 m <sup>3</sup> /s (-0.33, 0.12) m <sup>3</sup> /s
Change 2080 (%)	+74% (0, 123)	-21% (-79, +51)	-59% (-113, +9)	-14 <mark>8</mark> % (-2 <mark>82</mark> , -36)

Figure A.1. Bootstrap distribution of trend projection for Hoalp, period 2065 for (2051-2080)



Figure A.2. Bootstrap distribution of trend projection for Muhlv, period 2065 for (2051-2080)



Histogram of t

Histogram of t







Figure A.2. Bootstrap distribution of trend projection for Buwe, period 2065 for (2051-2080)



Histogram of t



Formatiert: Kopfzeile Formatiert: Zeilenabstand: einfach

# 1 A three-pillar approach to assessing climate impacts on 2 low flows

3 4

5

14

- G. Laaha<sup>1</sup>, J. Parajka<sup>2</sup>, A. Viglione<sup>2</sup>, D. Koffler<sup>1</sup>, K. Haslinger<sup>3</sup>, W. Schöner<sup>4</sup>, J. Zehetgruber<sup>1</sup> and G. Blöschl<sup>2</sup>
- 6 [1]{Institute of Applied Statistics and Computing, University of Natural Resources and Life
  7 Sciences (BOKU), Vienna, Austria}
- 8 [2]{Institute for Hydraulic and Water Resources Engineering, Vienna University of 9 Technology, Vienna, Austria}
- 10 [3]{Climate Research Department, Central Institute for Meteorology and Geodynamics,
   11 Vienna, Austria}
- 12 [4]{Department of Geography and Regional Science, University of Graz, Graz, Austria}
- 13 Correspondence to: G. Laaha (gregor.laaha@boku.ac.at)

### 15 Abstract

16 The objective of this paper is to present a new strategyframework for assessing climate impacts on future low flows and droughts. The strategy is termed a three pillar approach as 17 itthat combines different sources of information. The first pillar, trend extrapolation, exploits, 18 19 termed pillars. To illustrate the temporal patterns framework three pillars are chosen: (a) Extrapolation of observed low flows and extends themflow trends into the future. The second 20 21 pillar, rainfall; (b) Rainfall-runoff projections uses precipitation and temperature based on 22 climate scenarios from elimate models as an input to rainfall runoff models to project future 23 low flows. The third pillar; (c) Extrapolation of changing stochastic projections, exploits the 24 temporal patterns of observed precipitation and air temperature and extends themrainfall 25 characteristics into the future to drive rainfall runoff projections. These pieces of information combined with rainfall-runoff modelling. Alternative pillars could be included in 26 the overall framework. The three pillars are combined by expert judgement based on a 27 synoptic view of data and, model outputs, taking and process reasoning. The 28 29 consistency/inconsistency between the respective uncertaintiespillars is considered an 30 indicator of the methods into account.certainty/uncertainty of the projections. The viability of the approachframework is demonstrated illustrated for four example catchments from Austria 31 32 that represent typical climate conditions in Central Europe. The projections differ in terms of their signs and magnitudes. The degree to which the methods agree depends on the regional 33 elimate and the dominant low flow seasonality. In the Alpine region where winter low flows 34 35 dominate, trend projections and climate scenarios yield consistent projections of consistently 36 increasing low flows, although of different magnitudes. In the region north of the Alps, 37 consistently small changes are projected by all methods. In the regions in the South and 38 Southeast, more pronounced and mostly decreasing trends are projected but there is 39 disagreement in the magnitudes of the projected changes. These results suggest that conclusions drawn from only one pillar of information would be highly uncertain. The The 40 process reasons for the consistencies/inconsistencies are discussed. It is argued that the three-41 42 pillar approach offers a systematic framework of combining different sources of information aiming at more robust projections than obtained from each pillar alone. 43

Formatiert: Deutsch (Österreich)

### 1 Introduction

1 2

3 Streamflow regimes are changing around the world due to human intervention. Low flows are often particularly affected. Direct human impacts such as abstractions or storage effects are 4 5 not quite easy to quantify. Forecasts of the impacts of a changing climate are even more 6 difficult (Blöschl and Montanari, 2010). Yet, the quantification of future water resources is a 7 key requirement for water management. An increasing number of studies has therefore been 8 conducted in recent years to assess climate change impacts on low flows and streamflow 9 droughts. From a modelling perspective, and also from a systemic one, these studies fall into 10 two groups of approaches (Sivapalan et al., 2003).

11 The first group of studies assesses climate impacts from observed streamflow records. This is sometimes termed a data driven or downward approach. As discussed in (Sivapalan et al., 12 13 2003) the defining feature of the downward approach to hydrologic modelling is the attempt 14 of predicting catchment functioning based on an interpretation of the observed response of the 15 catchment. The approach provides a systematic framework of learning from data, including 16 the testing of hypotheses at every step of analysis. In the context of hydrological change and low flows, the downward approach usually involves statistical trend analyses of observed low 17 18 flow characteristics such as the annual minima. There has been a considerable number of low 19 flow trend studies across Europe and around the world, including (Giuntoli et al., 2013) for 20 France, (Hannaford and Buys, 2012) for UK, (Wilson et al., 2010) in Nordic Countries, 21 (Lorenzo Lacruz et al., 2012) for the Iberian peninsula, and (Lins and Slack, 1999) and 22 (Douglas et al., 2000) for the US. Trend testing is usually performed on a station by station basis. Often, the studies are therefore not fully conclusive at the larger scale of climate 23 processes. Only a few studies tested trends in a regional context, using field significance 24 25 statistics or block bootstrapping procedures (e.g. Renard et al., 2008; Wilson et al., 2010), 26 while other studies interpret trend patterns rather than significance levels which avoids 27 assumptions of spatial correlations but makes the results less comparable with other studies (e.g. Stahl et al., 2010). An important step in the downward approach is the interpretation of 28 29 detected trends in order to gain an understanding of the processes giving rise to observed changes. At least some interpretation of low flow trends in the context of climate variables is 30 31 usually performed, either relative to observed changes or to projected changes. Most studies, 32 however, perform trend interpretations in the sense of a plausibility control rather than in a 33 deductive way, therefore not exploiting the full potential of the downward approach.

of studies simulates future changes from climate scenarios. From a 1 The groun 2 systemic perspective, this may be termed a mechanistic or upward approach, as physically 3 based models are used to generate climate projections. When the focus is on river flows, model caseades of atmospheric-land surface-catchment models are usually employed. General 4 5 Circulation Models (GCMs) simulate the climate system's future response to emission 6 scenarios and other human activities that affect the climate system. The GCM outputs are then 7 downscaled to the scale of the catchment of interest, and the resulting projections of climate 8 variables such as precipitation and air temperature are used as inputs of a hydrological model to project streamflow. Applications of the upward approach to streamflow projections are 9 10 numerous, but relatively few of these studies focus on low flows. These few examples include large river basin studies such as (De Wit et al., 2007) for the Meuse, (Hurkmans et al., 2010) 11 12 for the Rhine, and (Majone et al., 2012) for the Gállego river in Spain. All of these studies used distributed or gridded hydrological models to simulate the projected response of the 13 entire basin. Similar to the downward approach, regional studies are rare. Large national 14 15 studies include (Wong et al., 2011) for Norway, (Prudhomme et al., 2012) for Britain, (Chauveau et al., 2013) for France, and (Blöschl et al., 2011) for Austria. These studies make 16 17 use of readily available regionalised rainfall runoff models developed in prior studies to 18 assess regional patterns of low flow indices. Often, these models are not specifically parameterised for low flows, and therefore associated with higher uncertainty. An alternative 19 approach consists of using global hydrological models instead of regionalised rainfall runoff 20 21 models at the end of the model cascade (Prudhomme et al., 2013). Global models make it 22 easier to understand large scale changes but the projections are coarser with respect to both 23 spatial scale and the degree of process realism.

Both approaches have their strengths and weaknesses (see Hall et al., 2014) for a comparison 24 25 of the two methods in the context of floods). The downward approach is the method with a 26 minimum number of assumptions, since it is directly based on observations. If the data are reliable, recent changes of the low flow regime can be related to a changing climate. Recent 27 changes in air temperature have been quite consistent over time in many parts of the world. In 28 the European Alps, for example, the increase in air temperature since 1980 has been about 29 30 0.5°C/decade with little variation between the decades (Böhm et al., 2001; Auer et al., 2007). 31 If one assumes that air temperature is the main driver of low flows and air temperature changes will persist into the near future in the same way as in the past, one can also assume 32 that observed low flow changes can be extrapolated into the near future. Of course, such an 33

extrapolation hinges on the realism of the assumptions and is likely to be applicable only to a limited time horizon. Also, reliable runoff data over the past five decades are needed. In its own right, such low flow extrapolations may therefore not be very conclusive in terms of future low flow changes.

5 The alternative, upward approach exploits information from global and regional climate models to project future low flows as a consequence of climate change. An advantage of 6 7 GCMs is their process basis and their ability to perform multiple simulation experiments for different greenhouse gas emissions scenarios or shared socio economic pathways. These 8 9 simulations can be useful for gaining an understanding of the major controls of climate 10 variables and the range of possible projections. However, their spatial resolution is rather coarse (e.g., 10 km for the dynamically downscaled reclip:century simulations used in this 11 study), so small scale climate features, such as cloud formation and rainfall generation, 12 eannot be resolved. Also one cannot test such projections as they extend into the future. The 13 14 consequence is that air temperature projections from climate models tend to be robust, while 15 precipitation projections tend to exhibit considerable uncertainties. If precipitation is the main 16 driver of low flow changes, these uncertainties translate into large uncertainties in projected low flows. The uncertainties may be particularly large in complex terrain, such as Alpine 17 landscapes and adjacent transition zones, where climate models are least reliable (Field and 18 19 Intergovernmental Panel on Climate Change, 2012; Haslinger et al., 2013). Low flow projections may, therefore, vary wildly between scenarios and models for the same region so, 20 21 again, may not be very conclusive of climate change impacts when taken by itself.

Streamflow regimes are changing around the world due to multiple factors and low flows are 24 often particularly affected. Direct human impacts, such as abstractions, and climate impacts 25 are difficult to isolate (Blöschl and Montanari, 2010), yet understanding the causes of changes 26 is essential for many water management tasks. Research into assessing low flow and drought 27 changes falls into two groups (Sivapalan et al., 2003).

The first group infers catchment functioning from an interpretation of the observed 28 29 streamflow response at the catchment scale. It includes statistical trend analyses of observed low flow characteristics, such as the annual minima, supported by analyses and interpretations 30 31 of the process causes (e.g. Giuntoli et al. (2013) in France, Hannaford and Buys (2012) in the 32 UK, Wilson et al., (2010) in the Nordic Countries, Lorenzo-Lacruz et al. (2012) on the Iberian 33 peninsula, and Lins and Slack, (1999) and Douglas et al., (2000) in the US). Most trend 34 analyses are performed locally on a station-by-station basis and are therefore not fully conclusive at the larger scale of climate processes. Regional trend analyses are based on field 35 significance statistics or block-bootstrapping procedures (e.g. Renard et al., 2008; Wilson et 36

al., 2010) or, alternatively, a regional interpretation of trend patterns (e.g. Stahl et al., 2010). 1 Most studies perform trend interpretations in a heuristic way without cross checking against 2 3 alternative sources of information. The second group involves a model cascade, where General Circulation Model (GCMs) 4 5 outputs are fed into Regional Climate models (RCM), the outputs of which (usually 6 precipitation and air temperature) are fed into hydrological models to project future 7 streamflows. Low flow examples include De Wit et al. (2007) for the Meuse, Hurkmans et al. 8 (2010) for the Rhine and Majone et al. (2012) for the Gállego river in Spain. National studies 9 include Wong et al., (2011) in Norway, Prudhomme et al. (2012) in the UK, Chauveau et al. 10 (2013) in France and (Blöschl et al., 2011) in Austria. The hydrological models used in these

studies are often not specifically parameterised for low flows which results in considerable

13 The two approaches have relative strengths and weaknesses (see Hall et al., 2014 for the flood 14 case). The first approach makes fewer assumptions and is more directly based on observations 15 but any extrapolation into the future is more speculative. Recent changes in air temperature have been quite consistent over time in many parts of the world. In the European Alps, for 16 example, the increase in air temperature since 1980 has been about  $0.5^{\circ}$ C/decade with little 17 variation between the decades (Böhm et al., 2001; Auer et al., 2007), and the expected trends 18 are similar. If one assumes that air temperature is the main driver of low flow changes, 19 20 persistence of low flow changes into the near future is therefore a reasonable assumption. Of 21 course, such an extrapolation hinges on the realism of the assumptions and is likely only 22 applicable to a limited time horizon. The second approach on the other hand is more process 23 based, so has more potential for projections into the future, but the spatial resolution of the atmospheric models is rather coarse (e.g., 10 km for dynamically downscaled reclip:century 24 25 simulations), so small-scale climate features, such as cloud formation and rainfall generation, 26 cannot be resolved. As a consequence, air temperature projections tend to be more robust than 27 precipitation projections, in particular in Alpine landscapes (Field and Intergovernmental 28 Panel on Climate Change, 2012; Haslinger et al., 2013). There is value therefore in confronting such projections with results from other approaches. 29

## 2 Three-pillar approach

11

12

30

31

uncertainties.

The upward and downward approaches have complementary strengths and weaknesses. 32 Importantly they use different sources of information. If a single approach is used, not the 33 entire spectrum of information that may be available is exploited. Current trend studies focus 34 35 on trend tests, on spatial patterns, or on temporal aspects of trends, but do not combine these aspects with information from elimate scenarios. In a similar way, rainfall-runoff projections 36 37 typically use climate scenarios, but we are not aware of any studies that also exploit the information of the observed low flow time series. Consequently, there may be substantial 38 value in combining the upward and downward approaches in order to build on their respective 39 strengths. The value of combining different pieces of information has been demonstrated by 40 41 (Gutknecht et al., 2006), (Merz and Blöschl, 2008) and (Viglione et al., 2013) in the context 42 of flood estimation.

Formatiert: Kopfzeile

**Formatiert:** Zeilenabstand: einfach

In this paper we propose combining the most relevant pieces of information contained in low 1 flow observation, climate observations and climate projections using a three pillar approach 2 3 (Fig. 1). The first pillar is the assessment of trends in the low flow observations. If observed 4 trends are related to climate, continuing trends may be a realistic scenario for the near future. 5 The second pillar is rainfall runoff projections based on climate scenarios. If the downscaled 6 GCM signal is reliable, the coupled model will give projections of future catchments 7 response. As these pillars do not fully exploit the information of locally observed climate, we 8 add a third pillar of stochastic rainfall runoff projections based on local climate observations. This pillar is anticipated to facilitate interpretation of past trends and trend based 9 10 extrapolations into the future and assist in linking the other two pillars with each other.

The three pillar approach allows us to assess climate impacts from independent sources of 11 information each of which may have different error structures. The combination of the 12 13 individual assessments therefore opens up a number of opportunities. The first opportunity is 14 to obtain a judgement about the credibility of the individual approaches. This is achieved by 15 comparing observed and simulated low flow time series. Low flow observations will 16 generally be most reliable as they provide direct measurements of the variable of interest. Hence, they can be used to assess the performance of stochastic projections and climate 17 models for the observation period, i.e. without assumptions about the future development. 18 19 This provides insight into the predictive performance of the rainfall-runoff model during the 20 calibration period and its skill of tracing changes of the climate signal down to low flows 21 (dynamic performance). On the other hand, the comparison may yield insight into the GCM performance, as reanalysis runs contain all necessary information to get an appreciation of the 22 realism of (downscaled) GCM signals, when being compared to observed climate and runoff 23 24 signals. However, also low flow observations may be inaccurate and trends may be artefacts 25 from instrumentation changes or the limited observation window. The mutual comparison of 26 observed low flows with the rainfall runoff reanalysis offers the opportunity of verifying trends in both climate and runoff signals, as a solid basis for future projections. 27

28 The second opportunity offered by the three-pillar approach is to better understand the 29 response of low flow regimes to climate change. This is achieved by comparing climate 30 signals and runoff signals. Such an analysis may first focus on the observation period in order 31 to understand observed changes of the low flow regime. In a second step, the analysis may be 32 extended to the future, in order to put projected changes into the context of the past. Low

flows are a result of the complex interactions of climate drivers with catchment processes 1 a direct comparison of climate and low flows may be difficult. A stochastic rainfall runoff 2 3 projection method may assist in such a comparison as it can trace low flow trends back to trends in the meteorological variables. A stochastic rainfall and temperature model typically 4 5 decomposes meteorological signals into components such as linear trends and cyclical 6 fluctuations. The joint analysis of these components with the low flow signal may yield 7 insight into the co behaviour of low flows and climate variables in cases where low flow 8 signals are contaminated by noise. From the analysis we can expect a better understanding of climate change dynamics, and of the resilience and sensitivity of low flow generation 9 10 processes to changes in the climate conditions.

11 Thirdly, the three pillar approach offers a more complete way of assessing the uncertainty of projections than each of the pillars alone. This is because one can safely assume that the 12 13 errors are, at least partly, disjoint because of the different data sources. Given the substantial 14 uncertainty associated with climate impact studies, more detailed information on the 15 uncertainty is certainly attractive, even though a full assessment is likely not possible given 16 the partial information available in such studies. For rainfall runoff projections the sources of uncertainty include their sensitivity to climate scenarios, climate model and downscaling 17 errors, and the prediction uncertainty of the rainfall runoff models themselves which arise 18 19 from the model structure and parameters. The latter are related to the choice of the objective function and the calibration period. For trend studies, uncertainty can be assessed by 20 21 statistical significance tests, subject to the assumptions made, and by confidence bounds of 22 trends.

23 All of the opportunities combine the information of the three pillars in some way. Of course, 24 the idea of combining different sources information has already often been used and tested in hydrology. Examples include the combination of local and regional hydrological information 25 26 (e.g. Kuczera, 1982; Stedinger and Tasker, 1985), short and long low flow records (e.g. Laaha 27 and Blöschl, 2007), hard and soft hydrological information (e.g. Winsemius et al., 2009), and uncertainty estimates in ungauged basins based on the downward and upward approaches 28 29 (Gupta et al., 2013). The combination can be based on formal methods (e.g. Viglione et al., 2013) which typically assume that the different pieces of information are all random samples 30 from the same distribution, and they differ only due to their sampling variability. The 31 32 distribution of the entire population is then estimated by Bayesian or other methods. As an

alternative, expert judgement can be used to combine the different sources of information 1 (e.g. Merz and Blöschl, 2008). The disadvantage is that it is less objective but the advantage is 2 3 its flexibility as it is based on a reasoning on the strengths and weaknesses of the individual 4 pillars. In this paper, we use expert judgement to combine the findings from the three pillars. 5 In Sections 4.6 we present the methods and assessments for each pillar separately. The strategy and application of the synthesis method are presented in Section 7, followed by 6 7 discussion and conclusions. The three pillar approach offers a systematic way of obtaining an 8 overall assessment of future climate impacts, including an appreciation of the reliability of 9 each method gleaned from the consistence of the pillars. We illustrateIn this paper we propose 10 a framework that combines complementary pieces of information on low flows in order to 11 enhance the reliability of the projections. The overall philosophy has been inspired by the concept of multi model climate projections where the projections from a group of models 12 13 together are considered to be more robust than the individual projections, and the difference 14 between the individual models represents an indicator of the uncertainty associated with the 15 projections. Knutti et al. (2010, p. 2), for example, states: "Ensemble: A group of comparable 16 model simulations. The ensemble can be used to gain a more accurate estimate of a model 17 property through the provision of a larger sample size, e.g., of a climatological mean of the frequency of some rare event. Variation of the results across the ensemble members gives an 18 estimate of uncertainty." The concept of combining different sources of information has, of 19 course, a long tradition in other fields of hydrology such as flood estimation (Stedinger and 20 Tasker, 1985, Gutknecht et al., 2006, Merz and Blöschl, 2008), low flow estimation, (Laaha 21 22 and Blöschl, 2007) and, more generally, uncertainty estimation in ungauged basins (Gupta et 23 al., 2013). 24 The combination can be based on formal methods such as Bayesian statistics (Viglione et al., 25 2013) or on a heuristic process reasoning based on expert judgement (Merz and Blöschl, 2008). The latter is able to account for a broader class of information sources but it is more 26 27 subjective. In this paper, we chose a heuristic approach because of its flexibility but, as 28 demonstrated by Viglione et al. (2013), this could be formalised. 29 We illustrate the framework by choosing three pillars or sources of information to assist in projecting low flows into the future. The first pillar consists of extrapolating observed low 30 31 flow trends into the future. The second pillar consists of rainfall-runoff projections driven by 32 GCM based climate scenarios. The third pillar extrapolates observed trends in stochastic 33 rainfall and temperature characteristics into the future, combined with rainfall-runoff 34 modelling. Alternative or additional pillars could be used, e.g., the "trading space for time" 35 approach (Perdigão and Blöschl, 2014) where spatial gradients are transposed into temporal 36 changes. 37 The data and assumptions of the three pillars differ, so one would also expect the error structures to be different which will have a number of benefits for the projections. 38 Comparisons of observed and simulated low flow time series at the decadal time scale provide 39 40 insight into the performance of the runoff models as well as the climate hindcasts which gives 41 an indication of their performance for the future. The analysis and projection of the stochastic climate and low flow behaviour shed light on their co-behaviour, the sensitivity of low flows 42 43 to changing climate variables and the role of noise over decadal time scales. Finally, the consistency of the projections by the different methods sheds light on the robustness of the 44 45 overall projections. 8

We demonstrate the viability of the approach for four example regions in Austria and discuss<sup>4</sup> the findings in the context of hydrological climate impact studies.

**Formatiert:** Kopfzeile **Formatiert:** Zeilenabstand: einfach

## 3 Example data set

1

2

3 4

### 5 3.13 StudyCase study regions and hydrologic data

6 The four example regions used here to illustrate the three pillar approach are representative of
7 the main climatological units in Austria. In each of them a typical catchment was selected
8 which are a subset of a classification ("low flow hot spots") used in previous low flow and
9 drought studies (Haslinger et al., 2014; Van Loon and Laaha, 2015). Although Austria is
10 highly diverse with respect to climate and physiography, each of the regions is rather
11 homogeneous in terms of climate and the hydrological regime.

The first region The four example regions are representative of the main climatological units
 in Austria. Although Austria is quite diverse, each of these regions is rather homogeneous in
 terms of climate and hydrological regime. Within each region, a typical catchment was
 selected guided by previous low flow and drought studies (Haslinger et al., 2014; Van Loon
 and Laaha, 2015).

17 The Hoalp region (for Hochalpen) is located in the Alps and exhibits a clear winter low flow 18 regime. Freezing is the driving factor of low flows in this region\_where freeze and snow 19 processes are important, so long-term trends may beare expected to be related to changing air 20 temperatures. The region, termed Hoalp in the following (for Hochalpen), is represented by 21 the catchment of the Matreier Tauernhaus stream gaugecatchment at the Tauernbach (area is 22 60 km<sup>2</sup>, altitude is<sup>2</sup> area, 1502 m.a.s.l., observation period is 1951-2010).

23 . altitude). The secondMuhlv region (for Mühlviertel) is located north of the Alps withand 24 exhibits a dominant summer low flow regime. The region exhibits a quite humid climate as it 25 receives substantial as a result of summer precipitation from northern and western air masses. Seasonal and evaporation, so precipitation deficits are the driving forces of low flows so long-26 27 term trends are likely related to changes in precipitation and air temperature. will be 28 important low flow controls. The region, termed Muhlv in the following (for Mühlviertel), is 29 represented by the catchment of the Hartmannsdorf stream gauge catchment at the Steinerne Mühl (area is 138 km<sup>2</sup>,<sup>2</sup> area, 500 m altitude is 500 m.a.s.l., observation period is 1956 2010). 30 31 ). The thirdGurk region (for Gurktal) is located south of the Alps, and also exhibits a 32 dominant summer low flow regime. Precipitation enters the area from the Northwest through

Atlantic cyclones, although screened to some extent by the Alps, as well as from the South

34 | through Mediterranean cyclones, which is particularly the case in autumn. Again, seasonal

**Formatiert:** Überschrift 1, Einzug: Links: 0 cm, Hängend: 0,76 cm, Keine Aufzählungen oder Nummerierungen, Tabstopps: 0,76 cm, Listentabstopp + Nicht an 1,02 cm precipitation deficits are the driving forces of low flows so long term trends tend to be related to changes in precipitation. Precipitation and <u>air temperature</u>, are important for low flows. The region, termed Gurk in the following (for Gurktal), is represented by the <u>Zollfeld</u> catchment of the Zollfeld streamgauge at the Glan (area is 432 km<sup>2</sup>,<sup>2</sup> area, 453 m altitude is 453 m.a.s.l., beservation period is 1965–2010).

6 ). The fourthBuwe region (for Bucklige Welt) is located in the Southeast of Austria. This 7 region is situated in the lee of the Alps, at the transition to a Pannonic climate. The 8 precipitation is lowest in this region, and low. Low flows exhibit a dominant mainly occur in 9 summer low flow regime. Seasonal with precipitation deficits are the driving forces of low 10 flows and so the long-term trends should be related to changes in precipitation and air temperature- as important controls. The region, termed Buwe in the following (for Bucklige 11 12 Welt), is represented by the eatchment of the Altschlaining stream gaugecatchment at the 13 Tauchenbach (area is 89 km<sup>2,2</sup> area, 316 m altitude is 316 m.a.s.l., observation ). Streamflow records in the four catchments over the period is 1966 2010).1976-2008 were used for all 14 15 three pillars.

Climate records were used for two out of the three pillars, i.e., the rainfall runoff projections
 and the stochastic simulations. They serve for two purposes.

18 Firstly, climate records are required for calibrating the hydrological model. the second and 19 third pillars. Gridded data sets of daily precipitation, air temperature, and potential 20 evaporation and snow depthover the period 1976-2008 were used. for calibrating the 21 hydrological model. These data sets are based on measurements of measured daily 22 precipitation and snow depths at 1091 stations and daily air temperature at 212 elimatic stations. Potential evapotranspiration-evaporation was estimated by a modified Blaney-23 24 Criddle method based on daily air temperature and potential sunshine duration, (Parajka et al., 25 2007). For details about the estimation and interpolation methods see (Parajka et al., 2007).

Secondly, climate records provide the main input to the stochastic simulations, which are used
 to decompose the signal of climate drivers in the past as the basis for extrapolations into the

28 **future.** For this purpose, one climate station was selected for each example catchment in their

29 proximity and at similar altitudes. Precipitation, precipitation and temperature records at one

30 <u>representative station</u> over the period 1948-2010 were used for the selected stations.

## 31 3.2 Climate simulations

For the rainfall runoff projections we used four regional climate model (RCM) runs which\*
 were selected from the reclip:century 1 project (Loibl et al., 2011). The variability of climate
 projections is represented by COSMO CLM RCM runs forced by ECHAM5 and HADCM3

35 global circulation models and three different IPCC emission scenarios (A1B, B1 and A2). A

Formatiert: Kopfzeile

Formatiert: Zeilenabstand: einfach

Formatiert: Zeilenabstand: einfach

10

simple but effective way to check the realism of the ensemble of climate simulations with 1 2 respect to low flows is to use an index that combines temperature and precipitation signals in 3 analysed as a way that represents the climate forcing in low flow generation. One index 4 commonly used in atmospheric drought studies is the Standardized Precipitation Evaporation 5 Index, SPEI (Vicente Serrano et al., 2010), which represents the total effect of precipitation and temperature changes on the climatic water balance. The SPEI is defined as the Gaussian-6 7 transformed standardized monthly difference of precipitation and evapotranspiration based on 8 an accumulation period of one to several months. Values below/above zero indicate 9 deficits/surpluses in the climatic water balance, and values below 1.0 indicate drought 10 conditions. (Haslinger et al., 2014) demonstrated that the SPEI is well correlated with summer 11 low flows, and indeed more relevant for low flow generation than precipitation alone. basis of 12 the stochastic simulations (third pillar). 13 Figure 2 shows the evolution of SPEI of the four regions stratified by summer and winter 14 months. Each value corresponds to the seasonal (three month) average of SPEI(1), i.e. the 15 Standardized Precipitation Evaporation Index based on an aggregation period of one month. 16 For the winter months (Fig. 2, lower panels), SPEI remains stable which is equivalent to a 17 stationary precipitation signal. This is because the projected temperature increase is not 18 reflected by the SPEI due to the low evaporation rates in winter. However, the timing of 19 snowmelt is likely to change. For Hoalp and Muhly, the climate simulations for the winter 20 month fit well to the observations (light red and red lines). For Gurk and Buwe, the climate 21 simulations seem to be somewhat less realistic. 22 For the summer season, the SPEI simulations suggest much dryer atmospheric conditions in 23 the future, which will decrease the low flows. Overall, the elimate simulations do not fit so well to the observations as for the winter, and the plausibility of the projections varies 24 25 between regions. For the Muhlv region, the SPEI signal fits relatively well to the 26 observations, for Gurk the simulated signal drops somewhat more steeply than expected, and 27 for Buwe the signal is much steeper than the observed signal, which does not show a falling 28 trend over the last 50 years. Interestingly, all summer SPEI graphs are relatively stable until 2050, and drop in the second half of the 21<sup>th</sup> century. This is mainly due to the characteristics 29 30 of the ECHAM5 simulations which show only minor precipitation changes until the middle of the century, and after 2050 an enhanced decrease in rainfall. Such an effect is not observed in 31 32 the other models or ECHAM5 runs, and contributes to the overall uncertainty of the scenario 33 approach. The extremely negative trends in the summer SPEI should also be treated with 34 caution because the potential evapotranspiration calculations within the SPEI algorithm is

known to overestimate climate change signals expressed by surface temperature trends
 (Sheffield et al., 2012). Overall, the SPEI values of climate simulations do suggest decreasing

1

low flows in summer and perhaps stable low flows in winter, although SPEI is less well suited for predicting winter conditions. From the fit to observations, climate simulations seem more realistic for Hoalp and Muhlv, somewhat less realistic for Gurk, and least realistic for Buwe.

### 4 Observed trends - extrapolation

## 4.14\_Methods\_used for the pillars

As a starting point, we are interested in evidence for climate change from the low flow observations. Similar to other studies, we performed trend analyses of annual low flow series, using the Sen's slope estimator (e.g. Stahl et al., 2010). Instead of fitting a regression line to all data points simultaneously, the trend is estimated as the median of all slopes between pairs of sample points. This makes the trend estimates insensitive to outliers and more suitable for heteroscedastic data.

For each station, analyses were performed for annual series of the Q<sub>95</sub> low flow quantile (i.e. the flow that is exceeded 95% of the time of the respective year). A common observation period (1976-2008) was used to make the trend estimates comparable across gauges. Based on autocorrelation analysis, we decided not to prewhiten the data (remove first order autocorrelation effects from the time series) as proposed in some studies, because the serial correlations in the annual low flow series were mostly insignificant. Significance testing of trends was performed using a standard Mann Kendall test. The results were finally compared with significance statistics of prewhitened series obtained by the Yue Pilon method for trendfree prewhitening (Yue et al., 2002) but there was almost no difference.

Under the assumption that observed changes are linear and persistent, the trends may be extrapolated as a simple, observation based scenario for future low flows. It is realised that this is quite a strong assumption, which will be more realistic for the near future than for a longer time horizon. Both the estimation of trends and their extrapolation into the future are clearly subject to considerable uncertainty that needs to be considered in the final combination of the three pillars. We therefore estimate expected low flows together with their confidence bounds. We use a simple linear regression estimator of the expected value in a specific year  $t_0$ : Formatiert: Kopfzeile

Formatiert: Überschrift 1, Einzug: Links: 0 cm, Hängend: 0,76 cm, Keine Aufzählungen oder Nummerierungen, Tabstopps: 0,76 cm, Listentabstopp + Nicht an 1,02 cm

## 1 4.1 Extrapolation of observed low flow trends

2 The stream flow records of the four stream gauges were analysed to estimate  $Q_{95}$  low flow 3 quantiles (i.e. the flow that is exceeded 95% of the time) for each year. The serial correlations 4 of these annual low flow series were mostly insignificant, so they were not prewhitened (Yue 5 et al., 2002). Trends were tested for significance by a standard Mann-Kendall test. The trends 6 were estimated as the medians of all slopes between pairs of sample points (Sen's slope, Sen, 7 <u>1968</u>) with regression parameters  $\hat{a}$  and  $\hat{b}$ :

$$\hat{Q}_{95}(t_0) = \hat{a} + \hat{b}t_0$$

8

(1)

9The uncertainty of the trends was assessed by a nonparametric bootstrapping approach, which10provides accurate confidence bounds in the case of non-Gaussian regression residuals (Efron11and Tibshirani, 1993). The approach simulates the uncertainty distribution of trend estimate at12time  $t_0$  by resampling 5000 replications from the annual  $Q_{95}$  series and calculating the13regression parameters  $\hat{a}$  and  $\hat{b}$  for each of them. Equation (1) applied to these parameter14distributions yields the uncertainty distribution of trend estimate at time  $t_0$ , and its 0.025 and150.975 empirical quantiles constitute the bounds of a two-sided 95% confidence interval.

For the purpose of this paper we assumed that the trends are linear and persistent, and so
 extrapolated them into the future. This is of course a strong assumption less likely to be valid
 with increasing time horizon.

## 19 4.2 Climate projections and runoff modelling

20 Four regional climate model (COSMO-CLM) runs were selected from the reclip:century 1 21 project (Loibl et al., 2011) forced by ECHAM5 and HADCM3 GCMs for three IPCC 22 emission scenarios (A1B, B1 and A2). These scenarios were selected for consistency with 23 other ongoing studies in Austria (e.g. Parajka et al., 2016). In order to check their realism with 24 respect to droughts and low flows, the Standardized Precipitation Evaporation Index, SPEI 25 (Vicente-Serrano et al., 2010) was evaluated, which is the Gaussian-transformed standardized 26 monthly difference of precipitation and evaporation. Values below zero indicate deficits in the 27 climatic water balance, and values below -1 indicate drought conditions. The SPEI has been 28 adopted here for its simplicity and because it can be calculated from the HISTALP data (Auer 29 et al., 2007) back to the year 1800. Haslinger et al. (2014) demonstrated that the SPEI is 30 correlated well with summer low flows in the study region. In the winter (Fig. 1, bottom 31 panels), the simulations (light red lines) for Hoalp and Muhlv seem to be more consistent with 32 decadal observed fluctuations from the HISTALP data set (red lines) than for Gurk and Buwe. 33 Note that the comparison should focus on the long term (decadal) dynamics rather than 34 individual years due to the nature of the climate simulations. Overall, SPEI remains rather 35 stable which is due to little change in winter precipitation. In the summer (Fig. 1, top panels), 36 the simulations are somewhat less consistent with the observations than for the winter, in 37 particular for Buwe where the simulations show a decreasing trend in the overlapping period 38 (1961-2003) while the observations show little change. Overall, the summer SPEI projections 39 show a decreasing trend indicating a dryer future and the trend tends to steepen beyond 2050. 40 This is mainly due to the precipitation characteristics of the ECHAM5 simulations used and not reflected in the other models or ECHAM5 runs. The extremely negative trends in the 41 42 summer SPEI should therefore be treated with caution.

Runoff is simulated by the delta change approach (e.g. Hay et al., 2000; Diaz-Nieto and
 Wilby, 2005). A conceptual rainfall runoff model (TUWmodel) is used here which simulates

Formatiert: Kopfzeile

**Formatiert:** Einzug: Erste Zeile: 1,25 cm, Zeilenabstand: einfach

1	the daily water balance components from precipitation, air temperature and potential				
2	evaporation inputs (Viglione and Parajka, 2014; Parajka et al., 2007; Ceola et al., 2015). The				
3	routing component of the model, which is most relevant for low flows, consists of a number				
4	of reservoirs with different storage coefficients. The model was calibrated against observed				
5	streamflow by the SCE-UA procedure (Duan et al., 1992). The objective function $(Z_Q)$ was				
6	chosen on the basis of prior analyses in the study region (see e.g. Parajka and Blöschl, 2008)				
7	<u>as</u>				
8	$\underline{Z}_Q = w_Q \cdot M_E + (1 - w_Q) \cdot M_E^{log} $ (2)				
9	where $w_0$ and $(1 - w_0)$ are the weights on high and low flows, respectively, and $M_E$ and $M_E^{log}$				
10	are estimated as				
10					
11	$\underline{M}_{E} = 1 - \frac{\sum_{i=1}^{n} (Q_{obs,i} - Q_{sim,i})^{2}}{\sum_{i=1}^{n} (Q_{obs,i} - Q_{sim,i})^{2}} $ (3)				
	$\sum_{i=1}^{N} (Q_{obs,i} - Q_{obs})$				
	$\sum_{i=1}^{n} \left(\log(0, \cdot, \cdot) - \log(0, \cdot, \cdot)\right)^2$				
12	$M_E^{log} = 1 - \frac{\sum_{i=1}^{n} (\log(q_{OBS,i}) - \log(q_{SIII,i}))}{\sum_{i=1}^{n} (4)}$				
	$\sum_{ij=1}^{\infty} \left( \log(Q_{obs,i}) - \log(Q_{obs}) \right)^{-1}$				
13	$Q_{obs,i=}$ Note that in our robust regression framework, $\hat{a}$ and $b$ are the Sen slope estimates of				
14	the regression parameters. The uncertainty of the trend estimate is given by the confidence				
15	bound of the regression line:				
16	$O_{\mu} = \left(\hat{z} + \hat{k}_{\mu} + z_{\mu}\right) = \left(\frac{1}{2} + \frac{(t_{\mu} - \hat{t})^2}{(t_{\mu} - \hat{t})^2}\right) $ (2)				
10	$\frac{Q_{95} \in \left(a + bt_0 \pm z_{n-2;1-\alpha/2} \cdot s_{n-1} + \frac{(a-1)s_{p}^2}{(n-1)s_{p}^2}\right)}{(2)}$				
17	Again, $\hat{a}$ , $\hat{b}$ are the Sen slope estimates of the regression parameters, $z_{n-2:1-\alpha/2}$ is the				
18	quantile of the Student distribution $(7 - 2.04$ for a two sided 05% confidence interval) n				
10	quantite of the Student distribution ( $z_{n=33}$ -2.04 for a two-sided 95% confidence interval), $\pi$				
19	is the sample size (number of observed years), t and $s_t^{\pm}$ the mean and the variance of t.				
20	Making use of the robustness of the Sen slope estimator, a robust estimate of the error				
21	variance s <sup>±</sup> may be obtained from b by:				
22	$s^{2} = \frac{(n-1)}{(n-2)} \left( s_{\theta}^{2} - \hat{b}^{2} s_{\xi}^{2} \right) $ (3)				
	$\left(\frac{n-2}{2}\right)$				
22	where $s^2$ is the variance of the annual $\Omega_{re}$ values. As can be seen from the squared term				
23	where s <sub>q</sub> is the variance of the annual Q <sub>95</sub> values. As can be seen from the squared term				
24	$(t_0 - \bar{t})^2$ in Eq. 2, the uncertainty is lowest at the mid point of the observation period and				
25	increases as one moves away from it. The confidence bounds therefore reflect the increasing				
26	uncertainty of extrapolations of the observed trends into the future.				
	· ·				

Formatiert	[1]
Formatiert	[2]
Formatiert	[3]
Formatiert	[4]
Formatiert	[5]
Formatiert	[6]
Formatiert	[7]
Formatiert	[8]
Formatiert	[9]
Formatiert	[10]
Formatiert	[11]
Formatiert	[ [12]
Formatiert	[13]
Formatiert	[14]
Formatiert	[15]
Formatiert	[16]
Formatiert	[17]
Formatiert	[18]
Formatiert	[19]
Formatiert	[20]
Formatiert	[21]
Formatiert	[22]
Formatiert	[23]
Formatiert	[24]
Formatiert	[25]
Formatiert	[26]
Formatiert	[27]
Formatiert	[28]
Formatiert	[29]
Formatiert	[30]
Formatiert	[31]
Formatiert	[32]
Formatiert	[33]
Formatiert	[34]
Formatiert	[35]
Formatiert	[36]
Formatiert	[37]
Formatiert	[38]
Formatiert	[39]
Formatiert	[ [40]
Formatiert	[41]
Formatiert	[42]
Formatiert	[ [43]
Formatiert	[44]
Formatiert	[45]
Formatiert	[46]

1 is the observed discharge on day i,  $\overline{Q_{obs}}$  is its average over the calibration (or verification) 2 period of n days, and  $Q_{sim,i}$  is the simulated discharge.

In order to assess the uncertainty of low flow projections from a hydrological modelling
perspective, different calibration variants were evaluated by varying the weights of Eq. (2),
following the methodology of (Parajka et al., 2016). In order to assess the impact of time
stability of the model parameters, the model was calibrated separately for three different
periods (1976-1986, 1987-1997, 1998-2008), following the methodology of (Merz et al.,
2011).

Air temperatures and precipitation of the four regional climate model runs were then
 evaluated for a reference period (1976-2008) and compared with two future periods (2021 2050 and 2051-2080) for each month separately. The differences (delta) were added to the
 observed daily air temperatures and precipitation values for the four catchments from which
 future stream flow was simulated using the rainfall-runoff model.

## 14 4.3 Extrapolation of stochastic rainfall characteristics and runoff modelling

 A stochastic model is used to investigate what would happen if the trend of observed precipitation and air temperature characteristics in the period 1948-2010 would persist into the future. The results of the stochastic model are used to drive a lumped version of the TUWmodel which is similar to the one used in the delta-change approach.

19 The precipitation model is the point model of Sivapalan et al. (2005) which simulates discrete 20 rainfall events whose storm durations, interstorm periods and average event rainfall intensities 21 are all random, governed by specified distributions whose parameters vary seasonally. The 22 model was run on a daily time step without considering within-storm rainfall patterns as the 23 interest was in low flows. A storm-separation algorithm was applied to the precipitation data 24 of the four stations, based on a minimum duration of dry periods, in order to isolate 25 precipitation events. From the event time series the temporal trends of three model parameters (mean annual storm duration, mean annual inter-storm period and mean annual storm 26 intensity) were estimated by the Theil-Sen algorithm, to serve as the trend components of the 27 28 precipitation model. The trends in these precipitation model components were subsequently 29 extrapolated into the future. Similar to the low flow extrapolation, this is a strong assumption 30 less likely to be valid with increasing time horizon. The remaining rainfall model parameters were calibrated to the precipitation data as described in Viglione et al. (2012) and were kept 31 constant for the entire simulation period. The stochastic rainfall model was finally used to 32 simulate an ensemble of 100 possible time series of precipitation affected by trends in the 33 three model parameters for the period 1948-2080. 34

For air temperature, instead, 100 possible time series were obtained by randomising the
observations in the following way. The time series of daily temperatures were detrended
according to the observed trend of mean annual temperatures, the years were randomly mixed
(with repetition), and the trend was added to the reshuffled series. The trend in the
temperatures was reflected by an analogous trend in potential evaporation.

40

## 1 4.25 Results

# 2 5.1 Extrapolation of observed low flow trends

Table 1 summarizes the results of the trend analyses. For two catchments, the trends are significant but with different signs. of Q<sub>95</sub> low flows. The Hoalp catchment exhibits a strongly positivesignificantly increasing trend indicating that the catchment has become wetter over the observation period. A negative trend is observed for while the Buwe catchment, which became dryer. Negative (drying) trends are also observed for the indicates a significantly decreasing trend. Muhlv and Gurk eatchments but these are show decreasing trends which are, however, not significant at the 0.05 level.

10 While our focus is on the four example catchments, it is important to put the local analyses in a regional context to avoid the detection of local effects on the flow regime, such as 11 anthropogenic impacts. Equally important, the regional context assists in a more meaningful 12 interpretation of regional climate scenarios that are valid for footprints of a few hundreds of 13 square kilometres or more. Figure 32 shows the trends of the four example gauges used in this 14 study, catchments together with trends atof 408 stream gauges in Austria and neighbouring 15 16 regions. The map indicates characteristictrend patterns for the study area, which correspond 17 well to are in line with the main hydro-climatic units represented by the four catchments. Significant positive trends (Significantly increasing dischargestrends (large blue points) such 18 as in the Hoalp catchment are generally found forin the Alpine region. Some 19 negativeDecreasing trends (decreasing discharges) are found in the southeast of Austria and in 20 Upper Austria in the large red points) occur north of the Alps but, here, the number of stations 21 22 with significant trends is low compared to the total number of stations and, more frequently, in 23 the Southeast of Austria. Additional regional analyses (not shown here), including field 24 significance testing, confirm the finding that the decreasing trends in the Southeast are more 25 significant than in the North. The Buwe region appears to be notably particularly affected by 26 climate change as low flows show a strong decrease at the end of the observation period-Trends in the Muhlv region north of the Alps are less severe, as they relate to single 27 catchments and do not show a consistent regional behaviour. Alpine catchments in the Hoalp 28 region, however, seem to have benefited from atmospheric wetting and this trend seems to 29 30 persist into the future.

31 Table 2 givespresents the projections obtained from trend extrapolation for the four 32 eatchments extrapolations together with their confidence bounds. The projections for the 33 period 2021-50 indicate an Extrapolating observed trends to 2021-2050 would give a 39% increase of low flows in the Q<sub>95</sub> for Hoalp catchment of 42% if the present trend persists until 34 35 2050. The, but the uncertainty of this projection is, however, quite large, as indicated by thea range of the confidence interval (5 from -7 to 88%). For 71%. Trend extrapolations for the 36 remainingother catchments, a decreasing trend is projected result in decreases which is 37 lowestare smallest in Muhlv (-108%), moderate in Gurk (-36%),%) and very stronglargest in 38 39 Buwe (-89%). Again, there is substantial-90%). The uncertainty when extrapolating the trends to the 2050 time horizon. For instance, the confidence interval of range is large, e.g. -40 41<del>Muhly ranges from 51</del>% to +32%,34% for Muhly, which is a range eight</del>almost ten times 41 the expected value of the projected changes. Hence, from the available dataset, trend 42 43 extrapolation can only provide a very approximate estimate of future low flows. .The mean 44 change. Clearly, trend extrapolations involve a lot of uncertainty, and this uncertainty 45 increases when predicting changes for a as one moves to the more distant time horizon of 2051-2080 (Table 2). The extrapolations result in ), including negative values discharges for 46 47 the discharge of the Buwe basin, and Gurk indicating that the stream may fall dry during the

#### Formatiert: Kopfzeile

Formatiert: Überschrift 1, Einzug: Links: 0 cm, Hängend: 0,76 cm, Keine Aufzählungen oder Nummerierungen, Tabstopps: 0,76 cm, Listentabstopp + Nicht an 1,02 cm

Formatiert: Zeilenabstand: einfach

low flow periodephemeral behaviour. Obviously, one would have very low confidence in the absolute figures of such trend scenarios for the more distant future.

#### Rainfall-Climate projections and runoff projections based on climate 5

## scenarios

## 5.1 Methods

A common method for projecting river discharge regime into the future is 5.2 the delta change approach (e.g. Hay et al., 2000; Diaz-Nieto and Wilby, 2005). The idea of this concept is to remove biases of regional climate model (RCM) simulations when using them as inputs to hydrologic models. First, a hydrologic model is calibrated for the reference period by using observed climate variables, typically precipitation and air temperature. In the next step, the differences between RCM simulations of the reference (control) and future periods are estimated on a monthly basis. These differences (delta changes) are then added to the observed model inputs and used in the hydrological modelling for simulating the future. The differences between the discharge simulations in the reference and future periods are used to assess potential impacts of a changing climate on future river flows. A conceptual rainfall runoff model (TUWmodel, Viglione and Parajka, 2014) is used here. The model simulates the water balance components with a daily time step based on precipitation, air temperature and potential evaporation data as inputs. Details on the model structure and applications are given in (Parajka et al., 2007) and (Ceola et al., 2015). TUWmodel is calibrated by the SCE UA automatic calibration procedure (Duan et al., 1992). The objective function  $(Z_{o})$  of the calibration is selected on the basis of prior analyses performed in different calibration studies in the study region (see e.g. Parajka and Blöschl, 2008). It consists of two variants of Nash Sutcliffe Model efficiency,  $M_E$  (Eq. 5) and  $M_E^{log}$ (Eq. 6) that emphasize high and low flows, respectively.  $Z_{\theta}$  is defined as  $Z_O = w_O \cdot M_E + (1 - w_O) \cdot M_E^{log}$ (4)

29

where  $w_Q$  represents the weight on high flows and  $(1 w_Q)$  the weight on low flows.  $M_E$  and 30

 $M_{F}^{log}$  are estimated as 31

32 
$$M_E = 1 - \frac{\sum_{i=1}^{n} (Q_{obs,i} - Q_{sim,i})^2}{\sum_{i=1}^{n} (Q_{obs,i} - \overline{Q_{obs}})^2}$$
(5)

Formatiert: Überschrift 2, Einzug: Links: 0 cm, Hängend: 1,02 cm, Mit Gliederung + Ebene: 2 + Nummerierungsformatvorlage: 1, 2, 3, ... + Beginnen bei: 1 + Ausrichtung: Links + Ausgerichtet an: 0 cm + Tabstopp nach: 0 cm + Einzug bei: 0 cm, Trennen, Tabstopps: 1,02 cm, Listentabstopp + Nicht an 0 cm

 $M_{E}^{log} = 1 - \frac{\sum_{i=1}^{n} (\log(Q_{obs,i}) - \log(Q_{sim,i}))^{2}}{\sum_{i=1}^{n} (\log(Q_{obs,i}) - \overline{\log(Q_{obs,i})})^{2}}$ 1 Where  $Q_{stm.t}$  is the simulated discharge on day i,  $Q_{obs,i}$  is the observed discharge, 2 average of the observed discharge over the calibration (or verification) period of n days 3 4 In order to assess the uncertainty of low flow projections from a modelling perspective, different variants of model calibration were evaluated by varying the weights of Eq. 4, 5 following the methodology of (Parajka et al., submitted to HESSD). In order to assess the 6 7 impact of time stability of model parameters, TUW model was calibrated separately for three

8 different decades (1976-86, 1987-97, 1998-08), following the methodology of (Merz et al., 9 2011).

#### 10 5.2 Results

11 Table 3 summarizes the runoff model efficiencies ZQ- The results indicate that the differences in runoff for different weights in the objective function.  $w_Q = 0$  emphasises low flows, while 12  $w_0 = 1$  emphasises high flows in the calibration. With the exception of Gurk, there is a clear 13 14 trend of increasing (calibration) model performance from high flows to low flows. The model 15 performance between the calibration decades are rather small, varies little. Overall, Hoalp 16 gives the largest efficiency which is a reflection of the strong seasonality associated with 17 snow storage and melt while Buwe gives the lowest efficiency is obtained for the Hoalp basin, which is characterised by a very consistent hydrological regime throughout the years (Fig. 4). 18 19 Snow accumulation and melt have a dominant effect on the hydrologic regime, as they affect 20 the timing of low flow periods in winter and flood events in summer. In contrast, the lowest 21 model efficiency is found for Buwe. The shape of most hydrographs is very due to the flashy 22 and thus verynature of runoff that is difficult to model on a daily time step. (Fig. 3). The 23 flashy runoff response of Buwe is related to shallow soils, efficient drainage and frequent 24 convective storms (see Gaál et al., 2012). Additionally, there are only two climate stations in 25 the catchments, which makes it difficult to captureBuwe catchment, so local precipitation 26 events such as summer storms. The fast runoff response is caused by shallow soils and 27 efficient drainage (see Gaál et al., 2012). Both low flow periods and floods mainly occur in 28 summer. may not always be captured well. The event variability is large between and within 29 the years (Fig. 4).-3). Both low flows and floods mainly occur in summer. As compared to other catchments in Austria (Parajka et al., submitted to HESSD2016), the Hoalp and Buwe 30 31 catchments represent typical conditions withof high and low model performanceperformances, respectively. 32 Figure 54 left shows the results of the model simulations in terms of simulated annual  $Q_{95}$  low 33 34 flow quantiles Q<sub>95</sub> in flows for the reference period 1976-2008. The hydrologic model is 35 calibrated for a selected decade, but the model simulations are performed, based on 36 calibrations for the entire reference period. The left panels of Fig. 5 showtwo subperiods 37 (yellow and blue), in each case indicating the variability of  $Q_{95}$  estimated from due to 11

Formatiert: Zeilenabstand: einfach

Formatiert: Tiefgestellt

Formatiert: Englisch (USA) Formatiert: Englisch (USA)

Formatiert: Kopfzeile

1 variants of objective functions. The range of Q<sub>95</sub> for the 11 calibration variants is plotted in

- 2 yellow and blue for the calibration periods 1976 86 and 1998 08, respectively, and their
- 3 overlap is plotted in green.

The calibration variants with different weights  $w_0$  in the objective function (Table 3). The 4 5 right panels show the simulations for two sets of weights (light orange and red), in each case 6 indicating the variability of  $Q_{95}$  due to model parameters obtained from different decades for 7 two weightings:  $w_0=0.5$  (light orange) and  $w_0=0.0$  (red). Although the model has not 8 specifically been calibrated directly to Q95 quantiles, it simulates Q95 rather well in the 9 example basins and the. The differences between the two weighting variants (Fig. 4 right) are 10 small-or moderate in absolute terms. The effect of temporal instability of the model 11 parameters is clearly visible in the Buwe and Gurk basins, where (Fig. 4 left), as the model 12 calibrated to the 1976-1986 period tends to overestimate Q<sub>95</sub> in the period 1998-2008. The 13 decade 1976-1986 represents a colder period with less evapotranspirationevaporation and 14 relatively higher runoff generation rates which is reflected by lower values of the soil 15 moisture storage parameter (FC) and lower values of the parameter controlling runoff generation (BETA). The model therefore overestimates runoff when applied to the drier and 16 17 warmer period 1998–2008. Even though Table 3 indicates that Buwe has the lowest model performance, this is not reflected in the Q<sub>95</sub> low flow simulations in Fig. 4. This is because the 18 19 model does not simulate the fast runoff fluctuations well, however, it does much better with prolonged drought spells. 20

21 Figure 5 further 4 also shows that the uncertainty of  $Q_{95}$  estimates is the largest in the Alpine 22 basin with dominant winter low flow regime. Alpine river regimes are characterised by a 23 greaterHoalp. The seasonal runoff variability of dischargesAlpine rivers is larger than that of 24 low-land regimes (Fig. 4). Because of this, rivers which makes the model calibration is more 25 sensitive to the weights assigned to high and low flows. The Alpine basinHoalp is also more 26 sensitive to the choice of the calibration period. The strong seasonality of the Alpine regime 27 which is a reflection of athe high sensitivity of discharge generation low flows to seasonal 28 climate. Decadal climate variation will therefore have a similarly strong effect on discharges and, through discharges, on model calibration. The strong sensitivity to weighting and the 29 30 calibration period are a result of the highly seasonal regime and make projections in Alpine 31 catchments more uncertain than in lowland catchments. In contrast, the uncertainty is smallest 32 in the Gurk and Buwe basinscatchments where, interestingly, the effect of time variability of 33 the model parameters is of similar magnitude as the effect of the weighting weights in the objective function. 34

35 Scenarios of air temperature and precipitation from the four RCM-climate model runs are 36 presented in Fig. 65. The largest warming in the four basins is obtained by simulations driven by-HADCM3. An with an increase of more than 2°C is projected forin January and the 37 summer months. The largest difference between the ECHAM5 scenarios occurs inIn January-38 39 While the ECHAM5-A2 run simulates a decrease in mean monthly air temperature, the A1B2 emission scenario projects and while the other runs simulate an increase in monthly air 40 41 temperature of almost 2°C in all selected basins. The ECHAM5 scenarios are consistent for 42 the summer months with an increase in air temperature of about 1°C. The precipitation 43 projections are regionally less consistent and vary mostly around  $\pm 15\%$ . Exceptions are the 44 HADCM3 run which simulates a decrease of almost 30% in the Gurk and Buwe 45 basinscatchments in August, and the ECHAM5-A1B2A1B run which simulates an increase of 46 about 30% in the Hoalp and Muhly basinscatchments in December.

Formatiert: Kopfzeile

Formatiert: Zeilenabstand: einfach

The delta change projections of low flow quantiles Q95 are finally presented in Figure 7. The 1 projections for the period 2021-2050 relative to simulated runoff in the reference period are 2 3 shown in Fig. 6. They indicate an increase of annual  $Q_{95}$  low flows  $(Q_{95})$ -in the Alpine Hoalp basin, on average catchment which is in the range of 15 to 30% and 20 to 45% for the different 4 5 climate projections and calibration weightingsweights, respectively. In the Muhly basin, no significant change in Q<sub>95</sub> is expected. The median of catchment, changes is in the range of 6 7 ±5%. Larger are small, while for Gurk and Buwe decreases are projected for Gurk (which are 8 around 7-13%)% and Buwe (15-20%). A comparison of uncertainty and range of future 9 projections indicates that the estimation of Q<sub>95</sub> is <u>%</u>, respectively. Q<sub>95</sub> is not only sensitive-not 10 only to the selection of the climate scenarios, but also to the selection of the objective 11 function and the calibration period. The uncertainty is largest in the Hoalp basincatchment, 12 where the selection of the objective function is more important than choice of the selection of 13 climate scenarios. The mean winter mean air temperature in the Hoalp basin is about -6.0°C 14 and the which is projected increases range from to increase by 2 to 2.5°C, depending on the 15 scenario. These differences are of little relevance for snow storage and snowmelt runoff during the winter low flow period. A large uncertainty and sensitivity to the choice of 16 objective function and calibration period is also obtained for the Muhlv and Buwe basins. 17 Only in the Gurk basin the sensitivity to the choice of objective function is smaller than the 18 time stability of model parameters. This is a result of the relatively high sensitivity to the 19 ealibration period (Fig. 5) in combination with relatively small differences between climate 20 21 water balances resulting from different scenarios (as reflected by the small spread of SPEI 22 projections in Fig. 2). The projections based on the period 1976 1986 tend to simulate a larger variability of Q<sub>95</sub> than those calibrated to the period 1998 2008, however the variability is 23 24 similar to Buwe and Muhl basins. Muhlv and Buwe are also sensitive to the choice of 25 objective function and calibration period, while for the Gurk the choice of climate scenario is 26 more important.

#### 28 6 Stochastic projections based on rainfall model extrapolation

# 29 6.1 Methods

27

While in Section 4 observed trends of Q<sub>95</sub> were extrapolated, and in Section 5 RCM scenarios 30 were used to anticipate future low-flows, this section adopts a different approach which, 31 32 conceptually, is between the two. We use a stochastic model to investigate what would happen if the trend of observed precipitation and temperature in the period 1948 2010 would 33 persist into the future. The stochastic model allows us to simulate future time series of climate 34 35 drivers based on extrapolating components of precipitation and temperature models. These 36 simulations are then employed to drive the rainfall runoff model of Section 5. 37 The precipitation model used here is the point stochastic model of (Sivapalan et al., 2005).

38 The model consists of discrete rainfall events whose arrival times (or interstorm periods),
 39 duration and average rainfall intensity are all random, governed by specified distributions

40 whose parameters are seasonally dependent. In this paper, the model was run on a daily time

Formatiert: Kopfzeile Formatiert: Zeilenabstand:

einfach, Trennen

No fractal temporal downscaling of within storm rainfall intensities was performed. 1 2 since the interest was in low flows which are not expected to depend much on within storm 3 time patterns. For air temperature, instead, the-100 possible time series were obtained by randomising the 4 5 observations in the following way. The time series of daily temperatures were detrended

6 according to the observed trend of mean annual temperatures, the years were randomly mixed

7 (with repetition), and the trend was added to the reshuffled series. The trend in the

8 temperatures was reflected by an analogous trend in potential evapotranspiration.

9 A storm separation algorithm was applied to the precipitation data of the four stations, based

on a minimum duration of dry periods, in order to isolate precipitation events. The temporal 10

11 trends of three rainfall model parameters (mean annual storm duration, mean annual inter-

12 storm period and mean annual storm intensity) were then estimated from the event time series

13 with the Theil Sen algorithm, to serve as trend components in the stochastic precipitation model.

# 14

#### 15 Extrapolation of stochastic rainfall characteristics and runoff modelling 5.3

16 Figure <u>87</u> shows that the estimated trend components fit well to the precipitation statistics. Annual mean storm duration decreases quite strongly for the Alpine Hoalp eatchment (by 17 about -0.8 days / 100 yrs). There is also a slight decrease for the Gurk (-0.4 days / 100 yrs) 18 19 and Buwe eatchments (-0.3 days / 100 yrs). -Interstorm period and storm intensity (Fig. 87, 20 centre and right panels) show no significant changes for most regions, apart from the Gurk 21 catchment-where the annual mean interstorm period increases by about 1 day / 100 yrs, and 22 annual mean storm intensity increases by 2 days /mm/day per 100 yrs (which is a 30% 23 increase per 100 yrs .- ). The trends in these precipitation model components were subsequently 24 extrapolated into the future.- The remaining rainfall model parameters were calibrated to the 25 precipitation data as described in (Viglione et al., 2012) and were kept constant for the entire 26 simulation period. The stochastic rainfall model was finally used to simulate an ensemble of 27 100 possible time series of precipitation affected by trends in the three model parameters for 28 the period 1948-2080.

#### 29 6.2 Results

30 Figure 9 shows the The stochastic simulations of (Fig. 8) indicate no trends in mean annual 31 daily precipitation and mean annual temperature for the four example catchments, together 32 with the observed signals. No trends of precipitation (left panels) are visible for Muhlv in the 33 North and Gurk in the South. A- of Austria, a drying trend is visible for Buwe in the Southeast 34 and for the Alpine-Hoalp catchmentin the Alps, but in the latter case the observations exhibit 35 a rather complex signal which seems not well represented by the linear model. Temperature simulationsThe simulated temperatures (Fig. 98, right panels) correspond much better toare 36 37 more consistent with the observations. They consistently show with a persistently increasing

Formatiert: Zeilenabstand: einfach

Formatiert: Zeilenabstand: einfach

Formatiert: Kopfzeile
1 trends for the whole study area<u>trend in all catchments</u>. The trend is most pronounced in the 2 Alps (+ 4.4 °C / 100 yrs), somewhat less pronounced in the South and Southeast (+2.8 and 3 +2.6 °C / 100 yrs), and there is only a weak trend in the North (+1.7 °C / 100 yrs)<del>,</del> of Austria.

4 Figure  $\frac{109}{100}$  shows the stochastic projections of annual runoff and  $Q_{95}$  low flows (red lines) 5 together with the observations (black line) for part of the period.lines). For the-Hoalp region (Fig. 10, (top row)  $Q_{95}$  decreases only slightly- despite the simulated large decrease of annual 6 runoff and precipitation. This is because winter low flows are more controlled by air 7 8 temperature temperatures which would be expected to increase the low flows, and the two 9 effects essentially cancel. For the Muhly region (second row in Fig. 109), the model 10 extrapolates a slight reduction of  $Q_{95}$  in the future, even though there is hardly any change in 11 the annual precipitation (second row in Fig. 98), which is due to increases in the 12 evapotranspiration.evaporation. For the-Gurk region (third row in Fig. 109), the model also 13 extrapolates a slight decrease in Q95. This change echoes both which is a result of the 14 increasing trends in evapotranspirationboth evaporation and in-the interstorm period (Fig. 97 15 and 8). For the Buwe region (bottom row in Fig. 10) the extrapolated reduction9), the extrapolations yield a moderately decreasing trend of  $Q_{95}$  is quite important. In this case, the 16 annual which results from the combined effect of slightly decreasing precipitation slight 17 decreases (Fig. 9), which adds to the effect of theand increasing 18 19 evapotranspirationevaporation.

20 The underlying assumption of observed trends in precipitation and temperature to persist into 21 the future is quite strong. In contrast to Section 4the other pillars, here we do not consider the 22 uncertainty associated with the estimation (and extrapolation) of the trends. The confidence 23 bounds in Figures 10Fig. 9 and 11 are associated with 10 represent the modelled variability of 24 the low-flow producing processes, as represented by the stochastic precipitation and 25 temperature models, which are assumed to be known both in the present and in the future. 26 Despite the strong assumption assumptions made, it should be noted that the results of this 27 approach are non-trivial-and very interesting in their own right. For instance, as the way the 28 trends in precipitation and temperature translate into trends in low-flows differs between the 29 catchments because of the nonlinear hydrological processes process interactions between 30 precipitation and temperature...

#### 32 **76** Three-pillar synthesis

31

33 **7.1<u>6.1</u>** Combination of information

34 The concept of multi-model ensembles starts from the premise that (a) a group of model 35 projections will give more reliable results than the individual analyses project low flow changes from different sources of information. The first pillar, trend extrapolation, exploits 36 the temporal patterns of observed low flowsmodels alone and extrapolates them into the 37 38 future. The second pillar, rainfall runoff projections is based on climate scenarios(b) the 39 consistency/inconsistency of precipitation and temperature to drive a rainfall runoff model. 40 The third pillar, stochastic the model results is an indicator of the robustness or reliability of the projections, exploits the temporal patterns of observed precipitation and temperature and 41 extrapolates them into the future in a stochastic way to drive a rainfall runoff model. From the 42

**Formatiert:** Einzug: Links: 0 cm, Hängend: 1,02 cm, Zeilenabstand: einfach, Tabstopps: Nicht an 0 cm assessments it is clear that the individual projections are rather uncertain because of limited

#### 2 data and uncertain models or assumptions.

3 The (Knutti et al., 2010). In the context of the three-pillar approach proposed here, the methods and information used in each pillar are largely independent from each other, so one 4 5 would also expect the errors to be close to independent. A, and a combination of the projections should therefore indeed increase the overall reliability of the projection. The 6 7 combination is We will evaluate heuristically to what degree this premise can be achieved here 8 bybased on hydrological reasoning based on and visual comparison comparisons of synoptic plots of the individual estimates and their respective confidence bounds. The reasoning 9 10 accounts for the differences in the nature of the uncertainties of the projections and gives 11 more weight to the more reliable pieces of information. 12 When combining comparing the projections two cases exist. In the first case, projections are

13 consistent within their confidence bounds. This will lend credence to all projections as they

- 14 | support each other<del>. The confidence one has in the projection will depend on how strongly the</del>
- 15 pillars agree, and on their individual uncertainties. The overall uncertainty will be expressed
- 16 here as three levels of confidence (high, medium, low), which is in accordance with the
- 17 uncertainty concept of the IPCC report (Field and Intergovernmental Panel on Climate
- 18 Change, 2012).

1

19 , in particular if the changes of the driving hydrological processes (precipitation, snow storage 20 and melt, evaporation) are consistent. The overall uncertainty will be expressed here as three 21 levels of confidence (high, medium, low) (Field and Intergovernmental Panel on Climate 22 Change, 2012). In the second case, the individual projections are not consistent within their 23 uncertainty bounds which will suggest lower confidence in the overall projections. Rather 24 than simply averaging the individual projections, here, the analysis aims at understandingwe 25 explore the reasons for the disagreement, by checking the credibility of each projections projection based on the data used and the assumptions made. The confidence 26 bounds of the individual projections are a starting point for assessing the credibility of each 27 28 pillar. Additionally, the plausibility of the precipitation and temperature scenarios simulated 29 by the climate model can be checked by comparing them with the observations. The plausibility of the trend extrapolations can be checked, at least for the immediate future, by 30 examining the consistency of the trend within the observations. 31

- 32 **7.26.2** Application to the study area
- The synthesis plots for the four regions in Austria are presented in Fig. 11. Each panel
   provides a synoptic view of the three pillar projections. Observed annual low flows as plotted
   as black lines. Trend estimates and confidence bounds are plotted as blue lines. As can be
   seen, the uncertainties increase drastically with the extrapolation length.
- 37 The climate scenario based rainfall runoff projections are given as box plots representing the
- 38 averages of each of the two time horizons, 2021 2050 and 2051 2080. The ranges of the box

**Formatiert:** Einzug: Links: 0 cm, Hängend: 1,02 cm, Zeilenabstand: einfach, Tabstopps: Nicht an 0 cm

**Formatiert:** Zeilenabstand: einfach

Formatiert: Kopfzeile

Formatiert: Zeilenabstand: einfach

plots indicate different parameters of the hydrological model, and colours indicate climate 1 2 scenarios. Model simulations for the observation period are shown as grey lines. They allow 3 conclusions about the performance of the rainfall runoff modelling. 4 Finally, the red lines represent the stochastic simulation runs for the past and the future from 5 which confidence bounds (dashed and dotted lines) were calculated. Figure 10 compiles the  $Q_{95}$  projections from the three pillars, and Fig. 11 shows their 6 probability density functions for the period 2021-2050. 7 8 For the Hoalp region in the Alps (Fig. <u>410</u>, top left), both the extrapolation of observed low 9 flow trends and the climate scenario based rainfall runoff projectionsscenarios suggest 10 increases in low flows. In this region, low flows occur in winter due to snow storage processes which are mainly driven by seasonal temperature. This process should be captured 11 12 well by the climate scenarios, which tend to simulate temperatures more accurately than precipitation. In fact, (Schöner et al., 2012) (Fig. 3). Schöner et al. (2012) showed that the 13 14 temperature scenarios correspond well with regional climate models are able to simulate the 15 observed increase of winter temperature temperatures in the Alpine region since the 1970s-The plot does show well, which suggests that the rainfall-runoff projections from 16 different winter low flow changes are captured well by the climate scenarios. However, a lot 17 18 of uncertainty is introduced by the parameterisations vary strongly of the rainfall-runoff 19 model as indicated by the wide boxes in Fig. 10. This uncertainty is mainly due to the lower low flow performance of rainfall runoff models in sensitivity of the simulations to the model 20 21 parameters in an Alpine landscapes.environment (Fig. 4 and 6). From a regional perspective, 22 (Fig. 2), the observed low flow trends are significant, i.e. the percentage of stations with a 23 significant trend is significantlymuch greater than expected by chance (Blöschl et al., 2011; 24 Laaha at al., in preparation). This finding adds credence to the low flow trend extrapolation, 25 as on can assume). This means that the observed air temperature trends will persist 26 intoclimate scenarios and the future.trend extrapolations can be reconciled, at least in terms of 27 the sign of the changes. The stochastic projectionsextrapolations, in contrast, predict a project no or even slightly decreasing low flow trend which is inconsistent with the other two 28 29 pillars.trends. A closer inspection of the stochastic model components observed air 30 temperatures suggests that the temperature trends in the Alps are not captured well by the model. This is because the model is based on annual temperature parameters, but the winter 31 temperature changes do differ from those of the annual means, winter temperatures (+0.65 32 °C/10 yrs) have changed more by half than the annual average (+0.46 °C/10yrs in the period 33 1976-2010). However, the stochastic model assumes a constant change throughout the year 34 which results in underestimates of future  $Q_{95}$ . Of course, the model could be straightforwardly 35 36 extended to include seasonal variations in the changes but, as it is now, it nicely illustrates the case of an inconsistency that is well understood. Because of this, little weight is given to the 37 stochastic projections in the overall assessment. From the combined information of observed 38 low flow trends and climate projections of low flows, and one would expect an increase in 39 40 low flows by at least 20-40% for the 2020-2050 period (with medium to high confidence) and an increase by at least 30 50% for the 2050 2080 period (medium confidence). ..... 41 42 For the Muhlv region north of the Alps, the extrapolation of observed low flow trends corresponds well with the stochastic projections (Fig.  $\frac{+10}{10}$  top right). Both methods project a 43 slightly decreasing trend, corresponding to a slight reduction of about 5-10% for the 2020-44

45 2050–2021-2050. Seasonal air temperature trends are similar to the annual trends (0.43

Formatiert: Zeilenabstand: einfach

Formatiert: Kopfzeile

°C/10yrs in the period-1976-2010), so the structure of the stochastic model is appropriate 1 here. The rainfall-runoff simulations capture the observed trend well for the observation 2 3 period so also the future simulations will likely be reliable in terms of the hydrological 4 processes. From the elimate. The elimate scenarios predict a slight increase in Q<sub>95</sub> for the 5 near future would be projected. This is somewhat contradictory to the trend extrapolation and 6 stochastic projections but still lies in the confidence bounds of these methods. Low flows in 7 this region occur in summer and are therefore more precipitation driven than temperature 8 driven, so the climate scenario based rainfall runoff projections are likely less reliable. 2021-9 2050 but there is a lot of variability between the scenarios (also see Fig. 5). On a regional 10 level, Blöschl et al. (2011) and Laaha et al. (in preparation) reported littleno field significance 11 of the observed low flow trends in this region which fits well into the findings of, together 12 with the three-pillar projections. Overall there is perhaps pillars here suggests a slight 13 tendency for decreasing dischargeslow flows in the 2020-2050 period but this trend is not 14 strong. This conclusion is relatively certain (with medium confidence) because of the good 15 agreement of all individual assessments. For the 2050-2080 period further in the future, the low flow trend extrapolation will be less reliable, as reflected by the wide confidence bounds, 16 but it is consistent with the decreasing trend of the stochastic projections. The climate 17 scenario based rainfall-runoff projections suggest a stronger drying trend, corresponding to a 18 reduction of about 50 60%. The range of different rainfall runoff projections is outside the 19 20 confidence bounds of the stochastic projections. Low flows are precipitation driven in this 21 area and so the confidence in the rainfall runoff projections should be low. Overall, this 22 suggests a slight drying trend for the 2050 2080 periodall methods become more uncertain, 23 but all point towards a drying trend (low to medium confidence).

24 The Gurk region south of the Alps (Fig. 4410 bottom left) shows a somewhat similar 25 behaviour to that of Muhly, although the observed low flow pattern is rather nonlinear. There 26 is with a decreasedrop at the beginning of the observation period followed by observations 27 and a flattening out after 1990. The Extrapolating a linear trend model does not fit very well 28 to the observed low flows which reduces the confidence one should have in this pillar. 29 However, the observations are reproduced quite well by the stochastic projections. The 30 slightly decrease by around 10 to 20% until 2080. The climate scenario based rainfall runoff 31 projections increase for the 2020 2050 period and decrease for the 2050 2080 period, the latter by about 50 to 60%. However, the performance of the model is low as can be seen by a 32 comparison of the simulated low flows (grey in low flows may therefore not be reliable. The 33 34 stochastic projections are more in line) with the observed low flows (thin black line). 35 Asobservations, and indicate a consequence, slight decrease until 2080. Winter SPEI in the rainfall-runoff projections seem to be less reliable. Nevertheless, period 1961-2003 is not 36 simulated well (Fig. 1) which suggests issues with the rangeseasonal water balance of 37 different rainfall runoff projections is still within the confidence bounds of GCM based 38 simulations. However, the climate scenario projections are in line with extrapolated trends 39 and stochastic projections. Combining all pieces of evidences, one would expect no 40 41 significant change All pillars point to a slight to moderate drying trend in low flows for the 42 2020-2050 period (medium confidence) and towards a somewhat stronger drying trend-of about 20-30% for the 2050-2080 period (low to medium confidence). 43

The Buwe region in the South-east gives biggerlarger changes (Fig. <u>110</u>, bottom right). The
observed low flow trends are strongly influenced by the recent dry years between 2000 and
2005. This which is consistent with the regional behaviour corresponds with the nonlinear,
increasingly drying trend detected by (Fig. 2 and Blöschl et al. (2011) and Laaha et al. (in
preparation). However, a.)). A linear trend extrapolation of the magnitude as estimated is,

however, does not seem very plausible given that, in particular because the most recent year 1 in the data set (2008) was less dry. In fact, more recent data for 2009-2014 (not included in 2 3 the analysis) show that low flows have partly recovered (annual Q95 values ranging from 0.1 to  $0.3 \text{ m}^3 \text{s}^{-1}$  illustrating the limitations of trend extrapolation. The stochastic projection yields 4 5 a moderately decreasing trend, which is more plausible. The change is about 15% and 25% 6 for the two projection periods. An examination of the model components suggests that the 7 predicted changes are due to an, and related to both increasing trend in temperature (Fig. 9-8 right column, high confidence) and a slightly temperatures and decreasing precipitation (Fig. 9 8). The climate scenarios give slightly stronger decreasing trends for the two periods, but it 10 should be noted that, in contrast to the other catchments, the summer SPEI trend in the period 1961-2003 is not captured well and likely overestimated by the climate simulations (Fig. 1, 11 12 top right). Fig. 2 shows consistently decreasing trend in precipitation (Fig. 9 left column, 13 medium to low confidence). The simulated signals correspond well with observed climate 14 signals in thistrends of observed streamflow in the region. By comparison, climate projections 15 seem to overestimate low flows for the nearer future relative to the stochastic simulations, but correspond well with the projections for 2050 2080. A regional trend analysis (Fig. 3) shows 16 17 consistent behaviour in the Buwe region. Overall, there is moderate confidence in a slight Overall, the pillars therefore point towards a slight to moderate drying trend for 2020-2050, 18 and a stronger drying trend for the 2020 2050 period, and a stronger drying trend of about 20-19 30% for the 2050-2080 period 2050-2080 with medium confidence. 20

#### 22 87 Discussion

21

#### 23 8.1 Realism of trend scenarios

#### 24 7.1 Extrapolation of observed low flow trends

25 The trend scenarios are based on the assumption that changes are linear over time. This is a 26 simplifying view of non-stationarity-which, however, is parsimonious. Although the. The 27 Earth system is clearly non-linear, these often regime shifts are observed rather than trends. These can be detected in a similar way as trends (see, e.g., Rodionov, 2006) but it is more 28 29 difficult to make assumptions of persistence of change than for the case of linear trends. In the 30 European Alps, annual air temperatures in the European Alps have increased linearly since the mid-1970s, so a continuing trend is an obviousa plausible assumption. Similar to spatial 31 low flow models (Laaha and Blöschl, 2006), seasonality plays an important role in for the 32 near future. Trends in air temperatures translate into changes in low flows in a non-linear way 33 and this depends on the time trends of low flows. In the Alps, year low flows occur in winter 34 35 as (Laaha and Blöschl, 2006). Winter low flows are a consequence of frost and snow storage and these processes are closely related to air temperature. A trend in air temperature would 36 37 therefore be expected to directly translate into, which is reflected by a remarkable co-38 behaviour of observed low flows (Blöschl and Montanari, 2010). This is borne outwith 39 temperature for the Alpine Hoalp catchment (Fig. 1110 top left) which exhibits a remarkable 40 co behaviour with temperature.).

# For the other catchments that exhibit a summer low flow regime, the past changes of low flows are more subtle. Here the flow records seem too short to conclude about low flow trends, so we need additional, external information. (Haslinger et al., 2014) found that the

	•	Eormatier
1	SPEI representing the net precipitation input to the catchment is a good proxy of summer low	Formatien
2	flows and this is supported by a comparison of the trends in SPEI for the summer (Fig. 2,	
3	upper panels) with the low flows in the summer dominated regions (Fig. 11, Muhlv, Gurk,	
4	Buwe). Interestingly, projected SPEI signals (Fig. 2) do not flatten out at the end as it is the	
5	case for the SPEI based on observations, and a similar effect cam be observed for low flow	
6	trends and observations. SPEI of climate scenarios are in line with low flow trends, and both	
7	point to a decrease of low flows that extends to the future. These trends are rather weak for	
8	Muhly in the North but pronounced in The flow records are rather short, so discerning trends	
9	from long range fluctuations is difficult (Montanari et al., 1997). Gurk in the South. For the	
10	Buwe catchment SPEI values suggest a similar decrease as Gurk basin but here the temporal	
11	pattern of low flows is different and not easy to interpret.	
12 13 14 15 16 17 18 19 20 21 22 23 24 25 26 27 28	In all cases, the uncertainty of the trend scenarios is large, as indicated by the wide confidence bounds. It should be noted that the confidence bounds are conditional on the assumption that the linear trend model applies. If one relaxed this assumption, the bounds would be even wider. Part of the uncertainty comes from the relatively short record length (33 years). For example, (Hannaford et al., 2013) have shownHannaford et al. (2013) showed that low flow trends in European regimes are subject to pronounced decadal-scale variability so that even post-1960 trends (50 years) are often not consistent with the long-term pieture. Laaha et al. (in preparation) concluded from the magnitude of decadal trend variability in Austria that more than three decades are needed for recognizing the nature of trends as a basis for obtaining robust estimates. Overall, the trend scenarios of catchments with summer low flow regime are less reliable than those for winter low flow regimes, but they do constitute a scenario of a possiblepattern. Long climate records may assist in trend detection. Haslinger et al. (2014) found that the Standardized Precipitation Evaporation Index (SPEI) is a good proxy of summer low flows in the study area where the HISTALP data set (Auer et al., 2007) allows analysing climate fluctuations back to the year 1800 (Fig. 1). The decreasing trends of summer SPEI from the climate projections (Fig. 1) are in line with the low flow trends in Muhlv and Gurk, and both point to a decrease of low flows that extends into the future.	Formatier
29	8-27.2 Uncertainty of rainfall-runoff Climate projections and runoff modelling	Formatier Hängend:
30	The realism of predicted impacts is also a key question for the rainfall runoff Similar to the	einfach, Ta
31	ensemble projections based on climate scenarios. We performed an assessment of uncertainty	
32	of low flow projections, using a similar ensemble based framework as in the studies of (Wong	
33	et al., 2011) for Norway, (Majone et al., 2012) for the Gállego river basin in Spain, and (De	
34	Wit et al., 2007) for Meuse river in France. Weof Wong et al. (2011), Majone et al. (2012)	
35	and De Wit et al. (2007) we assessed the uncertainty arising from the choice of the climate	
36	model and the emission scenario by an ensemble of three equally possible emission scenarios	
37	and two different climate models (ECHAM5 and HADCM3). Unlike (De Wit et al., 2007) we	
38	. We did not assess possible downscaling errors, as De Wit et al. (2007) did, as we believe	
ļ	27	

#### tie r**t:** Kopfzeile

t: Zeilenabstand: einfach

r**t:** Einzug: Links: 0 cm, 1,02 cm, Zeilenabstand: bstopps: Nicht an 0 cm that RCMs tend tothey usually play a minor role when using a delta change approach which accounts for local effects.

1 2

3 that applies a change factor to locally observed signals. Uncertainty of arising from the 4 hydrological part of the model cascadestructure may also be assessed by a model ensemble 5 (e.g. Habets et al., 2013). We Habets et al., 2013) but we have chosen to focus on the 6 parameters instead. We show, for the case study. The results suggest that the  $Q_{95}$  projections are not only sensitive not only to the selection of climate scenarios, but also to the 7 8 selection choice of climate scenarios, but also to the objective function and the calibration 9 period. The ealibration-uncertainty is-associated with the objective function is largest in the 10 Alpine Hoalp basincatchment, where the winter low flow regime is less sensitive tostrong 11 streamflow seasonality makes the projected increase of air temperature. When comparing 12 results from different weighting between high and low flows particularly important. The uncertainty associated with the calibration periods, the effect of temporal parameter instability 13 14 is clearly visible period is largest in the Buwe and Gurk basins where parameters from a colder 15 period with less evapotranspirationevaporation tend to overestimate runoff in warmer periods. 16 A similar effect is expected for a future, warmer climate, so the projected low flows may decrease more strongly than the projected average. This finding is in contrast with (Hay et al., 17 18 2000) who identified This finding may depend both on model type and the climate region. Hay 19 et al. (2000), for example, found a minor role of the hydrological model. The difference may 20 be related to Hay et al. (2000) only assessing hydrological model performance of best fit 21 models and not accounting for uncertainty arising from calibration variants and for three river 22 basins in the US, although they did not specifically examine the time stability of model parameters. On the other hand, the finding in this paper is in line with (Bosshard et al., 2013). 23 24 The similarity may be due to the proximity of study areas with similar climate and catchment 25 controls, and the similar sources of uncertainty Bosshard et al. (2013), on the other hand, 26 suggested that the hydrological model accounted for-

Even though the analysis in this paper provides a proxy of uncertainty rather than a direct
statistical measure they are considered very useful in the context of the three-pillar framework
as they may assist in the process reasoning. For example, because of the more important role
of air temperature <u>5-40%</u> of the total streamflow ensemble uncertainty in the Alpine
catchments one can have higher confidence in the scenarios than in the lowlands.

Formatiert: Kopfzeile

#### 8.3 Potential of stochastic simulations

1

2

3

4

5 6

7

8

9

As opposed to low flow trends and rainfall runoff projections, which are widely used in elimate impact studies of low flows, stochastic simulations are relatively rare. The main strength of the stochastic model is that it accounts for the local trends of precipitation and air temperature and captures the stochastic variability of climate. It therefore provides information complementary to Rhine. Similarly, Samaniego et al. (2013) found that of the elimate scenarios. accounting for hydrological model parameter uncertainty is essential for identifying drought events, and multi-parameter ensembles were efficiently able to identify the magnitude of that uncertainty. ExtrapolatingLow flow projections are challenging because low flows are typically driven by

10 groundwater discharge processes (both recharge and discharge). These processes are difficult 11 to understand and model due to their local nature. Fleckenstein et al. (2006), for example, 12 13 found that the percentage of river channel responsible for 50% of total river seepage during 14 low flow conditions in the Cosumnes River, California ranged from 10 to 26% depending on the spatial configuration of hydrogeologic heterogeneity. This heterogeneity has not been 15 resolved in the present study and is rarely resolved in catchment scale climate assessment 16 studies. It is therefore important to note that, while the climate drought processes tend to be 17 rather large scale, the catchment response during low flow periods can have specific local 18 19 effects which differ from those of the larger scale pattern.

#### 20 7.3 Extrapolation of stochastic rainfall characteristics and runoff modelling

Stochastic models of rainfall characteristics can be conditioned to future climates in a number 21 22 of ways (see, e.g. Hall et al., 2014). A common method is to first calibrate the model 23 parameters to the current climate and then adjust the parameters to precipitation from climate scenarios at daily, seasonal and annual time scales (e.g. Hundecha and Merz, 2012; Blöschl et 24 25 al., 2011). To illustrate the three-pillar approach we have adopted here the very simple 26 assumption of extrapolating the trends in the rainfall model parameters and air temperature 27 trends involves a similar temperatures linearly into the future. The reasoning-as the-, and the 28 limitations, are similar to the direct trend extrapolation of low flow trends discussed above 29 and builds flows, building on the inertia of the climate system. Consequently, the extrapolation 30 of temperature may will be more appropriate than those that of precipitation and the extrapolation into the near future maywill be more appropriate than those that into the more 31 32 distant future. The model we use (Viglione et al., 2012) makes some simplifying assumptions which could 33

34 be easily relaxed. First, the long range dependence of streamflow (Szolgayová et al., 2014)

- 35 could be considered by extending the stochastic precipitation model (e.g. Thyer and Kuczera,
- 36 2003). Second, the correlations between precipitation and air temperature could be accounted

37 for (Hundecha and Merz, 2012). Third, changes in seasonal temperatures could be

- 38 incorporated in the model as they do seem to play a role in some of the catchments.
- 39 As the main point of the stochastic model was to illustrate the three-pillar approach, we
- 40 believe that it provides an attractive method that complements the traditional climate impact
- 41 studies on hydrology.

**Formatiert:** Kopfzeile

Formatiert: Zeilenabstand: einfach

#### 8.4 Benefits of the synthesis

1

2 The rationale of the three pillar approach is that different data and methods of the three pillars 3 will result in errors that are, at least partly, independent. Combining the pillars therefore involvesAlternative stochastic models could be used within the same three-pillar framework. 4 5 The model could be adjusted to climate scenarios in a similar ways as the model of Hundecha 6 and Merz (2012), and correlations between precipitation and air temperature could be 7 accounted for. Also, the long range dependence of streamflow (Szolgayová et al., 2014) could 8 be considered by extending the stochastic precipitation model (e.g. Thyer and Kuczera, 2003). 9 This will result in more complex patterns of future simulated low flows.

#### 10 7.4 Assessing the value of synthesis

11 <u>Climate impact and assessment studies in hydrology have traditionally been dominated by the</u>

12 paradigm of modelling cascades (Blöschl and Montanari, 2010), so a fresh look at the

13 problem for the particular case of low flows opens up a number of benefits.

14 First, the synthesis framework may assist in obtaining a judgement about the credibility of the

15 individual approaches and increases the reliability of the overall assessment.opportunities.

16 The three pillar approach allows for a diverse set of methods based on different assumptions

17 and data to be compared and combined in a coherent way. For the case study catchment

18 Muhlv in the region north of the Alps, for example, consistently small low flow changes are

19 predicted projected by all methods. The fact that all methods yield similar results which adds

20 credence to allthe projections as they support each other.

21 Second, the synthesis. The synthesis framework proposed here puts a lot of emphasis on 22 heuristic process reasoning. This may contribute to a better understanding of the low flow 23 response of low flow regimes to a future changed climate. For the case study catchment Buwe 24 in the Southeast, for example, the observed low flow signal shows a non linear drying trend. 25 Anto a future climate than a mere examination of the model components of the stochastic 26 scenario results. For an alpine region such as Austria the key to understanding low flows is 27 whether they are controlled by freezing and snow melt processes, or by the summer moisture 28 deficit associated with evaporation. Understanding of the key processes helps putting the 29 projections suggests that the predicted changes are due to an from the diverse methods into perspective. For example, for the Alpine Hoalp catchment this reasoning points towards 30 increasing trend in temperaturelow flows which is also consistent with all three pillars 31 32 adopted here. In a similar way, Luce and Holden (2009) and a slightlyLuce et al. (2013) 33 explained decreasing trend inlow flow trends in the Pacific Northwest of the US by declines in mountain precipitation. GCM scenarios correspond well with these trends, and this in turn 34 35 lends a relatively high credence to the rainfall runoff projections of climate 36 scenariossuggested that this trend will persist into the future.

Third, it is believed that the The three pillar approach allows also provides opportunities for a
 more complete wayassessment of assessing the uncertainty of the projections. For the case
 study catchment Hoalp in the Alpine region, trend projections and climate scenarios yield
 consistent projections of increasing low flows, although of different magnitudes. The inter-

Formatiert: Kopfzeile

comparison of allmulti-model ensemble premise of variations between ensemble members 1 being an indicator of projection uncertainty is consistent with the case study findings of this 2 3 paper. For example, the comparisons of the methods including process reasoning in every analysis step enables us to better assess their individual uncertainties. This information is vital 4 5 for weighting the projections when performing a synthesis, to gain a more informed estimate 6 of expected changes and their uncertainties. For for the Hoalp catchment highlighted issues 7 with the assumption of a uniform seasonal temperature change of the stochastic model, so less 8 credibility was given to this pillar in this particular case. For the Buwe catchment, non-linear 9 changes of observed low flows shed doubts on the linear-trend assumption, so less credibility 10 was given to the low flow extrapolation pillar. On the other hand, for predicting near-future low flows in the Hoalp catchment, the trend model-extrapolation appears most reliable-and 11 12 receives most weight. From trend predictionsextrapolations alone one would conclude aninfer a 39% increase by +42 % in low flows until 2021-2050 (Table 2) but with a very wide 13 range of the uncertainty (about ±100% of the expected value), so one would have low 14 confidence in the absolute figures of projected change is of equal magnitude. Additional 15 information from rainfall runoff projections (that suggest an increase of about 15up to 30%) 16 17 has been useful to  $\frac{1}{20}$  constrain the projected increase to about 20 to 40%. The more complete information reduces the uncertainty of projected changes and this increases our confidence in 18 low flow projections. 19

20 In the context of water resources management, all three benefits are considered to be relevant. 21 Decision decision makers are usually reluctant to use the output from black box models as the 22 sole basis of their decisions. Just as important as the expected changes in the water system are 23 the uncertainties associated with the changes as well as a process reasoning in terms of cause 24 and effect. This is particular the case if robust drought management strategies, such as the vulnerability approach, are to be adopted. The vulnerability approach differs from the 25 predictive climate scenario approach in that it aims at reducing vulnerability and enhancing 26 resilience of the water system (Wilby and Dessai, 2010) ; (Blöschl et al., 2013). Typically, 27 28 the strategies are not optimal from an economical perspective but they are robust, i.e. they (Wilby and Dessai, 2010; Blöschl et al., 2013). Typically, these strategies are designed to 29 30 perform well over a wide range of assumptions about the future and potentially extremely 31 negative effects. Central to the approach is an understanding of the cause-effect relationships 32 within the water system under a variety of conditions, as well as an appreciation of the 33 possible uncertainties. For example, (Watts et al., 2012) tested the resilience of drought plans in England to droughts that are outside recent experience using nineteenth century drought 34 records. Methods often involve exploratory modelling approaches which fit well with the 35 three pillar approach proposed here. Methods often involve exploratory modelling approaches 36 (Watts et al., 2012) which fit well with the three pillar approach proposed here. We therefore 37 believe that the approach put forward in this paper can play an important role in assisting risk 38 39 managers in developing drought management strategies for the practice.

40

#### 41 9<u>1\_Conclusions</u>

42 In-It should be emphasised that the extrapolation pillars have been adopted here to illustrate 43 the framework and could be replaced by other methods such as the "trading space for time" 44 approach (Perdigão and Blöschl, 2014) where spatial gradients are transposed into temporal 45 changes. Also, heuristic process reasoning has been adopted to compare the pillars based on 46 expert judgement because of its flexibility. The combination could be based on formal 47 methods (e.g. Bayesian methods, Viglione et al., 2013) that allow accounting for subjective information on low flows and their process causes. Finally, the three-pillar approach presented in this paper is not necessarily restricted to low flows and could be adapted to other hydrologic characteristics.

Formatiert: Kopfzeile

#### Conclusions 8

1

2 3

4 5

6

7

8

9

, we we propose a framework that combines low flow projections from different sources of information. These pillars of information are , termed pillars. To illustrate the framework three pillars have been chosen: (a) direct extrapolation of low flow trends in observed(b) estimation of low flows, rainfall\_from GCM-projected climates using a runoff model, and (c) 10 stochastic simulations from trend-extrapolated climates using a similar runoff model.

11 The methods and information used in each pillar are largely independent from each other, so one would expect the errors to be close to independent, and a combination of the projections 12 based on climate scenarios, and stochastic projections based on local hydro-meteorological 13 data. The pillars are either observation based or process based and therefore combine 14 elements of upward and downward approaches in hydrology. should increase the overall 15 reliability of the projection. We evaluate heuristically to what degree this premise can be 16 achieved for four example regions in Austria, based on hydrological reasoning and visual 17 comparisons of synoptic plots of the individual estimates and their respective confidence 18 19 bounds.

20 The methodology is demonstrated for four example catchments in Austria that represent typical climate conditions in Central Europe. The results of the individual projections 21 sometimes differ in terms of their signs and magnitudes, mainly depending on the dominant 22 23 low flow seasonality. For the Alpine region where winter low flows dominate, trend 24 projections and climate scenarios yield consistent projections of a wetting trend but of 25 different magnitudes. For the region north of the Alps, all methods project rather small 26 changes. For the regions in the South and Southeast more pronounced and mostly decreasing trends are projected but there is disagreement in the magnitude of the projected 27 changes changes. The synthesis of the case study projections suggests that the framework (i) 28 29 tends to enhance the robustness of the overall assessment, (ii) adds to the understanding of the cause-effect relationships of low flows, and (iii) sheds light on the uncertainties involved 30 31 based on the consistency/inconsistency of the pillars.

32 The systematic combination of different sources of information in the framework of the three-

33 pillar approach offers a number of opportunities for drought projections: (i) checking the

plausibility of individual projections and improving the reliability of the overall assessment, 34

(ii) understanding the cause effect relationships involved, and (iii) enhancing the 35

understanding of the uncertainties of the assessment based on the consistency of the 36 37 individual pillars.

Application to the case study catchments suggest that the approach is viable. As the methods 38 and information used in each pillar are largely independent from each other, the combined 39 assessment is likely more accurate than each of the individual projections. The synthesis or 40 41 combination of information may be performed by expert judgement as shown in this paper.

Formatiert: Zeilenabstand: einfach

1 Alternatively, more formal methods exist which could also be used. In all cases, the

2 confidence in the combined projection will depend on how closely the pillars agree, and on

3 the individual uncertainties.

Future work may be directed towards adding <u>pillars</u>, or replacing some of the <u>pillars</u> used<sup>•</sup> <u>here</u>. One <u>possibility is</u> historic information <u>as an additional pillar</u>. Historic information <u>may</u> <u>come from archival data</u>, <u>from archives and</u> tree ring <u>analysis and other sources</u>. They <u>analyses which</u> would allow assessment of a <del>still</del>-wider spectrum of <u>drought</u> conditions-than those analysed in this paper and may contribute additional benefits to water management <u>decisions</u>. Other possibilities are the "trading space for time" approach as well as more formal multi-model ensembles.

#### 10 11

21

4 5

6

7 8

9

#### 12 Acknowledgements

13 The paper is a contribution to UNESCO's FRIEND-Water program. The authors would like 14 to thank the Austrian Climate Research Program ACRP for financial support through the 15 projects CILFAD (GZ B060362) and DALF-Pro (GZ B464822), and the Austrian Academy 16 of Sciences for financial support through the 'Predictability of Runoff' project. We thank the 17 Central Institute for Meteorology and Geodynamics (ZAMG) and the Hydrographical Service 18 of Austria (HZB) for providing meteorological and hydrological data, and Tobias Gauster for 19 help with Fig. 11. assistance with Fig. 10. We would like to thank Luis Samaniego, Charlie 20 Luce and an anonymous reviewer for their useful comments on the manuscript.

#### 22 References

23	Auer, I., Böhm, R., Jurkovic, A., Lipa, W., Orlik, A., Potzmann, R., Schöner, W.,
24	Ungersböck, M., Matulla, C., Briffa, K., Jones, P., Efthymiadis, D., Brunetti, M., Nanni, T.,
25	Maugeri, M., Mercalli, L., Mestre, O., Moisselin, J. M., Begert, M., Müller Westermeier, G.,
26	Kveton, V., Bochnicek, O., Stastny, P., Lapin, M., Szalai, S., Szentimrey, T., Cegnar, T.,
27	Dolinar, M., Gajic Capka, M., Zaninovic, K., Majstorovic, Z. and Nieplova, E.: HISTALP
28	historical instrumental climatological surface time series of the Greater Alpine Region, Int. J.
29	Climatol., 27(1), 17-46, doi:10.1002/joc.1377, 2007.
30	Blöschl, G. and Montanari, A.: Climate change impacts throwing the dice?, Hydrol.
31	Process., 24(3), 374–381, 2010.
32	Blöschl, G., Viglione, A., Merz, R., Parajka, J., Salinas, J. L. and Schöner, W.: Auswirkungen
33	des Klimawandels auf Hochwasser und Niederwasser, Österr. Wasser Abfallwirtsch., 63(1-

34 <del>2), 21 30, 2011.</del>

35 Blöschl, G., Viglione, A. and Montanari, A.: Emerging Approaches to Hydrological Risk

36 Management in a Changing World, in Climate Vulnerability, pp. 3–10, Elsevier. [online]

Formatiert: Kopfzeile

http://linkinghub.elsevier.com/retrieve/pii/B9780123847034005050 Available from: 1 2 (Accessed 3 November 2015), 2013. 3 Böhm, R., Auer, I., Brunetti, M., Maugeri, M., Nanni, T. and Schöner, W.: Regional 4 temperature variability in the European Alps: 1760 1998 from homogenized instrumental time series, Int. J. Climatol., 21(14), 1779-1801, doi:10.1002/joc.689, 2001. 5 6 Bosshard, T., Carambia, M., Goergen, K., Kotlarski, S., Krahe, P., Zappa, M. and Schär, C.: 7 Quantifying uncertainty sources in an ensemble of hydrological climate impact projections, 8 Water Resour. Res., 49(3), 1523-1536, doi:10.1029/2011WR011533, 2013. 9 Ceola, S., Arheimer, B., Baratti, E., Blöschl, G., Capell, R., Castellarin, A., Freer, J., Han, D., Hrachowitz, M., Hundecha, Y., Hutton, C., Lindström, G., Montanari, A., Nijzink, R., 10 11 Parajka, J., Toth, E., Viglione, A. and Wagener, T.: Virtual laboratories: new opportunities for collaborative water science, Hydrol. Earth Syst. Sci., 19(4), 2101-2117, doi:10.5194/hess 19-12 13 2101 2015, 2015. 14 Chauveau, M., Chazot, S., Perrin, C., Bourgin, P. Y., Sauquet, E., Vidal, J. P., Rouchy, N., 15 Martin, E., David, J., Norotte, T., Maugis, P. and De Lacaze, X.: Quels impacts des 16 changements climatiques sur les eaux de surface en France à l'horizon 2070?, Houille Blanche, (4), 5-15, doi:10.1051/lhb/2013027, 2013. 17 18 De Wit, M. J. M., Van den Hurk, B., Warmerdam, P. M. M., Torfs, P. J. J. F., Roulin, E. and 19 Van Deursen, W. P. A.: Impact of climate change on low flows in the river Meuse, Clim. 20 Change, 82(3 4), 351 372, doi:10.1007/s10584 006 9195 2, 2007. 21 Diaz Nieto, J. and Wilby, R. L.: A comparison of statistical downscaling and climate change 22 factor methods: impacts on low flows in the River Thames, United Kingdom, Clim. Change, 69(2-3), 245-268, 2005. 23 24 Douglas, E., Vogel, R. and Kroll, C.: Trends in floods and low flows in the United States: 25 impact of spatial correlation, J. Hydrol., 240(1-2), 90-105, 2000. 26 Duan, Q., Sorooshian, S. and Gupta, V.: Effective and efficient global optimization for 27 conceptual rainfall runoff models, Water Resour Res, 28(4), 1015-1031, 1992. 28 Field, C. B. and Intergovernmental Panel on Climate Change: Managing the risks of extreme 29 events and disasters to advance climate change adaption: special report of the

30 Intergovernmental Panel on Climate Change, Cambridge University Press, New York., 2012.

34

Formatiert: Kopfzeile

1	
1	Gaál, L., Szolgay, J., Kohnová, S., Parajka, J., Merz, R., Viglione, A. and Blöschl, G.: Flood
2	timescales: Understanding the interplay of climate and catchment processes through
3	comparative hydrology, Water Resour. Res., 48(4), W04511, 2012.
4	Giuntoli, I., Renard, B., Vidal, J. P. and Bard, A.: Low flows in France and their relationship
5	to large scale climate indices, J. Hydrol., 482, 105–118, doi:10.1016/j.jhydrol.2012.12.038,
6	<del>2013.</del>
7	Gupta, H.V., Blöschl, G., McDonnel, J., Savenije, H., Sivapalan, M., Viglione, A. and
8	Wagener, T.: Synthesis. Chapter 12, in G. Blöschl, M. Sivapalan, T. Wagener, A. Viglione,
9	H. Savenije (Eds.) Runoff Prediction in Ungauged Basins – Synthesis across Processes, Places
10	and Scales., pp. 361–383, Cambridge University Press, Cambridge, UK., 2013.
11	Gutknecht, D., Blöschl, G., Reszler, C. and Heindl, H.: Ein "Mehr Standbeine" Ansatz zur
12	Ermittlung von Bemessungshochwässern kleiner Auftretenswahrscheinlichkeit, Österr.
13	Wasser Abfallwirtsch., 58(3-4), 44-50, 2006.
14	Habets, F., Boé, J., Déqué, M., Ducharne, A., Gascoin, S., Hachour, A., Martin, E., Pagé, C.,
15	Sauquet, E., Terray, L., Thiéry, D., Oudin, L. and Viennot, P.: Impact of climate change on
16	the hydrogeology of two basins in northern France, Clim. Change, 121(4), 771-785,
17	<del>doi:10.1007/s10584-013-0934-x, 2013.</del>
18	Hall, J., Arheimer, B., Borga, M., Brázdil, R., Claps, P., Kiss, A., Kjeldsen, T. R.,
19	Kriaučiūnienė, J., Kundzewicz, Z. W., Lang, M., Llasat, M. C., Macdonald, N., McIntyre, N.,
20	Mediero, L., Merz, B., Merz, R., Molnar, P., Montanari, A., Neuhold, C., Parajka, J.,
21	Perdigão, R. A. P., Plavcová, L., Rogger, M., Salinas, J. L., Sauquet, E., Schär, C., Szolgay,
22	J., Viglione, A. and Blöschl, G.: Understanding flood regime changes in Europe: a state of
23	the art assessment, Hydrol. Earth Syst. Sci., 18(7), 2735-2772, doi:10.5194/hess 18-2735-
24	<del>2014, 2014.</del>
25	Hannaford, J. and Buys, G.: Trends in seasonal river flow regimes in the UK, J. Hydrol., 475,
26	<del>158–174, 2012.</del>
27	Hannaford, J., Buys, G., Stahl, K. and Tallaksen, L. M.: The influence of decadal scale
28	variability on trends in long European streamflow records, Hydrol. Earth Syst. Sci., 17(7),
29	2717 2733, doi:10.5194/hess 17 2717 2013, 2013.

Haslinger, K., Anders, I. and Hofstätter, M.: Regional climate modelling over complex 1 2 terrain: an evaluation study of COSMO CLM hindcast model runs for the Greater Alpine Region, Clim. Dyn., 40(1-2), 511-529, 2013. 3 4 Haslinger, K., Koffler, D., Schöner, W. and Laaha, G.: Exploring the link between 5 meteorological drought and streamflow: Effects of climate catchment interaction, Water Resour. Res., 50(3), 2468-2487, doi:10.1002/2013WR015051, 2014. 6 7 Hay, L. E., Wilby, R. L., Leavesley, G. H. and others: A comparison of delta change and 8 downsealed GCM scenarios for three mountainous basins in the United States., J. Am. Water 9 Resour. Assoc., 36(2), 387-397, 2000. 10 Hundecha, Y. and Merz, B.: Exploring the relationship between changes in climate and floods 11 using a model based analysis, Water Resour. Res., 48(4) [online] Available from: http://onlinelibrary.wiley.com/doi/10.1029/2011WR010527/pdf (Accessed 3 November 12 13 2015), 2012. 14 Hurkmans, R., Terink, W., Uijlenhoet, R., Torfs, P., Jacob, D. and Troch, P. A.: Changes in 15 streamflow dynamics in the Rhine basin under three high-resolution regional climate 16 scenarios, J. Clim., 23(3), 679-699, 2010. 17 Kuczera, G.: Combining site specific and regional information: An empirical Bayes 18 Approach, Water Resour. Res., 18(2), 306-314, 1982. 19 Laaha, G. and Blöschl, G .: Seasonality indices for regionalizing low flows, Hydrol. Process., 20 20, 3851 3878, doi:10.1002/hyp.6161, 2006. 21 Laaha, G. and Blöschl, G.: A national low flow estimation procedure for Austria, Hydrol. Sci. 22 J., 52(4), 625 644, 2007. Laaha, G., Koffler, D., Zehetgruber, Judith, Haslinger, K., Schöner, W., Parajka, J., Viglione, 23 A. and Blöschl, G.: Low flow trends in Austria from local and regional information, Hydrol. 24 25 Earth Syst. Sci., (in preparation). 26 Lins, H. F. and Slack, J. R.: Streamflow trends in the United States, Geophys. Res. Lett., 27 26(2), 227 230, 1999. 28 Loibl, W., Formayer, H., Schöner, W., Truhetz, H., Anders, I., Gobiet, A., Heinrich, G.,

Köstl, M., Nadeem, I., Peters Anders, J. and others: Reclip: century 1 Research for climate

29

Formatiert: Kopfzeile

protection: century climate simulations: models, data and ghg scenarios, simulations, ACRP 1 2 Final Rep. Reclip Century Part Vienna, 2011. 3 Lorenzo Lacruz, J., Vicente Serrano, S. M., López Moreno, J. I., Morán Tejeda, E. and Zabalza, J.: Recent trends in Iberian streamflows (1945-2005), J. Hydrol., 414-415, 463-475, 4 5 doi:10.1016/j.jhydrol.2011.11.023, 2012. 6 Majone, B., Bovolo, C. I., Bellin, A., Blenkinsop, S. and Fowler, H. J .: Modeling the impacts 7 of future climate change on water resources for the Gállego river basin (Spain), Water Resour. 8 Res., 48(1), doi:10.1029/2011WR010985, 2012. 9 Merz, R. and Blöschl, G.: Flood frequency hydrology: 2. Combining data evidence, Water 10 Resour. Res., 44(8), doi:10.1029/2007WR006745, 2008. Merz, R., Parajka, J. and Blöschl, G.: Time stability of catchment model parameters: 11 12 Implications for climate impact analyses, Water Resour. Res., 47(2), W02531, doi:10.1029/2010WR009505, 2011. 13 Parajka, J., Blaschke, A. P., Blöschl, G., Haslinger, K., Hepp, G., Laaha, G., Schöner, W., 14 Trautvetter, H., Viglione, A. and Zessner, Mathias: Uncertainty contributions to low flow 15 16 projections in Austria, Hydrol. Earth Syst. Sci., (submitted to HESSD). Parajka, J., Merz, R. and Blöschl, G.: Uncertainty and multiple objective calibration in 17 18 regional water balance modelling; case study in 320 Austrian catchments, Hydrol. Process., 19 21(4), 435-446, doi:10.1002/hyp.6253, 2007. 20 Prudhomme, C., Young, A., Watts, G., Haxton, T., Crooks, S., Williamson, J., Davies, H., 21 Dadson, S. and Allen, S.: The drying up of Britain? A national estimate of changes in seasonal river flows from 11 Regional Climate Model simulations, Hydrol, Process., 26(7), 22 23 1115 1118, doi:10.1002/hyp.8434, 2012. 24 Prudhomme, C., Giuntoli, I., Robinson, E. L., Clark, D. B., Arnell, N. W., Dankers, R., Fekete, B. M., Franssen, W., Gerten, D., Gosling, S. N., Hagemann, S., Hannah, D. M., Kim, 25 H., Masaki, Y., Satoh, Y., Stacke, T., Wada, Y. and Wisser, D.: Hydrological droughts in the 26

27 21st century, hotspots and uncertainties from a global multimodel ensemble experiment, Proc.
28 Natl. Acad. Sci., doi:10.1073/pnas.1222473110, 2013.

- 29 Renard, B., Lang, M., Bois, P., Dupeyrat, A., Mestre, O., Niel, H., Sauquet, E., Prudhomme,
- 30 C., Parey, S., Paquet, E., Neppel, L. and Gailhard, J.: Regional methods for trend detection:

1	
1	Assessing field significance and regional consistency, Water Resour. Res., 44(8), W08419,
2	doi:10.1029/2007WR006268, 2008.
3	Schöner, W., Böhm, R. and Auer, I.: 125 years of high mountain research at Sonnblick
4	Observatory (Austrian Alps) from "the house above the clouds" to a unique research
5	platform, Theor. Appl. Climatol., 110(4), 491–498, 2012.
6	Sheffield, J., Wood, E. F. and Roderick, M. L.: Little change in global drought over the past
7	60 years, Nature, 491(7424), 435-438, 2012.
8	Sivapalan, M., Blöschl, G., Zhang, L. and Vertessy, R.: Downward approach to hydrological
9	prediction, Hydrol. Process., 17(11), 2101–2111, doi:10.1002/hyp.1425, 2003.
10	Sivapalan, M., Blöschl, G., Merz, R. and Gutknecht, D.: Linking flood frequency to long-term
11	water balance: Incorporating effects of seasonality, Water Resour. Res., 41(6),
12	<del>doi:10.1029/2004WR003439, 2005.</del>
13	Stahl, K., Hisdal, H., Hannaford, J., Tallaksen, L. M., van Lanen, H. A. J., Sauquet, E.,
14	Demuth, S., Fendekova, M. and Jódar, J.: Streamflow trends in Europe: evidence from a
15	dataset of near natural catchments, Hydrol. Earth Syst. Sci., 14(12), 2367-2382,
16	<del>doi:10.5194/hess-14-2367-2010, 2010.</del>
17	Stedinger, J. R. and Tasker, G. D.: Regional hydrologic analysis: 1. Ordinary, weighted, and
18	generalized least squares compared, Water Resour. Res., 21(9), 1421-1432, 1985.
19	Szolgayová, E., Laaha, G., Blöschl, G. and Bucher, C.: Factors influencing long range
20	dependence in streamflow of European rivers, Hydrol. Process., 28(4), 1573-1586, 2014.
21	Thyer, M. and Kuczera, G.: A hidden Markov model for modelling long term persistence in
22	multi site rainfall time series 1. Model calibration using a Bayesian approach, J. Hydrol.,
23	<del>275(1), 12–26, 2003.</del>
24	Van Loon, A. F. and Laaha, G.: Hydrological drought severity explained by climate and
25	catchment characteristics, J. Hydrol., 526, 3-14, doi:10.1016/j.jhydrol.2014.10.059, 2015.
26	Vicente Serrano, S. M., Beguería, S. and López Moreno, J. I.: A multiscalar drought index
27	sensitive to global warming: the standardized precipitation evapotranspiration index, J. Clim.,

28 23(7), 1696-1718, 2010.

Formatiert: Kopfzeile

ĺ	<b>4</b>
1	Viglione, A. and Parajka, J.: TUWmodel: Lumped Hydrological Model for Education
2	Purposes. R package. [online] Available from: http://CRAN.R-
3	project.org/package=TUWmodel, 2014.
4	Viglione, A., Castellarin, A., Rogger, M., Merz, R. and Blöschl, G.: Extreme rainstorms:
5	Comparing regional envelope curves to stochastically generated events, Water Resour. Res.,
6	4 <del>8(1), doi:10.1029/2011WR010515, 2012.</del>
7	Viglione, A., Merz, R., Salinas, J. L. and Blöschl, G.: Flood frequency hydrology: 3. A
8	Bayesian analysis, Water Resour. Res., 49(2), 675–692, doi:10.1029/2011WR010782, 2013.
9	Watts, G., von Christierson, B., Hannaford, J. and Lonsdale, K.: Testing the resilience of
10	water supply systems to long droughts, J. Hydrol., 414, 255–267, 2012.
11	Wilby, R. L. and Dessai, S.: Robust adaptation to climate change, Weather, 65(7), 180-185,
12	<del>2010.</del>
13	Wilson, D., Hisdal, H. and Lawrence, D.: Has streamflow changed in the Nordic countries?
14	Recent trends and comparisons to hydrological projections, J. Hydrol., 394(3-4), 334-346,
15	doi:10.1016/j.jhydrol.2010.09.010, 2010.
16	Winsemius, H. C., Schaefli, B., Montanari, A. and Savenije, H. H. G.: On the calibration of
17	hydrological models in ungauged basins: A framework for integrating hard and soft
18	hydrological information, Water Resour. Res., 45(12) [online] Available from:
19	http://onlinelibrary.wiley.com/doi/10.1029/2009WR007706/full (Accessed 3 November
20	<del>2015), 2009.</del>
21	Wong, W. K., Beldring, S., Engen Skaugen, T., Haddeland, I. and Hisdal, H.: Climate
22	Change Effects on Spatiotemporal Patterns of Hydroclimatological Summer Droughts in
23	Norway, J. Hydrometeorol., 12(6), 1205–1220, doi:10.1175/2011JHM1357.1, 2011.
24	Yue, S., Pilon, P., Phinney, B. and Cavadias, G.: The influence of autocorrelation on the
25	ability to detect trend in hydrological series, Hydrol. Process., 16(9), 1807–1829, 2002.
26 27 28 29 30	Auer, I., Böhm, R., Jurkovic, A., Lipa, W., Orlik, A., Potzmann, R., Schöner, W., Ungersböck, M., Matulla, C., Briffa, K., Jones, P., Efthymiadis, D., Brunetti, M., Nanni, T., Maugeri, M., Mercalli, L., Mestre, O., Moisselin, JM., Begert, M., Müller-Westermeier, G., Kveton, V., Bochnicek, O., Stastny, P., Lapin, M., Szalai, S., Szentimrey, T., Cegnar, T., Dolinar, M., Gajic-Capka, M., Zaninovic, K., Majstorovic, Z. and Nieplova, E.: HISTALP— historical instrumental climatological surface time series of the Greater Alaine Pagion. Let J.
32	Climatol., 27(1), 17–46, doi:10.1002/joc.1377, 2007.

1	
1 2	Blöschl, G. and Montanari, A.: Climate change impacts—throwing the dice?, Hydrol. Process., 24(3), 374–381, 2010.
3 4 5	Blöschl, G., Viglione, A., Merz, R., Parajka, J., Salinas, J. L. and Schöner, W.: Auswirkungen des Klimawandels auf Hochwasser und Niederwasser (Climate impacts on floods and low flows), Österr. Wasser- Abfallwirtsch., 63(1-2), 21–30, 2011.
6 7 8 9	Blöschl, G., Viglione, A. and Montanari, A.: Emerging Approaches to Hydrological Risk Management in a Changing World, in Climate Vulnerability, pp. 3–10, Elsevier. [online] Available from: http://linkinghub.elsevier.com/retrieve/pii/B9780123847034005050 (Accessed 3 November 2015), 2013.
10 11 12	Böhm, R., Auer, I., Brunetti, M., Maugeri, M., Nanni, T. and Schöner, W.: Regional temperature variability in the European Alps: 1760-1998 from homogenized instrumental time series, Int. J. Climatol., 21(14), 1779–1801, doi:10.1002/joc.689, 2001.
13 14 15	Bosshard, T., Carambia, M., Goergen, K., Kotlarski, S., Krahe, P., Zappa, M. and Schär, C.: Quantifying uncertainty sources in an ensemble of hydrological climate-impact projections, Water Resour. Res., 49(3), 1523–1536, doi:10.1029/2011WR011533, 2013.
16 17 18 19 20	Ceola, S., Arheimer, B., Baratti, E., Blöschl, G., Capell, R., Castellarin, A., Freer, J., Han, D., Hrachowitz, M., Hundecha, Y., Hutton, C., Lindström, G., Montanari, A., Nijzink, R., Parajka, J., Toth, E., Viglione, A. and Wagener, T.: Virtual laboratories: new opportunities for collaborative water science, Hydrol. Earth Syst. Sci., 19(4), 2101–2117, doi:10.5194/hess-19- 2101-2015, 2015.
21 22 23 24	Chauveau, M., Chazot, S., Perrin, C., Bourgin, PY., Sauquet, E., Vidal, JP., Rouchy, N., Martin, E., David, J., Norotte, T., Maugis, P. and De Lacaze, X.: Quels impacts des changements climatiques sur les eaux de surface en France à l'horizon 2070?, Houille Blanche, (4), 5–15, doi:10.1051/lhb/2013027, 2013.
25 26 27	De Wit, M. J. M., Van den Hurk, B., Warmerdam, P. M. M., Torfs, P. J. J. F., Roulin, E. and Van Deursen, W. P. A.: Impact of climate change on low-flows in the river Meuse, Clim. Change, 82(3-4), 351–372, doi:10.1007/s10584-006-9195-2, 2007.
28 29 30	Diaz-Nieto, J. and Wilby, R. L.: A comparison of statistical downscaling and climate change factor methods: impacts on low flows in the River Thames, United Kingdom, Clim. Change, 69(2-3), 245–268, 2005.
31 32	Douglas, E., Vogel, R. and Kroll, C.: Trends in floods and low flows in the United States: impact of spatial correlation, J. Hydrol., 240(1-2), 90–105, 2000.
33 34	Duan, Q., Sorooshian, S. and Gupta, V.: Effective and efficient global optimization for conceptual rainfall-runoff models, Water Resour Res, 28(4), 1015–1031, 1992.
35 36 37	Field, C. B. and Intergovernmental Panel on Climate Change: Managing the risks of extreme events and disasters to advance climate change adaption: special report of the Intergovernmental Panel on Climate Change, Cambridge University Press, New York., 2012.
38 39	Fleckenstein, J. H., Niswonger, R. G., & Fogg, G. E. (2006). River-aquifer interactions, geologic heterogeneity, and low-flow management. Ground water, 44(6), 837-852.
40 41	Gaál, L., Szolgay, J., Kohnová, S., Parajka, J., Merz, R., Viglione, A. and Blöschl, G.: Flood timescales: Understanding the interplay of climate and catchment processes through

timescales: Understanding the interplay of climate and catchment processes through comparative hydrology, Water Resour. Res., 48(4), W04511, 2012. 

**---**

I	
1 2 3	Giuntoli, I., Renard, B., Vidal, JP. and Bard, A.: Low flows in France and their relationship to large-scale climate indices, J. Hydrol., 482, 105–118, doi:10.1016/j.jhydrol.2012.12.038, 2013.
4 5 6 7	Gupta, H.V., Blöschl, G., McDonnel, J., Savenije, H., Sivapalan, M., Viglione, A. and Wagener, T.: Synthesis. Chapter 12, in G. Blöschl, M. Sivapalan, T. Wagener, A. Viglione, <u>H. Savenije (Eds.) Runoff Prediction in Ungauged Basins - Synthesis across Processes, Places</u> and Scales., pp. 361–383, Cambridge University Press, Cambridge, UK., 2013.
8 9 10	Gutknecht, D., Blöschl, G., Reszler, C. and Heindl, H.: Ein "Mehr-Standbeine"-Ansatz zur Ermittlung von Bemessungshochwässern kleiner Auftretenswahrscheinlichkeit, Österr. Wasser- Abfallwirtsch., 58(3-4), 44–50, 2006.
11 12 13 14	Habets, F., Boé, J., Déqué, M., Ducharne, A., Gascoin, S., Hachour, A., Martin, E., Pagé, C., Sauquet, E., Terray, L., Thiéry, D., Oudin, L. and Viennot, P.: Impact of climate change on the hydrogeology of two basins in northern France, Clim. Change, 121(4), 771–785, doi:10.1007/s10584-013-0934-x, 2013.
15 16 17 18 19 20 21	Hall, J., Arheimer, B., Borga, M., Brázdil, R., Claps, P., Kiss, A., Kjeldsen, T. R., Kriaučiūnienė, J., Kundzewicz, Z. W., Lang, M., Llasat, M. C., Macdonald, N., McIntyre, N., Mediero, L., Merz, B., Merz, R., Molnar, P., Montanari, A., Neuhold, C., Parajka, J., Perdigão, R. A. P., Plavcová, L., Rogger, M., Salinas, J. L., Sauquet, E., Schär, C., Szolgay, J., Viglione, A. and Blöschl, G.: Understanding flood regime changes in Europe: a state-of- the-art assessment, Hydrol. Earth Syst. Sci., 18(7), 2735–2772, doi:10.5194/hess-18-2735- 2014, 2014.
22 23	Hannaford, J. and Buys, G.: Trends in seasonal river flow regimes in the UK, J. Hydrol., 475, 158–174, 2012.
24 25 26	Hannaford, J., Buys, G., Stahl, K. and Tallaksen, L. M.: The influence of decadal-scale variability on trends in long European streamflow records, Hydrol. Earth Syst. Sci., 17(7), 2717–2733, doi:10.5194/hess-17-2717-2013, 2013.
27 28 29	Haslinger, K., Anders, I. and Hofstätter, M.: Regional climate modelling over complex terrain: an evaluation study of COSMO-CLM hindcast model runs for the Greater Alpine Region, Clim. Dyn., 40(1-2), 511–529, 2013.
30 31 32	Haslinger, K., Koffler, D., Schöner, W. and Laaha, G.: Exploring the link between meteorological drought and streamflow: Effects of climate-catchment interaction, Water Resour. Res., 50(3), 2468–2487, doi:10.1002/2013WR015051, 2014.
33 34 35	Hay, L. E., Wilby, R. L., Leavesley, G. H. and others: A comparison of delta change and downscaled GCM scenarios for three mountainous basins in the United States., J. Am. Water Resour. Assoc., 36(2), 387–397, 2000.
36 37 38 39	Hundecha, Y. and Merz, B.: Exploring the relationship between changes in climate and floods using a model-based analysis, Water Resour. Res., 48(4) [online] Available from: http://onlinelibrary.wiley.com/doi/10.1029/2011WR010527/pdf (Accessed 3 November 2015), 2012.
40 41 42	Hurkmans, R., Terink, W., Uijlenhoet, R., Torfs, P., Jacob, D. and Troch, P. A.: Changes in streamflow dynamics in the Rhine basin under three high-resolution regional climate scenarios, J. Clim., 23(3), 679–699, 2010.
43 44	Knutti, R., G. Abramowitz, M. Collins, V. Eyring, P.J. Gleckler, B. Hewitson, and L. Mearns, 2010: Good Practice Guidance Paper on Assessing and Combining Multi Model Climate

Projections. In: Meeting Report of the Intergovernmental Panel on Climate Change Expert 1 2 Meeting on Assessing and Combining Multi Model Climate Projections [Stocker, T.F., D. 3 Qin, G.-K. Plattner, M. Tignor, and P.M. Midgley (eds.)]. IPCC Working Group I Technical 4 Support Unit, University of Bern, Bern, Switzerland. 5 Kuczera, G.: Combining site-specific and regional information: An empirical Bayes Approach, Water Resour. Res., 18(2), 306-314, 1982. 6 7 Laaha, G. and Blöschl, G.: Seasonality indices for regionalizing low flows, Hydrol. Process., 8 20, 3851–3878, doi:10.1002/hyp.6161, 2006. 9 Laaha, G. and Blöschl, G.: A national low flow estimation procedure for Austria, Hydrol. Sci. 10 J., 52(4), 625–644, doi:10.1623/hysj.52.4.625, 2007. Lins, H. F. and Slack, J. R.: Streamflow trends in the United States, Geophys. Res. Lett., 11 26(2), 227-230, 1999. 12 13 Loibl, W., Formayer, H., Schöner, W., Truhetz, H., Anders, I., Gobiet, A., Heinrich, G., 14 Köstl, M., Nadeem, I., Peters-Anders, J. and others: Reclip: century 1 Research for climate protection: century climate simulations: models, data and ghg-scenarios, simulations, ACRP 15 16 Final Rep. Reclip Century Part Vienna, 2011. 17 Lorenzo-Lacruz, J., Vicente-Serrano, S. M., López-Moreno, J. I., Morán-Tejeda, E. and Zabalza, J.: Recent trends in Iberian streamflows (1945-2005), J. Hydrol., 414-415, 463-475, 18 doi:10.1016/j.jhydrol.2011.11.023, 2012. 19 20 Luce, C. H., and Holden, Z. A.: Declining annual streamflow distributions in the Pacific Northwest United States, 1948-2006, Geophys. Res. Lett., 36, L16401, 21 22 doi:10.1029/2009GL039407, 2009. 23 Luce, C. H., Abatzoglou, J. T., and Holden, Z. A.: The Missing Mountain Water: Slower 24 Westerlies Decrease Orographic Enhancement in the Pacific Northwest USA, Science, 342, 25 1360-1364, DOI: 10.1126/science.1242335, 2013. 26 Majone, B., Bovolo, C. I., Bellin, A., Blenkinsop, S. and Fowler, H. J.: Modeling the impacts of future climate change on water resources for the Gállego river basin (Spain), Water Resour. 27 Res., 48(1), doi:10.1029/2011WR010985, 2012. 28 29 Merz, R. and Blöschl, G.: Flood frequency hydrology: 2. Combining data evidence, Water Resour. Res., 44(8), doi:10.1029/2007WR006745, 2008. 30 31 Merz, R., Parajka, J. and Blöschl, G.: Time stability of catchment model parameters: Implications for climate impact analyses, Water Resour. Res., 47(2), W02531, 32 doi:10.1029/2010WR009505, 2011. 33 34 Montanari, A., Rosso, R., & Taqqu, M. S. (1997). Fractionally differenced ARIMA models 35 applied to hydrologic time series: Identification, estimation, and simulation. Water Resources Research, 33(5), 1035-1044. 36 37 Parajka, J., Blaschke, A. P., Blöschl, G., Haslinger, K., Hepp, G., Laaha, G., Schöner, W., 38 Trautvetter, H., Viglione, A., and Zessner, M.: Uncertainty contributions to low-flow 39 projections in Austria, Hydrol. Earth Syst. Sci., 20, 2085-2101, doi:10.5194/hess-20-2085-2016, 2016. 40 41 Parajka, J., Merz, R. and Blöschl, G.: Uncertainty and multiple objective calibration in 42 regional water balance modelling: case study in 320 Austrian catchments, Hydrol. Process., 21(4), 435-446, doi:10.1002/hyp.6253, 2007. 43

1	<b>4</b>
1 2 3	Perdigão, R. A. P., and G. Blöschl (2014) Spatiotemporal flood sensitivity to annual precipitation: Evidence for landscape-climate coevolution, Water Resour. Res., 50, 5492-5509, doi:10.1002/2014WR015365.
4 5 6 7	Prudhomme, C., Young, A., Watts, G., Haxton, T., Crooks, S., Williamson, J., Davies, H., Dadson, S. and Allen, S.: The drying up of Britain? A national estimate of changes in seasonal river flows from 11 Regional Climate Model simulations, Hydrol. Process., 26(7), 1115–1118, doi:10.1002/hyp.8434, 2012.
8 9 10 11 12	Prudhomme, C., Giuntoli, I., Robinson, E. L., Clark, D. B., Arnell, N. W., Dankers, R., Fekete, B. M., Franssen, W., Gerten, D., Gosling, S. N., Hagemann, S., Hannah, D. M., Kim, H., Masaki, Y., Satoh, Y., Stacke, T., Wada, Y. and Wisser, D.: Hydrological droughts in the 21st century, hotspots and uncertainties from a global multimodel ensemble experiment, Proc. Natl. Acad. Sci., doi:10.1073/pnas.1222473110, 2013.
13 14 15 16	Renard, B., Lang, M., Bois, P., Dupeyrat, A., Mestre, O., Niel, H., Sauquet, E., Prudhomme, C., Parey, S., Paquet, E., Neppel, L. and Gailhard, J.: Regional methods for trend detection: Assessing field significance and regional consistency, Water Resour. Res., 44(8), W08419, doi:10.1029/2007WR006268, 2008.
17 18	Rodionov, S. N. (2006). Use of prewhitening in climate regime shift detection. Geophysical Research Letters, 33(12).
19 20 21	Samaniego, L., Kumar, R., & Zink, M. (2013). Implications of Parameter Uncertainty on Soil Moisture Drought Analysis in Germany. Journal of Hydrometeorology, 14(1), 47–68. http://doi.org/10.1175/JHM-D-12-075.1
22 23 24	Schöner, W., Böhm, R. and Auer, I.: 125 years of high-mountain research at Sonnblick Observatory (Austrian Alps)—from "the house above the clouds" to a unique research platform, Theor. Appl. Climatol., 110(4), 491–498, 2012.
25 26	Sen, P. K. (1968). Estimates of the regression coefficient based on Kendall's tau. Journal of the American Statistical Association, 63(324), 1379-1389.
27 28	Sheffield, J., Wood, E. F. and Roderick, M. L.: Little change in global drought over the past 60 years, Nature, 491(7424), 435–438, 2012.
29 30	Sivapalan, M., Blöschl, G., Zhang, L. and Vertessy, R.: Downward approach to hydrological prediction, Hydrol. Process., 17(11), 2101–2111, doi:10.1002/hyp.1425, 2003.
31 32 33	Sivapalan, M., Blöschl, G., Merz, R. and Gutknecht, D.: Linking flood frequency to long-term water balance: Incorporating effects of seasonality, Water Resour. Res., 41(6), doi:10.1029/2004WR003439, 2005.
34 35 36 37	Stahl, K., Hisdal, H., Hannaford, J., Tallaksen, L. M., van Lanen, H. A. J., Sauquet, E., Demuth, S., Fendekova, M. and Jódar, J.: Streamflow trends in Europe: evidence from a dataset of near-natural catchments, Hydrol. Earth Syst. Sci., 14(12), 2367–2382, doi:10.5194/hess-14-2367-2010, 2010.
38 39	Stedinger, J. R. and Tasker, G. D.: Regional hydrologic analysis: 1. Ordinary, weighted, and generalized least squares compared, Water Resour. Res., 21(9), 1421–1432, 1985.
40 41	Szolgayová, E., Laaha, G., Blöschl, G. and Bucher, C.: Factors influencing long range dependence in streamflow of European rivers, Hydrol, Process., 28(4), 1573–1586, 2014.

---

1 2 3	Thyer, M. and Kuczera, G.: A hidden Markov model for modelling long-term persistence in multi-site rainfall time series 1. Model calibration using a Bayesian approach, J. Hydrol., 275(1), 12–26, 2003.
4 5	Van Loon, A. F. and Laaha, G.: Hydrological drought severity explained by climate and catchment characteristics, J. Hydrol., 526, 3–14, doi:10.1016/j.jhydrol.2014.10.059, 2015.
6 7 8	Vicente-Serrano, S. M., Beguería, S. and López-Moreno, J. I.: A multiscalar drought index sensitive to global warming: the standardized precipitation evapotranspiration index, J. Clim., 23(7), 1696–1718, 2010.
9 10 11	Viglione, A. and Parajka, J.: TUWmodel: Lumped Hydrological Model for Education Purposes. R package. [online] Available from: http://CRAN.R- project.org/package=TUWmodel, 2014.
12 13 14	Viglione, A., Castellarin, A., Rogger, M., Merz, R. and Blöschl, G.: Extreme rainstorms: Comparing regional envelope curves to stochastically generated events, Water Resour. Res., 48(1), doi:10.1029/2011WR010515, 2012.
15 16	Viglione, A., Merz, R., Salinas, J. L. and Blöschl, G.: Flood frequency hydrology: 3. A Bayesian analysis, Water Resour. Res., 49(2), 675–692, doi:10.1029/2011WR010782, 2013.
17 18	Watts, G., von Christierson, B., Hannaford, J. and Lonsdale, K.: Testing the resilience of water supply systems to long droughts, J. Hydrol., 414, 255–267, 2012.
19 20	Wilby, R. L. and Dessai, S.: Robust adaptation to climate change, Weather, 65(7), 180–185, 2010.
21 22 23	Wilson, D., Hisdal, H. and Lawrence, D.: Has streamflow changed in the Nordic countries? – Recent trends and comparisons to hydrological projections, J. Hydrol., 394(3-4), 334–346, doi:10.1016/j.jhydrol.2010.09.010, 2010.
24 25 26 27 28	Winsemius, H. C., Schaefli, B., Montanari, A. and Savenije, H. H. G.: On the calibration of hydrological models in ungauged basins: A framework for integrating hard and soft hydrological information, Water Resour. Res., 45(12) [online] Available from: http://onlinelibrary.wiley.com/doi/10.1029/2009WR007706/full (Accessed 3 November 2015), 2009.
29 30 31	Wong, W. K., Beldring, S., Engen-Skaugen, T., Haddeland, I. and Hisdal, H.: Climate Change Effects on Spatiotemporal Patterns of Hydroclimatological Summer Droughts in Norway, J. Hydrometeorol., 12(6), 1205–1220, doi:10.1175/2011JHM1357.1, 2011.
32 33	Yue, S., Pilon, P., Phinney, B. and Cavadias, G.: The influence of autocorrelation on the ability to detect trend in hydrological series, Hydrol. Process., 16(9), 1807–1829, 2002.
34	
35	

						<b>4</b>	Formatiert: Kopfzeile
1							
2	Table 1. Trend estim	ates of observed	2 <u>95</u> low flows in th	ne period 1976-200	8 (Mann-Kend	all	Formatiert: Zeilenabstand: einfach
3	test). Relative trends	refer to the trend of	over the observatio	n period relative to	its mean.		
		Hoalp	Muhlv	Gurk	Buwe	4	Formatierte Tabelle
	t <del>rend<u>Trend</u> (m³/s per 100 yrs)</del>	+0.24 <u>**</u>	-0.28	-1.45	-0.34 <u>*</u>	•·	<b>Formatiert:</b> Zeilenabstand: einfach
	relative <u>Relative</u> trend (% per year)	+1.21 <u>**</u>	-0.38	-0.78	-1.88 <u>*</u>	<b>•</b>	Formatiert: Zeilenabstand: einfach
	p-value	0.009	0.377	0.053	0.045	•·	Formatiert: Zeilenabstand: einfach

4 Significance codes: \*\* p<0.01; \* p<0.05

1 2 3

4

## 2051-2080 based on observed trends. Changes (%) refer to the $Q_{95}$ in the future period relative to the average $Q_{95}$ in the reference period (1976-2008). Values in parentheses indicate 95% confidence intervals.

		<u>Hoalp</u>	Muhlv	<u>Gurk</u>	Buwe
<u>2021-2050</u>	<u>Q<sub>95</sub> (m<sup>3</sup>/s)</u>	0.28 (0.19, 0.37)	0.68 (0.45, 1.02)	<u>1.19 (0.58, 2.00)</u>	0.02 (-0.14, 0.14)
2021-2050	Change (%)	<u>+39 (-7, +71)</u>	<u>-8 (-41, +34)</u>	<u>-36 (-72, -1)</u>	<u>-90 (-177, -22)</u>
<del>p value</del> <del>prewhitene</del> <del>d</del> 2051- 2080	<u>Q<sub>95</sub> (m³/s)</u>	0. <del>003</del> 35 (0.22, <u>0.45)</u>	0. <del>250</del> 60 (0.15, _ <u>1.14)</u>	0. <del>178</del> 74 (-0.23, <u>2.01)</u>	<u>-0.<del>058</del>08(-0.33,</u> <u>0.12)</u>
significanc e2051- 2080	<u>**Change</u> (%)	+74 (0, 123)	<u>-21 (-79, +51)</u>	<u>*-59 (-113, +9)</u>	<u>-148 (-282, -36)</u>

Table 2. Trend extrapolations of average Q<sub>95</sub> low flows (m<sup>3</sup>/s) for the periods 2021-2050 and

5 Significance codes: \*\* <0.01 ; \* < 0.05

#### Eingefügte Zellen

Formatiert: Schriftart: 11,5 Pt., Schriftartfarbe: Automatisch

Formatiert: Zeilenabstand: einfach

### **Formatiert:** Schriftart: 11,5 Pt., Schriftartfarbe: Automatisch

Formatiert: Zeilenabstand: einfach

#### Formatierte Tabelle

Formatiert: Schriftart: 11,5 Pt., Schriftartfarbe: Automatisch

**Formatiert:** Schriftart: 11,5 Pt., Schriftartfarbe: Automatisch

**Formatiert:** Schriftart: 11,5 Pt., Schriftartfarbe: Automatisch

**Formatiert:** Schriftart: 11,5 Pt., Schriftartfarbe: Automatisch

Formatiert: Schriftart: 11,5 Pt.

Formatiert: Zeilenabstand: einfach

**Formatiert:** Schriftart: 11,5 Pt., Schriftartfarbe: Automatisch

**Formatiert:** Schriftart: 11,5 Pt., Schriftartfarbe: Automatisch

**Formatiert:** Schriftart: 11,5 Pt., Schriftartfarbe: Automatisch

#### Eingefügte Zellen

Formatiert: Zeilenabstand: einfach Formatiert: Block, Zeilenabstand:

einfach

Formatiert: Schriftart: 11,5 Pt.

Formatiert: Schriftart: 11,5 Pt.

1 2 Table 2. Trend predictions of average Q95 low flows (m³/s) for the periods 2021 2050 and

2051-2080 based on extending observed trends. Predicted changes (%) relative to average low

flow discharge Q95 of the reference period (1976 2008). Values in parenthesis refer to the

3 4

95% confidence interval.

	Hoalp	Muhlv	Gurk	Buwe
<del>2021-2050</del>				
<del>Q95</del>	<del>0.28 (0.19, 0.38)</del>	<del>0.67 (0.36, 0.97)</del>	<del>1.17 (0.48, 1.87)</del>	<del>0.02 ( 0.10, 0.14)</del>
<del>change</del>	+42 ( 5, +88)	<del>-10 ( 51, +32)</del>	<del>-36 ( 74, +1)</del>	<del>-89 (-156, -21)</del>
<del>2051-2080</del>				
<del>Q95</del>	<del>0.35 (0.20, 0.51)</del>	<del>0.58 (0.07, 1.09)</del>	<del>0.74 ( 0.42, 1.90)</del>	<del>-0.08 ( 0.29, 0.12)</del>
<del>change</del>	+ <del>78 (+1, +156)</del>	<del>-21 ( 91, +48)</del>	<del>-60 (-123, +3)</del>	<del>-145 ( 258, -33)</del>

5 6

--- **Formatiert:** Zeilenabstand: einfach

Formatiert: Kopfzeile

Formatiert: Kopfzeile Formatiert: Schriftart: Kursiv

1	Table 3. Runoff model efficiency Z <sub>0</sub> (Eq. 42) obtained for different weights $w_0$ (Eq. 4) in the
2	four selected basins catchments for three different calibration periods. $w_0 = 0$ and $w_0 = 1$
3	emphasise low flows and high flow, respectively, in the calibration. $Z_0$ are listed in the
4	sequence of the calibration periods: 1976-1986/1987-1997/1998-2008.

WO	Hoalp	Muhlv	Gurk	Buwe	*><	Formatiert: Schriftart: Kursiv
00	0.96/0.95/0.90	0 82/0 84/0 86	0 79/0 73/0 79	0 46/0 52/0 59	•	Formatierte Tabelle
0.0	0.95/0.93/0.90	0.02/0.04/0.00	0.79/0.79/0.79	0.27/0.52/0.59	· · · ·	<b>Formatiert:</b> Zeilenabstand: einfach
0.1	0.95/0.93/0.90	0.81/0.83/0.86	0.79/0.73/0.79	0.37/0.52/0.58		Formatiert: Zeilenabstand: einfach
0.2	0.94/0.92/0.90	0.80/0.82/0.86	0.78/0.74/0.79	0.35/0.53/0.58	*	Formatiert: Zeilenabstand: einfach
0.3	0.93/0.90/0.90	0.79/0.81/0.86	0.78/0.74/0.79	0.34/0.54/0.58	<b>*</b>	Formatiert: Zeilenabstand: einfach
0.4	0.92/0.89/0.89	0.79/0.80/0.86	0.78/0.74/0.79	0.40/0.54/0.57	<b>*</b>	Formatiert: Zeilenabstand: einfach
0.5	0.91/0.88/0.89	0.77/0.79/0.86	0.78/0.75/0.78	0.36/0.55/0.56	<b>*</b>	Formatiert: Zeilenabstand: einfach
0.6	0.90/0.86/0.89	0.77/0.78/0.86	0.78/0.75/0.78	0.30/0.56/0.55	<b>*</b> ·	Formatiert: Zeilenabstand: einfach
0.7	0.89/0.85/0.89	0.76/0.78/0.86	0.78/0.75/0.78	0.30/0.57/0.55	<b>*</b> ·	Formatiert: Zeilenabstand: einfach
0.8	0.88/0.83/0.75	0.76/0.77/0.81	0.78/0.76/0.80	0.30/0.58/0.49	<b>*</b> ·	Formatiert: Zeilenabstand: einfach
0.9	0.88/0.82/0.73	0.75/0.76/0.81	0.78/0.76/0.80	0.28/0.59/0.49	<b>*</b>	Formatiert: Zeilenabstand: einfach
1.0	0.87/0.82/0.72	0.75/0.75/0.81	0.78/0.77/0.81	0.29/0.60/0.49	<b>*</b> '	Formatiert: Zeilenabstand: einfach
					4	Formatiert: Zeilenabstand: einfach



### 



Figure 1. Three-pillar approach of low flow projection: The first pillar, streamflow trend extrapolation, exploits information of the observed low flow signal. The second pillar, rainfall runoff projections, exploits information of climate scenarios. The third pillar, stochastic projections, extrapolates trends of observed climate signals. Intercomparisons (indicated by arrows) allow interpretation of trends, validation of rainfall runoff projections, and alternative scenarios. The combination of the three pieces of information yields estimates consistent with all the information, together with an appreciation of their uncertainty.



Figure 2. Observed (HISTALP, black) and projected (reclip:century ensemble spread, grey)\* evolution of the standardized Standardized precipitation evaporation index (SPEI) in summer 1 2

3

(upper panel<u>top</u>) and winter (lower panel<u>bottom</u>) (three month averages of monthly values) for the four example catchments in Austria; the red. Observed (HISTALP, Auer et al., 2007, black) and projected (reclip:century ensemble spread, grey). Red and light red lines represent the Gaussian low-pass filterfiltered values of the observed and projected SPEI-time series,

4 5 6

7 respectively. Formatiert: Kopfzeile





2 3 4

5

6

7

8

Figure <u>32</u>. Observed trends of <u>annual</u>  $Q_{25}$  low flows in Austria in the period 1976-2008. Colours correspond to the sign and the magnitude of the trends (blue = increasing, red = decreasing). Size indicates significance of trends. Units of the trends are standard deviations per year. Squares indicate example catchments; West: Tauernbach at Matreier Tauernhaus (Healp); North: Steinerne Mühl at Harmannsdorf (Muhlv): South: Glan at Zollfeld (Gurk); East: Tauchenbach at Altschlaining (Buwe). From (Laaha et al., in preparation).

Formatiert: Tiefgestellt





Figure 4<u>3</u>: Observed daily discharge for the periods 1976-1986 (blue <u>linelines</u>) and 1998-2008<sup>•</sup> (red <u>linelines</u>) in the Buwe (<u>upper paneltop</u>) and Hoalp (bottom-<u>panel</u>) <u>basins</u>) <u>catchments</u>.





Figure 54. Annual  $Q_{95}$  low flow quantiles  $Q_{95}$  estimated flows from observed data (black linelines) and from hydrologic model simulations (coloured bands). for the four catchments. Band widths in the left panels show the variability due to different weights  $w_Q$  in the objective function (Table 3) for two calibration periods (1976-1986 and 1998-2008). Band widths in the right panels show the variability due to different decades used for model calibration for two sets of weights ( $w_Q=0.5$  and  $w_Q=0.0$ ).




1 2

Figure <u>65</u>. Projections of air temperatures and precipitation for <u>the</u> four <u>basins</u> in <u>Austriacatchments</u> simulated by regional climate models. Shown are long-term monthly
changes of the future period (2021-2050) relative to the reference period (1976-2008). Shaded
area indicates areas indicate the range of climate scenarios/models.

Formatiert: Zeilenabstand: einfach

120 Variability: 11 objective functions (scenario HADCM3-A1B) Variability: 4 climate scenarios (calibration  $w_{\rm Q}\text{=}0.5)$ Hoalp 1976-86 1998-08 AQ95 (%) -40 Muhlv AQ95 (%) -40 Gurk AQ95 (%) -40 Buwe AQ95 (%) -40 Year Year

Formatiert: Kopfzeile



Figure 7<u>6</u>. Projections of <u>annual</u>  $Q_{95}$  low flows for <u>the</u> four <u>basins in Austriacatchments</u> in terms of <u>the</u>-changes of the future period (2021-2050) relative to <u>simulated runoff in</u> the reference period (1976-2008). Band widths in the left panels show the variability due to <u>11</u> <u>ealibration variants fordifferent weights wo</u> in the objective function (Table 3) using HADCM3. Band widths in the right panels show the variability due to the choice of climate projections for calibration variant w<sub>Q</sub>=0.5. Yellow and blue colours relate to two calibration periods for the hydrological model.

Formatiert: Zeilenabstand: einfach





- 4 Figure 8.-Observed trendtrends in the precipitation statistics for the climate stations: St.\_Jakob\*
- 5 Def (Hoalp), Pabneukirchen (Muhlv), Klagenfurt (Gurk<del>),</del> and Woerterberg (Buwe). The
- 6 trend lines (dashed) have been fitted with the Theil-Sen method.

Formatiert: Kopfzeile

Formatiert: Zeilenabstand: einfach





Figure 8. Figure 9. Stochastic simulations of mean annual daily precipitation and mean annual

temperature (red lines) for St.\_Jakob Def (Hoalp), Pabneukirchen (Muhlv), Klagenfurt (Gurk $\frac{1}{2}$ ) and Woerterberg (Buwe). 100 simulated time series for each station. For comparison,

observations are shown (black lines).











Feldfunktion geändert

Figure <u>1110</u>. Three-pillar projections of <u>annual  $Q_{95}$  low flows  $Q_{95}$ -for the four example</u> catchments: a) Steinerne Mühl at Harmannsdorf (Hoalp, Muhlv), b) Glan at Zollfeld (, Gurk), e) Tauchenbach at Altschlaining (Buwe), and d) Tauernbach at Matreier Tauernhaus (Hoalp).Buwe catchments. Black lines refer to observed annual Q95. Pillar 1: trend lineextrapolation of observed low flow trends (blue) and 0.95 level confidence bounds (blue curved lines); bold/thin parts refer to observation/extrapolation period. Pillar 2: simulated Qas 8 9 forsimulations in the observation period (gray line)), and climate scenario based average Q95projections and runoff modelling for 2021-2050 and 2051-2080 (box plots, coloursshades 10 11 of green indicate different climate scenarios, range of box plots indicates different parameters 12 of the hydrological model). Pillar 3: Stochastic simulations of Q95-extrapolation of stochastic 13 rainfall characteristics and runoff modelling (100 realisations, red lines) assuming linear 14 extrapolation of rainfall model parameters with 0.50 level confidence bounds (black dashed 15 lines) and 0.90 level confidence bounds (black dotted lines) confidence bounds.



9

Figure 11. Probability density functions (pdf) of annual  $Q_{95}$  low flows 2021-2050 of the threepillar projections for the Hoalp, Muhlv, Gurk and Buwe catchments as in Figure 10. Pillar 1: extrapolation of observed low flows (blue). Pillar 2: climate projections and runoff modelling (different shades of green) Pillar 3: Extrapolation of stochastic rainfall characteristics and runoff modelling (red). The pdfs represent both variability within the period and uncertainty (pillars 1 and 2) and variability alone (pillar 3). For comparison, observed  $Q_{95}$  in the reference period (1976-2008) is shown (dashed grey line).

Seite 1: [1] Formatiert	laaha	22.06.2016 11:22:00
Kopfzeile		
Seite 14: [2] Formatiert	laaha	22.06.2016 11:22:00
Schriftart: 11 Pt.		
Seite 14: [3] Formatiert	laaha	22.06.2016 11:22:00
Schriftart: 11 Pt.		
Seite 14: [4] Formatiert	laaha	22.06.2016 11:22:00
Schriftart: 11 Pt.		
Seite 14: [5] Formatiert	laaha	22.06.2016 11:22:00
Schriftart: 11 Pt.		
Seite 14: [6] Formatiert	laaha	22.06.2016 11:22:00
Schriftart: 11 Pt.		
Seite 14: [7] Formatiert	laaha	22.06.2016 11:22:00
Schriftart: 11 Pt.		
Seite 14: [8] Formatiert	laaha	22.06.2016 11:22:00
Schriftart: 11 Pt.		
Seite 14: [9] Formatiert	laaha	22.06.2016 11:22:00
Schriftart: 11 Pt.		
Seite 14: [10] Formatiert	laaha	22.06.2016 11:22:00
Schriftart: 11 Pt.		
Seite 14: [11] Formatiert	laaha	22.06.2016 11:22:00
Schriftart: 11 Pt.		
Seite 14: [12] Formatiert	laaha	22.06.2016 11:22:00
Schriftart: 11 Pt.		
Seite 14: [13] Formatiert	laaha	22.06.2016 11:22:00
Schriftart: 11 Pt.		
Seite 14: [14] Formatiert	laaha	22.06.2016 11:22:00
Schriftart: 11 Dt		

Seite 14: [15] Formatiert	laaha	22.06.2016 11:22:00
Schriftart: 11 Pt.		
Seite 14: [16] Formatiert	laaha	22.06.2016 11:22:00
Schriftart: 11 Pt.		
Seite 14: [17] Formatiert	laaha	22.06.2016 11:22:00
Schriftart: 11 Pt.		
Seite 14: [18] Formatiert	laaha	22.06.2016 11:22:00
Schriftart: 11 Pt.		
Seite 14: [19] Formatiert	laaha	22.06.2016 11:22:00
Schriftart: 11 Pt.		
Seite 14: [20] Formatiert	laaha	22.06.2016 11:22:00
Schriftart: 11 Pt.		
Seite 14: [21] Formatiert	laaha	22.06.2016 11:22:00
Schriftart: 11 Pt.		
Seite 14: [22] Formatiert	laaha	22.06.2016 11:22:00
Schriftart: 11 Pt.		
Seite 14: [23] Formatiert	laaha	22.06.2016 11:22:00
Schriftart: 11 Pt.		
Seite 14: [24] Formatiert	laaha	22.06.2016 11:22:00
Schriftart: 11 Pt.		
Seite 14: [25] Formatiert	laaha	22.06.2016 11:22:00
Schriftart: 11 Pt.		
Seite 14: [26] Formatiert	laaha	22.06.2016 11:22:00
Schriftart: 11 Pt.		
Seite 14: [27] Formatiert	laaha	22.06.2016 11:22:00
Schriftart: 11 Pt.		
Seite 14: [28] Formatiert	laaha	22.06.2016 11:22:00
Schriftart: 11 Pt.		

Seite 14: [29] Formatiert	laaha	22.06.2016 11:22:00
Schriftart: 11 Pt.		
Seite 14: [30] Formatiert	laaha	22.06.2016 11:22:00
Schriftart: 11 Pt.		
Seite 14: [31] Formatiert	laaha	22.06.2016 11:22:00
Schriftart: 11 Pt.		
Seite 14: [32] Formatiert	laaha	22.06.2016 11:22:00
Schriftart: 11 Pt.		
Seite 14: [33] Formatiert	laaha	22.06.2016 11:22:00
Schriftart: 11 Pt.		
Seite 14: [34] Formatiert	laaha	22.06.2016 11:22:00
Schriftart: 11 Pt.		
Seite 14: [35] Formatiert	laaha	22.06.2016 11:22:00
Schriftart: 11 Pt.		
Seite 14: [36] Formatiert	laaha	22.06.2016 11:22:00
Schriftart: 11 Pt.		
Seite 14: [37] Formatiert	laaha	22.06.2016 11:22:00
Schriftart: 11 Pt.		
Seite 14: [38] Formatiert	laaha	22.06.2016 11:22:00
Schriftart: 11 Pt.		
Seite 14: [39] Formatiert	laaha	22.06.2016 11:22:00
Schriftart: 11 Pt.		
Seite 14: [40] Formatiert	laaha	22.06.2016 11:22:00
Schriftart: 11 Pt.		
Seite 14: [41] Formatiert	laaha	22.06.2016 11:22:00
Schriftart: 11 Pt.		
Seite 14: [42] Formatiert	laaha	22.06.2016 11:22:00
Schriftart: 11 Pt.		

Seite 14: [43] Formatiert	laaha	22.06.2016 11:22:00
Schriftart: 11 Pt.		
Seite 14: [44] Formatiert	laaha	22.06.2016 11:22:00
Schriftart: 11 Pt.		
Seite 14: [45] Formatiert	laaha	22.06.2016 11:22:00
Schriftart: 11 Pt.		
Seite 14: [46] Formatiert	laaha	22.06.2016 11:22:00
Schriftart: 11 Pt.		