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Hydrology and Earth System Sciences Discussions

Interactive comment on "A comparative analysis of projected impacts of climate change on river runoff from global and catchment-scale hydrological models" *by* S. N. Gosling et al.

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This paper addresses uncertainties in quantifying future climate change impacts on river runoff. Uncertainties due to the degree of spatial aggregation in the hydrological model are compared to uncertainties caused by variations in future climate change predicted by various climate models. The paper is well written, clearly structured, and of interest to the HESS readership. Overall, the work constitutes a nice contribution and should be suitable for publication after minor revisions. Briefly, additional discussion is needed to address issues related to methods and conclusions, and some changes to

the presentation are suggested to improve impact.

Thank you for taking the time to review our research and for your positive comments and suggestions to improve the manuscript. We have addressed each comment in turn. Our responses are provided below.

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Methods and conclusions

One of the main conclusions is that climate model uncertainty dominates hydrological model uncertainty. However, this conclusion is based on the prior uncertainty assigned to both climate and hydrological models; in other words, the (subjective) selection of models and scenarios included in the analysis determines the outcome. Two questions arise:

1. Do the selected models adequately account for model structural uncertainty? For example, one could argue that hydrological model uncertainty is underestimated since only two hydrological models are considered in each basin.

This relates to a point made by the other reviewer. We have added the following text to the Discussion section to address this: "A key conclusion is that climate model uncertainty dominates hydrological model uncertainty. However, it is acknowledged that this conclusion is based on the prior uncertainty assigned to both climate and hydrological models. Moreover, we have not sampled downscaling uncertainty, emissions uncertainty, and hydrological model parameter uncertainty (see Fig. 1). Therefore, we are likely underestimating the magnitude of climate and hydrological uncertainty in our analysis. Given the constraints of computational resources, we considered seven climate models and two hydrological models for each catchment. It can be argued that the application of seven climate models presents a reasonable representation of climate model structural uncertainty, given that previous climate change hydrological impact assessments have tended to apply a similar or lower number of climate models (Arnell et al. in review; Hayashi et al. 2010; Prudhomme et al. 2003). The prior uncertainty from climate model structural uncertainty could be reduced by comparing GCM simulations of baseline climate with observations. Such considerations have led to the calculation of performance metrics for GCMs, such as ranking them according to a measure of relative error (Gleckler et al., 2008). Forming a single index of model performance, however, can be misleading in that it hides a more complex picture of the relative merits of different models. Furthermore, for one specific region, Chiew et al. (2009) concluded that there was no clear difference in rainfall projections between the 'better' and 'poorer' 23 GCMs included in the CMIP3 archive (7 of which we applied here) based on their abilities to reproduce observed historical rainfall. Therefore in their analysis, using only the better GCMs or weights to favour the better GCMs gave similar runoff impact assessment results as the use of all the 23 GCMs. Moreover, on a conceptual level, it has been argued that, because of deep and structural uncertainty, it is not appropriate to seek to estimate the relative weight of different GCMs, and to do so would lead to significant over-interpretation of model-based scenarios (Stainforth et al., 2007): all models are only partial representations of a complex world, and miss important processes. For these reasons, in the present analysis, we assumed that all the GCMs are equally credible, although they are not completely independent. The computational resources required to perform multiple GHM simulations are relatively small compared with those required to run multiple CHMs because in previous work ClimGen was integrated with the GHM and adapted to run by high throughput computing (HTC) on the University of Reading Campus Grid, which reduced simulation time by a factor of over 80 relative to running on a single compute node (see Gosling et al. 2010). A more thorough consideration of downscaling uncertainty would apply climate projections from regional climate models (RCMs), which have been dynamically downscaled, and/or a range of different statistical downscaling algorithms other than that included in ClimGen (e.g. see Maraun et al. 2010). However, this would effectively at least double the computing and time resources required from what was used in the present analysis. A more thorough consideration of hydrological model

uncertainty would explore 1) hydrological model parameter perturbations, and 2) the application of several CHMs for each catchment. However, this would be demanding in terms of computational and human resources. For instance, to address the latter suggestion above, each CHM (SLURP, SWAT, etc.) would need to be calibrated for each individual catchment (Liard, Mekong etc.) and would then involve performing 216 CHM simulations (6 CHMs x 6 catchments x 6 increases in global-mean air temperature) for a single GCM pattern. As such, a computer cluster with around 216 nodes would be ideal, but each CHM would need to be adapted for running by HTC. This is not straightforward; see Gosling et al. (2010) for a detailed discussion on the issues regarding adapting a hydrological model to run by HTC. To address the former suggestion, Multi-Method Global Sensitivity Analysis (MMGSA; Cloke et al., 2007) presents a method for systematically perturbing all model parameters systematically but again, the extensive computing resources required for this precluded such an analysis here. Moreover, each CHM and GHM will include different parameters, so a like-with-like comparison is not straightforward. Nevertheless, Arnell (this issue) demonstrates that the uncertainty associated with 100 CHM model parameter sets is vastly smaller than the uncertainty across 21 GCM climate projections, which supports our conclusion that climate model uncertainty dominates hydrological model uncertainty. Moreover, evidence from other climate change impact assessment sectors (e.g. agriculture; Challinor et al. 2009) suggests that climate model uncertainty is effectively damped once other non-climatic uncertainties, such as decision-making processes or socio-economic uncertainties are considered, in a wider decision-making framework."

2. Can the prior uncertainty be reduced by confronting the models (climate and hydrological) to historical data? For example, it may turn out that some climate models perform much better on historical data from the specific basins in this study than other models, thereby reducing climate (posterior) model uncertainty. The authors touch upon this at the end of the discussion section, but I think this issue should be made more explicit throughout the paper.

We have added the following text to the Methods section (Section 2.2.) and to the Discussion section, to address this comment, and to make sure the point is made explicitly relatively early on in the paper:

To the Methods we have added: “The prior uncertainty from climate model structural uncertainty could be reduced by comparing the GCM simulations of baseline climate with observations (e.g. Gleckler et al. 2008) but the calculation of single indices of model performance can be misleading because it hides a more complex picture of the relative merits of different GCMs (see Arnell (this issue) for a more detailed discussion). Therefore all seven GCMs are assumed to be equally credible in this analysis.”

To the Discussion we have added: “A key conclusion is that climate model uncertainty dominates hydrological model uncertainty. However, it is acknowledged that this conclusion is based on the prior uncertainty assigned to both climate and hydrological models. Moreover, we have not sampled downscaling uncertainty, emissions uncertainty, and hydrological model parameter uncertainty (see Fig. 1). Therefore, we are likely underestimating the magnitude of climate and hydrological uncertainty in our analysis. Given the constraints of computational resources, we considered seven climate models and two hydrological models for each catchment. It can be argued that the application of seven climate models presents a reasonable representation of climate model structural uncertainty, given that previous climate change hydrological impact assessments have tended to apply a similar or lower number of climate models (Arnell et al. in review; Hayashi et al. 2010; Prudhomme et al. 2003). The prior uncertainty from climate model structural uncertainty could be reduced by comparing GCM simulations of baseline climate with observations. Such considerations have led to the calculation of performance metrics for GCMs, such as ranking them according to a measure of relative error (Gleckler et al., 2008). Forming a single index of model performance, however, can be misleading in that it hides a more complex picture of the relative merits of different models. Furthermore, for one specific region, Chiew et al. (2009) concluded that there was no clear difference in rainfall projections between the

‘better’ and ‘poorer’ 23 GCMs included in the CMIP3 archive (7 of which we applied here) based on their abilities to reproduce observed historical rainfall. Therefore in their analysis, using only the better GCMs or weights to favour the better GCMs gave similar runoff impact assessment results as the use of all the 23 GCMs. Moreover, on a conceptual level, it has been argued that, because of deep and structural uncertainty, it is not appropriate to seek to estimate the relative weight of different GCMs, and to do so would lead to significant over-interpretation of model-based scenarios (Stainforth et al., 2007): all models are only partial representations of a complex world, and miss important processes. For these reasons, in the present analysis, we assumed that all the GCMs are equally credible, although they are not completely independent.”

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- Can the authors discuss other uncertainties that have not been accounted for, such as within-model uncertainties (due to parameter errors, data mismatch...)?

We now discuss uncertainties that we have not accounted for, in the Discussion. Please see our response to the previous comment for details.

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- An implicit assumption is that the CHM can be used as a reference to evaluate the GHM (see eg p. 7205, line 27). It seems that the CHMs should indeed be better since they were calibrated on the specific basins, but that should be shown with explicit numbers in a table by comparing all models to historical data.

We have included in Table 1 now, a summary of Nash-Sutcliffe model efficiency coefficients that are calculated in each of the respective CHM papers in the Special Issue. It is attached here to this HESSD comment. Furthermore, we have edited the Methods section to include the following text: “All the CHMs had already been calibrated typically using local gauge networks. For each catchment, the CHM was re-calibrated for use with gridded (0.5°x0.5°) climate data from the CRU TS 3.0 dataset (Mitchell and

Jones, 2005) for the period 1961-90. This process is described in each of the individual papers in this issue, listed in Table 1. A summary of the Nash-Sutcliffe model efficiency coefficients (E) (Nash and SutcliïňĂe, 1970) that were calculated in validation exercises presented by each paper is also presented in Table 1. According to the classification scheme of Henriksen et al. (2008), the CHMs generally performed “fair” to “excellent”, although for a very small number of gauging stations in the Okavango and Mekong, the performance was “poor” (see Hughes et al. (this issue) and Kingston et al. (this issue) for more details).”

The references list has been updated accordingly, with the following new references:

Henriksen, H. J., Troldborg, L., Højberg, A. J., and Refsgaard, J. C.: Assessment of exploitable groundwater resources of Denmark by use of ensemble resource indicators and a numerical groundwater – surface water model, J. Hydrol., 348, 224–240, 2008.

Nash, J. E. and SutcliïňĂe, J. V.: River ïňĆow forecasting through conceptual models: Part 1 – a discussion of principles, J. Hydrol., 10, 282–290, 1970.

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- I believe that ideally all models should have been calibrated using downscaled GCM output, as that is what is used to estimate future impacts. That would make for a more consistent approach and allow the model parameters in calibration to compensate for some of the errors in the downscaled GCM output. Can the authors comment on this? Calibration with downscaled GCM output was not necessary for this analysis. This is because we used ClimGen to create the climate change scenarios. ClimGen essentially applies GCM-derived changes in mean climate to the baseline climate, to produce climate change scenarios. This means that the baseline and climate scenarios are compatible. Importantly, the result of this is that the simulated flows calculated from the different forcing GCMs can be compared. This is described in Todd et al. (this issue), but we have added the following text to the Methods section anyway, just to make this point clearer: “All the CHMs had already been calibrated typically using local

gauge networks. For each catchment, the CHM was re-calibrated for use with gridded (0.5°x0.5°) climate data from the CRU TS 3.0 dataset (Mitchell and Jones, 2005) for the period 1961-90. This dataset was the baseline for all analyses presented here and for the papers listed in Table 1. Importantly, the climate change scenarios (described in Section 2.2.) are compatible with the baseline (Todd et al. this issue), which is why each CHM was re-calibrated against the baseline.”

- p. 7197, line 12: since GHM grids are disconnected, why not run the model for only the grid cells in the basins of interest? That would reduce the computational load to a few hundred grid cells (based on numbers in Table 1).

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This could have been done. However, the preferred choice was to run the GHM globally, i.e. for all ∼65,000 cells because the output from the model will be, and has been used in other, larger spatial scale analyses. Moreover, given that the GHM had already been integrated with ClimGen and setup to run by high throughput computing (HTC), it was actually easier to run the model globally, rather than for just a few hundred grid cells. This did, of course, produce a much larger amount of output, than if the model was run for a few hundred cells, but like we mention above, this data has and will be used for further analyses.

Presentation

- A diagram or flowchart may be beneficial in clarifying the various uncertainties that come into play when assessing climate change impacts on river runoff. This would clearly show which uncertainties are accounted for here and which uncertainties are ignored; that may also help the discussion later on.

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We have created a new Figure, Fig. 1, which is attached with this HESSD comment. The figure summarises the main stages of a climate change hydrological impact assessment and the inherent uncertainties. The figure highlights which uncertainties we sample in our analysis. We have also added the following text to the manuscript, in a new sub-section ("1.3 Uncertainties in climate change hydrological impact assessment"), to support the new figure: "Climate change will affect the global terrestrial hydrological system (Kundzewicz et al., 2007) and there is evidence that it has already responded to the observed warming over recent decades (Bates et al., 2008). The most common method for assessing the magnitude of this impact is to run a hydrological model driven by various climate projections from general circulation models (GCMs, i.e. global-scale climate models) as input forcing data (e.g. Gosling et al., 2010). The simulations of key hydrological indicators, such as river runoff, can then be used to assess the potential impact of climate change and to inform policy- and decision-making. However, there are a number of uncertainties associated with making such projections. Fig. 1 summarises the four main stages of performing a climate change hydrological impact assessment, which is broadly similar to other climate change impact sector assessments (Gosling et al. 2009). The first stage is to determine the greenhouse gas emissions scenarios with which the climate model (e.g. a GCM) will be driven with, in order to produce the climate change projections (the second stage). GCMs typically represent the atmosphere, ocean, land surface, cryosphere, and biogeochemical processes, and solve the equations governing their evolution on a geographical grid covering the globe. Some processes are represented explicitly within GCMs, large-scale circulations for instance, while others are represented by simplified parameterisations. The use of these parameterisations is sometimes due to processes taking place on scales smaller than the typical grid size of a GCM (a horizontal resolution of between 250 and 600 km) or sometimes to the current limited understanding of these processes. Different climate modelling institutions will use different plausible representations of the climate system, which is why climate projections for a single greenhouse gas emissions scenario will differ between modelling institutes. Two main methods can be used to sample this so called "climate model structural uncertainty". The first is to use a range of climate projections from ensembles of plausible GCMs, to produce an

ensemble of impact projections for comparison. Such multi-model datasets are often described as "ensembles of opportunity", e.g. the World Climate Research Programme Third Coupled Model Intercomparison Project (WCRP CMIP3; Meehl et al. 2007). A second approach generates a "perturbed physics ensemble" (PPE) that introduces perturbations to the physical parameterisation schemes of a single climate model, leading to many plausible versions of the same underlying model. If sufficient computer power is available, then very large ensembles can be generated in this way. For example, Stainforth et al. (2005) ran an ensemble of 2,578 simulations that sampled combinations of low, intermediate, and high values of 6 parameters. As well as climate model structural uncertainty, climate models are sensitive to the initial conditions with which the models are initialised, which adds a further level of uncertainty. The third stage of a climate change hydrological impact assessment is to downscale the climate model output to a finer resolution, suitable for application to a hydrological model. Two approaches are typically available, statistical downscaling and dynamical downscaling. The former uses statistical relationships to convert the large-scale projections from a GCM to fine scales. Different statistical methods can be applied for the downscaling, which introduces uncertainty. The latter approach uses a dynamic model similar to a GCM to cover a region. The dynamic model is then forced at its lateral boundaries using results from the coarse scale GCM. The dynamic method is typically more computationally expensive but does not rely on the central assumption of most statistical downscaling, that the downscaling relationship derived for the present day will also hold in the future. In the final stage, the downscaled climate data is applied to a hydrological model. Uncertainty at this stage can arise from the application of different hydrological models, e.g. CHMs and GHMs (similar in essence to the uncertainty that can be sampled from a GCM ensemble of opportunity), and from different parameters sets and perturbations within a given hydrological model, i.e. parameter uncertainty (similar in essence to the uncertainty that can be sampled from a GCM PPE). For six catchments, we compare the simulated runoff response of a GHM and CHM to projected future climate associated with (1) several prescribed increases in global-mean temperature from a single GCM to explore simulated response to different amounts of climate forcing, and (2) a prescribed increase in global-mean temperature of 2.0°C for seven GCMs to explore response to climate model structural uncertainty. The main sources of uncertainty sampled by this methodological framework are shaded in Fig. 1. Note that emissions uncertainty and downscaling uncertainty are not sampled, i.e. they are held constant, and nor do we consider GCM perturbed physics or hydrological model parameter uncertainty."

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- Hydro-models calibration results: I understand that details of the model calibrations have or will be reported in separate papers; however, it would still be necessary to report here a summary of the calibration results, for example listing some performance metrics of each model in each basin in a table or figure. That would give the reader some feeling for the relative performance of these models, including how the CHMs compare to the GHM.

We have included in Table 1 now, a summary of Nash-Sutcliffe model efficiency coefficients that are calculated in each of the respective CHM papers in the Special Issue. Furthermore, we have edited the Methods section to include the following text: "All the CHMs had already been calibrated typically using local gauge networks. For each catchment, the CHM was re-calibrated for use with gridded (0.5°x0.5°) climate data from the CRU TS 3.0 dataset (Mitchell and Jones, 2005) for the period 1961-90. This process is described in each of the individual papers in this issue, listed in Table 1. A summary of the Nash-Sutcliffe model efficiency coefficients (E) (Nash and SutcliïňĂe, 1970) that were calculated in validation exercises presented by each paper is also presented in Table 1. According to the classification scheme of Henriksen et al. (2008), the CHMs generally performed "fair" to "excellent", although for a very small number of gauging stations in the Okavango and Mekong, the performance was "poor" (see Hughes et al. (this issue) and Kingston et al. (this issue) for more details)."

The references list has been updated accordingly, with the following new references:

Henriksen, H. J., Troldborg, L., Højberg, A. J., and Refsgaard, J. C.: Assessment of exploitable groundwater resources of Denmark by use of ensemble resource indicators and a numerical groundwater – surface water model, J. Hydrol., 348, 224–240, 2008.

Nash, J. E. and SutcliïňĂe, J. V.: River ïňĆow forecasting through conceptual models: Part 1 – a discussion of principles, J. Hydrol., 10, 282–290, 1970.

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- Please clarify in the abstract already that the main difference between the GHM and CHMs is the level of spatial aggregation of hydrological processes. And I guess also the fact that the GHM does not include lateral flow between elements.

The following text has been added to the abstract: "The CHMs typically simulate water resource impacts based on a more explicit representation of catchment water resources than that available from the GHM and the CHMs include river routing, whereas the GHM does not."

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- Abstract, line 21: specify here how big the "substantial differences" are

The text has been edited to read: "We find that the differences in projected changes of mean annual runoff between the two types of hydrological model can be substantial for a given GCM (e.g. an absolute GHM-CHM difference in mean annual runoff percentage change for UKMO HadCM3 2°C warming of up to 25%)."

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- Throughout the paper I suggest replacing "inter-comparison" by "comparison"

In cases where "inter-comparison" was referred to, this has been replaced with "comparison".

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- Section 3.1: instead of showing global maps of projected precipitation changes (figs. 2 and 3), it would be more relevant to show specific results for the basins studied in this paper, eg time-series plots of climate time-series for each basin.

The other reviewer made a similar comment, and we are in agreement that this is more useful. Therefore we have replaced the maps with graphs that show percentage change in average annual runoff for each catchment. They are attached with this HESSD comment.

Furthermore, we have edited the text in Section 3.1. to read: "Precipitation is the main driver of runoff (Chiew et al., 2009) so it is important to understand the magnitude by which it changes in each of the climate change scenarios we considered. Fig. 3 shows the percentage change from baseline in total-annual precipitation for UKMO HadCM3 prescribed warming of 1-6°C, for each catchment. The greatest changes in precipitation are observed for the Liard (around +33% with 6°C prescribed warming), Xiangxi (around +31% with 6°C prescribed warming) and Okavango (around -44% with 6°C prescribed warming). Harper's Brook is associated with a small change in precipitation with 6°C prescribed warming (-7%). Analyses in Section 3.2. demonstrate how the simulated changes in precipitation from each prescribed increase in global-mean air temperature are realised in changes in runoff. Fig. 4 shows the percentage change from baseline in total annual precipitation projected by seven GCMs for a prescribed increase in global-mean air temperature of 2°C, for each catchment. Whilst all GCMs simulate increases in precipitation with climate change for the Liard, there is not consensus in the sign of precipitation change across the seven GCMs for the remaining catchments. For instance, with the Mekong, four GCMs simulate increases in precipitation with climate change and three GCMs simulate decreases. It could be argued that this precludes a hydrological analysis using all seven GCMs. However, given the large dependence of runoff on precipitation (Chiew et al., 2009) and that complex non-linear interactions are common between

climate forcing and runoff (Majone et al. 2010), it is important to demonstrate how the uncertainty in the projections of precipitation across GCMs translates into runoff projections. Moreover, the consequent uncertainty across runoff simulations could have important implications for water resources management. Analyses in Section 3.3. demonstrate how the simulated changes in precipitation from each GCM are realised in changes in runoff."

Please also note the supplement to this comment:
http://www.hydrol-earth-syst-sci-discuss.net/7/C4123/2010/hessd-7-C4123-2010-supplement.pdf

Interactive comment on Hydrol. Earth Syst. Sci. Discuss., 7, 7191, 2010.

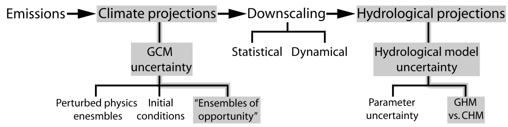

Fig. 1. Figure 1. The four stages of a climate change hydrological impact assessment and the inherent uncertainties. The shaded areas denote the uncertainties we considered in this analysis.

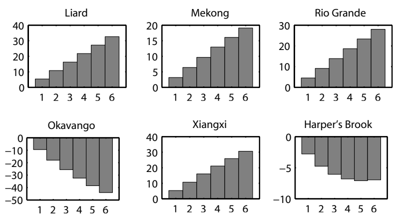

Fig. 2. Figure 3. Change in total-annual precipitation relative to baseline (vertical axis; %) for UKMO HadCM3 prescribed warming of 1-6°C (horizontal axis), for each catchment.

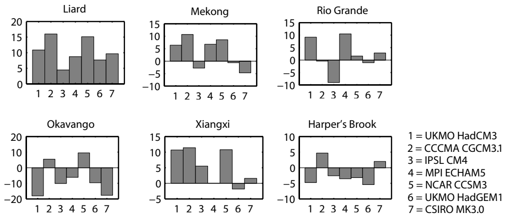

Fig. 3. Figure 4. Change in total-annual precipitation relative to baseline (vertical axis; %) for for the 7 GCMs under 2°C prescribed warming (horizontal axis), for each catchment.