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Key Points:

- Runoff sensitivity to temperature depends on the considered timescale
- Observational constraints based on interannual variability can thus lead to overconfident projections
- Observational constraints based on historical trends can be effective if such trends are driven by human emissions of greenhouse gases

Supporting Information:

Supporting Information may be found in the online version of this article.

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Revisiting the Potential to Narrow Model Uncertainty in the Projections of Arctic Runoff

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Abstract Despite multiple advances in the understanding of the water cycle intensification in a warmer climate, climate models still diverge in their hydrological projections. Here we constrain annual runoff projections over individual and aggregated Arctic river basins. For this purpose, we use two ensembles of global climate models and two statistical methods: a regression scheme assuming similar runoff sensitivities at interannual versus climate change timescales, and a Bayesian method where models are used to derive a posterior runoff response conditioned on historical observations. While both techniques are shown to narrow model uncertainties, more or less substantially depending on rivers, the Bayesian method is less sensitive to the choice of the model ensemble and is more skillful when tested with synthetic observations. It has also been applied over the whole Arctic watershed, showing so far a limited narrowing of the inter-model spread, but its skill will further improve with increasing climate change.

Plain Language Summary Despite considerable progress in understanding the intensification of the water cycle in response to global warming, projections of changes in the various components of the continental water balance remain highly model-dependent. This is particularly the case for the evolution of runoff, which remains very sensitive to the way atmospheric and continental processes are represented. Here we evaluate and compare two statistical methods to constrain climate projections of annual runoff at high latitudes via available or synthetic observations. Our Bayesian method, based on historical observations, is found to be more robust than a previous method based on observed interannual climate variability. It underlines the importance of having reliable flow reconstructions to constrain runoff projections and of using empirical observational constraints with caution, as they are likely to lead to over-confident projections.

1. Introduction

Hydrological projections at the regional scale are still very uncertain despite a robust theoretical understanding of the water cycle intensification at the global scale (AR6 WG1, Douville et al., 2021). More specifically, there is low confidence in the sign and magnitude of projected changes in global land runoff in all illustrative Shared Socio-economic Pathway (SSP) scenarios scrutinized in the sixth phase of the Coupled Model Intercomparison Project (CMIP6). There are however some regional exceptions, especially in the northern high latitudes where there is high confidence that projected increases in precipitation amount and intensity will be associated with increased runoff throughout the 21st century.

Much of the uncertainty in hydrological projections arises from global climate model (GCM) uncertainty rather than emission scenario uncertainty, while internal climate variability also plays a key role in the near-term (Douville et al., 2021; Lehner et al., 2020). Moreover, CMIP6 often shows larger model uncertainties than CMIP5 (Lehner et al., 2020), which may be partly due to a wider range of climate sensitivity (Hausfather et al., 2022). Yet, this explanation may not hold for runoff whose regional response does not scale with global warming across multiple models given the influence of other potential drivers, including model-dependent changes in large-scale circulation (Douville et al., 2022; Elbaum et al., 2022).

A recent global evaluation of runoff simulations, from both CMIP6 GCMs and off-line global hydrological models, suggests that models perform better in non-cold environments and that the multi-model ensemble average is not systematically an effective way to reduce bias compared to individual models (Hou et al., 2023). These results further support previous findings based on CMIP5 that urged caution in the direct use of climate model runoff for hydrological and water security applications (Lehner et al., 2019). Regional climate models at higher resolution are extremely useful to project runoff in small watersheds but do not necessarily provide more reliable projections

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in large-scale river basins since they are strongly constrained by their driving GCMs. Non-linearities in the runoff response to global warming may also challenge the use of simple pattern-scaling techniques to produce reliable hydrological projections at the regional scale (Douville et al., 2021; Zhang et al., 2018).

In response to these difficulties, an increasingly popular approach is to use emergent constraints to link future changes to present-day or recent climate features across multiple GCMs. Unfortunately, most emergent constraints that have been proposed after CMIP5 do not perform as well with CMIP6 models (Sanderson et al., 2021). Such constraints should be based on an independently verifiable physical mechanism (e.g., Hall & Qu, 2006) and considered with great caution when there is no such dominant single mechanism. Emergent constraints have thus the potential to produce overconfident projections (Sanderson et al., 2021). Moreover, they sometimes assume a time-invariance so that the mechanisms that dominate future climate changes are considered to be similar and observable on shorter timescales (Douville et al., 2006; Hall & Qu, 2006; Lehner et al., 2019). This is a strong hypothesis given the growing evidence that climate feedbacks may not only vary across timescales (e.g., Dessler & Forster, 2018) but may also be time-dependent on climate change timescales (e.g., Andrews et al., 2022).

Only few CMIP studies have quantified regional runoff projections, generally demonstrating a wide inter-model spread but a strong consistency in the ensemble mean model behavior across emissions scenarios or model generations (e.g., Giuntoli et al., 2018; Tang & Lettenmaier, 2012; Zhang et al., 2018). Even less studies have tried to go beyond the “one model one vote” approach in assessing the regional runoff sensitivity (e.g., Lehner et al., 2019; hereafter L19). Runoff sensitivity is rarely explicitly tuned in GCMs, thus offering an opportunity to develop an observational constraint unaffected by model calibration efforts. In L19, there are however two key sensitivities for which the time-invariance assumption has been made: the precipitation sensitivity of runoff (sometimes termed “runoff elasticity”; e.g., Tang & Lettenmaier, 2012), defined as the percent change in runoff induced by a 1% change in precipitation ($\Delta Q/\Delta P$); and the temperature sensitivity of runoff, defined as the percent change in runoff for a 1°C change in temperature ($\Delta Q/\Delta T$). Such metrics can be diagnosed from observations but their relevance is not guaranteed when it comes to constrain runoff projections across the whole 21st century.

In the present study, we illustrate this issue by revisiting the L19 potential to constrain the long-term runoff response from observed interannual variability. As in L19, the focus is on the northern high latitudes where a significant fraction of runoff originates as snowmelt and may be thus particularly sensitive to global warming (e.g., Li et al., 2017). After a brief description of the various datasets and statistical methods (Section 2), the L19 limitations are first shown by using two runoff definitions and two GCM generations over four northern high-latitude river basins (Section 3). The L19 results are also compared to those obtained with the alternative Kriging for Climate Change (KCC; Ribes et al., 2021; Qasmi & Ribes, 2022) method developed at CNRM. Finally (Section 4), the reasons for the better behavior of KCC are briefly discussed and the method is also applied to constrain runoff projections over the aggregated “Arctic” basin (i.e., river basins whose outlet is in the Arctic ocean or neighboring seas).

2. Data and Methods

We work with three main variables, total precipitation (P), near-surface air temperature (T) and total runoff (R), that have been averaged over large river basin and throughout the hydrological year (from October of the year N to September of the year N + 1, as in L19). The focus is on the northern high-latitudes where there is an amplification of global warming, a human-induced increase in annual mean precipitation (Douville et al., 2021) and an expected climate change signal in the observed runoff reconstructions.

2.1. Observed and Simulated Data

The main observed monthly datasets used are 1901–2018 precipitation (P) from the Global Precipitation Climatology Centre (GPCC, <https://www.dwd.de/EN/ourservices/gpcc/gpcc.html>), 1901–2019 near-surface air temperature (T) from the Met Office Hadley Centre observations (CRUTEM4, <https://www.metoffice.gov.uk/hadobs/crutem4/>), and 1902–2013 reconstructed runoff (R) from Ghiggi et al. (2019) (GRUN, <https://doi.org/10.6084/m9.figshare.9228176>). Note that GRUN does not provide “real” observations, but is based on a machine learning method that estimates R from T and P observations (Ghiggi et al., 2019). The model is trained with monthly observations at the scale of relatively small catchments and is then applied to global T and P products. All gridded datasets are available at a 0.5° resolution. Moreover, the observed global mean surface temperature (hereafter

GMST, which is a combination of near-surface air T over land and sea ice and of sea surface T over the ocean) has been derived over 1850–2020 from HadCRUT5 (<https://www.metoffice.gov.uk/hadobs/hadcrut5/>) and will be also used in the present study as a global rather than basin-scale observational constraint on runoff projections.

For simulated data, historical and corresponding future simulations (1850–2100) are taken from the last two phases of the Coupled Model Intercomparison Project (CMIP5 and CMIP6). We worked with the comparable although slightly different high-emission scenarios (RCP8.5 and SSP5-8.5 for CMIP5 and CMIP6 respectively) in order to maximize the signal-to-noise ratio. We distinguished several multi-model ensembles: two ensembles with data from the first available member of each model (we named these ensembles rcp81 and ssp51 respectively); a CMIP6 ensemble with at least three members for each model (but thus fewer models) although we only used the average of all available members for each model (named ssp50), as well as mono-model ensembles (ssp5x) with 1–25 individual members considered for the selected model alone. As for observations, we will here work with monthly model outputs for variables P, T, and R, where R is the total runoff computed as the sum of surface and subsurface runoff simulated by the land surface component of the climate models.

2.2. Statistical Methods Used to Constrain Basin-Scale Runoff Projections

The CMIP projections of 12-month runoff averaged from October to next September (the so-called water year) have been constrained with two different statistical methods. The first method is the L19 method depicted in Lehner et al. (2019) and based on runoff predictions from a multiple linear regression whose coefficients are constrained with the observed interannual variability. In the end, we can compute the basin-wide average runoff anomaly $\Delta R = a_0\Delta P + b_0\Delta T$, where a_0 and b_0 are the regression coefficients computed from observations (observed interannual variability) over the common 1902–2013 period. This period will be also referred to as the training period when L19 will be evaluated with model outputs as synthetic observations.

The second method (KCC) was developed by Ribes et al. (2021) and Qasmi and Ribes (2022) and is based on Bayesian statistics where a *prior* distribution, $\pi(x)$, of the forced response to anthropogenic forcings is first derived from raw model outputs and then constrained directly with observations of one or more variables (here both observed global mean surface temperature and reconstructed basin-wide average runoff). The *prior* is estimated using a Generalized Additive Model (assuming the additivity of the model responses to individual forcings) and a simple Energy Budget Model (allowing us to diagnose the runoff response to volcanic eruptions; for more details, see Supporting Information S1 from Ribes et al., 2021). For the sake of simplicity, this *prior* is assumed to follow a normal distribution and thus only needs an estimate of the ensemble mean and spread. Next, observations y are used to derive a *posterior* distribution (after constraint). We suppose that observations can be described as: $y = \mathcal{H}x + \epsilon$, where \mathcal{H} is a pseudo-observation operator allowing to extract the part of x observed in y and ϵ corresponds to internal variability and observational errors (if available). Since $\pi(x)$ and ϵ are assumed to follow normal distributions, the *posterior* can be easily derived using the Gaussian conditioning theorem (for more information, see Supporting Information S1 from Ribes et al., 2021).

These two statistical methods are thus very different. L19 is using the observed internal variability to constrain the regression coefficient of a multiple regression scheme aimed at predicting the long-term evolution of runoff from the evolution of the basin-wide average precipitation and near-surface temperature. In contrast, KCC is using directly the observed evolution of runoff and/or of global warming over the historical period to constrain the forced response of the simulated runoff with a Bayesian statistical method. Given the use of interannual runoff fluctuations to fit the regression scheme, L19 needs individual members of each model. For the sake of simplicity and of a fair comparison between the two methods, we thus start to work with the ssp51 and rcp81 multi-model ensembles. Yet, KCC focuses on the forced response and is thus expected to provide even better results when using as many members as possible for each model, hence also the use of the ssp50 ensemble based on the average of all members for each model.

2.3. Pseudo-Observations and Related Scores

To assess and compare the reliability of the L19 and KCC methods, we decided to work with pseudo-observations (as done in Ribes et al., 2021). The idea is that we extract one of the models and we use it as synthetic observations of both past and future variations of T, P and R. In the end, after constraining our remaining projections using the early pseudo-record (1901–2013), we can check if they are getting closer to our R pseudo-observations over the end of the 21st century compared to the raw (i.e., unconstrained) runoff projections. Each model provides successively

the reference pseudo-observations, so that we can compute several probabilistic scores to assess the quality and reliability of our constrained projections. Beyond the inter-model spread or the multi-model 90% confidence interval, two main scores were computed in this study: the coverage probability (CP) and the CRPS change.

- Coverage probability (CP): for each iteration, we check that the future pseudo-observations for the 2081–2100 period are in the 5–95% confidence interval of the constrained projections. In the end, we get a CP percentage corresponding to the number of reference models (POBS) in this confidence interval, which should be as close to 90% as possible.
- CRPS is a common probabilistic score quantifying the distance between the (pseudo-)observations and the distribution of predicted anomalies over the same 2081–2100 period. A negative relative change in CRPS for constrained versus unconstrained model distributions thus means an improved model distribution. For each basin, we averaged this CRPS change after using successively each model as pseudo-observations.

3. Results

Our main purpose here is first to constrain the ssp51 and rcp81 ensembles of runoff projections with observations, using two different statistical methods. We will compare the robustness and reliability of the two methods by first checking the sensitivity to the chosen model ensemble (CMIP6 vs. CMIP5), and then computing statistical scores using the idealized pseudo-observation framework.

3.1. Assessing the Robustness of the L19 Method

In Lehner et al., 2019, the L19 method was applied to CMIP5 models and runoff was estimated as precipitation minus evapotranspiration (E), thus assuming no change in water storage. In the present study, we work with CMIP6 models and genuine simulated runoff (rather than P-E) outputs. In agreement with L19 (cf. their Figure 1), Figure S1 in Supporting Information S1 shows that runoff anomalies computed with a multiple linear regression (using both P and T predictors) performs better than a simple regression (using P only) to predict runoff anomalies over the training period (1901–2013). Note that other regressions could be also tested but would not be as effective or based on less reliable predictors in the instrumental record. We thus choose to work with the same basin-wide average P and T predictors as in L19. A similar figure but using P-E instead of R (as in Lehner et al., 2019) is shown in SI (Figure S2 in Supporting Information S1). Not surprisingly, regressions show an improved skill when using P-E rather than R. Thus, using P-E as an approximation of R can lead to overconfident projections when using the L19 method. Thereafter we will work with the R variable averaged throughout the water year, for which river the observed river discharge provides reasonable estimates.

The L19 method apparently succeeds in narrowing uncertainty in runoff projections. Indeed, the 5–95% confidence interval is reduced after the L19 constraint (black and green line, Figure 1) compared to the simulated and raw predicted anomalies at the end of the 21st century. Overall, even when uncertainties in the observed regression coefficients are accounted for (green thin line), we obtain a systematic reduction of the 90% confidence interval. Similar qualitative results are obtained when using P-E as a surrogate of runoff (Figure S3 in Supporting Information S1). Yet, our results are basin-dependent and also sensitive to the choice of the multi-model ensemble as shown by the comparison between CMIP6 (Figure 1) and CMIP5 (Figure S4 in Supporting Information S1).

To sum up, the L19 method seems to succeed in narrowing the uncertainties in runoff projections over the four selected northern high-latitude river basins: Columbia, Kolyma, Lena and Mackenzie. However, these results rely on severe assumptions that have not been tested properly and may lead to overconfident projections. This is the reason why we will further evaluate the reliability of the L19 method by using synthetic observations of both past and future climate in Section 3.3.

3.2. Assessing the Robustness of the KCC Method

The KCC method was also applied to constrain both CMIP6 and CMIP5 annual runoff projections. Two metrics were used as observational constraints: the global mean near-surface air temperature from HadCRUT5 (including an estimate of observational errors) and/or the basin-wide average runoff from GRUN (without error estimates and based on reconstructed runoff from observations rather than genuine river discharge measurements). For the four selected river basins, the CMIP6 inter-model spread of the distribution is reduced by around 10%–35% in 2100 after applying the KCC observational constraint (Figure 2). Similar results are obtained with the CMIP5 models (Figure S5 in Supporting Information S1). The limited narrowing of model uncertainty, compared to the

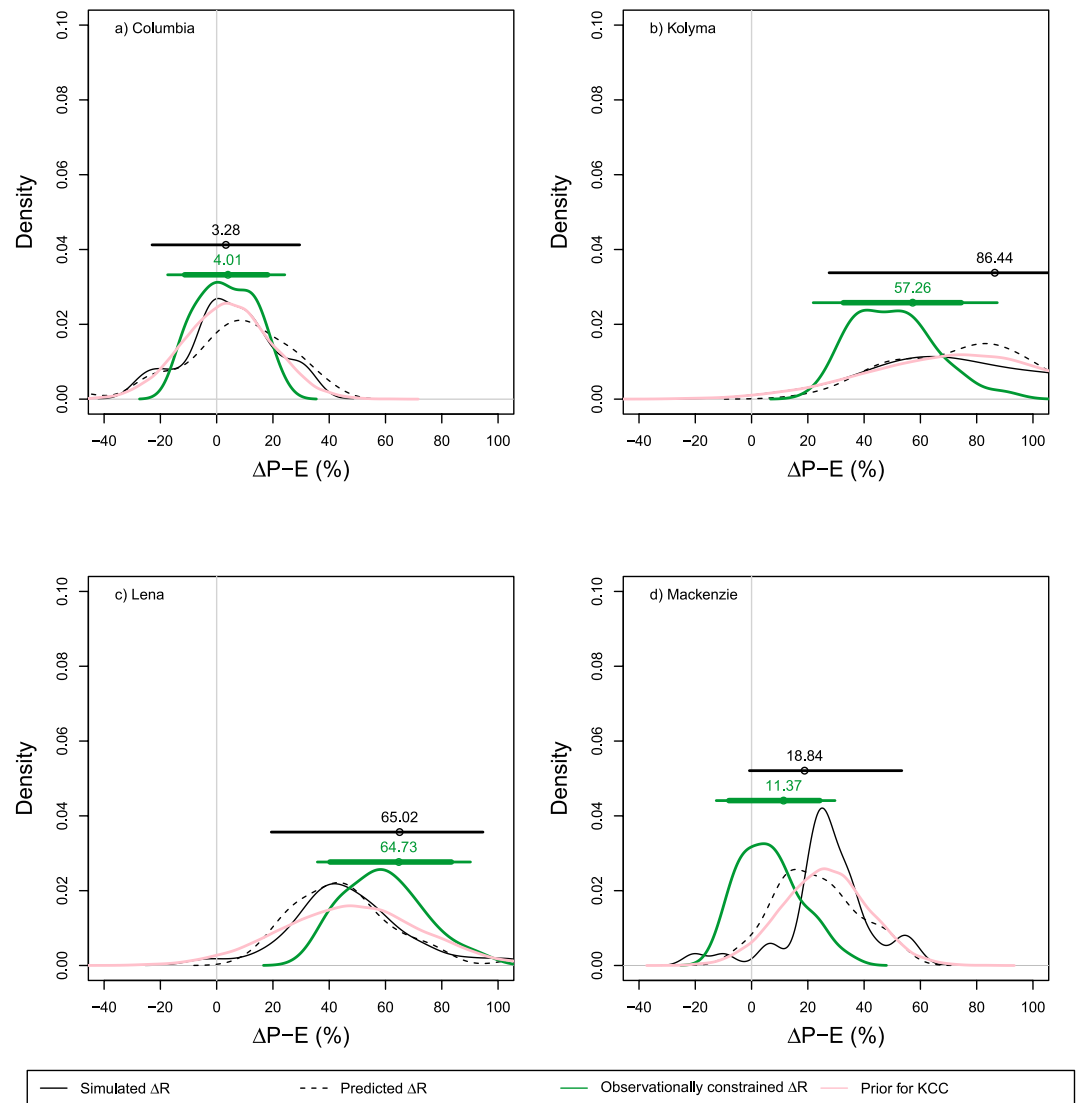


Figure 1. Constrained versus unconstrained distributions of water-year mean relative runoff anomalies (%) from the CMIP6 model ensemble under the SSP5-8.5 high-emission scenario: (a) Columbia, (b) Kolyma, (c) Lena, and (d) Mackenzie. Kernel density functions of runoff anomalies as simulated by CMIP6 models and as predicted and constrained by the L19 method (runoff anomalies are averaged over the 2081–2100 period). The KCC prior distribution is also shown ($\pi(x)$ in red) in order to highlight that the normal distribution assumption has a significant impact on the prior distribution given the limited size of the CMIP6 ensemble. Predicted runoff anomalies are those computed from the L19 multiple regression but without constraining the regression coefficients with observations. The black and green horizontal lines represent the 5%–95% confidence interval of the simulated and the L19 constrained projections respectively. The green confidence interval includes uncertainties in the regression coefficients as estimated with a bootstrap method (green thin line).

use of L19 and in particular for the Columbia river also considered in L19, is consistent with the lack of an obvious long-term trend in the GRUN reconstruction. When comparing the constrained projections between ssp51 (Figure 2) and ssp50 (with multiple members for each model, Figure S6 in Supporting Information S1), similar results are found thereby suggesting that internal climate variability is not responsible for the apparently lower performance of KCC.

The KCC method was also applied using only either the global mean surface temperature observations (GSAT from the HadCRUT5 data set, consisting of 200 members to account for observational uncertainties) or the basin-wide runoff GRUN reconstruction (assuming no observational uncertainty). When using only GSAT observations, the inter-model spread is not much reduced, thereby supporting the claim that regional hydrological changes are not heavily constrained by global warming (Douville et al., 2022). This finding highlights the need

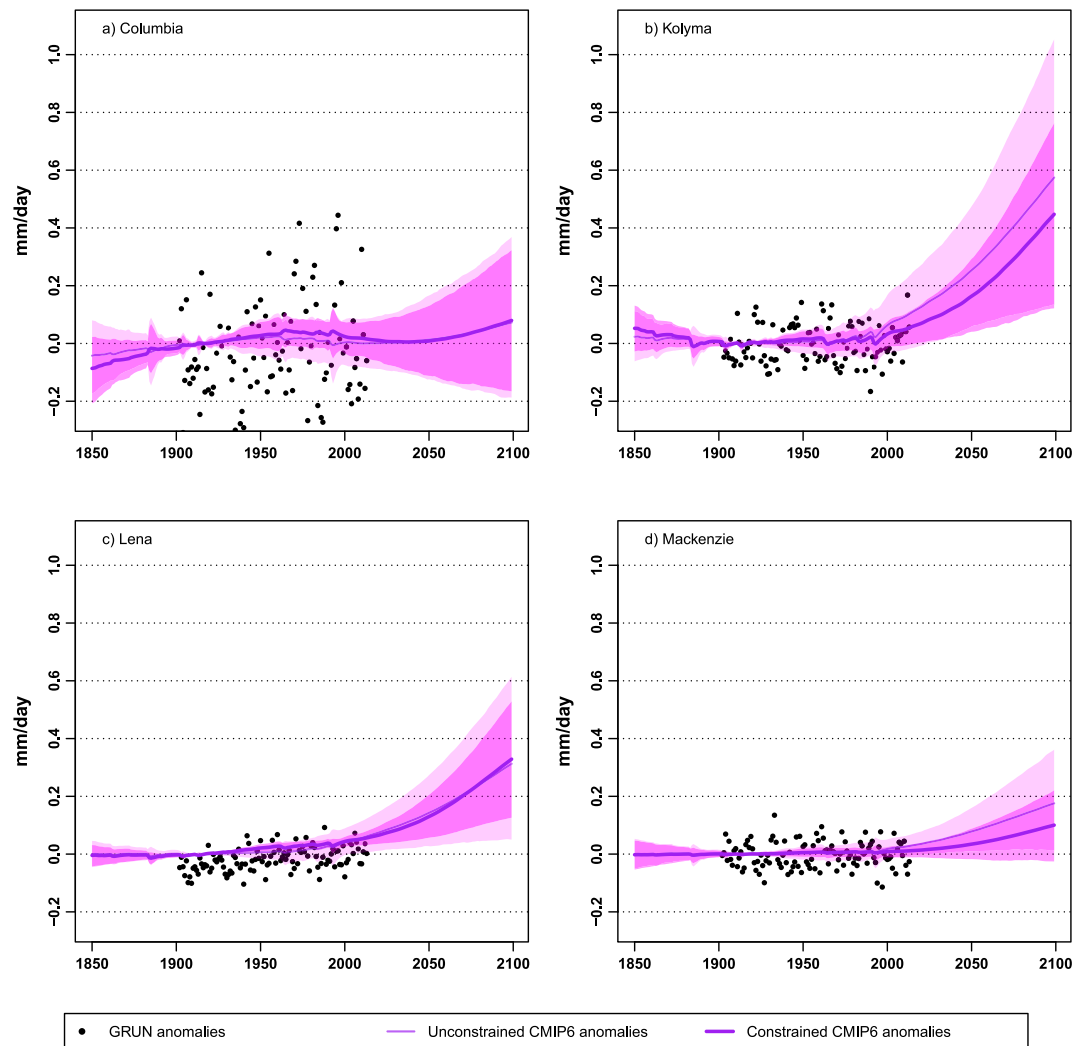


Figure 2. Constrained versus unconstrained water-year runoff anomalies (mm/day) using the ssp51 ensemble (a single member of each CMIP6 model under the SSP5-8.5 scenario). Black dots correspond to the GRUN water-year runoff anomalies. Both GRUN runoff and HadCRUT5 GSAT observations are used to constrain the simulated runoff anomalies. The thick lines denote the best estimate of each distribution (i.e., the ensemble mean) while shadings denote the corresponding 5%–95% confidence intervals.

for monitoring river discharge and providing estimates of water withdrawals versus natural runoff, including observational uncertainties, for better constraining runoff projections.

To sum up, KCC was also applied to Columbia, Kolyma, Lena and Mackenzie and led to a weaker (by 10%–35%) but more robust (CMIP5 vs. CMIP6) narrowing of model uncertainty in the highest emissions scenarios and using a single member for each model. Yet, the performance of KCC is expected to improve with the emerging influence of climate change in the observed time series, in contrast to L19 where longer observed time series will only have a limited impact on the observed regression coefficients dominated by interannual variability. Moreover, a fair comparison between KCC and L19 necessitates a different setting where physically-consistent pseudo-observations are derived from a randomly-chosen climate model in order to assess the constrained projections based on the other models.

3.3. Validation of These Results With Pseudo-Observations

We showed that both L19 and KCC methods have the potential to reduce model uncertainty on projected runoff anomalies in a warmer climate. Yet, we do not know so far the extent to which these results are reliable. As in

Ribes et al. (2021), we now use a pseudo-observation framework and compute three probabilistic scores (CP, CRPS change and reduction of spread) in order to assess the robustness and reliability of our methods (see Section 2.2 for details). Results are compared over the four selected watersheds in order to get an overall picture of the relative performance of the L19 and KCC methods (Tables S1, S2, and S3 in Supporting Information S1). As a reminder, and beyond the expected reduction in the inter-model spread, CP has to be as near to 90% as possible and CRPS has to be as low (close to zero) as possible after constraining the projections. Therefore, the change in CRPS and spread have to be negative for the constraint to be reliable and effective.

Although leading to a fairly similar systematic reduction of uncertainty, the L19 and KCC methods show contrasted scores in terms of both CP and CRPS. For the L19 method, CP is far from 90% and changes in CRPS are systematically positive, thus providing clear evidence that the method leads to overconfident projections, likely due to a timescale-dependent temperature effect on runoff (cf. Figures S7 and S8 in Supporting Information S1). For the KCC method, CP is above 80% for three out of four basins (Table S3 in Supporting Information S1) and CRPS changes are either negative or slightly positive. While these results suggest a cautious use of both methods, they clearly emphasize the superiority of the Bayesian KCC technique compared to the more empirical L19 emergent constraint.

Regarding the KCC method, scores are generally (and as expected) slightly improved if one uses several rather than just one member to assess the forced response of each model (ssp50, compared to ssp51; better spread reduction, overall better change in CRPS but slightly worse CP). Yet, they are still basin-dependent and better when using the local (GRUN) constraint only (not shown here). This finding highlights again that the observed global historical warming is not very helpful to constrain the basin-scale runoff and further supports the cautious statement of Douville et al. (2022) regarding the scalability of hydrological changes with global warming across multiple models.

Note that we also tried to constrain the basin-scale projections of precipitation and temperature using KCC, before applying the L19 method (multiple linear regression with observationally-constrained regression coefficients) to constrain the projections of runoff. However, this combined method led to even more overconfidence than applying the L19 method only when tested with pseudo-observations, so that the results were not included in this article.

To sum up, scores are overall better when using the KCC method to constrain runoff projections with pseudo-observations compared to the use of the more empirical L19 method. The overconfidence of L19-constrained runoff projections arises primarily from the different runoff sensitivity to temperature and precipitation at climate change versus interannual timescale (cf. Figures S7 and S8 in Supporting Information S1).

4. Discussion and Conclusion

Two statistical methods were applied with available observations, and compared in a more idealized setting, to reduce the uncertainty about projected northern-latitude runoff changes throughout the 21st century at the basin-scale: the L19 method (Lehner et al., 2019) and the KCC method (Ribes et al., 2021). After using pseudo-observations to compute statistical scores and assess the reliability of our results, we found that the L19 method is systematically overconfident, which means that there is a greater than 10% probability for the actual runoff evolution to lie outside the constrained 5–95% confidence interval. Generally speaking, the KCC method leads to more reliability and better scores, though variable from one basin to another depending on the observed trend in the GRUN natural runoff reconstructions (not accounting for a direct human influence through water withdrawals and river management). The overconfidence of the L19 results is primarily due to a wrong hypothesis regarding the runoff sensitivity to temperature and precipitation at different timescales (e.g., Zhang et al., 2022). Our results thus illustrate the danger of using emergent constraints without having first tested them in an idealized context (Sanderson et al., 2021). Furthermore, they highlight the potential of more direct observational constraints whose power should increase with further climate change and stronger signal-to-noise ratio in observed runoff time series.

To conclude this study, we have thus decided to apply the KCC method to the aggregated “Arctic” basin by merging all watersheds whose outlets are in the Arctic Ocean and nearby seas. Results of the individual and combined constraints are shown in Figure 3. Overall, the constraint using both GSAT and runoff observations (GRUN and HadCRUT5) allows KCC to reduce the CMIP6 inter-model spread in Arctic runoff by 22% (Figure 3c)

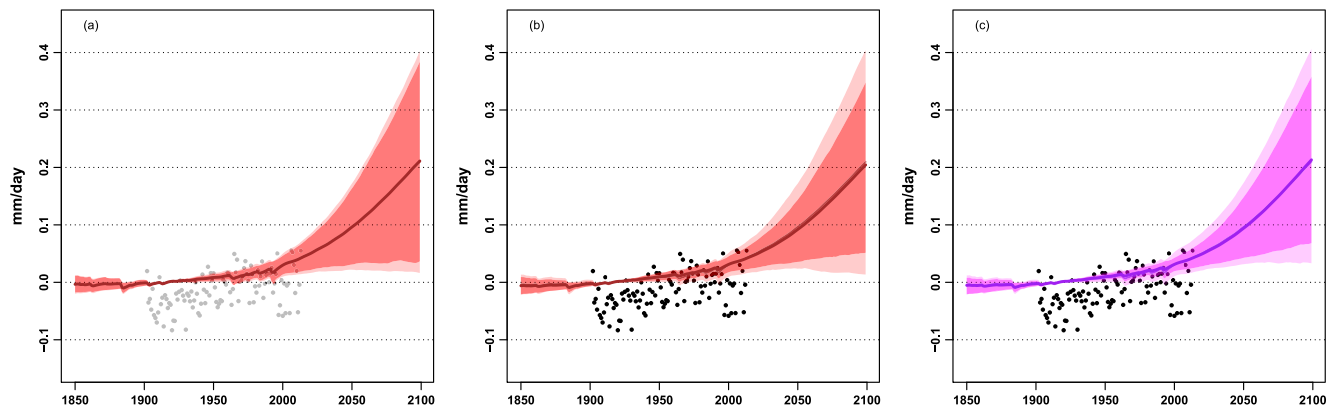


Figure 3. Constrained (dark shading) versus unconstrained (light shading) aggregated Arctic water-year runoff anomalies (mm/day) using the ssp50 ensemble (a) KCC constraint using only the HadCRUT5 GSAT observations. (b) KCC constraint using only the GRUN runoff reconstruction. (c) KCC constraint using both HadCRUT5 and GRUN observational constraints. Black dots correspond to the GRUN water-year anomalies; they are colored in gray (rather than black) when GRUN is not used to constrain the projections. The thick lines (here superimposed) denote the best estimate of each distribution (i.e., the ensemble mean) while shadings denote the corresponding 5%–95% confidence intervals.

in 2100 (even more in the early 21st century). As expected when increasing the signal-to-noise ratio through spatial aggregation, this combined constraint is more efficient than the individual ones using either HadCRUT5 or GRUN reconstructions. Scores with pseudo-observations for the whole Arctic basin (not shown) were also computed. They are quite promising and suggest even better results after one more decade of observations. Our study thus emphasizes the need of more reliable and routinely updated runoff observations (compared to GRUN for instance) to constrain model projections that, unfortunately, do not show a spread reduction from one model generation to the next despite the sustained efforts of global modeling centers to improve and evaluate such models.

Data Availability Statement

The CMIP5 and CMIP6 archive are available on the ESGF archive at <https://esgf-node.llnl.gov/>. The GRUN runoff reconstruction is available from <https://doi.org/10.3929/ethz-b-000324386>, and HadCRUT5 observations from <https://www.metoffice.gov.uk/hadobs/hadcrut5/>. The KCC statistical package is accessible under a GNU General Public License, version 3 (GPLv3), at <https://doi.org/10.5281/zenodo.5233947>. Other codes for data curation and visualization are based on the CliMAF package available at: <https://climaf.readthedocs.io/en>.

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