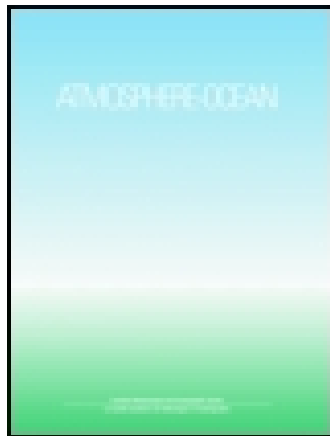


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Uncertainty in Regional Climate Model Mean Runoff Projections under Climate Change: Case Study of Labrador's Churchill River Basin

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ABSTRACT *An ensemble of seven climate models from the North American Regional Climate Change Assessment Program (NARCCAP) was used to examine uncertainty in simulated runoff changes from a base period (1971–2000) to a future period (2041–2070) for the Churchill River basin, Labrador, Canada. Three approximations for mean annual runoff from each ensemble member were included in the analysis: (i) atmospheric moisture convergence, (ii) the balance between precipitation and evaporation, and (iii) instantaneous runoff output from respective land-surface schemes. Using data imputation (i.e., reconstruction) and variance decomposition it was found that choice of regional climate model (RCM) made the greatest contribution to uncertainty in the climate change signal, whereas the boundary forcing of a general circulation model (GCM) played a smaller, though non-negligible, role. It was also found that choice of runoff approximation made a substantial contribution to uncertainty, falling between the contribution from RCM and GCM choice. The NARCCAP output and imputed data were used to calculate mean and median annual changes and results were presented via probability distribution functions to facilitate decision making. Mean and median increases in runoff for the basin were found to be 11.2% and 8.9%, respectively.*

RÉSUMÉ [Traduit par la rédaction] *Nous avons utilisé un ensemble de sept modèles climatiques du North American Regional Climate Change Assessment Program (NARCCAP) pour examiner l'incertitude dans les changements du ruissellement simulé entre une période de référence (1971–2000) et une période future (2041–2070) dans le bassin du fleuve Churchill, au Labrador, au Canada. L'analyse comportait trois approximations pour le ruissellement annuel moyen selon chaque membre de l'ensemble : (i) la convergence de l'humidité atmosphérique, (ii) l'équilibre entre les précipitations et l'évaporation et (iii) la sortie de ruissellement instantané des schémas de surface respectifs. En utilisant l'imputation de données (c. à d. la reconstruction) et la décomposition de la variance, nous avons trouvé que c'est le choix du modèle climatique régional qui a le plus contribué à l'incertitude dans le signal de changement climatique, alors que le forçage aux limites d'un modèle de circulation générale a joué un rôle moins important, quoique non négligeable. Il apparaît aussi que le choix de l'approximation du ruissellement a apporté une contribution importante à l'incertitude, se situant entre celle du choix du modèle climatique régional et celle du choix du modèle de circulation générale. Nous avons utilisé la sortie du NARCCAP et les données imputées pour calculer les changements annuels dans la moyenne et la médiane et nous avons présenté les résultats sous forme de fonctions de distribution de probabilités pour faciliter la prise de décision. Il ressort que les accroissements pour la moyenne et la médiane du ruissellement dans le bassin sont de 11,2% et 8,9%, respectivement.*

KEYWORDS climate change; climate models; uncertainty; atmospheric water balance; terrestrial water balance; ensemble analysis

1 Introduction

Climate change is already having a noticeable effect on earth's hydrological cycle (Déry, Hernández-Henríquez, Burford, & Wood, 2009; Trenberth, Dai, Rasmussen, & Parsons, 2003). As the changing climate's influence becomes more apparent, the need to investigate its potential impacts increases. However, impact assessments are complicated by the

uncertainty present in all climate simulations. Uncertainty results from having limited knowledge of how society will develop and how the climate system will react to that development. This leads to the inability to predict the impacts of climate change exactly and necessitates the representation of a range of possible outcomes (vis-à-vis uncertainty), for which informed adaptation decisions can be made (Foley, 2010).

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Primary sources of uncertainty in climate change studies include greenhouse gas emissions scenarios, climate model selection, downscaling method, and sampling uncertainty (Déqué et al., 2007; Maurer, 2007; Shrestha, Berland, Schnorbus, & Werner, 2011; Thorne, 2011). Sampling uncertainty, which exists because climate statistics are estimated from a finite sample that does not cover the entire range of natural variability, is often marginal (Déqué et al., 2007). A notable exception is the case of estimating climate extremes (e.g., 100-year return periods derived from 30 years of climate simulation). For hydrological impact studies, the selection and implementation of a land-surface hydrology model and the ability of a climate model to simulate the water cycle adequately, with its complex and multi-scale processes, is also of interest (Music & Caya, 2007). Multiple studies (e.g., Mitchell & Hulme, 1999; Wilby & Harris, 2006) examined several of these sources of uncertainty individually and described the “cascade of uncertainty” and how it propagates from emissions scenario down to sampling uncertainty.

It is unknown how society will develop in the coming decades and, therefore, impossible to ascertain total atmospheric greenhouse gas concentrations for the future. There are several greenhouse gas emissions scenarios that provide a range of plausible future pathways for carbon dioxide, methane, and other greenhouse gas concentrations (IPCC, 2000). In order for a climate study to capture this uncertainty, multiple emissions scenarios would need to be employed.

Uncertainty in climate modelling is introduced by an incomplete understanding of the climate system and all its processes, as well as an inability to fully and accurately represent the processes that are understood. No single model is best at simulating all aspects of the climate system (Christensen & Christensen, 2007; Maraun et al., 2010), meaning a variety of climate models that use different algorithms and parameterization schemes (i.e., a multi-model ensemble) should be used to address this type of uncertainty (Kotlarski et al., 2005; Murphy et al., 2004).

Downscaling of a general circulation model (GCM) can be divided into two approaches: (i) dynamic downscaling in which a regional climate model (RCM) of relatively high resolution is driven at its geographic boundaries over a specific region by a global GCM and (ii) statistical downscaling in which a statistical relationship is established between large-scale atmospheric variables and specific local situations (Fowler, Blenkinsop, & Tebaldi, 2007). This study focuses on dynamic downscaling, in which the choice of RCM introduces an additional level of uncertainty because of differing modelling structures, processes, and parameterization schemes. Statistical downscaling methods, which also have been found to introduce additional uncertainty, though less than that of GCM choice (Chen, Brissette, Chaumont, & Braun, 2013; Vano et al., 2014), are not discussed further here.

Parameterization schemes are methods of approximating physical processes that occur on too small a scale to be

resolved by a climate model. Some examples of processes that require parameterization schemes are large-scale condensation, convection, soil processes, snow–albedo feedback, and evaporation. All parameterizations contribute to bias in RCM output (Fowler, Kilsby, & Stunell, 2007; Hagemann et al., 2004), meaning that variables other than precipitation, which is often a focus of hydrological studies, also contribute to runoff bias (Gagnon, Konan, Rousseau, & Slivitzky, 2009). This creates the need to analyze multiple components of the simulated hydrological system to best capture uncertainty when investigating the impacts of climate change on the hydrology of a basin.

The primary constraint on quantifying the impacts of climate change on water resources and the hydrological system is often touted as GCM projection uncertainty (Bennett, Werner, & Schnorbus, 2012; Minville, Brissette, & Leconte, 2008; Wilby & Harris, 2006; Xu, Taylor, & Xu, 2011). Differences between individual GCMs have been found to result in a larger impact on simulated hydrological change than differing emissions scenarios (Graham, Andréasson, & Carlsson, 2007), though emissions scenarios still play a role (Jasper, Calanca, Gyalistras, & Fuhrer, 2004). Thorne (2011) found that even with a prescribed +2°C global mean temperature change, a selection of GCMs gave different outcomes for the Liard River Basin in northern Canada because of differences in algorithms, parameterizations, and feedback mechanisms. As such, it is recommended that multiple GCMs should be selected for use in impact studies (Ghosh & Mujumdar, 2009; Kingston, Thompson, & Kite, 2011; Thorne, 2011).

The RCM formulation has been found to have a comparable, or sometimes dominant, influence on the uncertainty of simulated variables (Déqué et al., 2007; Roberts, Pryse-Phillips, & Snelgrove, 2012; Rowell, 2006), and relative contributions to uncertainty vary according to spatial domain, region, season, and variable (Déqué et al., 2005; Fowler, Blenkinsop et al., 2007). GCMs and RCMs contribute more uncertainty to simulated runoff than hydrological models, though the influence of hydrological model selection becomes stronger during low-flow periods and in arid watersheds (Maurer, Brekke, & Pruitt, 2010; Najafi, Moradkhani, & Jung, 2011; Velázquez et al., 2013). Therefore, it is important to include multiple climate models in a climate change impact study to best capture the range of uncertainty (Fowler, Blenkinsop et al., 2007; Hingray, Mezghani, & Buishand, 2007).

There are many components of the hydrological system represented by climate models including the advection of moist air in the atmosphere, precipitation and evaporation, as well as runoff. The primary objective of this paper is to investigate the importance of GCM and RCM uncertainty in the mean runoff climate change signal compared with the choice of mean runoff approximation as derived from atmospheric and terrestrial water balance components. A secondary objective is to investigate the climate change signal for mean annual runoff in Labrador’s Churchill River basin.

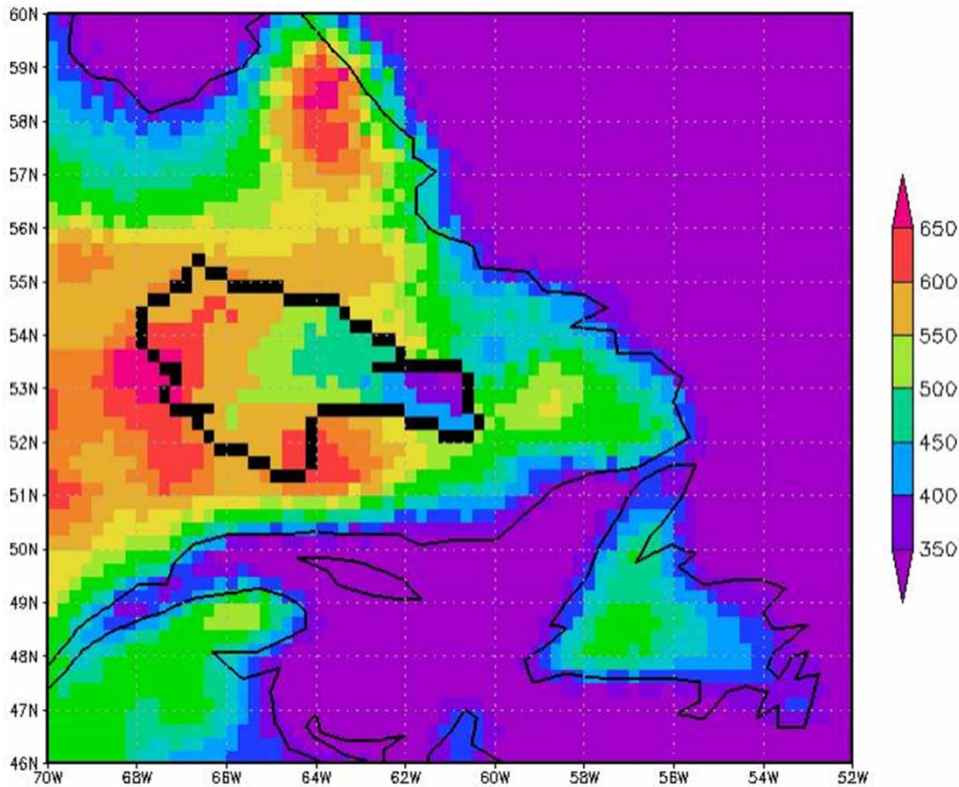


Fig. 1 Topography, location, and representation of Churchill River basin (thick black line; coastline is represented by thin black lines). Elevation scale is in metres.

2 Background

a Churchill River Basin

The Churchill River basin is located in Newfoundland and Labrador, Canada, and has an area of approximately 92,500 km². The basin is sparsely populated but contains the sites for existing and future large-scale hydroelectric power production facilities. At Muskrat Falls, the outlet located at the eastern edge of the basin, a hydroelectric facility is currently under construction. Figure 1 shows the location of the Churchill River basin outlined by a thick black line. The resolution of Fig. 1 is the common 0.25 degree grid to which all RCM output was regridded for this study. The soil is predominantly well-drained podzolic soil in the forested areas that are dominated by black spruce or poorly drained organic soil in the extensive wetlands. Elevation ranges from 1550 m at the highest point in the west to near sea level at the basin outlet in the east.

According to Environment Canada's in situ meteorological stations, the mean annual precipitation in the basin is 890 mm (with an interannual standard deviation of 130 mm), with a relatively even split between rain and snow (Environment Canada, 2014). The mean annual temperature is -3.5°C with a standard deviation of 1.1°C. There are only four observation stations with multi-decadal records covering the entire basin, so there is relatively large uncertainty in these values. Observed mean annual streamflow at Muskrat Falls (the basin outlet) is roughly 1825 m³ s⁻¹ (Water Survey of Canada, 2010), with a standard deviation of 255 m³ s⁻¹.

It has been shown that even small changes in the distribution of precipitation can significantly alter mean annual runoff (Muzik, 2001). Additionally, modest perturbations in natural inflow tend to have amplified effects on reservoir storage levels (Christensen et al., 2004; Minville et al., 2008). As such, the impact of climate change on the basin's runoff is of great interest.

b Climate Models

Frigon, Music, and Slivitzky (2010) and Eum, Gachon, Laprise, and Ouarda (2012), among others, recommend using the North American Regional Climate Change Assessment Program (NARCCAP) for climate change and uncertainty analysis. The NARCCAP is an international collaboration designed to investigate the uncertainties in future climate projections at a regional level using a design of experiments (DOE) approach (Mearns et al., 2007, 2009). It employs a selection of RCMs nested within multiple GCMs. The GCMs provide the initial conditions for the RCMs, as well as boundary conditions including large-scale atmospheric fields, sea surface temperatures, and sea ice. This boundary control from the GCMs constrains the RCM simulation to be consistent with the global simulation, while the higher resolution of the RCMs allows for better representation of regional phenomena (Christensen et al., 2007). The land surface of the GCM does not help drive that of the RCM. Each RCM has its own land-surface scheme that

TABLE 1. The RCM–GCM combinations used in this study are denoted by X.

RCM	GCM		
	CCSM	CGCM3	GFDL
CRCM	X	X	—
HRM3	—	—	X
RCM3	—	X	X
WRFG	X	X	—

interacts with the lower levels of the RCM atmospheric simulation. Each GCM is driven by the Intergovernmental Panel on Climate Change (IPCC) Special Report on Emissions Scenarios (SRES) A2 scenario, which is at the higher end of the IPCC emissions scenario spectrum (IPCC, 2000). The ensemble approach of NARCCAP allows the representation of uncertainties introduced by GCM choice, RCM choice, and their respective structural formulations (Maraun et al., 2010). The time frames covered are 1968 to 2000 for the base reference period and 2038 to 2070 for the future period, including three years of model spin-up data at the beginning of each run, which are not included in this analysis.

Because of budget constraints not all of NARCCAP's possible RCM–GCM combinations are being run. Each GCM will be coupled with half the RCMs and vice versa, resulting in a representative sample of twelve simulations. Although the various ensemble members each have a 50 km horizontal resolution, they employ a variety of map projections, vertical coordinate systems, dynamics and physics schemes, land-surface schemes, vegetation classes, and time steps among other varying parameters and characteristics. Output from the various ensemble members is released incrementally in conjunction with the completion of post-processing and only those combinations published at the time of analysis are included in this work (Table 1). The simulations cover a base period, 1971–2000, and a future period, 2041–2070. The GCMs used in this study include the Community Climate System Model (CCSM; Collins et al., 2006), the Third Generation Coupled Global Climate Model (CGCM3; Flato, 2005; Scinocca & McFarlane, 2004), and the Geophysical Fluid Dynamics Laboratory (GFDL) model (GFDL, 2004), while RCMs include the Canadian Regional Climate Model (CRCM; Caya & Laprise, 1999), the Hadley Regional Climate Model (HRM3; Jones et al., 2004), the Regional Climate Model, version 3 (RCM3; Giorgi, Marinucci, & Bates, 1993; Giorgi, Marinucci, Bates, & De Canio, 1993; Pal, Small, & Eltahir, 2000; Pal et al., 2007), and Weather Research and Forecasting Grell (WRFG; Skamarock et al., 2005) model. The models are discussed in detail in Roberts and Snelgrove (2015) and on the NARCCAP website (<http://www.narccap.ucar.edu/>).

3 Methodology

This study uses a three-pronged approach that incorporates a broad range of simulated hydrological data from an

ensemble of RCMs and GCMs. This includes analysis of (i) the atmospheric moisture convergence, (ii) the balance between precipitation and evaporation, and (iii) the instantaneous runoff, herein referred to as the upstream, mid-stream, and downstream approaches, respectively (note that these are analysis approaches and not part of a physical river). The upstream approach examines upper air climatic variables (wind and specific humidity levels) that are primarily driven by model dynamics and minimally influenced by parameterization (Serreze et al., 2002). The midstream approach uses precipitation and evaporation, which occur at the land surface and are strongly influenced by various parameterization schemes. The downstream approach analyzes the RCM's simulated runoff, which is the end result of the land-surface scheme and a multitude of parameterizations.

Each of the analysis streams can be used as an approximation of mean annual runoff (discussed below) effectively providing three runoff approximations per RCM–GCM. By incorporating hydrological components in these various stages of simulation (i.e., a fullstream approach), it is possible to capture a range of intra-model uncertainty and provide a more inclusive projection for the amount of runoff in the Churchill River basin. Note that uncertainty about the amplitude of future greenhouse gas concentrations is not included in this study because NARCCAP models are driven by a single greenhouse gas scenario.

a Water Balance Equations

The fullstream approach used here is based on atmospheric and terrestrial water balances, Eqs (1) and (2), respectively, which can be found in Rasmusson (1968) and Peixoto and Oort (1992).

$$-\frac{\partial W}{\partial t} - \nabla_H \bar{Q} = P - E \quad (1)$$

$$P - E = r + \frac{\partial s}{\partial t} \quad (2)$$

Here, W is the precipitable water content of the atmosphere; $-\nabla_H \bar{Q}$, is the vertically integrated horizontal atmospheric moisture convergence; P is precipitation; E is evaporation, r is runoff; t is time; and s is land-surface water storage (including soil moisture and snowpack).

The terrestrial water storage component in Eq. (2) tends to zero over long periods of time (as ∂t gets very large), implying that mean annual runoff can be represented by $P - E$. Subsequently, mean runoff can also be represented by the atmospheric moisture convergence from Eq. (1), because the precipitable water tendency is also negligible over long periods. As such, RCMs are able to provide three representations of mean annual runoff for analysis, corresponding to the respective components of the fullstream approach: (i) $-\nabla_H \bar{Q}$, (ii) $P - E$, and (iii) r .

More details on the calculation of the components of Eqs (1) and (2) can be found in Roberts and Snelgrove (2015).

b Variance Decomposition and Imputation

There are several interpretations of the meaning of uncertainty in climate simulations. For the purposes of this work, uncertainty is treated as the variability of the climate change signal in ensemble results. The approach used in this work follows Déqué et al. (2007), Ferro (2004), and von Storch and Zwiers (1999) and can be used to isolate and compare magnitudes of each source of uncertainty. Variance decomposition is used to take full advantage of DOE for individual statistics while data imputation (the process of replacing missing data with substituted values) reduces the bias in the overall estimation of uncertainty due to overrepresentation by a given GCM or RCM.

The average climate response of the change in the modelled representation of runoff over the entire Churchill River basin can be denoted by X_{ijk} ; where i varies from 1 to 4 according to RCM (R), j varies from 1 to 3 according to GCM (G), and k varies from 1 to 3 according to analysis stream (S). The variance of X can be split into orthogonal positive contributions, as in Eq. (3), where a dot (\bullet) represents the mean of the index it has replaced.

$$V(X) = R + G + S + RG + RS + GS + RGS, \quad (3)$$

where

$$R = \frac{1}{4} \sum_{i=1}^4 (X_{i\bullet\bullet} - X_{\bullet\bullet\bullet})^2$$

$$RG = \frac{1}{12} \sum_{i=1}^4 \sum_{j=1}^3 (X_{ij\bullet} - X_{i\bullet\bullet} - X_{\bullet j\bullet} + X_{\bullet\bullet\bullet})^2$$

$$RGS = \frac{1}{36} \sum_{i=1}^4 \sum_{j=1}^3 \sum_{k=1}^3 (X_{ijk} - X_{ij\bullet} - X_{i\bullet k} - X_{\bullet jk} + X_{i\bullet\bullet} + X_{\bullet j\bullet} + X_{\bullet\bullet k} - X_{\bullet\bullet\bullet})^2.$$

To obtain the total amount of variance contributed by RCMs, for example, the components of variance in X above which contain R need to be summed: $V(R) = R + RG + RS + RGS$. This way the magnitude of varying RCMs, GCMs, and analysis streams can be determined with respect to climate response uncertainty.

To analyze the complete matrix of RCM, GCM, and analysis stream combinations in an unbiased manner, data imputation is required. This is performed by minimizing the influence of interaction terms from Eq. (3) (e.g., RG , RGS), per Déqué et al. (2007).

The first step in the iterative process is to calculate the full average ($X_{\bullet\bullet\bullet}$) and the double averages ($X_{i\bullet\bullet}$, $X_{\bullet j\bullet}$, and $X_{\bullet\bullet k}$) with available data, as defined above. This is relatively straightforward because there are several values for each RCM, GCM, and analysis stream meaning that an average of available values is taken.

Next, the simple averages must be calculated ($X_{ij\bullet}$, $X_{i\bullet k}$, and $X_{\bullet jk}$). Some of these averages cannot be calculated directly

because of missing data (e.g., for $X_{ij\bullet}$, where $i = \text{CRCM}$ and $j = \text{GFDL}$, no data are available for any of the three analysis streams), so the principle of minimizing interaction terms is used. For example, to minimize the RG interaction term from Eq. (3) one can set $X_{ij\bullet} = X_{i\bullet\bullet} + X_{\bullet j\bullet} - X_{\bullet\bullet\bullet}$ when $X_{ij\bullet}$ is missing.

The RGS interaction term from Eq. (3) can be minimized because first estimates are available for all variables except certain X_{ijk} . The missing X_{ijk} are calculated by setting $X_{ijk} = X_{ij\bullet} + X_{i\bullet k} + X_{\bullet jk} - X_{i\bullet\bullet} - X_{\bullet j\bullet} - X_{\bullet\bullet k} + X_{\bullet\bullet\bullet}$, similar to above.

Now that there are initial estimates for all X_{ijk} the process above of calculating full, double, and simple averages and minimizing two-term and three-term interaction terms can be repeated. This iteration continues until the incremental change of missing X_{ijk} is less than 0.01%.

4 Results

a Base Period Simulation

Results from the base period (1971–2000) simulation of the ensemble members can be found in Table 2. The simulated runoff values bookend the Churchill River’s observed mean streamflow of roughly $1825 \text{ m}^3 \text{ s}^{-1}$ (1.7 mm d^{-1}) (Water Survey of Canada, 2010) for the time period in question though no analysis preference is given to ensemble members that most accurately represent reality. Even though the results of this work were not processed by a routing model, they are presented in cubic metres per second because streamflow (for which runoff can be used as an approximation) is often reported in cubic metres per second and hydropower operators find this useful for water management decisions. Precipitation, evaporation, and runoff variables from NARCCAP were published in units of kilograms per metre squared per second, which were then converted to cubic metres per second by multiplying by the area of the basin ($9.25 \times 10^{10} \text{ m}^2$) and by one cubic metre per 1000 kg water. The calculation of atmospheric moisture convergence is more involved and is covered by Roberts and Snelgrove (2015). For the Churchill River basin $1070.6 \text{ m}^3 \text{ s}^{-1}$ is equivalent to 1.00 mm d^{-1} .

TABLE 2. Base period (1971–2000) annual runoff ($\text{m}^3 \text{ s}^{-1}$) for each ensemble member and analysis stream.

RCM	Stream	GCM		
		CCSM	CGCM3	GFDL
CRCM	up	1482	1510	—
	mid	1593	1586	—
	down	1610	1606	—
HRM3	up	—	—	1748
	mid	—	—	1665
	down	—	—	1697
RCM3	up	—	3899	3732
	mid	—	2030	2092
	down	—	1631	1688
WRFG	up	1114	1474	—
	mid	1084	1152	—
	down	1119	1218	—

According to Eqs (1) and (2), one intuitively expects that each of the three analysis streams would produce identical (or at least very similar) approximations of runoff. Roberts and Snelgrove (2015) examined the water balance components in detail and found that there were three primary contributing factors to the discrepancies found in Table 2. The proximity of the study basin to the lateral outflow boundaries of the RCMs' domains may have led physical inconsistencies in the buffer zones to propagate back into the main grid space (Lucarini, Danihlik, Kriegerova, & Speranza, 2007). Additionally, NARCCAP's three-dimensional atmospheric data were published on 28 pressure levels common to all ensemble members. Modelling groups had to interpolate model output from their original vertical coordinates to these pressure levels. Subsequently, vertical integration using these pressure level data was used to calculate the atmospheric moisture convergence. This process is known to introduce some mass imbalance. The third factor was the introduction of mass imbalance by the various RCMs' parameterization schemes and model processes. See Roberts and Snelgrove (2015) for more details.

b Imputation

Absolute and relative changes in runoff between the base period (1971–2000) and the future period (2041–2070) are presented in Table 3. Absolute changes are used to illustrate the climate signal in raw data output and highlight the results from individual RCM–GCM–stream ensemble members. That being said, ensemble members that have higher than average approximations for simulated runoff during the base period also have higher than average projected runoff changes, likewise for members with lower than average values. This implies that this “overestimation” (or “underestimation”) is systemic and also manifests itself in the climate change signal. Because the climate models are prone to systemic biases and no bias correction is taking place, changes relative to the base period are investigated and discussed throughout.

To determine whether the imputation procedure produced reasonable results, a check was completed using the RCM3–CGCM3 ensemble member. Each of the three analysis streams was removed, one at a time, from the dataset and then reconstructed using the remaining data (i.e., RCM3–CGCM3–upstream was removed then reconstructed using the imputation method discussed earlier and also for RCM3–CGCM3–midstream and RCM3–CGCM3–downstream). Root mean square differences (RMSDs) between actual and reconstructed values were calculated and compared with RMSDs from other RCM3 and CGCM3 ensemble members as well as the two remaining streams. As shown in Table 4, the RMSD from the actual values is lowest for the reconstructed RCM3–CGCM3 values, indicating that the imputation method is satisfactory.

The probability density functions (PDFs) in Fig. 2 assume that individual results from Table 3 have an equal likelihood of occurrence. (This does not imply that there is no added value in modelling beyond the upstream atmospheric moisture convergence in RCMs; it simply gives equal weight to the various non-storage water balance components and makes for the straightforward creation of PDFs. The added value of modelling midstream and downstream components becomes apparent in studies focusing on shorter time frames and temporal variability.) The PDFs were created using a smoothed empirical distribution with Gaussian kernel density estimation. The probability that mean runoff will change by a given value or percentage is represented by the area under the curve to the left of said value. This means that there is an equal probability that runoff changes could be above or below the projected ensemble median value.

PDFs are useful in risk analysis and economic decision making. They recognize that climate projections are not perfect and provide a spectrum of potential outcomes. To take full advantage of climate projections in PDF form the costs and risks of an erroneously high runoff projection must be compared with those of a low runoff projection. For example, if potential climate change impacts for the site of a future dam and hydroelectric development were being

TABLE 3. Projected runoff changes (between 1971–2000 and 2041–2070), including results of imputation (in bold).

		Absolute Change ($\text{m}^3 \text{s}^{-1}$)			Relative Change (%)				
RCM	Stream	GCM			RCM	Stream	GCM		
		CCSM	CGCM3	GFDL			CCSM	CGCM3	GFDL
CRCM	Up	83	219	271	CRCM	Up	5.6	14.5	7.2
	Mid	146	178	147		Mid	9.2	11.2	8.0
	Down	110	179	113		Down	6.8	11.1	6.3
HRM3	Up	18	5	121	HRM3	Up	12.2	4.5	6.9
	Mid	95	152	97		Mid	6.0	7.3	5.8
	Down	131	196	121		Down	7.9	9.0	7.2
RCM3	Up	533	456	695	RCM3	Up	21.8	11.7	18.6
	Mid	121	114	182		Mid	6.7	5.6	8.7
	Down	99	100	149		Down	7.4	6.1	8.8
WRFG	Up	357	180	388	WRFG	Up	32.1	12.2	19.3
	Mid	159	227	178		Mid	14.7	19.7	15.0
	Down	174	218	165		Down	15.5	17.9	14.0

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TABLE 4. Differences between reconstructed RCM3–CGCM3 data and comparable categories.

Category		Actual Value	RCM3-GFDL	CRCM-CGCM3	WRFG-CGCM3	Upstream	Midstream	Downstream
Absolute Changes ($\text{m}^3 \text{s}^{-1}$)	Upstream	42	196	279	318	—	384	398
	Midstream	17	50	45	95	323	—	18
	Downstream	4	53	83	122	360	18	—
	RMSD	46	209	294	354	484	384	399
Relative Changes (%) ^a	Upstream	0.3	7.2	3.1	0.8	—	5.8	5.3
	Midstream	2.8	0.3	2.8	11.3	3.3	—	2.3
	Downstream	1.2	1.5	3.8	10.6	4.4	1.7	—
	RMSD	3.1	7.4	5.6	15.5	5.5	6.0	5.8

^aPercentages under Relative Changes refer to relative changes in Stream values and not differences between reconstructed values.

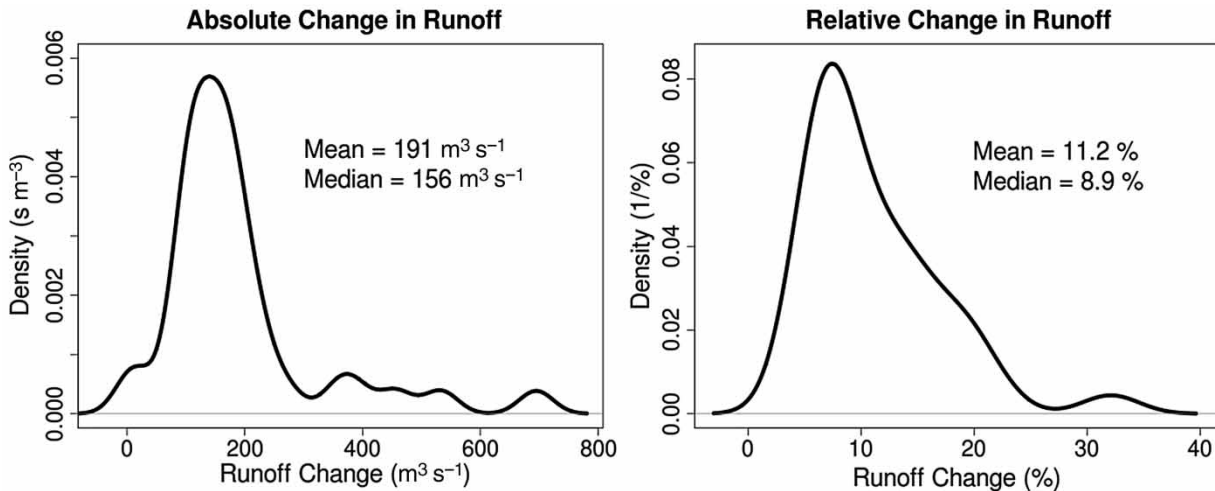


Fig. 2. PDFs of absolute (left panel) and relative changes (right panel) in runoff, including imputed data.

investigated, then a runoff projection that is too low may increase the risk of wasting water over a spillway. An erroneously high runoff projection on the other hand may lead to an increase in construction costs (because a higher capacity would be required) without the benefit of increased power generation. The costs and risks of each scenario must be balanced to determine the “best” projection to use for project design, which is not necessarily the annual mean or median.

The simulations indicate that annual basin runoff is expected to increase. The ensemble median increase is roughly $156 \text{ m}^3 \text{ s}^{-1}$ (0.14 mm d^{-1}), or 9%, while the mean increase is roughly $191 \text{ m}^3 \text{ s}^{-1}$ (0.18 mm d^{-1}), or 11%. There are some outliers on the far right of the PDF that suggest that runoff increases may be as high as $700 \text{ m}^3 \text{ s}^{-1}$ (0.65 mm d^{-1}), or 35%, but the increase most likely lies between 25 and $250 \text{ m}^3 \text{ s}^{-1}$ (0.02 and 0.23 mm d^{-1}), or between 1 and 25%.

c Variance Decomposition

Variance decomposition was performed on the full set of data, including imputed values, the results of which can be found in Table 5. Of the three primary factors, RCM (*R*) had the highest values for both absolute and relative changes, followed by analysis stream (*S*). The GCM primary factor (*G*) appears to contribute very little to variance, though its influence increases

once the interaction terms (*RG*, *GS*, and *RGS*) are taken into account. The *RS* interaction term was dominant for absolute changes, which contributed to the relatively large total variance attributed to the analysis streams (Total $S = S + RS + GS + RGS$). The total variances do not add up to 100% because of the interaction terms. The *RG* term, for example, which is the interaction between the RCM choice and GCM choice contributes to both the total variance explained by RCM choice and the total variance explained by GCM choice.

A subset of the data consisting of two RCMs (CRCM and WRFG), two GCMs (CCSM and CGCM3), and all three streams that contain no holes also exists in the data matrix, negating the need for imputation. Variance decomposition was performed on this subset (also available in Table 5) as further confirmation of the validity of the data reconstruction method as well as a quick sensitivity test of the impact of changing the number of RCM–GCM ensemble members. Results are similar to those for the full dataset with RCMs contributing the most to variance, though in the data subset GCMs have a much larger role than they do in the full dataset.

Figure 3 presents the data from Table 2 as boxplots to reinforce the results of the variance decomposition in Table 5. It is also possible to visualize the amount of uncertainty introduced by each RCM, GCM, and analysis stream. It is apparent that different RCMs contribute a range of

TABLE 5. Variance decomposition results as a percentage of variance explained.

Data	Change	R	G	S	RG	RS	GS	RGS	Total R	Total G	Total S
Full Dataset	Absolute	22	2	20	3	44	7	3	71	15	73
	Relative	47	1	11	9	11	9	11	79	31	42
Data Subset	Absolute	20	4	5	11	10	10	40	81	65	65
	Relative	28	0	3	8	14	12	36	85	55	64

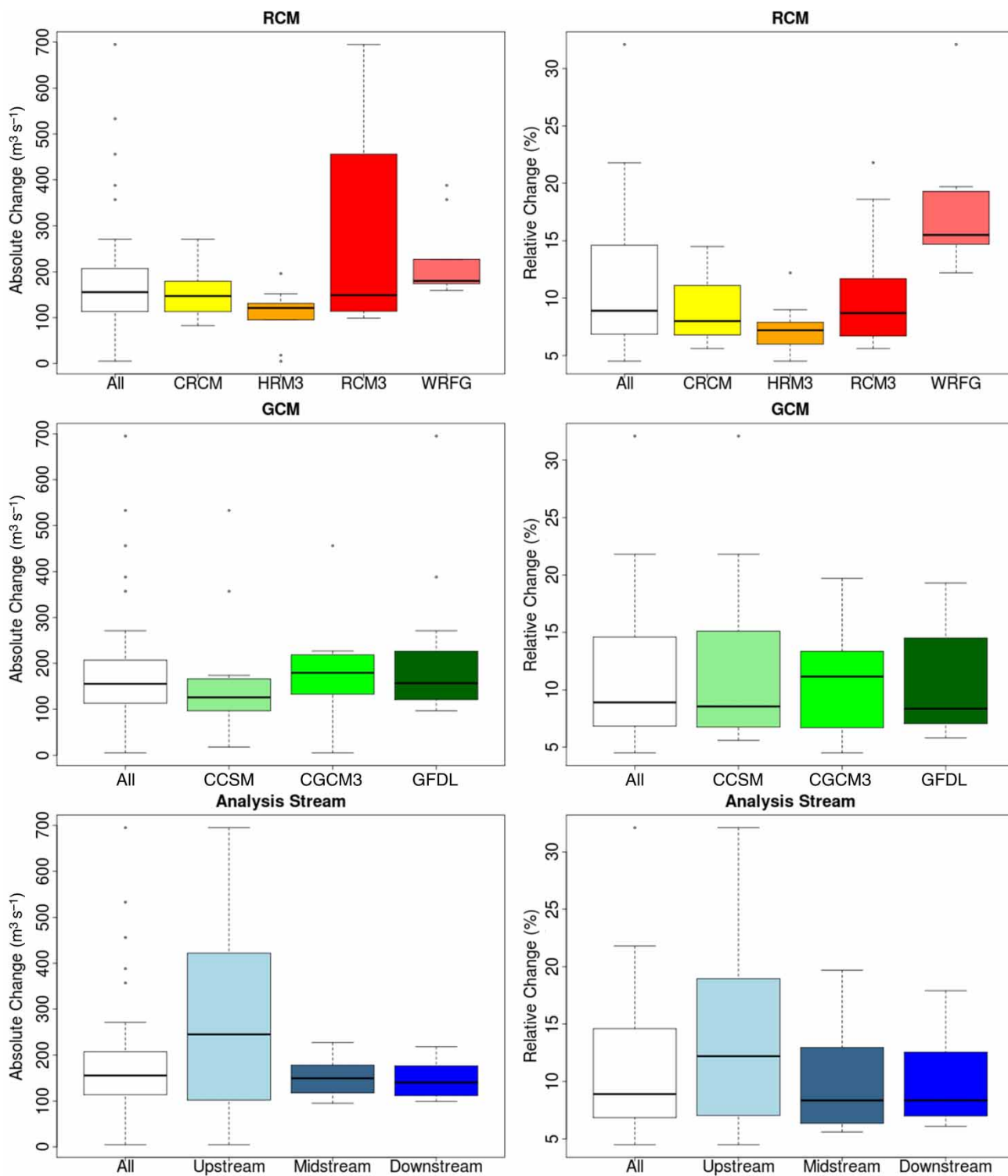


Fig. 3 Boxplots of absolute (left panels) and relative (right panels) changes in runoff including imputed data, grouped according to RCM (top row), GCM (middle row), and analysis stream (bottom row). White boxplots include the full dataset for comparison.

projections, increasing the overall ensemble uncertainty. RCM3 contributes the most uncertainty when considering absolute change due primarily to its anomalously high upstream projections. This corresponds well with the results for choice of analysis stream, where the upstream analysis contributes the most uncertainty for both absolute and relative changes. Midstream and downstream projections are relatively similar, though the midstream projection does introduce slightly more uncertainty. The GCM choice also contributes to uncertainty, though which GCM contributes the most is not immediately clear upon inspection.

5 Discussion

a Climate Change Signal

The climate change impacts found here (by comparing 1971–2000 with 2041–2070) for the Churchill River basin corroborate those found in other studies. The IPCC used a multi-model ensemble (Bates, Kundzewicz, Wu, & Palutikof, 2008) based on the SRES A1B emissions scenario (IPCC, 2000). The results from this coarse-resolution study indicate that Labrador can expect between a 10% and 20% increase in mean annual runoff between 1980–1999 and 2080–2099. Frigon et al. (2010) used a five-member ensemble of various CRCM–CGCM3 configurations to show that the Churchill River, upstream of the existing Churchill Falls hydroelectric facility, can expect a change in runoff of $21 \pm 6\%$ (where 6% is the maximum deviation from the median ensemble value) from the recent past (1961–1990) to the future (2041–2070). Frigon et al. (2010) also showed that the ensemble spread of basin runoff related to natural variability is typically around $\pm 10\%$. Roberts et al. (2012) used bias-corrected precipitation and temperature from an ensemble of six NARCCAP models to drive a hydrological model in a sub-basin of the Churchill River. Their results indicate a roughly 9% increase in mean streamflow.

b Uncertainty

It is apparent from the variance decomposition of the full set of data that RCM (*R*) choice plays a major role in contributing to uncertainty whether investigating absolute or relative changes (71% and 79%, respectively). Analysis stream (*S*) choice (analysis stream refers to a method of runoff approximation and not a physical stream) also has a strong influence on variability in the climate change signal, with a contribution comparable to RCM choice for absolute changes (73%) and approximately half the RCM contribution for relative changes. GCM (*G*) choice has the smallest, though non-negligible, role in contributing to uncertainty.

Each RCM, GCM, and analysis stream contributed to the overall uncertainty of the ensemble (Fig. 3) though some introduced larger amounts of projection variability than others, as discussed in Section 4c. Several outliers contributed to the absolute change uncertainty, primarily from the RCM3-upstream projections (533, 456, and $695 \text{ m}^3 \text{ s}^{-1}$). The only

outlier for relative changes was WRF–CCSM-upstream (32.1%). For relative changes, the RCMs had moderate overlap in their projections and each contributed a comparable amount to overall ensemble uncertainty. HRM3 contributed the least, which may be a result of it having only one GCM pairing to contribute to the imputation process, giving it extra influence on the imputed HRM3 data. No GCM stood out as contributing more to uncertainty than the others because there was extensive overlap between the GCM projections for both absolute and relative changes.

The upstream projection contributed the most uncertainty of any analysis stream (projections ranged from 5 to $695 \text{ m}^3 \text{ s}^{-1}$ and 4.5 to 32.1%). In part, this was because the atmospheric data required for the analysis are more sensitive to two of the major contributors to imbalance (Section 4a and Roberts & Snelgrove, 2015) than the data required for the other streams. In particular, it was sensitive to the conversion to, and subsequent calculation in, NARCCAP's common pressure level vertical coordinates and the proximity to the lateral buffer zone at the outflow edge of the RCM domains. These factors would have affected each RCM differently (causing a wider spread of projections) because they each have unique native vertical coordinate systems and approaches to dealing with buffer zones. The midstream projection (95 to $227 \text{ m}^3 \text{ s}^{-1}$ and 5.6% to 19.7%) introduced slightly more uncertainty than the downstream projection (99 to $218 \text{ m}^3 \text{ s}^{-1}$ and 6.1% to 17.9%), which likely resulted from the different parameterizations and model processes involved in each RCM.

The results from the data subset (Table 5) corroborate the above results that RCM choice plays the dominant role in contributing to uncertainty. The GCM choice plays a more influential role in the subset analysis, nearly doubling for relative changes (to 55%) and increasing by a factor of four for absolute changes (to 65%). The impact of the primary factor *G* differed only minimally from the full dataset, so the contributions must come from the interaction terms. In fact the contribution of the three-factor interaction term *RGS* was the highest of any terms for both absolute and relative changes (40% and 36%, respectively) in the subset. This increased the total contributions for RCM, GCM, and analysis stream, explaining why their relative ranks were not substantially altered (aside from the equal contributions of GCM and analysis stream for absolute changes). Stream choice contributes comparably to uncertainty in the full dataset and subset, with a slight decrease for absolute changes (from 73% to 65%) and a 50% increase for relative changes (from 42% to 64%). When considering relative changes, "Total *S*" contributes roughly 10% more than "Total *G*" for both datasets.

Overall, the most substantial differences between the full dataset and the subset occur for absolute changes, whereas total contributions to uncertainty for relative changes, which are of primary interest, remained fairly consistent. This implies that neither the data imputation nor the modification of the ensemble size had a drastic effect on the relative contributions to uncertainty, providing additional confidence in the results.

It is important to note that there are several potentially influential sources of uncertainty that were not included in this study, including greenhouse gas emissions scenario, downscaling method, and hydrological model selection. In particular, it is impossible to fully cover GCM uncertainty with the small ensemble examined here. Although the need for statistical downscaling is generally eliminated, a limited GCM sample size is one of the major drawbacks of using the dynamic downscaling approach with an ensemble of computationally expensive RCMs. It was attempted in this study to expand the number of runs for the three GCMs by means of data imputation; however, as stated earlier, these are only estimates and would not result in projections identical to actual RCM–GCM runs. This means it is not a comprehensive overview of climate change projection uncertainty and should be interpreted with caution (Bennett et al., 2012; Chen, Brissette, & Leconte, 2011; Mitchell & Hulme, 1999; Poulin, Brissette, Leconte, Arsenault, & Malo, 2011).

There are many potential sources that could influence each contribution to uncertainty, but without a much larger dataset it is difficult to pinpoint exact causes. Nevertheless, likely reasons are discussed below.

Uncertainty from GCM choice can be attributed to model structure, formulations, and climate sensitivity. These factors would influence broad temperature features that, in turn, play a role in evaporation and precipitation. At a basin scale, the RCM would play the dominant role in determining exact values and patterns. In addition to the driving GCM data, differences in RCM vertical coordinate and resolution choice may contribute to variability in upstream runoff projections. Parameterization schemes for precipitation and evaporation contribute to differences in midstream runoff projections, though the parameterization inputs vary between ensemble members and also play a large role. Each RCM has a different land-surface scheme, which contributes to variability in downstream runoff projections. Again, inputs to these schemes vary between members.

While the imputation method used minimizes the contributions of interaction terms, the results of Table 5 indicate that interaction is non-negligible when investigating relative contributions to uncertainty. The interaction effect RS makes an unusually high contribution to variance in absolute change of the full dataset because the upstream (atmospheric moisture convergence) output of RCM3 was approximately double that of other RCM3 streams and upstream values of other ensemble members. Correspondingly, the absolute difference between base and future period simulations was also noticeably higher. As expected, this effect is less noticeable while analyzing relative changes, implying that the uncertainty contributions for relative (as opposed to absolute) changes provide a more robust interpretation of the results. The three-factor interaction effect of RGS is fairly prominent in the data subset but is less so once the full dataset is examined. This effect is likely caused by the imputation method, which assumes that higher-order interaction terms are

TABLE 6. Options for applying the fullstream method to annual hydrographs.

	Option 1	Option 2
Upstream	$-\frac{\partial W}{\partial t} - \nabla_H \bar{Q}$	$-\frac{\partial W}{\partial t} - \nabla_H \bar{Q} - \frac{\partial s}{\partial t}$
Midstream	$P - E$	$P - E - \frac{\partial s}{\partial t}$
Downstream	$r + \frac{\partial s}{\partial t}$	R
Advantage	No disproportionate influence	Traditional hydrograph
Disadvantage	No traditional hydrograph	Disproportionate influence of $\frac{\partial s}{\partial t}$

minimal. A larger matrix of data would be beneficial to further understanding the interaction effects.

c Creating Hydrographs with the Fullstream Method

It is possible to use a modified version of the fullstream method to examine hydrographs and interannual variability. By focusing on shorter, sub-annual, time frames it is no longer possible to assume that the storage tendency terms—precipitable water content (PRW), snow water equivalent (SWE) and soil moisture—in Eqs (1) and (2) are negligible. Two options remain for analysis, as described below and in Table 6, each with their own advantages and disadvantages.

The first is to look at the annual cycle of how much total water is in the basin at any given time of year. This means, for the downstream approach, it would not be possible to plot a typical hydrograph because changes in soil moisture and SWE are combined with runoff (i.e., during the spring melt, SWE is either converted to runoff or additional soil moisture and would not result in the typical spike for snow-dominated basins). The midstream approach's balance of precipitation and evaporation would remain unchanged because there are no storage terms, while the upstream approach, which includes atmospheric moisture convergence and PRW tendency, would barely change because the tendency term contributes very little compared with all other water balance components.

The second option, which would result in more traditional hydrographs, would be to move the terrestrial water storage terms to the other side of the water balance equations, as shown in Table 6. This means that soil moisture and SWE would be counted in both the upstream and midstream analyses, resulting in a disproportionate influence on the results.

6 Summary and conclusions

The work presented here provides a useful method for measuring the impacts of climate change on surface runoff in a basin. Results of mean runoff changes are consistent with a variety of other studies.

The primary contribution of this study is that it highlights the value of considering multiple aspects of the simulated hydrological cycle in order to capture the broadest range of uncertainty possible, given a set of RCM–GCM output.

RCM, GCM, and analysis stream all contribute substantially to uncertainty in the climate change signals of the mean basin runoff, with RCM tending to dominate. With regard to individual RCMs, GCMs, and analysis streams, RCM3 contributed the most to uncertainty of any RCM, while each GCM contributed a comparable amount, and the upstream approach contributed more than midstream and downstream approaches.

These results differ from most uncertainty attribution studies because runoff, as opposed to temperature or precipitation, is examined here. While runoff ultimately includes all the factors and inputs that influence mean simulated temperature and precipitation it also incorporates additional parameterizations and inputs such as soil moisture and depth, vegetation classes, and evaporation. Many, if not all, of these are strongly dependent on local processes and result in RCM choice being the greatest overall contributor to uncertainty. Choice of analysis stream also plays a substantial role because there are different inputs, processes, parameterizations, and assumptions for each, resulting in a variety of approximations for simulated runoff.

Also of note are the differences in the contributions to relative uncertainty between absolute and relative changes in mean runoff. The primary distinction is the importance of analysis stream choice, with 73% and 42% of the variance explained for absolute and relative changes, respectively. This is caused primarily by the anomalously high atmospheric moisture convergence of RCM3 and its proportional effect on the simulated climate change signal. This implies that with

respect to the climate change signal and ensemble member intercomparison it is more insightful to examine relative changes in runoff in which RCM, GCM, and stream choice explain 79%, 31%, and 42% of variance, respectively. All of which are substantial, and none of which should be ignored.

Future work will include reproducing the analysis on different watersheds to explore regional influence as well as examining the effects of climate change on the annual runoff cycle. Investigating changes in the annual hydrograph according to the options presented in Section 5c is also of interest.

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Disclosure statement

No potential conflict of interest was reported by the authors.

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