The uncertainty associated with estimating future groundwater recharge: A summary of recent research and an example from a small unconfined aquifer in a northern humid-continental climate

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Abstract:

Global climate models (GCMs) project significant changes to regional and globally-averaged precipitation and air temperature, and these changes will likely have an associated impact on groundwater recharge. A common approach in recent climate change-impact studies is to employ multiple downscaled climate change scenarios to drive a hydrological model and project an envelope of recharge possibilities. However, each step in this process introduces variability into the hydrological results, which translates to uncertainty in the future state of groundwater resources. In this contribution, seven downscaled future climate scenarios for a northern humid-continental climate in eastern Canada were generated from selected combinations of GCMs, emission scenarios, and downscaling approaches. Meteorological data from the climate scenarios and field data from a small unconfined aquifer were used to estimate groundwater recharge with the soil water balance model HELP3. HELP3 simulations for the period 2046-2065 indicated that projected recharge was most sensitive to the selected downscaling/ debiasing algorithm and GCM. Projected changes in average annual recharge varied from an increase of 58% to a decrease of 6% relative to the 1961-2000 reference period. Such a large range in projected recharge provides very little useful information regarding the future state of groundwater resources. Additional results from recent comparable studies are discussed, and the benefit of performing similar studies without better constraining future climate projections is questioned. Based on the results obtained from the present cast study and the other studies reviewed, the limitations of current approaches for

projecting future recharge are identified, and several suggestions for research opportunities to advance this field are offered.

Keywords
Groundwater recharge, climate change, climate scenarios, downscaling, snowmelt, uncertainty, post-processing

Highlights

1. Future projections for groundwater recharge are highly uncertain.
2. This uncertainty stems primarily from the variability in climate projections.
3. We simulated future recharge in a northern climate using seven climate scenarios.
4. The recharge was most sensitive to the choice of the post-processing method.
5. Suggestions for advances in future climate change-recharge projections are given.

1. Introduction

Climate change has resulted in increases in globally-averaged mean annual air temperature and variations in regional precipitation, and these changes are expected to continue and intensify in the future (Solomon et al., 2007). Projected climate data are generated by simulating global atmospheric, oceanic, and surficial processes in global climate models (GCMs), which are driven by emission scenarios that require forecasts of future population growth and technology (Nakicenovic and Swart, 2000). GCM simulations are performed using coarse computational grids, and the results should be downscaled to produce local climate conditions that may subsequently be used for hydrology applications (Wilby and Wigley, 1997; Wilby et al., 2000).

The impact of climate change on the quantity and quality of groundwater resources is of global importance because between 1.5 and 3 billion people rely on groundwater as a drinking water source (Kundzewicz and Döll, 2009). Despite the importance of the relationship between climate conditions and groundwater reserves (Taylor et al. 2012), research examining the effects of future climate change on groundwater has lagged corresponding research for surface water resources (Green et al., 2011). The IPCC Fourth Assessment Report stated 'knowledge of current [groundwater] recharge and levels in both developed and developing countries is poor. There has been very little research on the impact of climate change on groundwater' (Kundzewicz et al., 2007). This statement spurred an initiative to fill this research void, and a number of studies have emerged in the past five years that address the relationship between climate change and groundwater recharge (e.g., Aguilera and Murillo, 2009; Ali et al., 2012; Allen et al., 2010; Crosbie et al., 2010; Crosbie et al., 2011; Crosbie et al., 2013; Crosbie et al., 2012b; Dams et al., 2012; Döll, 2009; Ficklin et al., 2010; Green et al., 2011; Herrera-Pantoja and Hiscock, 2008; Holman et al., 2009; Jackson et al., 2011;

Jyrkama and Sykes, 2007; Leterme et al., 2012; Liggett and Allen, 2010; McCallum et al., 2010; Mileham et al., 2009; Serrat-Capdevila et al., 2007; Taylor et al., 2012; Thampi and Raneesh, 2012; Toews and Allen, 2009b; Wegehenkel and Kersebaum, 2009).

Recently there has been a discernible shift in the approaches used to examine climate change impacts on groundwater recharge. Rather than simulating changes for a single climate scenario, researchers have been employing multiple climate change scenarios generated from a variety of methods to produce a range, or envelope, of projected changes in recharge. Holman et al. (2012) suggested that the best practice for using climate model projections to assess the impact on groundwater was to 'use climate scenarios from multiple GCM or RCMs [regional climate models] …use multiple emission scenarios…[and] consider the implications of the choice of the downscaling method'. This approach introduces additional variability in the climate data, which translates into uncertainty in future groundwater recharge. For example, when more than 10 GCMs were employed for projecting future precipitation, it was found that less than 80% of the GCMs agreed 'in whether annual precipitation will increase or decrease' in most regions other than at high northern latitudes and in the Mediterranean region (Döll, 2009). The majority of uncertainty in the projected climate data (and consequently in the projected recharge) appears to stem from the selection of the GCM (Kay et al., 2009), although other factors, such as the emission scenarios, downscaling methods, or the hydrological model can also contribute uncertainty (Crosbie et al., 2011; Holman et al.. 2009; Rowell, 2006).

Several recent groundwater recharge studies, employing multiple climate change scenarios, have been conducted at a very large scale. Döll (2009) simulated the vulnerability of groundwater to climatic change at the global scale using the hydrology model WaterGAP driven by climate data from two GCMs and two emission scenarios, and concluded that the uncertainty in projected precipitation from the climate scenarios resulted in uncertainty in recharge estimates, but this uncertainty was spatially heterogeneous (e.g., see Australia, Figure 1, Döll 2009). Crosbie et al. (2013) simulated the changes in recharge for a 2050 climate for the entire continent of Australia using climate data from 16 GCMs and three emission scenarios to drive the WAVES hydrological model. Their study indicated that the range of projected changes in recharge was large and spatially variable and that it was generally difficult to project the magnitude or even direction of future recharge changes, although in certain regions of southern Australia, all 48 climate variants projected a decrease in recharge.

Many more regional scale studies have been conducted to investigate the link between climate change and groundwater recharge. For example, Serrat-Capdevila et al. (2007) used climate data for the San Pedro Basin from 17 GCMs to estimate recharge

from a simple empirical equation. In the case of the drier climate projections, their simulations indicated that groundwater recharge could cease completely. Holman et al. (2009) simulated groundwater recharge using one GCM, two emission scenarios, and two downscaling methods (a stochastic weather generator and the change factor method) and found that the uncertainty due to the downscaling method was greater than the uncertainty associated with the emission scenario. Allen et al. (2010) used climate data from four GCMs, one emission scenario, and one downscaling algorithm to drive simulations within a hydrology model of the Abbotsford-Sumas aquifer. Crosbie et al. (2011a) simulated groundwater recharge changes at three locations in southern Australia using multiple GCMs, downscaling methods, and hydrology models and found that the highest uncertainty in modeling future recharge arose from the selection of the GCM. Dams et al. (2012) used 28 climate scenarios to simulate a range of changes in mean annual recharge for a catchment in Belgium. Table 1 gives a summary of the results from these and other recent regional, continental, and global groundwater recharge studies.

Table 1

An overview of several recent studies that have employed multiple climate change scenarios to examine the impact of projected climate change on groundwater recharge

Study Reference	Number of GCMs	Number of ES[1]	Number of DM[2]	Scale of Studies	Max Changes in Avg. Recharge (%)[3]
Serrat-Capdevila et al. (2007)	17	4	1	Regional	-100% to ~+35%
Döll (2009)	2	2	NA	Global	~-30 to +100%[4]
Holman et al. (2009)	1	2	2	Regional	-14 to -37%
Allen et al. (2010)	4	1	1	Regional	-1.5 to +23%
Crosbie et al. (2010)	15	3	1	Regional	<-50 to >+50%
Crosbie et al. (2011a)	5	1	3	Regional	-83 to +447%
Jackson et al. (2011)	13	1	1	Regional	-26 to +31%
Crosbie et al. (2013)	16	3	1	Continental	+45% to +283%[5]
Dams et al. (2012)	5	2	1	Regional	-20 to +7%
Ali et al. (2012)	15	3	1	Regional	-33% to +28%[6]

[1]ES= emission scenarios (A1F1, A2, A1B, B1, etc.)
[2]DM= downscaling methods
[3]For studies with multiple locations this column lists the results from the locations with the highest uncertainty in the mean annual recharge estimations.
[4]Estimated from the southwestern Australian region in Figure 1 of Döll (2009)
[5]Taken from Appendix C of Crosbie et al. (2011b), these results were for Brunswick Coastal Sands for the median dry climate and the median wet climate.
[6]Taken from Table A1 of Ali et al. (2012), these results were from the Southern Perth Basin for the wet and dry simulations compared to the recent recharge.

The purpose of this contribution is to provide a case study that adds to the recent body of literature by examining the uncertainty in projected recharge for a humid-continental climate in which snow accumulation and melt are important factors affecting groundwater recharge. Seven climate scenarios generated from multiple (1) GCMs, (2) emission scenarios, and (3) downscaling/debiasing methods were utilized to drive simulations of projected future (2046-2065) groundwater recharge for a small, shallow, unconfined aquifer in central New Brunswick, Canada. Others (e.g., Jackson et al., 2011; Serrat-Capdevila et al., 2007) have examined the uncertainty in groundwater recharge due to varying one or two of the climate modeling options noted above, but this is the first contribution to examine the effect of varying all three following the recommendations of Holman et al. (2012). The uncertainty in recharge projections obtained in this study is also compared to the uncertainty reported in several recent groundwater recharge studies. Recommendations for future research opportunities are suggested based on the results obtained from the present case study and the studies summarized in Table 1.

2. Methods

The approach for estimating recharge was based on techniques similar to those recently employed by others (e.g., Jackson et al., 2011; Jyrkama and Sykes, 2007; Scibek and Allen, 2006; Toews and Allen, 2009b). We first obtained an array of future climate projections that were developed using several documented and established techniques. These climate scenarios were selected because they span the range of plausible future climatic conditions for the study location. The observed climate data and the projected climate series were then used to drive a simple water balance hydrology model to simulate historic and future groundwater recharge.   In general, a parsimonious hydrological modeling approach was employed. For example, although it is known that increased CO_2 concentrations will affect canopy density and evapotranspiration and thereby impact groundwater recharge (Ficklin et al., 2010; Green et al., 2007), like many previous studies, the biophysical parameters (e.g., maximum leaf area index) were assumed to be temporally invariant so as to isolate the effect of the driving climate data on groundwater recharge.

The approach outlined above was used to investigate the inherent uncertainty involved when using climate projections to drive simulations of groundwater recharge due to the uncertainty arising from the selection of the (1) GCM, (2) downscaling method, and (3) emission scenario. In this work, the uncertainty in projected groundwater recharge is defined as the magnitude of the range in changes to the projected mean annual groundwater recharge. The projected changes in mean annual groundwater recharge are quantified as the % difference from the simulation for the reference period (1961-2000). Uncertainty arising from the selection of (1), (2), and (3) is propagated through the

climate and groundwater recharge modeling processes. However, following the approach of others who have demonstrated the uncertainty in groundwater recharge projections (e.g., Crosbie et al., 2011a, Jackson et al. 2011), we have not attempted to conduct a formal uncertainty propagation analysis for each step in the modeling process. Rather, the uncertainty arising from the selection of (1), (2), and (3) was investigated by holding two climate simulation approaches constant while varying the third. For example, the effect of the downscaling algorithm was investigated by examining the difference in the resultant climate data and simulated recharge when the GCM and emission scenario were identical in two runs, but the downscaling method was varied.
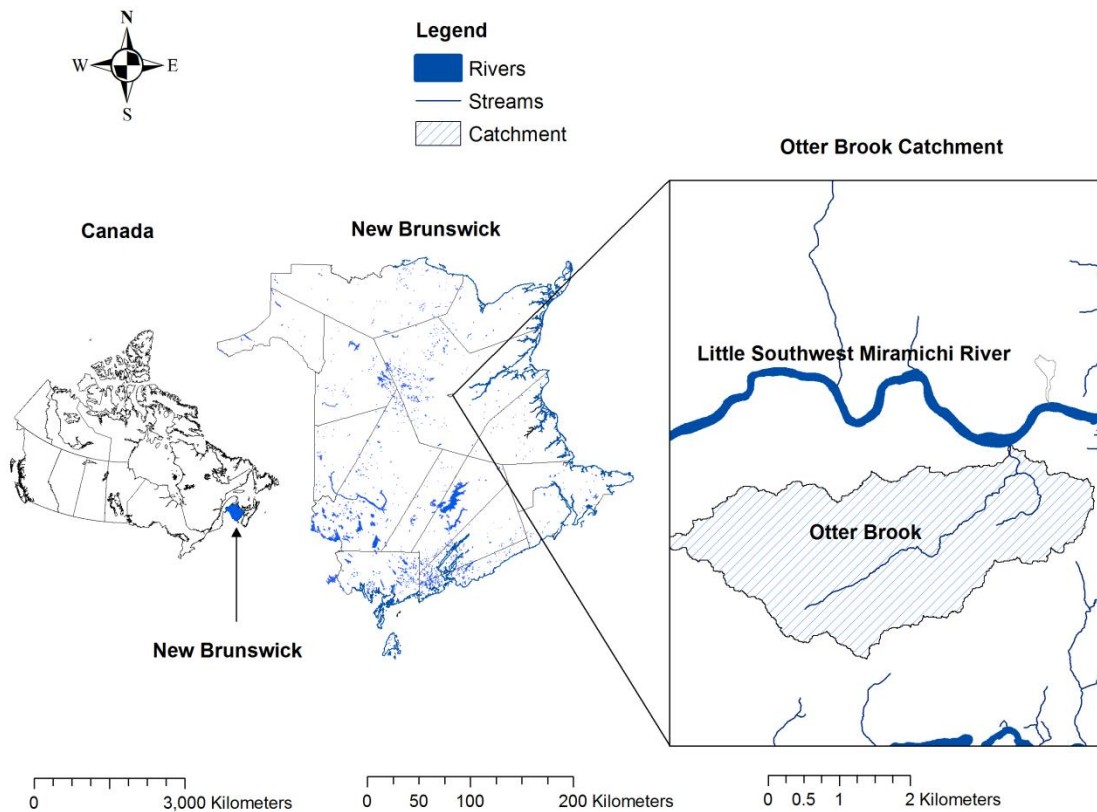

Figure 1. The location of the Otter Brook catchment within the province of New Brunswick, Canada (data from NBADW, 2011).

2.1 Geographical setting

The geographic location for our simulations is the Otter Brook catchment in central New Brunswick, Canada (N46 52 W66 02). Otter Brook is a second order tributary of the Little Southwest Miramichi River (Figure 1) that is predominately fed by

6

groundwater baseflow. Lavergne and Hunter (1982) mapped the surficial geology surrounding Otter Brook and determined that the brook lies within a glaciofluvial outwash deposit that mainly consists of sand and gravel. In a more recent investigation, multiple test holes were excavated within the Otter Brook catchment. Aerial photography and samples from these test holes indicate that the Otter Brook deposit is primarily composed of glaciofluvial outwash sediments, varying from cross-bedded sand to thick-bedded coarse gravel (Allard, 2008). The results from a ground penetrating radar survey indicated that the groundwater table is at a depth of about 7.5 m and that the surficial sand and gravel deposit is approximately 10 m thick (Allard 2008).

The Otter Brook catchment has a land surface cover similar to the surrounding region, which is forested with a coniferous (65%) and deciduous (35%) canopy (Cunjak et al., 1990). The annual precipitation in the region is 1230 mm; with approximately 33% falling as snow (EC, 2010a). The region experiences a humid-continental climate characterized by arid, cold winters (Cunjak et al., 1993). This particular catchment was selected because it is part of a study area in which climate-induced thermal and hydrologic changes to salmonid habitat are being investigated.

2.2 Emission scenarios, downscaling algorithms and GCMs

The three emission scenarios that we have utilized in this study are B1, A1B, and A2 (Nakicenovic and Swart. 2000). Climate simulations driven by emission scenario A2 typically project more pronounced climatic changes than those driven by emission scenarios A1B or B1; however, the effects of each emission scenario may not be realized for several decades.

Downscaling approaches have been thoroughly reviewed in the literature (e.g., Maraun et al., 2010; Wilby and Wigley, 1997; Xu, 1999). A simple downscaling approach is the daily translation (DT) method, which is in the family of 'statistical' or 'quantile-quantile mapping' downscaling techniques (Teutschbein and Seibert, 2012). In the DT method, a GCM is initially run for a reference period containing local observations. Scaling factors for precipitation and AT are then determined from the distributions of the reference period simulation and the local observations using empirical cumulative distribution functions. GCM simulations for a future time period/emission scenario are then downscaled by applying the scaling factors. This approach differs from the often criticized delta method by adopting variable scaling factors (Huard, 2011).

Many more complex statistical downscaling methods have been developed; one of these is the hybrid multivariate linear regression (HMLR) model (Jeong et al., 2012a; Jeong et al., 2012b). Regression-based statistical downscaling techniques are predicated on the assumption that local climate conditions can be determined from large-scale

climate variables using linear or non-linear transfer functions (Jeong et al., 2012a). Because regression-based methods often have difficulty producing the observed variability in local climate predictands, a stochastic generator is used to increase the variance in the datasets. In the HMLR method, the local climate variables are obtained from the GCM simulations using multiple regression functions determined from reference period simulations.

The output from GCMs can also be dynamically downscaled by performing simulations with finer resolution RCMs, which are driven at the boundaries by the results from GCMs. However, RCMs tend to introduce additional biases, thus the results are often further debiased/downscaled by comparing simulations for a reference period to observations to determine scaling factors, and then making corrections to the generated dataset for a future period. For the present study, additional debiasing/downscaling was performed to RCM climate series using the DT method (Huard, 2011). Debiasing and downscaling are often collectively referred to as 'post-processing'.

Table 2
Details for the climate simulations utilized in this study

Emission Scenario	Model Type	Model Name	GCM Driver	ID -	Post-processing Method	Contributor Organization
A2	GCM	CGCM3	-	-	Statistical-HMLR	INRS (Jeong et al., 2012b)
A2	RCM	CRCM 4.2.3	CGCM3	Aev	Dynamical	Ouranos (Huard, 2011)
A2	RCM	CRCM 4.2.3	Echam5	Agx	Dynamical	Ouranos (Huard, 2011)
B1	GCM	CSIRO Mk3.0	-	-	Statistical-DT	Ouranos (Huard, 2011)
B1	GCM	CSIRO Mk3.5	-	-	Statistical-DT	Ouranos (Huard, 2011)
A1B	GCM	Miroc3.2 Hires	-	-	Statistical-DT	Ouranos (Huard, 2011)
A1B	GCM	CGCM3	-	-	Statistical-HMLR	INRS (Jeong et al., 2012b)

The HMLR downscaled climate data were contributed by the Université du Québec Institut National de la Recherche Scientifique (INRS) (D. Jeong, personal communication), while the other climate data series were produced from the third Coupled Model Inter-comparison Project database of GCM output (CMIP3, Meehl et al., 2007) and dynamically downscaled using the Canadian Regional Climate Model (CRCM4.2.3; de Elia et al., 2008; Huard, 2011) or statistically downscaled with the DT method (Huard, 2011). In total, seven projected climate scenarios (Table 2) were produced for the period of 2046-2065 using six GCMs, two downscaling methods, and three emission scenarios. These climate data provide the basis for projecting future groundwater recharge. The 'ID' in Table 2 refers to a particular simulation performed in

the RCM; in this case the primary difference between the two RCM runs is the GCM driver (CGCM3 or Echam5).

Figure 2 shows the projected changes in mean annual precipitation and air temperature for each of the seven combinations given in Table 2 compared to reference period climate data obtained from Environment Canada (EC, 2010b). All of the scenarios project an increase in air temperature (range of 0.4 to 3.9°C), but the projections for precipitation vary significantly in magnitude and direction (-12% to +49%).
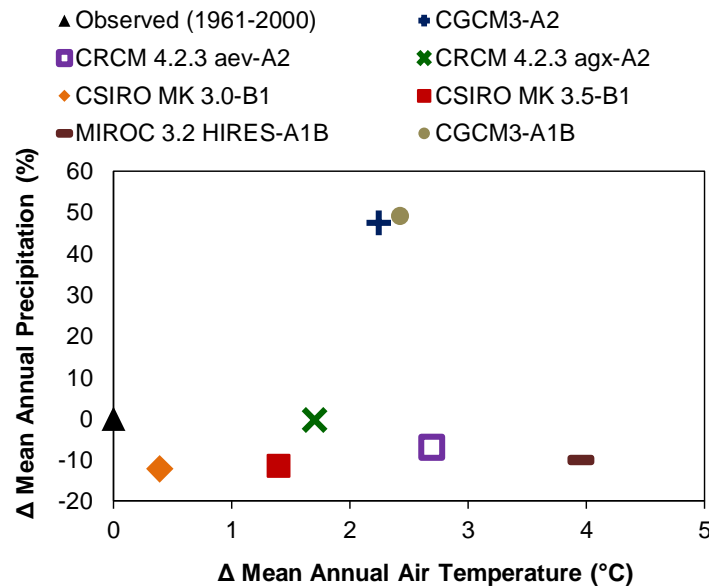

Figure 2. Projected changes in mean annual air temperature and precipitation for the Otter Brook catchment for the period 2046-2065 (data provided by D. Huard of Ouranos and D. Jeong of INRS).

2.3 The hydrology model: HELP3

Downscaled climate data can be utilized to drive simulations within hydrology models. Kingston and Taylor (2010) determined that the selection of the GCM yielded far more uncertainty in their climate-hydrology simulations than their hydrological model parameterization. Crosbie et al. (2011a) found that the selection of the hydrology model contributed less uncertainty to recharge estimations than did the choice of the downscaling scenario or the GCM. Teng et al. (2012) simulated the impact of climate change on runoff and also found that the selection of the GCM contributed far more uncertainty to the hydrological simulation results than the selection of the hydrological

model. In light of these three recent studies, only one hydrological model was employed for the present study.

We performed daily point simulations of recharge using the soil water balance hydrology model HELP3 (Hydrologic Evaluation of Landfill Performance, version 3), which simulates surface and shallow subsurface processes, including snow storage, snowmelt, interception, infiltration, runoff, evaporation, transpiration, and drainage (Schroeder et al., 1994). HELP3 is a one-dimensional model that simplifies horizontal lateral flow and the interactions between the hydrologic processes. For example, HELP3 does not allow water to be rerouted upwards once it has passed the evaporative zone depth (EZD) (Toews and Allen, 2009b). For the purpose of this study, water passing the EZD is assumed to result in groundwater recharge. HELP3 has been used in several recent studies (e.g., Allen et al., 2010; Crosbie et al., 2011a; Jyrkama and Sykes, 2007; Liggett and Allen, 2010; Scibek and Allen, 2006; Toews, 2007) to project future groundwater recharge rates from climate scenarios. Our modeling approach in HELP3 follows the processes detailed by these previous contributions, and additional details on the HELP3 model can be found in these studies. Limitations of the HELP3 model, particularly for application in arid regions, are discussed by Berger (2000) and Scanlon et al. (2002).

2.4 The hydrology model input data

HELP3 is driven by daily values of mean air temperature, precipitation, and solar radiation, and by annual average wind speed and quarterly relative humidity. The mean daily air temperature was determined by averaging the maximum and minimum daily temperatures provided in the post-processed climate datasets. Quarterly relative humidity values were extracted from the Environment Canada database (EC, 2010a) and held constant for each simulation. When needed, daily solar radiation data were generated using the methodology proposed by Hargreaves and Samani (1982) and expanded on by Allen (1997). This is a self-calibrated approach to determining solar radiation based on extraterrestrial radiation and the diurnal range in temperature.

In addition to climate data, HELP3 also requires several soil and land cover parameters. Because the Otter Brook catchment is small (9.5 km^2) and has a relatively homogeneous land cover, spatial variability in surface characteristics was not considered in the present study. For the subsurface, HELP3 requires that the saturated hydraulic conductivity, field capacity, porosity, evaporative zone depth, and wilting point be specified. These subsurface properties were determined from a combination of site visits, soil gradation analyses (Allard, 2008), soil pedotransfer function ranges (Balland et al., 2008), previous HELP3 recharge simulations studies (Toews, 2007), and model-recommended values (Waterloo Hydrogeologic, 2002). The surface parameters, including

the maximum leaf area index, and runoff curve number, were specified based on previous recharge studies (Liggett and Allen, 2010; Toews and Allen, 2009a), standards (United States Soil Conservation Service and Water Resources, 1985), climate data, and model recommendations (Schroeder et al., 1994; Waterloo Hydrogeologic, 2002). The growing season length was adjusted for each climate scenario based on the annual temperature cycle (i.e., when daily temperature exceeded 10°C). A summary of the key input data is given in Table 3.

Table 3
A summary of the HELP3 surface and subsurface input parameters

Parameter	Value	Reference
Hydraulic cond.	0.25 cm/s	(Hazen, 1892; 1911)
Evaporative depth	150 cm	(Toews, 2007)
Deposit thickness	9.5 m	(Allard, 2008)
Depth to GWT	7.5 m	(Allard, 2008)
Field capacity	0.031 (vol/vol)	(Balland et al., 2008)
Wilting point	0.019 (vol/vol)	(Balland et al., 2008)
Porosity	0.417	(Waterloo Hydrogeologic, 2002)
Unfrozen curve number	50	(US Soil Conservation Service and Water Resources, 1985)
Max leaf area index	4	(Toews, 2007)

      The flow of data from the GCMs through to the HELP3 model is indicated in Figure 3. Although not depicted in Figure 3, there are feedback loops between the land surface/subsurface characteristics and the climate data. For example, the maximum leaf area index is specified explicitly by the user, but HELP3 simulates an annual cycle for the vegetative density and leaf area index as a function of the air temperature and solar radiation (Schroeder et al., 1994). This will impact the timing and magnitude of the evapotranspiration regime. During the winter when air temperature is low, recharge ceases, and the precipitation increases the snowpack thickness. HELP3 also simulates a decrease in late fall and early spring recharge by increasing the runoff curve number for colder air temperatures.
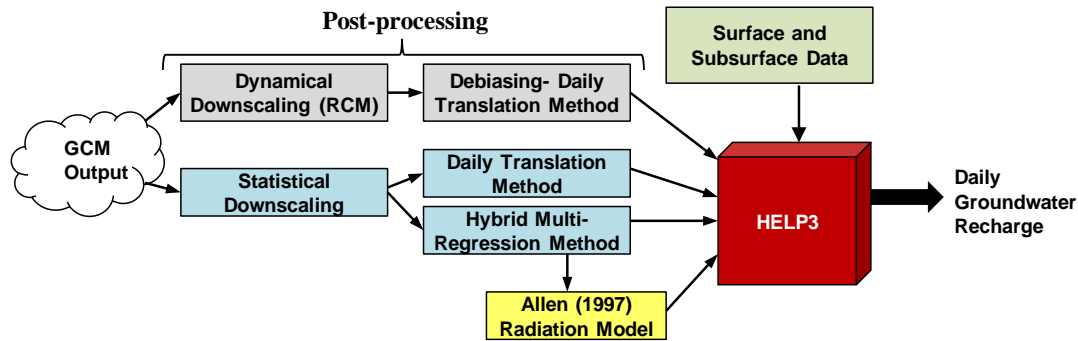
Figure 3. Algorithm for translating global climate model results into projections of temporal groundwater recharge.

3. Results

In general, the post-processing (see Figure 3) of the GCM and RCM climate data had a significant impact on the resultant climate series. Figure 4 shows the change in mean annual precipitation and air temperature due to the downscaling (HMLR or DT) and debiasing processes (DT, for the RCM simulations). The results demonstrate that near surface climate data (e.g., precipitation and air temperature) produced by a statistical downscaling method can deviate significantly from the climate data produced by the GCM, as many statistical downscaling methods (e.g., HMLR) are driven by upper-air field predictors from the GCM (Jeong, 2013, pers. communication).

The HELP3 simulations were not calibrated, but the percent of annual precipitation simulated to result in groundwater recharge for the reference period (range = 32-56%, mean =44%) generally concurs with previous hydrograph studies (45%, Noble and Bray, 1995) and water balance techniques (48% in 1994, Jones, 1997) for unconfined aquifers in the Little Southwest Miramichi River catchment. Figure 5 presents the annual average groundwater recharge simulated for the reference period (1961-2000) and for each climate scenario given in Table 2 for the future period (2046-2065). The most pronounced increase (58%) in annual average recharge, compared to the reference period, was obtained for the CGCM3-A2 climate data, while the most pronounced decrease in the average annual recharge (-6%) was obtained for the MIROC 3.2 HIRES-A1B climate data.

In addition to variations in annual recharge, the HELP3 hydrology simulation results also indicated changes to the timing of recharge. Figure 6 gives the monthly

distribution of simulated average annual recharge for the observed climate data and the CGCM3-A1B, CSIRO Mk3.0-B1, and MIROC 3.2 HIRES-A1B climate simulations. Results for these three simulations are presented because they span the range in projected annual average recharge. The normalized December recharge increases for all three future climate scenarios, while the normalized May recharge significantly decreases for two of the three climate scenarios. Little to no recharge occurs in January and February because precipitation during those months is mainly in the form of snow.
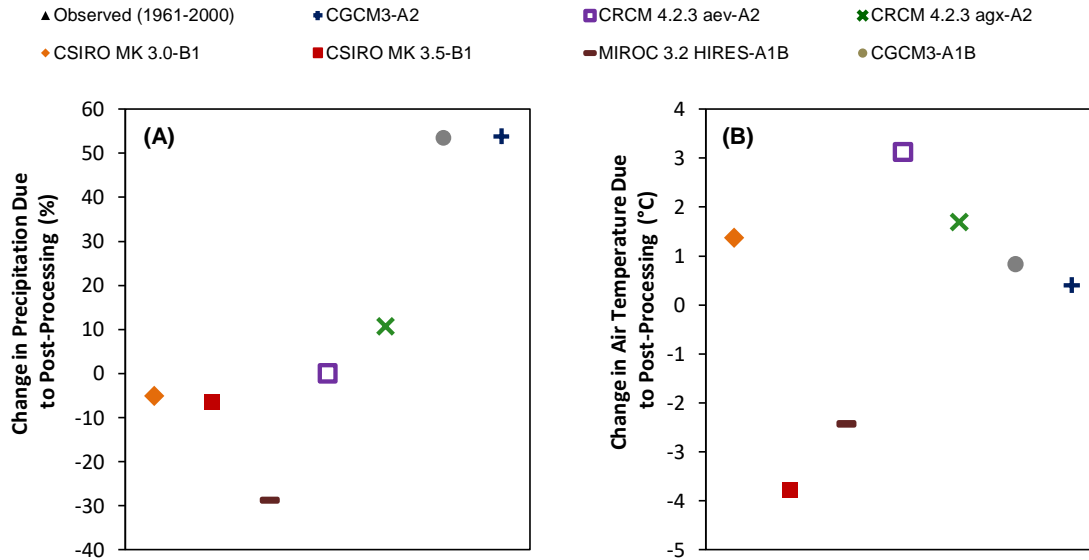

Figure 4. Changes in (a) mean annual precipitation (%) and (b) air temperature (°C) due to the post-processing of the GCM/ RCM data. The point of reference is the raw GCM/ RCM data for each climate scenario not the reference period data.

4. Discussion

4.1 The impact of the GCM, emission scenario, and downscaling method on the magnitude and timing of groundwater recharge

As indicated in Figures 2, 4, 5, and 6, the local projected climate data and the simulated groundwater recharge are dependent on the selected GCM, emission scenario, and downscaling method. For example, the CRCM 4.2.3 aev-A2 and CRCM 4.2.3 agx-A2 climate scenarios were both generated with the A2 emission scenario, dynamically downscaled with the CRCM 4.2.3 model, and further downscaled/debiased using the DT method. However, the CRCM 4.2.3 aev-A2 and CRCM 4.2.3 agx-A2 data produced projected changes in mean annual recharge of +3.4% and +14.7% respectively (Figure 5). Applying our definition of uncertainty yields a GCM-induced recharge uncertainty of 11.3% for these two climate-hydrology simulations. This significant difference can be

13

attributed to the two GCMs, Echam5 and CGCM3 (Table 2), that were selected to drive the CRCM 4.2.3 simulations.
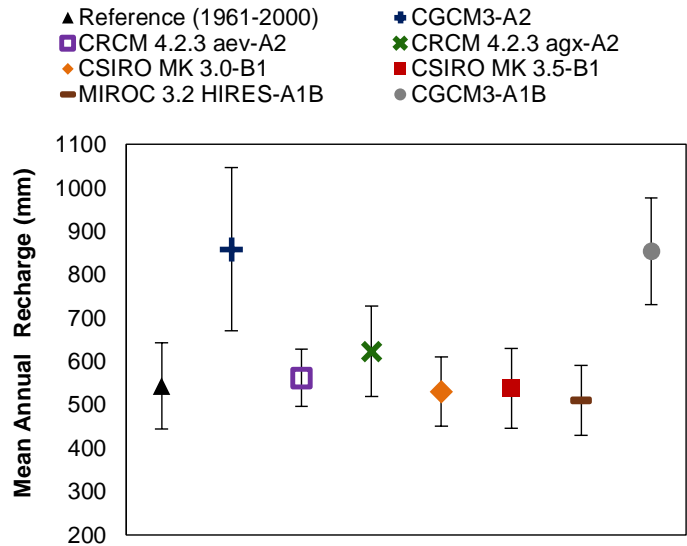

Figure 5. Average annual groundwater recharge for each climate-hydrology simulation. The recharge results obtained using the reference climate data (1961-2000) are indicated by the far left data point. The error bars indicate one standard deviation in the annual average recharge results

The effect of the choice of the emission scenario can be seen in the CGCM3-A2 and CGCM3-A1B climate data. These climate series were both generated by the CGCM3 and downscaled using the HMLR algorithm. Figures 2 and 5 illustrate that the emission scenario had very little impact on the resultant annual average climate data and subsequent simulated recharge, but the CGCM3-A2 recharge results are characterized by more annual variability (higher standard deviation). Thus, in this case, the selection of the emission scenario contributed very little uncertainty in the climate-hydrology simulations, at least on an annual average basis. In this case, the CGCM3-A1B data actually showed greater changes in the precipitation and temperature data than the CGCM3-A2 data. Although A2 is a higher emission scenario on a global scale, these effects may not be manifested at a local scale for a given GCM and time period. The effect of the emission scenario would be expected to be more pronounced in later decades (e.g. 2061-2100) due to the thermal inertia of the ocean (Huard 2011). It cannot be concluded from such a limited sample that the emissions scenario will always have the least impact on simulated groundwater recharge.
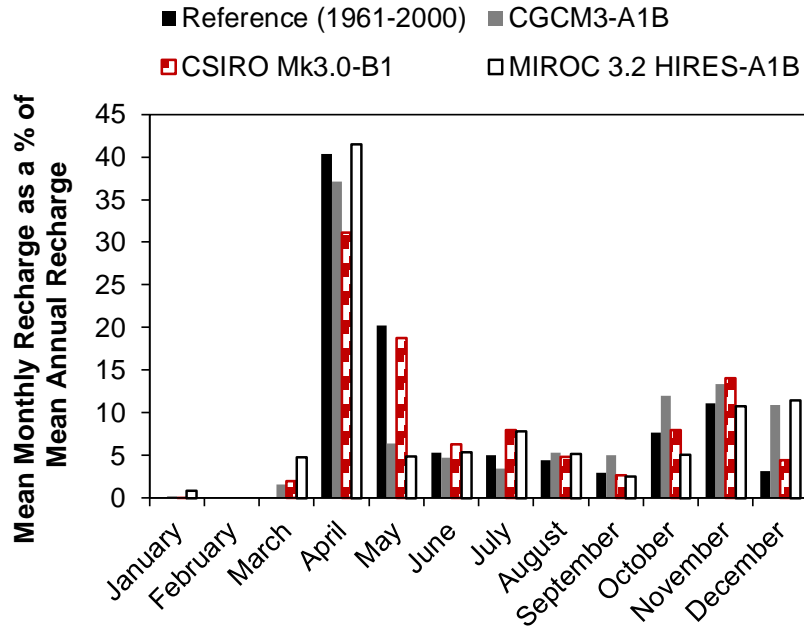
Figure 6. The monthly distribution of average annual groundwater recharge for the 1961-2000 period (reference) and three climate-hydrology simulations for 2046-2065

The effect of the downscaling/debiasing method is demonstrated by differences between the CGCM3-A2 and CRCM 4.2.3 aev-A2 precipitation and air temperature data indicated in Figure 2. Both of these climate scenarios were generated with the same GCM and emission scenario (Table 2), but one was dynamically downscaled with an RCM and debiased with the DT method, while the other was statistically downscaled using the HMLR algorithm. HELP3 simulated a 58% increase in annual average recharge for the CGCM3-A2 climate data and only a 3% increase for the CRCM 4.2.3 aev-A2 data (Figure 5). Thus, the differences in downscaling/debiasing techniques contributed significant recharge uncertainty (55%) when comparing these two climate-hydrology simulations. These results are predictable given the significant effect that different post-processing techniques have on the resultant climate series (Figure 4).

The changes to the timing of the recharge indicated in Figure 6 are a result of changes to the timing of the projected precipitation and air temperature. On average, monthly precipitation remained relatively constant throughout the year for the reference period. However, in general, the projected climate scenarios were characterized by increased variability in the distribution of monthly precipitation. The change in available soil moisture during these periods will directly impact groundwater recharge for that season. The decreases in May recharge projected for several of the climate scenarios are a result of an increase in winter temperature and consequently an earlier shift in the timing

15

of the snowmelt. This phenomenon is apparent in Figure 6 where the MIRCO 3.2 Hires-A1B normalized recharge increases in March and April and decreases in May compared to the simulations conducted for the reference period. However, this effect is not as apparent for the CSIRO Mk 3.0-B1 data (Figure 6), which is likely due to the relatively small increase in annual average air temperature when compared to the MIRCO 3.2 Hires-A1B data (Figure 2). Thus, at northern latitudes, the selection of the GCM, downscaling/debiasing algorithm, and emission scenario may all have a significant effect on the timing of the simulated snowmelt and consequently, the timing of the simulated recharge.

4.2 Comparison to other recharge studies with multiple climate scenarios

The uncertainty in the projected annual average recharge for the present study (range = -6% to +58%, uncertainty = 64%) is larger than the uncertainty in recharge simulated by Allen et al. (2010) and Dams et al. (2012) (Table 1), and this likely arises because the present study considered multiple downscaling/debiasing methods in addition to multiple GCMs. However, as shown in Table 1, the uncertainty in the current study is approximately the same as ranges simulated by Holman et al. (2009), Jackson et al. (2011) and Ali et al. (2012) and considerably less than those simulated by Serrat-Capdevila et al. (2007), Döll (2009), Crosbie et al. (2010), Crosbie et al. (2011a), and Crosbie et al. (2013).

These uncertainties primarily arose from the approaches used to generate the climate data that drive the hydrologic models. Holman et al. (2009) indicated that more uncertainty arose from the choice of the downscaling method than the choice of the emission scenario. Crosbie et al. (2011a) found that the largest source of uncertainty could be attributed to the GCM, while the choice of the downscaling method was of secondary importance. The information given in Table 2, Figure 5, and the discussion above indicates that the variability in simulated future recharge for the present study arose primarily from the downscaling method, secondly from the GCM, and thirdly from the emission scenario. These findings generally agree with those of Holman et al. (2009), although that study only employed one GCM. However, these findings contrast with the study by Crosbie et al. (2011a) by suggesting that the downscaling/debiasing method has more impact on the resultant climate data than the choice of the GCM. This difference likely arises from the more limited suite of GCMs utilized in the present study. Thus, this study suggests that in any projected recharge study, multiple downscaling methods should be employed if a full range of uncertainty in the associated impact is to be determined.

For all of the studies summarized in Table 1, the magnitude of the change in future groundwater recharge was difficult to forecast given the uncertainty in climate-

hydrology modeling. For example, Döll (2009) stated: 'climate change scenarios cannot be used to quantitatively project the future development of groundwater resources.' Furthermore, many of these studies produced ranges that made it difficult to project the future trajectory of groundwater recharge. For example, Crosbie et al. (2010) concluded, 'it [is] difficult to project the direction of the change in recharge…let alone the magnitude' and 'such variability in recharge estimates using different climate sequences means that making recommendations for water-resources management…is highly uncertain'. Crosbie et al. (2013) stated: 'for most of [Australia] there is no consensus amongst the models on the direction of the change in recharge'. The present study produced an average change in mean annual recharge of +16% (Figure 5), but similar to what others has concluded, it would seem presumptuous to suggest that future recharge will increase given that three of the seven climate scenarios resulted in a decrease in recharge.

Several authors have attempted to address the uncertainty in recharge projections by applying a probabilistic approach or averaging the results (e.g., Jackson et al., 2011; Ali et al., 2012; Crosbie et al., 2013). This approach may assist water resource managers in understanding the uncertainty in future recharge projections; however, the findings are prone to being statistically insignificant. For example, Jackson et al. (2011) found that the sign of the change in potential groundwater recharge could not be determined at the 95% confidence interval. Additionally, a problem arises when assigning probabilities to distinct climate scenarios, each of which should not necessarily be considered equally likely to occur.

A number of recent groundwater recharge studies have suggested that considerable value remains in projecting future recharge, despite the uncertainty in the simulated results. Serrat-Capdevila et al. (2007) suggested that their study could benefit policy makers because almost three quarters of their GCM simulations indicated a decreasing trend in precipitation; however, the present study suggests that their results would likely exhibit more uncertainty if they had employed more than one downscaling method. Döll (2009) suggested that valuable information can still be obtained from these studies to demonstrate the possible ranges in future groundwater resources that will require an adaptive response. Crosbie et al. (2013) stated that their study demonstrated that water resources managers should understand the uncertainty involved with making future groundwater resource decisions. In general, we agree that the major contribution of the studies summarized in Table 1 has been to demonstrate that future groundwater resources could potentially change significantly, but that the magnitude and trajectory of this change in uncertain. These results are not surprising considering that precipitation is poorly resolved and inconsistent in GCMs (Döll 2009), and that variations in recharge can be 2-3 times greater than variations in precipitation (Ali et al. 2012).

4.3 Suggestions for future research investigating the impact of climate change on groundwater recharge

Given the number of recent studies, including the present example, that explicitly or implicitly suggest it is difficult to predict the magnitude and direction of groundwater recharge, perhaps it is time that we refocus our efforts rather than continue with similar simulation approaches. The following suggestions for future research are offered based on the findings of the illustrative case study detailed above and the gaps identified in the literature reviewed:

1. To date, groundwater recharge projections have exhibited significant uncertainty. Thus, there should be an exploration of new techniques for a) better quantifying and communicating the uncertainty in projected recharge, such as employing probabilistic approaches that recognize that projected emission scenarios may not have equal likelihood, and b) reducing the uncertainty in the driving climate data and resultant recharge projections. Because it appears that hydrologic models used to estimate groundwater recharge contribute relatively little to the overall uncertainty (Kingston and Taylor, 2010; Crosbie et al., 2011a; Teng et al., 2012), the focus for improvements should be the GCMs, post-processing methods, and emission scenarios. For example, uncertainty in the driving data could be reduced by abandoning climate modeling techniques (e.g., coupled GCM-downscaling method simulations) that do not adequately reproduce recently measured climate data (e.g., 2000-2010).

2. Studies investigating the impacts of climate change on groundwater recharge should employ multiple post-processing methods in addition to multiple GCMs and emission scenarios. There has been a tendency to deemphasize the impact of the downscaling/debiasing methods, but recent studies, included the present one, have demonstrated that downscaling may contribute significant uncertainty in the resultant climate data utilized to drive groundwater recharge simulations. In accordance with the first suggestion, only downscaling methods that have been shown to perform well for the study region in question should be employed.

3. There remains a lack of data on the relationship between long-term climate change and groundwater recharge, although several studies (e.g., Chen et al., 2004; Hughes et al., 2012; Rivard et al., 2009) have examined the relationship between seasonal or decadal climate variations and groundwater levels. Kundzewicz et al. (2007, Table 3.1) found 'no evidence for [a] ubiquitous climate-related trend' for groundwater resources. Thus, there should be an

increase in field-based studies that track climate change-induced impacts on groundwater recharge.

4. If recharge projections are to be obtained for a period only a few decades into the future, it may be reasonable to assume constant land cover conditions. However, for recharge projections for time periods in the more distant future there should be an increased effort to address simultaneous changes to the socioeconomic environment, land cover, and climate conditions. It seems unreasonable to project climate change impacts on groundwater recharge for a century into the future and assume that water supply needs and land cover conditions will be intransient (Döll, 2009; Holman, 2006; Holman et al., 2012).

5. Climate-groundwater interactions are currently simulated by explicitly coupling GCMs with hydrological models. Because of the interdependence on groundwater and land-energy feedbacks (Maxwell and Kollet, 2008) it may be more appropriate to directly simulate the groundwater recharge response to climate change within the land surface model of the GCM. Perhaps more hydrogeologists should be researching and improving the groundwater components of the existing GCM land surface models (Gulden et al., 2007).

5. Conclusions

Downscaled climate scenarios for central New Brunswick, Canada were used to drive HELP3 and simulate future groundwater recharge. The simulated data exhibited uncertainty both in the direction and magnitude of future changes in mean annual recharge (-6 to +58%). The variations arose from the selection of the GCMs, emission scenarios, and downscaling algorithms employed to generate the climate data. For the particular combinations examined, the largest variations resulted from the choice of the post-processing approach (i.e., statistical versus dynamical downscaling with statistical debiasing).

This study has demonstrated the limitations inherent in predicting future changes in groundwater recharge using downscaled climate change scenarios. For example, a single projection of climate based on one emission scenario, simulated with one GCM, and downscaled using only one approach, will provide limited insight into potential changes in recharge. Although significant efforts are required to produce downscaled climate data using a variety of GCMs, emission scenarios and downscaling methods, it is concluded that this approach will provide a more honest representation of the uncertainty involved in assessing the hydrogeological impacts of climate change.

The IPCC correctly identified a gap in the knowledge of the impact of climate change on groundwater resources (Kundzewicz et al. 2007), and numerous recent studies have attempted to bridge this gap. However, these studies have demonstrated that we do not currently have the ability to quantitatively predict the magnitude or direction of the impact of climate change on groundwater resources with a high degree of confidence. This does not imply that we should abandon the modeling of projected recharge; indeed there are many opportunities for advancing this field, including constraining climate projections; collecting extensive time series of recharge and climate data; simulating simultaneous changes in land cover, water withdrawals and climate change; and developing increasingly complex land surface models within GCMs.

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7. References

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