Modeling climate change impacts on groundwater resources using transient stochastic climatic scenarios

Pascal Goderniaux,[1,2,3] Serge Brouyère,[1] Stephen Blenkinsop,[4] Aidan Burton,[4] Hayley J. Fowler,[4] Philippe Orban,[1] and Alain Dassargues[1]

[1]   Several studies have highlighted the potential negative impact of climate change on groundwater reserves, but additional work is required to help water managers plan for future changes. In particular, existing studies provide projections for a stationary climate representative of the end of the century, although information is demanded for the near future. Such time-slice experiments fail to account for the transient nature of climatic changes over the century. Moreover, uncertainty linked to natural climate variability is not explicitly considered in previous studies. In this study we substantially improve upon the state-of-the-art by using a sophisticated transient weather generator in combination with an integrated surface-subsurface hydrological model (Geer basin, Belgium) developed with the finite element modeling software "HydroGeoSphere." This version of the weather generator enables the stochastic generation of large numbers of equiprobable climatic time series, representing transient climate change, and used to assess impacts in a probabilistic way. For the Geer basin, 30 equiprobable climate change scenarios from 2010 to 2085 have been generated for each of six different regional climate models (RCMs). Results show that although the 95% confidence intervals calculated around projected groundwater levels remain large, the climate change signal becomes stronger than that of natural climate variability by 2085. Additionally, the weather generator's ability to simulate transient climate change enabled the assessment of the likely time scale and associated uncertainty of a specific impact, providing managers with additional information when planning further investment. This methodology constitutes a real improvement in the field of groundwater projections under climate change conditions.

1.   Introduction

[2]   According to the Fourth Assessment Report (AR4) of the Intergovernmental Panel on Climate Change [*IPCC*, 2007, p. 30], "Warming of the climate system is unequivocal." One of the most important indirect issues linked to climate change relates to water supply, which is essential for most human activities, including agriculture and associated food security issues. Groundwater represents a large percentage of total water supplies across the world [*Morris et al.*, 2003], in arid zones, but also in countries which experience temperate climates, such as Belgium, where approximately 80% of the water supply comes from aquifers [*DGARNE*, 2009]. Groundwater will continue to be a vital resource in the future as it constitutes an important part of available freshwater on our planet, but also because groundwater is relatively less sensitive than surface water to short-term and seasonal climatic variations.

[3]   During the last decade, several studies on groundwater have shown that climate change will have a negative impact on groundwater reserves in many parts of the world [*Goderniaux et al.*, 2009a, 2009b; *Van Roosmalen et al.*, 2009; *Scibek et al.*, 2007; *Serrat-Capdevila et al.*, 2007; *Woldeamlak et al.*, 2007; *Holman*, 2006; *Scibek and Allen*, 2006b, 2006a; *Allen et al.*, 2004; *Brouyère et al.*, 2004a; *Chen et al.*, 2004; *Loáiciga*, 2003; *Chen et al.*, 2002; *Yusoff et al.*, 2002; *Loaiciga et al.*, 2000]. These studies have highlighted the problems associated with changes in climate for water resource management systems which have historically been designed under the assumption of climate stationarity [*Milly et al.*, 2008]. However, additional work is also required to help the managers take actions to plan for future changes:

[4]   (1) The uncertainty associated with projected groundwater levels can be very large and needs to be better quantified. The absence of information about the quality of model projections is often used as an argument for inertia. Nevertheless, evaluating the possible range of variation of

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[1]Group of Hydrogeology and Environmental Geology - Aquapôle, University of Liège, Liège, Belgium..

[2]National Funds for Scientific Research of Belgium, Brussels, Belgium..

[3]Now at Geosciences Rennes, UMR 6118 Université de Rennes 1 - CNRS, Rennes, France..

[4]Water Resource Systems Research Laboratory, School of Civil Engineering and Geosciences, Newcastle University, Newcastle upon Tyne, UK..

projected impacts is useful and frequently demanded by water managers who undertake risk and cost-benefit analyses as part of the decision-making process. However, in previous climate change impact studies on groundwater, the estimation of uncertainty has been relatively limited.

[5] (2) Knowledge of the timing of potential climate change impacts on groundwater is also crucial for managers, as it assists the adequate planning of further costly investment (e.g., new pumping installations, prospection for alternative resources, etc.). Existing studies typically estimate the magnitude of climate change impacts for a stationary climate representative of the end of the 21st century due to the easy access to time-slice simulations from climate models. In reality, climatic conditions will continuously evolve over the 21st century and catchment management plans may be needed for the near future rather than for the end of the century.

[6] These important needs for the optimal management of groundwater resources have not yet been addressed in previous studies mainly due to inadequacies in climate model outputs. Output from atmosphere-ocean general circulation models (GCMs) cannot be used directly in most hydrological models as the scale is too coarse (∼250 km) and thus does not adequately resolve spatial variability in important climatic variables [*Fowler et al.*, 2007]. Dynamical downscaling using regional climate models (RCMs) generates output with a finer spatial resolution (normally ∼25–50 km) but biases are still observed between RCM outputs and observed climatic statistics. These are in part inherited from the GCM providing the boundary conditions, but also from the RCM model structure, parameterization, and resolution. As a consequence, further statistical downscaling is generally required to provide outputs at a relevant scale for hydrological impact studies. Most climate change impact studies on groundwater resources use the simple "perturbation" or "delta change" method [*Prudhomme et al.*, 2002] to statistically downscale climate change scenarios to the scale of the study area [e.g., *Brouyère et al.*, 2004a; *Yusoff et al.*, 2002]. The method applies "change factors," calculated as the difference (relative or absolute) between the control and future climate model simulations, to observed climatic data. This method has the advantage of being very simple, but it has the limitation that the generated climate change scenarios are strongly conditioned by observed historical data. As a consequence, the perturbation method does not allow altering the frequency of wet and dry days, or changing of the occurrence, persistence, and intensity of extreme events, which could have a strong influence on groundwater recharge processes (Figure 1). These simple methods also have the limitation that the climate change time series are representative of a stationary climate over a 30 year period, rather than a transient climate. Furthermore, such scenarios do not allow for consideration of the uncertainty linked to natural climate variability.

[7] Despite these limitations, simple downscaling methods are still widely used in hydrological studies [*Fowler et al.*, 2007]. In this study we substantially improve upon the state-of-the-art by applying a sophisticated transient stochastic downscaling technique in combination with an integrated surface-subsurface hydrological model to: (1) better estimate climate change impacts on groundwater resources; (2) evaluate the uncertainty linked to natural
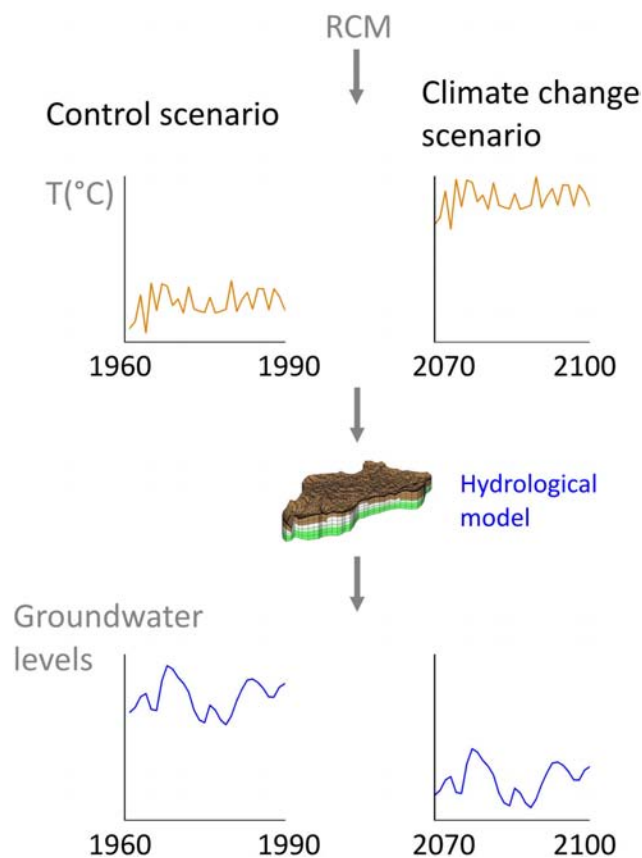

Figure 1. Downscaling approach classically used in hydrological impact studies (perturbation method). Illustrative example with temperature and groundwater levels.

climate variability; (3) provide an indication of the uncertainties associated with internal climate model structure and boundary conditions; and (4) consider the transient aspects of climate change over the whole 21st century.

2. Methodology

[8] We use an advanced and recently developed downscaling technique which combines the change factor and stochastic "weather generator" approaches to generate transient climate change scenarios [*Burton et al.*, 2010; *Kilsby et al.*, 2007; S. Blenkinsop, H. J. Fowler, C. Harpham, A. Burton, and P. Goderniaux, Modelling transient climate change with a stochastic weather generator. Projected temperature changes for the Geer catchment, Belgium, manuscript in preparation, 2011 (hereinafter, Blenkinsop et al., manuscript in preparation, 2011)]. In the approach, change factors are calculated according to GCM/RCM relative change and used for perturbing observed climate statistics and therefore assumes that relative changes in GCM/RCM simulations over time are more reliable than the absolute value of the simulations, which are generally biased [*Fowler et al.*, 2007]. For future climate scenarios the stochastic weather generator components are then calibrated separately to the perturbed climate statistics, and used to simulate future climate time series that match these statistics.

[9] This technique improves on the delta change method by calculating change factors for a wide range of climate statistics (including probability of a dry day, daily mean

precipitation, daily and monthly precipitation variance, precipitation autocorrelation, precipitation skewness, daily mean temperature, and temperature standard deviation) rather than the mean alone. Thus RCM control biases are removed and projected changes in rainfall occurrence and variability and extremes can be better simulated by this approach. The weather generator technique is relatively more efficient at simulating both climatic variability and extremes in comparison with simpler downscaling techniques [*Wilks and Wilby*, 1999] as the statistical distribution of each climatic variable can be adjusted to represent the changes in variability and the occurrence of extreme events.

[10] Generally downscaling is applied directly to stationary climate simulations from GCMs/RCMs over 30 year time slices (e.g., 2071–2100). In this study the approach has been adapted to simulate climatic time series that represent fully transient climate change conditions from 2010 to 2085. This is achieved using climate projections, downscaled to the 25 km resolution using an ensemble of RCM experiments, from which change factors for the year 2085 are calculated using the relative changes between the RCM simulations representative of a stationary climate for the periods 1961–1990 (control) and 2071–2100 (future). Change factors for each year between 2010 and 2085 are calculated assuming that changes vary in proportion to the global temperature evolution of the driving GCM, which provides simulations representative of the climate between 2010 and 2085, and by scaling the change factor of the year 2085 accordingly [*Burton et al.*, 2010]. To generate the complete climate change time series, the weather generator models are successively calibrated to the scaled observed statistics of each year between 2010 and 2085. The weather generator models then provide a continuous simulation of rainfall and other weather variables for the period 2010 to 2085.

[11] This methodology enables the stochastic generation of large numbers of equiprobable climatic time series, to model natural variability, with little computational resource and the assessment of possible impacts in a probabilistic way (see *Ng et al.* [2010] and *Holman et al.* [2009] for examples on groundwater recharge only). The change factors are calculated from a multimodel ensemble of six RCMs driven by two different GCMs (PRUDENCE project, *Christensen and Christensen* [2007]), to consider uncertainty from both driving GCMs and RCMs. As noted previously, climate models vary in their ability to reproduce the observed characteristics of regional climate due to differences in model structure and parameterizations, and uncertainty estimates from this source is necessary. In this study, 30 equiprobable daily climate change time series from 2010 to 2085 have been generated for each RCM experiment and for a control simulation assuming no climate change (Figure 2). These were applied as input variables to a hydrological model.

[12] Moreover, the advantages of the climatic scenarios are here combined with those of a catchment-scale fully integrated surface-subsurface model [*Goderniaux et al.*, 2009b], where flow equations in all domains are solved simultaneously. Integrated models enable the simulation of feedbacks between the surface and subsurface domains and represent groundwater recharge more realistically, which depends on the hydraulic conditions in both domains simultaneously. A good representation of this groundwater recharge

and the whole dynamic of water exchanges between the surface and subsurface domains is crucial in the context of climate change, as they constitute the connection between atmospheric and groundwater flow processes. In this context, assessing climate change impacts on groundwater by only considering the subsurface part of the system is very difficult and potentially unusable [*Goderniaux et al.*, 2009b]. To simultaneously represent runoff, recharge, and groundwater fluctuations, daily climatic inputs are required. Compared to monthly inputs, this enables, for example, the difference between short intense rainfall and prolonged light rainfall to be distinguished, and their effect on groundwater recharge be taken into account.

[13] This approach involving transient stochastic climate change scenarios and surface-subsurface integrated hydrological models is original in the field of groundwater modeling and climate change impacts. More technical details about the application of the change factor approach to the stochastic weather generator and of the integrated hydrological model are provided in Sections 4 and 5.

3. The Geer Basin

[14] This approach is used to evaluate climate change impacts on groundwater resources of the Geer basin located in eastern Belgium, northwest of the city of Liège, in the intensively cultivated "Hesbaye" region. The hydrological basin extends over approximately 480 km^2, on the left bank of the Meuse River (Figure 3). The Geer catchment is strategically important for Liege city and its suburbs and it is exploited for drinking water, primarily through a network of pumping galleries of more than 40 km located in the chalk layers (Figure 3). According to *Hallet* [1998], extracted groundwater volumes represent between 6% and 11% of total annual precipitation ($\sim$800 mm yr^{-1}).

[15] The geology of the Geer catchment essentially consists of Cretaceous chalky formations which constitute the main aquifer of the region. These chalk formations dip northward and overlie 10 m of smectite clays of very low hydraulic conductivity. The total thickness of the chalk ranges from a few meters up to 70 m. A flint conglomerate of dissolved chalk residues overlies this, with a maximum thickness of 10 m. Tertiary sand lenses of small extension are found locally above this conglomerate and a thick layer (up to 20 m) of quaternary loess is observed throughout the catchment [*Orban et al.*, 2010; *Visser et al.*, 2009; *Orban et al.*, 2006; *Hallet*, 1998].

[16] The chalk aquifer is unconfined over most of the basin. Subsurface flow is from south to north and the aquifer is mainly drained by the Geer River (Figure 3) [*Orban et al.*, 2006]. The chalk porous matrix, whose total porosity is estimated between 40% and 50%, enables the storage of large quantities of groundwater. Fast preferential flow occurs through fractures, which represent approximately 1% of the total porosity [*Brouyère*, 2001; *Hallet*, 1998]. At a macroscopic scale, zones characterized by a higher degree of fracturing and higher hydraulic conductivity are associated with "dry valleys" mostly oriented south to north. For the larger part of the Geer catchment, the saturated zone is exclusively located in the chalk formations. The thick loess layer located above the chalk controls the water infiltration rate from the land surface to the chalky aquifer, resulting in smoothed
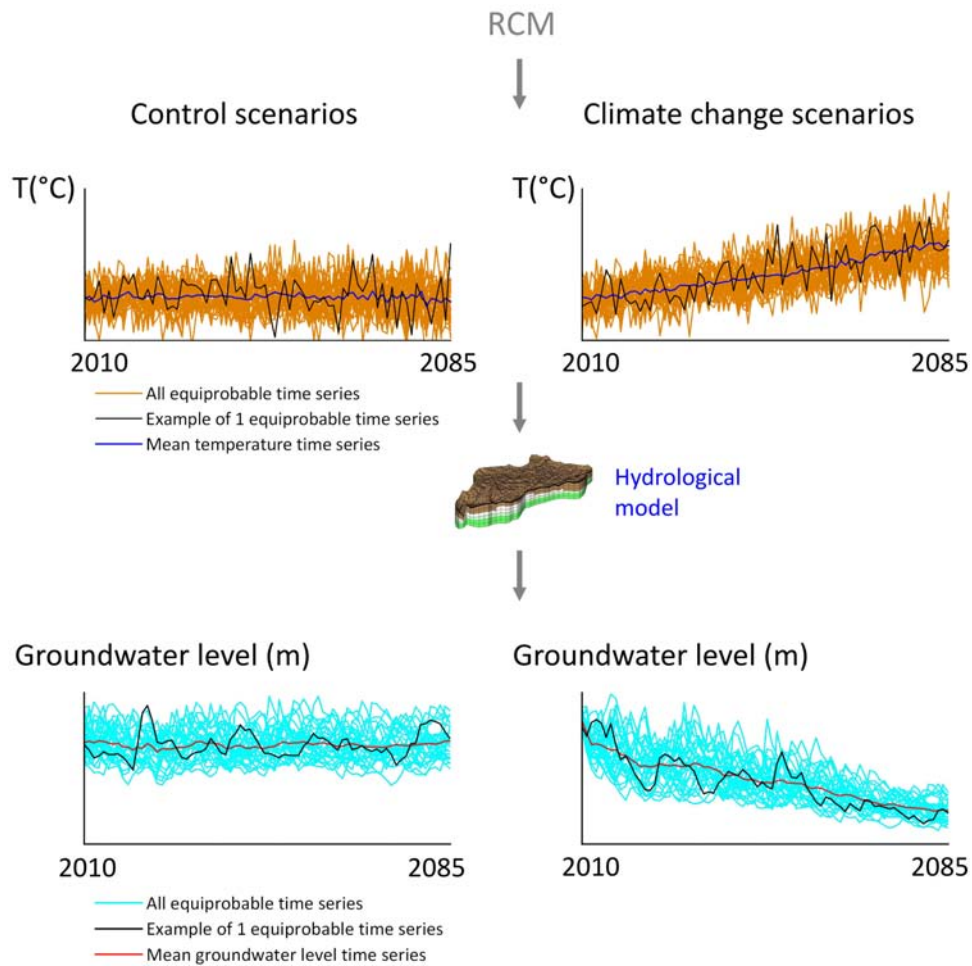
Figure 2. Transient stochastic weather generator downscaling approach and its use to derive transient impact on groundwater as used in this study. Illustrative example with temperature and groundwater levels.
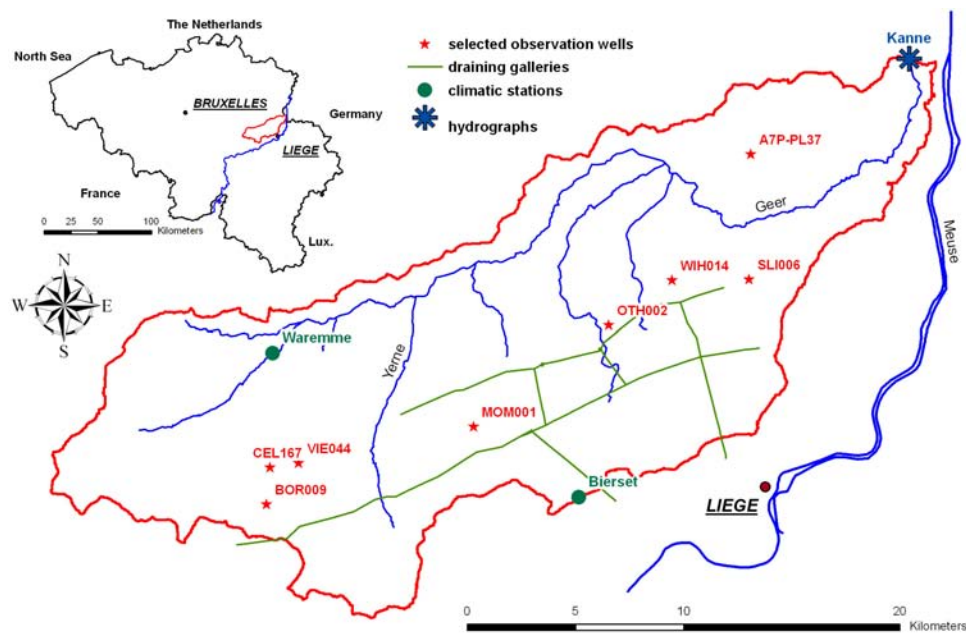

Figure 3. Location of the Geer basin.

recharge fluxes at the groundwater table and attenuation of seasonal fluctuations of hydraulic heads that are better characterized by multiannual variations [*Brouyère et al.*, 2004b].

4. Climate Change Scenarios

[17] The generation of large numbers of equiprobable climate change scenarios with the weather generator methodology is performed in two main steps. First, the daily precipitation time series from 2010 to 2085 are generated using the transient version of the rainfall model RainSim [*Burton et al.*, 2010; *Burton et al.*, 2008]. Second, the precipitation time series generated with RainSim are used as input to the "CRU daily weather generator" [*Kilsby et al.*, 2007; *Watts et al.*, 2004], hereafter referred to as CRU-WG, to produce a data time series of the other weather variables. Daily precipitation time series are generated separately from the other variables because precipitation is conceptualized as clustered rainfall events, while the other meteorological variables, considered as continuous phenomena, are more easily simulated by regression procedures.

4.1. RainSim

[18] RainSim [*Burton et al.*, 2008] is based on the Neyman-Scott rectangular pulses (NSRP) model [*Cowpertwait*, 1991; *Neyman and Scott*, 1958] which conceptualizes each rainfall event as the aggregation of several "rain cells" each characterized by a rainfall intensity and duration. The properties of all rainfall events and their associated rain cells are determined by five random variables governed by specific statistical distributions and specified parameters (Table 1). These parameters are calibrated to match observed climate statistics for the "control" simulations (without any climate change) and to the projected future statistics of each year between 2010 and 2085, based on RCM projections, for the climate change simulations. Precipitation statistics used by RainSim in this study are:

    daily mean precipitation,
    daily precipitation variance,
    monthly precipitation variance,
    probability of a dry day (<1 mm),
    daily lag-1 autocorrelation,
    daily skewness coefficient $= \dfrac{E\{[Y_d - E(Y_d)]^3\}}{\sigma_{Y_d}^3}$,

Y_d: daily rain accumulation, and
$\sigma_{Y_d}^2$: variance of the daily rain accumulation.

4.2. CRU Daily Weather Generator

[19] The CRU-WG is based on observed correlation and autocorrelation relationships between climate variables (precipitation, maximum and minimum temperature, sunshine

hours, vapor pressure, and wind speed). Here simulations are generated using the transient implementation demonstrated for the Geer basin by Blenkinsop et al. (manuscript in preparation, 2011). Observed data for all variables are first separately partitioned by all half months of the calendar (12 × 2), and by four different transition types between days (wet-wet, dry-dry, wet-dry, and dry-wet) determined depending on the wet/dry status of the preceding and current day. These data are then normalized (to have zero mean and unit standard deviation) and modeled using a cascade of regressive and autoregressive relationships for each of the 96 distributions (12 × 2 × 4). An example of one such relationship is given by equation (1) for the temperature variable:

$$Ti = aT_{i-1} + bP_{i-1} + c + r \qquad (1)$$

[20] T_i: normalized daily temperature on day *i*,

[21] P_i: normalized daily precipitation on day *i*,

[22] *a,b,c*: regression weights determined from observed data, and

[23] *r*: normally distributed random variable maintaining the variance of T_i.

[24] These relationships have the advantage of preserving the correlation and autocorrelation between all variables. During a simulation they are used to produce new normalized time series which are subsequently denormalized using constants (the means and standard deviations) corresponding to the target climate [*Kilsby et al.*, 2007]. For future projections the denormalization constants are calculated by applying RCM-derived change factors for mean temperature and temperature standard deviation and here correspond to the projected transient climate change statistics for each year between 2010 and 2085.

[25] The associated potential evapotranspiration time series are calculated by the weather generator using the Penman-Monteith equation [*Allen et al.*, 1998]. Further details of the CRU-WG can be found by *Kilsby et al.* [2007].

4.3. Pattern Scaling Between 2010 and 2085

[26] The expected climate change statistics used by RainSim and the CRU-WG are evaluated from data provided by RCM and GCM experiments. In this method, described in detail by *Burton et al.* [2010] and Blenkinsop et al. (manuscript in preparation, 2011), the stochastic downscaling applies change factors to observed statistics. These change factors are derived from the relative or absolute change between stationary RCM time slices for 1961–1990 and 2070–2100 which are then scaled for each year between 2010 and 2085. This pattern scaling [*Mitchell*, 2003; *Santer et al.*, 1990] provides a pragmatic means to produce scenarios for periods not covered by GCM/RCM simulations. Here, scaling is performed by assuming that changes vary in proportion to the global temperature response of the GCM providing the RCM boundary conditions with the scaling factor of the years 1975 and 2085 being 0 and 1, respectively. *Mitchell* [2003] and *Tebaldi et al.* [2004] have analyzed a range of GCM experiments and found these assumptions to be generally accurate for temperature and precipitation change at seasonal and grid scales. The scaling factor is then calculated for the years 2025 and 2055, based on the central years of GCM time-slice experiments (2011–2040 and 2041–2070) with the scaling factor interpolated linearly between the years 1975,

Table 1. Random Variables Used in the NSRP Model

| Random Variable	Statistical Distribution of the Random Variable
Time interval between rain events (T)	Exponential
Number of "rain cells" for each rain event (−)	Poisson
Time interval between the origin of each "rain cell" and the origin of the corresponding rain event (T)	Exponential
Intensity of each "rain cell" (LT^{-1})	Exponential
Duration of each "rain cell" (T)	Exponential
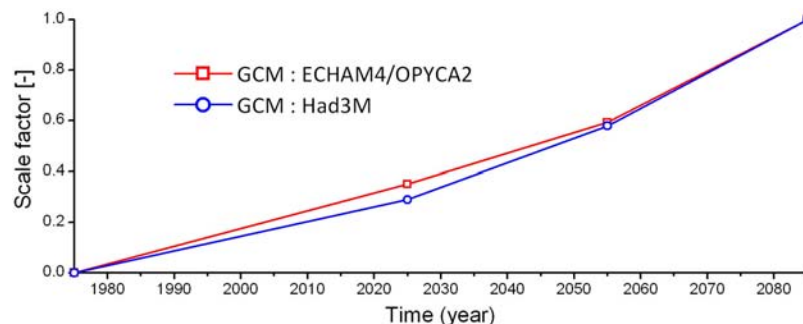
Figure 4. Evolution of the scaling factor between 1975 and 2085 for the GCMs ECHAM4/OPYCA2 and Had3M.

2025, 2055, and 2085. As an illustration, Figure 4 presents the scaling factor evolution between 1975 and 2085 for the GCMs ECHAM4/OPYCA2′ and HadAM3 which drive the boundary conditions of the RCMs used in this study (see Table 2). According to this graph, the rate of change is expected to be greater at the end of the 21st century for both GCMs.

4.4. RCM Ensemble

[27] An ensemble of six RCM experiments provided by the PRUDENCE ensemble [*Christensen et al.*, 2007] was selected to demonstrate the application of the downscaling framework (Table 2). The models are selected to assess the combined uncertainty in the response of the Geer basin to both RCM and GCM selection. Details of RCM structures are provided by *Jacob et al.* [2007]. PRUDENCE provides stationary climate model simulations for the periods 1961–1990 (control) and 2071–2100 (future), the latter assuming the SRES A2 greenhouse gas emissions scenario (medium-high) [*Nakicenovic et al.*, 2000] which is consistent with recent observed increases in atmospheric carbon dioxide concentrations [*Rahmstorf et al.*, 2007]. Using different RCM experiments allows the range of variation or uncertainty associated with climate model structure and parameterizations to be evaluated although, as discussed later, the nature of the PRUDENCE ensemble does not provide a comprehensive coverage of climate model uncertainty. Figure 5 presents the climate change statistics for each RCM (for the 2071–2100 time slice) for mean temperature and precipitation. All RCMs project a general temperature increase throughout the year with a higher increase during summer months. Similarly, all RCMs project an annual precipitation decrease, with precipitation increasing during winter months and decreasing during summer months.

4.5. Model Validation and Simulations

[28] Comprehensive case studies validating the rainfall model RainSim, CRU-WG, change factor approach, and the transient climate change rainfall model may be found by *Burton et al.* [2008], *Jones et al.* [2009], and *Burton et al.* [2010]. In this study, RainSim and the CRU-WG were used to downscale 30 equiprobable daily climate change time series from 2010 to 2085 for each RCM. In addition 30 scenarios were produced without any climate change as stationary control simulations. Observed climate data (1960–1990), from which future climate statistics are scaled, are from the Waremme climate station for precipitation and from the Bierset climate station for all other climate variables (Figure 3). The observed data set is assumed to be representative of a stationary climate. A validation of the results is provided by *Goderniaux* [2010] for rainfall and Blenkinsop et al. (manuscript in preparation, 2011) for the other climate variables. As presented in these papers, the resulting fit between the observed and simulated statistics (1960–1990), as well as between the target and simulated statistics (2010–2085) is very good and satisfactory for hydrological impact studies. In summary, Figure 6 shows the rainfall statistics for the control period 1961–1990, as observed, simulated by the RCM ensemble and simulated by RainSim. Figure 6 demonstrates three achievements. (1) For all statistics, RCMs' simulations contain significant biases compared to observations. This is particularly notable for the "probability of a dry day" and "skewness" which are significantly biased by RCMs. (2) It is more appropriate to calibrate the weather generator using change factors applied to observed statistics rather than directly to RCM output statistics. (3) The weather generator simulations match the target statistics well.

Table 2. Selected RCMs With Corresponding GCM and Meteorological Institute

| Institute	RCM	GCM	A2 Scenario	
			PRUDENCE Acronym	AQUATERRA Acronym
Danish Meteorological Institute	HIRHAM	HadAM3H A2	HS1	HIRHAM_H
Danish Meteorological Institute	HIRHAM	ECHAM4/OPYCA2	ecscA2	HIRHAM_E
Hadley Centre for Climate Prediction and Research	HadRM3P	HadAM3P A2	adhfa	HAD_P_H
Swedish Meteorological and Hydrological Institute	RCAO	HadAM3H A2	HCA2	RCAO_H
Swedish Meteorological and Hydrological Institute	RCAO	ECHAM4/OPYCA2	MPIA2	RCAO_E
Météo-France	Arpège	HadCM3 A2	DE6	ARPEGE_H
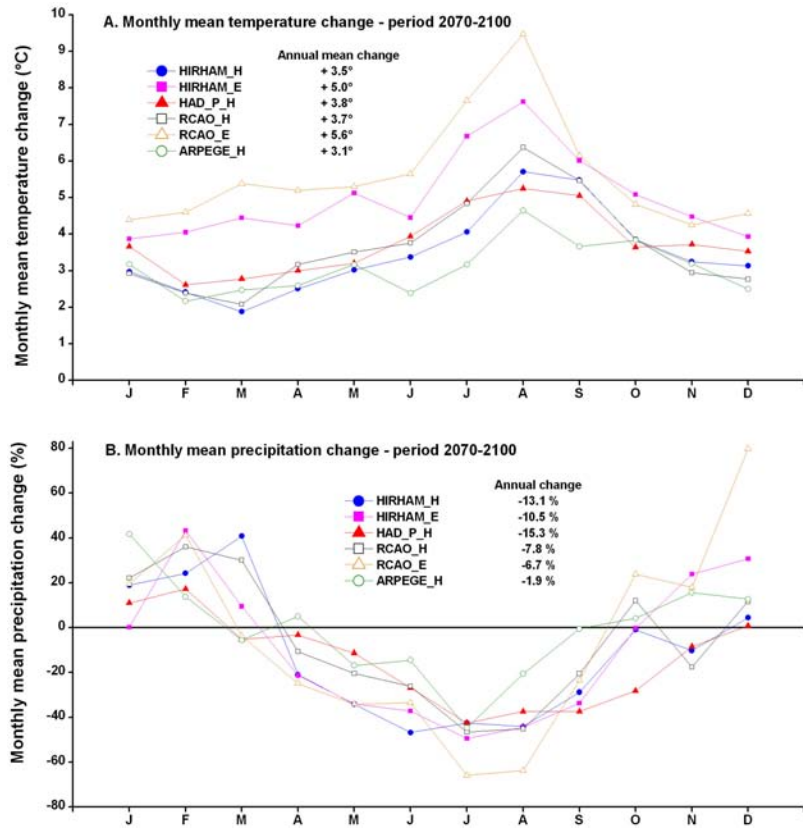
Figure 5. Monthly climatic changes in the Geer basin for each RCM for the 2071–2100 period relative to 1961–1990. (a) Temperature. (b) Precipitation [modified from *Goderniaux et al.*, 2009].
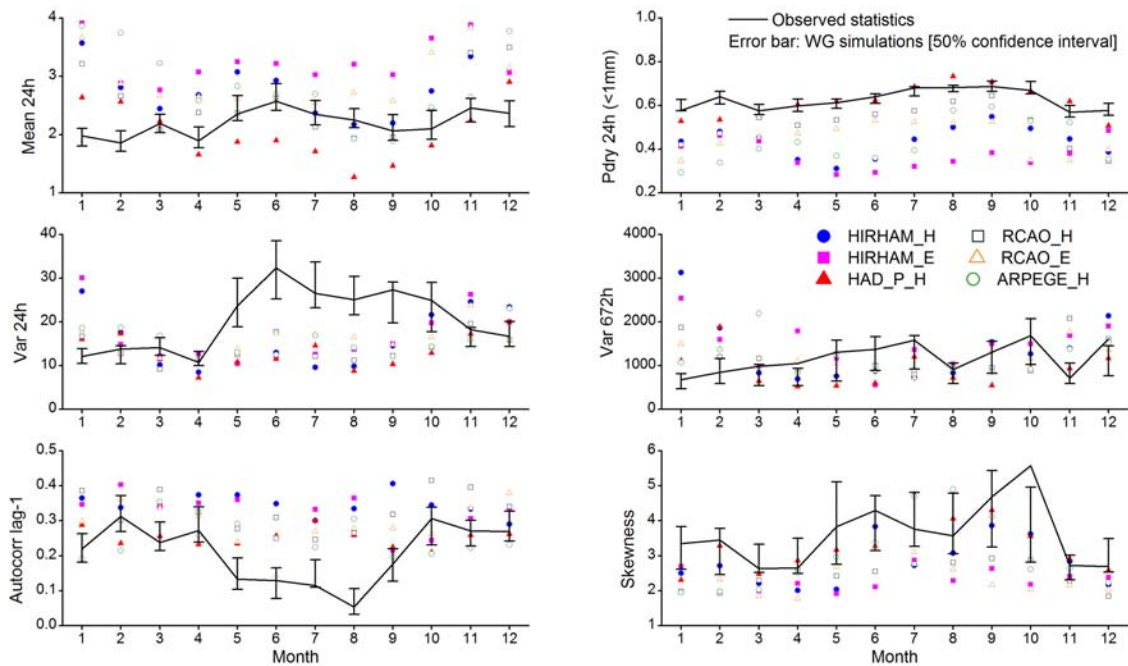

Figure 6. Rainfall statistics (control period 1961–1990) for the observed climate, RCM simulations, and RainSim simulations. The errors bars correspond to the intervals [mean ± one standard deviation] calculated across the 30 RainSim control simulations.

[29] As explained by *Burton et al.* [2010] and *Katz and Parlange* [1998], the stochastic structure of the NSRP model does not explicitly model low frequency variability, which could imply underestimation of the observed interannual variability. For the Geer basin, the standard deviation of the annual total rainfall amount (which is not used to calibrate the rainfall simulations) is 136 mm for the period 1961–1990. For the 30 control simulations from RainSim, the standard deviation of annual rainfall totals ranges from 101 to 169 mm with a mean of 120 mm and a 95% confidence interval between 90 and 151 mm. Although this may represent a slight undersimulation of the observed interannual variability, the interannual standard deviation of the observed data is within the 95% confidence interval calculated for the RainSim simulations. Similarly, the standard deviation for annual precipitation outputs directly from the RCM simulations range from 106 to 148 mm with a mean of 124 mm. This means that the interannual variability in precipitation amounts for the WG is comparable to that of the RCM outputs and only slightly lower than the observed value. Figure 7 shows the downscaled temperature and precipitation time series (2010–2085) for February and August for the RCM experiment RCAO_E which projects the largest climatic changes in the region. These downscaled scenarios preserve the projected changes in the RCM statistics, for example, temperature time series project larger increases for August (summer month) than for February (winter month) while precipitation time series indicate decreases for August and increases for February.

5. Groundwater Modeling

[30] The Geer basin model has been developed using the finite element modeling software HydroGeoSphere. It is one of the few models which fully integrate the surface flow, subsurface flow, and the calculation of the actual evapotranspiration and can perform partially saturated fully integrated flow and transport simulations [*Li et al.*, 2008; *Sudicky et al.*, 2008; *Therrien et al.*, 2005]. This integration allows for a better representation of the whole hydrologic system because the water exchanges and feedbacks between subdomains are calculated internally as functions of the hydraulic conditions in all subdomains simultaneously. From the perspective of the groundwater resources, the recharge is calculated internally by HydroGeoSphere as a function of the surface and subsurface conditions, and the actual evapotranspiration, all of them being interconnected. Its more realistic representation in fully integrated models constitutes an improvement compared to externally calculated recharge [*Goderniaux et al.*, 2009b].

[31] HydroGeoSphere simultaneously solves the Richard's equation and the diffusion wave approximation of the Saint Venant equations to simulate variably saturated subsurface flow and surface flow, respectively. Water exchanges between nodes of the subsurface and surface domains are calculated at each time step. Similarly, the actual evapotranspiration at each time step is calculated internally by HydroGeoSphere using the model of *Kristensen and Jensen* [1975], where actual evapotranspiration depends on potential evapotranspiration, water available in the surface domain, soil moisture at each node belonging to the specified evaporative and root zones, the leaf area index (LAI), and the canopy storage. More details about the numerical model can be found by *Therrien et al.* [2005].

[32] The Geer hydrographical basin has been meshed using six-node triangular prismatic elements in the subsurface domain and three-node triangular elements in the surface domain (Figure 8). The typical mean horizontal size of the elements is approximately 500 m. The vertical discretization of the subsurface domain is finer just below the ground surface (1 m thick elements) to more accurately
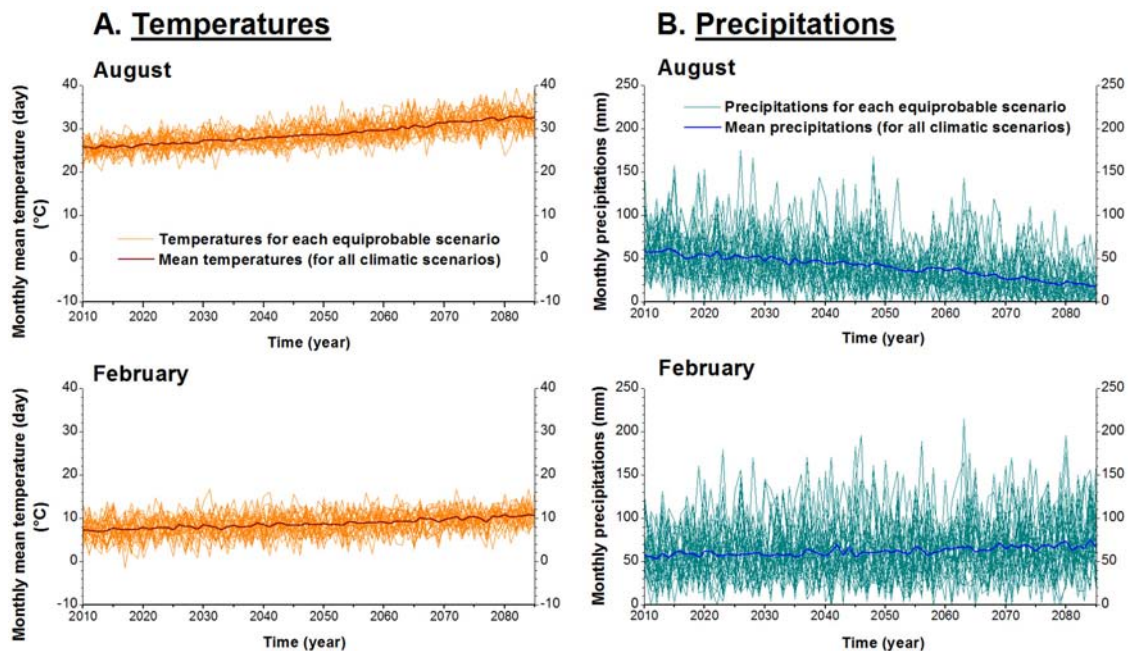

Figure 7. Downscaled stochastic climate change scenarios for the RCM RCAO_E. Thirty scenarios are shown in terms of monthly mean temperature and precipitation for February and August.
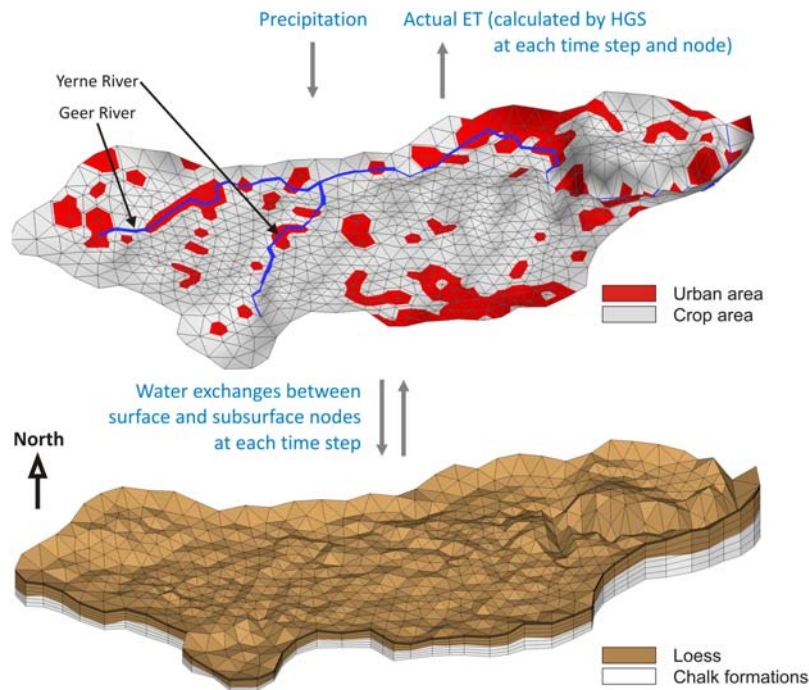
Figure 8. Spatial discretization of the surface and subsurface domains in the Geer basin.

represent the variation of the evaporative and root depths. In the subsurface domain, no flow boundary conditions are specified along the western, southern, eastern, and bottom boundaries. Along the northern boundary, a head-dependent flux condition is specified to take into account groundwater losses northward from the Geer basin. In the surface domain, a no-flow boundary condition is prescribed along the hydrographical limits of the catchment. A critical-depth boundary condition is prescribed at the outlet of the catchment, at the level of the Kanne gauging station. This kind of boundary condition forces the water elevation to be equal to the critical depth, which is the water elevation for which the energy of the flowing water relative to the stream bottom is at a minimum [*Therrien et al.*, 2005; *Hornberger et al.*, 1998].

[33] Surface parameters have been distributed based on land use [*EAA*, 2007] and soil maps [*DGA*, 2007]. Subsurface variably saturated parameters have been distributed using hydrogeological and geological maps [*DGARNE*, 2010b, 2010a], field tests, and laboratory tests [*Brouyère et al.*, 2004b; *Brouyère*, 2001; *Hallet*, 1998; *Dassargues and Monjoie*, 1993; *Dassargues et al.*, 1988]. The model is calibrated to observed hydraulic heads at eight observation wells and to surface flow rates at the catchment outlet (Kanne), for the period 1967–2003. The calibration was originally performed using mean monthly precipitation and potential evapotranspiration inputs [*Goderniaux et al.*, 2009b]. Simulations with daily inputs further enabled the improvement of the quality of the transient calibration [*Goderniaux*, 2010]. Such inputs enable to make a difference between a short intense rainfall and a prolonged period of light rainfall, and their different effect on groundwater recharge. Monthly inputs do not allow it because all precipitations are smoothed over each month. Generally, the model is able to satisfactorily reproduce the interannual variations of the groundwater levels. The water balance of the basin is well fitted, and the

model overestimates by only 1% (0.3% of the total precipitation amount) the water flow rates at the Kanne gauging station over the calibration period (1967–2003). Imperfections remain for seasonal variations which are too high compared to observed data. As explained by *Goderniaux et al.* [2009b], a calibration of a fully integrated hydrological model, using both observed hydraulic heads and surface water flow rates, is original and enables the parameters and water balance terms to be better constrained.

6. Results

6.1. Climate Change Impacts on the Geer Basin

[34] For each RCM, 30 equiprobable climate change scenarios (2010–2085) were applied as input to the Geer basin hydrological model. Thirty additional scenarios relative to a stationary "control scenario" (2010–2085) without any climate change were also used as a reference data set. For each RCM and at each observation well (Figure 3), mean groundwater levels and surface flow rates are calculated for each day between 2010 and 2085, using the 30 scenarios. These means express the average behavior given the 30 equiprobable outcomes. Figure 9 presents the evolution of groundwater levels between 2010 and 2085 for all 30 downscaled scenarios of the RCM RCAO_E. Figure 10 shows the mean groundwater levels between 2010 and 2085 for the 6 RCMs and the control scenario. Figure 11 presents a similar analysis for the mean annual surface water flow rates at the outlet of the catchment. The evolution of mean flow rates is also shown separately for February and August to more clearly examine the seasonality of changes in flow.

[35] For all RCMs and observation points, mean groundwater levels and flow rates present a decreasing trend between 2010 and 2085. By the year 2085, mean
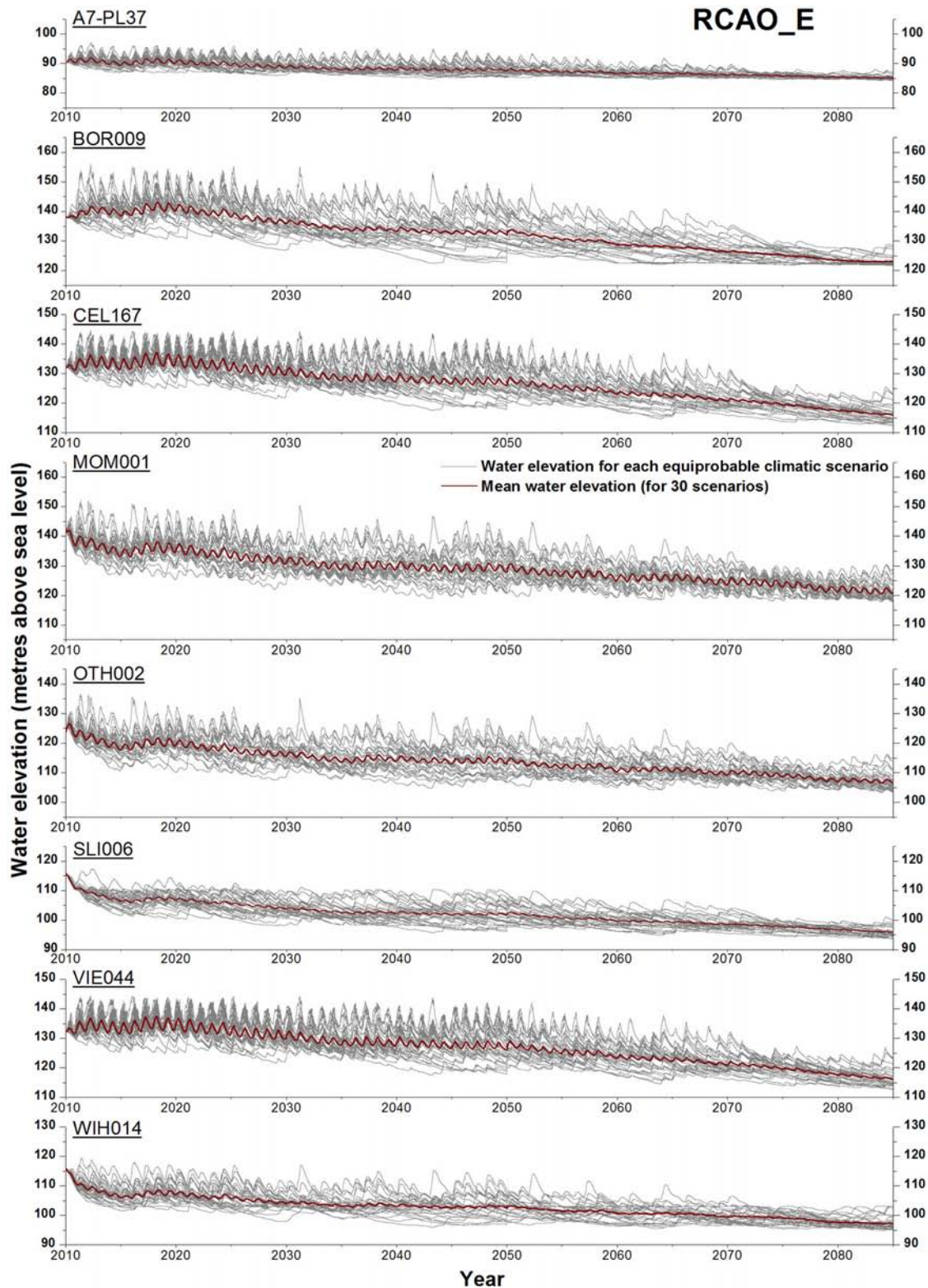
Figure 9. Evolution of daily hydraulic heads at the selected eight observation wells for 30 equiprobable climate scenarios of RCAO_E (2010–2085).

groundwater levels are projected to decrease by 4 to 7 m at A7-PL37′ and by 9 to 21 m at CEL167′, depending on the RCM, in comparison to the mean groundwater levels of the control scenario simulations. Results for the other observation points are between these two most extreme ranges (Figure 10). The different curves of mean groundwater levels show clear seasonal variations, which are a combination of higher or lower seasonal fluctuations visible for each individual scenario. Similarly, annual water flow rates at Kanne are expected to decrease between 44% and 70% by 2085,
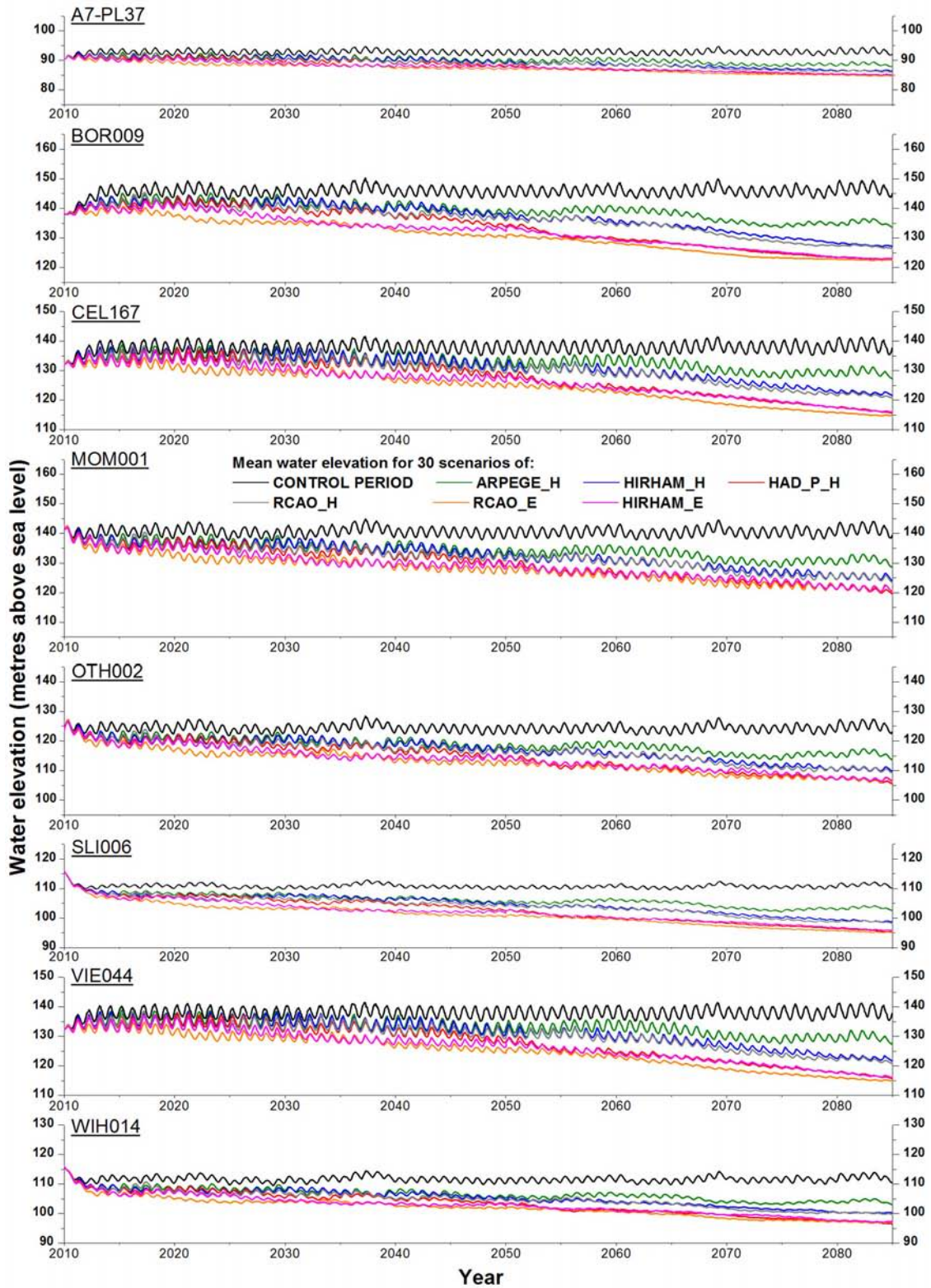
Figure 10. Mean daily hydraulic heads at the eight selected observation wells for each of the six downscaled RCM (30 scenarios).

depending on the RCM. Decreases are more significant during February than during August but occur throughout the year, despite climate models projecting a precipitation increase during winter months. Runoff is limited in the Geer

basin, due to flat topography and silty soils. The flow rate in rivers is therefore strongly dependent on the groundwater discharge and groundwater level, which are insensitive to seasonal fluctuations of the weather. Generally, scenarios
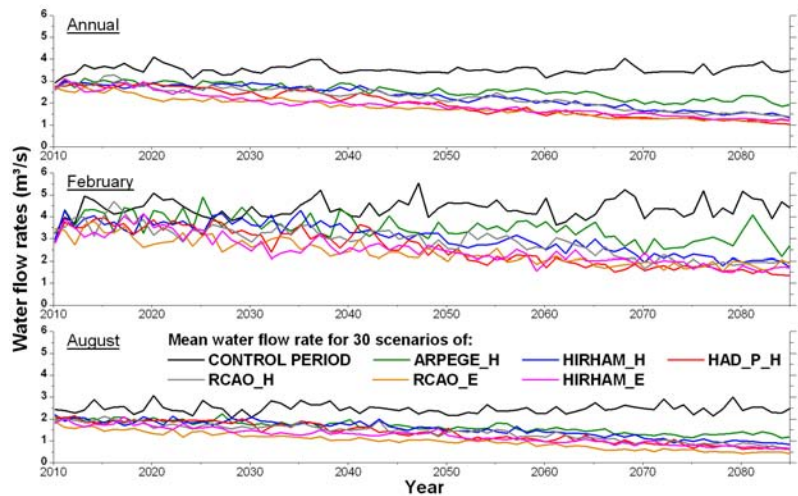
Figure 11. Mean water flow rate at the outlet of the basin for each of the six RCMs (30 scenarios).

corresponding to RCMs driven by ECHAM4/OPYCA2 (HIRHAM_E and RCAO_E) project the largest decreases. These RCMs are also those which project the greatest monthly climate changes but not necessarily the largest decreases in annual precipitation (see Figure 5). Conversely, ARPEGE_H projects the lowest decreases in groundwater levels and flow rate.

6.2. Uncertainty of Projected Impacts

[36] Using a large number of stochastic climate change scenarios enables the uncertainty linked to the natural variability of the weather to be evaluated. Figure 12 presents the intervals containing 95% of the climate change simulations for the control scenarios and the two RCMs showing the most contrasting projections—ARPEGE_H and RCAO_E. The mean and 95% intervals are calculated considering that the distributions of groundwater levels and surface flow rates at each specific time are normal and lognormal, respectively. Results for the other RCMs are intermediate between these two RCMs and are not presented in Figure 12 to avoid overloading of the graphs. The results presented in Figure 12 show that the intervals related to the different climate models and the control simulations overlap. This is observed not just from 2010, but also at the end of the century when climate changes are greater. The uncertainty associated with the natural variability of the weather on future groundwater levels and flow rates is thus high (around 10 m when translated to groundwater levels at OTH002′). Nevertheless, by year 2085, the 95% intervals of ARPEGE_H and RCAO_E, which are expected to give the lowest and highest decreases (Figure 10), are entirely located below the mean curve related to the 30 control simulations. This indicates that, even if the uncertainty of projections remains high when considering a specific time
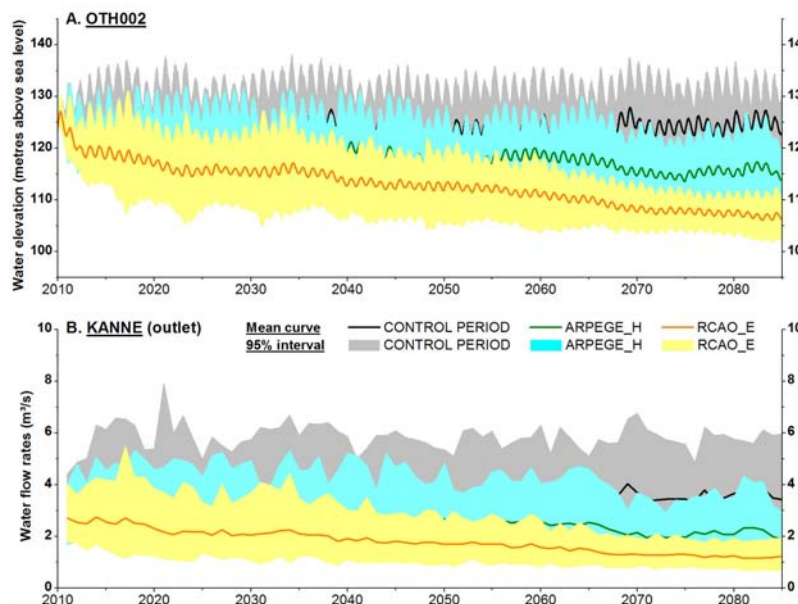

Figure 12. (a) Mean groundwater levels (30 scenarios) and 95% interval at observation point OTH002, (b) mean annual water flow rates (30 scenarios) and 95% interval at Kanne, for the control simulations and the climate models ARPEGE_H and RCAO_E.

scale, it is very likely that groundwater levels and annual surface water flow rates will decrease and the climate change signal becomes stronger than that of natural variability by 2085. Across the year, the 95% confidence intervals for flow rates are larger during winter months than summer months, due to higher runoff and variability (results not shown). The difference is less significant for groundwater levels which are more characterized by multiannual variations. Finally, it should also be mentioned that the width of the 95% intervals tends to decrease with groundwater levels. This is due to the increasing importance of the unsaturated zone which smoothes groundwater recharge fluxes and attenuates more of the climatic fluctuations.

6.3. Uncertainty in Transient Simulation

[37] With existing downscaling techniques it is possible to answer questions about the increase or decrease of groundwater levels for a stationary climate representative of a specific time slice, typically 2071–2100. Using the "transient weather generator" downscaling technique allows the simulation of the change of mean climate statistics in a fully transient way. It is then possible to evaluate the impact of climate change on groundwater as well as the uncertainty associated with the natural variability of the weather for time periods between 2010 and 2085. Additionally, it is also possible to make the inverse analysis and answer questions on a temporal axis, i.e., when the magnitude of change is expected to reach a specified decrease in groundwater levels, and to evaluate the associated uncertainty on the same temporal scale. This approach is demonstrated by Blenkinsop et al. (manuscript in preparation) for a simple temperature index, but here a more meaningful illustration is provided associated with a specific application.

[38] We pose the hypothetical question: "By when might we expect abnormally severe and prolonged periods of low groundwater levels to occur?" Such events are important for water management as smaller quantities of water are available for pumping during these periods. In this study we define such periods in terms of "periods of 10 consecutive years during which the mean annual groundwater level at OTH002 is 10 m lower than the mean groundwater level of the control simulations." In the Geer basin, where groundwater level variability is naturally high, such an event is considered highly unusual under current climatic conditions, and has not been observed during the last 60 years. For each of the 180 climate change scenarios tested in this study, the first occurrence of this specific event is identified. A total of eight decadal time intervals are defined between 2010 and 2085 and for each simulation the first year of occurrence of the first event is allocated to the relevant interval. Across the 30 simulations for each RCM, the total number of instances in which the first event is identified for each time interval is calculated and plotted in Figure 13a. The climate models RCAO_E and HIRHAM_E project the fastest decreases. Conversely, ARPEGE_H shows a wider distribution with the highest numbers of outcomes occurring later in the century. Using these distributions, it is then possible to evaluate the uncertainty in the time of occurrence and to calculate some confidence intervals. The mean and standard deviation of the distribution of all instances for all RCMs are equal to 2035 and 14 years, respectively. In Figure 13b the corresponding normal probability density function (pdf) has been plotted. According to this normal pdf, the 50% interval for the year of occurrence would be between 2025 and 2044. This interval is wide and is probably influenced by the behavior of
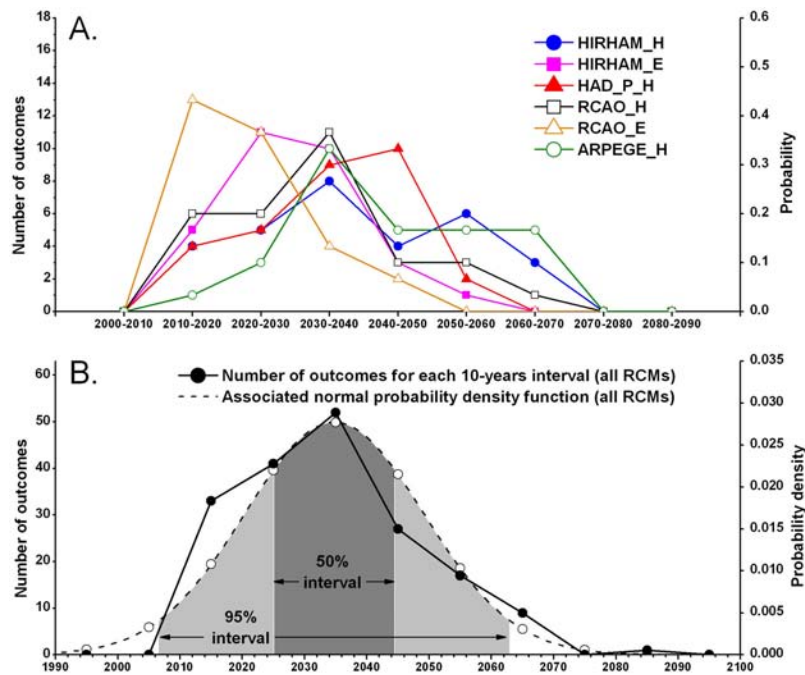

Figure 13. (a) Number of outcomes (10 m decrease in OTH002 groundwater level) for each time interval and each climate model of first instance of abnormally severe low groundwater levels. (b) Probability density function and 95% interval for all RCMs (OTH002).

groundwater levels in the Geer basin, which are prone to natural prolonged multiannual variations.

[39] This kind of analysis can be easily reproduced for each climate model, for each location in the basin and for any particular impact, given the identification of an adequate theoretical statistical distribution to associate with the experimental distribution. In Figure 13a all distributions can indeed not be associated with normal probability density functions, as illustrated by the RCM RCAO_E which rather presents a lognormal shape.

7. Discussion of the Results

7.1. Uncertainties

[40] The uncertainty linked to RCMs must be distinguished from that associated with natural climatic variability. Uncertainty linked to RCMs is related to climate modeling and to the fact that any given model is actually an imperfect simplification of reality. In this study, this kind of uncertainty has been evaluated by using a multimodel ensemble of RCMs. On the other hand, the uncertainty linked to natural climatic variability has been assessed by using 30 stochastic generations of climate time series for each RCM. If the interest is the impact of climate change on groundwater levels at a specific time only, the 95% confidence intervals calculated in Figure 12 express uncertainty and must be combined with other types of uncertainties. On the contrary, if the interest is the mean behavior over a period of several years, the 95% confidence intervals may be considered as an indicator of the range of variation of groundwater levels around the mean impact. In other words, the 95% confidence intervals express how groundwater levels will naturally vary around an average position and give information about groundwater level extremes. In this case, the calculated intervals can more difficulty be added to other types of uncertainties related to model errors that can be systematic across time.

[41] It is acknowledged that all aspects of uncertainty have not been considered in this study. Future projections have only considered the A2 emissions scenario. The PRUDENCE ensemble does not fully explore the GCM-RCM matrix and so the ensemble employed here may be termed an "ensemble of opportunity" [*Tebaldi and Knutti*, 2007]. However, the methodology described here may readily employ other RCM outputs, for example those subsequently made available by the ENSEMBLES project [*Hewitt and Griggs*, 2004]. Alternative statistical approaches to downscaling such as weather typing and multiple regression have been widely employed, and some of these can also account for changes in weather variability [see, for example, *Bardossy and Pegram*, 2011; *Johnson and Sharma*, 2011; *Fowler et al.*, 2007]. However, all methods have their own merits and disadvantages. The skill of different downscaling methods has thus been demonstrated to vary spatially, temporally, and with climatic variable [e.g., *Haylock et al.*, 2006] and ideally different types of downscaling models should be incorporated into local-scale climate change projections. In comparison with other advanced methods, the benefits of this weather generator approach lie in the capability to produce large number of equiprobable time series which are representative of transient climate change conditions. In addition to consideration of uncertainty related to climate projections, a complete treatment of uncertainty should also address that associated with the hydrological model. *Kay et al.* [2009] indicated that for flood frequency analysis associated with two catchments in the UK, uncertainty from this source is less than that associated with climate modeling. Further similar analyses of this nature for different hydrological systems for specific models and under different climates are required, with the difficulty that hydrological model uncertainty is very often underestimated [*Rojas et al.*, 2010].

7.2. Downscaling Method

[42] One of the main advantages of this downscaling methodology relates to the use of many equiprobable climate change scenarios representative of transient climate change. Nevertheless, the underlying drawback when using these scenarios with catchment-scale hydrological models is the very large computing time required to perform the climate change simulations. In this case, a unique simulation between 2010 and 2085 with daily input precipitation and potential evapotranspiration takes more than 20 days on a 3.0 GHz Pentium4 desktop machine equipped with 4 Gb RAM. Considering the number of scenarios (30 by RCM) and RCM experiments (six), it represents a huge volume of calculations to be performed. Given these considerations, the choice of the downscaling methodology in terms of climate change scenarios to be applied as inputs to hydrological models should be strongly dependent on the objectives of the study [*Fowler et al.*, 2007]. If the objective is, for example, to evaluate the mean groundwater level for the end of the century, using stochastic scenarios may not be appropriate and a more simple downscaling method should be selected [e.g., *Goderniaux et al.*, 2009b]. On the contrary, if the extremes are of interest, the uncertainty at a specific time, or the likelihood of a specific impact, using the weather generator and applying equiprobable scenarios as input to the hydrological model represents significant added value.

[43] In this last case, a question arises about the number of climatic scenarios that is adequate to represent the uncertainty in natural variability for each climate model. Here 30 equiprobable climate change scenarios for each climate model have been used, but the weather generator downscaling technique allows the generation of many scenarios in a short period of time. To answer this question, 100 scenarios of ARPEGE_H were generated and used as input to the hydrological model. The results (not shown here) have been compared with those achieved using 30 scenarios only. The difference was shown to be very small and mostly related to smoothing of the mean curves and confidence interval limits. Results and underlying interpretations remain however basically identical. Conclusions are also similar concerning the time period of occurrence of a specific impact.

8. Summary and Conclusions

[44] In this study, a physically based, surface-subsurface integrated model is combined with transient climate change scenarios generated with a stochastic weather generator and using change factors projected by an ensemble of six RCM experiments. The methodology enables (1) the simulation of flow conditions under the full transient climate

change between 2010 and 2085; and (2) an evaluation of the uncertainty in projected groundwater levels and surface flow rates, due to both natural climatic variability and climate model structures and parameterizations. For each of six different RCM experiments, 30 equiprobable climate change scenarios are generated and applied as input to the Geer basin hydrological model. Climate scenarios project a mean temperature increase for all calendar months, an increase of precipitation during winter, and a decrease of precipitation during summer. Mean groundwater levels and surface flow rates are projected to decrease. Confidence intervals remain large relative to the expected decrease but the climate change signal becomes stronger than the natural variability by the end of the century.

[45] The methodology presented in this paper combines the advantages of stochastic climate change scenarios with those of a fully integrated surface-subsurface hydrological model. The integration of surface and subsurface flow in the same model provides more realism in the simulation of water exchange terms between all subdomains and allows a better representation of groundwater recharge, which is highly important in the context of impacts on groundwater resources. However, nonlinear responses of the integrated hydrological model mean that daily, rather than monthly, climatic inputs are required. Change factors, which are used for generating local and regional climate change scenarios and have been widely applied in climate change impact studies, are here calculated for a wide range of weather statistics (including probability of a dry day, daily and monthly precipitation variance, precipitation autocorrelation, precipitation skewness, daily mean precipitation and temperature, and temperature standard deviation). The methodology is therefore able to reflect changes in the temporal sequencing and persistence of the projections provided by the RCMs but without the biases identified in the RCM control simulations and assumed to remain in future projections. The downscaled precipitation simulations have also been shown to better match observed statistics than those of the RCMs. Although there is a slight underestimation of interannual variability in the stochastic precipitation simulations this is comparable with that simulated by the RCM control experiments.

[46] In conclusion, the change factor approach has been combined with a stochastic model in a state-of-the-art statistical downscaling technique which allows analysis of transient climate change impacts in a probabilistic way. To our knowledge, this is the first time that such transient stochastic scenarios have been used in combination with an integrated surface-subsurface hydrological model, and this advanced methodology has provided an improvement in the reliability and robustness of groundwater projections. The results presented in this paper are interesting tools in the context of groundwater management. The fact that projections are calculated along with probabilities and uncertainty gives credibility to the results. For water managers, knowing the possible range of variation of groundwater levels is often more useful than the evaluation of the impact without additional information. Moreover, the ability to calculate confidence intervals around the time of occurrence of a specific impact provides managers with additional valuable information when planning further investment (e.g., new wells or galleries, alternative resources, etc.).

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S. Blenkinsop, A. Burton, and H. J. Fowler, Water Resource Systems Research Laboratory, School of Civil Engineering and Geosciences, Cassie Building, Newcastle University, Newcastle upon Tyne, NE1 7RU, UK.

S. Brouyère, A. Dassargues, and P. Orban, Group of Hydrogeology and Environmental Geology - Aquapôle, University of Liège, Chemin des Chevreuils, 1, Building B52/3, BE-4000 Liège, Belgium.

P. Goderniaux, Geosciences Rennes, UMR 6118 Université de Rennes 1 - CNRS, Rennes, France. (pascal.goderniaux@ulg.ac.be)