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Climate change impacts on groundwater hydrology – where are the main uncertainties and can they be reduced?

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Climate change impacts on groundwater hydrology – where are the main uncertainties and can they be reduced?

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Climate change impacts on groundwater hydrology – where are the main uncertainties and can they be reduced?

JC Refsgaard¹

TO Sonnenborg¹

MB Butts⁵

JH Christensen⁴

S Christensen³

M Drews^{4,7}

KH Jensen²

F Jørgensen¹

LF Jørgensen¹

MAD Larsen^{2,7}

SH Rasmussen^{4,8}

LP Seaby^{1,9}

D Seifert⁶

TN Vilhelmsen³

1 Geological Survey of Denmark and Greenland (GEUS), Denmark

2 Department of Geoscience and Natural Resources, University of Copenhagen, Denmark

3 Department of Geoscience, Aarhus University, Denmark

4 Danish Meteorological Institute, Copenhagen, Denmark

5 DHI, Hørsholm, Denmark

6 Alectia A/S, Virum, Denmark

7 Now at Technical University of Denmark (DTU), Denmark

8 Now at Envidan, Kastrup, Denmark

9 Now at Roskilde University (RUC), Denmark

Abstract

This paper assesses how various sources of uncertainty propagate through the uncertainty cascade from emission scenarios through climate models and hydrological models to impacts with particular focus on groundwater aspects for a number of coordinated studies in Denmark. We find results similar to surface water studies showing that climate model uncertainty dominates for projections of climate change impacts on streamflow and groundwater heads. However, we find uncertainties related to geological conceptualisation and hydrological model discretisation to be dominating for projections of well field capture zones, while the climate model uncertainty here is of minor importance. The perspectives of reducing the uncertainties on climate change impact projections related to groundwater are discussed with particular focus on the potentials for reducing climate model biases through use of fully coupled climate-hydrology models.

Key words: climate change, hydrological change, uncertainty cascade, groundwater, coupled climate-hydrology model

1. Introduction

Numerous studies of climate change impacts on hydrology have been presented during the past decade (Bates *et al.* 2008, Jiménez Cisneros *et al.* 2014). The present climate projections exhibit large uncertainties arising from assumptions on greenhouse gas emissions, incomplete climate models, and initial conditions (IPCC 2013, Hawkins and Sutton 2009, 2011). When assessing the climate change impacts on groundwater and surface water, uncertainties related to downscaling or bias correction of climate data and uncertainties in hydrological models must also be addressed. The key sources of uncertainty related to hydrological models originate from data, parameter values, and model structure (Refsgaard *et al.* 2007). The model structural uncertainty includes aspects related to process equations, conceptualisation of the local hydrological system being studied, spatial and temporal discretisation and numerical approximations. For groundwater models, conceptualisations of the geology often constitute a major source of the (model structural) uncertainty (Bredehoeft 2005, Refsgaard *et al.* 2012). As uncertainties from the ‘upstream’ sources propagate through the chain of calculations (greenhouse gas emission scenarios → general circulation models (GCMs) → regional climate models (RCMs) → downscaling/bias correction methods → hydrological models → hydrological impacts), the complete suite of uncertainties has been referred to as the uncertainty cascade (Foley 2010, Refsgaard *et al.* 2012).

Several studies have assessed the uncertainty propagation through parts of the cascade using Monte Carlo techniques (Bastola *et al.* 2011, Poulin *et al.* 2011, Dobler *et al.* 2012, Velazquez *et al.* 2013, Vansteenkiste *et al.* 2014). Complexities and computational aspects involved prevent inclusion of all sources of uncertainty in one study, and we are not aware of any study where uncertainties originating from all sources in the uncertainty cascade from emission scenarios to hydrological change have been quantified. Few studies have attempted to include more than a couple of uncertainty sources in one analysis. Wilby and Harris (2006) used information from two emission scenarios, two GCMs, two downscaling methods, two hydrological model structures and two sets of hydrological model parameters for assessing uncertainties in climate change impacts on low flows in the UK. Using a similar probabilistic approach, Chen *et al.* (2011) combined results from an ensemble of two emission scenarios, five GCMs, five GCM initial conditions, four downscaling methods, three hydrological model structures and 10 sets of hydrological model parameters for studying uncertainties in climate change impacts on streamflows in Canada.

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4 As uncertainties related to climate projections are often considerable (Jiménez Cisneros *et al.* 2014),
5 many stakeholders and policy makers may, at a first glance, get scared of the propagation and
6 addition of new uncertainties through the uncertainty cascade, where it may be perceived that
7 uncertainties will increase dramatically. The impacts of the different sources of uncertainties on the
8 resulting hydrological change uncertainty are, however, context specific (Refsgaard *et al.* 2013).
9 Most studies have found that uncertainty related to climate models were more important than
10 hydrological model structure uncertainty (Wilby and Harris, 2006, Chen *et al.* 2011, Dobler *et al.*
11 2012), while some studies found hydrological model structures to be equally important, in particular
12 for low flow simulations (Bastola *et al.* 2011, Velazquez *et al.* 2013). Similarly, in a study on
13 groundwater well field capture zones, Sonnenborg *et al.* (2015) found that the uncertainty at a
14 'downstream' point (geology) in the calculation chain dominated, making the effects of climate
15 model uncertainty negligible.
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24 Since it is not feasible to make calculations for the entire uncertainty cascade and since the
25 dominating sources of uncertainty are context specific, there is a need for guidance on which
26 sources of uncertainty to include in a specific hydrological impact uncertainty assessment. Useful
27 guidance related to river runoff can be found in e.g. Wilby and Harris (2006), Chen *et al.* (2011)
28 and Bastola *et al.* (2011). Much less studies have been performed for groundwater aspects, and to
29 our knowledge no guidance exist on the relative importance of the various sources of uncertainty
30 affecting climate change impacts on groundwater.
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36 The large uncertainties on the hydrological impacts render the results not easily applicable in
37 practical water management, where climate change adaptation decisions require more accuracy than
38 often possible with today's knowledge and modelling tools. Kundzewicz and Stakhiv (2010) argue
39 that climate models, because of their large inherent uncertainties, are not ready for water resources
40 management applications, while Wilby (2010) argues that relatively little is known about the
41 significance of climate model uncertainty. Depending on the nature of the uncertainty sources the
42 strategies to deal with uncertainty in climate change adaptation may vary from reducing the
43 uncertainty by gaining more knowledge (epistemic uncertainty) to living with the uncertainty that is
44 non-reducible (aleatory uncertainty) (Refsgaard *et al.* 2013). In this respect it is interesting to
45 evaluate which sources of uncertainty in the uncertainty cascade could potentially be reduced.
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53 As climate models are acknowledged to reproduce observed climate data with significant biases
54 (Anagnostopoulos *et al.* 2010, Huard, 2011, Koutsoyiannis *et al.* 2011, Boberg and Christensen,
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2012, Seaby *et al.* 2015), the perspectives for improving climate models are particularly relevant. The current climate models have several recognized weaknesses, e.g. related to descriptions of atmospheric processes and spatio-temporal resolutions (Stevens and Bony 2013, Kendon *et al.* 2014, Rummukainen *et al.* 2015). In the present paper we will, however, limit our analysis to the hydrologically relevant interaction between land surface and atmosphere. Climate models only include a simplistic description of land surface and subsurface processes, and similarly hydrological models generally only include atmospheric processes in a surface-near layer in the scale of meters. Proper representation of land surface conditions is recognised as being crucial for describing the energy balance of the land-atmosphere interaction (Sellers and Hall 1992). It can therefore be hypothesised that a fully coupled climate-hydrology model with more comprehensive and complete description of subsurface processes instead of simplified parameterizations or ignorance of processes (i.e. subsurface lateral flow of water and connection with deeper aquifers) could reduce the bias and hence the uncertainty of climate and hydrological change projections. Several research groups are therefore experimenting with various concepts of fully coupled models. Zabel and Mauser (2013) showed results from the 76,665 km² Upper Danube catchment in Central Europe using a coupling between the hydrological land surface model PROMET and the regional climate model MM5. Goodall *et al.* (2013) established a technically sophisticated coupling between the SWAT surface water hydrological model and the Earth System Modelling Framework. In order to include the feedback from groundwater systems as well, Maxwell *et al.* (2007), Kollet and Maxwell (2008), Rihani *et al.* (2010) and Maxwell *et al.* (2011) established a number of couplings between the ParFlow hydrological model, land surface models (CLM, Noah) and atmospheric models (ARPS, WRF), while Butts *et al.* (2014) established a coupling between the regional climate model HIRHAM and the MIKE SHE hydrological model code.

The objectives of the present paper are (i) to assess the relative importance of the different sources in the uncertainty cascade in climate change impact projections with focus on groundwater; and (ii) to evaluate the perspectives for reducing uncertainty in groundwater impact projections.

2. Methodology

The present paper analyses results from a large number of recently published studies on climate change impacts on groundwater in Denmark. These studies each focussed on individual aspects, while we here synthesise the findings into an uncertainty cascade framework discussing them in an

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4 international state-of-the-art context. In order to complete the analysis, we in addition present one
5 new analysis.
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8 Comparison of results from the different studies is facilitated by common approaches as explained
9 below.
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11 12 13 **2.1 Uncertainty cascade**

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15 The uncertainty cascade from emission scenarios to hydrological change projections is illustrated in
16 Figure 1, where the topics shown in boxes with thick/bold frames are illustrated by a synthesis of
17 results from the Danish studies, while the elements in boxes with thin frames are only discussed
18 based on international literature. Overall, the approach has been to address some key sources of
19 uncertainty both in the climate modelling and in the hydrological modelling, and quantify them in a
20 variety of cases with different contexts. The key reasons to give priority to many different test cases
21 rather than a more comprehensive uncertainty analysis for a single case like Wilby and Harris
22 (2006) and Chen *et al.* (2011) are: (i) we want to analyse how different sources of uncertainty
23 dominate for different model projection purposes and for different hydrological regimes; and (ii)
24 some of the elements that we do not address such as uncertainty of hydrological parameter values
25 have been extensively studied previously.
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35 **2.2 Study sites and site specific purposes**

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37 Table 1 provides an overview of the studies carried out highlighting the context, variables of
38 interest and uncertainty sources included. The location of the Danish study sites are shown in Figure
39 2. The international study site was the FIFE area in Kansas, USA.
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44 **2.3 Climate modelling**

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46 The analyses of climate modelling uncertainty were based on results from the ENSEMBLES project
47 (van der Linden and Mitchell 2009) that ran multiple pairings of GCMs and RCMs for climate
48 projections using the A1B emission scenario. For the present study a subset of 11 climate models
49 (GCM-RCM pairings) with 25 km resolutions and projections to the end of the 21st century were
50 selected from the ENSEMBLES matrix (Seaby *et al.* 2013).
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55 Climate systems show a strong element of natural variability. Therefore, different plausible initial
56 or boundary conditions for climate models may result in significantly different climate projection
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4 pathways (Hawkins and Sutton 2009). This inherent natural climate variability was analysed using
5 different configurations of RCMs in terms of domain sizes and spatial grid resolution for WRF over
6 USA (Rasmussen *et al.* 2012b) and for HIRHAM over Denmark (Larsen *et al.* 2013). In addition,
7 experiments were made with perturbations of initial conditions in a coupled HIRHAM-MIKE SHE
8 modelling covering part of Denmark (Larsen *et al.* 2014). Finally, extreme value analyses reflecting
9 natural climate variability were presented for a study of extreme groundwater levels in Silkeborg,
10 Denmark (Kidmose *et al.* 2013).
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18 **2.4 Statistical downscaling and bias correction of climate model output**

19 Daily data for the period 1951-2100 on precipitation, temperature and the other variables required
20 for performing Penman calculations of reference evapotranspiration (radiation, temperature, wind
21 speed and relative humidity) were downloaded from the ENSEMBLES data base and converted
22 from the 25 km RCM grids to the 10 km grid used by Danish Meteorological Institute in its gridded
23 product of observed precipitation (Seaby *et al.* 2013). The raw data from the RCMs were compared
24 with observed data for 1991-2010 (reference period) for precipitation, temperature and reference
25 evapotranspiration. To reduce substantial biases, two different correction methods were initially
26 applied: (i) the traditional delta change method (DC) with monthly change factors (Figure 3)
27 reflecting the differences in climate model projections between the reference period and the future
28 study period (Hay *et al.* 2000); and (ii) a distribution based scaling (DBS) for precipitation using
29 double Gamma distributions for the lower 95% and the upper 5% of the data (Piani *et al.* 2010)
30 supplemented with a simple bias removal for temperature and reference evapotranspiration applied
31 on a seasonal basis. These two methods were used on six different domains covering Denmark
32 (43,000 km²) resulting in a set of change and scaling factors each representing one of the six sub-
33 domains across Denmark (Seaby *et al.* 2013). While preserving a zero overall bias for each domain,
34 the DBS corrected precipitation data turned out to inherit a considerable spatial bias within each of
35 the six domains, and two additional DBS based methods were therefore introduced for precipitation
36 data: (iii) DBS with scaling in six domains across the country supplemented by a grid-by-grid
37 removal of the bias in average precipitation; and (iv) DBS scaling of precipitation on a 10 km grid
38 basis. Thus altogether four bias correction methods were tested for precipitation (Seaby *et al.* 2015).
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2.5 Hydrological impact modelling

The hydrological modelling was in most cases based on coupled groundwater-surface water modelling using the MIKE SHE code with 3D groundwater, 1D unsaturated zone including an evapotranspiration routine, 1D river routing and 2D overland flow modules enabling a direct use of the bias corrected climate model output as forcing data for the hydrological model. The models were in all cases auto-calibrated using PEST (Doherty 2010). In one case a pure MODFLOW based groundwater model was used (Vilhelmsen 2012), but here the groundwater recharge input was calculated with the Danish national water resources model (Henriksen *et al.* 2003) using MIKE SHE.

Two specific model structure related sources of uncertainty were examined in two different cases:

- The *geological conceptualisation* was studied by establishing six hydrological models that were based on six different geological conceptualisations but otherwise identical (Seifert *et al.* 2012).
- The influence of *numerical discretization and geological resolution* on simulations of groundwater flow was studied by using a regional model having a 500 m grid and two models with locally refined 100 m grids but different with respect to geological resolution (Vilhelmsen 2012).

2.6 Coupled HIRHAM – MIKE SHE model

The coupling concept is illustrated schematically in Figure 4. The two model codes can only be executed on two different software platforms, Linux and MS Windows, which technically is a substantial complication described in detail by Butts *et al.* (2014). The coupled model was tested on the 2,500 km² groundwater dominated Skjern River catchment (Larsen *et al.* 2014). The model domains for HIRHAM and MIKE SHE are shown in Figure 2. HIRHAM was run for a 2,800 km x 4,000 km domain, while MIKE SHE was confined to the 2,500 km² catchment. Outside the Skjern River catchment HIRHAM used its own land surface scheme, which then was replaced by the MIKE SHE coupling within the catchment. HIRHAM operated with a time step of two minutes, while the basic time step in MIKE SHE was one hour. Various coupling intervals for exchange of data between the two models were analysed concluding that a 30 minutes data exchange interval provides a good trade-off between accuracy and computational demand (Larsen *et al.* 2014). The coupled model was run for a one year period with additional spin-up periods of three months for HIRHAM and MIKE SHE's unsaturated zone and several years for the saturated zone.

3. Results and discussion

3.1 Emission scenarios

The studies listed in Table 1 do not include evaluations of alternative emission scenarios. Other studies have concluded that the uncertainty due to unknown future emissions can be considered small compared to climate model uncertainty and natural variability for the coming decades (Wilby and Harris 2006, Chen *et al.* 2011, Hawkins and Sutton 2011), while the importance at the end of the century (Hawkins and Sutton 2011) and for high-end CO₂ emissions (Karlsson *et al.* 2015) may be significant.

As the actual future emissions result from human decisions, reduction of uncertainties on emissions is beyond natural science analysis.

3.2 Climate modelling

GCMs and RCMs and coupled climate-hydrology models

Seaby *et al.* (2013, 2015) show that the climate model uncertainty is substantial, in particular for precipitation as illustrated in Figure 3. This finding is well in line with international literature (Wilby and Harris 2006, Chen *et al.* 2011), where uncertainties related to GCM/RCMs often constitute the dominating source compared to bias correction methods and hydrological impact models. The same conclusion has been reached for streamflow and groundwater heads in Denmark (Seaby *et al.* 2015, Karlsson *et al.* submitted).

Each climate model has its own set of biases (Seaby *et al.* 2015). Bias correction methods can remove the biases when calibrated against observations from the present climate. However, as the climate model biases in projected climates are expected to be different from the biases in the present climate, the bias correction methods will likely only be able to reduce, but not to fully remove, climate model biases for projected future climates (Teutschbein and Seibert 2013, Seaby *et al.* 2015). As these biases of projected future climates cannot be known, the bias correction methods contribute substantially to the impact uncertainty. Based on tests of four bias correction methods for 11 climate models Seaby *et al.* (2015) suggest that the bias corrections are more robust the smaller the biases are. So, altogether the climate model uncertainty will be reduced if the basic model biases are reduced.

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4 Significant improvements in modelling approaches and improved confidence in precipitation
5 projections have been seen recently, amongst others because of higher resolution in space and time
6 (Kendon *et al.* 2014). In addition, the potential of using coupled models to improve the land surface
7 atmosphere description of water and energy fluxes is obvious (Maxwell and Kollet 2008). The
8 establishment of a fully coupled, operational HIRHAM-MIKE SHE model (Figure 4) (Butts *et al.*
9 2014, Larsen *et al.* 2014, Larsen *et al.* 2016) opens the possibility to analyse whether a coupled
10 model is able to reduce the biases of a regional climate model.
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16 While Zabel and Mauser (2013) found that the biases were reduced when using a fully coupled
17 model, Larsen *et al.* (2014) found that results from the coupled HIRHAM-MIKE SHE for a one
18 year period have similar or slightly larger biases than results from HIRHAM stand-alone for many
19 of the standard meteorological variables, i.e. precipitation, air temperature, wind speed, relative
20 humidity, radiation and atmospheric pressure. This implies that substituting HIRHAM's land
21 surface scheme by MIKE SHE does not in itself reduce all biases, even if MIKE SHE has a
22 spatially and physically much more detailed process description of the land surface processes that
23 has been calibrated against field data (Larsen 2013). While this at a first glance may seem
24 discouraging, it is quite logical. HIRHAM has over the years been adjusted to perform better
25 against observational data, and the HIRHAM setup used in the present coupling was selected
26 among eight model setups with different domain coverage and spatial resolution as the one with the
27 smallest overall bias in precipitation (Larsen *et al.* 2013). Graham and Jacob (2000) report a similar
28 case, where replacing the land surface scheme in an RCM with a hydrological model resulted in
29 poorer performance of streamflow simulation due to compensational errors in the various
30 components of the RCM. A similar explanation may apply in our case, where the calibrated MIKE
31 SHE model inevitably calculates different energy and water fluxes compared to the HIRHAM land
32 surface scheme it is replacing. As this is the case, a recalibration of the coupled HIRHAM-MIKE
33 SHE model may be required in order to produce simulations with smaller biases. Such simulations
34 are quite similar to what was realised when the first major efforts toward fully coupled atmosphere-
35 ocean models were made. For many years, a flux correction technique had to be applied in order to
36 keep the coupled model system in balance avoiding it from drifting into a model state not looking
37 much like the real world, while each component alone would seem to perform reasonably
38 (Somerville *et al.* 2007).
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55 Previous coupling studies have either been confined to surface water hydrological models (Goodall
56 *et al.* 2013, Zabel and Mauser 2013) or, in case of inclusion of groundwater, been limited to
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4 relatively small domains (up to a few hundred km²) and short periods (a few days) both for the
5 climate and the hydrological models (Maxwell *et al.* 2007, Kollet and Maxwell 2008, Rihani *et al.*
6 2010, Maxwell *et al.* 2011). In this respect, the Danish results (Butts *et al.* 2014, Larsen *et al.* 2014)
7 are novel by including an integrated groundwater-surface water hydrological model in the coupled
8 climate-hydrology model simulation over a long period (more than a year) and a large area (2,800
9 km x 4,000 km for the RCM and 2,500 km² for the hydrological model). In a follow-up study
10 Larsen *et al.* (submitted) found on the basis of a seven years simulation that the coupled HIRHAM-
11 MIKE SHE model performed significantly better than HIRHAM model with respect to simulation
12 of precipitation.
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20 *Natural variability – inherent climate model uncertainty*

21 From analyses of multiple setups of HIRHAM and WRF over the USA, Rasmussen *et al.* (2012b)
22 found that the RCM predictions show a high degree of randomness in the precise location of
23 precipitation events at length scales below 130 km, while Larsen *et al.* (2013) found that HIRHAM
24 showed significantly reduced spatial precision for ranges less than 70 km for monthly precipitation
25 over Denmark. Finally, using the coupled HIRHAM-MIKE SHE model, Larsen *et al.* (2014)
26 showed that for a full year (1st July 2009 to 30th June 2010) up to 10% differences were found in
27 simulated catchment precipitation among eight model runs that were identical except for different
28 starting dates (between 1st and 8th of March 2009). These results clearly reflect the inherent
29 uncertainties in regional scale climate processes treated in climate models.
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37 Kidmose *et al.* (2013) performed extreme value analyses to infer maximum groundwater levels with
38 50 and 100 years recurrence intervals (T_{50} , T_{100} events) for climate conditions 2081-2100, using
39 nine climate models, two bias correction methods and a hydrological model. Furthermore, they
40 assessed the uncertainties on the extreme events originating from climate models, bias correction
41 and natural variability (confidence intervals in statistical predictions of extreme events using the
42 Gumbel distribution to extrapolate from the 20 year data series to T_{50} and T_{100} events). They found
43 that the natural climate variability constitutes between 60% and 75 % of the total prediction
44 uncertainties, while the climate model uncertainty contribute between 20% and 35%, and the bias
45 correction methods around 5% (Figure 5).
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53 In an analysis of uncertainties in projected decadal mean precipitation over Europe, Hawkins and
54 Sutton (2011) conclude that uncertainty originating from inherent climate variability is of the same
55 order of magnitude as climate model uncertainty, while the effect of using different greenhouse gas
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(GHG) emission scenarios is negligible. Natural climate variability is known to decrease with increasing spatial and temporal scales of aggregation (Hawkins and Sutton, 2011; Rasmussen *et al.* 2012b, Larsen *et al.* 2013). Hence, the findings of Kidmose *et al.* (2013) showing that natural climate variability is twice as large as climate model uncertainty for very small temporal (extreme events) and spatial scales are well in line with previous findings in literature on this matter.

As the natural variability often dominates over other sources of uncertainty for climate change impact projections in the next few decades, it is interesting to evaluate the potential for reducing it. The inherent climate model uncertainty that is often assumed equivalent to the natural climate variability originates from uncertainty on climate model initialization. In this respect, Hawkins and Sutton (2009) note that while the contribution from internal variability is not reducible far ahead, proper initialization of climate models with observational data should enable some reduction of this uncertainty of the next decade or so. Along the same line Olsson *et al.* (2011) discusses the possibility of reducing this uncertainty by initializing a GCM so that it generates interannual variability in phase with historical periods.

3.3 Statistical downscaling and bias correction

Seaby *et al.* (2015) applied several bias correction methods and propagated the uncertainty from both climate models and bias correction methods through the Danish national water resources model and inferred the contributions from these two sources of uncertainty on projected groundwater heads and streamflows for Sjælland (Figure 2). They found that the climate model uncertainty is by far the more important, and that the bias correction methods only explain around 10% of the total uncertainty. They concluded that bias correction contributes relatively more to uncertainty on precipitation than to hydrological uncertainties, and relatively more to uncertainty on extreme events than to values that are averaged over time and space. This finding is well in line with Kidmose *et al.* (2013) who found climate model uncertainty to be about five times larger than bias correction uncertainty for extreme groundwater events at local scale, as well as with van Roosmalen *et al.* (2011) who found that two different bias correction methods, DC and DBS, showed only marginal differences for projections of average groundwater levels. Our findings are also supporting Dobler *et al.* (2012) who concluded that bias correction has the largest influence on projections of extreme events.

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4 A fundamental difference between the DC and the DBS bias correction methods is that DC operates
5 with change factors on the observed climate data, while DBS scales the output from climate models
6 implying that projected changes in the structure of e.g. precipitation regime in terms of changes in
7 length of dry periods and variations between years is only reflected in the second method. This
8 difference turned out to have significant importance in a study by Rasmussen *et al.* (2012a) who
9 used one climate model and the two bias correction methods to assess the changes in irrigation
10 requirements for 2071-2100. They found that irrigation will be significantly underestimated when
11 using the DC method due to its inability to account for changes in inter-annual variability in
12 precipitation and reference evapotranspiration.
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20 Uncertainty reduction in bias correction and statistical downscaling deals with developing and
21 selecting accurate and robust methods. A fundamental assumption in statistical downscaling of
22 climate model projections is that the climate model biases are stationary (Refsgaard *et al.* 2014).
23 Teutschbein and Seibert (2013) applied a differential split-sample test (Klemes 1986) to evaluate
24 different bias correction methods. They found that the simpler correction methods, such as the DC,
25 are less robust to a non-stationary bias compared to more advanced correction methods. On the
26 other hand, Seaby *et al.* (2015) found that if bias correction methods are overparameterised, they
27 may be less robust in climate conditions different from the reference period for which they were
28 fitted, and that this problem increases the larger the initial bias in the climate models are.
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36 37 **3.4 Hydrological impact modelling**

38 Refsgaard *et al.* (2012) provide a review of strategies to deal with geologically related uncertainties
39 in hydrological modelling. One of the strategies, to use multiple geological interpretations, was
40 pursued by Seifert *et al.* (2012) who established six alternative geological conceptualisations for a
41 465 km² well field area around Lejre (Figure 2) and calibrated six hydrological models against the
42 same groundwater head and streamflow data series using PEST. The calibration results showed
43 similar overall performance for the six models, where some models were better than others for
44 streamflow but worse for groundwater head simulations and vice versa, while none of the models
45 were superior to the others in all aspects. The six models were then used for projections of
46 hydrological change due to climate change for the period 2071-2100 (Sonnenborg *et al.* 2015).
47 Figure 6 shows the climate change impacts on groundwater heads averaged over the period and
48 over the well field area. From this figure it is evident that the spread between climate models are
49 larger than the spread between geological models, and that the differences between geological
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4 models become more important the larger the climate change. Analyses of streamflow (not shown
5 here) reveal similar results, namely that the climate model uncertainty dominates geological
6 uncertainty. Figure 7 shows projections of well field capture zones when using six geological
7 models and one climate model (left) and one geology and 11 climate models (right). This shows
8 that the climate model uncertainty has negligible impacts on the capture zone location, while the
9 geological uncertainty clearly dominates, i.e. the opposite conclusion as for groundwater heads and
10 streamflow.

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12 For the present paper we made a similar analysis for the Ristrup well field (Figure 2) which pumps
13 from a complex network of buried valleys eroded into low-permeable sediments. Deep aquifers fill
14 the buried valleys, while shallow aquifers are found on the plateaus. The analysis was made using
15 three model setups: a regional scale groundwater model with a 500 m x 500 m grid (Coarse grid –
16 coarse geology), and two locally refined groundwater models having 100 m x 100 m grids
17 embedded into the regional model. One of the locally refined models also has a refined geological
18 resolution in the vicinity of the well field (Fine grid - fine geology), while the other (Fine grid -
19 coarse geology) has the same geological resolution as the regional model (Vilhelmsen 2012). The
20 three models were calibrated against groundwater head time series data covering a six year period
21 (1996-2001) and subsequently used to project changes in groundwater heads due to climate change
22 by using recharge series estimated from the same 11 climate models applied by Sonnenborg *et al.*
23 (2015). Figure 8 shows the relative change in head elevations caused by the different climate
24 models for each of the three groundwater models. Similar to Sonnenborg *et al.* (2015), we find that
25 the uncertainty in projected heads explained by the climate model exceeds the uncertainties
26 explained by the choice of discretization in groundwater models. However, when projecting the
27 capture zones from a well field located in one of the buried valleys (Figure 9), we find that the
28 difference between capture zones caused by difference in numerical grid resolution dominates over
29 the difference in capture zones caused by geological resolution, while the smallest difference in
30 capture zones is caused by the choice of climate model input.

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32 The importance of site specific conditions on the uncertainty propagation was evident in a national
33 study of climate change impacts on groundwater levels and extreme river discharge (T_{100}), where
34 Henriksen *et al.* (2012) found significant regional patterns. For example, some regions show small
35 climate change impacts, including small uncertainties, on groundwater heads but large impacts and
36 uncertainties on river discharge, while other regions show the opposite. These differences may be
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4 explained by differences in hydrogeological regimes such as confined/unconfined aquifers and
5 degree of tile drainage (Henriksen *et al.* 2012).
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8 The above findings nicely supplement the international literature confirming that uncertainties in
9 climate change impacts on streamflow are dominated by climate modelling uncertainty. The above
10 Danish studies did not assess the uncertainty due to model structures (process equations) and
11 parameter values of the hydrological models. The impacts of these sources of uncertainty on
12 streamflow projections have, in international studies, been evaluated in general to also be smaller
13 than climate model uncertainty (Wilby and Harris 2006, Chen *et al.* 2011, Dobler *et al.* 2012,
14 Bastola *et al.* 2011). Furthermore, Bastola *et al.* (2011) and Velazquez *et al.* (2013) found that
15 hydrological model structure uncertainty in some cases are substantial, while Wilby and Harris
16 (2006) and Poulin *et al.* (2011) found that model structure uncertainty is more important than
17 parameter uncertainty. The novelty of the Danish studies lies in their focus on geological
18 uncertainty and groundwater, illustrating that the dominating sources of uncertainties are context
19 specific.
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28 Reduction of uncertainties related to hydrological impact modelling is, in general, possible by
29 collecting additional high-quality data and, in some cases, also by enhancing the used modelling
30 techniques (Refsgaard *et al.* 2007).
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36 **4. Conclusion**

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38 Through a number of coordinated studies with climate projections towards the end of the present
39 century, we have assessed the uncertainties originating at different locations in the chain of
40 calculations (the uncertainty cascade) between greenhouse gas (GHG) emissions and hydrological
41 change, and analysed how various uncertainties are amplified or reduced in their downstream
42 propagation towards hydrological change. For the variable of principle interest in hydrological
43 studies, precipitation, we find that the two dominating climate related sources of uncertainty are the
44 natural climate variability and the climate models. Both of these sources are much larger than the
45 uncertainties related to GHG emissions found in other studies (van Roosmalen *et al.* 2007, Hawkins
46 and Sutton 2011) and much larger than the uncertainties related to bias correction methods (Dobler
47 *et al.* 2012, Kidmose *et al.* 2013, Seaby 2013). In addition, uncertainties related to the hydrological
48 model are important.. Complementary to other studies focussing on model structure (process
49 equations) uncertainty and parameter uncertainty (Wilby and Harris 2006, Bastola *et al.* 2011,
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4 Poulin *et al.* 2012, Velazquez *et al.* 2013) we have analysed the impacts of geological uncertainty
5 and alternative model discretisation. In one case study (Sonnenborg *et al.* 2015) we showed that
6 climate model uncertainty dominates over geological uncertainty for projections of streamflow and
7 groundwater heads, while the impacts of geological uncertainty increase with increasing climate
8 change. The same case study showed, however, that the geological uncertainty dominates over
9 climate model uncertainty for projections of well field capture zone. This illustrates that the various
10 uncertainties will propagate differently for different projection variables, and in some cases a large
11 climate uncertainty will have negligible impacts. We found similar results for another case
12 (Vilhelmsen 2012) where different numerical and geological models were used. Again, climate
13 model uncertainty dominated over groundwater model uncertainty when projecting the mean
14 change in head, whereas the numerical resolution of the groundwater model, and to a lesser degree
15 its geological resolution, were the dominant contributors to the uncertainty when projecting well
16 field capture zones.

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26 Altogether, we can conclude that no generic ranking of the relative importance of the sources of
27 uncertainty can be found. The ranking will be context specific depending on the projection variable
28 and the hydrogeological regime. Having said that we also need to emphasise that there is robust
29 evidence that natural climate variability and climate model uncertainty often dominate, also for
30 groundwater variables. The exemption we found that uncertainties on geological conceptualisation
31 and numerical discretisation overrule climate model uncertainty for projections of groundwater flow
32 paths and well field capture zones may have some generic validity, but as no other studies reported
33 in literature have dealt with this issue have dealt with this issue, we only have evidence from our
34 own two case studies in Denmark to support such suggestion.

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42 The uncertainties on impact projections are so large that they, in practice, constrain climate change
43 adaptation (Kundzewicz and Stakhiv 2010). Hence, there is an urgent need for reducing
44 uncertainties. This can be done in the traditional way of collecting more high-quality data and using
45 better techniques for bias correction and impact modelling. However, as the largest uncertainty in
46 most cases relate to climate modelling, emphasis should be given to reducing biases in climate
47 models. In addition to the improvement of the climate models themselves (Stevens and Bony 2013,
48 Kendon *et al.* 2014, Rummukainen *et al.* 2015), there is a considerable potential for reducing
49 uncertainties by applying fully coupled climate-hydrology models like HIRHAM- MIKE SHE
50 (Butts *et al.* 2014). Fully coupled models have now proven their capability to be able to carry out
51 comprehensive experiments, which are needed to fully evaluate to which extent the potentials will
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materialise. The recent follow-up study by Larsen *et al.* (submitted) showing significantly more accurate precipitation simulations with the coupled model is very encouraging in this respect.

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Tables

Table 1. Overview of studies addressing uncertainties at different steps in the uncertainty cascade

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Figure captions

Figure 1. The uncertainty cascade from emission scenarios to hydrological change projections. The elements for which results from the Danish studies are shown in the paper are marked with grey.

Figure 2. Location of study sites in Denmark and the extent of the HIRHAM domain covering northern Europe

Figure 3. Monthly delta change factors for precipitation projections for Denmark for 2071-2100 compared to the 1991-2010 reference period for 11 climate models. Figure from Seaby et al. (2013).

Figure 4. Schematic of the HIRHAM-MIKE SHE coupling. Both model codes have been extended with OpenMI Linkable Components, exposing selected variables to each other within the OpenMI platform. The MIKE SHE code runs on the same PC (MS Windows) as the OpenMI software, whereas the HIRHAM code runs on a massively parallelized Cray XT5 high performance computer system (HPC). Linking directly to the HPC is not possible, necessitating data exchange by files and introducing a considerable overhead in simulations. Figure from Butts et al. (2014).

Figure 5. Uncertainty on estimation of future extreme groundwater levels originating from climate models, bias correction methods and natural climate variability (extreme value analysis). The curves relate to the absolute values in m (left axis) while the background colouring refer to the relative contribution (right axis). Figure modified from Kidmose et al. (2013).

Figure 6. Projected change in mean groundwater level in well field area for 11 climate model projections for 2071-2100. The six lines correspond to the six hydrological models with the corresponding six geological models. Figure based on results from Sonnenborg et al. (2015).

Figure 7. Impacts of geological uncertainty and climate model uncertainty on the location of well field capture zones. The colour indicates percentage of shared capture zones. The figure to the left

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12 Figure 8. Mean relative change in head using recharge data from 11 climate models. The lines
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14 resolution.
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22 refined numerical grid but coarse geological resolution, and c. the locally refined model also
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Case/purpose	Catchment Area	Variables of interest	Uncertainty sources	Reference
Inherent variability in climate model	Denmark (43,000 km ²)	Seasonal precipitation	Climate variability	Larsen et al. (2013)
Inherent variability in climate model	FIFE, Kansas, USA (15 km x 15 km)	Daily precipitation	Climate variability	Rasmussen et al. (2012b)
Land surface - atmosphere fluxes	FIFE, Kansas, USA (15 km x 15 km)	Precipitation, temperature, humidity, wind speed, radiation	Feedbacks between climate models and hydrological models	Larsen et al. (2015)
Land surface - atmosphere fluxes	Skjern Å catchment (2,500 km ²)	Precipitation, temperature, humidity, wind speed, radiation	Feedbacks between climate models and hydrological models	Butts et al. (2014) Larsen et al. (2014)
Future precipitation 2011-2100	Denmark (43,000 km ²)	Annual precipitation Extreme precipitation	Climate models Bias correction	Seaby et al. (2013)
National climate adaptation planning 2021-2050	Denmark (43,000 km ²)	Groundwater level (average, min, max) Discharge (average, min, max)	Climate models Parameter uncertainty	Henriksen et al. (2012)
Future hydrology 2071-2100	Sjælland (7,200 km ²)	Groundwater level (average, min, max) Discharge (average, min, max)	Climate models Bias correction	Seaby et al. (2015)
Water resources impact 2071-2100	Vidaa catchment (850 km ²)	Irrigation requirements Low flow	Bias correction	Rasmussen et al. (2012a)
Motorway, design and construction 2081-2100	Silkeborg (103 km ² - nested into larger model)	Extreme groundwater levels	Climate variability Climate models Bias correction	Kidmose et al. (2013)
Water works, water supply 2071-2100	Lejre (465 km ²)	Discharge Groundwater levels Well field capture zone	Climate models Hydrological model structure (geology)	Seifert et al. (2012) Sonnenborg et al. (2015)

1 2 3 4 5 6 7 8	Well field, water supply 2081-2100	Ristrup (18.4 km ² - nested into larger model)	Groundwater level drawdown when abstracting groundwater	Climate models Hydrological model structure (discretization, resolution)	Vilhelmsen (2012)
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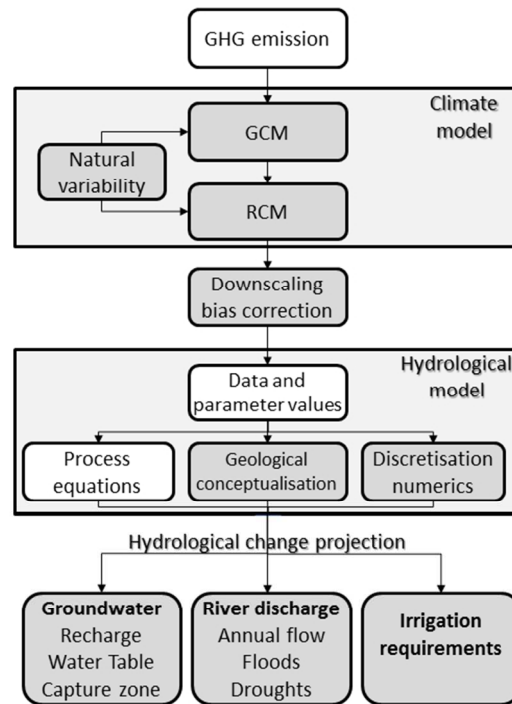


Figure 1. The uncertainty cascade from emission scenarios to hydrological change projections. The elements for which results from the Danish studies are shown in the paper are marked with grey.
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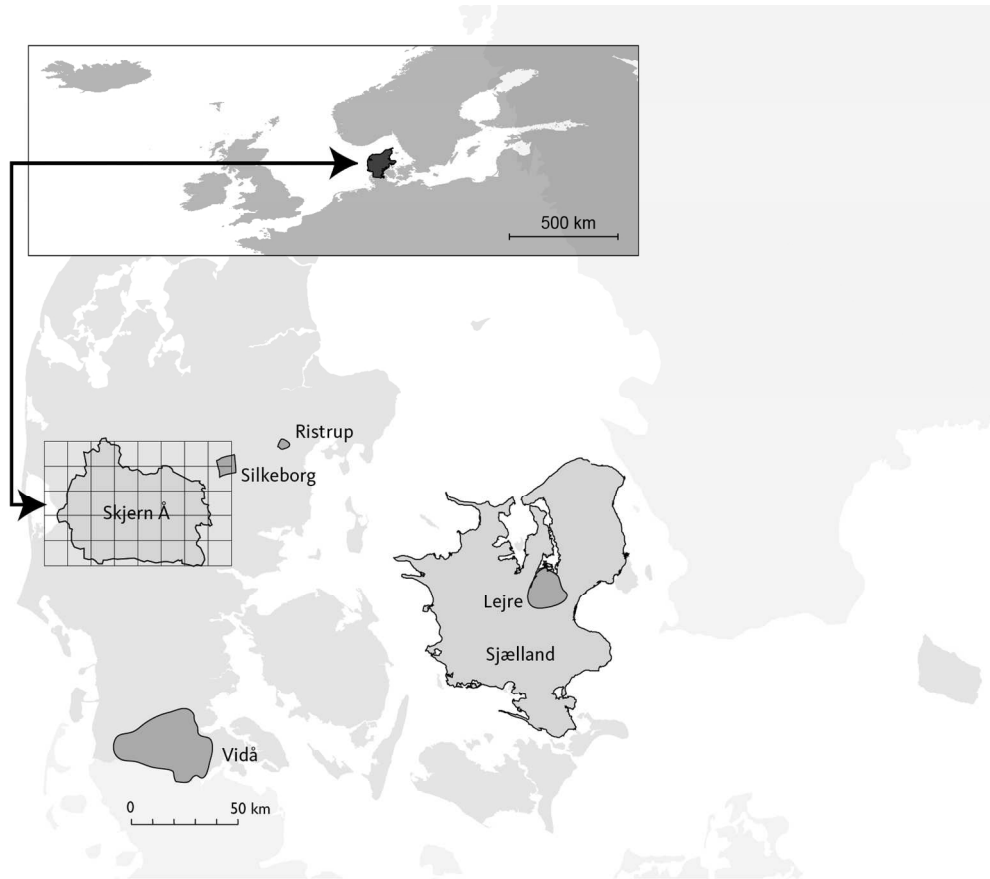


Figure 2. Location of study sites in Denmark and the extent of the HIRHAM domain covering northern Europe

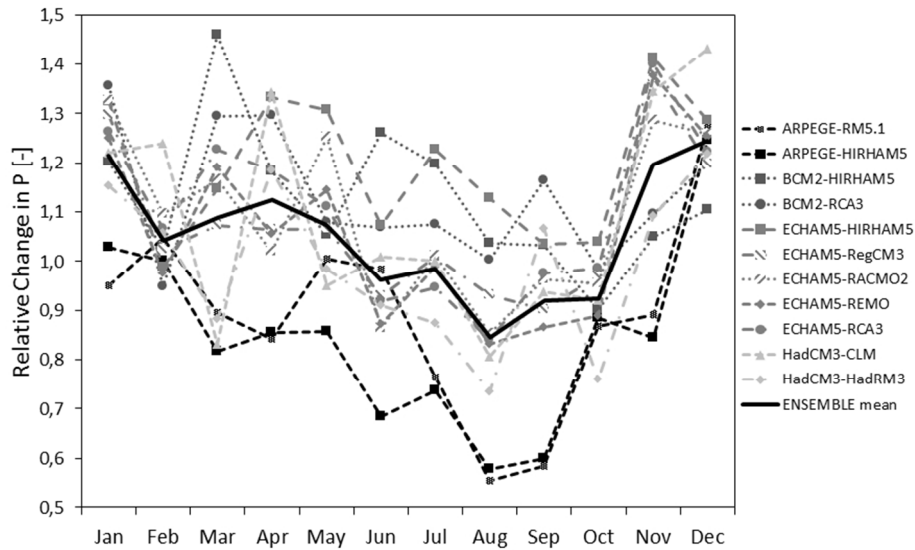


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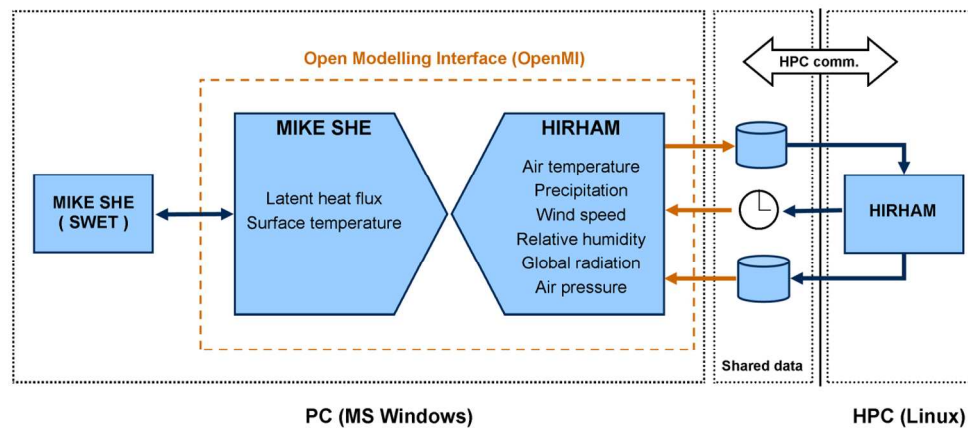


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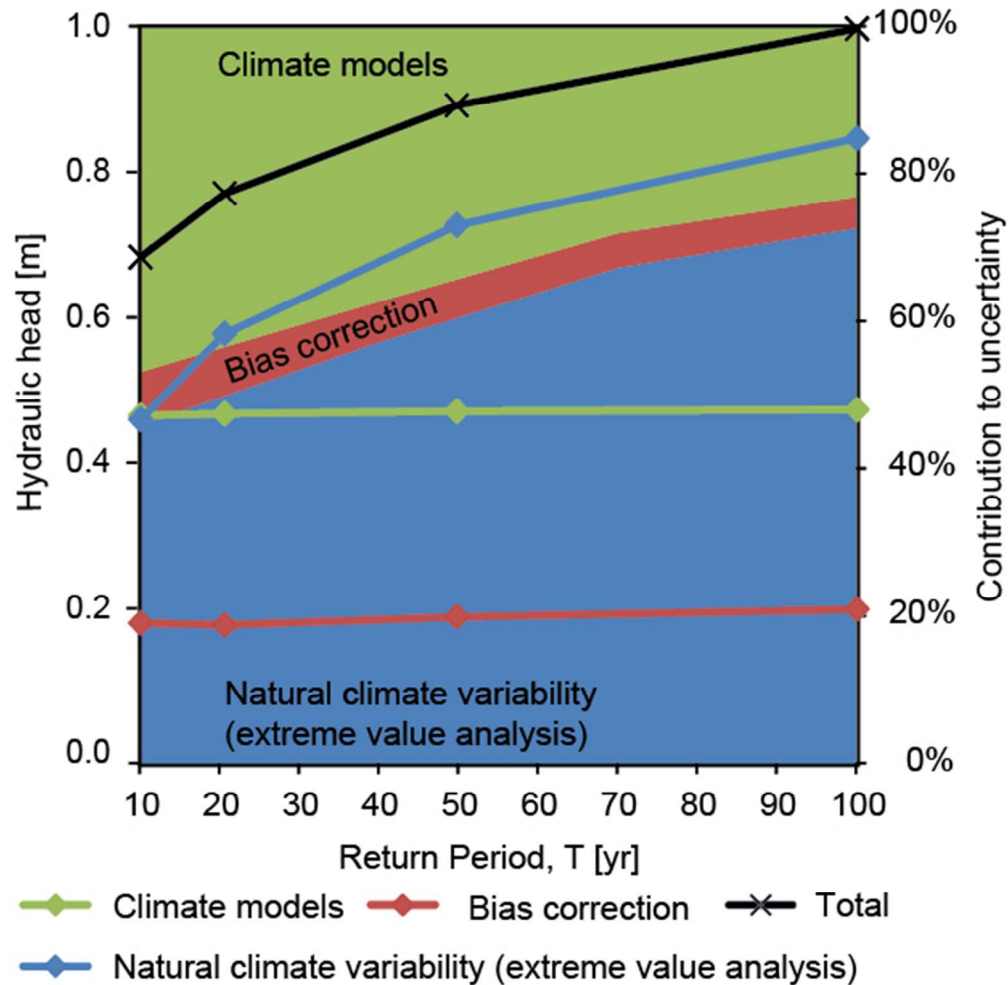


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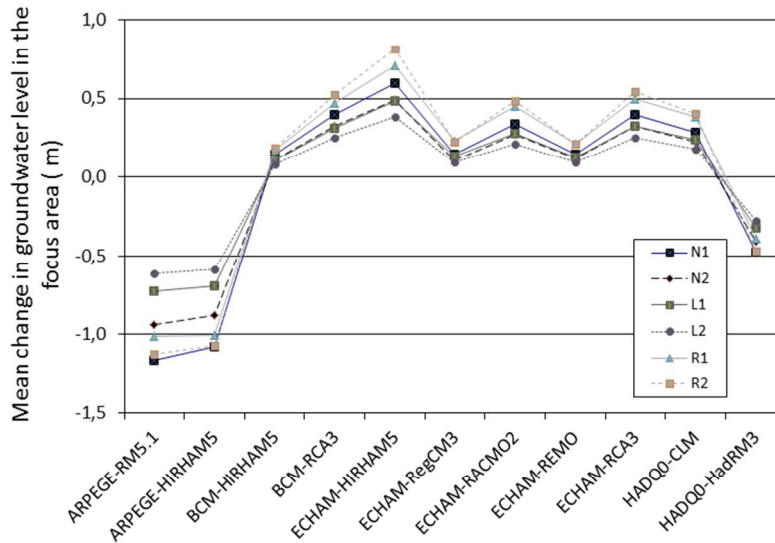


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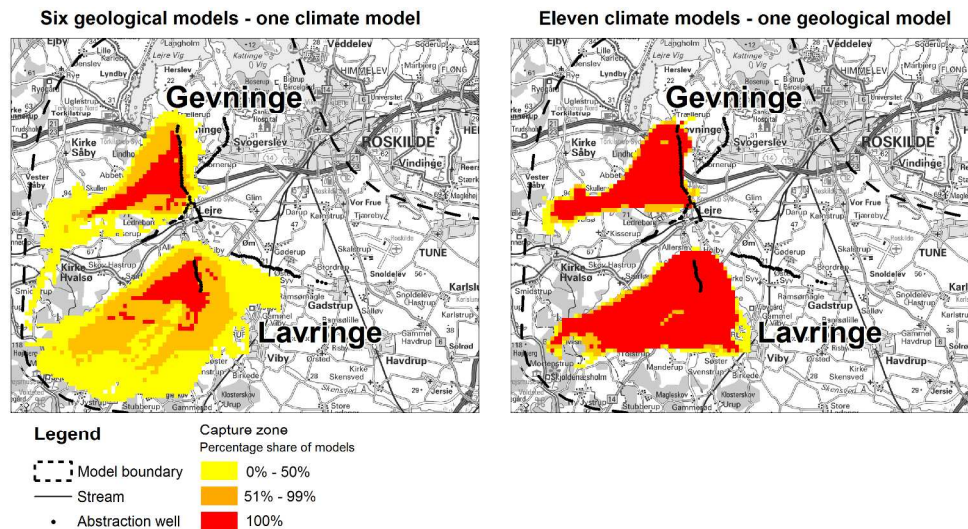


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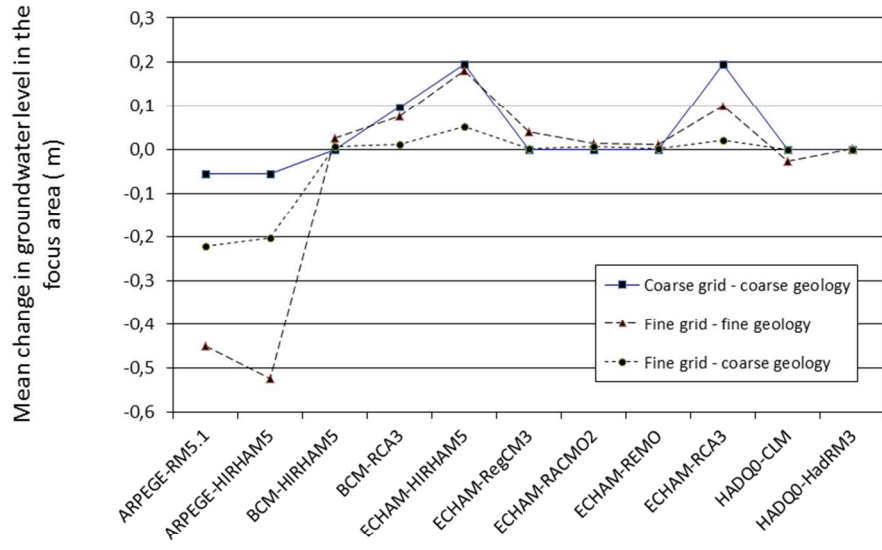


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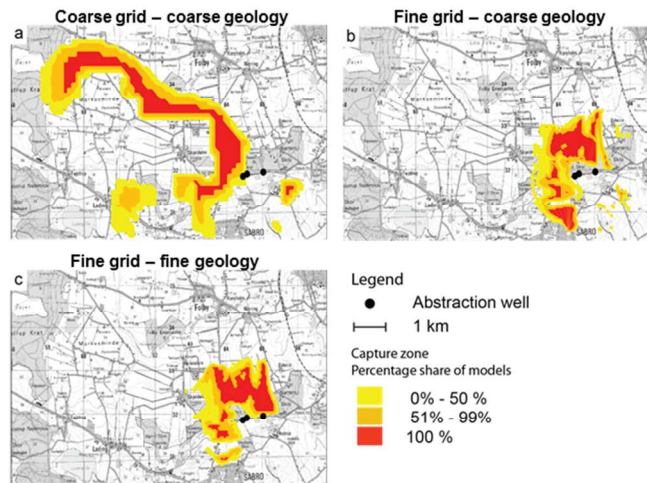


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