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Climate change impact on groundwater levels: ensemble modelling of extreme values

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Abstract

This paper presents a first attempt to estimate future groundwater levels by applying extreme value statistics on predictions from a hydrological model. Climate for the future period, 2081–2100, are represented by projections from nine combinations of three global climate models and six regional climate models, and downscaled with two different methods. An integrated surface water/groundwater model is forced with precipitation, temperature, and evapotranspiration from the 18 model – and downscaling combinations. Extreme value analyses are performed on the hydraulic head changes from a control period (1991–2010) to the future period for the 18 combinations. Hydraulic heads for return periods of 21, 50 and 100 yr (T_{21-100}) are estimated. Three uncertainty sources are evaluated; climate models, downscaling and extreme value statistics. Of these sources, downscaling dominates for the higher return periods of 50 and 100 yr, whereas uncertainty from climate models and downscaling are similar for lower return periods. Uncertainty from the extreme value statistics only contribute up to around 10 % of the uncertainty from the three sources.

1 Introduction

Climate change adaptation is a more and more recognized component in planning of infrastructure development. Infrastructures such as roads are designed to be able to withstand extreme hydrological events. Hydrological extreme events have commonly been estimated from historical data, but the evidence of a changing climate implies that estimates of future climatic conditions should be used instead. Estimates for the future temperature and precipitation can be generated by Global Climate Models (GCMs) with grid resolutions of typically 200 km. This resolution is too coarse for further application in hydrological models (Fowler et al., 2007), thus downscaling to a more local scale is necessary either by dynamical downscaling to Regional Climate Models (RCMs) or by statistical downscaling. The inherent uncertainty in the climate models (CMs) should

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carefully be considered because this is possibly the largest source of uncertainty in hydrological climate change studies (Allen et al., 2010). Hawkins and Sutton (2011) analysed the uncertainty cascade for projections of precipitation from a GCM ensemble. They concluded that relative to scenario uncertainty from emission scenarios, natural climate variability and climate model uncertainty dominated, even at the end of the 21st century. For hydrological models, precipitation and temperature are driving parameters and therefore the response of the uncertainty for these parameters should be shown in the hydrological model predictions. One way to do this is via a probabilistic modelling approach with multiple climate change models (e.g. Tebaldi et al., 2005; Smith et al., 2009; Deque and Somot, 2010; Sunyer et al., 2011). The impact of climate change related to subsurface water has been considered in around 200 studies according to a recent review by Allen et al. (2011). Only a few of these simulate groundwater conditions with a physically based groundwater flow model (e.g. Yosoff et al., 2002; Scibek and Allen, 2006; van Roosmalen et al., 2007; Candela et al., 2009; Toews and Allen, 2009). The general interest of these studies is water resources, where quantifications of groundwater recharge and responding groundwater levels at seasonal time scales are adequate. To the knowledge of the authors, no reported studies have focused on extreme values of groundwater heads under future climatic conditions. The estimates of future groundwater head extremes would inherit key sources of uncertainty from the climate model projections which are; (i) climate models and (ii) downscaling methods. Opposite to water resources assessment, analyses of groundwater head extremes are highly relevant for roads in contact or close to groundwater tables since groundwater flooding and drainage issues can compromise the use of the road.

The use and concept of Extreme Value Analysis (EVA) are well known within the hydrological sciences. The design of urban drainage systems are often planned to withstand or handle an extreme rain event, which means that the capacity for routing drainage water is sufficient for a given rain event, e.g. a 5 or 10 yr event. For example, at an urban runoff system in Toronto, Canada, Guo and Adams (1998a) compared volumes of runoff return periods for an analytical expression, based on exponential

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probability density functions of rainfall event characteristics, with return periods from the Storm Water Management Model (SWMM). In Guo and Adams (1998b), return periods for peak discharge rates from the analytical model and SWMM was compared. Bordi et al. (2007) used the Generalized Pareto distribution for analysing return periods of extreme values for wet and dry periods at Sicily using precipitation observations and a Standardized Precipitation Index for wetness and dryness. A peak over threshold methodology was used and spatial contour maps for return periods for the wet and dry thresholds produced, based on data from 36 rain gauges. Palynchuk and Guo (2008) used EVA statistics to develop design storms, standardized distribution of rainfall intensity with time, which conventional is developed from depth duration frequencies of rainfall, or storm event analysis, where actual rainstorms are fitted to appropriate probability density functions. EVA has also been used in climate change impact studies. Burke et al. (2010) applied EVA to calculate drought indices for UK, based on projections of future precipitation and an observed baseline period. Return periods for different drought indices were estimated with an above-threshold concept using a Generalised Pareto distribution. Sunyer et al. (2011) compared the distribution of extreme precipitation events (>25 mm day^{-1}) from four projections of future climate at a location just north of Copenhagen, Denmark, with distributions derived from observed precipitation, 1979–2007.

The lack of EVA for climate change studies of groundwater systems is concordant with the relatively few groundwater studies describing unusually high or groundwater flooding events. The area of groundwater flooding received increasing attention after flooding events in the winter–spring 2000–2001 from chalk-aquifers in UK and Northern Europe (e.g. Tinch et al., 2004; Pinault et al., 2005; Morris et al., 2007; Upton and Jackson, 2011; Hughes, 2011) but very few studies have dealt with groundwater flooding in a frequency analysis context. One study (Najib et al., 2008) developed a groundwater flood frequency analysis method to estimate T-year hydraulic heads for a given return period (T). The tool was developed to a building construction project at

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a karstic aquifer in Southern France where heavy rainfall induced a groundwater table rise and thereby flooding.

The objectives of this study are to: (1) investigate the impacts of climate change on extreme groundwater levels in relation to infrastructure design; and (2) assess the uncertainty of extreme groundwater level estimates considering the key sources of uncertainties on the future climate.

2 Study area

The study area is located at the city of Silkeborg in the central part of Jutland, Denmark (Fig. 1). The area is dominated by deeply incised valleys formed during melt off from the glacial retreat of the North East and the Baltic ice sheets 16 000–18 000 yr ago. The subsequent Gudenå River system flows through the city with a topography ranging from 20 to 95 m a.s.l. (meters above sea level). The area in focus is just north of the Gudenå River, in a part of Silkeborg, where a new motorway is planned.

Toward northwest, north and east, smaller Gudenå River tributaries form natural hydrogeological boundaries. Toward west a topographical height forms a groundwater divide for the upper hydrogeological units and toward south the Gudenå River Valley delineates the hydrological model referred to as the Silkeborg model. The motorway crosses the river valley at the location of the city, and therefore the road level is constructed 6 m below topography, with a concrete bottom and vertical sheet piling walls. The groundwater level of the shallow terrace aquifer in the river valley is critically near to the motorway.

2.1 Hydrogeology

The near surface geology at Silkeborg is dominated by clayey tills in the upland areas. Thicknesses of these are up to 35 m and mostly formed as lodgement tills below Weichelian glaciers, when the main advance was located west of Silkeborg before

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18 K yr BP. Below this, coarser glacial sediments of sand and gravel form an upper unconfined aquifer with thicknesses up to 50 m. This hydrogeological sand unit is properly deposited during retreat of former ice sheets, although it is perturbed by clayey sediment, mostly in the lower part, evidencing a more complex depositional history. The glacial till and sand are not observed in the valley of Gudenå River at Silkeborg. In the valley, at least 3 erosional levels and fluviatile sandy sediments are observed (terrace sediments). The terrace sand were deposited when the glacial front had withdrawn to east of Silkeborg and the Gudenå River system were used as drainage for the melting ice to the Limfjord and later on to Kattegat with connection to the North Atlantic (Fig. 1). A geological cross section is shown in Fig. 2.

Below the Quaternary sediments, Oligocene and Miocene mica-clay, mica-sand and quartz-sand are found. These sediments are observed down to 80–100 m b.s.l. where Eocene marls are found. In the eastern part of the modelled area, buried valleys are included in the geological model. The buried valleys are 6–8 km long, up to 1 km wide, and eroded about 75 m into pre-quaternary sediments (Jørgensen and Sandersen, 2009). The valleys are possibly backfilled with re-deposited Miocene sediments.

2.2 Hydrology

The humid climate in Denmark is dominated by the weather systems of the North Atlantic and the European continent. At the Jutlandien peninsula, precipitation varies from coastal to in land areas with around 200 mm yr^{-1}. Highest precipitation is found at the North-South trending topographical ridge just vest of Silkeborg. The average precipitation at Silkeborg during the period of 1961–1990 was 903 mm yr^{-1} with max. monthly values in November of 101 mm month^{-1} and min. amount in April of 50 mm month^{-1} (Scharling et al., 2000, with correction factors from B type shelter from Allerup et al., 1998). Average potential evapotranspiration for the same period was 546 mm yr^{-1}, with max. and min. in July and December of 100 and 4 mm month^{-1}, respectively (Scharling et al., 2000). Average monthly temperature peaked in July and August with 15.2 °C and

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had a low in January and February of $-0.3\,^{\circ}$C (Scharling et al., 2000). These conditions result in recharge of groundwater aquifer during late autumn, winter and early spring.

3 Methodology

The study applies EVA on model predictions of future groundwater levels representing the period of 2081 to 2100. The levels are extracted at a groundwater-sensitive part of the planned motorway from an integrated groundwater surface water model. Results representing a historic baseline period (1991–2010) and the future period (2081–2100) are compared. Estimates of groundwater levels are produced with a nested modelling approach, where a large regional model is used to calculate Boundary Conditions (BC) for a local model at Silkeborg. Although this approach doubles the number of model runs and data processing, it supplies the primary local model with more realistic BC's for the simulations representing the future (Toews and Allan, 2009). In recent studies the MikeShe code (Abbott et al., 1986; Refsgaard and Storm, 1995) has been used to evaluate the effect on surface and sub-surface hydrology by climate change (van Roosmalen et al., 2007; van Roosmalen et al., 2009; Stoll et al., 2011). The Danish National Water Resources Model, also called the DK-model (Henriksen et al., 2003) was used to produce BC's for a local model at Silkeborg.

3.1 Hydrological models

3.1.1 Regional model

The DK-model consists of 7 subareas with area 5 covering the middle part of Jutland. Figure 3 shows the DK-model area 5, further referred to as the DK-model. The model covers 12 501 km^2 with a 500 × 500 m numerical grid discretisation. The model is setup with the MikeShe code coupled with the Mike11 code and describes overland flow, evapotranspiration, flow in the unsaturated zone, the saturated zone with drainage

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routing, and river flow. Numerical layering follows a hydro-stratigraphic model with 11 units. Geology was initially interpreted in a voxel (volume pixel) framework with cell size of $1000 \times 1000 \times 10$ m (xyz). During the latest model update (2005–2009), the voxel model was superimposed by local geological models based on the hydro-stratigraphic model (Højbjerg et al., 2010).

The model is bounded by the North Sea and Kattegat towards West and East, respectively. Toward North and South the model is bounded by topographical catchment boundaries. The model was calibrated transient for the period 2000–2003 with 2592 groundwater head (h) observations and 66 time series of river discharge (Q) with the automated parameter optimiser PEST ver. 11.8 (Doherty, 2010). Besides these observations, observations of mean h, 1990–1999 was also used to design an objective function with 8 weighted criteria representing, water balance, transient error on h and Q, mean error on h and Q. Performance criteria and calibration parameters are summarized in Table 1. Further detail on the DK-model and the calibration of the latest release version can be found in Henriksen et al. (2003) and Højbjerg et al. (2010).

3.1.2 Local model

The geology illustrated in Fig. 2 was used for the local groundwater and surface water model at Silkeborg. As with the regional model, the model was developed with the coupled MikeShe – Mike11 framework. The model was set up with a 100×100 m numerical grid with 3 vertical layers and a model domain of 103 km^2, Figs. 3 and 4. The top most layer, layer 1, follows the terrace sand in the river valleys and glacial clay in the higher elevated areas. This is possible because the MikeShe code allows for separate geological and numerical models, with the parameterization following the geological model. Layer 2, follows the glacial sand and layer 3 the pre-quaternary sediments. Boundary conditions for the three numerical layers are different. The southern boundary at layer 1 is a lake, Silkeborg Langsø (A–B, Fig. 4) and was simulated as a time-variant specified head with daily time steps. In order to estimate lake water stage (h) beyond periods with observations (1990–1995) a Q/h relation was established. Lake

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stage observations were received from the Silkeborg municipality and flow (Q) from a river discharge station 21.109 (Resenbro, Danish monitoring programme, location A, Fig. 4) just downstream of the lake.

Besides section C–D (Fig. 4), boundaries for layer 1 are smaller streams toward west and north (B–C, D–G) and at Gudenå River toward east (G–A). The specified head elevations used to simulate these boundaries are adopted from a detailed digital elevation model. Section C–D follows a topographical low with small ponds but without any connecting stream. The section probably drains toward the southern or northern stream sections and is therefore simulated as a no-flow BC. The glacial sand in layer 2 terminates toward the River Valleys surrounding the model (e.g. at the valley slope illustrated in Fig. 2) and therefore a no-flow BC is used for this layer. The pre-quaternary sediments defining layer 3 crosses the model boundary and interacts with regional groundwater systems in areas with coarse sediments, mica and quartz sand. At the southern and eastern model boundary, only the fine-grained pre-quaternary sediments are observed and section F–B is therefore defined as a no-flow BC. The remaining boundary for layer 3 (B–F) is open for exchange via a transient specified head BC. Daily head levels are simulated by the regional model for which, one of the layers is vertically aligned with layer 3 in the local model. The different horizontal cell discretization's between the model, 500 m and 100 m, involve that several boundary cells in the local model receives head levels from the same 500 m cell from the regional model.

The area in focus is located in the City of Silkeborg and therefore a paved area coefficient is used to describe direct runoff in urbanized areas to streams. Paved areas are illustrated in Fig. 1. The chosen coefficient of 0.33 for the town area is derived from an estimate that one third of the town area is covered by pavement or buildings whereas the rest is covered by recreational areas (grass/forest). In the model the paved area coefficient implies that one third of the precipitation for each time step is routed directly to the closest stream, whereas the rest will be available for infiltration.

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3.1.3 Silkeborg model calibration

Calibration of the model focused on the critical zone for the motorway regarding groundwater flooding (Fig. 2). Optimization of model parameters was done inversely with PEST vers. 11.8 (Doherty, 2010). PEST optimization is not available within the MikeShe graphical user interface and setup of PEST and optimization was therefore performed outside this. The model was run for the period 1990–2011 with 1990–2005 as warm up and 2005–2011 as calibration period. The warm up period is relatively long because of large groundwater extractions in the early 1990's in the terrace aquifer and because the initial conditions affect model predictions for several years. Groundwater extraction in the terrace aquifer has been steady the last 15 yr. Observation data consist of a number of head measurements from two categorizes: (i) historical head measurements from the Danish national borehole archive (Jupiter), often with a single or a few measurement dating from 1990–2010. (ii) Time series of daily head measurements for the period 2010–2011. The objective function (Eq. 1) was defined with 5 weighted groups considering mean error for daily hydraulic head measurements, error on maximum amplitude for hydraulic heads, and error on mean heads (1990–2010). The weighing of groups was done according to the modelling purpose of predicting hydraulic heads in the terrace aquifer. Thus observations in the HTS_ME group receive highest weight. Furthermore, this group only contain observations from the actual calibration period opposite Hobs_mean1–3. The HTS_MaxHDiff group receives the second highest weight because a good fit of the annual hydraulic head variation is sought.

$$\begin{aligned}\mathrm{Obj} = {} & \sum\nolimits_i (w_i \times \mathrm{HTS\_ME}_i)^2 + \sum\nolimits_j (w_j \times \mathrm{Hobs\_means1}_j)^2 + \sum\nolimits_k (w_k \times \mathrm{Hobs\_mean2}_k)^2 \\ & + \sum\nolimits_l (w_l \times \mathrm{hobs\_mean3}_l)^2 + \sum\nolimits_m (w_m \times \mathrm{HTS\_MaxHDiff}_m)^2 \qquad (1)\end{aligned}$$

Selection of calibration parameters was limited by the available type of observation data. It was not possible to calibrate parameters describing surface runoff, the root zone and unsaturated zone because of their sensitivity toward (non-available) river discharge or water balance related data. For the same reason, observation data could not

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support calibration of specific yield and specific storage for the saturated zone. In contrast, hydraulic conductivities for the 5 geological units were sensitive to the observed hydraulic heads and therefore selected for calibration. Horizontal hydraulic conductivity (K_h) was tied to vertical hydraulic conductivity (K_v) as one order of magnitude higher. Furthermore, it was assumed that leakage coefficients for the lake, the southern BC, would be sensitive to head variations in the terrace aquifer. Initial calibrations did not support this assumption, thus the parameter was not included in a final calibration. The reason for the insensitivity is likely due to a low hydraulic contact between the terrace aquifer and the lake. Observed hydraulic heads in the terrace aquifer are different from water stage fluctuations at the lake (the reason for this is discussed later).

3.2 Climatic baseline data

Daily climatic data for the hydrological models, i.e. precipitation (P), temperature (T), and potential evapotranspiration (E_p), were obtained for the period 1991–2010 (baseline period) in a grid format from The Danish Metrological Institute. Calculation of areal grid-values, 20 × 20 km size for T and E_p, and 10 × 10 km size for P, relies on a nationwide network of climate stations. The methodology used for making the grid interpolations can be found in Scharling et al. (2000). Grid values of P was catch corrected with a dynamic correction model originally developed by Allerup et al. (1998) but applied on grid values by Stisen et al. (2012). The catch correction model is a spatially distributed model which mainly uses wind speed to correct measured daily rainfall.

3.3 Climate change projections

3.3.1 Ensemble of climate models representing future weather

In the ENSEMBLES project (Christensen et al., 2009) future climate projections have been made for Europe with many combinations of GCMs and RCMs for the A1B emission scenario. In the present study we have used data from nine of these GCM-RCM combinations (Table 2) for the period 1991–2010 (control period) and 2081–2100. Output from the RCMs have been transferred to a 10 × 10 km grid discretisation for precipitation, temperature and potential evaporation and two different methods for bias correction have been applied:

- Delta Change (DC) – DC is the simplest and the most common downscaling method. The key principle is that the future climate is described by the historical climate data corrected by monthly change factors derived from the climate model projections, e.g. daily precipitation values for January 2081 consist of observed precipitation for January 1991 multiplied by the ratio between average January precipitation projected for the future period 2081–2100 and average January values projected for the control period 1991–2010. This implies that results from the climate models are not used directly, only the change in projected average monthly precipitation is used. DC is well proven and well suited for studies focussing on effects of average climate factors such as groundwater recharge and average groundwater heads (van Roosmalen et al., 2007; van Roosmalen et al., 2011).

- Distribution Based Scaling (DBS) – DBS is a so-called direct method which corrects the outputs from the climate model and only uses observed data to estimate correction parameters (Piani et al., 2010). In the DBS method the climate model data and the observed data in the control period are fitted to two different double gamma distributions. The difference between these two gamma distributions represents the correction made by the DBS and the climate model simulations for the future period are then corrected by using this correction. While the DC can preserve the projected changes in mean values, the DBS can also preserve the projected changes in other statistical properties and is therefore theoretically better suited for extreme values.

More information on the DC and DBS methodologies and their implementation is provided by Seaby et al. (2012), who documented that the DBS is able to correct direct

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data from all RCMs so that they reproduce extreme precipitation in the control period. For the present study we have extracted climate model results from the 10 km grid covering the local model area in Silkeborg.

3.3.2 Climate change simulation with groundwater models

Applying a hydrological model developed for present conditions to simulate future conditions involves a number of assumptions. Calibration parameters and model structure are assumed constant throughout the 21st century. Land use and agricultural practice will most likely change but how and to which degree is uncertain. Future groundwater extraction is assumed to be the same as the average for the period 2003–2010. The baseline model run, applying climatic observations from 1991–2010, is also run with the constant pumping value from 2003–2010.

3.4 Extreme value analysis

Extreme Value Analysis (EVA) was applied to predictions of future groundwater levels from the hydrological model. EVA focuses on the tail of the distribution, e.g. the lowest or highest percentile of values in a dataset. A suitable probability distribution is fitted to the selected extreme values and from this values corresponding to given return periods can be estimated. Within hydrology the double exponential or Gumbel distribution often approximates events (x) in the upper tail of distribution (Eq. 2, Gumbel, 1958).

$$F(x) = e^{-e^{\alpha(x-\beta)}}, \quad -\infty < x < \infty \tag{2}$$

Parameters α and β are found by a maximum likelihood method and the standard error of the estimate of the extreme value with a T year return interval is calculated with 95 % confidence limits as:

$$s_T = \frac{s_x}{\sqrt{n}} \cdot [1 + 1.14 \cdot K_T + 1.1 \cdot K_T^2]^{1/2} \tag{3}$$

The calculated 95 % confidence limits will be referred to as the error bound for the Gumbel distribution.

Model predictions of (five-day-average) hydraulic head in the upper aquifer from 20 zones along the motorway were extracted from the baseline and ensemble runs. Annual maxima for the 20 yr were then found and sorted according to value. Two approaches were used to analyse differences, i.e. climate change impacts, for simulated hydraulic heads of the future and the present period at each zone. (i) The maxima for the baseline period, simulated with observation data, were subtracted from the maxima from each of the DC members and the results sorted again from highest to lowest. Thus resulting in a dataset with 9 series of 20 annual maxima changes between future and baseline simulated hydraulic head (at each of the 20 zones). From this mean values and values of upper 95 % confidence limits of the dataset were calculated. Gumbel distributions were then fitted to both the mean dataset and the upper 95 % dataset. (ii) The procedure for the DBS method was the same as for the DC method except for one thing. The baseline simulation results were generated by 9 models with input data from the same 9 climate models instead of one model with the observed data as with the DC method.

The reason for selection of the mean dataset and the dataset with the 95 % limit was its relevance for the motorway design, where the lower extreme values are unimportant.

4 Results

4.1 Model calibration

The calibrated model shows a distribution of mean error with best fit in the terrace sand (Fig. 5). This is not surprising because a majority of observations are located in this part of the model and HTS_ME with all its observations in the terrace sand has more than half of the total weight in the objective function (Table 1). At areas of the model with

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high topographical gradients (e.g. where the motorway leaves the river valley toward north vest) high mean errors are seen.

A likely reason is the transition between the river valley deposits and the upland glacial sand and clay. The model discretization and heterogeneous geology are too coarse to resolve variation in hydraulic heads in this area. Figure 5b also shows error on max. seasonal amplitude, which in some areas in the terrace aquifer is up to 0.6 m. A smaller error for this component of the objective function might be expected for a model of this size and discretisation. One explanation could be the location in an urbanized zone, where the hydrology is somewhat dominated by paved areas. Although the MikeShe code accounts for paved areas, besides surface runoff, evapotranspiration and unsaturated zone flow, the physical description seems to be insufficient in the urban zone to simulate observed groundwater fluctuations. Optimized hydraulic conductivities for the glacial units (terrace sand, glacial sand, glacial clay) are within expected values and the 95 % confidence limits are relatively narrow except for the glacial clay, Fig. 6. This is likely because of a small number of observations in this clay unit and the K_h seems to be in the upper end of expected.

The range between K_h for Pre-quaternary sand and clay appears to be a bit narrow and confidence limits utterly overlap, especially because of the wide confidence limit of the clay (2.5 orders of magnitude). Boreholes penetrating the pre-quaternary deposits seem to evidence that only a small lithological difference is present between the two units, e.g. sand layers dominated by fine-sand, and clays layers by silt. This is also exemplified by K_h for the lowest of the two pre-quaternary sand units is close the value of the pre-quaternary clay.

4.2 Climate change parameters

Results from the DC and DBS climate ensembles are compared with observations from the baseline period (1991–2010) for precipitation, temperature and evapotranspiration, Fig. 7. Predictions of future precipitation are the most varying climate variable (Fig. 7). The DC method (ensemble average) predicts future precipitation similar to baseline

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observations from February to June, a decrease June to October and an increase in November, December, and January. The distribution based scaling (ensemble average) predicts a decrease in February and from July to October and an increase in January, from March to May, and in November and December. The climate models disagree most during the summer and in September, whereas predictions are more similar from October to May. Except for November, ranges of predictions in the DBS ensemble are wider than in the DC ensemble.Temperatures are predicted to increase throughout the year with highest relative increase during winter. The narrow confidence intervals, well separated from the observed 1991–2010, indicate a clear trend for the future period. Predicted future E_p shows the same trend as temperature which is not surprising because of its direct correlation.

4.3 Analysis of extreme groundwater levels

EVA was performed for the 20 zones at the motorway with estimation of Gumbel parameters for each zone. Figure 8 shows Gumbel distributions for the change in extreme values for zone 34 and 50 with results where the mean of the climate ensemble is subtracted by the baseline result. The two zones are selected because they represent highest and lowest changes between the future and baseline period. Furthermore, the two zones clearly display the difference for extreme values by using the DC or DBS methodology, with higher changes for the DBS method. At zone 34, high changes occur with 0.48 and 1.16 m for the DC and DBS 100 yr event (T_{100}), respectively. At zone 50 lower changes are seen with 0.23 and 0.37 m for the DC and DBS T_{100}, respectively. The difference of T_{100} values between DC and DBS estimates is then 141 % at zone 34 and 61 % at zone 50. Zones with higher changes of extreme hydraulic heads seem to be more sensitive to the downscaling method. The calculated error bound for the Gumbel distributions are similar for both ensembles. For instance, at zone 34 the error bounds are 31 % higher (or lower) than the T_{100} estimate for the DC, and 26 % for the DBS. At zone 50, these numbers are 31 and 28 %. Besides Gumbel distributions based on the mean of extreme values of the DC and DBS ensemble, Gumbel distributions based on calculated upper 95 % confidence limits of the ensemble extreme values are shown in Fig. 9.

Results illustrated in Fig. 9 contain a T_{100} at zone 34 of 0.81 m for the DC ensemble and a T_{100} of 1.64 m for the DBS ensemble, which are significantly higher than the values of 0.48 and 1.16 for the mean ensemble. The differences for T_{100} are similar at zone 50, Table 3.

4.4 Uncertainties of future extreme groundwater levels

The results illustrate several sources of uncertainty affecting the estimation of future extreme groundwater levels. First of all, the estimation of the future climate is challenging. In this study it is handled by applying an ensemble of climate projections from 9 combinations of global and regional climate models. Secondly, climate model results are downscaled using two different methods. Thirdly, estimation of extreme values from the simulated groundwater levels involves uncertainty related to fitting the Gumbel distribution, and this uncertainty is described by error bounds on the estimated extreme values.

We will characterise the uncertainty from these three sources as the interval between the upper and lower 95 % confidence values, equivalent to four times the standard deviation of an estimated value. Based on the results shown in Table 3 we find:

- Extreme Value Analysis – the ± in Table 3 represents half of the 95 % confidence interval. Hence, the uncertainty related to the Gumbel distribution is quantified as the average of the error from each of the two downscaling methods and the two climate values (mean and upper 95 % ensemble) multiplied with 2. For instance, at zone 30 the EVA uncertainty for T_{21} would be $((0.07 + 0.16 + 0.07 + 0.19)/4) \cdot 2 = 0.25$ m.

- Climate models – the difference between mean ensemble and upper 95 % ensemble represents half of the 95 % confidence interval. Hence the climate model uncertainty is estimated as this difference multiplied with 2, averaged over the two

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downscaling methods. For example, at zone 30 the climate model uncertainty for T_{21} would be $(((0.51-0.29)+(1.06-0.68))/2)\cdot 2 = 0.60$ m.

- Downscaling – if the two downscaling methods were assumed equally likely the uncertainty could strictly be considered as four standard deviations, where the standard deviation is calculated from the two known random variables (the DC and DBS estimate). For example, at zone 30 the downscaling uncertainty for T_{21} would be $4\cdot((\text{StandardDeviation}\{0.29;\ 0.68\}+\text{StandardDeviation}\{0.51;\ 1.06\}/2) = 1.33$ m. We argue, however, that the two downscaling methods are not equally likely. While we have no reason to assume that the DBS does not represent a central estimate, the DC is known to only preserve the mean but underestimate the variance of the future climate data. The DC is therefore likely to underestimate the extreme values and hence provide an estimate at the low end of the uncertainty interval. Assuming that the DBS estimate represents the statistical mean value, while the DC represents the lower 95 % confidence estimate, the downscaling uncertainty for T_{21} would correspond to only two standard deviations or 0.67 m.

Assuming that the three sources of uncertainty are independent the *total uncertainty*, σ_{total}, can be assessed by:

$$\sigma_{\text{total}} = \sqrt{\sigma^2_{\text{climatemodel}} + \sigma^2_{\text{downscaling}} + \sigma^2_{\text{EVA}}} \quad (4)$$

where $\sigma_{\text{climatemodel}}$, $\sigma_{\text{downscaling}}$ and σ_{EVA} are the uncertainties related to climate models, downscaling and extreme value analysis. Figure 10 shows the three uncertainty components with downscaling calculated as two standard deviations. The results in the figure are calculated as the average of the 20 zones for each T event.

From Fig. 10 it is seen that the uncertainty from climate models and downscaling methods are the two dominating sources of uncertainty. Climate modelling uncertainty is almost constant for different return periods, while downscaling uncertainty increases with higher return period (also see Figs. 9 and 10).

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5 Discussion

5.1 Climate change impacts on extreme groundwater levels in relation to infrastructure design

The development of extreme groundwater levels from today's climate toward future climate is modest. The extreme value analysis shows changes of up to 1.7 m for T_{100} events (zone 32). This estimate is based on the upper 95 % confidence limit of the prediction with the 9 climate model. A more likely T_{100} estimate at zone 32 is the one based on the mean value, and gives a 1.2 m change.

The modest climate change impact at the investigated aquifer is a result of site specific conditions. Two interacting groundwater conditions, drainage and the hydraulic conductivity of the aquifer, affect extreme groundwater levels. The high conductivity of the aquifer will remove groundwater towards hydraulic boundaries as drains, streams and lakes with a relatively low response time, implying that higher groundwater levels quickly will be reduced. With a good connectivity between the aquifer and the drainage system, the elevation of the drains will confine groundwater levels. In contrary to drainage of the aquifer which reduces the extreme events, increased recharge from connecting aquifers and the unsaturated zone will tend to amplify extreme events. At the situation at Silkeborg it seems that the potential rate of drainage is high compared to the potential rate of recharge. This relation between aquifer recharge/discharge is obviously very site-specific and therefore, the potential impact of climate change for extreme groundwater levels is also very site-specific. One aspect not considered in the study is the anthropogenic influence on the hydrological systems in the future. Changing land use and development of the drainage system could affect the aquifer recharge/discharge relation and thereby extreme groundwater levels. Drainage systems and land use will be part of future adaptation measures and include feedback to the groundwater system (Holman et al., 2012). This is not taken into account in the present study.

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Extreme value analysis for groundwater systems in a future climate is to the knowledge of the authors not presented in the literature before. As noticed, attempts have been made to use an EVA methodology within the area of groundwater flooding. The study by Najib et al. (2008) introduced a methodology to perform flood frequency analysis and estimate hydraulic heads for 100 yr events (T_{100}). The underlying objective; to implement flood hazard assessment at a groundwater dominated hydrological regime by estimating the 100 yr event at a given site is the same as in the present study. Three major differences between the studies are seen. First of all, Najib et al. (2008) investigate a dual or triple porosity carbonate aquifer with hydraulic head variations of up to 90 m, whereas the terrace sand aquifer in Silkeborg only have a few meters of observed variation and is relative homogeneous compared to the aquifer in Southern France. Secondly, Najib et al. (2008) reconstruct hydraulic heads used for the EVA by a global reservoir model with a non-physically based parameterisation. Calibration of parameters is done for individual sites with observed hydraulic head and precipitation data. This is fundamentally different from the three dimensional, physically based groundwater – surface water modelling used in the present study. The non-physical description in Najib et al. (2008) fits observed data very well, because parameterisation is done locally toward local observations, whereas calibration of a 3-D groundwater model, through the objective function, attempts to make the best overall parameterisation toward widely distributed observations. The general discussion for and against models as global reservoir models versus more physically based models as MikeShe or MODFLOW models is beyond the scope of this paper. Nevertheless, in respect to simulation of future conditions one could argue that a physically based parameterisation is maybe more robust for simulations with changing climatic input, because at least the physical system is described with some confidence. Thirdly, the present study includes climate change impacts in the EVA for hydraulic heads. This leads to an estimation of T years representing the last 20 yr of the 21th century and not a representation of the next 100 yr with today's climate as shown by Najib et al. (2008).

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5.2 Uncertainty of extreme groundwater level estimates

The largest uncertainty for the extreme groundwater levels is the downscaling method. Results clearly show that when dealing with the upper part per thousand of the distribution for groundwater head predictions, the choice of downscaling method dominates the uncertainty. Uncertainty for climate models is also substantial for the predictions but opposite downscaling uncertainty it is stable around 0.65 m for all T estimations (0.65–0.67 m, Fig. 10). In other words, the uncertainty from climate models is the same for a T_{21} and a T_{100} estimate of hydraulic head. This is maybe not surprising, because the changes applied through the DC and DBS methods are uniform throughout the simulated future period of 2081–2100. On the other hand, estimates of extreme hydraulic heads are simulated by a complex model, where many processes affect the prediction.

Uncertainty on the Gumbel prediction ranges between 0.21 and 0.39 m from T_{10} to T_{100} (Fig. 10). This uncertainty is a result of uncertainty in estimation of parameter values in the Gumbel distribution with the EVA uncertaintylimited data, and hence it could be reduced by selecting a longer period than 20 yr. Another uncertainty related to extreme value analysis that we have not addressed in the present study is related to parameter estimation methods, selection of extreme values etc. Najib et al. (2008) compared six different T_{100} estimates using an annual maximum serie methodology, a peak over threshold methodology, both with parameter estimations using the method of moments, the maximum likelihood method and the probability weighted moment method. These six combinations of methods gave very similar T_{100} estimates and standard deviations for the estimate of hydraulic head and this justify the current use of only one method. In climate change studies it is critical to select too long periods because the climate conditions do not honour the stationarity condition, which is an underlying assumption used in extreme value analysis. Our results suggest that when choosing a 20 yr period the uncertainty due to the extreme value analysis is much smaller than the uncertainties due to climate models and downscaling methods.

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The lack of studies investigating extreme groundwater conditions under future climate makes it difficult to compare the relative size of uncertainty sources found in this study. General comparison can nevertheless be made to impact studies within other areas of hydrology. One study supporting the uncertainty distribution found in the present investigations is Graham et al. (2007), where future river runoff is estimated with a combination of GCM's, RCM's and two downscaling methods equivalent to the DC and DBS methods. Graham et al. (2007) conclude that large uncertainty is associated with the choice of climate model and more important in relation to the present study, the choice of downscaling methods affects prediction of extreme runoff events and seasonal dynamics, whereas the prediction of runoff volumes are not sensitive to downscaling method. In this context testing of different downscaling methods is very relevant when dealing with extreme hydrological events. A groundwater recharge study by Allen et al. (2010) also conclude that downscaling from climate models can be particularly difficult and related with high uncertainty when estimations of extreme values are investigated.

The findings from the Silkeborg case are in principle site-specific. The estimated changes for future extreme groundwater levels are a result of the hydrogeological setup for the aquifer at Silkeborg, the climatological changes projected for this region, and the hydrological model's ability to simulate the natural, but also the highly urbanized area in a trustworthy manner. One model limitation is the model-ability to simulate annual groundwater fluctuations in the terrace aquifer. Further model development should facilitate a better replication of these relative low fluctuations observed in the aquifer and this again should be supported by more than one year of detailed head measurement in order to simulate fluctuations on a seasonal, annual, and inter annual perspective. Another limitation, and probably the most crucial, is the future changes of land-use, urbanization, drainage system development and other anthropogenic introduced changes on the hydrological system.

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6 Conclusions

Changes of extreme groundwater levels found in this study in terms of T_{21-100} events are modest. For a 100 yr event, a variation of 0.37 to 1.22 m is estimated (mean ensamble, DBS). The used downscaling methods, Delta Change and Distribution Based Scaling, demonstrate large differences in the prediction of extreme groundwater levels. The variation for a 100 yr event using the DC method shows a variation between 0.23 and 0.51 m compared to 0.37 to 1.22 m for the DBS method (mean ensamble). These results emphasise the importance of downscaling methodology when estimating hydrological extreme values for a future climate. The two downscaling methods are not considered as equally possible, because the DBS methodology most likely has an advantage over a DC methodology for downscaling of extreme events. Therefore, we argue that most weight should probably be put on the results with the DBS methodology and we use the DC method as an indicator of the lower end of the confidence interval. Even with this assumption the downscaling uncertainty still dominates over climate model uncertainty and uncertainty from the extreme value statistics. If downscaling uncertainty is considered in this simplistic way, downscaling accounts for 57 % of uncertainty from the three sources, climate models for 32 %, and extreme values statistics for 11 % (for estimation of a 100 yr event). These uncertainty contributions come from estimates of 0.87 m of uncertainty from downscaling, 0.66 m from climate models, and 0.39 m from extreme value statistics. Compared to the estimates of groundwater levels during a 100 yr event (0.23–1.22 m), the uncertainties from the three sources are very high.

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Table 1. Definition of groups in the objective function.

Group	Definition	Observation period	Weight, w_{i-m}	No. Obs.
HTS_ME	Mean error of time series of hydraulic head (daily data)	2010–2011	10	33
Hobs_mean1	Error of average hydraulic head for the 1990–2010, in layer 1	1990–2010	1	20
Hobs_mean2	Error of average hydraulic head for the 1990–2010, in layer 2	1990–2010	1	29
Hobs_mean3	Error of average hydraulic head for the 1990–2010, in layer 3	1990–2010	1	61
HTS_MaxHDiff	Error of maximum annual amplitude of hydraulic head (daily data)	2010–2011	5	33

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Table 2. Climate model ensemble, combinations of GCM and RCM.

Model name	Global Climate Model (GCM) Model name – institution	Regional Climate Model (RCM) Model name – institution
ARPEGE-CNRM	ARPEGE – Centre National de Recherche Météorologiques, France	RM5.1 - Centre National de Recherche Météorologiques, France
ARPEGE-DMI	ARPEGE – Centre National de Recherche Météorologiques, France	HIRHAM5 – Danish Meteorological Institute
BCM-DMI	BCM – Bjerknes Centre for Climate Research and Nansen Center, Norway	HIRHAM5 – Danish Meteorological Institute
BCM-SMHI	BCM – Bjerknes Centre for Climate Research and Nansen Center, Norway	RCA3 – Swedish Meteorological and Hydrological Institute, Sweden
ECHAM-DMI	ECHAM – Max Planck Institut for Meteorology, Germany	HIRHAM5 – Danish Meteorological Institute
ECHAM-ICTP	ECHAM – Max Planck Institut for Meteorology, Germany	REGCM3 - International Centre for Theoretical Physics, Italy
ECHAM-KNMI	ECHAM – Max Planck Institut for Meteorology, Germany	RACHMO2 - Royal Netherlands Meteorological Institute, The Netherlands
ECHAM-MPI	ECHAM – Max Planck Institut for Meteorology, Germany	REMO - Max Planck Institute for Meteorology, Germany
ECHAM-SMHI	ECHAM – Max Planck Institut for Meteorology, Germany	RCA3 – Swedish Meteorological and Hydrological Institute, Sweden

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Table 3. Estimated climate induced increases in extreme groundwater table and associated Gumbel (EVA) error bounds (±) in m for return intervals of 20 (T_{21}), 50 (T_{50}) and 100 (T_{100}) years for different zones along the motorway.

	Mean ensemble				Upper 95% ensemble				Mean ensemble			
	DC		DBS		DC		DBS		DC		DBS	
Zone	T_{21}	±	T_{21}	±	T_{21}	±	T_{21}	±	T_{50}	±	T_{50}	±
30	0.29	0.07	0.68	0.16	0.51	0.07	1.06	0.19	0.34	0.09	0.79	0.20
31	0.37	0.10	0.94	0.22	0.71	0.10	1.43	0.23	0.44	0.13	1.08	0.27
32	0.38	0.10	0.95	0.22	0.72	0.10	1.46	0.23	0.45	0.13	1.10	0.28
33	0.36	0.10	0.92	0.21	0.70	0.10	1.41	0.22	0.43	0.13	1.06	0.27
34	0.35	0.10	0.90	0.21	0.68	0.10	1.37	0.22	0.42	0.13	1.04	0.26
35	0.36	0.10	0.92	0.21	0.70	0.10	1.41	0.22	0.43	0.13	1.07	0.27
36	0.35	0.10	0.89	0.21	0.68	0.10	1.36	0.21	0.42	0.13	1.03	0.26
37	0.36	0.10	0.91	0.21	0.69	0.10	1.38	0.22	0.43	0.13	1.05	0.26
38	0.35	0.10	0.86	0.20	0.65	0.10	1.30	0.20	0.42	0.13	0.99	0.25
39	0.35	0.10	0.87	0.20	0.67	0.10	1.33	0.21	0.42	0.13	1.01	0.25
40	0.34	0.10	0.83	0.19	0.63	0.09	1.26	0.20	0.41	0.12	0.96	0.24
41	0.32	0.09	0.78	0.18	0.59	0.08	1.18	0.19	0.38	0.11	0.91	0.23
42	0.33	0.09	0.79	0.18	0.59	0.08	1.19	0.19	0.39	0.11	0.91	0.23
43	0.31	0.08	0.73	0.17	0.55	0.07	1.09	0.18	0.36	0.10	0.85	0.21
44	0.29	0.08	0.68	0.16	0.51	0.07	1.02	0.16	0.34	0.10	0.79	0.20
45	0.27	0.07	0.62	0.14	0.48	0.07	0.93	0.15	0.32	0.09	0.72	0.18
46	0.28	0.07	0.62	0.14	0.48	0.07	0.93	0.15	0.33	0.09	0.72	0.18
47	0.28	0.07	0.63	0.14	0.49	0.07	0.94	0.15	0.34	0.09	0.73	0.18
48	0.26	0.07	0.58	0.13	0.45	0.07	0.85	0.14	0.31	0.09	0.67	0.17
49	0.23	0.06	0.46	0.11	0.37	0.06	0.67	0.11	0.27	0.08	0.53	0.13
50	0.17	0.05	0.28	0.07	0.26	0.05	0.40	0.07	0.20	0.06	0.33	0.09

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Table 3. Continued.

	Upper 95% ensemble				Mean ensemble				Upper 95% ensemble			
	DC		DBS		DC		DBS		DC		DBS	
Zone	T_{50}	±	T_{50}	±	T_{100}	±	T_{100}	±	T_{100}	±	T_{100}	±
30	0.56	0.09	1.19	0.24	0.38	0.11	0.88	0.23	0.60	0.11	1.29	0.28
31	0.78	0.12	1.59	0.28	0.50	0.15	1.20	0.32	0.84	0.14	1.71	0.33
32	0.79	0.13	1.62	0.29	0.51	0.15	1.22	0.32	0.85	0.15	1.74	0.34
33	0.77	0.13	1.56	0.28	0.49	0.15	1.18	0.31	0.82	0.15	1.68	0.32
34	0.75	0.12	1.52	0.27	0.48	0.15	1.16	0.30	0.81	0.15	1.64	0.32
35	0.77	0.13	1.56	0.28	0.49	0.15	1.18	0.31	0.82	0.15	1.68	0.32
36	0.75	0.12	1.51	0.27	0.48	0.15	1.15	0.30	0.80	0.15	1.62	0.31
37	0.76	0.13	1.53	0.27	0.49	0.15	1.17	0.31	0.82	0.15	1.65	0.32
38	0.72	0.12	1.44	0.26	0.47	0.15	1.10	0.29	0.77	0.14	1.56	0.30
39	0.73	0.12	1.47	0.26	0.48	0.15	1.12	0.29	0.79	0.14	1.58	0.31
40	0.70	0.11	1.40	0.25	0.46	0.14	1.07	0.28	0.75	0.13	1.51	0.29
41	0.65	0.10	1.31	0.24	0.43	0.13	1.01	0.26	0.69	0.12	1.42	0.28
42	0.65	0.10	1.32	0.24	0.43	0.13	1.01	0.26	0.69	0.12	1.42	0.28
43	0.60	0.09	1.22	0.22	0.41	0.12	0.94	0.25	0.64	0.11	1.31	0.26
44	0.56	0.09	1.13	0.21	0.38	0.11	0.87	0.23	0.60	0.10	1.22	0.24
45	0.52	0.08	1.03	0.19	0.36	0.11	0.80	0.21	0.56	0.10	1.11	0.22
46	0.53	0.09	1.03	0.19	0.37	0.11	0.80	0.21	0.57	0.10	1.12	0.22
47	0.54	0.09	1.05	0.19	0.38	0.11	0.81	0.21	0.58	0.10	1.13	0.22
48	0.50	0.08	0.95	0.18	0.35	0.10	0.74	0.20	0.53	0.10	1.03	0.21
49	0.41	0.07	0.75	0.14	0.31	0.09	0.59	0.16	0.45	0.09	0.81	0.17
50	0.29	0.06	0.45	0.09	0.23	0.07	0.37	0.10	0.32	0.07	0.49	0.11

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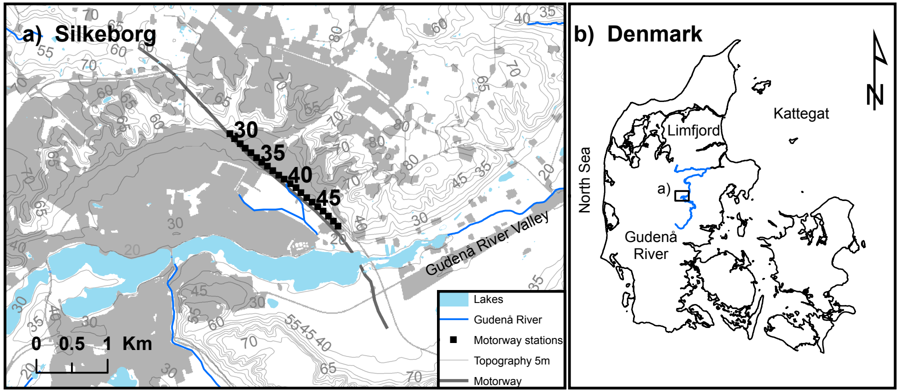

Fig. 1. Location of Silkeborg in Denmark (right) and the new motorway (left). **(a)** The motorway stretch where construction will be below present ground level with a road surface around 6 m below surface. Zones are used for groundwater head analyses (Motorway stations). The grey shaded polygons indicate paved ares. **(b)** Denmark, and location of Silkeborg and Gudenå River.

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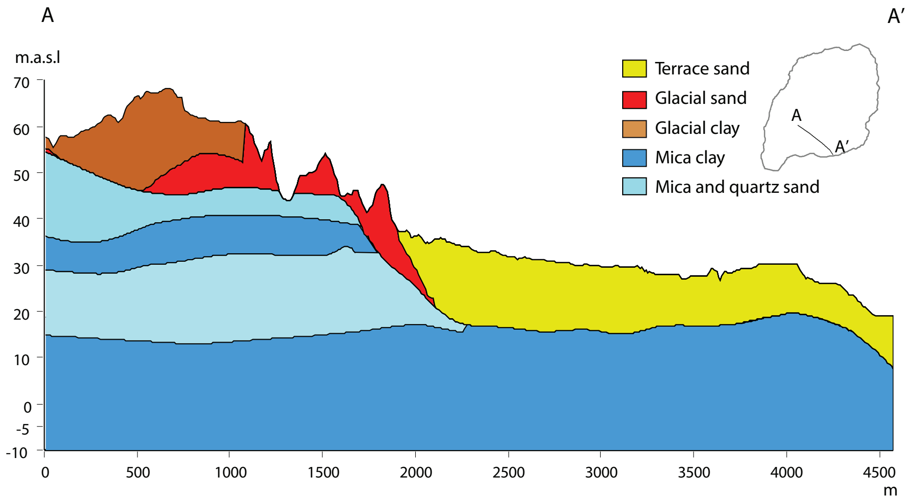

Fig. 2. Geological cross section along the planned motorway. Location of cross section is show in upper right corner together with Silkeborg model boundary; see later Figs. 3 and 4.

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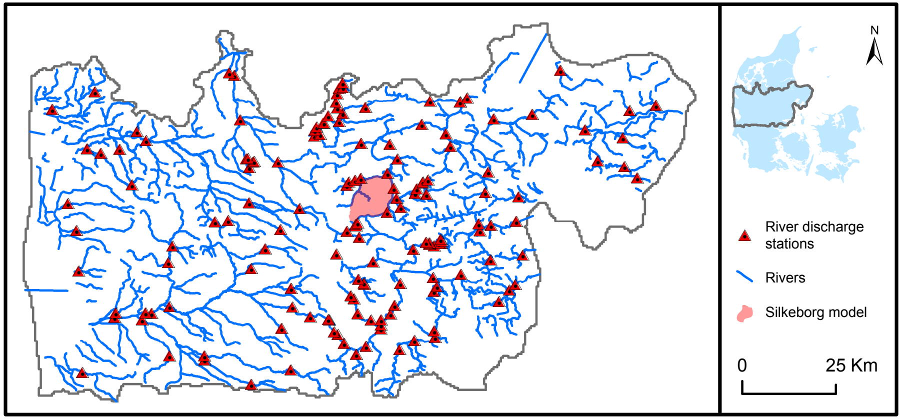

Fig. 3. Setup of nested model approach with the Regional DK-model area 5.

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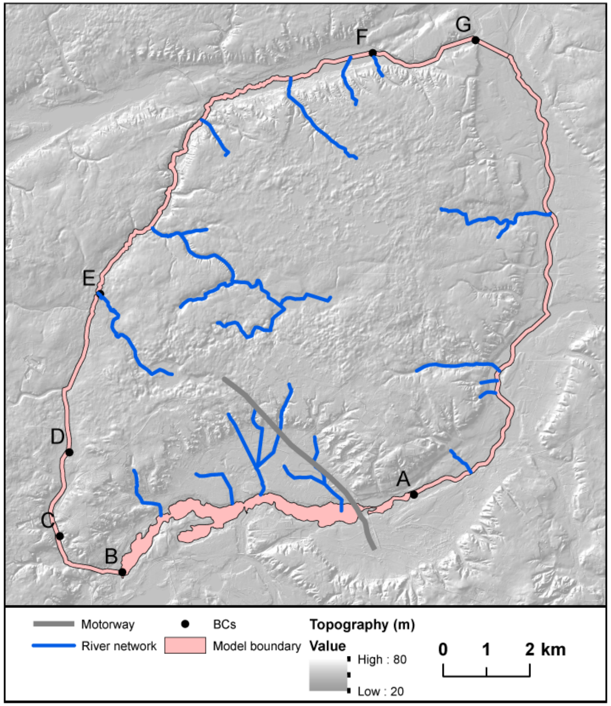

Fig. 4. Local model setup. Model boundary (section A-G), Mike11 river network, and topography. Model area is 103 km^2.

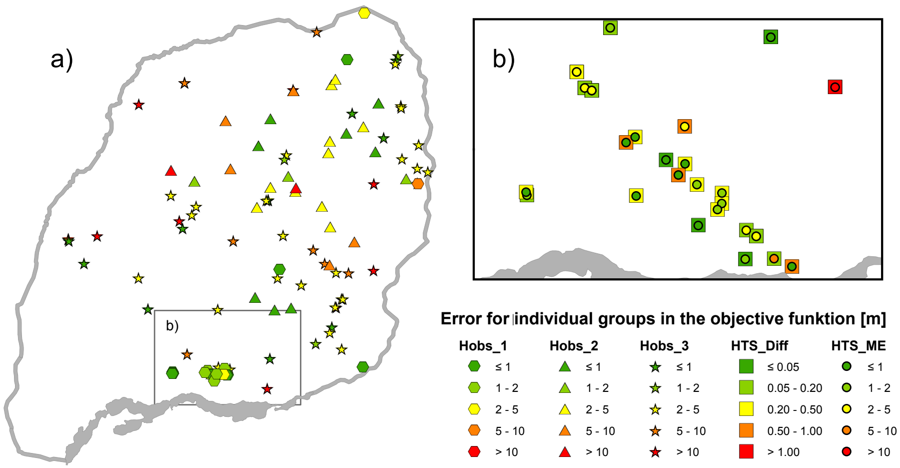

Fig. 5. Model error of hydraulic head. **(a)** Mean error of hydraulic head layer 1–3 (Hobs_mean1–2). **(b)** Error of max. seasonal amplitude of hydraulic head (HTS_maxHDiff) and mean error of hydraulic head with time series observations (HTS_ME).

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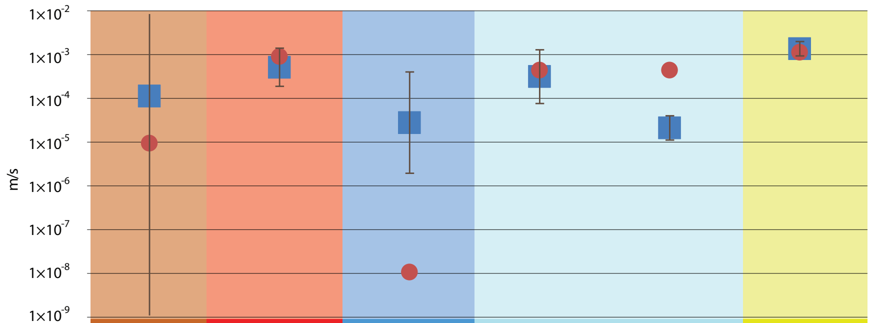

	Glacial clay	Glacial sand	Mica clay	Mica sand 1	Mica sand 2	Terrace sand
optim	1.24×10^{-4}	5.81×10^{-4}	2.99×10^{-5}	3.52×10^{-4}	2.27×10^{-5}	1.57×10^{-3}
init	1.00×10^{-5}	1.03×10^{-3}	1.00×10^{-8}	5.00×10^{-4}	5.00×10^{-4}	1.30×10^{-3}
Up 95%	1.18×10^{2}	1.61×10^{-3}	4.51×10^{-4}	1.49×10^{-3}	4.36×10^{-5}	2.31×10^{-3}
Low 95%	1.30×10^{-10}	2.10×10^{-4}	1.99×10^{-6}	8.34×10^{-5}	1.19×10^{-5}	1.07×10^{-3}

Fig. 6. Optimized values of hydraulic conductivity, initial parameters values, and calculated 95 % confidence limits by PEST. Geological units are shown in Fig. 2.

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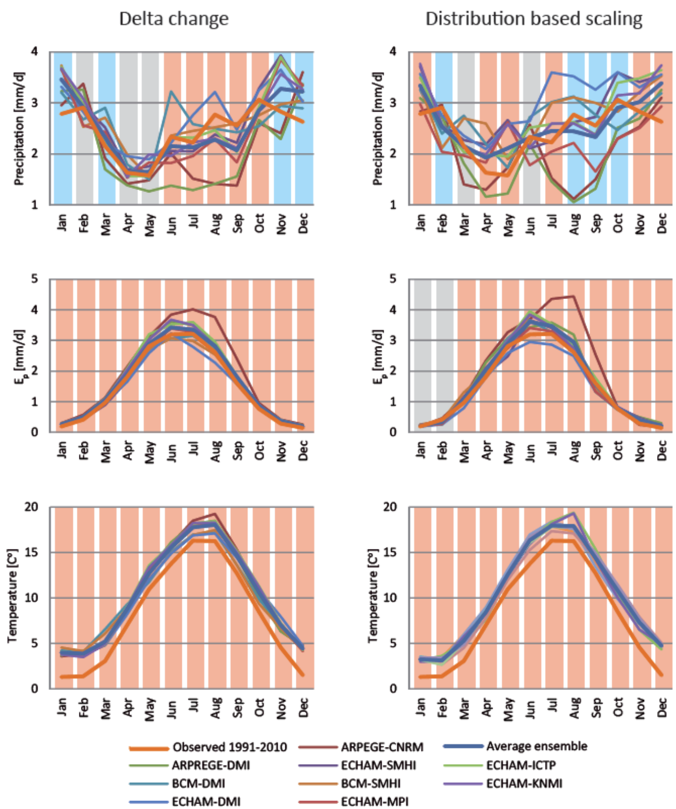

Fig. 7. Monthly average for precipitation, evapotranspiration (E_p), and temperature from the climate models for the period 2081–2100 and observed for 1991–2010. Average ensemble values are calculated from the 9 ensemble members for the DC and DBS ensembles, respectively. Red, blue and grey background bars illustrate months where the ensemble average show reduced, increased or unchanged precipitation, E_p or temperature.

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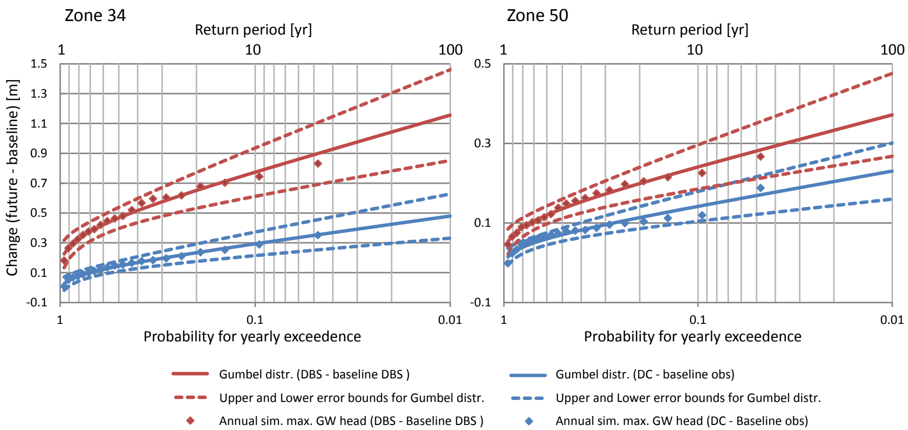

Fig. 8. Gumbel distributions for zone 34 and 50 at the motorway calculated from mean of ensembles. Distributions and associated error bounds marked with blue are based on delta change (DC) data. In the same way results using the distribution based scaling (DBS) are marked with red. Values used to parameterise the Gumbel distribution, annual max. hydraulic heads (future) – annual max. hydraulic heads (baseline), are shown as red and blue dots.

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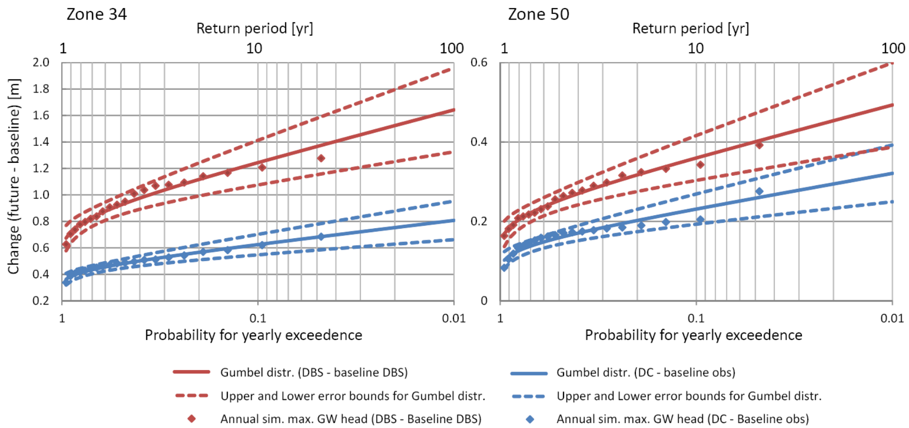

Fig. 9. Gumbel distributions for zone 34 and 50 at the motorway calculated from upper 95 % limit of ensembles. Distributions and associated error bounds marked with blue are based on delta change (DC) data. In the same way results using the distribution based scaling (DBS) are marked with red. Values used to parameterise the Gumbel distribution, annual max. hydraulic heads (future) – annual max. hydraulic heads (baseline), are shown as red and blue dots.

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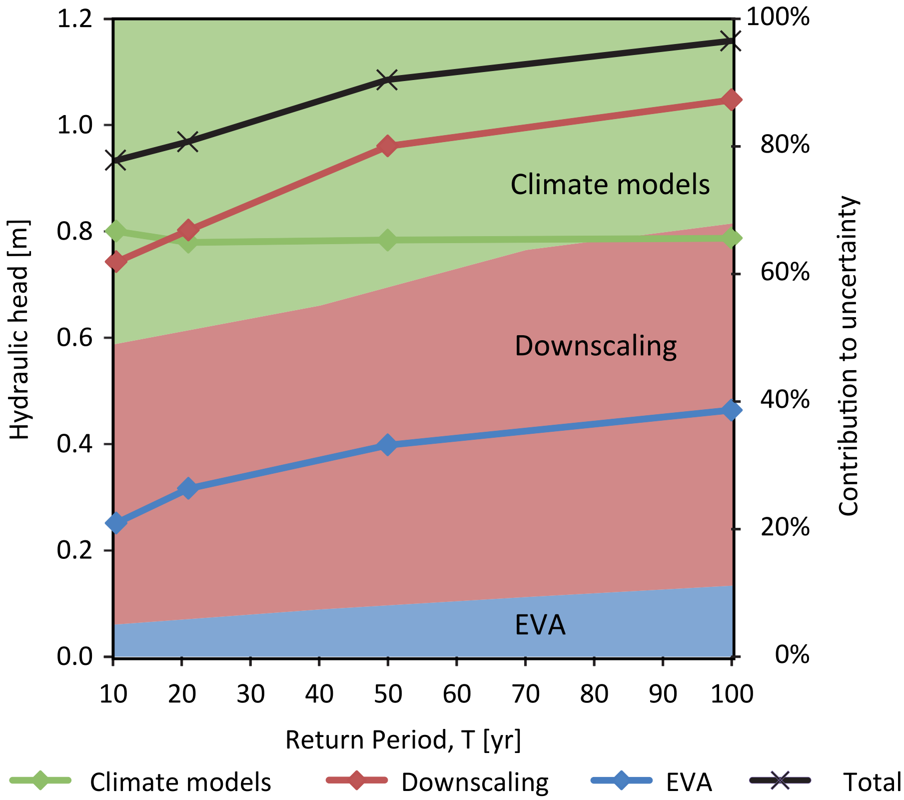

Fig. 10. Propagation of uncertainty for estimation of future extreme groundwater levels. Uncertainty from Climate models, downscaling and Gumbel distribution are shown with absolute values (left axis) and percentage contribution (right axis) with background colouring.

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