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1 *In Press with PNAS. Classification: Physical Sciences*

2 **Enhanced groundwater recharge rates and altered**
3 **recharge sensitivity to climate variability through**
4 **subsurface heterogeneity**

5

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24 **Keywords**

25 Groundwater recharge, subsurface heterogeneity, water resources, climate variability, climate
26 change

27

1 **Abstract**

2 Our environment is heterogeneous. In hydrological sciences, the heterogeneity of subsurface
3 properties, such as hydraulic conductivities or porosities, exerts an important control on water
4 balance. This notably includes groundwater recharge, which is an important variable for
5 efficient and sustainable groundwater resources management. Current large-scale
6 hydrological models do not adequately consider this subsurface heterogeneity. Here we show
7 that regions with strong subsurface heterogeneity have enhanced present and future recharge
8 rates due to a different sensitivity of recharge to climate variability compared to regions with
9 homogeneous subsurface properties. Our study domain is comprised of the carbonate rock
10 regions of Europe, Northern Africa and the Middle East, which cover ~25% of the total land
11 area. We compare the simulations of two large-scale hydrological models, one of them
12 accounting for subsurface heterogeneity. Carbonate rock regions strongly exhibit
13 “karstification”, which is known to produce particularly strong subsurface heterogeneity.
14 Aquifers from these regions contribute up to half of the drinking water supply for some
15 European countries. Our results suggest that water management for these regions cannot rely
16 on most of the presently available projections of groundwater recharge because spatially
17 variable storages and spatial concentration of recharge result in actual recharge rates that are
18 up to 4 times larger for present conditions and changes up to 5 times larger for potential future
19 conditions than previously estimated. These differences in recharge rates for strongly
20 heterogeneous regions suggest a need for groundwater management strategies that are adapted
21 to the fast transit of water from the surface to the aquifers.

22 **Significance**

23 Understanding the implications of climate changes on hydrology is crucial for water resources
24 management. Widely-used global hydrological models generally assume simple
25 homogeneous subsurface representations to translate climate signals into hydrological
26 variables. We study groundwater recharge in the carbonate rock regions of Europe, Northern
27 Africa and the Middle East, which are known to exhibit strong subsurface heterogeneity. We
28 demonstrate that subsurface heterogeneity alters the sensitivity of recharge to climate
29 variability and enhances recharge estimates resulting in potentially more available water per
30 capita, than previously estimated. Our results are opposing previous modeling studies on
31 future groundwater availability that assumed homogeneous subsurface properties everywhere.

1 We suggest that water management strategies in regions with heterogeneous subsurface
2 properties need to consider these revised estimates.

3 \body

4 **Introduction**

5 Groundwater recharge is a crucial component of the global water balance, feeding the world's
6 groundwater storages and thereby supplying fresh water to large parts of the global population
7 (1–4). Comparing groundwater recharge with groundwater use and ecological water demand
8 helps to distinguish between over-used aquifer systems and aquifer systems that still allow for
9 more abstraction in a sustainable way (5, 6). The importance of managing groundwater
10 sustainably will increase in the future given the growing dependence on this resource in many
11 parts of the world (7). Subsurface heterogeneity notably affects groundwater recharge (4),
12 especially in weathered carbonate rock regions (8). Spatially variable soil thickness and
13 hydraulic conductivity in the subsurface produce fast, localized vertical water movement,
14 thereby enhancing groundwater recharge (9). Our study is the first to take into account the
15 impact of subsurface heterogeneity on present and potential future recharge rates at a
16 continental scale. Subsurface heterogeneity evolves for various reasons (10). In this paper, we
17 confine our modelling domain to carbonate rock regions. Such regions typically exhibit the
18 most extreme subsurface heterogeneity in terms of hydraulic conductivities and storage
19 capacities due to the weathering of carbonate rock, a process also referred to as
20 “karstification” (11, 12). We focus on Europe, Northern Africa and the Middle East, where
21 ~560 Million people depend on drinking water from karst aquifers (13, 14), and where
22 information on karst recharge is most available.

23 We simulate groundwater recharge (defined here as the simulated vertical downward flux
24 entering the saturated zone) using both a homogeneous and a heterogeneous subsurface
25 representation (Figure 1). The global hydrological model PCR-GLOBWB (15) is used for the
26 homogeneous subsurface representation, while the karst recharge model VarKarst-R (16),
27 which includes variable thickness of the soil, epikarst (the weathered interface of soil and
28 carbonate rock) and hydraulic conductivity, is used for the heterogeneous representation. The
29 structure of VarKarst-R is particularly adapted to the dominant hydrological processes of
30 carbonate regions allowing for focused preferential recharge and variable subsurface
31 dynamics that are found in humid, Mediterranean, mountainous and desert karst regions (16).

1 These processes are not included in the PCR-GLOBWB model or other comparable large-
2 scale hydrological models. We use the output of five general circulation models (GCMs of the
3 ISI-MIP model ensemble (17), 0.5x0.5 degree resolution) to simulate groundwater recharge
4 with each of these two subsurface representations, from 1991 to 2099 under the highest
5 emission scenario (RCP8.5 (18), increasing radiative forcing, $>8.5\text{Wm}^{-2}$ by 2100, and
6 increasing atmospheric CO_2 concentrations, $> 1,370$ ppm. CO_2 -equiv. by 2100). In order to
7 avoid biasing our results by selecting one specific GCM, we use ensemble means for all our
8 interpretations after applying all five GCMs individually to both subsurface representations,
9 respectively.

10 We assess recharge sensitivity to climate variability using the statistical *elasticity* measure.
11 Beyond a correlation analysis that simply evaluates the strength of relations between
12 variables, elasticity quantifies “how responsive one variable is to change in another variable”
13 or “the percentage change in a first variable to the percentage change in second variable,
14 when the second variable has a causal influence on the first variable” (19, 20). Among several
15 applications of elasticity on stream flow (21–23), we are one of the first in hydrology to apply
16 elasticity to groundwater recharge. Here we define *recharge sensitivity* as the median ratio of
17 inter-annual changes of recharge rates to the inter-annual changes of three climatic variables
18 that drive recharge and evapotranspiration using a 20-year period: (1) Annual precipitation
19 expresses general water availability, (2) mean annual temperature is used as proxy for
20 potential evapotranspiration, and (3) the mean intensity of high-intensity events is used to
21 account for the non-linear impact of strong rainfall events (24). Similar to (23) we preferred
22 temperature over net radiation as a proxy for potential evapotranspiration because net
23 radiation is temperature dependent and temperature is the best-understood and most common
24 input variable to large-scale hydrological models. Recharge sensitivity with large positive or
25 negative values indicates that recharge is highly sensitive to variations of these input
26 variables. Values closer to 0 indicate a low sensitivity. Recharge sensitivity to precipitation
27 and to high intensity events is calculated with changes normalized by their 20-year average
28 ($\%\%^{-1}$), while recharge sensitivity to temperature is expressed by normalized changes of
29 recharge per absolute change of temperature ($\%\text{C}^{-1}$). Further elaborations on the simulation
30 models, the input variables and the recharge elasticity are provided in the Methods section.

1 **Realism of heterogeneity processes**

2 A comparison with observations indicates that the heterogeneous model provides more
3 realistic simulations of recharge than the homogeneous model because it includes
4 heterogeneity processes. For validation we compare the recharge simulations of the two
5 models driven by the 5 climate models for the present period (1991-2010) with independent
6 recharge observations for 38 karst systems in Europe for which we could obtain recharge
7 values from the literature ((16), Table S1). To better understand how far subsurface
8 heterogeneity is actually responsible for the differences of recharge estimations of the two
9 models, we additionally compare the observations from our literature review with simulations
10 of a version of the heterogeneous model where the heterogeneity processes are turned off (i.e.,
11 homogeneous subsurface, no lateral flow concertation but surface runoff leaves the grid cell).
12 We find that, although significant remains, the simulations of the heterogeneous model plot
13 around the 1:1 line (average deviation 55.8 mma^{-1} ; Figure 2), while most of the homogeneous
14 models simulations tend to under-estimate recharge (average deviation -232.9 mma^{-1} ; Figure
15 2). When we turn off the heterogeneity processes of the heterogeneous model, its simulations
16 also fall in large parts below the 1:1 line, plotting closer to the simulations of the
17 homogeneous model (average deviation -167.4 mma^{-1}). These results do not mean that
18 subsurface heterogeneity is the only reason for the different simulated recharge rates of the
19 heterogeneous and homogeneous subsurface representations, since the models also differ with
20 respect to other processes, such as interception or capillary rise of groundwater (see Methods
21 section). However, our comparison suggest that disregarding heterogeneity processes can
22 result in an overall under-estimation of recharge, at least for the 38 karst systems that we used
23 in our evaluation.

24 **Recharge sensitivity to climate variability**

25 We further find that the two subsurface representations exhibit different sensitivities to
26 climate variability. We divide all carbonate rock areas into 4 regions defined by cluster
27 analysis using climatic and topographic descriptors (16) (Figure 4): humid (HUM), mountains
28 (MTN), Mediterranean (MED), and deserts (DES). Recharge sensitivities to climate
29 variability are calculated for the time period of 1991-2010. Between the four regions, we find
30 a mixed pattern of sensitivity values (Figure 3, Figure S1). We can see that recharge
31 sensitivities to rainfall change from high to low values when moving from wet (humid) to dry
32 (desert) regions for both model representations. The Mediterranean and desert regions mostly

1 exhibit a higher sensitivity to climate variability. The same gradient from wet to dry is found
2 for high-intensity events. We observe the opposite trend for recharge sensitivity to
3 temperature, which increases from humid towards the Mediterranean regions but decreases
4 again in the desert.

5 For the Mediterranean and desert regions, the heterogeneous representation shows higher
6 sensitivity to changes in annual precipitation, mean annual temperature and high-intensity
7 rainfall events. Recharge estimates of the homogeneous model tends to be more sensitive to
8 changes in precipitation in the humid and mountain regions, as well as to changes in high-
9 intensity rainfall events in the mountain regions. Sensitivities to temperature changes in the
10 humid and mountain regions and to high-intensity rainfall events in the humid regions are
11 similar for both subsurface representations. The general pattern of recharge sensitivities can
12 be explained through the increased fractions of precipitation that become evapotranspiration
13 (25, 26) when moving from the humid toward the desert regions. Water availability
14 (precipitation) is the most important control on recharge sensitivities in the humid region,
15 while temperature is the stronger control in the Mediterranean regions. In the desert region,
16 recharge sensitivity generally decreases, as there is simply little water available for
17 evapotranspiration.

18 The different recharge sensitivities with respect to climate variability for the two subsurface
19 representations can be explained by the interplay of two different simulated processes. (1)
20 Variable fractions of surface runoff, which dynamically increase or reduce infiltration and (2)
21 different dynamics of evapotranspiration that change the amount of water available for
22 downward percolation. The first explains the higher sensitivities of the homogeneous
23 subsurface representation to humid and mountain region precipitation. The homogeneous
24 model calculates fractions of surface runoff with a non-linear relationship to wetness that is
25 more sensitive for the wet conditions prevailing in humid and mountain regions (Eq. (1) in
26 Methods section). The same process explains the higher sensitivity of the homogeneous
27 model to high-intensity rainfall events. No such partitioning takes place for the heterogeneous
28 model, which produces focused recharge instead of surface runoff and therefore is less
29 sensitive to changes in precipitation and high-intensity rainfall events in those wet regions
30 (humid, mountain). On the other hand, the explicit calculation of soil storages with variable
31 storage capacities in the heterogeneous subsurface representation (Figure 1b, Eq. (2) in
32 Methods section) results in different evapotranspiration dynamics than found in the

1 homogeneous model. While soil compartments with small storage capacities saturate rapidly
2 and produce focused recharge even during small and moderate rainfall events, the uniform
3 soil storages of the homogeneous model (Figure 1a) remain unsaturated more often and
4 produce more evapotranspiration. This stronger pronunciation of evapotranspiration in the
5 homogeneous model is the reason why its simulated recharge is less sensitive to all three
6 input variables for the Mediterranean and the desert regions.

7 **Future groundwater recharge**

8 The differences in recharge sensitivity to variability in climate result in different simulated
9 present and future recharge rates over Europe's carbonate rock regions. Compared to the
10 homogeneous subsurface representation, the heterogeneous subsurface representation shows
11 enhanced and more variable recharge rates, for both present and future conditions (Figure 4,
12 Figure S3). In the present period (1991-2010), the simulated recharge rates of the
13 heterogeneous subsurface representation are 2.1 to 4.3 times larger than the recharge rates of
14 the homogeneous representation. Towards the end of the century (2080-2099), the five GCMs
15 indicate that in the humid region, future annual precipitation will remain more or less the
16 same (2% of absolute increase), while considerable decreases are projected for the mountain
17 (-14%), Mediterranean (-19%) and desert regions (-12%). Temperatures are predicted to
18 increase for all regions, by 2.0°C, 4.9°C, 5.2°C and 8.1°C in the humid, mountain,
19 Mediterranean and desert regions, respectively. Future mean intensity of high-rainfall events
20 is predicted to increase for the humid (11%), mountain (8%) and Mediterranean (7%) regions,
21 while there is no trend for the desert region (1% increase) (Figure S2).

22 As result of the projected climatic change we find a general reduction of recharge rates for
23 both subsurface representations, which is consistent with previous findings on the changes of
24 future stream flow during low-flow conditions (27). The relative decrease of the two
25 subsurface representations is in the same direction. We find reductions of 7-32% and 11-44%
26 for the heterogeneous and the homogeneous representation, respectively (Figure 4; Figure
27 S3). But the absolute reductions of simulated recharge rates of the heterogeneous
28 representation (3–138 mma^{-1}) are 2.2 to 5.3 larger than the simulated reductions of the
29 homogeneous representation (2-79 mma^{-1}). Inter-annual variability of recharge is also
30 becoming more pronounced for the heterogeneous representation. This variability increases
31 from the humid and mountain regions to the deserts, likely due to the increased variability of
32 rainfall events in dry regions (28). In particular, convective storm events are known to

1 produce large fractions of preferential recharge in semi-arid or arid regions (9). While
2 recharge rates of both simulations are predicted to decrease in all regions, temporal variability
3 within the 20-year averages does not change significantly over the same time horizon. Hence,
4 with a general decrease of recharge rates, the inter-annual variability of groundwater recharge
5 in heterogeneous regions will gain more importance, especially in the Mediterranean, where
6 we expect an increase in impact of high-intensity events.

7 **Discussion**

8 Focused recharge is known to be an important process of recharge generation in regions with
9 heterogeneous subsurface characteristics (4, 29) and its strong impact on overall groundwater
10 recharge amounts has been shown in several studies at the catchment scale (30–32). Our
11 recharge sensitivity analysis reveals that accounting for this process and the variability of soil
12 storages at a much larger spatial scale results in different recharge sensitivities compared to a
13 homogeneous subsurface representation that does not consider focused recharge. We
14 demonstrate that a heterogeneous recharge modeling approach is more consistent with
15 independent recharge estimates of other studies for karst regions, and therefore more likely to
16 be a reasonable representation of the water balance separation occurring across the study
17 region than current modelling approaches. Our subsequent findings indicate that the water
18 balance of heterogeneous areas in the Mediterranean and desert regions will be less dominated
19 by evapotranspiration, as compared to regions with homogeneous subsurface properties
20 because water is rapidly passed downwards. The heterogeneous subsurface representation
21 also suggests smaller amounts of surface runoff than the homogeneous representation. On the
22 other hand, the presence of focused recharge and variable soil storage capacities generally
23 results in higher recharge rates, which are less affected by the variability of precipitation and
24 high-intensity events in the humid and mountain regions.

25 Hence, due to the presence of heterogeneity processes, a greater proportion of the water cycle
26 is active in the subsurface, meaning the risk of overexploitation may be lower than previously
27 considered. Dividing the difference of recharge simulations of the heterogeneous model and
28 mean recharge simulations of the homogeneous model in the four regions by their population
29 (Figure S4) indicates that an additional ~1000-3300 m³ of groundwater per capita per year are
30 potentially available at the present (2900, 3300, 1500 and 950 m³ per capita per year for the
31 humid, mountain, Mediterranean and desert region, respectively). Especially in the
32 Mediterranean, where previous modeling studies expect significant groundwater stress (5), the

1 additional future recharge of 1000 m³ of groundwater per capita per year may potentially lead
2 to less future groundwater stress than previously expected.

3 However, estimated groundwater recharge volumes do not equal exploitable groundwater
4 fluxes since a number of factors can limit the use of this simulated surplus recharge. First,
5 groundwater pumping likely decreases groundwater discharge significantly, spring flow and
6 baseflow impacting environmental flow (1, 33). Second, groundwater recharge in carbonate
7 rock aquifers may quickly leave the aquifer through large conduit systems and springs (8).
8 Third, recharge that is stored within the aquifer may not be fully available for development as
9 abstraction wells are usually unable to access the entire volume of the aquifer (33). Forth, the
10 high temporal variability of recharge in heterogeneous regions, which is most pronounced at
11 the Mediterranean and desert regions (Figure 4), may prohibit continuous withdrawal of
12 groundwater. And finally, higher recharge rates imply an increased vulnerability to surface
13 contamination due to preferential recharge, which might reduce the value of the groundwater
14 resource (34).

15 Possible water management strategies include adapted water management plans that take into
16 account the variable flow dynamics of these aquifers with heterogeneous recharge behavior.
17 For instance, groundwater pumping rates could be adapted to the temporally variable water
18 availability (35). Additionally, temporal variability could be compensated for by artificially
19 recharging aquifers with longer residence times using water discharged from the more
20 heterogeneous regions (36, 37). Regardless, the requirements to sustain environmental flow
21 (1) and the increased vulnerability to contamination due to preferential recharge (34) have to
22 be accounted for in any water management plan. The concerns are especially acute in the
23 Mediterranean region where the expected increase of rainfall intensity and the high inter-
24 annual variability of recharge will require adapted measures for water resources management
25 and protection to finally use the potentially additional recharge that we found in our study.
26 Such management strategies are important since 116 million inhabitants and 80% of
27 agriculture depend on irrigation (Figure S4) in the Mediterranean region.

28 This study focuses on how to represent subsurface heterogeneity in large-scale hydrological
29 models. Our results imply that subsurface heterogeneity significantly alters groundwater
30 recharge and its sensitivity to climate variability at large spatial scales. The explicit
31 consideration of variable storage capacities and focused recharge within the heterogeneous
32 model is novel compared to previous large-scale modeling studies that considered their soil

1 layers to be homogenous (38, 39). Considering heterogeneity processes within our model
2 produces less evapotranspiration and surface runoff and more groundwater recharge. This
3 difference produces and potentially more available groundwater per capita than previously
4 estimated (15). Current simulations of land surface-atmosphere coupling (26), drought
5 occurrence (27, 40), flood frequency projections (41) or water scarcity assessment (42) are
6 currently based on large-scale hydrological models with homogeneous subsurface
7 representations. Our study shows that their results may have reduced utility for groundwater
8 management for regions with pronounced subsurface heterogeneity. Through our
9 parsimonious simulation approach, we also provide a promising direction to include
10 subsurface heterogeneity evolved due to karstification into any large-scale hydrological model
11 to obtain more realistic simulations.

12

13

1 **Materials and Methods**

2 *The homogeneous model – PCR-GLOBWB*

3 The PCR-GLOBWB model(15) simulates the terrestrial water balance on a 0.5° x 0.5° grid
4 using a daily temporal resolution. Soil water balance of two homogeneous soil layers and a
5 single underlying aquifer layer is calculated at each time step. Simulated hydrological
6 processes comprise infiltration of rainfall and snowmelt, evapotranspiration, interception,
7 downward percolation from the upper soil layer to the lower soil layer and from the lower soil
8 layer to the aquifer layer (which is the flux we consider the simulated recharge of the
9 homogeneous model in this study), and capillary rise from the groundwater up to the
10 unsaturated soil. The model parameters are found using prior information from public
11 sources, e.g., the FAO Digital Soil Map of the World (43) or a simplified version of the
12 lithological map of the world (44). No calibration is performed.

13 Like other global hydrological models (38, 45), PCR-GLOBWB uses a distribution function
14 to account for the impact of spatial variability of land-surface properties on the generation of
15 surface runoff:

$$16 \quad x(t) = 1 - \left(\frac{S(t)}{S_{\max}} \right)^{\frac{b}{b+1}} \quad (1)$$

17 Where $x(t)$ is the fraction of effective precipitation at time t that becomes surface runoff, $S(t)$
18 is the total soil storage (layers 1+2) at time t , S_{\max} is the maximum total soil storage, and b is a
19 dimensionless shape factor based on subgrid information on the distribution of land-cover
20 classes with tall and short vegetation, paddy and non-paddy irrigation, land and open water,
21 and different soil types(46). The surface runoff calculated by Eq. (1) leaves the grid cell
22 towards the stream (Figure 1a in the research letter).

23 *The heterogeneous model – VarKarst-R*

24 The VarKarst-R(16) also simulates terrestrial hydrological processes on a 0.5° x 0.5° grid and
25 at a daily temporal resolution. Its structure considers infiltration of rainfall and snowmelt,
26 evapotranspiration, downward percolation from the upper soil layer to a lower soil epikarst
27 layer and vertical percolation from the epikarst layer towards the groundwater (which is the
28 flux we defined as simulated recharge of the heterogeneous model in this study). The epikarst
29 in the second layer is a typical feature of karst systems regarded as the hydrological unit that

1 controls the dynamic separation of focused and diffuse groundwater recharge (47, 48). In
2 general, the VarKarst-R model has a simpler structure (only 4 free parameters) compared to
3 PCR-GLOBWB (29 free parameters) as it uses less explicit representations of hydrological
4 processes, for instance it does not explicitly consider interception or capillary rise from the
5 groundwater.

6 The special feature of the VarKarst-R model is its assumption that even within the same
7 hydrological landscape type there is a distribution of subsurface properties. This variability is
8 expressed by distribution functions that allow for variability of soil and epikarst storage
9 capacities, as well as of epikarst hydraulic properties, over N horizontally parallel model
10 compartments (Figure 1b):

$$11 \quad S_{\max,i} = S_{\max,N} \left(\frac{i}{N} \right)^a \quad (2)$$

$$12 \quad K_{epi,i} = K_{epi,1} \left(\frac{N-i+1}{N} \right)^a \quad (3)$$

13 Where $S_{\max,i}$ [mm] is the soil or epikarst storage capacity of model compartment i , $S_{\max,N}$ [mm]
14 is the overall maximum storage capacity of the soil or the epikarst, $K_{epi,i}$ [d] is the storage
15 constant of the epikarst at model compartment i , $K_{epi,1}$ [d] is the storage constant of the
16 epikarst at model compartment 1, and a [-] is a dimensionless shape factor. Using the
17 distributions from Eqs. (2) and (3) soil and epikarst water balance are simultaneously
18 calculated at each time step and in each model compartment. The epikarst can only reach
19 saturation when infiltration exceeds vertical percolation (actual epikarst storage divided by
20 $K_{epi,i}$). The fraction of effective precipitation that exceeds soil and epikarst water deficit
21 becomes surface runoff. However, in contrast to PCR-GLOBWB, surface runoff is not routed
22 towards the streams but transferred laterally to the next model compartment (from i to $i+1$)
23 where it is added again to effective precipitation. Increasing epikarst permeability (Eq. (3))
24 therefore allows for lateral flow concentration along the model compartments (Figure 1b in
25 the research letter).

26 Since large-scale information on subsurface heterogeneity in carbonate rock regions is not
27 available, a new procedure to estimate the VarKarst-R model parameters was developed (16).
28 Based on cluster analysis and the concept of hydrological landscapes that includes climate
29 and topographic information (16, 49), carbonate rock regions are divided into 4 regions:

1 humid (HUM), mountains (MTN), Mediterranean (MED), and deserts (DES). A large sample
2 of initial model parameter sets (n=25,000) is iteratively reduced using prior information (e.g.,
3 the FAO Digital Soil Map of the World (43)), FLUXNET (50) latent heat flux observations
4 and soil moisture observations of the International Soil Moisture Network ISMN (51) in each
5 of the regions. For each karst landscape, the reduced parameters ranges of acceptable latent
6 heat flux and soil moisture simulations directly express the remaining parameter uncertainty.
7 For this study, we sampled 250 parameter sets from these reduced ranges to obtain an
8 ensemble of 250 model realizations in each grid cell to quantify the uncertainty of the
9 VarKarst-R recharge simulations due to the parameter estimation process.

10 *Climate change scenarios*

11 Both simulation models are driven by the same climate forcing derived from the bias-
12 corrected 5 GCMs of the ISI-MIP data (17). We chose the highest emission scenario of
13 available Representative Concentrations Pathways (RCP 8.5), with strongly increased
14 radiative forcing and atmospheric CO₂ concentrations(18) to obtain the worst case scenario
15 between current and future conditions. Similar to previous studies on climate change impacts
16 (26), we consider 20-year periods to analyze changes in climate and groundwater recharge.
17 By calculating running averages and their standard deviation of the GCM ensemble mean for
18 each of the four sub-regions, we can assess average recharge and its sensitivity to climate
19 variability, including their transitions towards the end of this century.

20 *Elasticity calculations*

21 We define recharge elasticity E_R [-] as the median of the inter-annual changes of recharge
22 rates R [mma⁻¹] according to trans-annual changes of a controlling variable X , normalized by
23 their annual means over a pre-defined period (e.g. 20 years):

$$24 \quad E_R = \text{median}\left(\frac{\Delta R}{\Delta X}\right) \quad (1.)$$

25 As in previous studies(19, 21) we prefer the median of trans-annual changes rather than their
26 mean so as to avoid bias due to outliers. As control variables, we consider annual
27 precipitation P [mm], temperature T [°C] and the annual mean of rainfall intensity of high
28 intensity events [mmd⁻¹], defined as the mean intensity of the upper quartile of rainfall
29 events. Hereby P represents the influence of the total annual water availability on recharge, T
30 is a proxy for the influence of energy available for evapotranspiration, and H_{INT} is an indicator

1 for the influence of strong rainfall events on recharge (also see elaborations in the letter
2 above). Similar to other studies (26), we consider 20 years long enough to reflect climatic
3 variability. While R , P and H_{INT} are normalized by their mean over this 20-year period, we do
4 not normalize T because temperature changes cannot be meaningfully represented as %.

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12 **Supplementary information**

13 A table listing all references for the evaluation of the models, maps of model input, simulation
14 results and calculated elasticities are provided in the supplementary information.

15 **Author contributions**

16 Andreas Hartmann performed the analysis and developed the manuscript. Tom Gleeson
17 provided guidance and advice during analysis and manuscript development. Yoshihide Wada
18 provided the PCR-GLOBWB data, guidance and advice during analysis and manuscript
19 development. Thorsten Wagener provided guidance and advice during analysis and
20 manuscript development.

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1 **Figure legends**

2 **Figure 1: A homogeneous and a heterogeneous representation of the subsurface.** Two different
3 representations of the subsurface of a simulation grid-cell (0.5x0.5 decimal degree); (a) homogeneous subsurface
4 representation by the PCR-GLOBWB global simulation model (15) and (b) heterogeneous subsurface
5 representation by the VarKarst-R large-scale karst recharge model (16).

6 **Figure 2: Comparison of simulations and observations.** Simulated recharge volumes of the heterogeneous
7 model (VarKarst-R), the homogeneous model (PCR-GLOBWB), and the heterogeneous model with subsurface
8 heterogeneity processes turned off plotted against observed recharge volumes (Table S 1); coloured and grey
9 whiskers indicate the simulation uncertainty (1 standard deviation) due to the 5 climate models and due to
10 parameter uncertainty (only heterogeneous model and heterogeneous model with heterogeneity processes turned
11 off, see Methods section), respectively. We find a significant difference ($p < 10^{-5}$) between the heterogeneous
12 model and the homogeneous model, as well as between the heterogeneous model and the heterogeneous model
13 with heterogeneity processes turned off. There is no statistical difference (5% significance level) between the
14 homogeneous model and the heterogeneous model with heterogeneity processes turned off, as well as between
15 the heterogeneous model and the observations.

16 **Figure 3: Sensitivity to climate variability.** Recharge sensitivity to (a) annual precipitation, (b) mean annual
17 temperature and (c) high-intensity events (mean intensity of the upper quartile of rainfall events) for the four
18 regions (HUM: humid, MTN: mountain, MED: Mediterranean, DES: desert) at the present (1991-2010);
19 uncertainty of simulated recharge sensitivities of the heterogeneous model due to parameter uncertainty (see
20 Methods section) to annual precipitant, temperature and strong rainfall events vary by 0.13 -0.24 % $^{\circ}$ $^{-1}$, 0.03-
21 0.18% $^{\circ}$ $^{-1}$ and 0.18-0.37 % $^{\circ}$ $^{-1}$, respectively (1 standard deviation, increasing from humid to desert regions).

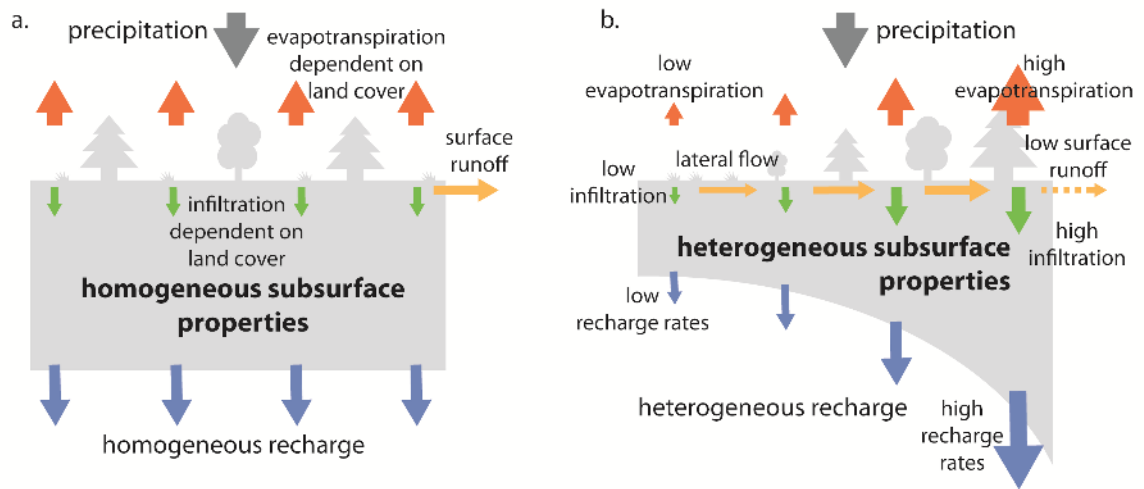
22 **Figure 4: Simulation of future groundwater recharge.** Simulation results for the two subsurface
23 representations for 4 regions; spatial variability within each region for the present (1991-2010) is presented by
24 the boxplots, temporal evolution of recharge rates is expressed by a 20-year moving average (centered around its
25 mean year, for instance the year 2000 for the 1991-2010 average); temporal variability within each 20-year
26 window is expressed by its standard deviation indicated by the grey shading round the mean (grey dashed line
27 represents lower boundary of the heterogeneous model temporal variability at the desert regions); simulation
28 uncertainty of the heterogeneous model due to parameter uncertainty (see Methods section) is indicated by the
29 dashed lines around the mean recharge.

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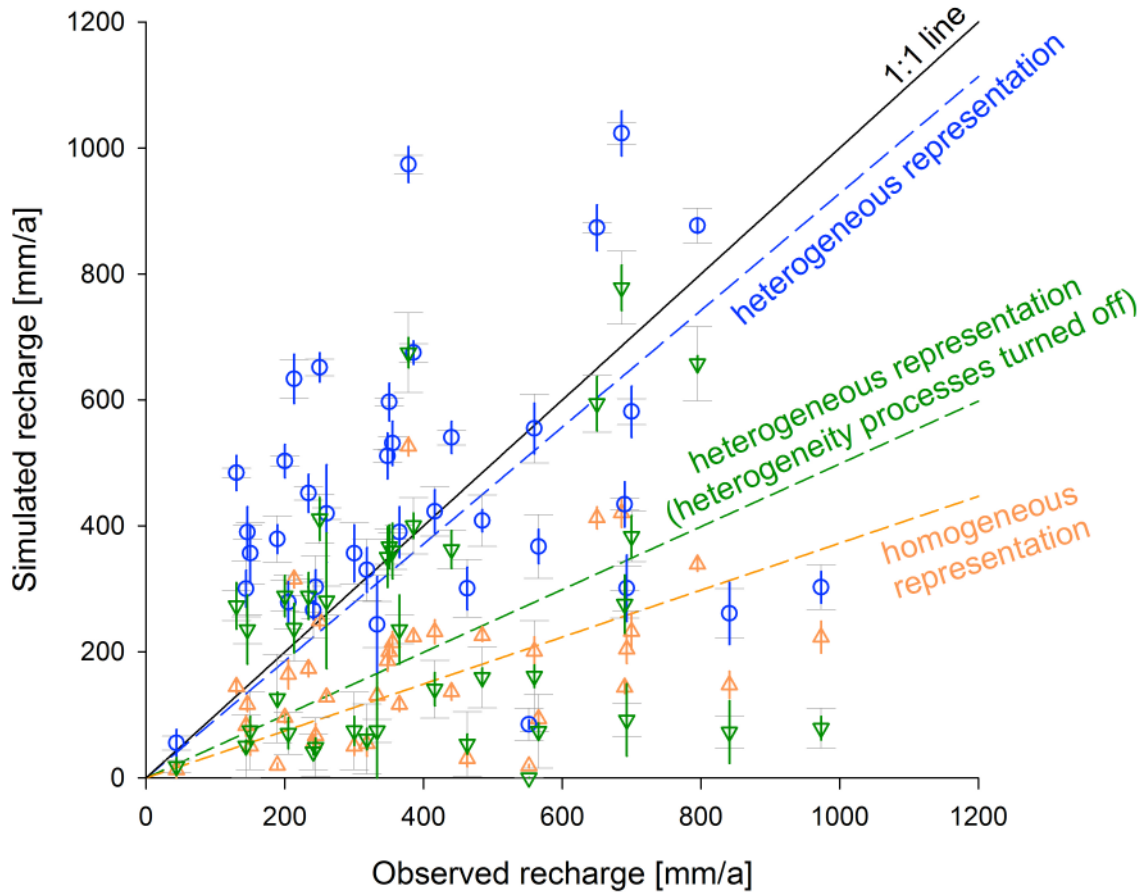
1 Figures



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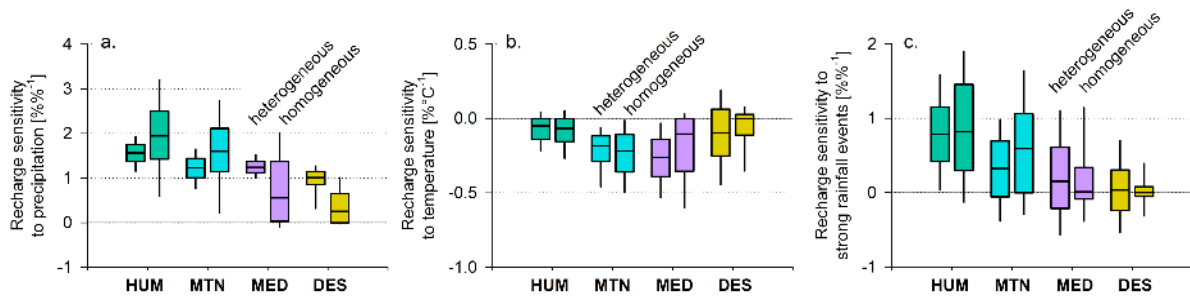
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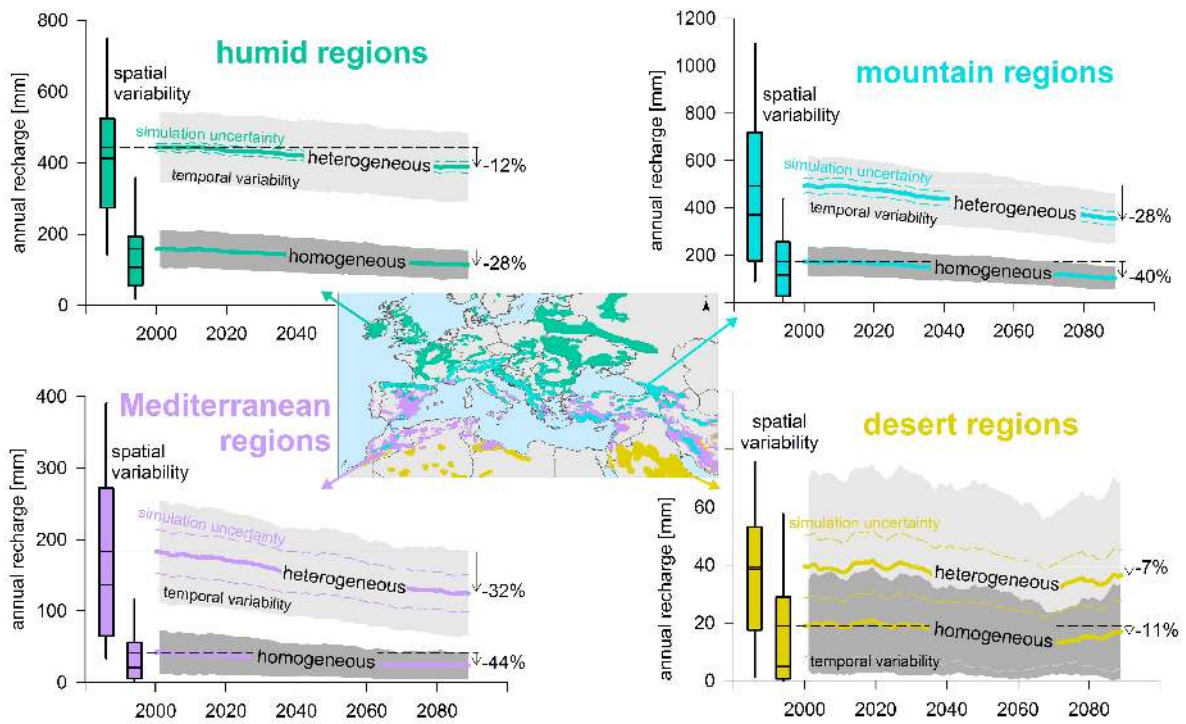


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