Dear Philippe Ackerer,

Thank you very much for your efforts in finding reviewers for this manuscript and the opportunity to revise it. Even though both reviewers certainly added interesting remarks on how to improve the paper, we are concerned that most of their suggestions are out of scope or would alter the paper to an extent that would significantly change the paper's character.

With this, we would also like to respond to your direct suggestions of:

(1) improve the discussion of some results (sometimes, it is too descriptive)

> *We assume that this request is linked to the reviewer comments to explain more deeply how the parametrisation of the models is linked to the responses in groundwater recharge and that it should be compared to other modelling efforts. As explained below, this entails a very complex and extensive analysis of the models going well beyond what we have intended for this paper. However, we now state more clearly where the model setup parameters can be found and discuss issues related to estimations of ET.*

(2) provide an insight on model reliability

> *In our manuscript model reliability, regarding the estimation of global-scale groundwater recharge, was evaluated by comparison to Mohan et al.. We agree that this can only be a first step into investigating the model reliability. However, providing insights on model reliability is challenging, which entails a better understanding of how uncertainties propagate through these complex models. As we discuss in more detail in the replies, we still lack the methods of, e.g., applying extensive sensitivity methods to GHMs to further investigate these issues. Some preceding work, e.g., Döll and Fiedler (2008), have been carried out to investigate simulated recharge reliability by using expert knowledge and some regional studies. This work is cited in our manuscript, but conducting additional experiments on this would go significantly beyond this paper's scope, which focusing on the differences among the models in the ISIMIP2 framework and the influence of CO2 changes on recharge.*
>
> *Also, investigating the reliability regarding future climate change-driven groundwater recharge changes cannot be investigated by comparison to observation data. We assume in our study, as it is usually done in multi-model climate change assessments, that all models are considered to be equally reliable.*

(3) provide some model parameters for some region.

> *We now explain more clearly that our study has been conducted in the framework of an established protocol (ISIMIP) and where to find more information about the models' parameterisation. A regional discussion (also for only one region) of parameters would require a different study setup that would require the concerted work of multiple model development teams over an extended timeframe, delaying the publication by years. Due to the complexity of daily simulations with multiple complex hydrological models (and different climate scenarios), truly knowledge-based statements about sensitivities in specific regions go well beyond the paper's scope.*

We want to emphasise that our rebuttal does not originate from an unwillingness to accept the reviewers' well-founded concerns but from our conviction of what is possible and what we deemed to be the core messages of the manuscript: (1) the inclusion of vegetation processes can substantially change the projection of groundwater recharge changes, (2) the estimation of recharge varies largely in-between models and requires further investigation, and that while (3) taking into account the model disagreements statistical significant changes of global groundwater recharge can be observed for specific regions under different global warming levels.

The following lists all comments of the two reviewers and our rebuttal in *italics*. Attached is a markup document that highlights the changes compared to the last submitted revision. Line numbers refer to the revised version of the document.

#1

1.1

3 reviewers have provided their insights in the first round. I strongly agree with reviewer 3 in the sense that the study is at its early stage and there are several things to be addressed. The reviewer raised some important and key points that the authors missed to address. I will advise the authors to address these issues (e.g. the use of groundwater recharge and the large uncertainties of their results). The authors would rather focus on fluxes and water storages which is what these models are actually simulating or clarify that they are showing an effective recharge, not the actual recharge, which is much more complex.

We agree that our work shows that global groundwater recharge in GHMs is still uncertain and needs to be investigated further. This is one of the main contributions of the paper and clearly stated.

Regarding the precise definition of the term "groundwater recharge", none of the models simulates the depth of the groundwater table beneath the land surface. Hoping to understand the reviewer correctly, we would agree that our models do not compute the actual timing of the groundwater recharges and in that sense not the "actual groundwater recharge", in particular, if the groundwater table is very deep. Therefore, the groundwater recharge response at the location of the groundwater table to climate change may be delayed in case of deep groundwater table occurring in particular in dry regions of the globe. We now explain this caveat in section 2.1:

*[132 ff]: "*We do not consider focused recharge in this study as no model offers a reliable implementation of these processes until now. Also, none of the models simulate he depth of the groundwater table beneath the land surface which does not allow to correctly attribute delays in recharge due to water table depth."

Overall we are convinced that it is time to do a study that aims to understand the best information we have on potential impacts of climate change on groundwater at the global scale, which is provided by the multi-model ensemble output analysed in this study. Our study's merit is similar to many climate change studies done with global climate models used in combination to impact models (e.g. global hydrological models to study climate change impacts on streamflow or global crop models to study impact of climate change on yield). It is well known that uncertainty of groundwater recharge estimates are high, in particular at the global scale, and that different global climate models project very different *future climatic changes in response to the same greenhouse gas emissions scenario; nevertheless, model-based assessments including an understanding of their uncertainties are of interest to many and inform decision-making regarding climate change mitigation and adaptation. We explicitly wanted to focus on uncertainties and not (impossible) predictions, which is also reflected by our manuscripts' title: "Uncertainty of simulated groundwater recharge …". The manuscript is also very clear that the implementation of recharge varies greatly in-between the models and may or may not include different specific recharge processes. Our study goes well beyond the current state-of-the-art (e.g. Döll and Fiedler, Swenson et al. (2015) or Portmann et al. 2013). Unlike Portmann et al. (2013), where only one global hydrological model was applied, this study is the first to include the uncertainties stemming from different global hydrological models and how they simulate evapotranspiration and thus also groundwater recharge.*

1.2

Reviewer 3 also suggested comparing GHMs against fully integrated hydrologic models that simulate recharge processes, but the authors failed to do so. It would be great to compare in some areas how their models performed compared to the integrated hydrologic models. These models are now run on a continental scale. The model outputs could also be compared to some global datasets to ensure that they are at least consistent with observations at this scale and resolution.

Parallel to our last response, we agree that such a comparison would be tremendous and should be targeted in future studies. However, implementing such a comparison in the current manuscript would go greatly beyond the paper's scope because a comparative framework (in terms of input data and modelling protocol) would be required. It is also essential to distinguish the capability of models to computed groundwater recharge during a historical time span from their capability to estimate changes of groundwater recharge due to climate change. The latter would be required to "validate" our study and is much more challenging. A future study might combine historical observations of groundwater recharge, integrated models and GHMs as driven by observational input data. We have added this to the outlook.

We have added the following text to the Discussion (after comparison to the independent global-scale estimate of Mohan et al.

[522]: "It is also important to distinguish the capability of models to computed groundwater recharge during a historical period from their capability to estimate changes of groundwater recharge due to climate change. A model that simulates the current groundwater recharge pattern correctly may be incapable of computing future groundwater recharge if it cannot correctly simulate the impact of climate change and changing atmospheric CO2 concentrations on actual evapotranspiration correctly".

1.3

The topic of this paper is relevant to the community. The authors mostly presented a bunch of results without explaining in detail why we are observing the changes and what is driving these changes, the most expecting part of this kind of study. In addition, the authors miss the opportunity to discuss the setting up of their models (initial conditions, parameterisation, etc.), model validation is also an important step in modeling.

Each of the presented models is very complex and describing the parameterisation, validation, initial conditions etc. of only one model is challenging. For example, see the most up to date descriptions of WaterGAP (https://gmd.copernicus.org/preprints/gmd-2020-225/) and PCR (https://gmd.copernicus.org/articles/11/2429/2018/). Summarising these descriptions of all models go well beyond the scope of this paper. We have cited all relevant publications that describe the models and their setup in the paper and summarised the implementation of the process we are focusing on (recharge). Everything beyond that is a review paper with a different focus.

*A paper that strives to summarise the model structure and parameterisation of all models that are considered in the study is now in review (*Telteu et al., 2021*). We have added this citation and clarified the parameterisation of the models. See also #1.7 for the altered text and #1.4 for an explanation regarding the drivers of change.*

1.4

Understanding what is driving the processes and the observed changes should be the key output of this study, this will advance not only our knowledge on the uncertainties associated with the simulated groundwater responses to climate change but also how can we reduce these uncertainties.

By assessing to what degree the projected groundwater changes depend on whether the global hydrological models take into account process related to an active vegetation (e.g. closing of stomata and/or at higher atmospheric CO2) is an attempt to understand the drivers of changed evapotranspiration and thus groundwater recharge. We agree that we need a more detailed understanding of the uncertainties and what processes contribute to them. A further attempt for a better understanding is the already mentioned model review of Telteu et al. (2021) that enables insights into the process representations of those models. Future work will need to extend the review of Telteu et al (2021) and the data analysis as shown here by applying extensive sensitivity methods even though this is a very challenging task and demands for new methods that currently do not exist for these complex models. This is now more clearly reflected in the conclusions:

[Last line] "Simulation of groundwater recharge in global models and the connected uncertainties need to be analysed in greater detail by, e.g., the application of extensive sensitivity analysis."

1.5

The authors have done tremendous work to develop such a global modeling framework. I would recommend the authors to thoroughly revise their paper, discuss the use of groundwater recharge, provide some explanations in the uncertainties they are observing, and compare these uncertainties to the ones associated with evapotranspiration.

Thank you for the encouraging comment. We need to state that the modeling framework is not specifically dedicated to compare simulated groundwater recharge but to assess the impact of climate change on a large number of hydrological variables such a total runoff or floods. This study is the first *impact multi-model assessment of groundwater recharge from the "Inter-Sectoral Impact Model Intercomparison Project" (ISIMIP, www.isimip.org). The setup of the framework is discussed in described in* Frieler et al. (2018): *https://gmd.copernicus.org/articles/10/4321/2017/ as cited in the manuscript.*

Regarding the term groundwater recharge, please refer to our answer to 1.1. Explanations of the uncertainties and their possible explanations are thoroughly laid out in the discussion section of the manuscript. To address this comment, we have further extended the discussion which now also compares the described uncertainties to the ones associated with evapotranspiration (see also Wartenburger *et al* (2018)*; https://iopscience.iop.org/article/10.1088/1748-9326/aac4bb for and extended discussion of evapotranspiration in ISIMIP).*

[517 now reads] "Further, important processes like evaporation, infiltration, percolation, or runoff and GWR separation are implemented with different equations and simplifications. For evapotranspiration, a standard deviation of 0.15 mm day^{-1} globally for 1989–2005 was found in the ISIMIP ensemble (Wartenburger et al., 2018)."

1.6

1. The table added in the revised manuscript is very helpful. Nonetheless, I will make the table clearer without text. The authors should also clearly discuss the differences in the processes resolved by these models.

It is unclear what the referee refers to here. Would the table be clearer with or without text? And is that related to the text within the table or the text that describes the table? The differences in implementation of the processes (We assume the referee refers to vegetation and recharge processes) are presented in the discussion section of the manuscript. We, however, recognise that a more extensive investigation in the uncertainties is merited. We state that now more clearly in the conclusions. See also #1.4 and #1.1.

1.7

2. The authors should dedicate a section to discuss the types of data they use to build their models. Did they use the same datasets for all these models? How did they initialise their models? Before jumping into model comparisons, one needs to clearly understand the differences in the model parameters and initialisations. The authors discuss the climate simulations but since their paper is focused on groundwater recharge, it is the groundwater models and their uncertainties in computing the recharge that needs to be discussed.

Again, we need to refer to the setup of the study clearly explained in the introduction of the paper that states that this assessment was conducted in the framework of the ISIMIP intercomparison protocol. It is likely that the referee assumes that this ensemble was only setup to compare groundwater recharge. See also our reply in #1.5. We further clearly stated that ensembles from this particular project have used for multiple other impact assessments "The ISIMIP2b ensemble has already been used in multiple climate change studies investigating, e.g., flood risk (Willner et al., 2018; Thober et al., 2017; Alfieri et al., 2017), low flows in Europe (Marx et al., 2018), evapotranspiration (Wartenburger et al., 2018), runoff and snow in Europe (Donnelly et al., 2017) or multi-sectoral impacts (Byers et al., 2018)."

We have updated this with recent publications and it now reads [105]:

"The ISIMIP2b ensemble has already been used in multiple climate change studies investigating, e.g., flood risk (Willner et al., 2018; Thober et al., 2017; Alfieri et al., 2017), low flows in Europe (Marx et al., 2018), evapotranspiration (Wartenburger et al., 2018), runoff and snow in Europe (Donnelly et al., 2017), drought severity (Pokhrel et al., 2021), heat uptake by inland waters (Vanderkelen et al., 2020) or multi-sectoral impacts (Byers et al., 2018; Lange et al., 2020)."

Please see also our responses to #1.3 and #2.2.

We have clarified where information on the parameterisation can be found:

[125 ff] "A comprehensive overview of GHMs and their properties can be found in Sood and Smakhtin (2014). Detailed model descriptions and evaluations of the models can be found in the primary publications referred to in the subsections below and Telteu et al. (2021) (for the model parameterisation see Sect. 2.2.)."

1.8

3. The outcome of the climate simulations should also be discussed in the paper to have an idea of how key forcing variables change over time and have a clear view of what should be expected in terms of groundwater changes.

The primary variable driving the results is precipitation which was assessed for two RCPs in Fig 7. However, the GCMs from CMIP5 considered in the ISIMIP framework differ both in space and time and per variable. A proper assessment of the GCM output data is clearly out of the scope of this study and not necessarily connected with the groundwater recharge simulation in the hydrological model (as the GHMs differ in terms of input variable requirements). Such an assessment could only be determined with an extensive extra study. An extensive analysis of the sensitivity of groundwater recharge simulation to changes in climate input is of course very interesting but out of scope of this study but might be targeted in future research. See also #1.4.

1.9

4. The authors discuss the trends they observed in the figures but there is no explanation about the drivers of these trends. One can expect to know why a region sees a high increase in groundwater recharge and other regions not. The sensitivity of a region to these changes should be discussed in this paper. These sensitivities are linked to the physical parameters of the region, these parameters aren't presented to it is really hard to understand the response of the region.

Based on our general experience with the quantification of climate change impacts on hydrological variables, we believe that a region sees a high increase in groundwater recharge because there is a very high increase in precipitation, while without a rather high increase in precipitation, a region will not see any increase. However, to understand how groundwater recharge in different regions would react to the same changes in climate would require a different study setup. Such an analysis would require the concerted work of the various model developers and a well thought through sensitivity analysis setup, due to the complexity of daily simulations with multiple complex hydrological models (and different *climate scenarios). Truly knowledge-based statements about sensitivities go well beyond the scope of the paper (see also #1.4). This study is the first of its kind investigating the impacts of CO2 changes on recharge on a global scale, which is of interest to the research community (#1.1 the reviewer agrees) but has not been examined in other studies yet. It thus lays the groundwork for future studies that may include the research suggested by the reviewer.*

1.10

5. Differences observed between different models should also be discussed and explained, these differences may be related to the processes that these models are reproducing among others.

We agree that the differences in model output relate to the differences in model implementation as discussed in the discussion section of the manuscript together with the comparison to Mohan et al. Dataset. Indeed, future research needs to investigate these differences further; this manuscript however is a start of such an assessment. We have contributed to a better understanding on how a changing climate impacts recharge by extensively discussing the effects of CO2 on the simulation of this process on large scales.

1.11

6. Investigating the impact of CO2 on groundwater is a very important topic, and there is a lot of interest in the community to understand to what extent accounting for CO2 in hydrology impact the projected changes in groundwater. Nonetheless, as for the other results, the authors should provide an explanation about why a particular area sees a high impact and other areas not.

We thank the referee for the agreement that investigating the CO2 effect is important. Nevertheless, we think that we have provided insights to the question raised by the referee. Figure 7 shows how particular regions differ in their response to modeled vegetation productivity. And the already existing paragraph below provides and explanation on why we see these differences:

"Decreases in precipitation may lead to a decrease in vegetation productivity (if not counteracted by an increased water-use efficiency due to elevated CO2 concentrations (Singh et al., 2020)) and thus to a decrease in transpiration. GHMs assume shares for evapotranspiration (ET) in relation to potential ET and the available precipitation. In contrast, transpiration in CO2-driven models responds to active vegetation as well as the relations between different water flux components that simpler GHMs do not. This can explain why the dynamic vegetation models exhibit inter-model regional differences in the GWR response to P decrease. Further, some models (MATSIRO) may not calculate LAI (leave area index), which impacts transpiration. For models with active vegetation, the increase in water use efficiency due to stomatal conductance (also referred to as CO2 fertilisation) can compensate for the decrease in precipitation to some extent, making more water available for groundwater recharge as compared to the GHMs (Table 1). Though in some regions, as seen in Figure 7 (and Fig. S10), this feedback is not enough to overcome the warmer and drier climate in terms of groundwater flux."

Please also see our answer to #1.9 why a regional assessment of drivers is a challenging exercise that is not easily added.

1.12

7. Given the types of models (not fully integrated hydrologic models) that the authors used, the uncertainties they are observing are likely tied to the uncertainties in the estimation of evapotranspiration. It would be great to discuss evapotranspiration first then the impacts on recharge and analyse how these two uncertainties differ.

We agree that an assessment of uncertainties of AET in the GHMs and how changes in AET relate to changes in GWR would undoubtedly be interesting to understand the differences in model behaviors better. However, we do not believe that such a quantification of AET changes and their uncertainties would be helpful to those who need to adapt to climate-driven groundwater changes which is the proposed main audience of our study. What we do in our study to account for this important discussion is that we investigate the differences between models with active vegetation and without to make the reader understand that future changes in groundwater recharge strongly depend on estimates of AET.

We added the line [463]: "Overall, the capability of a model to simulate actual ET largely influences its capability to simulate groundwater recharge."

#2

The manuscript deals with an important issue: the uncertainty on future groundwater recharge (GWR) due to climate change. This uncertainty is estimated using eights different global hydrological models (GHMs) and the outputs of four global circulation models (GCMs). I will not go into the debate of using GHMs instead of fully integrated physically based hydrologic models (IPHMs), even if the uncertainty would have been better estimated by using models with significant differences in their philosophy and conceptions. GHMs are valuable tools and the provided results are a good estimate of uncertainty in GWR at a global scale under this framework. Therefore, the manuscript is of a very good scientific level and suitable for publication in HESS.

Thank you for the encouraging comment and the overall positive evaluation.

2.1

1. The reliability of the GHMs is not convincingly described. A section should be dedicated to the description of the ability of GHMs to simulate real situations on different sites over the world. It should not be an exhaustive description of GHMs applications to real sites, but some examples found in the literature of different GHMs simulations of large scale watersheds under different climatic conditions. If GHMs are not able to estimate water balances including GWR properly at the time scale used in this work and over the last decades, the interest of this work appears to be limited.

Model reliability regarding estimation on current global-scale groundwater recharge was evaluated by comparison to Mohan et al.. Other work has been investing the reliability of estimating groundwater recharge in GHMs as well e.g., for WaterGAP in Döll and Fiedler (2008) (also cited and discussed in this manuscript).

Reliability regarding future climate change driven changes in groundwater recharge cannot be investigated by comparison to observation data, and we assume in our study, as it is usually done in multi-model climate change assessments, that all models are considered to be equally reliable. Projected groundwater recharge changes certainly depend strongly on projected evapotranspiration changes, which is why we investigated the differences between GHMs that simulate the impact of active vegetation on evapotranspiration (thus responding to atmospheric CO2 changes) and those that do not.

2.2

2. I missed GHMs parameters. Please provide an insight on models parameterisation.

We thank the referee for pointing out that parameterisation is important. We have revised this by now stating more clearly where the model inputs are coming from and where more information can be found (see also our answer to referee 1).

Groundwater recharge depends on parameterisations of canopy, snow and soil water balances as well as, e.g., assumed equations for potential evapotranspiration, we cannot provide more details beyond what is provided in section 2.1 specifically for groundwater recharge. We did add a sentence as provided in our answer to comment 1.7.

2.3

The last sentence in the abstract is awkward and has to be more specific. You cannot write 'additional research on simulating groundwater processes in GHMs is necessary' and use GHMs to estimate recharge.

The last sentence is now more specific and reads:

"Overall large uncertainties in the model outcomes suggest that additional research on simulating groundwater processes in GHMs is necessary."

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Uncertainty of simulated groundwater recharge at different global warming levels: A global-scale multi-model ensemble study

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Abstract. Billions of people rely on groundwater as an accessible source for drinking water and irrigation, especially in times of drought. Its importance will likely increase with a changing climate. It is still unclear, however, how climate change will impact groundwater systems globally and thus the availability of this vital resource. Groundwater recharge is an important indicator for groundwater availability, but it is a water flux that is difficult to estimate as uncertainties in the water balance accumulate, leading to possibly large errors in particular in dry regions. This study investigates uncertainties in groundwater recharge projections using a multi-model ensemble of eight global hydrological models (GHMs) that are driven by the bias-adjusted output of four global circulation models (GCMs). Pre-industrial and current groundwater recharge values are compared with recharge for different global warming (GW) levels as a result of three representative concentration pathways (RCPs). Results suggest that projected changes strongly vary among the different GHM-GCM combinations, and statistically significant changes are only computed for few regions of the world. Statistically significant GWR increases are projected for Northern Europe and some parts of the Arctic, East Africa and India. Statistically significant decreases are simulated in southern Chile, parts of Brazil, central USA, the Mediterranean, and southeast China. In some regions, reversals of groundwater recharge trends can be observed with global warming. Because most GHMs do not simulate the impact of changing atmospheric CO_2 and climate on vegetation and thus evapotranspiration, we investigate how estimated changes in GWR are affected by the inclusion of these processes. In some regions, inclusion leads to differences in groundwater recharge changes of up to 100 mm year^{-1}. Most GHMs with active vegetation simulate less severe decreases of groundwater recharge than GHMs without active vegetation and in some regions even increases instead of decreases. However, in regions where GCMs predict decreases in precipitation and groundwater availability is most important, model agreement among GHMs with active vegetation is lowest. Overall large uncertainties in the model outcomes suggest that a~~A~~dditional research on simulating groundwater processes in GHMs is necessary.

1 Introduction

The critical role of groundwater as an accessible source for irrigation and drinking water in particular during dry periods, droughts, and floods will intensify with climate change because increased precipitation variability is expected to decrease the reliability of surface water supply (Taylor et al., 2013; Döll et al., 2018; Kundzewicz and Döll, 2009). While demand for groundwater is likely to increase in the future, groundwater abstractions have already led to depleted aquifers in many regions around the globe (Thomas and Famiglietti, 2019; Cuthbert et al., 2019a; Wada et al., 2012; Konikow and Kendy, 2005; Döll et al., 2014b). They have also resulted in the reduction of groundwater discharge to rivers with negative impacts on water availability for humans and freshwater biota in particular during low-flow periods (Herbert and Döll, 2019). To what extent groundwater can serve for sustaining ecosystem health and for supporting human adaptation to climate variability and change strongly depends on future groundwater availability, which is strongly affected by climate change (Kundzewicz and Döll, 2009; Döll, 2009; Taylor et al., 2013; Cuthbert et al., 2019b).

Groundwater recharge (GWR) is a central indicator of potential groundwater availability (Herbert and Döll, 2019). GWR is the vertical water flux to the groundwater from the soil (diffuse GWR) and from surface water bodies (point or focused recharge) (Small, 2005). It is a function of the local climate, topography, soil, land cover, land use (urbanization, woodland establishment, crop rotation, and irrigation practices), atmospheric CO_2 concentrations, and geology (Small, 2005). Changes in GWR alter groundwater levels and their temporal patterns, which affect vital ecosystem services (Kløve et al., 2014). Knowledge of the dynamics and process interactions determining GWR is a fundamental prerequisite to assess groundwater quality and quantity under climate change (Green et al., 2011). The simulation of GWR is possibly one of the most challenging components of the water budget as it accumulates the uncertainties of all other components of the budget. Especially in semiarid regions, uncertainties in precipitation and evapotranspiration (Wartenburger et al., 2018)~~–~~ lead to considerable uncertainty in recharge. An additional factor in estimating groundwater recharge is the simulation of the groundwater table and thus capillary rise and focused recharge. This has not been achieved yet in GHMs, however, recently, global hydrological models (GHMs) started integrating gradient-based groundwater models to better estimate the flows between surface water and groundwater as well as the impact of humans and the changing climate on the groundwater system (de Graaf et al., 2019;

Reinecke et al., 2019). Neglecting capillary rise may lead to an overestimation of decreases and increases of GWR due to a changing climate.

Assessing the response of GWR to climate change is difficult even at the local scale, one of the reasons being that groundwater recharge, different from streamflow, is rarely measured, and long time series of groundwater recharge are not available (Earman and Dettinger, 2011). In local groundwater modelling, groundwater recharge is often determined by calibration using hydraulic head observation, while integrated modelling relies on the partitioning of precipitation into evapotranspiration, storage change, and runoff (GWR plus surface and subsurface runoff). Moreover, projections of GWR often neglect the impact of changing climate and higher CO_2 levels on plants and thus evapotranspiration and GWR (Taylor et al., 2013). With higher CO_2 levels, terrestrial plants open their stomata less, which reduces evapotranspiration and increases runoff (physiological effect) while they might grow better, increasing evapotranspiration (structural effect) (Gerten et al., 2014). Vegetation models that include these effects disagree about the balance of both effects (Gerten et al., 2014). However, based on a large ensemble of GCMs that include the impact of CO_2 and changing climate on vegetation and evapotranspiration, rising CO_2 can be expected to decrease transpiration and thus increase total runoff (Milly and Dunne, 2016). Therefore, GHMs that do not consider active vegetation may underestimate runoff, and thus GWR increases, or they may overestimate GWR decreases.

While there have been review articles on the relation of groundwater and climate change (Smerdon, 2017; Jing et al., 2020; Refsgaard et al., 2016), global-scale studies that quantify the impact of climate change on GWR are rare. They have evolved regarding the way climate scenarios were implemented and how many global climate models (GCMs) and GHMs were included in the study. While Döll (2009) could only use the delta change method to integrate information from two GCMs in the GHM WaterGAP (Alcamo et al., 2003; Müller Schmied et al., 2014), Portmann et al. (2013) could feed their simulations of future changes in GWR with WaterGAP directly by the bias-adjusted output with five GCMs. They found that changes in GWR increase with increasing greenhouse gas emissions. Acknowledging that not only GCMs but also GHMs contribute to the uncertain translation of emissions scenarios to changes in GWR (Moeck et al., 2016), the study of Döll et al. (2018) included two GHMs (WaterGAP and LPJmL, Rost et al. (2008), Schaphoff et al. (2013)) driven by the bias-adjusted of four GCMs. They evaluated relative changes of GWR with climate change, which can arguably serve as a better indicator of climate change hazard than absolute changes of GWR. On the other hand, the usage of relative change led to the result that change in GWR could not be reliably computed for 55% of the global land area due to very small GWR for the reference period simulated by LPJmL (Döll et al., 2018). While the LPJmL model considered, different from the WaterGAP model, the effect of rising CO_2 on groundwater recharge, the impact of this on GWR projections were not analyzed in Döll et al. (2018). In general, studies investigating the difference between GHMs with and without dynamic vegetation are rare (Davie et al., 2013).

This study assesses the impact of climate change on GWR based on the output of a multi-model ensemble encompassing eight GHMs, each forced by the bias-adjusted output of four GCMs under three different representative concentration pathways (RCPs). The ensemble was generated in the framework of the Inter-Sectoral Impact Model Intercomparison Project (ISIMIP) using simulation protocol ISIMIP2b (Frieler et al., 2017). The ISIMIP global water sector incorporates global models, including water resources models, land surface models, and dynamic vegetation models that can compute water flows and storages on the continents of the Earth; in this study, all three model types are referred to as GHMs. The ISIMIP2b ensemble has already been used in multiple climate change studies investigating, e.g., flood risk (Willner et al., 2018; Thober et al., 2017; Alfieri et al., 2017), low flows in Europe (Marx et al., 2018), evapotranspiration (Wartenburger et al., 2018), runoff and snow in Europe (Donnelly et al., 2017), drought severity (Pokhrel et al., 2021), heat uptake by inland waters (Vanderkelen et al., 2020) or multi-sectoral impacts (Byers et al., 2018; Lange et al., 2020).

We analyze how GWR is projected to change globally and regionally for multiple global warming (GW) levels, determine the contributions from GHMs and GCMs to the variance of simulated changes and discuss the implications for future assessments of global groundwater resources. Furthermore, we show the effect of including the physiological impacts of evolving CO_2 on global estimates of GWR. To this end, the remainder of this paper is structured as follows. Section 2 provides an overview of the used GHMs and the methods to calculate changes of GWR per GW level and sources of uncertainty. The results in section 3 show the significant changes in GWR per GW and the differences in between GHMs and GCMs. We then compare the influence of GCMs, GHMs, and RCPs on the variance of simulated GWR, assess the differences in GWR due to including dynamic vegetation in GHMs and compare the GHM simulations to interpolated measured GWR. The paper closes with a discussion of these findings (Sect. 4) and conclusions (Sect. 5).

2 Methods

2.1 Simulation of groundwater recharge

This study encompasses eight GHMs that differ in their representation of various hydrological processes. Four of these models~~, described in more detail in the following,~~ are able to simulate the impact of evolving CO_2 concentrations on vegetation: CLM 4.5, JULES-W1, LPJmL, MATSIRO (Table 1). In the following, we use the term *active vegetation* for models that consider the physiological effect of changes in CO_2 on vegetation and the term *dynamic vegetation* for the models that allow for changing vegetation regarding LAI and/or vegetation type. A comprehensive overview of GHMs and their properties can be found in Sood and Smakhtin (2014)~~ and~~. Detailed model descriptions and evaluations of the models can be found in the primary publications referred to in the subsections below and Telteu et al. (2021) (for the model parameterisation see Sect. 2.2.).~~Detailed model descriptions and evaluations of the models can be found in the primary publications referred to in the subsections below and Telteu et al. (2021, in review) (for the model parameterization see Sect. 2.2..).~~ The definition of GWR and groundwater varies in between GHMs (discussed in Sect. 4). The analysis in this study is based on monthly GWR (variable *qr* in ISIMIP) in 0.5° x 0.5° grid cells simulated by the eight GHMs taking part in the ISIMIP2b protocol (Frieler et al., 2017). Some GHMs contained small negative GWR values, e.g., due to capillary rise; these values were set to zero in the analysis. We do not consider focused recharge in this study as no model offers a reliable implementation of these processes until now. Also, none of the models simulate he depth of the groundwater table beneath the land surface which does not allow to correctly attribute delays in recharge due to water table depth.

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Table 1 Overview which models are able to simulate the impact of evolving CO_2 concentrations on vegetation and how it is implemented.

GHM	Considers CO_2	Summary of considered vegetation processes in ISIMIP2b	Reference
WaterGAP2	No	-	-
CLM4.5	Yes	Photosynthesis depends on root zone soil moisture availability. The description is similar to LPJmL listed below. The area a population of plant functional types (PFTs) takes up is prescribed and only changes if the input data changes.	(Di Liu and Mishra, 2017)
H08	No	-	-
JULES-W1	Yes	Evapotranspiration is considered from five PFTs and four non-vegetative surface types. Each grid cell is composed of different fractions of those nine surface types. Transpiration occurring from vegetation is based on photosynthetic process, which is subject to stomatal conductance regulated by the CO_2 concentration. Furthermore, transpiration is also controlled by soil moisture availability in the root zone.	(Best et al., 2011; Clark et al., 2011)
LPJmL	Yes	Vegetation composition is determined by the fractional coverage of PFTs at the grid-scale. PFTs are defined to account for the variety of structure and function within a stand and are therefore simulated as average individuals competing for light and water according to their crown area, LAI, and rooting profiles. The vegetation dynamics component of LPJmL includes carbon allocation to different PFT tissue compartments, PFT interaction, and establishment and mortality processes. Photosynthesis and stomatal response are simulated following Farquhar et al. (1980) and the generalization by Collatz et al. (1991) for global modelling, based on the function of absorbed photosynthetically active radiation, temperature, day-length, and canopy conductance for each PFT present in a grid cell.	(Schaphoff et al., 2018)
PCR-GLOBWB	No	-	-
CWatM	No	-	-
MATSIRO	Yes	The consideration of CO_2 effects is functionally similar to that in CLM, and there is no dynamic vegetation scheme. CO_2 is prescribed in the model, which is used in the photosynthesis scheme to calculate stomatal conductance, among other parameters, following Farquhar et al. (1980). Soil moisture stress on photosynthesis is considered using moisture availability in the root zone with root distribution fraction in each soil layer. All of that is done for different vegetation or plant functional types.	(Takata et al., 2003)

WaterGAP2

The WaterGAP2 model (Alcamo et al., 2003) computes human water use in five sectors and the resulting net abstractions from groundwater and surface water for all land areas of the globe, excluding Antarctica. These net abstractions are then taken from the respective water storages in the WaterGAP Global Hydrology Model (WGHM) (Müller Schmied et al., 2014; Döll et al., 2003; Döll et al., 2012; Döll et al., 2014b). With daily time steps, WGHM simulates flows among the water storage compartments canopy, snow, soil, groundwater, lakes, human-made reservoirs, wetlands, and rivers. GWR in WaterGAP2 is calculated as a fraction from runoff from land-based on soil texture, relief, aquifer type, and the existence of permafrost or glaciers, taking into account a soil texture dependent maximum daily groundwater recharge rate (Döll and Fiedler, 2008). If a grid cell is defined as semiarid/arid and has a medium or coarse soil texture, GWR will only occur if daily precipitation exceeds a critical value (Döll and Fiedler, 2008); otherwise, the water runs off. Runoff from land that does not contribute to GWR is transferred to surface water bodies as fast surface runoff. WaterGAP further computes focused recharge beneath surface water bodies in semiarid/arid grid cells, which is not considered in this study.

CLM4.5

The Community Land Model version 4.5 (CLM4.5) (Lawrence et al., 2011; Oleson et al., 2013; Swenson and Lawrence, 2015) is the land component of the Community Earth System Model (CESM), a fully-coupled, state-of-the-art earth system model (Hurrell et al., 2013). CLM is a land surface model representing the physical, chemical, and biological processes through which terrestrial ecosystems influence and are influenced by climate, including CO_2, across a variety of spatial and temporal scales (Lawrence et al. 2011). Individual land grid points can be composed of multiple land units due to the nested tile approach, which enables the implementation of multiple soil columns and represents biomes as a combination of different plant functional types. Groundwater processes, including sub-surface runoff, recharge, and water table depth variations, are simulated based on the SIMTOP scheme (Niu et al., 2007; Oleson et al., 2013).

H08

H08 (Hanasaki et al., 2018) is a GHM including various components for water use and management. It consists of five major components, namely, a simple bucket-type land surface model, a river routing model, a crop growth model which is mainly used to estimate the timing of planting, harvesting, and irrigation in cropland, a reservoir operation model, and a water abstraction model. The abstraction model supplies water to meet the daily water demand of three sectors (irrigation, industry, municipality) from six available and accessible sources (river, local-reservoir, aqueduct, seawater desalination, renewable groundwater, and non-renewable groundwater) and one hypothetical one termed unspecified surface water. It has two soil layers; one is to represent the unsaturated root zone, and the other the saturated zone (groundwater). The scheme of GWR computation is identical to Döll and Fiedler (2008).

JULES-W1

The Joint UK Land Environment Simulator (JULES) (Best et al., 2011) (W1 stands for water-related simulations in the ISMIP framework) is a land surface model initially developed by Met Office as the land surface component of Met Office Unified Model. JULES is a process-based model that simulates the carbon, water, energy, and momentum fluxes between land and atmosphere, including plant - carbon interactions (Clark et al., 2011). The rainfall that reaches the ground is partitioned into hortonian surface runoff and an infiltration component. Four soil layers represent the soil column with a total thickness of 3 m, with a unit hydraulic head gradient lower boundary condition, and no groundwater component. The water that infiltrates the soil moves down the soil layers updated using a finite difference form of the Richards equation (Best et al., 2011). The saturation excess water from the bottom soil layer becomes subsurface runoff that can be considered to be GWR (Le Vine et al., 2016).

LPJmL

Lund Potsdam Jena managed Land (LPJmL) is a dynamic global vegetation model that simulates the growth and productivity of both natural and agricultural vegetation as coherently linked through their water, carbon, and energy fluxes (Schaphoff et al., 2018). The soil column is divided into six active hydrological layers with a total thickness of 13 m depth. Percolation of infiltrated water through the soil column is calculated according to a storage routine technique that simulates free water in the soil bucket (Arnold et al., 1990). Excess water over the saturation levels produces lateral runoff in each layer (subsurface runoff). GWR is considered to be percolation (seepage) from the bottom soil layer. As there is no groundwater storage in LPJmL, for the ISIMIP2b protocol, seepage from the base soil layer is reported as both GWR and groundwater runoff, which is routed directly (no time delay) back into the river system.

PCR-GLOBWB

PCR-GLOBWB (PCRaster Global Water Balance; (Sutanudjaja et al., 2018) simulates the water storage in two vertically stacked soil layers and an underlying groundwater layer. Water exchanges are simulated in-between the layers (infiltration, percolation, and capillary rise) as well as the interaction of the top layer with the atmosphere (rainfall, evapotranspiration, and snowmelt). PCR-GLOBWB also calculates canopy interception and snow storage. Natural groundwater recharge is fed by net precipitation, and additional recharge from irrigation occurs as the net flux from the lowest soil layer to the groundwater layer, i.e., deep percolation minus capillary rise. The ARNO scheme (Todini, 1996) is used to separate direct runoff, interflow, and GWR. Groundwater recharge can be balanced by capillary rise if the top of the groundwater level is within 5 m of the topographical surface (calculated as the height of the groundwater storage over the storage coefficient on top of the streambed elevation and the sub-grid distribution of elevation).

CWatM

The Community Water Model (CWatM) is a large-scale integrated hydrological model, which encompasses general surface and groundwater hydrological processes, including human hydrological activities such as water use and reservoir regulation (Burek et al., 2019). CWatM takes six land cover classes into account and applies the tile approach. This hydrological model has three soil layers and one groundwater storage. Depth of the first soil layer is 5 cm, and the depth of second and third layers vary over grids depending on the root zone depth of each land cover class, resulting in total soil depth of up to 1.5 m. Groundwater storage is designed as a linear reservoir. CWatM includes preferential bypass flow directly into groundwater storage and capillary rise from groundwater storage, as well as percolation from the third soil layer to groundwater storage. Hence, the groundwater recharge reported by CWatM in ISIMIP2b is the net recharge calculated from these three terms.

MATSIRO

The Minimal Advanced Treatments of Surface Interaction and RunOff (MATSIRO; Takata et al. (2003)) is a global land surface model initially developed for an Atmospheric Ocean General Circulation Model, the Model for Interdisciplinary Research On Climate (Hasumi, H., and S. Emori, 2004). This process-based model calculates water and energy flux and storage at and below the land surface, considering the stomatal response to CO_2 increase as well in the photosynthesis process. The off-line version of MATSIRO used for ISIMIP2b simulation explicitly takes vertical groundwater dynamics into account, including groundwater pumping (Pokhrel et al., 2015; Pokhrel et al., 2012). Soil moisture flux between the 15 soil layers is expressed as a function of the vertical gradient of the hydraulic potential, which is the sum of the matric potential and the gravitational head, and soil moisture movement is calculated by Richards equation. MATSIRO calculates net groundwater recharge as a budget of gravitational drainage into and capillary rise from the layer where the groundwater table exists. A simplified TOPMODEL (Beven and Kirkby, 1979; Stieglitz et al., 1997) is used to represent surface runoff processes, and groundwater discharge is simulated by using an unconfined aquifer model (Koirala et al., 2014).

2.2 Model simulations

Each GHM is forced by bias-adjusted data from four GCMs: GFDL-ESM2M, HadGEM2-ES, IPSL-CM5A-LR, and MIROC5. Further details on the selection of climate models and the bias correction can be found in Frieler et al. (2017), Lange (2016), Hempel et al. (2013), Lange (2018), and online at ISIMIP (2018). The bias adjustment method used for the GCMs in ISIMIP2b is using a trend preserving algorithm (Frieler et al., 2017) with EWEMBI (Lange 2018) as baseline (reference) climate condition. The simulations in this study span the period 1861 till 2099. All GHMs (except for PCR-GLOBWB, which misses the RCP 8.5 run) simulate the RCPs 2.6, 6.0, and 8.5.

The pre-industrial period (PI) is defined in ISIMIP from 1661-1860, whereas the historical period is defined from 1861-2005. Additionally, to the RCP and historical simulations, ISIMIP defines PI simulations that represent an extended state of emissions scenarios from the PI period till 2099 (and partially till 2300, not applicable in this study). In this study, we always, if not stated otherwise, refer with PI to the simulation period 1960-2099 with the continued concentration levels of 1661-1860. Details on the simulation setup can be found on the ISIMIP webpage ISIMIP (2019) or in Frieler et al. (2017).

Regarding the non-climatic drivers, all GHMs use, for the time before 2006, so-called historical socio-economic pathway assumptions, e.g., historical water use, except for CLM 4.5, which used the socio-economic state of 2005. All simulations for 2006-2099 are based on this assumed socio-economic state of 2005. For some models this affects the abstraction from groundwater, which is not stimulated by all models (JULES-W1), or GWR directly due to irrigation (H08, CLM, PCR-GLOBWB). Details on the pertinent scenario variables can be found in the ISMIP protocol (Frieler et al., 2017). Land-use change was not considered.

2.3 Determining stabilized warming levels

In order to derive policy-relevant information, we assed impacts framed in terms of GW levels (1°, 1.5°, 2°, and 3°C) with respect to the GW of 0°C in PI conditions (James et al., 2017). The time of passing a warming level is defined as the first time the 31-year running mean of the global averaged annual mean temperature gets above that level. Each GCM reaches different GW at different times (Table 2), depending on the RCPs (van Vuuren et al., 2014). For each GW level (1°, 1.5°, 2°, and 3°C), time slice of 31 years (15 before the level was reached, and 15 after) for each GCM and for each RCP, in which that GW is reached, are used. Using this time slice, a yearly mean GWR at 0.5° was calculated for the GHMs that were forced with the particular combination of GCM and RCP~~.~~ (Fig. 1). Additionally, a PI reference was calculated for each GCM, RCP, and GHM combination for the same time-slice the GW level was reached in a particular RCP-GCM combination using the PI reference simulation (see section 2.2). Figure 1 illustrates the methodology by showing two unspecified RCPs and the PI comparison paths.

Considering that not all RCP/GCM combinations reach higher warming levels (Table 2~~1~~), not all ensembles have the same size. Theoretically, the maximum ensemble size is 96, a combination of 8 GHMs, 4 GCMs, and 3 RCPs (2.6, 6.0, and 8.5). Because projections under RCP 8.5 were not available for PCR-GLOBWB, the maximum ensemble size is 84. The smallest ensemble (for 3°C) consists of 36 members.

Table 2 Overview of the warming levels and in which year they are reached in the corresponding GCM (ISIMIP, 2019).

Warming Level	RCP	GFDL-ESM2M	HadGEM2-ES	IPSL-CM5A-LR	MIROC5
1°	2.6	2014	2012	1993	2015
	6.0	2016	2014	1993	2023
	8.5	2014	2012	1993	2014
1.5°	2.6	-	2026	2009	2048
	6.0	2056	2032	2010	2052
	8.5	2036	2025	2009	2033

2°	2.6 6.0 8.5	- 2076 2053	- 2050 2037	2029 2029 2024	- 2071 2048
3°	2.6 6.0 8.5	- - 2082	- 2076 2056	- 2068 2046	- - 2071

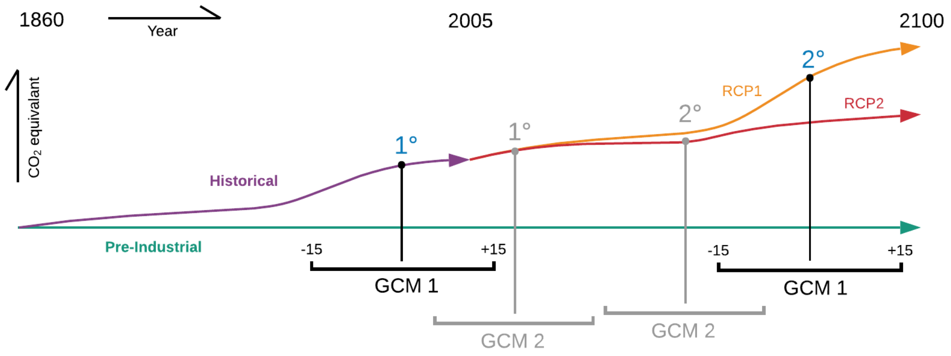

Figure 1 Conceptual representation of how GW levels are determined for different GCMs, RCPs, and the PI comparison period.

2.4 Calculation of model variance

To calculate whether the variance in absolute GWR change is mainly introduced through the GHMs or the GCMs, the following equation was applied per model grid cell and GW level.

$$Rvar_{GWR}^{model} = \sigma_{GWR}^{2}(GCMs) \Big/ \left(\sigma_{GWR}^{2}(GCMs) + \sigma_{GWR}^{2}(GHMs) \right) \qquad (1)$$

where $Rvar_{GWR}^{model}$ is the variance ratio of GCMs to GHMs, $\sigma_{GWR}^{2}(GHMs)$ is the average variance of GWR change of all GHMs per GCM per RCP, and σ_{GWR}^{2}(GCMs) is the average variance in GWR change of all GCMs per RCP per GHM. The variance relative to the choice in RCP $Rvar_{GWR}^{RCP}$ can be calculated similarly as

$$Rvar_{GWR}^{RCP} = \sigma_{GWR}^{2}(RCPs) \Big/ \left(\sigma_{GWR}^{2}(RCPs) + \sigma_{GWR}^{2}(GHMs) \right), \qquad (2)$$

where σ_{GWR}^{2}(RCPs) is the average variance in GWR of all RCPs per GCM per GHM.

2.5 Determining significant changes

A model ensemble allows us to consider the uncertainty in modeling physical processes as different model use different algorithms and parameters for computing groundwater recharge. To determine whether changes in GWR due to GW computed by the model ensemble are statistically significant, we used the two-sample Kolmogorov–Smirnov (K-S) test to compare the GWR values computed by all GHM-GCM model combinations under e.g., PI conditions with the values at the various GW levels. The use of a two-tailed t-test is not advisable in this setting due to the small sample size (max. 84 in this study). Because the K-S test does not allow to check whether the ensemble agrees on the sign of change in GWR, we applied an additional criterion to determine a significant change similar to Döll et al. (2018). A change is only marked as statistically significant if the K-S test indicates a significant difference and at least 60% of the model realizations of the ensemble (RCP, GCM and GHM combinations) agree on the sign of change (i.e. a decrease or increase). In case of a low significance, all models may show large responses to climate change while their agreement on the amount or sign of change is low.

3 Results

3.1 Changes of groundwater recharge at different warming levels

To assess the impact of GW on GWR, Fig. 2 shows the ensemble mean change of GWR between the current 1°C world and a potential 3°C GW. We chose to express changes as absolute change rather than relative change because zero, or close to zero, GWR in some regions of the world leads to not defined or extremely large percentage increases and decreases (Fig. S1 and S2). The model mean shows large decreases of over 100 mm year^{-1} in South America and in the Mississippi Basin and decreases of up to 50 mm year^{-1} in the Mediterranean, East China, and West Africa. Increases of over 100 mm year^{-1} are prominent in Indonesia and East Afrika. Individual GHM-GCM model combinations compute much larger changes.

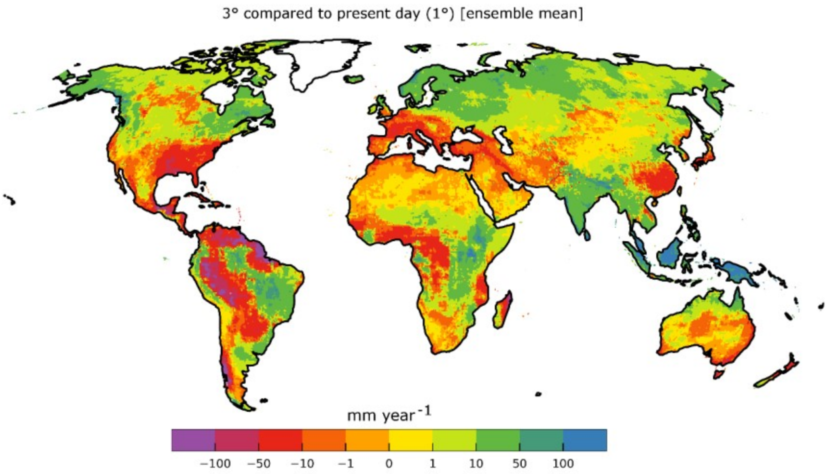

Figure 2 Ensemble mean change in GWR [mm year-1] between conditions of present day warming of 1 °C GW and at 3 °C GW, averaged over the GWR changes of all GHM-GCM model combinations.

Ensemble mean changes as shown in Fig.~~ure~~ 2 may be low in some areas, but this could be due to large positive changes compute by some GHM-GCM model combinations being cancelled by large negative changes by other model combinations. To assess the changes which show a high statistical agreement in-between the model combinations, we determine where computed changes of GWR are statistically significant (Section 2.5). As a reference for the intensity of the changes, Figure 3a shows the mean GWR at PI averaged over all GHMs, RCPs, and GCMs from 1861-2099. The spatial pattern of GWR roughly agrees with the pattern of Mohan et al. (2018) derived by inferring it from more than 700 small-scale GWR estimates. The global mean GWR for the PI period is 140 mm year^{-1}, which is very similar to the value of 134 mm yr^{-1} determined by Mohan et al. (2018) for the period 1981-2014 (see also Sect. 4~~3.4~~).

Figure 3b-e show the (statistical) significant (bright colors, Sect. 2.5) mean absolute changes in GWR of the multi-model ensemble under a GW of 1.0°C, 1.5°C, 2.0°C, and 3.0°C compared to PI, i.e., GWR of the PI runs for the corresponding time-slices (Sect. 2.3). For all GW levels compared to PI (Figure 3b-e), consistent patterns of decreasing GWR emerge for southern Chile, Brazil, central continental USA, the Mediterranean, and East China. Consistent and significant increases can be observed for northern Europe and in general northern latitudes and East Africa. Significant changes could only be derived for a small percentage of the total grid cells. Only about 15% of the cells, on average for all GW levels, show significant increases or decreases. However, the patterns of non-significant (light colors) mean changes are consistent with the significant changes and show, e.g., for the Amazon larger areas of increases and decreases around the significant changes. The identification of non-significance in most areas is due to the K-S test. The sign criterion affects mainly the Sahara and Central Asia.

At 1°C GW (Figure 3b), decreases of more than 100 mm year^{-1} are simulated in Southeast Asia, East China, Guyana, and southern Brazil. Decreases between 100 and 50 mm year^{-1} can be seen in central continental USA, southern Brazil, southern Chile, the Mediterranean, central Africa, and East China. Increases in GWR of 50 and over 100 mm year^{-1} are visible in the center of the Amazon while decreases show in the northeast and southern part that increase with GW. Overall, the significant global change is -17 mm year^{-1} at 1°C.

A 1.5°C GW shows only a limited increase in the Amazon but similar increases in the rest of the world. Decreases in GWR over 100 mm year^{-1} are now visible in Central America, but decreases for Southeast Asia have vanished. Smaller decreases, for example, in Australia, have vanished as well in a 1.5°C world. These effects are not necessarily due to no changes in GWR but due to disagreements in the ensemble that do not allow to determine a reliable and significant change for this warming level. The global significant mean change is -12 mm year^{-1} at 1.5°C GW.

At 2°C GW, increases in GWR over 100 mm year^{-1} are present in northern Java, Amazon, and East Africa. Decreases are similar to 1.5°C GW, except for southern Chile and the northern Andes, where decreases become more severe. However, on the significant global mean, these changes balance out to -1 mm year^{-1}.

In a 3°C world, large areas of decreases in GWR of over 100 mm year^{-1} in the Amazon Basin close to the Andes occur, also in Guyana, Venezuela, West Africa, and the Mississippi Basin. Increases in GWR of over 100 mm year^{-1}, in contrast, are visible in East Africa, India, and North Java. Increases of 50 to 100 mm year^{-1} dominate in northern latitudes at 3 °C warming compared to other GW levels. The global significant mean increases by +3 mm year^{-1}.

We have already reached a GW of approximately 1°C (IPCC, 2018). Figure 3f shows the changes in GWR of a 3° GW compared to the present-day GW of already 1°C instead of the PI. Overall, the agreement among the models is smaller than when the 3°C world is compared to PI. Only 8% of the cells show significant changes. Decreases over 100 mm year^{-1} are present in the Amazon Basin close to the Andes and on the coast of Guyana. Decreases of 50 to 100 mm year^{-1} are visible in Chile, the Mississippi Basin, the Caribbean, and southern France. Increases in GWR are again to be expected in the northern Latitudes, southern Brazil, East Africa, and Southeast Asia, whereas the latter shows increases over 100 mm year^{-1} for Malaysia. The global significant mean change is +8 mm year^{-1}. Figure S3 shows the mean and median changes of GWR per latitude for all four GW levels, together with the standard deviation without a significance test. A decrease in mean GWR can be observed for all GW levels at 40° S, around 20° S (Namibia, Australia), and 5° N (Guyana). Increases are visible at 60° N (North Europe) and southerly close to the Equator, presenting a large spread and sudden change in directions in the tropics. Increases at greater than 60° N are likely due to a combination of different rain and snow patterns as well as snowmelt timing.

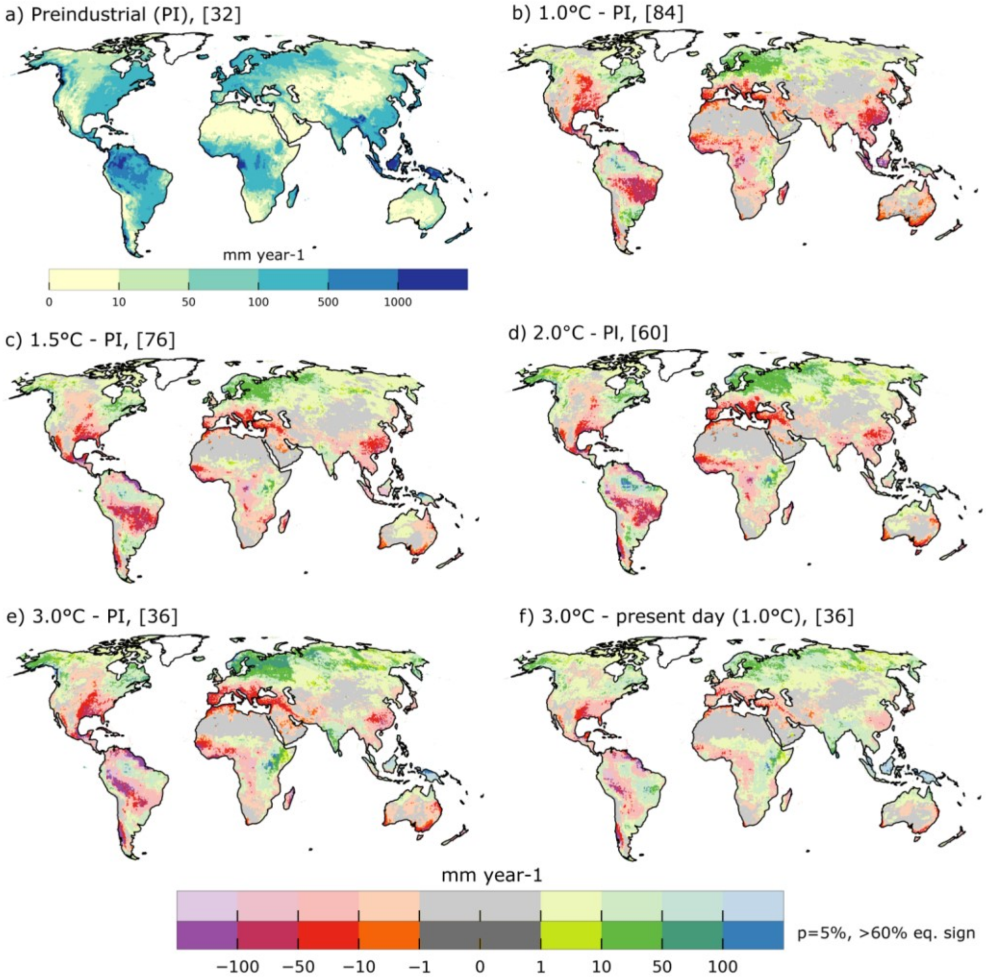

Figure 3 Mean GWR [mm year^{-1}] for pre-industrial greenhouse gas concentrations, averaged over the GWR of all GHMs and GCMs (a). Ensemble mean absolute change in GWR [mm year^{-1}] at 1.0 °C (b), 1.5°C (c), 2.0°C (d), and 3.0°C (e) GW compared to PI. The ensemble mean absolute change in GWR [mm year^{-1}] for 3.0°C GW compared to GWR at the current GW of 1°C (f). For (b) to (f) only those cells are displayed in solid colors where the Kolmogorov-Smirnov (K-S) test with a p of 5% indicated that the ensemble GWR distribution for PI (for (f) the GWR distribution at 1°C) and for the GW level differ, and at least 60% of the models agree on the sign of the change. The ensemble size is shown in brackets. Lighter colors (upper color bar) show (statistical) insignificant mean differences.

Large areas of insignificant changes of GWR (light colors) in Fig. 3 can be traced back to the uncertainty in GWR in between GHMs and GCMs. Figure 4 shows absolute GWR changes in a 1.5 °C world compared to PI (Fig. 3a,b) as well as PI GWR (Fig. 3c,d) for the SREX (Special Report on Managing the Risks of Extreme Events and Disasters to Advance Climate Change Adaptation, Murray and Ebi (2012)) region Amazon (left) and South Europe/Mediterranean (right). Corresponding plots for all other SREX regions are provided in the supplement. Similar to box plots, the letter-value plots in Fig. 4 show the distribution of values among the 0.5° grid cells belonging to the SREX region. Letter-value plots have the advantage of showing the distribution of values outside of the usual interquartile range (IQR, Q25 - Q75). For example, for Fig. 4b CLM 4.5 with GFDL-ESM2-ES, the mean change in GWR is -19 mm year^{-1}, the middlebox represents the IQR showing that 50% of changes are close to zero or smaller than zero, the smaller box towards the negative changes shows that 12.5% are smaller than -47 mm year^{-1}, whereas the additional missing box in the positive direction hints that almost no values are larger than zero. The horizontal size of the boxes is automatically scaled and does not carry any additional information.

Computed changes vary strongly among both GHMs and GCMs (Fig. 4a,b). In the Amazon, Jules-W1 shows a mean increase of 225 mm year^{-1}. Compared to WaterGAP2, Jules-W1 estimates of GWR change are 147 mm year^{-1} higher for MIROC5 and 44 mm year^{-1} lower for HadGEM. These differences are even large relative to the higher mean PI GWR in the Amazon compared to other regions of the world (compare to MED in Fig. 4). Nevertheless, also the PI estimates differ by, e.g., 122 mm year^{-1} between Jules-W1 and WaterGAP2 on the mean for all GCMs and RCPs, and PI GWR is 625 mm year^{-1} smaller for H08 than for MATSIRO in the Amazon.

In the Mediterranean, almost all GHMs show the largest decreases in GWR with IPSL-CM5a-LR, followed by GFDL input, while HadGEM results in almost no change. However, the changes computed with each GCM input vary strongly among the GHMs. In general, CLM 4.5 and PCR-GLOBWB project the most considerable changes. The decrease of GWR computed by CLM 4.5 with IPSL-CM5a-LR is 33% of the mean GWR calculated for PI with that model combination.

Conversely, JULES-W1 simulates for most grid cells in this SREX region the smallest PI GWR values (but also very high outliers), and likely related, the smallest (mean) changes, together with MATSIRO and CWatM, which show altogether small GWR changes in all grid cells of the SREX regions. H08 and WaterGAP2, which apply similar approaches to modeling GWR as a function of total runoff, show somewhat similar GWR changes.

The four GHMs that take into account the impact of increasing CO_2 (Sect. 2.1) do not result in similar changes as compared to the other four models. It is to be expected from literature (Davie et al., 2013) that with the physiological effect, the decreases of GWR would be slighter in the case of the CO_2-sensitive models, but that is not the case. This is likely due to the approach of analyzing GW levels instead of RCPs and periods because different GCMs reach a particular GW level at different times and CO_2 levels. This is further investigated in Sect. 3.3. On the global mean and for 1.5°C GW LPJmL simulates the lowest PI GWR, whereas MATSIRO and CLM 4.5 produce the highest global mean GWR (Fig. S4). PCR-GLOBWB simulates the largest global mean decreases with HadGEM (Fig. S5). In contrast, JULES-W1 and MATSIRO simulate increases of GWR on the global mean for all GCMs except for HadGEM (Fig. S5).

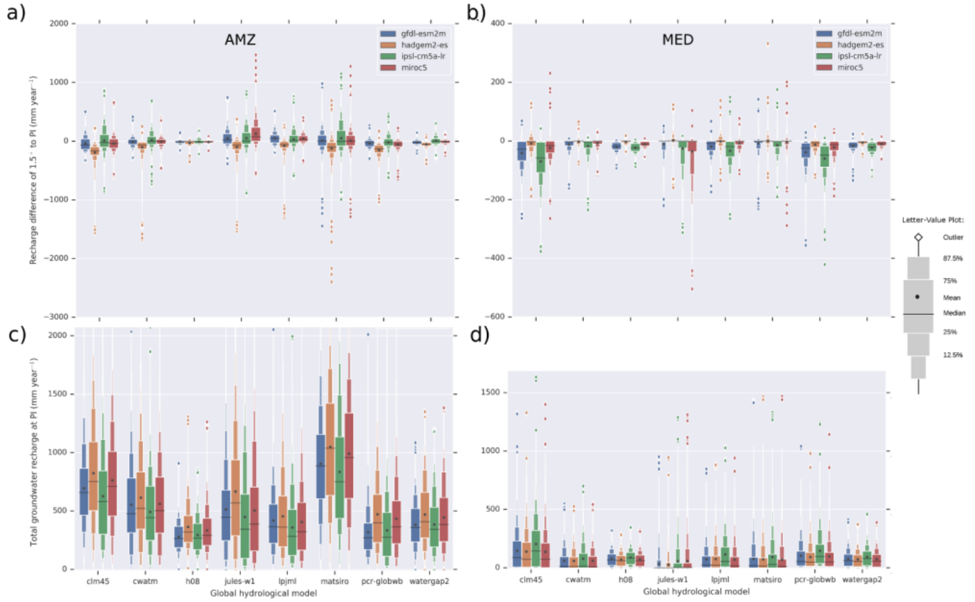

Figure 4 Letter-value plot (Hofmann et al., 2017) of absolute changes in GWR in 0.5° grid cells [mm year^{-1}] at 1.5°C GW compared to PI (a, b) and absolute PI GWR [mm year^{-1}] (c, d) for the Amazon (a, c) and South Europe/Mediterranean (b, d) SREX region (for all other regions and GW levels [2°C, 3°C] see supplement). No statistical test is applied and all grid cells inside a region are included. Each box may include multiple simulations with different RCPs.

To provide an overview of changes in GWR in each SREX region, Table 3 shows the median, mean and P_{25} and P_{75} changes in GWR compared to PI for all regions (see Fig. S6 for a map of the SREX regions). Overall, North Europe shows the largest consistent increases in GWR, whereas the Amazon shows the largest consistent decreases, except for 2°C, where South Europe/Mediterranean shows the largest decreases of 18.6 mm year^{-1} as the median. For 3°C, the Amazon shows the highest decreases in GWR of -41.0 mm year^{-1} as median. Notably, Southeast Asia is first showing decreases of 13.1 mm year^{-1} with 1.0°C GW and then no change with 1.5°C and 2°C and an increase in GWR of 13.5 mm year^{-1} with 3°. Relative to PI the changes of the 3°C GW in the Amazon only account for 10% of the GWR, compared to the 19% relative increase of GWR in North Europe with 3°C and the 40% decrease in GWR in South Europe/Mediterranean at 2°C GW.

Table 3 Median ($\widetilde{\boldsymbol{X}}$), mean ($\overline{\boldsymbol{X}}$), P_{25}, and P_{75} of absolute GWR change [mm year^{-1}] for four warming levels for each SREX region compared to PI. $\widetilde{\boldsymbol{X}}$, $\overline{\boldsymbol{X}}$, P_{25}, and P_{75} describe the distribution of changes of spatially averaged GWR in each SREX region among all 36-84 ensemble members (Sect. 2.3). $P_{25/75}$ are the 25th and 75th percentile in the ensemble for a given region and a given GW level. The last column shows absolute GWR at PI. The following regions are not included due to the coarse spatial resolution of the models and low confidence in the reliability of results: Artic, Canada/Greenland/Island, Antarctic, Pacific islands, Southern tropical pacific, Small Island Region Caribbean, West Indian Ocean. In bold maximum and minimum values per GW level. No statistical test is applied to filter the values.

		1.0°	**1.5°**	**2.0°**	**3.0°**	**PI**
		$\tilde{X}, \bar{X}$	$\tilde{X}, \bar{X}$	$\tilde{X}, \bar{X}$	$\tilde{X}, \bar{X}$	$\tilde{X}, \bar{X}$
SREX	**Name**	P_{25}, P_{75}	P_{25}, P_{75}	P_{25}, P_{75}	P_{25}, P_{75}	P_{25}, P_{75}
AMZ	Amazon	-10.7, -14.5	**-19.1**, -22.3	-14.6, -18.2	**-41.0**, -59.9	409.6, 550.4
		-30.4, -6.8	-38.3, -9.7	-34.5, 3.4	-81.1, -39.2	419.7, 614.6
CAM	Central	-2.4, -17.1	-4.8, -21.0	-4.3, -12.9	-10.0, -36.0	79.8, 280.4
	America/Mexico	-23.1, -6.5	-26.8, -9.0	-18.9, -7.7	-45.8, -24.0	222.3, 327.7
CAS	Central Asia	0.0, -0.4	0.0 0.0	0.0, -0.8	0.0, -2.6	1.8, 25.9
		-0.7, 0.3	-0.7, 1.0	-1.4, -0.3	-3.9, -1.4	17.2, 37.2
CEU	Central Europe	4.1, 6.8	1.2, 3.1	-0.4, 0.1	0.1, 2.8	114.6, 135.4
		0.5, 13.3	-5.5, 11.8	-9.7, 11.3	-9.9, 22.3	117.9, 155.8
CAN	Central North	-6.5, -16.7	-5.6, -18.3	-3.3, -16.6	-9.9, -30.5	98.1, 128.6
	America	-20.2, -12.3	-20.2, -12.7	-20.0, -12.5	-32.8, -18.2	76.4, 183.5
EAF	East Africa	0.0, -0.8	0.0, 2.7	0.0, 8.1	0.6, 23.3	32.2, 95.0
		-2.7, 3.3	-0.2, -7.8	1.2, 13.9	9.0, 32.4	63.4, 134.1
EAS	East Asia	-0.5, -15.7	0.0, -13.9	0.0, -10.3	0.0, -13.7	50.5, 147.3
		-20.0, -8.3	-16.9, -6.8	-10.7, -3.7	-14.2, -4.5	113.1, 154.3
ENA	East North America	3.3, 4.8	9.9, 11.9	10.6, 15.9	1.4, 2.5	221.8, 257.8
		-2.0, 11.2	-0.8, 19.8	-1.5, 26.3	-9.1, 20.5	167.4, 338.1
NAS	North Asia	0.4, 6.0	0.5, 7.9	3.1, 12.5	4.6, 18.5	24.2, 59.2
		3.0, 7.2	5.1, 9.1	9.0, 13.1	13.0, 20.4	46.2, 73.4
NAU	North Australia	0.0, -4.5	0.0, -2.7	0.0, 1.1	-0.9, -3.0	5.9, 43.1
		-6.9, -2.2	-3.9, -0.8	-0.8, 3.5	-7.1, 0.0	28.5, 52.1
NEU	North Europe	**13.1**, 24.9	**13.9**, 27.7	**18.6**, 34.9	**29.2**, 51.6	154.8, 226.4
		15.9, 35.7	14.7, 41.3	16.8, 53.0	25.0, 78.2	182.1, 280.4
NEB	North-East Brazil	-8.9, -30.3	-10.5, -22.9	-6.2, -14.4	-6.0, -9.4	161.6, 227.4
		-35.6, -21.2	-31.3, -13.2	-24.9, -2.1	-20.7, 2.1	147.1, 315.0
SAH	Sahara	0.0, -0.7	0.0, 0.3	0.0, -0.2	0.0, -0.4	0.1, 4.2
		-1.0, -0.3	0.1, 0.4	-0.2, 0.0	-0.5, 0.0	0.8, 4.4
SAS	South Asia	-3.3, -13.4	0.0, -4.8	-2.3, -11.6	3.8, 26.9	151.8, 274.9
		-15.9, -8.3	-6.1, 0.1	-17.5, -5.3	2.3, 45.5	229.5, 319.2
SAU	South Australia/New	-2.9, -8.6	-2.3, -10.3	-2.1, -15.3	-4.2, -20.0	18.1, 135.7
	Zealand	-11.1, -4.5	-12.4, -6.5	-17.8, -9.4	-22.2, -14.3	111.4, 157.6
MED	South	-3.9 -14.3	-6.3, -18.1	**-16.8**, -23.7	-12.5, -28.9	43.9 84.9
	Europe/Mediterranean	-17.6, -9.3	-21.6, -12.8	-27.4, -16.8	-31.8, -19.1	72.1, 87.6
SEA	Southeast Asia	**-13.1**, -36.1	-0.1, -5.2	-0.6, 23.1	13.5, 46.1	547.9, 725.2
		-55.7, -10.7	-18.0, 8.6	-1.7, 36.5	3.0, 68.9	528.0, 881.2
SSA	Southeastern South	0.0, -6.3	0.0, -5.2	0.0, -9.4	-1.4, -11.8	61.0, 129.5
	America	-8.3, -5.1	-8.9, -4.4	-12.9, -4.5	-15.7, 0.3	87.9, 164.6

SAF	Southern Africa	0.0, -8.1	-0.4, -10.3	0.0, -6.6	-0.1, -10.5	20.0, 95.9
		-13.0, -3.4	-15.9, -4.4	-10.7, -0.5	-16.3, -2.0	77.9, 102.0
TIB	Tibetan Plateau	0.0, -0.8	0.0, -0.3	0.0, 0.4	0.0, 1.1	0.0, 14.3
		-0.7, -0.3	-0.4, 0.4	-0.3, 1.1	-0.2, 1.6	9.3, 16.8
WAF	West Africa	-4.5, -28.4	-2.5, -21.8	-5.6, -25.6	-8.4, -26.5	175.3, 282.3
		-38.2, -20.4	-29.7, -11.0	-39.2, -10.3	-44.0, -6.1	215.0, 392.1
WAS	West Asia	0.0, -2.6	0.0, -3.9	0.0, -4.4	0.0, -6.7	0.4, 24.8
		-3.4, -1.4	-4.7, -2.5	-5.2, -2.8	-8.1, -4.6	18.3, 30.0
WSA	West Coast South America	0.0, -8.6	0.0, -10.5	0.0, -13.9	0.0, -21.2	57.2, 271.1
		-11.5, -5.5	-14.5, -5.5	-17.7, -7.6	-25.1, -15.2	186.9, 346.3
WNA	West North America	0.0, 3.4	0.0, -3.5	0.0, 6.2	0.0, 6.8	23.5, 104.8
		0.5, 5.6	-0.1, 7.1	1.1, 11.6	1.7, 14.7	81.9, 126.7

3.2 Sources of ensemble variance

To investigate whether the main variance in projected GWR changes is caused by GHMs, GCMs, or the different RCP scenarios, we apply the Eq. (1) and (2) (see Sect. 2.4) for 1.5°C and 3°C GW. Figure 5 shows the GCM to GHM variance ratio for 1.5°C (a) and 3°C (b) per grid cell; GHM RCP variance ratio is not shown here (see Fig. S7 in the supplement, mean of GHM RCP ratio: 22%) as the primary influence can be appropriated to the GCM and GHM selection (this is also the case when choosing only the CO_2 sensitive models). For the simulated variance at PI see Fig. S1 and S4.

Overall, GHMs cause more significant variance in 1.5°C than in a 3°C world, which is plausible because of increased GCM trends with increased CO_2 concentrations. Possibly this is also due to the missing RCP 8.5 simulations for PCR-GLOBWB for all GCMs. A clear spatial pattern of GCM influence shows in the Amazon that relates to the region of Fig. 3 where increases of GWR are calculated. On the other hand, the region in the Amazon where decreases are simulated (compare Fig. 3) shows mainly the GHMs as the source of variance. In the Mediterranean, the influence shifts as well from GCMs (1.5°C) to GHMs (3°C). This could be due to a high agreement in GCMs in this region and a considerable disagreement in GHMs. Similar patterns can be found when comparing absolute GWR, but the influence of GCMs is less pronounced, especially in the Amazon (Fig. S8).

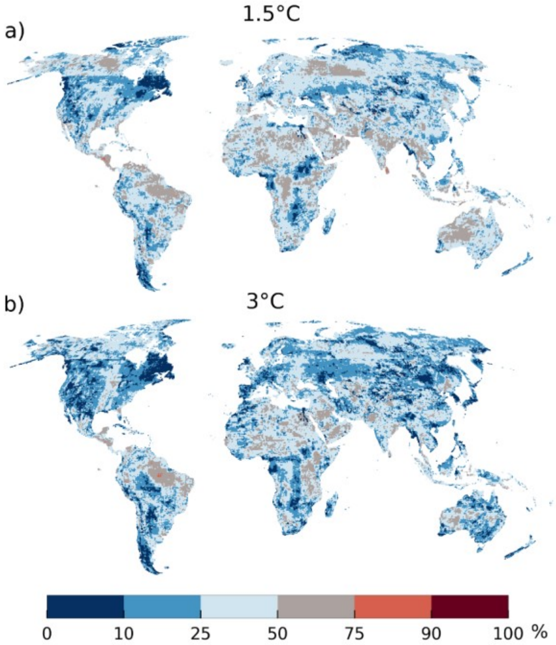

Figure 5 GCM variance in percent of the total variance of GWR change from eight GHMs and four GCMs at 1.5°C (a) and a 3°C (b) GW (see also Sect. 2.4). Red depicts areas where the GCMs are responsible for the majority of the variance in GWR change. Blue areas indicate where the main variance is introduced through GHMs.

3.3 Impacts of evolving carbon dioxide concentrations on groundwater recharge estimates

Including vegetation dynamics in GHMs may alter the model response in future estimates of GWR as evolving CO_2 concentrations alters fluxes of energy and water (Davie et al., 2013). To investigate the influence of simulating the physiological impacts of evolving CO_2 on GWR, we compared GWR changes computed by two CLM 4.5 runs, each of it driven by GFDL-ESM2M climate input: the standard run analyzed included in the ensemble analysis above, with CO_2 concentrations changing according to the RCP, and an additional run in which CO_2 concentrations after 2005 were held constant at the 2005 level. Unfortunately, no other GHM-GCM combinations with these alternative CO_2 concentration variants are available in the framework of ISIMIP2b.

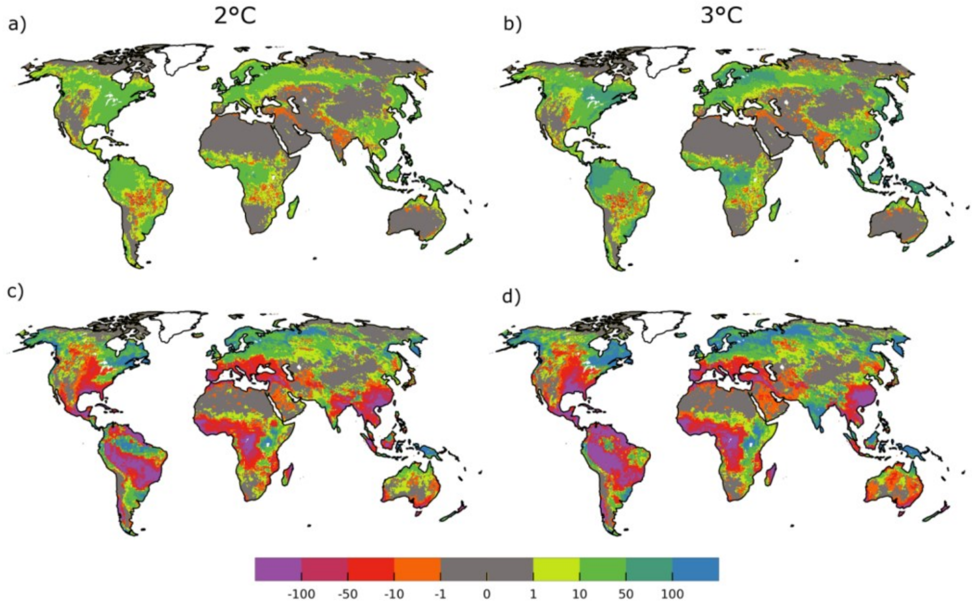

Figure 6 GWR (dynamic CO_2) – GWR (static CO_2) [mm year^{-1}] for 2.0°C (a) and 3.0°C (b) GW. GWR (dynamic CO_2) – PI (dynamic CO_2) [mm year^{-1}] for 2.0°C (c) and 3.0°C (d) GW. The figure only includes the GHM CLM 4.5 and the GCM GFDL-ESM2M. Maps show changes in GWR at a certain GW (including all RCPs that lead to that GW with a certain CO_2 concentration) with dynamically evolving CO_2 compared to static CO_2 concentrations from 2005. Green and blue means that GWR is higher when evolving CO_2 concentrations are considered, red and purple less GWR.

Figure 6 shows differences in simulated GWR between a dynamic and a static CO_2 simulation for 2°C (Fig. 6a) and 3°C (Fig 6b). In most grid cells, GWR simulated with dynamic CO_2 is larger than GWR simulated with static CO_2 levels of 2005 (Fig. 6a,b). In the tropics, GWR with dynamic CO_2 can be higher than with constant CO_2 by 10-50 mm year^{-1} for 2°C GW (Fig. 6a), while difference reaches 50-100 mm year^{-1} in the 3°C world (Fig. 6b). Decreases of GWR are spatially consistent (for example, Brazil, Central U.S., and India) at 2° and 3°C GW and rarely exceed 10 mm year^{-1}.

Compared to the absolute changes between PI and the GW levels for dynamic CO_2 (Fig 6c,d) the decreases in GWR are rather small (e.g., up -10 mm year^{-1} in Brazil (Fig. 6a,b), while change compared to PI exceeds -100 mm year^{-1} (Fig 6c,d)). Also, increases in GWR due to dynamic CO_2 are in regions with large (> 100 mm year^{-1}, Fig 6c,d) increases in recharge.

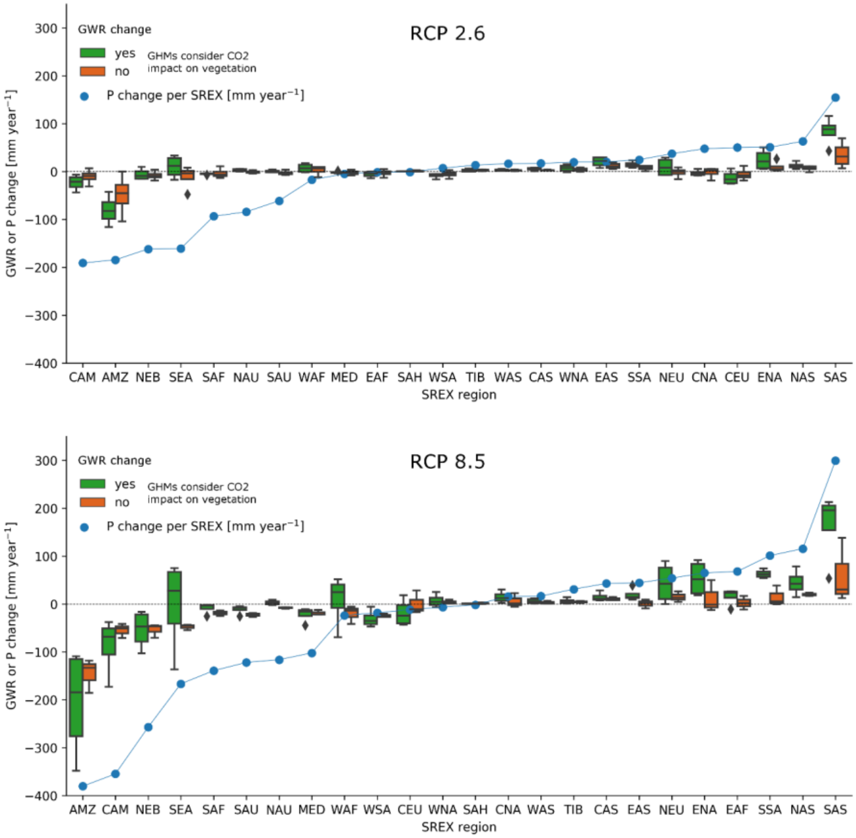

Figure 7 Relation of changes in precipitation (P) (mean(1981-2010) – mean(2070-2099)) to changes in GWR (mean(1981-2010) – mean(2070-2099)) depending on the model type (with or without CO_2; see also Table 1) per SREX (selection as in Table 3) for RCP 2.6 and RCP 8.5 for the GCM HadGEM2-ES.

The preceding analysis focused on GW levels parallel to other studies of GHM ensembles. To investigate the difference in including active vegetation processes in GHM further, we compared the four GHMs that include these processes with the four models that do not (Table 1). Because different RCPs decide the concentration of CO_2 in the atmosphere, we compare RCP 2.6 and RCP 8.5 time slices instead of GW levels.

Figure 7 compares the precipitation and GWR changes between the period 1981-2010 and the period 2070-2099 for the two RCPs and the two different model types for the SREX regions investigated in Table 3. Changes in precipitation and GWR are only based on the GCM HadGEM2-ES (see Fig. S9 for average over all GCMs) as the relationship between GWR and precipitation is not linear and the plot is comparable to Davie et al. (2013), who investigated differences in runoff. Compared to the average precipitation of all GCMs where only two regions show a decrease larger than 100 mm year^{-1} (Fig. S9 (b)), HadGEM2-ES shows seven regions for RCP 8.5 with such a decrease in precipitation.

GWR changes vary between RCPs and model type and in between GHMs (Fig. S10). The relation between precipitation and GWR and difference between model types becomes clearer with RCP 8.5 than with RCP 2.6. Models with active vegetation (Fig. 7, green markers) agree that with more precipitation GWR should increase, e.g., for SAS; however, they disagree in regions where decreases in precipitation are expected and risk for groundwater availability is highest, e.g., CAM and MED. GHMs without active vegetation (Fig 7, orange markers), on the other hand, show a more consistent decrease in GWR for regions with decreases in precipitation and only some agreement in regions with increased precipitation.

Decreases in precipitation may lead to a decrease in vegetation productivity (if not counteracted by an increased water-use efficiency due to elevated CO_2 concentrations (Singh et al., 2020)) and thus to a decrease in transpiration. GHMs assume shares for evapotranspiration (ET) in relation to potential ET and the available precipitation. In contrast, transpiration in CO_2-driven models responds to active vegetation as well as the relations between different water flux components that simpler GHMs do not. This can explain why the dynamic vegetation models exhibit inter-model regional differences in the GWR response to P decrease. Further, some models (MATSIRO) may not calculate LAI (leave area index), which impacts transpiration. For models with active vegetation, the increase in water use efficiency due to stomatal conductance (also referred to as CO_2 fertilization) can compensate for the decrease in precipitation to some extent, making more water available for groundwater recharge as compared to the GHMs (Table 1). Though in some regions, as seen in Figure 7 (and Fig. S10), this feedback is not enough to overcome the warmer and drier climate in terms of groundwater flux. Overall, the capability of a model to simulate actual ET largely influences its capability to simulate groundwater recharge.

CWatM often lies in the middle of simulated GWR changes at RCP 2.6. Davie et al. (2013) showed generally higher runoff values for JULES-W1 than for LPJmL, the reverse is true for GWR (Fig S.10). For RCP 8.5, CWatM always simulates the largest increases and lowest decreases in GWR of all models without active vegetation.

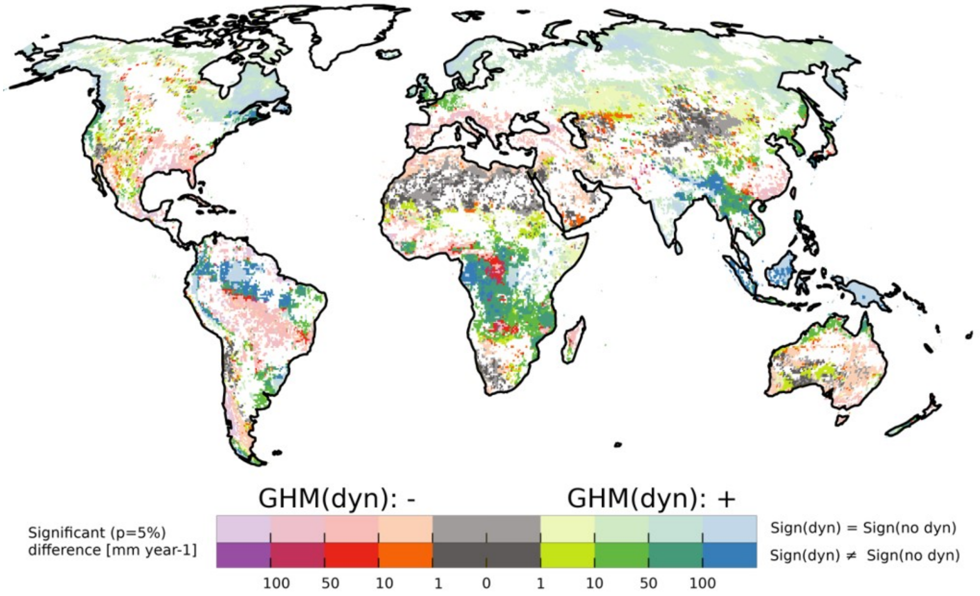

Figure 8 Significant absolute difference of GWR change between 1981-2010 and 2077-2099 for RCP 8.5 in between four GHMs with (dyn) and four GHMs without dynamic (or active) vegetation (no dyn). See also Table 1. Reddish (left side of the color bar) indicates that the mean change of GWR as computed by the models with dynamic vegetation is more negative or less positive than change computed by other models. White regions indicate no significance is based on the K-S test (Sect. 2.5). Solid colors indicate that the majority of the two model groups (3 out of 4 models for each group) do not have the same sign i.e. that including dynamic vegetation leads to different signs in GWR change. Lighter colors indicate where the majority agrees on the sign of change.

A spatially more refined difference between the model types is shown in Fig. 8 for RCP 8.5 (For RCP 2.6, almost no significant changes were found). For each grid cell, the map shows the significant (K-S test, p=5%) absolute difference of simulated change in GWR between models that include dynamic vegetation processes and models that do not include them. In the northern latitudes, both models with and without dynamic vegetation agree on an increase in GWR but differ by up to 100 mm year^{-1}. Similarly, in the Mediterranean and central Brazil, both model types simulate a decrease in GWR, but the magnitude is significantly different between the model groups. In the Amazon patches of significant differences between the models show increases of GWR computed by GHMs with dynamic vegetation, whereas GHMs without dynamic vegetation shows a decrease. A similar effect is visible in central Africa, India, and parts of Indonesia; however, also decreases are simulated instead of increases for the Congo and Zambesi catchment. Both in the Mediterranean and South America models with dynamic vegetation show up to 100 mm year^{-1} difference in change compared to models without, even though no physiological effect should be dominant. According to Fig. 6, this is likely due to CLM 4.5 because JULES-W1 and LPJmL show slighter GWR decrease than the models without dynamic vegetation. It is likely that the shown differences are due to the implementation of dynamic vegetation in the GHMs (compare Fig. S.10), however it is possible that other model peculiarities and processes are relevant as well.

4 Discussion

Estimating GWR is challenging (Moeck et al., 2016). Our results show that even for the PI period, the estimates of GWR vary largely among different GHMs. This is likely caused by the very different treatment of the runoff partitioning, implementation of the soil layer(s), inclusion of dynamic vegetation processes, and simulation of capillary rise. Because GWR is hard to measure directly (Scanlon et al., 2002), it is also challenging to verify the accuracy of the estimates.

To the best of our knowledge, the data-set of Mohan et al. (2018) is the only available gridded global GWR dataset that is not based on global hydrological modeling. This data set of mean 1981-2010 GWR in 0.5° grid cells was developed from a regression analysis that combined gridded datasets of mean precipitation and potential evapotranspiration as well as land use/land cover with local estimates of GWR at 715 locations worldwide. Figure 9 compares the GHMs under investigation for PI conditions to this dataset. The used data for comparison is one ensemble member of the analysis of Mohan et al. (2018) that was deemed best in their study. The global mean GWR in this member is slightly lower, 110 mm year^{-1}, than the reported mean of 134 mm year^{-1}. Overall, the GHMs best agree with Mohan et al. (2018) in arid regions like the Sahara, Australia, southern Africa, and the Andes. Underestimates are predominant in the northern Latitudes and Central Asia, whereas underestimates appear in Europe and the eastern USA for all models. All models, except for H08 and WaterGAP2, which show underestimates, result in overestimates in East Asia. In the Amazon, MATSIRO and CLM 4.5 overestimate by more than 100 mm year^{-1} compared to Mohan et al. (2018), whereas all other models show a mix of over and underestimate across continents. A similar pattern is visible in Central Africa where CLM, MATSIRO, and CWatM overestimate, and all other models show a mixture of over and underestimate of -100 – 100 mm year^{-1}. H08 and WaterGAP2 have the best agreement according to the NSE (Nash-Sutcliff Efficiency (calculated spatially); (Nash and Sutcliffe, 1970)) of 0.4 and 0.2 while the mean bias (mean(GHM Mohan et al.$^{-1}$)) is lowest for JULES-W1. All GHMs show much lower GWR in permafrost regions as they assume that there is no or little GWR in such regions. Possibly GWR of Mohan et al. (2018) is overestimated here as no measurements informed their results in these regions.

The variance in modeled GWR is possibly caused by the different implementation of the hydrological processes in between the models. Even more, models differ in their definition of groundwater and GWR. Some include groundwater storage that is recharged by a fraction of precipitation others do not include a groundwater component at all but define the saturation excess water from the bottom soil layer as GWR. Models may include only some of the processes that affect GWR, for example, capillary rise, percolation from the soil, preferential flow bypassing the soil matrix, the interaction between surface water and the aquifer, changing land use over time (not considered here), changing vegetation (e.g., reducing infiltration capacity). Further, important processes like evaporation, infiltration, percolation, or runoff and GWR separation are implemented with different equations and simplifications. For evapotranspiration, a standard deviation of 0.15 mm day^{-1} globally for the period 1989–2005 was found in the ISIMIP ensemble (Wartenburger et al., 2018). Some models even use sub-grid information or sub-daily time steps, e.g., for changes in unsaturated conductivity. Notably, models that include dynamic vegetation processes showed the largest spread in GWR in regions with decreasing precipitation.

It is also important to distinguish the capability of models to computed groundwater recharge during a historical period from their capability to estimate changes of groundwater recharge due to climate change. A model that simulates the current groundwater recharge pattern correctly may be incapable of computing future groundwater recharge if it cannot correctly simulate the impact of climate change and changing atmospheric CO_2 concentrations on actual evapotranspiration correctly.

~~It is also important to distinguish the capability of models to computed groundwater recharge during a historic time span from their capability to estimate changes of groundwater recharge due to climate change. A model that simulates current pattern of groundwater recharge correctly may be incapable of computing future groundwater recharge if it cannot correctly simulate the impact of climate change and changing atmospheric CO2 concentrations on actual evapotranspiration correctly~~

To illustrate the model differences further, the following describes the impact of changes in precipitation for WaterGAP and LPJmL representative for the different model types used in this study. In WaterGAP, a simulated percent change in total runoff translates to the same percentage change in GWR; unless, e.g., due to more extreme precipitation events, infiltration capacity is exceeded more often such that the relative increase in GWR is smaller than total runoff. Absolute changes in GWR are always smaller than changes in total runoff. In LPJmL, changes in total runoff do not translate to proportional changes in groundwater runoff and GWR. Any flux or storage that takes water before it is partitioned to the soil will impact the groundwater and GWR. Possible reasons for a reduction in GWR (percolation past the bottom hydrologically active layer (3 m deep); compare Sect. 2.1) can be changes in precipitation amount/intensity, transpiration due to vegetation productivity, transpiration due to changes in vegetation water use efficiency due to CO_2 fertilization, or changes in anthropogenic water use demands.

This difference in behavior is reflected in Fig. 7, where the response between precipitation and GWR of GHMs without any active/dynamic vegetation is relatively uniform. The non-uniform response of the models that include vegetation changes is likely due to the complicated process feedbacks between vegetation and water (transpiration changes due to available water together with vegetation productivity) and complex feedbacks in-between changes in CO_2, temperature, and precipitation which affect vegetation.

This study highlights that uncertainties and differences in GHMs need to be investigated further and that in order to estimate global groundwater vulnerability, improved estimates of global GWR are required.

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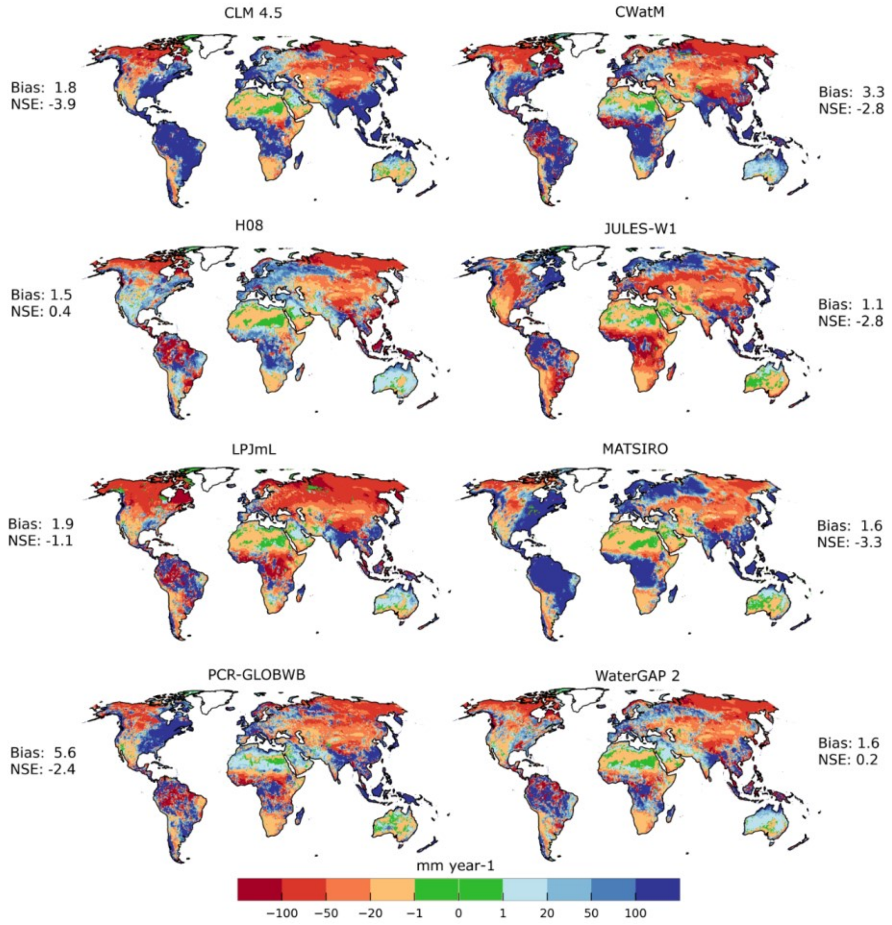

Figure 9 PI GWR per GHM – 34 years (1981-2014) mean GWR [mm year^{-1}] of Mohan et al. (2018). Bias: mean (GHM Mohan et al.$^{-1}$). NSE (Nash-Sutcliff Efficiency; (Nash and Sutcliffe, 1970)) is calculated spatially over all cells instead of time.

This study is limited not only by the uncertainty in correctly representing the process of GWR but also in the propagation and aggregation of uncertainties. Future greenhouse gas emission scenarios are created based on the input of integrated assessment models. They are translated into emission scenarios of atmospheric concentrations and forcings that are, in turn, used to evaluate their impacts on the climate simulated by GCMs. Outputs of the GCMs are then bias-adjusted and spatially downscaled to be used in the assessment with impact models like GHMs (Döll et al., 2014a). Furthermore, the analysis is limited by the number of GCMs that were used, as discussed in McSweeney and Jones (2016). Although the GCMs are carefully selected to be most representative of the CMIP (Taylor et al., 2012) ensemble.

The multi-model ensemble study presented here assesses GWR at GW of 1.5°C, 2°C, and 3°C compared to GWR simulated under pre-industrial climate conditions and 1°C of GW. Changes are assessed based on transient time slices of the 30 years around the year that crosses the specific warming level. These slices are an approximation of the stabilized climate state of that warming level; it relies on the assumption that for a given warming level the impacts are the same regardless of the time it took to reach it or whether equilibrium has been reached at all (Boulange et al., 2018). However, this kind of analysis has limitations as the transient nature of climate is aggregated over a relatively short period (31 years). Components like the ocean might not equilibrate at these timescales (Donnelly et al., 2017).

Additionally, different RCPs are combined, which limits the possibility to investigate processes that are sensitive to different CO_2 concentrations. Investigations in this study based on RCPs show the difference between these model types. On the other hand, using GW levels reduces the uncertainties from GCM variability due to the use of different time slices, depending on when a GCM reaches a GW level.

The variance in GWR is caused by GCMs and GHMs alike depending on the region similar to a multi-model ensemble study on the climate change impacts on streamflow (Schewe et al., 2014). Again, the assessment is limited by the number of used GCMs. Furthermore, this study did not include changes in land-cover and land-use, and thus irrigation which can have a tremendous impact on GWR, especially as irrigation patterns and used crops, will change with a changing climate (Hauser et al., 2019; Hirsch et al., 2017; Hirsch et al., 2018; Thiery et al., 2017; Thiery et al., 2020).

The only similar study on the global impacts of GW on GWR, to the knowledge of the authors, was conducted by Portmann et al. (2013). The study used five GCMs and one GHM, WaterGAP, which (a slightly different version) was also included in this study. Overall results are spatially consistent; however, Portmann et al. (2013) showed more consistent trends among GW levels (compare Table 3). Portmann et al. (2013) acknowledge that including impacts of evolving CO_2 levels on vegetation will have an impact on the simulated GWR and that WaterGAP is likely overestimating the decreases in GWR. Similarly, Davie et al. (2013) found that simulation of runoff was not consistent across models depending on whether CO_2 was considered. The results presented in this study show that this assumption is true for some regions, where differences of up to 100 mm year^{-1} can be observed.

Despite the uncertainties, this study provides further evidence that climate change will impact groundwater availability in many regions of the world. A notable decrease can be expected in the Mediterranean, Amazon, and Brazil, whereas increases can be expected in Northern Europe. It is nevertheless troublesome that, especially in regions that are known to be vulnerable to climate change, for example, South Africa, model agreement in between model types is that low.

5 Conclusions

Potential GWR changes due to climate change require increased attention from the scientific community as well as from decision-makers because they affect future water availability in many regions and thus the wellbeing of billions of people. This study shows that simulated global-scale estimates of GWR vary strongly among GHMs, which contribute more strongly to the overall uncertainty of future GWR than the applied GCM output. However, statistically significant increases and decreases of GWR could be identified in specific regions per GW level. The presented inter-model ranges of GWR changes are an important input for processes aiming at developing strategies for climate change adaptation, as risk-averse decision-makers may want to orient their strategies towards adapting to the worst-case GWR change and not to the projected ensemble mean change.

This study shows that including vegetation processes in GHMs can change projected GWR changes substantially. However, consideration of these processes does not lead to a uniform increase of groundwater recharge, as might be expected from the physiological effect of increasing atmospheric CO_2 concentration. In some regions with decreasing groundwater recharge, where groundwater availability is a major concern, models that include these processes show the largest differences among themselves. Further research is necessary to understand GWR on large scales, and how it is affected by climate. Simulation of groundwater recharge in global models and the connected uncertainties ~~by global hydrological models~~ need~~s~~ to be analyzed in greater~~more~~ detail by, e.g, the application of extensive sensitivity analysis.~~,~~ Such an assessment should also extend to ~~and~~ the benefit of integrating gradient-based groundwater flow models in GHMs.

~~should be assessed.~~

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Data availability

All simulations are available through the ISMIP project at https://www.isimip.org.

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Author contributions

RR led the conceptualization, formal analysis, methodology, software, visualization, and writing of the draft—original idea by HMS. HMS and PD supported review and editing, as well as the development of the methodology. TT supported editing and review. MF, SNG, MG, NH, AK, LS, WT, YW, YP, BP, and SY contributed to the model description in section 2 and made suggestions regarding wording, figures, and discussion. PD and HMS supervised the work of RR and made suggestions regarding the analysis, structure, and wording of the text and design of tables and figures.

Competing interests

No competing interests.

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We thank the three reviewers for the positive feedback on the work we have invested in this manuscript and the detailed comments to further improve it. We certainly acknowledge the uncertainties involved in the presented results and recognize that the submitted abstract might create false expectations. We have thus rewritten the abstract as well as the conclusions and are now more precise about the explanation of statistically significant changes. Furthermore, we added a new table (Table 1) that provides an overview on which vegetation processes are implemented in which model, added a new Figure 2 that shows the ensemble mean, and extensively revised Figure 7 (former Fig. 5). We are certain that the presented manuscript is an important study of the capabilities and limitations of global hydrological models.

The following lists all comments of all three reviewers and our rebuttal in *italics*. Attached is a markup document that highlights the changes compared to the initially submitted document. Line numbers refer to the revised version of the document.

Referee #1

1.1

Although the title of the paper and the results emphasize model uncertainties, I think the primary result based on the analysis is that recharge is not very sensitive to climate change as only 15% of cells show significant increases or decreases in recharge based on pre-industrial baseline and only 8% of cells show
significant change in recharge from current 1 degree to projected 3 degree condition.

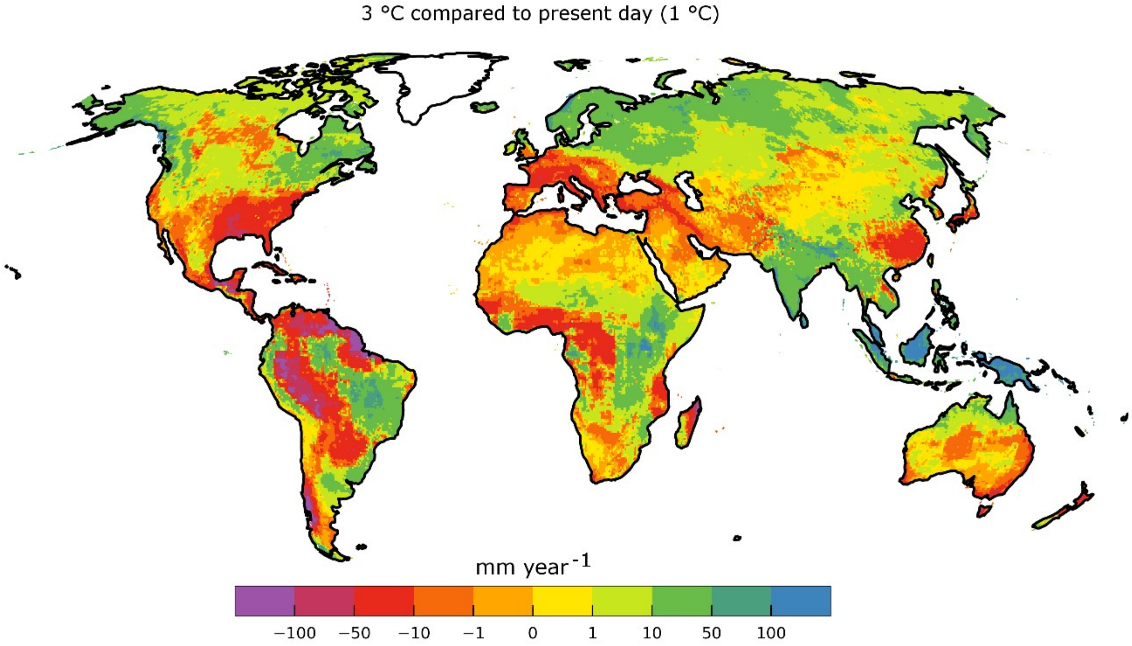
It is not correct to conclude from the fact the only 15% of cells show significant changes that groundwater "recharge is not very sensitive to climate change". This misunderstanding by the reviewer is caused by the various meanings the term "significant" has. In our paper, with "significant" we do not mean that there are "large" changes. We mean a statistical agreement or rather non-agreement between the two ensembles of simulated recharge, the one consisting of recharge computed by the various models under e.g. pre-industrial conditions and the other consisting of recharge computed by the various models at a certain global warming level (as tested here by a Kolmogorov-Smirnov test). To avoid this confusion, we have clarified this fact in Section 2.5 and for multiple references to the significance of the changes. We have also added a new Figure 2 that shows the ensemble mean difference between a 3° C warming and the present day without any statistical tests. We have also strongly modified abstract and conclusions to clearly express that significant refers to statistically significant (see response 3.1).

Section 2.5 now reads (Line 258 ff):

"A model ensemble allows us to consider the uncertainty in modeling physical processes as different model use different algorithms and parameters for computing groundwater recharge. To determine whether changes in GWR due to GW computed by the model ensemble are statistically significant, we use the two-sample Kolmogorov–Smirnov (K-S) test to compare the GWR values computed by all GHM-GCM model combinations under e.g., PI conditions with the values at the various GW levels. The use of a two-tailed t-test is not advisable in this setting due to the small sample size (max. 84 in this study). Because the K-S test does not allow to check whether the ensemble agrees on the sign of change in GWR, we apply an additional criterion to determine a significant change similar to Döll et al. (2018). A change is only marked as (statistically) "significant" if the K-S test indicates a significant difference and at least 60% of the model realizations of the ensemble (RCP, GCM and GHM combinations) agree on the sign of change (i.e. a decrease or increase". In case of a low significance, all models may show large responses to climate change while their agreement on the amount or sign of change is low. "

The new Figure and its description (Line 270 ff):

"To assess the impact of GW on GWR, Fig. 2 shows the ensemble mean change of GWR between the current 1°C world and a potential 3°C GW. We chose to express changes as absolute change rather than relative change because zero, or close to zero, GWR in some regions of the world leads to not defined or extremely large percentage increases and decreases (Fig. S1 and S2). The model mean shows large decreases of over 100 mm year-1 in South America and in the Mississippi Basin and decreases of up to 50 mm year-1 in the Mediterranean, East China, and West Africa. Increases of over 100 mm year-1 are prominent in Indonesia and East Afrika. Individual GHM-GCM model combinations compute much larger changes.



(new) Figure 2 Ensemble mean change in GWR [mm year-1] between conditions of present day warming of 1 °C GW and at 3 °C GW, averaged over the GWR changes of all GHM-GCM model combinations.

Ensemble mean changes as shown in Figure 2 may be low in some areas, but this could be due to large positive changes compute by some GHM-GCM model combinations being canceled by large negative changes by other model combinations. To assess the changes which show a high statistical agreement in-between the model combinations, we determine where computed changes of GWR are statistically significant (Section 2.5)."

1.2

It would be good to acknowledge that recharge is likely the most difficult component of the water budget to simulate because it is modeled as a residual, accumulating uncertainties in other water budget components.

We agree and accordingly have changed the abstract and introduction. (Line 27 and 60):

“Groundwater recharge is an important indicator for groundwater availability, but it is a water flux that is difficult to estimate as uncertainties in the water balance accumulate, leading to possibly large errors in particular in dry regions.” And “The simulation of GWR is possibly one of the most challenging components of the water budget as it accumulates the uncertainties of all other components of the budget. Especially in semiarid regions, uncertainties in precipitation and evapotranspiration lead to considerable uncertainty in recharge. An additional factor in estimating groundwater recharge is the simulation of the groundwater table and thus capillary rise and focused recharge.”

1.3

In addition, it is extremely difficult to simulate in semiarid regions because small uncertainties in precipitation and evapotranspiration can result in large uncertainties in recharge.

Has been addressed together with 1.2.

1.4

Many studies suggest that climate change will result in increased climate extremes (floods and droughts) that may result in increased recharge from focused rather than diffuse recharge; however, it seems that few of the models consider focused recharge.

We agree, however none of the models includes a reliable implementation of focused recharge. Current developments of global gradient-based groundwater models will improve the implementation of these processes further but currently we focus on diffuse GWR in this study.

This is a limitation now stated more clearly (Line 125):

“We do not consider focused recharge in this study as no model offers a reliable implementation of these processes until now.”

1.5

The authors refer to groundwater levels throughout the paper with respect to temperature levels; however, this is confusing as groundwater levels are generally considered water table levels. It might be good to include temperature when referring to these.

The submitted manuscript makes no assumptions about the effect of changes in groundwater recharge on groundwater levels. We assume that the referee misread parts of the manuscript as the abbreviation GW (Global Warming) can easily be confused with GroundWater in GWR (Groundwater Recharge). While we realize this is not a perfect choice for an abbreviation we chose to keep it.

1.6

I agree that it is good to focus on absolute changes in recharge rather than relative changes. The authors suggest that underestimating runoff would result in increased GWR; however, this would not
be the case if GWR is focused and derived from runoff as in semiarid regions (L. 74).

We are happy to hear that the reviewer agrees with our choice in using absolute changes. This is something we have debated extensively when writing this manuscript. We agree with the comment, however as stated in 1.4 this study mainly focuses on defuse groundwater recharge.

1.7

The authors repeatedly use present tense to refer to work that was done for this study. I think it would be more appropriate to use past tense.

The manuscript was heavily revised in this regard at multiple places and should now contain a more precise use of tenses. Please see the attached markup document.

1.8

The model CLM-5 has been upgraded substantially relative to CLM-4.5. It might be good to consider CLM-5 rather than CLM-4.5.

It is true that CLM-5 is an improved version of the model, however our analysis is based on the available ISIMIP 2.b outputs, where only the modeling team of CLM-4.5 has submitted groundwater recharge. Running additional simulations with another model would compromise the reproducibility of our findings and clear link to rigorous ISIMIP protocol. This study is not an investigation of a specific model but of a consistent model ensemble.

1.9

Soil thickness varies substantially among the models (e.g. LPJ 13 m thick). It would be good to comment on the impact of varying soil thickness on model results.

While we agree that such an analysis is of interest it is clearly out of scope for this paper. It would require to modify and rerun all the complex models in a sensitivity analysis. The corresponding author is not the developer of these models, which are very complex to setup and run and even harder to compare, this is why we are using the ISIMIP framework, which enables a baseline that allows for the complex model comparison shown in this manuscript. To allow for a more in-depth comparison on how different processes are implemented in GHMs there is currently a complex manuscript under development targeting the implementation differences in these models.

Referee #2

2.1

One of the main conclusions is that dynamic vegetation has a strong impact on the estimated GWR, which is far from being as obvious based on the results presented.

While we agree that there is a significant uncertainty on how changes in CO2 levels impact the water balance Figure 7 and 8 clearly shows substantial differences between the model types. Of course, this does not necessarily mean that this difference can only be explained through the simulation of dynamic vegetation. Nevertheless, it seems likely and supports that further research on this topic is necessary.
We added a sentence to make this clearer in our conclusions (Line 579 ff):

"However, consideration of these processes does not lead to a uniform increase of groundwater recharge, as might be expected from the physiological effect of increasing atmospheric CO_2 concentration. In some regions with decreasing groundwater recharge, where groundwater availability is a major concern, models that include these processes show the largest differences among themselves. Further research is necessary to understand GWR on large scales, and how it is affected by climate. Simulation of groundwater recharge by global hydrological models needs to be analyzed in more detail, and the benefit of integrating gradient-based groundwater flow models in GHMs should be assessed. "

2.2

In addition, some figures are difficult to read and seem to support only partially the comments.

We have improved the font size in multiple figures. See also comment 2.6.

2.3

Introduction: The choice is made to estimate ground water recharge throughout the continental part of the world. However, many areas have no extended groundwater. Whymap.org provides map of the extension of the aquifer. What does it mean to estimate GWR where there is no or local and shallows aquifer? Won't it be more interested to estimate the recharge on the aquifer domains?

Groundwater recharge is also of interest outside of the major global aquifers represented in WHYMAP in blue. In each 0.5° grid cell there are very likely local aquifers (e.g. in alluvial valleys, and confined aquifers are also affected by groundwater recharge. There are other studies which use WHYMAP e.g. Gleeson et al. 2012 Nature, or Taylor et al. 2013 NCC, however our analysis here firstly focuses on a grid-based analysis (allowing for a better understanding on the model differences), which could be in a follow-up study be applied on an aquifer scale.

2.4

Line 200: It is necessary to provide information on the bias-adjusted method? What is the assumption? What is the reference climate used?

A detailed explanation of the method is out of scope of the paper. We have added, to the existing reference to additional information on the climate inputs, a reference of the used method (line 213):

"The bias adjustment method used for the GCMs in ISIMIP2b is using a trend preserving algorithm (Frieler et al., 2017) with EWEMBI (Lange 2018) as baseline (reference) climate condition."

2.5

Section 2.1: I suggest to provide a table that summarizes if GHM includes or not in the GWR another part that a partition of the precipitation, especially, which GHM includes river to aquifer exchange, since this may be a very important difference in alluvial regions. Moreover, this table should also summarize which GHM integrates direct effect of CO2, explaining clearly if they account for stomatal aperture sensitivity to CO2 and/or for vegetation dynamic (LAI) (so far, this is not clear).

As explained in 1.4 we do not consider focused recharge or transmission losses in this study (see 1.4). Also, it might be difficult to distinguish specific alluvial regions on this coarse resolution. A new Table 1 has been added to summarize the implementation of CO2 related vegetation processes more clearly (Line 126 ff).

Table 1 Overview which models are able to simulate the impact of evolving CO_2 concentrations on vegetation and how it is implemented.

GHM	**Considers CO_2**	**Summary of considered vegetation processes in ISIMIP2b**	**Reference**
WaterGAP2	No	-	-
CLM4.5	Yes	Photosynthesis depends on root zone soil moisture availability. The description is similar to LPJmL listed below. The area a population of plant functional types (PFTs) takes up is prescribed and only changes if the input data does.	(Di Liu and Mishra, 2017)
H08	No	-	-
JULES-W1	Yes	Evapotransipration is considered from five PFTs and four non-vegetative surface types. Each grid cell is composed of different fractions of those 9 surface types. Transpiration occurring from vegetation is based on photosynthetic process, which is subject to stomatal conductance regulated by the CO_2 concentration. Furthermore, transpiration is also controlled by the soil moisture availability in the root zone.	(Best et al., 2011; Clark et al., 2011)
LPJmL	Yes	Vegetation composition is determined by the fractional coverage of PFTs at the grid scale. PFTs are defined to account for the variety of structure and function within a stand and are therefore simulated as average individuals competing for light and water according to their crown area, LAI, and rooting profiles. The vegetation dynamics component of LPJmL includes carbon allocation to different PFT tissue compartments, PFT interaction, and establishment and mortality processes. Photosynthesis and stomatal response are simulated following Farquhar et al. (1980) and the generalization by Collatz et al. (1991) for global modelling, based on the function of absorbed photosynthetically active radiation, temperature, day-length, and canopy conductance for each PFT present in a grid cell.	(Schaphoff et al., 2018)
PCR-GLOBWB	No	-	-
CWatM	No	-	-
MATSIRO	Yes	The consideration of CO_2 effects is functionally similar to that in CLM, and there is no dynamic vegetation scheme. CO_2 is prescribed in the model, which is used in the	(Takata et al., 2003)

> photosynthesis scheme to calculate stomatal conductance, among other parameters, following Farquhar et al. (1980). Soil moisture stress on photosynthesis is considered using moisture availability in the root zone with root distribution fraction in each soil layer. All of that is done for different vegetation or plant functional types.

2.6

Figure 2 is of bad quality.Is it necessary to have all the extremes? Is it reasonable to have a range over 2000mm/year? most aquifers recharge maps stop before 1000mm/year and often under 500. Are GWR values above 1500 in Figure 2 located in capacitive aquifers or in very local and shallow aquifer as defined by Whymap (see comment 1)? As this figure is difficult to read, it is impossible to check comments line 317-322

We think it is necessary to include all extremes even if it reduces the readability of the figure. Only by showing the outliers we are able to openly discuss what the models compute no matter if the values are reasonable or not. Again, the focus on specific aquifers is not something we target in this manuscript (See also 2.3).

2.7

Nice to disentangle the impact of GCM and GHM, but, fig3a includes 76 cases while fig b includes only 36 cases. How does this compare? In order to try to understand what the impact of GHM is, and what the impact of the response of GHM to GW is, it seems required to show the variance of the 8 GHMs on preindustrial case. Figure 7 shows that there are important change, but, variance will be helpful to compare with fig3a.

*As explained in 2.3 not all RCPs and GCM combinations may lead to a warming of 3°, thus the number of involved ensemble members changes. The simulation of PI GWR per GHM is already shown in S1 and S4. We now also refer to these figures in this paragraph: (Line 393) "*For the simulated variance at PI see Fig. S1 and S4.*"*

2.8

Figure 4 includes only one realization of one GHM and one GCM. Why this GCM? Why this GHM? Is this GCM includes dynamic vegetation? Is the dynamic vegetation of the GCM consistent with the one of the GHM? In any case, it would be nice to have some information on LAI changes;

This is stated at the end of the paragraph "Unfortunately, no other GHM-GCM combinations with these alternative CO_2 concentration variants are available in the framework of ISIMIP2b." Yes, GFDL includes dynamic vegetation as well. We agree that an assessment of the differences between the GHM and GCM implementation of the dynamic vegetation would be of interest, however, it is clearly out of scope of in this study. It is also unclear to us how information on LAI changes would provide more insights on the presented results.

2.9

Line 422 : Decrease of precipitation lead to a decrease of vegetation productivity⇒I guess it is more complicated than that, you may correct

Agreed it very much depends. We rephrased the sentence and added another relevant reference in this matter.

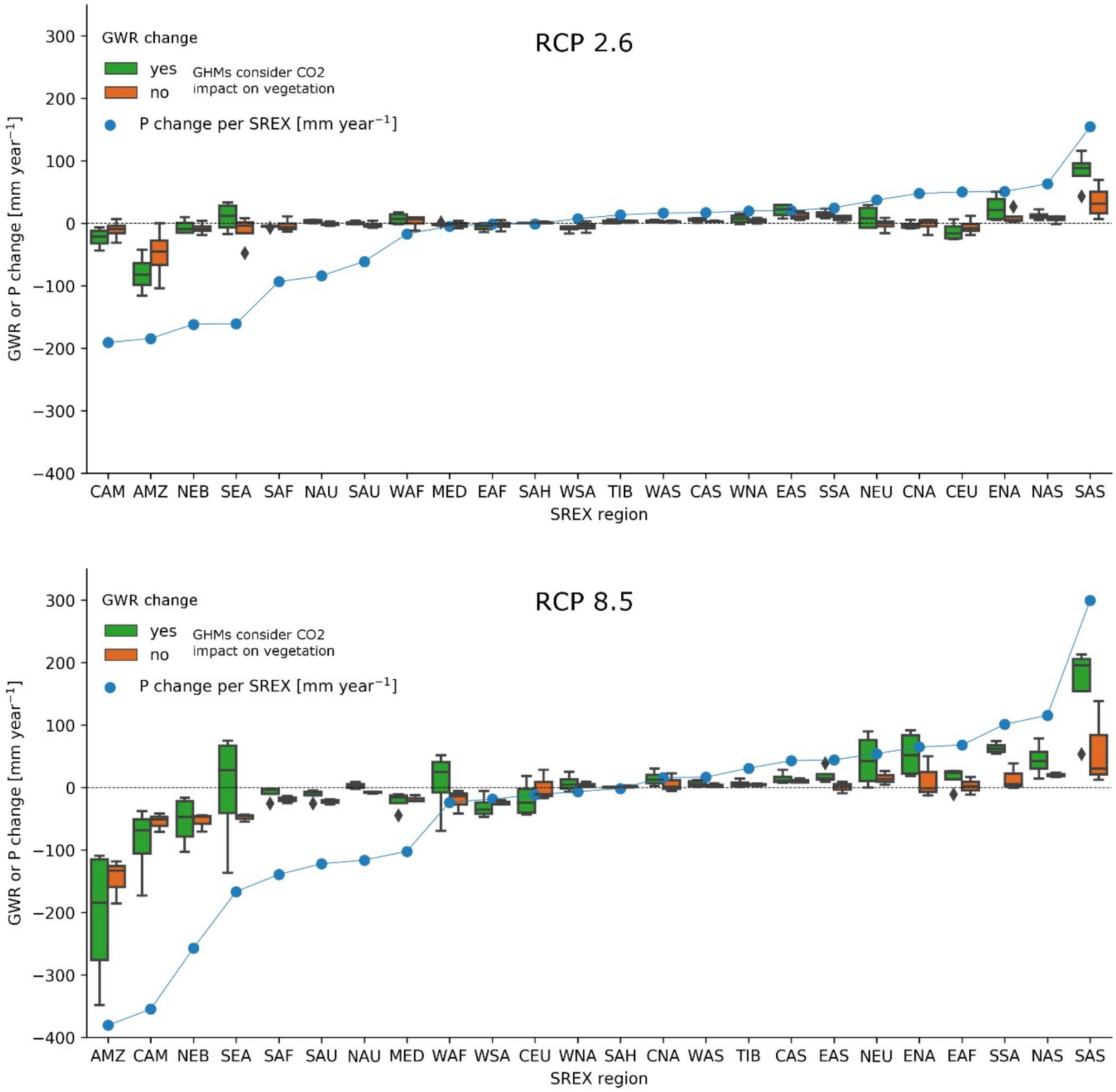
Now reads (Line 458 ff):

"Decreases in precipitation may lead to a decrease in vegetation productivity (if not counteracted by an increased water-use efficiency due to elevated CO_2 concentrations (Singh et al.; 2020))) and thus to a decrease in transpiration."

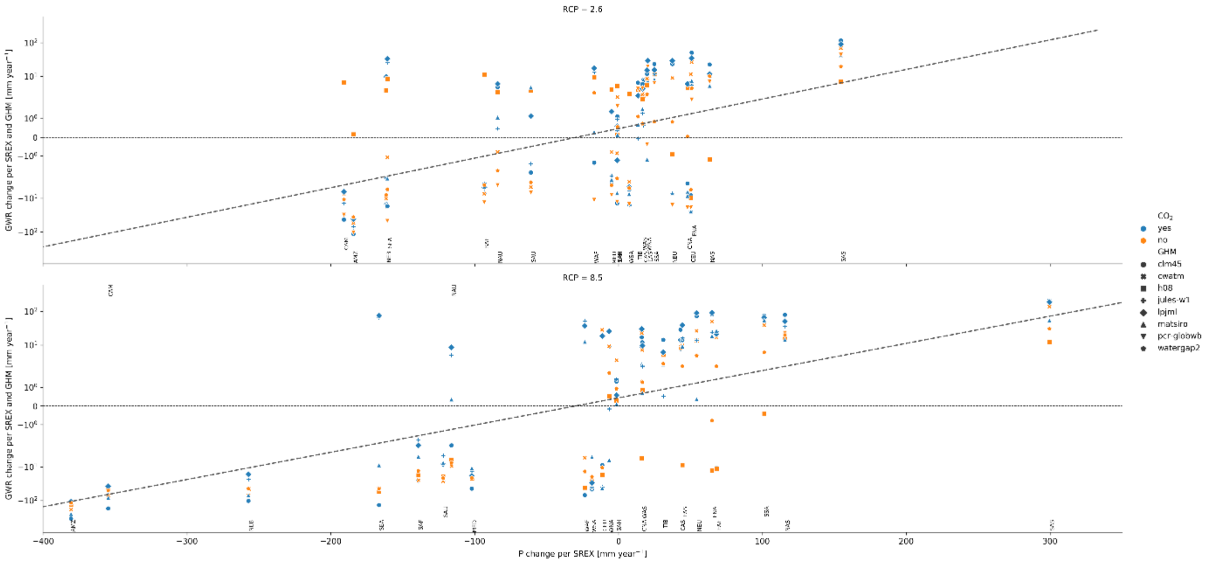
2.10

Figure 5: is this figure correct? a same GHM can appear twice for a subregion with the same colors▹A change of precipitation of 100mm/year can lead to an increase of GWR of the same amount▹Is the vegetation dead? It would be nice to better understand which process occurs in detail in one subregion?

Yes, the figure is correct. However, we realize that it might be difficult to distinguish between the amounts of markers. To allow for a more comprehensive figure we revised in heavily and summarized the models in a bar chart (see new Figure 7 below). We have furthermore improved the original plot and added it to the supplement to allow the interested reader to still investigate the model differences.
Concerning the large increases of GWR linked to large increases of precipitation, it is unclear which process is mainly responsible for this feedback. Possibly the increased water use efficiency of the vegetation allows for a large increase in GWR linear to the increase in P.



(heavily revised) Figure 1 Relation of changes in precipitation (P) (mean(1981-2010) – mean(2070-2099)) to changes in GWR (mean(1981-2010) – mean(2070-2099)) depending on the model type (with or without CO_2; see also Table 1) per SREX (selection as in Table 3) for RCP 2.6 and RCP 8.5 for the GCM HadGEM2-ES.



(new) Figure S10 Relation of changes in precipitation (P) (mean(1981-2010) – mean(2070-2099)) to changes in GWR (mean(1981-2010) – mean(2070-2099)) depending on the model type per SREX (selection as in Table 1) for RCP 2.6 and RCP 8.5 for the GCM HadGEM2-ES. Y-Achis is log-scaled. The dashed line is the 1:1 line.

2.11

Fig 6 compares 4 GHM with dynamic vegetation (change in LAI?) with the 4 others who assumes constant vegetation (but do they account sensitivity of the stomatal aperture to CO2?). The difference on the physics of the GHMs is large, but the impact seems reduced. How can we be sure that the difference is linked to the dynamic vegetation? Similar difference may well exist between this different GHMs without change in vegetation dynamic▹ Moreover, are the significant changes located where the aquifers are extended and capacitive, or where the aquifers are very shallow and local?

No, the other 4 models with constant vegetation do not account for the stomatal aperture. To clarify we now define the terminology much more clearly in 2.1 to avoid any confusion. Additionally, we added Table 1 to provide an overview on which model implements what kind of vegetation.

Now reads in S2.1:

“In the following, we use the term *active vegetation* for models that consider the physiological effect of changes in CO_2 on vegetation and the term *dynamic vegetation* for the models that allow for a changing vegetation regarding LAI and/or vegetation type.”

We agree that we cannot be sure without a further extended sensitivity analysis, which unfortunately is not possible at this point, that the differences we are seeing are solely due to the inclusion of vegetation. However, the only analysis possible in this regard with the available data shown in Figure 6 (based on new version) supports that assumption. We are now stating this more clearly:

Line 493: “It is likely that the shown differences are due to the implementation of dynamic vegetation in the GHMs (compare Fig. 6), however it is possible that other model peculiarities and processes are relevant as well.”

For your comment on specific aquifers see 2.3.

2.12

Assessment of the GHM should not appear in the discussion. It should be earlier, or in supplement.GWR estimates by Mohan is only the GWR from precipitation (no river inputs). How does this compare to the numerous GHM?

We don’t think that an earlier appearance is merited. The assessment of the models themselves is not the focus of this paper, thus a discussion of the figure at the beginning of the paper is not useful to convey our central messages. Moving them to the supplement is also not helpful as Fig. 9 transports important messages to understand the relevance of the presented results and conclusions correctly. We think that it is a helpful figure to discuss the limitations of the approach without skewing the central message of the paper. The discussion is thus the right place even though it might be unusual.
Concerning the question if the estimates are comparable see also our answer in 1.4.

2.13

Line 539: “Despite the uncertainties, this study shows that climate change will impact groundwater availability in many regions of the world”. this is naïve: it was already shown by numerous regional studies.

Additional evidence is always a good thing. We further provide three important additional messages that regional studies are not able to show: 1) We provide global patterns of change – also for regions that have not been studied yet and consistent patterns on much larger scales. 2) We present a multi-model ensemble approach, which is also not common in regional studies. 3) The used models operate at the coarse spatial resolution closer to climate models without the requirement to downscale uncertain climate input to specific regions.

We rephrased the conclusion and it now reads:
“Potential GWR changes due to climate change require increased attention from the scientific community as well as from decision-makers because they affect future water availability in many regions and thus the wellbeing of billions of people. This study shows that simulated global-scale estimates of GWR vary strongly among GHMs, which contribute more strongly to the overall uncertainty of future groundwater recharge than the applied GCM output. However, statistically significant increases and decreases of GWR could be identified in specific regions per GW level. The presented inter-model ranges of GWR changes are an important input for processes aiming at developing strategies for climate change adaptation, as risk-averse decision-makers may want to orient their strategies towards adapting to the worst-case GWR change and not to the projected ensemble mean change.

This study shows that including vegetation processes in GHMs can change projected GWR changes substantially. However, consideration of these processes does not lead to a uniform increase of groundwater recharge, as might be expected from the physiological effect of increasing atmospheric CO_2

concentration. In some regions with decreasing groundwater recharge, where groundwater availability is a major concern, models that include these processes show the largest differences among themselves. Further research is necessary to understand GWR on large scales, and how it is affected by climate. Simulation of groundwater recharge by global hydrological models needs to be analyzed in more detail, and the benefit of integrating gradient-based groundwater flow models in GHMs should be assessed."

2.14

Line 545: "Moreover, this study shows that including dynamic vegetation processes in GHMs can change the results substantially": this is not that clear from your results. I was expected more impact indeed▹

This relates to 2.5, 2.8, 2.9, 2.11 and should be much clearer now.

2.15

A map of the extension of the subdomain is required

We assume that the referee is referring to the SREX regions, which are provided in Fig S6.

2.16

Numbering of figures is wrong

Figure 1 existed twice in the manuscript. We apologize for any caused inconvenience. This was corrected.

2.17

Line 287: Masson-Delmotte et al

This has been corrected.

2.18

Figure S3 should be in the text since it is discussed

We disagree. It is only shortly mentioned and not necessary to understand to message of the paper. It would be possible to move it to the Appendix but we don't think that it adds any valuable information that is not already transported through the text.

Referee #3

3.1

I do appreciate the tremendous amount of work the authors put into the study and already apologize for not being able to be more positive. The study has a flaw in that it assumes/postulates that GHMs are able to simulate groundwater recharge processes (line 61). This remains to be shown (see specific comment below). The authors also compare to Mohan et al. (2018), a data set, which is also highly uncertainty itself, and show that all models essentially have no skill. Thus, the study is hypothetical and should be seen as a model sensitivity study, which does not necessarily reflect reality. The large uncertainty in the results supports that notion. The authors discuss the limitations in detail and come to the conclusion (line 538) “Despite the uncertainties, this study shows that climate change will impact groundwater availability in many regions of the world. “ Yes, that‘s probably true. But it’s sad that due to the large uncertainty, no additional concrete conclusions can be drawn from the results.

Because the detailed analyses and numbers have very low confidence, I am not able to comment on the simulation results. In summary, I find that GHMs have not been tested comprehensively especially with regard to complex processes such as groundwater recharge. Thus, in my opinion, the study is too early (first testing, then analyses). Looking at the description of the models, I would not even call the estimated flux groundwater recharge. If GHMs are applied I suggest to study the major fluxes of the water balance including their impact on the residuals of the balance equation in the models. In a way that’s what the authors are doing, yet the presentation does not show these results.

We appreciate the recognition of the amount of work that went into this study and strongly disagree with the conclusion of reviewer #3 that “the study is too early”. We think it is timely to do a study that aims at understanding the best information we have on potential impacts of climate change on groundwater at the global scale, which is provided by the multi-model ensemble output that is analyzed in this study. The merit of our study is similar to that of many climate change studies done with global climate models. It is well known that different global climate models project very different future climatic changes in response to the same greenhouse gas emissions scenario; nevertheless, their results including an understanding of their uncertainties are of interest to many and impact decision-making. We explicitly wanted to focus on uncertainties and not (impossible) predictions, which is also reflected by the title of our manuscripts: ““Uncertainty of simulated groundwater recharge …”.

It is definitely justified to criticize the ability of GHMs to simulate groundwater recharge, which we openly discuss in this publication. The referee himself/herself admits that “The authors discuss the limitations in detail”. *While the analysis has flaws the study discusses them openly and it provides new information and understanding. That no precise and certain prediction of future groundwater recharge are currently possible is certainly, using the word of the referee “sad”. However, the study does identify statistically significant increases and decreases in recharge in multiple regions of the world. And it provides a range of potential future recharge changes for each world region that persons in charge of climate change adaptation should take into account for lack of better knowledge.*

*The statement that “*that GHMs have not been tested comprehensively*” contradicts a substantial number of studies that have been published in the recent years devoted to the evaluation of GHMs, for example: (Scanlon et al., 2018; Müller Schmied et al., 2014; Döll and Fiedler, 2008; Döll and Flörke, 2005) and many more. Still, additional testing and improvement is still necessary and this study provides important pointers for future research. In any case, we agree that groundwater recharge is a complex process that needs to be developed further in GHMs. Our manuscript offers first insights on what these improvements might be by presenting a novel comparison of a large ensemble of models in this regard. The suggested approach of comparing other components of the water balance is something that has been done in the framework of ISIMIP in multiple other publications (*“e.g., flood risk (Willner et al., 2018; Thober et al., 2017; Alfieri et al., 2017), low flows in Europe (Marx et al., 2018), evapotranspiration

(Wartenburger et al., 2018), runoff and snow in Europe (Donnelly et al., 2017) or multi-sectoral impacts (Byers et al., 2018).”*) that are cited in the introduction of this manuscript.*

In reaction to the reviewer comment, we made substantial changes to both abstract and conclusions to focus less on specific numerical values than on explaining the potential benefits and applicability of the study results.

The new abstract:

“Billions of people rely on groundwater as an accessible source for drinking water and irrigation, especially in times of drought. Its importance will likely increase with a changing climate. It is still unclear, however, how climate change will impact groundwater systems globally and thus the availability of this vital resource. Groundwater recharge is an important indicator for groundwater availability but it is a water flux that is difficult to estimate as uncertainties in the water balance accumulate, leading to possibly large errors in particular in dry regions. This study investigates uncertainties in groundwater recharge projections using a multi-model ensemble of eight global hydrological models (GHMs) that are driven by the bias-adjusted output of four global circulation models (GCMs). Preindustrial and current groundwater recharge values are compared with recharge for different global warming (GW) levels as a result of three representative concentration pathways (RCPs). Results suggest that projected changes strongly vary among the different GHM-GCM combinations, and statistically significant changes are only computed for few regions of the world. Statistically significant GWR increases are projected for Northern Europe and some parts of the Arctic, East Africa and India. Statistically significant decreases are simulated in southern Chile, parts of Brazil, central USA, the Mediterranean, and southeast China. In some regions, reversals of groundwater recharge trends can be observed with global warming. Because most GHMs do not simulate the impact of changing atmospheric CO_2 and climate on vegetation and thus evapotranspiration, we investigate how estimated changes in GWR are affected by the inclusion of these processes. In some regions, inclusion leads to differences in groundwater recharge changes of up to 100 mm year^{-1}. Most GHMs with active vegetation simulate less severe decreases of groundwater recharge than GHMs without active vegetation and in some regions even increases instead of decreases. However, in regions where GCMs predict decreases in precipitation and groundwater availability is most important, model agreement among GHMs with active vegetation is lowest. Additional research on simulating groundwater processes in GHMs is necessary.”

The new conclusions:

“Potential GWR changes due to climate change require increased attention from the scientific community as well as from decision-makers because they affect future water availability in many regions and thus the wellbeing of billions of people. This study shows that simulated global-scale estimates of GWR vary strongly among GHMs, which contribute more strongly to the overall uncertainty of future groundwater recharge than the applied GCM output. However, statistically significant increases and decreases of GWR could be identified in specific regions per GW level. The presented inter-model ranges of GWR changes are an important input for processes aiming at developing strategies for climate change adaptation, as risk-averse decision-makers may want to orient their strategies towards adapting to the worst-case GWR change and not to the projected ensemble mean change.

This study shows that including vegetation processes in GHMs can change projected GWR changes substantially. However, consideration of these processes does not lead to a uniform increase of groundwater recharge, as might be expected from the physiological effect of increasing atmospheric CO_2 concentration. In some regions with decreasing groundwater recharge, where groundwater availability is a major concern, models that include these processes show the largest differences among themselves. Further research is necessary to understand GWR on large scales, and how it is affected by climate. Simulation of groundwater recharge by global hydrological models needs to be analyzed in more detail, and the benefit of integrating gradient-based groundwater flow models in GHMs should be assessed."

3.2

Only a couple specific comments Abstract: The reported percent increases/decreases of GWR suggest an accuracy that is simply not there; especially given the huge uncertainty in the results. Thus, the abstract sends the wrong message, especially to water managers and decision makers.

We agree that there should be no confusion on the main message of this manuscript and that the results should be considered with care. To attract the reader's attention on this matter and avoid any confusion for readers that might misinterpret the results we have greatly adapted the abstract. See also 3.1..

3.3

54: One of the most important factors is missing: Depth and dynamics of the free water table.

This is now mentioned (Line 63 ff):

"An additional factor in estimating groundwater recharge is the simulation of the groundwater table and thus capillary rise and focused recharge. This has not been achieved yet in GHMs, however, recently, global hydrological models (GHMs) started integrating gradient-based groundwater models to better estimate the flows between surface water and groundwater as well as the impact of humans and the changing climate on the groundwater system (de Graaf et al., 2019; Reinecke et al., 2019). Neglecting capillary rise may lead to an overestimation of decreases and increases of GWR due to a changing climate."

3.4

61: This is true, but has never been tested. I suggest to compare the GHMs against fully integrated hydrologic models, such as Cathy, Hydrogeosphere, OpenGeosys, ParFlow, etc. in order to test the ability of GHMs to simulate recharge processes. This is one of many tests that GHMs should undergo in my opinion.

The models currently under development have been compared to these models (e.g. ParFlow in Reinecke et al. 2019). We agree that this comparison needs to continue in the future.

We added a sentence to the conclusions to reflect that. See 3.1.

3.5

Section 2.2: Porbably I missed these details: what‘s the time step, the spatial resolution, etc?

The spatial resolution is 0.5° x 0.5° (described in section 2.1) and temporal resolution of the original GWR data is monthly, which was averaged to yearly values in this study (also described in 2.1). Time step is a term one might use in the context of numerical models, such as gradient-based groundwater models, which are not part of this study.

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Uncertainty of simulated groundwater recharge at different global warming levels: A global-scale multi-model ensemble study

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Abstract. Billions of people rely on groundwater as an accessible source for drinking water and irrigation, especially in times of drought. Its importance will likely increase with a changing climate. It is still unclear, however, how climate change will impact groundwater systems globally and thus the availability of this vital resource. Groundwater recharge is an important indicator for groundwater availability, but it is a water flux that is difficult to estimate as uncertainties in the water balance accumulate, leading to possibly large errors in particular in dry regions. This study investigates uncertainties in groundwater recharge projections using a multi-model ensemble of eight global hydrological models (GHMs) that are driven by the bias-adjusted output of four global circulation models (GCMs). Pre-industrial and current groundwater recharge values are compared with recharge for different global warming (GW) levels as a result of three representative concentration pathways (RCPs). Results suggest that projected changes strongly vary among the different GHM-GCM combinations, and statistically significant changes are only computed for few regions of the world. Statistically significant GWR increases are projected for Northern Europe and some parts of the Arctic, East Africa and India. Statistically significant decreases are simulated in southern Chile, parts of Brazil, central USA, the Mediterranean, and southeast China. In some regions, reversals of groundwater recharge trends can be observed with global warming. Because most GHMs do not simulate the impact of changing atmospheric CO_2 and climate on vegetation and thus evapotranspiration, we investigate how estimated changes in

GWR are affected by the inclusion of these processes. In some regions, inclusion leads to differences in groundwater recharge changes of up to 100 mm year^{-1}. Most GHMs with active vegetation simulate less severe decreases of groundwater recharge than GHMs without active vegetation and in some regions even increases instead of decreases. However, in regions where GCMs predict decreases in precipitation and groundwater availability is most important, model agreement among GHMs with active vegetation is lowest. Additional research on simulating groundwater processes in GHMs is necessary.

~~**Billions of people rely on groundwater as an accessible source for drinking water and irrigation, especially in times of**~~

The critical role of groundwater as an accessible source for irrigation and drinking water in particular during dry periods, droughts, and floods will intensify with climate change because increased precipitation variability is expected to decrease the reliability of surface water supply (Taylor et al., 2013; Döll et al., 2018; Kundzewicz and Döll, 2009). While demand for groundwater is likely to increase in the future, groundwater abstractions have already led to depleted aquifers in many regions around the globe (Thomas and Famiglietti, 2019; Cuthbert et al., 2019a; Wada et al., 2012; Konikow and Kendy, 2005; Döll et al., 2014b). They have also resulted in the reduction of groundwater discharge to rivers with negative impacts on water availability for humans and freshwater biota in particular during low-flow periods (Herbert and Döll, 2019). To what extent groundwater can serve for sustaining ecosystem health and for supporting human adaptation to climate variability and change strongly depends on future groundwater availability, which is strongly affected by climate change (Kundzewicz and Döll, 2009; Döll, 2009; Taylor et al., 2013; Cuthbert et al., 2019b).

Groundwater recharge (GWR) is a central indicator of potential groundwater availability (Herbert and Döll, 2019). GWR is the vertical water flux to the groundwater from the soil (diffuse GWR) and from surface water bodies (point or focused recharge) (Small, 2005). It is a function of the local climate, topography, soil, land cover, land use (urbanization, woodland establishment, crop rotation, and irrigation practices), atmospheric CO_2 concentrations, and geology (Small, 2005). Changes in GWR alter groundwater levels and their temporal patterns, which affect vital ecosystem services (Kløve et al., 2014). Knowledge of the dynamics and process interactions determining GWR is a fundamental prerequisite to assess groundwater quality and quantity under climate change (Green et al., 2011). The simulation of GWR is possibly one of the most ~~difficult~~challenging components of the water budget as it accumulates the uncertainties of all other components of the budget. Especially in semiarid regions, uncertainties in precipitation and evapotranspiration lead to ~~a larg~~considerable uncertainty in recharge.~~,~~ ~~Knowledge of the dynamics and process interactions determining GWR is a fundamental prerequisite to assess groundwater quality and quantity under climate change~~ (Green et al., 2011)~~.~~An additional factor in estimating groundwater recharge is the simulation of ~~the depth and dynamics of the groundwater table~~the groundwater table and thus capillary rise and focused recharge. This has not been achieved yet in GHMs, however, -r~~R~~ecently, global hydrological models (GHMs) started integrating gradient-based groundwater models to better estimate the flows between surface water and groundwater as well as the impact of humans and the changing climate on the groundwater system (de Graaf et al., 2019; Reinecke et al., 2019). Neglecting capillary rise may lead to an overestimation of decreases and increases of GWR due to a changing climate.~~Those~~

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~~models may allow taking into account~~considering ~~the impact of capillary rise on groundwater recharge and its climate-driven~~

Assessing the response of GWR to climate change is difficult even at the local scale, one of the reasons being that groundwater recharge, different from streamflow, is rarely measured, and long time series of groundwater recharge is not available (Earman and Dettinger, 2011). In local groundwater modelling, groundwater recharge is often determined by calibration using hydraulic head observation, while integrated modelling relies on the partitioning of precipitation into evapotranspiration, storage change, and runoff (GWR plus surface and subsurface runoff). Moreover, projections of GWR often neglect the impact of changing climate and higher CO_2 levels on plants and thus evapotranspiration and GWR (Taylor et al., 2013). With higher CO_2 levels, terrestrial plants open their stomata less, which reduces evapotranspiration and increases runoff (physiological effect) while they might grow better, increasing evapotranspiration (structural effect) (Gerten et al., 2014). Vegetation models that include these effects d~~o not ~~isagree about the balance of both effects (Gerten et al., 2014). However, based on a large ensemble of GCMs that include the impact of CO_2 and changing climate on vegetation and evapotranspiration, rising CO_2 can be expected to decrease transpiration and thus increase total runoff (Milly and Dunne, 2016). Therefore, GHMs that do not ~~take into account~~consider active vegetation may underestimate runoff, and thus GWR increases, or they may overestimate GWR decreases.

While there have been review articles on the relation of groundwater and climate change (Smerdon, 2017; Jing et al., 2020; Refsgaard et al., 2016), global-scale studies that quantify the impact of climate change on GWR are rare. They have evolved regarding the way climate scenarios were implemented and how many global climate models (GCMs) and GHMs were included in the study. While Döll (2009) could only use the delta change method to integrate information from two GCMs in the GHM WaterGAP (Alcamo et al., 2003; Müller Schmied et al., 2014), Portmann et al. (2013) could feed their simulations of future changes in GWR with WaterGAP directly by the bias-adjusted output with five GCMs. They found that changes in GWR increase with increasing greenhouse gas emissions. Acknowledging that not only GCMs but also GHMs contribute to the uncertain translation of emissions scenarios to changes in GWR (Moeck et al., 2016), the study of Döll et al. (2018) included two GHMs (WaterGAP and LPJmL, Rost et al. (2008), Schaphoff et al. (2013)) driven by the bias-adjusted of four GCMs. They evaluated relative changes of GWR with climate change, which can arguably serve as a better indicator of climate change hazard than absolute changes of GWR. On the other hand, the usage of relative change led to the result that change in GWR could not be reliably computed for 55% of the global land area due to very small GWR for the reference period simulated by LPJmL (Döll et al., 2018). While the LPJmL model considered, different from the WaterGAP model, the effect of rising CO_2 on groundwater recharge, the impact of this on GWR projections were not analyzed in Döll et al. (2018). In general, studies investigating the difference between GHMs with and without dynamic vegetation are rare (Davie et al., 2013).

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This study assesses the impact of climate change on GWR based on the output of a multi-model ensemble encompassing eight GHMs, each forced by the bias-adjusted output of four GCMs under three different representative concentration pathways (RCPs). The ensemble was generated in the framework of the Inter-Sectoral Impact Model Intercomparison Project (ISIMIP) using simulation protocol ISIMIP2b (Frieler et al., 2017). The ISIMIP global water sector incorporates global models, including water resources models, land surface models, and dynamic vegetation models that can compute water flows and storages on the continents of the Earth; in this study, all three model types are referred to as GHMs. The ISIMIP2b ensemble has already been used in multiple climate change studies investigating, e.g., flood risk (Willner et al., 2018; Thober et al., 2017; Alfieri et al., 2017), low flows in Europe (Marx et al., 2018), evapotranspiration (Wartenburger et al., 2018), runoff and snow in Europe (Donnelly et al., 2017) or multi-sectoral impacts (Byers et al., 2018).

We analyze how GWR is projected to change globally and regionally for multiple global warming (GW) levels, determine the contributions from GHMs and GCMs to the variance of simulated changes and discuss the implications for future assessments of global groundwater resources. Furthermore, we show the effect of including the physiological impacts of evolving CO_2 on global estimates of GWR. To this end, the remainder of this paper is structured as follows. Section 2 provides an overview of the used GHMs and the methods to calculate changes of GWR per GW level and sources of uncertainty. The results in section 3 show the significant changes in GWR per GW and the differences in between GHMs and GCMs. We then compare the influence of GCMs, GHMs, and RCPs on the variance of simulated GWR, assess the differences in GWR due to including dynamic vegetation in GHMs and compare the GHM simulations to interpolated measured GWR. The paper closes with a discussion of these findings (Sect. 4) and conclusions (Sect. 5).

2 Methods

2.1 Simulation of groundwater recharge

This study encompasses eight GHMs that differ in their representation of various hydrological processes. Four of these models, described in more detail in the following, are able to simulate the impact of evolving CO_2 concentrations on vegetation: CLM 4.5, JULES-W1, LPJmL, MATSIRO (Table 1). In the following, we use the term *active vegetation* for models that consider the physiological effect of changes in CO_2 on vegetation and the term *dynamic vegetation* for the models that allow for ~~a~~ ~~a~~ changing vegetation regarding LAI and/or vegetation type. A comprehensive overview of GHMs and their properties can be found in Sood and Smakhtin (2014) and the primary publications referred to in the subsections below. The definition of GWR and groundwater varies in between GHMs (discussed in Sect. 4). The analysis in this study is based on monthly GWR (variable *qr* in ISIMIP) in 0.5° x 0.5° grid cells simulated by the eight GHMs taking part in the ISIMIP2b protocol (Frieler et al., 2017). Some GHMs contained small negative GWR values, e.g., due to capillary rise; these values were set to zero in the analysis. We do not consider focused recharge in this study as no model offers a reliable implementation of these processes until now.

Table 1 Overview which models are able to simulate the impact of evolving CO_2 concentrations on vegetation and how it is implemented.

GHM	**Considers CO_2**	**Summary of considered vegetation processes in ISIMIP2b**	**Reference**
WaterGAP2	No	-	-

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CLM4.5	Yes	Photosynthesis depends on root zone soil moisture availability. The description is similar to LPJmL listed below. The area a population of plant functional types (PFTs) takes up is prescribed and only changes if the input data changes~~does~~.	(Di Liu and Mishra, 2017)~~TODO~~
H08	No	-	-
JULES-W1	Yes	Evapotrans~~ipp~~piration is considered from five PFTs and four non-vegetative surface types. Each grid cell is composed of different fractions of those ~~9~~nine surface types. Transpiration occurring from vegetation is based on photosynthetic process, which is subject to stomatal conductance regulated by the CO_2 concentration. Furthermore, transpiration is also controlled by ~~the~~ soil moisture availability in the root zone.	~~TODO~~(Best et al., 2011; Clark et al., 2011)
LPJmL	Yes	Vegetation composition is determined by the fractional coverage of PFTs at the grid~~-~~-scale. PFTs are defined to account for the variety of structure and function within a stand and are therefore simulated as average individuals competing for light and water according to their crown area, LAI, and rooting profiles. The vegetation dynamics component of LPJmL includes carbon allocation to different PFT tissue compartments, PFT interaction, and establishment and mortality processes. Photosynthesis and stomatal response are simulated following Farquhar et al. (1980) ~~Farquhar et al. (1980)~~ and the generalization by Collatz et al. (1991) ~~Collatz et al. (1991)~~ for global modelling, based on the function of absorbed photosynthetically active radiation, temperature, day-length, and canopy conductance for each PFT present in a grid cell.	~~TODO~~(Schaphoff et al., 2018)
PCR-GLOBWB	No	-	-
CWatM	No	-	-
MATSIRO	Yes	The consideration of CO_2 effects is functionally similar to that in CLM, and there is no dynamic vegetation scheme. CO_2 is prescribed in the model, which is used in the photosynthesis scheme to calculate stomatal conductance, among other parameters, following Farquhar et al. (1980). Soil moisture stress on photosynthesis is considered using moisture availability in the root zone with root distribution fraction in each soil layer. All of that is done for different vegetation or plant functional types.	~~TODO~~(Takata et al., 2003)

WaterGAP2

The WaterGAP2 model (Alcamo et al., 2003) computes human water use in five sectors and the resulting net abstractions from groundwater and surface water for all land areas of the globe, excluding Antarctica. These net abstractions are then taken from

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the respective water storages in the WaterGAP Global Hydrology Model (WGHM) (Müller Schmied et al., 2014; Döll et al., 2003; Döll et al., 2012; Döll et al., 2014b). With daily time steps, WGHM simulates flows among the water storage compartments canopy, snow, soil, groundwater, lakes, human-made reservoirs, wetlands, and rivers. GWR in WaterGAP2 is calculated as a fraction from runoff from land-based on soil texture, relief, aquifer type, and the existence of permafrost or glaciers, taking into account a soil texture dependent maximum daily groundwater recharge rate (Döll and Fiedler, 2008). If a grid cell is defined as semi-arid/arid and has a medium or coarse soil texture, GWR will only occur if daily precipitation exceeds a critical value (Döll and Fiedler, 2008); otherwise, the water runs off. Runoff from land that does not contribute to GWR is transferred to surface water bodies as fast surface runoff. WaterGAP further computes focused recharge beneath surface water bodies in semi-arid/arid grid cells, which is not considered in this study.

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CLM4.5

The Community Land Model version 4.5 (CLM4.5) (Lawrence et al., 2011; Oleson et al., 2013) is the land component of the Community Earth System Model (CESM), a fully-coupled, state-of-the-art earth system model (Hurrell et al., 2013). CLM is a land surface model representing the physical, chemical, and biological processes through which terrestrial ecosystems influence and are influenced by climate, including CO_2, across a variety of spatial and temporal scales (Lawrence et al. 2011). Individual land grid points can be composed of multiple land units due to the nested tile approach, which enables the implementation of multiple soil columns and represents biomes as a combination of different plant functional types. Groundwater processes, including sub-surface runoff, recharge, and water table depth variations, are simulated based on the SIMTOP scheme (Niu et al., 2007; Oleson et al., 2013).

H08

H08 (Hanasaki et al., 2018) is a GHM including various components for water use and management. It consists of five major components, namely, a simple bucket-type land surface model, a river routing model, a crop growth model which is mainly used to estimate the timing of planting, harvesting, and irrigation in cropland, a reservoir operation model, and a water abstraction model. The abstraction model supplies water to meet the daily water demand of three sectors (irrigation, industry, municipality) from six available and accessible sources (river, local-reservoir, aqueduct, seawater desalination, renewable groundwater, and non-renewable groundwater) and one hypothetical one termed unspecified surface water. It has two soil layers; one is to represent the unsaturated root zone, and the other the saturated zone (groundwater). The scheme of GWR computation is identical to Döll and Fiedler (2008).

JULES-W1

The Joint UK Land Environment Simulator (JULES) (Best et al., 2011) (W1 stands for water-related simulations in the ISMIP framework) is a land surface model initially developed by Met Office as the land surface component of Met Office Unified Model. JULES is a process-based model that simulates the carbon, water, energy, and momentum fluxes between land and atmosphere, including plant - carbon interactions (Clark et al., 2011). The rainfall that reaches the ground is partitioned into hortonian surface runoff and an infiltration component. Four soil layers represent the soil column with a total thickness of 3 m, with a unit hydraulic head gradient lower boundary condition, and no groundwater component. The water that infiltrates the soil moves down the soil layers updated using a finite difference form of the Richards equation (Best et al., 2011). The saturation excess water from the bottom soil layer becomes subsurface runoff that can be considered to be GWR (Le Vine et al., 2016).

LPJmL

Lund Potsdam Jena managed Land (LPJmL) is a dynamic global vegetation model that simulates the growth and productivity of both natural and agricultural vegetation as coherently linked through their water, carbon, and energy fluxes (Schaphoff et al., 2018). The soil column is divided into six active hydrological layers with a total thickness of 13 m depth. Percolation of infiltrated water through the soil column is calculated according to a storage routine technique that simulates free water in the soil bucket (Arnold et al., 1990). Excess water over the saturation levels produces lateral runoff in each layer (subsurface runoff). GWR is considered to be percolation (seepage) from the bottom soil layer. As there is no groundwater storage in LPJmL, for the ISIMIP2b protocol, seepage from the base soil layer is reported as both GWR and groundwater runoff, which is routed directly (no time delay) back into the river system.

PCR-GLOBWB

PCR-GLOBWB (PCRaster Global Water Balance; (Sutanudjaja et al., 2018) simulates the water storage in two vertically stacked soil layers and an underlying groundwater layer. Water exchanges are simulated in-between the layers (infiltration, percolation, and capillary rise) as well as the interaction of the top layer with the atmosphere (rainfall, evapotranspiration, and snowmelt). PCR-GLOBWB also calculates canopy interception and snow storage. Natural groundwater recharge is fed by net precipitation, and additional recharge from irrigation occurs as the net flux from the lowest soil layer to the groundwater layer, i.e., deep percolation minus capillary rise. The ARNO scheme (Todini, 1996) is used to separate direct runoff, interflow, and GWR. Groundwater recharge can be balanced by capillary rise if the top of the groundwater level is within 5 m of the topographical surface (calculated as the height of the groundwater storage over the storage coefficient on top of the streambed elevation and the sub-grid distribution of elevation).

CWatM

The Community Water Model (CWatM) is a large-scale integrated hydrological model, which encompasses general surface and groundwater hydrological processes, including human hydrological activities such as water use and reservoir regulation (Burek et al., 2019). CWatM takes six land cover classes into account and applies the tile approach. This hydrological model has three soil layers and one groundwater storage. Depth of the first soil layer is 5 cm, and the depth of second and third layers vary over grids depending on the root zone depth of each land cover class, resulting in total soil depth of up to 1.5 m.

Groundwater storage is designed as a linear reservoir. CWatM includes preferential bypass flow directly into groundwater storage and capillary rise from groundwater storage, as well as percolation from the third soil layer to groundwater storage. Hence, the groundwater recharge reported by CWatM in ISIMIP2b is the net recharge calculated from these three terms.

MATSIRO

The Minimal Advanced Treatments of Surface Interaction and RunOff (MATSIRO; Takata et al. (2003)) is a global land surface model initially developed for an Atmospheric Ocean General Circulation Model, the Model for Interdisciplinary Research On Climate (Hasumi, H., and S. Emori, 2004). This process-based model calculates water and energy flux and storage at and below the land surface, considering the stomatal response to CO_2 increase as well in the photosynthesis process. The off-line version of MATSIRO used for ISIMIP2b simulation explicitly takes vertical groundwater dynamics into account, including groundwater pumping (Pokhrel et al., 2015; Pokhrel et al., 2012). Soil moisture flux between the 15 soil layers is expressed as a function of the vertical gradient of the hydraulic potential, which is the sum of the matric potential and the gravitational head, and soil moisture movement is calculated by Richards equation. MATSIRO calculates net groundwater recharge as a budget of gravitational drainage into and capillary rise from the layer where the groundwater table exists. A simplified TOPMODEL (Beven and Kirkby, 1979; Stieglitz et al., 1997) is used to represent surface runoff processes, and groundwater discharge is simulated by using an unconfined aquifer model (Koirala et al., 2014).

2.2 Model simulations

Each GHM is forced by bias-adjusted data from four GCMs: GFDL-ESM2M, HadGEM2-ES, IPSL-CM5A-LR, and MIROC5. Further details on the selection of climate models and the bias correction can be found in Frieler et al. (2017), Lange (2016), Hempel et al. (2013), Lange (2018), and online at ISIMIP (2018). The bias adjustment method used for the GCMs in ISIMIP2b is using a trend preserving algorithm (Frieler et al., 2017) with EWEMBI (Lange 2018) as baseline (reference) climate condition. The simulations in this study span the period 1861 till 2099. All GHMs (except for PCR-GLOBWB, which misses the RCP 8.5 run) simulate the RCPs 2.6, 6.0, and 8.5.

The pre-industrial period (PI) is defined in ISIMIP from 1661-1860, whereas the historical period is defined from 1861-2005. ~~Additionally~~Additionally, to the RCP and historical simulations, ISIMIP defines PI simulations that represent an extended state of emissions scenarios from the PI period till 2099 (and partially till 2300, not applicable in this study). In this study, we always, if not stated otherwise, refer with PI to the simulation period 1960-2099 with the continued concentration levels of 1661-1860. Details on the simulation setup can be found on the ISIMIP webpage ISIMIP (2019) or in Frieler et al. (2017).

Regarding the non-climatic drivers, all GHMs use, for the time before 2006, so-called historical socio-economic pathway assumptions, e.g., historical water use, except for CLM 4.5, which used the socio-economic state of 2005. All simulations for 2006-2099 are based on this assumed socio-economic state of 2005. For some models this affects the abstraction from groundwater, which is not stimulated by all models (JULES-W1), or GWR directly due to irrigation (H08, CLM, PCR-GLOBWB). Details on the pertinent scenario variables can be found in the ISMIP protocol (Frieler et al., 2017). Land-use change was not considered.

2.3 Determining stabilized warming levels

In order to derive policy-relevant information, we assess impacts framed in terms of GW levels (1°, 1.5°, 2°, and 3°C) with respect to the GW of 0°C in PI conditions (James et al., 2017). The time of passing a warming level is defined as the first time the 31-year running mean of the global averaged annual mean temperature gets above that level. Each GCM reaches different GW at different times (Table 2~~Table 2Table 1~~), depending on the RCPs (van Vuuren et al., 2014). For each GW level (1°, time slice of 31 years (15 before the level was reached, and 15 after) for each GCM and for each RCP, in which that GW is reached, are used. Using this time slice, a yearly mean GWR at 0.5° is calculated for the GHMs that were forced with the particular combination of GCM and RCP. (Fig. 1). Additionally, a PI reference is calculated for each GCM, RCP, and GHM combination for the same time-slice the GW level was reached in a particular RCP + GCM combination using the PI reference simulation (see section 2.2)~~. Figure 1~~ illustrates the methodology by showing two unspecified RCPs and the PI comparison Considering that not all RCP/GCM combinations reach higher warming levels (Table 1), not all ensembles have the same size. Theoretically, the maximum ensemble size is 96, a combination of 8 GHMs, 4 GCMs, and 3 RCPs (2.6, 6.0, and 8.5). Because projections under RCP 8.5 are not available for PCR-GLOBWB, the maximum ensemble size is 84. The smallest ensemble (for 3°C) consists of 36 members.

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Table 22~~1~~ Overview of the warming levels and in which year they are reached in the corresponding GCM (ISIMIP, 2019).

Warming Level	RCP	GFDL-ESM2M	HadGEM2-ES	IPSL-CM5A-LR	MIROC5
1°	2.6	2014	2012	1993	2015
	6.0	2016	2014	1993	2023
	8.5	2014	2012	1993	2014
1.5°	2.6	-	2026	2009	2048
	6.0	2056	2032	2010	2052
	8.5	2036	2025	2009	2033
2°	2.6	-	-	2029	-
	6.0	2076	2050	2029	2071
	8.5	2053	2037	2024	2048
3°	2.6	-	-	-	-
	6.0	-	2076	2068	-
	8.5	2082	2056	2046	2071

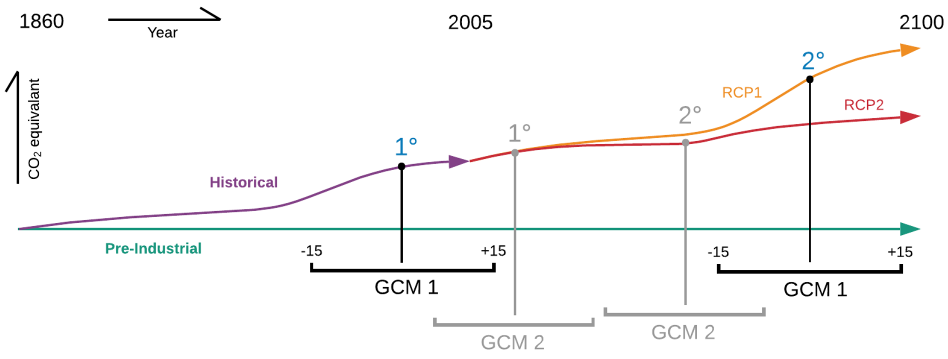

Figure 1 Conceptual representation of how GW levels are determined for different GCMs, RCPs, and the PI comparison period.

2.4 Calculation of model variance

To calculate whether the variance in absolute GWR change is mainly introduced through the GHMs or the GCMs, the following equation is applied per model grid cell and GW level.

$$Rvar_{GWR}^{model} = \sigma_{GWR}^2(GCMs) \Big/ \left(\sigma_{GWR}^2(GCMs) + \sigma_{GWR}^2(GHMs) \right), \qquad (1)$$

where $Rvar_{GWR}^{model}$ is the variance ratio of GCMs to GHMs, $\sigma_{GWR}^2(GHMs)$ is the average variance of GWR change of all GHMs per GCM per RCP, and $\sigma_{GWR}^2(\text{GCMs})$ is the average variance in GWR change of all GCMs per RCP per GHM. The variance relative to the choice in RCP $Rvar_{GWR}^{RCP}$ can be calculated similarly as

$$Rvar_{GWR}^{RCP} = \sigma_{GWR}^2(RCPs) \Big/ \left(\sigma_{GWR}^2(RCPs) + \sigma_{GWR}^2(GHMs) \right), \qquad (2)$$

where $\sigma_{GWR}^2(\text{RCPs})$ is the average variance in GWR of all RCPs per GCM per GHM.

2.5 Determining significant changes

A model ensemble allows us to consider the uncertainty in modeling physical processes as different model use different algorithms and parameters for computing groundwater recharge. To determine whether changes in GWR due to GW computed by the model ensemble are statistically significant, we use the two-sample Kolmogorov–Smirnov (K-S) test to compare the GWR values computed by all GHM-GCM model combinations under e.g., PI conditions with the values at the various GW levels. The use of a two-tailed t-test is not advisable in this setting due to the small sample size (max. 84 in this study). Because the K-S test does not allow to check whether the ensemble agrees on the sign of change in GWR, we apply an additional criterion to determine a significant change similar to Döll et al. (2018). A change is only marked as (statistically) "significant"

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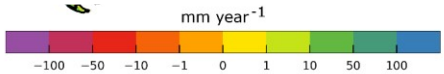
if the K-S test indicates a significant difference and at least 60% of the model realizations of the ensemble (RCP, GCM and GHM combinations) agree on the sign of change (i.e. a decrease or increase". In case of a low significance, all models may show large responses to climate change while their agreement on the amount or sign of change is low.

~~A model ensemble allows us to consider the uncertainty in modeling physical processes and the consequences of modeling decisions that lead to different results. To determine whether computed changes in GWR due to global warming are significant, we use the two-sample Kolmogorov–Smirnov (K-S) test to compare two the ensemble distribution of GWR under PI conditions and under conditions of global warming. The use of a two-tailed t-test is not advisable in this setting due to the small sample size (max. 84 in this study). Because the K-S test does not allow to check whether the ensemble agrees on the sign of change in GWR, we apply an additional criterion to determine a significant~~

3.1 Changes of groundwater recharge at different warming levels



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zero, or close to zero,

GWR in some regions of the world leads to not defined or extremely large percentage increases and decreases (Fig. S1 and S2). The model mean shows large decreases of over 100 mm year-1 in South America and in the Mississippi Basin and decreases of up to 50 mm year-1 in the Mediterranean, East China, and West Africa. Increases of over 100 mm year-1 are prominent in Indonesia and East Afrika. Individual GHM-GCM model combinations compute much larger changes. ~~We chose to express changes as absolute change rather than relative change because zero, or close to zero, GWR in some regions of the world then leads to infinite increases and decreases (Fig. S1 and S2).~~

Figure 2 Ensemble mean change in GWR [mm year-1] between conditions of present day warming of 1 °C GW and at 3 °C GW, averaged over the GWR changes of all GHM-GCM model combinations.

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Ensemble mean changes as shown in Figure 2 may be low in some areas, but this could be due to large positive changes compute by some GHM-GCM model combinations being canceled by large negative changes by other model combinations. To assess the changes which show a high statistical agreement in-between the model combinations, we determine where computed changes of GWR are statistically significant (Section 2.5).~~To assess the impact of GW on GWR, we calculate significant changes based on the model ensembles~~. ~~We chose to express changes as absolute change rather than relative change because zero, or close to zero, GWR in some regions of the world then leads to infinite increases and decreases (Fig. S1 and S2).~~ As a reference for the intensity of the changes, Figure 3~~Figure 3Figure 1~~a shows the mean GWR at PI averaged over all GCMs from 1861-2099. The spatial pattern of GWR roughly agrees with the pattern of Mohan et al. (2018) derived by inferring it from more than 700 small-scale GWR estimates. The global mean GWR for the PI period is 140 mm year^{-1}, which is very similar to the value of 134 mm yr^{-1} determined by Mohan et al. (2018) for the period 1981-2014 (see also Sect. 3.4).

Figure 3~~Figure 3Figure 1~~b-e show the (statistical) significant (bright colors, Sect. 2.5) mean absolute changes in GWR model ensemble under a GW of 1.0°C, 1.5°C, 2.0°C, and 3.0°C compared to PI, i.e., GWR of the PI runs for the corresponding time-slices (Sect. 2.3). For all GW levels compared to PI (Figure 3~~Figure 3Figure 1~~b-e), consistent patterns of decreasing southern Chile, Brazil, central continental USA, the Mediterranean, and East China. Consistent and significant increases can be observed for northern Europe and in general northern latitudes and East Africa. Significant changes could only be derived for a small percentage of the total grid cells. Only about 15% of the cells, on average for all GW levels, show significant increases or decreases. However, the patterns of non-significant (light colors) mean changes are consistent with the significant changes and show, e.g., for the Amazon larger areas of increases and decreases around the significant changes. The identification of non-significance in most areas is due to the K-S test. The sign criterion affects mainly the Sahara and Central Asia.

At 1°C GW (Figure 3~~Figure 3Figure 1~~b), decreases of more than 100 mm year^{-1} are simulated in Southeast Asia, East and southern Brazil. Decreases between 100 and 50 mm year^{-1} can be seen in central continental USA, southern Brazil, southern Chile, the Mediterranean, central Africa, and East China. Increases in GWR of 50 and over 100 mm year^{-1} are visible in the center of the Amazon while decreases show in the northeast and southern part that increase with GW. Overall the significant global change is -17 mm year^{-1} at 1°C.

A 1.5°C GW shows only a limited increase in the Amazon but similar increases in the rest of the world. Decreases in GWR over 100 mm year^{-1} are now visible in Central America, but decreases for Southeast Asia have vanished. Smaller decreases, for example, in Australia, have vanished as well in a 1.5°C world. These effects are not necessarily due to no changes in GWR but due to disagreements in the ensemble that do not allow to determine a reliable and significant change for this warming level. The global significant mean change is -12 mm year^{-1} at 1.5°C GW.

At 2°C GW, increases in GWR over 100 mm year^{-1} are present in northern Java, Amazon, and East Africa. Decreases are similar to 1.5°C GW, except for southern Chile and the northern Andes, where decreases become more severe. However, on the significant global mean, these changes balance out to -1 mm year^{-1}.

In a 3°C world, large areas of decreases in GWR of over 100 mm $year^{-1}$ in the Amazon Basin close to the Andes occur, also in Guyana, Venezuela, West Africa, and the Mississippi Basin. Increases in GWR of over 100 mm $year^{-1}$, in contrast, are visible in East Africa, India, and North Java. Increases of 50 to 100 mm $year^{-1}$ dominate in northern latitudes at 3 °C warming compared to other GW levels. The global significant mean increases by +3 mm $year^{-1}$.

We have already reached a GW of approximately 1°C (IPCC, 2018). Figure 3~~Figure 3Figure 1~~f shows the changes in GW compared to the present day GW of already 1°C instead of the PI. Overall the agreement among the models is smaller than when the 3°C world is compared to PI. Only 8% of the cells show significant changes. Decreases over 100 mm $year^{-1}$ are present in the Amazon Basin close to the Andes and on the coast of Guyana. Decreases of 50 to 100 mm $year^{-1}$ are visible in Chile, the Mississippi Basin, the Caribbean, and southern France. Increases in GWR are again to be expected in the northern Latitudes, southern Brazil, East Africa, and Southeast Asia, whereas the latter shows increases over 100 mm $year^{-1}$ for Malaysia. The global significant mean change is +8 mm $year^{-1}$. Figure S3 shows the mean and median changes of GWR per latitude for all four GW levels, together with the standard deviation without a significance test. A decrease in mean GWR can be observed for all GW levels at 40° S, around 20° S (Namibia, Australia), and 5° N (Guyana). Increases are visible at 60° N (North Europe) and southerly close to the Equator, presenting a large spread and sudden change in directions in the tropics. Increases at greater than 60° N are likely due to a combination of different rain and snow patterns as well as snowmelt timing.

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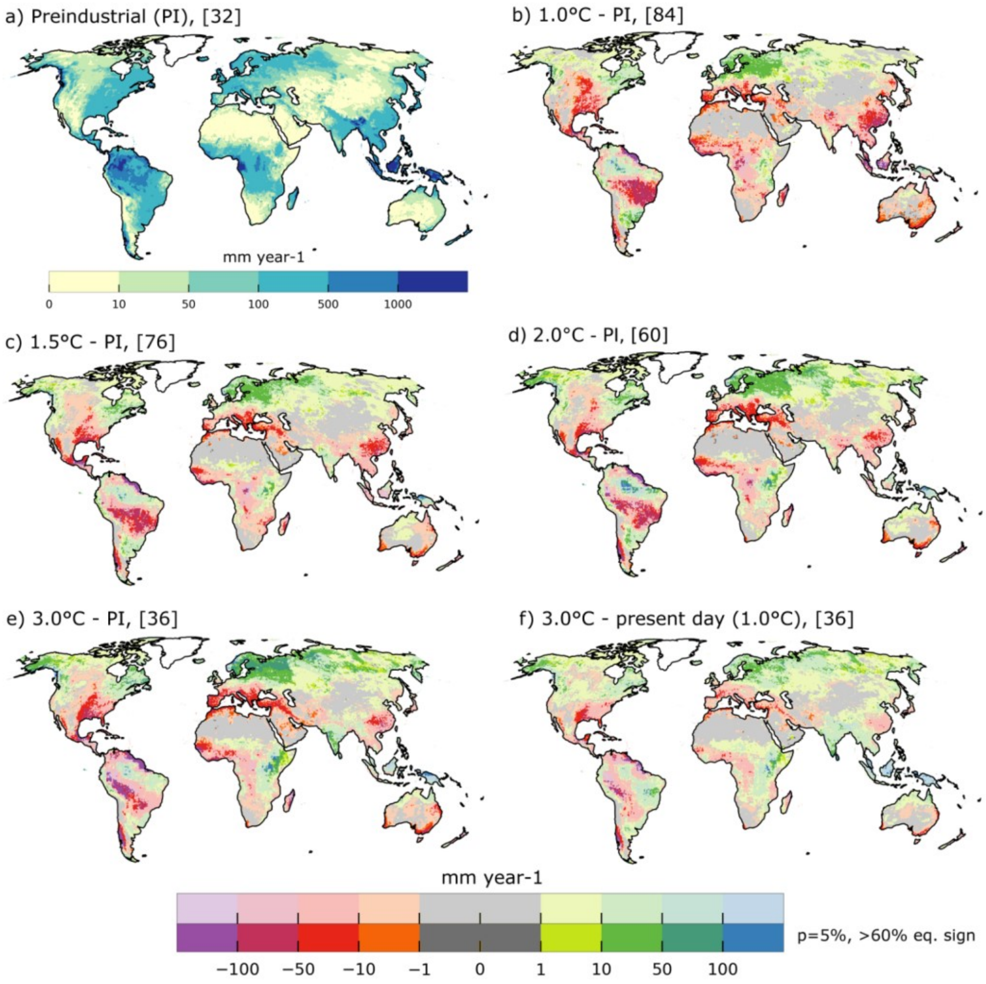

Figure 33~~1~~ Mean GWR [mm year^{-1}] for pre-industrial greenhouse gas concentrations, averaged over the GWR of all GHMs and GCMs (a). Ensemble mean absolute change in GWR [mm year^{-1}] at 1.0 °C (b), 1.5°C (c), 2.0°C (d), and 3.0°C (e) GW compared to PI. The ensemble mean absolute change in GWR [mm year^{-1}] for 3.0°C GW compared to GWR at the current GW of 1°C (f). For (b) to (f) only those cells are displayed in solid colors where the Kolmogorov-Smirnov (K-S) test with a p of 5% indicated that the ensemble GWR distribution for PI (for (f) the GWR distribution at 1°C) and for the GW level differ, and at least 60% of the models agree on the sign of the change. The ensemble size is shown in brackets. Lighter colors (upper color bar) show (statistical) insignificant mean differences.

Large areas of insignificant changes of GWR (light colors) in Fig. 2 can be traced back to the uncertainty in GWR in between GHMs and GCMs. Figure 4~~Figure 4Figure 2~~ shows absolute GWR changes in a 1.5 °C world compared to PI (Fig. 3a,b) as (Fig. 3c,d) for the SREX (Special Report on Managing the Risks of Extreme Events and Disasters to Advance Climate Change Adaptation, Murray and Ebi (2012)) region Amazon (left) and South Europe/Mediterranean (right). Corresponding plots for all other SREX regions are provided in the supplement. Similar to box plots, the letter-value plots in Figure 3 show the distribution of values among the 0.5° grid cells belonging to the SREX region. Letter-value plots have the advantage of showing the distribution of values outside of the usual interquartile range (IQR, Q25 - Q75). For example, for Fig. 3b CLM 4.5 with GFDL-ESM2-ES, the mean change in GWR is -19 mm year^{-1}, the middlebox represents the IQR showing that 50% of changes are close to zero or smaller than zero, the smaller box towards the negative changes shows that 12.5% are smaller than -47 mm year^{-1}, whereas the additional missing box in the positive direction hints that almost no values are larger than zero. The horizontal size of the boxes is automatically scaled and does not carry any additional information.

Computed changes vary strongly among both GHMs and GCMs (Fig. 3a,b). In the Amazon, Jules-W1 shows a mean increase of 225 mm year^{-1}. Compared to WaterGAP2, Jules-W1 estimates of GWR change are 147 mm year^{-1} higher for MIROC5 and 44 mm year^{-1} lower for HadGEM. These differences are even large relative to the higher mean PI GWR in the Amazon compared to other regions of the world (compare to MED in Fig. 3). Nevertheless, also the PI estimates differ by, e.g., 122 mm year^{-1} between Jules-W1 and WaterGAP2 on the mean for all GCMs and RCPs, and PI GWR is 625 mm year^{-1} smaller for H08 than for MATSIRO in the Amazon.

In the Mediterranean, almost all GHMs show the largest decreases in GWR with IPSL-CM5a-LR, followed by GFDL input, while HadGEM results in almost no change. However, the changes computed with each GCM input vary strongly among the GHMs. In general, CLM 4.5 and PCR-GLOBWB project the most considerable changes. The decrease of GWR computed by CLM 4.5 with IPSL-CM5a-LR is 33% of the mean GWR calculated for PI with that model combination.

Conversely, JULES-W1 simulates for most grid cells in this SREX region the smallest PI GWR values (but also very high outliers), and likely related, the smallest (mean) changes, together with MATSIRO and CWatM, which show altogether small GWR changes in all grid cells of the SREX regions. H08 and WaterGAP2, which apply similar approaches to modeling GWR as a function of total runoff, show somewhat similar GWR changes.

The four GHMs that take into account the impact of increasing CO$_2$ (Sect. 2.1) do not result in similar changes as compared to the other four models. It is to be expected from literature (Davie et al., 2013) that with the physiological effect, the decreases of GWR would be slighter in the case of the CO$_2$-sensitive models, but that is not the case. This is likely due to the approach of analyzing GW levels instead of RCPs and periods because different GCMs reach a particular GW level at different times and CO$_2$ levels. This is further investigated in Sect. 3.3. On the global mean and for 1.5°C GW LPJmL simulates the lowest PI GWR, whereas MATSIRO and CLM 4.5 produce the highest global mean GWR (Fig. S4). PCR-GLOBWB simulates the largest global mean decreases with HadGEM (Fig. S5). In contrast, JULES-W1 and MATSIRO simulate increases of GWR on the global mean for all GCMs except for HadGEM (Fig. S5).

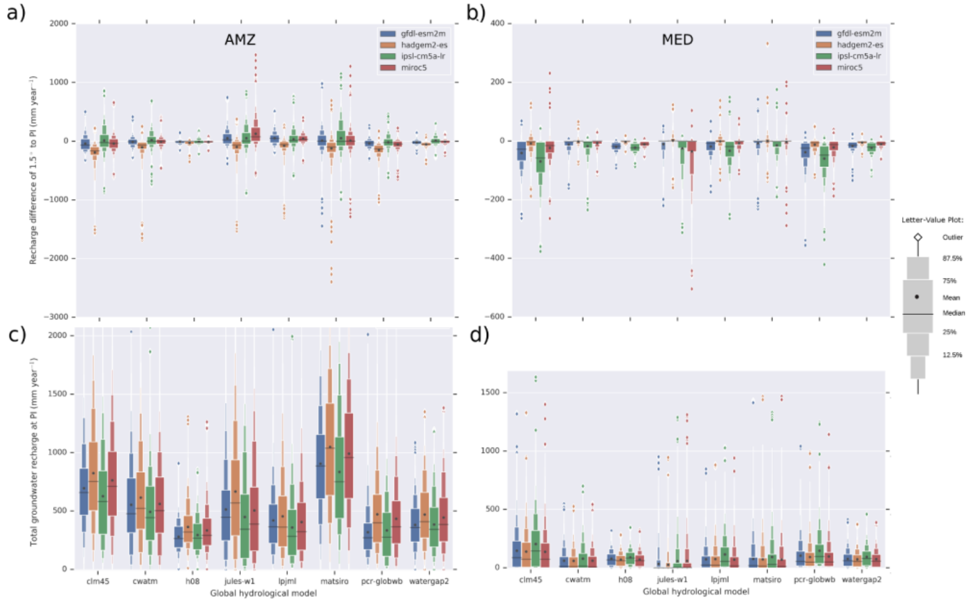

Figure 4~~42~~ Letter-value plot (Hofmann et al., 2017) of absolute changes in GWR in 0.5° grid cells [mm year^{-1}] at 1.5°C GW compared to (a, b) and absolute PI GWR [mm year^{-1}] (c, d) for the Amazon (a, c) and South Europe/Mediterranean (b, d) SREX region (for all other regions and GW levels [2°C, 3°C] see supplement). No statistical test is applied and all grid cells inside a region are included. Each box may include multiple simulations with different RCPs.

To provide an overview of changes in GWR in each SREX region, Table 3~~Table 3Table 2~~ shows the median, mean changes in GWR compared to PI for all regions (see Fig. S6 for a map of the SREX regions). Overall, North Europe shows the largest consistent increases in GWR, whereas the Amazon shows the largest consistent decreases, except for 2°C, where South Europe/Mediterranean shows the largest decreases of 18.6 mm year^{-1} as the median. For 3°C, the Amazon shows the highest decreases in GWR of -41.0 mm year^{-1} as median. Notably, Southeast Asia is first showing decreases of 13.1 mm year^{-1} with 1.0°C GW and then no change with 1.5°C and 2°C and an increase in GWR of 13.5 mm year^{-1} with 3°. Relative to PI the changes of the 3°C GW in the Amazon only account for 10% of the GWR, compared to the 19% relative increase of GWR in North Europe with 3°C and the 40% decrease in GWR in South Europe/Mediterranean at 2°C GW.

Table 3~~32~~ Median ($\widetilde{\boldsymbol{X}}$), mean ($\overline{\boldsymbol{X}}$), P_{25}, and P_{75} of absolute GWR change [mm year^{-1}] for four warming levels for each SREX region compared to PI. $\widetilde{\boldsymbol{X}}$, $\overline{\boldsymbol{X}}$, P_{25}, and P_{75} describe the distribution of changes of spatially averaged GWR in each SREX region among all 36-84 ensemble members (Sect. 2.3). $P_{25/75}$ are the 25th and 75th percentile in the ensemble for a given region and a given GW level. The last column shows absolute GWR at PI. The following regions are not included due to the coarse spatial resolution of the models and low confidence in the reliability of results: Artic, Canada/Greenland/Island, Antarctic, Pacific islands, Southern tropical pacific, Small Island Region Caribbean, West Indian Ocean. In bold maximum and minimum values per GW level. No statistical test is applied to filter the values.

		1.0°	**1.5°**	**2.0°**	**3.0°**	**PI**
		$\tilde{X}, \bar{X}$	$\tilde{X}, \bar{X}$	$\tilde{X}, \bar{X}$	$\tilde{X}, \bar{X}$	$\tilde{X}, \bar{X}$
SREX	**Name**	P_{25}, P_{75}	P_{25}, P_{75}	P_{25}, P_{75}	P_{25}, P_{75}	P_{25}, P_{75}
AMZ	Amazon	-10.7, -14.5	**-19.1**, -22.3	-14.6, -18.2	**-41.0**, -59.9	409.6, 550.4
		-30.4, -6.8	-38.3, -9.7	-34.5, 3.4	-81.1, -39.2	419.7, 614.6
CAM	Central America/Mexico	-2.4, -17.1	-4.8, -21.0	-4.3, -12.9	-10.0, -36.0	79.8, 280.4
		-23.1, -6.5	-26.8, -9.0	-18.9, -7.7	-45.8, -24.0	222.3, 327.7
CAS	Central Asia	0.0, -0.4	0.0 0.0	0.0, -0.8	0.0, -2.6	1.8, 25.9
		-0.7, 0.3	-0.7, 1.0	-1.4, -0.3	-3.9, -1.4	17.2, 37.2
CEU	Central Europe	4.1, 6.8	1.2, 3.1	-0.4, 0.1	0.1, 2.8	114.6, 135.4
		0.5, 13.3	-5.5, 11.8	-9.7, 11.3	-9.9, 22.3	117.9, 155.8
CAN	Central North America	-6.5, -16.7	-5.6, -18.3	-3.3, -16.6	-9.9, -30.5	98.1, 128.6
		-20.2, -12.3	-20.2, -12.7	-20.0, -12.5	-32.8, -18.2	76.4, 183.5
EAF	East Africa	0.0, -0.8	0.0, 2.7	0.0, 8.1	0.6, 23.3	32.2, 95.0
		-2.7, 3.3	-0.2, -7.8	1.2, 13.9	9.0, 32.4	63.4, 134.1
EAS	East Asia	-0.5, -15.7	0.0, -13.9	0.0, -10.3	0.0, -13.7	50.5, 147.3
		-20.0, -8.3	-16.9, -6.8	-10.7, -3.7	-14.2, -4.5	113.1, 154.3
ENA	East North America	3.3, 4.8	9.9, 11.9	10.6, 15.9	1.4, 2.5	221.8, 257.8
		-2.0, 11.2	-0.8, 19.8	-1.5, 26.3	-9.1, 20.5	167.4, 338.1
NAS	North Asia	0.4, 6.0	0.5, 7.9	3.1, 12.5	4.6, 18.5	24.2, 59.2
		3.0, 7.2	5.1, 9.1	9.0, 13.1	13.0, 20.4	46.2, 73.4
NAU	North Australia	0.0, -4.5	0.0, -2.7	0.0, 1.1	-0.9, -3.0	5.9, 43.1
		-6.9, -2.2	-3.9, -0.8	-0.8, 3.5	-7.1, 0.0	28.5, 52.1
NEU	North Europe	**13.1**, 24.9	**13.9**, 27.7	**18.6**, 34.9	**29.2**, 51.6	154.8, 226.4
		15.9, 35.7	14.7, 41.3	16.8, 53.0	25.0, 78.2	182.1, 280.4
NEB	North-East Brazil	-8.9, -30.3	-10.5, -22.9	-6.2, -14.4	-6.0, -9.4	161.6, 227.4
		-35.6, -21.2	-31.3, -13.2	-24.9, -2.1	-20.7, 2.1	147.1, 315.0
SAH	Sahara	0.0, -0.7	0.0, 0.3	0.0, -0.2	0.0, -0.4	0.1, 4.2
		-1.0, -0.3	0.1, 0.4	-0.2, 0.0	-0.5, 0.0	0.8, 4.4
SAS	South Asia	-3.3, -13.4	0.0, -4.8	-2.3, -11.6	3.8, 26.9	151.8, 274.9
		-15.9, -8.3	-6.1, 0.1	-17.5, -5.3	2.3, 45.5	229.5, 319.2
SAU	South Australia/New Zealand	-2.9, -8.6	-2.3, -10.3	-2.1, -15.3	-4.2, -20.0	18.1, 135.7
		-11.1, -4.5	-12.4, -6.5	-17.8, -9.4	-22.2, -14.3	111.4, 157.6
MED	South Europe/Mediterranean	-3.9 -14.3	-6.3, -18.1	**-16.8**, -23.7	-12.5, -28.9	43.9 84.9
		-17.6, -9.3	-21.6, -12.8	-27.4, -16.8	-31.8, -19.1	72.1, 87.6
SEA	Southeast Asia	**-13.1**, -36.1	-0.1, -5.2	-0.6, 23.1	13.5, 46.1	547.9, 725.2
		-55.7, -10.7	-18.0, 8.6	-1.7, 36.5	3.0, 68.9	528.0, 881.2
SSA	Southeastern South America	0.0, -6.3	0.0, -5.2	0.0, -9.4	-1.4, -11.8	61.0, 129.5
		-8.3, -5.1	-8.9, -4.4	-12.9, -4.5	-15.7, 0.3	87.9, 164.6

SAF	Southern Africa	0.0, -8.1	-0.4, -10.3	0.0, -6.6	-0.1, -10.5	20.0, 95.9
		-13.0, -3.4	-15.9, -4.4	-10.7, -0.5	-16.3, -2.0	77.9, 102.0
TIB	Tibetan Plateau	0.0, -0.8	0.0, -0.3	0.0, 0.4	0.0, 1.1	0.0, 14.3
		-0.7, -0.3	-0.4, 0.4	-0.3, 1.1	-0.2, 1.6	9.3, 16.8
WAF	West Africa	-4.5, -28.4	-2.5, -21.8	-5.6, -25.6	-8.4, -26.5	175.3, 282.3
		-38.2, -20.4	-29.7, -11.0	-39.2, -10.3	-44.0, -6.1	215.0, 392.1
WAS	West Asia	0.0, -2.6	0.0, -3.9	0.0, -4.4	0.0, -6.7	0.4, 24.8
		-3.4, -1.4	-4.7, -2.5	-5.2, -2.8	-8.1, -4.6	18.3, 30.0
WSA	West Coast South America	0.0, -8.6	0.0, -10.5	0.0, -13.9	0.0, -21.2	57.2, 271.1
		-11.5, -5.5	-14.5, -5.5	-17.7, -7.6	-25.1, -15.2	186.9, 346.3
WNA	West North America	0.0, 3.4	0.0, -3.5	0.0, 6.2	0.0, 6.8	23.5, 104.8
		0.5, 5.6	-0.1, 7.1	1.1, 11.6	1.7, 14.7	81.9, 126.7

3.2 Sources of ensemble variance

To investigate whether the main variance in projected GWR changes is caused by GHMs, GCMs, or the different RCP scenarios, we apply the Eq. (1) and (2) (see Sect. 2.4) for 1.5°C and 3°C GW. Figure 54 shows the GCM to GHM variance ratio for 1.5°C (a) and 3°C (b) per grid cell; GHM RCP variance ratio is not shown here (see Fig. S7 in the supplement, mean of GHM RCP ratio: 22%) as the primary influence can be appropriated to the GCM and GHM selection (this is also the case when choosing only the CO_2 sensitive models). For the simulated variance at PI see Fig. S1 and S4.

Overall, GHMs cause more significant variance in 1.5°C than in a 3°C world, which is plausible because of increased GCM trends with increased CO_2 concentrations. Possibly this is also due to the missing RCP 8.5 simulations for PCR-GLOBWB for all GCMs. A clear spatial pattern of GCM influence shows in the Amazon that relates to the region of Fig. 2 where increases of GWR are calculated. On the other hand, the region in the Amazon where decreases are simulated (compare Fig. 2) shows mainly the GHMs as the source of variance. In the Mediterranean, the influence shifts as well from GCMs (1.5°C) to GHMs (3°C). This could be due to a high agreement in GCMs in this region and a considerable disagreement in GHMs. Similar patterns can be found when comparing absolute GWR, but the influence of GCMs is less pronounced, especially in the Amazon (Fig. S8).

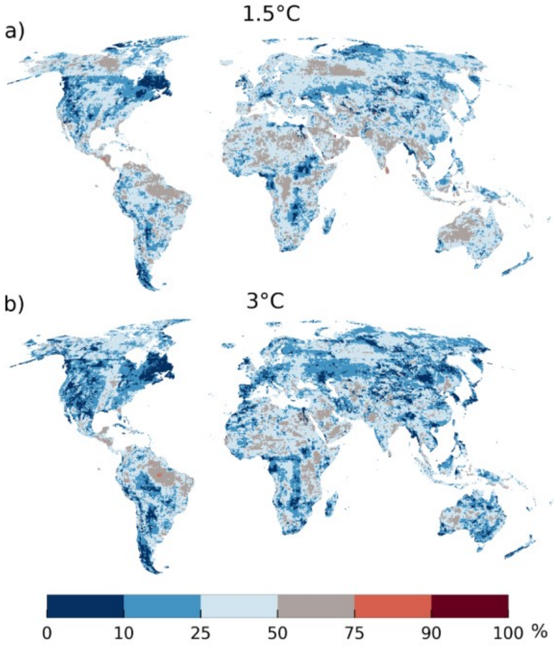

Figure 5~~53~~ GCM variance in percent of the total variance of GWR change from eight GHMs and four GCMs at 1.5°C (a) and a 3°C (b) GW (see also Sect. 2.4). Red depicts areas where the GCMs are responsible for the majority of the variance in GWR change. Blue areas indicate where the main variance is introduced through GHMs.

Including vegetation dynamics in GHMs may alter the model response in future estimates of GWR as evolving CO_2 concentrations alters fluxes of energy and water (Davie et al., 2013). To investigate the influence of simulating the physiological impacts of evolving CO_2 on GWR, we compared GWR changes computed by two CLM 4.5 runs, each of it driven by GFDL-ESM2M climate input: the standard run analyzed included in the ensemble analysis above, with CO_2 concentrations changing according to the RCP, and an additional run in which CO_2 concentrations after 2005 were held constant at the 2005 level. Unfortunately, no other GHM-GCM combinations with these alternative CO_2 concentration variants are available in the framework of ISIMIP2b.

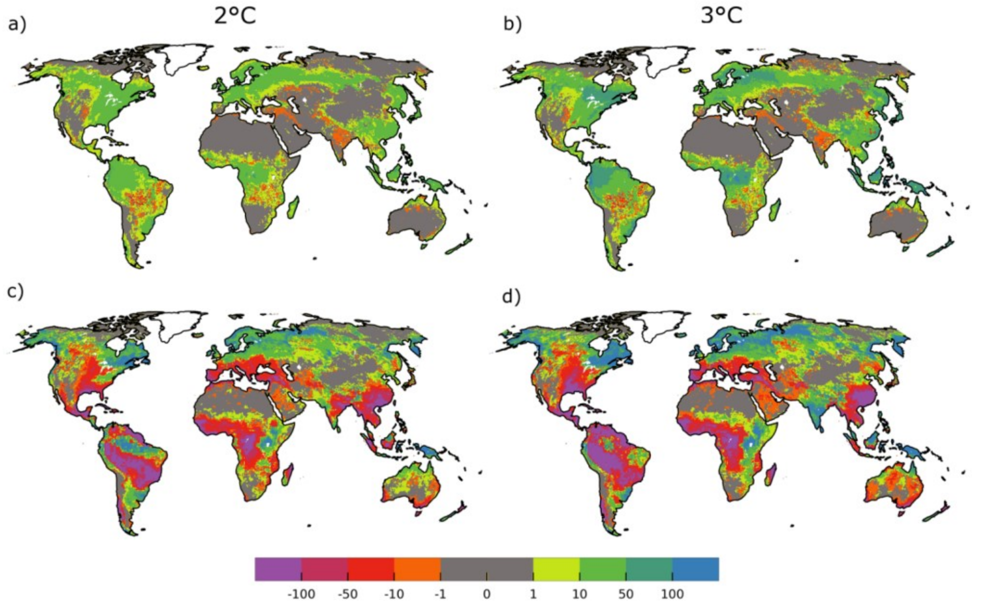

Figure 6~~64~~ GWR (dynamic CO2) – GWR (static CO2) [mm year^{-1}] for 2.0°C (a) and 3.0°C (b) GW. GWR (dynamic CO2) – PI (dynamic [mm year^{-1}] for 2.0°C (c) and 3.0°C (d) GW. The figure only includes the GHM CLM 4.5 and the GCM GFDL-ESM2M. Maps show changes in GWR at a certain GW (including all RCPs that lead to that GW with a certain CO2 concentration) with dynamically evolving CO2 compared to static CO2 concentrations from 2005. Green and blue means that GWR is higher when evolving CO2 concentrations are considered, red and purple less GWR.

Figure 6~~5~~ shows differences in simulated GWR between a dynamic and a static CO_2 simulation for 2°C (Fig. 6~~5~~a) and 3°C (Fig 6~~5~~b). In most grid cells, GWR simulated with dynamic CO_2 is larger than GWR simulated with static CO_2 levels of 2005 (Fig. 6~~5~~a,b). In the tropics, GWR with dynamic CO_2 can be higher than with constant CO_2 by 10-50 mm year^{-1} for 2°C GW (Fig. 6~~5~~a), while difference reaches 50-100 mm year^{-1} in the 3°C world (Fig. 6~~5~~b). Decreases of GWR are spatially consistent (for example, Brazil, Central U.S., and India) at 2° and 3°C GW and rarely exceed 10 mm year^{-1}.

Compared to the absolute changes between PI and the GW levels for dynamic CO_2 (Fig 6~~5~~c,d) the decreases in GWR are rather small (e.g., up -10 mm year^{-1} in Brazil (Fig. 6~~5~~a,b), while change compared to PI exceeds -100 mm year^{-1} (Fig Also, increases in GWR due to dynamic CO_2 are in regions with large (> 100 mm year^{-1}, Fig 6~~5~~c,d) increases in recharge.

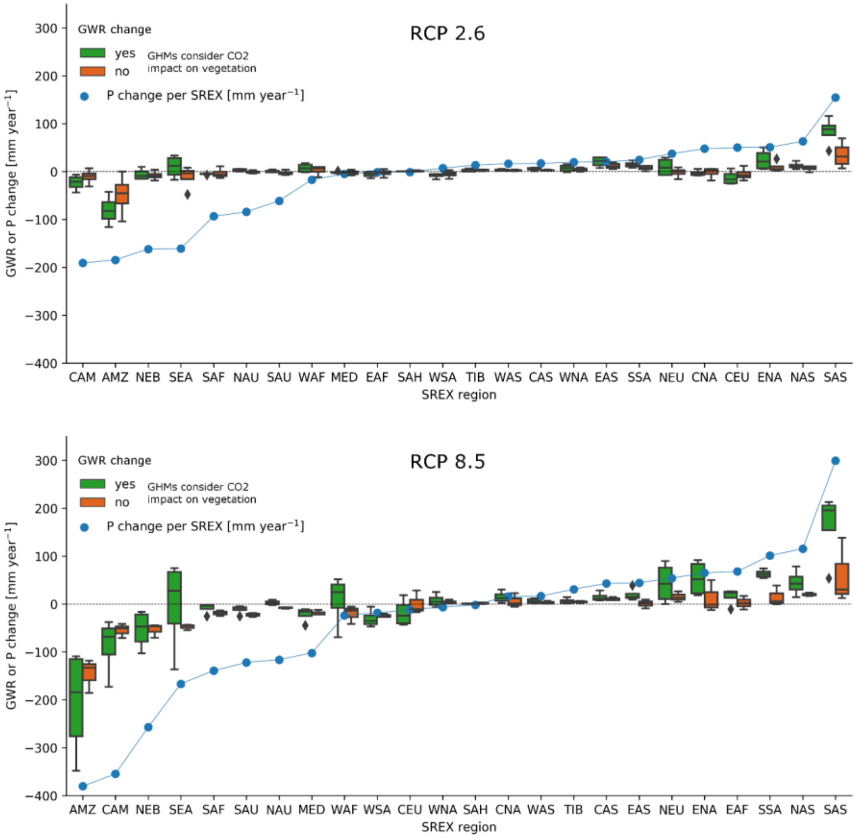

Figure 7~~75~~ Relation of changes in precipitation (P) (mean(1981-2010) – mean(2070-2099)) to changes in GWR (mean(1981-2010) – mean(2070-2099)) depending on the model type (with or without CO_2; see also Table 1) per SREX (selection as in Table 3) ~~(selection as in~~ and RCP 8.5 ~~(b)~~ for the GCM HadGEM2-ES. ~~Models that account for impacts of evolving CO_2 on vegetation are shown in blue. Both axis~~

The preceding analysis has focused on GW levels parallel to other studies of GHM ensembles. To investigate the difference in including ~~dynamic~~ active vegetation processes in GHM further, we compared the four GHMs that include these processes with the four models that do not (Table 1~~Sect. 2.1~~). Because different RCPs decide the concentration of CO_2 in the atmosphere, we compare RCP 2.6 and RCP 8.5 time slices instead of GW levels.

Figure 7~~6~~ compares the precipitation and GWR changes between the period 1981-2010 and the period 2070-2099 for the two RCPs ~~(Fig 6a,b)~~ and the two different model types for the SREX regions investigated in Table 3~~2~~. Changes in precipitation and GWR are only based on the GCM HadGEM2-ES (see Fig. S9 for average over all GCMs) as the relationship between GWR and precipitation is not linear and the plot is comparable to Davie et al. (2013), who investigated differences in runoff~~.~~, ~~and the plot is comparable to Davie et al. (2013), who investigated differences in runoff.~~ Compared to the average precipitation of all GCMs where only two regions show a decrease larger than 100 mm year^{-1} (Fig. S9 (b)), HadGEM2-ES shows seven regions for RCP 8.5 with such a decrease in precipitation.

GWR changes vary between RCPs and model type and in between GHMs (Fig. S10). The relation between precipitation and GWR and difference between model types becomes clearer with RCP 8.5 than with RCP 2.6. Models with active vegetation (Fig. 7~~6~~, green~~blue~~ markers) agree that with more precipitation GWR should increase, e.g., for ~~SAA~~SAS; however, they disagree in regions where decreases in precipitation are expected and risk for groundwater availability is highest, e.g., CAM and MED. GHMs without active vegetation (Fig 7~~6~~, orange markers), on the other hand, show~~s~~ a more consistent decrease in GWR for regions with decreases in precipitation and only some agreement in regions with increased precipitation.

Decreases in precipitation may lead to a decrease in vegetation productivity (if not counteracted by an increased water-use efficiency due to elevated CO_2 concentrations (Singh et al., 2020)) ~~(Singh et al.; 2020))~~ and thus to a decrease in transpiration. GHMs assume shares for evapotranspiration in relation to potential ET and the available precipitation. In contrast, transpiration in ~~dynamic vegetation~~CO_2-driven models responds to active vegetation as well as the relations between components that simpler GHMs do not. This can explain why the dynamic vegetation models exhibit inter-model regional differences in the GWR response to P decrease. Further, some models (MATSIRO) may not calculate LAI (leave area index), which impacts transpiration. For models with active vegetation, the increase in water use efficiency due to stomatal conductance (also referred to as CO_2 fertilization) can compensate for the decrease in precipitation to some extent, making more water available for groundwater recharge as compared to the GHMs (Table 1). Though in some regions, as seen in Figure 7 (and Fig. S10)~~6~~, this feedback is not enough to overcome the warmer and drier climate in terms of groundwater flux.

CWatM often lies in the middle of simulated GWR changes at RCP 2.6. Davie et al. (2013) showed generally higher runoff values for JULES-W1 than for LPJmL, the reverse is true for GWR (Fig S.10). For RCP 8.5, CWatM always simulates the largest increases and lowest decreases in GWR of all models without active~~dynamic~~ vegetation. ~~Opposite, H08 always shows the largest decreases in GWR. In regions with decreases over 100 mm year^{-1} for RCP 8.5, e.g., AMZ, CLM 4.5 always shows the largest decreases in GWR, whereas other models with dynamic vegetation lead to the lowest decreases or even~~

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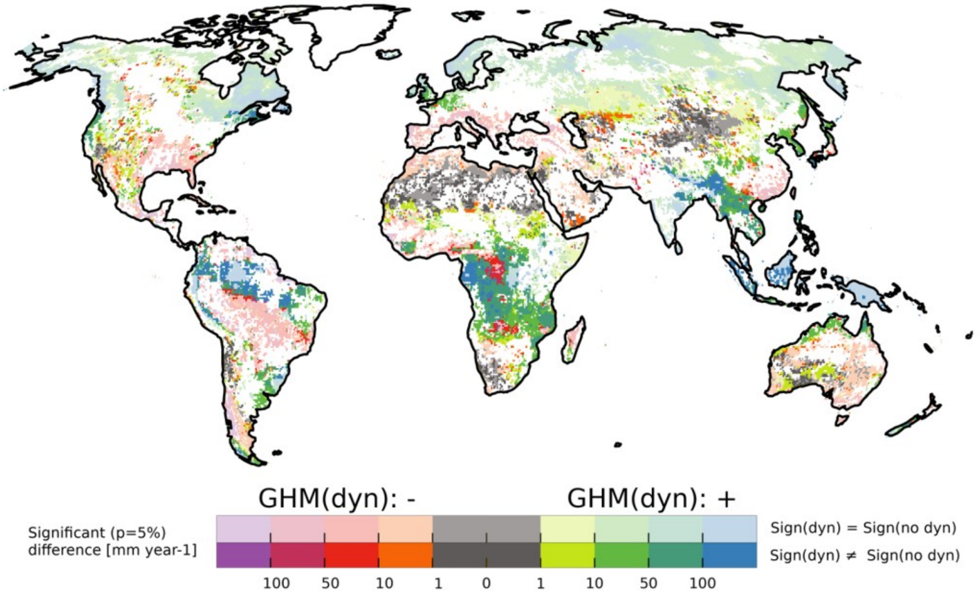

Figure 88~~6~~ Significant absolute difference of GWR change between 1981-2010 and 2077-2099 for RCP 8.5 in between four GHMs with and four GHMs without dynamic (or active) vegetation (no dyn). See also Table 1. Reddish (left side of the color bar) indicates that the mean change of GWR as computed by the models with dynamic vegetation is more negative or less positive than change computed by other models. White regions indicate no significance is based on the K-S test (Sect. 2.5). Solid colors indicate that the majority of the two model groups (3 out of 4 models for each group) do not have the same sign i.e. that including dynamic vegetation leads to different signs in GWR change. Lighter colors indicate where the majority agrees on the sign of change.

A spatially more refined difference between the model types is shown in Fig. 8~~7~~ for RCP 8.5 (For RCP 2.6, almost no significant changes were found). For each grid cell, the map shows the significant (K-S test, p=5%) absolute difference of simulated change in GWR between models that include dynamic vegetation processes and models that do not include them. In the northern latitudes, both models with and without dynamic vegetation agree on an increase in GWR but differ by up to 100 mm year^{-1}. Similarly, in the Mediterranean and central Brazil, both model types simulate a decrease in GWR, but the magnitude is significantly different between the model groups. In the Amazon patches of significant differences between the models show increases of GWR computed by GHMs with dynamic vegetation, whereas GHMs without dynamic vegetation shows a decrease. A similar effect is visible in central Africa, India, and parts of Indonesia; however, also decreases are simulated instead of increases for the Congo and Zambesi catchment. Both in the Mediterranean and South America models with dynamic vegetation show up to 100 mm year^{-1} difference in change compared to models without, even though no physiological effect should be dominant. According to Fig. 6, this is likely due to CLM 4.5 because JULES-W1 and LPJmL show slighter GWR decrease than the models without dynamic vegetation. It is likely that the shown differences are due to the implementation of dynamic vegetation in the GHMs (compare Fig. S.10~~6~~), however it is possible that other model peculiarities and processes are relevant as well.

4 Discussion

Estimating GWR is challenging (Moeck et al., 2016). Our results show that even for the PI period, the estimates of GWR vary largely among different GHMs. This is likely caused by the very different treatment of the runoff partitioning, implementation of the soil layer(s), inclusion of dynamic vegetation processes, and simulation of capillary rise. Because GWR is hard to measure directly (Scanlon et al., 2002), it is also challenging to verify the accuracy of the estimates.

To the best of our knowledge, the data-set of Mohan et al. (2018) is the only available gridded global GWR dataset that is not based on global hydrological modeling. This data set of mean 1981-2010 GWR in 0.5° grid cells was developed from a regression analysis that combined gridded datasets of mean precipitation and potential evapotranspiration as well as land use/land cover with local estimates of GWR at 715 locations worldwide. Figure 8 compares the GHMs under investigation for PI conditions to this dataset. The used data for comparison is one ensemble member of the analysis of Mohan et al. (2018) that was deemed best in their study. The global mean GWR in this member is slightly lower, 110 mm year^{-1}, than the reported mean of 134 mm year^{-1}. Overall, the GHMs best agree with Mohan et al. (2018) in arid regions like the Sahara, Australia, southern Africa, and the Andes. Underestimates are predominant in the northern Latitudes and Central Asia, whereas underestimates appear in Europe and the eastern USA for all models. All models, except for H08 and WaterGAP2, which show underestimates, result in overestimates in East Asia. In the Amazon, MATSIRO and CLM 4.5 overestimate by more than 100 mm year^{-1} compared to Mohan et al. (2018), whereas all other models show a mix of over and underestimate across continents. A similar pattern is visible in Central Africa where CLM, MATSIRO, and CWatM overestimate, and all other models show a mixture of over and underestimate of -100 – 100 mm year^{-1}. H08 and WaterGAP2 have the best agreement according to the NSE (Nash-Sutcliff Efficiency (calculated spatially); (Nash and Sutcliffe, 1970)) of 0.4 and 0.2 while the mean bias (mean(GHM Mohan et al.$^{-1}$)) is lowest for JULES-W1. All GHMs show much lower GWR in permafrost regions as they assume that there is no or little GWR in such regions. Possibly GWR of Mohan et al. (2018) is overestimated here as no measurements informed their results in these regions.

The variance in modeled GWR is possibly caused by the different implementation of the hydrological processes in between the models. Even more, models differ in their definition of groundwater and GWR. Some include groundwater storage that is recharged by a fraction of precipitation others do not include a groundwater component at all but define the saturation excess water from the bottom soil layer as GWR. Models may include only some of the processes that affect GWR, for example, capillary rise, percolation from the soil, preferential flow bypassing the soil matrix, the interaction between surface water and the aquifer, changing land use over time (not considered here), changing vegetation (e.g., reducing infiltration capacity). Further, important processes like evaporation, infiltration, percolation, or runoff and GWR separation are implemented with different equations and simplifications. Some models even use sub-grid information or sub-daily time steps, e.g., for changes in unsaturated conductivity. Notably, models that include dynamic vegetation processes showed the largest spread in GWR in regions with decreasing precipitation.

To illustrate the model differences further, the following describes the impact of changes in precipitation for WaterGAP and LPJmL representative for the different model types used in this study. In WaterGAP, a simulated percent change in total runoff translates to the same percentage change in GWR; unless, e.g., due to more extreme precipitation events, infiltration capacity is exceeded more often such that the relative increase in GWR is smaller than total runoff. Absolute changes in GWR are always smaller than changes in total runoff. In LPJmL, changes in total runoff do not translate to proportional changes in groundwater runoff and GWR. Any flux or storage that takes water before it is partitioned to the soil will impact the groundwater and GWR. Possible reasons for a reduction in GWR (percolation past the bottom hydrologically active layer (3 m deep); compare Sect. 2.1) can be changes in precipitation amount/intensity, transpiration due to vegetation productivity, transpiration due to changes in vegetation water use efficiency due to CO_2 fertilization, or changes in anthropogenic water use demands.

This difference in behavior is reflected in Fig. 6, where the response between precipitation and GWR of GHMs without any dynamic vegetation is relatively uniform. The non-uniform response of the models that include vegetation changes is likely due to the complicated process feedbacks between vegetation and water (transpiration changes due to available water together with vegetation productivity) and complex feedbacks in-between changes in CO_2, temperature, and precipitation which affect vegetation.

This study highlights that uncertainties and differences in GHMs need to be investigated further and that in order to estimate global groundwater vulnerability, improved estimates of global GWR are required.

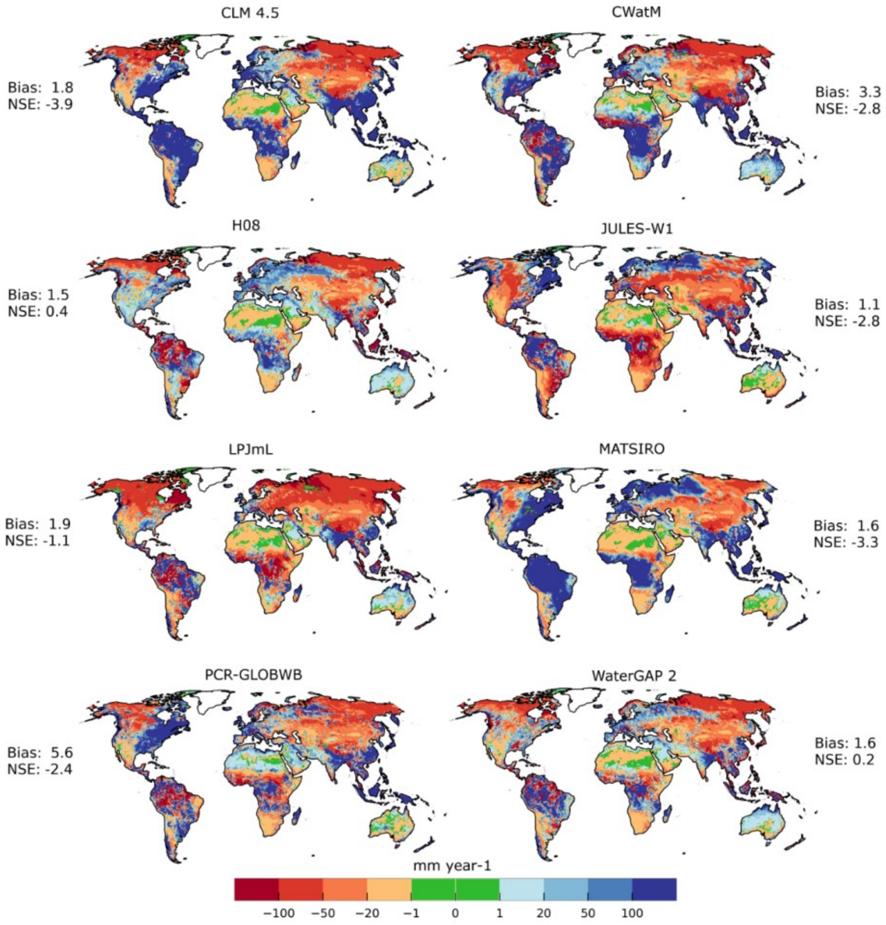

Figure 99~~7~~ PI GWR per GHM – 34 years (1981-2014) mean GWR [mm year^{-1}] of Mohan et al. (2018). Bias: mean (GHM Mohan et al.$^{-1}$). NSE (Nash-Sutcliff Efficiency; (Nash and Sutcliffe, 1970)) is calculated spatially over all cells instead of time.

This study is limited not only by the uncertainty in correctly representing the process of GWR but also in the propagation and aggregation of uncertainties. Future greenhouse gas emission scenarios are created based on the input of integrated assessment models. They are translated into emission scenarios of atmospheric concentrations and forcings that are, in turn, used to evaluate their impacts on the climate simulated by GCMs. Outputs of the GCMs are then bias-adjusted and spatially downscaled to be used in the assessment with impact models like GHMs (Döll et al., 2014a). Furthermore, the analysis is limited by the number of GCMs that were used, as discussed in McSweeney and Jones (2016). Although the GCMs are carefully selected to be most representative of the CMIP (Taylor et al., 2012) ensemble.

The multi-model ensemble study presented here assesses GWR at GW of 1.5°C, 2°C, and 3°C compared to GWR simulated under pre-industrial climate conditions and 1°C of GW. Changes are assessed based on transient time slices of the 30 years around the year that crosses the specific warming level. These slices are an approximation of the stabilized climate state of that warming level; it relies on the assumption that for a given warming level the impacts are the same regardless of the time it took to reach it or whether equilibrium has been reached at all (Boulange et al., 2018). However, this kind of analysis has limitations as the transient nature of climate is aggregated over a relatively short period (31 years). Components like the ocean might not equilibrate at these timescales (Donnelly et al., 2017).

Additionally, different RCPs are combined, which limits the possibility to investigate processes that are sensitive to different CO$_2$ concentrations. Investigations in this study based on RCPs show the difference between these model types. On the other hand, using GW levels reduces the uncertainties from GCM variability due to the use of different time slices, depending on when a GCM reaches a GW level.

The variance in GWR is caused by GCMs and GHMs alike depending on the region similar to a multi-model ensemble study on the climate change impacts on streamflow (Schewe et al., 2014). Again the assessment is limited by the number of used GCMs. Furthermore, this study did not include changes in land-cover and land-use, and thus irrigation which can have a tremendous impact on GWR, especially as irrigation patterns and used crops, will change with a changing climate (Hauser et al., 2019; Hirsch et al., 2017; Hirsch et al., 2018; Thiery et al., 2017; Thiery et al., 2020).

The only similar study on the global impacts of GW on GWR, to the knowledge of the authors, was conducted by Portmann et al. (2013). The study used five GCMs and one GHM, WaterGAP, which (a slightly different version) was also included in this study. Overall results are spatially consistent; however, Portmann et al. (2013) showed more consistent trends among GW levels (compare Table 2). Portmann et al. (2013) acknowledge that including impacts of evolving CO$_2$ levels on vegetation will have an impact on the simulated GWR and that WaterGAP is likely overestimating the decreases in GWR. Similarly, Davie et al. (2013) found that simulation of runoff was not consistent across models depending on whether CO$_2$ was considered. The results presented in this study show that this assumption is true for some regions, where differences of up to 100 mm year^{-1} can be observed.

Despite the uncertainties, this study provides further evidence~~shows~~ that climate change will impact groundwater availability in many regions of the world. A notable decrease can be expected in the Mediterranean, Amazon, and Brazil, whereas increases can be expected in Northern Europe. It is nevertheless troublesome that, especially in regions that are known to be vulnerable to climate change, for example, South Africa, model agreement in between model types is that low.

5 Conclusions

Potential GWR changes due to climate change require increased attention from the scientific community as well as from decision-makers because they affect future water availability in many regions and thus the wellbeing of billions of people. This study shows that simulated global-scale estimates of GWR vary strongly among GHMs, which contribute more strongly to the overall uncertainty of future groundwater recharge than the applied GCM output. However, statistically significant increases and decreases of GWR could be identified in specific regions per GW level. The presented inter-model ranges of GWR changes are an important input for processes aiming at developing strategies for climate change adaptation, as risk-averse decision-makers may want to orient their strategies towards adapting to the worst-case GWR change and not to the projected ensemble mean change.

This study shows that including vegetation processes in GHMs can change projected GWR changes substantially. However, consideration of these processes does not lead to a uniform increase of groundwater recharge, as might be expected from the physiological effect of increasing atmospheric CO_2 concentration. In some regions with decreasing groundwater recharge, where groundwater availability is a major concern, models that include these processes show the largest differences among themselves. Further research is necessary to understand GWR on large scales, and how it is affected by climate. Simulation of groundwater recharge by global hydrological models needs to be analyzed in more detail, and the benefit of integrating gradient-based groundwater flow models in GHMs should be assessed.

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~~Groundwater recharge (GWR) is an essential indicator of groundwater availability that is hard to measure directly but highly relevant in the face of global change. This study shows that simulated global estimates of GWR vary broadly between global hydrological models (GHMs) and show a higher uncertainty than the variance of the used climate model input. However, significant increases and decreases of GWR could be derived for specific regions and global warming levels. On average, a consistent increase of GWR in Europe and a decrease in the Amazon are simulated.~~

All simulations are available through the ISMIP project at https://www.isimip.org.

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Author contributions

RR led the conceptualization, formal analysis, methodology, software, visualization, and writing of the draft—original idea by HMS. HMS and PD supported review and editing, as well as the development of the methodology. TT supported editing and review. MF, SNG, MG, NH, AK, LS, WT, YW, YP, BP, and SY contributed to the model description in section 2 and made suggestions regarding wording, figures, and discussion. PD and HMS supervised the work of RR and made suggestions regarding the analysis, structure, and wording of the text and design of tables and figures.

Competing interests

No competing interests.

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