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Research papers

Time of emergence of impacts of climate change on groundwater levels in sub-Saharan Africa

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ABSTRACT

The impacts of climate change on groundwater are poorly constrained, particularly in regions such as sub-Saharan Africa where global circulation models (GCMs) project different directions of precipitation change. Moreover, the timing of when climate change impacts on groundwater can be differentiated from natural variability has not been quantified. Here, for the first time, we estimate the time of emergence (ToE) of climate change impacts on groundwater levels, using time series from eight sites across Burkina Faso, West Africa. We apply output data from historical and RCP8.5 runs of CMIP5 GCMs to lumped groundwater models for each site, and estimate ToE by calculating signal to noise ratios for each site and CMIP5 model. We show that in addition to inconsistent direction of climate change impacts across different GCMs, there is inconsistency in the ToE of climate change signals in future groundwater levels, particularly in drying GCMs. Across the eight sites, between 5 (4) and 13 (13) CMIP5 GCMs of a possible 23 show a ToE associated with decreases (increases) in groundwater levels. ToE from CMIP5 GCMs producing decreases in groundwater levels (i.e. drying) is highly variable between sites and GCMs (across all sites, median ToE = 2049, interquartile range = 48 years). For CMIP5 GCMs producing increases in groundwater levels (i.e. wetting), ToE appears to occur earlier and with less variability (across all sites median ToE = 2011, interquartile range = 11 years). These results underline the need for development of no-regrets adaptation measures in parallel with reductions in GCM uncertainty.

1. Introduction

Groundwater provides approximately 50% of the worlds drinking water supplies (Smith et al., 2016), as well as supporting livelihoods through productive uses and sustaining baseflow to surface waters. Although the potential for further development of groundwater in Sub-Saharan Africa (SSA) is recognised, groundwater is already a crucial source of supply for many, including dispersed rural populations and those in urban areas without access to piped supplies (Cobbing, 2020; MacDonald et al., 2012). Anthropogenic climate change is now unequivocal (IPCC, 2014), and a large number of studies have quantified the impacts of climate change on groundwater resources (see a synopsis of reviews by Smerdon (2017) and a more recent review by Amanambu et al. (2020)), including a number of studies in SSA (e.g. Badou et al. (2018); Cuthbert et al. (2019); Kingston and Taylor (2010); Mileham et al. (2009)). It has generally been concluded that the choice of global circulation model (GCMs) accounts for the greatest uncertainty in climate change impacts on groundwater (Smerdon, 2017). GCMs have been shown to disagree on the direction of climate change impacts on precipitation (and hence groundwater recharge and levels).

When assessing impacts of climate change on groundwater, a conventional approach often used (Ascott et al., 2019; Dams et al., 2012; Guardiola-Albert and Jackson, 2011; Jackson et al., 2011; Moeck et al., 2016) is to evaluate changes in groundwater recharge and levels in

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future time periods (e.g. the 2050s/2080s) in comparison to a baseline period (e.g 1950–2000). This approach is useful to understand the magnitude of potential changes in groundwater resources in future decades, and has been widely used for other hydroclimatic variables (Bornemann et al., 2019). However, the method provides no indication of when climate change signals emerge from natural variability. Such information, known as the Time of Emergence (ToE) of climate change signals, is highly relevant for decision makers. Natural and anthropogenic systems adapt to historic climate variability, and impacts may occur only when climate change causes local weather conditions to move beyond historic conditions. Understanding when this may occur in the future can help decision makers prioritise when to implement actions in response to climate change impacts. Numerous studies have estimated ToE for meteorological variables (Gaetani et al., 2020; Giorgi and Bi, 2009; Hawkins and Sutton, 2012; Mora et al., 2013; Nguyen et al., 2018; Sui et al., 2014), as well as for sea level (Lyu et al., 2014), ocean properties (Henson et al., 2017; Keller et al., 2014), aridification (Park et al., 2018) and fire-related weather indices (Abatzoglou et al., 2019). A small number of studies have estimated ToE for surface water resources (Chadwick et al., 2021; Leng et al., 2016; Muelchi et al., 2021; Zhou et al., 2018; Zhuan et al., 2018). To date, however, no research has assessed ToE for groundwater resources. In SSA, where existing shallow groundwater sources can be vulnerable to relatively small changes in groundwater recharge (MacDonald et al., 2009), understanding ToE can support decision makers in assessing the timing and scale of long-term impacts of climate change.

In this paper, the objective of this study is to quantify the ToE of climate change signals on groundwater levels for the first time. We hypothesize that in addition to the variability in the direction of climate change impacts on groundwater levels from GCMs, different GCMs show significant variability in the ToE of climate change signals. We address this hypothesis by applying transient climate data from the CMIP5 ensemble to eight lumped conceptual groundwater models across Burkina Faso developed by Ascott et al. (2020b), and consider implications for management of groundwater resources in the SSA context.

2. Methodology

2.1. Study area

The study area used in this research consisted of eight borehole sites across Burkina Faso, West Africa (Fig. 1). The boreholes are predominantly located in shallow weathered basement rocks, with one site (Dingasso) located on fractured metasediments. These sites are part of a wider long-term groundwater level monitoring network of 52 boreholes operated by the Direction Générale des Ressources en Eau (DGRE) of the Government of Burkina Faso. The boreholes used in this research have, in the African context, long time series of groundwater level observations, with records dating back to the 1970s. The boreholes have been subject to previous studies exploring precipitation:recharge relationships (Cuthbert et al., 2019; Filippi et al., 1990), reconstructing groundwater levels (Ascott, 2021; Ascott et al., 2020b; Martin and Thiéry, 1987) and evaluating multidecadal changes in groundwater resources (Mouhouyouddine et al., 2017). Ascott et al. (2020b) showed that, in comparison to other long-term monitoring boreholes in Burkina Faso, the eight boreholes in Fig. 1 are relatively unimpacted by changes in groundwater abstraction and land use, with changes in groundwater levels predominantly controlled by changes in climate. It should be recognised, however, that from the outset, the hydrogeological conceptualisation of the eight sites is limited. There is limited information on the aquifer properties and hydrostratigraphy and the nature of groundwater recharge (diffuse vs. focussed) and discharge (lateral groundwater flow, any evapotranspiration) processes. This places constraints on the extent to which differences in future groundwater level changes between sites can be related to real-world hydrogeological processes.

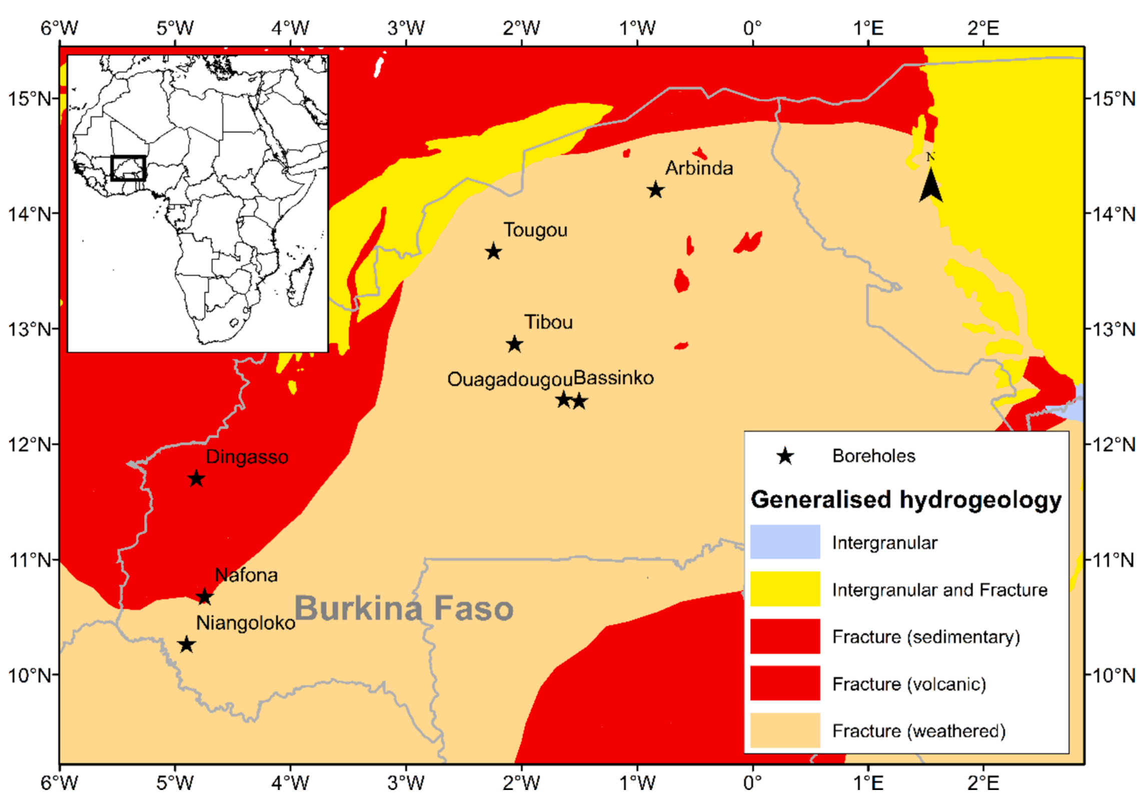

Fig. 1. Locations of boreholes used in this research and generalised regional hydrogeology. Hydrogeological map based upon mapping by MacDonald et al. (2012) provided by British Geological Survey © UKRI. Created using ArcGIS. Copyright © Esri. All rights reserved.

2.2. Groundwater model development and application of CMIP5 data

In this research, we used the lumped conceptual groundwater model AquiMod (British Geological Survey, 2019; Mackay et al., 2014b). The structure of AquiMod is shown in Fig. 2. AquiMod has been specifically designed for modelling groundwater level time series at observation boreholes and was used by Ascott et al. (2020b) in the development of groundwater level reconstructions at the eight sites used in this research (Fig. 1). AquiMod consists of three modules containing algorithms for soil drainage, unsaturated zone water transfer and saturated groundwater flow. The UN FAO method (Allen et al., 1998) is used to estimate soil drainage. This is then routed through the unsaturated zone using a Weibull distribution function. Discharge from the saturated zone is calculated based on Darcy's equation, and up to three layers can be used to represent changes in hydraulic conductivity with depth. Time series of rainfall and potential evapotranspiration (PET) are required as driving data, as well as observed groundwater level time series for calibration. For a full description of the model the reader is referred to Mackay et al. (2014b).

In this research, we used the AquiMod models and best parameter sets reported in Ascott et al. (2020b) and applied CMIP5 GCM data as driving data. We used a single parameter set for each model as this research focusses on exploring uncertainty in ToE associated with different GCMs, rather than uncertainty in model parameterisation. The calibrated models of Ascott et al. (2020b) consist of a single layer saturated zone model developed using the AquiMod code (Mackay et al., 2014b), which was shown to effectively match multidecadal groundwater level observations at the eight boreholes. However, it has been shown that some climate simulations in CMIP5 ensemble in West Africa predict much wetter futures (Black et al., 2020). As a result groundwater

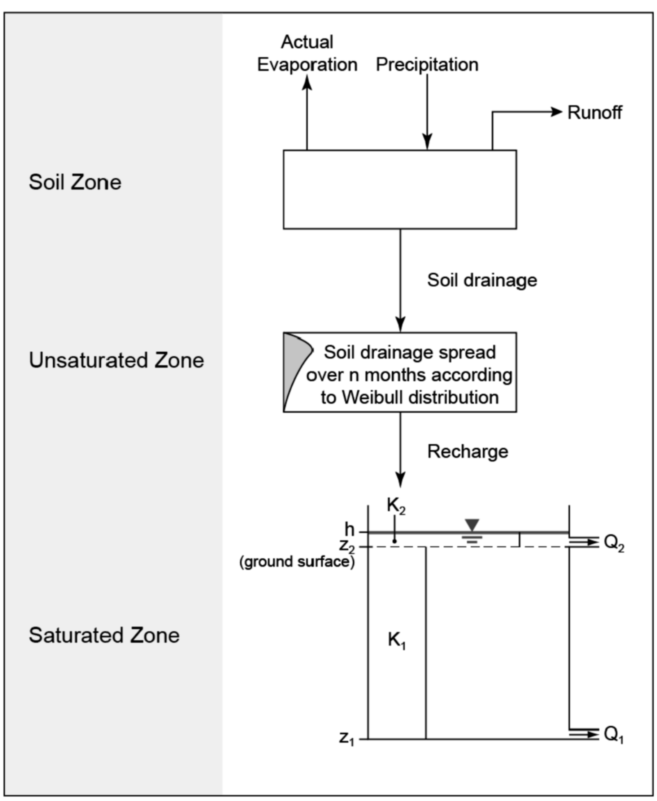

Fig. 2. The AquiMod structure used for the models in this research, including the modified 2 layer saturated zone. The groundwater level (h) is shown above the ground surface (Z_2) for clarity, however groundwater levels do not exceed the Z_2 due to the very high hydraulic conductivity of the upper layer (K_2). Modified after Mackay et al. (2014a). Contains BGS materials © UKRI. All rights reserved.

levels are likely to rise substantially when applying these data to the models developed by Ascott et al. (2020b). These single layer saturated zone models are not bounded by the ground surface, and consequently application of climate data which are significantly wetter than the historical data for which the models were developed may result in unrealistic predictions of groundwater levels above the ground surface. To address this, we modified the models of Ascott et al. (2020b) to incorporate a second layer which represents discharge at the land surface. This is shown conceptually in Fig. 2. The boundary between the upper and lower layer (Z_2) is defined as the ground surface, and the upper layer has a very high hydraulic conductivity. This acts to immediately discharge water from the model should groundwater levels reach the ground surface. Initially for all sites the hydraulic conductivity of the upper layer (K_2) was set to 10^6 m/day. This was successful in ensuring groundwater levels do not exceed the ground surface in five out of the eight models. For three boreholes this resulted in model instability, so we reduced K_2 by trial and error until the model produced stable results with groundwater levels not exceeding the ground surface. Table 1 shows the parameter sets we used for each model based on the calibration undertaken by Ascott et al. (2020b), as well as the values of K_2 and Z_2 used in modifications to AquiMod made in this research. The addition of the second layer did not change the model predictions of historic observed groundwater levels in comparison to the results of the single layer models reported by Ascott et al. (2020b), see near-identical Nash-Sutcliffe Efficiency (NSE) values for the different model structures reported in Table 1.

We used daily CMIP5 data which have been interpolated to 0.5 degree resolution and bias-corrected using the cumulative distribution function-transform method (Michelangeli et al., 2009). These data were reported by Famien et al. (2018) and also used by Gaetani et al. (2020) in estimation of ToE of precipitation changes in West Africa. We used the RCP8.5 future simulation, as this would produce the greatest climate change signal, and a smaller number of CMIP5 GCMs report the RCP4.5 (27 GCMs) and RCP2.6 scenarios (20 GCMs) in comparison to RCP 8.5 (all 29 GCMs). This limitation is discussed further in section 4.4. We used daily bias-corrected precipitation (PR) from the CMIP5 GCMs as direct inputs to AquiMod, and estimated Potential Evapotranspiration (PET) using the Penman-Monteith method (Allen et al., 1998), with input of daily net longwave radiation at the surface and air temperature, windspeed and vapour pressure at 2 m height. For each site PR and variables used to estimate PET were extracted from the 0.5 degree grid cell in which the site was located. Six (CMCC-CESM, CMCC-CM, CMCC-CMS, MPI-ESM-LR, MPI-ESM-MR, CNRM-CM5) out the 29 GCMs did not include relative humidity (used to calculate vapour pressure above), and thus we were unable to calculate PET using the Penman-Monteith method, which resulted in 23 GCMs in total being used for this research. Daily net longwave radiation was unavailable so this was calculated using air temperature, vapour pressure (to calculate emissivity) and the fraction of cloud cover (calculated using the downwelling shortwave radiation and its clear sky value, which depends on the latitude and time of year). For each site and CMIP5 model we applied a single daily time series for the historical and future (RCP8.5) run for 1950–2099. We used the mean value of the groundwater level observations reported by Ascott et al. (2020b), $\overline{GWL}$, as the initial head, h. We tested the sensitivity of the model results to the value of h by running the model projections with h as the mean groundwater level $\pm$ standard deviation, $\overline{GWL}_{+/-SD}$. For each site and GCM, we then calculated the normalised mean absolute error (NMAE, defined here as the ratio of mean absolute error to the range) between the modelled groundwater level time series driven using $h = \overline{GWL}$ and $h = \overline{GWL}_{+/-SD}$. We then averaged this across the 23 GCMs to derive an NMAE value per site. Across the eight sites NMAE ranged from 0.02% (Nafona) to 0.83% (Niangoloko), indicating that changes in the initial head did not make significant impact on the long term groundwater level projections.

Table 1
Borehole locations, AquiMod model parameter sets and NSE values for the models of Ascott et al. (2020b) and the modified 2 layer models developed in this research. With the exception of the new parameters K_2 and Z_2, model parameters are the best location-specific parameter sets derived from the calibrations undertaken by Ascott et al. (2020b).For detailed explanation of the parameters please refer to Ascott et al. (2020b).

Site Name		Arbinda	Bassinko	Dingasso	Nafona	Niangoloko	Ouagadougou	Tibou	Tougou
Longitude		−0.84	−1.64	−4.82	−4.74	−4.90	−1.50	−2.06	−2.24
Latitude		14.21	12.39	11.71	10.68	10.27	12.38	12.88	13.68
Soil Zone	Field Capacity (–)	0.28	0.28	0.32	0.30	0.29	0.32	0.30	0.27
	Wilting Point (–)	0.17	0.16	0.20	0.16	0.16	0.20	0.18	0.15
	Maximum Rooting Depth (mm)	101	209	107	152	2940	281	117	522
	Depletion Factor (–)	0.51	0.01	0.73	0.11	0.01	0.10	0.19	0.85
	Baseflow Index (–)	0.11	0.50	0.20	0.30	0.36	0.17	0.44	0.87
Unsaturated Zone	k (–)	5.88	1.69	1.85	3.30	1.93	1.89	5.33	3.02
	lambda (–)	5.19	2.76	4.20	1.13	1.55	5.26	5.40	2.65
	n (–)	6.00	6.00	6.00	6.00	6.00	6.00	6.00	6.00
Saturated Zone	K2 (m/day)	1.E + 06	1.E + 04	1.E + 04	1.E + 03	1.E + 06	1.E + 06	1.E + 06	1.E + 06
	K1 (m/day)	1.17	2.62	2.49	2.23	0.84	1.94	2.45	2.89
	S (–)	0.01	0.05	0.02	0.02	0.03	0.03	0.04	0.03
	Z2 (m a.s.l.)	321.10	302.00	337.70	287.90	337.00	294.10	336.10	326.00
	Z1 (m a.s.l.)	264	286	332	275	251	266	315	283
	x (m)	4832	1432	564	480	7063	3911	613	5408
NSE (1 layer model of Ascott et al (2020b))		0.83	0.67	0.79	0.56	0.64	0.83	0.58	0.56
NSE (2 layer model used in this research)		0.81	0.67	0.77	0.56	0.64	0.83	0.58	0.57

2.3. Estimation of time of emergence and evaluation of model results

Time of Emergence was estimated using the signal:noise approach, applied to driving data (daily PR and PET) and modelled groundwater level data. This approach has been applied extensively elsewhere (Gaetani et al., 2020; Hawkins and Sutton, 2012), and the method is as follows: (1) fit separate fourth order polynomials to the historical and future time series of the variable of interest; (2) the change in the fitted values of the future polynomial is signal; (3) the standard deviation of the residuals of the historic polynomial is the noise; (4) ToE is defined as the point in the future where the signal:noise ratio is >1 and remains so for the rest of the time series.

We first evaluated changes in groundwater levels from 1950 to 2100 for each site and CMIP5 model by visual inspection. To compare between the sites and between different CMIP5 model runs we normalised (mean = 0, standard deviation = 1) each groundwater level time series separately, and presented these as a heatmap. The ordering of the CMIP5 models in the heatmap was defined by the trend of the groundwater level changes from 1950 to 2100, with CMIP5 models ordered by those that produced groundwater levels with the greatest increasing (wetting) to decreasing (drying) trend. We evaluated ToE by splitting results by variable (PR (ToE_{PR}), PET (ToE_{PET}), groundwater level (ToE_{GWL})), site, and whether the variable shows an increasing or decreasing trend in the future (2005 – 2099) run. The direction of the future trend was defined by the sign of the linear term of the polynomial fitted to the future data. Using a Pearson's correlation matrix, we then explored the relationships between ToE_{GWL}, ToE_{PR}, ToE_{PET} and the following variables:

- the magnitude of changes in mean daily PR (dPR, mm/day),PET (dPET, mm/day) and groundwater level (dGWL, m) between the historic (1950–2005) and future periods (2005–2099)
- aridity index (AI, unitless, defined as the ratio of PR (mm) to PET (mm))
- modelled groundwater response time (GRT, years, defined as the inverse of hydraulic diffusivity multiplied by the square of the aquifer length (Ascott et al., 2020b; Cuthbert et al., 2019))

Not all borehole-CMIP5 model combinations produced a ToE for all variables (e.g. some borehole-CMIP5 model combinations produced a ToE for PET (ToE_{PET}) but not for groundwater levels (ToE_{GWL}) or PR (ToE_{PR})), which reduced the number of borehole-CMIP5 model combinations with a complete set of values for the variables in the correlation analysis above. We therefore also separately calculated correlations between (1) ToE_{GWL} and ToE_{PR},(2) ToE_{PR} and ToE_{PET} and dPR and dPET and (3) dGWL and GRT.

3. Results

3.1. Modelled changes in groundwater levels over 1950–2100

Fig. 3 shows changes in groundwater levels produced by AquiMod for the eight sites over 1950–2100 for each CMIP5 model. The CMIP5 models in each heatmap are ordered from models which result in increasing trends in groundwater levels (wetting) to those producing decreasing trends (drying) at Ouagadougou. It can be observed that there is no consistent direction of change in groundwater levels in the future, with some AquiMod models driven by the CMIP5 data projecting long-term increases in groundwater levels and some projecting decreases. There is some consistency across the different sites in terms of application of CMIP5 data resulting in higher (blue in the top right of the heatmaps) and lower (red in the bottom right of the heatmaps) groundwater levels in the future, albeit with some exceptions (for example, application of BNU-ESM results in higher groundwater levels in the future in all sites apart from Niangoloko). The magnitude of the temporal variability in groundwater level response to climate forcing also varies between sites. Arbinda, Bassinko, Niangoloko, Ouagadougou and Tougou show greater variability, whilst Tibou, Dingasso and Nafona show smaller variability. There is a significant positive correlation between dGWL and GRT ($p < 0.01$, Pearson's $r = 0.55$).

3.2. Time of emergence of climate change

Fig. 4 shows estimated time of emergence of climate change signals in PR, PET and groundwater levels for each of the eight sites. For each variable, ToE is split between CMIP5 models that show increasing or decreasing trends in the respective variable. Not all CMIP5 models result in a ToE between 2005 and 2100 for each site and variable. This is consistent with results presented for West Africa by Gaetani et al. (2020), and this results in different numbers of CMIP5 models contributing to the boxplots shown in Fig. 4. This limitation is discussed further in section 4.4. ToE_{PR} occurs later and with a greater spread for CMIP5 models with decreasing future PR (median ToE = 2077, IQR = 49 years) than for CMIP5 models with increasing future PR (median ToE = 2027, IQR = 23 years). For PET, 173 of a possible 184 borehole-CMIP5 model combinations produced a ToE, with 169/173 showing increasing trends in PET due to rising temperatures. ToE_{PET} occurs relatively early and with a small spread (median ToE = 2026, IQR = 26 years). ToE_{GWL} shows similar overall patterns to ToE_{PR}. ToE_{GWL} occurs later and with a

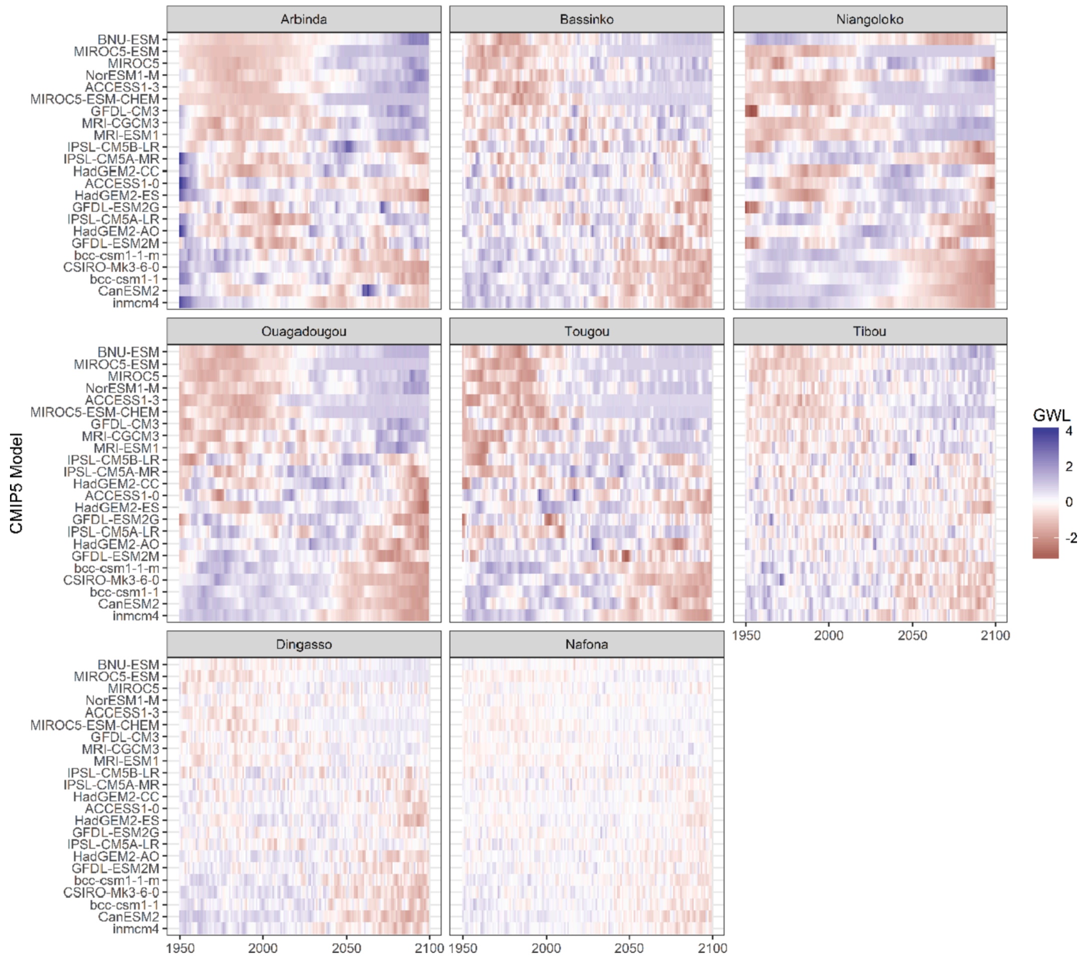

Fig. 3. Groundwater level changes from 1950 to 2100 for each borehole derived from AquiMod model runs driven by the CMIP5 historical and future model data. Groundwater levels (GWL, blue = higher/wetter, red = lower/drier) are presented as normalised values for each individual site and CMIP5 model driving dataset for comparability. CMIP5 models are ordered based on those showing the greatest increasing (wetting, top) to decreasing (drying, bottom) trend in modelled groundwater levels at Ouagadougou.

greater spread (median ToE = 2049, IQR = 48 years) when AquiMod driven by the CMIP5 data produces decreases in groundwater levels than when AquiMod produces increases in groundwater levels (median ToE = 2011, IQR = 11 years). In drying (i.e. decreasing PR, increasing PET and decreasing GWL) CMIP5 models ToE_{GWL} occurs earlier than ToE_{PR}, and later than that of ToE_{PET}.

Fig. 5 shows correlations between ToE_{PR}, ToE_{PET}, ToE_{GWL}, dPR, dPET, dGWL, AI and GRT. Correlations are for sites and CMIP5 models with a calculated ToE_{PR}, ToE_{PET} and ToE_{GWL} (n = 67). There are no significant correlations between ToE_{GWL} and AI or GRT. There are significant ($p < 0.05$) correlations between ToE_{GWL} and ToE_{PR}, dPR, ToE_{PET}, dPET.

Fig. 6 shows the relationship between ToE_{PR} and ToE_{GWL} for all sites, split between CMIP5 GCMs which project increasing and decreasing trends in PR. When considering all CMIP5 GCMs, there is a significant positive correlation between ToE_{PR} and ToE_{GWL} ($p < 0.05$, Pearson's r = 0.59, n = 77).

Fig. 7 shows the relationship between the dPR and ToE_{PET} and dPET and ToE_{PET}. There is a significant negative correlation between the dPR and ToE_{PR} ($p < 0.05$, Pearson's r = -0.44, n = 83). A significant negative correlation was also observed between dPET and ToE_{PET} ($p < 0.05$, Pearson's r = -0.42, n = 173).

4. Discussion

4.1. Differences in the direction and magnitude of changes in groundwater levels for 1950–2100

Application of CMIP5 data to the AquiMod models in this research has resulted in divergent projections of groundwater levels (Fig. 3) to 2100, with some CMIP5 models projecting increases and some projecting decreases. This is consistent with findings from global reviews of studies assessing impacts of climate change on groundwater which showed little consensus in the direction of change in the amount of groundwater recharge (Smerdon, 2017). Regionally this is also consistent with PR projections in West Africa reported by Gaetani et al. (2020), which show no consensus on the direction of change. The projections of PR characteristics (e.g. rainfall amount, intensity) in our study area are highly uncertain. Previous comparisons against observations do not attempt to identify certain GCMs as more or less reliable than others (Roehrig et al., 2013), and all coupled models are subject to similar biases in sea surface temperatures (SSTs) and hence PR seasonal cycle (Dunning et al., 2017). Further, good skill in the historical period is no guarantee that the future climate is projected accurately. The similarities across the sites in which CMIP5 models result in decreasing or increasing trends in future groundwater levels is unsurprising when considering the locations of the sites and the grid resolutions of the CMIP5 data. The sites cover an area of approximately 4 degrees of both longitude and latitude (Fig. 1, Table 1), and the bias-corrected CMIP5

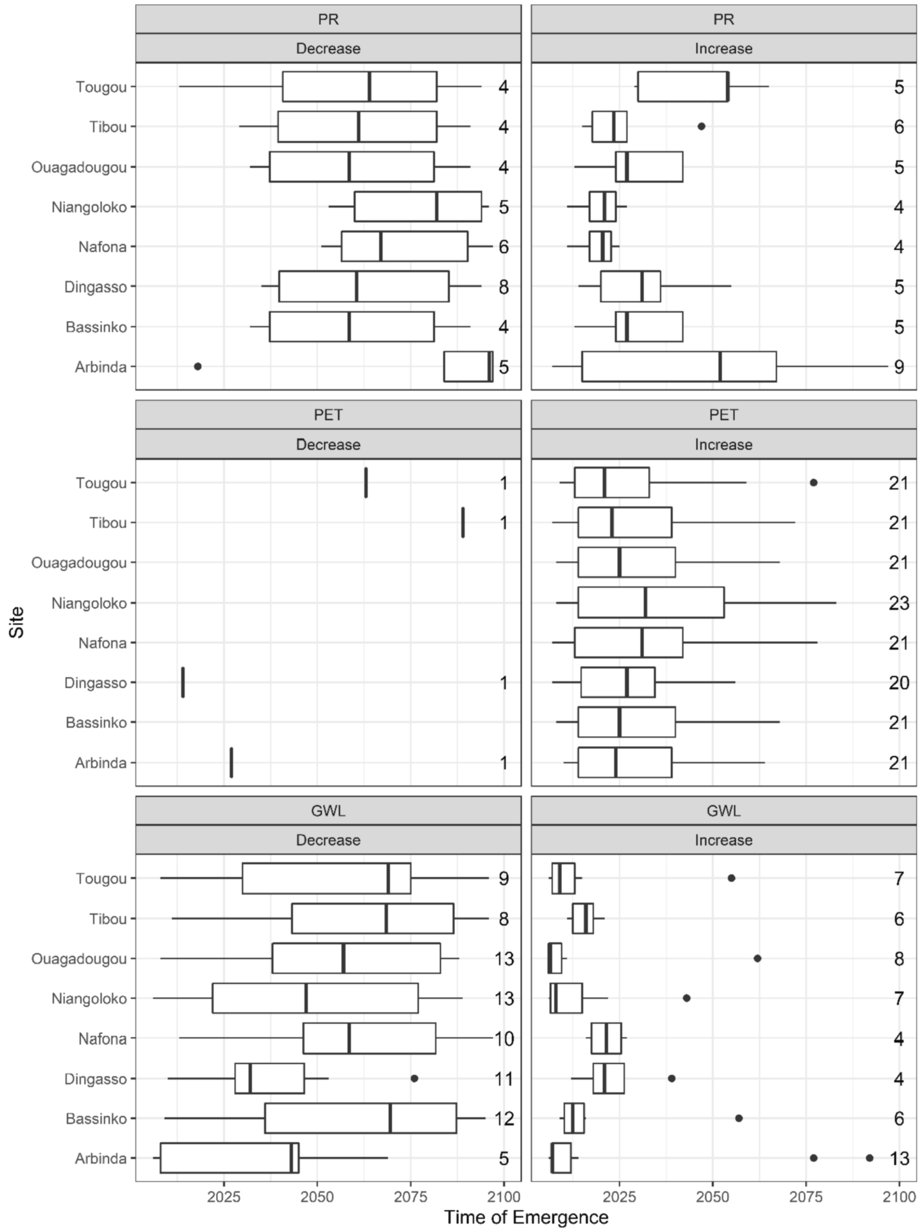

Fig. 4. Boxplots of the year of time of emergence of climate change signals in PR, PET and GWL for each borehole, split between CMIP5 models that show decreases or increases in the variable in each row. Numbers next to each boxplot indicate the number of CMIP5 models (for PR and PET) or CMIP5 driven AquiMod models (for GWL) that contribute to the boxplot.

data is at 0.5 degree resolution (Famien et al., 2018), with some of the CMIP5 model native grid resolution being up to 2.8 degrees (MIROC-ESM and MIROC-ESM-CHEM). Consequently, the sites only cover a small number of grid cells, with some sites (e.g., Ouagadougou and Bassinko) within the same grid cell. In these cases, sites have the same driving PR data and very similar PET data. Very small differences in PET occur in these cases due to differences in latitude used to estimate clear sky downwelling radiation within the Penman-Monteith method (Allen et al., 1998).

Whilst the direction of changes in groundwater levels is principally controlled by PR and PET projections derived from the CMIP5 GCMs, differences in the magnitude of long term groundwater level changes between the sites are likely to be due to differences in the calibrated hydraulic property values in the AquiMod models developed by Ascott et al. (2020b) and used in this research. Ascott et al. (2020b) showed that the eight boreholes could be split into those showing historic multi-decadal variability (Arbinda, Bassinko, Niangoloko, Ouagadougou and Tougou) and those showing intra-annual variability (Tibou, Dingasso, Nafona), with the modelled groundwater response time controlling the differences between the groups. These groupings are also apparent in the differences in the magnitude of future groundwater level changes between the sites shown in Fig. 3, and also highlighted by the significant positive correlation between dGWL and GRT presented in section 3.1. The sites showing greater long-term changes in future groundwater levels are those classified as showing historic multi-decadal variability by Ascott et al. (2020b). These sites have longer modelled GRT than those sites classified as showing intra-annual variability and smaller changes in future groundwater levels. Longer GRTs will result in a greater memory effect, with modelled groundwater levels being controlled by multiple years of recharge accumulations/deficits. As discussed in section 2.1, the limited conceptual information available for each of the sites makes it challenging to directly infer the real-world hydrogeological causes of the differences in the future magnitude of groundwater level changes between the sites. Nevertheless, Table 1

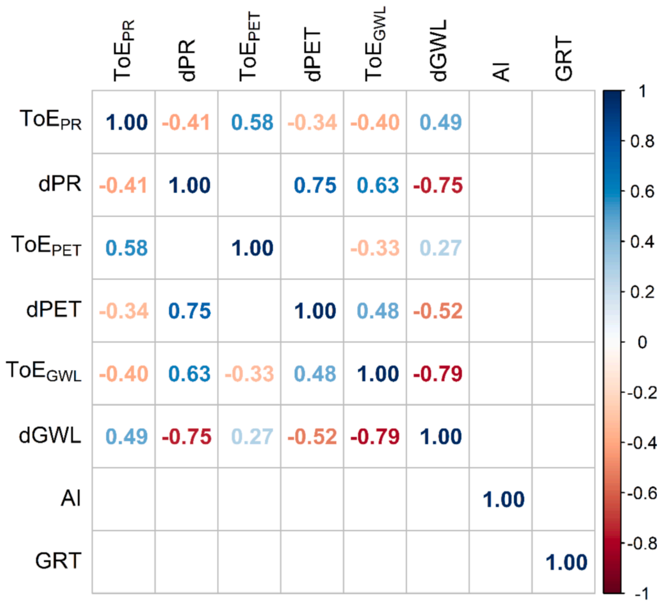

Fig. 5. Significant ($p < 0.05$) Pearson correlations between ToE$_{PR}$, ToE$_{PET}$, ToE$_{GWL}$, dPR, dPET, dGWL, AI and GRT. Blank cells indicate where no significant correlations were observed. Correlations are for sites and CMIP5 models with a calculated ToE for PR, PET and GWL ($n = 67$).

shows that the principal difference between the groupings in terms of the modelled hydraulic properties that make up the modelled GRT is differences in the modelled aquifer length, with this parameter varying by an order of magnitude between the two groups.

4.2. Groundwater level time of emergence and relationships with meteorological variables

Whilst numerous workers have estimated ToE for other hydrometeorological variables (as discussed in section 1), our study is the first to estimate ToE for groundwater levels. Our estimates of ToE for PR and groundwater levels (Fig. 4) agree with regional estimates of ToE for PR which showed no robust signal in change of cumulative PR in Burkina Faso (Gaetani et al., 2020). The correlation analyses presented in section 3.2 suggest that whilst the hydrogeological properties (characterised by the GRT) of each site appear to affect the magnitude of future groundwater level changes (as illustrated by the differences in responses between the sites in Fig. 3), there is no relationship between GRT or AI and ToE$_{GWL}$. ToE$_{GWL}$ appears to be principally controlled by ToE$_{PR}$ and ToE$_{PET}$ (Fig. 5, Fig. 6), which is an unsurprising result given the divergent predictions of ToE$_{PR}$ produced by the CMIP5 GCMs in the region (Gaetani et al., 2020). The relationship between ToE$_{PR}$ and ToE$_{GWL}$ differs between CMIP5 GCMs which show wetting and drying trends (Fig. 6). In CMIP5 GCMs which show decreases in future PR (Fig. 6 left), ToE$_{GWL}$ occurs earlier than ToE$_{PR}$ due to increases in PET (driven by increases in temperature) and early occurrence of ToE$_{PET}$ (Fig. 4). In CMIP5 GCMs which show increases in future PR (Fig. 6 right), ToE$_{GWL}$ results are more complex. Future increases in PR may be offset by increases in PET which may result in ToE$_{GWL}$-ToE$_{PR}$ relationships being closer to the 1:1 line. However, ToE$_{GWL}$ appears to still occur before ToE$_{PR,}$ which highlights the importance of ToE$_{PET}$ in controlling ToE$_{GWL.}$ The observed correlations between ToE$_{PR}$ and ToE$_{PET}$ and the change in absolute PR and PET (Fig. 7) respectively are also intuitive results. Larger absolute changes will result in a greater ToE signal (the changes in the fitted values of the future polynomial, see section 2.3) relative to noise, and so the point in the future where the signal:noise ratio is > 1 occurs earlier.

Differences between ToE of meteorological and hydrological (streamflow, reservoir levels) variables have been previously reported in studies by Zhuan et al. (2018) and Chadwick et al. (2021), and differences in ToE for PR, PET and groundwater levels reported in our study (Fig. 4) agree with this. This supports the assertion of Chadwick et al. (2021) that ToE of specific hydrological variables is of more relevance than meteorological variables for water resource applications. Interestingly, the early ToE$_{GWL}$ in comparison to ToE$_{PR}$ discussed above and presented in Fig. 6 contrasts with the results of Zhuan et al. (2018), who showed that in their study ToE of streamflow occurred after ToE$_{PR.}$ This was due to the GCM data used by Zhuan et al. (2018) always showing a significant wetting trend, and so increases in temperature (and PET) partially offset and delay impacts on streamflow. It should also be noted that there is a wide range of different approaches adopted to ToE estimation using different numbers of GCMs/RCMs, different approaches to GCM averaging and different approaches to estimation of ToE metrics. Consequently, it is challenging to make direct comparisons between results of different studies. To that end a set of common methodologies for estimation of ToE for hydrometeorological applications would be beneficial.

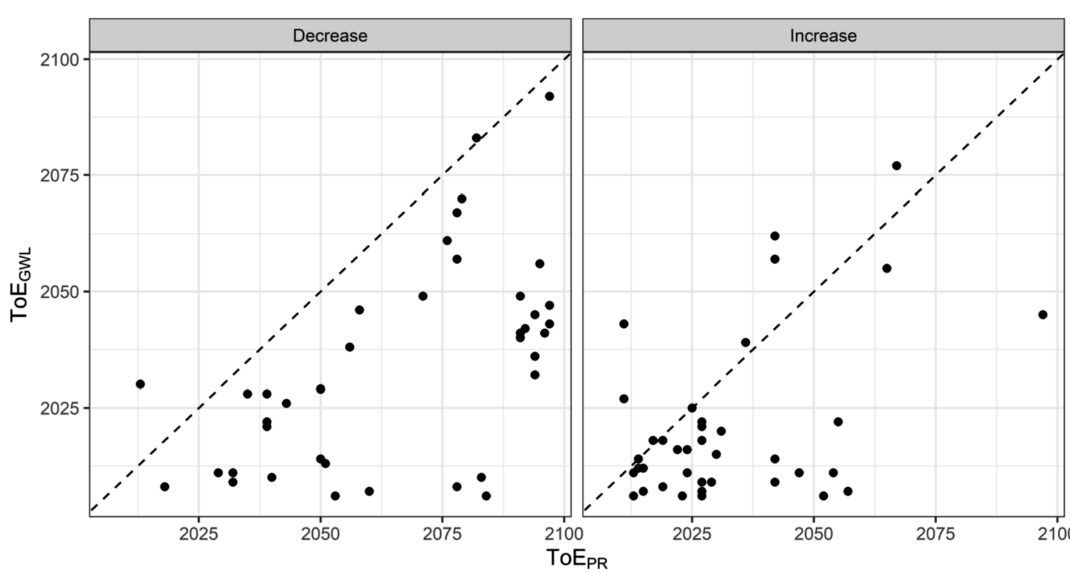

Fig. 6. Relationships between ToE$_{PR}$ and ToE$_{GWL}$ for CMIP5 models with decreasing (left) and increasing (right) future trends in precipitation.

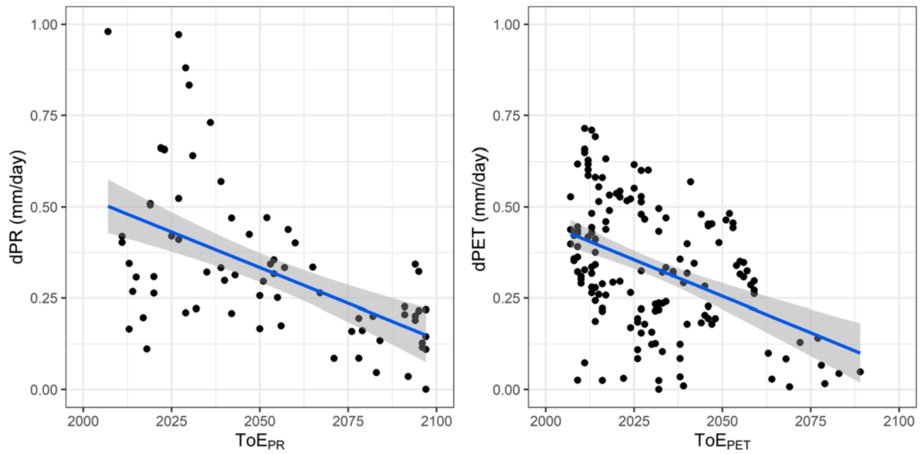

Fig. 7. Relationships between ToE$_{PR}$ and dPR (left) and ToE$_{PET}$ and dPET (right). Grey area indicates 95% confidence intervals for the linear regression line (blue).

4.3. Implications for groundwater management and climate change adaptation

This analysis shows no consistent direction of climate change impact on groundwater levels, nor when these impacts will occur. This highlights the need for improved GCMs over West Africa, in particular to achieve more consistency in the direction of change in the amount of PR. The lack of consistency in the ToE assessment poses significant challenges in developing specific groundwater management responses and adaptation measures, both in nature and timing. In this context, no-regrets approaches are the most appropriate. Groundwater development, although growing across SSA, is still relatively small compared with renewable groundwater resources (Cobbing, 2020; MacDonald et al., 2021). Although steps have been taken to address the imbalance, the current gap between demand and supply of water in SSA is generally still marked, with resulting challenges in meeting UN Sustainable Development Goal 6 ("Ensure access to water and sanitation for all") (Chitonge et al. (2020); Velis et al. (2017)). This gap is likely to widen with the large projected rise in population for most regions of SSA (Ezeh et al., 2020). With increasing PET, increasing demand for food and changes to rainfall patterns, there will also be the need for supplementary watering of crops (Abegunde et al., 2019; MacDonald et al., 2009). The development of groundwater through well-sited and constructed boreholes has the potential to meet local water supply needs where groundwater conditions are favourable, even where groundwater recharge sees a long-term decrease (Bianchi et al., 2020). In conjunction with effective water use and long-term monitoring of groundwater storage, development of groundwater abstraction is therefore the key no-regrets action to support water supply needs, which can be taken in spite of the uncertainty in the direction, magnitude and timing of climate change impacts on groundwater highlighted by this research.

4.4. Limitations and further work

There are a number of limitations to our research and areas of further work, which we detail herein. In this research we only used a single CMIP5 emissions scenario (RCP8.5). Under less extreme emissions scenarios (RCP2.6, 4.5) it would be anticipated that ToE may occur later in time or potentially not at all. There are a number of different methodologies in the climate science literature to estimate ToE, and further work to explore the sensitivity of ToE$_{GWL}$ to different methodologies (as has been undertaken for PR by Gaetani et al. (2020) and different emissions scenarios may be beneficial. This would support the development of a common set of methodologies for ToE estimation. Beyond the study area, application of the approach used in this research in an area with less divergent GCM predictions may yield more consistent results.

In this analysis we calculate ToE for each site, variable and CMIP5 GCM separately, split up by GCMs which show wetting and drying trends in the future. This approach is advantageous as it allows comparisons to be made in ToE between variables, sites and the direction of change, and to evaluate variability across the CMIP5 GCMs. This approach is limited, however, by some CMIP5 models not producing a ToE for certain variables and sites, resulting in different numbers of CMIP5 models contributing to the results (Fig. 4). The correlation analysis used to explore relationships between ToE of different variables (Figs. 5–7) was unaffected by this as we used a complete set of ToE results for the different variables. A detailed evaluation of the relationships between ToE for the different variables and sites for each individual GCM may be beneficial but is beyond the scope of this research.

The boreholes used in this research have been shown to be relatively unimpacted by changes in groundwater abstraction and land use, with historic changes in groundwater levels predominantly controlled by changes in climate (Ascott et al., 2020b). However, in the future, it is plausible that emergence of climate change impacts on rainfall and PET may cause feedbacks resulting in changes in abstraction and land use which could affect groundwater levels. For example, in a drying scenario (reduced PR and increased PET), aridification and less reliable rainfed agriculture may result in an increased reliance on groundwater abstraction, causing decreases in groundwater levels and earlier ToE$_{GWL}$. These feedbacks between climate drivers, groundwater levels and anthropogenic influences are complex, and highlights the importance of long-term monitoring that is unaffected by abstraction and land use change to detect impacts of climate change on groundwater levels (Ascott et al., 2020a; Cuthbert et al., 2019; Sorensen et al., 2021). It also highlights the need for the land surface schemes that are embedded in these climate models to better reflect the effects of anthropogenic influences on the water cycle (e.g. Pokhrel et al. (2012)). This, combined with high-resolution convection permitting model runs, should result in much more reliable PR predictions (see e.g. Kendon et al. (2021)).

We used one groundwater model structure and one parameter set for each borehole in this research. This is intentional as (1) this study is explicitly aiming to quantify uncertainty in ToE associated with different CMIP5 models and (2) there is uncertainty in the conceptual model which cannot justify the use of a more complex approach. When considering absolute impacts of climate change on groundwater levels, previous researchers have suggested that climate model uncertainty is more significant than groundwater model structure and parameter uncertainty (Smerdon, 2017). Further work to evaluate whether this is true in the case of ToE$_{GWL}$ is required.

In this research we report the direction of climate change, the relative magnitude of change (i.e. magnitude normalised for comparability between sites and CMIP5 GCMs) and ToE$_{GWL}$. We have not considered the absolute magnitude of changes in groundwater levels. When groundwater levels go beyond observed ranges there is low confidence in the magnitude of changes as groundwater levels may be affected by interaction with system boundaries (e.g. the land surface, lower permeability bedrock at depth), and our conceptual understanding of these boundaries is poor. Moreover, the conceptual model on which AquiMod is based may not capture processes occurring in future climatic and land use conditions that affect groundwater recharge and discharge, e.g. the potential for increased recharge with greater surface ponding of water from more intense rainfall events. There is a need for field investigations (e.g., long term pumping tests, groundwater recharge measurements) to better characterise groundwater flow at these sites, which would allow testing and refinement of different groundwater model structure and parameter sets, and more confidence in the magnitude of groundwater level changes associated with climate change when these are beyond observed ranges.

5. Conclusions

In this study we applied PR and PET inputs to the AquiMod model structure for eight boreholes in Burkina Faso to estimate time of emergence (ToE) of climate change impacts on groundwater levels for the first time. We conclude that:

- There is no consistent direction of climate change impacts on groundwater levels, with AquiMod producing groundwater levels with either increasing and decreasing trends depending on the CMIP5 GCM used as driving data.
- There is no consistent ToE of climate change signals in groundwater levels. ToE_{GWL} occurs later and with a greater spread when AquiMod driven by CMIP5 GCMs produces decreasing groundwater level trends (across all sites median ToE = 2049, interquartile range = 48 years) than those producing increasing groundwater level trends (across all sites median ToE = 2011, interquartile range = 11 years).
- Whilst hydraulic properties affect the magnitude of future groundwater level changes, ToE_{GW} is controlled by ToE_{PR} and ToE_{PET}. ToE_{PR} and ToE_{PET} are correlated with the magnitude of future changes in PR and PET.
- The results highlight the need for reductions in GCM uncertainty, and for implementation of no-regrets adaptation measures (such as the sustainable development of groundwater) which will be of benefit in any climate future.

6. Data statement

AquiMod is publicly available from the British Geological Survey (2019) under UK Open Government Licence. Bias corrected CMIP5 model data used in this research are available for download using the information at: https://www.amma2050.org/sites/default/files/Note_BC-CMIP5-final%20AMMA-2050.pdf.

CRediT authorship contribution statement

M.J. Ascott: Methodology, Formal analysis, Writing – original draft. **D.M.J. Macdonald:** Conceptualization, Writing – review & editing, Supervision, Project administration, Funding acquisition. **W.J.P. Sandwidi:** Writing – review & editing, Project administration. **E. Black:** Writing – review & editing, Funding acquisition. **A. Verhoef:** Writing – review & editing, Funding acquisition. **G. Zongo:** Writing – review & editing, Resources, Data curation. **J. Tirogo:** Writing – review & editing, Resources, Data curation. **P. Cook:** Writing – review & editing, Formal analysis.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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References

Abatzoglou, J.T., Williams, A.P., Barbero, R., 2019. Global Emergence of Anthropogenic Climate Change in Fire Weather Indices. Geophys. Res. Lett. 46 (1), 326–336. https://doi.org/10.1029/2018GL080959.

Abegunde, V.O., Sibanda, M., Obi, A., 2019. The Dynamics of Climate Change Adaptation in Sub-Saharan Africa: A Review of Climate-Smart Agriculture among Small-Scale Farmers. Climate 7 (11), 132.

Allen, R.G., Pereira, L.S., Raes, D., Smith, M., 1998. Crop evapotranspiration-Guidelines for computing crop water requirements-FAO Irrigation and drainage paper 56. FAO, Rome, 300(9): D05109.

Amanambu, A.C., Obarein, O.A., Mossa, J., Li, L., Ayeni, S.S., Balogun, O., Oyebamiji, A., Ochege, F.U., 2020. Groundwater system and climate change: Present status and future considerations. J. Hydrol. 589, 125163 https://doi.org/10.1016/j.jhydrol.2020.125163.

Ascott, M.J., 2021. Historic reconstructions of daily groundwater levels for eight boreholes in Burkina Faso. NERC EDS National Geosci. Data Centre. https://doi.org/10.5285/c9262369-4db1-48e1-9660-3ef8667ab19b.

Ascott, M.J., Bloomfield, J.P., Karapanos, I., Jackson, C.R., Ward, R.S., McBride, A.B., Dobson, B., Kieboom, N., Holman, I.P., Van Loon, A.F., Crane, E.J., Brauns, B., Rodriguez-Yebra, A., Upton, K.A., 2020a. Managing groundwater supplies subject to drought: perspectives on current status and future priorities from England (UK). Hydrogeol. J. https://doi.org/10.1007/s10040-020-02249-0.

Ascott, M.J., Macdonald, D.M.J., Black, E., Verhoef, A., Nakohoun, P., Tirogo, J., Sandwidi, W.J.P., Bliefernicht, J., Sorensen, J.P.R., Bossa, A.Y., 2020b. In Situ Observations and Lumped Parameter Model Reconstructions Reveal Intra-Annual to Multidecadal Variability in Groundwater Levels in Sub-Saharan Africa. Water Resour. Res., 56(12): e2020WR028056. DOI:10.1029/2020WR028056.

Ascott, M.J., Mansour, M., Bloomfield, J.P., Upton, K.A., 2019. Analysis of the impact of hydraulic properties and climate change on estimations of borehole yields. J. Hydrol. 123998 https://doi.org/10.1016/j.jhydrol.2019.123998.

Badou, D.F., Diekkrüger, B., Kapangaziwiri, E., Mbaye, M.L., Yira, Y., Lawin, E.A., Oyerinde, G.T., Afouda, A., 2018. Modelling blue and green water availability under climate change in the Beninese Basin of the Niger River Basin, West Africa. Hydrol. Processes 32 (16), 2526–2542. https://doi.org/10.1002/hyp.13153.

Bianchi, M., MacDonald, A.M., Macdonald, D.M.J., Asare, E.B., 2020. Investigating the Productivity and Sustainability of Weathered Basement Aquifers in Tropical Africa Using Numerical Simulation and Global Sensitivity Analysis. Water Resour. Res., 56 (9): e2020WR027746. DOI:10.1029/2020wr027746.

Black, E., Pinnington, E., Wainwright, C., Lahive, F., Quaife, T., Allan, R.P., Cook, P., Daymond, A., Hadley, P., McGuire, P.C., Verhoef, A., Vidale, P.L., 2020. Cocoa plant productivity in West Africa under climate change: a modelling and experimental study. Environ. Res. Lett. 16 (1), 014009 https://doi.org/10.1088/1748-9326/abc3f3.

Bornemann, F.J., Rowell, D.P., Evans, B., Lapworth, D.J., Lwiza, K., Macdonald, D.M.J., Marsham, J.H., Tesfaye, K., Ascott, M.J., Way, C., 2019. Future changes and uncertainty in decision-relevant measures of East African climate. Climatic Change. DOI:10.1007/s10584-019-02499-2.

British Geological Survey, 2019. AquiMod. https://www.bgs.ac.uk/research/environmentalModelling/aquimod.html.

Chadwick, C., Gironás, J., Barría, P., Vicuña, S., Meza, F., 2021. Assessing Reservoir Performance under Climate Change. When Is It Going to Be Too Late If Current Water Management Is Not Changed? Water 13 (1), 64.

Chitonge, H., Mokoena, A., Kongo, M., 2020. Water and Sanitation Inequality in Africa: Challenges for SDG 6. In: Ramutsindela, M., Mickler, D. (Eds.), Africa and the Sustainable Development Goals. Springer International Publishing, Cham, pp. 207–218. https://doi.org/10.1007/978-3-030-14857-7_20.

Cobbing, J., 2020. Groundwater and the discourse of shortage in Sub-Saharan Africa. Hydrogeol. J. 28 (4), 1143–1154. https://doi.org/10.1007/s10040-020-02147-5.

Cuthbert, M.O., Taylor, R.G., Favreau, G., Todd, M.C., Shamsudduha, M., Villholth, K.G., MacDonald, A.M., Scanlon, B.R., Kotchoni, D.O.V., Vouillamoz, J.-M., Lawson, F.M.A., Adjomayi, P.A., Kashaigili, J., Seddon, D., Sorensen, J.P.R., Ebrahim, G.Y., Owor, M., Nyenje, P.M., Nazoumou, Y., Goni, I., Ousmane, B.I., Sibanda, T., Ascott, M.J., Macdonald, D.M.J., Agyekum, W., Koussoubé, Y., Wanke, H., Kim, H., Wada, Y., Lo, M.-H., Oki, T., Kukuric, N., 2019. Observed controls on resilience of groundwater to climate variability in sub-Saharan Africa. Nature 572 (7768), 230–234. https://doi.org/10.1038/s41586-019-1441-7.

Dams, J., Salvadore, E., Van Daele, T., Ntegeka, V., Willems, P., Batelaan, O., 2012. Spatio-temporal impact of climate change on the groundwater system. Hydrol. Earth Syst. Sci. 16 (5), 1517–1531. https://doi.org/10.5194/hess-16-1517-2012.

Dunning, C.M., Allan, R.P., Black, E., 2017. Identification of deficiencies in seasonal rainfall simulated by CMIP5 climate models. Environ. Res. Lett. 12 (11), 114001 https://doi.org/10.1088/1748-9326/aa869e.

Ezeh, A., Kissling, F., Singer, P., 2020. Why sub-Saharan Africa might exceed its projected population size by 2100. The Lancet 396 (10258), 1131–1133.

Famien, A.M., Janicot, S., Ochou, A.D., Vrac, M., Defrance, D., Sultan, B., Noël, T., 2018. A bias-corrected CMIP5 dataset for Africa using the CDF-t method – a contribution to agricultural impact studies. Earth Syst. Dynam. 9 (1), 313–338. https://doi.org/10.5194/esd-9-313-2018.

Filippi, C., Milville, F., Thiery, D., 1990. Evaluation of natural recharge to aquifers in the Sudan-Sahel climate using global hydrological modelling: application to ten sites in Burkina Faso. Hydrol. Sci. J. 35 (1), 29–48. https://doi.org/10.1080/02626669009492403.

Gaetani, M., Janicot, S., Vrac, M., Famien, A.M., Sultan, B., 2020. Robust assessment of the time of emergence of precipitation change in West Africa. Sci. Rep. 10 (1), 7670. https://doi.org/10.1038/s41598-020-63782-2.

Giorgi, F., Bi, X., 2009. Time of emergence (TOE) of GHG-forced precipitation change hot-spots. Geophys. Res. Lett. 36 (6) https://doi.org/10.1029/2009GL037593.

Guardiola-Albert, C., Jackson, C.R., 2011. Potential impacts of climate change on groundwater supplies to the Doñana wetland, Spain. Wetlands 31 (5), 907.

Hawkins, E., Sutton, R., 2012. Time of emergence of climate signals. Geophys. Res. Lett. 39 (1) https://doi.org/10.1029/2011GL050087.

Henson, S.A., Beaulieu, C., Ilyina, T., John, J.G., Long, M., Séférian, R., Tjiputra, J., Sarmiento, J.L., 2017. Rapid emergence of climate change in environmental drivers of marine ecosystems. Nat. Commun. 8 (1), 14682. https://doi.org/10.1038/ncomms14682.

IPCC, 2014. Climate change 2013: the physical science basis: Working Group I contribution to the Fifth assessment report of the Intergovernmental Panel on Climate Change. Cambridge university press.

Jackson, C.R., Meister, R., Prudhomme, C., 2011. Modelling the effects of climate change and its uncertainty on UK Chalk groundwater resources from an ensemble of global climate model projections. J. Hydrol. 399 (1–2), 12–28. https://doi.org/10.1016/j.jhydrol.2010.12.028.

Keller, K.M., Joos, F., Raible, C.C., 2014. Time of emergence of trends in ocean biogeochemistry. Biogeosciences 11 (13), 3647–3659. https://doi.org/10.5194/bg-11-3647-2014.

Kendon, E.J., Prein, A.F., Senior, C.A., Stirling, A., 2021. Challenges and outlook for convection-permitting climate modelling. Philos. Trans. R. Society A: Math., Phys. Eng. Sci. 379 (2195), 20190547. https://doi.org/10.1098/rsta.2019.0547.

Kingston, D.G., Taylor, R.G., 2010. Sources of uncertainty in climate change impacts on river discharge and groundwater in a headwater catchment of the Upper Nile Basin, Uganda. Hydrol. Earth Syst. Sci. 14 (7), 1297–1308. https://doi.org/10.5194/hess-14-1297-2010.

Leng, G., Huang, M., Voisin, N., Zhang, X., Asrar, G.R., Leung, L.R., 2016. Emergence of new hydrologic regimes of surface water resources in the conterminous United States under future warming. Environ. Res. Lett. 11 (11), 114003.

Lyu, K., Zhang, X., Church, J.A., Slangen, A.B.A., Hu, J., 2014. Time of emergence for regional sea-level change. Nature Climate Change 4 (11), 1006–1010. https://doi.org/10.1038/nclimate2397.

MacDonald, A.M., Calow, R.C., Macdonald, D.M.J., Darling, W.G., Dochartaigh, B., 2009. What impact will climate change have on rural water supplies in Africa? Hydrol. Sci. J. 54 (4), 690.

MacDonald, A.M., Bonsor, H.C., Dochartaigh, B.É.Ó., Taylor, R.G., 2012. Quantitative maps of groundwater resources in Africa. Environ. Res. Lett. 7 (2), 024009.

MacDonald, A.M., Lark, R.M., Taylor, R.G., Abiye, T., Fallas, H.C., Favreau, G., Goni, I.B., Kebede, S., Scanlon, B., Sorensen, J.P.R., Tijani, M., Upton, K.A., West, C., 2021. Mapping groundwater recharge in Africa from ground observations and implications for water security. Environ. Res. Lett. 16 (3), 034012 https://doi.org/10.1088/1748-9326/abd661.

Mackay, J., Jackson, C., Wang, L., 2014a. AquiMod user manual (v1.0), British Geological Survey, Nottingham, UK.

Mackay, J., Jackson, C., Wang, L., 2014b. A lumped conceptual model to simulate groundwater level time-series. Environ. Modelling & Software 61, 229–245.

Martin, J., Thiéry, D., 1987. Analyse d'une longue série piézométrique au Burkina Faso - Étude de la variabilité climatique. Hydrogéologie 2, 137–145.

Michelangeli, P.-A., Vrac, M., Loukos, H., 2009. Probabilistic downscaling approaches: Application to wind cumulative distribution functions. Geophys. Res. Lett. 36 (11) https://doi.org/10.1029/2009GL038401.

Mileham, L., Taylor, R.G., Todd, M., Tindimugaya, C., Thompson, J., 2009. The impact of climate change on groundwater recharge and runoff in a humid, equatorial catchment: sensitivity of projections to rainfall intensity. Hydrol. Sci. J. 54 (4), 727–738. https://doi.org/10.1623/hysj.54.4.727.

Moeck, C., Brunner, P., Hunkeler, D., 2016. The influence of model structure on groundwater recharge rates in climate-change impact studies. Hydrogeol. J. 24 (5), 1171–1184. https://doi.org/10.1007/s10040-016-1367-1.

Mora, C., Frazier, A.G., Longman, R.J., Dacks, R.S., Walton, M.M., Tong, E.J., Sanchez, J.J., Kaiser, L.R., Stender, Y.O., Anderson, J.M., Ambrosino, C.M., Fernandez-Silva, I., Giuseffi, L.M., Giambelluca, T.W., 2013. The projected timing of climate departure from recent variability. Nature 502 (7470), 183–187. https://doi.org/10.1038/nature12540.

Mouhouyouddine, A.H., Yameogo, S., Genthon, P., Paturel, J.E., Guilliod, M., 2017. Groundwater level changes since 1978 in an African city on basement rocks: the case of the CIEH borehole in Ouagadougou (Burkina Faso). J. Water Resour. Protection 9 (10), 1097–1118.

Muelchi, R., Rössler, O., Schwanbeck, J., Weingartner, R., Martius, O., 2021. River runoff in Switzerland in a changing climate – runoff regime changes and their time of emergence. Hydrol. Earth Syst. Sci. 25 (6), 3071–3086. https://doi.org/10.5194/hess-25-3071-2021.

Nguyen, T.-H., Min, S.-K., Paik, S., Lee, D., 2018. Time of emergence in regional precipitation changes: an updated assessment using the CMIP5 multi-model ensemble. Clim. Dyn. 51 (9), 3179–3193. https://doi.org/10.1007/s00382-018-4073-y.

Park, C.-E., Jeong, S.-J., Joshi, M., Osborn, T.J., Ho, C.-H., Piao, S., Chen, D., Liu, J., Yang, H., Park, H., Kim, B.-M., Feng, S., 2018. Keeping global warming within 1.5 °C constrains emergence of aridification. Nature Clim. Change 8 (1), 70–74. https://doi.org/10.1038/s41558-017-0034-4.

Pokhrel, Y., Hanasaki, N., Koirala, S., Cho, J., Yeh, P.-J.-F., Kim, H., Kanae, S., Oki, T., 2012. Incorporating Anthropogenic Water Regulation Modules into a Land Surface Model. J. Hydrometeorol. 13 (1), 255–269. https://doi.org/10.1175/jhm-d-11-013.1.

Roehrig, R., Bouniol, D., Guichard, F., Hourdin, F., Redelsperger, J.-L., 2013. The Present and Future of the West African Monsoon: A Process-Oriented Assessment of CMIP5 Simulations along the AMMA Transect. J. Clim. 26 (17), 6471–6505. https://doi.org/10.1175/jcli-d-12-00505.1.

Smerdon, B.D., 2017. A synopsis of climate change effects on groundwater recharge. J. Hydrol. 555, 125–128. https://doi.org/10.1016/j.jhydrol.2017.09.047.

Smith, M., Cross, K., Paden, M., Laban, P., 2016. Spring - Managing groundwater sustainably. IUCN, Gland, Switzerland.

Sorensen, J.P.R., Davies, J., Ebrahim, G.Y., Lindle, J., Marchant, B.P., Ascott, M.J., Bloomfield, J.P., Cuthbert, M.O., Holland, M., Jensen, K.H., Shamsudduha, M., Villholth, K.G., MacDonald, A.M., Taylor, R.G., 2021. The influence of groundwater abstraction on interpreting climate controls and extreme recharge events from well hydrographs in semi-arid South Africa. Hydrogeol. J. https://doi.org/10.1007/s10040-021-02391-3.

Sui, Y., Lang, X., Jiang, D., 2014. Time of emergence of climate signals over China under the RCP4.5 scenario. Clim. Change 125 (2), 265–276. https://doi.org/10.1007/s10584-014-1151-y.

Velis, M., Conti, K.I., Biermann, F., 2017. Groundwater and human development: synergies and trade-offs within the context of the sustainable development goals. Sustain. Sci. 12 (6), 1007–1017. https://doi.org/10.1007/s11625-017-0490-9.

Zhou, T., Voisin, N., Leng, G., Huang, M., Kraucunas, I., 2018. Sensitivity of Regulated Flow Regimes to Climate Change in the Western United States. J. Hydrometeorol. 19 (3), 499–515. https://doi.org/10.1175/jhm-d-17-0095.1.

Zhuan, M.-J., Chen, J., Shen, M.-X., Xu, C.-Y., Chen, H., Xiong, L.-H., 2018. Timing of human-induced climate change emergence from internal climate variability for hydrological impact studies. Hydrol. Res. 49 (2), 421–437. https://doi.org/10.2166/nh.2018.059.