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Discussions

Evaluation of impact of climate change and anthropogenic change on regional hydrology

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Abstract

General circulation models (GCMs) have been widely used to simulate current and future climate at the global scale. However, the development of frameworks to apply GCMs to assess potential climate change impacts on regional hydrologic systems and compliance with water resource regulations is more recent. It is important to predict potential impacts of future climate change on streamflows and groundwater levels to reduce risks and increase resilience in water resources management and planning. This study evaluated future streamflows and groundwater levels in the Tampa Bay region in west-central Florida using an ensemble of different GCMs, reference evapotranspiration (ET_0) methods, and water use scenarios to drive an integrated hydrologic model (IHM). Eight GCMs were bias-corrected and downscaled using the Bias Correction and Stochastic Analog (BCSA) downscaling method and then used, together with three ET_0 methods, to drive the IHM for eight different human water use scenarios. Results showed that changes in projected streamflow were most sensitive to GCM selection, however, projections of groundwater level change were sensitive to both GCM and water use scenario. Projected changes in streamflow and groundwater level were relatively insensitive to the ET_0

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methods evaluated in this study. Six of eight GCMs projected a decrease in streamflow and groundwater level in the future regardless of water use scenario or ET method. These results indicate a high probability of a reduction in future water supply in the Tampa Bay region if environmental regulations intended to protect current aquatic ecosystems do not adapt to the changing climate.

1. Introduction

The Intergovernmental Panel on Climate Change (IPCC) along with many other studies have indicated that climate change is likely to alter both the global hydrologic cycle and regional hydrologic cycles (Aalst et al., 2014; Déry et al., 2009; Diffenbaugh and Field, 2013; Georgakakos et al., 2014; Hawkins et al., 2014; Milliman et al., 2008; Vano and Lettenmaier, 2013; Walsh et al., 2014). These studies have indicated that climate change is likely to increase the frequency of droughts, as well as the magnitude of floods in many regions. It is necessary to investigate future climate change and its potential impacts on the natural environment in order to reduce risks and increase resilience for future water resources planning and management.

General Circulation Models (GCMs) and hydrologic models have been widely used to evaluate future climate change and its impact on regional hydrologic cycles. However, there are a variety of barriers to direct use of GCMs to drive regional hydrologic models. For example, the current generation of GCMs contain biases that prevent accurate reproduce of historic hydrological conditions when used to drive hydrologic models. In addition, the coarse resolution of GCMs prevents direct use of their results with regional hydrologic models that need higher resolution climate variables. Many bias correction methods and downscaling methods have been developed and evaluated to overcome these limitations (Boé et al., 2007; Chen et al., 2013; Ghosh & Mujumdar, 2008; Hwang & Graham, 2013; Langousis et al., 2015; Maurer & Hidalgo, 2008; Muerth et al., 2013; Quintana Seguí et al., 2010; Stoll et al., 2011; Zhang & Georgakakos, 2012).

In addition to studies that focus on climate impacts on the hydrological cycle, it is also necessary to evaluate the effects of direct human behavior (Haddeland et al., 2014). Human activities such as agricultural production, irrigation, municipal pumping, deforestation, and urban

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development alter regional hydrologic behavior. For water resources management and planning, better understanding of the influence and relative importance of climate change and human-induced change on hydrology and water resources is essential (Chang et al., 2016; Gupta et al., 2015; Haddeland et al., 2014; Ma et al., 2008; Patterson et al., 2013; Siriwardena et al., 2006; Tan & Gan, 2015; Wang & Hejazi, 2011; Ye et al., 2013; Zheng et al., 2009).

The relative contributions of climate change and human activities to hydrologic responses have been evaluated using GCM data to drive hydrologic models with plausible future anthropogenic scenarios (Liu et al., 2013; Maurer et al., 2010; Wood et al., 2002). Murray et al. (2012) used the Land-surface Processes and eXchanges (LPX) dynamic global vegetation model and the WaterGAP hydrological model to evaluate the impacts of climate change and socio-economic change on global hydrologic response for the 2070 – 2099 time period. They found that climate change and population growth increased water stress in many regions, and change in runoff was most highly correlated with precipitation change in large global catchments. Harding et al. (2012) applied downscaled outputs of 16 GCMs with the VIC model to investigate the future change in streamflow for the Colorado river basin. They suggested that impact analyses relying on only a few scenarios were unacceptably influenced by the choice of GCM projections.

For studies using GCMs to project future hydrologic responses, uncertainties resulting from the choice of GCM, RCP (Representative Concentration Pathways) trajectory, and reference evapotranspiration (ET_0) estimation methods are all significant, and it is important to quantify the relative uncertainties of these factors (Chang et al., 2016; Hawkins & Sutton, 2009, 2010; Kingston et al., 2009; Koedyk & Kingston, 2016; McAfee, 2013; Thompson et al., 2014; W. Wang et al., 2015). The effects of climate change on groundwater levels have not explored as extensively as the effects of climate change on surface water flows (Green et al., 2011; Kløve et al., 2014). Kløve et al. (2014) suggested that the uncertainties of groundwater projections attributed to climate model, downscaling techniques, emission scenarios, land use changes and social economic development should be evaluated.

This study evaluated the future projections of regional hydrologic response using eight GCMs, three ET_0 estimation methods, and eight human water use scenarios to drive a calibrated regional hydrologic model developed for the Tampa Bay region. A comprehensive evaluation of the relative sensitivity of projections of regional hydrologic response to the choice of GCM, ET_0

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estimation method, and human water use scenario was conducted. In addition, statistical analyses were performed to determine whether differences in streamflow and groundwater level between retrospective hydrologic and projected future climate, ET_0 estimation method, and water use scenarios were statistically significant given these underlying prediction uncertainties.

2. Materials and Methods

2.1 Study Region

Tampa Bay Water operates a diverse regional water supply system in the Tampa Bay region. The Tampa Bay Water supply region includes Hillsborough, Pasco, Pinellas, Manatee, Polk and Sarasota Counties and the cities of Tampa, St. Petersburg, and New Port Richey (Geurink & Basso, 2013; Hwang & Graham, 2014; Xian et al., 2007). The fresh groundwater system in this region is composed of two aquifer systems, a thin surficial aquifer and the thick and highly productive carbonate rocks of the Floridan aquifer system (Tihansky & Knochenmus, 2001). Dynamic interacting surface-water and groundwater systems characterize the region and must be considered in the management of water resources (Tihansky, 1999). This study focused on the Integrated Northern Tampa Bay (INTB) model domain (Geurink & Basso, 2013; Hwang & Graham, 2014). The INTB region consists of grass/pasture (25 %), urban (22 %), forested (15 %), mining/other (7 %), agriculture/irrigated land (6 %), open water (4 %), and wetlands (21 %).

Figure 1 shows the model domain, model sub-basins and locations of four streamflow gauges and four monitoring wells used to evaluate the impact of climate and anthropogenic change on regional hydrologic response in this study.

2.2 The Integrated Northern Tampa Bay Model

Tampa Bay Water and the Southwest Florida Water Management District (SWFWMD) developed the Integrated Hydrologic Model (IHM) simulation engine which integrates the EPA Hydrologic Simulation Program-Fortran (Bicknell et al., 2005) for surface water modeling with the U.S. Geological Survey (USGS) MODFLOW96 (Harbaugh and McDonald, 1996) for groundwater modeling. The IHM simulates the dynamic interaction of surface water and groundwater systems within the INTB region including all processes which affect flow and water levels in uplands, within the unsaturated soil, and within wetlands, rivers and aquifers. In

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addition, the INTB model can account for variability in climate and anthropogenic stresses such as land use change, groundwater pumping, and diversions to/from rivers, lakes, and wetlands.

Tampa Bay Water and the SWFWMD calibrated model parameters to simulate streamflows, groundwater levels, and wetland hydroperiods in the INTB model region. The INTB model was calibrated from 1989 to 1998 and verified years 1999 to 2006. Precipitation data for calibrating and validating the model were obtained from 302 point gages maintained by National Oceanic and Atmospheric Administration (NOAA), the SWFWMD, and Tampa Bay Water in the model region. Maximum and minimum daily temperature was obtained from six NOAA stations within the INTB region and used to estimate ET using the Hargreaves method (Geurink and Basso, 2013). Average annual precipitation was 1308 mm/year and average annual actual evapotranspiration was 940 mm/year in the INTB region over the calibration and validation period (1989 to 2006), resulting in net available water (precipitation-actual evapotranspiration) of 368 mm/yr. During this period surface discharge from the domain was 272 mm/year (74 % of net available water), well pumping was 69 mm/year (19 %), surface water diversions for water supply were 10 mm/year (3 %), and irrigation applied within the domain was 18 mm/year (5 %). More details about the processes and results of model calibration and validation are described in Geurink and Basso (2013).

Predictions at four United States Geological Survey (USGS) gauging stations including the Hillsborough river (USGS ID: 02303330), Alafia river (USGS ID: 02301500), Cypress creek (USGS ID: 02303800), and Pithlachascotee river (USGS ID: 02310300) were used in this study to evaluate retrospective and future IHM streamflow predictions and quantities of surface water available for public supply. Four Tampa Bay Water monitoring wells (NWH-RMP-08s, STK-STARKEY-20s, CBR-SERW-s, NWH-RMP-13s) were used to evaluate retrospective and future groundwater level predictions and compliance with environmental regulations intended to protect nearby wetlands.

2.3 Climate Data

Forcing data from Phase 2 of the North American Land Data Assimilation System (NLDAS-2) from 1982 to 2005 were used as historical reference climate data for bias correction. Hourly precipitation, air temperature, solar radiation (surface downward longwave radiation and surface downward shortwave radiation), surface pressure and average wind speed were obtained

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from the NLDAS-2 archive and aggregated to the daily scale at a 1/8th-degree grid spacing over the Tampa Bay region.

For retrospective and future climate data, the Coupled Model Intercomparison Project 5 (CMIP5) General Circulation Models (GCMs) data set for the 1982-2005 period was used for the retrospective period and 2030-2060 and 2070-2100 were used as future periods. Gridded daily precipitation, air temperature, solar radiation, surface pressure, and average wind speed were obtained for eight GCMs. Only the RCP 8.5 scenario data was utilized for the future analyses because a previous study showed the choice of RCP trajectory was significantly less important than the choice of GCM or ET_0 estimation method for projection of future climate over the Southeast USA. (Chang et al., 2016). The eight GCMs used in this study, listed in Table 1, were chosen because they had daily values available for all the parameters needed to estimate Penman-Monteith reference evapotranspiration. Mean changes in precipitation projected by these GCMs ranged from -68 mm/year to 293 mm/year over the 2030-2060 period, and from 154 mm/year to 400 mm/year over the 2070-2100 period. Mean changes in ET_0 ranged from 24 mm/year to 137 mm/year over the 2030-2060 period and from 122 mm/year to 351 mm/year over the 2070-2100 period. Mean changes in P-ET_0 ranged from -162 mm/year to 220 mm/year over the 2030-2060 period and from -420 mm/year to 159 mm/year over the 2070-2100 period.

2.4 BCSA Downscaling Method

The BCSA downscaling method, developed by Hwang and Graham (2013, 2014), preserves both the cumulative frequency distribution of observed daily precipitation as well as the spatial autocorrelation structure of observed daily precipitation fields. BCSA downscaling consists of two separate steps for bias-correction and stochastic analog spatial downscaling. In the first step, a cumulative distribution function (CDF) mapping approach (Block et al., 2009; Hwang et al., 2013, 2014; Hwang & Graham, 2014; Ines & Hansen, 2006; Teutschbein & Seibert, 2012) is used to reduce the biases in raw GCM output at the GCM scale. In this study, NLDAS-2 P and ET_0 were aggregated up to the GCM scale and P and ET_0 from the raw GCMs were bias corrected at the GCM scale using the sequential univariate CDF mapping method (Chang, 2017).

The second step in the BCSA method is stochastic analog (SA) spatial downscaling (Hwang & Graham, 2013, 2014) for P. In this method, an ensemble of synthetic P fields that

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preserve observed NLDAS-2 daily P spatiotemporal statistics is generated separately for each month in order to reproduce seasonal differences spatiotemporal statistics for daily rainfall over the year. An ensemble of 3,000 P realizations for each month was generated for use in this study. For each simulation day one P realization was randomly selected from the appropriate monthly ensemble such that the areal average of the spatially correlated P realization matched the bias-corrected GCM-scale P value. For more details on the BCSA method, see (Hwang & Graham, 2013, 2014). ET_0 was not downscaled in this study because observed spatial variability of ET_0 over the INTB region is very small, and the spatial correlation is large, compared to P (Chang, 2017).

2.5 Water Withdrawals

Warming temperatures and reduced precipitation due to climate change, and increases in water withdrawal for agriculture and other human uses, are potentially significant causes of declining river flow and groundwater levels (ALCAMO et al., 2003; Vorosmarty et al., 2000). Water withdrawals for human uses in the INTB region consist of both groundwater pumping and surface water extractions.

The SWFWMD regulates all groundwater pumping and surface water extraction in the INTB model region to protect natural aquatic ecosystems and prevent saltwater intrusion. Water-use types in the INTB model region are comprised of five categories; 1) public supply (average of 36 mm/yr over the calibration-validation period over the INTB region), 2) agricultural (18 mm/yr), 3) industrial/commercial (9 mm/yr), 4) mining (6 mm/yr), and 5) recreational (e.g. golf course irrigation, 3 mm/yr) (Geurink and Basso, 2013). In this study, we lumped agricultural pumping and recreational pumping into agricultural pumping (21 mm/yr) and lumped public supply, industrial/commercial, and mining into urban pumping (51 mm/yr).

The AFSIRS (Agricultural Field-Scale Irrigation Requirements Simulation) model developed by the Institute of Food and Agricultural Sciences (IFAS) at the University of Florida (Jacobs and Dukes, 2007; Smajstrla, 1990) was used to estimate climate-driven irrigation demand. The AFSIRS model tracks the water budget in the crop root zone including inputs from rain and irrigation, and outputs from the root zone by drainage and evapotranspiration. The AFSIRS model defines the water storage capacity in the crop root zone as the product of the water-holding capacity of the soil (estimated by the difference between field capacity and wilting

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point) and the depth of the effective root zone for the crop being grown. Crop evapotranspiration (ETc) is estimated from the product of potential evapotranspiration (ETp) and crop water use coefficients. The AFSIRS model subdivides the crop root zone into irrigated and non-irrigated zones and maintains separate water budgets for both zones in order to simulate different types of irrigation systems, such as surface irrigation and subsurface irrigation.

In this study, we used the AFSIRS model as a basis to estimate irrigation demand using CMIP5 bias-corrected downscaled daily P and bias-corrected $ET_{0,}$ assuming the land use remained the same as in the calibrated model throughout the retrospective (1982-2005) and future periods (2030-2060 and 2070-2100). Crop coefficients (K_c) for estimating ET_c were obtained from the calibrated INTB model database (Geurink and Basso, 2013) for all vegetative covers except row crops. The crop coefficient for row crops was estimated by the superposition of crop coefficients for tomato and strawberry (Dukes et al., 2012), the two dominant row crops in the region. The relative proportion of these two crops constituting the row crop land use were calculated based on water usage records for the region for 2011 (Jackson and Albritton, 2013). The root zone depth, field capacity, wilting point and other information needed for the AFSIRS model were taken from the calibrated INTB model database.

Tampa Bay Water has a consolidated permit for its eleven wellfields (the Consolidated Wellfields, hereafter referred to as the CWF for convenience). The CWFs are operated as an interconnected system with a combined maximum permitted pumping rate of 90 MGD (13 mm/yr over the INTB region). Individual well pumping rates are optimized to limit groundwater level declines near sensitive wetlands to meet regulatory requirements. The four monitoring wells evaluated in this study are located near wetlands adjacent to the CWFs (Fig. 1).

For this study, diversions rates for pumping from the Hillsborough river reservoir by City of Tampa and from the Tampa Bay Canal by Tampa Bay Water were set at the historical average daily rate spanning 2003 to 2009 for all simulation periods. All other diversion rates were set to zero including the Withlacoochee-Hillsborough overflow. Lateral boundary conditions were defined for each of the three model layers representing the three aquifer systems. A repeating annual cycle of daily General Head Boundary (GHB) time series for the retrospective and future periods IHM simulations was derived using the ensemble daily average of the historical daily GHB time series spanning 2000 to 2006. More details about the water withdrawals such as

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groundwater pumping, agricultural irrigation, CWFs, diversions and boundary conditions are described in Geurink and Basso (2013).

2.6 Human Water Use Scenarios

To assess the relative importance of climate change and anthropogenic impact, eight human water use scenarios were developed (Table 2). Water use scenarios were designed to evaluate alternative urban pumping and agricultural irrigation pumping regimes on surface water flows and groundwater levels in the region. These eight human water use scenarios were grouped into eight types: 1) No pumping, 2) No agricultural pumping, 3) No urban pumping, 4) Agricultural adaption, 5) Business as usual, 6) Increased agricultural demand, 7) Relaxed regulatory requirements for urban pumping (increased urban pumping), and 8) Relaxed regulatory requirements for all groundwater pumping (increased all pumping).

The business as usual scenario (scenario 5 in the Table 1) used irrigation demand estimated by the AFSIRS model using P and ET_0 from the appropriate bias corrected downscaled GCM. Groundwater pumping for irrigation assumed 85 % irrigation efficiency, i.e.,

$$agricultural\ pumping = irrigation\ demand\ \times \frac{100\ \%}{85\ \%} \tag{3}$$

For the business as usual scenario the CWF pumping remained at the maximum permitted 90 MGD capacity (13 mm/year over the INTB region) and other urban pumping remained at average pumping rates between years 1989 to 2006, as reported by the SWFWMD.

The no pumping scenario (scenario 1) assumed that there was no human water use in the region. For this scenario, irrigation demand, agricultural pumping, and urban pumping (including CWF pumping, industrial and mining) were set to zero. For the no agricultural pumping scenario (scenario 2) irrigation demand and agricultural pumping were set to zero however, urban pumping assumed equal to the business as usual scenario. For the no urban pumping scenario (scenario 3) urban pumping including CWF pumping, industrial and mining was set to zero and irrigation demand and agricultural pumping were assumed to the business as usual scenario.

The agricultural adaption scenario (scenario 4) assumed that alternative water sources for agricultural irrigation replaced 40 MGD (6 mm/year) of groundwater pumping for agricultural irrigation. The other conditions were same as the business as usual scenario. The increased agricultural demand scenario (scenario 6) assumed that irrigation demand increased by 40 MGD

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(6 mm/year) due to more intensive farming. The relaxed regulatory requirements for urban pumping (scenario 7) assumed an increase of CWF pumping up to 130 MGD (19 mm/year) from the current 90 MGD (13 mm/year) due to increase in public water demand. The relaxed regulatory requirements for all groundwater pumping (scenario 8) assumed all urban pumping, including CWF pumping, industrial and mining, increased 44 %, i.e. at the ratio 130/90 used for scenario 7. Thus scenario 8 includes 192 MGD (28 mm/year) of agricultural pumping and 514 MGD (74 mm/year) of urban pumping. These human water use scenarios consist of projected agricultural and urban pumping volumes that represent from 0 % to 27 % of historic P-ET_0.

2.7 Reference evapotranspiration estimation methods

All hourly climate variables described in section 2.3 were aggregated to the daily scale and used to calculate daily ET_0 using the Penman-Monteith (Allen et al., 1998), Hargreaves (Hargreaves and Allen, 2003), and Priestley-Taylor methods (Allen et al., 1998). These three methods are widely used in the Southeast USA, and represent a range of different types of reference evapotranspiration estimation methods including a temperature based method (Hargreaves), a radiation based method (Priestley-Taylor), and a combination method (Penman-Monteith).

2.8 Variance-Based Global Sensitivity Analysis

Variance-based sensitivity analysis is a global sensitivity analysis (GSA) method (Saltelli et al., 2008, 2010) used to apportion the total model output uncertainty simultaneously onto all the uncertain input factors, and thus is preferred over the local, one factor at a time, sensitivity analyses (Homma and Saltelli, 1996; Saltelli, 1999). In this research the sensitivity of changes between future and retrospective streamflow and groundwater levels projected by IHM simulations was evaluated using the variance-based GSA method described in Chang et al. (2016b).

Using the variance-based GSA method the first order sensitivity coefficient is expressed as:

$$S_i = \frac{V_{X_i}(E_{X_{\sim i}}(Y|X))}{V(Y)} \quad (1)$$

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where $V(Y)$ the total variance of Y over all X_i. S_i is a normalized index varying between 0 and 1, because $V_{X_i}\left(E_{X_{\sim i}}(Y|X_i)\right)$ varies between 0 and $V(Y)$ according to the identity (Mood et al., 1974):

$$V_{X_i}\left(E_{X_{\sim i}}(Y|X_i)\right) + E_{X_i}\left(V_{X_{\sim i}}(Y|X_i)\right) = V(Y) \quad (2)$$

The first order sensitivities of future changes in mean seasonal streamflow and groundwater level to the choice of GCM, ET_0 estimation method, and human water use scenario were calculated for each future period in order to evaluate the relative contributions of each of these factors on the uncertainty in projections of future changes.

3 Results and Discussion

3.1 Global Sensitivity Analysis of Projected Changes

The variance-based global sensitivity analysis was conducted for both the wet season (June – September) and the dry season (October – May) to evaluate the relative uncertainty of projected changes in hydrologic response attributed to the choice of GCM, the choice of water use scenario, and the choice of ET_0 method. Tables 3 and 4 show the first order sensitivity indices of changes in future streamflow and groundwater level (defined as average seasonal future streamflow – average seasonal retrospective streamflow and average seasonal future groundwater level – average seasonal retrospective groundwater level, respectively).

Change in streamflow was much more sensitive to the choice of GCM than to the choice of ET_0 method or water use scenario for all river gages, both seasons, and both future periods (Table 3). Similarly, projected changes in groundwater level were generally more sensitive to the choice of GCM across monitoring wells and seasons. However, unlike the projected changes in streamflow, changes in groundwater level at the monitoring wells were also quite sensitive to the choice of water use scenario, except for well NWH-RMP-13s which is located the furthest from the consolidate well fields (Table 4 and Fig. 1). The higher sensitivity of groundwater level to groundwater pumping is expected since the monitoring wells are intentionally located near the consolidated wellfields to detect and mitigate the localized impacts of urban pumping on nearby wetlands. On the other hand, the stream gages are located further from the consolidated well fields and accumulate flow from a large area of the model domain. The first order sensitivity

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index of groundwater level to water use scenario decreased in future period 2 over future period 1, due to the increased variability of GCM precipitation projections in future 2 versus future 1.

Chang et al. (2016b) evaluated projected changes in P – ET_0 over the continental USA using nine GCMs, ten ET_0 estimation methods, and three RCP scenarios. They found that the change in P – ET_0 was sensitive to both the choice of GCM and the choice of ET_0 method and that the relative sensitivities of GCM and ET_0 method varied depending on season and the region. They showed that for the Southeast U.S., where the INTB region is located, the choice of GCM and ET_0 method had approximately equal influence on changes in future P – ET_0 throughout most of the year. Because this study eliminated several ET_0 estimation methods that produced unreasonably high and low historic ET_0 estimates for the study region using the NLDAS-2 data, the first order sensitivity index for ET_0 is significantly lower in this study than in their results. Since the GSA results show that changes in streamflow and groundwater level are relatively insensitive to the choice of ET_0 estimation method, the remainder of this paper will focus on uncertainties due to GCM selection and water use scenario, using only the Hargreaves method to estimate ET_0. Results using other two ET_0 methods are very similar and can be found in (Chang, 2017).

3.2 Projections of Streamflow

The INTB was run to compare hydrologic response due to retrospective climate and human water use scenarios to historical data and model predictions generated with NLDAS-2 data, as well as to evaluate alternative future climate change and human water use scenarios. Figure 2 and Figures S1 – S3 in the supplemental materials show retrospective and future mean daily streamflow by month for the Hillsborough river (Fig. 2), Alafia river, Cypress creek, and Pithlachascotee (Figs. S1 – S3, respectively) for each of the human water use scenarios. The boxplots represent the range of mean daily streamflow projections over eight GCMs for each human water use scenario. Retrospective GCMs for the business as usual scenario accurately reproduced observed mean daily streamflow and mean daily streamflow simulated using historic NLDAS-2 data for all four river gages. (Note the retrospective plots on all water use scenario assume the business as usual scenario during the retrospective period.)

All results show a large range of mean daily streamflow values, with future streamflow showing more variation than retrospective streamflow for all water use scenarios. The

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differences among retrospective and future scenarios are more visually apparent in the high flow summer months, with lower median streamflows generally projected for future periods (especially future 2) compared to the retrospective period for all water use scenarios. Differences among water use scenarios are small compared to differences in predictions across GCMs.

The variation in flow duration curves over GCMs for fixed water use scenario (Fig. 3a, the spread represents the differences attributed to GCMs) is greater than the variation of flow duration curves over water use scenario for fixed GCM (Fig. 3b, the spread represents the differences attributed to water use scenarios). For example, the wider spread of green lines in the business as usual scenario in Fig. 3a represents the larger variation attributed to different GCMs in future period 2 for fixed water use scenario (business as usual scenario), whereas, the narrower spread of green lines in Fig. 3b represents the smaller variation attributed to different water use scenarios in future period 2 for fixed GCM. Water use scenarios that significantly increased groundwater pumping (i.e., increased agricultural demand, relaxed regulatory requirements for urban pumping, and relaxed regulatory requirements for all groundwater pumping) generally projected lower streamflow, with the lowest streamflow condition projected for the increase all pumping scenario (Fig. 3a). The variability of projected streamflow was greatest in future period 2 among the three different time periods, however, the shifts of streamflow projected for future periods varied significantly based on the GCM (Fig. 3b). For example, the future streamflow projected by GFDL-ESM2G is lower than the retrospective period business as usual streamflow for all water use scenarios, whereas, the future streamflow projected by MRI-CGCM3 is higher than the retrospective period business as usual streamflow for all water use scenarios.

3.3 Projections of Groundwater Level

Mean daily groundwater levels for the four monitoring wells were calculated over the eight GCMs for the retrospective period (1982-2005) and two future periods (2030-2060 and 2070-2100) for each water use scenario. Figure 4 and Figures S4 – S6 in the supplemental materials show the mean daily groundwater level by month for the NWH-RMP-08s, CBR-SERW-s, NWH-RMP-13s, and STK-STARKEY-20s wells, respectively. Groundwater levels projected by retrospective GCMs using the business as usual scenario are very similar to groundwater levels simulated using the historic NLDAS-2 data for all four wells. Although

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observed seasonal patterns were reproduced accurately for all wells during the retrospective period, the NWH-RMP-08s groundwater level predictions were lower than observed groundwater levels throughout the year (Fig. 4), whereas the CBR-SERW-s and STK-STARKEY-20s groundwater lever predictions were higher than observed groundwater levels throughout the year (Figs. S4 and S6). These deviations (which are generally less than 0.5m) are consistent with deviations between the observed data and groundwater levels simulated by the calibrated model using the observed local weather data.

For the business as usual scenario the ensemble mean groundwater levels averaged over GCMs for future period 1 were similar to, or slightly lower than, the ensemble mean retrospective groundwater levels. However, ensemble mean groundwater levels for future 2 were significantly lower than mean groundwater levels in the retrospective period (Figs. 4 and S4-S6). Both the no pumping scenario and the no urban pumping scenario projected increased mean future groundwater levels over the retrospective business as usual scenario. However, all other water use scenarios projected lower mean future groundwater levels than the retrospective business as usual scenario, with increased pumping producing lower groundwater levels as expected (Figs. 4 and 5). Water use scenarios had more influence on groundwater level projections than streamflow projections.

Figure 5a shows the groundwater level exceedance curves for all GCMs for each water use scenario, similar to Fig. 3a for streamflow. Likewise Fig. 5b shows the groundwater level exceedance curves for all water use scenario for each GCM, similar to Fig 3b. The variation across GCMs in future periods is greater than in the retrospective period (Fig. 5a). Unlike the results of streamflow, the variation across water use scenarios (Fig. 5b) for fixed GCM are similar to the variation across GCMs (Fig. 5a) for fixed water use scenario, i.e., water use scenario and GCM had approximately equivalent impacts on groundwater level projections.

3.4 Changes in Future Water Availability for Public Supply

Tampa Bay Water operates surface-water pumps on the Hillsborough and Alafia rivers to help meet public water demand. The volume of flow permitted for extraction varies daily based on maintaining sufficient in-stream flows and spring flows to protect aquatic ecosystems. In this study, the percent of time that maximum water could be withdrawn for public water supply and the percent of time that no water could be withdrawn were analyzed to evaluate changes in future

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water availability. Boxplots in Fig. 6a show the variation of the projected change in the percent of the time that maximum water can be withdrawn from the Hillsborough river (the percent of the time that maximum water can be withdrawn in future streamflow – the percent of the time that maximum water can be withdrawn in retrospective business as usual streamflow) over all GCMs for each water use scenario. The boxplots show large variations due to large differences in future streamflow projections. All boxplots encompass both positive and negative changes for both future periods, but indicate generally lower water availability in future 2 than future 1. Figure 6b compares the change in the projected percent of the time that maximum water can be withdrawn from the Hillsborough river over water use scenarios for each GCM. While there is some variation across water use scenarios, Fig. 6b clearly shows that projected changes in future water availability depend strongly on choice of GCM, with 5 GCMs showing less water availability in the future and 3 GCMs showing more water availability.

The differences among human water use scenarios were evaluated for statistical significance using Tukey's HSD (honest significant difference) test (left hand portion of Table 5). The mean change in percent of the time that maximum water could be withdrawn from the Hillsborough river and the Alafia river over all GCMs for each water use scenario was calculated and pairwise compared to all other water use scenarios (two scenarios with different subscripts in Table 5 are significantly different). In addition, the two sample t-test was conducted to evaluate differences between the mean percent of the time that maximum water could be withdrawn for the retrospective business as usual scenario and the mean percent of time that maximum water for each other water use scenario calculated over all GCMs.

The HSD test indicated that none of the differences in the change in percent of the time that maximum water can be withdrawn in the future were statistically significant for the different water use scenarios at either of the two river gages. These results imply that due to the large spread in climate projections over different GCMs, changes in streamflow due to alternative human water use scenarios cannot be reliably predicted. The two sample t-test indicated that, at the 0.05 significance level, only the no pumping and no urban pumping scenarios in future 1 showed significant differences from the retrospective business as usual scenario in the percent of time maximum water could be withdrawn from the Alafia river (marked as † on the left hand portion of Table 5). For the Hillsborough river none of the future scenarios were statistically significantly different from the retrospective business as usual scenario.

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The differences between the mean change in percent of the time that maximum water could be withdrawn from the Hillsborough river and the Alafia river for individual GCMs over water use scenarios were also compared by Tukey's HSD test (right hand portion of Table 5). Unlike results for the water use scenarios, many GCMs showed statistically different differences in change in percent of time that maximum water could be withdrawn in the future for both river gages. For both gages more GCMs in future period 2 were significantly different from the retrospective period than future period 1 (marked as † in right hand portion of Table 5). These results imply that the choice of GCM has a significant effect on the projection of water availability for public supply, especially in future period 2, and that most GCMs projected significantly different streamflows in the future. Two GCMs show a distinct increase water availability from these rivers for public supply (GFDL-CM3 and MRI-CGCM3) however, most of GCMs show a decrease in water availability (BNU-ESM, GFDL-ESM2G, MIROC-ESM, NorESM1-M, and BCC-CSM). This implies that future availability of public water supply from these rivers will be driven more strongly by changes in climate than changes in human water use. These results are similar to previous studies (Bosshard et al., 2013; Forzieri et al., 2014; Guimberteau et al., 2013; Harding et al., 2012; Kay and Davies, 2008) that showed climate models are a large source of uncertainty for climate-impact projections because of the divergence of GCM projections.

The change in percent of the time that no water can be withdrawn from the Hillsborough river and the Alafia river in order to protect in-stream flows were also evaluated over water use scenarios and GCMs. Boxplots showing the variation over GCMs for each human water use scenario encompass both positive and negative changes for both future periods, but water use scenarios that increase groundwater pumping indicate generally higher percent of time that water cannot be withdrawn, especially in future 2 (Fig. 7a). Boxplots showing variation over water use scenarios for each GCM show that only GFDL-CM3 and MRI-CGCM3 projected a smaller percent of the time that water cannot be withdrawn in future periods compared to the retrospective period for the Hillsborough river (Fig. 7b). Six of the eight GCMs project a decrease in the availability of water for public supply from the Hillsborough river and the Alafia river in the future, with larger decreases in future 2 than future 1. These results suggest it is unlikely that human water use can be manipulated in a future climate to preserve in stream flows needed to protect current aquatic ecosystems. Thus environmental regulations may need to

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change with the changing climate if surface water is to remain available for public supply in the Tampa Bay region.

Results of the HSD test and the two sample t-test reinforce the finding that the change in percent of the time that water cannot be withdrawn is more sensitive to the choice of GCMs than the choice of water use scenario for both rivers (Table 6). These results clearly show that uncertainty due to GCM selection is the dominant cause of uncertainty in future streamflow projections and future water availability in the Tampa Bay region.

The results that future streamflow projections are not strongly sensitive to water use scenarios are contrary to that of Dale et al. (2015). They used historical streamflow and climate data to evaluate the impacts of anthropogenic change on streamflow and found that for an irrigation intensive watershed located in an area with hot summer and limited precipitation (North Central Oklahoma, U.S.) irrigation from groundwater pumping increased antecedent soil moisture and played an equally important role in streamflow variability as climate change. These differences are likely due to that fact that the region studied here is wetter than their study region, and land use change were not considered in this study.

3.5 Changes in Compliance Groundwater Level Regulations

Groundwater pumping for water supply in the Tampa Bay region is regulated to maintain groundwater levels that promote environmental protection of lakes and wetlands near wellfields. In this study the relative importance of water use scenario and GCM selection on the percent of the time that groundwater levels were above the target levels for four monitoring wells was evaluated.

Figure 8a shows the change in percent of the time that groundwater level is above the target level (the percent of the time that groundwater level is above the target level for future water scenario – the percent of the time that groundwater level is above the target level for retrospective business as usual) in the NWH-RMP-08s well over all GCMs for different human water use scenarios. Both the no pumping scenario and the no urban pumping scenario indicate an increase in percent of the time that groundwater is above the target level in the future. However, increased groundwater pumping scenarios (e.g. increased urban pumping scenario and increased all pumping scenario) indicate a decrease in the percent of the time that groundwater is above the target level in the future periods compared to retrospective periods. The changes in the

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percent of the time that groundwater level is above the target level for the no pumping scenario and the no urban pumping scenario were statistically significantly different than the changes in the percent of the time that groundwater level is above the target level for all other human water use scenarios in two monitoring wells (NWH-RMP-08s, and STK-STARKEY-20s; Table 7). In addition, the percent of the time that groundwater level is above the target level for the no pumping scenario and the no urban pumping scenario in the NWH-RMP-08s, CBR-SERW-s and STK-STARKEY-20s wells were significantly different than the percent of the time that groundwater level is above the target level for the retrospective business as usual scenario (marked as † in the Table 8).

The mean change in percent of the time that groundwater is above the target level in the monitoring wells for different GCMs (averaged over human water use scenarios) showed similar results to those discussed previously. Two GCMs (GFDL-CM3 and MRI-CGCM3) projected a statistically significant increases in the mean percent of the time that groundwater is above the target level for both future periods (Fig. 8b and Table 8). Four GCMs clearly projected a decrease in percent of the time that groundwater level is above the target level in the future. More GCMs showed significant differences in future period 2 than in future period 1 because the differences among climate model projections increase in the later future. These results show that, depending on how rainfall changes in the future climate, groundwater level regulations may be difficult to achieve regardless of groundwater pumping scenario, and thus may have to change with the changing climate.

4 Conclusions

It is important to evaluate possible changes in future streamflow and groundwater levels to evaluate risks in water resources management and planning. This study evaluated the uncertainty of projected future streamflow and groundwater levels in the Tampa Bay region attributed to eight GCMs, eight human water use scenarios and three ET_0 methods using an integrated hydrologic model.

Results of this study indicate that uncertainties caused by differences in GCMs were the dominant factor driving different future streamflow projections. In contrast uncertainties attributed to both GCMs and water use scenarios were important in predicting different future

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groundwater level projections. For the three ET_0 methods used in this study streamflow and groundwater level projections were relatively insensitivity to ET_0 method.

The eight GCMs projected diverse changes in streamflow and groundwater level, with most GCMs projecting statistically significant different future streamflow and groundwater levels than the current condition. Six of the 8 GCMs projected a decrease in future streamflow and groundwater level in the INTB region, resulting in a reduction in permitted streamflow withdrawal and a reduction in compliance with current groundwater level regulations. Two GCMs (GFDL-CM3 and MRI-CGCM3) predicted increased streamflow and groundwater levels. These results suggest that it is more likely than not that climate change will reduce the availability of both surface and groundwater for public supply in the Tampa Bay Region. Current regulations on water withdrawals (surface water withdrawal permit thresholds and target levels in monitoring wells near lakes and wetlands) may have to adapt to future climate conditions since it is unlikely that human water use can be manipulated in the future to maintain retrospective hydrologic regimes and associated aquatic ecosystems.

The anthropogenic change scenarios in this study only considered changes in water use, however, other types of anthropogenic change such as land use change may also be important (Gupta et al., 2015; Lin et al., 2015; Matheussen et al., 2000; Yan et al., 2013). To better understand the impacts of climate change and anthropogenic change on regional hydrology, future studies should include the effects of land use change, in addition to climate change and water use change, on future streamflow and groundwater level.

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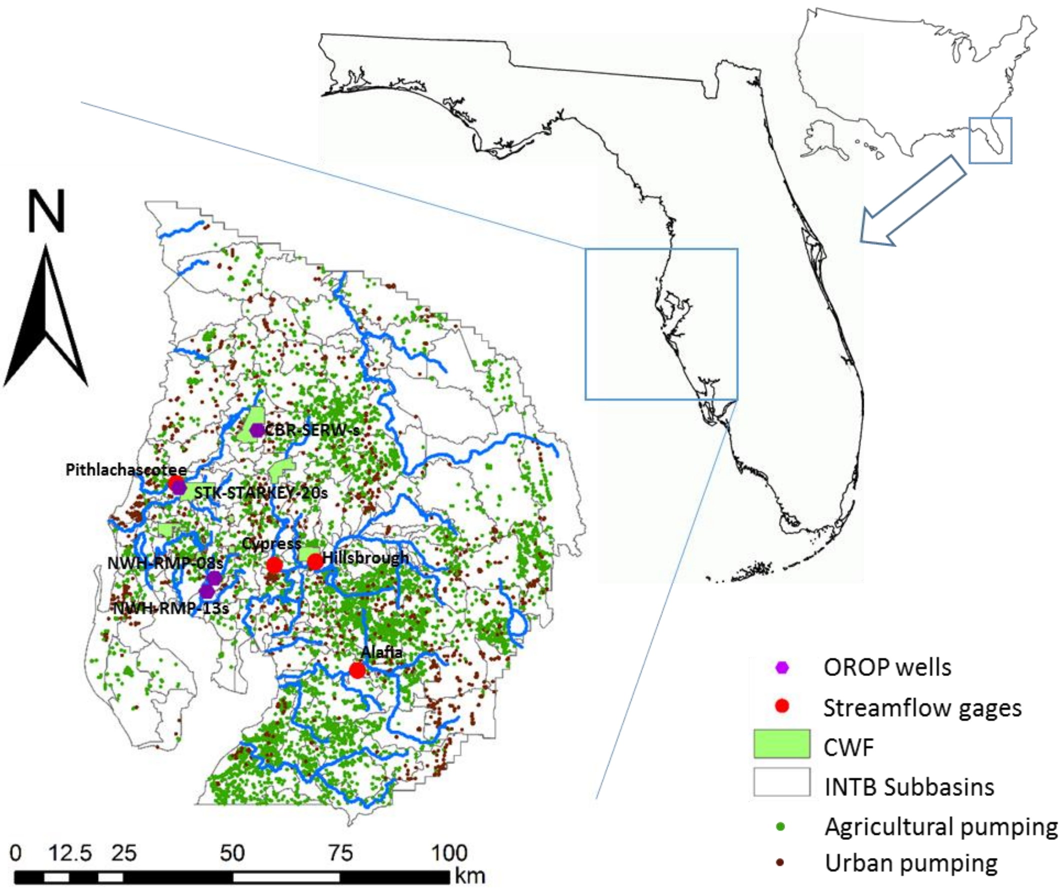

Figure 1. Study region, the INTB model domain and locations of four streamflow gages and four monitoring wells. CWF indicates the regions encompassing Tampa Bay Water's consolidated well fields for public water supply.

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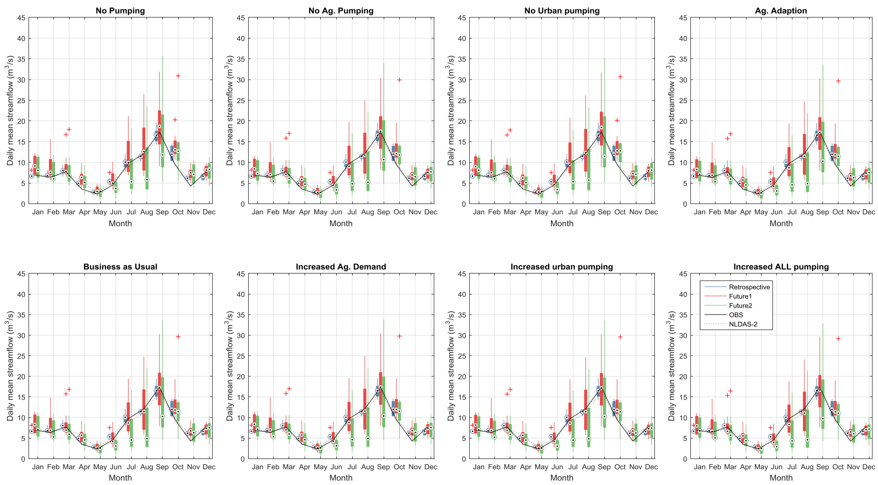

Figure 2. Mean daily streamflow by month for the Hillsborough river for each water use scenario (white circles in the boxplots represent median value, Hargreaves ET_0 method, all retrospective simulations with the business as usual scenario).

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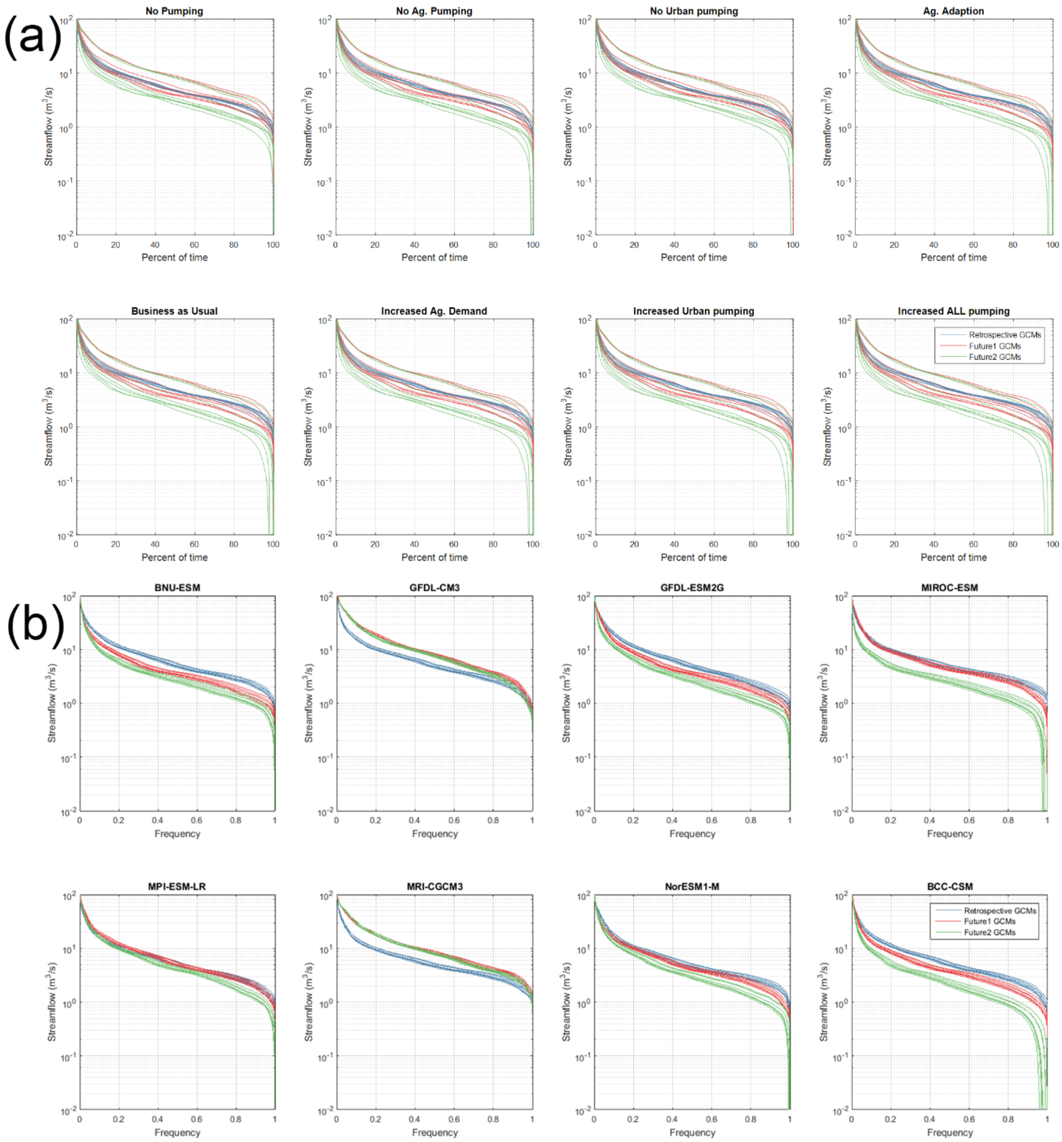

Figure 3. The comparison of flow duration curves by (a) water use scenarios and by (b) GCMs (Hillsborough river, Hargreaves ET_0 method, all retrospective simulations with the business as usual scenario).

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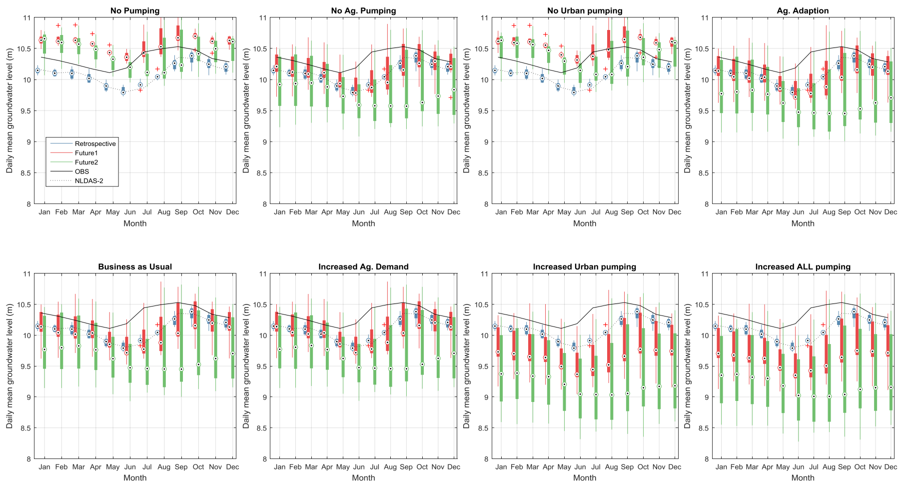

Figure 4. Mean daily groundwater level by month for NWH-RMP-08s well (white circles in the boxplots represent median value, Hargreaves ET_0 method, all retrospective simulations with the business as usual scenario).

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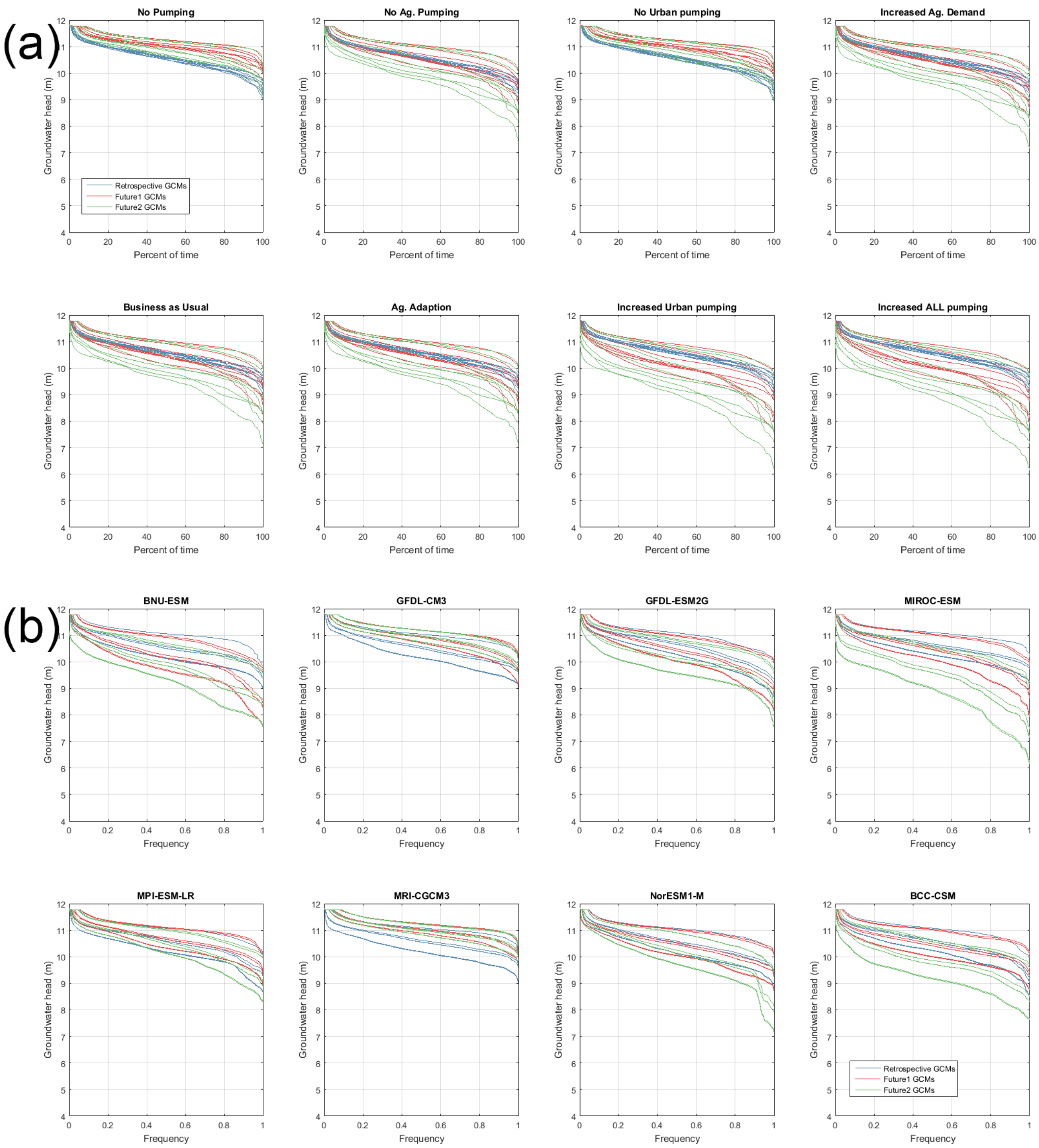

Figure 5. The comparison of daily CDFs of groundwater elevation by (a) water use scenario by (b) GCMs (NWH-RMP-08s, Hargreaves ET_0 method, all retrospective simulations with the business as usual scenario).

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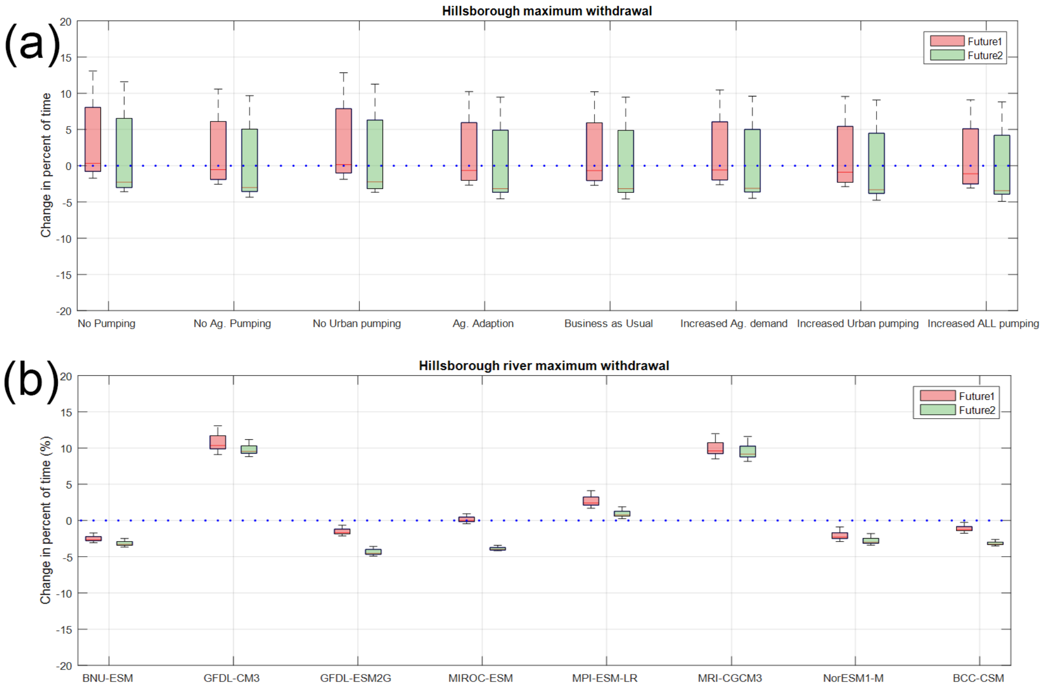

Figure 6. The change in percent of time that maximum water can be withdrawn from Hillsborough river by (a) different human water use scenarios and by (b) different GCMs.

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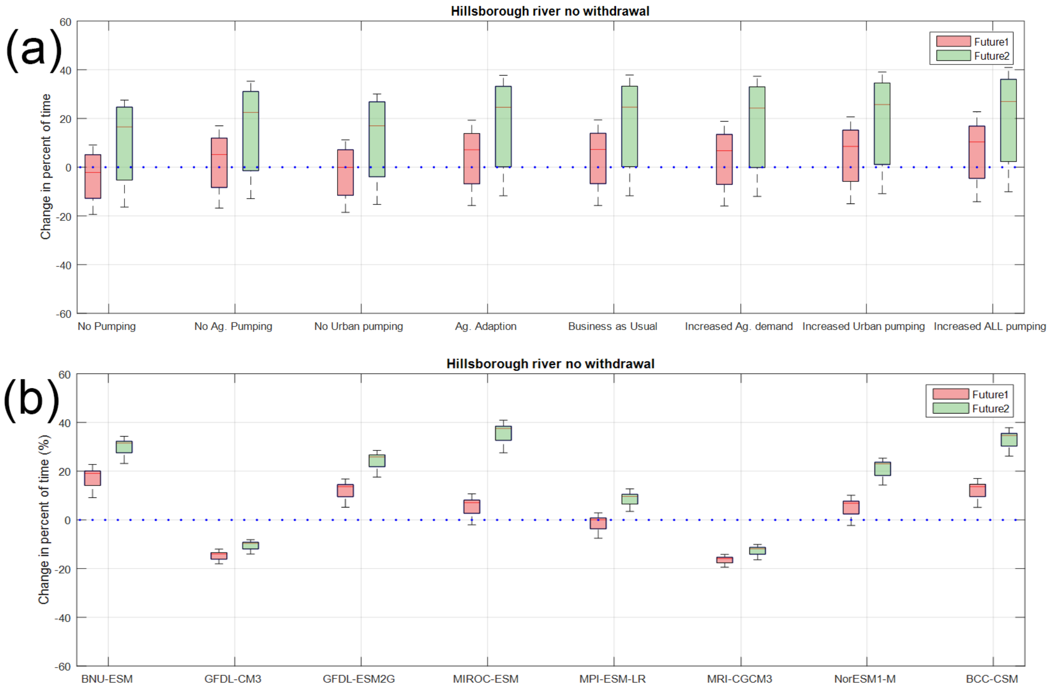

Figure 7. The change in percent of the time that water cannot be withdrawn from the Hillsborough river by (a) different water use scenarios by (b) different GCMs.

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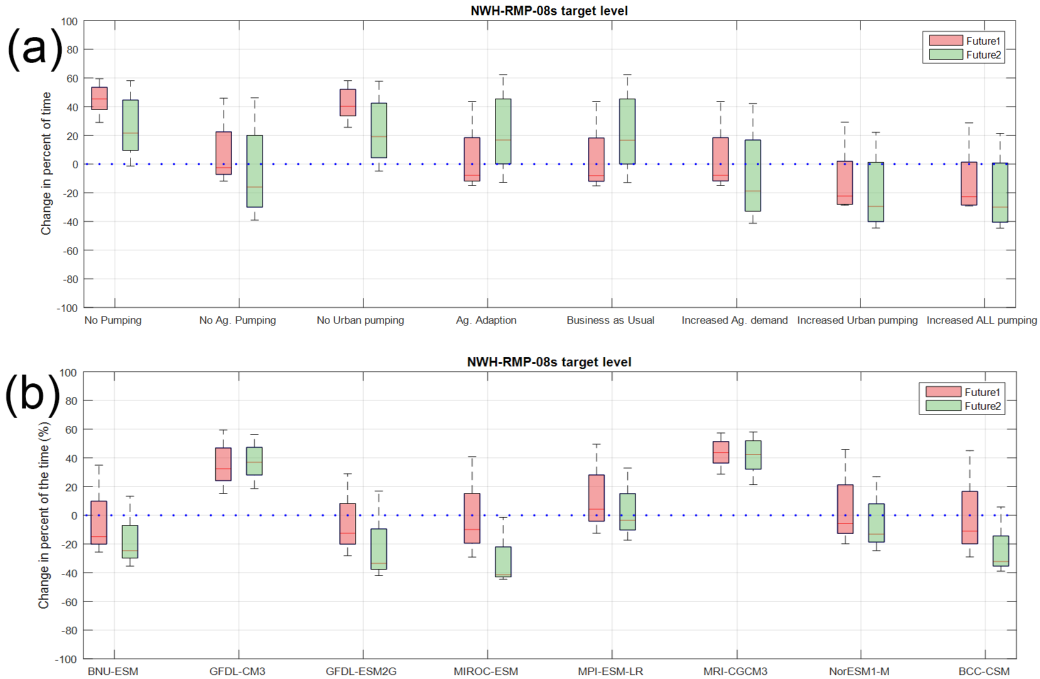

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853 Figure 8. The change in the percent of the time that groundwater level is above the target level
854 for NWH-RMP-08s well by (a) different water use scenario and by (b) different GCMs.

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856 **Table 1.** Description of the CMIP5 models used in this study.

Model	Institute (country)	Resolutions	Calendar	Reference
(1) BNU-ESM	College of Global Change and Earth System Science, Beijing Normal University (China)	2.8° lat × 2.8° lon	No leap	Ji et al. (2014)
(2) GFDL-CM3	NOAA/Geophysical Fluid Dynamics Laboratory (USA)	2.0° lat × 2.5° lon	No leap	Guo et al. (2014)
(3) GFDL-ESM2G	NOAA/Geophysical Fluid Dynamics Laboratory (USA)	2.0° lat × 2.5° lon	No leap	Taylor et al. (2012)
(4) MIROC-ESM	Atmosphere and Ocean Research Institute, National Institute for Environmental Studies, and Japan Agency for Marine-Earth Science and Technology (Japan)	2.8° lat × 2.8° lon	Leap year	Watanabe et al. (2011)
(5) MPI-ESM-LR	Max Planck Institute for Meteorology (Germany)	1.87° lat × 1.87° lon	Leap year	Block and Mauritsen (2013)
(6) MRI-CGCM3	Meteorological Research Institute (Japan)	1.12° lat × 1.12° lon	Leap year	Yukimoto et al. (2012)
(7) NorESM1-M	Norwegian Climate Centre (Norway)	1.9° lat × 2.5° lon	No leap	Bentsen et al. (2013)
(8) BCC-CSM1.1	Beijing Climate Center (China)	2.8° lat × 2.8° lon	No leap	Xiao-Ge et al. (2013)

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Table 2. Future scenario summary

Index	Scenario	Irrigation	Agricultural pumping	Urban pumping
No pumping	1	No	No	No
No agricultural pumping	2	No	No	CURR[**] (CWF 13 mm/yr, Total 51 mm/yr)
No urban pumping	3	AFSIRS[*] (23 mm/yr)	85 % efficiency (27 mm/yr)	No
Agricultural adaption	4	AFSIRS (23 mm/yr)	85 % efficiency but groundwater pumping offset by 6 mm/yr (22 mm/yr)	CURR (CWF 13 mm/yr, Total 51 mm/yr)
Business as Usual	5	AFSIRS (23 mm/yr)	85 % efficiency (27 mm/yr)	CURR (CWF 13 mm/yr, Total 51 mm/yr)
Increased agricultural demand	6	Increased by 6 mm/yr (29 mm/yr)	85 % efficiency (34 mm/yr)	CURR (CWF 13 mm/yr, Total 51 mm/yr)
Relaxed regulatory requirements for urban pumping	7	AFSIRS (23 mm/yr)	85 % efficiency (27 mm/yr)	Increase CWF by 6 mm/yr to 19 mm/yr (CWF 19 mm/yr, Total 57 mm/yr)
Relaxed regulatory requirements for all pumping	8	AFSIRS (23 mm/yr)	85 % efficiency (27 mm/yr)	Increase all urban pumping by 130/90 (CWF 19 mm/yr, Total 74 mm/yr)

* AFSIRS: irrigation water demand estimated by AFSIRS model using GCMs.

** CURR: groundwater pumping in the future will be equal to current water pumping.

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Table 3. The first order sensitivity index of change in streamflow (future – retrospective period).

River gage	Season	Period	GCM	ET_0	Water use scenario
Hillsborough	Wet season	Fut1	0.944	0.002	0.016
		Fut2	0.940	0.041	0.006
	Dry season	Fut1	0.948	0.012	0.029
		Fut2	0.961	0.001	0.018
Alafia	Wet season	Fut1	0.928	0.010	0.031
		Fut2	0.952	0.021	0.012
	Dry season	Fut1	0.876	0.012	0.072
		Fut2	0.927	0.001	0.068
Cypress	Wet season	Fut1	0.867	0.007	0.043
		Fut2	0.890	0.050	0.017
	Dry season	Fut1	0.831	0.0360	0.067
		Fut2	0.890	0.002	0.039
Pithlachascotee	Wet season	Fut1	0.848	0.036	0.032
		Fut2	0.918	0.009	0.012
	Dry season	Fut1	0.813	0.056	0.038
		Fut2	0.866	0.006	0.031

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Table 4. The first order sensitivity index of change in groundwater level (future – retrospective period).

Monitoring well	Season	Period	GCM	ET_0	Water use scenario
NWH-RMP-08s	Wet season	Fut1	0.442	0.005	0.501
		Fut2	0.576	0.004	0.278
	Dry season	Fut1	0.475	0.007	0.435
		Fut2	0.550	0.002	0.288
CBR-SERW-s	Wet season	Fut1	0.656	0.000	0.214
		Fut2	0.755	0.002	0.143
	Dry season	Fut1	0.639	0.001	0.221
		Fut2	0.747	0.002	0.146
NWH-RMP-13s	Wet season	Fut1	0.829	0.003	0.030
		Fut2	0.870	0.013	0.003
	Dry season	Fut1	0.754	0.010	0.061
		Fut2	0.847	0.004	0.020
STK-STARKEY-20s	Wet season	Fut1	0.604	0.000	0.325
		Fut2	0.718	0.004	0.198
	Dry season	Fut1	0.584	0.002	0.330
		Fut2	0.707	0.001	0.200

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Table 5. The results of Tukey's HSD test of mean change (%) in maximum water can be withdrawn from Hillsborough river or Alafia river for each human water use scenario or for each GCM (Comparison of all possible pairs of means).

By human water use scenario	Hillsborough		Alafia		By GCM	Hillsborough		Alafia	
	Fut1 mean	Fut2 mean	Fut1 mean	Fut2 mean		Fut1 mean	Fut2 mean	Fut1 mean	Fut2 mean
No Pumping	3.32 a	1.31 a	2.23 a†	0.93 a	BNU-ESM	-2.52 e†	-3.17 e†	-1.96 f†	-2.28 ef†
No Ag. Pumping	1.92 a	0.29 a	1.42 a	0.32 a	GFDL-CM3	10.75 a†	9.77 a†	6.73 b†	6.73 b†
No Urban Pumping	3.13 a	1.18 a	2.34 a†	1.03 a	GFDL-ESM2G	-1.53 de†	-4.37 e†	-0.55 e†	-2.84 g†
Ag. Adaption	1.76 a	0.13 a	1.53 a	0.40 a	MIROC-ESM2G	-0.13 c	-3.90 e†	-0.44 d†	-2.44 fg†
Business as Usual	1.74 a	0.12 a	1.53 a	0.40 a	MPI-ESM-LR	2.67 b†	0.92 c†	1.74 c†	0.06 c
Increased Ag. Demand	1.86 a	0.20 a	1.67 a	0.49 a	MRI-CGCM3	9.95 a†	9.52 b†	7.95 a†	7.89 a†
Increased Urban pumping	1.40 a	-0.12 a	1.53 a	0.40 a	NorESM1-M	-2.09 de†	-2.80 d†	-0.50 e†	-1.17 d†
Increased All Pumping	1.12 a	-0. 31 a	1.24 a	0.17 a	BCC-CSM	-1.13 cd†	-3.16 e†	-0.36 e†	-1.79 e†

Means with different subscripts were significantly different in Tukey's HSD test.

†: The results were significantly different than retrospective BAU by two sample t-test at the 0.05 significance level.

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Table 6. The results of Tukey's HSD test of mean change (%) in water cannot be withdrawn from Hillsborough river or Alafia river for each human water use scenario or for each GCM (Comparison of all possible pairs of means).

By human water use sceanrio	Hillsborough		Alafia		By GCM	Hillsborough		Alafia	
	Fut1 mean	Fut2 mean	Fut1 mean	Fut2 mean		Fut1 mean	Fut2 mean	Fut1 mean	Fut2 mean
No Pumping	-3.72 a	10.40 a	-8.06 a†	-1.42 a†	BNU-ESM	17.30 e†	30.03 d†	11.68 d†	22.35 d†
No Ag. Pumping	2.24 a	15.83 a	0.45 a	12.54 ab	GFDL-CM3	-14.63 b†	-10.44 b†	-6.04 ab†	-4.54 ab†
No Urban Pumping	-2.02 a	11.81 a	-5.07 b†	2.54 ab	GFDL-ESM2G	12.17 d†	24.35 d†	1.87 bc	15.60 cd†
Ag. Adaption	4.00 a	17.72 a†	3.25 b	15.85 ab	MIROC-ESM2G	5.56 d†	35.72 e†	1.76 bc	20.86 d†
Business as usual	4.08 a	17.80 a†	3.36 b	15.95 ab	MPI-ESM-LR	-1.27 c	8.68 c†	0.19 abc	7.41 bc†
Increased Ag. Demand	3.65 a	17.44 a†	2.94 b	15.49 ab	MRI-CGCM3	-16.40 a†	-12.61 a†	-7.87 a†	-7.34 a†
Increased Urban pumping	5.19 a	18.86 a†	3.40 b	16.02 ab	NorESM1-M	5.22 d†	21.18 cd†	0.88 abc	17.26 cd†
Increased All Pumping	6.76 a	20.18 a†	7.65 b	20.60 b†	BCC-CSM	12.23 d†	33.12 de†	5.45 cd	25.97 d†

Means with different subscripts were significantly different in Tukey's HSD test.

†: The results were significantly different than retrospective BAU by two sample t-test at the 0.05 significance level.

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Table 7. The results of Tukey's HSD test of mean change (%) in the percent of the time that groundwater level is above the target level for monitoring wells over all GCMs for each water use scenario (Comparison of all possible pairs of means).

By human water use scenario	NWH-RMP-08s		CBR-SERW-s		NWH-RMP-13s		STK-STARKEY-20s	
	Fut1 mean	Fut2 mean	Fut1 mean	Fut2 mean	Fut1 mean	Fut2 mean	Fut1 mean	Fut2 mean
No Pumping	45.25 a†	25.98 a†	37.77 a†	20.80 a	5.98 a	-2.13 a	27.17 a†	12.17 a†
No Ag. Pumping	7.44 b	-5.64 ab	12.33 a	2.83 a	0.82 a	-6.49 a†	0.53 b	-9.61 b
No Urban Pumping	41.93 a†	23.05 ab†	37.27 a†	20.69 a	5.27 a	-2.75 a	26.36 a†	11.55 a
Ag. Adaption	3.23 b	-8.64 ab	12.10 a	2.69 a	0.15 a	-7.11 a†	-0.37 b	-10.35 b†
Business as usual	3.08 b	-8.72 ab	12.04 a	2.66 a	0.16 a	-7.11 a†	-0.33 b	-10.33 b†
Increased Ag. Demand	3.29 b	-8.62 ab	12.74 a	3.00 a	0.16 a	-7.11 a†	-0.24 b	-10.25 b†
Increased Urban pumping	-12.04 b	-19.91 b†	3.49 a	-2.21 a	-1.97 a	-8.94 a†	-9.96 b†	-17.99 b†
Increased All Pumping	-12.57 b	-20.36 b†	1.96 a	-3.68 a	-2.13 a	-9.06 a†	-12.30 b†	-20.02 b†

Means with different subscripts were significantly different in Tukey's HSD test.

†: The results were significantly different than retrospective BAU by two sample t-test at the 0.05 significance level.

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Table 8. The results of Tukey's HSD test of mean change in percent of the time that groundwater level is above the target level for monitoring wells over all water use scenarios for each GCM (Comparison of all possible pairs of means).

By GCM	NWH-RMP-08s		CBR-SERW-s		NWH-RMP-13s		STK-STARKEY-20s	
	Fut1 mean	Fut2 mean	Fut1 mean	Fut2 mean	Fut1 mean	Fut2 mean	Fut1 mean	Fut2 mean
BNU-ESM	-5.14 d	-18.12 cd[†]	-10.77 c[†]	-16.15 c[†]	6.15 e[†]	-7.84 e[†]	-9.89 cd	-17.60 bcd[†]
GFDL-CM3	35.24 a[†]	37.44 a[†]	51.11 a[†]	54.15 a[†]	33.28 b[†]	34.17 a[†]	24.60 ab[†]	24.20 a[†]
GFDL-ESM2G	-6.00 cd	-23.32 d[†]	-9.62 c[†]	-23.68 c[†]	7.07 e[†]	-0.99 d	-14.18 d[†]	-23.35 cd[†]
MIROC-ESM	-2.09 bcd	-32.34 e[†]	5.12 c	-15.20 c[†]	13.82 d[†]	-14.83 f[†]	-9.70 cd	-35.69 d[†]
MPI-ESM-LR	11.69 b	2.28 b	28.80 b[†]	12.75 b[†]	22.76 c[†]	14.25 b[†]	11.66 bc	1.53 b
MRI-CGCM3	43.61 a[†]	41.50 a[†]	63.11 a[†]	56.29 a[†]	42.48 a[†]	37.75 a[†]	37.95 a[†]	28.69 a[†]
NorESM1-M	3.93 bc	-5.65 bc	1.72 c	-9.33 c	14.22 d[†]	5.01 c[†]	1.38 bcd	-4.54 bc
BCC-CSM	-1.59 bcd	-24.62 d[†]	0.23 c	-12.04 c[†]	10.39 de[†]	-8.39 e[†]	-10.96 cd	-28.08 d[†]

Means with different subscripts were significantly different in Tukey's HSD test.

[†]: The results were significantly different than retrospective BAU by two sample t-test at the 0.05 significance level.