Climate change impacts on the water and groundwater resources of the Lake Tana Basin, Ethiopia

Tibebe B. Tigabu, Paul D. Wagner, Georg Hörmann, Jens Kiesel and Nicola Fohrer

ABSTRACT

Climate change impacts on the water cycle can severely affect regions that rely on groundwater to meet their water demands in the mid- to long-term. In the Lake Tana basin, Ethiopia, discharge regimes are dominated by groundwater. We assess the impacts of climate change on the groundwater contribution to streamflow (GWQ) and other major water balance components in two tributary catchments of Lake Tana. Based on an ensemble of 35 bias-corrected regional climate models and a hydrologic catchment model, likely changes under two representative concentration pathways (RCP4.5 and 8.5) are assessed. No or only slight changes in rainfall depth are expected, but the number of rainy days is expected to decrease. Compared to the baseline average, GWQ is projected to decrease whereas surface runoff is projected to increase. Hence, rainfall trends alone are not revealing future water availability and may even be misleading, if regions rely heavily on groundwater.

Key words | climate change, Ethiopia, groundwater, surface runoff, SWAT, water balance

HIGHLIGHTS

- Change in the rainfall intensity affects the availability of groundwater in a catchment.
- Rainfall projections from different global and regional climate models show disparities among each other.
- The projected actual evapotranspiration is expected to decrease in the future for the study region due to less water availability.

INTRODUCTION

Climate change causes strong impacts on the natural systems of all continents (Field et al. 2014). Likewise, the hydrological cycle and its components are highly affected by climate change. According to Marx et al. (2018), half of the rivers in Europe will experience a decrease of low flows (7–12%) under 1.5 K warming for the period 2047–2076. A review paper by Meixner et al. (2016) reported likely declines in the recharge of aquifers in the western US during the end of the 21st century. Under RCP4.5, Ndhlouvu & Woyessa (2020) found a slight decrease (1%) in the annual rainfall, whereas water yield and runoff will increase by 5 and 6%, respectively, for the period of 2020–2050 in the Zambezi River Basin, Africa. According to Koch & Cherie (2013), the flow of the Upper Blue Nile is expected to decline from 10 to 61% during the 2050 and 2090s compared to the 20th century average flow. Gebremeskel & Kebede (2018) reported 15 and 14% declines of surface runoff under A1B and B1 scenarios, respectively, for the period 2015–2050 in Werrii watershed of the Tekeze River, Ethiopia. The annual mean soil...
moisture is also anticipated to decrease in most subtropical regions (IPCC 2014). Consequently, uncertainties associated with future water resources management are growing due to the effect of climate change (Abbaspour et al. 2015).

To minimize uncertainties associated with future water management plans and to secure the future water needs of the global community, many efforts have been made to investigate the impact of climate change on water resources across the planet. However, the majority of the studies focus more on surface water bodies than on groundwater (Meixner et al. 2016; Saha et al. 2017), and African countries are underrepresented in these efforts (Field et al. 2014). It is well known that the social-ecological systems of developing countries are severely impacted by climate change due to the lowest capacity to adapt (Dile et al. 2018). This indicates that more efforts are required to investigate the effect of climate change in developing countries like Ethiopia.

Compared to surface water, groundwater is a reliable and cost-effective resource especially in many African countries and other parts of the world where availability of surface water is limited (Bovolo et al. 2009). One-third of the global freshwater is extracted from the groundwater source (Taylor et al. 2013). On Ethiopia’s national level, as well as in the Lake Tana basin, groundwater provides 80% of the water demand (Kebede 2013).

In the Lake Tana basin, being a home for more than three million people and a headwater source of the Blue Nile River, several studies were carried out to investigate the impact of climate change on its hydrology. Nevertheless, the vast majority of the climate change studies were focused on streamflow or runoff analyses and there are disagreements in their findings (Abdo et al. 2009; Taye et al. 2011; Dile et al. 2013). Abdo et al. (2009) and Dile et al. (2013) studied the hydrologic responses of Gilgelabay catchment under climate change. According to Dile et al. (2013), the monthly mean volume of runoff in Gilgelabay catchment tends to increase significantly (up to 135%) for the mid- and long-term of the 21st century. Contrary to Dile et al. (2013), Abdo et al. (2009) reported decreases in the monthly mean runoff in the same catchment. Taye et al. (2011) also studied the future development of streamflow in the Lake Tana basin under climate change. In this study, both increases and decreases (−75 to 81%) of streamflow are expected during the 2050s in different catchments in the Upper Blue Nile Basin. Groundwater contributes a substantial amount of water to the flow of streams in the Lake Tana basin. Even though it has a significant contribution to the streamflow (Setegn et al. 2008; Tigabu et al. 2019), all past studies ignored it in their analyses. The only studies that addressed multiple water balance components and groundwater flow analyses under climate change in the Lake Tana basin are Setegn et al. (2011) and Woldesenbet et al. (2018). Setegn et al. (2011) analysed the responses of streamflow, actual evapotranspiration (AET), soil moisture, and groundwater contribution to the streamflow based on 17 GCM outputs from the World Climate Research Programme’s Coupled Model Intercomparison Project phase 3 (CMIP3). Their results indicated that the annual streamflow tends to decline significantly for most of the GCMs considered for the study, while the AET is expected to increase. A likely decrease in groundwater flow and soil moisture was reported. However, the magnitudes of changes in the groundwater flow as well as the spatial patterns of changes were not considered. Woldesenbet et al. (2018) also studied the impacts of future climate change on the hydrological components of the Lake Tana Basin under RCP6.0. Their results showed that the groundwater contribution to the streamflow, percolation, and AET would increase on the annual time scale, but decreases are expected during the small rainy season compared to their reference period (1980–2005). Although this research is comprehensive in addressing the major water balance components, it does not address the impact of climate change on the major hydrological components during the mid-term and long-term of the 21st century as the authors focused only on a short-term period (2016–2030). In addition, the high-level representative concentration pathway (RCP8.5) was not considered.

Thus, the main purpose of this study is to enhance our understanding of how projected changes in rainfall and temperature will affect the groundwater contribution to the streamflow and other major water balance components in Gilgelabay and Gumara catchments, which are the two major tributaries of Lake Tana during the mid-term (2031–2060) and long-term (2065–2094). The specific objectives are (i) to assess if groundwater contribution to the streamflow and other major water balance components has significantly changed in response to climate change.
and (ii) to determine if changes in the groundwater contribution to the streamflow show a distinct spatial pattern in the study area.

MATERIALS AND METHODS

Study area

The Lake Tana basin is entirely located in the Amhara regional state in the north-western highlands of Ethiopia (Figure 1). It is one of the sub-basins of the Blue Nile River in which the largest fresh water lake in the country is found. The total catchment area of the Lake Tana basin is 15,321 km². More than 40 streams flow into Lake Tana (Alemayehu et al. 2010). Gilgelabay (catchment area ∼5,004 km²) and Gumara (catchment area ∼1,394 km²) contribute about 70% of the inflow to the lake. The Blue Nile (locally referred to as Abay) is the only surface outflow from the lake with an average annual flow volume, as calculated from raw data (1973–2014), of 3.9 billion m³ (123 m³/s) measured at the lake outlet.

Similar to its hydrologic variability, the Lake Tana basin has a heterogeneous hydrogeology. According to Kebede et al. (2005), areas surrounding Lake Tana are covered by quaternary basalts and alluvial sediments. Being driven by the diversified parent geology, the soil structure, lateral and vertical extents, and hydraulic conductivity, the basin is highly diversified. The soils vary from hydrologic group B to group D, which represent infiltration rates from moderate to very slow. Additional information can be found in Tigabu et al. (2019). Gilgelabay and Gumara are the two perennial rivers that are characterized by a succession of bedrock types in their higher reaches and alluvial types with floodplains in their lower reaches (Poppe et al. 2013). There is significant topographic variation between the lowland and the mountain ranges. This diversified topographic feature of the catchment and the movement of the intertropical convergence zone (ITCZ) results in a spatially varying rainfall pattern in the basin. June to September is the rainy season in the catchment corresponding to the ITCZ position north of the Equator. The amount of average annual rainfall is directly related to elevation above mean sea level: high rainfall (1,600 mm) is observed in the highlands, whereas low rainfall (815 mm) is measured in the lowlands (Tigabu et al. 2020). Moreover, large (global) atmospheric circulation and sea surface temperatures, such as large-scale forcing through El Niño Southern Oscillation, Quasi-Biennial Oscillation, as well as west-east sea surface temperature gradients over the equatorial Indian Ocean are significantly influencing rainfall variability (Omondi et al. 2014). The catchments are characterized by intensive agriculture with about 60% of the catchments under cultivation.

Data base

Daily rainfall and minimum and maximum temperature values from five meteorological stations for the years 1980–2014 were used, which were provided by the National Meteorological Service Agency (NMA 2016). Daily streamflow data of Gilgelabay near Merawi and Gumara near Bahirdar gauging stations for the years 1980–2014 were obtained from the Department of Hydrology, Ministry of Water, Irrigation and Electricity of the Ethiopian Government (MoWIE 2016).

Hydrological modeling

Numerous hydrological models have been used to study the impact of climate change on water resources. The semi-distributed, continuous eco-hydrological model SWAT (Soil and Water Assessment Tool) (Arnold et al. 1998; Arnold & Fohrer 2005) is widely applied. The model is capable of simulating water balance components based on hydrological response units. Groundwater processes are represented by a shallow and a deep aquifer in the model. The shallow aquifer in the SWAT model is defined as an unconfined aquifer that contributes to streamflow in the main channel of the respective sub-basin (Neitsch et al. 2011). The input component to the hydrologic balance equation is rainfall and is partitioned into AET, water entering to the vadose zone, and surface runoff.

In this study, calibrated SWAT models for Gilgelabay and Gumara catchments (Tigabu et al. 2019) were used. As the catchments are characterized by diversified soil, topographic, and hydrogeological features, model parameters that are related to the groundwater flow system were...
adjusted through intensive sensitivity analysis tests in SWAT-CUP (Abbaspour et al. 2007). Considering the availability and continuity of the streamflow data of the catchments, we split our modeling period into a warmup period (1980–1984), calibration period (1985–1995, Gumara; 1988–1996, Gilgelabay), and validation period (1996–2014, Gumara; 1997–2011, Gilgelabay). The model parameter settings were defined using the Latin hypercube sampling algorithm implementation in hydroGOF (Zambrano-Bigiarini 2014). Six thousand model simulations that include different combinations of 10 sensitive parameter values were tested, and then the best model run was chosen based on the optimized Nash–Sutcliffe efficiency (NSE) from 6,000 simulations. Moreover, other objective functions, such as Kling–Gupta efficiency (KGE), percent bias (PBIAS), and standardized root mean square error (RSR) were also used to test the model performance.

In addition to statistical indices, the fitness of the models in capturing the monthly streamflow data was also evaluated by comparing the measured and simulated streamflow hydrographs and flow duration curves. The flow duration curves showed very good agreement for the middle and
low flow conditions in both catchments, which are indicative of representing groundwater contribution to streamflow (refer Tigabu et al. 2019). Hence, the model is suitable for assessing the impacts of climate change on groundwater and water resources in the two catchments. Detailed information on the parameters and calibration procedures are available in Tigabu et al. (2019). As the magnitude of groundwater flow in a catchment is counterbalanced by the other hydrologic components, we also analysed ET, SURQ, soil moisture content, and percolation.

**Projected climate change data**

To assess the impacts of future climate change on water resources, different emission scenarios as expressed in the representative concentration pathways (RCPs) are used. Global Circulation Models (GCMs) and the Coordinated Regional climate Downscaling Experiment (CORDEX) are the most commonly applied and physically based ways of formulating different climate scenarios (Elshamy et al. 2009). Nevertheless, GCMs are unsuitable for local climate impact studies due to their coarse spatial resolution and incapability to capture local effects (Navarro-Racines et al. 2020). To overcome these limitations, regional climate models (RCMs) are applied to downscale general circulation model (GCM) outputs (Eden et al. 2014; Mascaro et al. 2015). CORDEX coordinates RCMs to improve regional climate downscaling models and techniques and to produce coordinated sets of regional downscaled projections worldwide (Giorgi & Gutowski Jr 2013). There are multiple CORDEX domains worldwide including the CORDEX-African domain. Although RCM outputs provide a better spatial and temporal resolution than GCM outputs, projected temperature and rainfall are still biased (Berg et al. 2012). Consequently, a number of bias correction (BC) methods are available to overcome this problem. The main adjustment methods are based on the mean, both mean and variance, and quantile values. Among others, linear scaling and local intensity scaling, power transformation method, distribution mapping or quantile mapping are widely applied (Smitha et al. 2018).

Climate models can project future rainfall and temperature. However, there are considerable differences and uncertainties in the projected rainfall among the different climate models (Kling et al. 2012; Kiesel et al. 2019). According to Mascaro et al. (2015), the CORDEX-African RCMs have significant biases among the individual models. For this reason, an ensemble modeling approach that depends on a number of climate models is required to minimize biases and obtain a representative result (Kling et al. 2012).

Past climate change studies in the Lake Tana basin were mainly based on single GCM (Abdo et al. 2009; Dile et al. 2015; Adem et al. 2016) using the Coupled Model Intercomparison Project version 3 (CMIP3) results. However, model outputs from CMIP3 have course spatial resolutions and are not as comprehensive as model outputs from CMIP5 (Taylor et al. 2012). According to Taylor et al. (2012) and Stocker et al. (2013), climate models under CMIP5 are capable of representing bio-geological processes, aerosols, and carbon cycles that interact with physical climate. As a result, better simulations are expected under CMIP5 than under CMIP3. Reports by Meher et al. (2017) and Kusunoki & Arakawa (2015) indicated that annual and seasonal rainfall simulated from CMIP5 showed higher reproducibility than CMIP3 over the western Himalayan and East Asia regions, respectively. Consequently, we used daily rainfall and temperature data of 35 RCMs for RCP4.5 and RCP8.5 (Table 1) from CORDEX Africa which are driven by GCMs in CMIP5 (Mascaro et al. 2015). These data are available at a grid resolution of 44 km which is the finest available for the African domain (Kisembe et al. 2019).

**Bias correction**

Climate model data can differ considerably from the measured data. This bias needs to be corrected prior to using climate change scenario data in hydrological impact studies (Berg et al. 2012). For this study, we applied five BC methods: distribution or quantile mapping (pDM) and linear scaling (pLS) for both rainfall and temperature, and local intensity scaling (pLIS) and power transformation for rainfall (pPT), as well as variance scaling for temperature data. We used 30 years of data for the BC (1986–2015) to reduce the impact of natural variability. The seasonal patterns and median values of the climate data before and after BC were compared with the observed climate data for the period (1980–2005). Even though the measured climate data were available for the period 1980–2015, the
A comparison of rainfall outputs from CORDEX with the measured ones was carried out for the period 1980–2005. This is because climate data from GCM-RCMs were free from radiative forcing only before the year 2006 (IPCC 2014).

We took a subset of the available GCM-RCMs outputs based on the plausibility of the simulated rainfall outputs, as rainfall is the most important input for hydrologic modeling. The following criteria for model selection were applied.

First, we analyzed the GCM–RCM data before any BC method was applied. The monthly average rainfall of the climate scenario data (1980 to 2005) was compared to the measured data (Figures 2 and 3). Those GCM–RCM outputs that did not follow the observed bimodal rainfall pattern were removed. Five BC methods were then applied using an adapted version of the software CMHyd (Rathjens et al. 2016).

Next, the bias-corrected climate data were compared with observed rainfall data for each station based on the root mean square error computed using long-term mean monthly average values. The RMSE computation was applied for the dry season, wet season, and all months independently to identify a dry/wet bias in the scenario data. Finally, bias-corrected GCM–RCM outputs that showed an RMSE value of <0.5 mm/day and represented the seasonality (Figure 4) were selected for climate change impact analysis. The selected GCM and regional climate model (RCM) combinations, their full names, and institutions are given in Table 1. Detailed information about the BC methods used for this study is available in Teutschbein & Seibert (2013).

### Table 1

<table>
<thead>
<tr>
<th>GCM/RCM</th>
<th>Institution name</th>
<th>Expanded name of RCM</th>
<th>BC method</th>
<th>RMSE before BC (mm/day)</th>
<th>RMSE (mm/day)</th>
<th>Suitable GCM–RCM</th>
</tr>
</thead>
<tbody>
<tr>
<td>Gilgelabay</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>CCCma/RCA4</td>
<td>Canadian Climate Model</td>
<td>Regional-scale model</td>
<td>pDM</td>
<td>3.28</td>
<td>0.17</td>
<td>2</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td>pLS</td>
<td>0.16</td>
<td>2</td>
<td></td>
</tr>
<tr>
<td>IPSL-M5/REMO2009</td>
<td>Institut Pierre Simon Laplace</td>
<td>Regional climate model</td>
<td>pLS</td>
<td>1.69</td>
<td>0.16</td>
<td>1*</td>
</tr>
<tr>
<td>IPSL/RCA4</td>
<td></td>
<td>Regional-scale model</td>
<td>pDM</td>
<td>1.69</td>
<td>0.16</td>
<td>2</td>
</tr>
<tr>
<td>MIROC/REMO2009</td>
<td>University of Tokyo, Japan</td>
<td>Regional climate model</td>
<td>pLS</td>
<td>5.31</td>
<td>0.22</td>
<td>1*</td>
</tr>
<tr>
<td>NCC/RCA4</td>
<td>National Climate Center of China</td>
<td>Regional-scale model</td>
<td>pDM</td>
<td>5.38</td>
<td>0.24</td>
<td>2</td>
</tr>
<tr>
<td>NOAA/RCA4</td>
<td>Geophysical Fluid Dynamics Laboratory of the US</td>
<td>Regional-scale model</td>
<td>pLS</td>
<td>4.75</td>
<td>0.23</td>
<td>2</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td>pLIS</td>
<td>0.23</td>
<td>2</td>
<td></td>
</tr>
<tr>
<td>Total</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td>16</td>
</tr>
</tbody>
</table>

| Gumara | | | | | |
| CCCma/RCA4 | Canadian Centre for Climate Modeling and Analysis | Regional-scale model | pLS | 2.32 | 0.35 | 2 |
| CSIRO/RCA4 | Climate Change Information for Australia | RCA4 | pPT | 3.23 | 0.23 | 2 |
| MIROC/RCA4 | | | pDM | 6.4 | 0.16 | 2 |
| MIROC/ REMO2009 | University of Tokyo, Japan | Regional Climate Model | pDM | 4.9 | 0.13 | 1* |
| MPIM/CLM-4-8-17 | Max Planck Institute for Meteorology | Climate limited area modeling community | pDMLIS | 3.44 | 0.16 | 2 |
| MPIM/REMO2009 | Max Planck Institute for Meteorology | Regional Climate Model | pDMLIS | 2.32 | 0.34 | 2 |
| MPIM/RCA4 | Max Planck Institute for Meteorology | Regional-scale model | pDMLIS | 3.34 | 0.50 | 2 |
| NCC/RCA4 | National Climate Center of China | RCA4 | pLS | 2.32 | 0.20 | 2 |
| NOAA/RCA4 | Geophysical Fluid Dynamics Laboratory of the US | | pLS | 4.15 | 0.13 | 2 |
| | | | pDM | 4.15 | 0.23 | 2 |
| Total | | | | | | 19 |
Climate change impact investigation

Thirty-five bias-corrected GCM–RCM rainfall and temperature outputs (19 for Gumara, 16 for Gilgelabay) were used as an input to the hydrologic model SWAT to investigate the future hydrologic balance of the two catchments. In this regard, it was assumed that the calibrated hydrologic model parameters for the baseline period as well as the land-use land cover condition remain the same in the future. Only the projected rainfall and temperature data...
were used to replace the baseline ones. The major hydrologic components were analysed for the mid-term (2031–2060) and long-term (2065–2094) future. Model uncertainties associated with the future simulation due to model parameters were minimized through a thorough multimetric calibration to the baseline period (1985–2014). Additionally, expected uncertainties from GCM–RCM outputs were minimized through BC and comparing the rainfall outputs with historical records for 1980–2005.

It is reported that projected results for future climate change differ among the different sets of GCM–RCM outputs resulting in considerable uncertainty (Huang 2014; Kisembe et al. 2019). This in turn results in variation of the projected water balance components depending on the selected BC method (Table 1).

The changes in the major water balance components were computed with reference to SWAT model simulated results using observed climate data (1985–2014), hereafter called the baseline period. Tukey’s multiple mean comparison test was applied to investigate the projected water balance changes. Here, factor variables named baseline, mid-term, and long-term were assigned for each year corresponding to the three time periods. Then, a Tukey multiple mean comparison test (95% confidence level) that is based on a two-way ANOVA model (Yandell 1997) was applied.

\[ \phi_m = \sum_{i=1}^{n} \left( \frac{\phi_{rcm1} f_{rcm1} + \phi_{rcm2} f_{rcm2} + \ldots + \phi_{rcmn} f_{rcmn}}{f_{rcm1} + f_{rcm2} + \ldots + f_{rcmn}} \right) \]  (1)

where \( n \) stands for the number of RCMs, \( \phi_m \) for the ensemble mean hydrologic variable (e.g. rainfall, GWQ, SURQ, ET, PET, PERC), and \( \phi_{rcm1}, \phi_{rcm2}, \phi_{rcmn} \) represent the value of hydrologic variable at the given RCM 1, 2, 3…\( n \) and \( f \) represents the frequency of the RCM depending on the selected BC method (Table 1).

Figure 4 | Exemplary plots presenting seasonal patterns and agreement of the bias-corrected mean monthly rainfall generated from regional climate model (1980–2005) with the monthly mean of observed rainfall of Gumara catchment. The red lines represent the monthly mean rainfall of different climate models before bias correction was applied and the other colours represent the rainfall after different bias correction methods were applied. Suitability of bias correction methods differs from one regional climate model to the other. Here, we presented the rainfall data generated from different regional climates that showed good agreement with observed rainfall at Debretabor station only as an example.
between the baseline and mid-term, baseline and long-term, mid-term and long-term major water balance components and climate time series.

Prior to evaluating the effect of projected climate change on the hydrologic balances, uncertainties related to the hydrologic model and to GCM–RCM outputs are investigated with reference to measured streamflow and rainfall data. According to the PBIAS results for the calibration and validation period, the simulated streamflow is underestimated in both catchments. Moreover, standardized root mean square error (RSR) is also estimated and model performance is good (Table 2). The applied BC methods reduced the uncertainties introduced by GCM–RCM models on the projected rainfall and temperature data. Root mean square error (RSME) values computed for the rainfall data from different GCM–RCM and BC methods range from 0.13 to 0.50 (Table 1). Thus, it is believed that the uncertainty in the surface water and groundwater from GCMs and the SWAT model are acceptable.

RESULTS AND DISCUSSION

Projected changes of rainfall and temperature

Rainfall comparison between observations and the climate scenario data for the period 1980–2005 showed that there is no single BC method that performed best for all RCMs (Table 1). We observed a variation in matching the measured mean monthly rainfall. In the case of CCCma–RCA4 and NCC–RCA4, all BC correction methods showed mismatches (RMSE values vary between 1.53 and 3.34) on the mean monthly rainfall values except the pLS (Table 1) method. The pLS BC method showed relatively better matching of the mean value for each month than the other BC methods (RMSE <0.35). pPT was the best BC method in fitting the mean rainfall values and maintaining the seasonal patterns in the case of CSIRO–RCA4 outputs (Figure 4). The rainfall data from the family of MPIM-RCM (1980–2005) showed good agreement with the observed one in the case of pDMLIS and pDM BC methods, and pLS and pDM methods resulted in good performance in the case of NOAA–RCA4 outputs (Figure 4). Moreover, RCM outputs from CNRM, ICHEC, IPSL, and MOHC showed high variation in the seasonal patterns and mean monthly values of the rainfall compared to the observed ones (RMSE >0.5). The differences in the mean monthly rainfall values are very pronounced in June and September. There is also variation in the annual rainfall among different GCM–RCM outputs. As an example, future annual rainfall values significantly vary between MIROC and CSIRO families in the case of Gumara (Figure 5). Annual rainfall outputs derived from the MIROC family for the mid- and late-terms of the 21st are expected to increase significantly compared to the baseline average for both RCP4.5 and RCP8.5 (p-value <0.001). On the contrary, in the case of the CSIRO family scenario, a significant decrease is expected (Figure 5).

There is also variation in the ensemble mean rainfall changes between the mid- and long-term of the century for both RCPs. Compared to the baseline average, the ensemble RCM mean rainfall of Gumara catchment under RCP4.5 is expected to increase by 4.4% and decrease by 0.7% during the mid-term and long-term of the 21st century, respectively. Similarly, an increase of 0.4% and a decrease of 2.2% for the mid-term and long-term periods, respectively, are expected under RCP8.5. The direction of rainfall changes is consistent with the findings of Roth et al. (2018) and Gebremeskel & Kebede (2018). Unlike in the Gumara catchment, expected changes of the ensemble mean rainfall in Gilgelababy catchment under RCP8.5 are negative for both time periods. About 3% decline is expected for the mid- and long-term of the century. Nevertheless, the overall average values for the two time periods will not change significantly compared to the baseline average. Similarly, Setegn et al. (2011) reported that there was no significant change in the ensemble median rainfall from 18 GCMs.

### Table 2: Model evaluation statistics that were computed in comparison of measured and SWAT simulated monthly streamflow time series for Gilgelababy and Gumara catchments

<table>
<thead>
<tr>
<th>Objective function</th>
<th>Gilgelababy</th>
<th>Gumara</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Calibration</td>
<td>Validation</td>
</tr>
<tr>
<td>NSE</td>
<td>0.71</td>
<td>0.94</td>
</tr>
<tr>
<td>KGE</td>
<td>0.50</td>
<td>0.62</td>
</tr>
<tr>
<td>R²</td>
<td>0.83</td>
<td>0.83</td>
</tr>
<tr>
<td>PBIAS</td>
<td>6.89</td>
<td>16.95</td>
</tr>
<tr>
<td>RSR</td>
<td>0.54</td>
<td>0.25</td>
</tr>
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</table>
While the direction of projected rainfall changes varies across the GCM–RCM outputs (Figure 6), all models show a rising trend in both minimum and maximum temperature. Setegn et al. (2011) also concluded that there is no consensus on the direction of rainfall changes of different GCMs. In our study, we noticed that each and every 30 years moving average maximum and minimum temperatures (for a data series from 1985 to 2100) is expected to be higher than the preceding one (Figure 7). The absolute temperature change varies between 1.3 to 2.7 °C and 2.0 to 3.8 °C for the mid- and long-term of the century, respectively. The mid-term projection deviates from the baseline average for
all RCMs, but is not as pronounced as for the long-term period. These findings are also confirmed for the entire Blue Nile basin (Roth et al. 2018). A similar study conducted on the Upper Blue Nile River basin by Kim & Kaluarachchi (2009) reported an increase of 2.6 °C for the 2050s, which is close to our results. The slight differences in the temperature changes between the current study, Roth et al. (2018), and Kim & Kaluarachchi (2009), might be due to the differences in the future time window considered as well as the differences in GCM outputs used for the studies. Our study is based on RCM results under the AR5 assumption report of IPCC (2014), while Kim & Kaluarachchi (2009) used global climate model outputs under the IPCC (2000) emission scenario.

**Expected impacts of climate change on water balance components**

Our results indicate various changes in the water balance components are expected in the two catchments. Water yield is expected to rise for the mid-term of the century in the Gumara catchment under both RCP4.5 and RCP8.5. However, for the long-term period, a drop for RCP4.5 and a rise for RCP 8.5 are expected. These changes follow the direction of rainfall changes (Table 3). A small change in the rainfall amount can result in more pronounced changes in the water balance components. This is related to an increase in rainfall intensity. The ensemble average rainfall is expected to be more variable and intense than during the baseline period (Figure 8). Rainy days with higher rainfall intensity are expected during the dry season in both mid- and long-term periods for both catchments (Figure 9). A 4.6% increase in the annual rainfall in Gumara catchment resulted in about 6.8% increase in the water yield.

Likewise, in Gilgelabay catchment, a 3% drop in rainfall for both mid-term and long-term results in about 1 and 5% reduction in water yield, respectively, under RCP8.5. There are clear differences in the projected rainfall and water balance changes between Gilgelabay and Gumara under the two RCPs. For example, in Gilgelabay catchment, the weighted ensemble mean rainfall values (for both mid- and long-term of the century) under RCP8.5 are expected to decrease by 3%, and these changes in turn affect the water yield to decrease by about 1–5% when compared to the baseline average. Whereas, in Gumara catchment, an increase for the mid-term and a decrease for the long-term are expected. These results suggest that the local conditions also contribute strongly to how the climate change signal affects water balance components.
Table 3  Average increase/ decrease in the SWAT simulated major water balance components with p-value (***p-value < 0.001, **0.001 < p-value < 0.01, *0.01 < p-value < 0.05) computed based on Tukey multiple mean comparison method (95% confidence level) for the mid-term, long-term with reference to the baseline period, and between the mid-term and long-term of the twenty-first century

<table>
<thead>
<tr>
<th>Variable</th>
<th>RCP 4.5</th>
<th>RCP 8.5</th>
<th>△ between mid- and long-terms</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Mid-term baseline</td>
<td>Long-term baseline</td>
<td>Mid-term baseline</td>
</tr>
<tr>
<td>Gumara</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Rainfall (mm)</td>
<td>66.10</td>
<td>–10.5</td>
<td>6.40</td>
</tr>
<tr>
<td>Mean temp °C</td>
<td>1.99***</td>
<td>2.72***</td>
<td>2.49***</td>
</tr>
<tr>
<td>ET (mm)</td>
<td>–4.8</td>
<td>–11.80</td>
<td>–2.4</td>
</tr>
<tr>
<td>GWQ (mm)</td>
<td>–70.3***</td>
<td>97.75***</td>
<td>–61.8***</td>
</tr>
<tr>
<td>PERC (mm)</td>
<td>–85.62***</td>
<td>–118.04***</td>
<td>–73.28***</td>
</tr>
<tr>
<td>SURQ (mm)</td>
<td>161.52***</td>
<td>130.97***</td>
<td>89.0***</td>
</tr>
<tr>
<td>WYLD (mm)</td>
<td>67.35</td>
<td>–2.71</td>
<td>6.45</td>
</tr>
<tr>
<td>Gilgelabay</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Rainfall (mm)</td>
<td>26.30</td>
<td>–35.34</td>
<td>–48.53</td>
</tr>
<tr>
<td>Mean Temp °C</td>
<td>2.07***</td>
<td>2.87***</td>
<td>2.72***</td>
</tr>
<tr>
<td>ET (mm)</td>
<td>–56.21***</td>
<td>–46.47***</td>
<td>–38.17***</td>
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<tr>
<td>GWQ (mm)</td>
<td>14.39</td>
<td>–20.80</td>
<td>–15.31</td>
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<tr>
<td>PERC (mm)</td>
<td>20.00</td>
<td>–31.00</td>
<td>–23.00</td>
</tr>
<tr>
<td>SURQ (mm)</td>
<td>64.71***</td>
<td>48.43***</td>
<td>20.42</td>
</tr>
<tr>
<td>WYLD (mm)</td>
<td>84.83</td>
<td>14.07</td>
<td>–5.38</td>
</tr>
</tbody>
</table>

The numbers represent the absolute change (first number) and p-value (second number), where numbers in bold indicate significant changes.

Figure 8  Thirty years moving average projected rainfall of different GCM-RCM outputs under the middle level (RCP4.5) and highest (RCP8.5) concentration pathway (Gumara).
Impacts on groundwater

During the baseline period, groundwater accounts for more than 50% of the streamflow for each catchment (Tigabu et al. 2019). Under RCP4.5, the groundwater contribution to the streamflow (GWQ) is decreased. The decreases of GWQ vary between 3 and 57%. These decreases are projected even for positive changes in the projected rainfall. For instance, in the Gumara catchment, statistically significant decreases in GWQ (high confidence, p-values = 0.001) for both time periods are likely (Table 3) while a slight increase in rainfall is expected. This implies that the slight increases in rainfall are expected to cause an increase in surface runoff and a decrease in infiltration due to the higher rainfall intensities. The effect of temperature on groundwater is not easily measurable, but its effect can be inferred from other hydrologic components such as AET.

A positive or negative change of one hydrologic component could have an effect on the other component. The correlation matrix computed for the major hydrologic components confirms this (Table 4). Considering the correlation of the hydrologic components with rainfall and temperature, GWQ shows a very high positive correlation coefficient with rainfall and a slight negative correlation with temperature. Surprisingly, the AET correlation with temperature shows small positive values in Gilgelabay and negative ones in Gumara. Temperature is therefore not the major driving factor for AET. While this is true for potential evapotranspiration (PET), AET also relies on the available water, which may be (seasonally) limited. Additionally, an increase in the rainfall intensity contributes to this, as it favors fast overland flow and reduces infiltration.

Compared to the Gumara catchment, the changes in GWQ for Gilgelabay catchment are less pronounced. In fact, the likely changes are not significant for the two time periods under both RCPs. However, the annual changes in rainfall show a high temporal variability from a decrease of −1 to −25% that in turn changes the annual GWQ from −3 to −51%. The projected decreases in GWQ in the mid-term for both RCPs can be explained by the increases of surface runoff for both catchments. Changes in rainfall for the given time periods are considered as the main driving force. The 30-year moving average values of GWQ show a decrease for both RCPs in both catchments and only a few years show higher GWQ than in the baseline for Gilgelabay catchment (Figure 10(a)). More severe changes are expected for the long-term period in the case of Gilgelabay, and for both...
periods for Gumara (Figure 10(b), Table 3). In summary, changes related to GWQ are mainly negative for both catchments under the two RCPs, and these changes are being driven by the increasing level of rainfall intensity that could increase SURQ. Moreover, the annual percolation will decrease under the given RCPs (Table 3), resulting in a drop of the water table of the shallow aquifer. Thus, a drop in the water table in turn would cause a reduction in the volume of groundwater discharge to the stream. These results are in agreement with the findings of Setegn et al. (2011) and Koch & Cherie (2013) who applied climate change scenarios for the same region.

Table 4  Correlation matrix of annual hydrological variables computed using Pearson Correlation method for the time series (2031–2100) for Gilgelabay and Gumara catchments (numbers in bold colour show either strong positive or negative correlation)

<table>
<thead>
<tr>
<th></th>
<th>Gilgelabay</th>
<th>Gumara</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Rainfall</td>
<td>ET</td>
</tr>
<tr>
<td>Rainfall</td>
<td>1.00</td>
<td>0.64</td>
</tr>
<tr>
<td>ET</td>
<td>0.64</td>
<td>1.00</td>
</tr>
<tr>
<td>SURQ</td>
<td>0.69</td>
<td>0.10</td>
</tr>
<tr>
<td>GWQ</td>
<td>0.94</td>
<td>0.44</td>
</tr>
<tr>
<td>WYLD</td>
<td>0.94</td>
<td>0.38</td>
</tr>
<tr>
<td>Mean temperature</td>
<td>-0.12</td>
<td>0.01</td>
</tr>
</tbody>
</table>

Figure 10  The annual percentage changes of GWQ (a) from baseline average and 30-year moving average (b) for the ensemble mean of simulated GWQ under RCP4.5 and RCP8.5 for Gilgelabay (Gil) and Gumara (Gum).
Surface runoff

Under the assumption that agricultural management stays the same, our results indicate that SURQ in Gumara is more considerable than in the Gilgelabay catchment (Figure 11). For the selected two future time periods, significant increases are likely in Gumara catchment. For instance, under RCP4.5 for the year 2045 (mid-term) time horizon, a 40% increase in catchment rainfall is expected to result in a 220% increase in SURQ. This change is associated with a 1.8 °C increase in mean temperature. Likewise, under RCP8.5, a 27% increase in rainfall is likely to increase SURQ by 156%, and the expected mean temperature change associated with this is about 2.3 °C. In the Gilgelabay catchment, significant increasing changes (p-value << 0.001) are expected for the two time horizons under RCP4.5, and for the long-term under RCP8.5 (p-value = 0.001). On the contrary, no significant change is expected for mid-term under RCP8.5. Obviously, the SURQ response is more sensitive to the changes in rainfall than to changes in temperature (Table 4). A study conducted by Conway (1996) about the impacts of climate variability on the Nile water resources reported that a 10% increase in rainfall in the Blue Nile basin was resulting in an increase of 34% SURQ, and the relationship between change in rainfall and change in SURQ was nearly linear.

Actual evapotranspiration

Changes in projected temperature and rainfall can be translated to PET and AET. Results of the current study revealed that the overall annual PET is expected to rise significantly across all time periods and RCPs due to the significant increase in temperature. AET is also expected to generally increase with increasing temperatures, however, limited by the water availability. We found a decrease in annual actual ET compared to the baseline average. The changes are significant for Gilgelabay catchment except for the long-term period under RCP8.5. On the contrary, the changes for Gumara catchment are not significant. This decline can be explained by a (seasonal) limitation of water availability that limits the AET responses to warming (Condon et al. 2020; Wagner et al. 2015). About 51% of ET takes place during the dry season (October–May), when less water is available. It is not uncommon to get less AET in areas where the available water volume is small, and the available water volume and soil moisture are regularly correlated with rainfall. For the current study, the decreases
in the future AET changes in Gumara and Gilgelabay catchments are limited by the available water. A significant increase in SURQ, and a significant decrease in the soil moisture content, are expected under both RCPs and time periods that will likely cause less AET. The projected ensemble mean rainfall datasets show that the future rainy days are expected to decrease compared to the number of rainy days during the baseline period even though the expected changes of total annual rainfall are not significant. In the Gumara catchment, the average number of days with non-zero rainfall records was 170 during the baseline period, while 160 and 154 rainy days for the mid-term and long term are projected, respectively. Likewise, in Gilgelabay catchment, the future rainy days are expected to decrease with a slope of 0.05 per day which is about a drop of 7–10 days when compared to the baseline. This indicates that the rainfall intensity is expected to increase, which in turn causes higher surface runoff and less AET. High-intensity rainfall may reduce ET as there will be less water interception and lower soil moisture content. This can explain why less AET is simulated even for positive changes of rainfall. Furthermore, AET change rates differ among catchments depending on the land cover types and different underlying surfaces processes (Woldesenbet et al. 2017; Wagner et al. 2019).

Spatial patterns of changes in GWQ

Besides the expected temporal changes of GWQ in the study catchments, changes are also projected in the spatial patterns. Influences of the projected rainfall and temperature vary from the highland to the lowland portion of the catchments. The projected changes are higher in the lowlands than in the highlands for both catchments. For Gumara catchment, the expected changes are negative and vary from −3 to −32% for both RCPs (Figure 12). Although we expect differences in the magnitude of changes between RCP4.5 and RCP8.5 for both mid- and long-term periods, our results reveal that spatial differences between RCPs are small (Figure 12). On the contrary, in Gilgelabay catchment, the degree of influence of the two RCPs on the spatial variability differs more considerably. Under RCP8.5, projected changes will mostly be negative while positive changes are expected under RCP4.5 (Figure 13). Compared to Gumara, the percentage changes in Gilgelabay show a wider range that varies from 26 to −58%. This wide range

![Figure 12](https://iwaponline.com/jwcc/article-pdf/12/5/1544/923474/jwc0121544.pdf)
of changes in Gilgelabay catchment can be explained by the variability in rainfall. Four rainfall stations were used for Gilgelabay, while only one station was used for Gumara (Tigabu et al. 2019).

**CONCLUSION**

In this study, we investigated the future (2031–2060 (mid-term), 2065–2094 (long-term)) temporal changes of groundwater contribution to streamflow and of major water balance components in two catchments (Gilgelabay and Gumara) of the Lake Tana basin, in north-western Ethiopia under RCP4.5 and RCP8.5 using CORDEX datasets (CMIP5). Impacts on water resources were assessed using the hydrological model SWAT under the assumption that the current agricultural management practices and land cover conditions would not change.

Distinct spatial patterns are expected in the groundwater contribution to streamflow for the two catchments. The declines of groundwater contribution to streamflow will be higher in lowland portions of the two catchments than in the highlands.

The ensemble mean rainfall is not expected to show significant change for both the mid- and long-term periods. However, the rainfall intensity is expected to be higher than during the baseline period. Consequently, the anticipated surface runoff is expected to increase, whereas groundwater contribution to streamflow is projected to decline. Therefore, we recommend to analyse changes in rainfall intensities alongside changes in rainfall amounts prior to a hydrologic impact assessment.

The higher projected surface runoff that results from the increases in rainfall intensity will lead to an increase in soil erosion in both catchments. Moreover, the floodplain area of Gumara catchment may experience a higher flood risk in the future. Hence, to mitigate erosion and flood risks that are anticipated as a result of increasing surface runoff, the construction of small scale reservoirs to store more surface water for domestic water supply and small scale
irrigation may be advisable. Furthermore, agricultural management practices that enhance infiltration can be recommended to mitigate climate change impacts.

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**DATA AVAILABILITY STATEMENT**

All relevant data are included in the paper or its Supplementary Information.

**REFERENCES**


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