Coupled application of R and WetSpa models for assessment of climate change impact on streamflow of Werie Catchment, Tigray, Ethiopia
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ABSTRACT
This research assesses the streamflow response of Werie River to climate change. Baseline (1980–2009) climate data of precipitation, maximum and minimum temperature were analyzed using delta based statistical downscaling approach in R software packages to predict future 90 years (2010–2099) periods under two emission scenarios of Representative Concentration Pathways (RCP) 4.5 and RCP 8.5, indicating medium and extremely high emission scenarios respectively. Generated future climate variables indicate Werie will experience a significant increase in precipitation, and maximum and minimum air temperature for both RCPs. Further, Water and Energy Transfer between Soil, Plants, and Atmosphere (WetSpa) was applied to assess the water balance of Werie River. The WetSpa model reproduced the streamflow well with performance statistics values of $R^2 = 0.84$ and 0.85, Nash-Sutcliffe efficiency $= 0.72$ and 0.72, and model bias $= -0.14$ and $-0.15$ for the calibration data set of 1999–2010 and validation data of 2011–2014 respectively. Finally, by taking the downscaled future climate variables as input, WetSpa future prediction shows that there will an increase in the Werie catchment mean annual streamflow up to 29.6% for RCP 4.5 and 35.6% for RCP 8.5 compared to the baseline period.

Key words | climate change, Ethiopia, RCP, R-programming, streamflow, WetSpa

HIGHLIGHTS
- In this study integrating AgMIP climate downscaling script in R-program with hydrological WetSpa model for prediction of catchment wide stream flow response to climate change have been proven to give acceptable results.
- Future climate change predictions for Werie catchment were analyzed using R software packages considering two emission scenarios of Representative Concentration Pathways called as RCP 4.5 and RCP 8.5.
- Future climate change assessment in Werie catchment showed a significant increase of precipitation, minimum and maximum temperatures.
- Application of a fully distributed hydrological WetSpa; Water and Energy Transfer between Soil, Plants, and Atmosphere, model in Werie catchment revealed that the model performs well to reproduce the observed stream flow values, hence can be used in similar climatic and hydrological conditions.

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In the 21st century stream flow in Werie catchment in response to climate change is expected to experience an increase during the rainy summer (June to September) season and a decrease in the dry (October to May) season.

INTRODUCTION

According to the International Panel on Climate Change (IPCC 2001, 2007) scientific assessment report, global average temperature will rise between 1.4 and 4.0 °C by 2100, relative to 1980–1990, with the doubling of the CO₂ concentration in the atmosphere. The term climate change refers to any change in climate over time, whether due to natural causes or as a result of human activities (IPCC 2001). Changes in average climate, frequency and intensity of extreme weather events are likely to have a major impact on natural and human systems (Aerts & Droogers 2004). A major effect of climate change is alterations in the hydrologic cycle and changes in water availability. Changes in evaporation and precipitation characteristics have the potential to affect runoff, frequency and intensity of floods and droughts, soil moisture, and water supplies for domestic use, irrigation and hydroelectric generation.

The IPCC (2007) findings indicate that developing countries such as Ethiopia will be more vulnerable to climate change and may have far reaching implications for various reasons; mainly the economy largely depends on agriculture, and a large part is highly prone to desertification and drought (Alemayehu & Fantahun 2012). Particularly in Africa, climate change has the potential to impose additional pressures on water availability and water demand by 2100, dryland crop net revenues could rise by 51% if future warming is mild and wet but fall by 43% if future climates are hot and dry (Seo & Mendelsohn 2008).

In Ethiopia, both instrumental and proxy records have shown significant variations in the spatial and temporal patterns of climate. According to NMA (2006), the country experienced ten wet years and 11 dry years over the past 55 years analyzed, demonstrating a strong inter-annual variability. Between 1951 and 2006, the annual minimum temperature in Ethiopia increased by about 0.37 °C every decade. The UNDP Climate Change Profile for Ethiopia (McSweeney et al. 2010) also shows that the mean annual temperature increased by 1.3 °C between 1960 and 2006, at an average rate of 0.28 °C per decade. It is reported that the average number of hot days per year has increased by 73 and the number of hot nights has increased by 137 between 1960 and 2006. Over the same period, the average number of cold days and nights decreased by 21 and 41, respectively (McSweeney et al. 2010).

The average temperature of Ethiopia has risen a little more than 1 °F during the past 100 years or so (Gene Jiing-Yun You 2010). Similarly, the results of IPCC’s mid-range emission scenario as per the NMA-NAPA (2007) show that compared to 1961–1990, the average mean annual temperature across Ethiopia will increase by between 0.9 and 1.1 °C by the year 2030 and from 1.7 to 2.1 °C by the year 2050. The temperature across the country could rise by between 2.7 and 3.6 °C by 2080. Unlike the temperature trends, it is very difficult to detect long-term rainfall trends in Ethiopia due to the high inter-annual and inter-decadal variability. A small increase in annual precipitation is expected over the country (NMA-NAPA 2007). Therefore, the projection of climate change impact on water resources of any catchment in the country should not be neglected in the future development plan.

Climate change impacts can vary between catchments even within relatively small areas. This is due to local climate depending on specific watershed processes and the difference in geophysical characteristics of watersheds. Modeling climate change impacts on hydrology on a local and national scale is needed to infer reliable estimates of the climate change impact on hydrology. The current study investigates impacts of climate change on streamflow in Werie catchment with the coupled application of AgMIP climate downscaling and project script in R-programming and the WetSpa hydrological model. The Werie river is one of the few rivers providing a source of water in
Tigray regional state, northern Ethiopia, where different water users compete, hence, there is a need to model its streamflow response to climate change. Potential impacts of climate change on water resources are usually assessed by applying climate projections (temperature and precipitation) derived from global circulation models (GCMs) using a hydrologic model (Kopytkovskiy et al. 2015). Therefore, this research tries to address how the future climate such as precipitation, maximum temperature, and minimum temperature will change compared to the present conditions and subsequently investigate the potential future impacts of climate change on the streamflow of Werie catchment. Our current study analyzes changes in precipitation, temperature, and streamflow using current GCM and downscaling approaches coupled with a watershed model. This gives great importance to understand how future conditions of local water resources may change and will enable the decision-makers to enforce appropriate adaptive strategies of the water resources.

**METHODS**

**Study area**

The Werie river is one of the largest sources of water in Tigray regional state, Ethiopia, and it is mainly used for public water supply and irrigation purposes. This river, with Tsedia, Chemit and Meseuma rivers as its main tributaries, drains into the Tekeze River basin which in turn joins the Nile in Sudan. The catchment is located at 15°43'0"–14°4'0" North and 35°50'0"–39°20'0") East (Figure 1).

Topographically, the catchment is highly vulnerable to soil erosion by water and has become eroded due to steep land features. The undulating terrain and steep slopes, fragile environment, erratic precipitation, and sparse vegetation coverage characterize it, which in turn facilitates soil erosion by water. The elevation of the catchment ranges from 1,079 to 2,494 meters above sea level (MASL)
and the mean elevation is 1,786 MASL. Werie catchment lays between Kola (low land) and Woina Dega (middle) agro-climatic zones.

**R-programming and WetSpa model**

**Climate downscaling using AgMIP in R-programming package**

R-software (Figure 2) is an integrated suite of software facilities for data manipulation, calculation and graphical display. It is an environment within which many classical and modern statistical techniques have been implemented and climate downscaling is one of the applications. Agricultural Model Inter-comparison and Improved Project (AgMIP) scenario generation scripts within the R analytical tool (Rosenzweig et al. 2012; AgMIP 2013a, 2013b) was used to generate the daily data of rainfall, minimum and maximum temperatures, by perturbing the daily baseline data (1980–2009) using the Delta method of downscaling (Ramirez-Villegas & Jarvis 2010; Navarro-Racines et al. 2020). AgMIP Climate Scenario Generation scripts are designed to load the required R-packages automatically (Hudson & Ruane 2018). The script has its own statistical analysis for quality control, filling of missing data, homogeneity analysis and projection of future temperature (maximum and minimum) and precipitation (AgMIP 2013a; Herrera 2014). Many authors, such as Ramirez-Villegas & Jarvis (2010), Abera et al. (2018, 2019) and Navarro-Racines et al. (2020), used this method to assess the impact of climate change by downscaling climate variables and then predicting future values for various applications of climate change impact assessment in Ethiopia and globally.

The Delta method downscaling approach presented here is a simple form of bias correction in which a change factor or ‘delta’ is derived from the GCM, and then added onto the observations (WorldClim). This method of downscaling works based on the sum of interpolated anomalies to high resolution monthly climate surfaces from WorldClim (Hijmans et al. 2005; Fick & Hijmans 2017) and GCM data produces a smoothed (interpolated) surface of changes in climates (deltas or anomalies) and then applies this interpolated surface to the baseline climate (from WorldClim), taking into account the possible bias due to the difference in baselines. Application of such a procedure provides a bias-corrected and high-resolution representation of the mean climates, and for this reason it employs the change factor as the difference between the long-term (30-year) mean of a climate variable in the future and the historical period. The method makes the following two gross assumptions: (1) Changes in climates vary only over large distances (i.e. as large as GCM side cell size); and (2) Relationships between variables in the baseline (‘current climates’) are likely to be maintained towards the future. The process of delta downscaling consists of the following seven steps:

1. Gathering of baseline data (current climates corresponding to WorldClim from www.worldclim.org/).
2. Gathering of full GCM timeseries.
3. Calculation of 30-year running averages for present day simulations (1980–2009) and three future periods.
4. Using Equations (1) and (2) calculation of anomalies as the ratio of absolute difference between future values in each of the three variables to be interpolated (minimum and maximum temperature, and total precipitation) against 30-year running averages for present day simulations:

\[ \Delta X_i = X_{Fi} - X_{Ci} \]  
\[ \Delta X_i = \frac{X_{Fi} - X_{Ci}}{X_{Ci}} \]  

where \( \Delta X_i \) is the delta change, \( X_{Ci} \) the 30-year mean of the variable in the current climate, and \( X_{Fi} \) the 30-year mean.
mean of the variable in the future climate of each GCM in a time $i$.

(5) Interpolation of these anomalies using centroids of GCM cells as points for interpolation.

(6) Addition of anomalies to the interpolated surfaces baseline climates from WorldClim to get the downscaled future, using absolute sum for temperatures, and addition of relative changes for precipitation.

\[
X_{DCI} = X_{OBS} + \Delta X_i
\]

\[
X_{DCI} = X_{OBS} \times (1 + \Delta X_i)
\]

where $X_{OBS}$ is the current climate from observations (i.e. WorldClim); $\Delta X_i$ is the interpolated anomaly (delta); and $X_{DCI}$ is the downscaled future climate of each GCM in the time $i$.

(7) Calculation of mean temperature as the average of maximum and minimum temperatures.

**Modeling climate change.** Climate change is the most serious problem that the whole world is facing today. It is now widely accepted that climate change is already happening and further change is inevitable. Over the last century climate variations and changes caused by external forcing may be partly predictable, particularly on the larger continental and global spatial scales. Because human activities, such as the emission of greenhouse gases or land-use change, do result in external forcing, it is believed that the large-scale aspects of human-induced climate change are also partly predictable.

In order to estimate the impacts of anthropogenic emissions on climate, a mathematical model called a global circulation model (GCM) has to be constructed of the complete climate system, which must include the atmosphere, oceans, land and cryosphere (glaciers and ice sheets). This model is a mathematical description of the earth’s climate system, first broken down into layers (both above and below sea level) and then each grid is broken down into boxes or cells. A number of research centers around the world have developed their own versions of GCMs, but all predictions contain uncertainties. For example, because future emissions of greenhouse gases are unknown, numerous emissions scenarios have been developed; therefore, different scenarios will obviously produce different results. However, the largest uncertainty arises from the models themselves. Even if each of the different GCMs uses the same emissions scenario, they will give quite different predictions due to the different ways they represent aspects of the climate system.

**Climate change scenarios.** Hydrologic models have been used to investigate the relationship between climate and water resources. GCM is an important tool and is preferred for use in the assessment of impacts of climate change. Using the climate dataset, climate variables are downscaled by 20 AgMIP general circulation models and the average result was taken because high uncertainty is expected with climate change impact studies if the simulation is a result of a single GCM (Hagemann et al. 2013). Baseline climate data was then projected to give climate characteristics including precipitation, maximum and minimum temperature of the future 90 years by dividing into three periods as near time (2010–2039), mid-time (2040–2069) and end time (2069–2099) under two scenarios which are representative concentration pathways (RCP 4.5 and 8.5). The time period for climate change was classified according to the Agricultural Model Inter-comparison and Improvement Project (AgMIP) protocol as: 1980–2009 (baseline period), 2010–2039 (near-term), 2040–2069 (mid-term) and 2070–2099 (end-term) periods respectively (Thomson et al. 2011). According to the IPCC (2014), these two scenarios indicated that in the future there will be medium and extremely high emissions of greenhouse gas, respectively.

RCP 4.5 was developed by the Global Change Assessment Model, Pacific North West National Laboratory, USA (GCAM) modeling team at the Pacific Northwest National Laboratory’s Joint Global Change Research Institute (JGCRI) in the United States. It is a stabilization scenario in which total radiative force will stabilize, without overshoot pathway in which global warming is limited up to 2 °C by the end of 2,100, to 4.5 W/m² (−650 ppm CO2 eq) at stabilization after 2,100. RCP 8.5 was developed using the MESSAGE model (Model for Energy Supply Strategy Alternatives and their General Environmental Impact) and the Integrated Assessment Framework by the International Institute for Applied Systems Analysis (IIASA), Austria. This RCP is characterized by increasing greenhouse gas
emissions over time, representative of scenarios that lead to high greenhouse gas concentration levels, i.e. rising radioactive forcing pathway leading to 8.5 W/m² (~1,370 ppm CO2 eq) by 2,100.

A paired sample t-test was used to analyze the significant changes between baseline climate data and the future predicted ones. The IBM SPSS statistics version 20 was used to perform the paired-sample t-test in between baseline and near term; baseline and mid-term; and baseline and end-term climate predictions.

Historical climate data from two different sources were used for Thiessen polygons development to compute the areal precipitation of the catchment. First, data sources were collected using the seven grid point corresponding to the towns of Beleda, Endabano, Koraro, Lalay Adihug, Menji, Maykuhli, and Tsae located within the Werie catchment while the second data source was collected from the Ethiopia Meteorology Agency for the five stations of Adwa, Abi-adi, Axum, Hawzen and Adigrat near to the catchment. Accordingly, using ArcGIS software developed Thiessen polygons the average annual precipitation of the catchment was calculated as 672 and 707 mm for the grid points and nearby stations, respectively. The average mean monthly precipitation of both station data and grid data were compared using the prepared Thiessen polygons, accordingly during Bega and Belg they are much more similar but in Kiremt season there is a small difference of 11%.

To simulate the present and future flow of the river, WetSpa (Water and Energy Transfer between Soil, Plants, and Atmosphere) was applied which is suitable for studying the impact of climate change on the hydrological behaviors of a catchment. WetSpa was calibrated and validated for the study area by using two separate sets of daily streamflow data from 1999 to 2010 and from 2011 to 2014 respectively.

WetSpa distributed hydrological model

**LULC change, climate change and WetSpa model.** Land cover/land cover map is one of the most important products of remote sensing and undergoes continuous change from time to time. It is the basic and primary input of many hydrologic models. Understanding impacts of land use/land cover change on hydrologic conditions is therefore needed for optimal management of natural resources.

Changes in global climate are the main reasons leading to an increase in frequency and magnitude of hydro-meteorological conditions, which will consequently have ramifications on ecological as well as social and economic systems. Climate variations and changes caused by external forcing may be partly predictable, particularly on the larger continental and global spatial scales. Because human activities such as the emission of greenhouse gases or land-use change do result in external forcing, it is believed that the large-scale aspects of human-induced climate change are also partly predictable (Abayneh 2011).

Hydrological models classification according to spatial representation can be either lumped or distributed. In lumped models, the entire river basin is taken as one unit where spatial variability is disregarded (Moradkhani & Sorooshian 2008). In such a modeling approach the outputs are elaborated without considering the spatial processes, patterns and organization of the catchment, whereas distributed models break the catchments fully into discrete units (Abbott & Refsgaard 1996) so the parameters, inputs, and outputs vary spatially. Some physically based spatially distributed models are the IHDM model (Calver & Woord 2001), TOPMODEL (Beven & Kirkby 1979), MIKE-SHE model (Refsgaard & Storm 1995), the WETSPA model (Wang et al. 1997), HBV model (Lindstrom et al. 1997) and SWAT model (Arnold et al. 1998). Hence, physically based spatially distributed hydrological models are an effective means to assess the impacts of climate change and/or land use/land cover change on hydrological response, as they are able to capture the spatial variability of hydrological processes throughout complex watersheds (Bathurst et al. 2004). The WetSpa model is one of the spatial hydrological models widely used to analyze the impact of land use/land cover changes on watershed surface hydrology (Liu & De Smedt 2004; Bahremand & De Smedt 2007), and climate change effects (Nurmoehamed et al. 2006; Tavakoli & De Smedt 2011; Goitom et al. 2012) on a catchment scale.

**Model structure.** Hydrological modeling provides a strong tool to investigate the impacts of land use and climate changes on water balance and hydrological processes. The WetSpa model is a spatio-temporal and GIS-based, fully distributed hydrological model for rainfall-runoff simulations at the catchment scale. It has been developed by the
The model simulates several physical processes at the raster cell level such as interception, depression storage, evapotranspiration, runoff, interflow, groundwater recharge and groundwater flow (at sub-catchment level). The simulated hydrological system consists of four control items: plant canopy cover, the soil surface, the root zone, and the saturated groundwater aquifer. Figure 3 shows schematically an overview of the model water balance at the cell level.

The total water balance for each raster cell is composed of a separate water balance for the vegetated, bare-soil, open water and impervious part of each cell. This allows accounting for the non-uniformity of the land use per cell, which is dependent on the resolution of the grid. A mixture of physical and empirical relationships is used to describe the hydrological processes in the model. The model predicts peak flows and hydrographs in any location of the channel network and the spatial distribution of hydrological characteristics in each cell. Hydrological processes in each grid cell are set in a cascading way, starting from a precipitation event. Incident rainfall first encounters the plant canopy, which intercepts all or part of the rainfall until the interception storage capacity is reached. Excess water reaches the soil surface and can infiltrate the soil zone, enter depression storage, or be diverted as surface runoff. Depression storage is subject to evaporation and further infiltration. The sum of the interception and depression storage forms the initial losses at the beginning of a storm, and does not contribute to the storm flow. For each grid cell, the root zone water balance is modeled continuously by equating inputs and outputs (Bahremand & De Smedt 2007):

\[ P = RT + ET + \Delta SS + \Delta SG \]

where \( P \) is the total precipitation in the watershed over the simulation period (mm), \( RT \) and \( ET \) are total runoff and total evapotranspiration (mm), respectively, \( \Delta SS \) is the change in soil moisture storage for the watershed between the start and the end of the simulation period (mm), and \( \Delta SG \) is the change in groundwater storage of the watershed (mm).

Assuming the cell as a reach with 1-D unsteady flow conditions and neglecting the inertial terms in the St. Venant momentum equation, the flow process in the cell can be modelled by the diffusive wave equation as (Miller & Cunge 1975):

\[ \frac{\partial Q}{\partial t} + c_i \frac{\partial Q}{\partial x} - d_i \frac{\partial^2 Q}{\partial x^2} = 0 \]
where $Q$ (m³/s) is the flow discharge at time $t$ (s) and location $x$ (m), $c_i$ is the kinematic wave celerity at cell $i$ (m/s), $d_i$ is the dispersion coefficient at cell $i$ (m²/s). Considering a system bounded by a transmitting barrier upstream and an adsorbing barrier downstream, the solution to Equation (6) at the cell outlet, when the flow velocity and diffusion coefficient are constant, can be obtained by the first passage time density distribution of a Brownian motion and expressed as (Eagleson 1970):

$$U_i(t) = \frac{l}{2\sqrt{\pi dt^2}} \exp\left(\frac{(c_it - l_i)^2}{4dt_t}\right)$$

(7)

where $u_i(t)$ is the cell impulse response function (1/s), and $l_i$ is cell size (m). Two parameters $c_i$ and $d_i$ are needed to define the cell response function, which can be estimated using the relation of Manning as (Henderson 1966):

$$l_i = \sum_{i=0}^{n} \left(\frac{1}{c_i}\right) l_i$$

and

$$\sigma^2 = \sum_{i=0}^{N} \left(\frac{2d_i}{c_i^2}\right) l_i$$

(8)

where $L$ is the size of a grid cell, which is a constant for available spatial maps. The summations presented in Equation (8) can be calculated for each grid cell as a flow length to the water outlet or any downstream converging point with standard GIS tools. The flow response at the end of a flow path, to an arbitrary input at the start, can be calculated by convolving the input runoff volume by the flow path unit impulse response function. From a physical point of view, this is equivalent to decomposing the input into infinite impulses and adding all the responses into a single response (Liu & De Smedt 2004):

$$c_i = \frac{5}{3} v_i$$

and

$$d_i = \frac{v_i R_i}{2S_i}$$

(9)

where $R_i$ is the average hydraulic radius of cell $i$ (m), $S_i$ is the cell slope (m/m), and $v_i$ is the flow velocity of the cell $i$ (m/s).

The hydraulic radius is determined by a power law relationship with an exceeding probability (Molnar & Ramirez 1998), which relates hydraulic radius to the controlling area and is seen as a representation of the average behavior of the cell and the channel geometry:

$$R_i = a_p(A_i)^{b_p}$$

(10)

where $A_i$ is the drained area upstream of the cell (km²), which can be easily determined by the flow accumulation routine in ArcView GIS, $a_p$ is a network constant and $b_p$ is a geometry scaling exponent, both depending on the discharge frequency. The flow velocity is calculated by the Manning’s equation as:

$$v_i = \frac{1}{n_i} R_i^{2/3} S_i^{1/2}$$

(11)

where $n_i$ is the Manning’s roughness coefficient (–), which depends upon land use categories and the channel characteristics, $R$ is the river channel hydraulic radius (m) and $S$ is longitudinal slope of the river bed (–). The velocity calculated by Equation (11) may be very large or even zero due to variations in land surface slope. Therefore, it is bounded between predetermined limits $v_{\text{min}}$ and $v_{\text{max}}$ during model calculation.

**Evaluation of hydrological model performance.** To evaluate how well the WetSpa model reproduces an observed hydrograph, a two-step approach is used which includes: first, a comparison of observed and simulated flow hydrographs; and second, a series of statistics criteria (Goitom et al. 2012; Desta et al. 2019). The statistical measures provide quantitative estimates for the goodness of fit between observed and simulated river flows and are used as indicators of the extent at which model predictions match observations (Liu & De Smedt 2004). The statistical criteria used in the distributed model performance analysis are model bias (MB), reflecting the ability of reproducing the water balance, the modified correlation coefficient ($r_{\text{mod}}$), which reflects differences both in hydrograph size and in hydrograph shape, and the Nash–Sutcliffe efficiency (NSE), which evaluates the ability of reproducing the streamflow hydrograph (Nash & Sutcliffe 1970), given by the following expressions.

CR1 – model bias. Model bias measures the systematic under or over prediction for a set of predictions (Gupta et al. 1999; Moriasi et al. 2015). A lower CR1 value indicates a better fit, and the value 0 represents the perfect simulation.
of observed flow volume:

\[
CR_1 = \frac{\sum_{i=1}^{N} (Q_{s,i} - Q_{o,i})}{\sum_{i=1}^{N} Q_{o,i}}
\]  

(12)

CR2 – model confidence. CR2 represents the proportion of the variance in the observed discharges that are explained by the simulated discharges (Moriasi et al. 2015). It varies between 0 and 1, with a value close to 1 indicating a high level of model confidence:

\[
CR_2 = \frac{\sum_{i=1}^{N} (Q_{s,i} - \bar{Q}_{o})^2}{\sum_{i=1}^{N} (Q_{o,i} - \bar{Q}_{o})^2}
\]  

(13)

CR3 – Nash–Sutcliffe efficiency. The Nash–Sutcliffe efficiency (Nash & Sutcliffe 1970) varies from a negative value to 1, with 1 indicating a perfect fit between observed and simulated hydrographs. When CR3 is below zero, it indicates that the average observed streamflow would have been as good a predictor as the modeled streamflow:

\[
CR_3 = 1 - \frac{\sum_{i=1}^{N} (Q_{s,i} - Q_{o,i})^2}{\sum_{i=1}^{N} (Q_{o,i} - \bar{Q}_{o})^2}
\]  

(14)

CR4 – model efficiency (low flows). CR4 is logarithmic Nash–Sutcliffe efficiency for evaluating the ability of reproducing the time evolution of low flows (Nash & Sutcliffe 1970). Similar to CR3, a perfect value of CR4 is 1:

\[
CR_4 = 1 - \frac{\sum_{i=1}^{N} [\ln(Q_{s,i} + \varepsilon) - \ln(Q_{o,i} + \varepsilon)]^2}{\sum_{i=1}^{N} [\ln(Q_{o,i} + \varepsilon) - \ln(\bar{Q} + \varepsilon)]^2}
\]  

(15)

CR5 – model efficiency (high flows). CR5 is an adapted version of the Nash–Sutcliffe criterion for evaluating the ability of reproducing the time evolution of high flows (Nash & Sutcliffe 1970). A perfect value of CR5 is 1:

\[
CR_5 = 1 - \frac{\sum_{i=1}^{N} (Q_{o,i} - \bar{Q}) (Q_{s,i} - Q_{o,i})^2}{\sum_{i=1}^{N} (Q_{o,i} - \bar{Q}) (Q_{o,i} - \bar{Q})^2}
\]  

(16)

where \(Q_{o,i}\) and \(Q_{s,i}\) are, respectively, the observed and simulated river discharge at time step \(i\), \(N\) is the number of time steps over the simulation period, and the bar above the variables means the average for the simulation period, and \(\varepsilon\) is an arbitrary chosen small value introduced to avoid problems with nil observed or simulated river discharges.

In this study the physically GIS-based fully distributed watershed model, WetSpa (developed for simulation of rainfall-streamflow processes in the catchment scale) was applied to simulate the hydrological process and, in a specific objective, the streamflow result for Werie catchment. To evaluate hydrological model performance, it is necessary to make sure that the result of Nash–Sutcliffe efficiency exceeding 0.85 is categorized as excellent and between 0.65 and 0.85 is very good, while an NSE value of less than 0.5 is an indication of unsatisfactory or very poor model performance. Table 1 shows the model performance categories usually used to indicate the goodness level of observed streamflow against the model simulated (Alireza et al. 2009; Porretta-Brandyk et al. 2011; Safari et al. 2012; Azizi et al. 2018).

**R and WetSpa models integration**

The assessment of streamflow response to climate change in Werie catchment is performed by using both coupled application of R-software package for climate projection and the

| Range of \(R^2\) | Range of \(C_1\) | Range of \(C_2\) | Aggregated measures (AM) |
|-----------------|-----------------|-----------------|--------------------------|
| \(0.99 \leq R^2 < 1.00\) | \(<0.05\) | \(>0.85\) | Excellent |
| \(0.95 \leq R^2 < 0.99\) | \(0.05-0.10\) | \(0.65-0.85\) | Very good |
| \(0.80 \leq R^2 < 0.95\) | \(0.10-0.20\) | \(0.50-0.65\) | Good |
| \(0.70 \leq R^2 < 0.80\) | \(0.20-0.40\) | \(0.20-0.50\) | Satisfactory/poor |
| \(R^2 < 0.70\) | \(>0.40\) | \(<0.20\) | Unsatisfactory/very poor |
calibrated WetSpa distributed hydrological model. The WetSpa model is first calibrated using observed data from 1999 to 2010 and then after observing good performance validation is done with distinct data from 2011 to 2014 to determine the reliability of the model for the study area. Finally, the streamflow response to climate change impact of Werie river is modeled using the outputs of the predicted climate variables from R software and predicting future streamflow of the river by applying the calibrated WetSpa model. A schematic illustration of coupled application of R and WetSpa models for predicting climate change impact on streamflow of the Werie catchment is depicted in Figure 4.

Data used

The basic data sets that are required to develop an input database for the two models are climate, streamflow, and digital elevation model (DEM), land use/landcover maps, and soil maps. The digital elevation model (DEM), land use/landcover map, and soil map of Werie catchment are shown in Figure 5. Daily precipitations and maximum and minimum temperatures are used. Further, spatial data of precipitation, maximum and minimum temperature, solar radiation, relative humidity, and wind speed data were obtained from WorldClim, available at www.worldclim.org/ (Fick & Hijmans 2017) for inter-compression of GCMs. These data are grid data set at different spatial resolutions and they are re-gridded to a common resolution of 5 km. Seven grid point weather stations are selected from the catchment for comparison against the RCP climate variables during the downscaling process using base line (1980–2014) weather data.

The daily potential evapotranspiration (PET) time-series data were calculated through the use of the Hargreaves equation (Allen et al. 1998). The double mass curve method was used for consistency testing in this study to assess the quality of the data and it was finally used as an input to the WetSpa hydrological model (Searcy & Hardison 1960). Additionally, hydrological daily streamflow data was required for calibrating and validation of the WetSpa model.

Figure 4 | Flow chart of R and WetSpa models integration.
A digital elevation model (DEM) of $30 \times 30$ m grid size, obtained from ASTER dataset of the National Aeronautics and Space Administration (NASA), and a land use map derived from two $30$ m grid size Landsat ETM+ images covering the study area were obtained from the official website of the United States Geological Survey (USGS). Moreover, major soil map data in the catchment were obtained from Tekeze Basin soil map.

To generate the future climate change of the study area, a delta based statistical downscaling approach of phase five coupled model inter-comparison (CMIP5) was used in R software, version 3.4.2. The Agricultural Model Intercomparison and Improvement Project (AgMIP) guidelines and scripts were used to run the model in ‘R’ software. The packages (‘R-Matlab’, ‘R-methodsS3’, ‘R-oo’, and ‘R-utils’) were installed in ‘R’ software for downscaling and projection.

RESULTS

Statistical downscaling

The GCM output was downscaled with the delta method using the baseline data of 1980–2009. The downscaled data consists of three future climate periods; 2010–2039 near time period, 2040–2069 mid-time period and 2070–2099 end-time period. The GCM output data are precipitation, minimum and maximum temperature.

Predicted changes in future precipitation

Generally, the future precipitation projections showed an increasing trend for both representative concentration pathways (Figure 6). The results indicated that there is a higher increase in RCP 8.5 than RCP 4.5 in all-time horizons.

Under the two RCPs comparing all stations, the precipitation increase in Menj will be high and there is a lower increase in Tsae. In order to investigate the changes in seasonal precipitation of the catchment, Figure 6 is structured based on the seasons in Ethiopia; such as: Kiremt: June, July, August and September (JJAS), Belg: February, March, April and May (FMAM), Bega: October, November, December and January (ONDJ).

Predicted future temperature

The maximum temperature projection result indicated that in Werie catchment’s future there will be higher maximum temperatures compared to the baseline period under both RCP 8.5 and RCP 4.5 scenarios.

The graphical trend of the maximum temperature predictions is depicted in Figure 7. It is found that under the RCP 4.5
scenario, maximum temperature will rise by 3.5 °C (13%) in near-future, by 4.4 °C (16%) in mid-future and by 4.8 °C (17%) in end-future, with respect to the baseline value. Similarly, under the RCP 8.5 scenario compared to the baseline period an increase in maximum temperature by 3.6 °C (13%), 5 °C (18%) and 8 °C (28%) in the near-future, mid-future and end-future periods respectively is expected.

Moreover, the minimum temperature projection result indicated that similar to the maximum temperature there will also be an increase in minimum temperature compared to the baseline period under both RCP 4.5 and RCP 8.5 scenarios.

As is depicted in Figure 8, it was found that under RCP 4.5 scenario minimum temperature will rise by 5.8 °C in near-future, 6.8 °C in mid-future and 8.8 °C in end-future with respect to the baseline value. Similarly, under the RCP 8.5 scenario compared to the baseline period, an increase in minimum temperature by 3.6 °C (13%), 5 °C (19%) and 8 °C (28%) in the near-future, mid-future and end-future periods respectively is expected.

Figures 7 and 8 clearly show that under both RCP 4.5 and RCP 8.5 scenarios, the increase in minimum and maximum air temperature is predicted in all the seven towns of Beleda, Endabano, Koraro, Layaladihug, Maykuhli, Menji and Tsea considered in the study.

Future changes in average temperature

According to the temperature scenarios generated (Figure 9), a change of the average temperature in percent showed an increase in all stations.

The range of percentage increase in average mean temperature under RCP 4.5 scenario is from 3.4% (September) to 10.9% (November) in Tsae and Maykuhli respectively at near term, from 7.6% (February) to 11.0% (November) in Koraro and Maykuhli respectively at midterm and from 7.2% (September) to 13.2% (November) in Koraro and Maykuhli respectively at end term.

For the RCP8.5 scenario the range of percentage increase in average mean temperature is from 2.36% (June) to 13.72% (December) in Koraro and Tsae respectively at near term, from 8.39% (September) to 16.44% (October) in Tsae and Beleda respectively at midterm and from 14.48% (March) to 23.59% (December) in Koraro and Tsae respectively at end term.

Results from both scenarios revealed that future temperatures will generally increase consistently across the
entire catchment and all the three-future periods. This result is in line with most studies undertaken in northern Ethiopia (Abayneh 2011; Alemayehu & Fantahun 2012; Goitom et al. 2012; Abera et al. 2018, 2019).

**Wetspa model calibration and validation**

For the modeling process of Wetspa, appropriate model calibration and validation were undertaken. The hydro-meteorological data were deliberately divided into two sets of duration extending from 1999 to 2009, and from 2010 to 2014 to be used for independent calibration and the validation process respectively. Hence, data recorded within a similar time scale for all the meteorological parameters and spatial data derived from the base maps of topography, land use, and soil texture were used for calibration as well as validation in the modeling processes.

The calibration and validation of Wetspa model were implemented by observing the graphical fitness between simulated and observed discharges and through the use of model performance evaluating criteria. The calibration process was performed by changing global model parameters of interflow scaling factor, baseflow recession coefficient, evapotranspiration coefficient, initial soil moisture,

![Graph showing future maximum temperatures prediction under RCP 4.5 and RCP 8.5 scenarios.](image)

**Figure 7** | Future maximum temperatures prediction under RCP 4.5 and RCP 8.5 scenarios.
groundwater storage, surface runoff exponent and rainfall intensity threshold, which are relevant to the study area (Table 2). Threshold melt temperature, melt-rate factor and rainfall melt-rate factors, which are related to snowmelt parameters, were not considered in the calibration process as such processes do not exist in the Werie catchment. In both cases the statistical and graphical comparisons of the observed and simulated discharge hydrographs have confirmed that WetSpa model is calibrated well in the modeling process. This calibration result was obtained manually with a repetitive trial and error to obtain the best possible fit of simulated values of the model against the observed values while the model global parameters were maintained in the range.

Both visual and statistical comparisons for the observed and simulated daily flow hydrographs at the station were performed for the calibration period of the model (Figure 10).

The visual and statistical comparisons for the observed and simulated daily flow hydrographs were performed for the validation period (Figure 11).

The statistical model performance evaluation results for both calibration and validation processes are indicated in Table 3. Model bias (MB), model confidence ($R^2$) and Nash–Sutcliffe efficiency (NSE) model performance criteria were evaluated. Accordingly, the calculated values of these model performance criteria are very close to their optimum best fit values. So far, the model can be
After having calibrated the WetSpa model, using the corresponding global model parameters, the water balance components were estimated based on the measured input parameters to the model. The daily precipitation, evapotranspiration, and runoff for the separate calibration and validation periods were used as input hydro-meteorological parameters in addition to the spatial catchment gridded maps from which the water balance parameters and spatial grid maps were simulated. Total interception, surface runoff, infiltration, percolation, actual evapotranspiration, interflow, groundwater drainage, soil moisture storage, and groundwater storage were then simulated for the catchment.

From Table 4 we can understand that the water balance in the catchment for the calibration period of the

| Parameters                                      | Symbol  | Value range | Calibrated value |
|-------------------------------------------------|---------|-------------|------------------|
| Interflow scaling factor (--)                  | $K_i$   | 0–10        | 0.5              |
| Groundwater recession coefficient (d–1)        | $K_g$   | 0–0.05      | 0.036            |
| Initial Soil Moisture (mm)                     | $K_{ss}$| 0–7–1.25    | 0.78             |
| Correction factor for PET (–)                  | $K_{ep}$| 0–1.5       | 0.97             |
| Initial active groundwater storage (mm)        | $G_0$  | 0–300       | 67.6             |
| Maximum active groundwater storage (mm)        | $G_{max}$| 50–3,000   | 107.85           |
| Threshold melt temperature (°C)                | $T^*$   | –1 to 1     | –1               |
| Melt-rate factor (mm °C$^{-1}$d$^{-1}$)         | $K_{snow}$| –1 to 2  | –1               |
| Rainfall melt-rate factor (°C$^{-1}$d$^{-1}$)   | $K_{rain}$| –1 to 1   | –1               |
| Moisture or surface runoff exponent (–)        | $K_{run}$| 1–8       | 2.26             |
| Maximum rainfall intensity (m)                 | $P_{max}$| 10–500     | 178.47           |
model constitutes 64% (4,796 mm) of the total precipitation is lost through evapotranspiration, 37% (2,800 mm) through runoff and 1% (92 mm) through percolation while the soil moisture reduced by 1% (~86 mm). It is also evident that the estimated total runoff value of 2,800 mm constitutes 2,580 mm (92%) surface runoff,
44 mm (1.6%) interflow and 176 mm (6%) groundwater flow, respectively.

**Streamflow prediction under climate change**

Annual mean streamflow for all time periods and scenarios considered showed that the flow will increase in the future. Streamflow will increase by 25, 24 and 27% in the periods of near, mid and end future respectively for RCP 4.5. Similarly, for the RCP 8.5 scenario, the results revealed that Werie streamflow will increase by 35, 26 and 36% for the near, mid and end future periods respectively.

**DISCUSSION**

**Climate change**

The climate change scenarios produced for this study were based on the outputs of GCM results established on the representative concentration pathways. The downscaled data consists of three future climate scenario periods that are near time period (2010–2039), mid-time period (2040–2069) and end-time period (2070–2099). The GCM output data are precipitation, minimum and maximum temperature. Both RCP 4.5 and RCP 8.5 emission scenarios consistently show future precipitation will experience an increase, however, the results indicated that there is a higher increase for the RCP 8.5 scenario compared with the RCP 4.5 in all-time horizons. Similarly, both the maximum and minimum temperatures will also increase in both emission scenarios with a higher increase in temperature being in RCP 8.5 scenario than RCP 4.5. Further, future temperatures have generally increased with the time period in both RCPs. Many similar studies also clearly indicated that minimum and maximum temperatures are expected to increase in the future (Abayneh 2011; Alemayehu & Fantahun 2012; Goitom et al. 2012; Abera et al. 2018, 2019).

From the WetSpa model results, the catchment is covered by 26% open shrub lands, 39.5% cropland, 15.2% bare land, 16.8% urban/built-up and 2.3% water bodies. The increments of both precipitation and temperature are the result of reduction of forests, open grass, croplands, and shrub lands.

**WetSpa model performance**

WetSpa model evaluation on the catchment, as indicated in Table 3 above, for the calibration period the model performs

**Table 3** | Model performance evaluation results for calibration and verification of WetSpa

| Period            | Model bias | $R^2$  | NSE  |
|-------------------|------------|--------|------|
| Calibration (1999–2009) | −0.14      | 0.84   | 0.744 |
| Validation (2010–2014)  | −0.15      | 0.81   | 0.720 |
| Optimum           | 0          | 1      | 1    |

**Table 4** | Water balance of the WetSpa model results

| Water balance Components | Calibration period (1999–2009) | Validation period (2010–2014) |
|--------------------------|---------------------------------|--------------------------------|
|                          | Total (mm) | Annual mean (mm/year) | Share % | Total (mm) | Annual mean (mm/year) | Share % |
| Precipitation            | 7,481      | 680                  | 100     | 339        | 679                  | 100     |
| Surface runoff           | 2,580      | 234                  | 34      | 1,201      | 240                  | 35      |
| Interflow                | 44         | 4                    | 1       | 19         | 4                    | 1       |
| Groundwater flow         | 176        | 16                   | 2       | 76         | 15                   | 2       |
| Total runoff (RT)        | 2,800      | 254                  | 37      | 1,297      | 259                  | 38      |
| Soil moisture storage ($\Delta SS$) | −86       | −8                   | −1      | −124       | −25                  | −4      |
| Evapotranspiration (ET)  | 4,796      | 436                  | 64      | 2,088      | 418                  | 61      |
| Groundwater storage ($\Delta SG$) | 92        | 8                    | 1       | 77         | 15                   | 2       |
| Summation of water balance components (RT + ET + $\Delta SS$ + $\Delta SG$) | 7,602 | 691 | 101 | 3,336 | 667 | 98 |
very well with overall NSE of 0.74. Similarly, the model validation results revealed that WetSpa model can reproduce the flow with overall NSE of 0.72. Hence, application of the WetSpa model for rainfall-streamflow simulation, flood prediction, and water balance assessment for Werie catchment in Northern Ethiopia gives a reliable result.

Streamflow response to climate change

In this paper, the response of streamflow to climate change has been assessed for Werie catchment in northern Ethiopia. Future percentage changes in the monthly mean of river flow, depicted in Figure 12, indicate the flow of the river will increase in the summer wet season which extends from June to September, whereas it will predominantly decrease in the dry season (October–May). This is consistent with the findings of similar studies at upper Guder catchment in north Ethiopia (Fentaw 2010). In many regions, changing precipitation or melting snow and ice are altering water resources in terms of quantity and quality. The result of climate change prediction clearly shows there will be an increment of precipitation over the Werie catchment with both RCP 4.5 and RCP 8.5 scenarios. Precipitation is higher in RCP 8.5 than RCP 4.5.
The increase in precipitation increases streamflow in the Werie catchment

CONCLUSIONS

Climate change predictions for the 21st century in Werie catchment showed that there will be a significant increase in precipitation, and minimum and maximum air temperatures, for both RCPs.

Application of Water and Energy Transfer between Soil, Plants, and Atmosphere (WetSpa), a fully distributed hydrological model in Werie catchment revealed that the model performs well to reproduce the observed streamflow values, hence it can be used in catchments of similar climatic and hydrologic conditions.

Werie will experience an increase in streamflow during the rainy summer season (June–September) and a decrease in the dry season (October–May). Most of the annual flow occurs in the wet summer season, hence, the streamflow in Werie catchment will increase due to future climate change, which includes an increase in both precipitation and air temperature.

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DATA AVAILABILITY STATEMENT

Data cannot be made publicly available; readers should contact the corresponding author for details.

REFERENCES

Abayneh, A. 2011 Evaluation of Climate Change Impact on Extreme Case Study: Addis Ababa and Surrounding Catchment. Addis Ababa University, Addis Ababa, Ethiopia. Abbott, M. B. & Refsgaard, J. C. 1996 Distributed Hydrological Modelling. Kluwer Academic Publishers, The Netherlands.

Abera, K., Crespo, O., Seid, J. & Mequanent, F. 2018 Simulating the impact of climate change on maize production in Ethiopia, East Africa. Environ. Syst. Res. 7, 1–12.

Abera, E. A., Getnet, M. & Ngatu, L. 2019 Impacts of climate change on bread wheat (Triticum aestivum L) yield in Adet, northwestern Ethiopia. J. Pet. Environ. Biotechnol. 10, 396. doi: 10.35248/2157-7463.19.10.396.

Aerts, J. & Droogers, P. 2004 Climate Change in Contrasting River Basins: Adaptation Strategies for Water, Food, and Environment. CAB International, Wallingford, UK, p. 288.

AgMIP 2015a Guide for Running AgMIP Climate Scenario Generation Tools with R in Windows. Center for Climate Systems Research, Earth Institute, Columbia University, AgMIP, New York, USA.

AgMIP 2015b The Agricultural Model Inter-Comparison and Improvement Project (AgMIP): Guide for Regional Integrated Assessments; Handbook of Methods and Procedures, Version 5. Center for Climate Systems Research, Earth Institute, Columbia University, AgMIP, New York, USA.

Alemayehu, K. & Fantahun, T. 2012 The effect of climate change on ruminant livestock population dynamics in Ethiopia. Livestock Res. Rural Dev. 24 (10), 185.

Allen, R. G., Pereira, L. S., Raes, D. & Smith, M. 1998 Cropl Evapotranspiration – Guidelines for Computing Crop Water Requirements. FAO Irrigation & Drainage Paper 56. FAO, Rome.

Arnold, J. G., Srinivasan, R., Mutthia, R. R. & Williams, J. R. 1998 Large area hydrologic modeling and assessment. Part I: model development. J. Am. Water Resour. Assoc. 34 (1), 73–89.

Ateya, K. & Abdolreza, B. 2011 Water balance of Gorganrood river basin East of Iran, Department of Watershed Management, Science and Research Branch, Islamic Azad University, Tehran, Iran. Afr. J. Agric. Res. 6 (25), 5591–5599.

Azizi, M., Mohajerani, A. & Akhavan, M. 2018 Simulating and prediction of flow using by WetSpa model in Ziyarat River Basin, Iran. Open J. Geol. 8, 298–312. https://doi.org/10.4236/ojg.2018.83019.

Bahremand, A. & De Smedt, F. 2007 Distributed hydrological modeling and sensitivity analysis in Torsya Watershed, Slovakia. Water Resour. Manage. 22, 393–408.

Beven, K. J. & Freer, J. 2001 Equifinality, data assimilation, and uncertainty estimation in mechanistic modelling of complex environmental systems. J. Hydrol. 249, 11–29.

De Smedt, F., Liu, Y. B. & Gebremeskel, S. 2000 Hydrological modeling on a catchment scale using GIS and remote sensed land use information. In: Risk Analysis II (C. A. Brebbia, ed.). WTI Press, Boston, pp. 295–304.

Desta, Y., Goitom, H. & Aregay, G. 2019 Investigation of runoff response to land use/land cover change on the case of Aynamel catchment, North of Ethiopia. J. Afr. Earth Sci. 155, 130–143. doi:10.1016/j.jafrearsci.2019.02.025.

Eagleson, P. S. 1970 Dynamic Hydrology. McGraw-Hill Publishers, New York, p. 462.

Fentaw, F. 2010 Assessment of Climate Change Impacts on the Hydrology of Upper Guder Catchment, Upper Blue Nile. Addis Ababa University, Addis Ababa, Ethiopia.
Fick, S. E. & Hijmans, R. J. 2017 Worldclim 2: new 1 km spatial resolution climate surfaces for global land areas. Int. J. Climatol. 37 (12), 4302–4315.

Fowler, H. J., Blenkinsop, S. & Tebaldi, C. 2007 Linking climate change modeling to impacts studies: recent advances in downscaling techniques for hydrological modeling. Int. J. Climatol. 27 (12), 1547–1578.

Gene Jiing-Yun You, C. R. Gupta, H. V., Sorooshian, S. & Yapo, P. O. 2009 Status of automatic calibration for hydrologic models: comparison with multilevel expert calibration. J. Hydrol. Eng. 4, 135–143.

Hagemann, S., Chen, C., Clark, D., Felow, S., Gosling, S. N., Haddeland, I. & Wiltshire, A. 2013 Climate change impact on available water resources obtained using multiple global climate and hydrology models. Earth Syst. Dynam. 4, 129–144.

Henderson, F. M. 1966 Open Channel Flow. McMillan, New York, p. 522.

Herrera, L. Z. 2014 RClimTool User Manual. Clima y sector agropecuario Colombiano, Colombia, p. 17.

Hijmans, R. J., Cameron, S. E., Parra, J. L., Jones, P. G. & Jarvis, A. 2005 Very high-resolution interpolated climate surfaces for global land areas. Int. J. Climatol. 25 (15), 1965–1978.

Hudson, N. I. & Ruane, A. C. 2015 Guide for Running AgMIP Climate Scenario Generation Tools with R in Windows (Appendix 2), Version 2.3. Columbia University, New York, USA.

Intergovernmental Panel on Climate Change IPCC. 2001 Climate change 2001: the scientific basis. In: Contribution of Working Group I to the Third Assessment Report of the Intergovernmental Panel on Climate Change (J. T. Houghton, Y. Ding, D. J. Griggs, M. Noguer, P. J. van der Linden, X. Dai, K. Maskell & C. A. Johnson, eds). Cambridge University Press, Cambridge, UK and New York, NY, USA, p. 881.

Intergovernmental Panel on Climate Change IPCC. 2007 Synthesis Report. Contribution of Working Groups I, II and III to the Fourth Assessment Report of the Intergovernmental Panel on Climate Change. Intergovernmental Panel on Climate Change, Geneva. Available from www. IPCC. ch/IPCC reports/ar4-syr.

Intergovernmental Panel on Climate Change IPCC. 2014 Impacts, adaptation, and vulnerability. Part B: regional aspects. In Contribution of Working Group II to the Fifth Assessment Report of the Intergovernmental Panel on Climate Change, Cambridge University Press, New York, USA.

Kopytovskiy, M., Gezah, M. & McCray, J. E. 2015 Climate-change impacts on water resources and hydropower potential in the Upper Colorado River Basin. J. Hydrol. Reg. Stud. 3, 473–493.

Liu, Y. B. & De Smedt, F. 2004 WetSpa Extension, A GIS-Based Hydrological Model for Flood Prediction and Water Management, Documentation and User Manual. Department of Hydrology and Hydraulic Engineering, Vrije University Brussels, Belgium.

Liu, Y. B., Gebremeskel, S., De Smedt, F., Hoffmann, L. & Pfister, L. 2005 A diffusive transport approach for flow routing in GIS-based flood modelling. J. Hydrol. 285, 91–106.

McSweeney, C., New, M. G., Lizzano, G. & Lu, X. 2010 The UNDP climate change country profiles: improving the accessibility of observed and projected climate information for studies of climate change in developing countries. Bull. Am. Meteorol. Soc. 91 (2), 157–166.

Miller, W. A. & Cunge, J. A. 1975 Simplified equations of unsteady flow in open channels. In: Unsteady Flow in Open Channels, Vol. II (K. Mahmood & V. Yevjevich, eds). Water Resources Publications, Fort Collins, CO.

Moradkhani, H. & Sorooshian, S. 2008 General review of rainfall-runoff modeling: model calibration, data assimilation, and uncertainty analysis. In: Hydrological Modelling and the Water Cycle (V. P. Singh, ed.). Springer, Berlin, Heidelberg, p. 291.

Moriais, D. N., Gitau, M. W., Pai, N. & Daggupati, P. 2015 Hydrologic and water quality models: performance measures and evaluation criteria. Trans. ASABE 58, 1763–1785.

Nash, J. E. & Sutcliffe, J. V. 1970 River flow forecasting through conceptual models, part 1. A discussion of principles. J. Hydrol. 10, 282–290.

National Meteorology Agency NMA 2006 Agro-meteorology Bulletin. National Meteorology Agency, Ministry of Water Resources, Addis Ababa, Ethiopia.

Navarro-Racines, C., Tarapues, J., Thornton, P., Jarvis, A. & Ramirez-Villegas, J. 2020 High-resolution and bias-corrected CMIP5 projections for climate change impact assessments. Sci. Data 7 (1), 7. doi:10.1038/s41597-019-0343-8.

NMA-NAPA 2007 Climate Change National Adaptation Program of Action (NAPA) of Ethiopia. Ministry of Water Resources, Addis Ababa, Ethiopia.

Nurmomamed, R., Naipa, S. & De Smedt, F. 2006 Modeling hydrological response of the Upper Suriname river basin to climate change. J. Spatial Hydrol. 7 (1), 1–22.

Ramirez-Villegas, J. & Jarvis, A. 2010 Downscaling Global Circulation Model Outputs: The Delta Method Decision and Policy Analysis Working Paper No. 1. International Centre for Tropical Agriculture, CIAT, Cali, Colombia.

Refsgaard, J. C. & Storm, B. 1995 Mike she. In: Computer Models of Watershed Hydrology (V. P. Singh, ed.). Water Resources Publications, Highlands Ranch, Colorado, pp. 809–846.

Rosenzweig, C., Jones, J. W., Hatfield, J. L., Ruane, A. C., Boote, K. J., Thorburn, P., Antle, J. M., Nelson, G. C., Porter, C., Janssen, S., Asseng, S., Basso, B., Ewert, F., Wallach, D., Baigorria, G. & Winter, J. M. 2012 The agricultural model intercomparison and improvement project (AgMIP): protocols and pilot studies. Agric. For. Meteorol. 170, 166–182. https://doi.org/10.1016/j.agrformet.2012.09.011.
Safari, A., De Smedt, F. & Moreda, F. 2012 Wetspa model application in the distributed model intercomparison project (DMIP2). *J. Hydrol* 418–419, 78–89. doi:10.1016/j.jhydrol.2009.04.001.

Searcy, J. K. & Hardison, C. H. 1960 *Double-mass Curve*. United States Government Printing Office, Washington, DC, USA.

Seo, S. N. & Mendelsohn, R. 2008 Measuring impacts and adaptations to climate change: a structural ricardian model of african livestock management. *Agric. Econ.* 38 (2), 151–165.

Tavakoli, M. & De Smedt, F. 2011 Impact of climate change on streamflow and soil moisture in the Vermilion basin, Illinois, USA. *J. Hydrol. Eng.* 17 (10), 1059–1070. doi:10.1061/(ASCE)HE.1943-5584.0000546.

Thomson, A. M., Calvin, K. V., Smith, S. J., Kyle, G. P., Volke, A., Patel, P., Delgado-Arias, S., Bond-Lamberty, B., Wise, M. A. & Clarke, L. E. 2011 RCP4.5: a pathway for stabilization of radiative forcing by 2100. *Clim. Chang.* 109 (1–2), 77. doi: 10.1007/s10584-011-0151-4.

Wang, Z., Batelaan, O. & De Smedt, F. 1997 A distributed model for water and energy transfer between soil, plants and atmosphere (WetSpa). *Phys. Chem. Earth* 21, 189–193.

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