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Hydroclimate Impact Analyses and Water Management in the Central Rift Valley Basin in Ethiopia

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Abstract: This study explores the impacts of climate change on the major components of the water balance such as surface runoff (Q), water yield (WY), and evapotranspiration (ET) in the Central Rift Valley Basin (CRVB) in Ethiopia. Projected climate data from the climate emission scenarios were used for the analyses. Representative concentration pathway (RCP) data from the MIROC-RCA4 ensemble driving climate models were downscaled, bias-corrected, and applied for impact analyses. Climate scenario analyses for the near-term (2031–2060) and long-term (2070–2099) periods were used to assess the conditions of the water balance components. The endo hydrogenic CRVB was divided into three sub-basins, and their respective hydroclimatic impacts were simulated separately with calibrated Arc-SWAT models. The future impacts simulated on the annual average basis vary in their maximum ranges from −65.2% to +85.8% in Q, from −42.2% to +23.9% in WY, and from −4.1% to +17.3% in ET compared to the baseline data outputs in the individual sub-basin. Water management options according to the water balance sensitivities to the climate impacts were proposed for each of the sub-basins. SWAT-based studies aimed at balanced water resources management in combination with agricultural practices within the CRVB are recommended for future research.

Keywords: Arc-SWAT; climate change; climate scenario; water balance sensitivity; water management

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1. Introduction

Sub-Saharan Africa is a region that is very sensitive to, and is highly affected by recurrent droughts, flooding, and untimely weather conditions. Floods and droughts have affected water supplies and have set a challenge for water management. At the same time, water management practices in these developing regions are not adequate for dealing with the challenges of significant changes in climate [1–4]. Increasing pressure on land and water resources due to population growth and human activities have also resulted in the degradation of vulnerable ecosystems and in reduced biodiversity [4–6]. Moreover, this degradation of ecosystems hinders the potential use of ecosystem services [7].

In addition, climate change is a driver of many societal and environmental problems of the 21st century [8,9]. Together with the impacts of population growth, it puts pressure on the management of natural resources such as water resources [5,10]. It can also alter the hydrological cycle, resulting in large-scale impacts on water availability. These impacts could be temporal or become permanent. Climate change can also affect the temporal conditions of the water balances [11]. Water balances are components of the water cycle that exist at different scales and in different conditions in each locality. They are highly affected by the state of the environment and by the climate. Climate change highly affects the water balance conditions both spatially and temporally at the local or regional scale. For instance, Africa is vulnerable to inter-annual climate variations due to the El-Niño southern oscillations [12,13]. To evaluate the conditions of water resources in a basin or region, it is essential to know the water balance conditions under certain circumstances. The water balance components may vary due to different spatial and temporal aggregations, reference periods, and climate change impacts, as well as the interventions of humans for the purpose of water use [14].

Climate change refers to changes in conditions such as temperature and rainfall over long periods of time in a region. It has been caused by the increasing concentration of greenhouse gases (GHGs) in the atmosphere since the pre-industrial era. The Intergovernmental Panel on Climate Change (IPCC) concluded that more than 90% of the accelerated warming of the past five decades has been caused by the industrial release of GHGs such as CO_2 into the atmosphere [15].

In the CRVB, there are high levels of rainfall variability, water scarcity, and weather variability, and it is a place where water resources planning and management are greatly challenged by the impacts of climate change [16]. For example, an increase in temperature and variability in rainfall affected the seasonal and total water supply and led to the occurrence of extreme hydrological events [17]. It is therefore essential to know the trend of climate change over a long period of time to manage possible extreme hydrological events, either droughts or flooding, in the region [15,18–20].

A climate impact study can also provide a reliable basis for water resources planning [21]. Nowadays, long-term water resources planning studies need to take into consideration ongoing and future global climate changes in order to curb the uncertainties in the management of water resources [22]. In such studies, the effects of climate change must be quantified with high spatial and temporal resolutions at basin scale [1,23–25].

Various studies have been carried out on the water resources of the Central Rift Valley Basin (CRVB) in an attempt to describe and evaluate the impact of climate change on existing water resources [16,26–30]. However, only a few of these studies have been aimed at analyzing the impacts of climate change based on various regional concentration pathway (RCP) simulations in different climate scenarios to evaluate the conditions of the components of the water balance in the sub-basins. For example, in Ethiopia, Legesse et al. (2003) used the Precipitation Runoff Modeling System (PRMS) model to simulate runoff, and they predicted a 30% decrease in runoff in response to a 10% decrease in the amount of precipitation [26,31]. A 1.5 °C increase in temperature resulted in a 15% decrease in runoff [32]. Similarly, it was indicated that a higher temperature leads to an increase in evaporation rates, reductions in stream flow, and an increase in the frequency of droughts [28]. In addition, a vast number of studies have been conducted to analyze the impacts of climate change on crop productions [17,18,33–35]. However, very little consideration has been given to the potential impact of climate change on the current and future water balance components in the region and on their management methods. Therefore, a deep understanding of the effects of climate change on the components of the water balance for identifying site-specific climate-smart agricultural water management measures is necessary. In this context, the findings of this study can contribute the input information for the purpose of agricultural water management in the CRVB to adapt to the impacts of climate change.

An analysis of the impact of climate change on the components of the water balance involves hydrological models and projected plausible future climate change variables from global circulation models (GCMs) [23,36–38]. The GCMs determine the effects of changing concentrations of greenhouse gases on global climate variables such as temperature, rainfall, evapotranspiration, humidity, and wind speed [38]. Similarly, global circulation models that predict long-term climate trends (rainfall, temperature, and humidity) are often unsuitable for regional scale studies because of their coarse grid-size resolution. It is therefore essential to downscale GCM data to the region-specific climate impact through the use of statistical or dynamical downscaling techniques [38,39].

Various hydrological models can be applied to analyze the impacts of changes in the climate [10]. These models investigate the degree to which observed changes in climate may affect the resources due to natural variability, human activity, or a combination of both [40]. The results and projections produced by such models provide essential information for making decisions of local, regional, and national importance on matters such as water resources management, agriculture, transportation, and urban planning [41]. However, hydrological models need to be calibrated to site-specific conditions before they are used for climate change impact analyses [22].

The general procedure for assessing the impacts of climate change on water resources and on watershed processes can be determined by physically-based distributed models. Due to its wider applicability and utility, different versions of SWAT have been used for several studies throughout the world [38]. SWAT has been used for hydrological modeling, soil erosion and sediment transport modeling, climate impact studies on stream flows, and modeling land use change and management impacts on sediment and stream flows. It can also be used for nutrient transport modeling in agricultural fields [38]. These studies have confirmed the successful use of the SWAT model across different watersheds on different scales and across different environmental, climatological, and hydrologic conditions [36,42,43].

The study presented here is therefore aimed at analyzing the impacts of climate change according to the regional RCP scenarios on the water balance components of the CRV sub-basins in Ethiopia. The results of the SWAT models integrating CMhyd, WGEN, and SWAT-CUP software packages, were used to identify possible sub-basin-wide water management options.

2. Materials and Methods

2.1. Description of the Study Location

The Central Rift Valley Basin (CRVB) is in Ethiopia between 38°15′ E and 39°30′ E longitude and 7°10′ N and 8°30′ N latitude, (Figure 1). It covers an area of approximately 9112.5 km^2. It is a hydrologically closed lakes region with no known outlets for its total basin [27]. The study basin is a vast closed area and thus was divided into smaller sub-basins with known outlets (Ketar, Meki, and Shalla sub-basins).

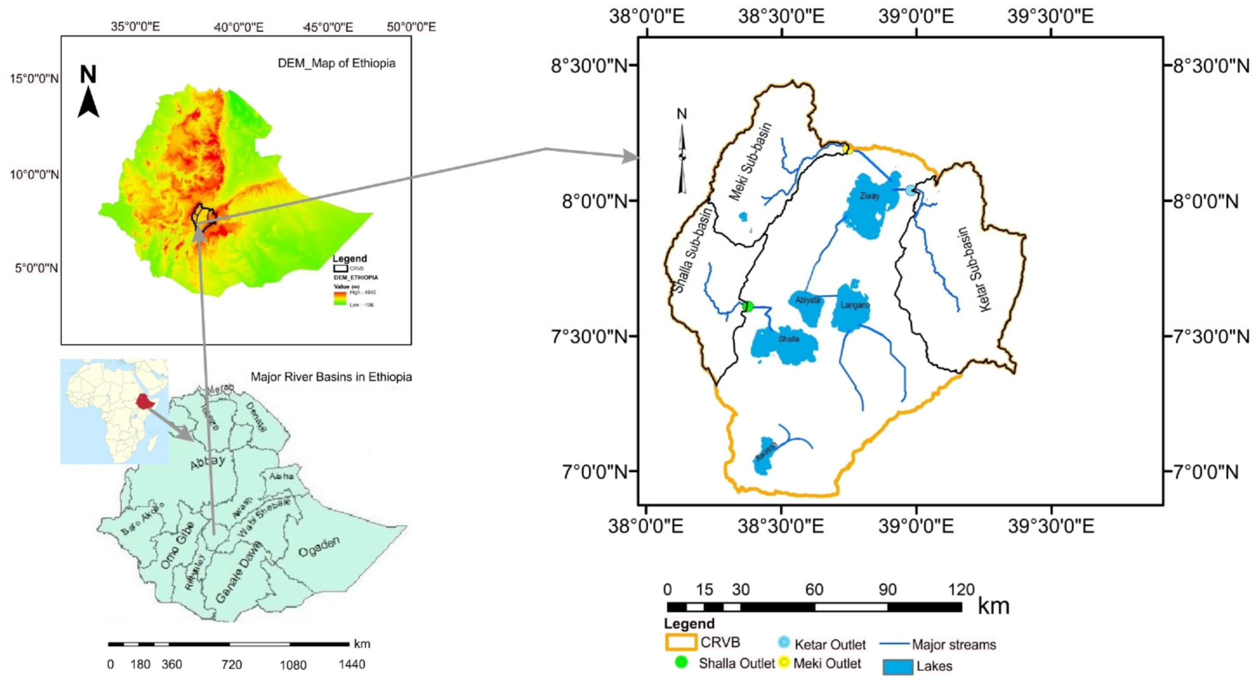

Figure 1. Location of Ethiopia in Africa, and the major river basins (bottom left); location of the study area within Ethiopia (top left), and the study sub-basins with their major stream outlets.

The mean annual rainfall of the study area varies between 600 mm near the lakes and 1200 mm–1600 mm in the highlands. The average minimum temperature is 10.5 °C, while the average maximum temperature is 24.3 °C [16]. CRVB comprises four major lakes:

Ziway, Shalla, Abiyata, and Langano. It also has perennial rivers, which include the Meki, the Ketar, and the Jidu rivers [16].

The CRVB has diverse soil types. It has varying infiltrability and associated runoff potential. Coarse-textured soils (LT Leptosols) with high infiltrability are dominant in the eastern and western highlands and in the valley floor around the lakes. Medium-textured soils (Euvertisols) with moderate infiltrability dominate the eastern and western mid-altitudes of the CRVB, whereas the lower reaches of the western highlands and some places in the central part of the eastern CRVB are dominated by fine-textured black soils (Vertisols) with lower infiltrability (Figure 2) [19].

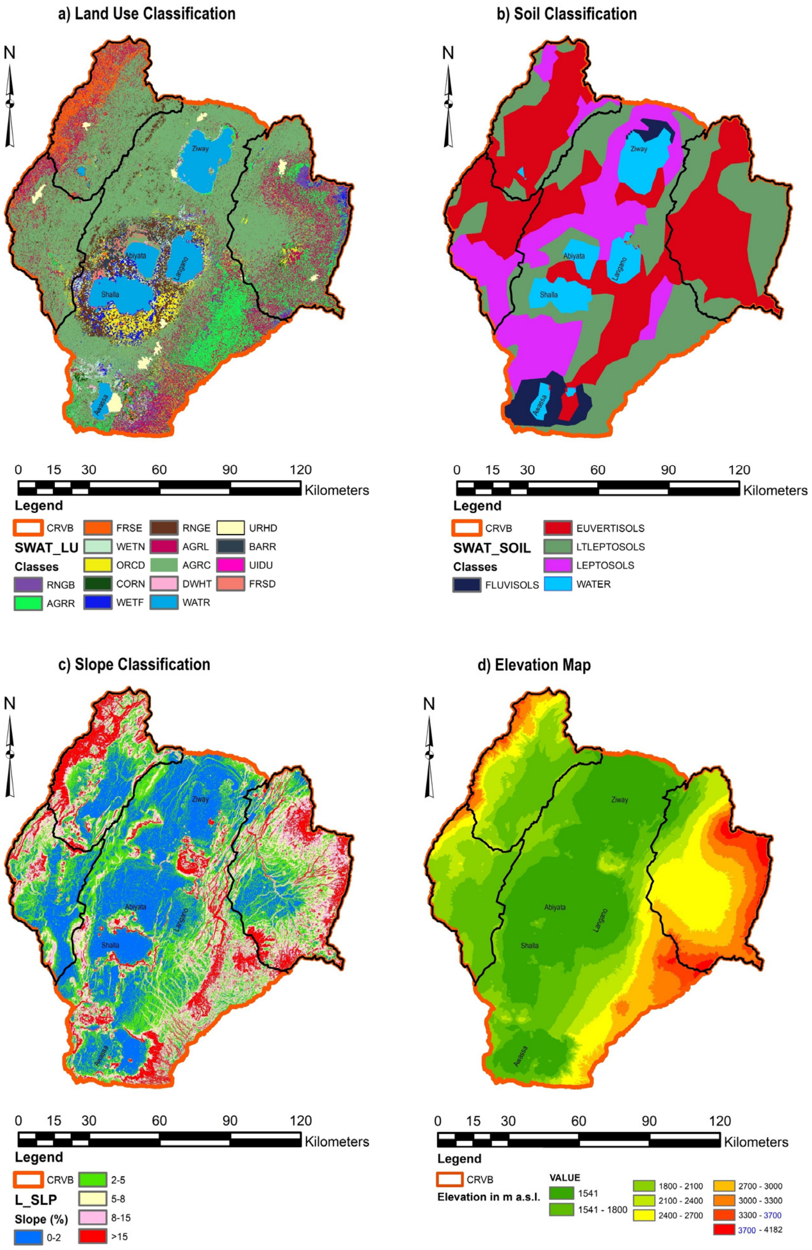

Figure 2. Distributions of land use, soil, slope, and elevation ranges in the CRVB (Note: the land use and soil codes are according to the SWAT classification standard as indicated in Tables S1 and S3 in the Supplementary File).

2.2. Sub-Basin Selection Methods (Boundary Delineation)

The hydrologically closed CRVB comprises many sub-basins. It was delineated and subdivided into major sub-basins in GIS according to their river systems, using the outlet points [16] as indicated in Figures 1 and 3. The DEM data were delineated in Arc SWAT and with the spatial analyst tool in ArcGIS. The total area of CRVB was delineated based on the watershed boundaries or water divide lines obtained from the Ministry of Water Resources of Ethiopia. The CRVB is an endo hydrogenic basin [27]. Since there is no single outlet for the CRVB, this study aims to investigate the hydroclimatic impacts via its major sub-basins with monitored outlets (Ketar, Meki, and Shalla). The selected sub-basins form parts of the CRVB with different characteristics which, when summed up, can generally characterize the climate impact conditions of the CRVB. The sub-basins were selected based on differences in agroecology, microclimate, and socio-environmental interactions. The analyses were performed for each of the sub-basins separately. The outlet locations of each sub-basin are indicated in Figures 1 and 3.

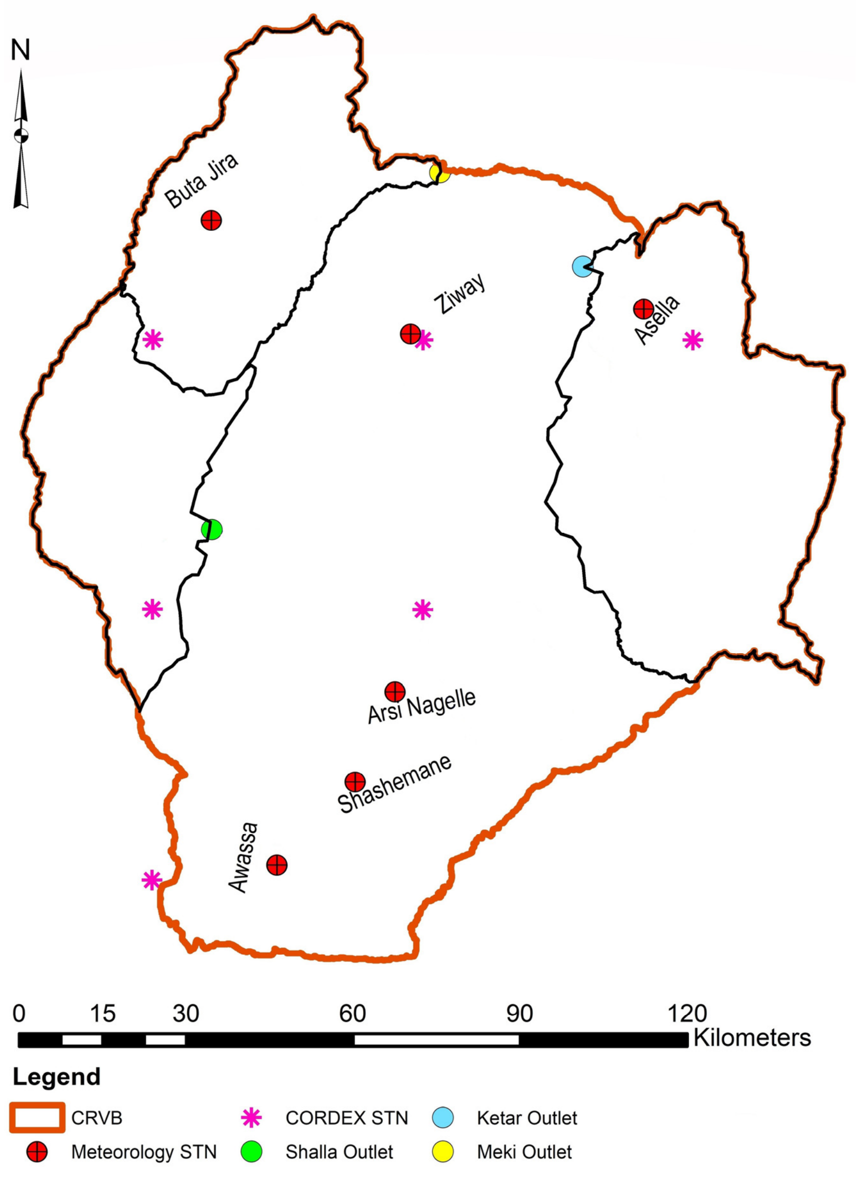

Figure 3. Locations of meteorology stations (Meteorology STN), CORDEX grid point (CORDEX STN), and outlets (Discharge monitoring stations).

2.3. Data Definition

2.3.1. Spatial Data

The spatial data used for the modeling were analyzed step-by-step. Initially, the digital elevation model (DEM) data of the CRVB was delineated with GIS into Ketar, Meki, and Shalla. They were divided into sub-basins based on the topography and the river systems. Each sub-basin was consequently subdivided into hydraulic response units (HRUs) according to the land-use features, soil profile, and slope within SWAT. The major data inputs and their utilization are indicated in Table 1. The land uses characterize the hydrological process in the sub-basins. The land use map of the CRVB was obtained from the Ethiopian Geospatial and Information Institute (GSII).

The soil hydro-physical properties determine the existence and the quantity of each component of the water balance [44]. The soil physical properties and the area coverage of each of the soil types were classified based on the SWAT classification standards. The digitalized soil data for the study region with a resolution of 1ha was obtained from the Ministry of Agriculture and Natural Resources (MANR) of Ethiopia. The details are in the Supplementary File in Table S1. The spatial information maps of the study region including land use information, distribution of soil types, slope, and elevation information are indicated in Figure 2.

Table 1. Major input data used in the SWAT model.

	Data					
	Type	Format	Source	Year/scale	Resolution	Purpose
Weather data	Relative humidity	.xls	NMA	1984–2010	Daily	Analyze water balance (WB)
	Rainfall	.xls	NMA	1984–2010	Daily	Analyze rainfall trend and WB
	Sunshine hours	.xls	NMA	1984–2010	Daily	Analyze WB and solar radiation
	Temperature (Max and Min)	.xls	NMA	1984–2010	Daily	Analyze WB, and temp trend
	Wind	.xls	NMA	1984–2010	Daily	Analyze WB and wind trade
Spatial data	Land use	.shp	GSII	1996–2008	ha	Model land use and runoff
	Soil	.shp	MANR	NA	ha	Determine soil hydrology group
	DEM	.tiff	OBANR	2003–2008	30 m	Analyze location data sets
Hydrology data	River Discharge	.xls	MW	1900–2010	Monthly average	Analyze discharge trend, for model calibration and sensitivity

Note: NMA—National Meteorological Agency, GSII—Geospatial and Information Institute, MANR—Ministry of Agriculture and Natural Resources, OBANR—Oromia Bureau of Agriculture and Natural Resources, MW—Ministry of Water Resources.

2.3.2. Climate Data

Daily data on minimum and maximum temperature, hours of sunshine, relative humidity, wind speed, and precipitation from six meteorological stations, located in and near the sub-basins, were introduced into the model to simulate the water balances of the sub-basins (Table 1 and Figure 3). Hydrology data for stream flows were collected at the outlets indicated for each sub-basin. The CORDEX grid locations in the study area, based on which the climate data were downscaled and extracted, are also presented in Figure 3. The coordinate locations of the meteorology stations are indicated in Supplementary File in Table S2.

2.3.3. Baseline Data Processing with SWAT Weather Generator (SWAT-WGEN)

The weather data were statistically analyzed, and data qualities such as errors and outliers were assessed and adjusted by the weather database generator software (SWAT-WGEN). The data and their respective station coordinates (X, Y, and Z) were synchronized by the SWAT-WGEN. As a result, the SWAT model recognized the spatial distribution of the data supplied. SWAT-WGEN helps in statistical analyses, in data coding for SWAT use, and for data gap analyses as well as for spatial interpolation of the missed datasets. Special care was given to the input data within this study. The background data provided by the authorities were carefully checked and missing data were supplied if available. The data gaps in the collected baseline data were scattered, but on some days, they were sequential. These sequential data gaps ranged from one to only ten days maximum for some stations. The gaps were filled via interpolation by the software. These data gaps accounted for not more than 65 days out of the total 27 years per station, which is less than 0.66% of the data items. Simple arithmetic means (taking the averages of the values of the data series available before and after the missed data dates) were also applied to those stations where the gaps were scattered and not sequential to restore the missing values.

2.4. Arc SWAT Application

Arc SWAT 2012 was used for the hydroclimatic impact assessment of the CRVB. Arc SWAT 2012 is an Arc GIS extension program used for watershed modeling. The Soil and Water Assessment Tool (SWAT) is a widely used model for analyzing the water balances of a basin using long-term meteorological and spatial data of the area [45]. It is a physically-based, deterministic, continuous, watershed-scale simulation model developed by the U.S. Department of Agriculture—Agricultural Research Service (USDA) [45,46]. It is a model written in Fortran to analyze mainly water, nutrient, and sediment conditions in large basins and the behavior under climate changes [46]. It can also be applied to evaluate the impacts of various human, environmental, and infrastructural management interventions in basins. It involves systematic and interconnected spatial and weather data analyses to evaluate the intended goal at each hydraulic response unit (HRU).

In the application of the model, the Penman–Monteith method for evapotranspiration, the soil conservation service (SCS) curve number method for surface runoff determination, and the variable storage method to simulate channel water routing are employed to analyze the water balances.

The Water Balance Equations

In the analysis of the impacts of climate change on water balance components, the model operates based on the water balance equation indicated in Arnold et al. (2011) which is defined as:

$$SWt = SW_0 + \sum_{i}^{t}(Rday_i - Qsurf_i - Ea_i - Wseep_i - Qgw_i) \quad (1)$$

where SWt is soil water content (mm) at time t, SW_0 is initial soil water content (mm), t is simulation period (days), $Rday_i$ is amount of precipitation on the i-th day (mm), $Qsurf_i$ is amount of surface runoff on the i-th day (mm), Ea_i is amount of evapotranspiration on the i-th day (mm), $Wseep_i$ is amount of water entering the vadose zone from the soil profile on the i-th day (mm), and Qgw_i is amount of base flow on the i-th day (mm) [45].

Moreover, one of the critical parameters that are evaluated for sustainable water resource management of the study area is the water yield. The water yield is the aggregate sum of water leaving the HRU and entering the principal channel during a time step [45]. The water yield within a basin is evaluated by the model based on Equation (2). Considering the hydrological processes taking place continuously in the basin, the water yield, i.e., the net amount of water flowing past a given point on a stream during a given period, can be described by a basic model equation:

$$W_{yld} = Q_{sur} + Q_{lat} + Q_{gw} - T_{loss} \quad (2)$$

where W_{yld} is the water yield (mm), Q_{sur} is the surface runoff (mm), Q_{lat} is the contribution of the lateral flow to the stream (mm), Q_{gw} is the contribution of the groundwater to the streamflow (mm), and T_{loss} is the transmission losses (mm) from the tributary in the HRU by means of transmission through the bed.

2.5. Model Parameter Sensitivity Analysis

For a particular area of interest (CRVB), Arc-SWAT contains many hydrological parameters that need to be considered. However, not all the parameters may be contributing significantly to the model output, and it is therefore necessary to identify the input parameters that are significant [46]. In addition, the heterogeneity of the area makes it difficult for all SWAT parameters to be monitored simultaneously. Calibration and validation are required to identify the parameters to use for the specific area in a balanced way [47]. The parameter sensitivity scale developed by Lenhart et al. (2002) was used to classify the sensitivity of the parameters in the sub-basins [48]. It was scaled to the mean of index (I) values (Table 2).

Table 2. Parameter sensitivity scale classes assigned in SWAT as adapted from Lenhart et al. (2002) [48]).

Class	Mean of Index (I)	Category of Sensitivity
1	$0 \leq I \leq 0.05$	Small to negligible
2	$0.05 \leq I \leq 0.2$	Medium
3	$0.2 \leq I < 1$	High
4	$I \geq 1$	Very high

In addition, the most sensitive parameters used for stream flow analyses in the CRVB were selected on the basis of a tropical nature environment review recommendations [49]. The sensitivity ranking of the parameters (mean of index) is defined through an analysis of the values of the "t-stat" and "*p*-value" indexes in SWAT-CUP during calibration. The "t-stat" values are the t statistics. The t statistic is a measure of how extreme a statistical estimate is, and is calculated as:

$$t = \frac{M - \mu}{S_m} \tag{3}$$

Where t = t-stat, M = sample mean, μ = population mean and S_m = estimated standard error. The identified sensitive parameters are indicated in Table 3 with their descriptions.

Table 3. The most sensitive SWAT parameters identified in the CRV sub-basins, and their descriptions.

	Parameter	Description
1	CN2	SCS runoff curve number
2	ALPHA_BF	Base flow recession constant (days)
3	GW_DELAY	Ground water delay time for recharging the aquifer (days)
4	GWQMN	Water limit level in the aquifer for the occurrence of base flow (mm)
5	REVAPMN	Water limit level in the aquifer for revap to occur (mm)
6	GW_REVAP	Groundwater revap coefficient
7	ESCO	Soil evaporation compensation factor
8	EPCO	Plant uptake compensation factor
9	SURLAG	Delay time of direct surface runoff (days)
10	SOL_AWC	Available water capacity of the soil layer (mm mm^{-1})
11	SOL_K	Saturated hydraulic conductivity of the soil (mm h^{-1})
12	CH_K2	Effective hydraulic conductivity of the main channel (mm h^{-1})
13	SOL_Z	Depth from soil surface to the bottom of the layer (mm)
14	RCHRG_DP	Deep aquifer percolation fraction
15	HRU_SLP	Average slope steepness (m m^{-1})
16	BIOMIX	Bio-mixing efficiency

2.6. Model Calibration and Validation

Calibration and validation of the SWAT models were carried out using SWAT-CUP, a calibration uncertainty program for SWAT with the SUFI-2 algorithm, which is sequential uncertainty fitting, version 2. The program performed calibration, validation, sensitivity analysis (one at a time), and uncertainty analysis. In addition, the program links SUFI2, GLUE, ParaSol, MCMC, and PSO algorithms to SWAT [50]. The models were calibrated and validated using monitored stream flows from the outlets of the Ketar, Meki, and Jidu (Shalla) Rivers. The outlet locations were set at the flow gauging stations. The models were set to run for the baseline periods from 1984 to 2010 for each of the sub-basins (Ketar, Meki, and Shalla).

Calibration and validation help the model to resemble the study area in its operation by adjusting the sensitive model parameters. In this study, the observed stream flow data from 1990 to 2001, obtained from the Ministry of Water Resources of Ethiopia (MW), were used for calibration, and data from 2004 to 2010 were used for validation. The models of each of the sub-basins were calibrated and validated separately with their respective stream flow data from each sub-basin outlet (Figure 4). During calibration, the data from the first three years were kept as a warming-up period. These data allow the model to warm up, initialize, and approach reasonable initial values of the state variable of the model [50]. The adjusting values, as modified by SWAT-CUP to fit the values of the parameters to site-specific ranges, and the adjusting methods are presented in Table 4. The adjusting methods are indicated in the prefix of the parameter (V_, R_, and A_) and they are described in the table caption.

Table 4. Adjusting values and methods as adjusted by SWAT-CUP for the parameters.

Ketar		Meki		Shalla	
Parameter	Adjusting value	Parameter	Adjusting value	Parameter	Adjusting value
R__CN2.mgt	−0.44	R__CN2.mgt	−0.586	R__CN2.mgt	−0.155
V__ALPHA_BF.gw	0.629	V__ALPHA_BF.gw	0.348	R__ALPHA_BF.gw	−0.35
A__GW_DELAY.gw	12.251	A__GW_DELAY.gw	−17.291	A__GW_DELAY.gw	3.283
A__GWQMN.gw	336.23	A__GWQMN.gw	109.676	A__GWQMN.gw	−819.543
A__REVAPMN.gw	13.917	A__REVAPMN.gw	−126.446	A__REVAPMN.gw	213.915
A__GW_REVAP.gw	0.0403	A__GW_REVAP.gw	0.143	V__GW_REVAP.gw	0.18
V__ESCO.bsn	0.98	V__ESCO.bsn	0.43	V__ESCO.bsn	0.412
V__EPCO.bsn	0.221	R__EPCO.bsn	−0.662	V__EPCO.bsn	0.417
A__SURLAG.bsn	20.086	A__SURLAG.bsn	16.174	V__SURLAG.bsn	25.349
R__SOL_AWC(..).sol	1.29	R__SOL_AWC(..).sol	1.274	R__SOL_AWC(..).sol	NA*
R__SOL_K(..).sol	−0.661	R__SOL_K(..).sol	0.166	R__SOL_K(..).sol	0.149
V__CH_K2.rte	79.915	V__CH_K2.rte	NA*	A__CH_K2.rte	−74.91
R__SOL_Z(..).sol	0.665	R__SOL_Z(..).sol	NA*	R__SOL_Z(..).sol	NA*
R__RCHRG_DP.gw	−0.122	V__RCHRG_DP.gw	NA*	V__RCHRG_DP.gw	0.093
R__HRU_SLP.hru	NA*	R__HRU_SLP.hru	0.783	R__HRU_SLP.hru	NA*
R__BIOMIX.mgt	NA*	R__BIOMIX.mgt	0.205	R__BIOMIX.mgt	NA*

Note: R = relative, the parameter will be multiplied by the relative value as follows: value* (1 + R); V = replace, the parameter value will be replaced by the new values in the model; A = absolute, the parameter value will be added to the values in the model as follows: value + A; NA* = unchanged default values in the model.

2.7. Model Performance Evaluations

Before applying for analysis, the models' performances were assessed. Three main statistical parameters were used to evaluate the performance of the models: the coefficient of determination (R^2), the Nash–Sutcliffe efficiency (*NSE*), and the percentage of bias (*PBIAS*) [51]. R^2 is calculated as :

$$R^2 = \left[\frac{\sum_{i=1}^{N}(O_i - O)(S_i - S)}{\left[\sum_{i=0}^{N}(O_i - O)^2\right]^{0.5}\left[\sum_{i=0}^{N}(S_i - S)^2\right]^{0.5}} \right]^2 \quad (4)$$

R^2 ranges from 0.0 to 1.0. A higher value of R^2 indicates better performance of the model. The formula for calculating *NSE* is:

$$NSE = 1 - \frac{\sum_{i=1}^{N}(O_i - S_i)^2}{\sum_{i=1}^{N}(O_i - O)^2} \quad (5)$$

Nash–Sutcliffe Efficiency (*NSE*) is a normalized statistic, which measures the relative magnitude of the residual variance in comparison with the variance of the measured data. Like R^2, the higher the value of *NSE*, the better the performance of the model. *NSE* indicates the statistical relationship between simulated model values and observed values. It was stated that the "values of *NSE* vary from $-\infty$ to 1" [51,52].

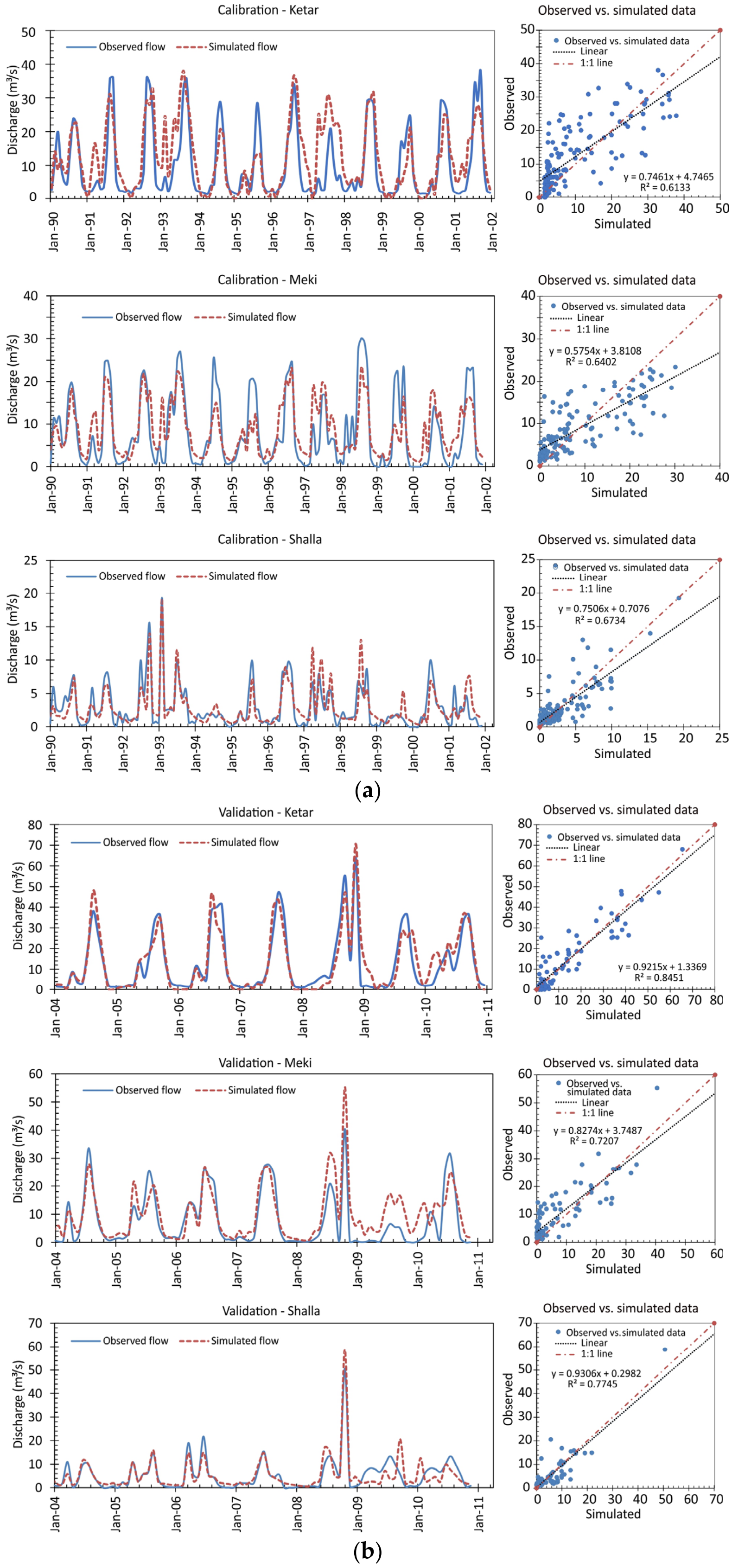

Figure 4. Calibration (**a**) and validation (**b**) results of the models for the CRV sub-basins.

PBIAS is calculated as:

$$\text{PBIAS} = \frac{\sum_{i=1}^{N}\left(S_i - O_i \right)}{\sum_{i=1}^{N} O_i} \times 100 \quad (6)$$

PBIAS measures the average tendency of the simulated values to be larger or smaller than their respective observed values. Positive *PBIAS* values indicate underestimation by the model, and negative values indicate overestimation. From the general statistics, the range within ±25% is acceptable [52].

In Equations (4)–(6), S is the mean of the simulated stream flows, O is the mean of the observed stream flows, S_i is the simulated stream flows, O_i is the observed stream flows, and N is the number of observations.

2.8. The Climate Scenario Application and Analyses Methods

2.8.1. Climate Scenario Analyses Setting and Simulation

An Arc-SWAT-based modeling approach to analyzing the impacts of climate change in the sub-basins of the CRV lakes region, and optimum agricultural water use and optimization strategies with respect to the identified impacts were carried out. Separate modeling for the selected sub-basins was performed. The climate scenarios (CSc) were set to analyze the impacts of climate change on the components of the water balance in the near-term (2031–2060) and in the long-term (2070–2099) periods for each of the regional concentration pathway (RCP) emission scenarios. The emission scenarios are RCP2.6 (low emission scenario), RCP4.5 (medium emission scenario), and RCP8.5 (high emission scenario). The simulations were categorized into seven CSc analyses, including the baseline data as listed in Table 5. The options for agricultural water use management are indicated based on the resulting water balance components affected by the changes in climate for each sub-basin.

The climate data were downscaled, bias corrected, analyzed, and simulated in an integrated manner with WGEN, CMhyd, and Arc SWAT. The WGEN software interlinks station coordinates and elevations with their respective data. All data statistics, such as average, standard deviation, mean, variance, etc., for each of the weather components downscaled were calculated and synchronized to their respective stations with WGEN. Rain Years, dew point, and other important variables useful for calculating the water balance components were also calculated and generated in WGEN. Finally, these climate data were imported into the SWAT models and simulated to see the changes in the components of the water balance that are especially useful for surface water sources.

2.8.2. Data Downscaling

Climate data stored in the World Climate Research Program (WCRP) databases were used. The data are from the experiments of CMIP5–RCP (RCP2.6-CMIP5, RCP4.5-CMIP5, and RCP8.5-CMIP5). These data were derived by the MIROC-RCA4 ensemble driving climate models under the GCM. The GCM data of these RCP data variables were regionalized to the regional climate model (RCM) with the Coordinated Regional Downscaling Experiment (CORDEX) for Africa, CORDEX-AFR-44. Both, historical data as well as the data of RCP2.6, RCP4.5, and RCP8.5 were downscaled by RCA4 models. RCA4 is the fourth version of the Rossby Center Regional Atmospheric model. It was originally developed by the Swedish Meteorological and Hydrological Institute within the CORDEX initiative. It is a dynamic downscaling method widely used with the CORDEX [23,53]. The downscaled datasets were daily precipitation, daily maximum near-surface air temperature, daily minimum near-surface air temperature, daily sunshine duration, near-surface relative humidity, and near-surface wind speed for future periods from 2006 to 2100. The duration of daily sunshine in units of seconds (s) was extracted from the model and adjusted to daily solar radiation with the units of kilowatt per square meter (KW/M^2) for SWAT use and to the SWAT input data standard units using Angstrom techniques [54].

2.8.3. Bias Correction

The data for precipitation and temperature were bias-corrected via linear scaling methods with CMhyd software, which is a SWAT community tool, before they were applied in the SWAT simulation. The need for bias correction is mainly due to onshore and offshore trade wind disturbances. The historical data from the model and the observed locational dataset from six stations in the study region were applied to the software. Data ranges from 1990 to 2006 were applied from the historical dataset of the climate model. Furthermore, observed datasets from the same periods were used to correct the biasedness created due to trade winds in the climate models. Parameters or correction factors for each month were developed in relation to the observed data range of the same time periods. Based on the parameters, the software adjusted the predicted rainfall and temperature values from the downscaled data. The corrected data values were applied to WGEN for statistical analyses and then to SWAT for simulation.

Table 5. Applied climate scenarios for analyzing the impacts of climate change on the major components of the water balance in the sub-basins.

Climate Scenario		
No.	Code	Description (Years)
1	NT-RCP2.6	RCP2.6 (2031–2060)
2	LT- RCP2.6	RCP2.6 (2070–2099)
3	NT-RCP4.5	RCP4.5 (2031–2060)
4	LT- RCP4.5	RCP4.5 (2070–2099)
5	NT-RCP8.5	RCP8.5 (2031–2060)
6	LT-RCP8.5	RCP8.5 (2070–2099)
7	BD	Observed baseline data (1984–2010)

Note: NT = Near term and LT-Long term.

3. Results and Discussion

3.1. Results of the Model Parameters Sensitivity Analyses

The parameter sensitivity analyses were carried out together with the calibration process, as it is necessary to include the flows estimated by SWAT and the monitored flows in the sub-basins. In general, a higher "t-stat" and a lower p-value indicate that the parameter is sensitive [55]. Based on the sensitivity scale developed by Lenhart et al. (2002), shown in Table 2, the following parameters were identified as highly sensitive in the Ketar sub-basin: EPCO, RCHRG_DP, SOL_K, GW_DELAY, CN2, REVAPMIN, and SURLAG. Similarly, ESCO, REVAPMIN, GWQMN, HRU_SLP, and GW-DEALY were very highly sensitive parameters in the Meki sub-basin, and ESCO, CH_K2, SOL_K, and GWQMN were very highly sensitive in the Shalla sub-basin. The description of the parameters is presented in Table 3. The differences in the sensitivity of the hydrological parameters in the sub-basins indicate that the sub-basins are heterogeneous, although they refer to a single, closed, lakes region. The differences are mainly due to land use, soil, hydrogeologic, and anthropogenic variations. The t-stat values of each of the selected parameters for each sub-basin are indicated in Table 6. The parameter description and their adjusting values are indicated in Tables 3 and 4.

3.2. Results of the Calibration and Validation of the Model

The calibration results indicate good agreement between the simulated and observed discharges in the sub-basins. The results for simulated and observed discharges in the sub-basins were evaluated against R^2, *NSE*, and *PBIAS* during calibration and validation. The values in the Ketar sub-basin are in good agreement with $R^2 > 0.6$, $NSE > 0.5$, and $PBIAS \leq$ "±"25, (Figure 4a,b). Similarly, the results showed that the simulated and observed monthly discharges were in a good agreement during calibration and validation for the Meki and Shalla sub-basins (Table 7).

Table 6. Sensitivity or mean of index I values of the selected parameters for the sub-basins, according to their "t-stat" results as per the scale indicated in Table 2.

	Ketar		Meki		Shalla	
Parameter **	t-stat value	Sensitivity	t-stat value	Sensitivity	t-stat value	Sensitivity
R__CN2.mgt	1.408	Very high	−0.394	Negligible	−0.111	Negligible
V__ALPHA_BF.gw	0.046	Low	−0.997	Negligible	−1.643	Negligible
A__GW_DELAY.gw	1.206	Very high	1.951	Very high	−1.032	Negligible
A__GWQMN.gw	0.783	High	1.564	Very high	2.685	Very high
A__REVAPMN.gw	1.970	Very high	1.441	Very high	−1.116	Negligible
A__GW_REVAP.gw	0.710	High	0.844	High	NI*	NI*
V__ESCO.bsn	0.905	High	1.181	Very high	1.739	Very high
V__EPCO.bsn	1.013	Very High	−1.210	Negligible	−1.513	Negligible
A__SURLAG.bsn	2.329	Very high	−1.242	Negligible	0.744	High
R__SOL_AWC(..).sol	−1.034	Negligible	−3.957	Negligible	NI*	NI*
R__SOL_K(..).sol	1.202	Very high	−1.417	Negligible	1.197	Very high
V__CH_K2.rte	−0.551	Negligible	NI*	NI*	1.926	Very high
R__SOL_Z(..).sol	NI*	NI*	NI*	NI*	NI*	NI*
V__RCHRG_DP.gw	1.137	Very high	NI*	NI*	−1.986	Negligible
R__HRU_SLP.hru	NI*	NI*	1.799	Very high	0.084	Low
R__BIOMIX.mgt	NI*	NI*	1.669	Very high	0.798	High

Note: NI* = not identified, ** Parameter description is presented in Table 3.

Table 7. Model performance statistics for the Ketar, Meki, and Shalla sub-basins.

Sub-Basin	Calibration Statistics			Validation Statistics		
	R^2	*NSE*	*PBIAS*	R^2	*NSE*	*PBIAS*
Ketar	0.61	0.54	−22.5	0.85	0.84	−2.6
Meki	0.64	0.63	−4.81	0.72	0.64	−32.17
Shalla	0.67	0.66	0.2	0.77	0.74	1.34

Overall model performance statistics (R^2, *NSE*, and *PBIAS*) for the Ketar, Meki, and Shalla sub-basins are presented in Table 7.

3.3. Climate Scenario Analyses Results and Discussion

The results of the impacts of climate change on the major components of the water balance such as surface runoff (Q), water yield (WY), and evapotranspiration (ET) were evaluated in terms of their annual, seasonal, and monthly variations. The Q, WY, and ET were identified as the most sensitive elements of the water balance components in the CRVB. The simulated impacts of the climate scenarios on the water balance components are substantial. The percentage change in the Q, WY, and ET from their baseline simulated outputs for each sub-basin are presented in Table 8, together with the indication of the baseline annual rainfall data (averaged for years 1984–2010).

Table 8. The simulated mean annual changes, as a percentage, from the annual average values of the baseline outputs for the major components of the water balance in the sub-basins.

Sub-Basins	Ketar			Meki			Shalla		
Annual average rainfall (mm)		798.1			674.4			713.4	
Water balance components	Q	WY	ET	Q	WY	ET	Q	WY	ET
Baseline annual average output (mm)	103.8	492.2	282.5	53.5	257.5	393.1	44.2	326.7	363.8
			% of Δ						

Table 8. *Cont.*

Sub-Basins		Ketar			Meki			Shalla		
Scenarios	NT-RCP2.6	−62.2	−34.9	17.3	58.1	17.0	4.5	−3.5	0.9	12.2
	LT-RCP2.6	−55.0	−30.3	13.3	60.2	19.9	2.6	31.6	12.0	9.3
	NT-RCP4.5	−13.7	−35.9	−4.1	6.0	−1.1	5.6	−21.9	−10.1	9.2
	LT-RCP4.5	22.9	−28.7	−9.4	47.7	11.2	2.6	32.8	4.2	7.8
	NT-RCP8.5	−65.2	−42.2	7.4	58.3	13.0	6.4	−7.7	−2.4	10.8
	LT-RCP8.5	−60.5	−39.7	8.8	85.8	23.9	9.4	23.5	7.1	15.1

Note: % of Δ = Percentage of change of the component from its baseline output.

3.3.1. Ketar Sub-Basin

The resulting simulated ET, WY, and Q mean monthly values for the Ketar sub-basin are graphically displayed in Figure 5a. Changes in the Q pattern over the seasons in the Ketar sub-basin can be observed in Figure 5a. The highest Q season has shifted both in the near and long term of RCP4.5 to the months from March to May while it used to be between mid-June to the end of September in the baseline data outputs. The simulated annual variations from the base data are between −65.2% (LT-RCP8.5) and 22.9% (LT-RCP4.5). RCP 2.6 and RCP 8.5 analyses indicate that the expected runoff will decrease both in the near term and in the long term in relation to the baseline data simulation outputs. In all the seasons, for all RCPs, the runoff condition in the long term (LT) is higher than the runoff in the near-term (NT) period. However, the general trend indicates that the runoff is decreasing in this sub-basin in relation to the historical (baseline) period, but the rate of its reduction differs from one RCP to another and from one period to another.

In similar analyses, the WY in the Ketar sub-basin decreases for all RCPs, in both the NT and LT periods, except in the long-term periods of RCP4.5 for the months from April to June (Figure 5a). Generally, the impact is expected to reduce the WY in all projected scenarios, especially for the periods from July to October. However, the rate of reduction varies from RCP to RCP and varies from season to season. Nevertheless, the annual WY generation capacity of the Ketar sub-basin is higher than in the Meki and Shalla sub-basins, corresponding to the annual precipitation that is supplied. Almost half of the rainfall, 50% on an average, goes to the WY in all the scenarios, while the proportion is about 40% in the Meki sub-basin and about 44% in the Shalla sub-basin. The simulated WY in the RCPs follows a similar pattern to the observed base year simulations. It means that the seasonal change in WY is not disturbed in pattern but in quantity.

The ET in the sub-basin has bi-annual peaks between March and mid-May, and between July and September (Figure 5a). The ET is relatively low between mid-May and June. The rate of ET decreases between March and May in all the scenarios in relation to the observed data simulations except between June and September. ET will be higher in the Ketar sub-basin for RCP2.6 and RCP8.5, between June and September, than outputs from the base data. The significant change in ET mainly reflects the increase in temperature. Therefore, according to the RCP2.6 and RCP8.5 climate projections, the increase in ET will be higher than the RCP4.5 projections for ET. This is in line with the works of Musie et al. (2020) and Gadissa et al. (2019) in the Lake Ziway and CRV basins in Ethiopia, respectively [21,33]. Musie et al. (2020) used the SWAT model to evaluate the impacts of regional climate variabilities and land use change on the water resources in the Lake Ziway basin. They found an increase in surface runoff and water yield due to the climate scenarios from the year 2000 to 2017. Gadisa et al. (2019) used projected climate scenarios to evaluate stream flows for the medium-term (2040 to 2070) periods for the RCP4.5 and RCP8.5 scenarios.

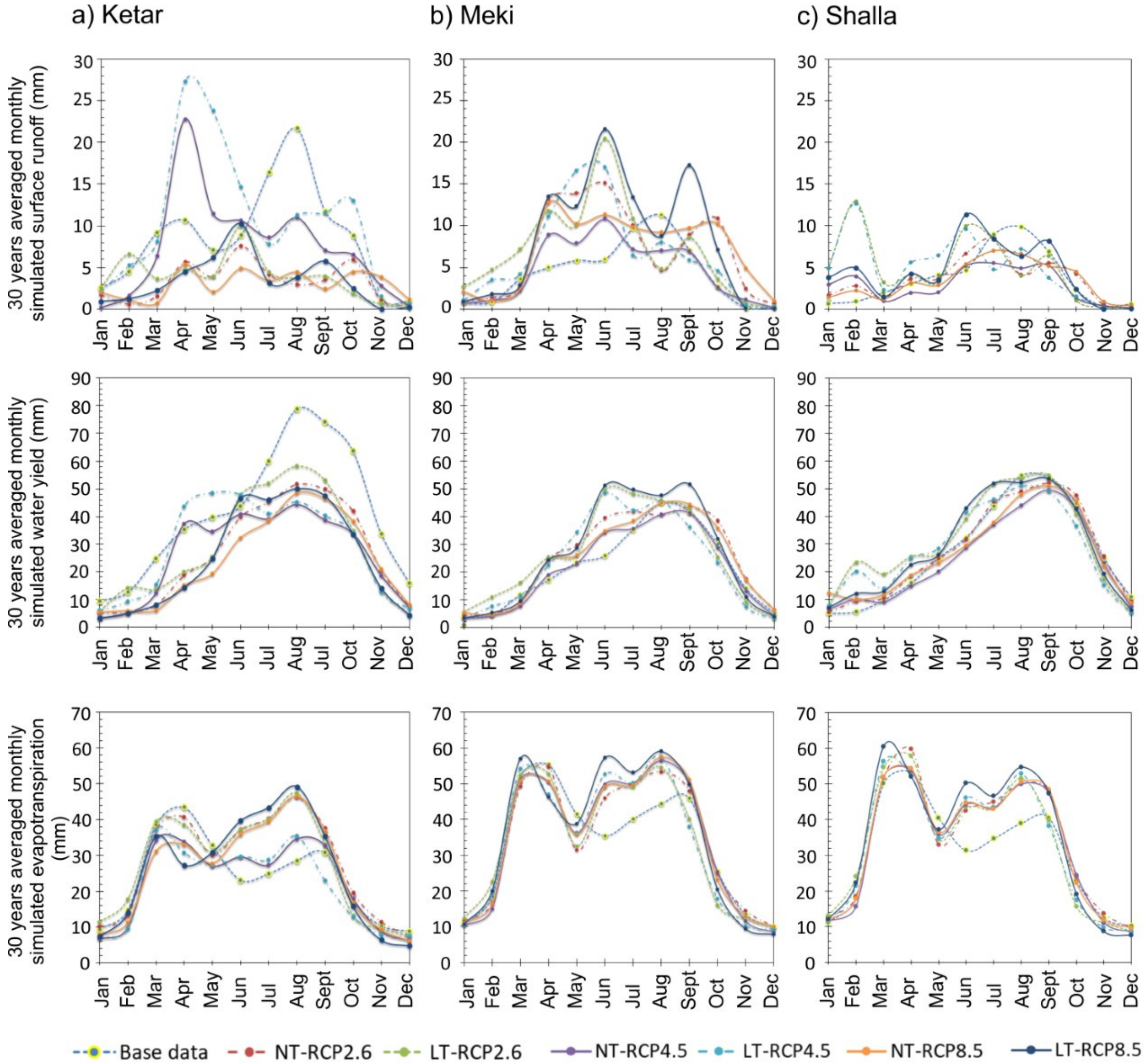

Figure 5. The simulated monthly distributions of Q, WY, and ET in the Ketar, Meki, and Shalla sub-basins for the applied climate scenarios. (**a**) Ketar, (**b**) Meki, (**c**) Shalla.

The results reported in both studies, and in Getnet et al. (2014), in the CRVB indicated that the hydrologic variations in water balance due to climate variability were highly significant [20,27,32]. However, in contrast to the study by Musie et al. (2020) [20], the hydroclimate in our study was more predominant in WY than ET in the Ketar sub-basin. Another study conducted in the CRVB in 2007 on climate change impacts on water availability with a SWAT model indicating an increase of averaged annual rainfall from 2001 to 2099 can also be found [56]. However, Gadissa et al. (2019) projected a reduction in precipitation by 7.97% and 2.55% under RCP4.5 and RCP8.5 respectively for the future period from 2040 to 2070 [32]. Reduction in precipitation has strong correlation with reduction in water yield and surface runoff. Our study is thus in line with the findings of Gadissa et al. (2019) [32] with minimal differences in the periods of occurrences. There are seasonal shifts in the pattern of occurrences of the components of the water balance when compared with the baseline data sets. These shifts are mainly from the changes in precipitation, temperature, and humidity patterns caused by greenhouse gases and other emissions.

3.3.2. Meki Sub-Basin

The Meki sub-basin is characterized by greater annual amounts of ET than in the Shalla and Ketar sub-basins. The annual surface runoff rises in all the RCP scenarios. There will be a seasonal shift of the peak runoff period from the usual July-to-September period to April-to-June in the sub-basin (Figure 5b). In the long-term periods of RCP2.6 and RCP8.5, the runoff will increase greatly in relation to the baseline data simulation outputs. However, RCP4.5 will create a moderate range of changes in relation to RCP2.6 and RCP8.5. The change in annual average runoff varies from 6% to 85% in reference to the baseline outputs. The projected monthly distribution shows that this water balance component varies significantly over the months in both the NT and LT period.

The change in averaged annual WY ranges from −1.1% to +23.9% in relation to the baseline data simulated. The scenario analysis also showed a remarkable increment in the WY amount between May and October for all RCP outputs. ET is the major water balance component of the sub-basin (Figure 5b). About 56% of the rainfall on average turns into ET. This indicates that the sub-basin water balance is highly sensitive to changes in temperature. Even though WY is good in the rainy seasons, most of it will be lost via ETs. Thus, for the Meki sub-basin, the impacts were more predominant in ET than in WY. This indicates the high seasonal weather variabilities in the sub-basin and its low hydroclimatic impact resilience. Similar findings were reported by Gadissa et al. (2019) and Musie et al. (2021) for this sub-basin. They used modeling approaches of RCM projections to assess the conditions of the Q, ET, and stream flows using the SWAT and WEAP models, respectively. In addition, Molla, (2014) has used physical assessment methods to indicate the sub-basin climate conditions [16,17,36]. These studies reported that the Meki sub-basin is the most hydroclimate-sensitive region. The strong weather variabilities in the sub-basin have resulted in wide ranges of changes in water resources similar to the findings of another study conducted by Getnet et al. (2014) in the CRVB [16,26,27]. The annual variations in this study are also relatively large for the sub-basin (Table 8). The modeling results in this study for the sub-basin are thus inconsistent with the above study findings.

3.3.3. Shalla Sub-Basin

The response of this sub-basin to the analysis in the model indicates a stronger range of variations in its water balance components. However, the Shalla sub-basin has a lower annual runoff amount than the Ketar and Meki sub-basins (Figure 5c). However, the changes in annual runoff vary between −21.9% and +32.8% from the baseline data simulation outputs. The average annual changes in WY vary from −10.1% to +12.0% because of the impacts. The changes in ET vary from +7.8% to +15.1%. The detail annual variations in percentage for each CSc and each component in each sub-basin are indicated in Table 8. ET increases significantly between June and September for all RCP projections. ET is the largest component, and most of the rainfall turns into ET. Because of the high ET and the small runoff, the entire sub-basin is characterized as a water-scarce region. The WY result for the Shalla sub-basin was moderate for all the CSc. Compared to other previous studies (for example Ayenew, 2007; Gadissa, et. al., 2018), Shalla has small WY output, but in the analyses conducted in this study, the sub-basin yielded a relatively higher amount [5,32]. The difference could possibly be due to its complex hydrogeologic setting that needs to be verified in further studies. However, there is agreement on the fact that its surface water availability will be depleted due to the high ET and the low Q occurrences.

The projected monthly average values of each of the water balance components in each sub-basin with their respective baseline monthly average output values for each of the scenarios are presented in Figure 6. It indicates that the hydroclimatic impacts in the future in the CRVB are very high. The baseline data outputs are indicated with yellow rings around their graphs.

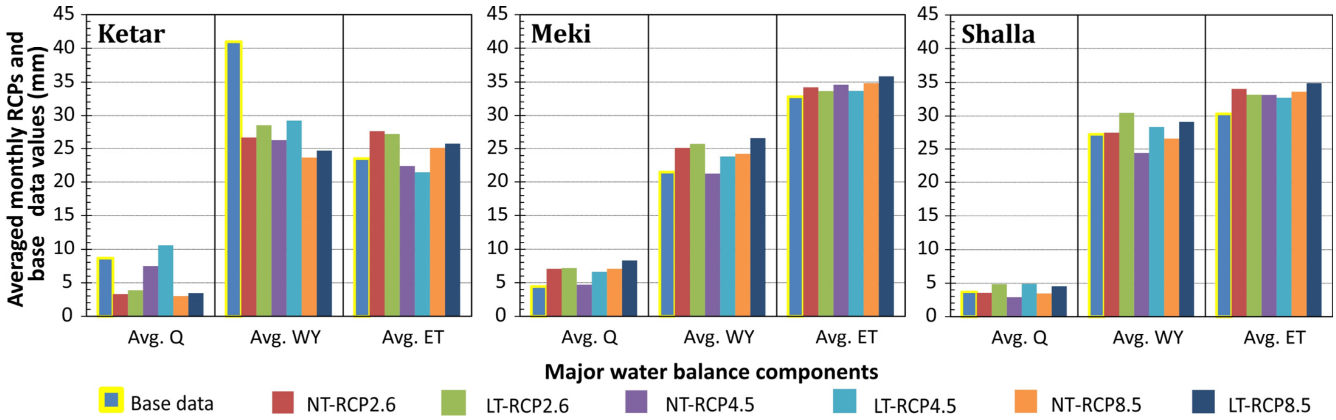

Figure 6. Monthly average values of 30 years of surface runoff (Q), water yield (WY), and evapotranspiration (ET) in the Ketar, Meki, and Shalla sub-basins for different climate scenario simulations in relation to the baseline data simulation outputs.

4. Discussion for Water Management Options

From the projected analyses of the impacts of climate change in the model, the major water balance components such as surface runoff and water yield are mainly expected to decrease, and evapotranspiration is projected to increase in the sub-basins. This will have an impact on the increasing demands for agricultural water in the sub-basins. Seasonal shifts in the patterns of the projected water balance distributions were also observed. Therefore, water management strategies that help mitigate the impacts should be identified and applied. Their application might help to face the food security challenge caused by the water shortage that would occur due to climate changes.

Based on the resulting projected water balances, agricultural water management in the Ketar sub-basin should, in the future, focus on the time modification of farm operations, and on water harvesting to store excess water occurring in the unusual months. Scarcity of water for agriculture is inevitable from the analyses (Figure 5a). Therefore, water saving, and water use optimization must be sought and applied in the future. The WY is the major water balance component of the Ketar sub-basin in all the scenarios, and its enhancement together with conservation, will make the basin rich enough in water to curb the impacts of climate change. In addition, irrigation water supply scheduling based on the modified climate pattern is the recommended method of agricultural water management for the Ketar sub-basin.

High water losses through ET in the Meki sub-basin can be mitigated by water management interventions such as crop mulching, farm operations during minimum evaporation seasons, favoring minimum tillage to reduce soil evaporation, selecting crops that are more resistant to high levels of evaporation, favoring efficient irrigation water application, and introducing regular soil and water conservation practices to reduce the high seasonal runoff and ET. In the Meki sub-basin, water harvesting and storage during periods of high runoffs can also reduce water scarcity during peaks in demand. High runoff management and protection infrastructures are also inevitable as there will be untimely and repeated higher runoff expected beyond the usual baseline trends, as per the analysis.

The high ET rates and low runoff makes the Shalla sub-basin a water-scarce region. The water scarcity problem in the sub-basin should be mitigated by improving WY via yield enhancement approaches that also help to reduce evaporation losses. These include soil and water conservation to improve subsurface storage, crop selection, farm operation scheduling based on the new climate pattern and minimum tillage to reduce soil evaporation, and the selection of highly ET-resistant crop varieties. Investigating afforestation for controlling ET losses, and controlled farm operations are also very crucial. Furthermore, inter-basin water transfers are recommended for adapting to the impacts on the sub-basin.

A study conducted by Kassie et al. (2015) applied an effective fertilizer with irrigation water as an adaptation measure to climate change for the maize crop in the CRVB. The study assessed the potential impacts of climate change on maize yield and explored specific adaptation options under climate change scenarios for the CRVB of Ethiopia by mid-century. They used GCM, RCPs, and crop models to search for adaptation options. The climate change impacts in their study are consistent with our study results. Their adaptation option offsets the severe impacts of yield loss in the area due to the climate impacts [34]. Thus, the effective application of fertilizer while producing the maize crop in the region together with irrigation water is crucial. In addition, the positive effects of changing the planting date were indicated in their study in offsetting the severe climate impacts on the maize crop [34].

Amare and Endalew (2016) assessed the importance of farm mechanization in rural Ethiopia for smallholder farmers. In their assessment, they indicated that mechanized farming helps in reducing water loss at the farms [57]. The study results showed that water distribution efficiencies in irrigated farms have been improved in the study regions, including the CRVB. This may be achieved by incorporating land use planning in a manner that its water allocations and use efficiencies will improve, for instance, farm mechanization and land leveling to minimize water loss and enhance even distribution [57]. Therefore, extensive farm mechanization and land leveling works are recommended as a means to improve water use and reduce its loss in the sub-basins' irrigated farm fields. These will help to increase the resilience capacity of the CRVB to the impacts of future climate changes.

Adaptation to climate impacts via water allocation planning based on weather, soil, and ecological characteristics and social benefit priorities can also reduce the unnecessary loss that may occur due to misallocation and weather variabilities. For instance, the cropping pattern alternatives that favor better gain based on the rainfall patterns of the rift valley region were adopted by some farmers, as indicated in the study conducted by Belay et al. (2017) [2]. The farmers applied a method of using different crop varieties of maize during long rainy seasons and during short rainy seasons. This has improved the gain in the worst water shortage seasons in the region, as reported in [2]. Accordingly, preparing alternative plans for seasonal climate change conditions for agricultural production, and for water use plans that can mitigate the dual impacts of climate and environmental changes while maximizing the benefits during the worst climate seasons are thus necessary. Hence, the possible alternative plans and the locally adopted measures by the farmers should be further assessed, tested, and applied in the worst seasons in the CRVB and in similar regions in the country. The plans need to be based on reliable data and on studies carried out for particular areas. This study aims to contribute to such a knowledge helping in the creation process of such adaptation plans for the CRVB in Ethiopia.

In addition, Kifle and Gebretsadikan (2016), conducted an experiment on the controlled application of irrigation water for potato production in the water-scarce region of Tigrai in Ethiopia [58]. They found positive effects of controlled irrigation water applications on potato production without losses for the deficit application of water with proper timing as means to curb water shortage due to climate changes. One of the best adaptation options for agricultural water uses in the sub-basins is thus the introduction of controlled irrigation that applies the water resources efficiently and that applies only the required amount of water at the proper time for effective use of the crops [58]. Controlled irrigation also helps avoid seepage and salinity problems via water applications to the required depth [58]. In addition, selecting fast-growing, highly productive quality seeds will help to save the resource for other economic and social uses. Controlled irrigation is thus recommended as a mitigating strategy for water scarcity and for environmental challenges that would occur due to the impacts of climate change and population growth.

For the CRVB, Musie et al., (2020) used SWAT models to assess the water conditions of terminal lakes in the CRVB and water management adaptation options. They recommended avoiding pollution of water sources and conserving the terminal lakes from pollution damages, both from sedimentation and other environmental pollutants. Thus, controlling the water level of the lakes, avoiding water quality degradations due to industrial and environmental wastes, and improving the storage capacity in the sub-basins will favor better use of the resources during peaks in demand [20].

Climate-based integrated development and use plan for the utilization of water resources according to its economic and social benefits, while safeguarding environmental sustainability, should be further assessed, modeled, and applied for its equitable use in equilibrium in the closed CRVB. Moreover, considering the response of the sub-basins to hydroclimatic impact while planning water use is crucial.

5. Conclusions

This paper investigated the impacts of future climate change on the major components of the water balance in the central rift valley basin in Ethiopia from the seasonal and spatial points of view. The evaluations are based on the magnitude of water yield, evapotranspiration, and surface runoff components change in relation to the baseline data outputs. Regional climate models (RCM) data in CORDEX—Africa were applied for the investigation. RCP data from the MIROC-RCA4 ensemble driving climate models were downscaled, bias-corrected, and used for the analyses. The methodology followed a calibrated Arc-SWAT modeling approach to search for basin-wide climate impacts on water resources and to indicate possible agricultural water management and adaptation strategies. The findings are solely based on model simulation outputs within the scope of its evaluations and error limitations.

Accordingly, the study identified a general decrease in water yield and surface runoff and a seasonal increase in evapotranspiration in the Ketar and Shalla sub-basins in both the near-term (2031–2060) and long-term (2070–2099) periods in comparison to the baseline period (1984–2010). However, all three water balance components projected were showing an increment in the Meki sub-basin for all the periods. The sub-basins were also found to be heterogeneous, and they showed variabilities in terms of their hydroclimatic reactions to the impacts of climate change even though they are in one endo hydrogenic region. In the sub-basins, some similarities were also found in the ways in which the pattern of the water balance components will be changed. However, the magnitudes of the impacts varied from sub-basin to sub-basin, between the RCPs, and between near-term and long-term periods due to the projected climate changes. These indicate that each of the sub-basin has a unique water balance environment.

The study also indicated the huge impacts of regional climate models (RCM) on surface components of the regional water cycle. These RCMs are a derivative of the Global Circulation Models (GCM).

The management interventions to mitigate the climate impacts should therefore be carried out according to the sub-basin water balance sensitivities while keeping the equilibrium in the closed CRVB water requirements. Finally, an investigated integrated watershed, agricultural water use, and farm management in the water–agriculture–land and climate nexus approaches following each sub-basin's climate responses, and other alternative resource management options for the closed CRVB must be determined and applied to cope with the hydroclimatic impacts.

The calibrated SWAT model has proved to be a useful tool for analyzing and identifying the temporal and spatial conditions of the water resources at a basin level under different climate change conditions in the CRVB. Therefore, further studies dealing with climate-based water resource management in combination with farming practices using the SWAT model would bring additional benefits.

Supplementary Materials: The following supporting information can be downloaded at: https://www.mdpi.com/article/10.3390/w15010018/s1, Table S1: Some physical properties of major soils in the CRV sub-basins; Table S2: Location of meteorological stations used for the analysis of the weather parameters in the CRVB; Table S3: SWAT land use code and their description.

Author Contributions: Conceptualization, L.A.T.; Methodology, L.A.T. and K.B.; Software, L.A.T. and K.B..; Validation, L.A.T., S.M. and K.B.; Formal Analysis, L.A.T.; Investigation, L.A.T. and K.B.; Resources S.M.; Data Curation, L.A.T. and K.B.; Writing—Original Draft Preparation, L.A.T.; Writing—Review & Editing, K.B.; Visualization, L.A.T., Svatopluk Matula; Supervision, Svatopluk Matula; Project Administration, S.M. and K.B.; Funding Acquisition, S.M. All authors have read and agreed to the published version of the manuscript.

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Data Availability Statement: The source data and materials used in this study will be made available upon reasonable request from the corresponding author.

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