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A thesis on:

Estimation of Daily Streamflow Using Remote Sensing Data: The Case of Bilate River Sub-Basin, Ethiopia

A Thesis Submitted to the School of Graduate Studies of Addis Ababa University in Partial Fulfillment of the Requirements for the Degree of Master of Science in Civil Engineering

(In Hydraulic Engineering)

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Estimation of Daily Streamflow Using Remote Sensing Data

(The Case of Bilate River Sub-Basin, Ethiopia)

A thesis submitted to the school of graduate studies in partial fulfilment of the requirements for the Master of Science degree in civil and engineering (Hydraulics engineering stream)

By

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Declaration

I, Cherinet Yacob, here by present for consideration by the School of Civil and Environmental Engineering, my Thesis in partial fulfillment of the requirement for the Degree of Master in Civil Engineering (Hydraulic Engineering), which entitled as “Estimation of Daily Streamflow Using Remote Sensing Data: The Case of Bilate River Sub-Basin, Ethiopia”. I declare that this work has been completed according to the guidelines established by the faculty and this thesis is the product of my own efforts except as specified in the references. The work has not been presented elsewhere for assessment. The materials that have been used from other sources are acknowledged or referred properly.

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Estimation of daily streamflow using remote sensing data | **2024**

Certification

This is to certify that I am responsible for the work submitted in this thesis entitled by "Estimation of Daily Streamflow Using Remote Sensing Data: The Case of Bilate River Sub-Basin, Ethiopia". And hereby recommend for acceptance by the Addis Ababa University in partial fulfillments of the requirements for the Degree of Masters of Science (MSc) in Civil and Environmental Engineering (in Hydraulic Engineering).

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Abstract

Most river basins in the world are ungauged. Especially in developing countries, catchments have less coverage of gauging stations. In Ethiopia, most river basins are ungauged. Streamflow data are collected at more than 506 operational gauging stations. Improving data accuracy and reliability of streamflow estimation in poorly gauged stations is mandatory. Different Streamflow estimation methods are developing from time to time. Traditionally, streamflow is directly measured through manual or automated ground based instruments installed within a monitoring station. In fact, there are different methods of Streamflow estimation. This study was conducted to gain better understanding on the use of remote sensing products for streamflow estimation in Bilate River sub-basin, Ethiopia. Four Remote sensed (satellite/reanalysis) precipitation products of different categories, source and resolution, namely GPM_3IMERGM v 07, CHIRPS 4.8 Daily, TRMM 3B42 v7 and ERA5 AG were compared against in situ observations. The main aim was estimating streamflow using bias-corrected remote sensed products and comparing the results with observed flows. Statistical measures such as Bias measurements, Coefficient of Regression, the Root Mean Square Error and the Mean Error were used. Also, Bias Component Hits, Missed and False rainfall and rainfall detection capability analysis and contingency table score such the Critical Index Success, Probability of Detection, Bias Frequency, and False Alarm Ratio were used to compare the satellite precipitation products with the gauge station data. The comparison were made depending on the stations' locations, point-to-pixel and sub basin scale analysis. Eight meteorological stations and five hydrological stations within the catchment were screened as reference data. The result from the comparison of observed daily time series data for 32 years (1991-2022) with satellite precipitation product indicates CHRIPs and IMERG performed better in terms of rainfall depth than TRMM and ERA5. Also, the degree of agreement R^2 using the four satellite precipitation products in Bilate river sub basin shows 0.9, 0.87, 0.8 0.77 for IMERG, CHRIPs, TRMM and ERA5 Ag respectively. For model calibration 11 years (2001-2011) and for validation process 4 years (2012-2015) were used to simulate HBV Light model. The model performance was evaluated based on three objective functions namely: Nash Sutcliffe Efficiency Coefficient (NSE), Relative Volumetric Error (RVE), and the Root Mean Square Error (RMSE). Satellite precipitation products IMERG and CHRIPS with ERA5 Ag Satellite (Temperature and potential evapotranspiration) products used as an input for HBV Light model. The calibration results for IMERG R^2 =0.7431 and PBIAS=1.08, objective functions NSE= 0.54, RMSE =0.87 and RVE =-1.37 for CHRIPS R^2 =0.7474 and PBIAS=4.94, objective functions NSE = 0.51, RMSE =3.59 and RVE = -5.65.

Keywords: Streamflow, Remote sensing, Bias-correction, HBV Light, Bilate River, Ethiopia

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List of Abbreviations

DEM	Digital Elevation Model
FB	False Rainfall Bias
GPS	Global Positioning System
HBV	HydrologiskaByråns Vattenbalansavdelning model
HEC-HMS	Hydrologic Engineering Centre Hydrological Modelling Software
HB	Hit Bias
MB	Missed Rainfall Bias
IMERG	Integrated Multi-satellite Retrievals for GPM
LZ	Lower Zone Storage reservoir
MSWEPv2	Multi-Source Weighted Ensemble Precipitation
PET	Potential evapotranspiration
PTQ	Precipitation-Temperature-Discharge
Qobs	Measured stream flow at gauged station
Qsim	Simulated stream flow at gauged station
RVE	Relative volume error
RMSE	Root Mean Square Error
R^2	Regression coefficient
SPP	Satellite precipitation products
TRMM	Tropical Precipitation Measuring Mission
UZ	Upper zone storage to facilitate rapid runoff

1 Introduction

1.1 Background

Rivers are part of the water cycle, which is a natural flow of fresh water that flows from higher to lower altitudes to the sea, lake or dries up through the land without reaching any other body of water. The main sources of river water are direct precipitation, surface or subsurface runoff and groundwater flow. Continuous flow recording is necessary because technical studies on the development and management of water resources rely heavily on hydrological data.

River discharge is the measurement of water flow in a river over a defined period of time. Which is one of the most important hydrological variables in the planning, management and use of water resources. Gauge stations used to collect Hydro meteorological data such as precipitation, streamflow, Temperature and other climatic data in the watershed. Data from measuring stations used for various purposes, including: flood forecasting, planning and design of water resources, hydrological research, operation of hydraulic systems. However, only a small percentage of watersheds from worldwide are equipped with a gauge. In developing countries, most measuring stations provide unsatisfactory data due to equipment failures and measurement program interruptions. Even most of the stations have poor data quality due to damaged equipment and stations with bad condition. Replacing and maintaining of the stations is needed. (Haile et al. 2013)

Ungauged basin is defined as a catchment in which the record of hydrological observations is insufficient to enable the calculation of relevant hydrological variables at appropriate spatial and temporal scales and with acceptable accuracy for practical applications (Sivapalan et al. 2003). Streamflow estimation in poorly gauged and ungauged basins presents a unique challenge for the international hydrological community. Accurate estimation of river flows and water storage is essential in planning and managing water resources. Whether the watershed is measured or not. Various methods have been used to estimate discharges at different time scales (daily, monthly, annually) in sparse and surveyed watersheds. To solve the problem related to hydrological data, we can estimate streamflow using direct and indirect methods. Using indirect method to estimate Streamflow in rainfall-runoff modeling requires precipitation information as the primary input. Ground-based gauge stations are usually used to collect precipitation data. However, Rain gauges are rare, unevenly distributed and have missing data problem. Precipitation data gaps needs to be properly filled by using gap-filling methods such as Arithmetic mean, Normal ratio, Inverse distance method and Aerial Precipitation Ratio. Due to the importance of hydro Meteorological data for proper planning and management of water resources we need to see other options such as community based monitoring and alternative data source like satellite remote sensing products.

Satellite-based precipitation estimates, such as remote sensing techniques, are becoming increasingly popular in monitoring global precipitation. Precipitation assessment with high temporal and spatial resolution can be achieved using satellite remote sensing. Precipitation estimation using remote sensing data is cost-effective because most satellite data is publicly available. In recent years, advances have been made in the technology of remote sensing of precipitation products using remote sensing technology. (Gusset et al., 2018). The data quality, accuracy and precision of these products are improved by incorporating instrument-based observations to correct biases in precipitation estimates. (Zhang et al. 2019). Some of those Satellite gauge products are GPCP, CHIRPS, TRMM, TMPA, IMERG, ERA5, CMORPH and PERSIANN. GLDAS, GLEAM & MODIS are some of Satellite based Evapotranspiration products which have being used at a global scale. (Numan Zahid Khan et al 2022) Satellite products provides nearly global coverage have the potential to replace daily time series data with an acceptable accuracy and can be alternatives to gauge observations. On the other side comparison of satellite precipitation products with gauge observations, implies the existence of biases, which needs to be corrected. (Zhang Y et al 2021)

Bias correction is the process of minimizing the differences between satellite products and rain gauge recorded data. Previous studies revealed that bias correction is needed before utilizing those satellite products by using different methods.(Gella et al.2018) In addition, some studies show the performance of bias corrected satellite products were good in rainfall-runoff models simulation. Habib in 2014 applied bias-corrected remote sensed products as an input on rainfall runoff model to show the effect of bias correction. Power transformation bias-correction method were used in Lake Ziway for CHIRP satellite precipitation product and the performance were evaluated by HBV model. (Demelash et al 2020)

Rainfall runoff models are tools used to simulate catchment response, discharge and water balance components result. (Seibert et al 2012) Different Hydrological models used for different purpose based on the aim of the study. Some of popular rainfall runoff models are SWAT, HECRAS, MIKE SHE, HBV and HEC HMS. In Ethiopia, several studies show the performance of those rainfall runoff models. The model performance comparison of HBV light and SWAT in Geba Catchment, Upper Tekeze Basin. (Abebe Temesgen et al 2019) The performance of different satellite precipitation products . For example, Awel Haji Ibrahim and Dagnachew Daniel Molla in 2022 shows the performance of satellite precipitation products CHIRPSv2, MSWEP and TRMM as an input to simulate HEC-HMS rainfall runoff model in Bilate river basin. Three daily satellite precipitation products ARC2,CHRIPS, COMRPH and potential evapotranspiration satellite product (FEWSNET) used as input to stimulate streamflow using HBV Light hydrological model in Wabi watershed.(Alato et al 2019) Satellite precipitation products CPC,TRMM,COMRHP,TMPA 3B42 and Evapotranspiration product FEWSNET using Hydrological model HBV 96 in Upper and Middle Awash River sub-basin.(Habte et al 2013).

Many studies reveled the existence of gauging stations data quality problem, also the number of actively gauging station decreasing from time to time. (World Bank et al. 2018) The study aim to introduce different satellite precipitation, Temperature and potential evapotranspiration product as an alternative data source in Bilate River sub basin. In addition, the study focus on comparing satellite products with the gauge observation, bias correction and using bias corrected satellite products s an input for rainfall-runoff hydrological models. The model selection were depending on its availability, less input requirement and its simulation performance in different countries with different climate conditions.

1.2 Statement of the problems

Many river sub basins in developing countries lack ground based streamflow observations, which means gauge stations with hydrological data are sparse. Although, gauge stations with ground based streamflow observations have poor data quality and completeness. The main reason are failure of monitoring equipment, limited accessibility to sites, difficult weather conditions, observation errors, code entering and transmission errors, and other processes of data collection.For all those reason the number of actively gauging stations decreasing,instead of showing improvements, in recent years they becoming worse all around the world (Global Runoff Data Center 2014).

Establishing and maintaining ground based gauge stations is expensive, labour intensive, and can place personnel at risk. Therefore, hydrologists should have to develop methods and techniques for estimating stream flow at ungauged catchments (Wagener et al. 2011).

The quality of hydrological data mainly depends on method used to collect data at the field and off the field. It is difficult to make a direct and continuous measurement of discharge in a stream but relatively simple to obtain a continuous record. Without a complete data set on river flow, water resource planning and design cannot be implemented properly. Different gap filling methods and bias correction methods are available to improve the quality of hydrological data from different sources. (Lusajo et al.2018), (Katiraie et al.2020).

In Ethiopia, Ministry of Water and Energy (MoWE) collects hydrological data such as stream flow data from 560 gauging stations in 12 basins in the country, however, most river basins have less coverage of hydrological gauging stations. This constrains proper planning, Water resource projects design and management. In most parts of the country river basins hydro-meteorological data are characterized by poor data quality such as long years missing, unrealistic and extreme values. Some of the errors, manual or machine, might exist in the streamflow observation. The major gauging stations in the country were equipped with non-recording type devices (staff gauge) which needs frequent maintenance and monitoring. (Ayana, et al 2019).In the meantime, The MoWE need updating the rating curve from time to time. However, updating the rating curve was not done frequently as required in the Ministry. This might be due to lack of budget, adequate human resources, and problems related to access to remote stations. The poorly gauged and ungauged basins problem should be addressed using new methodologies.

In Bilate river sub basin there are six gauge stations recording daily streamflow data. However, those stations have poor data quality, characterized by short and long duration of missing data. Improving the quality of streamflow data for hydrological analysis is mandatory. There are advanced technologies and methods that can be used to generate the missing hydrological data including streamflow. Remote sensing represents an appealing alternative means of obtaining streamflow data. As in the case of hydrologic variables such as precipitation, complete historical records are necessary in order to use rainfall runoff models. In current years Satellite precipitation products having acceptance in Hydrology and Meteorology, However, they have bias in there Estimation which, should be corrected using different bias correction methods. In this investigation, an effort was made to estimate the daily streamflow using gauge stations data and remote sensing data as an input for rainfall-runoff modeling in poorly gauged stations of Bilate River sub basin. The finding of the study will contribute to better understand the temporal and spatial variability of water yield in the sub basin and water resource developments and management works.

1.3 Objective of the Study

1.3.1 General objective

This study intends to gain better understanding of daily streamflow estimation in poorly gauged and ungauged stations using remote sensing and gauging stations' data as input for stream flow modeling in Bilate rivers sub basin.

1.3.2 Specific objectives

The specific objectives of the study include:

- To evaluate the adequacy and quality of the Hydro-meteorological gauged data of Bilate river sub-basin
- To evaluate and select suitable remote sensing rainfall products
- To bias-correct the selected remote sensing rain fall products for Bilate river sub-basin
- To simulate Bilate River Runoff using bias-corrected rain-fall product

1.4 Research Questions

1. What is the percentage of missing data in poorly gauging stations of Bilate River sub basin?
2. What are the main causes of missing data in Bilate River gauging stations?
3. Which gap filling method is preferable in Bilate River gauging stations?
4. Which remote sensing rainfall product is available for Bilate river sub-basin?
5. Which remote sensing data source is more suitable for stream flow modeling?
6. What is the extent of bias between gauging stations and satellite based rainfall products?
7. Which bias correction Methods are good for correcting satellite based rainfall products?
8. Which rainfall-runoff model is appropriate for Bilate river sub-basin?
9. How good is the performance of rainfall-runoff model?
10. What is the simulated Runoff time series data?

1.5 Significance of the study

Ethiopia is the 10th largest country in Africa with Surface area, due to the size of the country and the complexity of its water resources most river basins are poorly gauged or ungauged. To overcome these challenges we need to use new technologies and methods as alternative data source to simulate the stream flow to those poorly gauged or ungauged catchments. Finding of this study will offered vital information to the decision makers for wide variety of purposes

- Water resources planning and design
- Hydrological research
- Operation of hydraulic structures and water supply
- Navigation
- Recreation
- Management of in stream habitat and
- Predicting and monitoring of floods in Bilate River sub-basin.

Remote sensing observations in Estimation of daily stream flow will have

- Greater efficiency,
- Expanded coverage,
- Increased measurement frequency,
- Cost savings, and

Reduced risk to field hydrographers remote-sensing instruments provide increased safety to the technicians and are less likely to be lost during major floods than fixed, traditional stream gauging in Bilate River sub-basin.

1.6 Scope of the study

Conceptually, the study will mainly concern on the Estimation of daily streamflow for poorly gauged and ungauged stations by using different methods. Methodologically, the research is focused in the rift vally river basin hence, the study is confined to the Rift Vally River basin, which is geographically limited at Bilate River catchments using both remote sensing observations and ground based catchment process.

1.7 Limitation of the Study

To concentrate on all gauging station in the entire country was impossible because of the limited period and amount of fund. Another limitation of the study related to the resolution of available satellite products, which are coarse.

2 Literature Review

These chapters will gives an overview of literatures that are related to the research problem and it introduces literature thought like concepts of Estimating daily streamflow using remote sensing data in hydrological models.

2.1 Ground based gauged station data

2.1.1 Hydrological data

An accurate estimate of water flow is the most important information hydraulic engineers and hydrologists need. Observed flow data are important for hydrological research, flood forecasting, and water resource planning and design. Discharge time series for gauging stations are often calculated using a phase performance curve that relates measured river level to discharge. (Singh et al, 2014).

Data quality refers to the relative accuracy and precision of a particular database. Correctly, captured data provides an absolute measure of data quality. However, some errors may occur when observing, transmitting or recording the stream, such as random, systematic or non-uniform errors. The quality of hydrological data is assessed according to current standards. Although it is very difficult to maintain certain standards of reliability and accuracy of time series data, data collection and processing is crucial, especially in the case of national databases. A total of observation networks worldwide are getting worse rather than better (World Bank et al. 2018).

Ethiopia has twelve river basins based on hydrological boundaries. The Ministry of Water and Energy (MoWE) collects hydrological data such as flow data from many rivers in the country. MoWE is responsible for data collection, processing and analysis. Most measuring stations were equipped with staff gauge. They need frequent maintenance and monitoring. Due to various factors, low data quality, missing values over long years, unrealistic and extreme values are some of the characteristics of the country's watersheds (Ayana et al. 2019). Many researchers have pointed out the lack of high-quality hydrological data in Ethiopia. In the Upper Blue Nile Basin (Haile et al.2017), in the Omo-Gibe River basin (Degefu and Bewket 2017) and in the Ziway-Shala basin (Goshime et al. 2019).

The quality of flow data from measuring stations is unsatisfactory in most parts of the country for various reasons, such as damage to most measuring stations after floods, delays in the collection and payment of observer salaries, and the lack of digital data exchange. No further quality assessment by water technicians, rating curves are out of date. (Haile et al. 2023).The Ministry of Water and Energy is not updating the rating curve frequently as required due to lack of budget, adequate human resources, and problems related to access to remote stations.(Ayana, et al 2019)

In this study the Bilate river sub basin which is the part of Rift valley lake basin has six Hydrological gauge stations from those ground based stations streamflow data quality assessment and filling missing values to those station data was implemented.

2.1.2 Meteorological data

The overall discharge from the river basin depends on the relationship between precipitation, evapotranspiration and storage factors. Precipitation is any product of the condensation of atmospheric water vapor that falls from clouds in the forms of drizzle, rain, sleet, snow etc. Precipitation is measurement taken as a vertical depth of water that would accumulate on the horizontal surface with measurement units: mm, cms, inches, and feet. Rain gauge is an instrument used to collect& measure rainfall and it is the main input of hydro meteorological models (Kidd and Huffman2011).

Ground-based rain gauge data sets are widely used in water management and hydrological studies. However, the scarce distribution or poor coverage of rain gauges due to rain gauges have trouble observing precipitation in remote areas such as oceans, polar areas, and mountainous regions (Kidd et al. 2017). In addition, the number of ground rain gauges continues to declining all over the world (Shiklomanov et al. 2002).

Hydrological analysis and design need complete measurement of precipitation data but there are missing values. There are many causes of missing rainfall data such as failure of the observer, vandalism of recording gages (damage in gauge stations), and instrumental failure. Etc. (Ngene et al 2015).

Due to technical or maintenance issues, metrological data production and management is difficult tasks. There are gaps in the data set those missing intervals in the time series represent a loss of information (Tencaliec et al. 2015). The missing data problem should be addressed using different gap-filling techniques such as simple arithmetic means, normal ratio method, correlation coefficient weighing, inverse distance weighting, multiple linear regression, empirical quantile mapping, and empirical quantile mapping plus. (Chinasho et al 2021)

The National Meteorological Agency (NMA) of Ethiopia collects daily rainfall data from more than 1200 conventional stations, 25 automatic stations, an upper air observation, and AWOS at different airports of the country. There are 919 active meteorological stations in the country. (NMA 2013)

The quality of ground based meteorological gauge station data can be screened using Grubbs T-test to identifying outliers in the observed data, F and t-test to stability of variance and mean, Average minimum flow are estimated for D-days. (Ayana, et al 2019)

Rainfall runoff models depend on the precipitation records from gauge station, but recording rain gauges have missing value problem, those missing value can be fill using different gap filing methods. In this study, ground based meteorological data for Bilate watershed and surrounding gauge stations collected from NMA of Ethiopia. Then gap filling for missing values and fixing the extreme values using different techniques for those selected station takes place.

2.1.3 Filling the missing hydro meteorological gauged station data

In most of ground based gauge stations, due to technical or maintenance issues observed streamflow records contain missing values that make it difficult for hydrological modelling (Tencaliecetal.,2015).In the large-scale monitoring system, Missing data is a common phenomenon. Hydro meteorological time series data has collected at regular time intervals. When there is no hydro meteorological data observation for some period due different reasons, in order to make analysis we need to fill those missing values properly in the data set. There are different reasons to the existence of missing values in the data set some of those reasons are failure of monitoring equipment, extreme weather conditions, limited accessibility to measurement sites, absence of observers, human induced errors, budget restraints, and political conflicts among other factors (Elshorbagy et al., 2000).

In the past decades, the number of actively operating streamflow stations with long historical records decline (Hannah et al., 2011). There are different types of missing data such as missing completely at random, missing at random, missing not at random.(Sharma et al.,2022)Missing data are universal Problem in hydrology, but it's becoming worth in developing countries where limited resources exist for data collection, quality assessment, repository provision, and maintenance.(Ekeuwei et al. 2018)

The choosing the appropriate infilling technique depends on different factors such as the length of the missing values, the seasons of gap occurrence, the climatic region of the observation sites, the characteristics of the existing time series and the purpose of the use of the gap-filling (Dembele et al., 2019). Performances of different gap-filling methods were assessed using Mean Absolute Error, Root Mean Square Error, and Nash-Sutcliffe efficiency. In order to test the accuracy of methods used in estimation of missing data.(Caldera et al 2016)

Gap filling techniques such as simple arithmetic means, normal ratio method, correlation coefficient weighing, inverse distance weighting, multiple linear regression, empirical quantile mapping, and empirical quantile mapping plus were selected and there performance evaluated using mean absolute error, root mean square error, skill scores, and Pearson's correlation coefficients in southern part of Ethiopia.(Chinasho et al 2021)

Even if there are different methods of filling of missing hydrological data, there is no single gap filling techniques that we can be consider as universally best. When we come to filling missing data, all gap filling method have their own advantages and disadvantage depending on the characteristics of the time series data. (Lusajo et al., 2018)

In Ethiopia, the hydro meteorological gauging stations data quality characterized by short and long period of missing data. So, in order to improving the quality of those ground based time series datasets , we need to use the appropriate gap filling techniques before we make any hydrological analysis.(Ayana et al., 2019).

In this study, the quality assessment of hydro-meteorological time series data for ground based six hydrological and eight meteorological stations located in Bilate river sub-basin was made using different gap filling techniques and there performance evaluated.

2.2 Satellite based precipitation products

Rainfall-runoff modeling and flood forecasting require information on precipitation as a major input. Traditionally, meteorological information on precipitation is available and collected from ground based meteorological gauging stations. Rain gauges have trouble observing precipitation in the remote area such as oceans, polar areas, and mountainous regions. We need alternative source of information on precipitation other than in-situ estimates such as space born estimates. Luckily, observing global precipitation using remote sensing techniques having progress. The two major remote sensing techniques in precipitation observation are weather radars and space-based meteorological satellites. (Hong et al. 2019).Rainfall estimation using satellite remote sensing data is cost effective because most of the satellite data is available free of cost. Publicly available precipitation products classified in to rain gauge data, single satellite sensor, multiple satellite sensors and combination of multiple sensors with gauge data. Satellite based precipitation data sets extracted by satellite radiometers such as visible (VIS) or infrared (IR) sensor; passive (PM) and active microwave (AM) method; merging of IR and microwave data; and precipitation radar (PR).(M L Tan et al 2014)

In recent years, several improvements have been carried out in satellite based precipitation products which leading to unprecedented accuracy and precision (Muhammad et al., 2020). Evaluation of Satellite based precipitation estimates such as CHIRPS, TRMM 3B42 V7 and PERSIANN-CDR products in various climate regimes.(Zhang et al., 2021). Some products such as TRMM, TMPA, CMORPH and PERSIANN have been tested (Beighley et al., 2009). Satellite rainfall estimates CHIRPSv2 products used in Africa (Funk et al., 2015). The most widely used satellite precipitation and temperature products includes ERA5-Land, which is a reanalysis dataset providing, Mean Temperature, Precipitation, and Wind Speed. With spatial resolution of 11.1-km (0.125-deg x 0.125-deg) starting from 1963 to Present

GLDAS Data set generates Evapotranspiration, Surface Runoff. With Spatial resolution of 24-km grid (1/4-deg) Starring from 2000 to Present which is available free to the user's.

TRMM/3B42 Precipitation Estimates TRMM DAILY (Derived from 3-hourly) with spatial resolution of 28-km (1/4-deg) starting from 1998 to Present Variables. This dataset is in the public domain and is available without restriction on use and distribution

CHIRPS Daily starting from 1981 to Present (updated monthly). The Climate Hazards Group Infrared Precipitation with Station data is a 35+-year global rainfall data set with Spatial resolution of 4.8-km grid (1/20 deg). These datasets are in the public domain.

PERSIANN-CDR is a daily global precipitation product that spans the period from 1983 to present with spatial resolution of 24-km grid (1/4-deg) starting from 1983 to present which is publicly available. GPM Global Precipitation Measurement is an international satellite mission to provide next generation observations of rain and snow worldwide every three hours with spatial resolution of 11-km (1/10-deg) starting from 2000 to Present. Daily data is updated every 30-minute which is freely available for the public. Amongst the Satellite remote sensing product some of commonly used are shown in Table below.

Table: 2.1 Satellite precipitation products

Satellite products	Spatial resolution	Period coverage	Temporal resolution	Source	Reference
TRMM (the Tropical Rainfall Measuring Mission)	**0.25°**	From 1997 to 2015	After the spacecraft depleted its fuel reserves	http://disc2.nascom.nasa.gov/opendap/TRMM_L3/TRMM_3B42 /	(Kummerow et al. 2000)
TAMSAT (Tropical Application of Meteorology Using Satellite Data and Ground-Based Observations)	**0.0375°**	From 1983 to the delayed present	Daily to seasonal time-step	http://www.tamsat.org.uk/	(R. Maidment's et al.2020)
IMERG (Integrated Multi-satellite Retrievals for GPM)	**0.1**◦	TRMM (2000 - 2015)GPM (2014 - present)	Daily, monthly annual	https://gpm.nasa.gov/data/imerg	(R. K. Pradhan et al.2022)
CHIRPS (Climate Hazards Group Infrared Precipitation with Station data)	**0.05**◦**.**	From 1981 to present	Daily, monthly and annual scales	https://www.chc.ucsb.edu/data/chirps	(Ayehu et al. 2018)
GPCC (Global Precipitation Climatology Cent	**1.0° , 2.5°,0.5**	From 1982 to present	Daily,monthly	https://www.dwd.de/EN/ourservices/gp	(F. G. Paveh et al.2022)
CMORPH (Climate Prediction Center's morphing technique)	**0.25°**	From1998–present	30 min ,Daily	ftp//ftp.cpc.ncep.noaa.gov/preci p/CMORPH_V1.0/CRT/8km- 30min	(D. A. Zeweldi 2009)
ECMWF ERA5 (European Centre for Medium-RangeWeather Forecasts)	**0.1**◦	From1940 to present	hourly,Daily	https://opendata.dwd.de/climate_environment/ GPCC/	(Hersbach et al 2020)
PERSIANN(the Precipitation Estimation from Remotely Sensed Information using Artificial Neural Networks)	**0.04**◦	From 1983 to present	Daily	http://chrs.web.uci.edu/	(Yanget al 2022)
FWESNET (Famine Early Warning Systems Network) global evapotranspiration (PET)	**1**◦	From 2001	Daily, Monthly, Annually	http://earlywarning.usgs.gov/ ftp2 /bulkdaily%20data/global/pet/years/	(Shukla et al 2017)
MSWEP (Multi-Source Weighted-Ensemble Precipitation)	**0.1**◦	From 1979 to	3 hours,Daily	https://www.gloh2o.org/mswep/	(Beck et al., 2017)
GSMaP (Global Satellite Mapping of Precipitation)	**0.1°**	From 2002	hourly,Daily	https://sharaku.eorc.jaxa.jp/GSMaP/	(M. Darand et al 2021)

Overall Satellite precipitation products in Ethiopia

In Ethiopia, several studies evaluate the performance of different satellite precipitation products such as CHIRPS v2.0 (Ayehu et al. 2018), IMERG (Andualem et al.2020). The performance of satellite based rainfall estimates like CHIRPSv2, MSWEP, TRMM was evaluated against the rain gauge observation in order to use them for hydrological modeling in the Bilate River Basin.(Ibrahim et al, 2022;Ayehu et al., 2018; Dinku et al., 2018).CHIRPS2 performed the best in estimating and detecting rainfall (G.K.Wedajo et al 2021).According to Gella, Getachew. (2018) bias correction is needed before utilizing those satellite precipitation products in Eastern Ethiopian landscape. Also Kehase Neway in 2023 show the performance of satellite rainfall products such as CHIRPS.v2, TRMM.3B42v7, TAMSAT.v2, and CMORPH.CPC at the Gidabo catchment. In Wabi Shebelle river basin, the performance of MSWEP and TAMSAT showed better result than CMORPH, TRMM and CHIRPS. (Engdaw et Al 2022). From Southern Ethiopia Bale, Temesgen Gashaw in 2023 evaluate the performance of satellite/reanalysis rainfall products (CHIRPS v2.0, TAMSAT v3.1 and MSWEP v2.8) and temperature products (MERRA v2 and ERA5). Kirubel Mekonnen in 2021 implies the Suitability of satellite product such as TRMM 3B42v7, 16 IMERG v06B, and TAMSAT v3 to simulate discharge in Upper Awash Basin.

Overall, Satellite precipitation products are using as an alternative precipitation data sources for rainfall-runoff modeling in data scarce regions of Ethiopia. In Bilate watershed satellite based remote sensing products is a good alternative. However, those products contain uncertainties attributed to errors in sampling so bias correction is needed.

2.2.1 Bias correction

In recent years, advances in remote sensing technology have led to satellite estimates of precipitation gaining acceptance in the fields of hydrology, meteorology, and especially precipitation and runoff modeling. However, they are subject to systematic errors and repeated deviations from the ground station measurements. Bias correction is a statistical technique used to eliminate differences in an estimate. There are some differences between satellite estimates and ground measurements, and correction methods are needed to reduce systematic biases in these products. Bias in precipitation products must be corrected before being applied to precipitation runoff models. (Katiraie-Boroujerdy et al. 2013)

The first process in bias correction is biases identification between satellite rainfall estimates and observed data, then correcting satellite rainfall products by using several methods. There are different bias correction methods applied to reduce errors such as, precipitation threshold, scaling approach, power transformation, distribution transfer, precipitation model and empirical correction methods. (H. Daniel. et al. 2023) (Soo et al. 2020). (H. Daniel. et al. 2023). The most common bias correction methods are linear scaling (LS), local intensity scaling (LOCI), power transformation (PT), distribution mapping (DM) and quantile mapping (QM), while temperature transformations correction methods are LS, variance scaling (VARI) and DM, PT and QM methods performed equally best.(Fang et al., 2015). In this study bias correction of daily precipitation products using power transformation method to match the observed precipitation statistics, and to use in rainfall-runoff modelling.

Table: 2.2 Bias correction methods

Bias correction for precipitation		Advantage	Disadvantage
Linear scaling (LS)	to treat the gaps between ground/ observed data and raw/corrects the average precipitation value	Mean-based,It is the simplest BC method	does not correct the standard deviation or variance The daily precipitation sequence is the same as that of the RCM-simulated data
Local intensity scaling Method (LOCI)	is an advancement over linear scaling	Mean-based ,The wet-day frequency is corrected	It does not account for the different changes in the frequency distribution of precipitation
Power transformation (PT)	an exponential form to further adjust the standard deviation of precipitation series	Mean-based.Corrects mean and standard deviation (variance) events are adjusted non-linearly.	Adjustment of wet-day frequencies and intensities only to some extent.
Distribution mapping (DM)	the distribution function of the raw data to that of the observations	used to adjust the mean, standard deviation and quantiles	limitation due to the assumption that both the observed and raw meteorological variables follow the same proposed distribution, which may introduce potential new biases
Empirical quantile mapping (EQM)	It can effectively correct bias in the mean, standard deviation, and wet-day frequency as well as quantiles	This function transforms the raw model rainfall into corrected model rainfall	The limitation of the method is that It correct mean variance and frequency and intensity of wet days and does not account for temporal distribution of daily rainfall occurrence

2.3 Hydrological models

Hydrologic models can simplify a real world system that are important for a wide range of applications, including water resources planning, development and management, flood prediction and design. Rainfall-runoff model are important tool to understand and predict the different hydrological processes. Application of those models depends on the problem that we need to be address. (Singh et al 2002.) Most of streamflow forecasting models categorized under: conceptual (HBV model, TOPMODEL, SimHyd, IHACRES), metric (DBM, ANN, unit hydrograph), physics based (SHE or MIKESHE model, SWAT), and data-driven (ARMA ANN, SVR, WANN, and WSVR). The assumption of the first three models is the relation between the input and output. (Pechlivanidis et al. 2011). Some of the most common hydrological modelling software includes

SWAT (The Soil and Water Assessment Tool) is a physical-based semi distributed model developed to assess the impact that changing land management practices has on streamflow, nutrients and soil erosion of the catchments. (Arnold et al., 1998)

HEC-HMS (the Hydrologic Engineering Center-Hydrologic Modeling System) is hydrological modelling software developed by the US Army Corps of Engineers Hydrologic Engineering Centre. Which designed to simulate the precipitation runoff processes within a wide range of geographic areas such as large river basins and small urban or natural watersheds.

IHACRES is a product of collaborative research between hydrologists from the Australian National University, Canberra and Institute of Hydrology. It is model is being applied in a regionalization approach to develop streamflow predictions. The IHACRES rainfall-runoff model uses a non-linear loss module to calculate the effective rainfall and a linear routing module to convert effective rainfall into stream flow. (Mahmoud Ahmad et al 2019)

HBV-light model (the HydrologiskaByrånsVattenbalansavdelning light model) is a semi-distributed conceptual hydrologic model to simulate catchment runoff. Which needs a moderate amount of input data such as precipitation, Temperature, Potential evaporation. It can be used to extend runoff data series (or filling gaps), for runoff forecasting (flood warning and reservoir operation), to simulate discharge from ungauged catchments. The results of HBV-Light shows good performance efficiency. (Endalkachew et al.2019). The model simulates daily discharge using daily rainfall, temperature and potential evaporation as input. Precipitation is simulated to be either snow or rain depending on whether the temperature is above or below a threshold temperature (T. L. A. Driessen 2010).

Due to less number of model parameter requirements, the HBV model can be used for Ethiopian conditions with data usually less available without too much calibration work for simulating and predicting the daily, monthly and annual discharge (Demeke, et al, 2011).

In this study, we use bias corrected satellite based (remote sensing) data and gauging station data as a stream flow modeling input in Bilate rivers sub basin using HBV-light Hydrological models. Moreover, comparing the result by using those different satellite products as input in HBV Light model.

3 Study Area And Data Availability

3.1 The Study Area

3.1 .1 Location

Ethiopia is a nation located in the East Africa with total Area of 1.13million square kilometer from this dry land 1,119,683km² and water body 7,444km^2.Danakil Depression is the lowest altitude 125m below sea level and RasDashen Mountain is the highest 4600 m above sea level. The Mean annual temperature ranges between 150 to 200ºc and the Mean annual rainfall ranges between 200 to 2200mm.The Great Rift Valley of the eastern Africa divides the country into two plateaus. There are 12 basins in the country; eight of which are river basins; one of them is Lake Basin called Rift valley; and remaining three are dry basins.

Bilate River is a part of Rift Valley Lake Basin flows in south central Ethiopia. The Bilate river sub basin which is located at upper part of the Abaya Chamo Basin with a catchment area of 5756 km² and its elevation ranges from 1176 m in the south to 3328 m in the north. Bilate river sub basin is in between latitudes 06° 34′ 48″ N to 08° 09′ 00″ N and longitudes 37° 46′ 48″ E to 38° 20′ 00″ E. It rises from Gurage highland 6°2′N 38°7′E , flowing south along the western side of the Great Rift Valley to empty into Lake Abaya at 6°37′54″N 37°59′6″E. It is the longest river flowing into Lake Abaya and the one with the highest discharge. Rainfall is the primary source of water in the subbasin, and it originates from Bilate river watershed.

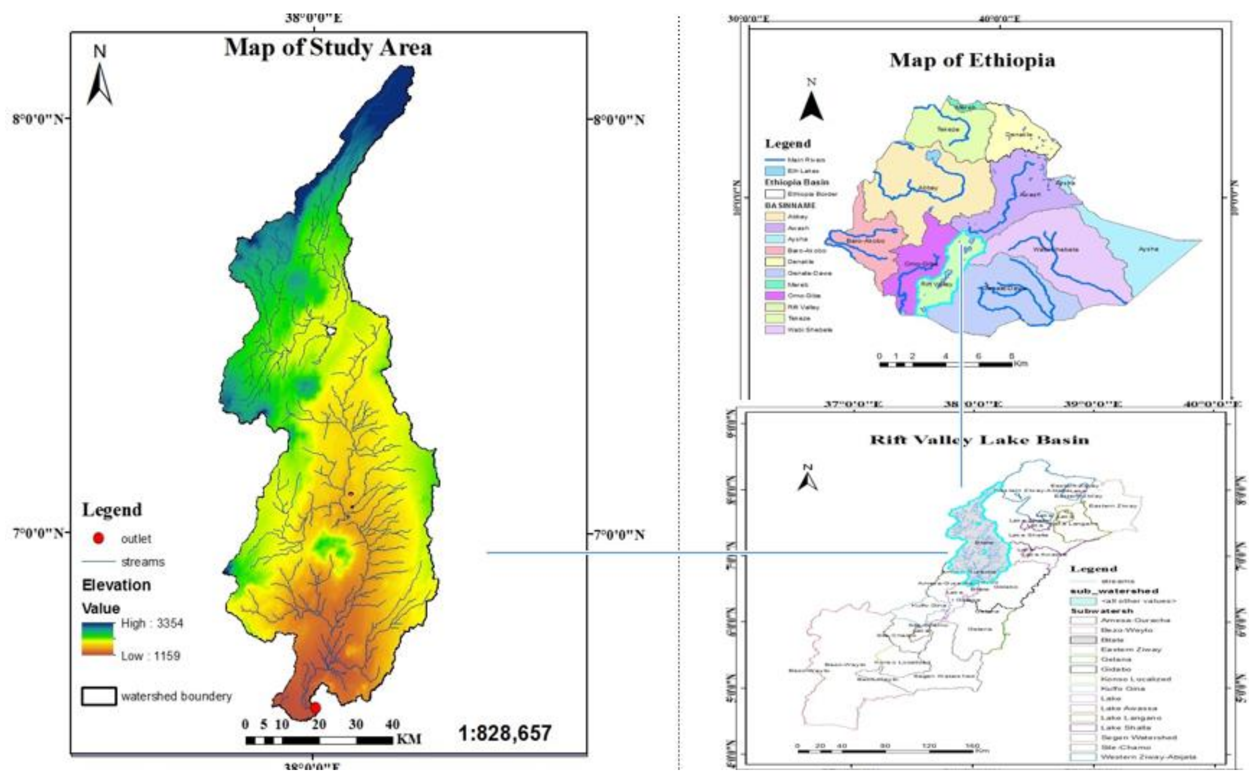


Figure 3.1: Location of study area

3.1.2 Climate and Hydrology

The country Ethiopia has climate, which mainly affected by the seasonal migration of the Intertropical convergence zone and topography. Ethiopians traditionally classify there climate zones based on altitudes and temperatures into five Wurch (cold climate above 3000 m altitudes),Dega (climate-highland between 2500-3000 m altitude),WoyinaDega (warm between 1500-2500 m altitude), Kola(hot and arid type, below 1500 m in altitude) and Bereha (hot and hyper-arid).

Woyina Dega and Kola are the two climate zones in Bilate river sub Basin. There wet season usually start from April through September; Especially June to September (locally called Kiremt) the main rains occur in the catchment. The average annual rainfall in the basin is from 1056 mm to 710mm, the temperature varies with altitude monthly average maximum of 25^0C and minimum 12^0 C temperature. The estimated potential evapotranspiration of Bilate sub-basin is 137mm per month. Bilate river sub Basin according to total annual rainfall classified into three sub-basins: the upper (1280 and 1339mm), middle (1061 to 1516mm) and lower sub-basins (769 to 956 mm).

The Bilate watershed has a catchment area of 5756 km² and its elevation ranges between 1176 m in the south and 3328 m in the north. Topographical effects cause considerable variability in mean yearly rainfall in the drainage basin. Bilate River has a length of 173km, Guder and Weira Rivers are the two main tributaries of the Bilate river, that formed after Boyo swampy lake. Batena and Konkoye are intermittent rivers to feed Guder and Weira Rivers respectively, which are originated from the north Hossana and Guragie. Boyo swamp which is located 26 km north of Alaba Kulito, in Hadiya Zone. The maximum stream length is about 197km. The mean minimum and maximum annual flows of the Bilate river varies between 0.82 to $22.33m^3/s$ at Weira, 1.2 to $31.25m^3/s$ at AlabaKulito and BilateTena (Dimtu) is 3 to 45.7m3/s. The catchment has 129mm estimated recharge. From 1231.6mm rainfall, groundwater recharge 10.5%, surface runoff 4.5% and 85% return to the atmosphere as groundwater and AET. Highlands of Gurage, Silte, Hadiya, Kambata and Wolaita zones are the source of water to the watersheds. The stream networks show parallel flow to the geologic structure mainly in the highland and develops dendritic drainage pattern in the lowland part.

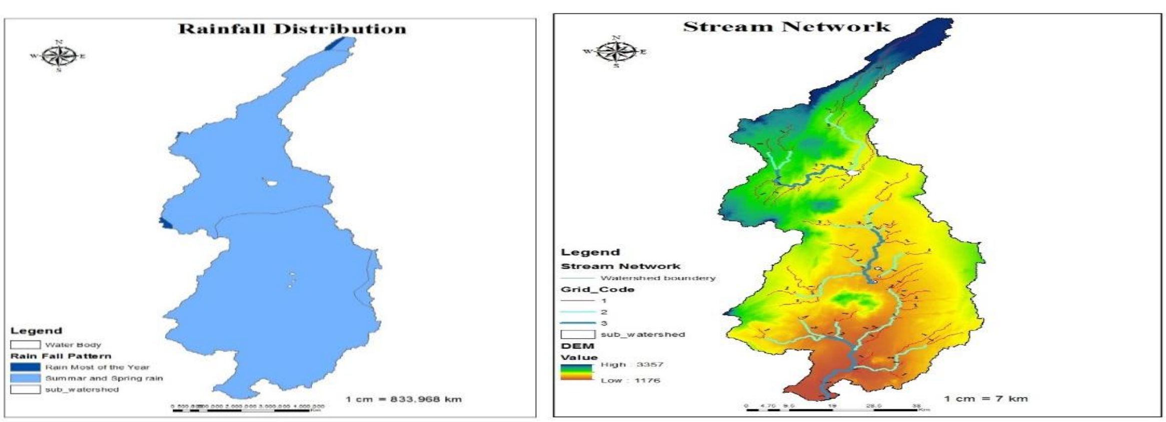


Figure 3.2: Hydrology of study area

3. 1.3 Topography

Bilate river watershed divided in to the rift, escarpment and highland physiographic zone. The drainage area is estimated about 5,019.7 km^2 at the entrance of Lake Abaya. The elevation of the area ranges from lowest elevation 1,116m at southern downstream near to Lake Abaya to the highest elevation3, 350m above sea level in the northern hill tip.

In the process of generating rainfall into run off slope is a key topographic feature, which uses in regulating the surface water flow. (Das et al. 2018).The slope of the study area was 0 % up to 8%. The least one is greater than 30%, which is coverage area, is small as compare the rest. Bilate catchment have five slope classes: very low slope, low slope, medium slope, high slope and very high slope.

The lowlands and highlands platea Misha Woreda to the north-west, Meserake and Meerab Azernet Berbere, Muhur Aklil, Gumere, and Alicho Wiriro Woreda to the north, and a portion of Angacha and Danboya woredas to the south-west differ greatly in topography.

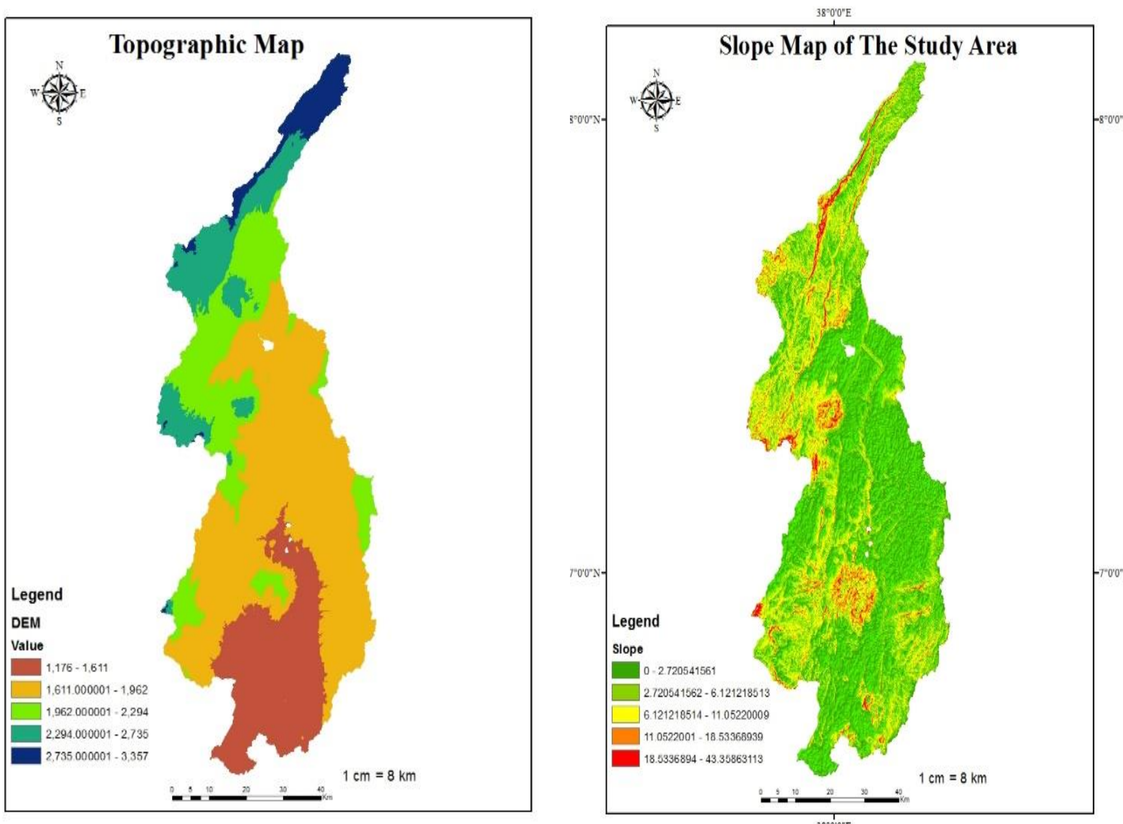


Figure 3.3: Topography and Slope of study area

3. 1.4 Land Cover

The ground's surface is actually displaying land cover as a natural or manmade entity. In Bilate River sub basin bare land, forest, grassland, cultivated land, marshland, moderately cultivated, shrub land, urban area and water body(Boyo swamp Lake) are the main land cover types in the basin.

Land use is human use of land by managing and modifying the natural environment to agricultural, residential, industrial, mining, and recreational uses. In Bilate River sub basin farmlands dominate the land use with more than half of the area were as Shrub land, Forest, Grassland, Cropland, Woodland, Vegetation and Bare land.

The Bilate River sub basin is characterized by mixed cultivation and supports irrigation to grow commercial plants. The agricultural system integrates cereal and root crops in afairly intensive manner. The main crops are teff, wheat and beans also they cultivate enset (false banana), as well as a range of vegetables. Here, two state farms and a military base are located in close proximity to the Bilate. The farms are irrigated and mainly cultivate tobacco and maize.

To estimate evapotranspiration, the area's land use and land cover map is consulted. It is prepared using satellite imagery and field observations.

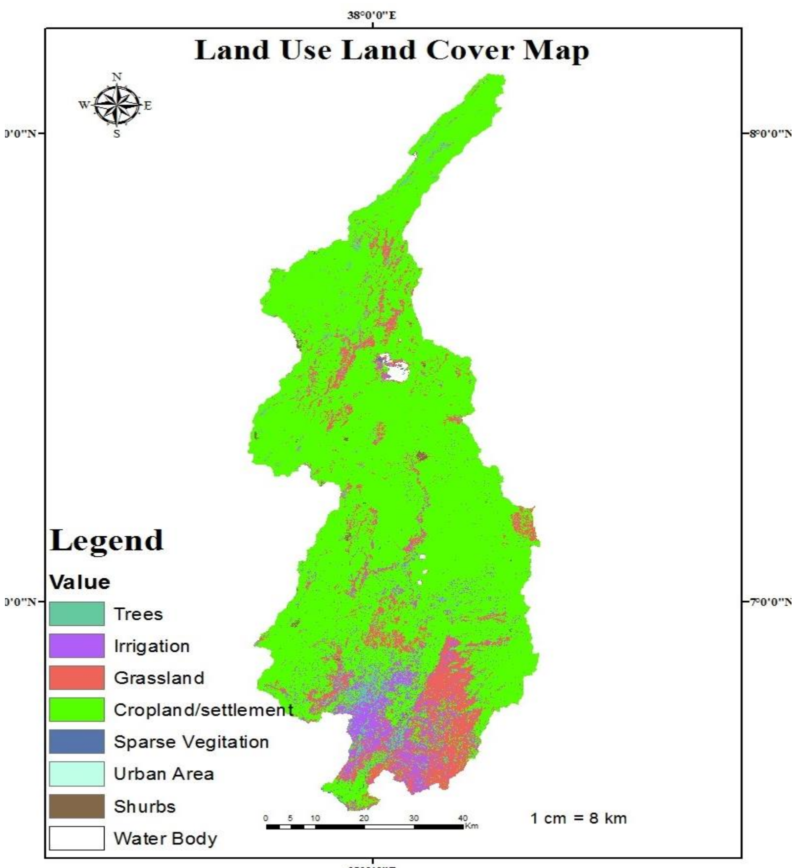


Figure: 3.4 Land use/land cover map (Ethiopia_Sentinel2_LULC2016)

3.1.5 Soil

The climate, physiography, geology, and other elements that influence soil formation and development all play a role in the formation of soils. In the Rift Valley, three major soil types are Vitric Andosols, Lithic Leptosols and eutric Vertisols, Chromic Luvisols. During rainfall-runoff process soil parameters such as permeability, infiltration rate and thickness of the soil layer have a direct impact. (Rimba et al. 2017).

The major soil types within the Bilate catchment are chromic vertisols, Vitric Andosols, Eutric Nitosols, Chromic luvisols, and lake. chromic vertisols is the dominated and the water body is the least one.(Meyer &Enzler, et al 2013).in upper sub-basin Chromic luvisols from clay to sandy loam,in the middle sub-basin vertic andosols with sandy loam, in the lower chromic vertisols. The soil type and nature found in the watershed influences the flood levels and the infiltration capacity.

Using the soil water balance technique, the soil water retention capacity of the research area's soil map was estimated during actual evapotranspiration.

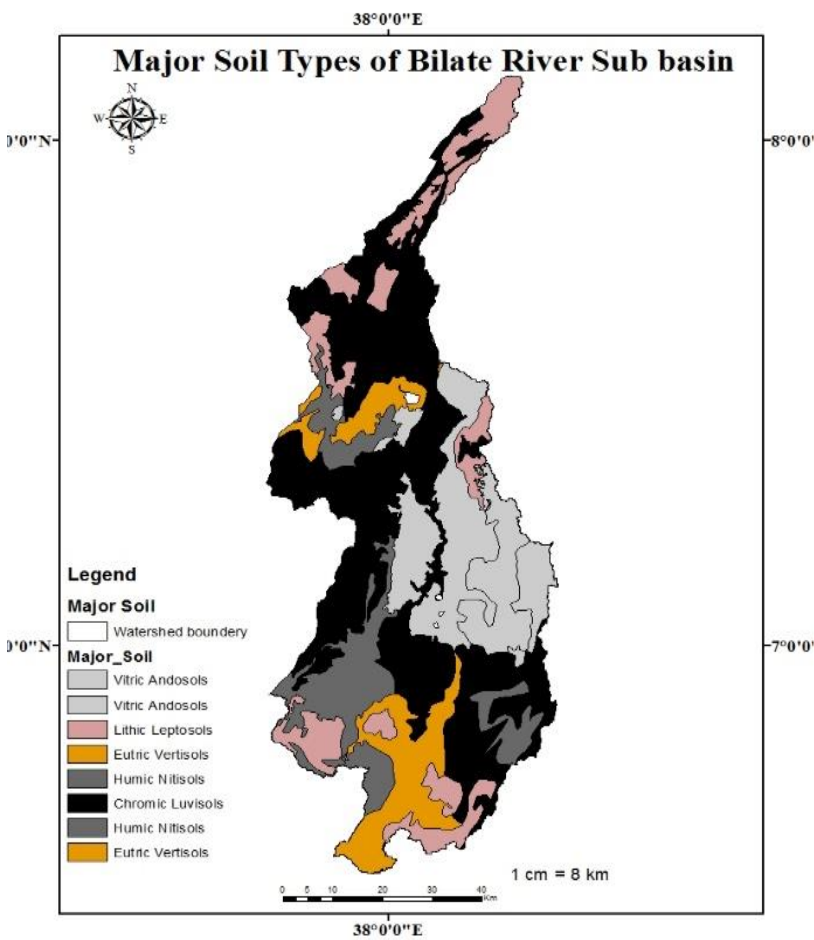


Figure: 3.5 Soil map of Bilate River sub basin

3.2 Data Availability

Primary and secondary data have been collected from the selected observation sites and secondary data source. Daily streamflow records and 30*30 m digital elevation model (D.E.M.) were gathered from the Ministry of water and Energy. Daily Metrological data (Rainfall, Temperature, Relative Humidity, and wind-direction.) were obtained from Ethiopian National Metrological Agency. Remote sensing satellite product downloaded from available sources. (https://www.climateengine.org)

Site Visit and Investigation

The Bilate River Basin is located in the Rift valley Basin. The catchment was found in the southern part of Ethiopia within the two new Regional States (Central Ethiopian Regions and South Ethiopian Region), which includes Garage, silte, Kenbata, Hadiya, Alaba and Wolita Zones.

Shone

Batena Hossana

Bilate Alaba

Figure: 3.6 Bilate River Site Visit and Investigation photos

3.2.1 Meteorological Data

In Bilate River sub basin, more than 15 metrological gauge stations are distributed within and around the catchment area. In the study, we use daily rainfall data's of eight metrological gauge stations from 1990 up to 2022.

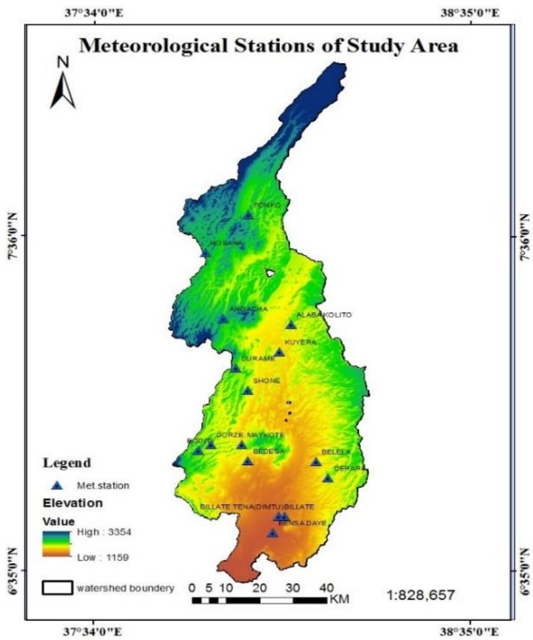


Figure: 3.7 Meteorological stations of Bilate River

The daily precipitation data of eight meteorological gauge station were collected from Ethiopian National Metrological Agency (ENMA)

Table: 3.1 List of Metrological gauge stations

No.	Station names	Location		Elevation	Record period	Missing (%)
		Latitude	Longitude			
1	Alaba	7.31058	38.093917	1772	1990-2022	4.023894
2	Angecha	7.34528	37.861111	2321	1990-2022	10.47042
3	BillateTena	6.91667	38.11667	1496	1990-2016	4.552829
4	Billate	6.82222	38.087778	1361	1990-2022	4.944827
5	Fonko	7.64233	37.968	2246	1990-2015	0.315922
6	Hosaina	7.56778	37.856111	2306	1990-2022	3.310379
7	Shone	7.1335	37.954444	1959	1990-2019	6.425116
8	Wulbareg	7.73833	38.122778	1996	1990-2022	7.632954

The minimum and maximum daily temperature used to estimate the mean daily temperature. For the period of 1990-2022, based on the completeness of the time series, three stations were chosen.

Wind direction wind speed and Relative Humidity data available in two stations Hossana (2013-2022) and Bilate (2014-2022).

3.2.2 Hydrological Data

Stream flow data is important for the rainfall runoff modeling process. In Bilate river sub basin there are six gauge stations recording daily stream flow data. However, those stations have poor data quality characterized by short and long duration of missing data. Batena River from Hossana feeds Guder and Konkoye River feed Weira Rivers. After Boyo swamp, they flow in to the main Bilate River.

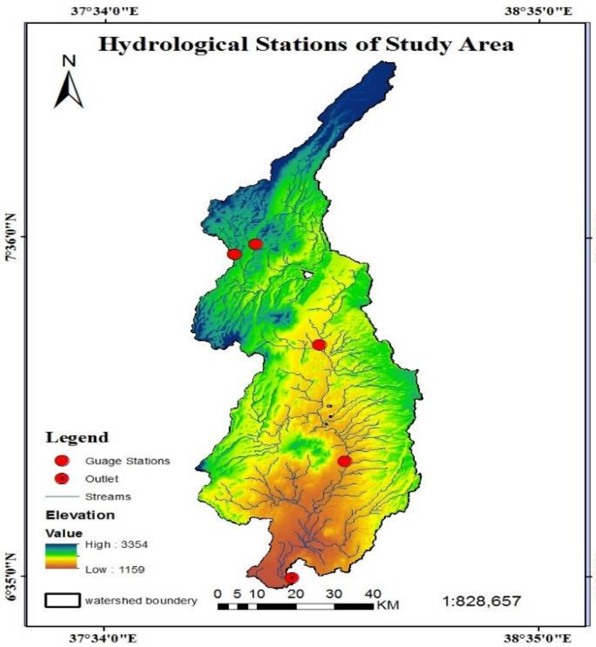


Figure:3.8 Hydrological gauge stations

The available streamflow record of six streamflow gauge station data for Twenty-Five years (1990-2015) were gathered from Ministry of water and Energy.

Table: 3.2 List of Hydrological gauge stations

No	Station Name	SITE	Station Number	Latitude	Longitude	Record period	Area (km²)	Elevation (M)	Missing (%)
1	Batena	Hosaina	82041	8.35	37.57	1990-2015	100	2157	46.67
2	BilateTena	BilateTena	82005	6.56	38.08	1990-2015	5518	2030	28.08
3	Billate	Nr. Alaba	82008	7.17	38.04	1990-2015	1980	1781	5.813
4	Gombera	Nr.Hosaina	82040	7.33	37.52	1990-2015	41	2157	18.85
5	Guder	Nr.Hosaina	82039	7.35	37.57	1990-2015	74	2157	9.446
6	Weira	Nr. Fonko	82031	7.35	37.55	1990-2015	472	2380	17.88

The available Hydrology and GIS data such as Topography, Land Cover, Land Use,DEM 30*30, Future plans in Bilate River basin and any resent Flood incidents information were collected from Ministry of water and Energy.

4 Materials and Methods

4.1. Materials

4.1.1. Satellite Products

Remote sensing is the art of collecting information about the object by measuring the electromagnetic radiations reflected, without actually being in contact. The output is usually an image representing the scene being observed analysis and interpretation is required. Remote sensing precipitation products are rapidly progressing with high spatial resolutions providing them to be combine with gauge data.

The selected remote sensing satellite rainfall products for this study are:

- CHIRPS satellite/reanalysis rainfall products with reference to the observed data.
- ERA5_AG agro-meteorological variables such as Temperature, precipitation, humidity and incoming solar radiation, Hargreaves Potential Evapotranspiration
- ERA5-Land is a reanalysis dataset providing Mean Temperature
- GPM_3IMERGDF_07 NASA Global Precipitation Measurement (GPM) Integrated Multi-satellite Retrievals for GPM (IMERG) 0.1° Resolution, 30 min Time interval
- TRMM_3B43_7 The Tropical Rainfall Measuring Mission

The study area precipitation, Temperature and Evapotranspiration data for the periods between (1st January 1990 to 30th December 2022) were downloaded from

http://climateengine.org/.

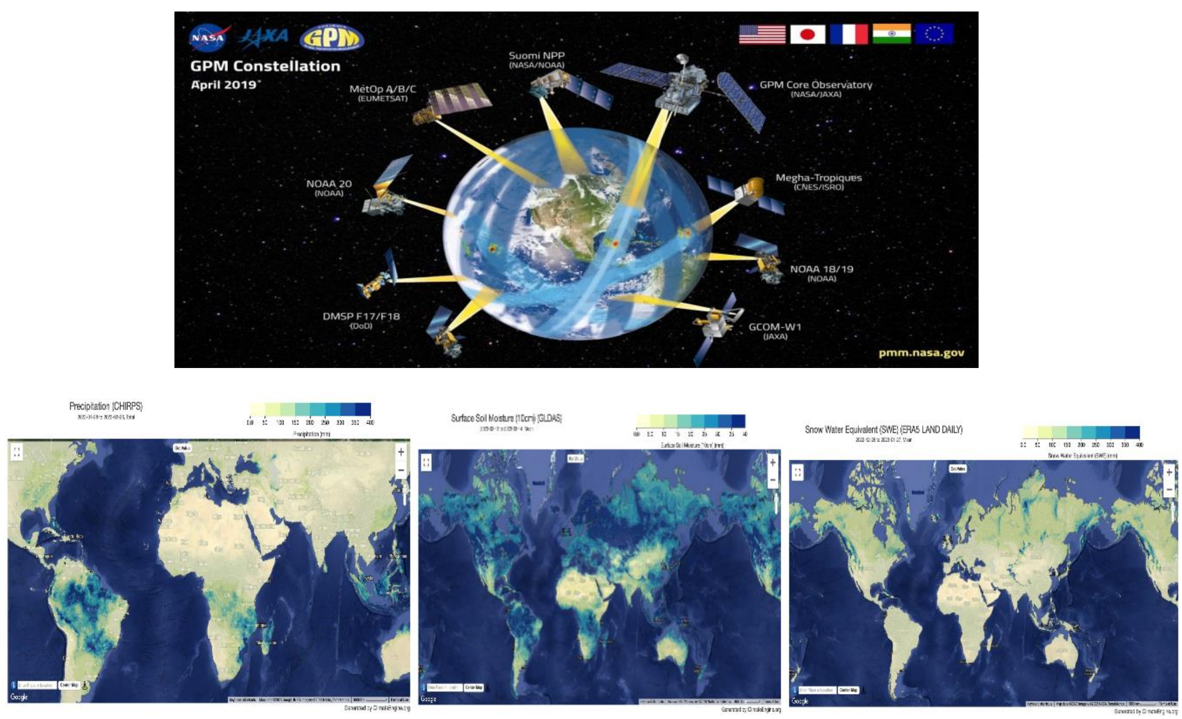


Figure: 4.1 CHRIPS, ERA5-AG, IMERG Remote sensing products source

CHIRPS rainfall Products

CHRIPS (Climate Hazards Group Infrared Precipitation with Station data) is Rainfall Estimates from Rain Gauge and Satellite Observations. CHRIPS data ranging from 1981 to near present (updated monthly) with 0.05º spatial resolution. CHIRPS daily Precipitation data in mm were downloaded from http://climateengine.org/ for five stations from1990-01-01 to 2022-12-31.

Table :4.1 List of remote sensed CHRIPS precipitation products

No.	Station names	Satellite product	Location		Record period
			Latitude	Longitude	
1	Alaba	CHIRPS Daily	7.31058	38.0939	1990-2022
2	BillateTena	CHIRPS Daily	6.91667	38.1167	1990-2022
3	Fonko	CHIRPS Daily	7.64233	37.968	1990-2022
4	Hosaina	CHIRPS Daily	7.56778	37.8561	1990-2022
5	Shone	CHIRPS Daily	7.1335	37.9544	1990-2022

ERA5_AG Temperature and Potential Evapotranspiration Products

ECMWF (the European Centre for Medium-Range Weather Forecasts) ERA5_AG is a reanalysis dataset providing a consistent view of the evolution of agro-meteorological variables over several decades at an enhanced resolution compared to ERA5 climate reanalysis, which combines model data with observations from across the world.

ERA5-Land and ERA5_AG agro-meteorological variables such as Temperature, precipitation, humidity and incoming solar radiation. Data ranging from1963-07-11 to Present (updated every 1-2 months) with 0.125º x 0.125ºspatial resolution. In Bilate River sub basin for five satellite, based Mean Temperature data were downloaded from http://climateengine.org/ from 1990-01-01 to 2022-12-31.

Table: 4.2 List of remote sensed ERA5_AG Temperature products

No.	Station Names	Satellite product	Location		Record period
			Latitude	Longitude	
1	Alaba	ERA5_AG	7.31058	38.0939	1990-2022
2	BillateTena	ERA5_AG	6.82222	38.0878	1990-2022
3	Fonko	ERA5_AG	7.64233	37.968	1990-2022
4	Hosaina	ERA5_AG	7.56778	37.8561	1990-2022
5	Shone	ERA5_AG	7.1335	37.9544	1990-2022

GPM_3IMERGDF_07 and TRMM_3B43_7 precipitation data were downloaded from https://giovanni.gsfc.nasa.gov/giovanni starting from 1990-01-01 to 2022-12-31.

4.1.2. Hydrological Model HBV-light
General Description

The HBV (HydrologiskaByransVattenavdelning) model is a rainfall runoff model, which is conceptual numerical descriptions of hydrological processes by dividing the catchment into zones according to altitude, lake area and vegetation. HBV has different model versionsHBV-96 and HBV-light applied in different countries all over the world. In this study, we aimed to use bias corrected satellite based (remote sensing) data and gauging station data as a stream flow modeling input in Bilate rivers sub basin using simulations of HBV-light.

HBV-light model (the HydrologiskaByrånsVattenbalansavdelning light model) is a semi-distributed conceptual rainfall runoff model to simulate runoff in the catchment. HBV-light version model was developed at Uppsala University in 1993.This model is advantageous because it’s data requirements for regions with limited observed data. HBV-light model is easy to understand and apply to filling gaps, to control data quality, to water balance studies, to forecast runoff and to simulate discharge from ungauged catchments. The main inputs for HBV Light model are

- P: Daily precipitation time series data(mm)
- T: Average temperature time series data (ºC)
- Q: Observed daily discharge time series data(mm)
- E: Potential evapotranspiration time series data (PET)

Model Structure

HBV model is a semi-distributed model; the catchment divided into sub catchment using different elevation, vegetation zones. The model structure of HBV-light consists four main subroutines (precipitation, soil, routing, and response).

- The snow accumulation and melt subroutines, Precipitation and snowmelt are the model's two main sources of water. Snow storage was neglected for this study.
- The soil moisture accounting subroutines, based on 3 parameters, Beta (β), FC, and LP.
- The lower linear response routine Interflow Q1 controlled with parameter K1.
- The triangular weight function of the base length, Maxbas used to route the three flow components. Which is a simple routing procedure between sub basins and in lakes

The water balance concept Equation use in HBV Light structural model

$$P - E - Q = \frac{d}{dt}[SP + SM + UZ + LZ + lakes] \dots\dots\dots\dots\dots\dots.. Equation\ 1$$

Where: UZ stands for upper ground zone, LZ for lower ground zone, LAKES for lakes that store water, P for precipitation, E for evapotranspiration, Q for runoff, SP for snow pack, and SM for soil moisture. For this study the available HBV-light Model version were downloaded from

https://www.geo.uzh.ch/en/units/h2k/Services/HBV-Model/HBV-Download.html.

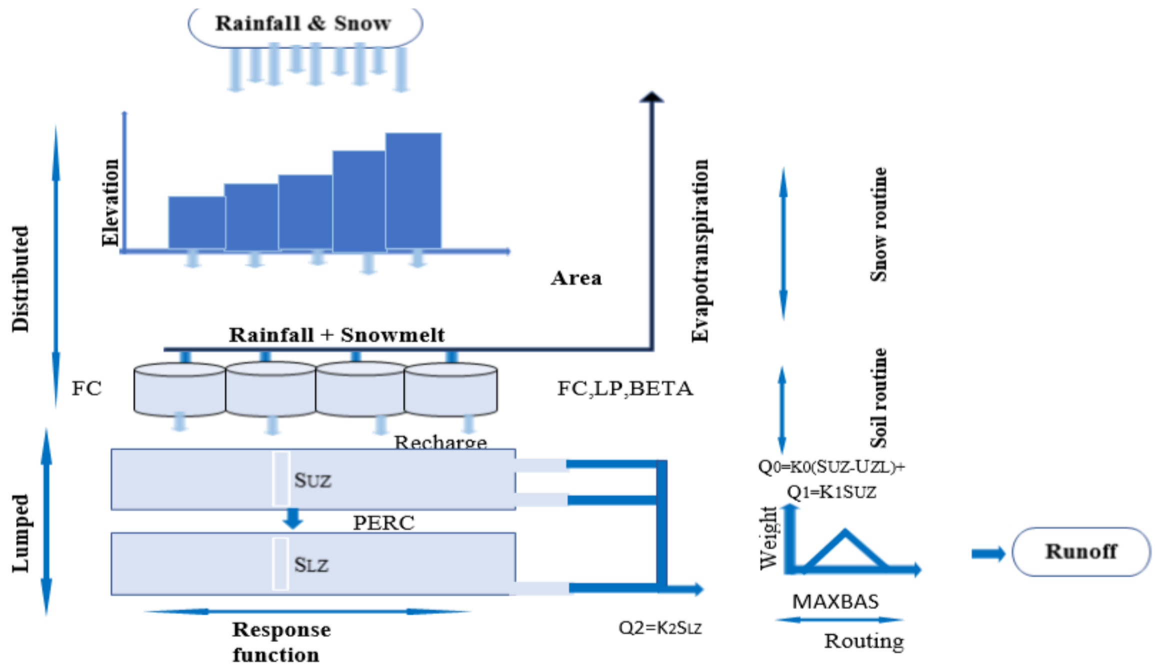


Figure: 4.2 A simplified schematization of the HBV Light model (after Seibert (2000)).

Estimation of daily streamflow by using Remote sensing products with bias error correction is rapidly progressing. In this study, accuracy of those method and models will be analyzed in Bilate River sub basin. For the analysis, using HBV Light model in catchment area 3 stations was used to represent. The upper (Hossana &Fonko), Middle (Alba), and Lower Bilate tena were selected.

The model have procedures for simulation of evapotranspiration, snowmelt, and soil moisture accounting. In the study, we use daily rainfall data's of eight metrological gauge stations from 1990 up to 2022 to run HBV Light rainfall runoff model in bilate watersheds.

Table:4.3 The study's software and their objectives

Software	**Use**
ArcGIS 4.8	To create the study area map. To analyze data To prepare Thiessen polygon ,LULC, Soil map for the watershed
Excel	To arrange meteorological and streamflow data
HBV Light	To simulate rainfall runoff model
SD GCM v 2.0	To bias-correct satellite precipitation products
Stata 14.2	To fill stream flow data

4.2. Methods

The methods employed in this study's initial phase, which involved data pre-processing, bias correction, and evaluation of satellite-based meteorological data step-by-step process that we use to Estimate Daily Streamflow in Bilate River Sub-basin

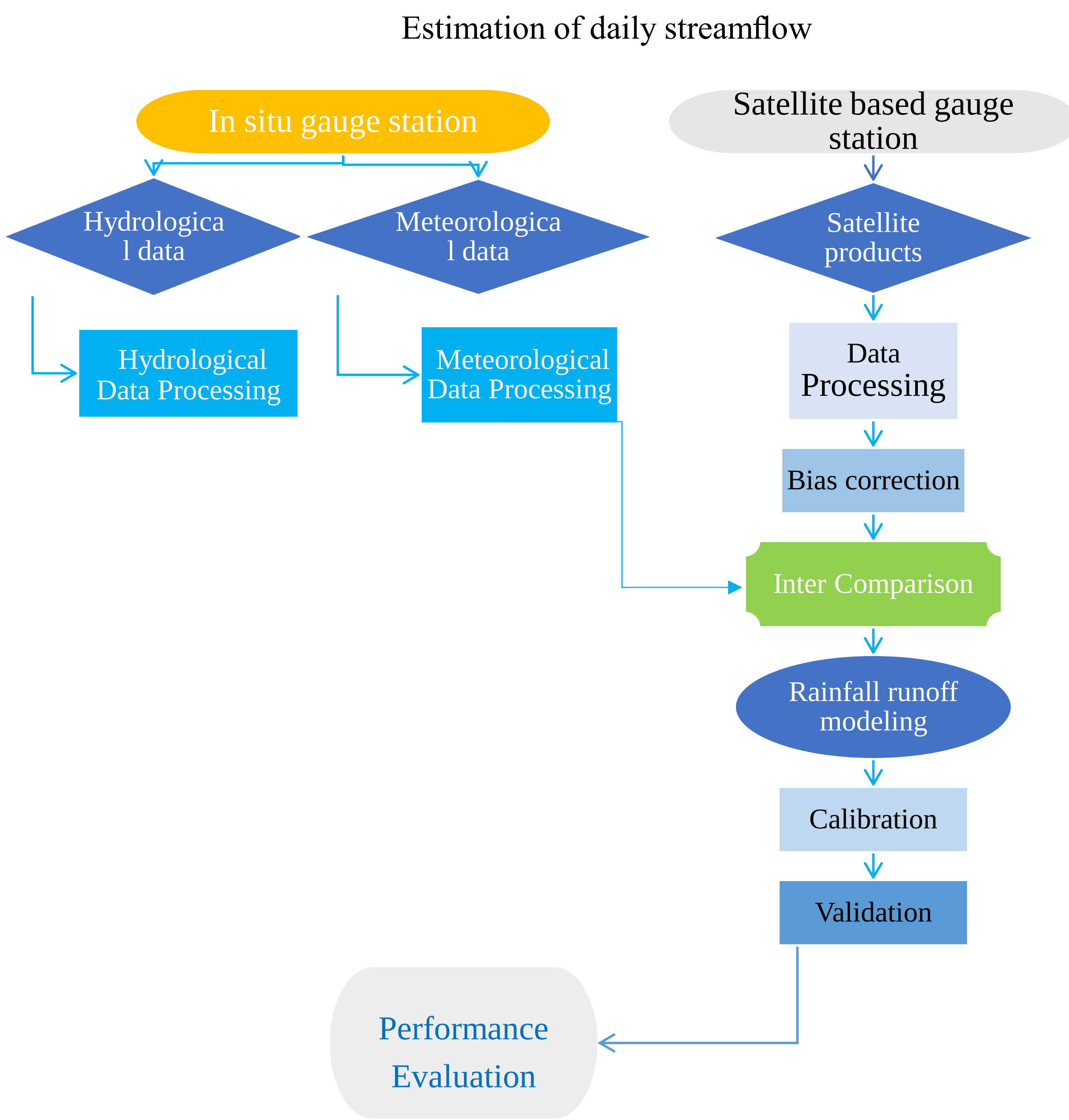


Figure: 4.3 Flow chart of the study

4.2.1. Quality and Reliability of Hydro Meteorological Gauge Station Data

Ground based Hydro-meteorological data series usually sampled in the field (gauge stations) recent advances in measurement equipment and data transfer process like automatic way of data sampling needs to be implemented. Which mainly relay on electronic devices and requires experts in maintenance and regular monitoring station checks. Even the quality of those devices have specific problem such as power supply shortages. The observed Hydro-meteorological data should be checked before we use them for Rainfall runoff modeling. Data quality and reliability influenced by decision-making abilities of experts.

Some of the factor that affect the performing good measurement are selection of measuring equipment, working conditions, proper position of measuring equipment, Data processing, quality control, Monitoring performance, Maintenance, Training and education to observers.

Figure: 4.4 Hossana Meteorological gauging station

There are more than fifteen meteorological gauge stations in bilate watersheds there are some problems in the quality of those station data. The main problems in Hossana meteorological station were equipment maintenance issue and data exchange. Previously they exchange data by telegram for the last five years meteorological data at the station have poor quality.

The current streamflow gauging stations collect stream flow data manually using staff gauge daily by observer and the velocity measurements took by hydrological technician at the gauging stations three times a year. The stream flow data in the sub basin have poor quality and there is no rating curve development by the Ministry of water and energy for the last eight years.

The Hydro Meteorological data quality problem and gaps indirectly affected by political issues in the Regions, the regional office almost closed and they are not responsible for the data and the new regional states are not ready for those kind of data. Information’s about recent flood incidents and data process procedures in gauge stations obtained from stakeholder by verbal interviews during field visits to gauging stations.

4.2.1.1 Meteorological Data Pre-processing

Meteorological data such as precipitation, Temperature, potential evapotranspiration are the main inputs for rainfall-runoff models. However, in situ Meteorological stations are randomly distributed and limited in bilate river sub-basin. On the other hand, the rainfall runoff models need all the necessary data from gauge stations. For this reason, we need to rearrange and pre-process gauge stations data before we use them for modeling.

Meteorological data is susceptible to various kind of errors. Missing observations is the most commonly observed problems in Meteorological data in order to use, the observed station data for further process we need to fill the missed data with the appropriate gap filling method.

The daily precipitation data of six meteorological gauge station were screened for the study. The precipitation data obtained from National Meteorological Agency needs preprocessing process before further processing in order to increase the performance accuracy. The first step after collecting the necessary precipitation data were normalization of all the time series data's by arranging them respectively. Then the next step were filling missed data and identifying unrealistic values by plotting the meteorological data collected throughout time at each location in comparison to data from nearby stations. Gauge stations maintenance problems and communication problems were the main factors for missing of daily precipitation data in Bilate watershed. There are different methods of filling missed data arithmetic mean method, normal ratio method and inverse distance weighting method are some of the most commonly applied using neighboring station in the sub basin.

Arithmetic mean method is the simplest method commonly used to fill the missing data when the normal annual precipitation is below or equal to 10% of the station.

$$px = \frac{1}{m}(p1 + p2 + \cdots + pm) \ldots\ldots\ldots\ldots\ldots\ldots..Equation\ 2$$

Where: P_x= the precipitation from the station with the missed record is P_1, P_2, P_3…P_n are the corresponding index station. N = number of index station.

Normal ration method used to fill the missing data when the normal annual precipitation of any index stations different from that of the precipitation station by more than 10%.

$$px = \frac{Nx}{m}\left[\frac{P1}{N1} + \frac{P2}{N2} + \cdots + \frac{Pm}{Nm}\right] \ldots\ldots\ldots\ldots\ldots\ldots\ldots..Equation\ 3$$

Where, Px=Estimate for the ungagged station Pi=Rainfall values

of rain gauges used for estimation Nx=Normal annual precipitation

of X station Ni=Normal annual precipitation of surrounding stations

m=No. of surrounding stations.

Modified Normal Ratio Method

Normal ratio method is modified to incorporate the effect of distance in the estimation of missing rainfall.

$$r_x = \frac{\sum_{i=1}^{n} D_i^{\,1/b} \left(\frac{\overline{r_x}}{\overline{r_i}}\right) r_i}{\sum_{i=1}^{n} D_i^{\,1/b}}$$ …………………….. Equation 4

Where is normal rainfall, is the distance between the index station i and the gauge station with missing data or ungauged station, n is the number of index stations and b is the constant by which the distance is weighted (normally 1.5-2.0) commonly used D0.5

Inverse distance weighting method can be used to fill the missing data When there is no normal annual precipitation for the station this method is not satisfactory for hilly regions.

Rainfall rx at station x is given by

$$r_x = \frac{\sum_{i=1}^{n} \left(\frac{r_i}{D_i^{\,b}}\right)}{\sum_{i=1}^{n} \left(\frac{1}{D_i^{\,b}}\right)}$$ …………………….. Equation 5

In this study, Normal ration method were used to fill the missing precipitation data. Normal ration method usually applied when the normal annual precipitation of any index stations different from that of the precipitation station by more than 10%.

Temperature data of three station (Hossana, Alaba and bilate) was screened and missing data's were filled using long time average of those stations.

Table: 4.4 Gauge Stations and filling method of missing data

No.	Station Names	Class	Elevation	Data Type	Record Period	Missing (%)	Gap Filling Methods
1	Alaba	3	1772	Precipitation	1990-2022	4.02	Normal ration method
				Tmax	1990-2022	4.53	Long time Average
				Tmin	1990-2022	4.17	
2	Angecha	3	2321	Precipitation	1990-2022	10.47	Normal ration method
				Tmax	1990-2022	11.22	Long time Average
				Tmin	1990-2022	11.58	
3	BillateTena	4	1496	Precipitation	1990-2016	4.55	Normal ration method
4	Billate	1	1361	Precipitation	1990-2022	4.94	Normal ration method
				Tmax	1990-2022	9.72	Long time Average
				Tmin	1990-2022	8.67	
5	Fonko	4	2246	Precipitation	1990-2015	0.32	Normal ration method
6	Hosaina	1	2306	Precipitation	1990-2022	3.31	Normal ration method
				Tmax	1990-2022	14.17	Long time Average
				Tmin	1990-2022	10.89	
7	Shone	4	1959	Precipitation	1990-2019	6.43	Normal ration method
8	Wulbareg	3	1996	Precipitation	1990-2022	7.63	Normal ration method
				Tmax	1990-2022	13.23	Long time Average
				Tmin	1990-2022	16.56	

4.2.1.2 Meteorological Data Quality control and Consistency Check

Meteorological data collection needs advancements in measurement equipment and data transfer methods. Electronic devices are preferable due to their highest quality despite of specific problem such as power supply shortages. As we all know, Meteorological data's are sampled in the field and there will be only remaining time series data as evidence after sampling. Those data's reliability and quality mainly depends on decision-making process. Gauge stations data processing in Bilate river watershed need to develop with new technological equipment and trained decision makers.

From the selected meteorological stations' only bilate gauge stations have all the required weather data (precipitation, temperature ranges, wind speed and humidity levels) even if there is still missing data problem in it. After, filling missing meteorological data, double mass curve graphical analysis was used to assess the consistency and quality of the data for all the chosen meteorological stations that had an impact on the study area. Double mass curve is a techniques used to assess data consistency of in situ meteorological gauge stations through comparative analyses.it is composed of cumulated values of a given station that are plotted against accumulated values of the average value of other gauge stations data, over the same period of time.

$\mathbf{P_{CX} = P_X * \frac{M_C}{M_a}}$ **.......** Equation 6 Where P_{cx} = corrected precipitation at any period time t_1 at station x ,$P_x$is the originally recorded precipitation at period time t_1 at station x,Mc is the corrected slope of the double-mass curve, Ma is the original slope of the double-mass curve.

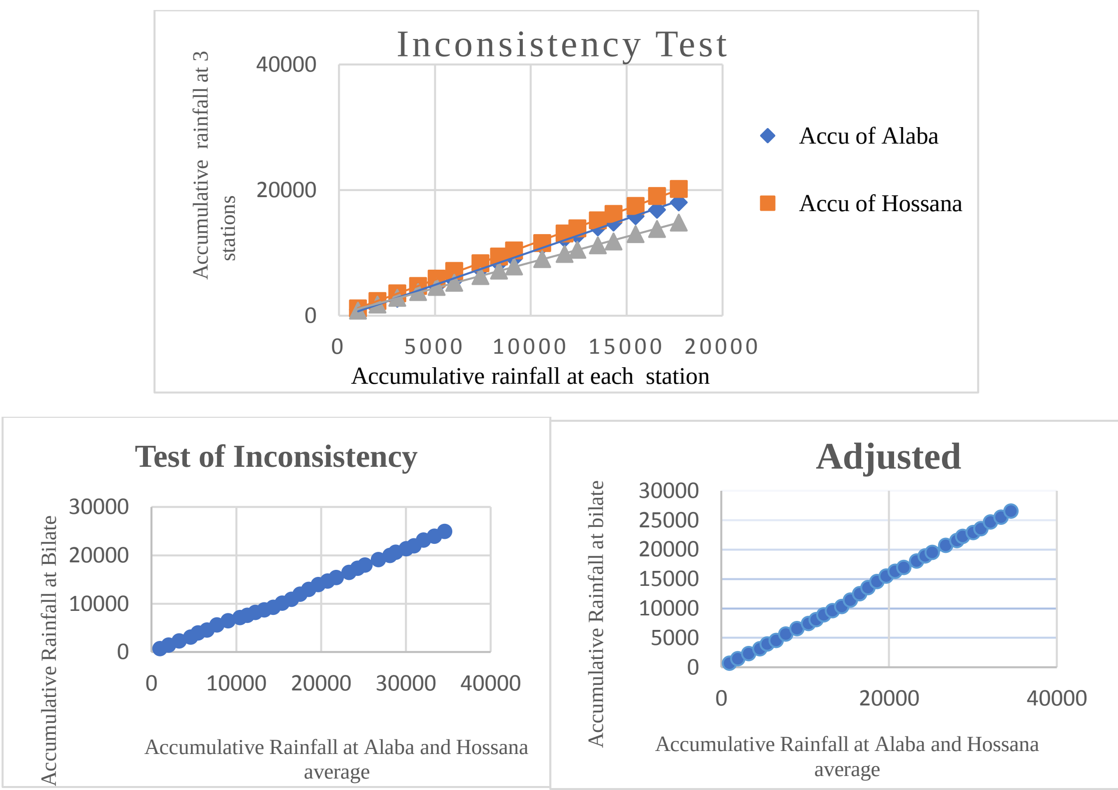


Figure:4.5 Consistency Check using Double mass curve

The in situ meteorological data's spatial representativeness

HBV Light model needs single time series data for every meteorological variable (precipitation, Temperature, Potential evapotranspiration) for each sub-catchment the model represents. Therefore, in order to represent the meteorological variables in the basin, it was first necessary to screen for stations that had readings that were located inside or adjacent to the study region, given that the meteorological stations are unevenly distributed and lack a clear network architecture over the area under study. This study employed the Thiessen polygon method, one of several ways to represent areal meteorological information, to spatially estimate several meteorological variables.

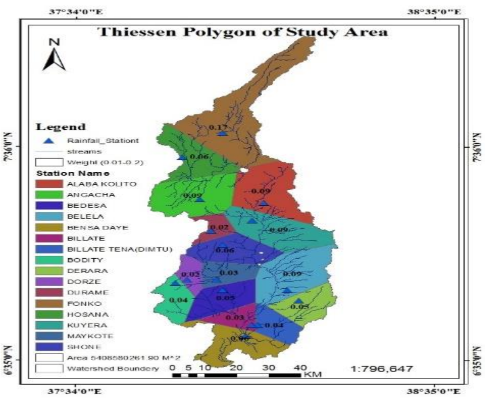


Figure:4.6 Thiessen polygon of study area

Checking Homogeneity

Test Homogeneity is an important issue to detect the variability of the data. In general, when the data is homogeneous, it means that the measurements of the data are taken at a time from the same environment. The collected data said to be homogenous if the measurements have been consistently done by the same method, with the same instrumentation, at the same time and place, and in the same environment (McCuenet al.1998).$\mathbf{P_i} = \frac{\bar{\mathbf{p}}_\mathbf{i}}{\bar{\mathbf{p}}}$Where: Pi - is the non-dimensional value of precipitation for the month in the station I,$\bar{Pi}$- is over year's average monthly precipitation for the station I,$\bar{P}$- is over year average yearly precipitation for station I.

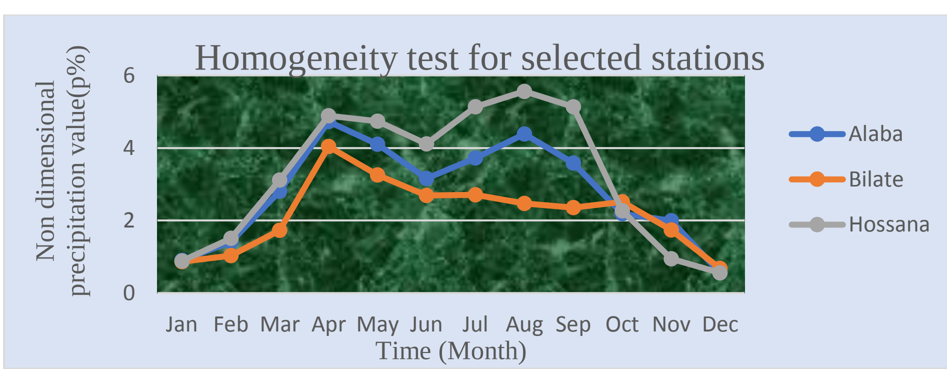


Figure: 4.7 Homogeneity test

Estimation of Potential Evapotranspiration

Evapotranspiration Station Data

For the period of 1990-2020, only five of eight stations were operational with Temperature maximum and minimum values. For the purposes of this study, three of the stations were deemed sufficient to estimate potential evapotranspiration. In the absence of any restrictions on the water supply, potential evapotranspiration, or PET, is a measurement of the atmosphere's capacity to evaporate and transpire water from the surface. Whereas transpiration is the loss from surfaces containing living plants, evaporation is the loss from open water bodies like lakes and reservoirs, marshes, bare soil, and snow cover. The primary determinants of the environment include solar radiation, open water surface area, relative humidity, wind direction, vegetation type and density, soil moisture availability, root depth, reflective features of the land surface, and time of year.

Potential evapotranspiration can be estimated using a variety of techniques. (FAO-Penman Monteith, Priestley & Taylor, Hargraves, Thonthwaite, Blaney-Criddle, Enku, Pan-Allen, Pan-Pereira, Piche-Stanhill and Piche-Adam & Ahmed methods); In this study, the daily potential evapotranspiration (PET) was calculated using the Hargreaves method, which uses the minimum and maximum temperatures as input.

$PET = 0.0023 Ra\ (Tmax - Tmin)\ 0.5(T\text{mean} + 17.8)$ Equation 7

Where PET denotes the Hargreaves potential evapotranspiration (mm/day); Ra =Extraterrestrial radiation (mm/day) that depend on latitude, sunshine hours, and solar constant)Tmin and TmaxThe minimum and maximum temperature (°C)

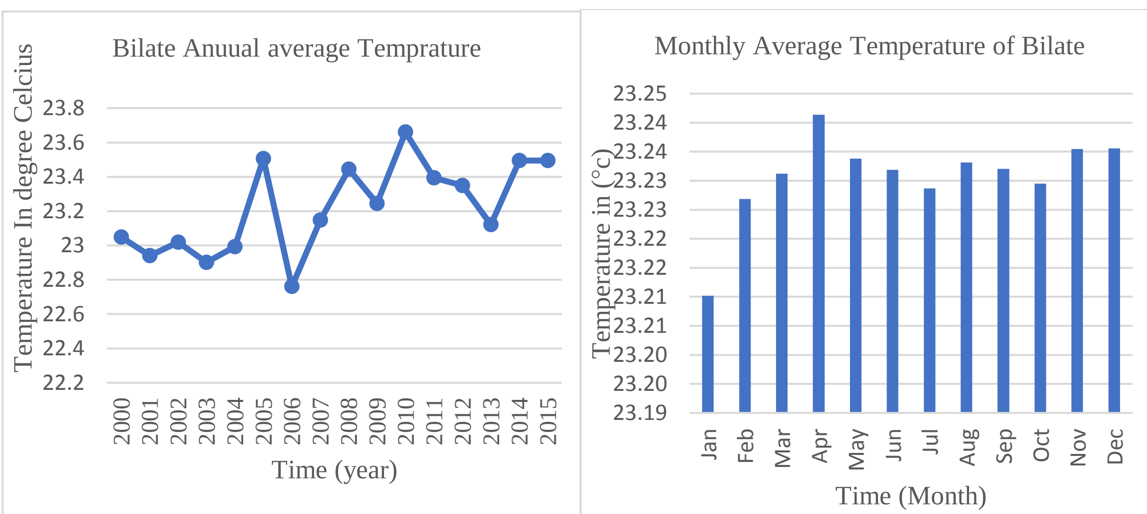


Figure: 4.8 Annual and monthly average Temperature of Bilate station

Table: 4.5 Potential Evapotranspiration calculated using Hargreaves method

Month	Tmax(°c)	Tmin(°c)	Temp(°c)	Ra(mm/d)	PET (mm/d)	PET (mm/month)
Jan	30.4	16.8	23.6	12.8	4.5	139.3
Feb	30.4	16.8	23.6	13.9	4.9	136.8
Mar	30.4	16.8	23.6	14.8	5.2	161.4
Apr	30.4	16.8	23.6	15.2	5.4	160.5
May	30.5	16.8	23.6	15.0	5.3	163.7
Jun	30.4	16.8	23.6	14.8	5.2	156.2
Jul	30.5	16.8	23.6	14.9	5.2	162.6
Aug	30.4	16.8	23.6	15.0	5.3	163.5
Sep	30.4	16.8	23.6	14.8	5.2	156.2
Oct	30.4	16.8	23.6	14.2	5.0	154.9
Nov	30.4	16.8	23.6	13.1	4.6	138.3
Dec	30.5	16.8	23.6	12.5	4.4	136.4

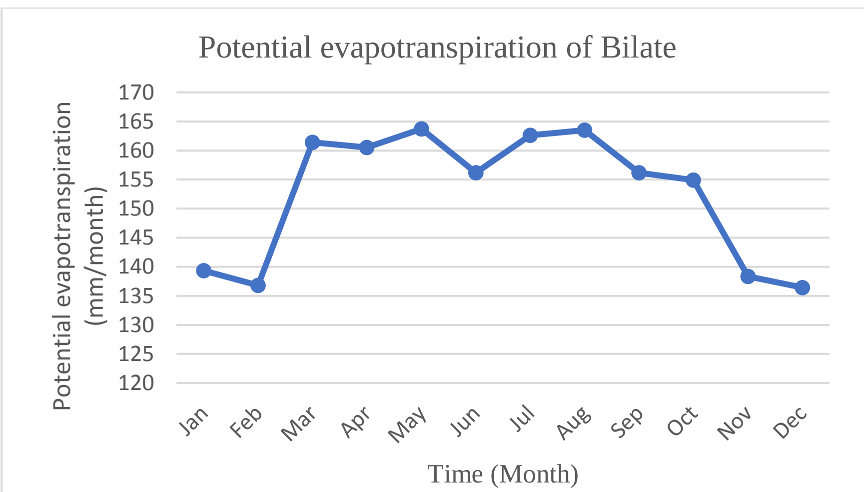


Figure:4.9 Monthly average potential evapotranspiration

4.2.2 Hydrological Data Processing

Hydrological Data processing is a system of arranging streamflow row data collected from the given gauge station in to a recognizable format. The process start by data acquisition from the field and database management in the office.Which include Error correction before entering the raw data and filling missing data at the station in order to get processed and analyzed data. Stream flow data in bilate river catchment collected in six stations however missing data is the main problem and for the last eight years, there is no available data in the Ministry of water and energy. For the year starting from 1990 up to 2015 hydrological data preparation and processing were applied in the selected stations of bilate river sub basin. The Hydrological data was screened to identify the reliable and unreliable data. Failure of any gauging stations or absence of observer causes a break in instantaneous daily-observed flow. Based on the visual observation the stream flow records of the gauging stations have short to high breaks in observed flow. So, filling those values in scientific and reasonable technique is not an option to arrive at reliable quantile estimate. Annual streamflow at bilate station were screened and arranged for further analysis.

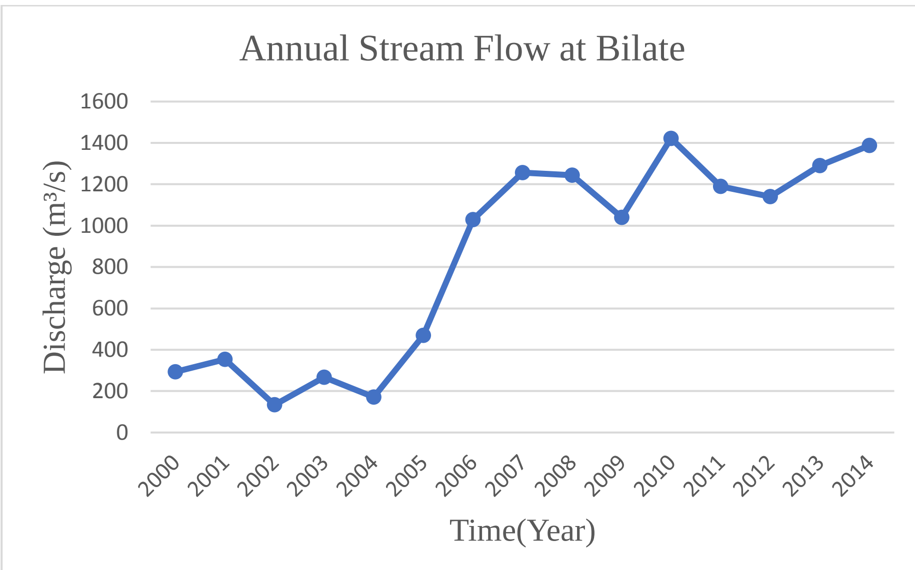


Figure:4.10 Annual Stream flow of Bilate river sub-basin

4.2.3 Processing of Meteorological Remotely Sensed Data

Climate Engine provided daily averages of temperature, evapotranspiration, and rainfall based on satellite data. Climate Engine is noncommercial users of all technical proficiencies to harness the power of cloud computing to analyze decades of Earth Observations data. Climate Engine tools use Google Earth Engine for on-demand processing of satellite and climate data on a web browser and features on-demand mapping of environmental monitoring datasets, such as remote sensing and gridded meteorological observations. Remotely sensed data are available from

CHRIPS (Climate Hazards Group Infrared Precipitation with Station data) were downloaded from http://climateengine.org/ for five stations from1990-01-01 to 2022-12-31.

GPM_3IMERGDF_07 and TRMM_3B43_7Remote sensed precipitation data were downloaded from https://giovanni.gsfc.nasa.gov/giovanni

ECMWF (the European Centre for Medium-Range Weather Forecasts) ERA5_AG Mean Temperature, Precipitation and Potential evapotranspiration data from 1990-01-01 to 2022-12-31.were downloaded from http://climateengine.org/

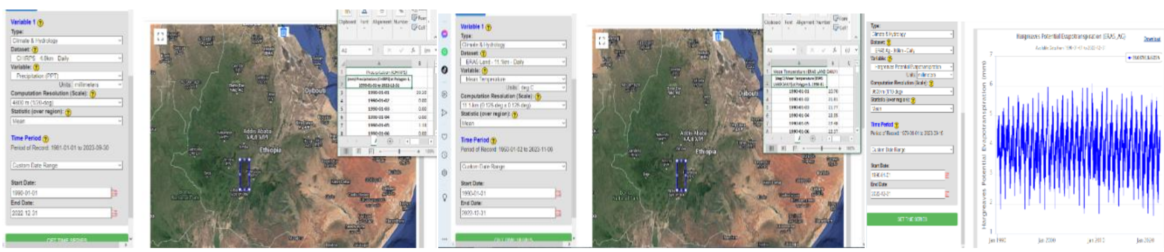


Figure: 4.11 Sources of Remote sensed products

To enable the process of retrieving daily satellite data time series at meteorological gauge station locations in order to compare data from satellites with measurements made in gauge stations, a map list covering the same 15-year period was prepared for each satellite meteorological product. The necessary satellite meteorological products selected by the following criteria's

- Date of acquisition of images according to the local calendar;
- Weather conditions (cloud cover) during the acquisition of images;
- Spectral and spatial resolution of images.

After examine, the selected satellite product under data preprocessing such as normalization, generalization and other techniques. Those data were preprocessed by arranging, by correcting errors related to coordinate systems. Some of the steps were

- Data cleaning consists of removing duplicate data points, and removing value outliers
- Data Interpolation procedure to change data resolution and to compute values for a common set of locations.
- Data Normalization is the scaling of data to a specified range.

4.2.4 Gauge Stations and Satellite Based Data Comparison

The objective of this study is to be able to use satellite products as alternative to gauge station data. The Meteorological data was taken from ground based gauge station and Remote sensed data from the ERA5_AGreanalysis dataset and CHIRPS dataset. An overlap period (1990–2022) were used to compare gauge data with the satellite data of three stations (the upper, middle, and lower) in bilate river sub basin. The comparisons of gauge station and Remote sensed data were based on daily basis of precipitation, Temperature and potential evapotranspiration time series data's of each station. Whereas, analyses for the sub basin were made by averaging the variables from the three stations.

Comparison of ERA5_AG and gauge station: The degree of correlation between the monthly rainfall Meteorological data such as precipitation, Temperature and potential evapotranspiration from gauge stations and satellite product ERA5_AG 9.6 km daily reanalysis dataset were compared. In this study, due to gauge station data availability three stations have been chosen for comparison.

CHIRPS daily Precipitation data data was statistically validated by comparing the average monthly rainfall data from CHRIPS 4.8 km daily in mm were compare with instu gauge stations Precipitation time sires data and also average rainfall from the rain gauge stations for an 30 year period, in bilate river sub basin.

The comparisons between in situ and satellite product data were based on visual interpretations of average time series data of precipitation, Temperature and potential evapotranspiration. Additionally, statistical analysis is performed using metrics like bias, correlation coefficient (R^2), mean error (ME), and root mean square error (RMSE).Systematic differences are measured by the ME and bias. When meteorological factors in the satellite products are overestimated, which is shown by an inverse sign and a mean error with a (-) sign, indicating underestimate when the bias is less than 1. In relation to the in situ data, the RMSE calculates the amount of cumulative mistakes and the precision of satellite rainfall estimations. Its values range from 0 to ∞, where 0 denotes very good precision. The R^2 measures the degree of agreement between meteorological estimates derived from gauge stations and satellites. It ranges from 0 to 1, indicating a high degree of agreement. There is no unit for the Bias or R^2, however the latter is occasionally represented as a percentage.

$$Bias = \frac{\sum_{i=1}^{n} S}{\sum_{i=1}^{n} G} \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots Equation\ 8$$

$$ME = \frac{\sum_{i=1}^{n} S - \sum_{i=1}^{n} G}{N} \ldots\ldots\ldots\ldots\ldots\ldots Equation\ 9$$

$$RMSE = \sqrt{\frac{\sum_{i=1}^{n}(S-G)^2}{N}} \ldots\ldots\ldots\ldots\ldots\ldots.. Equation\ 10$$

$$R^2 = \frac{\sum_{i=1}^{n}(S - Si)(G - Gi)}{\sqrt{\sum_{i=1}^{n}(S - Si)^2}\sqrt{\sum_{i=1}^{n}(G - Gi)^2}} \dots\dots\dots\dots\dots\dots\dots\dots Equation 11$$

Where S stands for data from satellites, G for data from gauge stations, and N for the total number of data pairings. Since these variables indicate water depths for both rainfall and potential evapotranspiration, they are calculated in millimeters.

Comparison of satellite product with gauge stations data Metrics

- Hit:- represent the number of days when rainfall events recorded at rain gauge (observed station) and the satellite able to predict.
- Miss represent the number of days where a rainfall event is not recorded in the satellite, still its presence Shown in the observed data set.
- False Alarm: - shows the rainfall event is recorded at the Satellite data when there is no event in the observed data.
- Correct negative show that when both satellite and observed didn't pick up any rainfall

In order to assess the satellite products' ability to detect meteorological events, Statistical metrics such as frequency bias (FB), probability of detection (POD), false alarm ratio (FAR), and critical success index (CSI, often referred to as threat score) were employed to assess the detection performance of the satellite-based meteorological products.

Probability of Detection (POD) determines the number of events correctly detect by the Satellite datasets concerning observed datasets

$$POD = \frac{hits}{hits + misses} \dots\dots\dots\dots\dots\dots Equation\ 12$$

False Alarm Ratio (FAR) false alarm shows the rainfall events is recorded at the satellite when no represented in observed data

$$FAR = \frac{false\ alarm}{hits + false\ alarm} \dots\dots\dots\dots\dots\dots.. Equation\ 13$$

Critical Success Index (CSI) shows the correct estimation the rainfall occurrence while removing the negative occurrence.it provides a critical success rate that blends the POD and the FAR, where a perfect score 1 implies zero false alarm and miss.

$$CSI = \frac{hits}{hits + false\ alarm + misses} \dots\dots\dots\dots\dots. Equation\ 14$$

Where the values of POD, FAR, and CSI vary from 0 to 1, where 0 represents a perfect FAR and 1 denotes a perfect POD and CSI. The FB has a desirable value of 1 and a range of 0 to ∞.

$$FB = \frac{hits + false\ alarm}{hits + misses} \dots\dots\dots\dots\dots\dots Equation\ 15$$

4.2.5 Bias Correction

After collecting the essential information and identifying the difference between satellite rainfall estimates and observed data, we use bias correction methods to correct satellite rainfall products. Global and Regional Climate models have systematic errors when we compare them with gauged data due to several factors such as limited spatial resolution and data processes. Bias correction is a statistical technique used to remove the differences between those satellite based estimations and ground measurements. Bias correction means bias adjustment as we all know there is no single bias correction method corrects all the differences between instu gauging and satellite products. The first step in bias correction is biases identifying by developing the relations between satellite rainfall estimates and observed data. Then correcting satellite rainfall products by using bias correction methods.

There are different bias correction methods applied to reduce errors. In this study, a power transformation method was applied for satellite rainfall products to correct both the coefficient of variation (CV) and the mean of rainfall data. In this nonlinear correction method, each daily precipitation amount P is transformed to a corrected P^* using:

$$\check{P} = a \times p^{b} \ldots\ldots\ldots\ldots\ldots Equation\ 16$$

Where P and P^* are the uncorrected and the corrected precipitation, respectively, and a and b are parameters that define the correction.

The three components of the bias in the satellite-based data are false events, missing events, and hit events. Components of bias were examined for every product and station in order to determine the source of bias.

$$Hit\ Events\ Bias = \sum_{i=1}^{n} (Si - Gi)(whwn\ Si > 0\ and\ Gi > 0) \ldots\ldots\ldots\ldots Equation\ 17$$

$$Missed\ Events\ Bias = \sum_{i=1}^{n} Gi(when\ Si = 0\ and\ Gi > 0) \ldots\ldots\ldots\ldots\ldots\ldots Equation\ 18$$

$$False\ Events\ Bias = \sum_{i=1}^{n} Si(when\ Si > 0\ and\ Gi = 0) \ldots\ldots\ldots\ldots\ldots\ldots Equation\ 19$$

Where S stands for data from satellites, G for data from gauge stations, and these bias components are given in millimeters.

4.2.6 Hydrological Modelling

A hydrologic model is a simplification of a real-world system (e.g., surface water, soil water, wetland, and groundwater) that aids in understanding, predicting, and managing water resources. Both the flow and quality of water are commonly studied using hydrologic models.

HBV-light was selected for hydrological model to analyze Bilate river discharge, because of low complexity, high agility, computational efficiency, and successful application used in numerous studies. Which is suitable for different purposes, such as simulation of long streamflow records, streamflow forecasting and hydrological process research. The flow chart below was used to guide the hydrological modeling portion of this study:

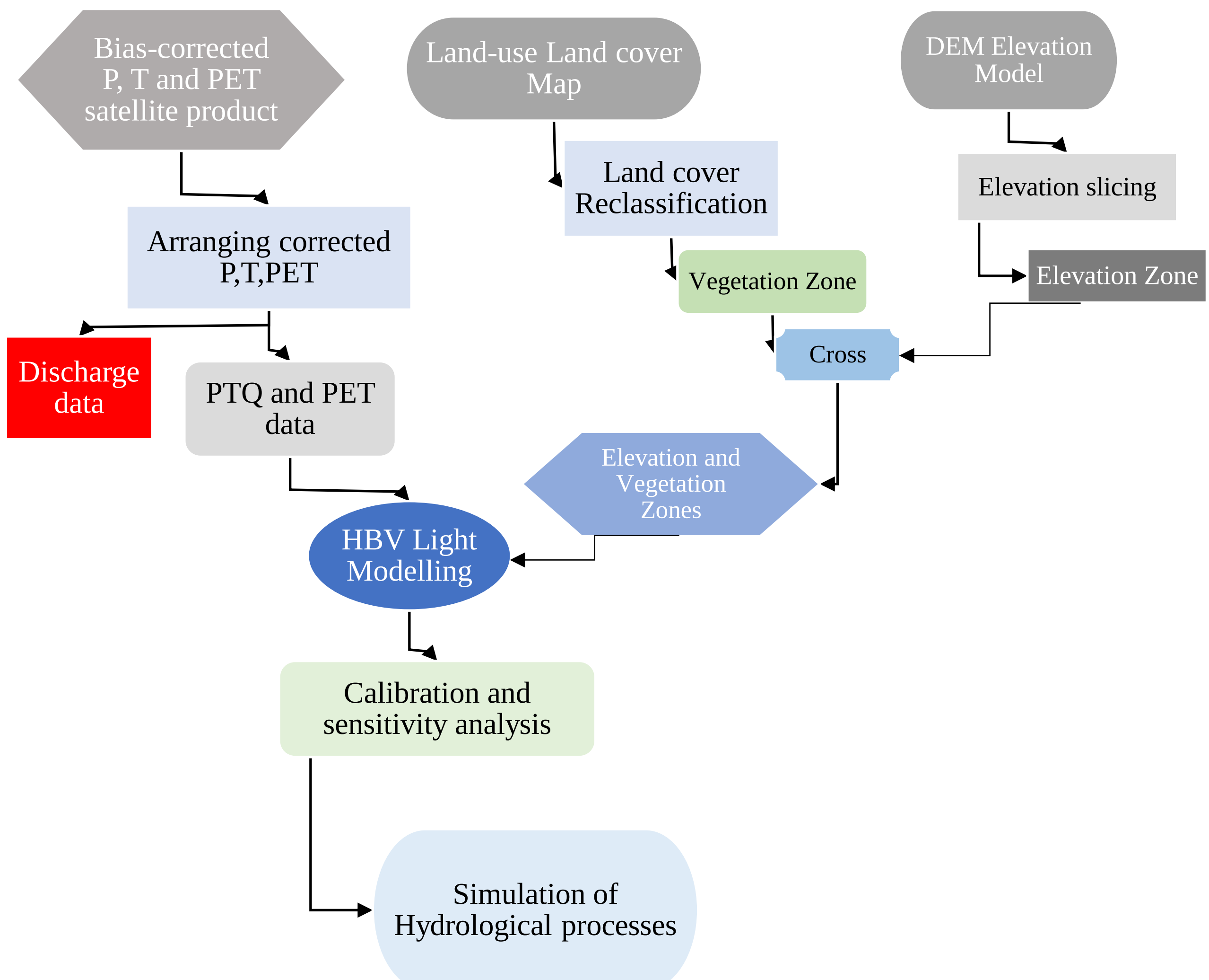


Figure: 4.12 HBV Light modelling flow chart

Model Set Up

Model Input Data daily time series of PTQ (precipitation in mm, Temperature in(o^c) the discharge recorded at the outlet in millimeters per day for each sub-basin, EVAP (potential evapotranspiration). Other inputs includes Elevation zones, DEM digital elevation model of 30m resolution, slope and elevation, Vegetation zones: land cover and land use map. Bilate River Downstream sub-basin area was divided by the discharges (m3/s) at the basin to convert them to millimeters per day. A text file containing the potential evapotranspiration time series is organized with one daily value for every month. As required by the HBV-light model, the PTQ and PTO file was created using three sets of 12 data for each of the three sub-basins, the monthly mean values over an extended period. A file called a sub-basin describes the spatial relationships between the many sub-basins, including the direction of water flow from one sub-basin to the next until the outlet was created and loaded into the model. The vegetation type and elevation zones of the studied area were determined and included into the HBV-light model.

Elevation zones

The country's catchments were defined by the Shuttle Radar Topography Mission (SRTM) digital elevation model of the Bilate River subbasin at a resolution of 30 m by 30 m. The elevation ranges known as elevation zones were used to categorize the sub-basins into hydrological units. This action was taken to enable the HBV Light model to account for the topography-specific slope, elevation, and distribution of meteorological factors in the area under study. The elevation of the area ranges from lowest elevation 1,116m at southern downstream near to Lake-Abaya to the highest elevation3, 350m above sea level in the northern hill tip. The study region was divided into four elevation zones due to its 0% to 8% slope. Figure 4.13 displays the results of the slicing.

Vegetation zones

Land cover is physically appearing on the surface of the ground as a natural or manmade entity. In Bilate River sub basin bare land, forest, grassland, cultivated land, marshland, moderately cultivated, shrub land, urban area and water body (Boyo swamp Lake) are the main land cover types in the basin. A 2016 land cover map was used for this research.This data set represents land cover map for the year 2016. This layer was clipped from Sentinel-2 global land cover data.

In order to comply with the HBV model's input requirements, the land cover map was reclassified. The land cover map classes were reorganized into four major groups, as illustrated in the figure below, because HBV only permits three types of vegetation, in addition to the lakes that are part of the catchment. Where 1 represent the 33% of the basin that is made up of forestlands, 2 represent the 63% that is made up of croplands, 3 represent the 3% that is made up of lakes, and 4 represent the 1% that is made up of built-up areas.

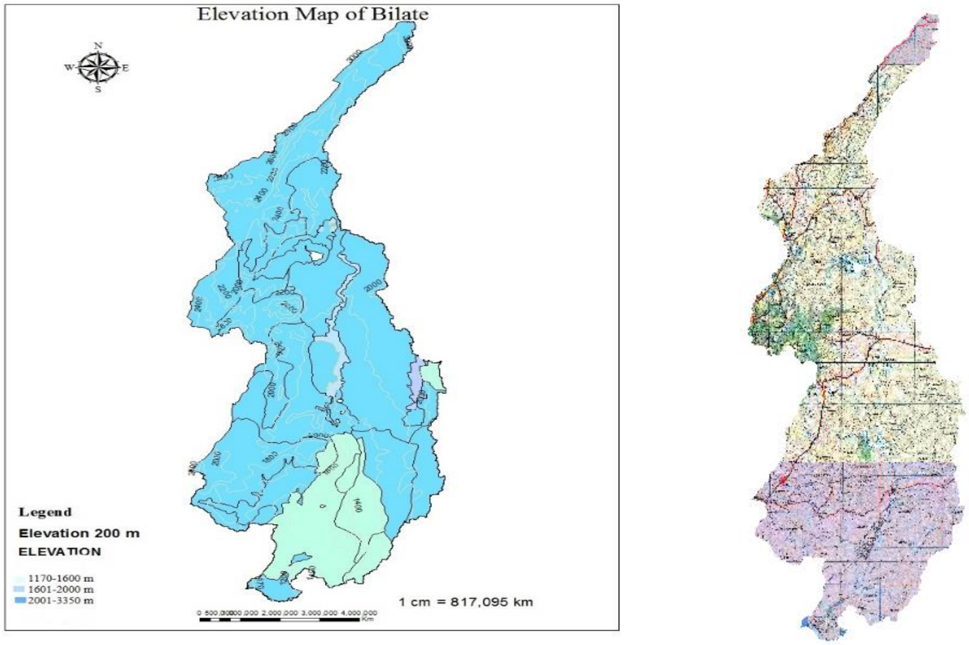


Figure: 4.13 Elevation Units in the 200-meter range of the Bilate river sub Basin

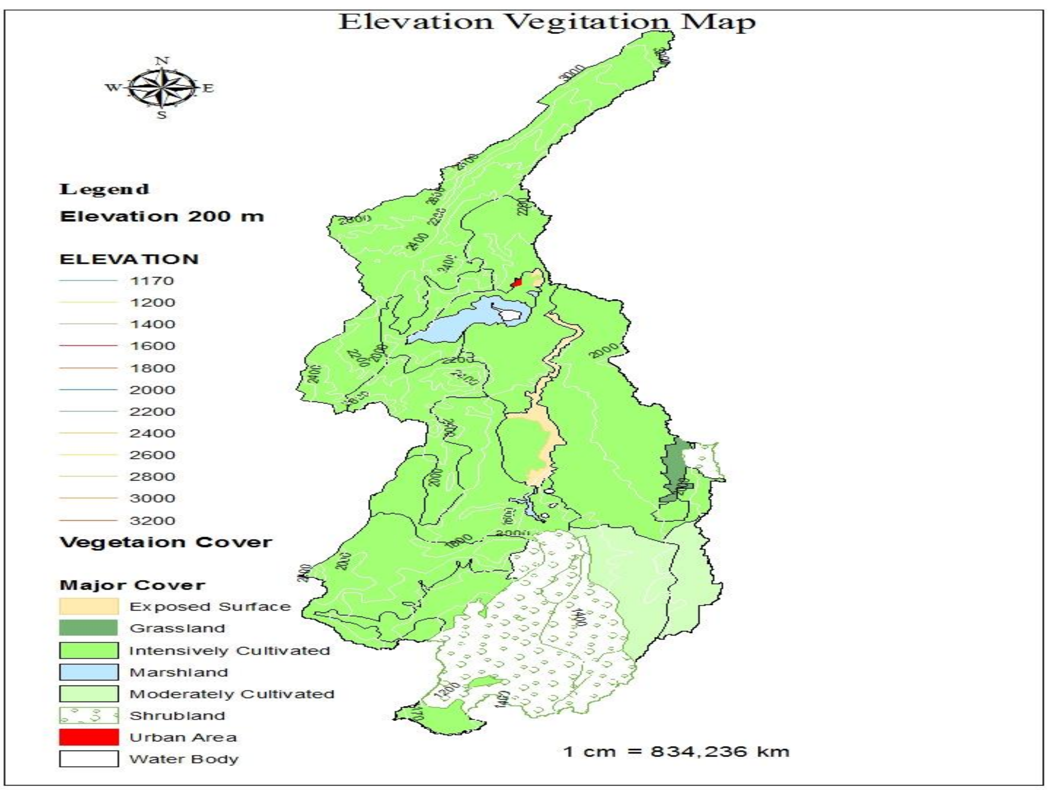


Figure: 4.14 The primary vegetation types and lakes within the sub basin

Model Calibration and validation

HBV-light model calibration made by different calibration approaches by changing sensitive input parameters within their respective predefined ranges until we reach to the certain acceptable model performance. There are different calibration approaches such as batch calibration, Monte-Carlo simulation, genetic algorithms, and manual trial and error. The HBV Light model was manually calibrated in this study by visually examining the model output until it reach the acceptable range.

Different criteria can be used to assess the fit of simulated runoff to observed runoff the model efficiency (Reff) and the mean difference (MeanDiff). The Nash-Sutcliffe coefficient (Reff) compares the prediction by the model with the simplest possible prediction. The coefficient of efficiency Reff = 1 Perfect when Q Simulated (t)= Q Observed(t) and Reff = 0 is good (poor) as the constant value prediction where as Reff<0 Very poor.

$$Reff = 1 - \frac{\sum(Qobs - Qsim)^2}{\sum(Qobs - Qsim)^2} \ldots\ldots\ldots\ldots. Equation\ 20$$

$$NSE = \frac{\sum_{n=1}^{n}(Qobs\ i - Qsim\ i)^2}{\sum_{n=1}^{n}\left(Qobs\ i - \dot{Q}obs\right)^2} \ldots\ldots\ldots\ldots\ldots. Equation\ 21$$

Where: NSE is the Nash-Sutcliffe coefficient The simulated flow is denoted by Qsim, the observed flow by $Q\overline{obs}$; and the number of days by n. The relative volume error (RVE) is goodness of fit measures, which zero value, indicates a perfect performance and values between -10 and -5 and +5 and +10 show that the model performs within reasonable bounds.

$$RVE = \left(\frac{\sum_{n=1}^{n} Qsim(i) - \sum_{n=1}^{n} Qobs(i)}{\sum_{i=1}^{n} Qobs(i)}\right)100\% \ldots\ldots\ldots\ldots\ldots. Equation\ 22$$

Where: the average daily error (RVE) between the measured flow and the prediction, The simulated flow is denoted by Qsim, the observed flow by Qobs, the time step by i, and the total number of time steps utilized in the calibration process by n..

After calibration model validation applied in order to minimize the differences between over or underestimation of model parameter. The calibration period should include a variety of hydrological events normally 5 to 10 years sufficient to calibrate the model validation: test of model performance with calibrated parameters for an independent period. Calibration of the HBV-light model parameters for bilate river sub-basin by trial and error until the result of the objective function became constant. After many trail and errors, the calibrated values of those parameters of the selected sub-basin were obtained.

The HBV-light model for the warm-up period of one year (2001) calibrated from 2001 to 2011 and validated from 2012 to 2015 using daily data from three selected stations. The model efficiencies such as Nash-Sutcliffe efficiency (NSE), coefficient of determination (R^2), root mean square error (RMSE), and the percentage of bias (PBIAS) of predicted and observed discharge were adopted after many trials and errors.

5. Results and Discussion

5.1. Precipitation Data Bias Correction and Comparison

Bilate River sub basin Precipitation time series data obtained from in situ measurements, and four-satellite reanalysis rainfall products (GPM_3IMERGM v 07, CHIRPS 4.8 Daily, TRMM 3B42 v7, ERA5 AG) were performed with reference to the observed data. From the catchment, four Meteorological stations were selected with their relatively data quality and comparing and bias correcting process applied for a period of twenty-one years from 01 January 2001up to 31 December 2021. The comparison between satellite based rainfall products and in situ data were take place in order to select the most reliable satellite precipitation product. Statistical estimator and graphical analysis were used to make the comparison some of the statistical estimator, including the coefficient of regression, mean error, root mean square error, and bias.

5.1.1. Utilizing Point to Pixel Analysis

Linking point to pixel which means plot (point) data obtained by satellite products with grid cell scale(pixel) comparison analysis was used in order to, compare the time series of rainfall data obtained at the chosen stations in the Bilate River sub-basin with their satellite-based equivalents at the pixels overlying the stations. A comparison between the satellite-based rainfall products and the accumulated rainfall estimates of the four stations that were chosen, averaged on an annual basis, is depicted in Figure 5.1. In order of low elevation (middle) to high elevation (left and right), the stations are arranged, and the following satellite precipitation products are compared: GPM_3IMERGM v 07, CHIRPS 4.8 Daily, TRMM 3B42 v7, and ERA5_AG. It is clear that the time step has an important influence on the quality of the satellite estimates. Point-pixel approach and averaged over a range of rainfall estimates for the four satellite products (i.e., GPM_3IMERGM v 07, CHIRPS 4.8 Daily, TRMM 3B42 v7, ERA5 AG) were compared in Bilate River sub-basin. In the catchment average annual rainfall increase with elevation except for stations, which located nearby the natural forest.

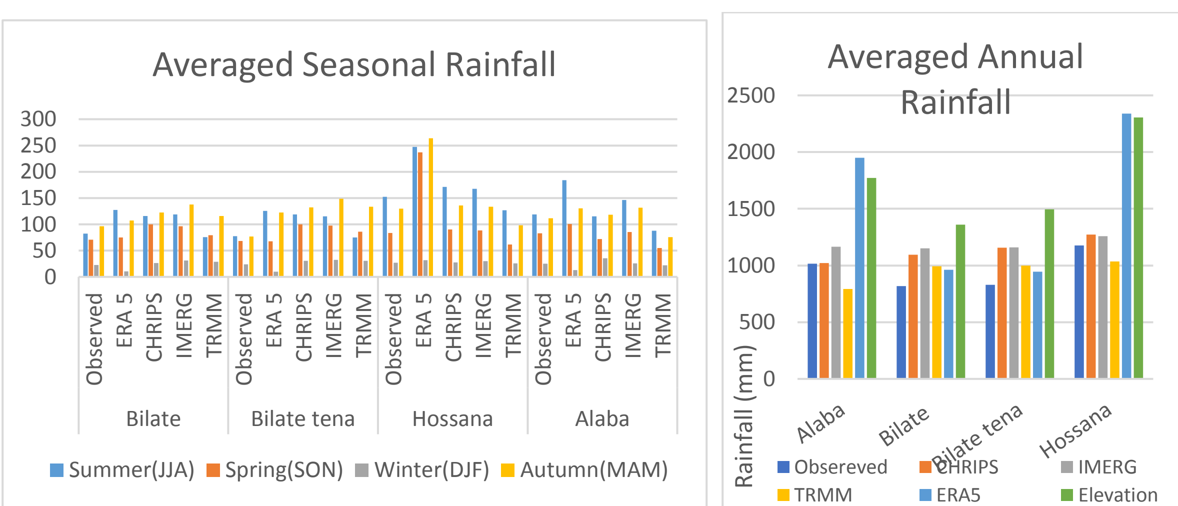


Figure: 5.1a An analysis of comparing average seasonal and annual rainfall (2001-2021)

Rainfall detection

To measure the ability of satellite products to detect any rainfall by using several metrics and compare to estimates using gauge measurements.

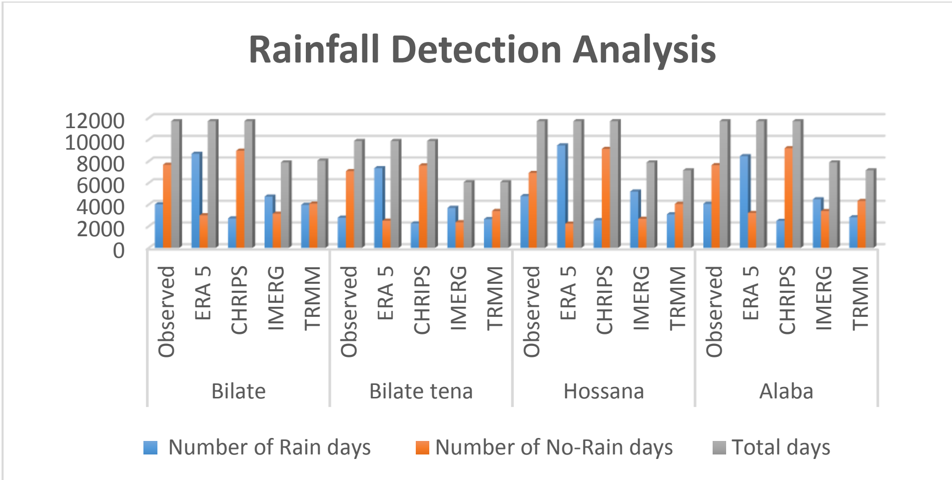


Figure: 5.1b An analysis of comparing rainfall Detection capabilities of SPP(1990-2021)

Rainfall detection analysis were made and the study's rainfall satellite products recorded rainfall occurrences, as indicated by the results in the table below. Counting Hits for 802 to 3686 days, counts of missed rainfall events range from 261 to 2251 days, while the counts of false events and correct negative events are between 738 and 3401 days and 3272 and 7395 days, respectively.

Table: 5.1 The ability of satellite rainfall product to detect rainfall in four stations

Station	SPPs	Hits Count	Miss Count	False Alarm Count	Correct Negative Count	Total
Alaba	CHRIPS 4.8 Daily	1426	1816	1051	7395	11688
	GPM_3IMERGDF_07	1632	539	1201	4512	7884
	TRMM_3B42RT_Daily_	1269	724	738	4422	7153
	ERA5_AG Daily	2666	576	3126	5320	11688
Bilate	CHRIPS 4.8 Daily	1313	1694	1392	7289	11688
	GPM_3IMERGDF_07	1493	509	1584	4298	7884
	TRMM_3B42RT_Daily_	1203	612	1298	4040	7153
	ERA5_AG Daily	2184	823	3401	5280	11688
Bilate tena	CHRIPS 4.8 Daily	802	516	2131	3926	7375
	GPM_3IMERGDF_07	880	1443	1374	6165	9862
	TRMM_3B42RT_Daily_	917	401	1468	3272	6058
	ERA5_AG Daily	1666	657	3046	4493	9862
Hossana	CHRIPS 4.8 Daily	1729	674	804	3946	7153
	GPM_3IMERGDF_07	1696	2251	848	6893	11688
	TRMM_3B42RT_Daily_	2085	560	1259	3980	7884
	ERA5_AG Daily	3686	261	3282	4459	11688

The Hits, Miss, False alarm and correct negative show the ability of each satellite products to detect rainfall observed in the watershed. The Maximum and minimum values indicates which satellite precipitation products having the detection capabilities in the watershed.

ERA5_AG daily precipitation product at Hossana station shows the highest rainfall event (Hits count); also, when we compare it with others it shows more yearly rainfall on average. The four precipitation products displayed the lowest false count at the Hossana station as well. CHRIPS Precipitation product at Bilate tena station showed the rainfall event with the fewest Hits, Also for IMERG and TRMM it showed the minimum rainfall event Hits count. The highest count of false rainfall events occurred at Bilate station by using four satellite rainfall products used.

Cross Tabulation Table

Based on the Cross Tabulation Table, which scores the forecast verifications in the Bilate River sub basin, the rainfall detection investigation were conducted. The elements that comprise it are the critical success index, false alarm ratio, frequency bias and the probability of detection as seen below. The frequency bias ranges from 0.64 to 2.72; CHRIPS at Hossana station showed the lowest frequency bias. While, Alaba station showed the highest frequency bias. Having the least POD for CHRIPS at Bilate tena station and the greatest for ERA5 at Hossana station and the rainfall products had a probability of detection ranging from 0.38 to 0.93. CHRIPS was identified on a scale that ranged from 0.33 to 0.84 in the false alarm ratio. Where, CHRIPS was discovered to have the greatest FAR at Alaba station and the least FAR at Hossana station. Using information from both false alarms and missing events, the critical index success, had a maximum value of 0.53 for IMERG at the Hossana station and a lowest value of 0.13 for CHRIPs Precipitation products at the Alaba station.

Table 5.2: Scores from 2001 to 2021 for satellite rainfall products contingency table.

Station	**Contingency Table Score**	**Satellite Precipitation Products**			
		CHRIPS	IMERG	TRMM	ERA5
Alaba	FB	2.72	1.30	1.01	2.46
	POD	0.44	0.75	0.64	0.82
	FAR	0.84	0.42	0.37	0.67
	CSI	0.13	0.48	0.46	0.31
Bilate	FB	0.90	1.54	1.38	1.86
	POD	0.44	0.75	0.66	0.73
	FAR	0.51	0.51	0.52	0.61
	CSI	0.30	0.42	0.39	0.34
Bilate tena	FB	0.97	1.81	2.23	2.03
	POD	0.38	0.70	0.61	0.72
	FAR	0.61	0.62	0.73	0.65
	CSI	0.24	0.33	0.23	0.31
Hossana	FB	0.64	1.26	2.36	1.77
	POD	0.43	0.79	0.72	0.93
	FAR	0.33	0.38	0.70	0.47
	CSI	0.35	0.53	0.27	0.51

All stations combined, IMERG had the lowest False Alarm Ratio, CHRIPS had the highest Probability of Detection, and CHRIPS had the lowest Critical Index Success, compared to IMERG's higher value.

Rainfall depth Measurements

A statistical analysis was performed on the rainfall depth over a catchment that was calculated from the remote sensing products. The results are displayed in the table below. The coefficient of regression, bias, root mean square error, and mean error all measured in millimeters of precipitation are among the statistical metrics that are employed. The largest bias was found to be less than one, indicating that the satellite precipitation products underestimate the rainfall at the stations in the Bilate River sub-basin. The ERA5 station at Hossana had the highest bias value of 1.94, while the TRMM station at Alaba had the lowest value. For the thirty-year study period, the mean error was found to be between 3.05 and -0.64 mm/day. TRMM 3B42 v7 at Alaba and ERA5 at Hossana stations were determined to have the lowest and largest mean errors, respectively. Typically, a bias of one or nearly one and a mean error value of zero or nearly zero would be optimal. In light of the acquired data, this indicates that the satellite products' performance in the basin is subpar. Thus, based on these findings generally, it was discovered that CHRIPs and IMERG performed better in terms of depth than TRMM and ERA5. Having a 1.01 overall bias, Underestimating occurred in TRMM 3B42 v7 with the rainfall in the basin by 0.5 millimeters per day. The ERA5 overestimated the basin's rainfall by an overall bias of 1.37.

Table: 5.3 Satellite rainfall product statistical analysis with respect to station data

Station	Statistical Analysis	Satellite Rainfall Products			
		CHRIPS	IMERG	TRMM	ERA5
Alaba	Bias	1.01	1.15	0.77	1.25
	ME	0.01	0.41	-0.64	0.71
	RMSE	8.17	7.72	6.84	7.32
	R^2	0.86	0.89	0.83	0.80
Bilate	Bias	1.35	1.41	1.20	1.21
	ME	0.77	0.91	0.45	0.45
	RMSE	7.72	7.02	6.70	6.29
	R^2	0.88	0.68	0.86	0.99
Bilate tena	Bias	1.31	1.40	1.20	1.08
	ME	0.73	0.90	0.46	0.20
	RMSE	9.06	7.57	7.46	7.37
	R^2	0.92	0.94	0.75	0.59
Hossana	Bias	1.08	1.07	0.87	1.94
	ME	0.26	0.22	-0.42	3.05
	RMSE	8.97	7.28	6.88	9.82
	R^2	0.97	0.97	0.94	0.78

To assess the degree of agreement between rainfall data from gauge stations and satellite-based data, The Root Mean Square Error and the correlation coefficient were used to compute the cumulative and random errors. The results indicate that the RMSE for ERA5 at Hossana station was 9.82 mm/day, while at Bilate station it was 6.29 mm/day. There is less agreement with the reference dataset when the RMSE value is larger.

The correlation coefficient highlights the variation seen in the rainfall readings at the station's satellite rainfall products in accordance with a linear trend line in their scatterplots, which represents the data distribution.R^2 has a range of 0% to 100%, with 100 representing the ideal correlation. The relationship between rainfall data from stations and satellites in the Bilate River sub-basin was found to be between 0.59% and 0.97%, with the maximum value for CHRIPs and IMERG at Hossana station and the least value for ERA5 at Bilate tena station. All satellite rainfall products were found to have low R^2 generally, however CHRIPs had a higher overall R^2 at the stations in the Bilate River sub basin, with a value of 0.91%, followed by IMERG (0.87%), TRMM 3B42 v7 (0.85%), and ERA5 (0.79%).

Based on research on rain detection, satellite estimations were further evaluated despite results indicating significant systematic inaccuracies. According to the explanation in section above, bias estimates were divided into three categories: The three types of rainfall bias are false, missed, and hit. For every station and every satellite-based rainfall estimate product, these bias components are provided in millimeters per day. Findings around zero indicate that the satellite product is operating well at the relevant station.

Table: 5.4 Rainfall bias components by daily depth

Station	Daily Depth of Rainfall Bias Components	Satellite Precipitation Products			
		CHRIPS	IMERG	TRMM	ERA5
Alaba	Hit event bias	0.37	0.10	-0.34	-0.52
	Missed event bias	1.37	0.59	0.85	0.45
	False event bias	1.00	0.85	0.52	1.59
Bilate	Hit event bias	0.47	0.17	0.02	-0.52
	Missed event bias	1.05	0.45	0.56	0.45
	False event bias	1.39	1.15	0.96	1.34
Bilate tena	Hit event bias	0.27	-0.24	-0.22	-0.78
	Missed event bias	1.37	0.56	0.77	0.59
	False event bias	1.85	1.65	1.42	1.49
Hossana	Hit event bias	0.91	0.26	-0.29	0.32
	Missed event bias	1.55	0.50	0.68	0.18
	False event bias	0.90	0.79	0.52	2.59

The Hit rainfall depth bias varied between -0.78 and 0.91 mm/day for CHRIPs and ERA5, having the most valuable recorded at Hossana station and the least at Bilate ten station. The total Hit rainfall bias depth revealed that, when rainfall is observed in both station measurements and satellite products, the satellite-based rainfall estimates generally overestimate rainfall depths. It was discovered that the bias from the missed rainfall depth ranged from 0.18 to 1.55 mm/day, with ERA5 at Hossana station having the lowest value and CHRIPs at Hossana station having IMERG trailed ERA5 in having the lowest overall missed rainfall bias depth. When the evaluation of the bias resulting from the inaccurately detected rainfall depth, it was discovered to range from 0.52 to 1.85 mm/day. At Bilate tena station, the CHRIPs value was the highest, while at Alaba and Hossana station, the TRMM value was the lowest. The findings are presented graphically in the figures. It is evident that of hit and false bias components has less impact on the bias than the depth of lost rainfall.

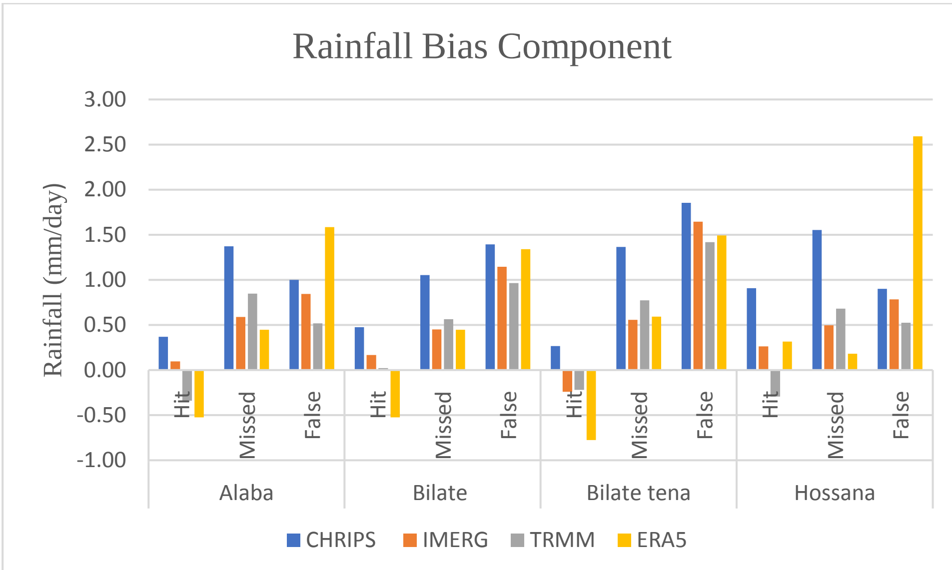


Figure: 5.2 Bias components for daily rainfall depth

5.1.2 Analysis in Sub-Basins Scale

Over each of the three catchments of the Bilate River subbasin, the rainfall depth was spatially averaged using gauge station data and remote sensed rainfall estimates. Thiessen polygons were utilized to calculate the the rainfall product's basic arithmetic mean values over the corresponding sub-basin, based on station observations. Three stations were utilized to represent the upper watershed (Hosana), the mid watershed (AlabaKulito), and the bottom watershed (Bilate Tena) for the analysis in the catchment region.

Precipitation incidents analysis

When the total rainfall estimates were computed and calculated, the average using an arithmetic mean across the catchments displayed in the Bilate River sub-basin. The remote sensing rainfall products' analysis of rainfall occurrence performed well in comparison to the detection analysis at the stations. There has been improvement in the hits, missed, and false rainfall events throughout a Fifteen-year period (2001-2015); the corrected negative occurrences fell within the identical depth. The proportion of days with fake rainfall incidents ranged from 5.6% to 12.6% for CHIRPS, 24.4 to 36.9% for IMREG, 13.4% to 25.7% for TRMM13, and 19.4% to 27.2% for ERA5. The percentage of rainfall events that occur in a single catchment is used to describe the number of days when rainfall occurs. This relationship is shown in the table below:

Table: 5.5 Rainfall incidence of satellite products in the Bilate sub basin (2001-2015)

Sub Cathement	CHRIPS				IMERG				TRMM				ERA5			
	Hits	Miss	False A	Corr.Neg	Hits	Miss	False A	Corr.Neg	Hits	Miss	False A	Corr.Neg	Hits	Miss	False A	Corr.Neg
Upper (Hossana)	16.0	23.7	5.0	55.2	37.8	1.9	24.4	36.0	30.4	9.3	13.0	47.3	39.4	0.3	40.9	19.4
Midle (Alaba)	14.1	21.2	7.0	57.7	32.2	3.1	25.8	38.8	23.3	12.1	18.0	46.6	34.2	1.2	37.4	27.2
Lower (Bilate tena)	11.1	16.4	12.6	59.9	24.0	3.5	36.9	35.5	18.7	8.8	25.7	46.8	26.3	1.2	47.4	25.0

Score on the contingency table

After calculating Score in the contingency table, the Critical Success Index (CSI) indicated notable gains, with every value above 0.3. In the Lower and Upper catchments, respectively, CHRIPs had the lowest CSI value while IMREG displayed the greatest value. The bias frequency was discovered to be between 0.7 to 2.4. IMERG within the catchment upstream having the highest frequency of bias and CHRIPs in the upper catchment having the lowest. The findings of Score in the contingency table for the incident of rainfall in the catchments are displayed in the table below.

Table 5.6 Scores Regarding the contingency table of satellite products (2001-2015)

Sub Cathement	CHRIPS				IMERG				TRMM				ERA5			
	FB	POD	FAR	CSI	FB	POD	FAR	CSI	FB	POD	FAR	CSI	FB	POD	FAR	CSI
Upper (Hossana)	0.7	0.4	0.2	0.4	2.4	1.0	0.4	0.6	1.9	0.8	0.3	0.6	1.9	1.0	0.5	0.5
Midle (Alaba)	0.7	0.4	0.3	0.3	2.0	0.9	0.4	0.5	1.4	0.7	0.4	0.4	1.9	1.0	0.5	0.5
Lower (Bilate tena)	0.8	0.4	0.5	0.3	0.7	0.9	0.6	0.4	1.3	0.7	0.6	0.4	1.5	1.0	0.6	0.4

When the satellite rainfall products' study of rainfall occurrence was conducted per watershed rather than per point location, the results indicated a stronger connection with the in situ readings.

Estimated depth of Precipitation

As result indicates in the above section, statistical and graphical analysis was used to determine the amount of rainfall in the sub-basins of the Bilate River. In contrast to the conclusions of the point-to-pixel analysis, the data displayed in Table 5.7 show greater values of RMSE, which range from 6.9 to 10.1 mm/day. The Hossana upstream catchment's CHRIPs had the highest RMSE value, while the Bilate Tena down stream’s ERA5 had the lowest. The bias was found to range from 0.8 to 2.0, with the Hossana upstream catchment's ERA5 having the largest bias and the Alaba Middle catchment's TRMM having the lowest value. The remote sensed products were overestimating the depth of rainfall in the Bilate River sub basin, as the point-to-pixel investigations also demonstrated, as evidenced by the fact that most of the bias values were found to be less than one and for certain rainfall products, it was discovered that the mean error was negative. Using the R^2 measure, the degree of agreement between the data from the satellite and an average of the in situ data throughout the sub-basins was calculated. With an overall value of 1.0%, it was discovered that R^2 was higher for IMERG than for CHRIPs, 0.9% for TRMM, and 0.75 for ERA5.

Table: 5.7 Satellite rainfall product statistical analysis with respect to in-situ measurements.

Sub Cathement	CHRIPS				IMERG				TRMM				ERA5			
	Bias	ME	RMSE	R²	Bias	ME	RMSE	R²	Bias	ME	RMSE	R²	Bias	ME	RMSE	R²
Upper (Hossana)	1.1	0.2	10.1	1.0	1.0	0.1	7.1	1.0	0.9	-0.3	6.9	0.9	2.0	3.3	10.1	0.7
Midle (Alaba)	0.9	-0.1	8.2	0.7	1.1	0.3	7.7	0.8	0.8	0.0	7.0	0.7	1.2	0.7	7.4	0.8
Lower (Bilate tena)	1.4	0.8	8.5	0.9	1.3	0.8	7.5	0.9	1.2	0.4	7.5	0.8	1.1	0.2	6.9	0.8

The three components of the bias the hit, missed rainfall and false rainfall biases were separated. The primary source of bias was found to be the Hits rainfall bias depth for ERA5 and CHRIPs, but for CHRIPs, it was the Missed rainfall bias depth. As seen in the figure below, the erroneous rainfall bias depth is larger for ERA5 in the upper (Hossana) canyon.

Table 5.8: Biases for Hit, Missed, and False rains

Sub Cathement	CHRIPS			IMERG			TRMM			ERA5		
	Hit bias	Missed bias	False bias	Hit bias	Missed bias	False bias	Hit bias	Missed bias	False bias	Hit bias	Missed bias	False bias
Upper (Hossana)	1.2	1.6	0.6	-0.3	0.1	0.5	-0.2	0.5	0.4	1.1	0.0	2.2
Midle (Alaba)	0.6	1.5	0.8	-0.1	0.3	0.7	-0.4	0.7	0.4	-0.5	0.1	1.2
Lower (Bilate tena)	0.4	1.2	1.6	-0.4	0.2	1.4	-0.2	0.6	1.2	-1.1	0.1	1.4

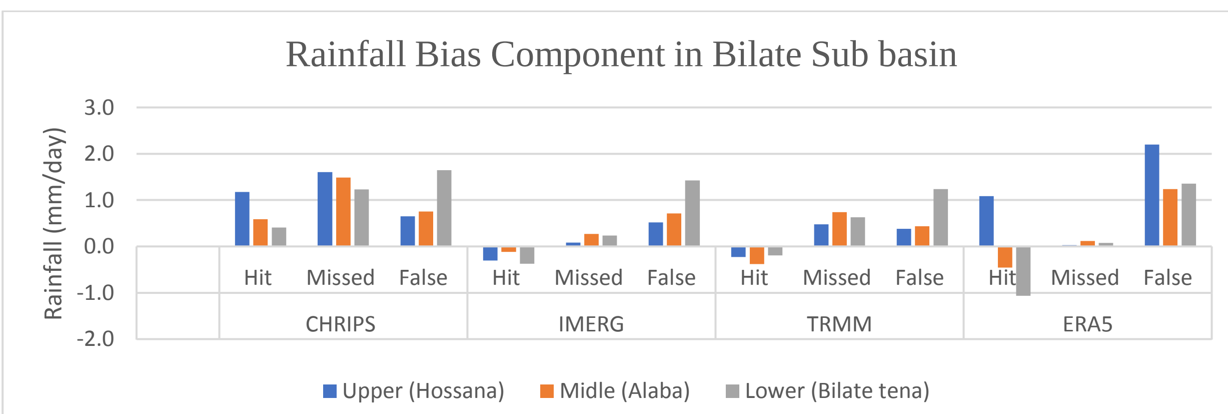


Figure: 5.3 Bias components for daily rainfall depth in Bilate river sub-basins

Satellite Precipitation Products Bias Correction

The bias correction was carried out per sub-basin using power transformation methods for the satellite precipitation products having the detection capabilities by relating with the in situ. Strong discrepancies were found between satellite rainfall products and in situ measurements at the sites using various error determination techniques. Because of this, bias adjustment was conducted to the information retrieved from the remote sensing precipitation products in order to prepare it for use in the hydrological modeling. Systematic mistakes discovered in the preceding section needed to be corrected. When comparing the bias corrected time series to the unprocessed satellite rainfall product data, a notable increase in rainfall depth was detected with respect to the in situ observations. This is demonstrated by the many graphical analyses that were conducted, as seen in the figure below.

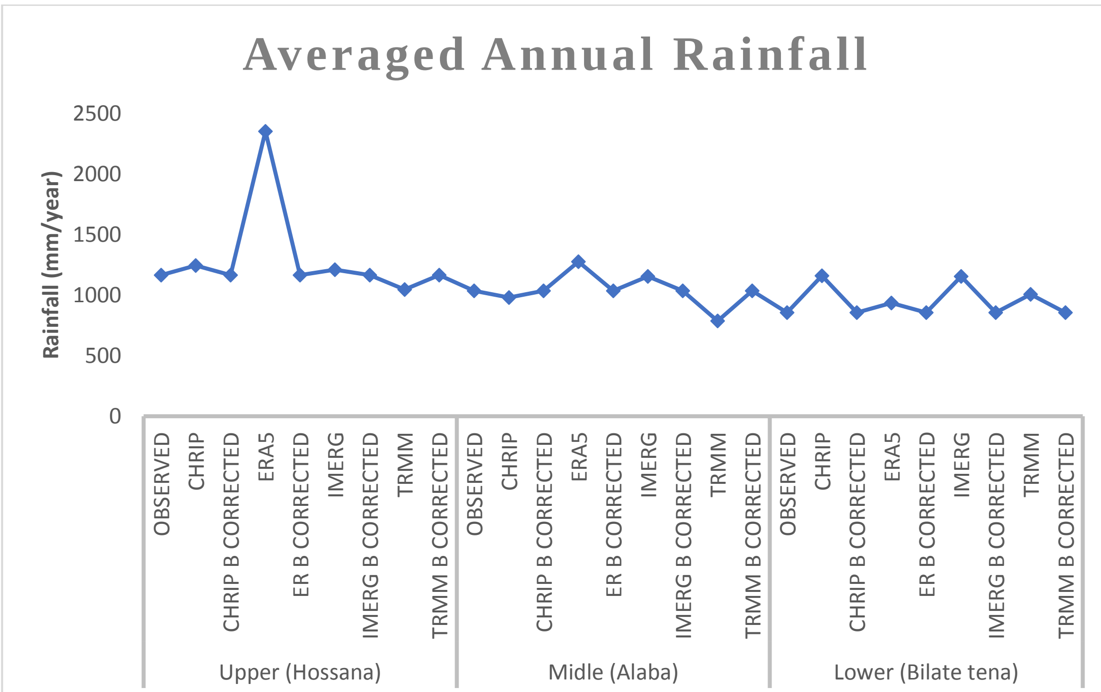


Figure: 5.4 Comparison of average yearly rainfall at the sub-basin scale

The average yearly rainfall graph illustrates what happened after the uncorrected data that was taken directly from the satellite rainfall products underwent bias adjustment. The in situ measurements and the derived bias corrected time series agreed on most aspects. It should come as no surprise that statistical examination of the bias-corrected time series' rainfall depths produced an RMSE and R^2 that showed a stronger correlation between the uncorrected satellite data and in situ observations.

Strong agreement was found between the time series with bias corrections based on the several products utilized in this investigation and the on-site measurements. As demonstrated by the uncorrected and bias-corrected satellite-based datasets in the figure below, as well as the cumulative mass curve plot of the areal rainfall representation of the sub-basins, additionally observed was the underestimating of rainfall depth found in the uncorrected satellite products.

IMERG and TRMM were the next two models shown to overestimate the rainfall depths in comparison to in situ data, after ERA5.

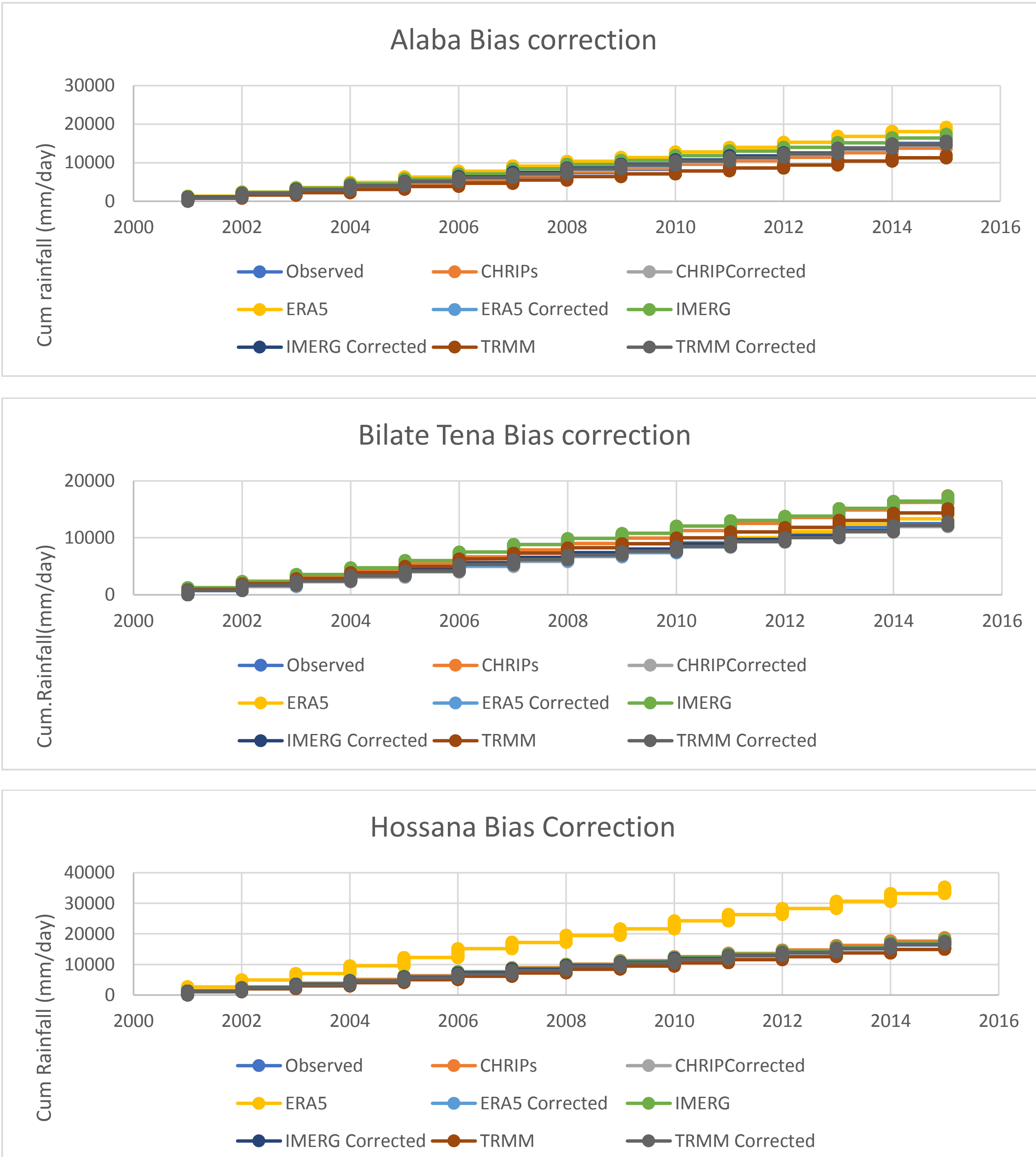


Figure: 5.5: Plots showing the accumulated mass curve for rainfall at the sub-basin scale from in situ measurements of satellite products with and without bias correction

5.2 Adjusting and Comparing Temperature Data Bias

The mean Temperature from in situ measurements and the satellite product employed in this investigation were also contrasted with ERA5Agro, the comparison's purposes was to assess temperature estimates derived from ERA5 satellite estimates (i.e. ERA5 Mean Temperature data) at daily base for the period 1990-2015. A statistical and graphical analysis served as the foundation for the comparison.

Analysis using Point to Pixel

The ERA5 averaged mean daily temperature was found to have higher values at the Bilate Tena station, according to a point-to-pixel study. The ERA5 Mean Temperature dataset and the station data showed no discernible relationship with elevation.

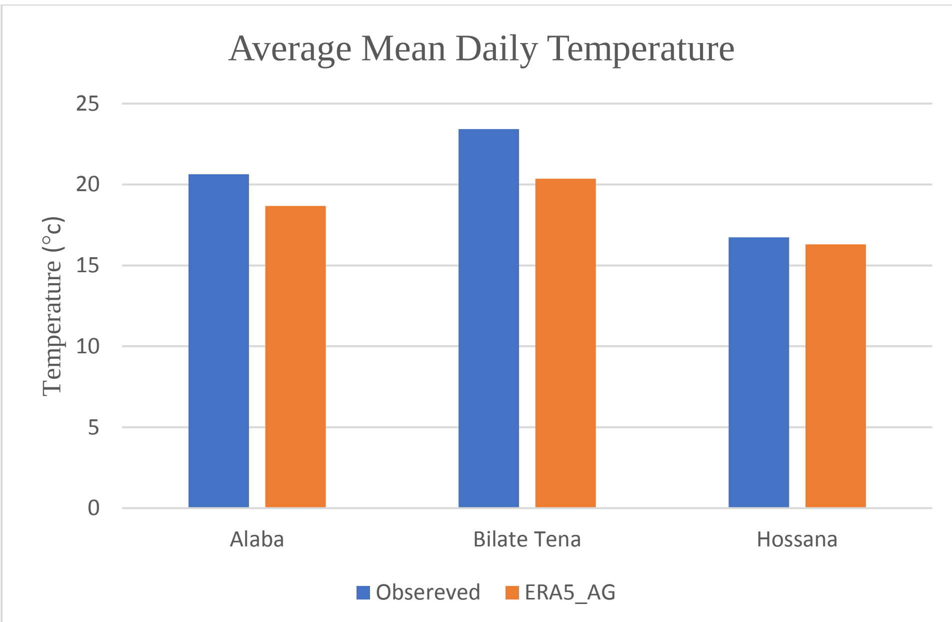


Figure: 5.6 In contrast of average yearly Temperature from ERA5_AG and from stations

Temperature estimates depth

The ERA5_AG Temperature product was analyzed using the same statistical method used to evaluate the satellite-based rainfall products, depth-wise, on a daily basis for the years 1990 to 2015. The in-situ data at meteorological gauge stations and the satellite product agreed on the temperature depth, with an RMSE ranging from 1.3 to 2.9 and an R^2 between 23.49% and 47.03%.

The mean error and bias for the 26-year time frame used in this investigation indicated that the ERA5_AG Temperature product was underestimated in comparison to measurements made by counterpart stations. The bias was found to vary between 0.86 and 0.97, with Hossana station having the highest bias of 0.97.

Sub-Basins Scale Analysis

Table 5.9: ERA5_AG Temperature statistically analyzed with respect to stations data.

Stations	Bias	ME	RMSE	R^2
Alaba	0.90464	-1.9685	2.91683	0.2349
Bilate Tena	0.86871	-3.0757	3.35641	0.4703
Hossana	0.97323	-0.4482	1.31704	0.3878

Utilizing a straightforward arithmetic mean of the pixel values spanning each catchment and Thiessen polygons for the in situ data, estimates from the ERA5_AG Temperature product and the gauge station estimates were spatially averaged throughout the Bilate River sub-basins.

The same scheme of analysis was used, and the results, which are presented in Table 5.9, demonstrate that, in comparison to the examination at the pixel level carried out in Section below, the temperature depth evaluation over sub-basins demonstrates better agreement than the estimates made in situ. The mean error in the Bilate Upstream and Bilate Downstream catchments was found to vary between 0.53 and 3.1, respectively. The bias varied between 0.86 and 0.96, as the table below illustrates.

Table 5.9: ERA5_AG Temperature estimates statistical analysis in Bilate river sub-basins.

Stations	Bias	ME	RMSE	R^2
Upper	0.968203	-0.53775	1.365666	0.3626
Middel	0.876851	-2.63988	3.416737	0.2122
Lower	0.866044	-3.16527	3.381688	0.5449

Mean Temperature Data Bias Correction

Before using the ERA5_AG Temperature product in hydrological modeling with HBV-light, bias correction was applied. The temperature dates were adjusted using the cumulative daily mean temperature estimates that were spatially averaged throughout the three Bilate River sub-basins. Similar to how the satellite rainfall product data were corrected. As seen in the figure below the bias-corrected and uncorrected time series for the ERA5_AG Temperature product, collectively with the aggregated daily mean temperature estimates from the stations, are plotted together for graphical study.

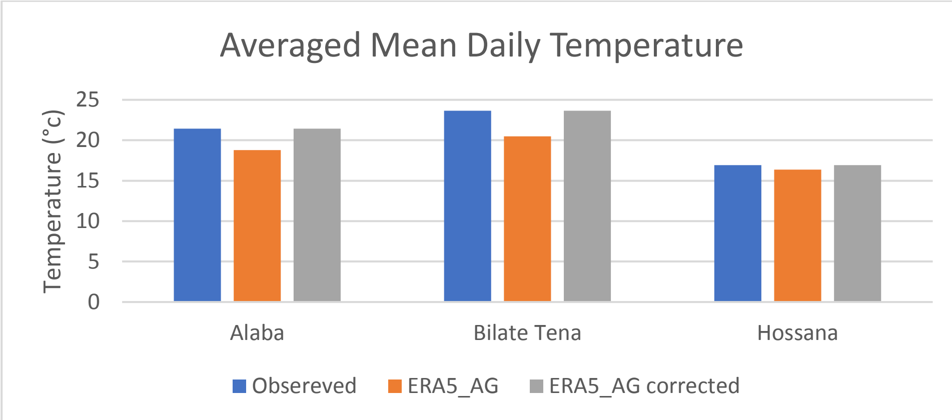
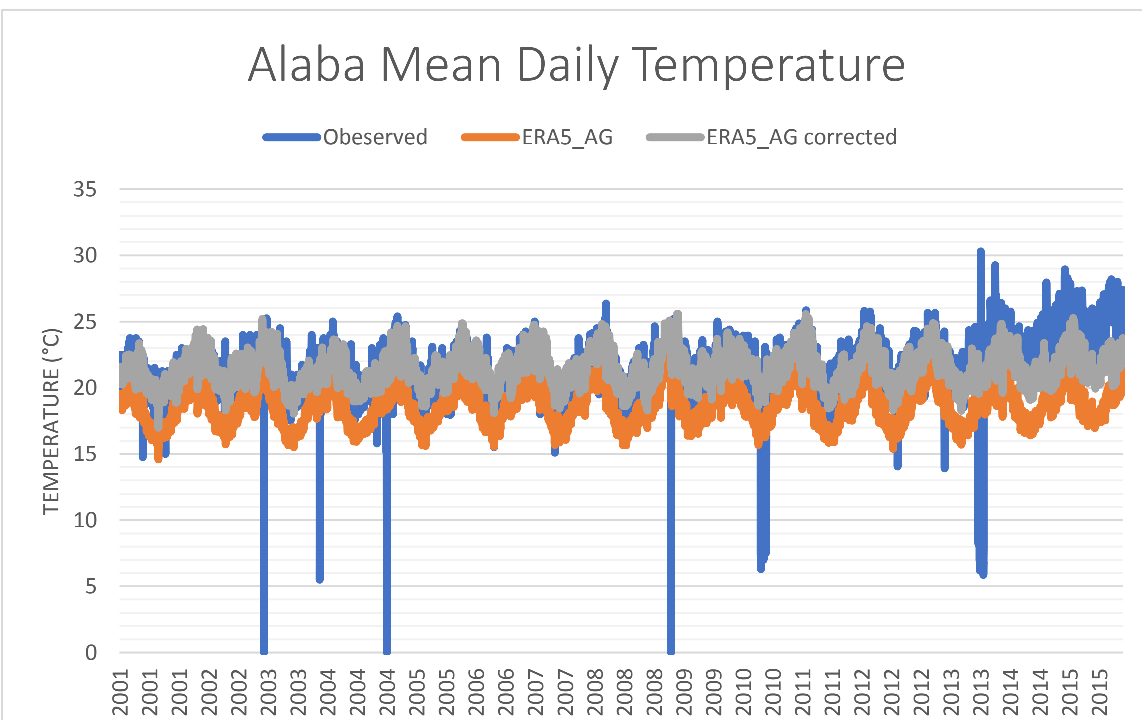
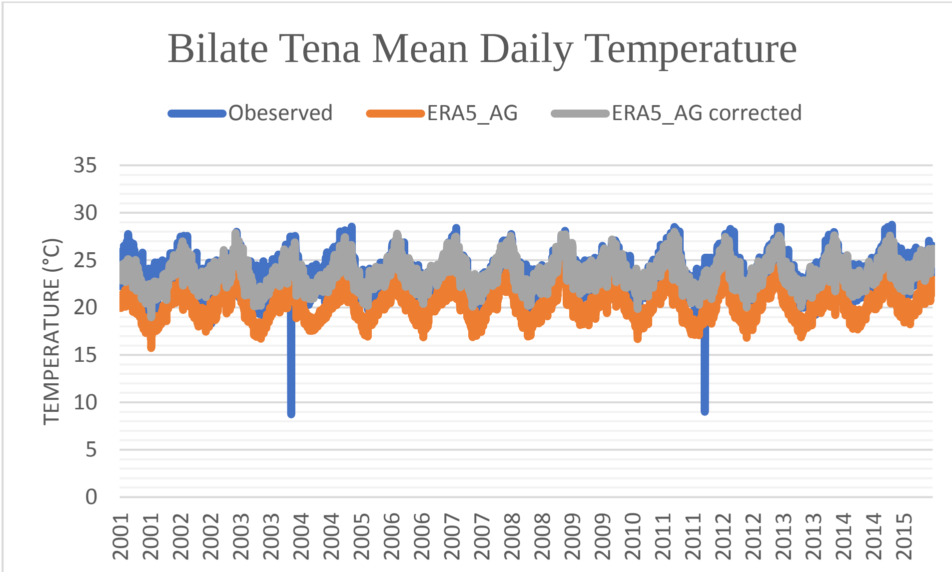


Figure: 5.7 Comparison of the daily mean temperature at the sub-basin scale

There is agreement between the bias corrected time series and the in situ data; however, the depth of the mean temperature estimations is now indicated to be underestimated. A higher correlation was observed between the bias-corrected daily mean temperature estimates time series and the in situ estimates by statistical analysis compared to the uncorrected satellite data. R^2 was discovered to be 21% in the Alaba catchment, 54% in the downstream catchment of Bilate tena, and 36% in the upstream catchment of Hossana. The range of the RMSE was 1.3 to 3.4.

The mean daily Temperature of average for sub-basins stations' Temperatures, the bias-corrected and uncorrected ERA5_AG Temperature product.





The mean daily Temperature of sub-basins averaged Temperature from the stations, the uncorrected and the bias corrected ERA5_AG Temperature product.

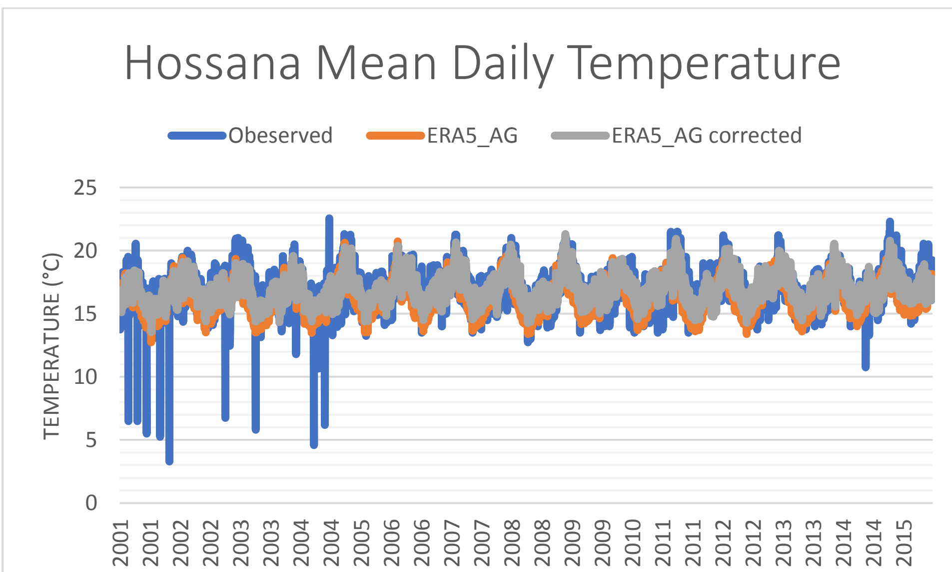


Figure: 5.8 The mean daily Temperature of sub-basins averaged Temperature.

In Figure above, the mean daily Temperature a sub-basin's chart aggregates of the in situ, the bias-corrected and uncorrected ERA5_AG Temperature product time series shown. Less difference are noted in Bilate tena downstream catchment.

5.3 Comparison of Potential Evapotranspiration Data and Bias Correction

The in situ data from Hargreaves Potential Evapotranspiration (ERA5_AG) satellite estimations (i.e., ERA5_AG PET product) at daily basis for the years 1990–2015 were also compared to the potential evapotranspiration product utilized in this work. The statistical and graphical analyses served as the foundation for the comparison.

Point to Pixel Analysis

The ERA5_AG PET averaged daily PET was determined to have lower values than stations, according to a point-to-pixel analysis. In the ERA5_AG PET dataset as well as the station dataset, there was no discernible relationship with elevation.

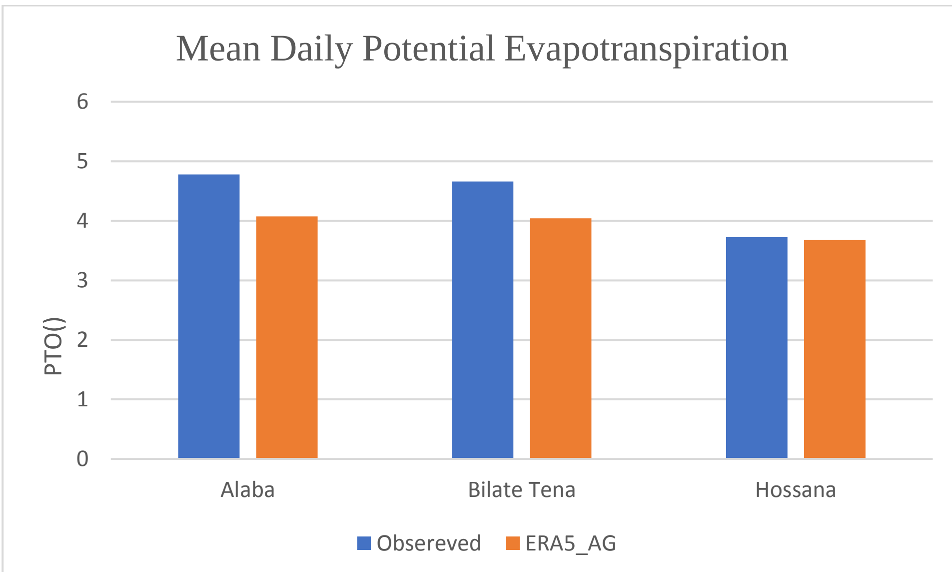


Figure: 5.9 A comparison of daily average PET from ERA5_AG and stations

PET calculates the depth

The ERA5_AG PET product was analyzed using the same statistical method used to evaluate the satellite-based rainfall products on a daily basis for the years 1990 to 2015. The satellite product and the in situ measurements at the evaporation gauge stations agreed on the depth of the PET, with an RMSE ranging from 0.74 to 1.23 and an R2 ranging from 1% to 53%. The mean error and bias for the 26-year timeframe used in this analysis indicated that the ERA5_AG PET was underestimated in comparison to the stations of peers. Bias was discovered to range from 0.99 to 1.17, with the latter being detected at Alaba station.

Table 5.10: ERA5_AG PET estimations statistical analysis in reference to stations data.

Stations	Bias	ME	RMSE	R^2
Alaba	1.17	-0.71	0.86	0.53
Bilate Tena	1.15	-0.62	1.23	0.01
Hossana	0.99	-0.05	0.74	0.06

Sub-Basins Scale Analysis

Over the sub-basins of the Bilate river catchment, estimates from the ERA5_AG PET product and the gauge station estimates were spatially averaged using Thiessen polygons for the in situ data and a basic arithmetic mean of the pixel values encompassing the relevant catchments. The PET depth assessment over sub-basins demonstrates higher agreement to the in situ estimations compared to the point-to-pixel analysis done in section 5.2.1, according to the identical scheme of analysis, the results of which are described in Table 5.11. It was discovered that the mean error varied between -0.93 and 0.16 in the catchments of Hossana Upstream and Bilate tena Downstream, respectively. The bias varied between 1.04 and 1.23, as Table 5.11 illustrates.

Table: 5.11 The statistical analysis of ERA5_AG PET estimates in with in situ estimates.

Stations	Bias	ME	RMSE	R^2
Alaba	1.17	-0.69	0.85	0.56
BilateTena	1.23	-0.93	1.32	0.01
Hossana	1.04	0.16	0.68	0.01

Bias Correction in Evapotranspiration Data

Before using the ERA5_AG PET product in hydrological modeling with HBV-light, bias bias adjustment were implemented. The process for correcting the remote sensed Precipitation product data was analogous to that used to correct the PET dates; it involved accumulating PET estimates and averaging them geographically throughout the three Bilate sub-basins. As illustrated in Figure 5.10, the uncorrected and bias corrected ERA5_AG PET product data, along with the mean yearly PET estimations from the stations, are plotted together for graphical study.

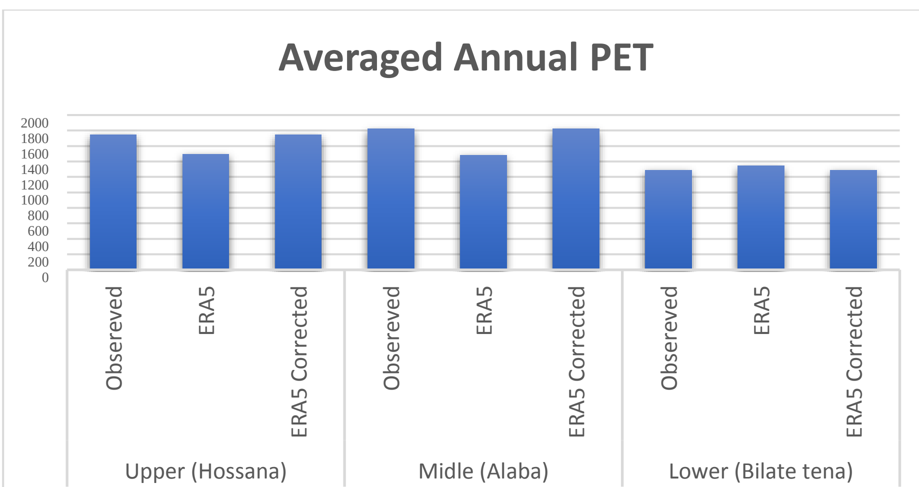


Figure: 5.10 Comparison of averaged yearly PET at the sub-basin scale

Although the underestimating of PET depth is now indicated, the bias corrected time series largely agrees with the in situ observations. A higher correlation than the uncorrected satellite data was found by statistically analyzing the bias corrected PET estimates time series with respect to the in situ estimates. In the Bilate Tena catchment, R^2 was determined to be 1%, in the middle catchment, Alaba 0.56%, and in the Hossana upstream watershed, 1%. The RMSE ranged from 0.68 to 1.32. The accumulated mass curve plots of the in situ sub-basin aggregates, both the bias-corrected and uncorrected ERA5_AG PET product time series, in Figure 5.11, display a linear trend with discernible variations in the accumulated PET depth over time. The Alaba middle catchment was similarly found to have a smaller bias value, indicating less difference.

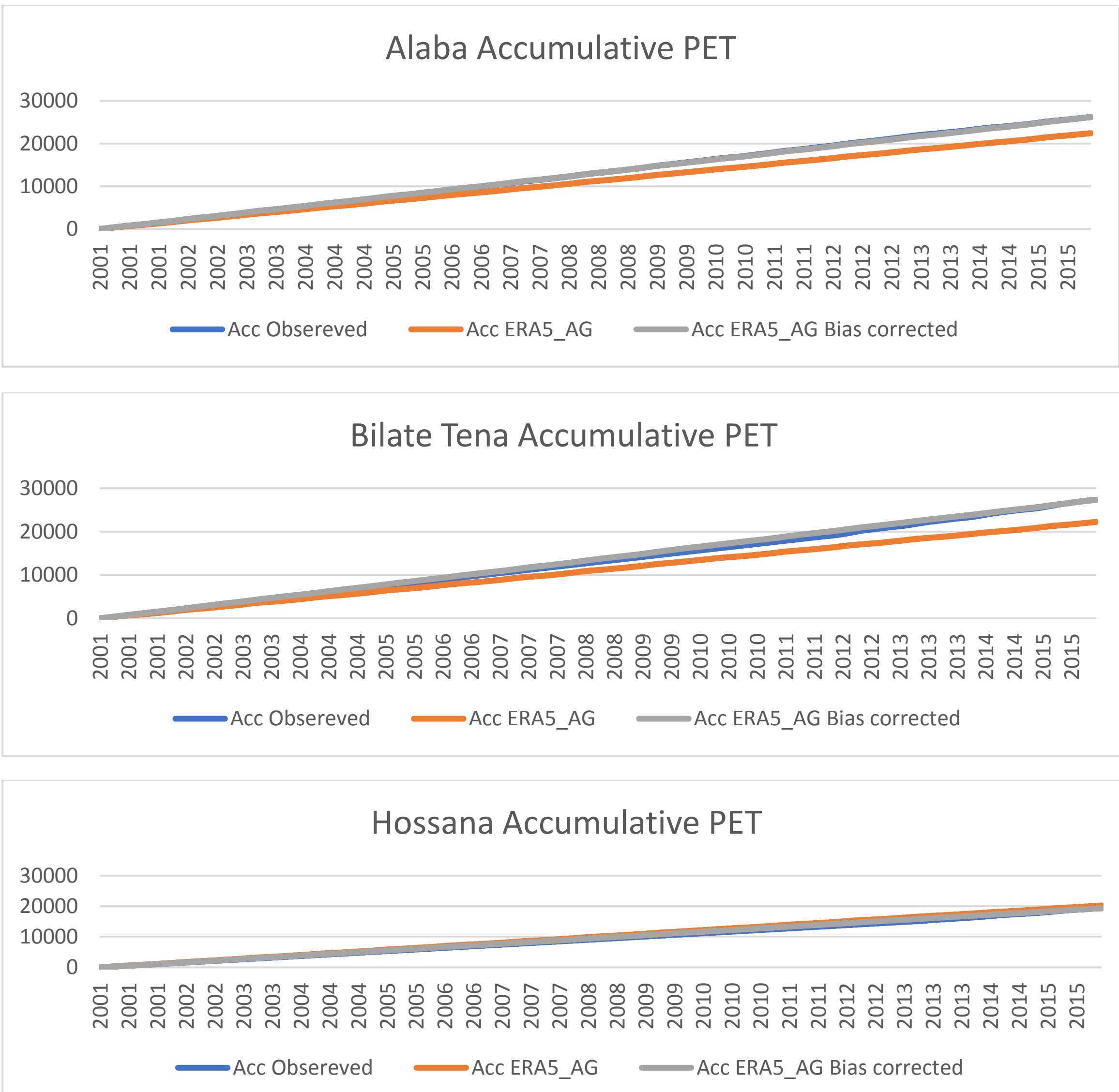


Figure: 5.11 Bias corrected PET estimates

As results, indicate satellite perception, Temperature and Evapotranspiration products compared with the gauged data then bias correction methods applied to minimize the difference before we use them as an input for hydrological model HBV Light.

5.4 HBV-light modelling

HBV-light rainfall runoff modelling were done using Hydro meteorological time series data. First, the in situ measurements were included in the model as the study's reference data and taken to represent the actual value. As required by the fundamental model parameters of HBV-light, daily hydro meteorological input data were included to the model along with additional sub-basin characteristics. Daily time series data were utilized in HBV-light for the daily stream flow simulation. For calibration reasons, the observed discharge values at Bilate station were also entered into the model.

After arranging all the necessary model inputs such as PTQ, T mean and EVAP text files for HBV light model by starting up the HBV program. The 'Open Catchment' form opens automatically.

```
HBV Hossana
date            Prec.m  Temp     Qobs
20010101         0.0    17.8    0.0
20010102         0.0    14.5    0.0
20010103         0.0    14.4    0.0
20010104         0.0    13.8    0.0
20010105         0.0    14.7    0.0
20010106         0.0    14.0    0.0
```

```
Hossana temp
17.8
14.5
14.35
13.75
14.65
14
15.85
```

```
Obsereved PTO
3.38
3.38
3.38
3.38
3.38
3.38
```

PTQ text file T mean text file EVAP text file

Elevation Vegetation Zones of Bilate river sub-basin

By navigating over the sub-basin boundaries, the vegetation type map, and the elevation zones map, the elevation vegetation zones were obtained. This process produced weights for each species of vegetation in each sub-basin's elevation zone, which were then entered into the model. The Bilate River Sub-basin was divided in to 12 elevation zones, with three different vegetation types, ranging in height from 1,116 meters to 3,350 meters, where

- Zone 1: Agriculture land (Intensive, moderate, grassland, shrub)
- Zone 2: Wet land (water body, Marshland)
- Zone 3: Urban(urban, exposed land)

Table: 5.12 Elevation Vegetation Zones of Bilate river sub-basin

Elevation (m.a.s.l)	Area (%)	Vegetation Zone		
		Zone-1	Zone- 2	Zone- 3
1116-1600	22.02%	93.86%	0.80%	5.34%
1601-2000	20.87%	97.01%	1.36%	1.63%
2001-3350	57.11%	74.30%	20.60%	5.10%

For the upper catchment, 200-meter elevation zones ranging from the 2001m to the 3,350m there are seven-elevation zone. For the middle catchment 200-meter elevation zones ranging from the 1601m to the 2000m 2-elevation zone. For the Lower catchment elevation zones of 200m ranging from the 1116 m to the 1601 m 3 elevation zone

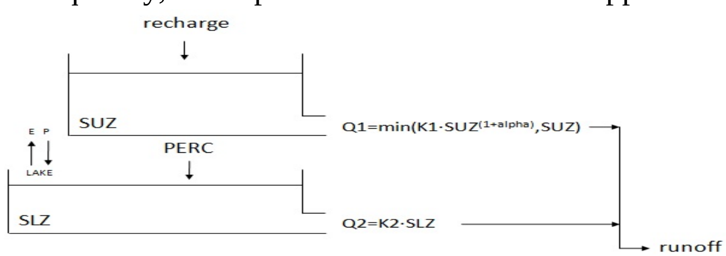
5.4.1 Runs of the HBV Light model and parameterization

The Nash-Sutcliffe coefficient (NSE), a measure of model efficiency, and the mean difference (MeanDiff) objective function are employed in the manner previously mentioned to evaluate the performance of the model. The hydrograph designs' best fit was determined by visually inspecting both the simulated and observed stream flows. The "trial and error" optimization process was used to calibrate the model, adjusting its parameters to better match the observed stream flow hydrographs with the simulation.

The calibration aim for the NSE objective function, which establishes the best overall performance of the model, is 1 or values near to 1, and the target value is a MeanDiff equal to zero or values near to zero. This relates to the RVE, which is frequently chosen over the MeanDiff despite the fact that both are focused on the system's water volume as mentioned in section 4.8.2.

First, the HBV-light standard model type was chosen together with the basic model variant. In situ measurements of the climatic variables were used for this, and the model's behavior indicated that the system's water accumulation increased over the course of the simulation. Since it was evident that the system's water release was occurring too slowly, this study employed the same basic model structure but a different sort of HBV-light model that used routing response with delay. According to Seibert (2005), the structure is intended for catchments with deep groundwater, such as the sub basin of the Bilate River.

The two model types are different in that all of the recharge water is moved right away from the soil moisture storage to the upper zone of the soil during the regular response routine. Subsequently, water percolates down from the upper zone of the soil to the lower zone store.



Procedure for standard model response

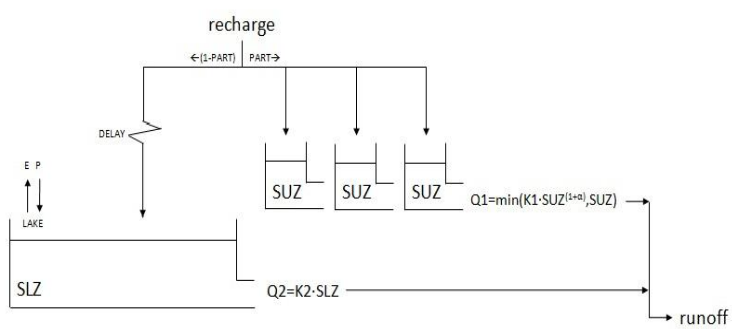


Figure 5-12: Type of routine response with delay model

Where K1 and K2 are the recession coefficients for the discharges from the higher (Q1) and lower (Q2) zones, respectively, and E and P are the evaporation and precipitation from the lakes, the storage in the upper zone, and the storage in the lower zone. In both scenarios, the parameter for the non-linearity of the Q1 is alpha, while the parameter for percolation is PERC.In the Response routine with delay model type, percolation is described as a water flux from the upper zone to the lower zone; in contrast, in the traditional structure model type, percolation is defined as the redistribution of recharge water from the soil moisture zone (PART). Whereas the amount contributed to the top zone reflects predicted recharge flow multiplied by PART, the fraction added to the lower zone reads recharge multiplied by 1-PART.

Table: 5.13 HBV Light Model optimum parameter

Parameters	Definition	Upper & Lower Limit		Unit	Valid range	Default value
		Minimum	Maximum			
FC	Maximum soil moisture storage	100	550	mm	(0,inf)	200
K0	Storage (or recession) coefficient 0	0.1	0.5	1/Δt	[0,1)	0.2
K1	Storage (or recession) coefficient 1	0.01	0.2	1/Δt	[0,1)	0.1
K2	Storage (or recession) coefficient 2	5.00E-05	0.1	1/Δt	[0,1)	0.05
UZL	Treshold parameter	0	70	mm	[0,inf)	20
Alpha	Non-linearity coefficient				[0,inf)	0
PERC	Treshold parameter	0	4	mm/Δt	[0,inf)	1
MAXBAS	Length of triangular weighting function	1	2.5	Δt	[1,100]	1
LP	Soil moisture value above which AET reac	0.3	1		[0,1]	1
BETA	Parameter that determines the relative con	1	5		(0,inf)	1
TT	Threshold temperature	-2	0.5	°C	(-inf,inf)	0
CFMAX	Degree-Δt factor	0.5	4	mm/Δt °C	[0,inf)	3
SP	Seasonal variability in degree-Δt factor	0	0		[-1,1]	0
SFCF	Snowfall correction factor	0.5	0.9		[0,inf)	1
CWH	Water holding capacity	0.1	0.1		[0,inf)	0.1

5.4.2 Sensitivity and Calibration HBV Light Model

In order to reach an acceptable match of the patterns of hydrographs between the simulated discharge (Qsim) and observed discharge (Qobs) several calibrations were applied by "trial and error" method, however, the values of the objective functions remained low. To minimize the gaps and to get optimal objective function values the model sensitivity was initiated.

HBV-light model parameters in the process are not physically measurable that is why they need be calibrated. As we all know, there is no single best method to estimate the model parameters we use different methods by selecting the minimum and maximum values of each parameter from autonomous calibrations and Monte Carlo runs based on the scores of three objective function. Observed and simulated discharge during the calibration for outlet three stations of the sub catchment one of which is considered as the final outlet point in the HBV-light model, some adjustments on the range of the parameter some values obtained from previous studies were used. In addition, 5000 Monte Carlo runs specifying certain threshold efficiency did sampling.

5.4.2.1 Model sensitivity analysis

As part of the model calibration process, a sensitivity analysis was conducted using in situ datasets to assess how sensitive the model was to variations in the values of its parameters. The goal of the sensitivity analysis was to assess the total uncertainty of our models by identifying the parameters that have the greatest influence on them and by distinguishing between sensitive and insensitive model parameters. The HBV-Light model sensitivity analysis was done to calibration parameters in order to determine which ones influence the model performance more than the other does. One model parameter was analyzed at a time, with its final calibration values changed by 10% to 100% at a time. The parameter was then reset to its starting value before another was altered. Since each model parameter's impact was examined using graphical plots for visualization and the NSE, RVE, and RMSE objective functions as the basis for analysis, parameters with abrupt slopes are thought to be more sensitive than those with gradual slopes, which are thought to be less sensitive.

The sensitivity analysis show the parameters calibrated more sensitively to the model performance more than others did. In this study model parameters which are more sensitive to the model performance were found to be k0 (Recession coefficient for the upper storage), K1 (recession coefficient for upper storage), K2 (recession coefficient for lower storage) and Beta (shape coefficient). FC (maximum of storage in the soil), LP (threshold for reduction of evaporation) and the MaxBas were determined to be reasonably rational.The sensitivity analysis of model performance was done with respect to three objective functions Nash Sutcliffe Efficiency Coefficient (NSE), Relative Volumetric Error (RVE), and the Root Mean Square Error RMSE). Also percentage of bias Pbias and Coefficient of determination R^2

$$NSE = 1 - \frac{\sum_{n=1}^{n}(Qobs\ i - Qsim\ i)^2}{\sum_{n=1}^{n}(Qobs\ i - \dot{Q}obs)^2} \ldots\ldots\ldots\ldots\ldots. Equation\ 22$$

$$RVE = \left(\frac{\sum_{n=1}^{n} Qsim(i) - \sum_{n=1}^{n} Qobs(i)}{\sum_{i=1}^{n} Qobs(i)}\right) 100\% \ldots\ldots\ldots\ldots\ldots. Equation\ 23$$

$$RMSE = \sqrt{\frac{\sum_{i=1}^{n}(Qobs\ i - Qsim\ i)^2}{n}} \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots. Equation\ 24$$

$$Pbias = \left[\frac{\sum_{i=1}^{n}(Qi\ obs - Qi\ sim)}{\sum_{i=1}^{n} Qi\ obs}\right] \ldots\ldots\ldots.\ldots\ldots\ldots. Equation\ 25$$

$$R^2 = \frac{(\sum(Qobs - Q\overline{obs})(Qsim - Q\overline{sim})^2}{\sum(Qobs - Q\overline{obs})2\sum(Qsim - Q\overline{sim})^2} \ldots\ldots\ldots\ldots\ldots\ldots. Equation\ 26$$

Where: n is number of observations, $Qobs$ is observed stream flow at gauged station (m3/sec), $\overline{Qobs}$ is mean of observed stream flow at gauged station (m3/sec), $Qsim$ is simulated stream flow at gauged station (m3/sec).

Finding which parameters to heavily optimize in order to get the best accuracy was made possible by the model parameter analysis. The sensitivity of model performance in bilate river catchment was found NSE, a RVE ranging between 0.4-0.8, 5 and -10 and a RMSE between 0 and 8. The sensitivity of the model performance based on three objective functions to more sensitive parameters that covered ten years shown in the figure below.

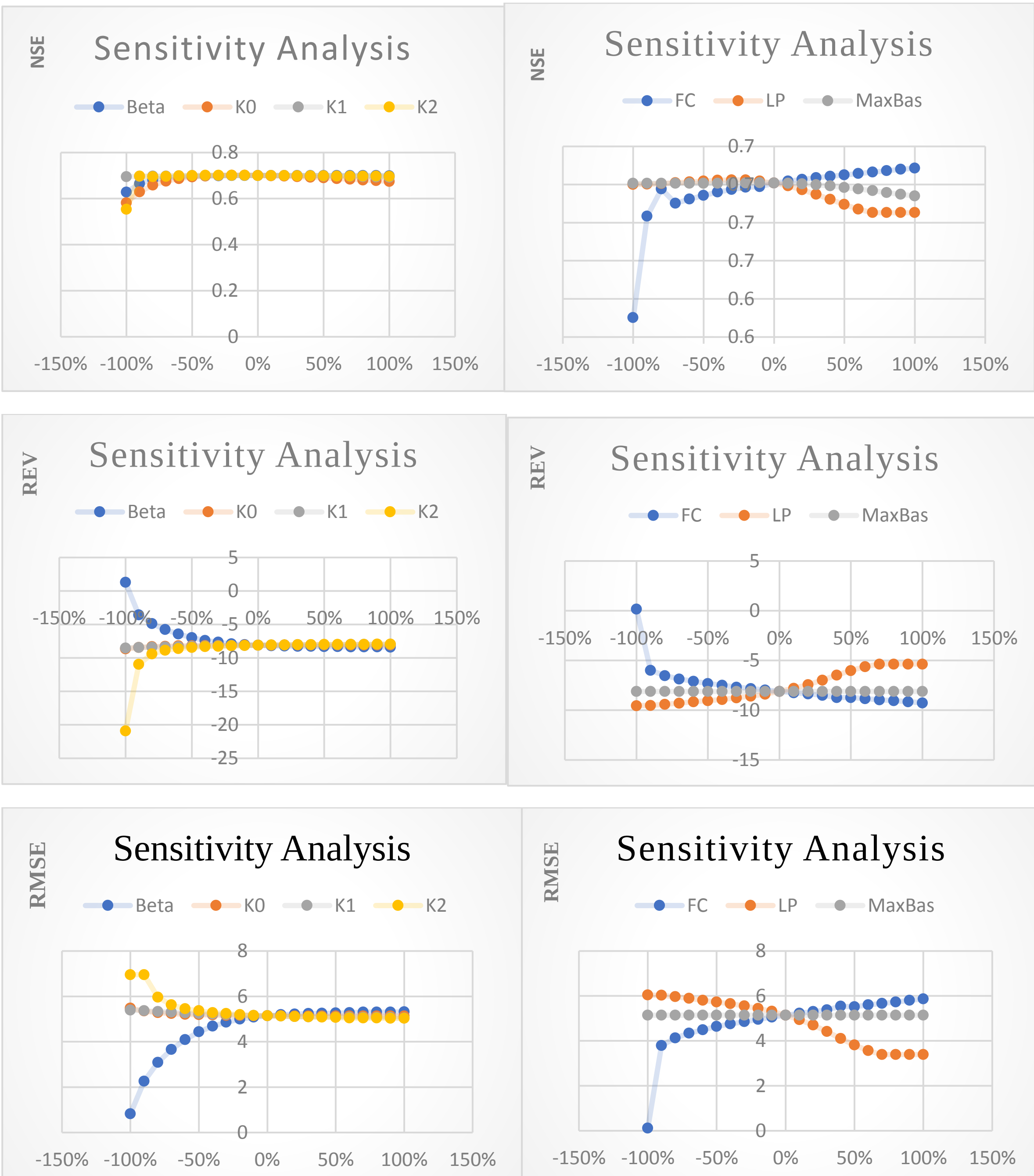


Figure: 5.13 Sensitivity evaluation based on objective functions NSE, RVE and RMSE

The result of sensitivity analysis indicated that the HBV Light model of the study area is most sensitive to volume controlling parameters (K0, K1, K2, FC, BETA, and LP).

5.4.2.2 Optimal calibration and model performance assessment

In this stage, Based on the lower and upper limits intervals for the very good simulations obtained during the parameter id using the Monte Carlo method. The model performance for each parameter set and the best parameters set was then obtained by optimizing the different objectives functions mentioned above. After warming up the model for the year 2001, the model calibration for the period of 2001-2011 is performed manually by trial and error changing one model parameter at a time. Finally, the sets of parameters that are performing best are adopted. The HBV Light model optimum parameter set for Bilate River sub basin is shown in table below.

Table: 5.15 Optimum parameter for Bilate River sub basin

Parameters	HBV-light Valid range	Model parameter range		Unit	Optimized model parameter
		Minimum	Maximum		
FC	(0,inf)	100	550	mm	100,100.4,104.3
K0	[0,1)	0.1	0.5	1/Δt	0.04
K1	[0,1)	0.01	0.2	1/Δt	0.011
K2	[0,1)	5.00E-05	0.1	1/Δt	0.027
MAXBAS	[1,100]	1	2.5	Δt	1.7
LP	[0,1]	0.3	1	_	0.6,0.4,0.7
BETA	(0,inf)	1	5	_	1,1,1

Model Calibration HBV Light model

Modifying the numerical values attributed to the parameters of the model by Calibrating until we observe best objective function. The process consists of adjusting manually by trial and error method and simulating HBV Light model by comparing the observed and simulated discharge. A daily time series for observed data on temperature, precipitation, potential evapotranspiration, and discharge for a single catchment from January 2001 to December 2015 was used to calibrate the HBV Light model in the Bilate River sub basin. The warm-up period is January 01, 2001 to 31-12-2001,The calibration period January 2001 to December 2011,For Validation, the model is set to the period January 01, 2012 to 31-12-2015. An automatic calibration based on the genetic method GAP optimization provided by HBV-light model was utilized to obtain the best fit between observed and simulated streamflow, and the calibration procedure was repeated iteratively until the best fit was reached.

GAP simulation technique and Monte Carlo Runs used to Automatic calibration. GAP (Genetic algorithm and Powell) model calibrating optimization approach. In addition, Monte Carlo tool is the maximum and minimum is set for all parameters for the HBV-land sub-basin. The number of model runs is set to 1000 and save objective function > 0.6" where the objective function is Reff. Calibrating and Evaluating Sensitivity analysis used to find the optimal parameters for the model performance. HBV Light Model input parameters used until we reach a certain acceptable model performance by maximizing the model parameters' values within each of their corresponding specified ranges.

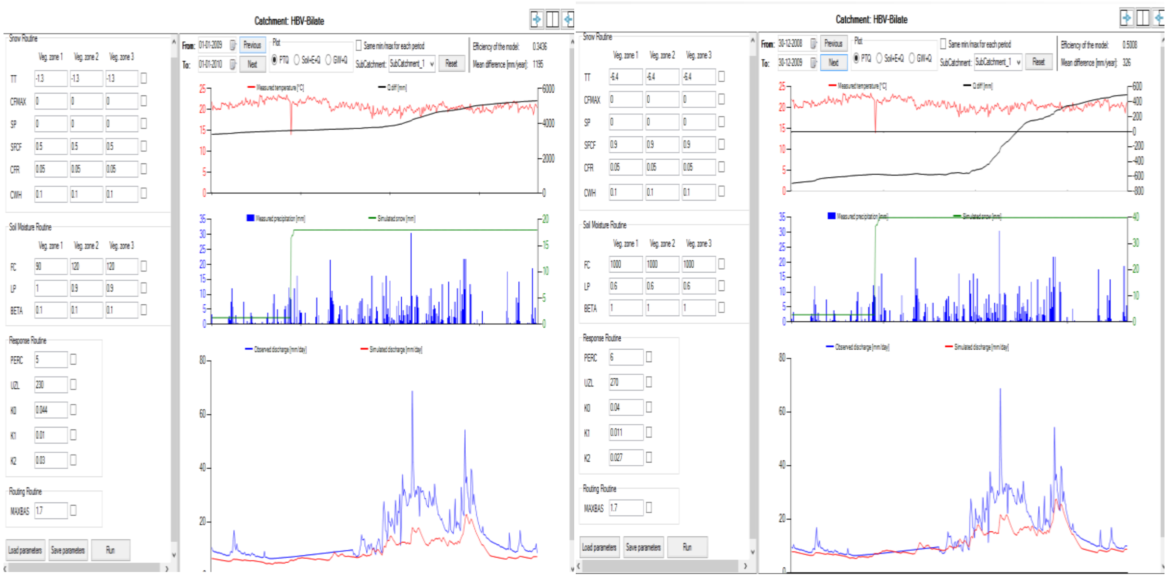


Figure: 5.14 Uncalibrated and Calibrated PTQ plot for the period 2001 to 2011.

5.4.2.3 HBV Light model Validation

Validation analysis can be conducted using various methods and techniques depending on the nature and format of remote sensing data and validation sources.In the validation step model's ability to simulate the present or the future forecasting can be investigated. In this work, the HBV Light model's calibration setup settings were employed for validation throughout a varying time period (January 1, 2012, to December 31, 2015), while maintaining all of the calibration's input values in order to see the response of simulation for the future period forecasting. Efficiency of the model were assessed by the objective functions. Therefore, the output is improved by changing the model parameters to calibrate with the observations data. Therefore, each time when we change model parameter it provide information about the catchment variables. In the validation period, the mean difference values is the discharge in most cases models estimatethe discharge simulated less than observed discharge.The calibration of the model was considered successful if the value of R^2 during validation is between 0.6 and 0.9. The performance of the calibrated model was validated using the rainfall input for the period 2012 to 2015. Moreover, the objective functions NSE, RVE and RMSE were used to evaluate performance for the validation period. Apart from the gauge stations data, satellite data on precipitation, temperature, and potential evapotranspiration products used as input for the HBV Light Modelling. Remote sensed products such as CHRIPS, IMERG, TRMM and ERA 5 AG were used after bias-corrected as an input PTQ and EVAP text file for model simulation. Model performance of HBV Light model using satellite product calibrated and validated using the input for the period January 2001 until December 2015.

$$Reff = 1 - \frac{\sum(Qobs - Qsim)^2}{\sum\left(Qobs - \overline{Qobs}\right)^2} \ldots \ldots \ldots \ldots Equation\ 27$$

Where: Reff is the model efficiency, Qobs observed discharge, Qsim simulated discharge

5.5 Comparison of simulated streamflow

One of the objectives of this work was to examine how well HBV Light hydrological models performed when used satellite products as input for models that were calibrated (2001–2011) and validated (2012–2015) on a daily streamflow data estimate of the Bilate River Sub-basin using remote sensed products, both in situ and satellite products.

HBV light model functionality parameters that come from calibrating the HBV Light simulation using two separate input data sets from two satellite-based data sets and in situ gauge station data sets. According to the table below, HBV Light modeling performs the satisfactory in the Bilate watershed when compared to other watersheds. Its performance is still good for the validation period, though, suggesting that the model can be used to investigate the relationships between rainfall and runoff in Bilate catchments.

As the table below demonstrates, the model performed well when used the in situ time series of rainfall and potential evapotranspiration; the relative volumetric error was less than zero.

Table 5.16 Model performance using bias-corrected data for NSE, RVE, and RMSE.

Purpose and Objective	On-site measurements	CHRIPS Bias corrected	IMERG Bias corrected	TRMM Bias corrected	ERA5 AG Bias corrected
Nash Sutcliffe Efficiency Coefficient (NSE)	0.71	0.51	0.54	0.42	0.41
Root Mean Square Error (RMSE)	5.14	3.59	0.87	1.21	0.17
Relative Volumetric Error (RVE)	-1.12	-5.65	-1.37	-0.32	-0.31

After that, time series from satellite-based meteorological products with bias corrected were utilized to simulate Bilate stream flow using the optimal model parameter set. HBV Light model performance was also demonstrated by the calibration findings for every time series. The streamflow measurements, however, were insufficient to validate the model. Not as much as the time series of in situ measurements, but nonetheless high NSE and RVE were detected in the bias corrected time series from various products.

The optimal outcomes for the satellite-based bias-corrected data were discovered when the in situ PET estimates were substituted with the ERA5 AG product as the model's input. IMERG and CHRIPS were the satellite rainfall products with bias correction that performed better when the HBV Light model accepts it as input in the Bilate River sub-basin. This aligns with the comparative analyses conducted between those two goods. Furthermore, even after bias correction, the simulated discharge showed the underestimation of rainfall projections derived on satellite data in comparison to the in situ data. When the model's inputs were the bias-corrected rainfall estimates from the satellite products, the in situ stream flow simulation data exceeded the other simulated streamflow.

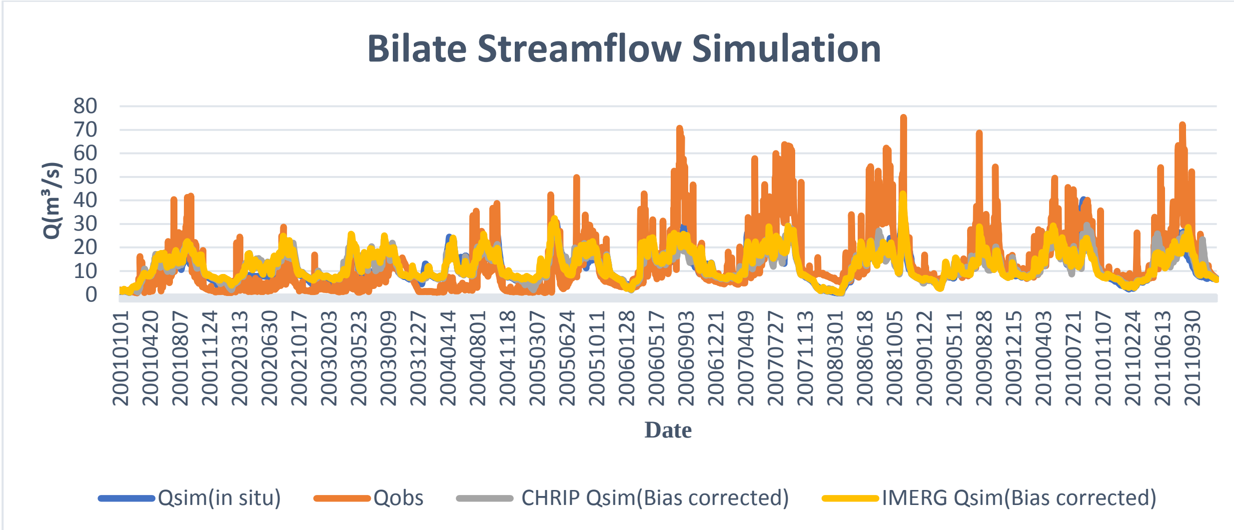


Figure: 5.15a Simulated Bilate streamflow utilizing bias-corrected satellite-based data

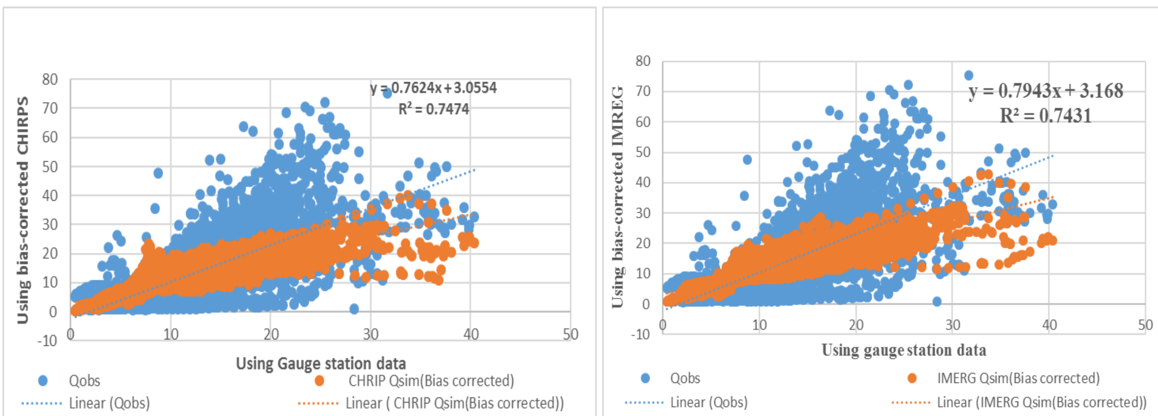


Figure: 5.15b Scattered plots for simulated streamflow utilizing remote sensed data

Since the bias has been adjusted in light of the in situ observations, the stream flow simulation using satellite-based meteorological time series that have been bias-corrected resembles the stream flow simulation using in situ measurements time series quite a bit. Considering the performance of the model, the findings were satisfactory. CHRIPS data R^2 =0.7474 and PBIAS=4.94 and IMERG R^2 =0.7431 and PBIAS=1.08.

With the exception of the ERA5 AG PET product, it was discovered that the optimum parameter set derived from the raw satellite data did not lend itself to in situ measurements, necessitating the calibration of each satellite product separately. For the satellite products, the model was calibrated before the in situ measurements parameter set. However, this was not feasible for the most sensitive model parameters, as the following illustrates. The model's results when using the uncorrected satellite data are shown below. The model performance was weak and showed different values of the objective functions;

Table 5.17 HBV-light optimized parameter using uncorrected satellite products

Parameters	HBV-light Valid range	Model parameter range		Unit	Optimized model parameter
		Minimum	Maximum		
FC	(0,inf)	100	550	mm	90,100,120
K0	[0,1)	0.1	0.5	1/Δt	0.05
K1	[0,1)	0.01	0.2	1/Δt	0.009
K2	[0,1)	5.00E-05	0.1	1/Δt	0.05
MAXBAS	[1,100]	1	2.5	Δt	1.5
LP	[0,1]	0.3	1	_	1,1,1
BETA	(0,inf)	1	5	_	2,2.3,2.2

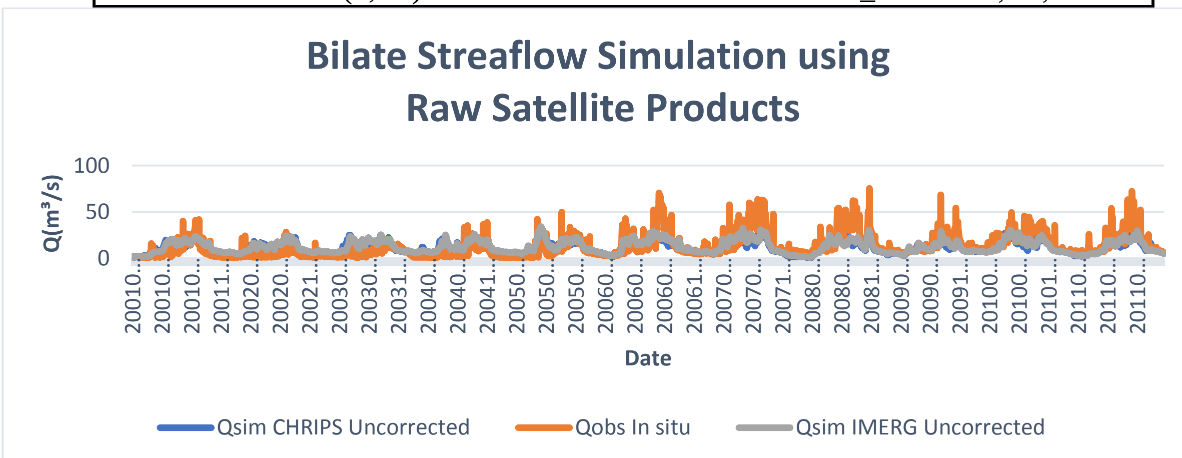


Figure: 5.16 simulated bilate stream flow with uncorrected satellite-based and in situ data

The Bilate River streamflow simulation produced lower than observed RMSE and REV values as well as low NSE values below 0.5 using uncorrected satellite-based rainfall products. When forcing data from CHRIPS and IMERG are used, the model performs worse despite the fact that it displays the simulated discharge hydrograph's pattern more clearly. The fact that CHRIPS had the lowest bias value in this analysis but a greater coefficient of correlation (R^2) may be attributed to result. This means that, compared to the other products, CHRIPS agrees with the station data more, but it also underestimates the recorded rainfall depth more, in accordance with the scatterplots' data distribution.

Table: 5.18 Results of model simulation with uncorrected satellite-based products

Objective Function	CHRIPS Uncorrected	IMERG Uncorrected	TRMM uncorrected	ERA5 AG uncorrected
Nash Sutcliffe Efficiency Coefficient (NSE)	0.41	0.4279	0.21	0.33
Root Mean Square Error (RMSE)	3.14	5.016	4.07	8.09
Relative Volumetric Error (RVE)	-4.32	-8.022	-12.42	-20.32

As results shown in Table 5.18 the Bilate River stream flow simulation showed lower RMSE and RVE values and low NSE values, despite using uncorrected satellite-based rainfall products. CHRIPS had the lowest bias value but a greater coefficient of correlation, indicating it agrees with station data but underestimates recorded rainfall depth.

Comparing the components of the model water balance using satellite products

An assessment of the water balance components was carried out in order to compare the model results for the two input datasets used in the HBV model. The hydrological year 2001-2011, which ran from September 2001, when the rainy season ended, to December 2011, was used for this purpose. The simulated real evapotranspiration and discharge time series' cumulative depth, changes in soil moisture storage, and the upper and lower zones of the soil are all displayed in the table below, which summarizes the results. Various forcing data are also used in the model.

When combined during the course of the hydrological year, the data collected in situ were demonstrated to have increased depth of rainfall and to approximate real estimates of evapotranspiration. Substituting the ERA5 AG product for in situ estimations in the model results in a notable alteration of the soil lower zone and high-simulated streamflow. The significant fluctuation of water storage in the lower zone of Southern Ethiopia can be explained by the regions groundwater basins' inter connectivity. The HBV Light model was evaluated using two Satellite precipitation products input datasets (CHIRPS and IMERG) from 2001-2011 for the study area.

Table 5.18 Components of the downstream catchment water balance (2001-2011).

Components of the water balance [mm]	On-site measurements	CHRIPS Bias corrected	IMERG Bias corrected
Rainfall	1028.8	1005.5	1043.7
Actual ET	1574.3	1618.7	1618.7
Q simulated	4278.1	4376.8	4548.7

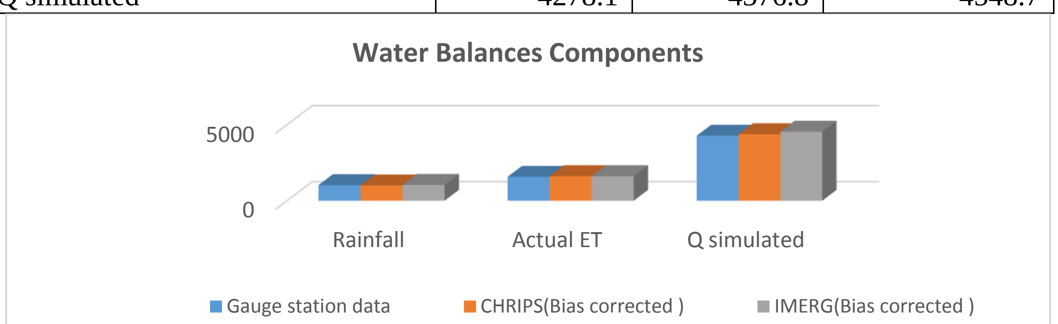


Figure: 5.17 Water balance components of HBV Light model output

Results showed that Comparison of 4 satellite rainfall products for a period of 21 years indicates the existence of difference between gauging station and Remote sensed products. A considerable increase in rainfall depth was found in the bias correction. Then using IMERG and CHRIPS to simulate streamflow in HBV Light model gives satisfactory results.

6 Conclusion and Recommendation

6.1 Conclusion

The main objective of this study was to gain better understanding of daily streamflow estimation in poorly gauged and ungauged stations using remote sensing and gauging stations' data as input for stream flow modeling in Bilate rivers sub basin. Estimating daily streamflow using bias-corrected remote sensed products and comparing the result with the in situ data by using several methodologies. The differences between ground based gauge station observing and meteorological products from satellites were expected as it was mentioned in a number of earlier research. Systematic discrepancies was observed by comparing four different precipitation datasets of different categories, source and resolution, namely GPM_3IMERGM v 07, CHIRPS 4.8 Daily, TRMM 3B42 v7and ERA5 AG with in situ observations. The differences were adjusted using bias correction and on-site assessments prior to being included as imposing data in the model's HBV-light streamflow simulation. Investigations were made on the impact of satellite products on hydrological model calibration, model predictions for bilate river sub-basin in Southern Ethiopia.

As the result shows, the comparisons between gauging station and Remote sensed Precipitation products were done based on visual interpretations of average time series data for the period of 21 years (2001-2021). The result shows ERA5 Ag overestimate in all selected four stations, TRMM overestimate at Bilate and Bilate tena station in other two stations (Alaba and Hossana) TRMM underestimate the average annual rainfall, IMERGM and CHIRPS relatively shows close results with observed data of average annual rainfall amount in the selected four stations.

Additionally, Comparisons between gauging station and Remote sensed Precipitation products were done based on statistical estimators and graphical analysis. The result shows the ability of four satellite products to detect rainfall in four stations using probability of detection (the number of events correctly detect by the Satellite datasets) ERA5 Ag 80%, IMERGM 75%, TRMM 65%, CHIRPS 42%. False alarm ratio (the rainfall events is recorded at the satellite when no represented in observed data) IMERGM 48%, CHIRPS 57%, TRMM 58%, ERA5 Ag 60%. Critical Success Index (shows the correct estimation the rainfall occurrence while removing the negative occurrence) IMERGM 44%, ERA5 Ag 36%, TRMM 33%, CHIRPS 32%. The frequency bias (has a desirable value of 1 and a range of 0 to ∞) CHIRPS 1.3, IMERGM 1.4, TRMM 1.7, ERA5 Ag 2.03. Mean Error and bias shows the systematic differences measured between gauging station and Remote sensed Precipitation products. If the mean errors with a (-) sign indicate overestimation TRMM in Alaba and Hossana stations shows -0.64 and -0.42 respectively. At the same time TRMM at those stations shows bias is less than 1 it indicates underestimation. The root mean square error indicates the amount of cumulative mistakes and the precision of satellite rainfall estimations with the values range from 0 to ∞, where 0 denotes very good precision. The average root mean square error of four Remote sensed Precipitation products in four stations were TRMM 6.97, IMERG 7.3, ERA5 7.7 and CHRIPs 8.4. The correlation coefficient indicates the degree of agreement between gauge stations and satellites products it ranges from 0 to 1. The degree of agreement R2 in four stations using the four satellite precipitation products shows CHRIPs 0.907, IMERG 0.87, TRMM 0.84 and ERA5 Ag 0.78.CHRIPs and IMERG performed better in terms of depth than TRMM and ERA5.

Analysis in Sub-Basins Scale using an arithmetic mean (average of stations) were utilized to represent the upper watershed (Hosana), the mid watershed (AlabaKulito), and the bottom watershed (Bilate Tena). The statistical estimators indicates the hits, missed and false rainfall events throughout a Fifteen-year period (2001-2015) in Bilate sub basin. IMERGM 31.3% Hits, 2.9% Miss, 29% False alarm and 36.8 correct negative. ERA5 Ag 33.3% Hits, 0.9% Miss, 41.9% False alarm and 23.86% correct negative. Shows better results than TRMM 24.13% Hits, 10.06% Miss, 18.9% False alarm and 46.9% correct negative. and CHRIPS 13.7% Hits, 20.4% Miss, 8.2% False alarm and 57.6% correct negative. The result shows the ability of four satellite products to detect rainfall in Bilate sub basin using probability of detection ERA5 Ag 94%, IMERGM 93%, TRMM 73%, CHIRPS 40%. False alarm ratio IMERGM 40%, CHIRPS 33%, TRMM 43%, ERA5 Ag 53%. Critical Success Index IMERGM 50%, ERA5 Ag 47%, TRMM 47%, CHIRPS 33%. The frequency bias CHIRPS 0.73, IMERGM 1.3, TRMM 1.53, ERA5 Ag 1.77. Mean Error and bias indicate overestimation of CHRIPS in Middle and TRMM Upper stations with -0.1 and -0.3 respectively. The average root mean square error of four Remote sensed Precipitation products in Bilate river sub basin TRMM 7.1, IMERG 7.4, ERA5 8.2 and CHRIPs 8.7. The degree of agreement R^2 using the four satellite precipitation products in Bilate river sub basin shows CHRIPs 0.87, IMERG 0.9, TRMM 0.8 and ERA5 Ag 0.77.CHRIPs and IMERG performed better in terms of rainfall depth than TRMM and ERA5. The three components of the bias the hit, missed rainfall and false rainfall biases were utilized for the four satellite precipitation products to represent the upper watershed, the middle watershed and the bottom watershed in order to determine the source of bias. IMERGM 20.3% Hits bias, 12.5% Miss bias, 67.18% False alarm bias, CHIRPS 23% Hits bias, 45.2% Miss bias,31.6% False alarm bias, TRMM 17.10% Hits bias, 39.47% Miss bias, 43.42% False alarm bias, ERA5 Ag 8.79% Hits bias, 3.29% Miss bias, 87.91% False alarm bias. As a result indicates the main source of bias were false alarm bias.

To improve the accuracy of the satellite/reanalysis products, the bias correction was carried out. A considerable increase in rainfall depth was found in the bias corrected time series compared to the uncorrected data, based on the in situ observed datasets. The result shows that rain fall depth of Bias corrected IMERG and CHRIPS have better when we comparing them with the other two satellite/reanalysis products. ERA5 AG averaged Mean daily Temperature underestimate the mean daily average Temperature in the sub basin when we compare it with the in situ measurement. Hargreaves Potential Evapotranspiration (ERA5_AG) satellite estimates were underestimate PET when we compare it to the in situ measurements. The bias corrected time series for every product exhibited similarity to the in situ time series; however, when the data were added up throughout the full period, underestimate of the measurements was noted. Over a 15-year period, the daily streamflow modeling of the Bilate River sub-basin was conducted using the bias corrected satellite products and the in situ time series in the HBV Light model. (01 Jan 2001 to 31 Dec 2015).

HBV-Light hydrological model were used to simulate the streamflow. In order to obtain optimal parameter values of model performance HBV Light model, calibration and sensitivity analysis was performed by utilizing the data from the in situ meteorological inputs to determine the model parameter that is sensitive for optimization and the performance evaluation.

According to the result, model parameter FC, BETA, and LP were found to be the most sensitive parameters followed by K0, K1, and K2 in the sub-basin of the Bilate River. The other parameters can be kept constant during the calibration of the model. HBV Light model calibration were taken using manual trail and errors method. In addition, useing Monte Carlo procedure and GAP optimization runs in calibrating and predicting uncertainties in model simulations. Following calibration, the RMSE=5.14, RVE = -1.12, and goodness of fit functions of 0.71 for the NSE were achieved for in situ measurements. Using the optimal set of model parameters, we simulate the model with the bias corrected meteorological variables. Moreover, the results were satisfactory. The model yielded those results after the bias adjusted using bias correction method. The results assess the fit between satellite product and gauged data using visual inspection, accumulated difference and statistical criteria

The calibration results of HBV light model for the period of 11 years (2001-2011) using bias corrected satellite products IMERG and ERA5Ag (Temperature and Evapotranspiration) satellite products. Produced results R^2 =0.7431 and PBIAS=1.08, objective functions NSE= 0.54, RMSE =0.87 and RVE =-1.37, and replacing IMERG with CHRIPS data R^2 =0.7474 and PBIAS=4.94, objective functions NSE = 0.51, RMSE =3.59 and RVE = -5.65 of the rainfall products. The streamflow of the Bilate River was simulated using uncorrected satellite-based meteorological data, and the hydrological model was unable to replicate the patterns seen in the hydrograph. The validation is the model performance test with calibrated parameters for an independent period in HBV light model for 4 years (2012-2015) and the validation results using bias-corrected IMERG and CHRIPs were R^2 =0.6588 NSE=0.5 which is satisfactory.

Using remote sensed products for estimation of streamflow using hydrological models show satisfactory results. Even when we compare the model performance of those bias corrected Satellite products, they produced comparable results. HBV Light model was able to simulate the overall pattern and timing of low and high flows. However, the magnitude of peak flows was not matched well in all sub-catchments. In general, the model performed with an acceptable degree of accuracy during both calibration and validation periods in Bilate River sub basin. As a result using the satellite/reanalysis meteorological products can be an alternative source of Hydro meteorological data in areas with sparse rain gauges and poorly gauged station.

Generally, the results show that both models can reproduce and replace the historical daily runoff series data with an acceptable accuracy. The coefficient's of NSE and R^2 indicates satisfactory results for calibration and validation periods. The results from the study revealed that bias-corrected Satellite products could be an alternative data source to estimate streamflow in data scarce areas.

6.2. Recommendations

The study states that planning, managing, and operation of water resources depend on the estimates of daily streamflow. The availability of data for ground-based hydro meteorological models is deteriorating, though, more gauging stations should be built and the current ones require regular maintenance. Furthermore, it is not questionable to use alternate Hydro meteorological data sources. The greatest alternative to inaccurately measured and ungauged stations is remote sensing equipment.

Four satellite/reanalysis products were used in this study: GPM_3IMERGM v 07, CHIRPS 4.8 Daily, TRMM 3B42 v7, and ERA5 AG with in situ observations. This was owing to their availability and the quality of their resolution. Utilizing alternative products with higher quality and resolution, such MSWEPv2, could yield superior outcomes. After performing bias-correction, the chosen remote sensing products provide satisfactory results when compared to in situ observations data. The temperature and precipitation product derived from satellite data was bias-corrected using the power transformation approach. It is advised to use alternative, more precise bias-correction techniques. Although, before using, choosing, preprocessing, bias correcting, and transforming datasets, it is crucial to comprehend the nature and quality of the data because these actions enhance the dataset's functionality.

Using bias-corrected remote sensing products, the HBV Light model was chosen as the conceptual hydrological model to estimate daily streamflow. A comparison was made between the observed streamflow data and the model's performance utilizing the input data (a satellite product) for the research area. Sensitivity analysis along with the manual calibration procedure yielded the ideal values for the model parameters. However, employing alternative automatic calibration methods, such as gap optimization runs and the Monte Carlo tool, is helpful because manual calibration using the trial and error method takes a lot of time.

In the HBV Light model the downstream Bilate station were selected, which is comparatively superior with all data, for the model calibration process due to the low availability of hydro meteorological data in the Bilate river sub basin. Better simulation results might be achieved if we calibrate the HBV Light model using regionalization, utilizing all of the meteorological and hydrological data.

Finally, our analysis indicates that the performance of integrating bias-corrected satellite products with in situ observation data to predict streamflow utilizing HBV Light models is comparable. In the future artificial intelligence and virtual gauging will make it incredibly useful. To obtain good results, data quality, model parameterization, and validation is required. Additional research is required to fine-tune model parameters and comprehend the advantages and disadvantages of the satellite products for the particular use and geographical area.

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List of Appendix

Appendix A: Averaged annual rainfall from satellite products and stations measurements for the year average from 2001 to 2021

Stations	**Observed**	**CHRIPS**	**IMERG**	**TRMM**	**ERA5**	**Elevation**
Alaba	1015.89	1021.533	1166.087	794.077	1949.0971	1772
Bilate	817.96	1095.3	1151.37	992.96	961.417	1361
Bilate tena	830.43	1155.89	1159.71	1000.174	944.46	1496
Hossana	1177.37	1272.27	1257.15	1036.98	2338.98	2306

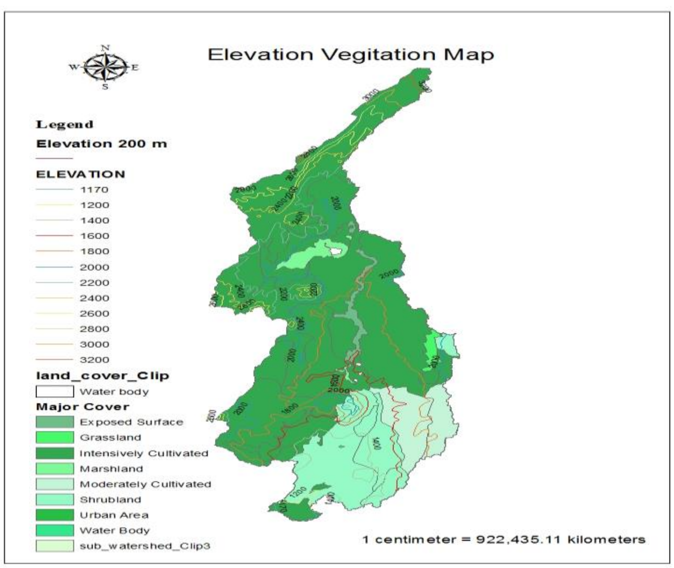
Appendix A1: Averaged annual PET from in situ, uncorrected and bias corrected ERA5_AG estimates

Station	**Observed**	**ERA5**	**ERA5 Corrected**
Upper (Hossana)	1748	1496	1748
Midle (Alaba)	1823	1483	1823
Lower (Bilate tena)	1290	1346	1290

Appendix A2: Averaged averaged daily mean temperature from in situ, uncorrected and bias corrected ERA5_AG Temperature estimates

Stations	**Average Mean Daily Temperature (°c)**	
	Observed	**ERA5_AG**
Alaba	21	19
Bilate Tena	23	20
Hossana	17	16

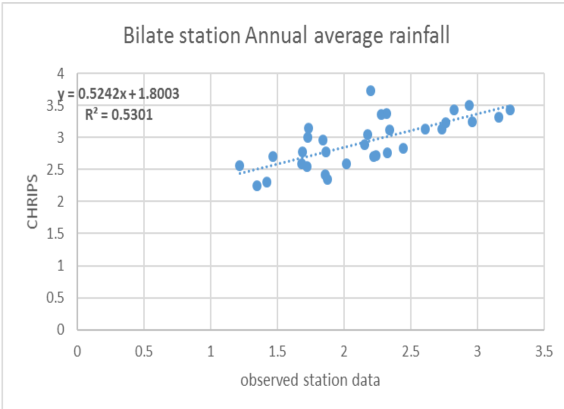
Appendix A3: Vegetation cover and Elevation units map of Bilate River sub basin with 200m

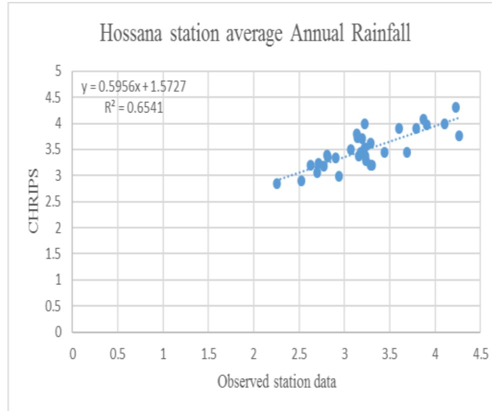


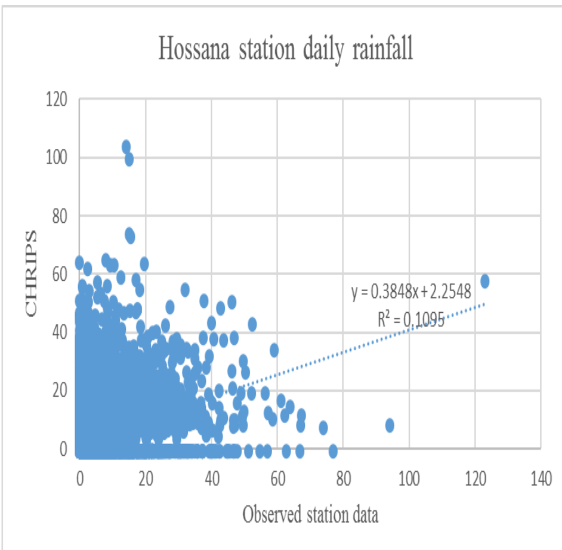
Appendix A4: Seasonal averaged rainfall Comparison of study area

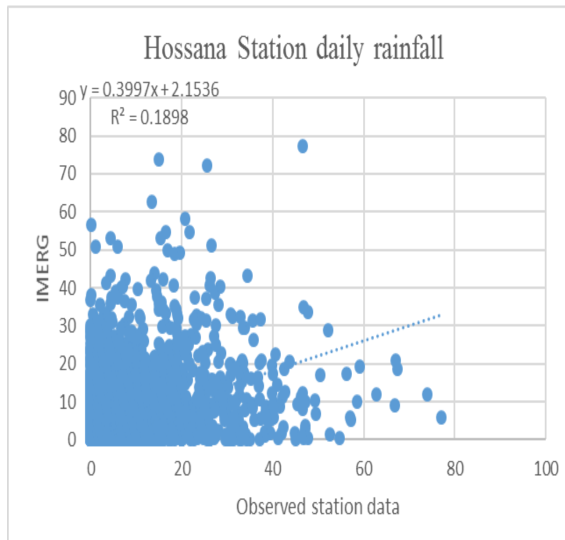
		Autumn				Summer				Spring				Winter			
		mar	apr	may	Average	jun	jul	aug	Average	sep	oct	nov	Average	dec	jan	feb	Average
	Observed	51.7	130.1	107.16520	96.3	82.0	81.6	83.7	82.4	72.9	81.3	58.9	71.0	22.7	23.2	22.9	22.90635
	ERA 5	49.0	118.8	154.7	107.5	102.8	133.2	146.3	127.4	129.2	73.2	22.2	74.9	8.0	9.0	15.0	10.68857
	CHRIPS	72.7	143.3	152.0	122.7	101.7	120.8	125.0	115.8	126.1	119.4	55.0	100.2	23.5	23.3	32.7	26.46847
	IMERG	93.0	161.4	158.4	137.6	115.8	111.2	129.3	118.8	118.4	110.3	59.4	96.0	28.1	29.6	36.4	31.38024
Bilate	TRMM	77.9	147.9	120.9	115.6	61.7	85.0	80.1	75.6	75.7	100.0	62.7	79.4	21.3	30.7	34.5	28.84429
	Observed	57.6	100.9	71.8	76.8	78.0	77.2	77.6	77.6	96.2	74.0	34.2	68.1	23.5	16.4	30.8	23.56162
	ERA 5	53.7	120.7	192.9	122.4	95.3	140.0	142.0	125.7	121.1	61.7	20.6	67.8	8.4	10.3	11.7	10.0954
	CHRIPS	80.3	156.2	160.6	132.4	104.5	118.0	133.2	118.6	121.1	126.8	52.8	100.2	28.0	28.5	34.7	30.39933
	IMERG	97.7	178.1	169.4	148.4	114.0	111.4	120.9	115.4	119.9	117.7	55.7	97.7	26.9	36.9	33.3	32.38198
Bilate tena	TRMM	80.1	186.1	133.7	133.3	56.9	91.6	76.1	74.9	77.6	103.1	77.5	86.1	22.8	35.3	33.9	30.6681
	Observed	99.9	139.9	148.9	129.6	121.4	159.2	176.3	152.3	159.1	55.5	35.7	83.4	17.4	25.7	38.4	27.16364
	ERA 5	137.5	283.1	371.3	264.0	238.9	238.2	264.0	247.0	396.8	239.5	74.1	236.8	25.8	28.2	41.7	31.87206
	CHRIPS	91.7	152.1	163.4	135.8	138.4	165.3	209.0	170.9	166.2	86.4	17.6	90.1	21.7	21.6	39.0	27.4435
	IMERG	93.0	143.1	164.8	133.6	143.2	170.0	189.3	167.5	163.7	70.3	30.7	88.2	23.4	30.0	35.7	29.73524
Hossana	TRMM	75.3	96.0	123.2	98.2	105.7	144.8	130.6	127.0	108.5	47.3	29.1	61.6	11.7	29.3	36.6	25.88667
	Observed	81.6	134.1	119.0	111.6	94.8	115.2	147.3	119.1	115.2	59.0	73.8	82.7	22.2	21.0	32.8	25.30708
	ERA 5	61.9	142.9	185.7	130.2	140.3	192.7	218.0	183.7	210.4	70.0	20.4	100.3	7.4	10.7	20.5	12.85698
	CHRIPS	97.9	138.2	118.8	118.3	74.9	128.5	141.2	114.9	117.9	60.2	38.6	72.2	6.4	29.8	69.5	35.23212
	IMERG	93.7	145.1	156.5	131.8	122.8	144.7	171.0	146.2	154.1	71.3	30.8	85.4	18.6	23.9	33.6	25.36
Alaba	TRMM	61.1	74.1	91.2	75.5	73.9	98.8	89.7	87.5	92.0	42.0	30.1	54.7	11.9	20.1	33.5	21.82952

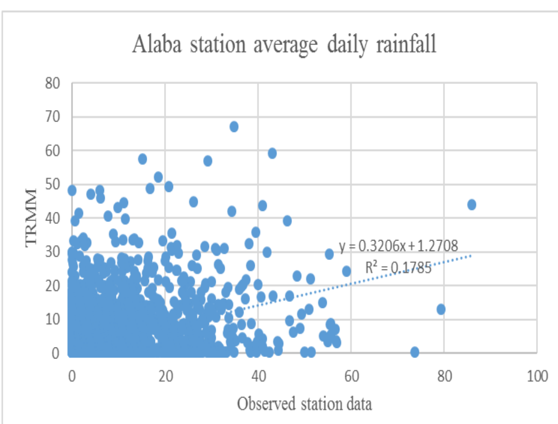
Appendix A5: Scattered plots for satellite precipitation products

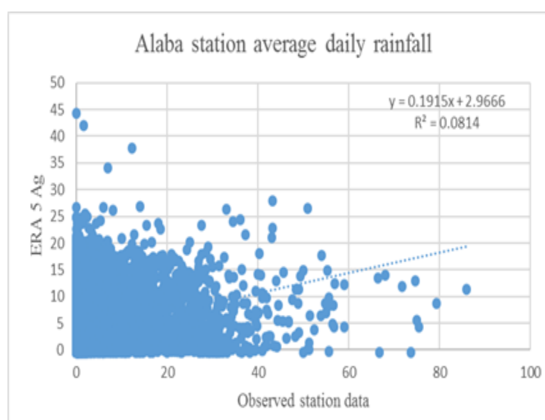








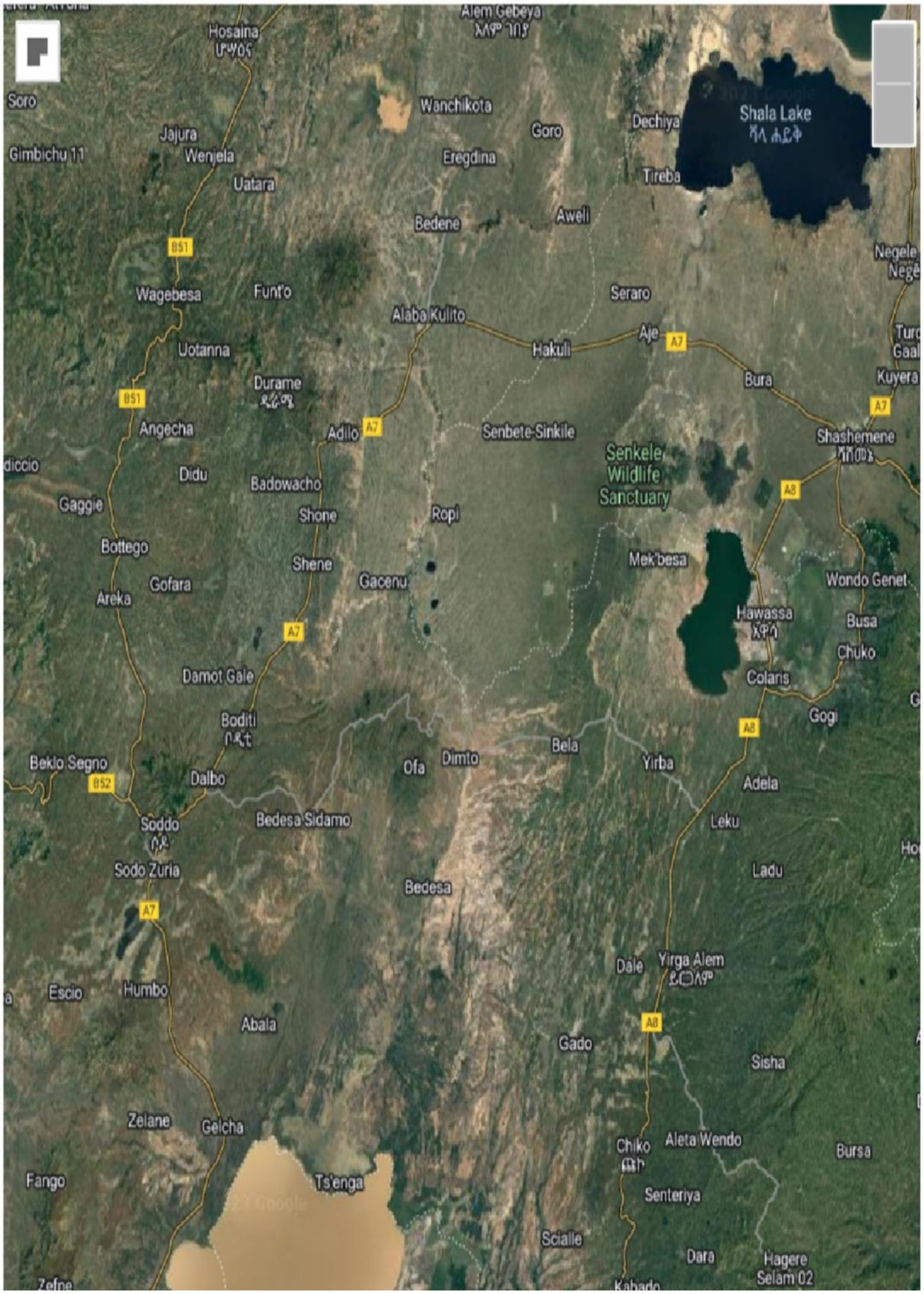




Appendix A6: Satellite precipitation products Number of Rainey days

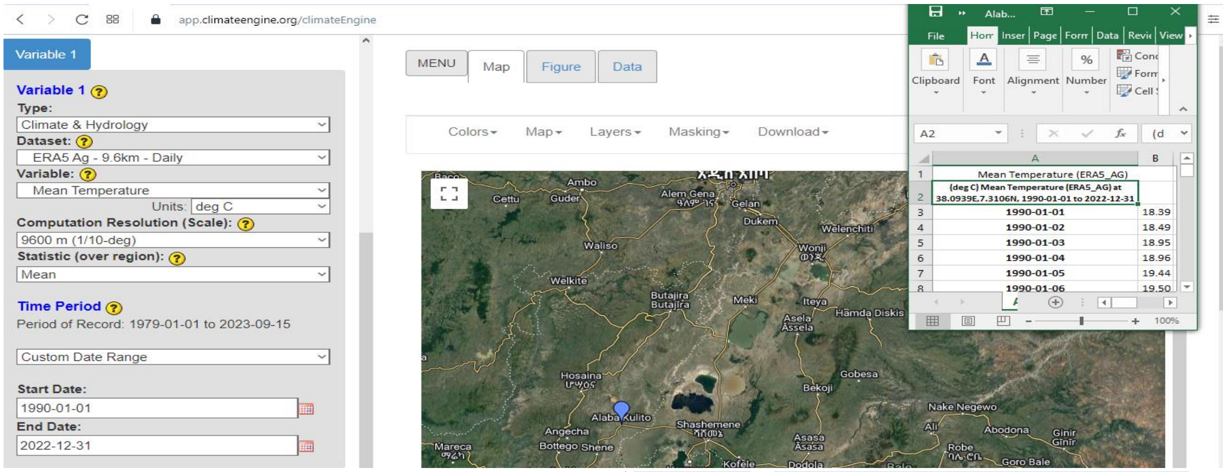
Stations	Data sets	Number of Rain days	Number of No-Rain days	Total days
Bilate	**Observed**	4020	7670	11690
	ERA 5	8684	3006	11690
	CHRIPS	2721	8969	11690
	IMERG	4733	3154	7887
	TRMM	3971	4082	8053
Bilate tena	**Observed**	2782	7082	9864
	ERA 5	7357	2507	9864
	CHRIPS	2258	7606	9864
	IMERG	3691	2367	6058
	TRMM	2651	3407	6058
Hossana	**Observed**	4774	6916	11690
	ERA 5	9458	2232	11690
	CHRIPS	2554	9136	11690
	IMERG	5200	2684	7884
	TRMM	3093	4060	7153
Alaba	**Observed**	4061	7629	11690
	ERA 5	8468	3222	11690
	CHRIPS	2493	9197	11690
	IMERG	4485	3399	7884
	TRMM	2823	4330	7153

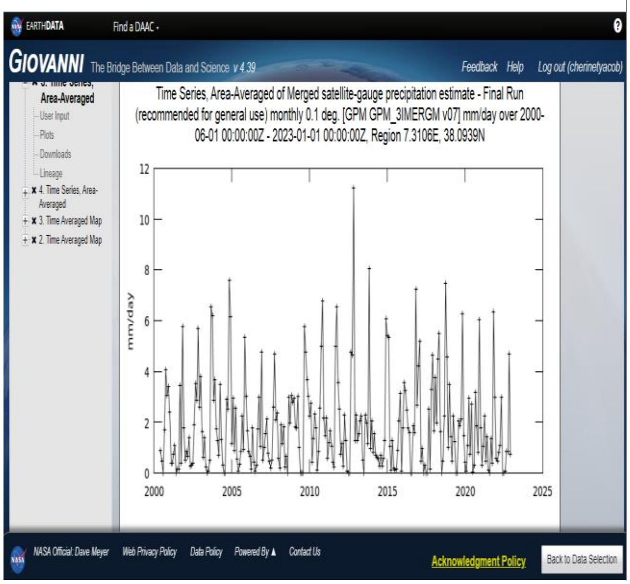
Appendix A7: Satellite image of the study area

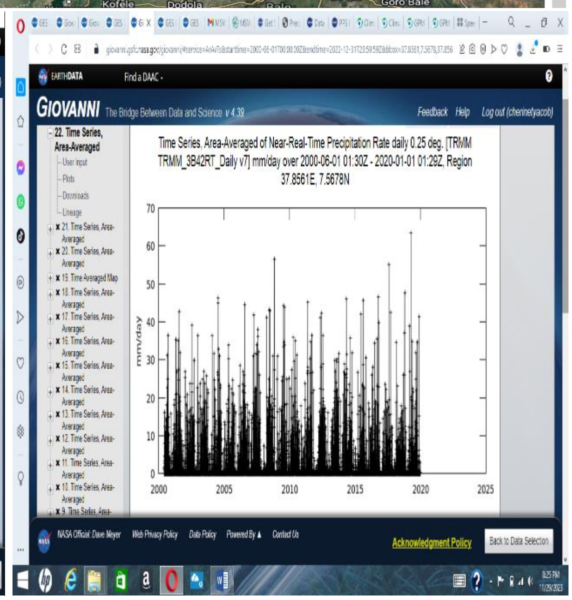


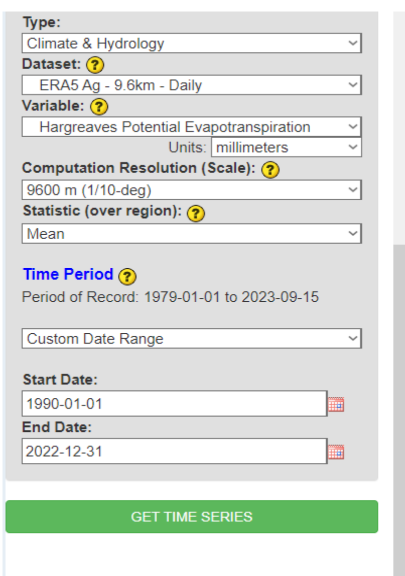
Latitudes
06° 34′ 48″ N to
08° 09′ 00″ N and
longitudes
37° 46′ 48″ E to
38° 20′ **00″ E.**

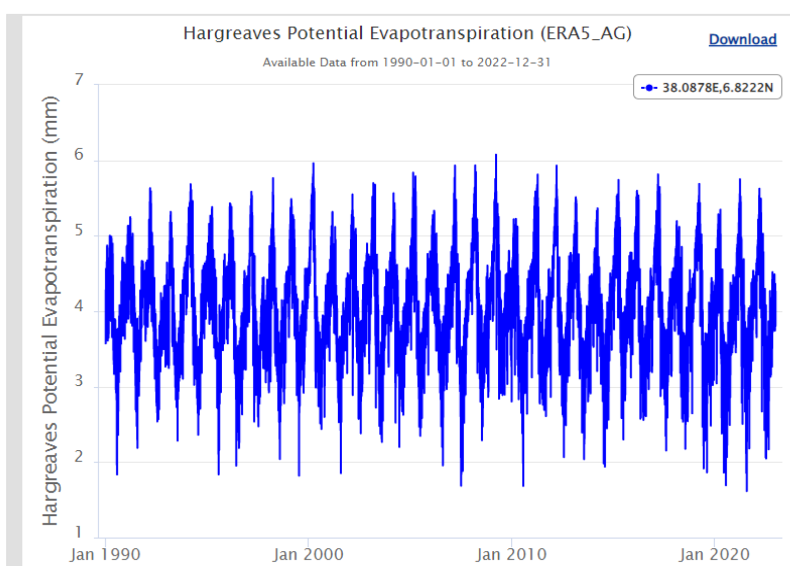
Appendix A8: Satellite image and satellite products source



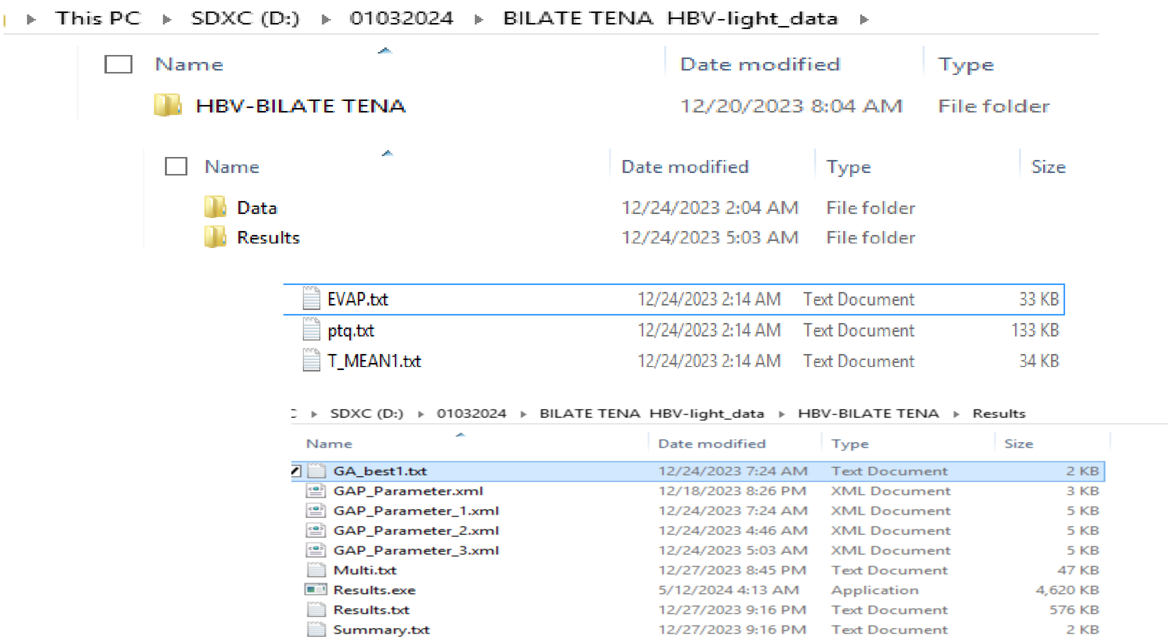


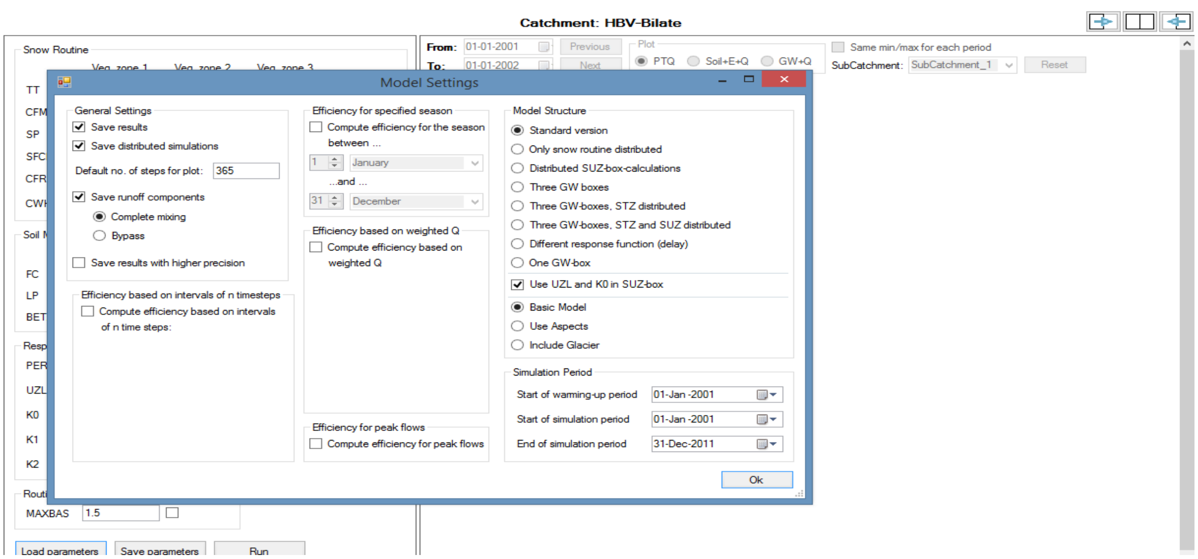


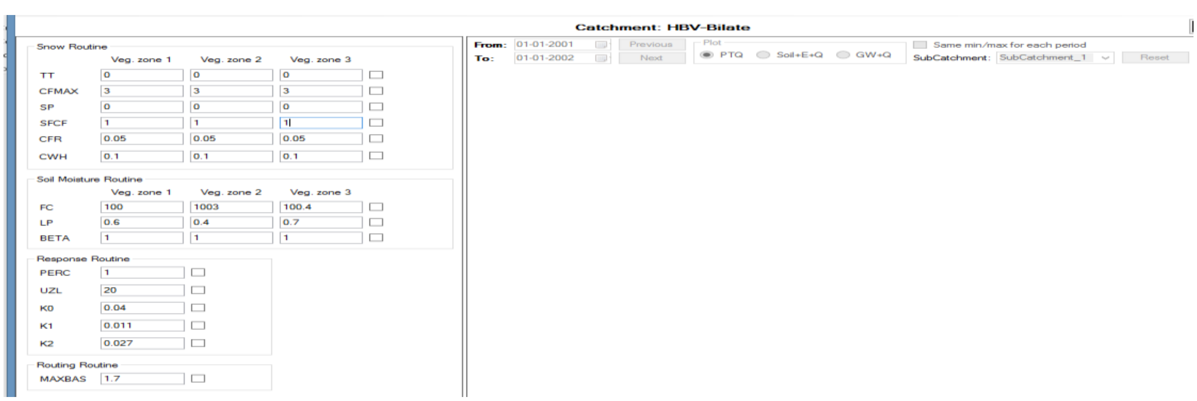


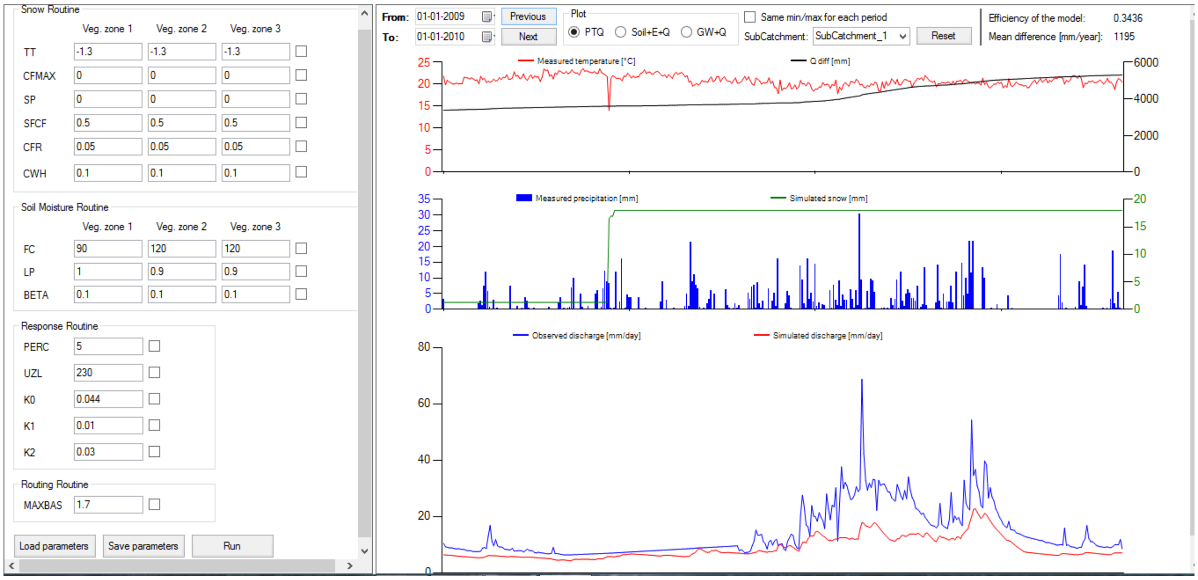


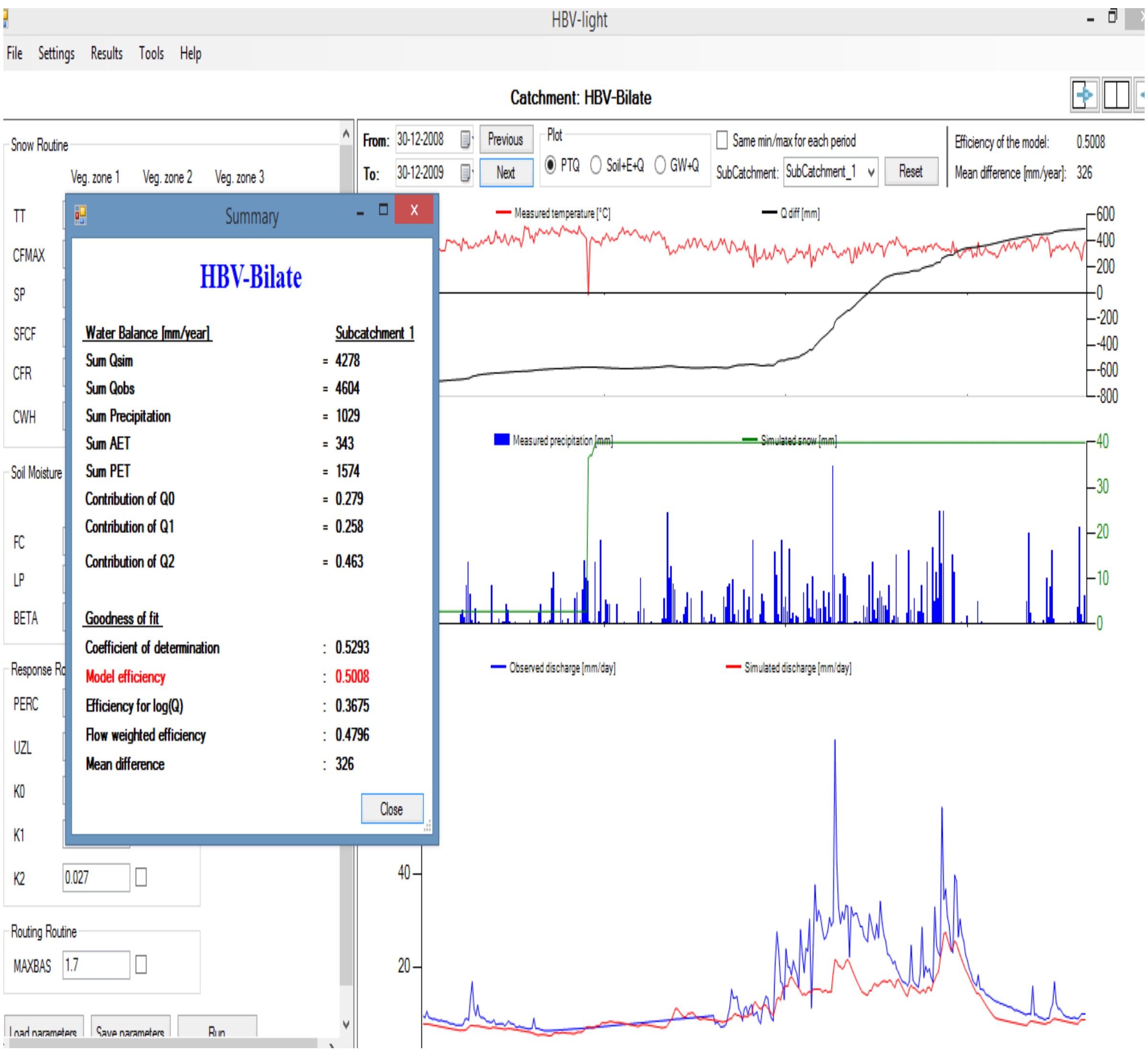
Appendix A9: HBV Light model simulation result



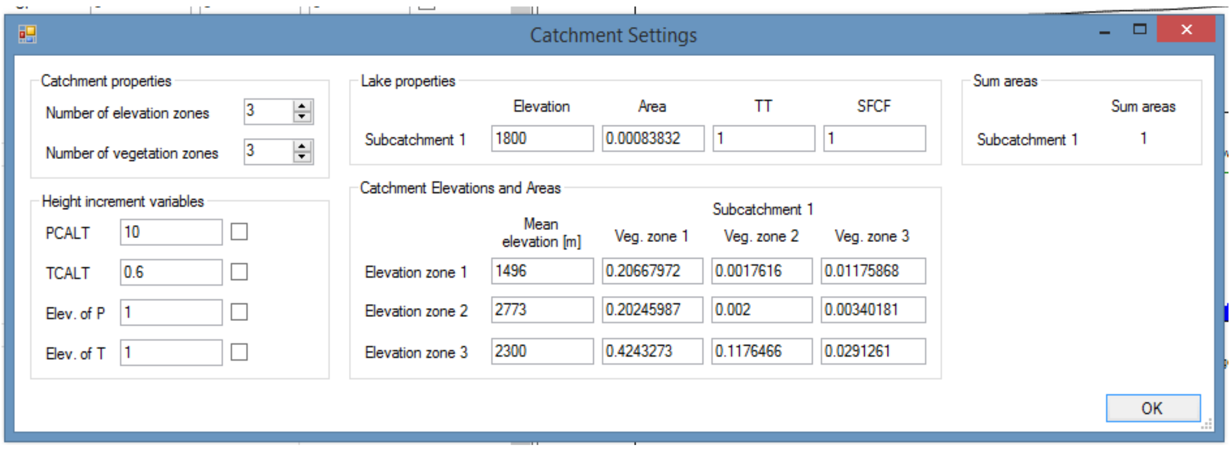


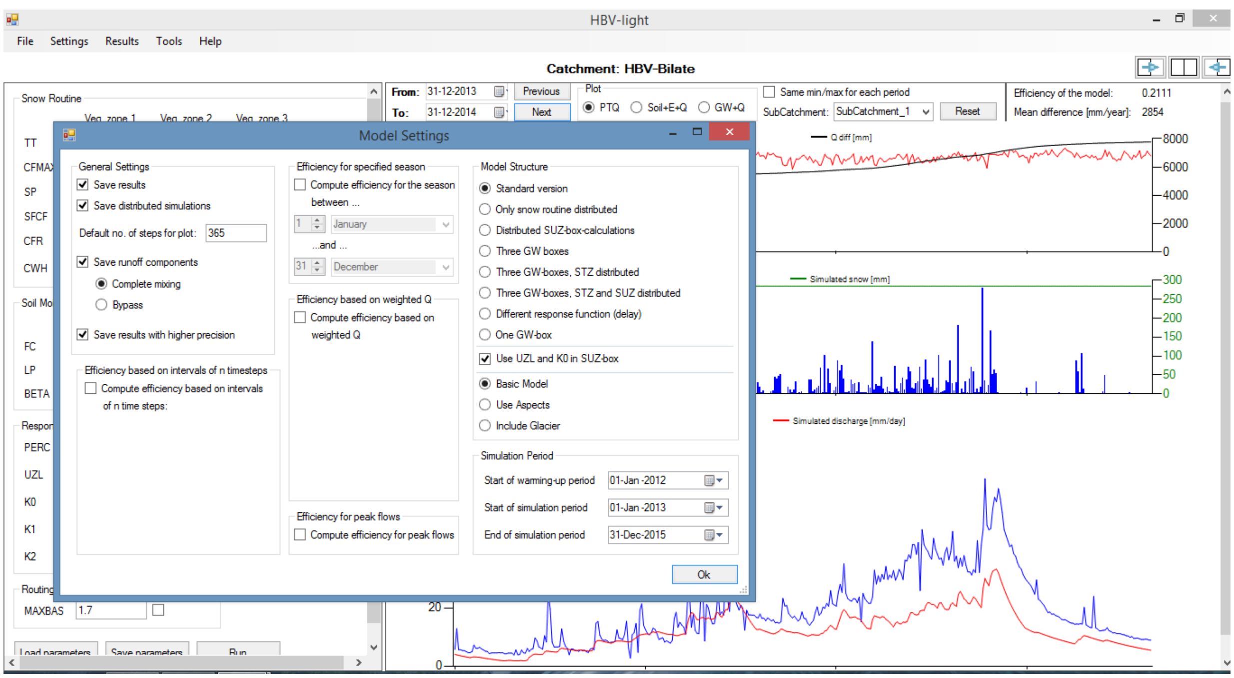


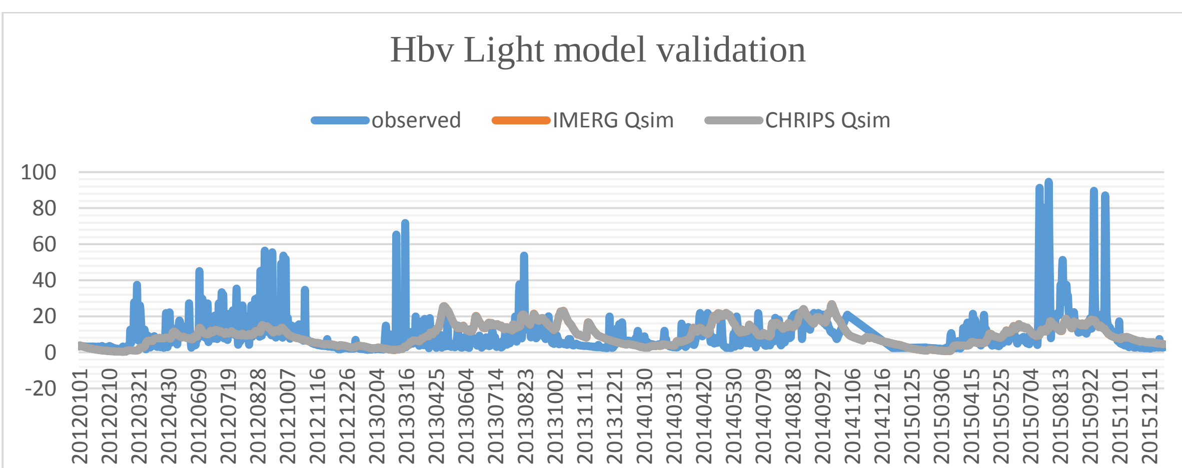

Snow Routine
Veg. zone 1
Veg. zone 2
Veg. zone 3
TT
CFMAX
SP
SFCF
CFR
CWH
Soil Moisture Routine
FC
LP
BETA
Response Routine
PERC
UZL
K0
K1
K2
Routing Routine
MAXBAS
Load parameters
Save parameters
Run
From: 01-01-2009
To: 01-01-2010
Previous
Next
Plot
PTQ
Soil+E+Q
GW+Q
Same min/max for each period
SubCatchment: SubCatchment_1
Reset
Efficiency of the model: 0.3436
Mean difference [mm/year]: 1195
Measured temperature [°C]
Q diff [mm]
Measured precipitation [mm]
Simulated snow [mm]
Observed discharge [mm/day]
Simulated discharge [mm/day]


HBV-light
File
Settings
Results
Tools
Help
Catchment: HBV-Bilate
From: 30-12-2008
To: 30-12-2009
Efficiency of the model: 0.5008
Mean difference [mm/year]: 326
Summary
HBV-Bilate
Water Balance [mm/year]
Subcatchment 1
Sum Qsim = 4278
Sum Qobs = 4604
Sum Precipitation = 1029
Sum AET = 343
Sum PET = 1574
Contribution of Q0 = 0.279
Contribution of Q1 = 0.258
Contribution of Q2 = 0.463
Goodness of fit
Coefficient of determination : 0.5293
Model efficiency : 0.5008
Efficiency for log(Q) : 0.3675
Flow weighted efficiency : 0.4796
Mean difference : 326
Close
Measured temperature [°C]
Q diff [mm]
Measured precipitation [mm]
Simulated snow [mm]
Observed discharge [mm/day]
Simulated discharge [mm/day]

For validation







Date	Qsim	Qobs	Precipitation	Temperature	AET	PET	Snow	Snowcover	SM	Recharge	SUZ	SLZ	Q0			
20010101	1.411	1.820	0.0	-0.1	4.38	4.39	0.0	0.00	1159.2	0.0	0.0	58.8	0.000	0.000	1.411	1.411
20010102	1.777	1.780	0.0	-1.7	4.34	4.36	0.0	0.00	1154.9	0.0	0.0	57.1	0.000	0.000	1.777	1.777
20010103	1.724	1.870	0.0	-1.9	4.30	4.34	0.0	0.00	1150.6	0.0	0.0	55.4	0.000	0.000	1.724	1.724
20010104	1.672	1.820	0.0	-1.1	4.23	4.28	0.0	0.00	1146.4	0.0	0.0	53.7	0.000	0.000	1.672	1.672
20010105	1.622	1.820	0.0	-1.1	4.11	4.18	0.0	0.00	1142.2	0.0	0.0	52.1	0.000	0.000	1.622	1.622
20010106	1.573	1.780	0.0	-0.8	4.05	4.13	0.0	0.00	1138.2	0.0	0.0	50.5	0.000	0.000	1.573	1.573
20010107	1.526	1.640	0.0	-0.6	4.04	4.13	0.0	0.00	1134.2	0.0	0.0	49.0	0.000	0.000	1.526	1.526
20010108	1.480	1.780	0.0	-0.3	4.07	4.18	0.0	0.00	1130.1	0.0	0.0	47.5	0.000	0.000	1.480	1.480
20010109	1.436	1.730	0.0	0.1	4.06	4.19	0.0	0.00	1126.0	0.0	0.0	46.1	0.000	0.000	1.436	1.436
20010110	1.392	1.730	0.0	-0.5	3.89	4.03	0.0	0.00	1122.1	0.0	0.0	44.7	0.000	0.000	1.392	1.392
20010111	1.350	1.730	0.0	-0.4	4.05	4.21	0.0	0.00	1118.1	0.0	0.0	43.4	0.000	0.000	1.350	1.350
20010112	1.463	1.640	13.7	0.3	4.11	4.27	0.0	0.00	1119.7	7.9	2.0	47.8	0.000	0.015	1.447	1.463
20010113	1.552	1.600	4.3	-0.3	3.94	4.10	0.0	0.00	1117.6	2.5	0.0	50.7	0.000	0.004	1.547	1.552
20010114	1.531	1.730	0.0	-0.4	3.90	4.07	0.0	0.00	1113.7	0.0	0.0	49.1	0.000	0.000	1.531	1.531
20010115	1.485	1.590	0.0	-0.2	3.93	4.12	0.0	0.00	1109.8	0.0	0.0	47.7	0.000	0.000	1.485	1.485
20010116	1.440	1.680	0.0	-0.2	3.95	4.15	0.0	0.00	1105.9	0.0	0.0	46.2	0.000	0.000	1.440	1.440
20010117	1.397	1.590	0.0	-0.7	4.13	4.36	0.0	0.00	1101.7	0.0	0.0	44.8	0.000	0.000	1.397	1.397
20010118	1.355	1.680	0.0	-0.8	4.14	4.39	0.0	0.00	1097.6	0.0	0.0	43.5	0.000	0.000	1.355	1.355
20010119	1.314	1.640	0.0	-0.9	4.13	4.39	0.0	0.00	1093.4	0.0	0.0	42.2	0.000	0.000	1.314	1.314
20010120	1.274	1.590	0.0	0.6	4.11	4.39	0.0	0.00	1089.3	0.0	0.0	40.9	0.000	0.000	1.274	1.274
20010121	1.277	1.640	3.1	0.1	4.08	4.37	0.0	0.00	1086.6	1.7	0.0	41.4	0.000	0.000	1.277	1.277
20010122	1.250	1.590	0.0	0.7	3.79	4.07	0.0	0.00	1082.8	0.0	0.0	40.1	0.000	0.000	1.250	1.250
20010123	1.212	1.510	0.0	0.8	4.00	4.31	0.0	0.00	1078.8	0.0	0.0	38.9	0.000	0.000	1.212	1.212
20010124	1.205	1.510	2.2	1.0	3.83	4.14	0.0	0.00	1076.0	1.2	0.0	39.0	0.000	0.000	1.205	1.205
20010125	1.177	1.550	0.0	-0.1	3.89	4.22	0.0	0.00	1072.1	0.0	0.0	37.8	0.000	0.000	1.177	1.177
20010126	1.159	1.500	1.3	0.4	3.77	4.10	0.0	0.00	1068.9	0.7	0.0	37.4	0.000	0.000	1.159	1.159
20010127	1.129	1.610	0.0	0.4	3.79	4.14	0.0	0.00	1065.1	0.0	0.0	36.2	0.000	0.000	1.129	1.129
20010128	1.095	1.540	0.0	0.0	4.03	4.41	0.0	0.00	1061.1	0.0	0.0	35.2	0.000	0.000	1.095	1.095
20010129	1.124	1.510	4.9	0.4	3.97	4.36	0.0	0.00	1059.4	2.7	0.0	36.7	0.000	0.000	1.124	1.124
20010130	1.108	1.500	0.0	0.6	4.02	4.43	0.0	0.00	1055.4	0.0	0.0	35.6	0.000	0.000	1.108	1.108
20010131	1.075	1.380	0.0	0.8	4.04	4.46	0.0	0.00	1051.3	0.0	0.0	34.5	0.000	0.000	1.075	1.075
20010201	1.042	1.920	0.0	-1.6	3.94	4.37	0.0	0.00	1047.4	0.0	0.0	33.5	0.000	0.000	1.042	1.042
20010202	1.011	1.380	0.0	-0.5	4.11	4.58	0.0	0.00	1043.3	0.0	0.0	32.5	0.000	0.000	1.011	1.011
20010203	0.981	1.300	0.0	0.3	4.09	4.58	0.0	0.00	1039.2	0.0	0.0	31.5	0.000	0.000	0.981	0.981
20010204	0.951	1.380	0.0	0.3	4.01	4.51	0.0	0.00	1035.2	0.0	0.0	30.5	0.000	0.000	0.951	0.951

HBV-Bilate SubCatchment_1
Water Balance [mm/year]:
Sum Qsim 4113.66682317771
Sum Qobs 4604.221944237
Sum Precipitation 1028.77389843166
Sum AET 351.077986532052
Sum PET 1574.26859225167
Contribution of Q0 0.266484802532725
Contribution of Q1 0.255866323250866
Contribution of Q2 0.47764887421641
Goodness of fit:
Coefficient of determination 0.553231640750898
Model efficiency 0.500466100775123
Kling-Gupta efficiency 0.465864012787963
Kling-Gupta efficiency ('non-parametric') 0.694234901436807
Efficiency for log(Q) 0.393365419005449
Flow weighted efficiency 0.453262869140718
Mean difference 490.555121059288
Volume Error 0.893455370527195
MARE Measure 0.0208286100307086
Lindstrom Measure 0.489811637827842
Spearman Rank 0.748834993380273

HBV-Bilate SubCatchment_1 CHRIPS
Water Balance [mm/year]:
Sum Qsim 4278.07996734279
Sum Qobs 4604.221944237
Sum Precipitation 1028.77389843166
Sum AET 343.181950750562
Sum PET 1574.26859225167
Contribution of Q0 0.278626963994381
Contribution of Q1 0.25804383276182
Contribution of Q2 0.463329203243799
Goodness of fit:
Coefficient of determination 0.529312871144712
Model efficiency 0.50077909575382
Kling-Gupta efficiency 0.491152469575516
Kling-Gupta efficiency ('non-parametric') 0.691611744012507
Efficiency for log(Q) 0.367467053613932
Flow weighted efficiency 0.479617410040034
Mean difference 326.141976894213
Volume Error 0.929164583974402

Appendix A10: HBV Light model simulation result of the study area

Date	Qsim (in situ)	Qobs	CHRIP Qsim(Bias corrected)	IMERG Qsim(Bias corrected)
20010101	1.2	1.8	1.5	1.5
20010102	1.8	1.8	1.7	1.7
20010103	1.7	1.9	1.7	1.7
20020204	2.4	0.9	3.3	6.0
20020205	2.4	0.9	3.1	5.9
20020206	2.3	1.0	3.0	5.6
20030307	4.7	1.3	6.9	7.0
20030308	4.6	1.3	6.9	7.0
20030309	4.6	1.3	6.8	6.9
20040409	12.3	5.4	12.8	12.4
20040410	15.1	5.5	13.6	13.1
20040411	17.2	5.8	16.6	13.7
20050513	29.5	21.9	29.2	31.0
20050514	28.7	17.4	28.3	30.4
20050515	28.0	19.6	27.7	30.0
20060616	13.8	15.0	16.4	15.8
20060617	13.1	14.8	15.7	15.5
20060618	14.1	14.6	14.9	15.5
20070719	14.5	32.9	12.7	16.2
20070720	14.8	31.7	13.1	15.6
20070721	14.6	23.2	12.6	15.5
20080822	19.9	32.8	22.0	18.7
20080823	20.0	38.3	21.2	18.4
20080824	20.7	29.9	20.1	17.7
20090925	16.1	24.6	12.9	14.1
20090926	15.5	17.2	14.1	14.1
20090927	15.4	16.4	13.7	13.9
20101028	8.6	12.1	10.3	8.2
20101029	8.5	11.9	10.3	8.1
20101030	8.4	11.7	9.9	8.1
20111201	7.4	12.4	9.4	8.6
20111202	7.3	9.7	9.1	8.5