WATER BALANCE APPROACH FOR STREAM FLOW ESTIMATION USING REMOTE SENSING DATA IN HUNZA AND ASTORE SUB BASINS

By

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DEDICATION

"Dedicated to my family. . ."

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Rashid Mahmood

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LIST OF ABBREVIATIONS

Abbreviation	Explanation
HKH	Hindu Kush Himalayas
UIB	Upper Indus Basin
ET	Evapotranspiration
DEM	Digital Elevation Model
SCS	Soil Conservation Service
TRMM	Tropical Rainfall Measurement Mission
MSWEP	Multi Source Weighted Ensemble Precipitation
CMORPH	Climate Prediction Center Morphing Technique
CMADS	China Meteorological Assimilation Driving Datasets
SMOS	Soil Moisture & Ocean Salinity Mission
WEAP	Water Evaluation and Planning System
SWAT	Soil & Water Assessment Tool
SEBAL	Surface Energy Balance Algorithm for Land
CGCM	Combination Generator Control Module
SRM	Snow-melt Runoff Model
HBV	

PMD	Pakistan Meteorological Department
WAPDA	Water and Power Development Authority
CHIRPS	Climate Hazards Group Infrared Precipitation Station
SSEBop	The Operational Simplified Surface Energy Balance
ASCAT	The Advanced Scatterometer
GDEM	Global Digital Elevation Model
NOAA	National Oceanic and Atmospheric Administration
NCDC	National Climatic Data Center
NASA	National Aeronotics and Space Administration
LAI	Leaf Area Index
FPAR	Fraction for Photosynthetically Active Radiation
SWI	Soill Water Index
WCavail	Available Water Content
MODIS	Moderate Resolution Imaging Spectroradiometer
PERSIANN	Precipitation Estimation from Remotely Sensed Information using Artificial Neural Networks

ABSTRACT

Because of changing climate, inadequate data and anthropogenic effects on water resources, spatial and temporal information about water resources is becoming necessary worldwide and this limitation can be overcome with the availability of open access earth observation datasets. The purpose of the study was to estimate the stream flow of Hunza and Astore sub-basin using remote sensing datasets and validate results with the field observation data using R2. Pixel-based water balance was quantified by segregating precipitation into evapotranspiration, runoff, and potential ground-water infiltration. Open access remotely sensed Rainfall products (TRMM and CHIRPS), evapotranspiration dataset (SSEBop), leaf area index dataset (MODIS), and soil Water Index (SWI) dataset of The Advanced Scatterometer (ASCAT) were used in the water balance equation for Rainfall-runoff estimation. In this study, precipitation dataset TRMM is used in water balance calculation because it represented a better relationship with gauge data R2= 0.74 for Astore basin and R2= 0.71 for Hunza basin as compared to CHIRPS precipitation data R2=0.68 for Astore basin and 0.66 for Hunza basin. Resulted values from the remote sensing model was compared and validated with field observation data using coefficient of determination R2. Results represented a good relationship among estimated runoff values from the water balance model and field data (WAPDA) with R2 value of 0.75 in Astore basin and R2 value of 0.70 in Hunza basin respectively. The presented approach can be used in ungauged basins without any need of field data. The study helped in estimating stream flow by fast and cost effective method without complex hydrological models requiring intensified data and tuning.

INTRODUCTION

Due to climate change water scarcity is one of the major issues worldwide, especially in arid and semi-arid conditions. Water shortage is becoming a big issue due to demographic and economic pressure. Climate change, floods and droughts have affected the fresh water availability and this shortage has become a big challenge for the agricultural areas, commercial use and human use (Rijsberman, 2006). Pakistan is an arid region with annual average Rainfall of 240mm that makes it one of the most extremely water-stressed countries in the world. Agriculture is the back bone of the economy of Pakistan and it is mainly dependent on the big irrigation system of the Indus River. The agriculture sector alone contributes to almost a quarter of the country's gross domestic product. 44% of the labor force is associated with agriculture that supports almost 75% of the population of Pakistan and contributes 60% of foreign exchange earnings. But water is under immense pressure in Pakistan, and irrigation is also in danger. The growing population needs more food, but water supplies are limited(Basharat, 2019) . In History, Pakistan's policy-making implies giving a unique place for water-related issues. This has led to an essential intense argument and disagreement for an extended period as proven by the issue of the construction of Dam at Kalabagh and the imbalanced supply of resources of water between different provinces of Pakistan(Akhtar et al., 2008) . The adverse effect of climate change on water resources, is predicted to disturb the irrigated agriculture. Variations of water flow into the rivers and disturbances in weather conditions can cause severe problems in downstream areas. These fluctuations can reduce the water flow in the dry seasons and cause high water flows, resulting in floods in wet seasons(Cook et al., 2013) .

HKH Region initiates the main river flow of the Indus basin and its tributaries. Major Indus river basins that contribute 70% to the discharge of Indus River are Hunza, Shyok, Astore, Sigar and Gilgit. These basins hold this huge percentage because of snow melt, glacier and monsoon patterns as Himalayan Mountains works as barrier to provide a big amount of Rainfall to these basins. More than 80% of discharge in the Indus river is supplied by the HKH region reaching the plains(Mukhopadhyay & Khan, 2014) .

The flow of water on the surface occurs due to the Rainfall, snow melt or storm water that cannot infiltrate into the soil and is not evaporated, this flowing surface water is called Runoff. Runoff is one of the most important hydrological phenomena when it comes to the water resources management. It is very difficult and time consuming to estimate and predict the rainfall runoff from the whole catchment into the rivers(Hammouri & El-Naqa, 2007) .

There are many places over the globe where due to inadequate data, the assessment of stream flow or ground water infiltration rates is not possible. 48 countries, including Pakistan is going to face a water shortage after 2025. Data scarcity and available data quality in the upper Indus basin is a huge concern for modelers to accurately simulate the water resources status of UIB(Cheema & Bastiaanssen, 2012) .

Timely information on water resources plays an important role in managing water resources and decision-making. Spatial and temporal information about water resources is becoming necessary because of changing climate and anthropogenic effects on water resources. Open access earth observation data based methods provide uncomplicated ways of spatial and temporal assessment of information on water resources(Poortinga et al., 2017) .

In ungauged basins, direct observations of hydrological variables are extremely difficult spatially and temporally, it is labor- intensive and really costly. These problems make it very difficult to predict and model the water resources. Open access earth observation-based methods can be used for frequent temporal and large spatial coverage in hydrological modeling and studies(Lakshmi, 2004) .

Rainfall is a vital element of water cycle, agriculture and other important fields of life. Accurate estimates of Rainfall are crucial in hydrological modelling and water withdrawal studies. Rain gauge stations at UIB are scarce and inadequate to plan water management applications. Typically Rainfall is measured by rain gauges at a particular point, but point based results are not appropriate spatially and temporally for a basin level. There are open source global databases for rainfall products with merged data from weather prediction models, satellite calculations, rain gauges and radar observations(Zandler et al., 2019) .

There are many countries facing water resources problems, but data about water usage and water availability is short. To overcome this issue, open-access global datasets obtained through remote sensing has been applied in hydrology studies. Satellite-based datasets of Rainfall, evapotranspiration (ET), Soil water Index of soil moisture, and leaf area (LAI) index are tried & true, found accurate and contains a robust physical foundation. For water balance, satellite based runoff datasets and ground water storage datasets are difficult to get and if available they have poor quality and errors. However, runoff flows and storage can be estimated purely through remote sensing products of precipitation, evapotranspiration, leaf area index, and soil moisture(Poortinga et al., 2017).

GIS and Remote sensing techniques have emerged as critical and efficient technologies for hydrological modeling and studies. Because a large portion of the Himalayan landscape is inaccessible, gathering data for any runoff research in the area is a considerable challenge. Remote sensing techniques aid in the creation of a consistent synoptic view of the Earth. The information gathered can be effectively used to estimate hydrological properties. GIS, on the other hand, makes it easier to include spatial data. Simple database queries, mapping, and vector and raster analysis are all examples of GIS applications, as are complicated inquiry and decision support systems. Remote sensing combined with geographic information systems (GIS) can provide a useful framework for mapping and modelling the environment in order to develop alternative scenarios for long-term natural resource management.(Dang & Kumar, 2017) .

In this study, a formula for estimating discharge of river and variations in storage for the basins without gauging stations is proposed. This ground-breaking technology is dependent on just open-source global remote-sensing datasets. Because it does not necessitate the use of complicated models of hydrology or a large number of physical parameters, the presented approach has a wide range of applications. As a result, changes in runoff and water storage can be computed in the absence of the use of supplementary data. In Pakistan, the work is presented in the Hunza and Astore sub-basins of the upper Indus basin. Due to water scarcity and competing interests, these sub-basins and upper Indus basins, like many other river basins in South Asia, face numerous water-related issues(Amin et al., 2018).

However, a full understanding of available water resources is hampered by a lack of data. These basins were chosen to see if this stream flow remote sensing model might be used in Pakistan's upper Indus basin.

.Global Satellite datasets can be used as a pre-analysis for hydrological modeling studies. Monthly satellite-based precipitation and ensemble ET actual were used to estimate water balance for different land use land cover types. Composite of satellite-derived precipitation and ensemble ET results spatially and temporally consonant with stream flow records(Simons et al., 2016) . The lateral flow of 15 sub-basins of the Nile River basin was computed using satellite-derived Rainfall products in conjunction with satellite-derived actual evapotranspiration datasets. Results show that P-ET information is importance for showing the redistribution of water resources in the absence of flow meters(Bastiaanssen et al., 2014) . Based on remotely sensed data a machine learning approach can be used for hydrological modeling to simulate the stream flow of the Upper Mississippi river. A good performance was seen compared to process-based approach(Bej & Baghmar, 2019) . HEC-HMS model can be used with assistance of GIS for simulation of runoff using DEM data, precipitation data and SCS curve number method was used in the model and the model can also be calibrated by applying for different curve numbers in the model. Storm runoff analysis depicts that runoff will be generated for an event of precipitation within 24 hours if value for that event exceeds 14.3mm(Hammouri & El-Naqa, 2007) . Four satellite-based rainfall products TRMM, PERSIANN, MSWEP, and CMORPH were downscaled and were combined with in situ measurements. Both downscaled and non-downscaled data sets were used for discharge simulation using the HBV model. TRMM and MSWEP datasets showed close agreement with in situ data and by using these datasets in the model shows good agreement with observed discharge data. By using downscaled data and by increasing the number of stations the results obtained by the model can be improved(López López et al., 2018) . The SWAT model can simulate runoff using four satellite precipitation products and can be compared to check the performance using statistical tests. The SWAT model requires a Topography map, land use map, soil map, meteorology, and hydrological data. TRMM and CMADS performed better than PERSIAN and PERSIANN-CDR(Vu et al., 2018) . For runoff simulation using SWAT, a dynamic ENKF approach can be used instead of a static approach for soil moisture vertical coupling in soil layers. Satellite-based products like SMOS can improve the stream flow simulation when used in large-scale hydrological models for daily estimates. Ensemble soil storages can improve the vertical coupling as compared to the static soil storage based approach. Durability of discharge estimates increased with effective update of sub surface flow(Patil & Ramsankaran, 2017) . Two alternate techniques can be used to calibrate TRMM rainfall dataset for different temporal and spatial distributions those techniques are regression analysis and geographical differential analysis. These techniques can be validated through Nash-Sutcliffe efficiency and the standard error of estimate. The geographical differential analysis technique can give accurate estimates even when applied to the areas with sparse rain gauges(Cheema & Bastiaanssen, 2012) . The process include land-use classification and 4 Landsat-5 TM images with remote sensing based cover coefficient estimate. Remote sensing based stream flow estimation can perform better and give better hydrological characteristics than traditional way(Chihda Wu et al., 2010) . Using WEAP model, management policies can be constructed to acquire water security and viability by different climatic and economic scenarios. Data for river basins can be calibrated and validated by WEAP model. Water demand for four different scenarios can be compared using WEAP Model(Amin et al., 2018) . Method of estimating Evapotranspiration cover coefficient K_c can be improved and estimated through remote sensing. To anticipate ET changes and land use, the SEBAL model, the CGMI model, and the Markov model can be employed. Estimated stream flow using remote sensing presents better hydrological outputs than traditional way(Chih Da Wu et al., 2010) . Study performed in Bias basin showed the estimation of runoff for each elevation zones from area with snow and areas without snow independently. The SRM computed runoff with 0.85 value of coefficient of determination(Prasad & Roy, 2005) . A comparison study was carried out for the Large Basin runoff model and HEC-HMS which specified that both the models could not capture the stream flow peaks during early spring periods and late winter time period whereas better accuracy was shown by HEC-HMS model(Gyawali & Watkins, 2013) . The HBV model was also used in the ungauged basin where the data availability is a biggest issue. These river basins have the feasibility of promising water resources schemes but lack hydrologic measurements due to which the HBV model has been used to generate time series stream flow(Shrestha & Alfredsen, 2012) . The hydrological model based on Rainfall like HEC-HMS is sensitive temperature and precipitation imputs, mainly in catchments of high altitudes(Ramly & Tahir, 2016) . A self-calibrated model using satellite derived products can be used for stream flow estimation of ungauged basin. Using water balance, the data sets involved in the calculation of stream flow are evapotranspiration (ET), soil moisture(SM), precipitation (P) and leaf area index (LAI). Remotes sensing-based stream flow model can represent a good agreement with observed discharge values. The Remote sensing-based model calibrates itself and can produce significant results(Poortinga et al., 2017).

1.1. RATIONALE

A slight change in climate and subsequent hydrological behavior can change the water demand and utilization at downstream level particularly rivers mainly dependent on rainfall runoff and snowmelt runoff for agriculture, power generation and domestic use. The changing climate and its influence on the hydrological regime of area performs a vital part in altering the agricultural water management system. Policy-makers need appropriate factual value for the change to cope with uncertainty issues in water resources management such as floods and droughts. The study could be persuaded to adopt the strategy for management of water resources of Pakistan by taking in view of the fluctuation in precipitation and stream flows. As UIB is a very important region for water resource of Pakistan, it needs prioritization to identify the effect of climate change on it.

1.2. OBJECTIVE

To estimate stream-flow using satellite derived products solely in Hunza and Astore Sub basins.

To validate the estimated results from the water balance model with observed field data using statistical tests.

1.3. SCOPE OF THE STUDY

The purpose of the study was to use a stream-flow estimation method that does not require tuning a complex hydrological model or field data but involves an efficient way of estimation discharge through remote sensing. The study was conducted to estimate stream-flow using only Remote-sensing datasets in upper Indus basin. Moreover, to analyze whether solely remote-sensing based approach shows constancy with field observation data. This study emphasizes simple and convenient way of estimating stream-flow using open-access datasets for water balance calculation of UIB. Hence, it can help in planning effective strategies in a short time for water management and use of water resources in a sustainable manner.

MATERIALS AND METHODS

The field data of precipitation and discharge were obtained from the hydro-meteorological stations of PMD and WAPDA for the selected study basins. Stream flow was calculated from the water balance model using remotely sensed products of Precipitation, evapotranspiration, Leaf Area Index and Soil Moisture. Two different rainfall products were compared and validated against field observation data to check the constancy between remotely sensed products and field data using R2. Field data records of Rainfall were obtained from Pakistan Meteorological Department (PMD) and Water and Power Development Authority (WAPDA) for Hunza and Astore basins. Satellite products for precipitation include CHIRPS precipitation dataset and TRMM precipitation dataset. Evapotranspiration product SSEBop was used in this study for use in water balance calculation. For soil moisture data, The Soil Water Index (SWI) of Advanced Scatterometer (ASCAT) product has been used. The interception was calculated using Leaf Area Index and precipitation. Interception also requires daily data that was taken from Pakistan Meteorological Department. Pixel-based Rainfall-runoff was calculated from year 2008 to year 2017. Estimated runoff using remote sensing model was aggregated for whole basin with storage changes to simulate stream flow and then validated with observed discharge field. Discharge data for Hunza and Astore basin was obtained from Water and Power Development Authority (WAPDA). Simulated stream flow has been compared with observed data using Coefficient of determination R2. Figure 1. Shows the methodology flow chart of the study.

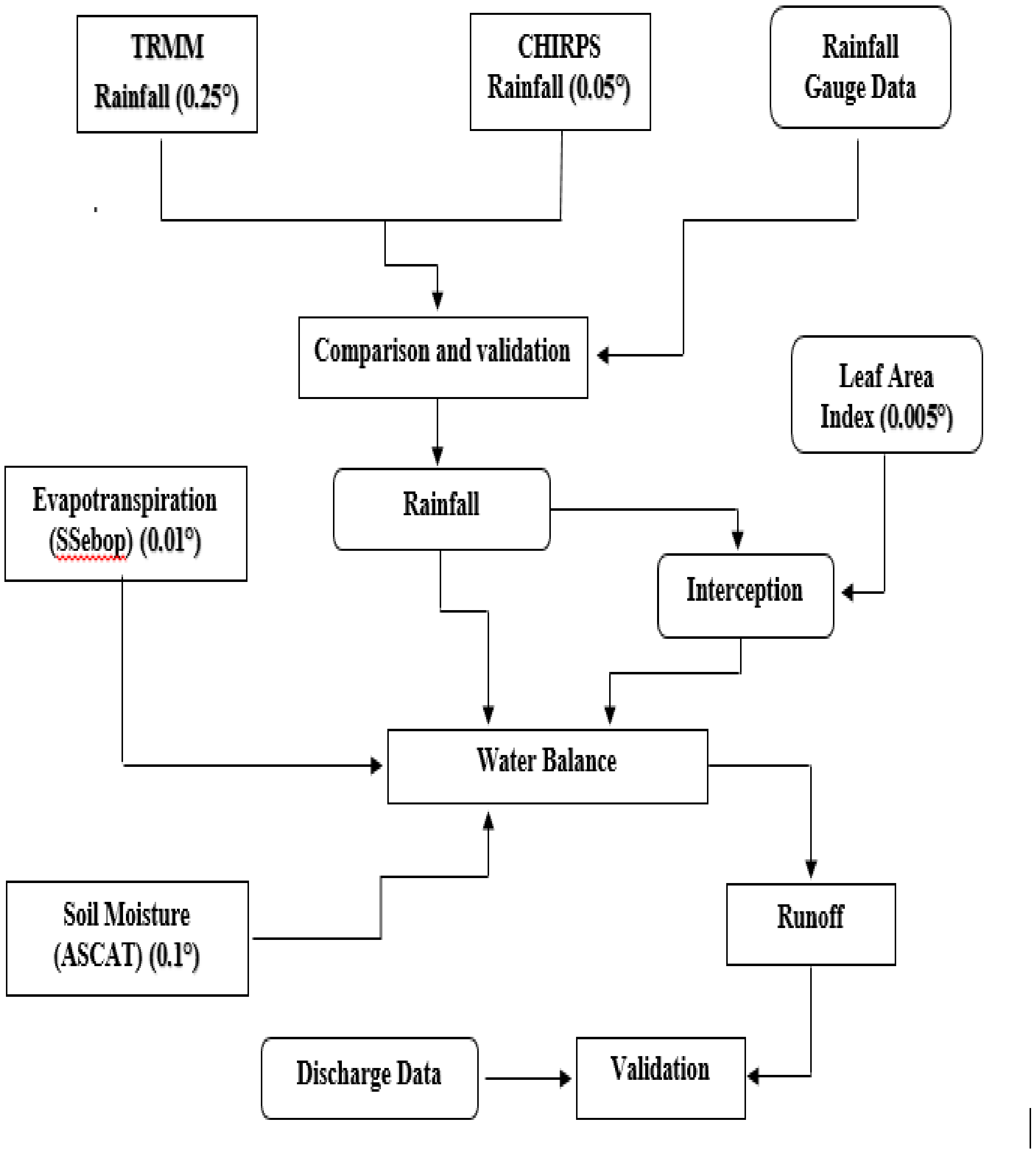


Figure 1. The methodology flow chart

2.1. STUDY AREA:

The main two catchments selected for the research work are the Hunza River basin and Astore River Basin that are situated in the Upper Indus Basin region of Pakistan, neighboring Afghanistan and China in the Hindu Kush-Karakoram-Himalaya (HKH) region as shown in figure 2. These sub-catchments are a part of the Upper Indus Basin (UIB). The UIB is located in the HKH region, the key water source for irrigated areas in Pakistan. The main basins i.e. Astore, Shyok, Gilgit, Hunza and Shigar lie within the UIB which mainly contributes to the Indus River discharge. Above 80% of Indus River flow attaining the lowland areas initiates in Hindu Kush, Western Himalayan and Karakoram mountainous areas (Liniger, Weingartner, Grosjean, & Agenda, 1998).

2.1.1. Hunza River Basin:

The Hunza River is the main tributary of the Indus River System. The glacier melt and seasonal snow mostly add the Hunza basin stream-flow with a minor effect of monsoon in summer. The precipitation in winter, also known as westerly circulations, portrays a substantial part in snow and glacier advancement. These phenomena are performing more critically in high altitude regions of the Hunza River basin (Tahir, Adamowski, Chevallier, Haq, & Terzago, 2016). The basin area of the Hunza catchment is 13,733 km2 while the mean elevation is 4631m. The main significant features of the Hunza basin are specified in Table 1. There are three main WAPDA stations installed at Hunza basin i.e., Khunjerab, Ziarat and Naltar. The mean annual precipitation is 146.19mm at Khunjerab, 706.27mm at Naltar and 282.97mm at Ziarat according to the 2007-2017 time period of the three meteorological stations of Hunza catchment as given in Table 2.

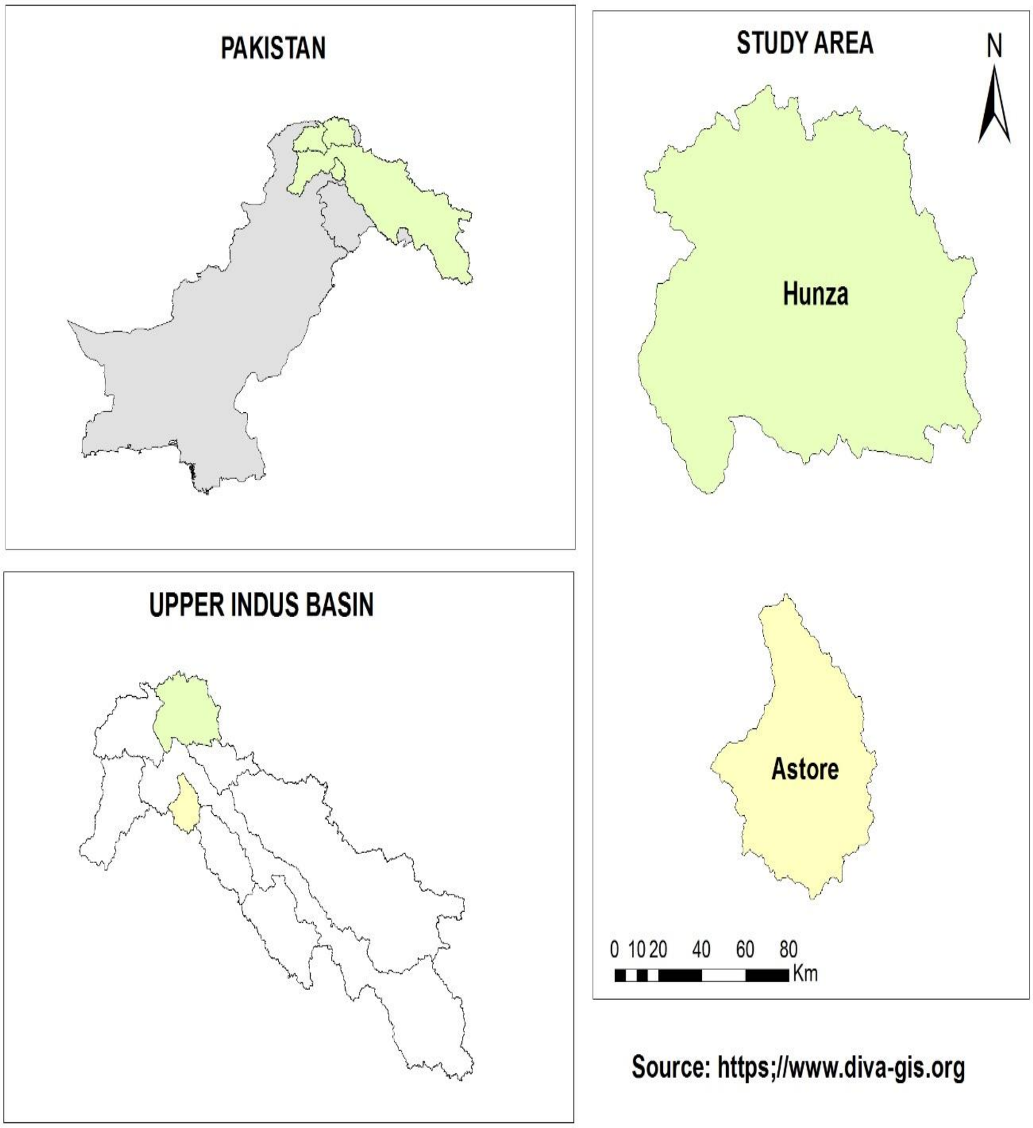


Figure 2. The study area map showing Upper Indus Basin in Pakistan with the Hunza and the Astore Sub-basins of UIB.

Table 1. The significant features of study area (Hunza and Astore)

Catchments	**Hunza**	**Astore**
River flow gauging Station	Daniyor bridge	Doyian
Drainage Area (km2)	13,733	3,990
Glacier covered Area (Km2)	3417	248
Mean elevation (m)	4631	4588
Elevation Range (m)	1395-7980	1225-8062
No. of meteorological Stations	3 (established by WAPDA) Khunjerab Ziarat Naltar 4440 m 3020 m 2898 m	3(1 established by PMD and 2 established by WAPDA) Astore Rama Rattu 2168 m 3179 m 2718 m

Table 2. Mean rainfall differences at climate stations of Hunza and Astore basin for the time period of 10 years

River Basin	**Stations**	**Elevation(m)**	**Mean Rainfall (mm)**		
			Annual (Jan-Dec)	**Winter (Oct-Mar)**	**Summer (Apr-Sep)**
Hunza	Naltar	2858	699.72	402.31	640.98
	Khunjerab	4730	152.32	79.89	138.07
	Ziarat	3669	277.83	197.88	224.94
Astore	Astore	2168	705.39	305.6	405.25
	Rama	3179	1287.14	745.67	530.21
	Rattu	2718	1390.87	712.45	679.09

2.1.2. Astore River Basin:

The Astore catchment is a snow contributing sub-basin of UIB. The Astore catchment lies in the western Himalayas at its southern foothills. It has a north-facing orientation, mid-altitude, the latitude of lower values and snow-fed regime. The discharge of the Astore River is affected by the Rainfall in winters at low - altitudinal areas, which unites with the precipitation in solid form in the winter seasons by westerly circulation. The basin area of the Astore catchment is 3990 km2, while the mean elevation is 3990m. The Global Digital Elevation Model (GDEM) shows that the altitudinal variation of the Astore basin lies from 1225m to 8062m. The important features of Astore basin are specified in Table 1. The three main stations installed at the Astore basin are Astore which is installed by PMD and Rama and Rattu which is installed by WAPDA (Table 1). The mean annual precipitation is 709.87mm at Astore, 1287.14mm at Rama and 1401.33mm at Rattu for the 10 years record of Astore River Basin stations (Table 2).

2.2. Description of Datasets

2.2.1 Datasets of Hydro meteorology:

The data of stream flows was obtained at the gauging stations of Hunza and Astore river basins. The data for Hunza river basin obtained during 2008-2017 time periods, while for Astore basin, the data was available for the time period of 2008-2017 from the project of hydrology for surface water of the Water and Power Development Authority (WAPDA). Table 3 shows the description of datasets used in this study.

Table 3. Specification and details of datasets used in the study.

Data	**Specification**	**Sources**
Satellite Data	Precipitation (0.25°) Precipitation (0.05°)	Tropical Rainfall Measurement Mission (TRMM) Climate Hazards Group Infrared precipitation Station (CHIRPS)
Satellite Data	Evapotranspiration(0.01°)	The Operational Simplified Surface Energy Balance. (SSEBop)
Satellite Data	Soil Moisture data (0.1°)	The Advanced Scatterometer (ASCAT)
Field Data	Discharge	Water and power development authority (WAPDA)
Field Data	Precipitation	Pakistan Meteorological Department (PMD)

PMD and WAPDA provided the precipitation data for six meteorological stations (3 each) positioned in Astore and Hunza River basin for similar periods as stream flow data. The meteorological stations and the precipitation gauges at altered elevations in their respective river basins are displayed in Table 1.

2.2.2 Remote Sensing datasets

Remote sensing datasets used in the study are precipitation, Leaf Area Index, soil moisture, and evapotranspiration. Data on canopy interception was also gathered. The monthly time resolution is used for all datasets. These products were used to calculate the water balance model.

2.2.3 Precipitation Datasets

To ensure that ground measurements and precipitation products were consistent, two precipitation datasets were plotted against each other for comparison and validation with rain gauge data (PMD). The analysis comprised a total of 6 rainfall gauges. Physical data records were gathered from PMD and the National Climatic Data Center (NCDC), and the National Oceanic and Atmospheric Administration (NOAA). The in situ readings were compared to two distinct global monthly precipitation products. The products were gathered from various sources over the time period 2008–2017, which corresponds to the in situ data's temporal coverage. The Climate Hazards Group InfraRed Precipitation Station (CHIRPS) and the Tropical Rainfall Measurement Mission (TRMM) products were used for comparison and then in water balance.

Table 4. Institutional rainfall products

Abbreviation	Product	Institute
TRMM	Tropical Rainfall Measurement Mission	NASA
CHIRPS	Climate Hazards Group InfraRed Precipitation Station	Climate Hazards Group

Table 5. Precipitation datasets specification

Abbreviation	Method	Resolution
TRMM	Microwave (TMI,SSMI,AMSU and AMSR) Infrared (GMS), Gauge data	0.25°
CHIRPS	CHPClim,Infrared & Microwave (TRMM (3B43) CFSv2. Gauge data	0.05°

Rainfall products are collected from different sources and use a variety of approaches to measure monthly precipitation (Table 4 & Table 5). TRMM precipitation dataset is derived from sensors (Passive microwave) and a radar (C-band) that are used for acquiring numerical rainfall details, that includes infrared measurements from TRMM and geostationary meteorological satellites (GMS). TRMM contains a 25*25 km resolution. CHIRPS precipitation dataset is an ensemble product with the highest spatial resolution 5*5 and is based on several interpolation algorithms employing a number of sources, including monthly Rainfall meteorological satellite measurements, a model (atmospheric) rainfall, and ground observations.(Funk et al., 2014) .

2.2.4 Evapotranspiration:

ET (evapotranspiration) contributes a crucial part in the hydrological process since it is responsible for a significant fraction of overall water discharge from the catchment. Vaporization from the earth, bodies of water, planted areas, and plant evapotranspiration are all examples of ET. In contrast to precipitation, data on ET is harder to come by. Unlike field data from rain gauges and satellite-based Rainfall datasets, data on evapotranspiration is generally limited, and its geographical and time to time variability can be very prominent. However, in recent decades, processes for estimating evapotranspiration from Satellite data utilizing the surface energy balance have upgraded, resulting in freely available global datasets. According to a review of (Karimi et al., 2015) Satellite based data techniques provide space to space thick measures of the actual evapotranspiration with a precision of 90%. In this study, the SSEBop (Operational Simplified Surface Energy Balance) was applied.

The Simplified Surface Energy Balance method (SSEB(Gabriel B. Senay et al., 2007)) is a world-wide implementation of the SSEB (Simplified Surface Energy Balance) technique that was primarily concentrated on tiny irrigation structures. SSEBop was successfully tested using Landsat data and lysimetere observations in the semi-arid Plains(G B Senay et al., 2014) , and was recently validated with 20 flux towers distributed across the country(Chen et al., 2016) . In the study of the Nile (Bastiaanssen et al., 2014) and the study of the Red River basins (Simons et al., 2016), SSEBop performed well.

2.2.5 Leaf Area Index (LAI):

In broadleaf canopies, LAI is defined as the one-sided green leaf area per unit ground area, while in coniferous canopies, it is defined as half of the total needle surface area per unit ground area. Green vegetation absorbs a percentage of photo synthetically active radiation (400-700 nm) called FPAR. Surface photosynthesis, evapotranspiration, and net primary production are calculated using both variables, which are then used to compute terrestrial energy, carbon, water cycle processes, and vegetation biogeochemistry. Over all biomes, algorithm enhancements have increased retrieval quality and consistency with field measurements, concentrating on woody vegetation.

2.2.6 Soil Moisture:

In catchment hydrology, groundwater plays a critical function. Despite advancements in obtaining groundwater estimates from gravimetric readings ((Yeh et al., 2006) , (Rodell et al., 2007)), estimating watershed-scale groundwater volumes remains problematic. However, remote sensing can be used to estimate the water quantity contained in the top strata of the soil(Nolet et al., 2014) . The ASCAT (The Advanced Scatterometer) is an operative microwave remote-sensing apparatus that is used in measuring wind over sea as well as soil moisture ((Wagner et al., 1999) ,(Naeimi et al., 2012)). In this study, Soil Water Index (SWI) is used to get information on the root-zone rather than just the top-layer. This tool estimates moisture present in the soil in relative units reaching from wilting to full congestion. The dataset uses an expanding colander to measure soil moisture in the deeper strata's (Albergel et al., 2008) . The software generates a set of 10 days moisture of soil estimations for each image using a different time integration, with longer time frames providing better estimates for deeper soil layers(Ceballos et al., 2005) . Data products produced over 60 days were aggregated into monthly maps to get information of water content in the soil layer. The maximum available moisture in soil and Soil Water Index were used to calculate the monthly soil water amount (swm;m). The WCavail (the available water content) between area capacity and wilting point was estimated using the depth of the soil layer (Zr ; m) and the available water content (WCavail).(Simons et al., 2020) , Who used pedotransfer functions to determine soil hydraulic parameters from the open-access global SoilGrids1*1 km dataset, provided maps of WCavail content (Hengl et al., 2014).

2.3 Processes Undertaken:

2.3.1 Data Preparation:

Remote Sensing datasets of precipitation, evapotranspiration, and Leaf Area Index and Soil moisture were converted to .tiff format. Each dataset was preprocessed and clipped according to the study Area i.e., Hunza and Astore Sub basins. Model Builder tool of Arc map was used for iteration of raster from the year 2007 to 2017. All datasets were projected to the same projected coordinate system, WGS_1984_UTM_zone_43N, for smooth process and calculations. For water balance calculation raster datasets were resampled to cell size (589.52m*589.52m). Rain gauge data obtained from PMD was daily estimates and converted to monthly values as the approach uses monthly datasets for better results.

2.3.2 The Coefficient of determination (R^2)

The R2 i.e., coefficient of determination is a coefficient of correlation squared value. The relationship is shown as follows:

$$R2 = \left(\frac{\Sigma ni = 1(Oi - O)(Pi - P)}{\sqrt{\Sigma ni = 1(Oi - O)2}\,\sqrt{\Sigma ni = 1(Pi - P)2}} \right) 2$$

Where, Oi is the observed value whereas Pi denotes the predicted value. It computes the mutual diffusion in contradiction of the single diffusion of the predicted and observed time series. The values of R2 ranges from 0 to 1 which depicts the diffusion in predicted in comparison with observed. A zero value indicates no correlation while 1 value indicates that the diffusion of the observed is precisely equal to the prediction. Comparison between remote sensing products of precipitation and meteorological data was made using R2. Two gridded data sets TRMM and CHIRPS were compared with PMD data to check their relationship with rain gauges data. R2 were also used to validate estimated rainfall runoff from the remote sensing model, and observed discharge field data from WAPDA.

2.3.3 Interception Calculation

Intercepted water from Rainfall by canopy cover is a vital mechanism in the water balance calculation since a segment of the captured water evaporates immediately and cannot be utilized for transpiration by runoff or vegetation. To measure the surface vegetation covered raea, the Leaf Area Index (LAI) was acquired from the Moderate Resolution Imaging Spectroradiometer (MODIS)(Boegh et al., 2002) . Equation (1) was used to compute the quantity of intercepted Rainfall (I; in mm) using the Leaf Area Index, precipitation, and an experiential coefficient (a) presenting the highest amount of water that can be trapped on a leaf. Value of empirical parameter (a) was used as a = 1 (mm/day) (1). The number of wet days per month and the remote sensing determined P were used to calculate daily Rainfall. The latter was derived from weather data.

$$I = a \times LAI \times 1 - \left(\frac{1}{1 + \left(\frac{1 + cc \times p}{a \times LAI} \right)} \right) \tag{1}$$

2.3.4. The Water Balance Model

The technique given is based on a water balance in a soil column with a defined depth using mass conservation principles. Monthly Rainfall in mm equals monthly discharge in mm, ET in mm, and changes in storage with no extra availability from stream input, flooding, and irrigation (soil moisture in mm). Sm-Sm-1 was used to calculate monthly storage changes.

$$Pm = Rm + ETm + \Delta Sm \tag{2}$$

The water present in the root area, SWm mentioned as the element of soil water, and an element of groundwater GWm, were separated from the component of water storage. The total of the two was used to determine the storage change.

$$\Delta Sm = \Delta GWm + \Delta SWm \tag{3}$$

Equation (4) was used to determine the pixel-wise surface runoff (Rm; mm) ((Choudhury & DiGirolamo, 1998),(Schaake et al., 1996)). The monthly variability of water on the ground soil, with Rainfall data and interception in mm and the root side moisture deficiency in mm, SWmax denotes the highest amount of soil moisture available (mm).

$$Rm = \frac{(Pm-Im)2}{Pm-Im+SWmax-swm} \tag{4}$$

Rm may produce reliable findings in small catchments, but it cannot be used in wider places because it does not feature a storage component or a retention time. As a result, a portion of total runoff is attributed to changes in storage, as illustrated in Equation (5), which combines Equations (2) and (4).

$$Pm - ETm = F \times \left(\frac{(Pm-Im)2}{Pm-Im+swmax-sw}\right) + (1-F) \times \Delta Sm \tag{5}$$

Remote sensing data can be used to solve Equation (4) and the left term of Equation (5). Modifications in GWm and SWm, on the other hand, are part of the storage changes. Microwave or thermal infrared measurements can be used to determine soil moisture (Nolet et al., 2014). Equation (6) closed the water balance because SWm can be determined from soil moisture maps. GWm is estimated from the discharge (Equation (7)), considering that slow groundwater runoff accounts for a percentage of the total discharge. The factor F is added to calibrate the model to ensure that the quantity of P-ET relates the stream flow and changes in storage on a basin level during the full catchment time. Because ΔS should be zero throughout the whole time period, parameter F is utilized to match the discharge with P-ET. As a result, since all components in Equation (6) are taken from the datasets obtained from remote-sensing, this statement can be stated that the calibration of factor F can be done without ancillary data.

$$Pm - ETm = F \times \left(\frac{(Pm - Im)2}{Pm - Im + swmax - sw}\right) + \Delta SWm + \Delta GWm \qquad (6)$$

$$\Delta GWm = (1 - F) \times (Rm - Rm - 1) \qquad (7)$$

For each gauging station, the monthly river flow was computed. Equation (8) was used to compute the monthly flow as the sum of the upstream area using direct runoff (Rm) and storage changes (ΔSm). Higher river levels arise with negative changes in ΔSm, while reduced direct runoff results from positive changes.

$$Qm = \Sigma Rm - \Delta Sm \qquad (8)$$

RESULTS AND DISCUSSIONS

3.1 Comparison and Validation of Precipitation:

Comparison and validation of satellite-derived monthly precipitation datasets was carried out with PMD rain gauge data from year 2007 to 2017. Regression analysis was used to examine the relationship between the satellite datasets and field data. Monthly datasets of TRMM rainfall and CHIRPS rainfall were plotted against monthly aggregated field data from PMD. Coefficient of determination were found useful in validating the datasets.

3.1.1 Astore Basin

For Astore Basin, TRMM and CHIRPS datasets were compared and validated against PMD data from the year 2007 to 2017. Comparison and distribution of field precipitation data at Rattu station with CHIRPS data is shown in figure 3. Figure represents that the CHIRPS data over estimates the precipitation values frequently in winters (December to February). It was noticed that precipitation is very high in summer with the highest precipitation in 2010. There are two main systems that contribute to Rainfall in winter (Western disturbances) and in summer (Monsoon). In winter, the satellite datasets represent higher precipitation estimated compared to the field data. The reason is the method (Cloud density measure) applied to estimate the Rainfall by satellite sensors. The gauging station are also very few and can be a cause of differences between remote sensing data and field data. In summer the satellite and field precipitation are mostly in a good relationship as shown in fig 3.

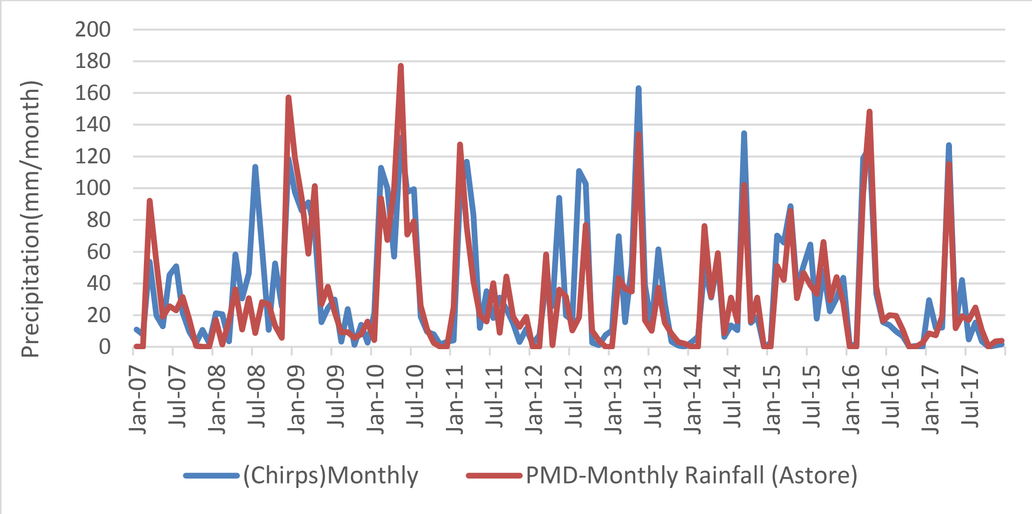


Figure 3. Represents a distribution and comparison between PMD and Chirps data precipitation in Astore basin (2007-2017).

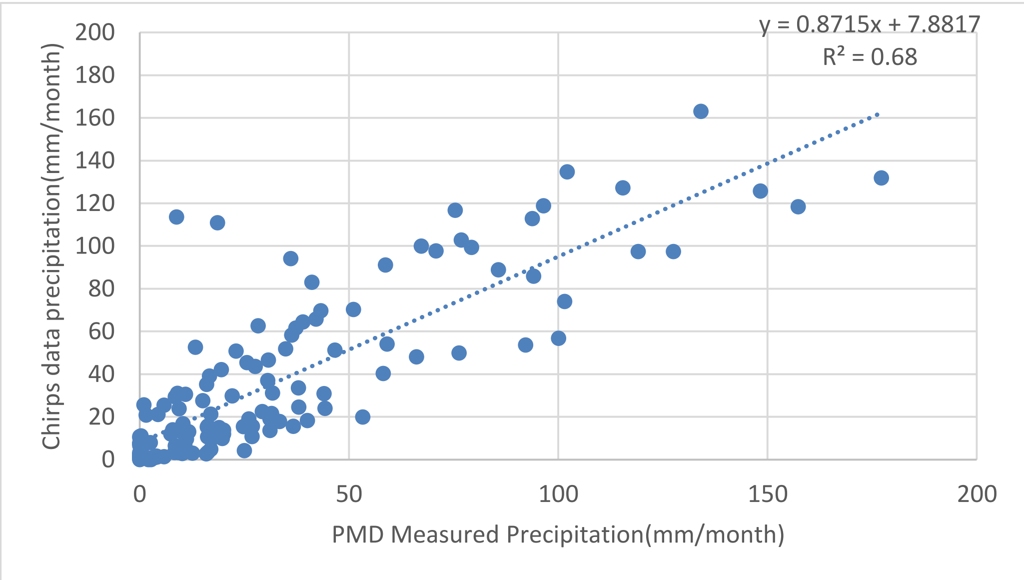


Figure 4. Comparison between PMD and Chirps data precipitation in Astore basin (2007-2017)

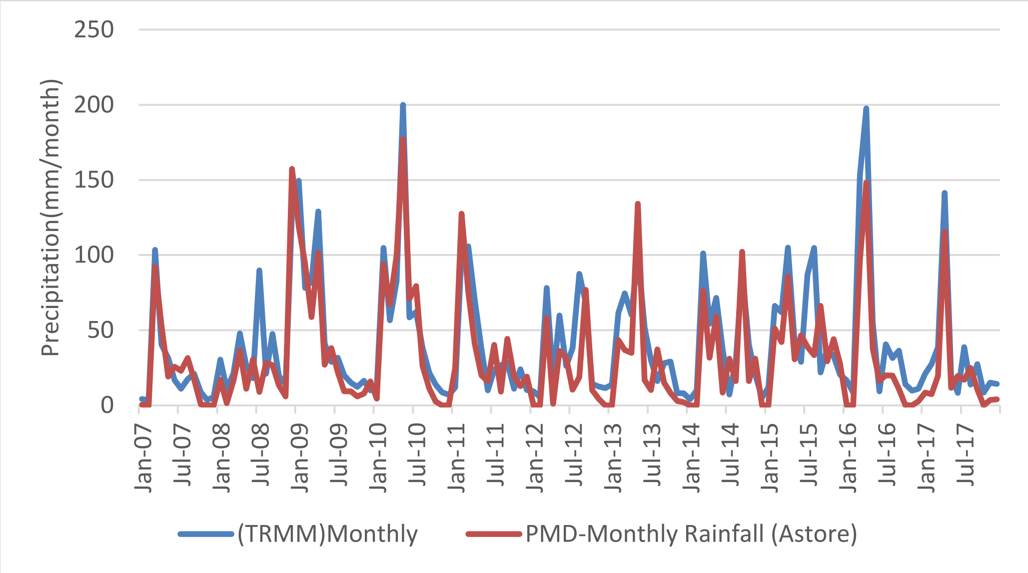


Figure 5. Represents a comparison between PMD and TRMM data precipitation in Astore Basin (2007-2017).

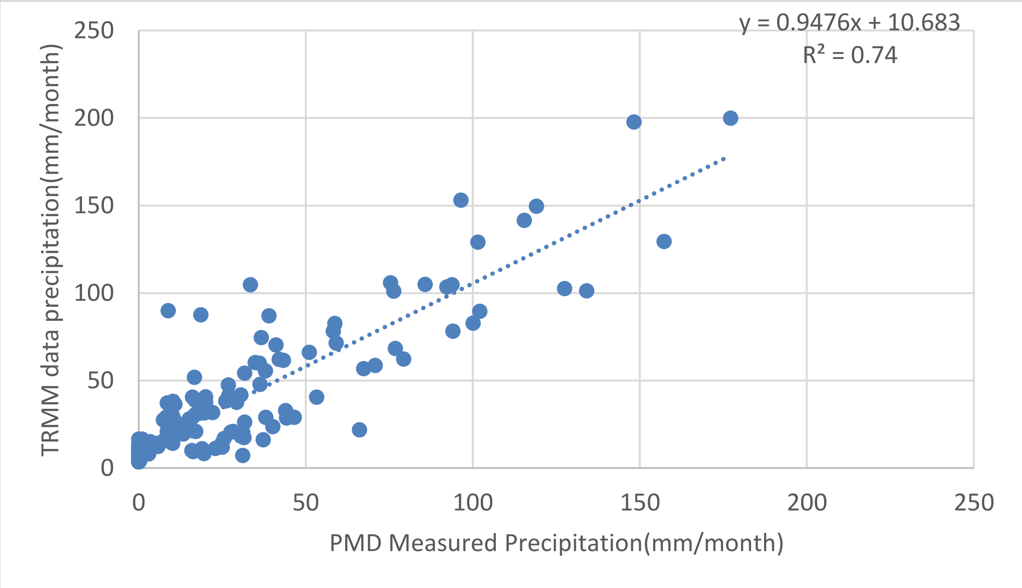


Figure 6. Represents a comparison between PMD and TRMM data precipitation in Astore Basin (2007-2017).

Coefficient of determination value R2 for Astore basin between CHIRPS data and rain gauge data was R2 = 0.68 as shown in figure 4. The R2 value does not represent a good relationship between CHIRPS and rain gauge data, however it can be consider as acceptable.

Monthly TRMM data from the year 2007 to 2017 was also used to compare and validate with field data from PMD. Field data from Rattu station of Astore is plotted with TRMM precipitation data as shown in figure 5. The monthly TRMM precipitation dataset presents a better relationship in the Astore basin with PMD field data.

R2 value for Astore basin by plotting TRMM data against PMD data was R2= 0.74 as shown in figure 6. The R2 value using the TRMM dataset presents a better relationship with PMD data than the CHIRPS precipitation dataset.

3.1.2 Hunza Basin

TRMM and CHIRPS precipitation datasets have also been compared and validated with PMD field data in Hunza basin from 2007 to 2017. CHIRPS precipitation dataset was plotted against PMD field data at Naltar Station of Hunza basin. Figure 7 shows the distribution of PMD rainfall from year 2007 to 2017 with CHIRPS precipitation dataset. It can be seen that Rainfall is also over estimated by CHIRPS data in Hunza Basin, especially in the winter season. Rainfall is also less in summers in the Hunza basin, with the highest precipitation in spring 2008.

Coefficient of determination R2 of CHIRPS data with PMD data from year 2007 to year 2017 in Hunza basin is R2= 0.66 (figure 8).

TRMM datasets for the Hunza basin has been compared and validated with PMD data from year 2007 to 2017. PMD data from Naltar station was plotted against the pixel based value of TRMM dataset. Figure 9 shows the distribution of Rainfall from 2007 to 2017 with a comparison of Rainfall between field data and TRMM data. The arrangement of TRMM values with PMD data shows better performance than CHIRPS dataset.

TRMM datasets for the Hunza basin has been compared and validated with PMD data from year 2007 to 2017. PMD data from Naltar station was plotted against the pixel based value of TRMM dataset. Figure 9 shows the distribution of Rainfall from 2007 to 2017 with a comparison of Rainfall between field data and TRMM data. The arrangement of TRMM values with PMD data shows better performance than CHIRPS dataset.

The coefficient of determination R2 of TRMM data with PMD data from year 2007 to year 2017 in Hunza basin is, R2= 0.71 (figure 10). TRMM dataset also presents better performance in Hunza basin as compared to CHIRPS dataset. In both Sub basins (Hunza & Astore) of the Upper Indus Basin, TRMM rainfall dataset performed better.

TRMM dataset shows good performance as compared to CHIRPS dataset in Hunza and Astore basins. CHIRPS precipitation data depicted very high values as compared to TRMM precipitation data. Despite high resolution of CHIRPS precipitation data the quality of TRMM precipitation data present better performance. Based on the performance and R2 values the TRMM dataset was used in remote sensing based water balance model.

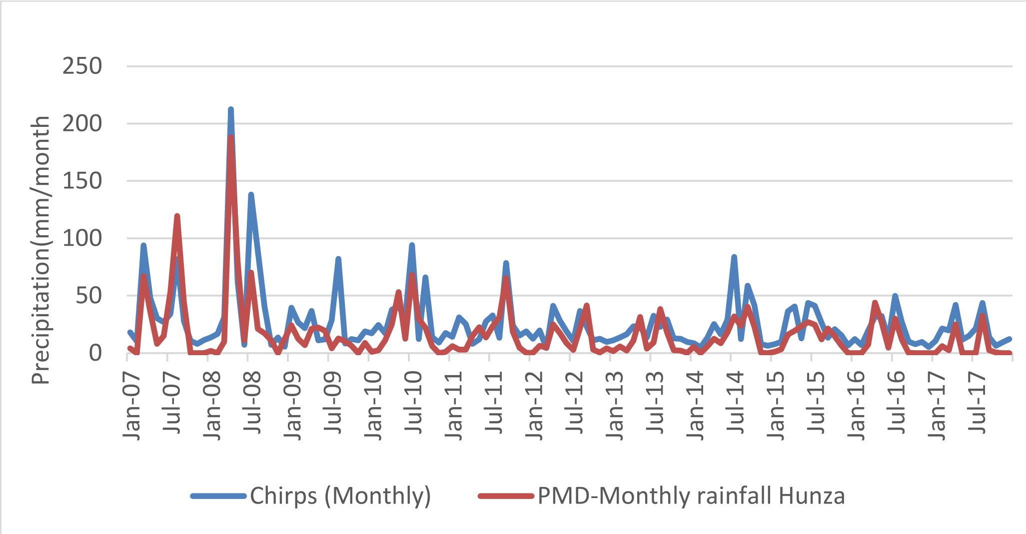


Figure 7. Represents a comparison between PMD and CHIRPS data precipitation in Hunza Basin (2007-2017).

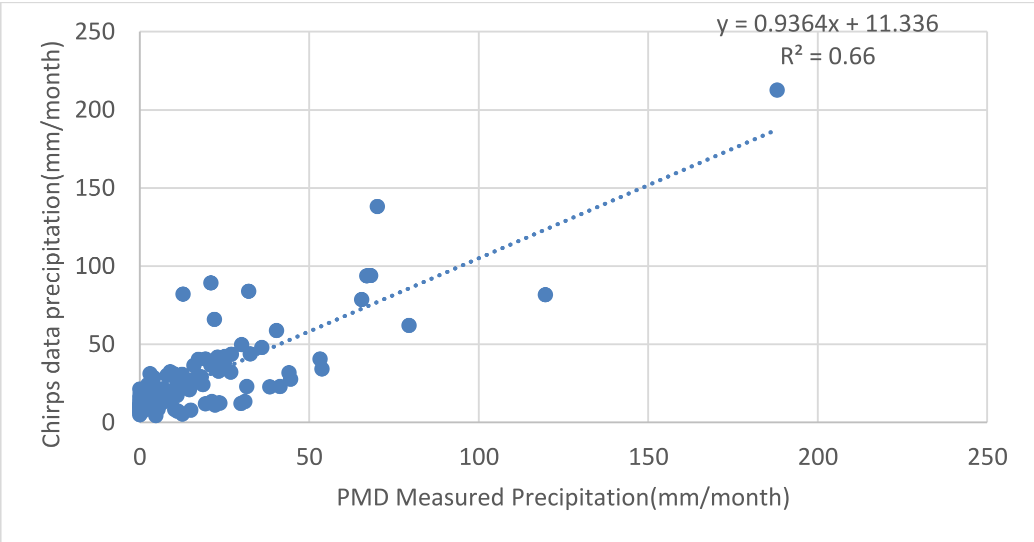


Figure 8. Represents a comparison between PMD and CHIRPS data precipitation in Hunza Basin (2007-2017).

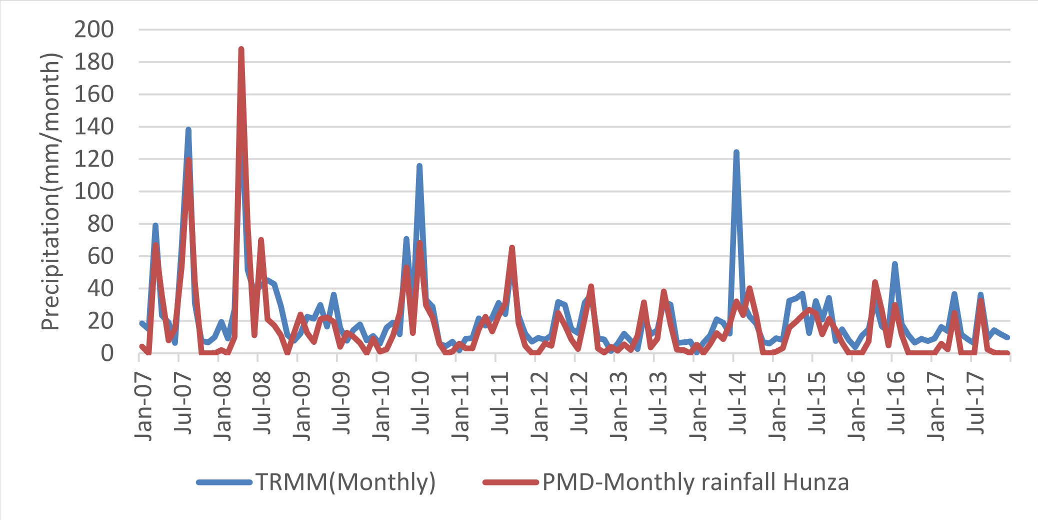


Figure 9. Represents a comparison between PMD and TRMM data precipitation in Hunza Basin (2007-2017).

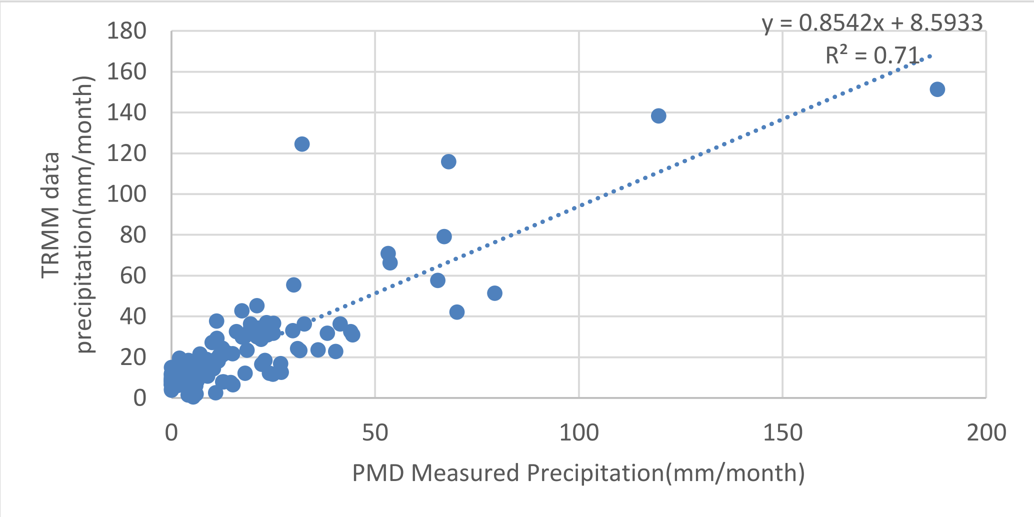


Figure 10. Represents a comparison between PMD and TRMM data precipitation in Hunza Basin (2007-2017).

3.2. Water Balance Model

The method produced significant and operational pixel based runoff estimates. For the process of interception calculation daily Rainfall data was used in order to acquire interception of every event of Rainfall. Rainfall runoff was calculated on raster images as implies by the method. Pixel based Rainfall runoff was calculated from year 2008 to 2017 in Arc map using raster images. Rainfall runoff maps from year 2008 to 2017 was generated for final discharge estimates using Zonal stat tool in Arc map. Some of the rainfall-runoff maps are shown ahead for March and July of year 2008, 2011, 2014 & 2017 respectively. Pixel-based rainfall runoff was calculated in mm/month. Rainfall-runoff maps for Astore basin are shown in figures.

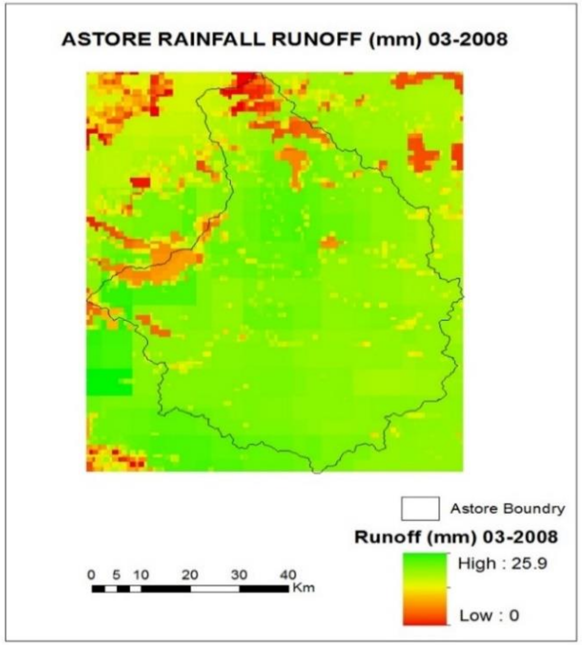
Rainfall runoff maps for Hunza basin from year 2008 to 2017 were generated using water balance equations and some of the maps of March and July for year 2008, 2011, 2014 & 2017 are shown in figures.

Runoff map of Astore Basin 03-2008 and 07-2008 with the highest value of 25.9mm/month and with the highest value of 213.4 mm/month respectively are shown in figure 11. Green pixels present higher Rainfall-runoff values and red pixels for low Rainfall-runoff in mm/month. Figure 12 presents the Runoff map of Astore Basin 07-2011 with the highest value of 206.8 mm/month and the Runoff map of Astore Basin 03-2011 with the highest value of 88.63 mm/month. The Rainfall-runoff is increased here in 03-2011, with less green pixels as compared to 03-2008. Runoff map of Astore Basin 03-2014 with highest value of 155.8 mm/month and the Runoff map of Astore Basin 07-2014 with highest value of 235.5 mm/month are presented in figure 13. The Runoff map of Astore Basin

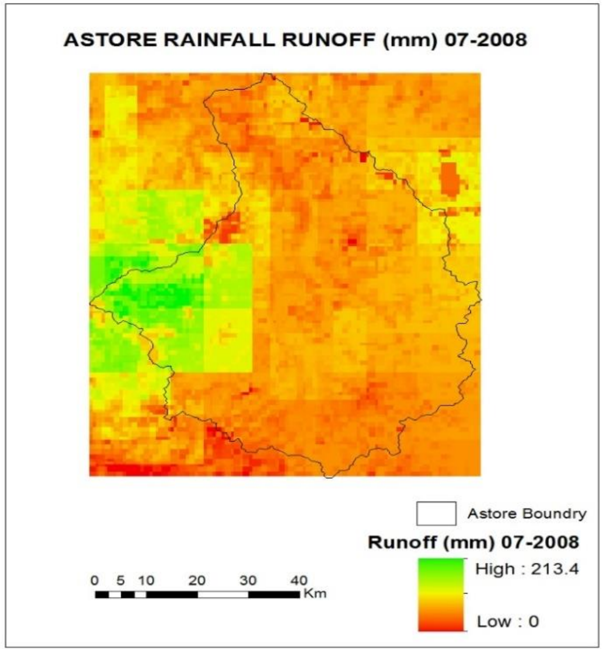
03-2017 with highest value of 53.21 mm/month and the Runoff map of Astore Basin 07-2017 with highest value of 190.7 mm/month (figure 14).

For the Hunza basin, figure 15 shows the Runoff map of Hunza Basin 03-2008 with highest value of 24.66 mm/month and the Runoff map of Hunza Basin 07-2008 with highest value of 226.7mm/month. Green pixels present higher Rainfall-runoff values and red pixels for low Rainfall-runoff in mm/month. The Runoff map of the Hunza Basin 03-2011 with highest value of 77.41 mm/month and the Runoff map of the Hunza Basin 07-2011 with highest value of 246.5 mm/month is shown in figure 16. Runoff map of the Hunza Basin 03-2014 with highest value of 86.22 mm/month and the Runoff map of the Hunza Basin 07-2014 with highest value of 218.5 mm/month (figure17). Figure 18 presents the Runoff map of Hunza Basin 03-2017 with highest value of 55.27 mm/month and the Runoff map of Hunza Basin 07-2017 with highest value of 231.6 mm/month. The runoff maps depicted that in monsoon season there is more rainfall that contributes to Rainfall runoff.

Water balance model has been implemented on monthly temporal resolution from 2008 to 2017. The resulted pixel-based runoff maps in mm has been displayed only for the month of March and July in year 2008, 2011, 2014, and 2017 for comparison of results. Maps were generated for all months from 2008 to 2017. Pixel-based rainfall runoff is used in estimating whole catchment discharge by sum of the upstream area with the help of zonal stat tool in Arc map. Rainfall-runoff sum and storage change gives the discharge estimates of the both basins. The table shows some of the estimated discharge values by water balance model from the year 2008 to 2017.

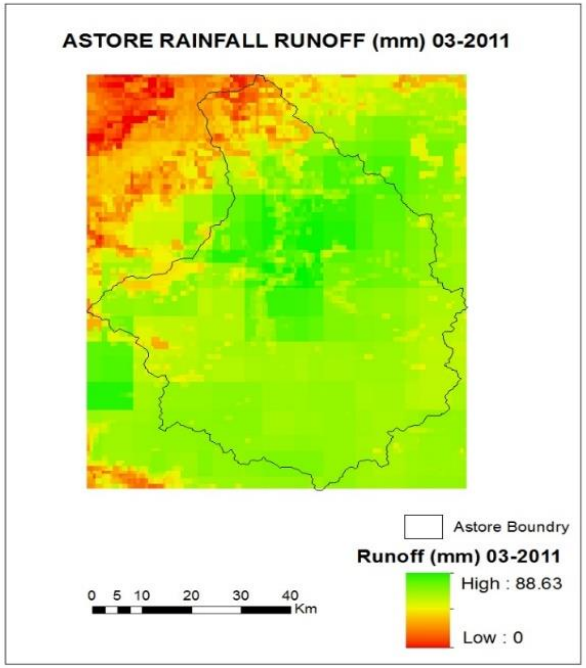


a)

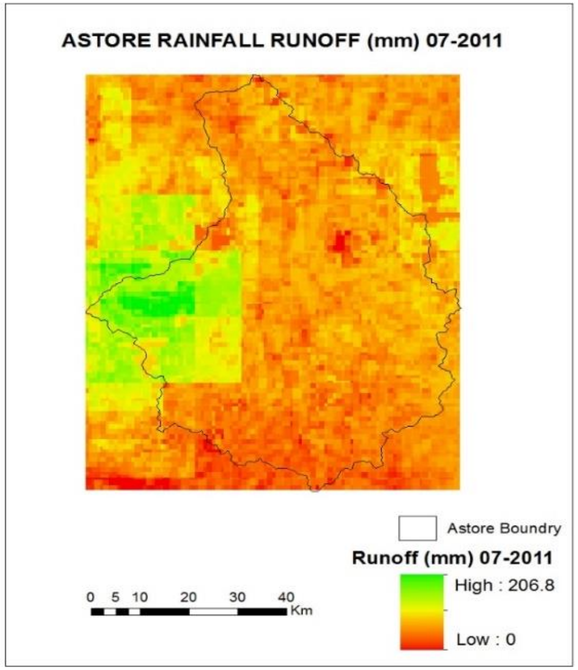


b)

Figure 11. Presents the Runoff map of the Astore basin 03-2008 (a) and 07-2008 (b).

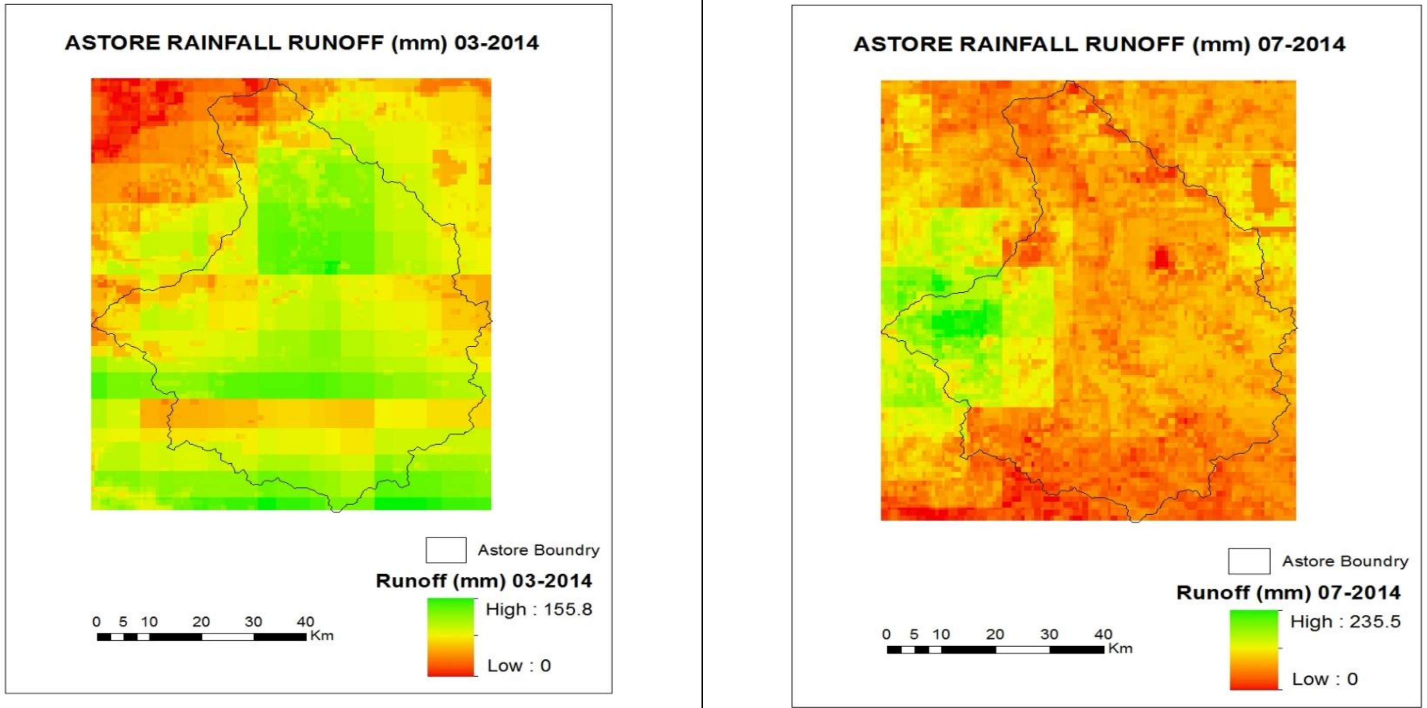


a)



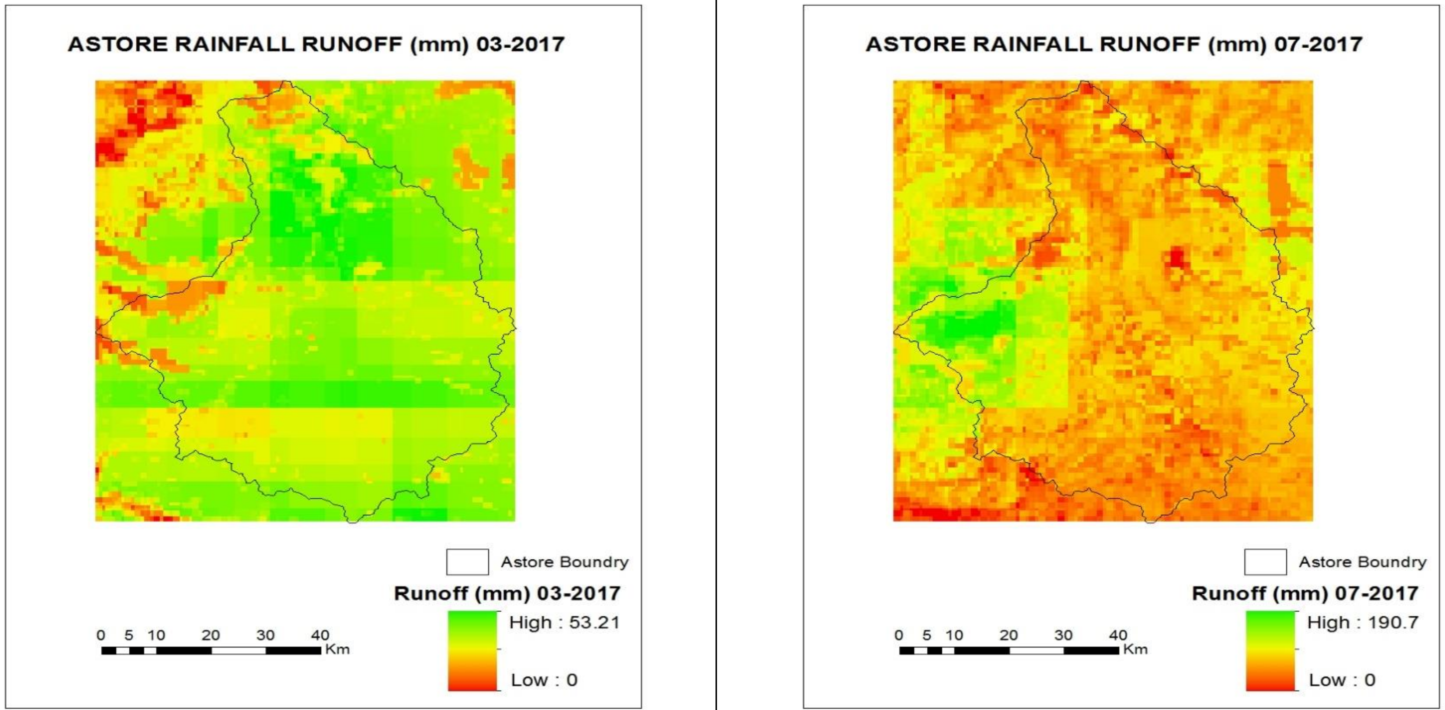
b)

Figure 12. Presents the Runoff map of the Astore basin 03-2011 (a) and 07-2011 (b).



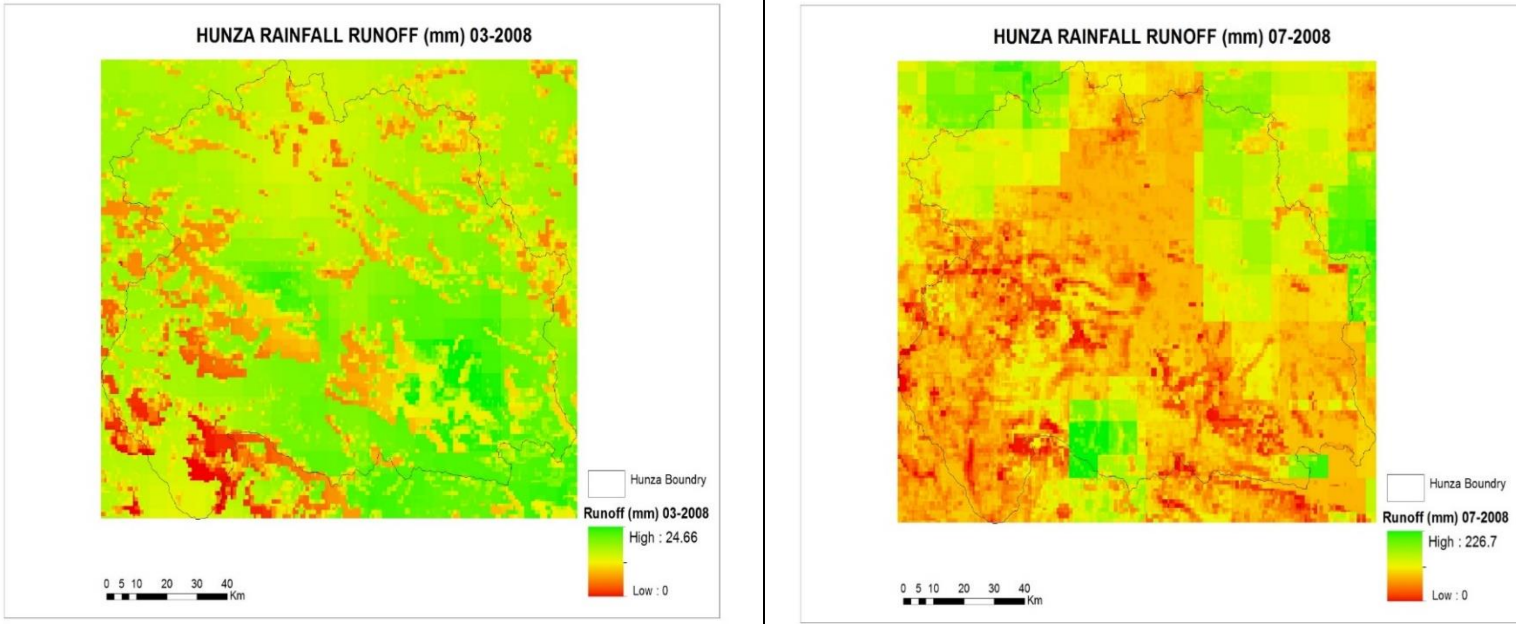
a) b)

Figure 13. Presents the Runoff map of the Astore basin 03-2014 (a) and 07-2014 (b).



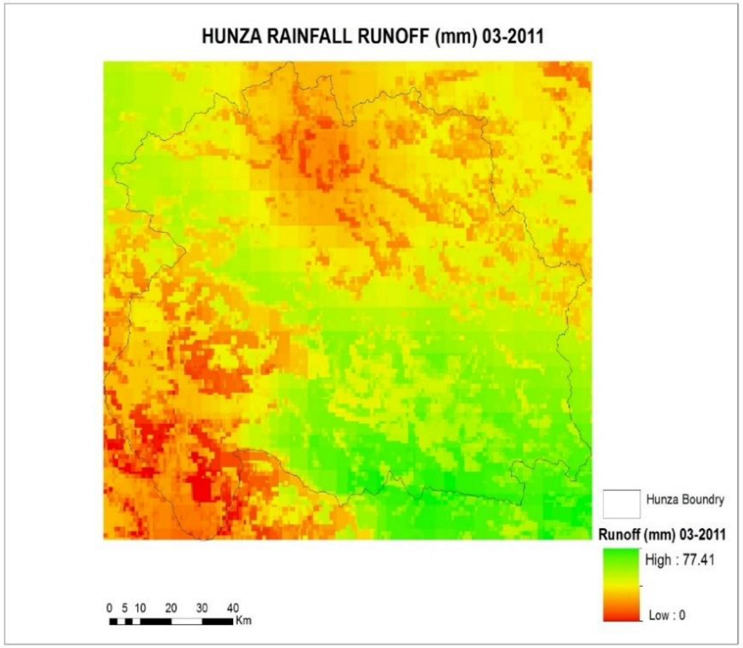
a) b)

Figure 14. Presents the Runoff map of the Astore basin 03-2017 (a) and 07-2017 (b).

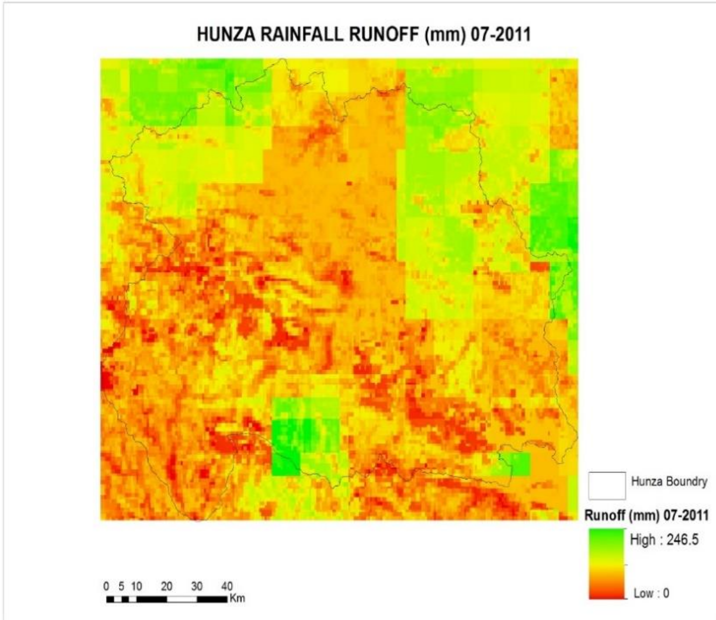


a) b)

Figure 15. Presents the Runoff map of the Astore basin 03-2008 (a) and 07-2008 (b).

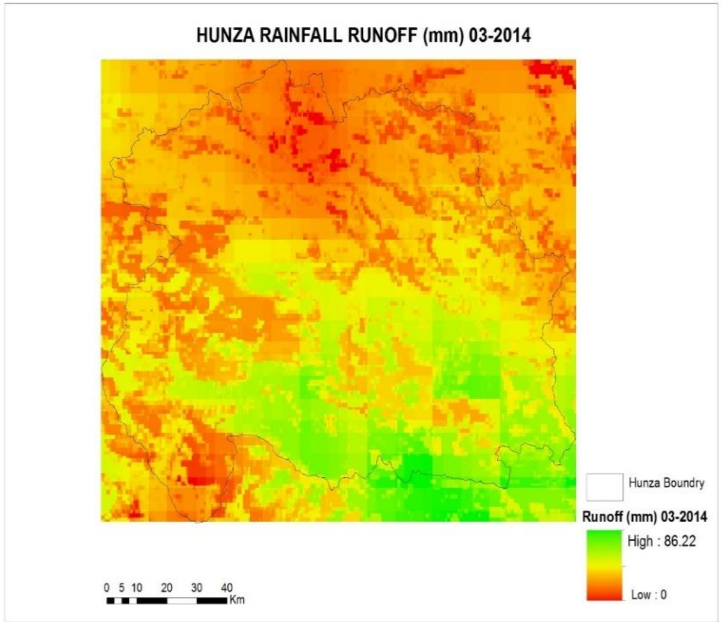


a)

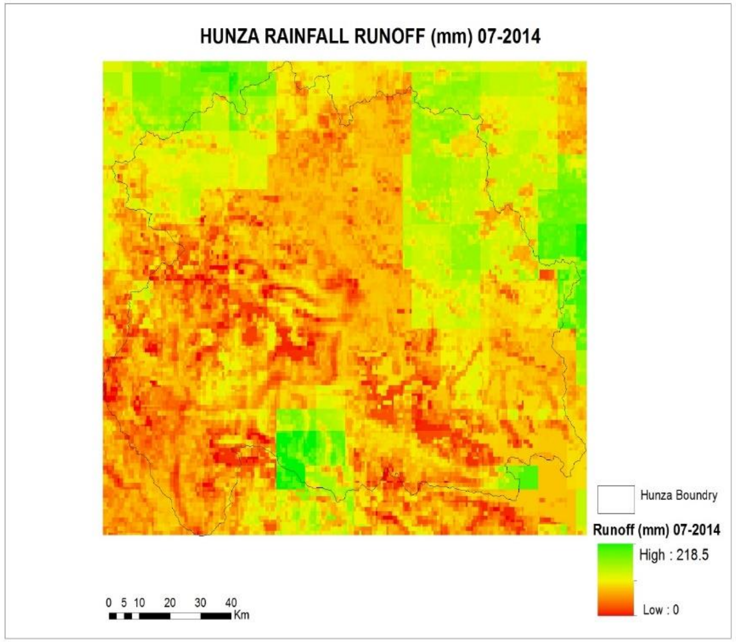


b)

Figure 16. Presents the Runoff map of the Hunza Basin 03-2011 and 07-2011.



a)



b)

Figure 17. Presents the Runoff map of the Hunza basin 03-2014 (a) and 07-2014 (b).

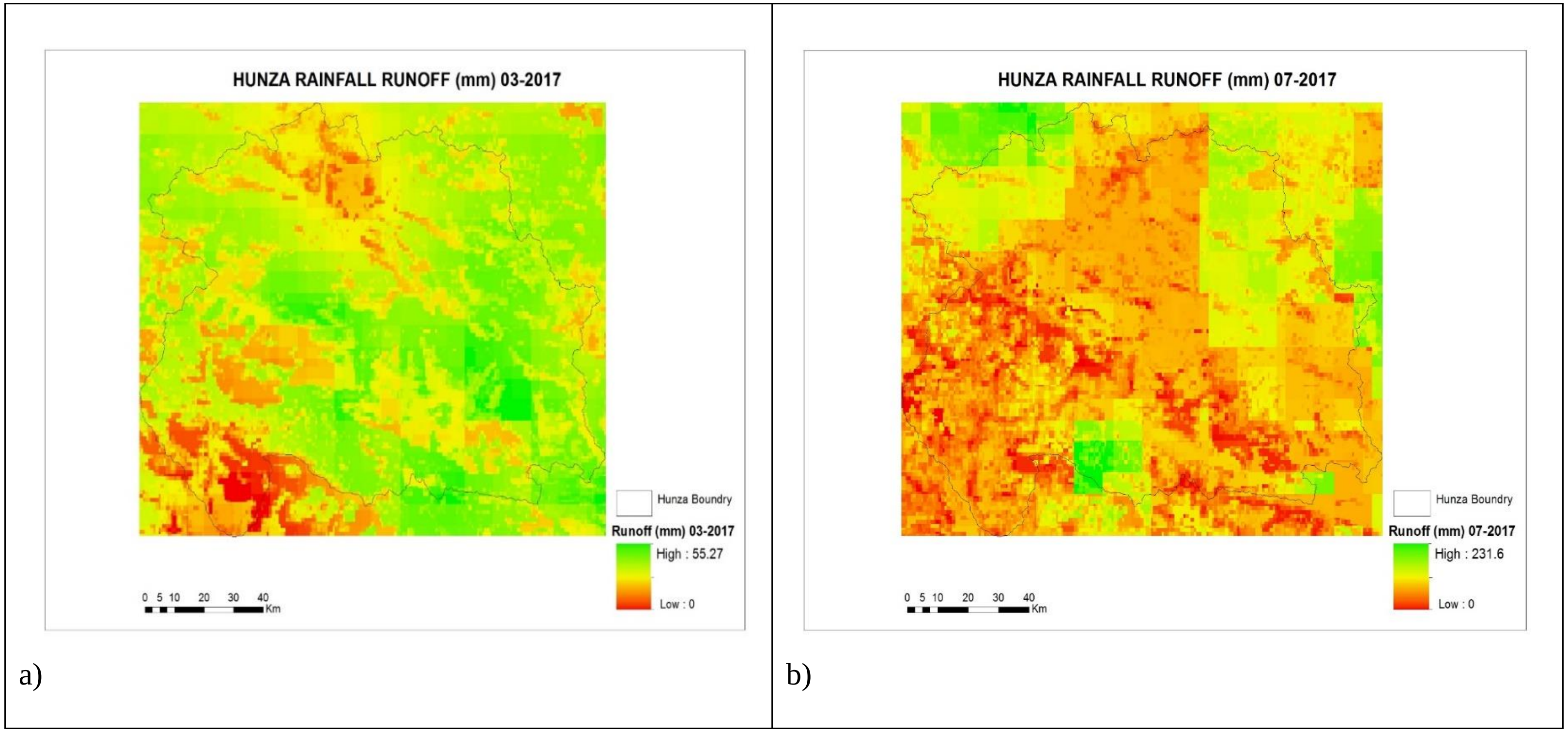


Figure 18. Presents the Runoff map of the Hunza basin 03-2017 (a) and 07-2017 (b).

3.3 Comparison and Validation of Runoff:

Comparison and validation of remote sensing-based derived monthly discharge estimates was carried out with WAPDA discharge station data from 2007 to 2017. Regression analysis was used to examine the relationship between the satellite datasets and field data. Monthly discharge estimates derived from remote sensing-based water balance model of Astore basin from 2008 to 2017 were validated with WAPDA station data. Discharge estimates of Hunza sub-basins were plotted against monthly aggregated field data from WAPDA stations from 2008 to 2017. Coefficient of determination were found useful in validating the datasets.

For Astore Basin, Estimated Rainfall-runoff was compared and validated against WAPDA station data from the year 2008 to 2017. The distribution of field discharge data at Doyian station with estimated discharge data from year 2008 to 2017, is shown in figure 19. The figure represents that the simulated runoff from the model over estimates the runoff values frequently in winters (December to February). The reason is that the method simulates Rainfall-runoff using satellite derived Rainfall products. These products over estimated the precipitation values in winters as already discussed. The coefficient of determination R2 of estimated discharge values with WAPDA station data from year 2008 to year 2017 in Astore basin is R2= 0.75 is, shown in figure 20. Calculated runoff from water balance model represented a good relationship with field data. For Hunza Basin, Estimated rainfall runoff was compared and validated against WAPDA station data from year 2008 to 2017. The distribution of field discharge data at Daniyor bridge station with estimated discharge data from year 2008 to 2017, is shown in figure 21.

The figure represents that the simulated runoff from model over estimates the runoff values frequently in winters (December to February). The reason is that the method simulates rainfall runoff using satellite derived rainfall products. These products over estimated the precipitation values in winters as already discussed.

The coefficient of determination (R2)of estimated discharge values with WAPDA station data from year 2008 to year 2017 in Astore basin is R2= 0.70 as shown in figure 22.

The coefficient of determination R2 were find useful in validation between field discharge and simulated discharge data. Remote sensing based water balance model performed better in Astore basin with R2 value of 0.75. This much R2 values are considered good in hydrological studies. The performance of model was also found acceptable in Hunza basin with R2 value of 0.70.

Table 6. Runoff of Astore Basin from 2008 to 2017

Sr. No.	Area	Month & Year	Calculated Runoff (m3/s)
1.	Astore	March 2008	68.91
2.	Astore	March 2011	116.89
3.	Astore	March 2014	88.31
4.	Astore	March 2017	67.12
5.	Astore	July 2008	376.34
6.	Astore	July 2011	186.63
7.	Astore	July 2014	391.77
8.	Astore	July 2017	254.39

Table 7. Runoff of Hunza Basin from 2008 to 2017

Sr. No.	Area	Month & Year	Calculated Runoff (m3/s)
1.	Hunza	March 2008	125.44
2.	Hunza	March 2011	144.52
3.	Hunza	March 2014	96.18
4.	Hunza	March 2017	83.92
5.	Hunza	July 2008	854.62
6.	Hunza	July 2011	602.94
7.	Hunza	July 2014	968.19
8.	Hunza	July 2017	982.14

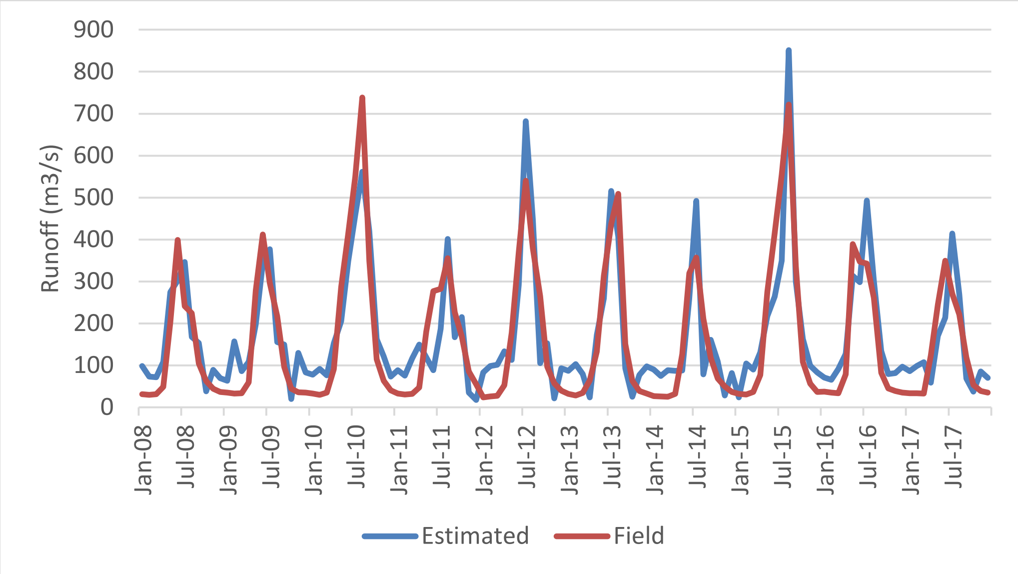


Figure 19. Compares the estimated runoff from model and WAPDA station data in Astore Basin (2008-2017).

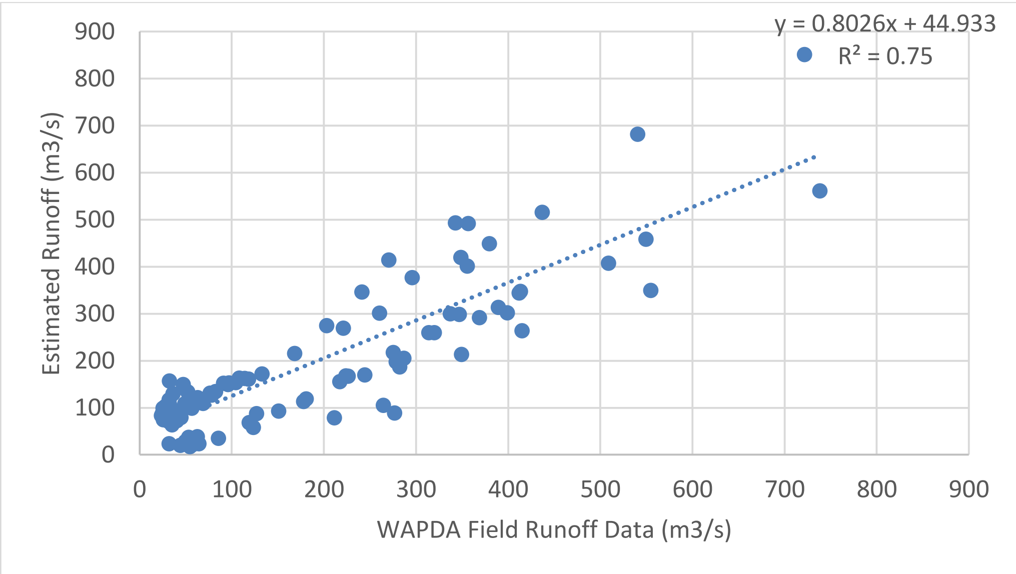


Figure 20. Compares the estimated runoff from model and WAPDA station data in Astore Basin (2008-2017).

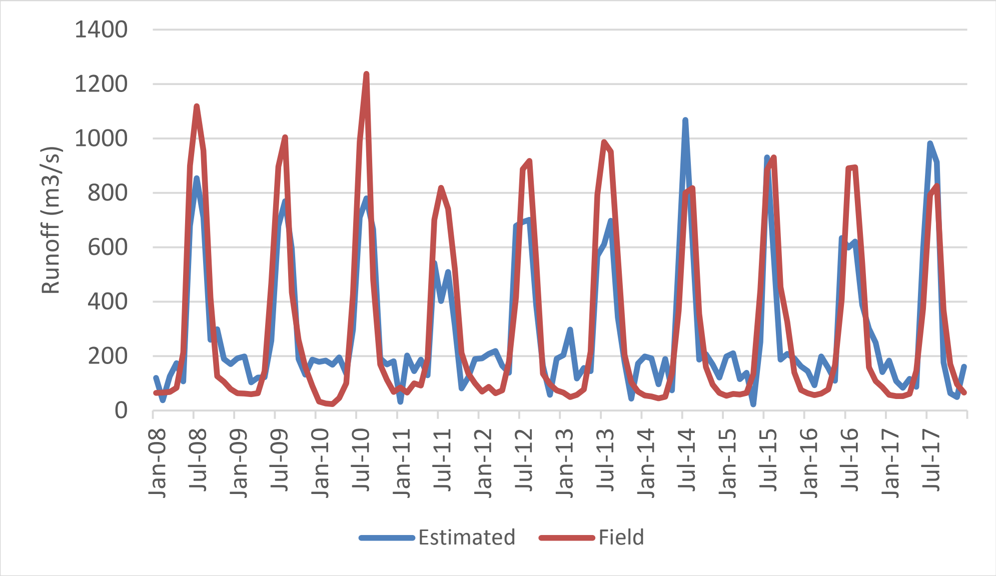


Figure 21. Compares the estimated runoff from model and WAPDA station data in Hunza Basin (2008-2017).

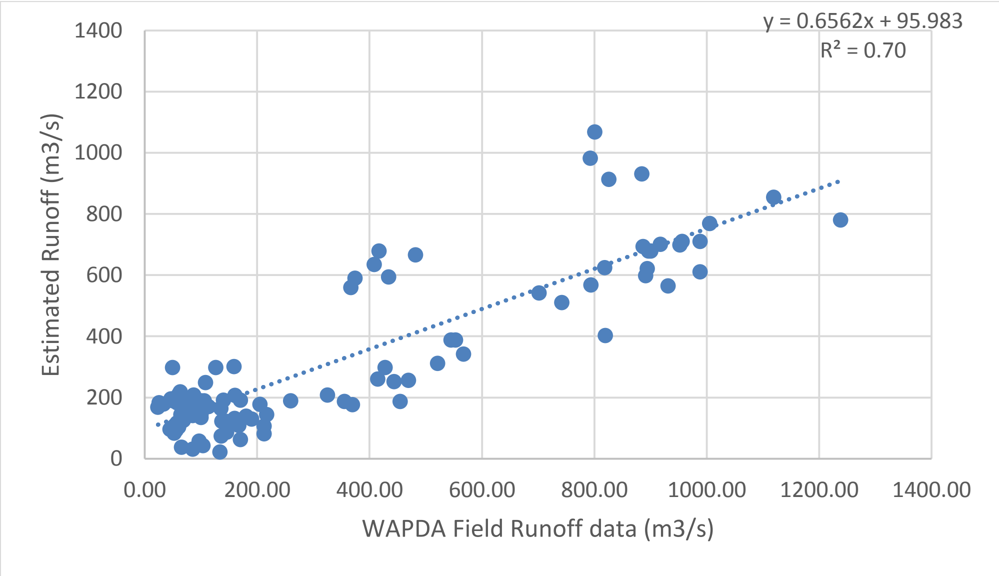


Figure 22. Compares the estimated runoff from model and WAPDA station data in Hunza Basin (2008-2017).

CONCLUSTION AND RECOMMENDATIONS

4.1 Conclusions

This study demonstrated completely remote sensing-based approach for stream flow estimation using water balance. The study examines the efficiency and accuracy of remote sensing derived precipitation datasets with rainfall gauging station data and the validation of remote sensing-based water balance estimation approach for stream flow estimation with river flow station observations. Performance of TRMM precipitation product with rainfall gauging station data was better in Astore and Hunza sub-basins as compared to CHIRPS precipitation data. In the Astore basin, the coefficient of determination R2= 0.74 of TRMM data shows a better relationship with gauge data than R2=0.68 of CHIRPS data. TRMM data also expressed acceptable and better performance in Hunza basin with R2 value of 0.71 as compared to the CHIRPS precipitation data with R2= 0.66. CHIRPS precipitation dataset present very high precipitation values despite higher resolution than TRMM precipitation dataset. TRMM precipitation dataset on the other hand performed better and presented higher R2 value than CHIRPS precipitation dataset.

Runoff estimation using remote sensing-based water balance demonstrated acceptable performance with river station data. In the Astore basin, discharge estimated using water balance R2= 0.75 depicts better correspondence with field observation data. Hunza basin R2= 0.70 also demonstrated acceptable performance with river station data. The reason behind the difference of efficiency between Hunza and Astore basin is that the following approach does not contain a temperature component in the model so it does not consider the runoff generated by snow melt. Hunza contains a high percentage of covered snow area and therefore with low R2 value. Whereas Astore receives a good amount of rainfall by moon soon and western disturbances with lesser snow covered area, eventually with better R2 values. The reason could also be the location of rain gauge. There is also an issue of correspondence of point location based gauge data and raster dataset. This technique offers a quick and accurate way for mapping water resources in ungauged basins with low budget cost, allowing the management to make decision in the environment of climate change and increased urge on minimized water resources.

4.2 RECOMMENDATIONS FOR FURTHER RESEARCH

The presented technique is limited to monthly and annual temporal resolution and is incapable of ingesting daily or hourly data, so a new, improved remote sensing-based method for this purpose is required to minimize this limitation. In this method, manmade interventions like irrigation systems and hydraulic infrastructure are ignored. Massive rearrangement of water resources, viewable from satellite and so included in evapotranspiration and soil water index calculations, is missing from the supply side of the water balance equation.

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