Streamflow and Sediment Yield Analysis for Evaluating Best Management Practices under Changing Climate

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by
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Dedicated to My Dear Childrens, Wife, Beloved Parents, and Family Members

Every challenging work needs self-efforts, hard work, and guidance from elders

NATIONAL INSTITUTE OF TECHNOLOGY
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CERTIFICATE

This is to certify that the thesis entitled **"STREAMFLOW AND SEDIMENT YIELD ANALYSIS FOR EVALUATING BEST MANAGEMENT PRACTICES UNDER CHANGING CLIMATE"** being submitted by **Mr. NAGIREDDY NAGESWARA REDDY** for the award of the degree of **DOCTOR OF PHILOSOPHY** in the Department of Civil Engineering, National Institute of Technology, Warangal, is a record of bonafide research work carried out by him under my supervision and it has not been submitted elsewhere for the award of any degree.

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Dissertation Approval

This dissertation entitled **"STREAMFLOW AND SEDIMENT YIELD ANALYSIS FOR EVALUATING BEST MANAGEMENT PRACTICES UNDER CHANGING CLIMATE"** by **Mr. Nagireddy Nageswara Reddy** is approved for the degree of **Doctor of Philosophy.**

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DECLARATION

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Abstract

Streamflow and sediment yield are the important aspects in river systems. Assessing the consequences of anthropogenic changes is important for optimal management of land and water resources in the basins. Soil erosion is a major environmental issue that has a harmful effects on crop yields, the quality of water, aquatic ecosystems, and river morphology. When soil erosion flows into reservoirs and rivers from croplands, it generates a variety of contaminants and causes a variety of water pollution issues. So, it is necessary to analyse the streamflow and sediment transport in the river basins to identify the critical source areas and to evaluate the Best Management Practices. In the present research work, Nagavali and Vamsadhara basins are considered as study area. These two east flowing medium-sized basins in Peninsular India are prone to frequent flooding due to heavy rainfall in the monsoon season and tropical cyclones formed by low-pressure depressions in the Bay of Bengal (BoB) during pre- and post-monsoon seasons. Based on the proposed objectives of the research work, a detailed methodology for the research is developed. With the developed methodology, work has been carried out in three modules.

In the first module, SWAT model calibration and validation, water balance components, spatial distribution of precipitation, streamflow, groundwater flow, evapotranspiration and sediment yield over Nagavali and Vamsadhara basins is analysed using Indian Meteorological Data. The critical sediment source areas are identified for both river basins. The obtained statistics over the Nagavali and Vamsadhara basins range from very good to satisfactory, indicating the SWAT model's acceptance. From the water balance analysis evapotranspiration is the dominant process, accounting for 63% of the average annual rainfall over the basins. From the sub-basin average annual sediment yield analysis, 26.5% of Nagavali and 49% of Vamsadhara basin area are falls under high erosion.

In the second module, the effect of climate change on streamflow and sediment yield is carried out using downscaled bias corrected GCMs under SSP245, SSP370 and SSP585 scenarios for three-time frames, historical (1975–2014), near future (2022–2060), and far future (2061–2100). Selection of climate models is carried out to identify the Wet and Dry models based on the changes in average annual precipitation (ΔP) and average temperature (ΔT) across the Nagavali and Vamsadhara watersheds between the model's historic data (1975–2015) and the projected future data (2022–2100). The implications of climate change on precipitation, streamflow and sediment yield is performed. The spatial distribution of precipitation, steamflow and sediment is performed under Cold-Wet and Warm-Dry models. From future projections, the increase in mean annual precipitation (ΔP) and mean temperature (ΔT) are expected to vary across different scenarios. The climate models provide divergent future scenarios for the Nagavali and Vamsadhara basins. The ACCESS-CM2 model predicts a Warm-Dry future, while the EC-Earth3 model predicts a Cold-Wet future. In the near and far future, the percentage change in precipitation for these watersheds will range from 5.35 to 35.1% and −1.57 to 8.48% under the Cold-Wet and Dry-Warm models, respectively. This indicates that there will be an increase in streamflow and sediment yield for these watersheds.

In the third module, four individual (i.e, filter strips, sedimentation ponds, contour farming and contour stone bunding) and four combined BMP scenarios are evaluated for effectiveness to reduction of sediment yield and streamflow at critical sub-basins. From the results, Filter strips with a width of 10 meters demonstrated notable efficiency in reducing sediment yield. Particularly, filter strips contributed to a substantial 73% reduction in sediment yield without influencing streamflow in the critical sub basins across both basins. It is concluded that 10-meter-wide filter strips exhibited the most efficient reduction in sediment yield under individual BMP scenarios, followed by filter strips of 6 meters, contour stone bunding, 3-meter-wide filter strips, sedimentation ponds, and contour farming. Similar results are observed in BMPs efficacy under future climate change scenarios. Sedimentation ponds produce more efficient reduction in streamflow followed by contour farming and contour stone bunding under individual BMP scenarios. Moreover, the combination of BMPs resulted in a substantial decrease in sediment yield by 37% and 72%, coupled with a reduction in streamflow by 16.50% and 54% over the Nagavali and Vamsadhara basins, respectively. This combined BMP approach proved to be highly effective in reducing sediment and streamflow at critical sub-basin and basin levels. Under future climate change scenarios, the combined BMPs from BMP1 to BMP4 yielded the higher reductions in sediment yield surpassing individual BMP impacts. By mitigating soil erosion and improving water management, this research will contribute to sustaining soil fertility and agricultural productivity. This is particularly crucial for the livelihoods of communities in the river basins, where agriculture is a primary occupation. Methodology developed in this research work can be easily extended for other river basins for controlling sediment yield.

Keywords: Best Management Practices (BMPs), Calibration, Climate Change, Critical Source Area (CSA), Sediment, Streamflow, and SWAT.

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Nomenclature

O_i	:	i^th Observed rainfall value
S_i	:	i^th Simulated rainfall value
O_i^{obs}	:	i^th Observed streamflow data
O_i^{sim}	:	i^th Simulated streamflow data
O_{mean}^{obs}	:	Mean of observed streamflow data
SW_{ti}	:	Soil water content at the end of the day (mm)
SW_O	:	Amount of initial soil water content on day i (mm)
R_{dayi}	:	Amount of precipitation on day i (mm)
Q_{surfi}	:	Amount of surface runoff on day i (mm)
E_{ai}	:	Amount of evapotranspiration on day i (mm)
W_{seepi}	:	Amount of water entering the vadose zone from the soil profile on day i (mm)
Q_{gwi}	:	Amount of return flow on day i (mm)
ΔP	:	Mean annual precipitation
ΔT	:	Mean annual temperature
$\log Q_T$	:	log of discharge of required return period
$Q_m \log Q$	:	Mean of log of annual maximum series
$\sigma \log Q$	:	Standard deviation of log of AMS
$K(T)$	:	Frequency factor of return period (T)
SY	:	Sediment yield (tons)
Q_{surf}	:	Surface runoff volume (mm/ha)
A_{hru}	:	area of HRU (ha)
q_{peak}	:	Peak runoff rate (m^3/s)
C	:	USLE cover and management factor
K	:	USLE soil erodibility factor
P	:	USLE support practice factor
LS	:	USLE topographic factor
$CFRG$	:	Coarse fragment factor

Abbreviations

AGNPS	:	Agricultural Non-point Source Pollution model
ALPHA_BF	:	Baseflow alpha factor
AMS	:	Annual Maximum Series
ANSWERS	:	Areal Nonpoint Source Watershed Environment Response Simulation
AR	:	Assessment Report
BMPs	:	Best Management Practices
BoB	:	Bay of Bengal
CMIP-6	:	Coupled Model Intercomparison Project-6
CSAs	:	Critical Source Areas
CWC	:	Central Water Commission
DEM	:	Digital Elevation Model
ESCO	:	Soil Evaporation Compensation factor
FLDAS	:	Famine Early Warning Systems Network Land Data Assimilation System
GCM	:	Global Climate Models
GHGs	:	Green house gases
GIS	:	Geographical Information System
GW	:	Ground Water
HRU	:	Hydrological Response Unit
IMD	:	India Meteorological Department
ISRIC	:	International Soil Reference and Information Centre
IPCC	:	Intergovernmental Panel on Climate Change
LULC	:	Land Use and Land Cover
M&ERO	:	Mahanadi & Eastern Rivers Organization
MUSLE	:	Modified Universal Soil Loss Equation
NRSC	:	National Remote Sensing Center
NSE	:	Nash–Sutcliffe Efficiency
PBias	:	Percent Bias
RCPs	:	Representative Concentration Pathways
RUSLE	:	Revised Universal Soil Loss Equation
SOL_AWC	:	Available Water Capacity of the Soil layer

SRTM	:	Shuttle Radar Topography Mission
SUFI - 2	:	Uncertainty in Sequential Uncertainty Fitting – 2
SSP	:	Shared Socioeconomic Pathways
SWAT	:	Soil and Water Assessment Tool
USGS	:	United States Geological Survey
USLE	:	Universal Soil Loss Equation
UTM	:	Universal Transverse Mercator
WEPP	:	Water Erosion Prediction Project
WGS	:	World Geodetic System

Chapter - 1 Introduction

1.1 Background

India is a historic, tropical nation where the primary industry is agriculture, which requires abundant water to flourish. The primary water sources for domestic and agricultural usage are groundwater from open wells and surface water from streams, rivers, lakes and man-made ponds to a large extent. The Himalayas are the source of several rivers in the country's north, which deposit a lot of gravel and alluvium as sediments in the northern plains. The region is extremely fruitful because to the good temperature and sufficient water supply in the Ganges and Indus plains, which are dominated by alluvium deposits. Moving towards the Deccan plateau and central islands of the peninsula, rivers like Narmada, Tapti, Mahanadi, Godavari, Krishna, Kaveri, Nagavali and Vamsadhara serve as primary water sources. However, India's diverse climatic conditions, varied topography, and extensive river networks pose significant challenges to its water resources, especially concerning streamflow and sediment dynamics. Soil erosion poses a significant threat to both land and water resources due to its adverse effects on soil fertility, agricultural productivity, and aquatic ecosystems. It results from a complex interplay of natural and human-induced factors, with erosion rates influenced by hydrological patterns, climatic conditions, soil characteristics, and land use changes at the local level. River basins, in particular, face substantial challenges associated with land degradation and the deterioration of water quality due to soil erosion. The transport of eroded soil from upland areas to riverbeds and reservoirs exacerbates issues such as flooding and loss of reservoir capacity (Narayana and Babu 1983, Xu et al. 2015). Several studies mentioned the alarming rates of soil erosion in India, exceeding permissible limits in many areas. Approximately 147 million hectares of land are degraded, with water erosion accounting for a significant portion. This highlights the importance of understanding water balance components and identifying critical source areas of land degradation to mitigate soil erosion's adverse impacts on agricultural lands and reservoir capacity.

Effective management practices are essential to address these challenges and minimize negative consequences on agricultural productivity and reservoir capacity. Thus, a comprehensive understanding of water resources and soil erosion dynamics is crucial for sustainable land and water management in India's agricultural dominant river basins.

1.2 Importance of Studying Streamflow and Sediment

Understanding the dynamics of streamflow and sediment transport is critical in the field of watershed management. These two components play critical roles in determining the physical and ecological characteristics of river systems, influencing water quality, erosion patterns, and overall watershed health. As human activities and climatic patterns change in unprecedented ways, understanding the complex interactions between streamflow and sediment becomes increasingly important. Streamflow, often referred to as the lifeline of watersheds, not only supports aquatic ecosystems but also serves as an essential resource for various human activities such as agriculture, industry, and domestic use. The quantification and analysis of streamflow patterns are critical for effective watershed management, ensuring sustainable utilization while preserving the ecological integrity of river ecosystems. Simultaneously, sediment transport within water bodies holds significance in shaping river channels, affecting aquatic habitats, and influencing water quality. Sedimentation processes have implications for infrastructure, navigation, and the overall geomorphological evolution of river systems. Studying sediment dynamics becomes imperative for mitigating the adverse impacts of erosion, preserving soil fertility, and maintaining the long-term stability of riverine landscapes.

1.3 Global Climate Models

The Intergovernmental Panel on Climate Change (IPCC) defines climate change as a shift in the parameters mean and/or variability over time brought on by both natural and human activity (IPCC, 2007). There has been an increase in the frequency of extreme weather occurrences, including powerful heat waves, intense hot extremes, extreme precipitation, floods and droughts in agriculture conditions (Masson-Delmotte et al. 2021). The IPCC AR5 study revealed an unparalleled increase in the earth's surface temperature in the past few decades, leading to significant adverse effects on climate parameters, as well as the biological, chemical and hydrological cycles worldwide. A notable rise in global temperatures is attributed to the escalating concentration of greenhouse gases (GHGs) in the atmosphere. Projections from the IPCC 5th Assessment Report (AR5) indicate an anticipated increase of 1.8 to 4°C by the conclusion of the 21st century due to this phenomenon (IPCC, 2014). Due to these effects the changes are expected in the availability of water and associated climate extremes, such as floods and droughts in river basins, as a result of fluctuations in the climatological parameters.

Climate models are instruments for determining how future natural processes and human activity can impact a region's ecosystem. There are two types of tools for the assessment of climate change studies i.e., Global Climate Models (GCMs) and Regional Climate Models (RCMs). GCMs are numerical models that mimic various physical processes that represent different components of the global climate system such as atmosphere, land surface, oceans and cryosphere (Anil et al. 2021). Gaps exist between the spatial and temporal realisation of hydrological features and GCMs, making it impossible for GCMs to accurately mimic hydro-meteorological processes at a finer scale. The resolution of GCMs is too coarse to be used as an input for studies on climate change and the raw outputs from GCMs are frequently biased with systematic errors when compared to the observed parameters. Future climate projections provide policymakers with valuable insights into the potential impacts of climate change, aiding in the formulation of recommendations and mitigation strategies (Nashwan and Shahid, 2019). Nevertheless, the accuracy of climate models varies by region due to uncertainties stemming from factors such as model structure, parameterization, and calibration (Anil et al. 2021).

The range of projections from Global Climate Models (GCMs) is quite broad, with high levels of uncertainty (Wilby et al. 2014). The GCMs were downscaled to higher resolution (0.25° × 0.25°) by considering local topographic and physical characteristics, which have gained popularity due to accurate and reliable estimation of future earth climate scenarios in regional hydrological impact studies (Mishra et al. 2020; Mohseni et al. 2023; Reshma and Arunkumar, 2023). Even after downscaling, future climate projections can vary significantly from one another, ranging from very wet to extremely dry, or from extremely hot to very cold. As a result, the models can be classified as representing the Warm-Wet, Warm-Dry, Cold-Wet, and Cold-Dry corners of the full spectrum.

IPCC continuously releasing many GCMs simulations based on the greenhouse gas emission scenarios as mentioned in the various Assessment Reports (ARs) from 1992 to 2023 The 5th AR of IPCC generated Representative Concentration Pathways (RCPs) to illustrate the various stages of greenhouse gas emissions as well as additional radiative forcings that could have an impact in the future. There are four routes (2.6, 4.5, 6.0 and 8.5 watt/m^2) that cover a broad range of forcing, but they lack any socioeconomic "narratives." The Shared Socio-economic Pathways (SSPs), based on five narratives that depict major socio-economic patterns that might affect society in the future, are developed by the IPCC 6th Assessment Report (AR6) to connect a wide range of research communities, including those involved in climate change mitigation and adaptation activities. SSP1-2.6, which represents the low end of the range of future forcing pathways with 2.6 W/m^2 radiative forcing (Sustainability), SSP2-4.5, which represents the medium end of the range of future pathways with 4.5 W/m^2 radiative forcing (Business as Usual), SSP3-7.0, which represents the medium to high end of the range of future forcing pathways with 7.0 W/m^2 radiative forcing (Fragmented World) and SSP5-8.5, which represents the high end of the range of future pathways with 8.5 W/m^2 radiative forcing (Regular Progress in terms of energy sources), are the four SSPs. The SSPs took into account the likely concentration of greenhouse gases assuming changes in the population, Gross domestic product growth, educational attainment and land use land cover, as well as the climate mitigation measures from the scenario. SSPs are incorporated into the Coupled Model Intercomparison Project-6 (CMIP6) models, enabling improved future effect assessments through improved parametrization. Integrated Assessment Models (IAMs) utilize both Shared Socioeconomic Pathways (SSPs) and Representative Concentration Pathways (RCPs) to generate climate projections, considering new emission and land use scenarios (O'Neill et al. 2016).

1.4 Climate Change and its Impacts on River Basins

The consequences of climate change on the hydrological components and water budgets have been extensively studied, and the findings highlight significant changes from global to regional scale (Seong et al. 2018; Sridhar and Anderson, 2017). Changes in temperature and precipitation caused by climate change can affect the flow and transport of sediment in watersheds (Ma et al. 2021). These changes in streamflow can affect water availability, which can then impact irrigation, urban water supply, and hydropower production (de Oliveira et al. 2017; Zhong et al. 2019). Additionally, changes in sediment load can affect river geomorphology, river ecosystems, and reservoir capacity (Ma et al. 2019). Average precipitation and temperature at the surface, floods, and droughts have changed significantly worldwide and are expected to continue (IPCC, 2007). Developing countries, such as India, are especially susceptible to the consequences of climate change on agriculture and water sectors (Aggarwal et al. 2009; Satish Kumar et al. 2020; Singh et al. 2020). Climate change is also affecting soil types, as soil erosion and sediment yield are controlled by rainfall and runoff (Nilawar and Waikar, 2019; Sujatha and Sridhar, 2017; Sujatha and Sridhar, 2021). Overall, climate change is altering the hydrological process by changing rainfall patterns and the timing and magnitude of streamflow. In recent years, the importance of streamflow forecasting has gained significant recognition (Ibrahim et al. 2022; Latif and Ahmed, 2023). On the other hand, streamflow prediction plays a vital role in long-term water resources planning and management

(Mohseni et al. 2023; Reshma and Arunkumar, 2023). Streamflow predictions are based on climate models and scenarios, which provide insights into potential changes in streamflow patterns under different climate change scenarios (Mahdian et al. 2023; Maurya et al. 2023; Nilawar and Waikar, 2019).

1.5 Hydrological Models for Streamflow and Sediment Simulations

A hydrological model represents the natural hydrological cycle in a simplified form and is mainly used for understanding, forecasting, and managing water resources. The best hydrologic model is the one that is less complex and uses the minimum amount of data to produce results that are similar to the observed values. The hydrologic model converts the rainfall into run-off by considering various hydrological processes including rainfall, evapotranspiration, and surface and sub-surface water flow. The essential input data necessary for the hydrological model include rainfall, temperature, solar radiation, wind speed, relative humidity, Land Use and Land Cover (LULC), Digital Elevation Model (DEM), and soil data (Godara and Bruland, 2019).

Over the past three decades, various physically based hydrological models have been utilized, including the Areal Nonpoint Source Watershed Environment Response Simulation (ANSWERS), Agricultural Non-point Source Pollution model (AGNPS), Water Erosion Prediction Project (WEPP), and Soil and Water Assessment Tool (SWAT) (Arnold et al. 1998; Beasley et al. 1980; Foster and Lane, 1987; Young et al., 1989). According to a comprehensive review by Roti et al. (2018), the SWAT model consistently demonstrates superior performance compared to AGNPS, ANSWERS, and WEPP models across both small and large areas (Matamoros et al. 2005; Mishra et al. 2008). SWAT's effectiveness has been demonstrated globally, yielding satisfactory results in capturing the spatio-temporal variability of hydrological processes (Borah and Bera, 2003; Gassman et al. 2007; Rossi et al. 2009).

Notably, recent studies have extensively utilized SWAT integrated with Geographical Information System (GIS) interfaces for various purposes. These include modeling runoff, sediment, and water balance (Dutta and Sen, 2018; Himanshu et al. 2017; Setti et al. 2018), assessing climate change impacts on water resources (Narsimlu et al. 2013; Reddy et al. 2018), and identifying critical source areas while evaluating Best Management Practices (BMPs) for sediments and nutrients (Himanshu et al. 2019; Mishra et al. 2007; Niraula et al. 2011; Ricci et al. 2018; Strauch et al. 2013) on a global scale. The prevalent use of SWAT in conjunction with

GIS underscores its versatility and effectiveness in addressing diverse hydrological and environmental research challenges worldwide.

1.6 Best Management Practices (BMPs)

Ensuring the well-being of humans, fostering growth, and sustaining food production necessitate the protection of water and soil. However, these crucial resources are facing growing threats. The quality and amount of water are changing dynamically as a result of human usage and changing climate (Loukika et al. 2022; Rodell et al. 2018; Sujatha and Sridhar, 2021). Regions effected by soil erosion are vulnerable to the loss of nutrients in the topsoil, reduced yields, increased water pollution, and the changes to wildlife habitats (Prager et al. 2011; Ricci et al. 2020). According to Pimentel and Burgess (2013), some of the main causes of soil erosion are improper land management, agricultural practices, in addition extreme precipitation, steep topography, low vegetation cover, overgrazing and forest destruction. Rainfall and surface runoff play a major role in accelerating erosion rates from hilly terrain to low lying areas (Dutta et al. 2017). Soil erosion and nutrient pollution can be reduced by implementing Best Management Practices (BMPs). The details of various BMPs are explained as follows:

1.6.1 Filter Strips

Filter strips are vegetated areas that exist between cropland, grazing land, forest land and surface water bodies. They are placed where rainwater leaves the land, which effectively filter sediment and nutrients and thus allow rainwater passage into the water body. The effect of filter strips practices in the river basins can be simulated by modifying the filter width (FILTERW) parameter in the SWAT model. Figure 1.1 illustrates a typical representation of filter strips.

Figure 1.1 Representation of Filter strips (source:https://en.wikipedia.org/wiki/Filter_strip)

1.6.2 Sedimentation Ponds

Sedimentation ponds are small, temporary ponds built across a marshland or channel. These are used to slow down the flow and prevent erosion in a marshland or channel. Sedimentation ponds are simulated as a pond in the SWAT model to maintain the capacity of reservoirs and channels, .pnd file contains parameter information used to model the water, sediment and nutrients for ponds. The parameters are as follows: the portion of the sub-basin area draining into ponds (PND-FR), the surface area of the pond when filled to the principle spillway (PND_PSA), the volume of water required to fill the pond to the principle spillway (PND_PVOL), and the hydraulic conductivity through the bottom of the pond (PND_K). Figure 1.2 illustrates a typical representation of sedimentation ponds.

Figure 1.2 Sedimentation ponds (source: https://city.milwaukee.gov/SWMP/Erosion-Control/Advanced-Control-Measures/Sediment-Basin)

1.6.3 Contour Farming

Contour farming changes the direction of surface runoff from directly downward to along the hillslope by forming ridges and furrows with tillage and planting. This BMP aims to reduce sheet and rill erosion, sediment transport, and increase water infiltration. Contour farming is implemented in SWAT by modifying USLE_P and curve number (CN2) on agricultural lands. Figure 1.3 illustrates a typical representation of contour farming A) represents the land levelling and B) represents the contour terraces.

Figure 1.3 (A) Land leveling, and (B) contour terraces (source:https://www.sciencedirect.com/topics/agricultural-and-biological-sciences/contour-farming)

1.6.4 Contour Stone Bunding

By decreasing the slope length and establishing retention areas, contour stone bunds minimise runoff and soil loss. The CN2, SLSUBBSN, and USLE_P parameter values are changed to replicate the impact of stone bund practice in the basin areas (Adams et al. 2022; Dibaba et al. 2021; Uniyal et al. 2020). Thus, the CN2, SLSUBBSN, and USLE_P parameter values were modified and applied to wastelands, rangelands, and cultivated lands. Figure 1.4 illustrates a typical representation of contour stone bunding.

Figure 1.4 Representation of Contour stone bunding (source: https://www.isqaper-is.eu/terrain-management/cross-slope-barriers/346-bunds)

These BMP input parameters are incorporated into the SWAT model for each Hydrologic Response Unit (HRU) involves a systematic process. For filter strips, the parameters include specifying the width of the filter strip, and the location of the HRUs where they will be applied, particularly adjacent to water bodies or at the edges of agricultural fields. These parameters are updated in the SWAT model's management files to enhance runoff reduction and sediment trapping efficiency. Sedimentation ponds are incorporated by defining their surface area, volume, and retention time, which influences settling rate of sediment. The ponds are strategically located in HRUs with high sediment yield or at critical points in the watershed, and the SWAT model's HRU management operations are adjusted to include these parameters. Contour farming involves adjusting slope length and steepness to reflect contour plowing and planting, reducing soil erosion and surface runoff. Crop management practices are updated to align with contour farming, and these changes are applied to HRUs with suitable topography. Contour stone bunding involves specifying the height, spacing, and material of the stone barriers, which are placed along the contours of sloped land to reduce runoff velocity and prevent soil erosion. Similar to contour farming, slope length and steepness parameters are adjusted, and these practices are applied to HRUs prone to severe erosion.

1.7 Research Motivation

Soil erosion presents a significant risk to both land and water resources, adversely impacting soil fertility, agricultural productivity, and the quality of water. In India, 147 million hectares of land are degraded, with water erosion alone accounting for 94 million hectares

(Bhattacharyya et al. 2015). The escalating concern is exacerbated by climate-induced alterations in precipitation and temperature, which can profoundly influence watershed hydrological regimes. In India, a considerable number of river basins grapple with issues of water quality and quantity due to shifts in precipitation and temperature patterns, necessitating a thorough assessment and the implementation of adaptive measures. Changes in temperature and precipitation, attributed to climate change (Aggarwal et al. 2009; Satish Kumar et al. 2020; Singh et al. 2020).

Given this scenario, it becomes imperative to assess the changes in streamflow and sediment in watersheds under different climate scenarios. Mitigating soil erosion and nutrient pollution can be achieved through the implementation of Best Management Practices (BMPs). The modeling and monitoring of sub-watersheds offer valuable insights into water, sediment, and nutrient transport processes at both the field and watershed scales (Himanchu et al. 2019). Internationally, the SWAT model has been widely employed to evaluate the effectiveness of BMPs, demonstrating satisfactory performance at sub-watershed and watershed scales.

The Central Water Commission (CWC) reports indicate a concerning trend of reservoirs in India losing storage capacity at a rate of 1% per year due to sedimentation (CWC, 2020). Regions inhabited by tribal communities in Andhra Pradesh, Odisha, Madhya Pradesh, Chhattisgarh, and Kerala face severe soil erosion, primarily attributed to shifting cultivation practices (Saroha, 2017). The eastern coastal belt along the Bay of Bengal, encompassing Tamil Nadu, Andhra Pradesh, and Odisha, experiences flooding from pre- and post-monsoon tropical cyclones originating in the Bay of Bengal (Amminedu et al. 2013; Rao et al. 2020;).

The two study basins Nagavali and Vamsadhara rivers, situated in the eastern region, face recurrent flooding triggered by heavy monsoon rains and tropical cyclones originating from low-pressure systems in the Bay of Bengal during pre- and post-monsoon periods. Over the past twenty years, both basins have experienced a rise in annual rainfall by approximately 100 mm. These basins are characterized by hilly uplands, making low-lying areas susceptible to inundation during intense rainfall events. Consequently, there has been a discernible increase in the frequency of prolonged floods in recent decades, leading to significant damage to soil fertility and reduction in reservoir capacity. Notably, the Gotta barrage on the Vamsadhara river basin reportedly lost approximately 62 percent of its live storage between 1977 and 2004 (CWC, 2020). Conducting a detailed streamflow and sediment yield analysis in these flood-prone, agriculturally significant Nagavali and Vamsadhara river basins is imperative. The aim is to develop effective Best Management Practices under changing climate conditions, addressing the complex challenges posed by soil erosion and sedimentation in these critical regions. The climate change may be the one of the main reason for the changes in runoff pattern and sediment yield, which need to be studied thoroughly with the climate model datasets.

The research outcomes from this study will play a crucial role in informing policy-making and practical applications in watershed management. The findings derived from streamflow and sediment yield analyses will provide a robust foundation for formulating effective watershed management policies. Policymakers can leverage these data to develop targeted strategies that address the specific challenges of soil erosion and sedimentation. Additionally, the study's insights into climate change impacts on watershed hydrology will inform the development of adaptive strategies for managing water resources more effectively under varying climatic conditions, ensuring long-term sustainability. Understanding sediment transport patterns will help devise strategies to minimize sedimentation in reservoirs, thereby prolonging their storage capacity and operational life, preventing the loss of valuable water resources, and ensuring a stable supply for irrigation and domestic use. The research can empower local communities with knowledge and tools to manage their natural resources better. Involving communities in BMP implementation fosters a sense of ownership and resilience against climate-induced water-related challenges.

1.8 Aim and Objectives of the Study

The aim of the present research work is to analyse the streamflow and sediment yield under climate change scenarios using distributed hydrological model and to suggest the Best Management Practices (BMPs). The specific objectives of research work are as follows:

- ❖ To analyse the water balance components and sediment yield over the study area
- ❖ To assess the climate change impact on streamflow and sediment yield over the study area
- ❖ To identify Critical Source Areas (CSA) for the sediment yield in the selected basins
- ❖ To evaluate effectiveness of Best Management Practices (BMPs) to be used in the study basins

1.9 Organization of the Thesis

This thesis has seven chapters which include introduction, literature review, methodology, study area and database preparation, model set-up, results and discussions, and summary and conclusions. The research motivation, problem statement, and research objectives are presented in the introduction chapter. Literature review on analysis of streamflow and sediment using hydrological models, identification of critical sediment source areas, assessment of climate change consequences on streamflow and sediment yield and evaluation of various BMPs have been presented in the second chapter. The research methodology is presented in the third chapter. The details about the study area, data used, database preparation, and SWAT model set-up for simulating streamflow and sediment are presented in the fourth chapter. Results and discussions are given in the fifth and sixth chapters, while the summary, conclusions, and limitations of the present research are explained in the concluding chapter.

Chapter - 2 Literature Review

2.1 General

Based on the framed objectives in the last chapter, the literature review is carried out on the aspects related to assessment of hydrological and sediment yield processes, influence of climate change on streamflow and sediment yield, identification of critical sediment source areas and evaluation of Best Management Practices (BMPs). A detailed description of the reviewed literature on the above aspects is given in the subsequent sections.

2.2 Assessment of Streamflow and Sediment using Hydrological Models

Water resource management studies, flood control and drought mitigations, planning and design of soil and water conservation projects, hydrologic response to climate change and so on rely on hydrologic models. Hydrologic models offer a framework for conceptualizing and exploring the dynamics between climate and water resources (Li *et al.* 2015). A systematically calibrated and validated hydrological model can offer helpful information for the management and planning of water resources. Hydrologic models typically operate at a river basin or a watershed scale. Soil erosion is a serious concern for land and water resources (Liu and Jiang 2019; Panda et al. 2021). However, runoff-induced soil erosion is a global problem (Novara et al. 2016; Oldeman, 1992; Restrepo and Escobar, 2018). Rainfall and surface runoff play a major role in accelerating erosion rates from hilly terrain to low-lying areas (Dutta et al. 2017). A number of studies were conducted in various regions of India by researchers and decision makers using laboratory, field scale, and modeling approaches to better understand sediment dynamics and their impact on reservoirs and crop productivity (Dutta and Sen 2018; Himanshu et al. 2017; Himanshu et al. 2019; Kolli et al. 2021; Kumar and Mishra, 2015; Mahapatra et al. 2018; Panda et al. 2021; Prasannakumar et al. 2012; Saha et al. 2018; Singh et al. 1992; Vaithiyanathan et al. 1988).

Singh et al. (1992) generated a comprehensive soil erosion rate map for India, employing the Universal Soil Loss Equation (USLE) to quantify soil losses. The investigation revealed that specific geographical regions had severe soil erosion rates exceeding 20 t/ha/yr. These regions included the Shiwalik hills, the north-western Himalayan areas, gorges, regions with shifting cultivation practices, the western coastal ghats, and the black cotton soil areas of Peninsular India.

Vaithiyanathan et al. (1988) conducted an experimental analysis involving the collection of samples from rivers, focusing on the Godavari, Krishna, and Cauvery rivers. Their estimations revealed the mean annual sediment transport to be 170 million tons for the Godavari, 4 million tons for the Krishna, and 1.5 million tons for the Cauvery rivers. Notably, the study highlighted that more than 95% of sediment transport occurs during the monsoon period. The findings led to the conclusion that tropical Indian rivers, particularly the Godavari, play a pivotal role in the transportation of the majority of the annual sediment yield from the river basin, and this process is concentrated on just a few days of the year.

Prasannakumar et al. (2012) applied the Revised Universal Soil Loss Equation (RUSLE) to assess the average annual soil loss in a small mountainous sub-watershed situated in the Pamba river basin, Kerala, India. The study identified a maximum soil loss of 17.73 tons per hectare per year, predominantly attributed to high LS-factors in areas characterized by degraded deciduous forest and grasslands.

Kumar and Mishra (2015) employed the Soil and Water Assessment Tool (SWAT) to delineate critical erosion-prone areas within the Damodar catchment, situated in the lower Ganges river region in Jharkhand, India. Their findings revealed that approximately 67.52% of the Damodar catchment falls within a critical erosion zone, primarily attributed to the combined influence of sandy loam soil, wasteland, and agricultural land use conditions.

Himanshu et al. (2017) utilized the SWAT model to assess the hydrology, water balance, and sediment yield in the Ken basin, India. The study findings highlighted the significance of evapotranspiration as a dominant component in the water balance analysis. The estimated average annual sediment yield for the Ken basin was reported to be 15.41 t/ha/yr.

Saha et al. (2018) calculated the average annual soil loss in the upper Kangsabati watershed of West Bengal using a RUSLE. The study identified the north-eastern part of the watershed as experiencing the highest rate of soil erosion, exceeding 13.42 t/ha/yr. The researchers concluded that the continuation of the current rate of soil erosion could render agricultural lands unsuitable for cultivation in the future.

Setti et al. (2018) conducted a spatiotemporal analysis of hydrological components in the Nagavali river basin using SWAT. Calibration and validation results on a monthly basis were found to be satisfactory. Spatial analysis of water balance components revealed significant differences in precipitation (ranging from 914 to 1319 mm) and streamflow (ranging from 82 to 246 mm) across the basin. The water budget assessment indicated that 70% of the annual rainfall and 73% of the annual runoff occurred during the monsoon season, highlighting the need for water harvesting structures. The study identified water stress in the Nagavali river basin

Das (2021) conducted a comprehensive analysis of the temporal patterns in streamflow and sediment load within 12 major tropical rivers in Peninsular India. Their study includes the Godavari, Mahanadi, Subarnarekha, Baitarni, Brahmani, Krishna, Pennar, Cauvery, Sabarmati, Mahi, Narmada, and Tapi river basins. Leveraging a dataset spanning 50 years of daily time series data, and applied the Mann-Kendall and Pettitt tests to assess annual variability, trends, and changes. The findings revealed that these 12 major Peninsular Indian rivers collectively contribute over 1% of the global river sediment flux. Notably, the Krishna, Cauvery, and Narmada rivers exhibited a significant decrease in streamflow over the past five decades, attributed to variations in precipitation patterns. The study highlighted that, post-2000, all 12 river basins experienced a remarkable more than 40% reduction in sediment load. This decline was attributed to the construction of reservoirs and dams, emphasizing the significant impact of anthropogenic interventions on sediment dynamics in these river systems.

Kolli et al. (2021) employed the RUSLE model to assess soil loss and sediment yield in the Kolleru catchment in India. The study determined that the average annual soil loss was 13.6 t/ha/yr, with a corresponding sediment yield of 7.61 t/ha/yr. Notably, the research highlighted that red soils and sandy clay soils were identified as the major contributors to sediment export in the Kolleru catchment.

2.3 Global Climate Models (GCMs)

Global Climate Models (GCMs), as physically-based models, are widely regarded as reliable and practical tools for forecasting changes in atmospheric variables within the context of climate change scenarios. These models encompass the dynamics of both the atmosphere and the oceans (Ghosh and Mujumdar, 2008). GCM projections, while well-suited for continental and hemispherical scales, often lack the finer resolution needed for regional impact analysis, particularly when examining changes in extreme events (Fowler et al. 2007). This limitation is due to their high spatial resolution, typically around 100-250 km. To overcome this challenge and assess the impact of climate change at a regional level, it is necessary to link large-scale climate variables to hydrologic variables at a finer scale. Downscaling methods are commonly employed to derive local to regional scale information from these large-scale climate projections. These methods can be broadly categorized as dynamic or statistical. Dynamic downscaling involves generating finer resolution output based on atmospheric physics over a specific region using GCMs boundary conditions (Teutschbein and Seibert, 2012). On the other hand, statistical downscaling methods establish empirical relationships between GCM outputs and observed climate data (Fan et al. 2021). By employing these downscaling techniques, researchers can bridge the gap between large-scale climate projections and the finer resolution needed for regional impact studies, thus enabling a more comprehensive analysis of climate change impacts on local and regional hydrology.

Giorgi and Mearns (1991) compared the empirical and GCM nested limited area modelling techniques and discussed the advantages, disadvantages, limitations and variability of their use. They observed that, though GCMs are capable of encompassing the wide range of climate variability and atmospheric phenomenon, they are complex and expensive. Here some of the statistical downscaling literature across the globe were discussed.

Statistical downscaling, unlike the computationally intensive dynamical downscaling, offers a simpler approach by developing empirical connection between local climate and GCM climate variables. These relationships do not involve the complex mass and energy exchange between the land and atmosphere. The statistical downscaling methods can be grouped into weather generators, transfer function and weather typing, each with its own approach to linking large-scale and local-scale climate data (Ghosh and Mujumdar, 2008).

Lin et al. (2017) used the KNN algorithm to develop a novel spatio-temporal downscaling method for hourly rainfall data. Tabari et al. (2021) compared four statistical downscaling techniques such as Change Factor of Mean (CFM), Bias correction (BC), an event-based Weather Generator (WG) and Quantile Perturbation (QP) to assess the impact of climate alteration on drought in the future (2071-2100) compared to a baseline period (1971-2000) for the Uccle region of Belgium. Their study used ensemble CMIP6-GCMs for downscaling, considering four future scenarios: SSP1-2.6, SSP2-4.5, SSP3-7.0 and SSP5-8.5. Among these methods, the QP technique demonstrated superior performance in replicating the amplitude and monthly pattern of the reported drought indicators.

2.4 Assessment of Streamflow and Sediment under Climate Change

Numerous studies have been conducted to assess the impact of climate change on streamflow and sediment dynamics in various river basins worldwide, highlighting the importance of understanding these phenomena and the need for proactive measures to mitigate and adapt to the anticipated impacts.

Swain (2014) investigated the consequences of climate variability on the Mahanadi basin and concluded that the effects would be severe for India's river basins. The findings suggest that the basin is prone to flooding and that the intensity may be severe in the future. Furthermore, rising mean temperatures and other issues such as silt deposition and storms in the Bay of Bengal may aggravate the situation.

Abbaspour et al. (2015) did a work to create and improve the SWAT hydrological model in order to examine the various aspects of managing water resources in light of climate change. The model provided a thorough and in-depth investigation of system behaviour by simulating several water resource components at monthly time intervals. This involved applying large-scale, high-resolution water resource models in both physically based and data-driven simulations. The paper offered a comprehensive explanation of the methods utilised for modelling uncertainty, the calibration procedure and the availability of data.

Azari et al. (2016) assessed the consequences of climate change on streamflow and sediment yield in Gorganroud watershed, Iran using the SWAT model. They observed that climate change had a greater consequence on sediment yield compared to streamflow. Overall, these studies highlight the importance of considering the consequences of climate change on river systems and need for proactive measures to mitigate and adapt to these impacts.

Pandey et al. (2017) quantified the consequences climate change on the hydrology of the Armur watershed in the Godavari basin using SWAT model, and concluding that an increase in mean annual temperature, rainfall, evapotranspiration, and water yield is expected under GHG scenarios in the future period.

Chanapathi et al. (2018) used the SWAT model to assess how climate change may affect the water balance components of the semi-arid Krishna river basin in Peninsular India. A shift in the maximum amount of long-term mean Indian Summer Monsoon Rainfall (ISMR) and surface runoff, an increasing trend in rainfall during October and November and some extreme rainfall events outside of the monsoon season were among the insights observed from the analysis. According to one of the climate models (CNRM-CM5), there would be mild drought episodes in 25% of cases, excessive rainfall in 7% of cases (> 25%) and extreme rainfall in 5% of cases (> 50%). Hengade et al. (2018) investigated the consequences of future daily rainfall on the hydrology of the Godavari basin under the CMIP5, two RCP scenarios, 4.5 and 8.5, and discovered an increase in future rainfall. The multimodel mean Indian monsoon rainfall also showed an increasing trend.

Jin et al. (2018) investigated the consequences of changing climate as well as socioeconomic conditions on the Mahanadi River watershed using the Integrated Catchment Model (INCA). They assessed future flows, changes in irrigation water demand, and the impact of changing land uses under various Shared Socioeconomic Pathways (SSPs). According to the findings of this study, monsoon flows are expected to significantly increase in the 2050s and 2090s under future climate conditions, and socioeconomic factors have a significant impact on water quality.

Bhatta et al. (2019) measured how climate change affected the Tamor River Basin's water balance in Nepal's eastern Himalayas. The evaluation of SWAT's response involved varying the quantity of sub-basins, HRUs and elevation bands. An ensemble of five linearly bias corrected CMIP5-GCMs and four RCMs under both RCP4.5 and RCP8.5 was used to estimate the future climate over three distinct time frames, namely the 2030s, 2060s and 2080s. This data was then utilised as input SWAT for simulating future streamflows at the watershed scale. According to observations, the latter part of the twenty-first century may see streamflow reductions of more than 8.5% under RCP8.5 scenarios.

Nilawar and Waikar (2019) analysed the effects of two RCP scenarios, 4.5 and 8.5, on streamflow and sediment at Purna river basin, India. They found that both of these variables increased during the monsoon months. Pandey and Palmate (2019) identified critical sub-watersheds in the Betwa basin, India that were most vulnerable to sediment yield under both current and future climate conditions using SWAT model. This information can be used to prioritize and manage these areas for better water resource management.

Mishra et al. (2020) estimated the frequency of temperature and rainfall extremes over the Godavari river basin using bias-corrected CMIP6 projections, finding that the far period had higher frequencies than the near-term climate. Rao et al. (2020) forecasted future variations in rainfall extremes throughout the northeast monsoon period over south India using statistically downscaled high-resolution NEX-GDDP datasets. They found that rainfall would increase in future.

Singh and Saravanan (2020) predicted the future hydrological component responses under RCP 4.5 and 8.5 scenarios over the Wunna, Mahanadi, and Bharathpuzha watersheds, with their results showing that surface runoff and sediment are expected to increase over the watersheds.

Ma et al. (2021) used the model to study the upstream region of the Mekong basin, finding that both temperature and precipitation were projected to increase, while changes in sediment load were inconsistent.

Mohseni et al. (2023) used the SWAT model to evaluate the impact of climate change and land use change on streamflow over the Parvara Mula basin, India. The findings of the study indicate an increase in streamflow for future periods.

2.5 Identification of Critical Source Areas

The literature demonstrates the extensive utilization of the SWAT model in identifying critical erosion-prone areas and assessing soil loss and sediment yield in various river basins and ecosystems across India.

Kumar and Mishra, (2015) identified the critical erosion prone areas using SWAT model at Damodar catchment, part of lower Ganges river, Jharkhand, India. Their findings revealed that 67.52% of the Damodar catchment area falls within the critical erosion zone due to a combination of sandy loam soil and land use conditions characterized by wasteland and agriculture.

Dutta and Sen (2018) utilized the SWAT model to predict sediment dynamics in the Mahanadi river basin, focusing specifically on the region up to the Hirakud dam. Their study identified critical erosion-prone areas at the sub-watershed level and reported an average annual sediment yield of 17.61 t/ha/yr for the entire watershed. Agricultural lands exhibited the highest annual sediment yield at the sub-watershed level, reaching 102.2 t/ha/yr. The study also reported an average soil loss of 181.73 t/ha/yr, providing valuable insights into sediment dynamics and erosion patterns in the Mahanadi river basin.

Mahapatra et al. (2018) conducted an assessment of soil loss in the Himalayan ecosystem of Uttarakhand, India, utilizing the Universal Soil Loss Equation. Their findings revealed that 6.71%, 8.84%, and 32.72% of the area experienced moderately severe, severe, and very severe soil loss, respectively. The study concluded that a significant portion, specifically 48.3%, of the state's soil loss surpassed the permissible limit of 11.2 t/ha/yr, highlighting the critical issue of soil erosion in Uttarakhand. Panda et al. (2021) utilized the SWAT to assess sediment yield and prioritize sub-watersheds in the upper Subarnarekha catchment in Odisha, India. The study determined that the average annual soil loss was estimated to be 4.84 t/ha/yr.

2.6 Evaluation of Best Management Practices (BMPs)

The following studies have utilized the Soil and Water Assessment Tool (SWAT) model to evaluate the effectiveness of various Best Management Practices (BMPs) in reducing sediment yield and improving water quality in different river basins and watersheds across India and other countries, highlighting the importance of implementing BMPs for sustainable watershed management.

Patil et al. (2017) employed the SWAT model to evaluate suggested BMPs, such as filter strips, stream bank stabilization and check dams at the Markhandeya basin, India. Results indicated that a 6 m-wide filter strip reduced sediment yield by 60.42%, while stream bank stabilization and check dams achieved reductions of 54.66% and 75.44%, respectively. As a result, installing a check dam in a scientifically appropriate location in the watershed is an important measure to prevent sediment transport.

Himanshu et al. (2019) assessed BMPs in the Marol watershed, India, using the SWAT model. They concluded that contour farming and filter strips effectively reduced sediment yield and nutrient losses in critical sub-watersheds, demonstrating their potential applicability in watersheds with similar hydro-climatic conditions.

Uniyal et al. (2020) proposed and evaluated various BMP combinations for the Baitarani catchment, India, using the SWAT model. Their analysis revealed that structural BMPs outperformed agricultural BMPs in reducing sediment yields at the watershed level. Combining multiple BMPs resulted in substantial reductions in sediment yields, emphasizing the effectiveness of BMP integration in sediment reduction strategies.

Dibaba et al. (2021) utilized the SWAT model to evaluate BMPs over the Finchaa catchment, Ethiopia, finding that contour strips and stone bunds were highly efficient in reducing sediment yield by 64%. Nepal and Parajuli (2022) assessed the efficiency of grassed waterways, vegetative filter strips, and grade stabilization structures using the SWAT model. Their results indicated significant sediment yield reductions, particularly with grassed waterways, emphasizing the importance of BMP selection for sediment reduction.

Risal and Parajuli (2022) evaluated BMPs using SWAT model over Big Sunflower and Stovall Sherard river watersheds. They found that filter strips were the most efficient BMP to reduce the sediment, and nutrients in that watersheds. Venishetty and Parajuli (2022) quantified the impact of BMPs on water quality parameters over the Yazoo river watershed using the SWAT model. Their findings highlighted the effectiveness of vegetative filter strips and riparian buffers in reducing sediment, total phosphorus, and total nitrogen.

Wu et al. (2022) investigated the effectiveness of six BMPs in reducing sediment yield in the Yanhe river watershed using an integrated SWAT model. They recommended residue cover tillage and strip tillage as efficient BMPs for sediment reduction. Leta et al. (2023) employed the SWAT to assess the impact of various BMPs at the Nashe catchment, Ethiopia, revealing significant reductions in sediment yield, particularly with soil/stone bund and terracing scenarios.

2.7 Critical Appraisal of Literature Review

Soil erosion and sediment poses a significant threat to land and water resources, impacting soil fertility, agricultural productivity, and aquatic environments (Liu and Jiang 2019; Panda et al. 2021). The quantity of sediment yield within a basin fluctuates due to factors such as hydrology, climate, topography, land use alterations, and soil composition (Dutta and Sen, 2018; Himanshu et al. 2019; Kumar et al. 2015; Saha et al. 2018). River basins globally face severe land degradation and water resource deterioration due to soil erosion, contributing to flooding and reservoir capacity loss (Kabir et al. 2014). Certain tribal-inhabited areas in Andhra Pradesh, Odisha, Madhya Pradesh, Chhattisgarh, and Kerala are particularly vulnerable to severe soil erosion, especially due to shifting cultivation practices (Saroha, 2017). Many studies provide insights into the average annual soil erosion rates, but there is a need to understand the temporal and spatial variability of soil erosion at finer scales. The impacts of climate change on the hydrological cycle and water budgets have been extensively studied, and the findings highlight significant changes from global to regional scales (Sridhar and Anderson, 2017; Seong et al., 2018). Changes in temperature and precipitation caused by climate change can affect the streamflow and transport of sediment in river basins (Ma et al., 2021). Some studies showed the increased streamflow and sediment under different climate change scenarios (Mishra et al. 2020; Nilawar and Waikar, 2019**)**. Climate change affects the soil erosion and sediment yield by influencing rainfall and runoff patterns. Limited studies conducted the understanding how changing climate patterns influence soil erosion rates in different regions of India. BMPs and their results highlighted the efficiency in reducing sediment yield, streamflow and increasing groundwater recharge (Dibaba et al. 2021; Leta et al. 2023; Nepal and Parajuli, 2022; Pandey et al. 2021; Uniyal et al. 2020). The use of BMPs are often discussed, but there is a limited research in assessing the long-term effectiveness of these measures for Indian conditions. Evaluation of BMPs in different agro-climatic regions of India are the ways towards the sustainable soil and water conservation strategies. Hence, in the proposed study two east flowing medium sized basins in India are taken for detailed study of the streamflow and sediment yield analysis under different management scenarios. Detailed methodology is presented in the next chapter based on the objectives proposed in chapter1 and the literature review presented in this chapter.

Chapter - 3 Methodology

3.1 General

Based on the objectives presented in chapter 1 and the literature review in chapter 2, the overall research methodology is prepared which is shown in Figure 3.1. The overall methodology is divided into three major components. First component include preparation of datasets such as slope map from DEM, LULC map, soil map, IMD rainfall and temperature data, streamflow, sediment data and climate models data in SWAT format. Second component include SWAT model setup, calibration, validation and sensitivity analysis. Third component include analysis of streamflow and sediment simulated under IMD data and CMIP6 climate models data followed by identification critical sediment source areas and evaluation of BMPs.

The distributed hydrological model SWAT is used to simulate the streamflow, sediment and evaluation of BMPs. Geospatial data such as Digital Elevation Model (DEM), LULC, and soil maps are required to set up SWAT model. The daily meteorological like rainfall, maximum and minimum temperatures are used to simulate the streamflow and sediment. Uncertainty in Sequential Uncertainty Fitting – 2 (SUFI-2) algorithm in the SWAT-CUP is used for calibration, validation, and sensitivity analysis. The observed streamflow and sediment load data at various gauge stations is used to calibrate and validate the SWAT model on monthly basis. Once the SWAT model calibration and validation is completed, the SWAT model will simulate the streamflow and sediment yield to identify the critical source areas of sediment yield, assessment of streamflow and sediment yield under climate change and BMPs are evaluated for the identified critical sediment source sub-basins.

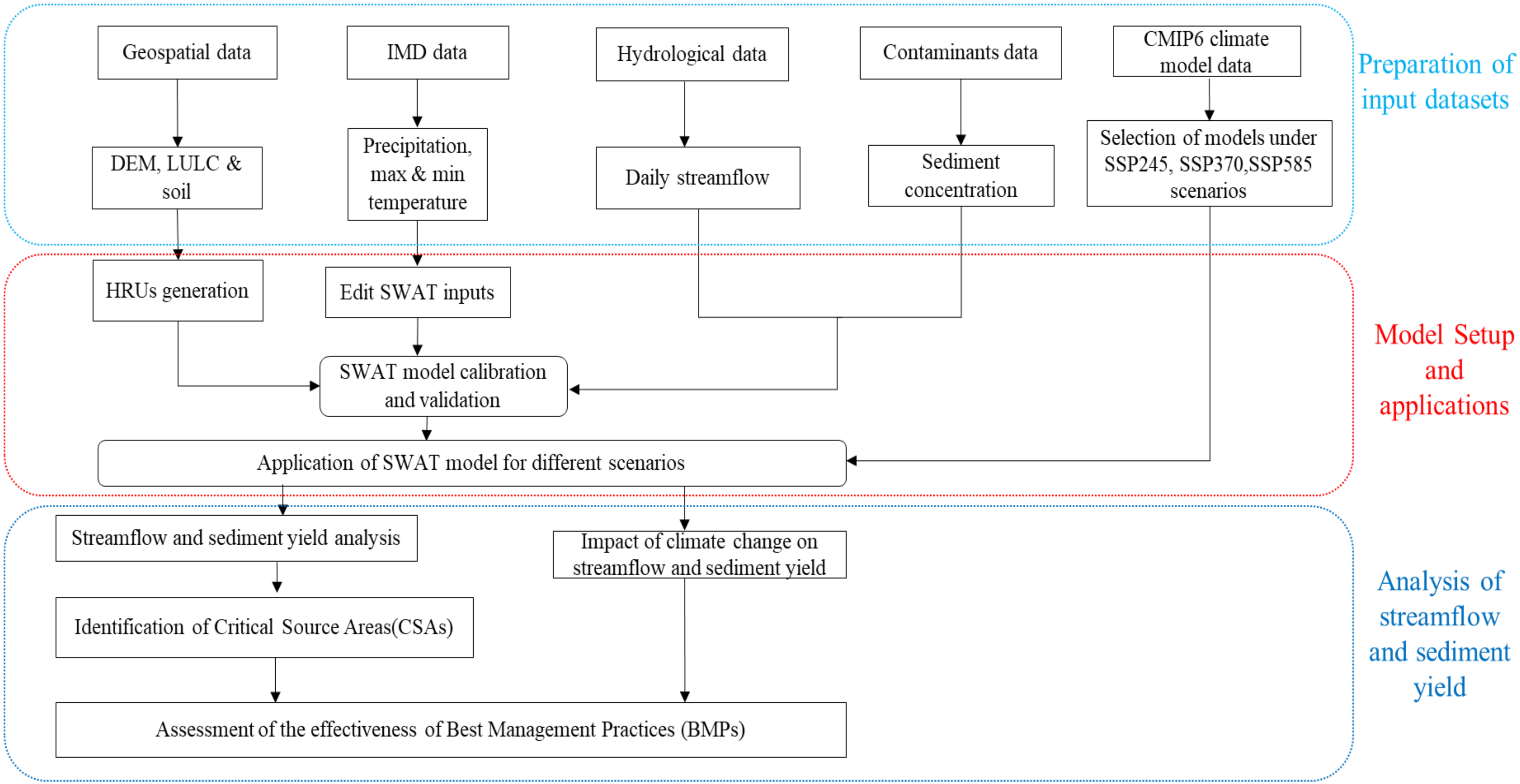


Figure 3.1 Overall methodology of the research work

3.2 Soil and Water Assessment Tool (SWAT)

The Soil and Water Assessment Tool (SWAT) operates on a continuous daily time step simulation model over extended periods. Renowned for its computational efficiency and physical-based approach, SWAT effectively models intricate spatial details by segmenting basins into sub-basins (Arnold et al. 2012). These sub-basins are delineated into Hydrologic Response Units (HRUs), representing homogeneous areas in terms of land use, slope bands, and soil characteristics. Through the integration of diverse climate data and LULC patterns, the SWAT model enables users to project various basin scenarios. Moreover, it facilitates the assessment of streamflow variability by incorporating future climate projections. Daily meteorological data, sourced either from observed datasets or generated by weather generator models, is a prerequisite for SWAT model operation.

Over the past three decades, various physically based hydrological models, including the ANSWERS, AGNPS, WEPP, HEC-HMS and SWAT (Arnold et al. 1998; Beasley et al. 1980; Foster and Lane, 1987; Young et al. 1989), have been utilized. According to a review by Roti et al. (2018), SWAT consistently outperforms than AGNPS, ANSWERS, and WEPP models across different scales (Matamoros et al. 2005; Mishra et al. 2008) and effectively captures the spatio-temporal variability of hydrological processes globally. SWAT offers several advantages over AGNPS, WEPP, and HEC-HMS, including comprehensive watershed-scale simulation capabilities, the ability to model both surface and subsurface water flow, and a broader range of applications such as sediment transport, nutrient cycling, and pesticide dynamics. Its modular structure facilitates integration with other models and data systems, providing flexibility and adaptability. Unlike HEC-HMS, which is typically used for event-based hydrological modeling, SWAT's continuous-time simulation provides detailed insights into cumulative watershed processes. The extensive user community, comprehensive documentation, and ongoing development further enhance SWAT's robustness and reliability for hydrological and environmental management.

The water balance equation, which governs the hydrological components of SWAT model, is as follows:

$$SW_{ti} = SW_O + \sum_{i=1}^{t}(R_{dayi} - Q_{surfi} - E_{ai} - W_{seepi} - Q_{gwi}) \tag{3.1}$$

Where,

SW_{ti} is soil water content at the end of the day (mm),

SW_O is the amount of initial soil water content on day i (mm),

t is the time in days,

R_{dayi} is the amount of precipitation on day i (mm),

Q_{surfi} is the amount of surface runoff on day i (mm),

E_{ai} is the amount of evapotranspiration on day i (mm),

W_{seepi} is the amount of water entering the vadose zone from the soil profile on day i (mm) and Q_{gwi} is the amount of return flow on day i (mm).

The Universal Soil Loss Equation (USLE) is a widely used empirical model developed to estimate average annual soil loss due to sheet and rill erosion. The equation incorporates factors such as rainfall erosivity, soil erodibility, topography, cover management, and support practices. SWAT employs the Modified Universal Soil Loss Equation (MUSLE), which adapts USLE for watershed-scale modeling by replacing the rainfall energy factor with a runoff factor, enhancing the prediction of sediment yields from storm events. The MUSLE equation in SWAT uses runoff volume and peak runoff rate alongside the traditional USLE factors to compute sediment yield. SWAT's parameterization process incorporates these factors using data from soil surveys, topographic maps, land use classifications, and management practice records. By simulating daily runoff and peak runoff rates, SWAT can model sediment transport and deposition across watersheds. This integration allows for robust erosion estimates and scenario analysis, informing policy decisions and watershed management plans.

To predict the sediment yield on a given day Modified Universal Soil Loss Equation (MUSLE) was used which is as follows (Wischmeier and Smith 1965):

$$SY = 11.8 \times (Q_{surf} \times q_{peak} \times A_{hru})^{0.56} \times C \times K \times P \times LS \times CFRG \quad (3.2)$$

Here,

SY is the sediment yield (tons),

Q_{surf} is the surface runoff volume (mm/ha),

A_{hru} is area of HRU (ha),

q_{peak} is peak runoff rate (m^3/s),

C is USLE cover and management factor,

K is USLE soil erodibility factor,

P is USLE support practice factor,

LS is USLE topographic factor,

$CFRG$ is coarse fragment factor

and $Q_{surf} \times q_{peak} \times A_{hru}$ represents the runoff erosive energy variable. Each factor in the MUSLE equation is crucial for determining sediment yield and must be accurately specified within the SWAT model. The runoff volume and peak runoff rate are calculated based on IMD rainfall data. The soil erodibility factor (K) reflects the soil's susceptibility to erosion and is derived from soil databases. The soil database information and textural classes data were collected from the International Soil Reference Information Center (ISRIC) database. The cover and management factor (C) varies with land uses and vegetation cover, with values specified for each HRU based on Land Use Land Cover data. The C factor values available in SWAT database. The support practice factor (P) accounts for soil conservation practices like contour farming, with values determined from literature. The topographic factor (LS) combines slope length and steepness effects, calculated using Digital Elevation Models (DEMs) used in the present study. In the present study, SWAT 2012 version and QSWAT3_64 was used for simulations of streamflow and sediment yield.

3.3 SWAT Model Performance Evaluation

The Nash-Sutcliffe efficiency coefficient (NSE) (Nash Sutcliffe, 1970), percent bias (PBias), and coefficient of determination (R^2) are used to assess the effectiveness of the SWAT model (Gupta et al. 1999). The detailed explanation about the R^2, NSE, and PBias are given below.

The coefficient of determination, denoted as R^2, ranges from 0 to 1 and is used to assess the accuracy of a statistical model in predicting results. The expression for R^2 is given below.

$$R^2 = \frac{n\sum_{i=1}^{n}\left(O_i^{obs} O_i^{sim}\right) - \left(\sum_{i=1}^{n}(O_i)\right)\left(\sum_{i=1}^{n}\left(O_i^{sim}\right)\right)}{\sqrt{\left[n\sum_{i=1}^{n}\left(O_i^{obs}\right)^2 - \left(\sum_{i=1}^{n} O_i^{obs}\right)^2\right]\left[n\sum_{i=1}^{n}\left(O_i^{sim}\right)^2 - \left(\sum_{i=1}^{n} O_i^{sim}\right)^2\right]}} \tag{3.3}$$

Where, O_i^{obs} is the ith observed data, O_i^{sim} is the ith simulated data, and n is the number of observations. The Percent bias (PBias) measures the average tendency of the simulated values to be larger or smaller than their observed values. The mathematical expression for PBias is given below.

$$PBias = \frac{\sum_{i=1}^{n}\left(O_i^{obs} - O_i^{sim}\right)^2}{\sum_{i=1}^{n}\left(O_i^{obs}\right)^2} \tag{3.4}$$

The Nash-Sutcliffe efficiency (NSE) is a standardized metric used to assess the proportion of residual variance relative to the variance of the observed data. The mathematical expression for NSE is given below:

$$NSE = 1 - \frac{\sum_{i=1}^{n}\left(O_i^{obs} - O_i^{sim}\right)^2}{\sum_{i=1}^{n}\left(O_i^{obs} - O_{mean}^{obs}\right)^2} \tag{3.5}$$

Where, O_i^{obs} is the i^{th} observed data, O_i^{sim} is the i^{th} simulated data, O_{mean}^{obs} is the mean of observed data and n is the number of observations.

The optimal value of PBias is 0, positive value represents the model bias towards underestimation and negative value denotes bias towards overestimation. The model performance was judged as satisfactory if NSE greater than 0.5 and PBias is less than ±25% for monthly streamflow and less than ±55% for sediment simulations (Moriasi et al. 2007).

3.4 Shared Socio-economic Pathways (SSPs)

Socio-economic changes, such as population growth, development of industries, agriculture, and land use change, can greatly impact the streamflow and water quality in watersheds. To address these issues, it is important to consider socio-economic pathways as a way to integrate the social aspects of future changes. According to IPCC, there are five different socio-economic pathways (SSPs) that can be used to analyze these changes. These SSPs include: SSP1 stands for Sustainability, SSP2 stands for Business as Usual, SSP3 stands for Fragmented World, SSP4 stands for Inequality Rules, and SSP5 stands for Regular Progress in terms of energy sources. Three SSP-based scenarios were considered in this study: SSP2, SSP3, and SSP5, which represent "medium, medium -, and medium +", respectively. These scenarios are regionally specific and align with the RCP 8.5 scenario (Jin et al. 2018; Kebede et al. 2018). The medium - and medium + scenarios indicate low and high growth in the economy, respectively. The medium scenarios were regionalization of the SSPs which is necessary for regional impact modelling. The medium - and medium + scenarios represent low economic growth and high economic growth, respectively. Up to 2050, all three SSPs fall within the band of results compatible with the RCP8.5. Beyond 2050, only SSP5 is consistent with RCP8.5 which can be associated to the highest population growth and highest emissions. Climate can significantly affect the hydrological conditions and water resources arising from change in precipitation intensity and frequency, which have resulted in extensive flooding and extended drought (IPCC, 2007). Additionally, socio-economic changes such as urbanization and population increase have put additional stress on water resources which can worsen the issues of water scarcity and food production (IPCC, 2014). The effects of climate change are anticipated to be particularly severe in countries like India, where the rural economy heavily relies on agriculture. Over two-thirds of India's population depends directly on agriculture, which is largely dependent on the south-west summer monsoon from June to October. Population growth, increased agricultural demands, and monsoon rainfall variability negatively impact soil fertility and water quality. Consequently, this study evaluates the impact of climate change on sediment yield in the Nagavali and Vamsadhara basins using three SSP-based scenarios: SSP2, SSP3, and SSP5. These scenarios help assess the effectiveness of Best Management Practices (BMPs) in mitigating sediment yield under varying socio-economic conditions.

3.5 Evaluation of BMP Scenarios

The methodology employed in this study for the assessment of BMPs across the Nagavali and Vamsadhara basins is presented in Figure 3.2. Various BMPs, namely filter strips with widths of 3 m, 6 m, and 10 m, sedimentation ponds, contour farming, contour stone bunding, and their combinations were chosen to assess their respective impacts on streamflow and sediment yield.

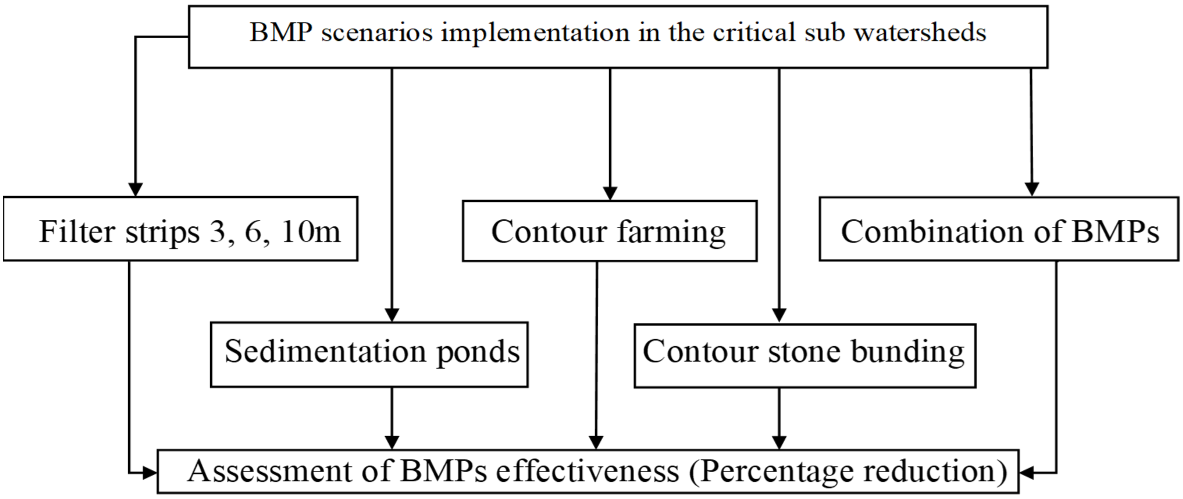


Figure 3.2 Methodology followed to evaluate the effectiveness of developed BMPs

These BMPs were specifically selected for their relevance in mitigating soil erosion and managing sediment dynamics. A comprehensive overview of the different BMPs, along with their pre- and post-BMP parameter values, is presented in Table 3.1. The evaluation focused on critical sediment source sub-basins and basin scales, utilizing SWAT.

Table 3.1 Development of BMP scenarios and their pre- and post-BMP parameter values

S. No	BMP Scenarios	Parameter	Pre-BMP/Calibrated value	Post-BMP/Modified value
1	Baseline	Simulated with calibrated model	-	-
2	Filter strips	FILTERW.mgt	0	3, 6, 10 m
3	Sedimentation ponds	PND-FR.pnd PND-PVOL.pnd PND-PSA.pnd PND-K.pnd	0 25 5 0	0.5 50 500 0.05
4	Contour farming	CN2.mgt USLE-P.mgt	Varies 0.5 or 1	Reduced by 3 units of calibrated value 0.6 for slope 1-2% 0.5 for slope > 2%
5	Contour stone bunding	CN2.mgt SLSUBBSN.hru USLE-P.mgt	Varies Varies 0.5 or 1	Reduced by 3 units of calibrated value 10 m for slope < 8% 9.1 m for slope > 8% 0.32

According to similar investigations (Admas et al. 2023; Dibaba et al. 2021; Gashaw et al. 2021; Leta et al. 2023; Nepal and Parajuli, 2022; Pandey et al. 2021; Uniyal et al. 2020), management strategies can be simulated in SWAT by modifying modelling parameters like the curve number (CN2), slope length (SLSUBBSN), slope steepness (HRU_SLP), erosion control practice factor (USLE_P), and filter strip width (FILTERW). Curve number (CN2) is an important parameter in estimating runoff and sediment yield. It is a dimensionless number that is used to represent the infiltration capacity of the soil based on land use, soil type, and hydrological conditions. The lower the CN2, the more permeable the soil is and the less runoff generated, this means that the runoff transports less sediment. The FILTERW parameter influences the effectiveness of the filter strip in intercepting runoff and trapping sediment. Wider strips generally provide more surface area for filtration and are more effective at reducing sediment. USLE_P factor in the SWAT model, is a critical parameter derived from the USLE. This factor is designed to represent the effectiveness of various erosion control practices in reducing soil erosion rates. The USLE_P factor adjusts the predicted soil loss by accounting for the implementation of specific Best Management Practices (BMPs) that aim to reduce the velocity of surface runoff and the detachment of soil particles. In SWAT, the USLE_P factor is applied at the Hydrologic Response Unit (HRU) level, allowing for detailed representation of erosion control practices across different land uses and management conditions within a watershed. Application of contour stone bunds reduce overland flow and sediment loss by shortening slopes and increasing watershed abstractions This strategy aims to decrease runoff, sheet scour, and slope length. Modifying parameters such as the length of slope (SLSUBBSN), curve number (CN2), and the erosion control practice factor(USLE_P) for key sub-basins simulate the impacts of contour stone bunds creation on steep grades. During periods of excessive precipitation, contour farming builds a water break, reducing the creation of rills and gullies. This conservation technique in SWAT model was reflected by adjusting CN2 and the corresponding USLE_P, which is a ratio that compares soil loss from one support system to soil loss from up and down cultivation.

The selected BMPs were systematically applied within the SWAT model to simulate their individual and collective effects on streamflow and sediment yield. The BMPs were assessed for their effectiveness in reducing simulated streamflow and sediment yield using Indian meteorological data and projections from the future Cold-Wet (EC-Earth3) model under the SSP585 scenario. The pre- and post-BMP parameter values served as critical indicators for assessing the efficacy of each BMP in achieving the desired outcomes.

The efficiency of BMP scenario was calculated using following equation:

$$Percentage\ reduction\ (\%)\ = \frac{(Post\ BMP\ scenario - Base\ scenario)}{Base\ scenario} \times 100 \quad (3.6)$$

Where, post BMP and base scenarios are the average annual streamflow and sediment yield after and before BMP application, respectively.

3.6 Closure

This chapter describes the overall methodology for evaluating the effectiveness of developed Best Management Practices for sediment yield and streamflow under IMD data simulations and downscaled GCM models data. The flowchart for the evaluation of individual and combined BMPs using SWAT model is given. Description of SWAT model to simulate streamflow and sediment yield is provided. Selected procedure of various BMPs has been explained.

Chapter - 4 Study Area and Database Preparation

4.1 Study Area

The selection of the study area is important for evaluating the efficient performance of the proposed methodology. Two medium size east-flowing river basins namely The Nagavali and Vamsadhara of India are selected in the present study. The study area, depicted in Figure 4.1, encompasses two significant river basins crucial for fulfilling irrigation and water supply needs in southern Odisha and northern Andhra Pradesh states. Situated between latitudes 18° 10' to 19° 45' N and longitudes 82° 54' to 84° 20' E, the Nagavali and Vamsadhara rivers are distinct, adjacent water bodies flowing eastward across state boundaries. Originating from the Thuamul Rampur block in Kalahandi district, southern Odisha, both rivers traverse nine districts before merging into the Bay of Bengal (BoB) at Bontala Koduru and Kalingapatnam in northeastern Andhra Pradesh, respectively. The Nagavali river spans approximately 256 km from its source to the Bay of Bengal, covering a catchment area of 9510 sq.km, while the Vamsadhara river extends about 254 km with a catchment area of 10830 sq.km. Annual rainfall in both basins typically ranges between 1200 and 1400 mm, accompanied by average minimum and maximum temperatures of 8 °C and 43 °C, respectively.

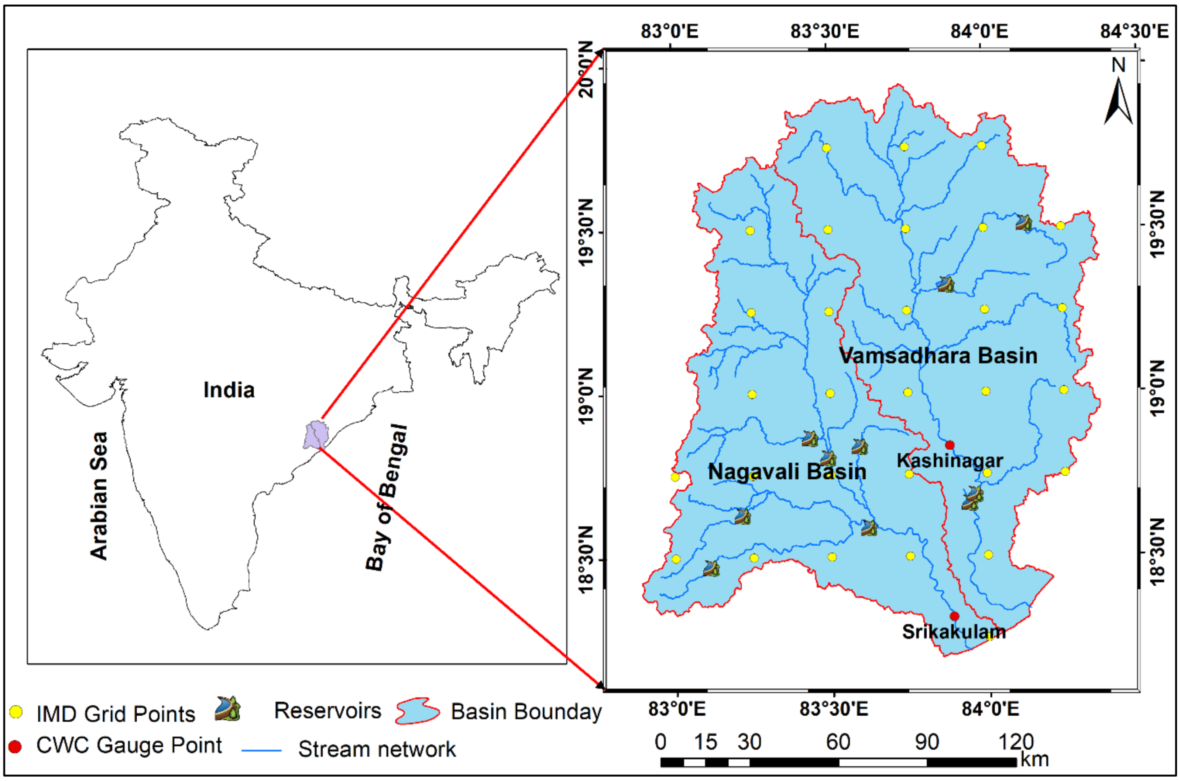


Figure 4.1 Geographical Location of the Study Area

Elevations in the Nagavali basin vary from 0 to 1634 meters, whereas the Vamsadhara basin elevations range from 0 to 1505 meters. The residents within the catchment area depend predominantly on agriculture for their livelihoods. Cultivation in the basins encompasses a variety of crops, including paddy, cotton, red gram, sugarcane, groundnut, and sesame, cultivated throughout both the Kharif and Rabi seasons. The field visit photos which shows the paddy crop, farmer interviews regarding agricultural activities, water with sediments at Gotta barrage, Hiramandalam are given in Figure 4.2. Typical agricultural management data collection sheet prepared for the field study is shown in Figure 4.3. Agricultural management practices including crop details, sowing and harvesting months, and fertilizer application details was collected through local farmer interviews and updated in SWAT management files (.mgt). Across the Nagavali and Vamsadhara basins, rice emerged as the predominant crop during both the kharif and rabi seasons, followed by crops such as banana, sugarcane, maize, and groundnut. The rice cultivation cycle typically involves sowing in June and harvesting in December. During the sowing phase, farmers judiciously applied di-ammonium phosphate (DAP) at a rate of 50 kg per acre. Subsequently, a combination of urea and potash, 25 kg per acre, was applied after 40 days, with a follow-up application in October. Banana cultivation, an annual crop in these basins, commenced in January and February. Fertilizer application for banana crops was executed rotationally from July to December, incorporating DAP and a combination of urea and potash at a rate of 150 kg each. This detailed integration of agricultural management practices into the SWAT model ensures a nuanced representation of the real-world scenarios, enhancing the model accuracy and reliability for simulating watershed dynamics.

4.2 Data Sources

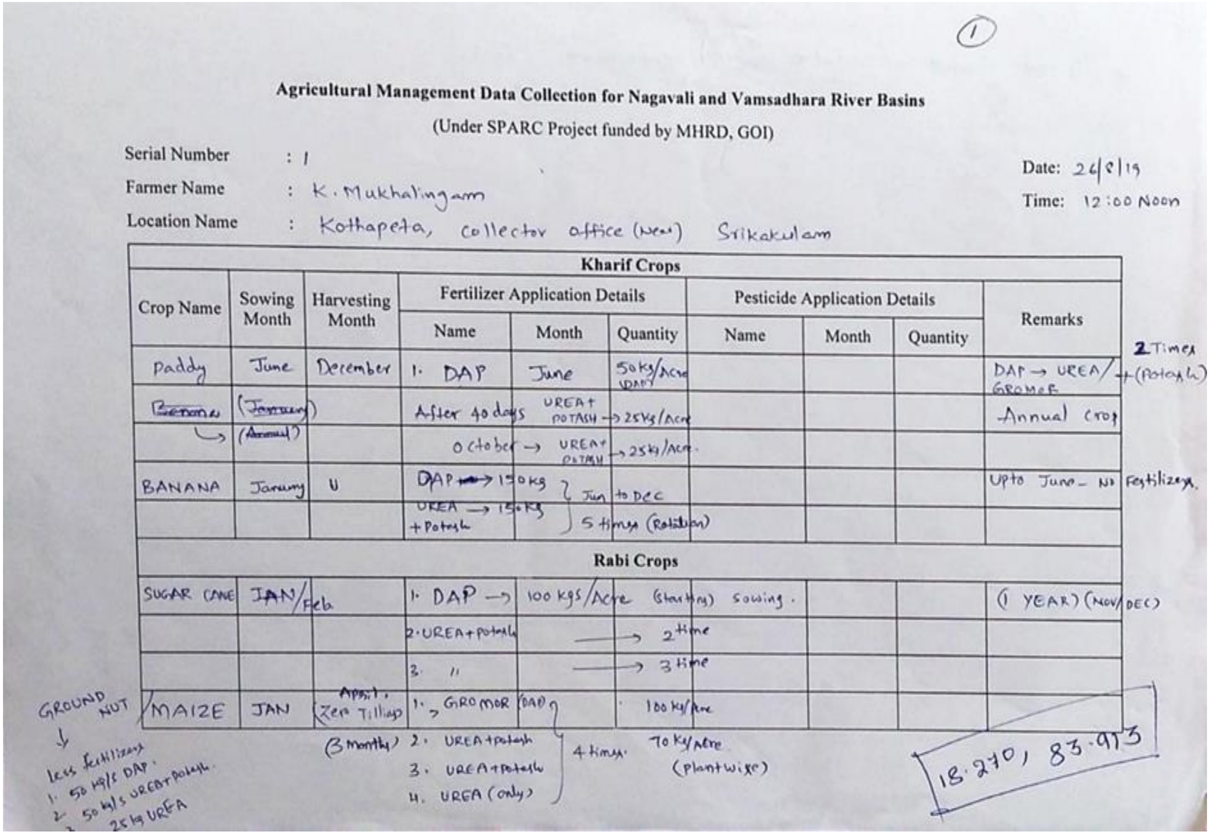
The input data used in the present study includes hydrometeorological data and geospatial data. Details about the data which includes spatial resolution, organization name, and web source are given in Table 4.1. Most of the spatial data, rainfall, and temperature data utilized in this study are publicly accessible. The following sections provide a comprehensive overview of the data employed in this research.

a) Paddy near kothapet, Srikakulam

b) Conducting farmer interviews

c) Presence of sediment in water at Gotta barrage, Hiramandalam

Figure 4.2 Field observation photos of Nagavali and Vamsadhara basins during 26th to 29th, August 2019



1

Agricultural Management Data Collection for Nagavali and Vamsadhara River Basins

(Under SPARC Project funded by MHRD, GOI)

Serial Number : 1

Farmer Name : K. Mukhalingam

Location Name : Kothapeta, collector office (Near) Srikakulam

Date: 26/8/19

Time: 12:00 Noon

Crop Name	Sowing Month	Harvesting Month	Fertilizer Application Details – Name	Month	Quantity	Pesticide Application Details – Name	Month	Quantity	Remarks
Kharif Crops									
Paddy	June	December	1. DAP	June	50 kg/Acre (DAP)				DAP → UREA/GROMOR + (Potash) 2 Times
~~Banana~~	(~~January~~)		After 40 days	UREA + POTASH	→ 25 kg/Acre				Annual crop
↳	(~~Annual~~)		October →	UREA + POTASH	→ 25 kg/Acre.				
BANANA	January	"	DAP → 150 kg	Jun to DEC					Upto June – No Fertilizers.
			UREA → 150 kg + Potash	5 times (Rotation)					
Rabi Crops									
SUGAR CANE	JAN/Feb		1. DAP →	100 kgs/Acre	(Starting) sowing.				(1 YEAR) (Nov/DEC)
			2. UREA + potash	→	2 time				
			3. "	→	3 time				
MAIZE	JAN	April. (Zero Tillage) (3 months)	1. GROMOR (DAP) 2. UREA + potash 3. UREA + potash 4. UREA (only)	4 times.	100 kg/Acre 70 kg/Acre (plantwise)				

GROUND NUT
↓
less fertilizers
1. 50 kg/s DAP.
2. 50 kg/s UREA + potash.
3. 25 kg UREA

18.270, 83.913

Figure 4.3 Agricultural management data collection sheet

Table 4.1 Details of the datasets used in the present research study

Dataset	Spatial Resolution	Organization Name	Web Source
Rainfall	0.25° × 0.25°	IMD	https://www.imdpune.gov.in/lrfindex.php
Temperature	1° × 1°		
Gauge Data (streamflow and sediment concentration)	------	CWC, India	Mahanadi & Eastern Rivers Organization (M&ERO), Bhubaneswar.
Downscaled GCM models	0.25° × 0.25°	CMIP6	https://zenodo.org/records/3873998
SRTM DEM	30 m × 30 m	SRTM	https://earthexplorer.usgs.gov/
Soil Data	1 km × 1 km	ISRIC	https://www.isric.org/explore/soil-geographic-databases
Land Use Land Cover (LULC)	1:250k	NRSC	https://bhuvan-app1.nrsc.gov.in/thematic/thematic/index.php

4.2.1 Weather Data

Gridded daily rainfall data with spatial resolution of 0.25° × 0.25° (Pai et al. 2014) and gridded daily maximum and minimum temperature with spatial resolution of 1° × 1° (Srivastava et al. 2009) datasets are collected from the Indian Meteorological Department (IMD) Pune, India. Srivastava et al. (2009) used a modified version of the Shepard's angular distance weighting algorithm for interpolating the station temperature data into 1° latitude × 1° longitude grids. The gridded temperature data was cross validated after development, and errors were estimated and less than 0.5 °C were found. More details about the IMD gridded data are reported in Pai et al. (2014) and Srivastava et al. (2009). The Nagavali river basin has 12 IMD rainfall grid points and the Vamsadhara river basin has 16 IMD rainfall grid points (Figure 4.1). Rao et al. (2020) compared and found a good correlation of 0.79 between IMD gridded rainfall and gauge rainfall data. Over the Nagavali river basin the annual average rainfall for the period of 1901–2018 is 1230 mm, annual average maximum temperature for the period of 1951–2018 is 32.05 °C and minimum temperature is 21.03 °C.

For the Vamsadhara river basin the annual average rainfall is 1260 mm, annual average maximum temperature is 32.21 °C and minimum temperature is 21.27 °C.

4.2.2 Hydrological Data

The details of the gauge data of the study basins are given in Table 4.2. Streamflow data and sediment data available at Srikakulam gauge station for the Nagavali river basin and Kashinagar gauge station for the Vamsadhara river basin. Streamflow and sediment data was obtained from Central Water Commission (CWC), Mahanadi and eastern rivers organization, Bhubaneshwar, Odisha. The maximum streamflow over the Nagavali river basin is 5624.74 m^3/sec recorded on 4 August 2006 and corresponding sediment load is 3.34 million tons. Over the Vamsadhara river basin the maximum streamflow is 7321.54 m^3/sec recorded on 7 August 2007 and corresponding sediment load is 1.97 million tons. The average annual streamflow is 79.22 m^3/sec for Nagavali basin and 82.1 m^3/sec for Vamsadhara basin. Annual average sediment load is 3.69 million ton over the Nagavali and 3.72 million ton over the Vamsadhara basin.

Figure 4.4 shows the inter-annual variability of rainfall and streamflow for the period of 24 years from 1991 to 2014. From Figure 4.4, it can be observed that over the Nagavali river basin the highest rain-fall observed is 1832 mm in the year 2006, the lowest rainfall observed is 850 mm in 2002, and average rainfall is 1248 mm. Over the Vamsadhara river basin the highest rainfall is 1889 mm in the year 1995, the lowest rainfall is 926 mm in 2011, and average rainfall is 1303 mm. It was observed in both the river basins that 1995 and 2010 are flood years and the immediately following years of 1996 and 2011 are observed as drought years.

Table 4.2 Details of the gauge data in Nagavali and Vamsadhara basins

Station Name	Latitude	Longitude	River Name	Data Availability	Data Type
Kashinagar	18° 50' 54'' N	83° 52' 23''E	Vamsadhara	July, 1980 – December, 2014	GDSQ
Srikakulam	18°18' 48''N	85°53' 03''E	Nagavali	March, 1988 – December, 2014	GDSQ

Note: *Data availability information (i.e., beginning and ending dates) specifies how long the data will be available. The data type indicates the type of data available at the given gauge station (i.e., G - Gauge data, D - Discharge data, S - Sediment data, Q - Water Quality data).*

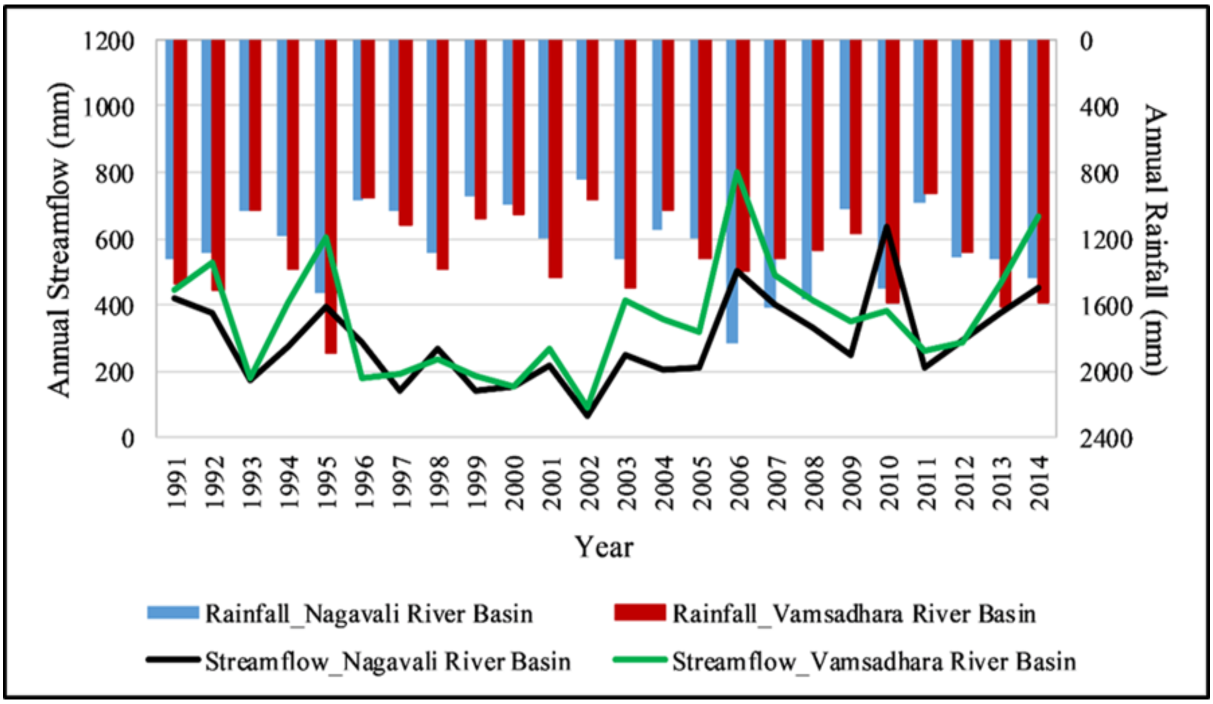


Figure 4.4 Annual rainfall and streamflow in the Nagavali and Vamsadhara river basins.

4.2.3 Geospatial Data

This research utilizes geospatial data including DEM, LULC, and a soil map. 30 m SRTM DEM sourced from the US Geological Survey (USGS) earth explorer, shows maximum elevations of 1634 m for the Nagavali basin and 1505 m for the Vamsadhara basin (Figure 4.5). Three slope bands (0–2%, 2–8% and more than 8%) are considered for both river basins. The LULC data for both basins were acquired from Bhuvan, NRSC, at a resolution of 1:250 km. The LULC categories used in the study were adapted into SWAT land cover codes and include various land types such as agricultural land, plantations, current fallow, evergreen and deciduous forests, scrub forest, wasteland, water bodies, and built-up areas. LULC map for the basins are presented in Figure 4.6, and the distribution of LULC types is detailed in Table 4.3. Soil maps were sourced from the International Soil Reference and Information Centre (ISRIC) soil data site, with the soil classification for the area depicted in Figure 4.7. Key soil types identified include loam, sandy loam, sandy clay loam, and clay loam, prevalent in both river basins.

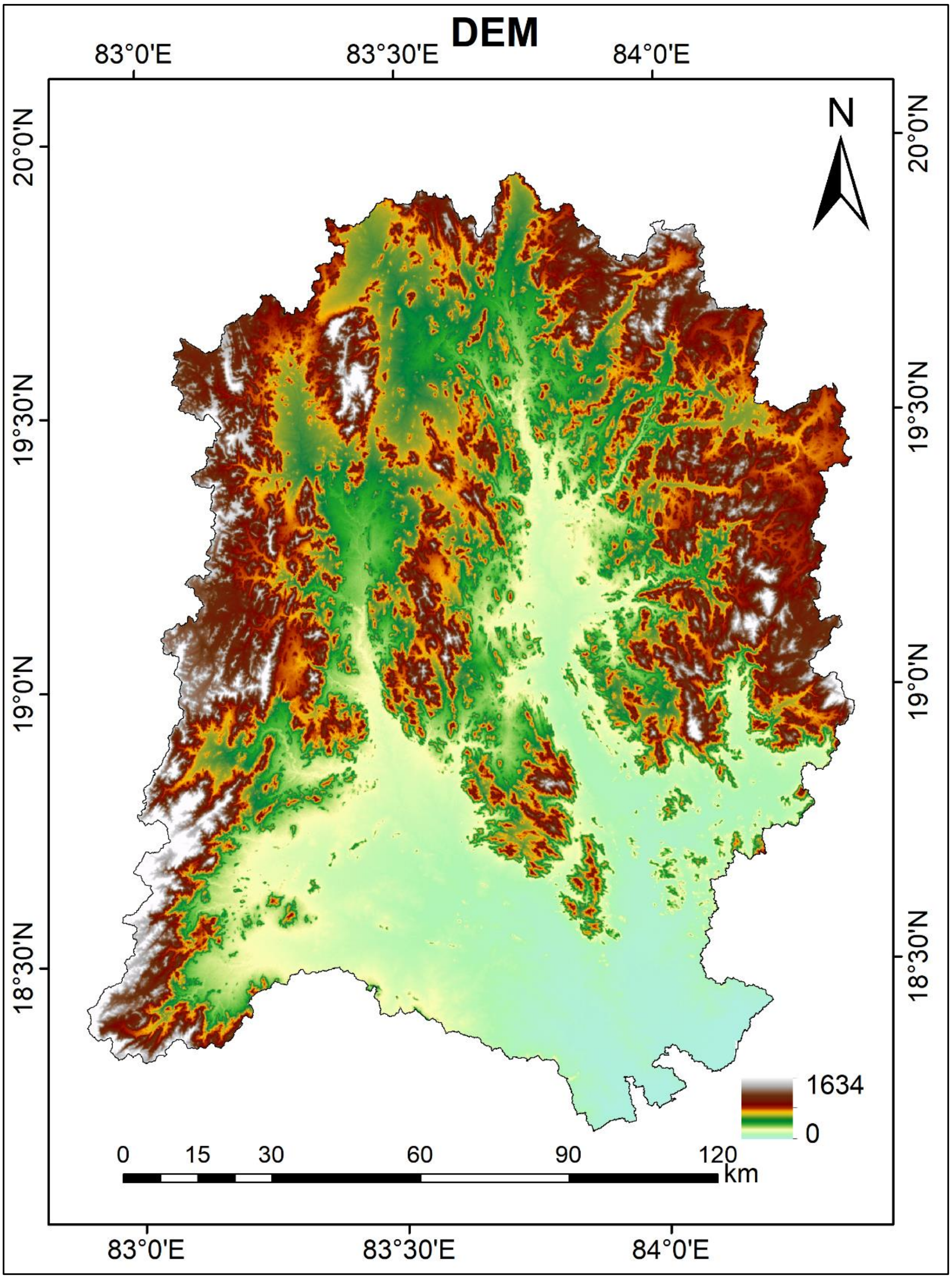


Figure 4.5 DEM for the study basins

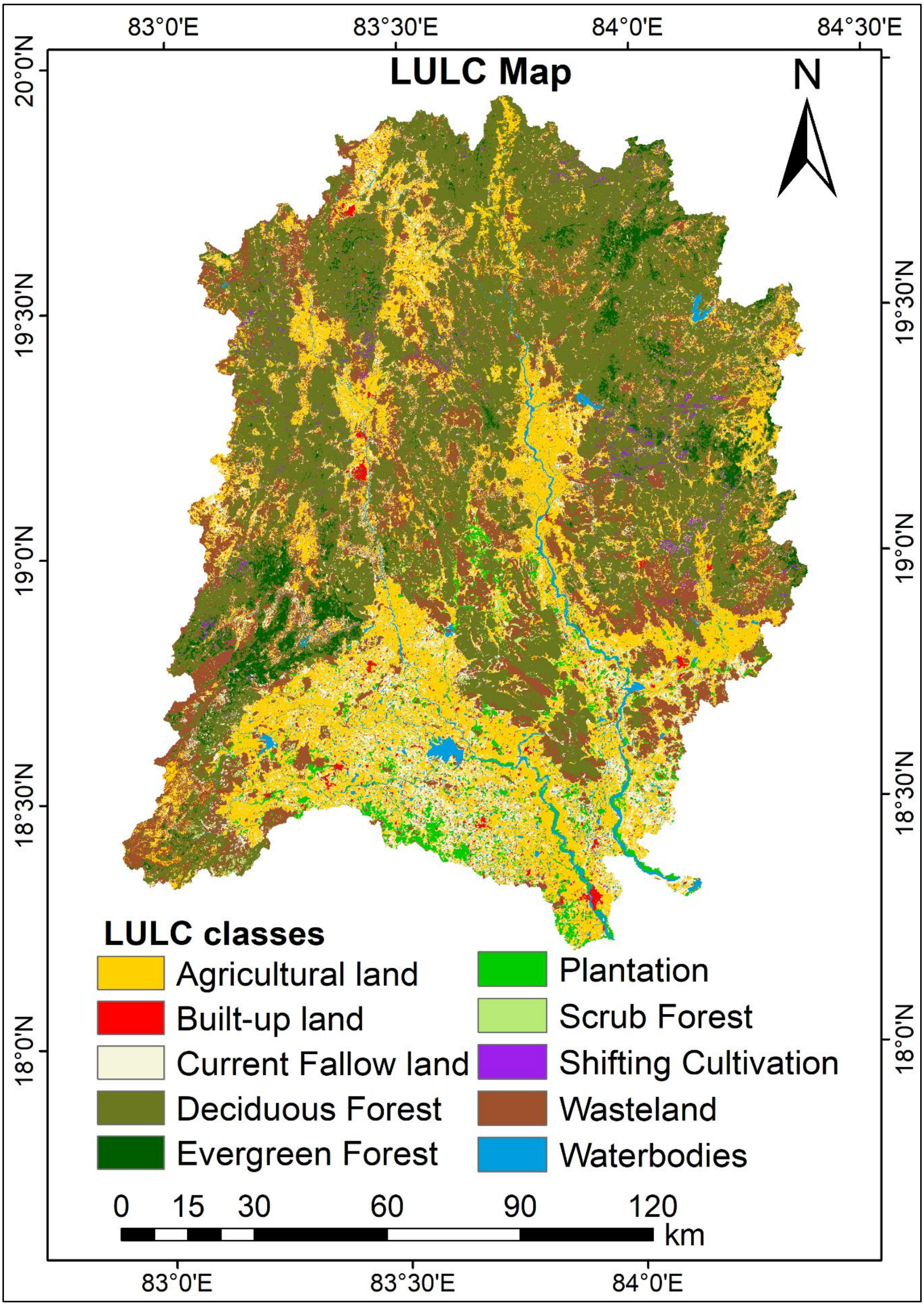


Figure 4.6 LULC for the study basins

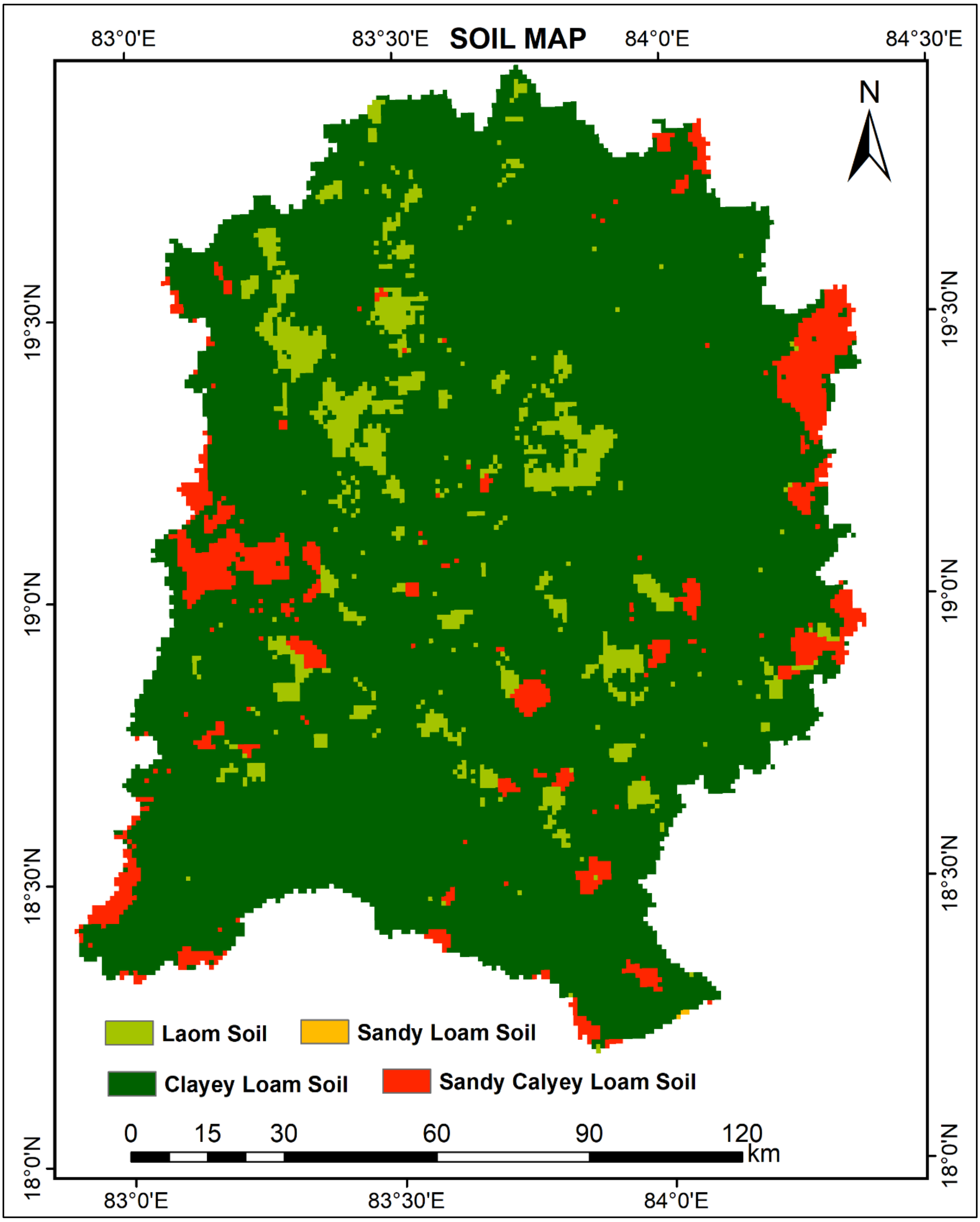


Figure 4.7 Soil Map for the study basins

Table 4.3 Percentage area of each LULC in Nagavali and Vamsadhara Baisns

S. No.	SWAT Code	Class Name	% of Area	
			Nagavali Basin	Vamsadhara Basin
1	RICE	Kharif crop	12.3	9.94
2	AGRL	Rabi crop	5.29	2.87
3	ORCD	Plantation	2.94	1.2
4	CRDY	Current fallow	12.21	7.63
5	AGRR	Double or Triple crop	10.22	7.67
6	FRSE	Evergreen forest	3.06	3.09
7	FRSD	Deciduous forest	29.34	46.65
8	RNGB	Degraded or Scrub-forest	1.53	1.44
9	BARR	Wasteland	19.05	17.23
10	WATR	Waterbodies	2.91	1.84
11	URBN	Built-up land	1.14	0.43

4.2.4 Climate Models Data

The study utilized a bias-corrected dataset created by Mishra et al. (2020) with a high resolution of 0.25° × 0.25° for historic and projected climates for the four SSP scenarios in South Asia. The dataset was developed using the Empirical Quantile Mapping (EQM) method and output from 13 GCMs as part of CMIP6. Mishra et al. (2020) compared the dataset against observations for average and extreme rainfall, maximum and minimum temperatures, using daily rainfall and temperature data from IMD for the Indian region. They found a dry bias in average annual rainfall for most of South Asia, a significant cold bias in the Himalayan region for mean annual maximum and minimum temperatures, and a warm bias in average annual minimum temperature for most of South Asia, excluding the Himalayas.

4.3 Selection of downscaled GCMs

The range of projections from global climate models (GCMs) is quite broad, with high levels of uncertainty (Wilby et al. 2014). The GCMs were downscaled to higher resolution (0.25° × 0.25°) by considering local topographic and physical characteristics, which have gained popularity due to accurate and reliable estimation of future earth climate scenarios in regional hydrological impact studies. (Mishra et al. 2020; Mohseni et al. 2023; Reshma and Arunkumar, 2023). Even after downscaling, future climate projections can vary significantly from one another, ranging from very wet to extremely dry, or from extremely hot to very cold. As a result, the models can be classified as representing the Warm-Wet, Warm-Dry, Cold-Wet, and Cold-Dry corners of the full spectrum. In the present study, model behavior with respect to future in terms of precipitation and temperature is considered. From the available 13 models under the SSP245, SSP370, and SSP585 scenarios, a selection was made based on the changes in average annual precipitation (ΔP) and average temperature (ΔT) across the Nagavali and Vamsadhara basins between the model's historic data (1975-2015) and the projected future data (2022-2100). According to Khan and Koch (2018), the 10th, 50th, and 90th percentile values for ΔP and ΔT were first calculated, as the goal was to select a few models that best represent the four corners and the center of the entire spectrum as shown in Table 4.4. Details about the results of selection procedure is presented in chapter 5.

Table 4.4 Selection criteria of GCM models.

S.No	Model Representing Corners in the Full Spectrum	Selection Criteria
1	Cold-Dry	10th percentile of %(ΔP) as well as 10th percentile of ΔT
2	Cold-Wet	90th percentile of %(ΔP) as well as 10th percentile of ΔT
3	Warm-Wet	90th percentile of %(ΔP) as well as 90th percentile of ΔT
4	Warm-Dry	10th percentile of %(ΔP) as well as 90th percentile of ΔT
5	Average	50th percentile of %(ΔP) as well as 50th percentile of ΔT

4.4 SWAT Model-Set-up

Initially, the setup of the SWAT model requires aligning the DEM, LULC, and soil data within the same projected coordinate system, specifically WGS 1984 UTM Zone 44N. The Nagavali river basin is segmented into 34 sub-basins and comprises 2153 hydrological response units (HRUs), while the Vamsadhara river basin is divided into 30 sub-basins containing 2183 HRUs. This delineation is based on uniformity in soil types, land usage, slope, and a minimum threshold area of 100 hectares (Ha). The reservoir information, as shown in Table 4.5, has been updated into the SWAT model database. Then the IMD data is provided to the model to run simulations.

Table 4.5 Details of existing reservoirs in the Nagavali and Vamsadhara river basins.

Reservoir Name	**RES_EVOL (10^4 m^3)**	**RES_ESA (Ha)**	**RES_PVOL (10^4 m^3)**	**RES_PSA (Ha)**	**RES_Operational Year**
Madduvalasa reservoir	9551	2673	9358	2405	2002
Thotapalli barrage	8503	1983	7105	1785	1908
Vottigedda reservoir	2713	440	2514	272	1976
Janjavathi reservoir	9628	2680	7855	2450	1978
Vengalarayasagar reservoir	4051	575	3646	518	1998
Vegavathi/Peddagedda reservoir	3038	294	2891	265	2003
Badnalla reservoir	5480	753	4932	678	1997
Harabhangi reservoir	11,116	1107	10,000	1000	1998

Note: RES_EVOL and RES_PVOL are the volumes of water needed to fill the reservoir to the emergency spillway and principal spillway, respectively. RES_ESA and RES_PSA are the reser-voir surface areas when the reservoir is filled to the emergency spillway and principal spillway, respectively.

4.5 SWAT Model Calibration, Validation, and Sensitivity Analysis

SUFI-2 algorithm in the SWAT-CUP (Abbaspour, 2011) was used for model calibration, validation, and sensitivity analysis. The observed streamflow and sediments from Srikakulam and Kashinagar stations were used to calibrate and validate the SWAT model over Nagavali and Vamsadhara river basins (Figure 4.1). Based on observed streamflow data, the model simulated monthly streamflow for both basins for 29 years, from 1986 to 2014. The first five years of these 29 years were used as a model warm-up period for variable initialization. The following 15 years, from 1991 to 2005, were considered for calibration, and the remaining 9 years, from 2006 to 2014, were considered for validation. Observed sediment concentration data was available for 12 years, from 2002 to 2013 in grams per liter, and is converted to sediment load (tons per month). Data from 2002 to 2010 were used for calibration, and data from 2011 to 2013 were used for validation of sediment yield simulations.

SWAT model is a conceptual, semi-distributed model based on a number of parameters that vary significantly on a spatial and temporal scale. During the calibration period, sensitivity analysis was performed to identify the key parameters. For monthly streamflow simulations, 15 parameters were taken into account. The significance of senstivity (P) and t-stat values were considered to identify sensitive parameters in Table 4.6. The sensitivity of the parameters increased with higher absolute values of the t-statistic. A p-value approaching zero suggests that the parameter is significantly influential. Thus, a lower p-value combined with a larger absolute t-stat value signifies greater sensitivity.

Table 4.6 Parameters that are sensitive in the Nagavali and Vamsadhara river basins

S. No.	Parameter_Name	Description	Nagavali Basin		Vamsadhara Basin	
			p-value	t-stat	p-value	t-stat
1	R__CN2.mgt	SCS runoff curve number	0.00	−8.74	0.00	−11.64
2	V__ALPHA_BF.gw	Baseflow alpha factor (days)	0.00	4.39	0.37	−0.90
3	A__GW_DELAY.gw	Groundwater delay (days)	0.31	1.03	0.36	0.91
4	A__GWQMN.gw	Threshold depth of water in the shallow aquifer (mm)	0.41	0.83	0.00	6.23
5	V__GW_REVAP.gw	Groundwater revap coefficient	0.49	0.69	0.00	3.99
6	A__RCHRG_DP.gw	Deep aquifer percolation fraction	0.62	0.50	0.87	0.16
7	A__REVAPMN.gw	Threshold depth of water in the shallow aquifer for revap	0.37	−0.90	0.35	−0.93
8	V__ALPHA_BF_D.gw	Alpha factor for groundwater recession curve of the deep aquifer (1/days)	0.11	−1.61	0.23	−1.21
9	R__SOL_AWC.sol	Available water capacity of the soil layer	0.87	0.16	0.01	−2.70
10	V__ESCO.hru	Soil evaporation compensation factor	0.41	0.82	0.38	−0.88
11	V__CANMX.hru	Maximum canopy storage	0.09	1.69	0.10	1.64
12	V__CH_N2.rte	Manning's n value for the main channel	0.12	−1.55	0.54	−0.62

13	V__CH_K2.rte	Effective hydraulic conductivity in main channel	0.02	−2.28	0.56	−0.58
14	V__CH_K1.sub	Effective hydraulic conductivity in tributary channel	0.01	2.47	0.00	6.17
15	V__CH_N1.sub	Manning's n value for the tributary channels	0.55	0.59	0.12	1.55

From Table 4.6, it is evident that CN2, ALPHA_BF, CH_K1, CH_K2, CH_N2, and CANMX are the most sensitive parameters for streamflow over Nagavali river basin and CN2, GWQMN, CH_K1, GW_REVAP coefficient, SOL_AWC, CH_K2 and CANMX are the most sensitive parameters for streamflow over Vamsadhara river basin. Because CN2 is the most sensitive and directly related to the runoff process in both river basins, changes in CN2 have a direct effect on streamflow and sediment yield. Table 4.7 represents the calibrated parameters and their fitted values over the Nagavali and Vamsadhara river basins for streamflow simulations, respectively. The parameters were described in detail in Arnold et al. (2012) and SWAT user manuals.

Table 4.7 Calibrated parameters and their fitted values for streamflow simulations. The numbers in parenthesis indicated sensitivity ranks

S. No.	Parameter_Name	Min_Value	Max_Value	Fitted Values (Sensitivity Ranks)	
				Nagavali Basin	Vamsadhara Basin
1	R__CN2.mgt	−0.1	0.1	−0.088 (1)	−0.092 (1)
2	V__ALPHA_BF.gw	0	1	0.642 (2)	0.093 (11)
3	A__GW_DELAY.gw	−30	90	84.300 (8)	−11.1 (10)
4	A__GWQMN.gw	−1000	1000	5 (10)	−345 (2)
5	V__GW_REVAP.gw	0.02	0.2	0.053 (12)	0.172 (4)
6	A__REVAPMN.gw	−750	750	−498.75 (9)	123.75 (9)
7	V__ALPHA_BF_D.gw	0	1	0.45 (6)	0.687 (8)
8	A__RCHRG_DP.gw	−0.05	0.05	−0.019 (14)	−0.036 (15)
9	R__SOL_AWC.sol	−0.1	0.1	0.04 (15)	−0.029 (5)

10	V__ESCO.hru	0.3	0.6	0.53 (11)	0.58 (12)
11	V__CANMX.hru	0	20	0.45 (5)	9.35 (6)
12	V__CH_N2.rte	0.01	0.1	0.033 (7)	0.084 (13)
13	V__CH_K2.rte	0	100	74.75 (4)	24.25 (14)
14	V__CH_K1.sub	0	100	73.25 (3)	91.75 (3)
15	V__CH_N1.sub	0.01	0.3	0.19 (13)	0.15 (7)

4.5.1 Streamflow Simulations

The statistical results from calibration and validation showed a good agreement between observed and simulated monthly streamflow as presented in Table 4.8. The NSE values for the monthly streamflow of the calibration and validation period were 0.84 and 0.71 at Srikakulam station in the Nagavali river basin and 0.8 and 0.73 at Kashinagar station in the Vamsadhara river basin. The percentage bias (PBias) for the calibration period was 3.4% for the Nagavali basin, indicating that it tends to under-predict, and −6.7% for the Vamsadhara basin, indicating that it tends to over-predict. During validation, PBias is 9.7% and 10.3% in the Nagavali and Vamsadhara river basins, respectively. The model tends to under-predict for the Nagavali and Vamsadhara river basins during the validation period. The statistics for the SWAT model setup for Vamsadhara and Nagavali river basins are good when compared to standard model statistics (Moriasi et al., 2007). Figures 4.7 and 4.8 show the observed versus simulated monthly streamflow at the Srikakulam and Kashinagar gauge stations over the Nagavali and Vamsadhara river basins, respectively.

Table 4.8 Calibration and validation statistics

River Basin	Gauge Station	Calibration				Validation			
		Period	R^2	NSE	PBias	Period	R^2	NSE	PBias
Monthly streamflow simulations									
Nagavali	Srikakulam	1991–2005	0.85	0.84	3.4	2006–2014	0.73	0.71	9.7
Vamsadhara	Kashinagar		0.82	0.8	−6.7		0.74	0.73	10.3
Monthly sediment simulations									
Nagavali	Srikakulam	2002–2010	0.86	0.85	−13.6	2011–2013	0.76	0.7	−14.3
Vamsadhara	Kashinagar		0.75	0.71	14.8		0.7	0.68	−42.8

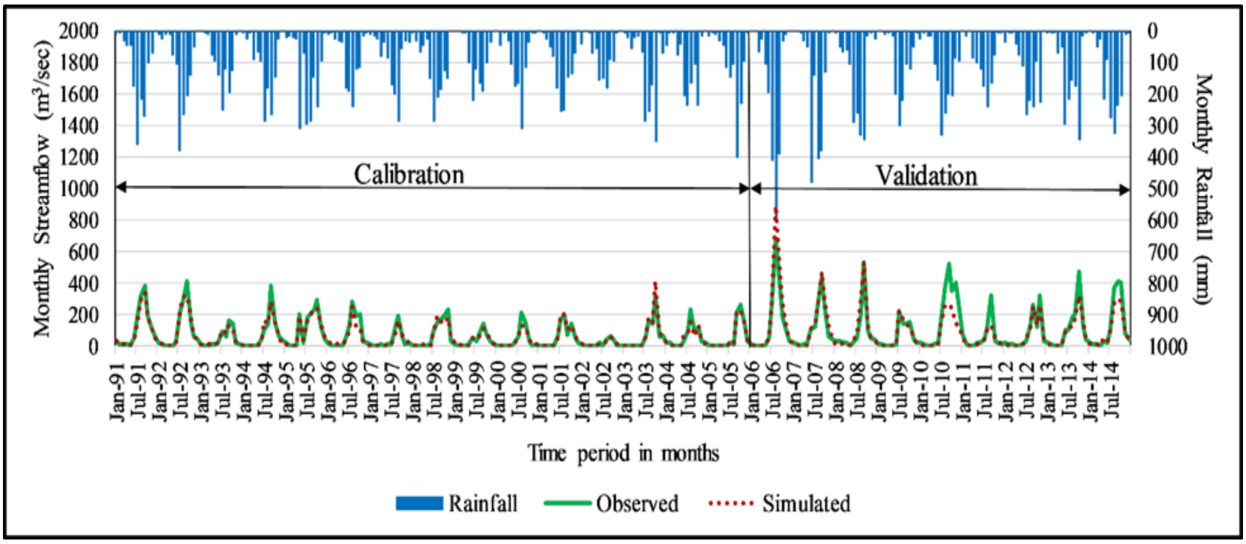


Figure 4.8 Observed versus simulated monthly streamflow during the calibration and validation period over the Nagavali river basin

Figures 4.7 and 4.8 clearly demonstrate that throughout both the calibration and validation periods, the simulated streamflow time series closely mirrors the precipitation patterns observed in the Nagavali and Vamsadhara river basins. This alignment between simulated and observed streamflow indicates a successful match between model outputs and real-world data. In the Vamsadhara and Nagavali river basins, the largest quantity of streamflow occurred from June to October in every year.

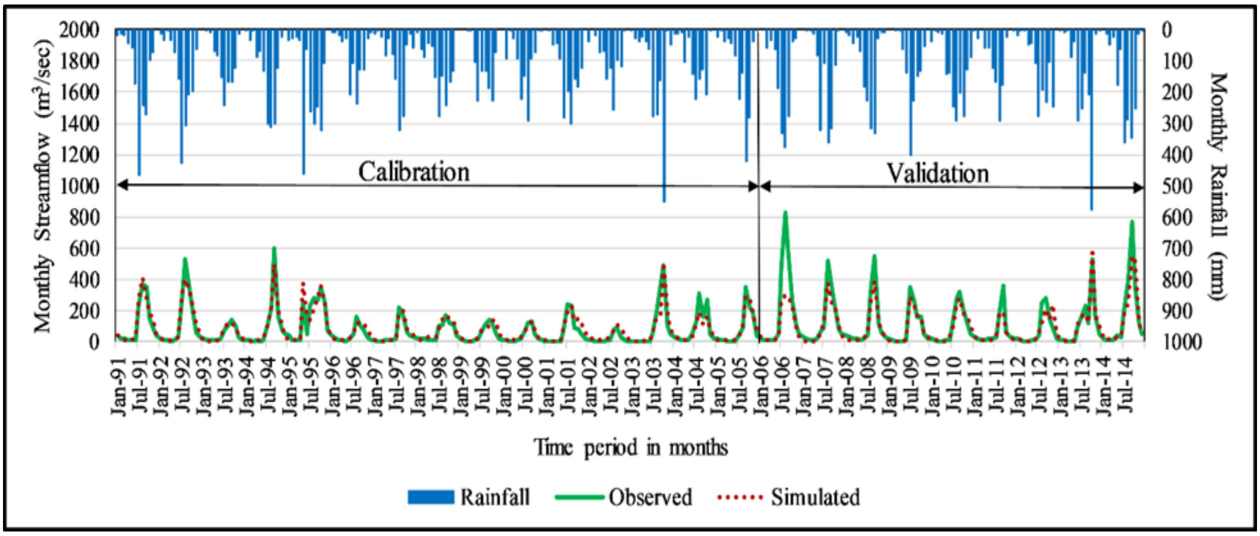


Figure 4.9 Observed versus simulated monthly streamflow during the calibration and validation period over the Vamsadhara river basin

4.5.2 Sediment Simulations

Following calibration of streamflow, the calibrated streamflow parameters were up-dated into the SWAT model, and sediment simulations were carried out. To reduce the high sediment yield from agricultural lands, manual calibration with landscape parameters influencing sediment yield from agricultural lands was performed first, followed by auto calibration (Arnold et al. 2012; Neitsch et al. 2005). Due to watershed uneven slope distribution, the initial LS factor (HRU_SLP and SLSUBBSN) is very high, resulting in an overestimation of sediment yield. Manual calibration was considered only for agricultural HRUs to reduce the sediment load with three landscape parameters (Bonuma et al. 2014) including USLE_P, HRU_SLP and SLSUBBSN.

To reduce sediment yield, the LS factors were reduced by replacing HRU_SLP (average slope steepness (m/m)) with 2% for agricultural HRUs and 0.5% for Rice crop HRUs and SLSUBBSN (average slope length (m)) with 75 m. These changes reduced the simulated sediment yield while limiting erosion from agricultural HRUs. The erosion process is influenced by the USLE P (USLE equation support practice) factor, which is reduced from the default value of 1 to 0.5 for agricultural HRUs. Decreasing of USLE_P has a greater impact on sediment yield from agricultural HRUs. After adjusting these three parameters manually, the simulated sediment yield from agricultural HRUs is less than 1 t/ha/yr. Following manual adjustment of these three parameters, auto calibration was performed using the five parameters presented in Table 4.9.

Table 4.9 Calibrated parameters and their fitted values for monthly sediment simulation

S. No.	**Parameter_Name**	**Min_Value**	**Max_Value**	**Fitted Values**	
				Nagavali Basin	**Vamsadhara Basin**
1	V__CH_COV1.rte	0	0.6	0.23	0.46
2	V__CH_COV2.rte	0	1	0.39	0.17
3	V__SPCON.bsn	0.0001	0.01	0.006	0.0068
4	V__SPEXP.bsn	1	1.5	1.12	1.08
5	R__USLE_K(..).sol	−0.2	0.2	−0.1	−0.09

As indicated in Table 4.8, the statistical findings between monthly observed and simulated sediment load obtained during calibration and validation revealed a good agreement for the Nagavali river basin and a satisfactory agreement for Vamsadhara river basin. For the calibration and validation periods, the NSE values for monthly sediment at Srikakulam gauge station for the Nagavali river basin were 0.85 and 0.7, respectively, and 0.71 and 0.68 at Kashinagar gauge station for the Vamsadhara river basin, respectively.

The percentage biases (PBias) for the calibration and validation periods were −13.6% and −14.3% for the Nagavali basin and 14.8% and −42.8% for the Vamsadhara basin. The PBias values for monthly sediment load show that the model tends to overpredict for the Nagavali river basin and underpredict during calibration, and overpredict during validation for the Vamsadhara river basin. The sediment load in the Nagavali and Vamsadhara river basins were overestimated due to basin barren and scant vegetation over the land-scapes, topography and its complexity, and steep slopes, whereas 60% of the basins area was covered by steep slopes that are more than 8 degrees.

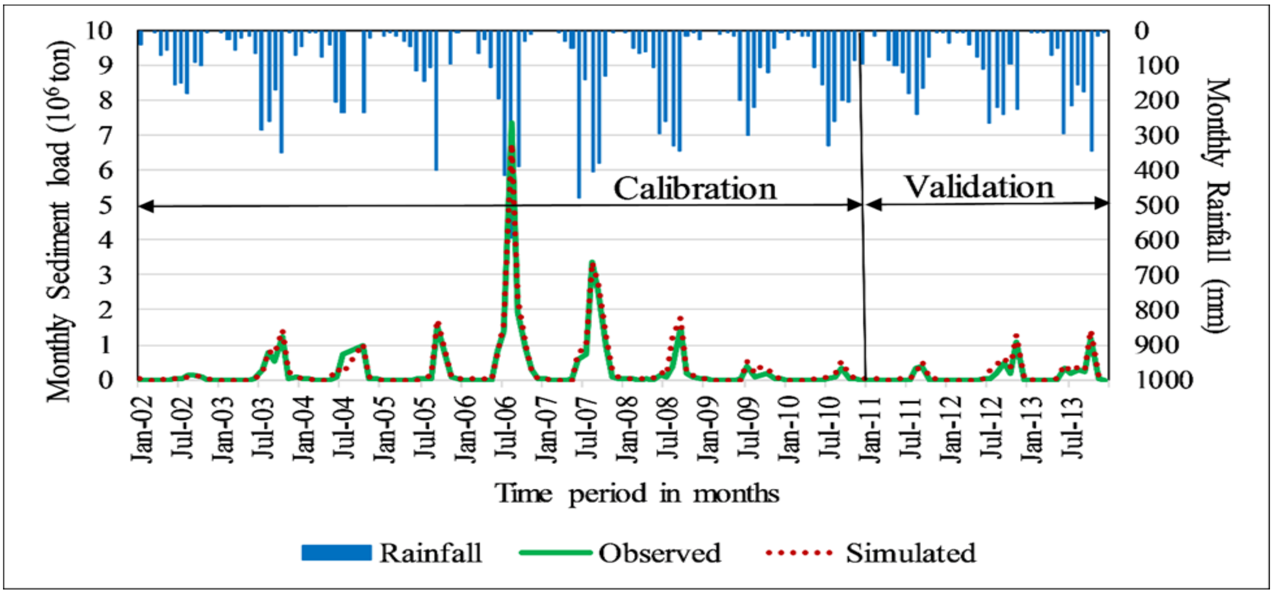


Figure 4.10 Observed versus simulated monthly sediment load during the calibration and validation period over the Nagavali river basin

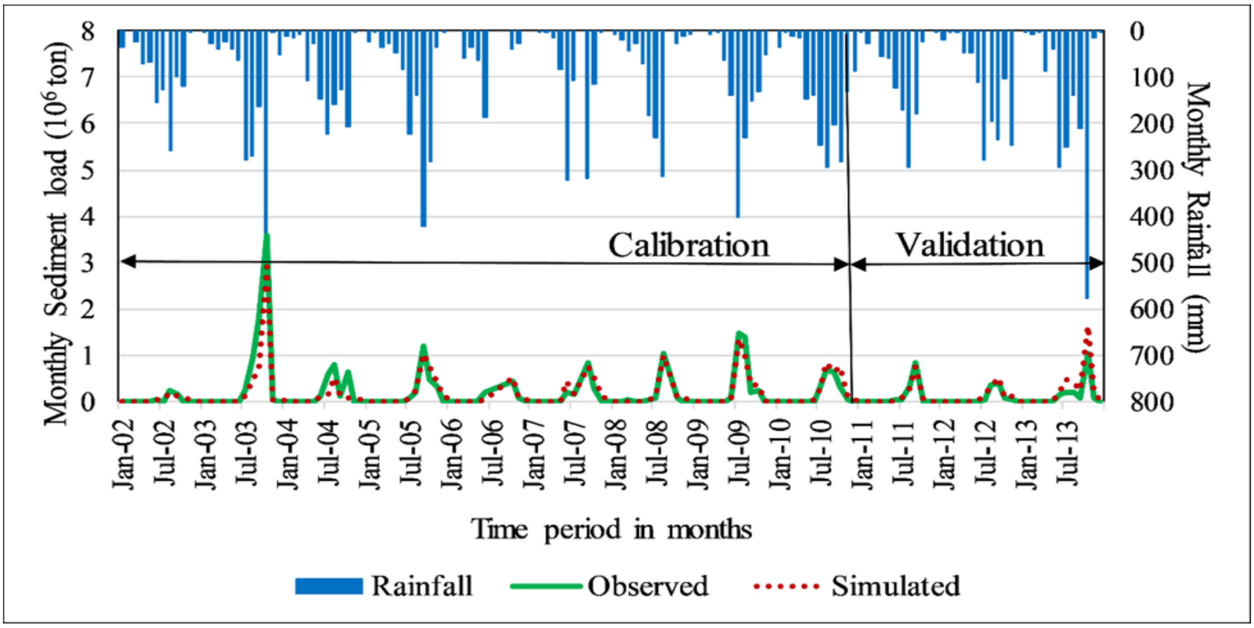


Figure 4.11 Observed versus simulated monthly sediment load during the calibration and validation period over the Vamsadhara river basin

Figures 4.9 and 4.10 show the observed and simulated monthly sediment load over the Nagavali and Vamsadhara river basins during the calibration and validation periods, respectively.

4.6 Closure

Two medium sized east flowing river systems, namely, Nagavali and Vamsadhara basins are chosen as study areas in the present research work. Geospatial database in the required format for the hydrological model (SWAT) is prepared. The SWAT model setup for simulating streamflow and sediment load in these basins has been carried-out. Furthermore, sensitivity analyses have been conducted for both streamflow and sediment load simulations.

Chapter - 5 Streamflow and Sediment Yield Analysis

5.1 General

For the selected study area, water balance components and sediment yield analysis was carried out using SWAT model. Spatial analysis of precipitation, surface runoff, lateral flow, evapotranspiration and sediment yield was analysed. Selection of climate models and their effects on streamflow and sediment under different SSP scenarios are assessed. A detailed explanation about the water balance components, spatial distribution and climate change impacts on precipitation, streamflow and sediment yield, and the identification of critical sediment source areas are given in the following sections.

5.2 Water Balance of Nagavali and Vamsadhara River Basins

Analyzing and quantifying various elements of hydrological processes occurring within the basin is required for various water management scenarios. Precipitation, surface runoff, water yield, lateral runoff, and evapotranspiration constitute the fundamental components of the water balance within the basin. The calibrated model results are scrutinized, focusing on these water balance components on a monthly basis spanning from 1991 to 2014. Figure 5.1 illustrates the monthly water balance, with an annual average rainfall amount of 1259 mm and 1332 mm in the Nagavali and Vamsadhara river basins respectively. Notably, 80% of the rainfall occurs during the monsoon season (June to October). Evapotranspiration emerges as the primary contributor to water loss in both basins, accounting for 63% of the total water loss.

The extent of water lost through evapotranspiration is influenced by factors such as the soil evaporation compensation factor (ESCO), the method used for estimating evapotranspiration (ET), and the leaf area index. Given the predominant forest and agricultural land cover in the catchment areas of the Nagavali and Vamsadhara river basins, evapotranspiration exerts a significant influence on the water resources of these basins. The heightened levels of plant growth, humidity, and wind velocities during the monsoon and post-monsoon months amplify the demand for evapotranspiration.

As depicted in Figure 5.1, during dry months, monthly evapotranspiration surpasses the total precipitation for both basins. This discrepancy is permissible due to the continuous nature of evapotranspiration, occurring at varying rates throughout the day and night, independent of precipitation. Moreover, water for evapotranspiration is sourced from near-surface soil moisture, with the depth of plant roots impacting the rate of evapotranspiration. Additionally, owing to the continuous modeling approach of the SWAT model, which considers changes in soil moisture content, it accommodates the incorporation of soil moisture from the preceding day. Consequently, in dry months, total precipitation in a given month may fall short of total evapotranspiration. From the water balance analysis, there is a need for water harvesting structures because both basins receive more than 80% of their rainfall during the monsoon season.

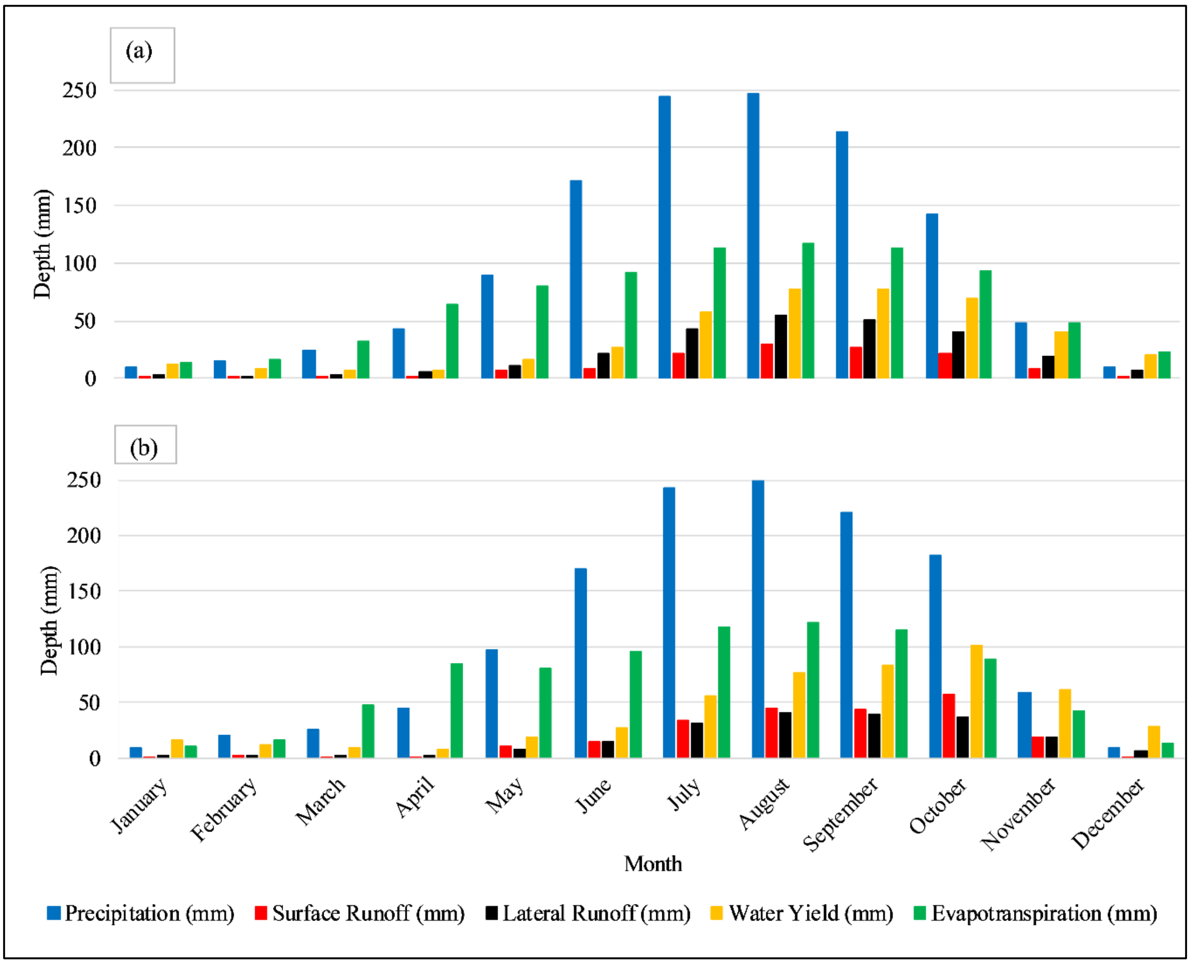


Figure 5.1 Mean monthly values of water balance components (a) Nagavali basin (b) Vamsadhara river basin.

5.3 Spatial Distribution of Water Balance Components

The spatial distribution of average annual values of various water balance components was visualized to better understand the hydrological cycle over the Nagavali and Vamsadhara river basins. Figure 5.2 shows the spatial distribution of average annual precipitation, surface runoff, groundwater flow over the Nagavali river basin. The upper sub-basins received the most precipitation over the Nagavali river basin, while the lower sub-basins received the least. Surface runoff ranges from 9 mm to 189 mm, with sub-basins 1, 2, 15, 17, 33 and 34 producing the most. The groundwater flow ranges from 9 mm to 250 mm, with sub-basins 5 and 7 producing the most groundwater flow.

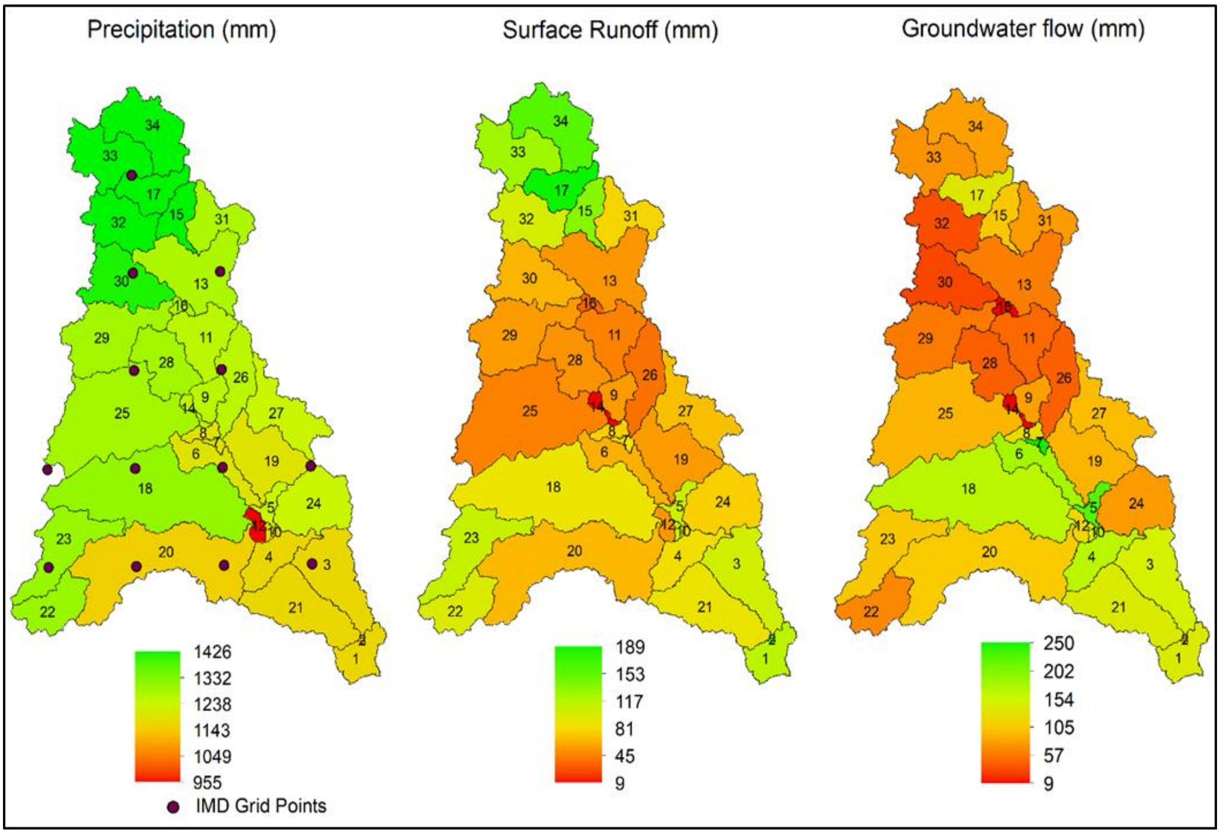


Figure 5.2 Spatial distribution of average annual precipitation, surface runoff and groundwater flow over the Nagavali river basin for the period of 24 years (1991–2014).

Figure 5.3 shows the spatial distribution of annual average evapotranspiration and its validation using the Famine Early Warning Systems Network Land Data Assimilation System (FLDAS). The SWAT model simulated evapotranspiration varying from 698 mm to 1050 mm. Sub-basins 7, 10 and 12 contribute the most evapotranspiration, while lower sub basins with waterbodies and agricultural lands contribute the least. The FLDAS dataset, on the other hand, ranged from 825 mm to 1131 mm over the Nagavali river basin. The difference in PBias between the SWAT simulated evapotranspiration and the FLDAS dataset is 15%.

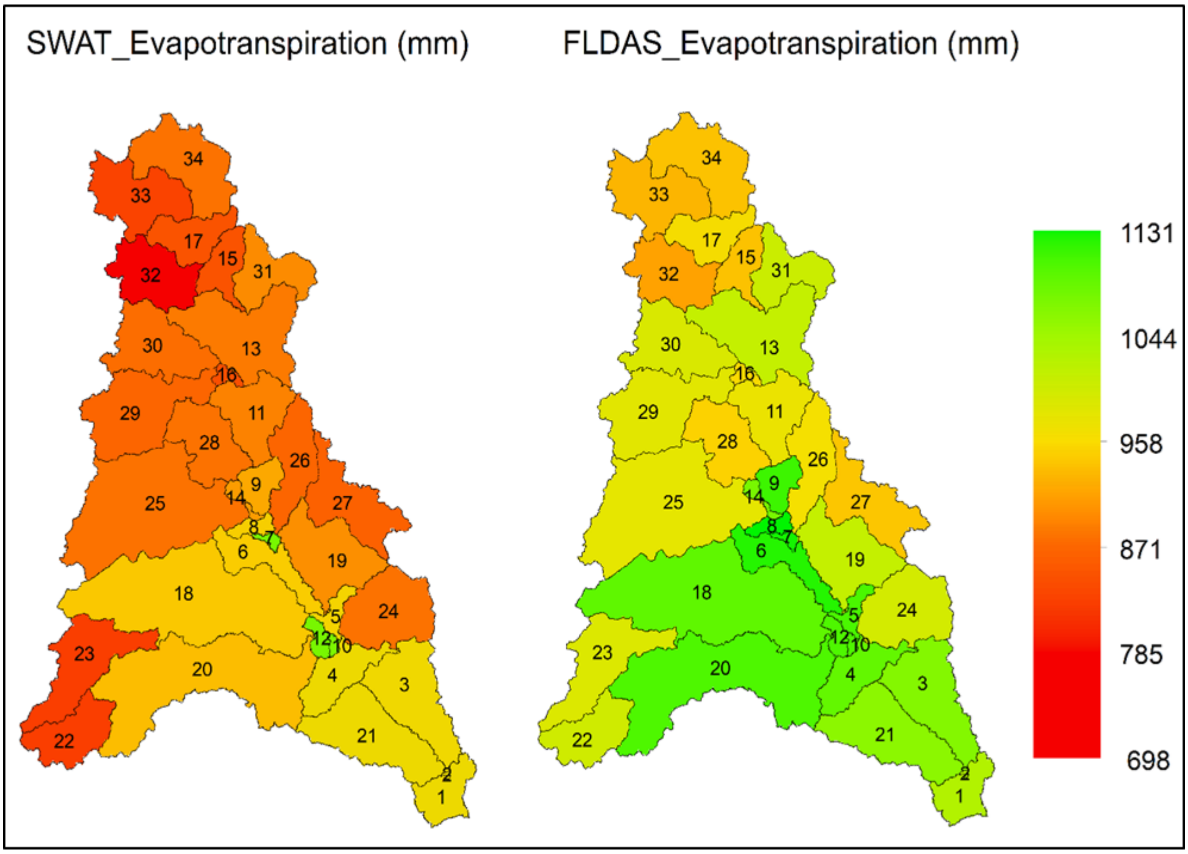


Figure 5.3 Spatial distribution of average annual evapotranspiration and its validation using FLDAS data over the Nagavali river basin for the period of 24 years (1991–2014).

The spatial distribution of average annual precipitation, surface runoff, and groundwater flow over the Vamsadhara river basin is depicted in Figure 5.4. The highest precipitation over the Vamsadhara river basin was 1410 mm in the upper sub-basins and the lowest was 1192 mm in the lower sub-basins. Surface runoff ranges from 43 mm to 172 mm, with sub-basins 8, 11, 12, 16, 25, and 29 producing the most. Groundwater flow ranges from 59 to 265 mm, with the majority of sub-basins contributing the most groundwater flow. Figure 5.5 shows the spatial distribution of average annual evapotranspiration and its validation using the FLDAS dataset. The SWAT simulated evapotranspiration varying from 730 mm to 941 mm, with sub-basins 2, 7 and 28 contributing the most. Whereas the FLDAS dataset ranged from 831 mm to 1075 mm over the Vamsadhara river basin. The difference in PBias between the SWAT simulated evapotranspiration and the FLDAS dataset is 11%.

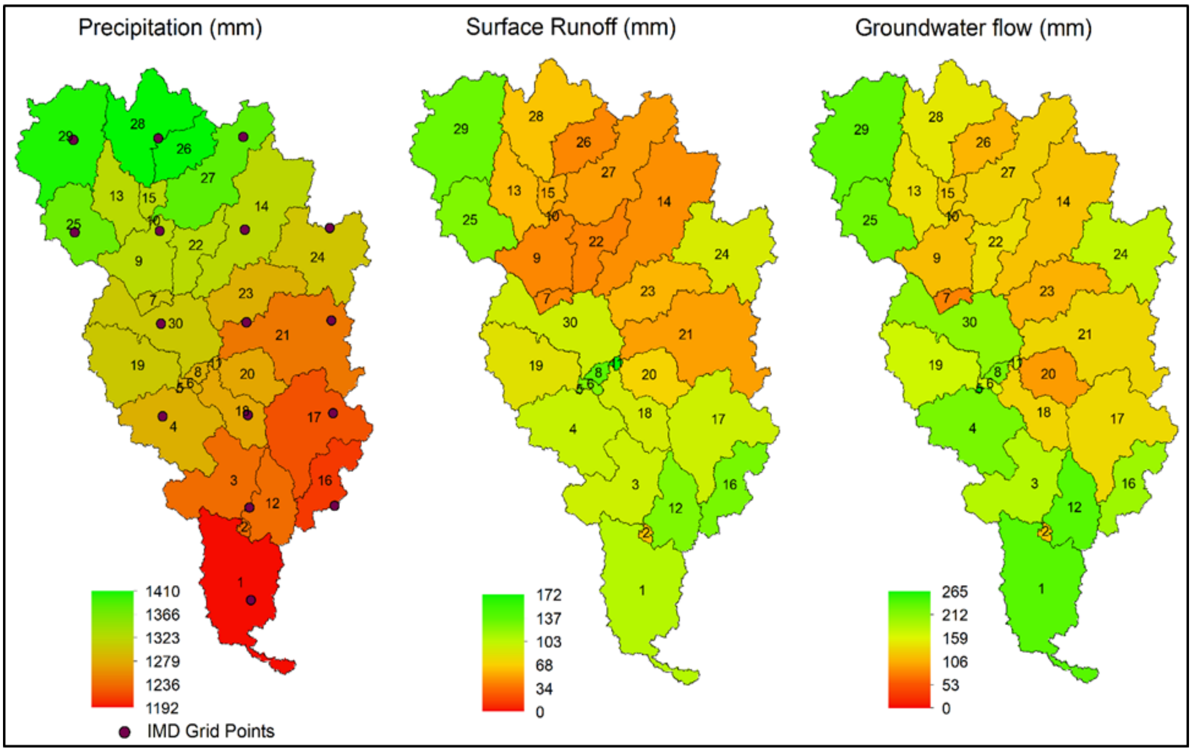


Figure 5.4 Spatial distribution of average annual precipitation, surface runoff and groundwater flow over the Vamsadhara river basin for the period of 24 years (1991–2014).

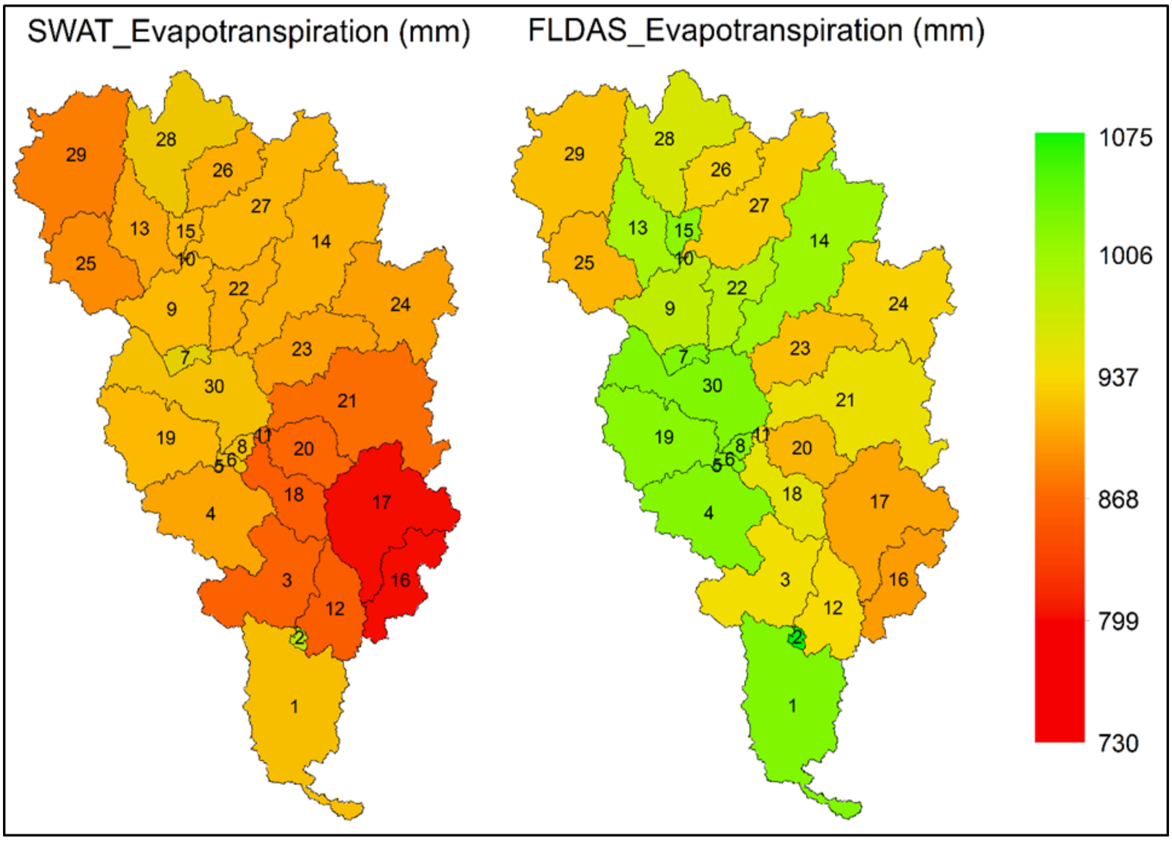


Figure 5.5 Spatial distribution of average annual evapotranspiration and its validation using FLDAS data over the Vamsadhara river basin for the period of 24 years (1991–2014).

Based on the spatial distribution of average annual hydrological components, it was concluded that the simulated precipitation over the basins for the period of 24 years from 1991 to 2014 showed a decreasing gradient from north to south and follows the altitude gradient over the two basins. Soil type and land use had the greatest influence on groundwater flow. The sub-basins with sandy soil and forest cover contributed the most groundwater flow. Sub-basins with bodies of water and agricultural lands with long-grown plants contribute the most evapotranspiration. The correlation between SWAT simulated evapotranspiration and the FLDAS dataset over the Nagavali and Vamsadhara river basins was 0.78.

5.4 Spatial Variability of Sediment Yield and Identification of Critical Source Areas

The sediment trapping efficiency of reservoirs was determined to be 77.65% and 67.59% for the Nagavali and Vamsadhara river basins, respectively. Figure 5.6 illustrates the spatial distribution of the average annual simulated sediment yield across these basins. Table 5.1 provides the average annual sediment yield (in t/ha/yr) categorized into three classes based on Singh's classification (1995) adapted for Indian conditions, as suggested by Tripathi et al. (2003) and Panda et al. (2021). Sub-basins are classified as experiencing slight erosion if the average annual sediment yield is less than 5 t/ha/yr, moderate erosion if it falls between 5 and 10 t/ha/yr, and high erosion if it exceeds 10 t/ha/yr, aiding in the identification of critical source areas of sediment yield. The average annual sediment yield from sub-basins serves as the foundation for identifying critical sediment source areas (Himanshu et al. 2019; Kumar and Mishra, 2015; Panda et al. 2021). This is useful for sub-watershed agricultural, structural, and watershed management planning.

Table 5.1 Areas subjected to various levels of soil erosion in the Nagavali and Vamsadhara basins

S. No.	Sediment Yield (t/ha/yr)	Soil Erosion Class	Nagavali River Basin		Vamsadhara River Basin	
			Percent Area	Sub-basin numbers	Percent Area	Sub-basin numbers
1	0–5	Slight	24	1–7,10,12–14,19,21	13	5, 10, 21, 22, 26
2	5–10	Moderate	49.5	8,9,11,16,18,20,25,26,28–31	38	1, 2, 4, 7–9, 13–15, 27, 30
3	>10	High	26.5	15,17,22–24,27,32–34	49	3, 6, 11, 12, 16–20, 23–25, 28, 29

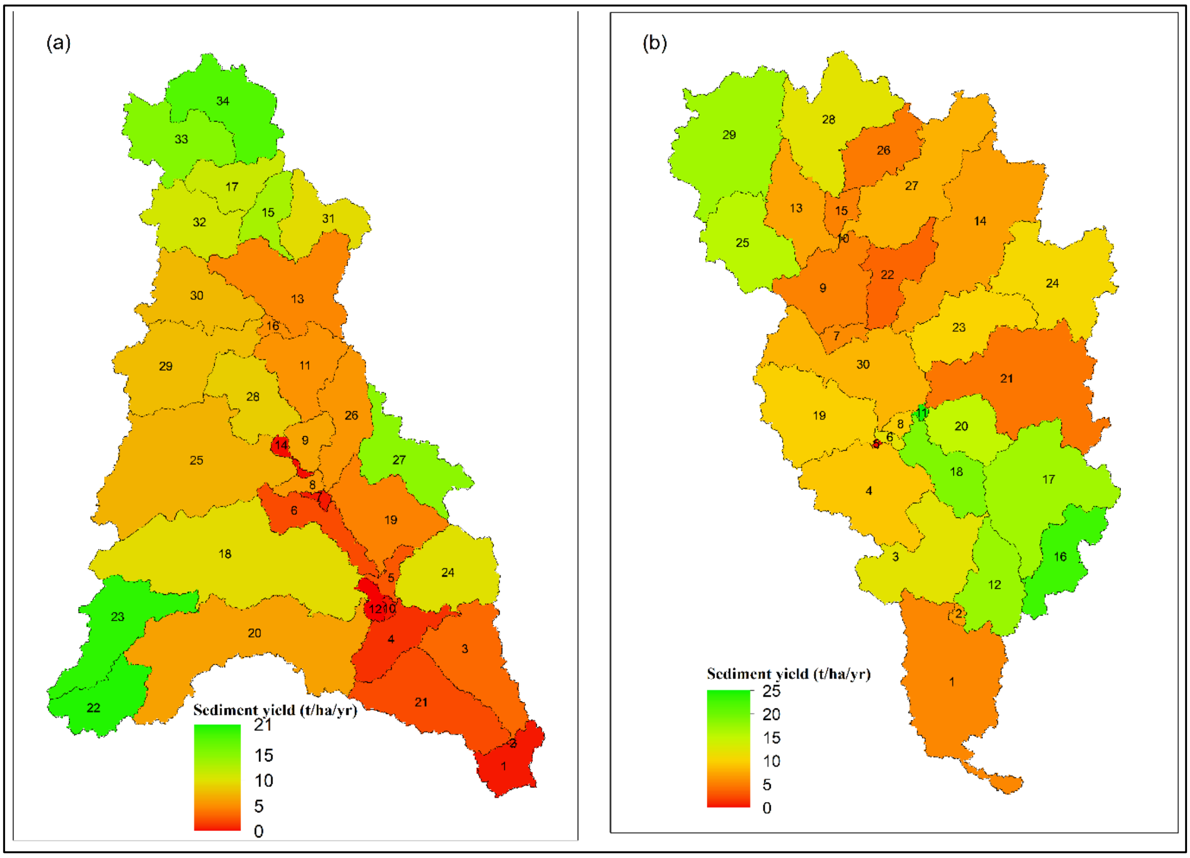


Figure 5.6 Spatial distribution of average annual sediment yield (a) over the Nagavali river basin (b) over the Vamsadhara river basin for the period of 13 years (2002–2013).

Figure 5.6 (a) shows that sub-basins 22, 23, and 34 have the highest sediment yield of 20.3 t/ha/yr. These sub-basins are characterized by moderate to steep slopes, and the majority of sub-basin areas are devoid of land use. Table 5.1 shows that 26.5% of the basin area is subject to high erosion (>10 t/ha/yr), with the corresponding sub-basins being 15, 17, 22 to 24, 27, 32, 33 and 34. These sub-basins are regarded as critical sediment source areas throughout the Nagavali river basin, and priority is given to them. In total, 49.5% of basin area is classified as moderate soil erosion (5–10 t/ha/yr) and 24% is classified as slight erosion (5 t/ha/yr). To reduce the severity of soil erosion caused by landscape and reservoir capacity loss, sub-basins with high sediment yields required immediate attention for soil conservation practices. The Nagavali river basin's average annual sediment yield was determined to be 7.18 t/ha/yr. In the Nagavali river basin, sub-basins with lower slopes and dense vegetation contribute a minor sediment yield. It has been observed that the lower portion of the basin produces a minor sediment yield.

Figure 5.6 (b) depicts the spatial distribution of average annual simulated sediment yield over the Vamsadhara river basin for 30 sub-basins. Sub-basins 11 and 16 have the highest sediment yield of 24.8 t/ha/yr. These sub-basins, like the Nagavali river basin, have a moderate to steep slope, and the majority of the sub-basin areas are covered in wasteland. Table 5.1 depicts the Vamsadhara river basin, with 49% of the basin area falling into the high erosion class (> 10 t/ha/yr), and the corresponding sub-basins being 3, 6, 11, 12, 16 to 20, 23 to 25, 28, and 29. These sub-basins are regarded as critical sediment source areas throughout the Vamsadhara river basin, and pri-ority is given to them. In total, 38% of basin area is subject to moderate soil erosion (5–10 t/ha/yr) and 13% is subject to slight erosion (5 t/ha/yr). To reduce the severity of soil ero-sion caused by landscape and reservoir capacity loss, the sub-basins contributing the most sediment yield required immediate attention to management practices. The average annual sediment yield of the Vamsadhara river basin, on the other hand, was found to be 10.7 t/ha/yr.

In both river basins, the majority of the sediment yield was contributed by wastelands with steep slopes (> 8°), followed by fallow lands, degraded deciduous forest lands, and agricultural lands. Tribal peoples live along the river and rely on shifting cultivation for a living (Amminedu et al. 2013). It could explain the high sediment yield from deciduous and degraded forest lands and wastelands.

Based on the analysis of average annual sediment yield, the Nagavali and Vamsadhara river basins exhibit average annual sediment yields of 7.18 and 10.7 t/ha/yr, respectively. These values fall within the permissible limit of 11.2 t/ha/yr (Mannering, 1981; Mahapatra et al., 2018). Within the basin area, specific sub-basins contribute significantly to sediment yield, with the highest contributions observed in sub-basins representing 26.5% and 49% of the Nagavali and Vamsadhara basins, respectively. These identified sub-basins are considered critical source areas. However, wastelands produced the highest sediment yield, followed by current fallow land, agricultural lands, degraded and deciduous forest lands with steep slopes in both river basins. According to Table 4.3, wastelands occupy 19.05% and 17.23% of the basin area of the Nagavali and Vamsadhara river basins, respectively. These lands are represented by hilly areas with less vegetation (scrub lands and barren lands), areas with mining activities, and areas where tribal communities previously prac-ticed shifted cultivation.

5.5 Selection of Climate Models

The results of the selection process for the downscaled General Circulation Models (GCMs) are presented in Figure 5.7. According to the Shared Socioeconomic Pathway (SSP) 245 scenario, the range of percentage change in mean annual precipitation (ΔP) and change in mean temperature (ΔT) in the future is between 2.3% and 13.5% and 0.7°C to 2°C, respectively. Under the SSP 370 scenario, the range is between 0% and 26.7% for ΔP and 0.89°C to 2.2°C for ΔT. For the SSP 585 scenario, the range is 3% to 41.69% for ΔP and 1.2°C to 2.67°C for ΔT. All available models predict an increase in mean rainfall and temperature in the future in all scenarios. During this process, the GCMs in all scenarios were evaluated based on the 10th, 50th, and 90th percentile values of ΔT (°C) and ΔP (%). Based on this approach, the Cold-Wet, Cold-Dry, Warm-Wet, Warm-Dry, and central (average) models are shown in Table 5.2. It is important to note that the phrase "Cold" in the "Cold-Wet" and "Cold-Dry" refers to a lower level of warming compared to the Warm models, rather than a future temperature that is colder than the reference period. Correspondingly, the phrase "Dry" in the "Cold-Dry" and "Warm-Dry" refer only to their position in comparison to other climate models.

Table 5.2 Climate models and the representing scenarios

Model name	**Representing scenario**
CanESM5	Warm-Wet
EC-Eearth3	Cold-Wet
INM-CM4	Central (average)
MPI-ESM1-2HR	Cold-Dry
ACCESS-CM2	Warm-Dry

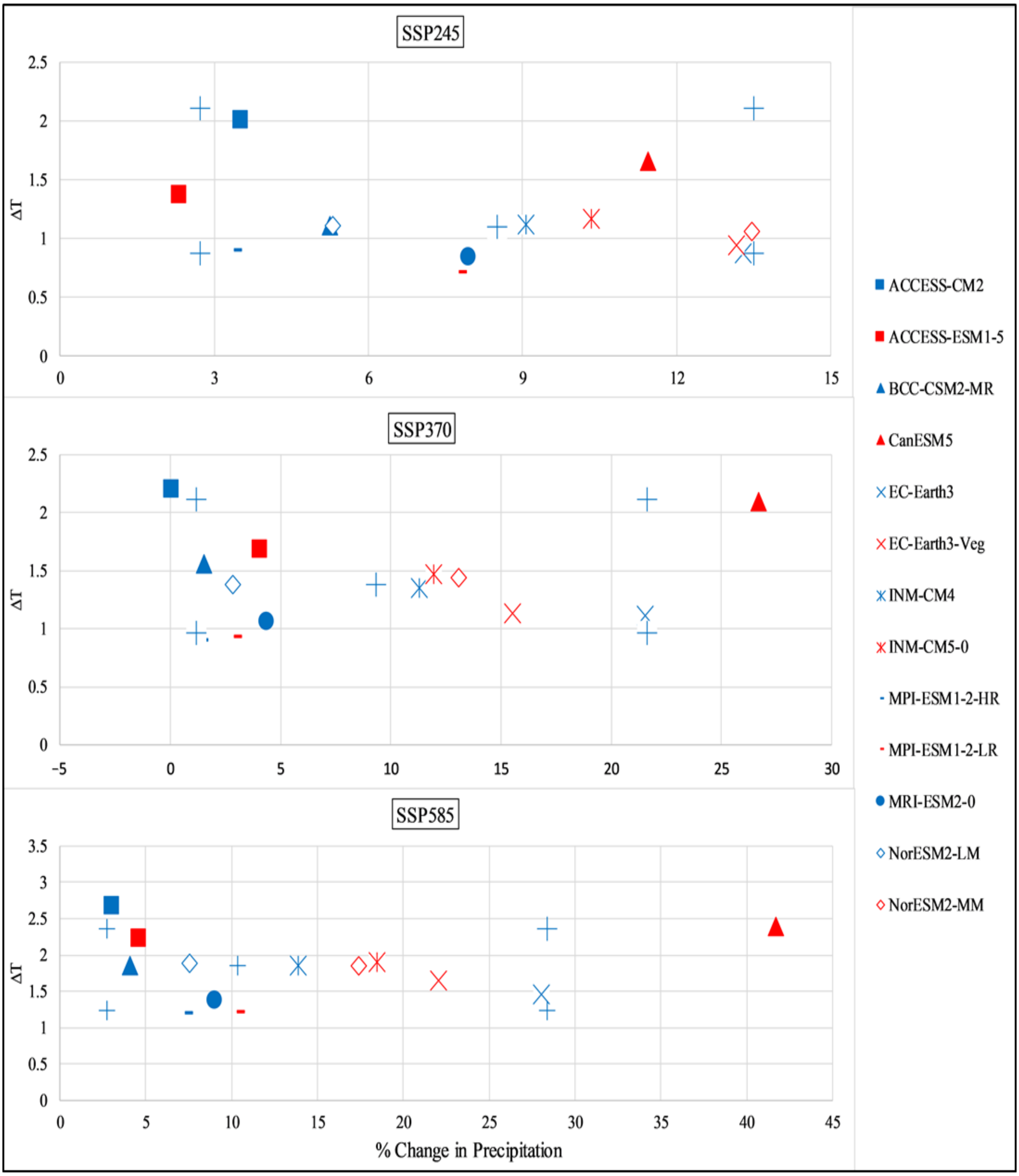


Figure 5.7 Predicted changes in average temperature (ΔT) and annual precipitation (%ΔP) from 2022 to 2100 compared to 1975 to 2015 using data from 13 different models. The blue crosses represent the 10th, 50th, and 90th percentile values for %ΔP and ΔT.

Here, brief explanation about each climate model selected in this study. The EC-Earth3 model is a state-of-the-art Earth System Model developed by a consortium of European research institutions. It has a spatial resolution of approximately 1.125° x 1.125°. This model is known for its ability to simulate various climate processes, including atmospheric, oceanic, and land surface interactions, making it a powerful tool for long-term climate projections. The MPI-ESM1-2HR model, developed by the Max Planck Institute for Meteorology in Germany, features a higher resolution of about 0.9375° x 0.9375°. This higher spatial resolution allows for more detailed regional climate simulations and improved accuracy in representing small-scale climate phenomena. CanESM5, the fifth version of the Canadian Earth System Model developed by Environment and Climate Change Canada, operates at a spatial resolution of about 2.8° x 2.8°. Despite its coarser resolution compared to some other models, CanESM5 is extensively used for global climate projections and assessments of climate change impacts due to its robust performance and comprehensive representation of climate processes. The INM-CM4 model, developed by the Institute of Numerical Mathematics in Russia, has a spatial resolution of around 2° x 1.5°. This model is known for its balance between computational efficiency and the ability to simulate key climate processes, making it suitable for both global and regional climate studies. ACCESS-CM2 model, part of the Australian Community Climate and Earth System Simulator suite, has a spatial resolution of approximately 1.25° x 1.875°. ACCESS-CM2 is utilized for a wide range of climate research, including the study of regional climate variability and change.

5.6 Consequence of Climate Change on Precipitation

The average annual precipitation for the Nagavali and Vamsadhara basins over a period of 40 years (1975–2014) is 1259 mm and 1314 mm, respectively.

Table 5.3 Percentage difference between the IMD data and the historical climate models data

Model Name	**% Bias in Precipitation**	
	Nagavali River Basin	**Vamsadhara River Basin**
EC-Earth3	+1.59	+3.49
MPI-ESM1-2HR	+0.63	+2.36
CanESM5	+0.69	+3.32
ACCESS-CM2	−4.73	−2.86
INM-CM4	+1.29	+3.71

Note: '+' sign indicates climate model value is lower than observed IMD value, '−' sign indicates climate model value higher than observed IMD value.

Table 5.3 shows the percentage bias between the precipitation predicted by the IMD gridded model and climate models for these basins. The climate models exhibited varying predictions, ranging from −4.73% to 1.59% for the Nagavali basin and −2.86% to 3.71% for the Vamsadhara basin. Four climate models (EC-Earth3, MPI-ESM1-2HR, CanESM5, and INM-CM4) slightly underestimate the precipitation, while the ACCESS-CM2 model slightly overestimates it in both basins.

Table 5.4 Percentage change in precipitation compared to historical data

SSP Scenario	Period	Representing Scenario	% Change in Precipitation	
			Nagavali basin	Vamsadhara basin
SSP245	Near future (2022–2060)	Warm-Wet	−4.51	−2.06
		Cold-Wet	+7.51	+5.35
		Average	+5.66	+4.47
		Cold-Dry	−1.33	−4.60
		Warm-Dry	−0.17	+0.96
	Far future (2061–2100)	Warm-Wet	+25.52	+24.58
		Cold-Wet	+19.91	+18.04
		Average	+13.27	+11.74
		Cold-Dry	+10.29	+7.80
		Warm-Dry	+7.89	+6.49
SSP370	Near future (2022–2060)	Warm-Wet	+17.79	+19.30
		Cold-Wet	+8.30	+7.06
		Average	+4.29	+2.54
		Cold-Dry	−2.68	−3.55
		Warm-Dry	−0.51	+0.45
	Far future (2061–2100)	Warm-Wet	+36.41	+35.93
		Cold-Wet	+34.73	+34.60
		Average	+19.45	+13.53
		Cold-Dry	+7.57	+4.34
		Warm-Dry	+1.65	−0.24
SSP585	Near future (2022–2060)	Warm-Wet	+23.88	+22.87
		Cold-Wet	+9.27	+7.69
		Average	+14.32	+10.60
		Cold-Dry	−1.09	−2.50
		Warm-Dry	−1.57	+0.44
	Far future (2061–2100)	Warm-Wet	+60.51	+59.09
		Cold-Wet	+35.10	+31.38
		Average	+22.11	+16.35
		Cold-Dry	+25.52	+19.46
		Warm-Dry	+8.48	+7.51

Note: ‘+’ sign indicates increasing in future, ‘−’ sign indicates decreasing in future

Table 5.4 presents the percentage change in precipitation predicted by climate models for the near future (2022–2060) and far future (2061–2100) compared to historical data (1975–2014) in both basins. The Cold-Dry model consistently underestimated precipitation across all three scenarios (SSP245, SSP370, and SSP585) in the near future. During the near future, the Warm-Wet model showed the highest overestimation of precipitation under the SSP370 and SSP585 scenarios, while the Cold-Wet model showed the greatest overestimation under the SSP245 scenario. In the far future, the Warm-Wet and Cold-Wet models showed the highest overestimation of precipitation, while the Warm-Dry model showed the lowest overestimation.

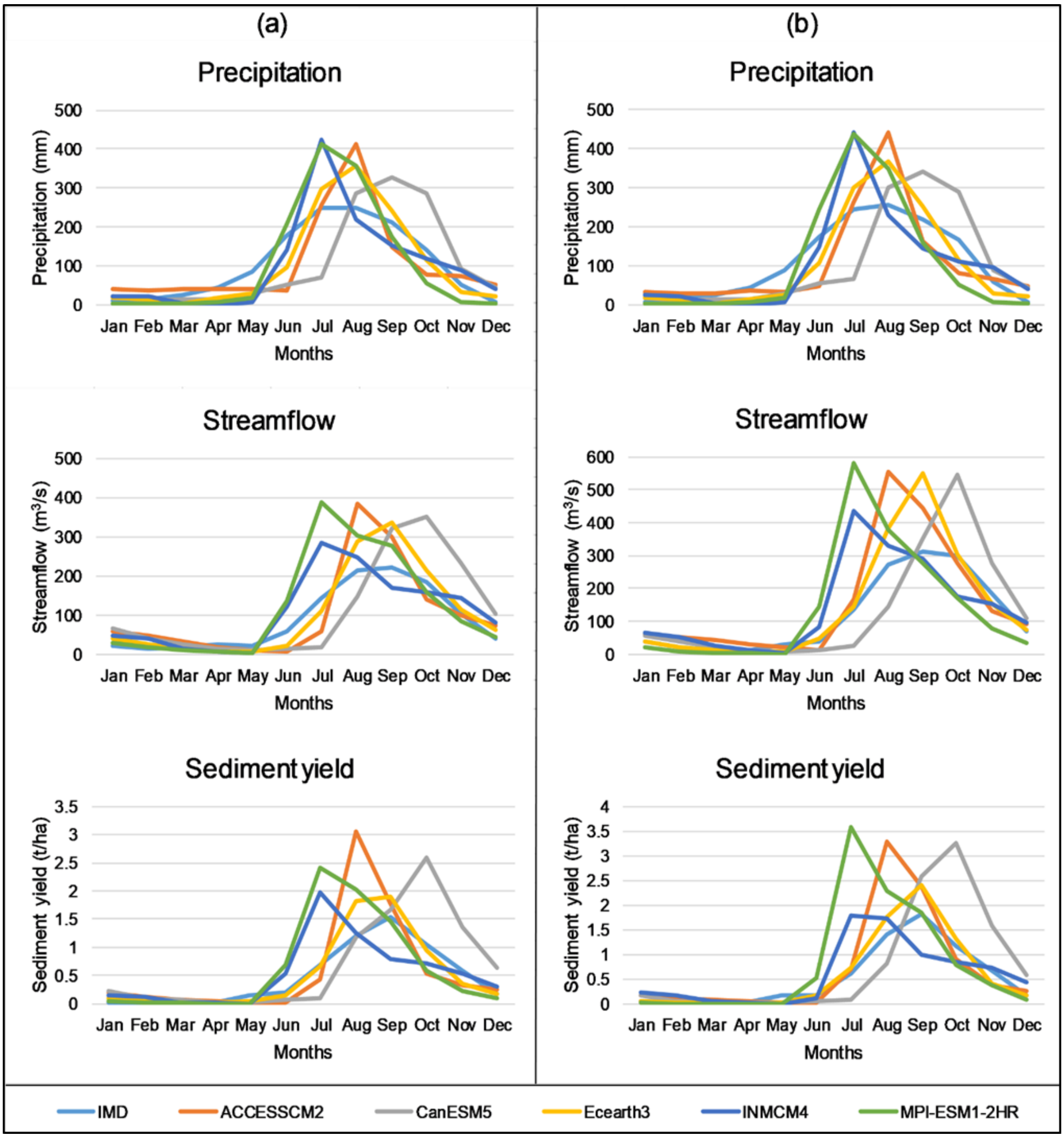


Figure 5.8 Mean monthly precipitation, streamflow, and sediment yield for the Nagavali basin (a) and the Vamsadhara basin (b) based on historical data from 1975 to 2014.

The highest levels of monthly precipitation patterns were observed in August for both the Nagavali and Vamsadhara basins (Figure 5.8), with intensities of 247.85 mm and 255.6 mm, respectively. However, the INM-CM4 and MPI-ESM1-2HR models showed their peak precipitation in July, while the ACCESS-CM2 and EC-Earth3 models showed their peaks in August, and the CanESM5 model showed their peaks in September for both basins. Figure 5.9 shows the future projections of mean monthly precipitation under different scenarios. These projections followed a similar pattern to the historical precipitation data. Figure 5.8 and 5.9 indicate that in both basins, the majority of rainfall occurs during the monsoon season, and approximately 80% of the annual runoff is generated during this period. These findings highlight the importance of implementing watershed management structures in both basins.

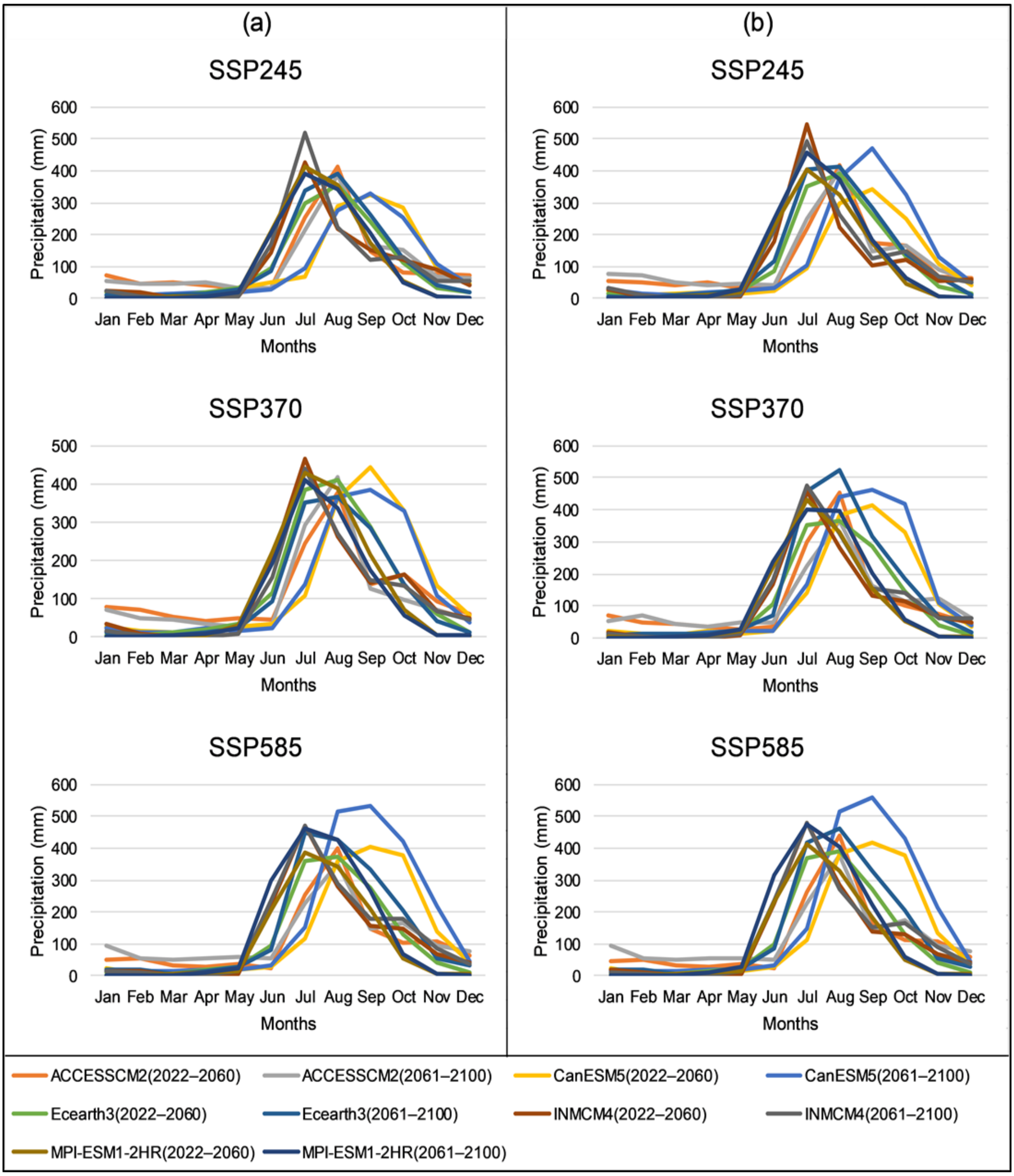


Figure 5.9 Projected mean monthly precipitation in the Nagavali and Vamsadhara basins under three different scenarios (SSP245, SSP370, and SSP585). Panel (a) represents the Nagavali basin and panel (b) represents the Vamsadhara basin.

5.7 Implications of Climate Change on Streamflow

The average annual streamflow for the Nagavali and Vamsadhara basins during the baseline period of 1975 to 2014 was 1061 m^3/s and 1425 m^3/s, respectively. Table 5.5 presents the percentage change in predicted streamflow for the near and far future scenarios compared to historical data

Table 5.5 Percentage change in streamflow and sediment yield compared to historical data

SSP Scenario	Period	Representing Scenario	% Change in Streamflow		% Change in Sediment Yield	
			Nagavali	Vamsadhara	Nagavali	Vamsadhara
SSP245	Near future (2022–2060)	Warm-Wet	−10.94	−0.83	−12.08	+2.58
		Cold-Wet	+5.62	+5.75	+1.93	+6.14
		Average	+1.96	+7.32	+4.63	+3.11
		Cold-Dry	−6.08	−11.24	−8.96	−8.91
		Warm-Dry	−7.85	−4.61	−15.59	−3.72
	Far future (2061–2100)	Warm-Wet	+41.19	+40.39	+37.23	+44.38
		Cold-Wet	+27.91	+26.98	+44.91	+43.45
		Average	+11.75	+14.67	+14.08	+17.11
		Cold-Dry	+7.24	+9.54	+4.47	+6.27
		Warm-Dry	+3.43	+0.42	+7.96	+5.65
SSP370	Near future (2022–2060)	Warm-Wet	+32.68	+38.01	+32.06	+46.99
		Cold-Wet	+3.21	+7.28	+1.09	+7.12
		Average	+1.62	+0.24	−6.71	−3.02
		Cold-Dry	−21.53	−9.78	−28.62	−12.82
		Warm-Dry	−6.47	+3.56	−1.08	+16.65
	Far future (2061–2100)	Warm-Wet	+77.71	+70.03	+121.86	+94.21
		Cold-Wet	+69.31	+60.88	+129.78	+107.62
		Average	+35.05	+19.21	+35.10	+21.04
		Cold-Dry	+4.38	+3.78	+5.97	+2.27
		Warm-Dry	−9.68	−12.06	−5.28	−12.49
SSP585	Near future (2022–2060)	Warm-Wet	+39.27	+38.71	+56.54	+36.06
		Cold-Wet	+5.88	+10.26	+6.62	+15.19
		Average	+21.51	+16.72	+30.92	+18.02
		Cold-Dry	−15.78	−6.77	−20.99	−3.57
		Warm-Dry	−2.38	+1.45	+2.48	+4.13
	Far future (2061–2100)	Warm-Wet	+134.41	+110.60	+166.49	+148.67
		Cold-Wet	+68.89	+53.04	+123.34	+95.03
		Average	+39.35	+22.38	+40.24	+39.54
		Cold-Dry	+37.84	+29.89	+45.54	+32.65
		Warm-Dry	−7.71	−7.55	−5.27	−6.71

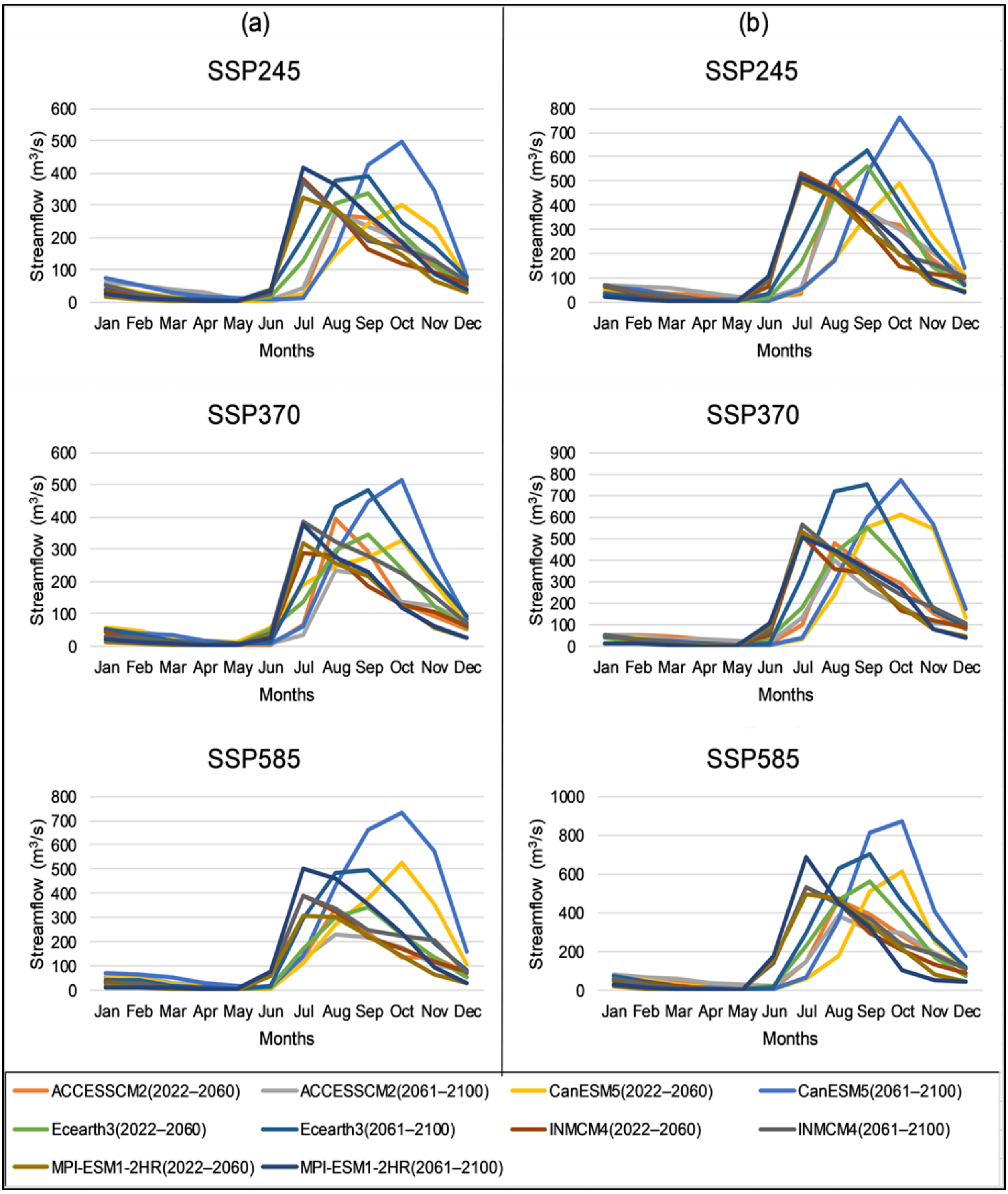


Figure 5.10 Projected mean monthly streamflow for the Nagavali and Vamsadhara basins under three different scenarios: SSP245, SSP370, and SSP585. Panel (a) shows the Nagavali basin and panel (b) shows the Vamsadhara basin.

In the near future, the Cold-Dry model under the SSP370 scenario predicts the highest decrease in streamflow for the Nagavali basin, while the same model under the SSP245 scenario forecasts the highest decrease in streamflow for the Vamsadhara basin. Conversely, the Warm-Wet model under the SSP585 scenario predicts the highest increase in streamflow for both basins. In the far future, the Warm-Dry model under the SSP370 scenario projects the highest decrease in streamflow, whereas the Warm-Wet model under the SSP585 scenario predicts the highest increase in streamflow for both basins.

Across the different SSP scenarios for the future period, the Warm-Wet model projects streamflow changes ranging from -10.94% to 134.41% for the Nagavali basin and -0.83% to 110.60% for the Vamsadhara basin. The Cold-Wet model forecasts streamflow changes from 3.21% to 69.31% for the Nagavali basin and 5.75% to 60.88% for the Vamsadhara basin. The Average model indicates streamflow changes ranging from 1.62% to 39.35% for the Nagavali basin and 0.24% to 22.38% for the Vamsadhara basin. The Cold-Dry model predicts streamflow changes from -21.53% to 37.84% for the Nagavali basin and -11.24% to 29.89% for the Vamsadhara basin. Lastly, the Warm-Dry model shows streamflow changes ranging from -9.68% to 3.43% for the Nagavali basin and -12.06% to 3.56% for the Vamsadhara basin.

The Cold-Dry model consistently decreased streamflow in both basins under all scenarios. The Warm-Dry model also exhibited a decrease in the Nagavali basin, while the Warm-Wet model showed the greatest increase under the SSP370 and SSP585 scenarios. The Cold-Wet model had the highest increase in the Nagavali basin under the SSP245 scenario, while the Average model had the highest increase in the Vamsadhara basin. In the far future, the Warm-Wet and Cold-Wet models had the highest increase of streamflow. The Cold-Dry model in the Nagavali basin under SSP370 in the near future and the Warm-Dry model in the Vamsadhara basin under SSP370 in the far future showed the maximum decrease of streamflow change. Conversely, the Warm-Wet model under SSP585 in the far future exhibited the maximum increase of streamflow change for both basins. The projections reveal a complex interplay of climate conditions influencing streamflow in the Nagavali and Vamsadhara river basins. Generally, Warm-Wet model lead to significant increases in streamflow, especially in the far future. Cold-wet scenarios also show positive impacts. Average conditions present moderate improvements, while cold-dry and warm-dry scenarios often result in reduced or minimally increased streamflow. These insights highlight the need for adaptive watershed management strategies to address varying climate impacts and ensure sustainable water resources in these river basins.

Figure 5.8 showed the highest observed streamflow in September for both basins, with variations among climate models regarding the timing of peak streamflow. The INM-CM4 and MPI-ESM1-2HR models showed peak streamflow in July, while the ACCESS-CM2 model indicated a peak in August. The EC-Earth3 model showed a peak in September for streamflow, while the CanESM5 model exhibited a peak in October. Figure 5.10 also showed the future streamflow predictions followed the similar historical patterns of streamflow peaks in both basins under all scenarios.

5.8 Implications of Climate Change on Sediment Yield

The sediment cycle in the Nagavali and Vamsadhara basins exhibits a strong correlation with streamflow and precipitation patterns. The mean peak sediment yield followed the mean peak streamflow patterns. During the 40-year baseline period (1975–2014), the average annual sediment yield was 6.68 t/ha/yr in the Nagavali basin and 7.3 t/ha/yr in the Vamsadhara basin. Table 5.5 presents the percentage change in sediment yield predicted by climate models for the near future (2022–2060) and far future (2061–2100) compared to the historical sediment yield (1975–2014). The percentage change in the sediment yield of different models under all scenarios followed the percentage change in streamflow patterns over both basins. In the near future, the Warm-Wet model shows the highest increase of sediment yield under the SSP370 and SSP585 scenarios. The average model exhibits the highest increase in the Nagavali watershed, while the Cold-Wet model shows the highest increase in the Vamsadhara basin under the SSP245 scenario.

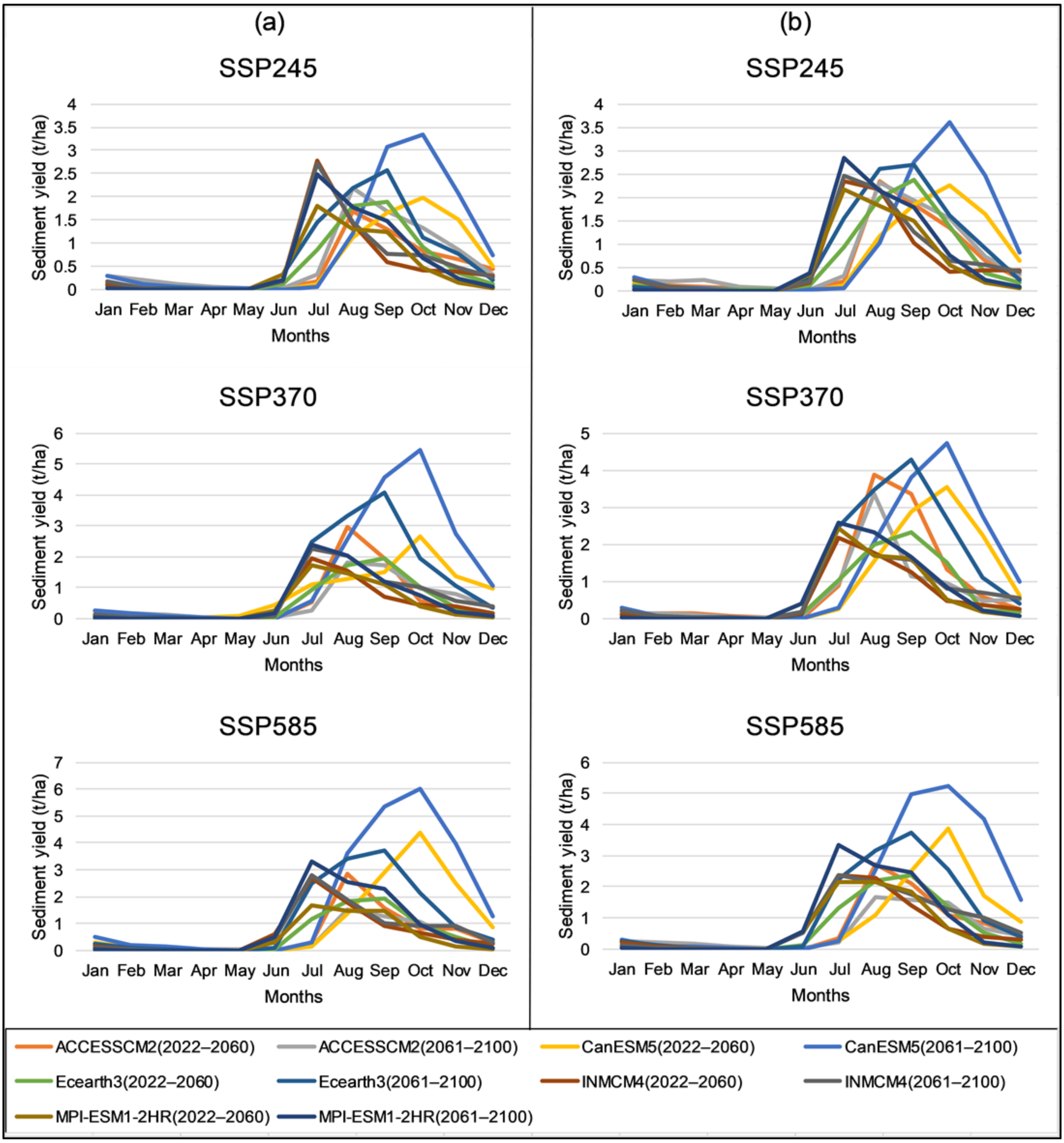


Figure 5.11 Projected mean monthly sediment yield for the Nagavali and Vamsadhara basins under three different scenarios: SSP245, SSP370, and SSP585. Panel (a) displays the Nagavali basin and panel (b) displays the Vamsadhara basin.

In the far future, the Warm-Wet and Cold-Wet models consistently show the highest increase of sediment yield under all scenarios. According to Figures 5.8 and 5.11, the historical and future sediment yield peaks under all scenarios align with streamflow peaks, indicating a strong correlation between these variables. However, the specific timing and intensity of monthly sediment yield values varied among the climate models. These findings highlight the uncertainties in predicting sediment yield under future climate scenarios and the importance of considering multiple climate models to capture the range of possible outcomes. Understanding sediment yield dynamics is crucial for effective watershed management, as increased sediment yield can negatively impact soil properties, reservoir capacity, and water quality.

Reservoirs estimated the average sediment trapping efficiency under IMD data over the Nagavali and Vamsadhara basins to be 85.14% and 62.1%, respectively, during a 40-year period (1975–2014). The sediment trapping efficiency, which is the ability of a reservoir to retain or trap sediment that flows into it from upstream areas, instead of allowing the sediment to continue downstream, in the Nagavali and Vamsadhara basins ranged from 78% to 88.21% and 61.56% to 64.3%, respectively, according to climate models. It will range from 71% to 88.5% and 61.5% to 65.43% in the near future, and from 61.26% to 86.34% and 61% to 64% in the far future over the Nagavali and Vamsadhara basins, respectively. In general, trap efficiency decreases with age because silt deposition reduces reservoir capacity. Future periods in both basins are expected to report lower sediment trapping efficiency than historical periods, while wetter models will have lower sediment trapping efficiency than drier models. According to a report by the Central Water Commission (CWC, 2020), many Indian reservoirs were reducing their storage capacity at a rate of 1% per year due to sedimentation. In order to save reservoir capacities, agricultural areas, and water quality in these basins, water and soil management practicess must be planned and implemented at identified critical sediment source areas.

5.9 Spatial Distribution of Precipitation, Streamflow and Sediment Yield under Dry-Warm and Cold-Wet Models

The bias corrected rainfall, maximum and minimum temperature data were used as inputs in the calibrated SWAT model to investigate the future consequences of the Dry-Warm and Cold-Wet models on streamflow and sediment yield in the Nagavali and Vamsadhara basins. According to Figure 5.12, historical precipitation, surface runoff, and sediment yield in these basins ranged from 1054 to 1473 mm, 7 to 182 mm, and 0 to 25 t/ha/yr. The upper sub-basins received the most precipitation while the lower sub-basins received the least. The catchment areas of the Nagavali and Vamsadhara basins are 9200 and 10,450 sq.km, respectively, with 2438 and 5120 sq.km of basin areas subjected to high soil erosion. In the Nagavali basin, out of 2438 sq.km, 635 and 645 sq.km of area belong to agricultural and barren land, respectively.

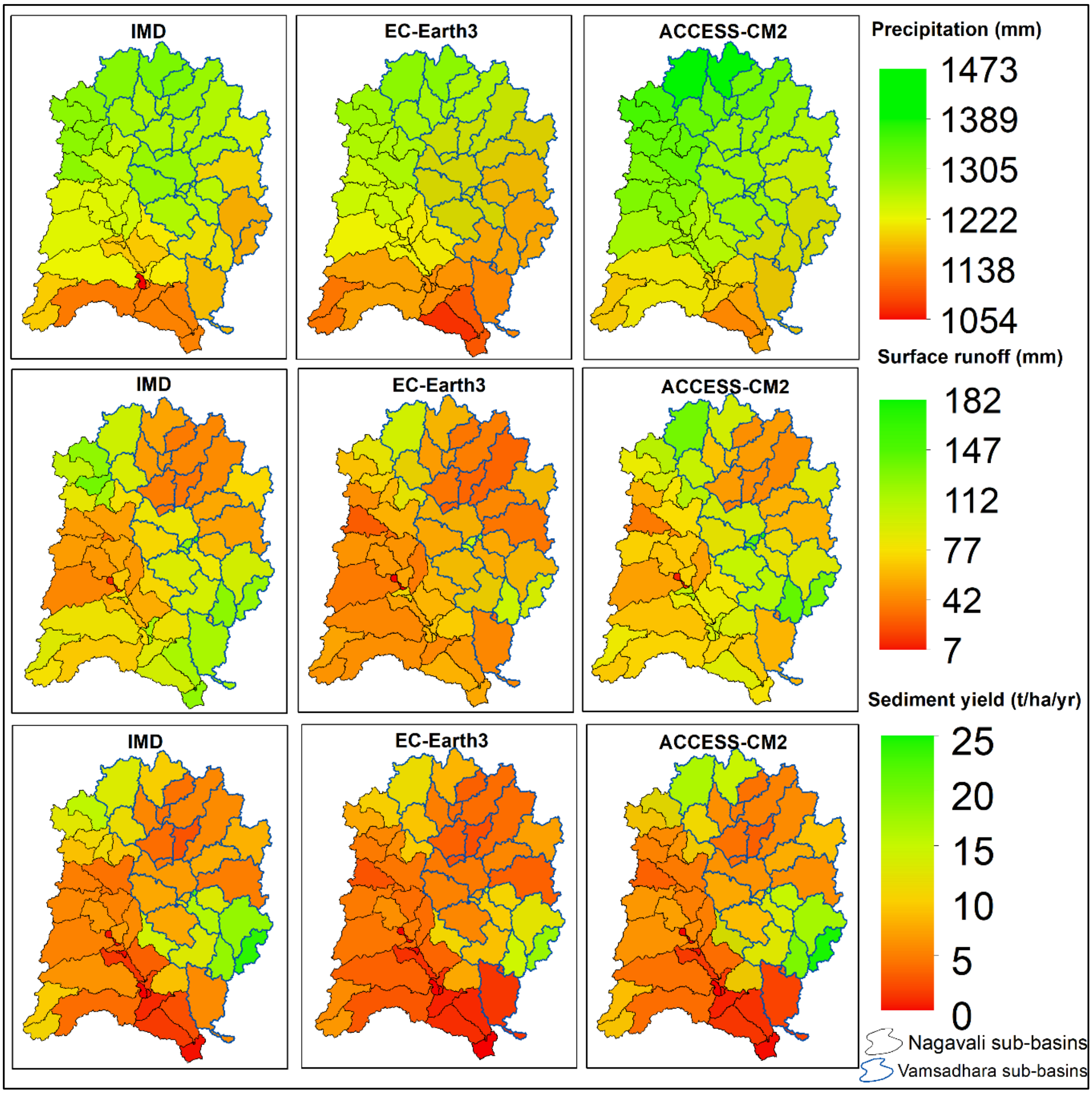


Figure 5.12 Spatial distribution of annual average precipitation, surface runoff, and sediment yield for the period of 1975–2014.

In Vamsadhara basin, out of 5120 sq.km, 1476 and 1066 sq.km of area belong to agricultural and barren land, respectively. The sub-basins with the highest sediment yield, representing 26.5% and 49% of the total basin area, were wastelands, followed by fallow land, agricultural land, and degraded and deciduous forest land with steep slopes in both basins. The near-level slope (0–2%) represents 19.21% and 14.32% of the basin area in Nagavali and Vamsadhara basins, respectively. The medium slope (2–8%) represents 23.26% and 19% of the basin area, while the steep slope (>8%) represents 57.33% and 66.68% of the basin area in the Nagavali and Vamsadhara basins, respectively. These figures suggest that Vamsadhara basin has more undulated areas than Nagavali basin.

Figure 5.13 shows the projected annual average precipitation, surface runoff, and sediment yield under the Dry-Warm model. The range for these variables under Dry-Warm and SSP245, SSP370, and SSP585 is 1116 to 1669 mm, 13 to 216 mm, and 0 to 30 t/ha/yr, respectively. These values are higher than the historical period. Figure 5.14 shows the same variables under the Cold-Wet model. The range under Cold-Wet and SSP245, SSP370, and SSP585 is 1130 to 1878 mm, 10 to 333 mm, and 0 to 49 t/ha/yr, respectively. Under Cold-Wet, the SSP585 scenario showed 7468 and 9426 sq.km of basin area subjected to high soil erosion over Nagavali and Vamsadhara basins, respectively, in far future. Therefore, based on the results of the Dry-Warm and Cold-Wet scenarios, it is important to implement soil water conservation measures in the observed critical sediment source areas in the Nagavali and Vamsadhara basins to mitigate the potential impact of climate change.

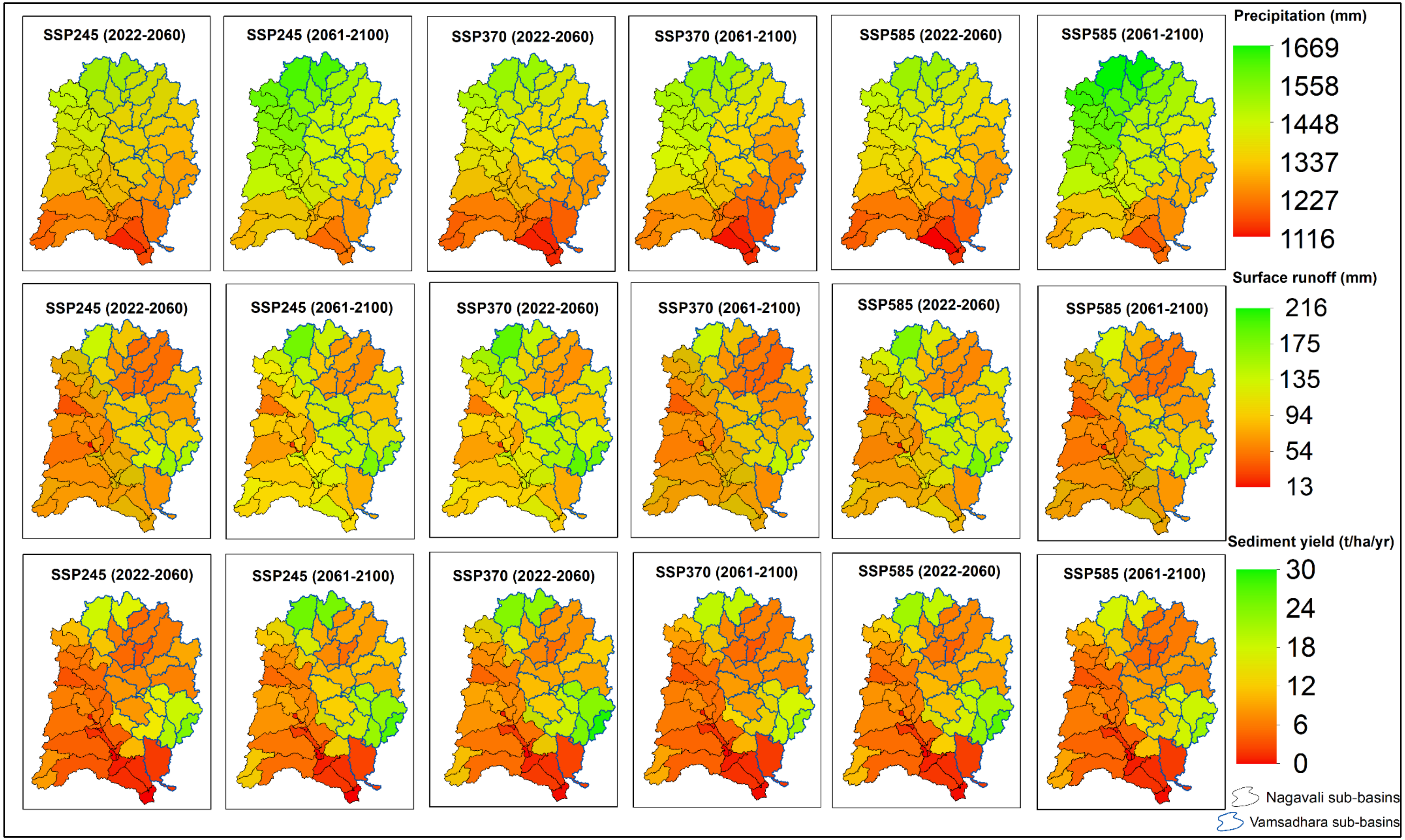


Figure 5.13 Spatial distribution of annual average precipitation, surface runoff and sediment yield based on the Dry-Warm (ACCESS-CM2) model.

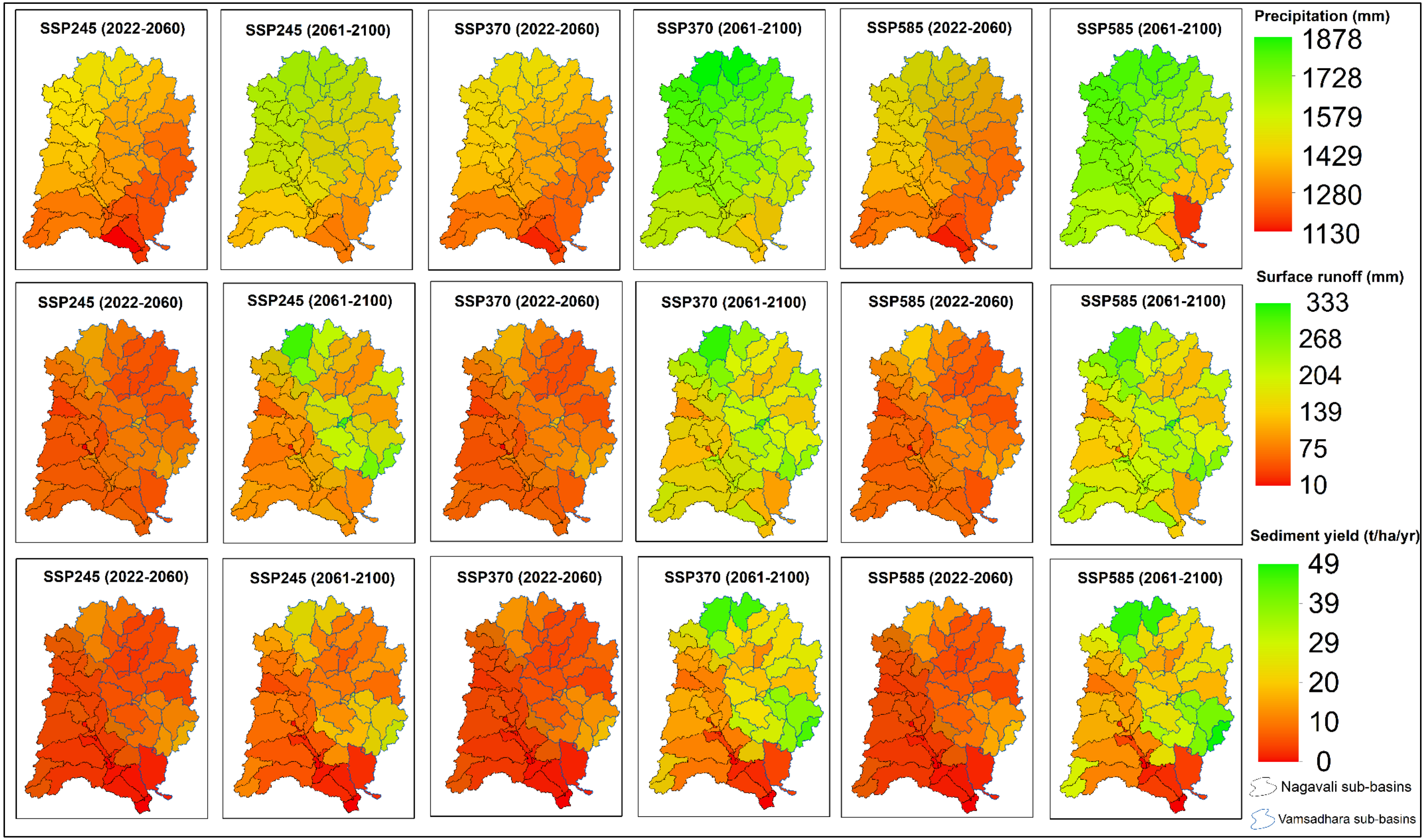


Figure 5.14 Spatial distribution of annual average precipitation, surface runoff, and sediment yield based on the Cold-Wet (EC-Earth3) model

5.10 Summary

SWAT model-based streamflow and sediment yield analysis of the Nagavali and Vamsadhara river basins, and critical sediment source areas were identified in order to recommend appropriate soil conservation measures at the sub-basin level. Sensitivity analysis reveals that initial SCS runoff curve number (CN2), effective hydraulic conductivity in tributary channel alluvium (CH_K1) are the most sensitive parameters in both river basins. For both river basins the SWAT model was evaluated with R^2, NSE and PBias. The obtained statistics over Nagavali and Vamsadhara river basins are varying from very-good to satisfactory and represents the acceptance of SWAT model. The Calibrated SWAT model simulated the streamflow generally capturing peak flow events in close correlation with extreme precipitation, model is influenced by both low and high precipitation events with underpredicted and overpredicted streamflow. The water balance study of Nagavali and Vamsadhara river basins showed the evapotranspiration is the dominant and account for 63 percent of the average annual rainfall. The calibrated SWAT model produced the average annual sediment yield of total basin is 7.18 t/ha/yr and 10.7 t/ha/yr over Nagavali and Vamsadhara river basins, these results are falling under moderate and high soil erosion class. From sub-basin wise average annual sediment yield analysis, it was noted that 26.5% and 49% of basin area falling under high erosion class over Nagavali and Vamsadhara river basins and considered as critical sediment source areas. The highest average annual sediment yield attributed with steep slope areas of wasteland followed by fallow lands, degraded, deciduous forests and agricultural lands. Over Nagavali river basin, the sub-basins 15, 17, 22-24, 27, 32-34 and over Vamsadhara river basin sub-basins 3, 6, 11, 12, 16-20, 23-25, 28 and 29 are identified as critical sub-basins for sediment source areas. These sub basins require immediate attention to management practices to improve the soil water conservation measures over Nagavali and Vamsadhara river basins.

From future projections, the increase in mean annual precipitation (ΔP) and mean temperature (ΔT) was expected to vary across different scenarios. These projections indicate the potential increase in both precipitation and temperature in the future, with the magnitude varying depending on the scenario considered. The climate models provide divergent future scenarios for the Nagavali and Vamsadhara watersheds. The ACCESS-CM2 model predicts a Warm-Dry future, indicating higher temperatures and decreased precipitation, while the EC-Earth3 model predicts a Cold-Wet future, suggesting lower temperatures and increased precipitation. During the baseline period of 1975-2014, the Nagavali and Vamsadhara watersheds received 1259 mm and 1314 mm of annual rainfall, respectively. The percentage bias between the Indian Meteorological Department's precipitation data and the climate model's historical precipitation data for these watersheds ranged from -4.73 to 3.71%, showing that the climate model's precipitation data is fairly well correlated with the IMD's data, with some slight under- and overestimations. In the near and far future, the percentage change in precipitation for these watersheds under the Cold-Wet and Dry-Warm models will range from 5.35 to 35.1% and -1.57 to 8.48%, respectively, indicating that there will be an increase in precipitation leading to an increase in streamflow and sediment yield for these watersheds. The climate models used in the study exhibit different trends in predicting precipitation, streamflow, and sediment yield. The Cold-Dry model consistently underestimates the precipitation, streamflow, and sediment yield, while the Warm-Wet and Cold-Wet model shows the maximum overestimation under all scenarios in the near future. In the far future, Warm-Wet and Cold-Wet models show the maximum overestimation of precipitation, streamflow, and sediment yield under all scenarios. Overall, the far future shows a greater percentage change in precipitation, streamflow, and sediment yield compared to the near future in all climate models and scenarios. These findings emphasize the importance of considering multiple climate models and scenarios to understand the range of possible outcomes and plan effective measures for managing water resources in the studied watersheds.

The analysis of IMD observed data and simulated results from different climate models reveals discrepancies in the timing of peak precipitation, streamflow, and sediment yield. Furthermore, the projected annual average precipitation, surface runoff, and sediment yield for the Dry-Warm and Cold-Wet models indicate a higher intensity compared to the historical period. This increase in sediment yield has negatively impacted the soil properties of agricultural lands, reservoir capacity, and drinking water quality in the Nagavali and Vamsadhara watersheds. These findings emphasize the necessity of implementing adaptive management strategies and watershed management structures to mitigate the adverse impacts of increased sediment yield and ensure the sustainable management of water resources in the Nagavali and Vamsadhara watersheds.

Chapter - 6 Evaluation of Best Management Practices (BMPs)

6.1 General

For the selected study area, based on the identified critical sediment source areas, the BMPs are developed and evaluated for the effectiveness of streamflow and sediment yield under IMD simulations and Cold-Wet model SSP585 scenario. A detailed explanation about the evaluation of BMPs for streamflow and sediment yield is given in the following sections.

6.2 BMP Application Areas

In section 5.4, sub-basins are classified as experiencing slight erosion if the average annual sediment yield is less than 5 t/ha/yr, moderate erosion if it falls between 5 and 10 t/ha/yr, and high erosion if it exceeds 10 t/ha/yr, aiding in the identification of critical source areas of sediment yield. The average annual sediment yield from sub-basins serves as the foundation for identifying critical sediment source areas (Himanshu et al. 2019; Kumar and Mishra, 2015; Panda et al. 2021). Critical sediment source areas within the Nagavali and Vamsadhara basins were identified for targeted intervention. A total of 9 sub-basins (26.5% of the Nagavali basin) and 14 sub-basins (49% of the Vamsadhara basin) were identified as high sediment production areas. Figure 6.1 illustrates the spatial distribution depicting critical sediment source sub-basins for both river basins.

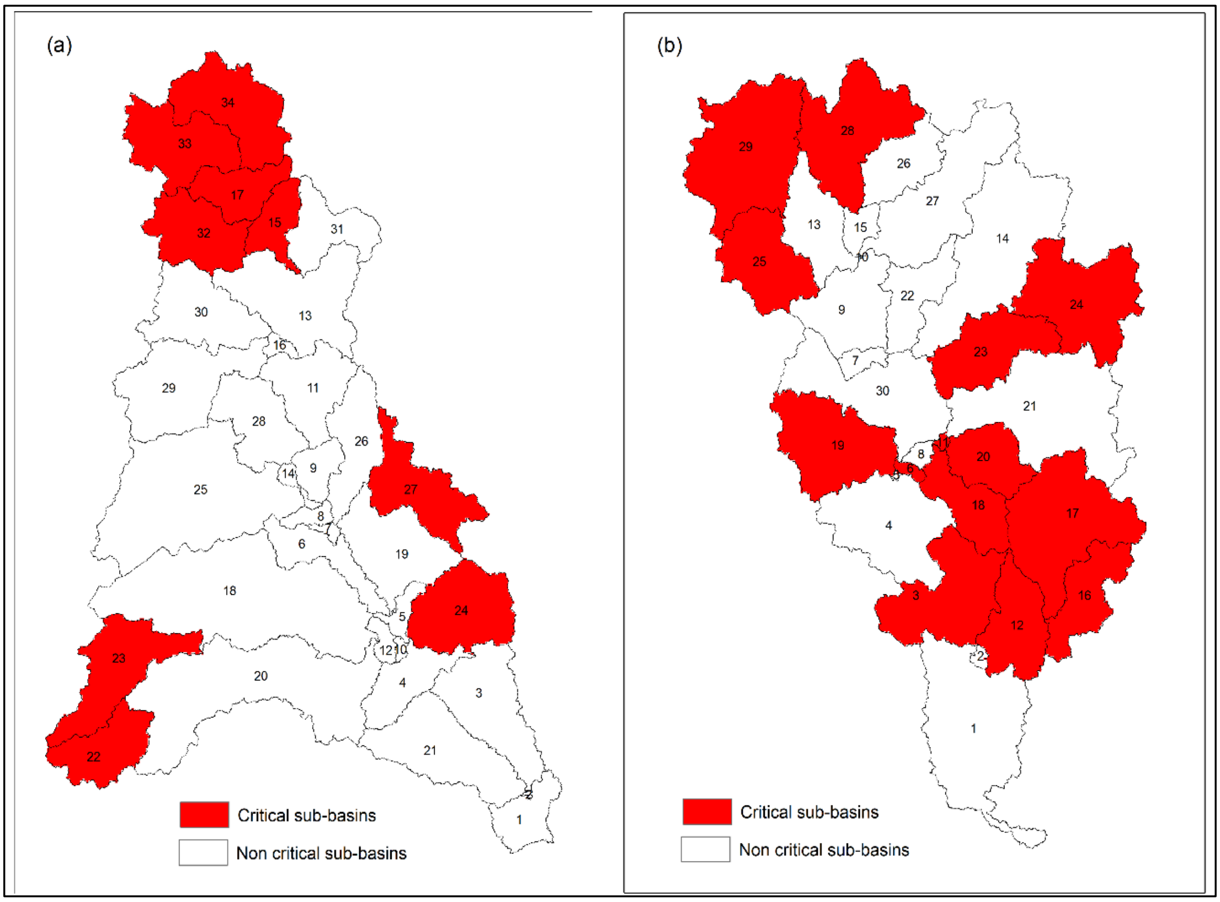


Figure 6.1 Spatial representation of critical sediment source sub-basins a) Nagavali b) Vamsadhara basins

Table 6.1 Percentage area under various land use classes and slope bands in critical sub-basins across Nagavali basin

Critical Sub-basins	**Area (sq.km)**	**Land use (%)**			**Slope band (% area)**		
		Forest	**Agriculture**	**Barren/Waste**	**0-2**	**2-8**	**>8**
15	132.60	48.8	28	21	10	16	74
17	175.37	45	40	13	10	26	64
22	225.82	50	10	35	1	5	94
23	345.78	24	25	45	4	6	90
24	338.47	41	29	25	13	22	65
27	299.27	47	8	35	5	8	87
32	267.54	71	10	16	1	7	92
33	308.32	56	12	30	4	9	87
34	349.14	65	5	24	5	15	80

Table 6.2 Percentage area under various land use classes and slope bands in critical sub-basins across Vamsadhara basin

Critical sub-basins	Area (sq.km)	Land use (%)			Slope band (% area)		
		Forest	Agriculture	Barren/Waste	0-2	2-8	>8
3	485.69	30	40	21	20	25	55
6	20.88	16	52	25	23	27	50
11	9.74	36	10	48	20	18	62
12	307.16	7	50	34	25	28	47
16	270.79	14	48	34	22	23	55
17	648.42	48	25	28	8	11	80
18	247.91	47	18	33	7	12	81
19	473.05	46	29	22	14	21	64
20	234.41	60	14	25	4	7	89
23	359.72	74	10	15	8	11	81
24	535.31	50	25	20	11	18	71
25	363.92	38	40	20	14	26	59
28	533.04	75	18	6	11	15	74
29	686.35	50	33	18	12	28	60

The analyses of critical sub-basins land use and slope distribution across the Nagavali and Vamsadhara basins are presented in Table 6.1 and Table 6.2, respectively. According to Table 6.1, in the Nagavali basin the critical sub-basins range in areas from 132.60 sq. km to 349.14 sq. km. Sub-basin 32 is characterized by 71% forest land, while sub-basin 17 exhibits the highest agricultural land percentage at 40%. Notably, sub-basin 23 demonstrates the highest barren land proportion, reaching 45%. Barren land, a significant sediment contributor, ranges from 13% to 45% across the Nagavali critical sub-basins. Table 6.2 provides insights into the Vamsadhara basin, with critical sub-basins ranging from 9.74 sq. km to 686.35 sq. km. Sub-basins 28 and 23 exhibit substantial forest cover, accounting for 75% and 74%, respectively. Additionally, sub-basins 6 and 12 showed agricultural land 52% and 50%, respectively. Barren land, contributing to sediment production, ranges from 6% to 48% across the Vamsadhara critical sub-basins. Notably, sub-basins 11, 12, and 16 have barren land exceeding 34% of the sub-basin area. Both Nagavali and Vamsadhara critical sub-basins predominantly fall into the high-slope band (>8), highlighting their varied sizes and diverse land use characteristics. The percentage distribution of slopes into three bands (0-2%, 2-8%, >8%) for each sub-basin reveals topographic variations within these critical areas. Considering these variations, the implementation of a combined BMP scenario at critical Hydrologic Response Units (HRUs) is recommended for effective sediment management and basin conservation.

The prioritization of BMPs for further analysis was then aligned with these identified sub-basins to address soil erosion concerns effectively. By focusing on sub-basins demonstrating higher sediment yield and surpassing the 10 t/ha/yr threshold, the study aimed to implement targeted BMPs in areas most urgently requiring intervention.

6.3 Impacts of BMPs on Streamflow and Sediment Yield

To control the generation of sediment yield and soil erosion from critical sub basins, an attempt has been made to identify BMPs over critical sub-basins while considering various management operations. The impact of the planned BMP scenarios was examined by considering the reduction of both specific sediment load (t/ha/yr) at the outlet and landscape sediment yield (t/ha/yr) at the sub basin levels. Simulations using the SWAT model were carried out for a period of 12 years from 2002 to 2013 to evaluate and compare the efficiency of BMP scenarios on streamflow and sediments. These BMP scenarios were assessed on a monthly time step and average annual flows and sediments were calculated at the critical sub basin outlets and main basin outlet for each basin. Then the percentage reduction in streamflow and sediment yield was calculated using equation (3.6).

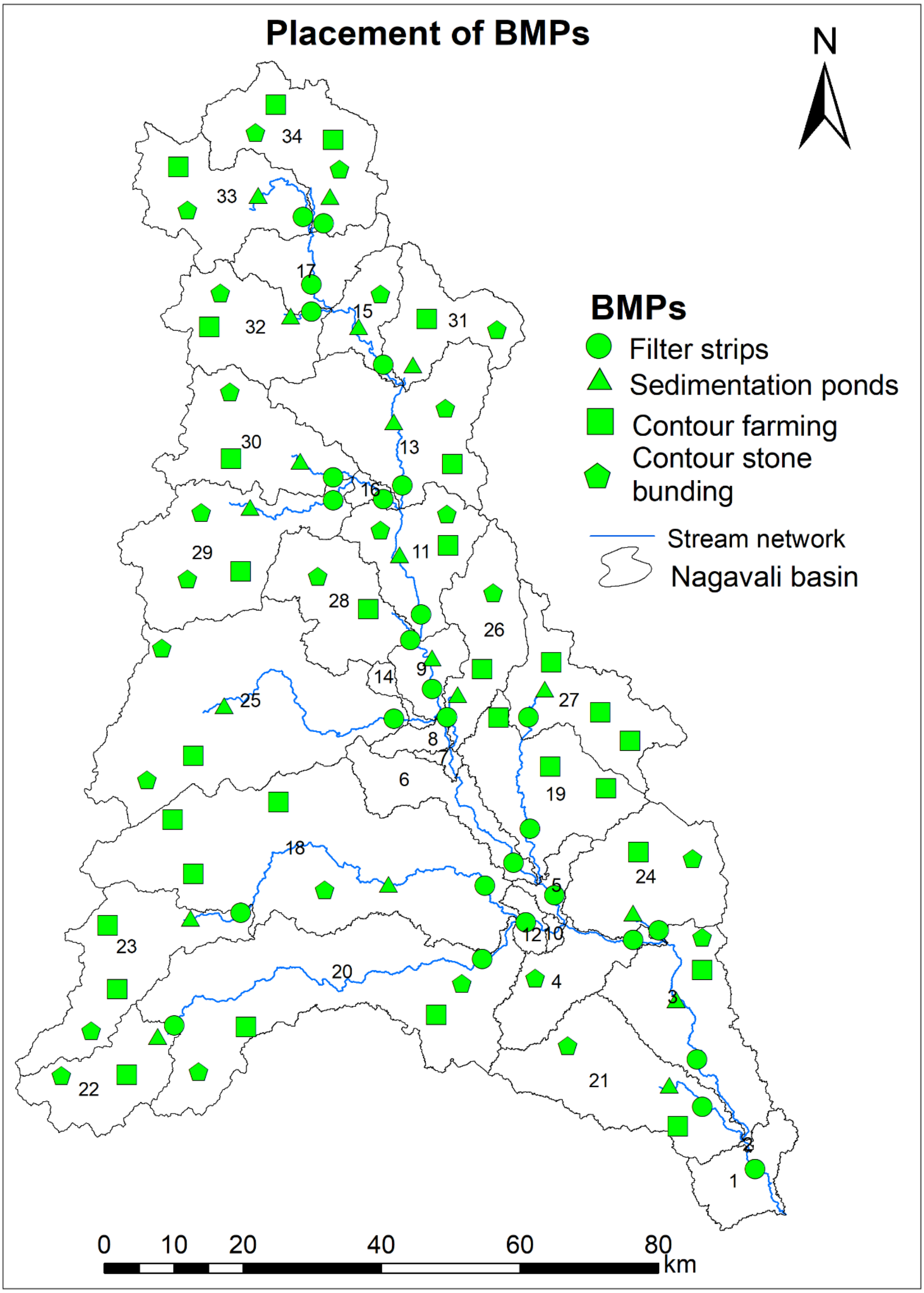


Figure 6.2 Placement of BMPs representation over Nagavali basin

The placement and implementation of chosen BMPs depicted in Figure 6.2 and Figure 6.3 over the Nagavali and Vamsadhara basins, respectively. The application of various BMPs produced promising results in terms of sediment yield reduction.

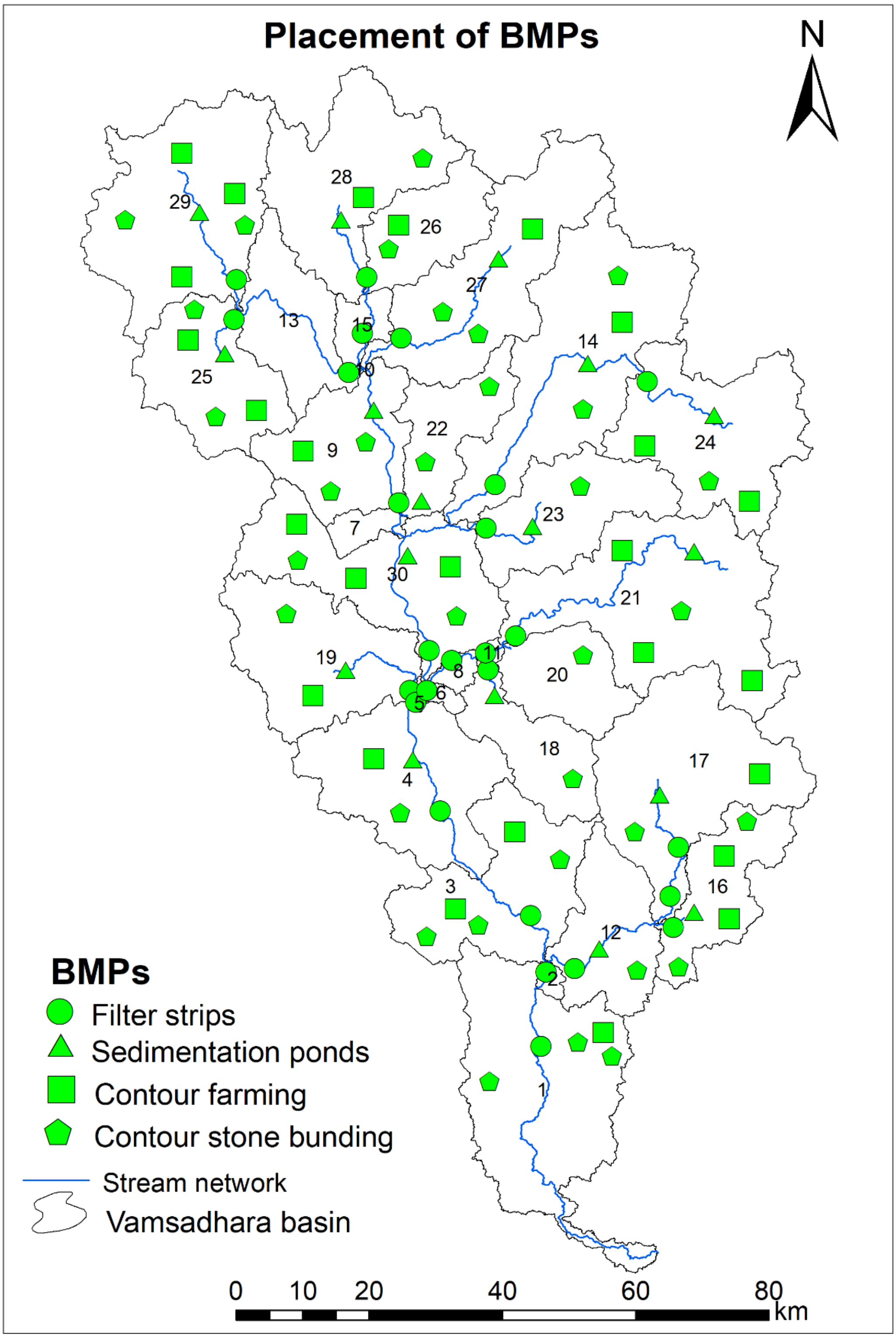


Figure 6.3 Placement of BMPs representation over Vamsadhara basin

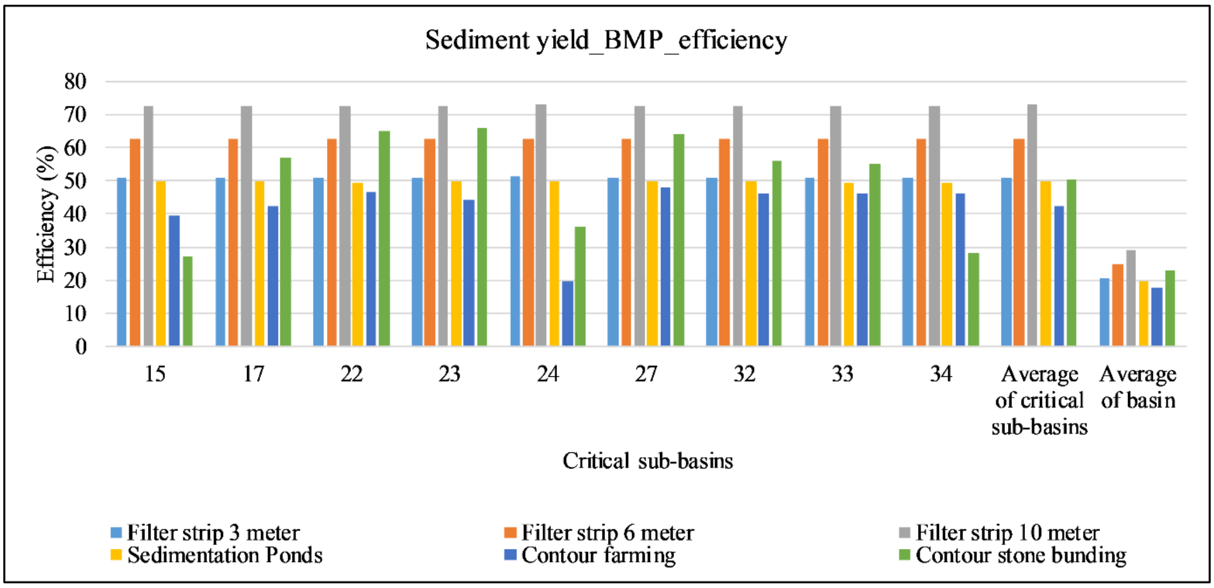


Figure 6.4 Effectiveness of individual BMPs in sediment reduction over Nagavali basin

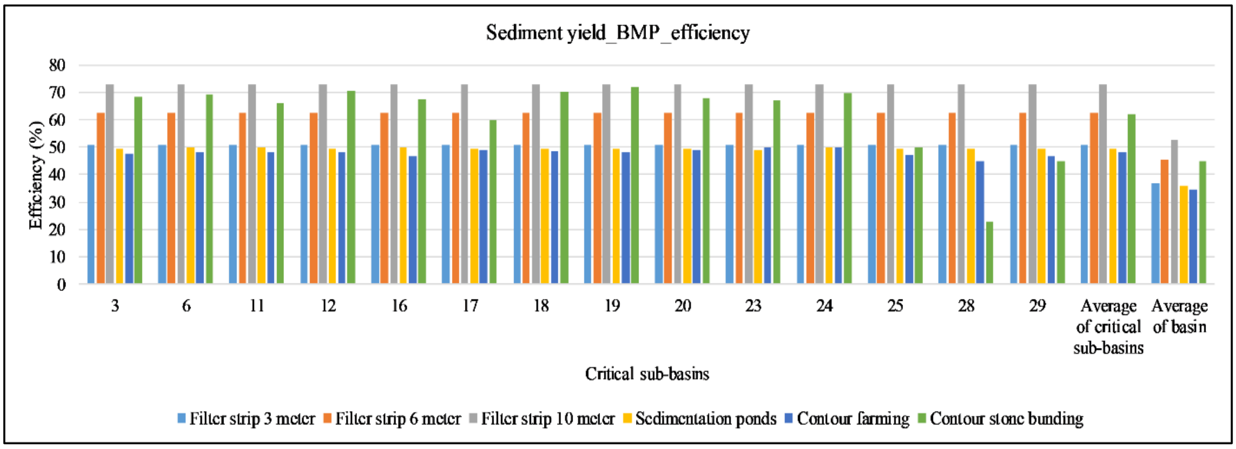


Figure 6.5 Effectiveness of individual BMPs in sediment reduction over Vamsadhara basin

At critical sub-basins and basin level, the percentage reduction of sediment under individual BMPs are visually depicted in Figure 6.4 and Figure 6.5 and percentage reduction of sediment yield and streamflow at critical sub-basins and basin level over the both river basins presented in Table 6.3. The filter strips width of 3, 6 and 10 meter was applied at the edge of agricultural lands, water bodies, wastelands. From Table 6.3, the use of 3-meter wide filter strips exhibited significant effectiveness, achieving an average reduction of 51% in the both basins across critical sub-basins. At the basin level, the corresponding reductions were 20% for Nagavali and 37% for Vamsadhara. The efficacy of the 3-meter filter strips ensured that, in the Nagavali basin, all critical sub-basins remained within the tolerable sediment yield limit of 11.2 t/ha/yr as defined by Mannering (1981). However, in the Vamsadhara basin, sub-basins 11 and 16 exceeded the tolerable sediment yield limit.

The 6-meter filter strip shows an average reduction of 62% sediment yield for both basins across the critical sub basins, and 25% for Nagavali and 45% for Vamsadhara over the basin level. Therefore, the effectiveness of the 6-meter filter strip demonstrated that, across both basins, the critical sub-basins maintained sediment yield levels within the tolerable limits. Similar results by Pandey et al. (2021), suggested that the 6-meter filter strip BMP completely nullified sediment erosion above the tolerable limits in the Tons river basin, India. Similarly, in 10-meter filter strips, a substantial reduction of 73% in sediment yield was observed across critical sub-basins for both the Nagavali and Vamsadhara basins, with corresponding reductions of 29% and 53% over the basin level, respectively. This emphasizes a positive correlation between the width of filter strips and their effectiveness in mitigating sediment yield. Notably, across all three widths of filter strips, there was no observed reduction in streamflow for both basins.

Table 6.3 Percentage reduction in sediment and streamflow under the application of BMPs

BMP scenario	**Percentage reduction in sediment yield**				**Percentage reduction in streamflow**			
	Average of critical sub-basins		**Average of basin**		**Average of critical sub-basins**		**Average of basin**	
	NB	**VB**	**NB**	**VB**	**NB**	**VB**	**NB**	**VB**
Filter strip 3 meter	50.89	50.85	20.37	36.91	0	0	0	0
Filter strip 6 meter	62.45	62.45	25.02	45.34	0	0	0	0
Filter strip 10 meter	72.70	72.67	29.12	52.76	0	0	0	0
Sedimentation ponds	49.59	49.52	19.86	35.97	50	50	14.80	28.68
Contour farming	42.05	47.96	17.92	34.66	12.80	14.39	3.60	7.89
Contour stone bunding	50.39	61.83	22.88	44.88	0	12.83	0	6.90
Combined BMP1	73.51	98.64	29.48	73.53	56.17	94.71	16.50	53.93
Combined BMP2	84.16	99.21	34.01	74	56.17	94.71	16.50	53.93
Combined BMP3	86.61	99.34	35.05	74.11	56.17	94.71	16.50	53.93

Combined BMP4	92.79	99.46	37.18	74.21	56.17	94.71	16.50	53.93

Note: NB – Nagavali basin, VB – Vamsadhara basin, combined BMP1 – sedimentation ponds+ contour farming + contour stone bunding, combined BMP2 – filter strip 3 m + sedimentation ponds + contour farming + contour stone bunding, combined BMP3 – filter strip 6 m + sedimentation ponds + contour farming + contour stone bunding, combined BMP4 – filter strip 10 m + sedimentation ponds + contour farming + contour stone bunding.

In the case of sedimentation ponds as a BMP scenario, a notable reduction of approximately 50% in both sediment yield and streamflow was observed across critical sub-basins in both the Nagavali and Vamsadhara basins. At the basin level, there was a significant reduction in sediment yield by 20% for Nagavali and 36% for Vamsadhara, along with a corresponding decrease in streamflow by 15% for Nagavali and 29% for Vamsadhara. These findings highlight the consistent and significant contribution of sedimentation ponds to the reduction of both sediment yield and streamflow. The findings emphasize the critical role of designed ponds in effectively trapping sediments and reducing their transport to downstream water bodies. This promotes the significance of incorporating sedimentation ponds into basin management practices as a viable and effective strategy.

Contour farming applied across the agricultural lands and waste lands with slopes greater than 2% yielded significant reductions in sediment yield and streamflow. Across critical sub-basins, there was a reduction of 42% in sediment yield for Nagavali and 48% for Vamsadhara, accompanied by a streamflow reduction of 13% for Nagavali and 14% for Vamsadhara. At the basin level, the impact persisted, with a sediment yield reduction of 18% for Nagavali and 35% for Vamsadhara. Additionally, streamflow exhibited reductions of 4% for Nagavali and 8% for Vamsadhara across the respective basins.

Sub-basins 22 and 23 in the Nagavali basin, as well as 11, 16, and 18 in the Vamsadhara basin, exhibited sediment yield levels above the tolerable threshold, the effectiveness of contour farming was moderate in reducing sediment and streamflow in both basins, it is noteworthy that the adoption of sedimentation ponds and contour farming collectively enhanced basin infiltration by mitigating streamflow. These findings highlight the sophisticated and context-dependent efficacy of various BMPs in influencing sediment dynamics and hydrological processes within basins.

The contour stone bunding scenario, when applied to wastelands, rangelands, and cultivated lands, exhibited notable effectiveness in sediment control. At the sub-basin level, a significant reduction of 50% in sediment yield was observed for Nagavali and an even more substantial reduction of 62% for Vamsadhara. This effectiveness extended to the basin level, with sediment yield reductions of 23% for Nagavali and 45% for Vamsadhara. The success of contour stone bunding, involving the strategic placement of stone bunds along contour lines, highlights its valuable contribution to reducing sediment yield. This BMP emerges as an effective solution, showcasing its potential significance in soil conservation efforts across diverse land types. Furthermore, the influence of contour stone bunding extended to streamflow, exhibiting reductions of 13% and 7% across the Vamsadhara sub-basin and basin levels, respectively. Finally, it was observed that the contour farming exhibited comparatively lower effectiveness than filter strips, contour stone bunding and sedimentation ponds while contributing to sediment reduction among the individual BMP scenarios.

This study results are comparable to previous studies conducted in different watersheds. For example, Risal and Parajuli, (2022) found that applying filter strips with 10, 20, and 30 m widths at the edge of agricultural fields in the Big Subflower River and Stovall Sherard watershed reduced sediment yield by 9%, 11%, and 12%, and 12%, 33%, 38% respectively. Similarly, Regasa and Nones, (2024) used similar management practices such as filter strips, stone bund and contour farming in the Fincha sub-watershed, Ethiopia to evaluate the reduction of sediment yield. Their results showed that filter strips were decreased the sediment yield by 65.64% and 58.77%, stone bund by 76.37% and 73.07%, contour farming by 79.79% and 75.86%, and for the years 2019 and 2050, respectively. Similar results found in the Nagavali and Vamsadhara basins.

Beyond the examination of individual BMPs, a holistic approach was undertaken by implementing four combined BMP scenarios. The percentage reduction in sediment and streamflow under both individual and combined BMP scenarios across the Nagavali and Vamsadhara basins is presented in Table 6.3. At the critical sub-basin level, this integrated strategy demonstrated remarkable effectiveness, resulting in sediment yield reductions from 74% to 93% for Nagavali and an even more substantial reduction from 98.64% to 99.64% for Vamsadhara. Correspondingly, streamflow exhibited significant reductions of 56% for Nagavali and 95% for Vamsadhara. Expanding the analysis to the basin level, the combined BMP scenario continued to deliver impressive outcomes. Sediment yield was notably reduced from 29% to 37% for Nagavali and an even more substantially reduced from 73.53% to 74.21% for Vamsadhara. Concurrently, streamflow experienced substantial reductions of 16.5% for Nagavali and 54% for Vamsadhara basins. These findings highlight the combined BMP scenarios could be a viable solution, achieving comprehensive reductions in both sediment yield and streamflow. The significant effectiveness observed in these basins highlights the importance of a multifaceted approach to sediment management practices. This comprehensive strategy, which incorporates a variety of BMPs, holds promise for achieving sustainable and integrated basin management goals, emphasizing the importance of combining complementary practices for enhanced sediment control effectiveness.

6.4 Evaluation of BMPs under Climate Change Cold-Wet (EC-Earth3) model

From the chapter 5, it was observed that the EC-Earth3 (Cold-Wet) model under SSP585 predicted the higher precipitation in the future period when compared to historical period, leading to increased streamflow and sediment yield in future. Resulting under Cold-Wet, the SSP585 scenario showed 7468 and 9426 sq.km of basin area subjected to high soil erosion over Nagavali and Vamsadhara basins, respectively, in the future. Therefore, based on the results of the EC-Earth3 (Cold-Wet) model under SSP585 scenario, it is important to test the BMPs in the observed critical sediment source areas in the Nagavali and Vamsadhara basins to mitigate the potential impact of climate change. To comprehensively evaluate the effectiveness of BMPs in mitigating potential impacts, this study focused on the Cold-Wet (EC-Earth3) model under the SSP585 scenario. The assessment involved simulating projected future data from 2025 to 2100 under SSP585, utilizing a calibrated SWAT model. This simulated future scenario served as the base scenario for the evaluation of BMPs. Within this baseline projection, the analysis revealed significant variations in sediment yield across sub-basins within the Nagavali and Vamsadhara basins. In the Nagavali basin, sub-basin 24 exhibited the highest sediment yield, reaching an average annual value of 24.1 t/ha/yr followed by sub-basin 34, contributing 21.7 t/ha/yr to the sediment yield under the established baseline scenario. Meanwhile, in the Vamsadhara basins, sub-basin 16 demonstrated the highest sediment yield, recording an average annual value of 36.29 t/ha/yr, followed by sub-basins 29, 11, and 28 contributed significantly, producing sediment yields of 33 t/ha/yr, 31.75 t/ha/yr, and 31.42 t/ha/yr, respectively. These findings highlight the spatial variability in sediment dynamics and identify specific sub-basins as focal points for implementing targeted BMPs to mitigate soil erosion and manage sediment yield effectively in the face of future climate scenarios.

In the context of climate change, a comprehensive evaluation of various BMPs was conducted, including filter strips of different widths (3 m, 6 m, and 10 m), sedimentation ponds, contour farming, contour stone bunding, and combinations of these BMPs. The analysis considered the percentage reduction in annual average sediment yield and streamflow, reflected historical trends. The percentage reduction in sediment and streamflow under climate change with respect to critical sub-basin and basin across the Nagavali and Vamsadhara basins were presented in Table 6.4. The application of filter strips with widths varying from 3 m to 10 m showed the percentage reduction of sediment yield ranged from 51% to 73% and 52% to 65% across the critical sub-basins, and 25% to 36% and 26% to 38% across the basin level over the Nagavali and Vamsadhara basins, respectively. In this context, the 10-meter-wide filter strip proved effective in reducing sediment yield below tolerable limits. Therefore, it is recommended to prioritize the implementation of wider filter strips, particularly those with a width of 10 meters, for enhanced sediment control.

Sedimentation ponds also demonstrated significant efficacy, yielding an approximate 50% reduction in both sediment yield and streamflow across critical sub-basins in Nagavali and Vamsadhara. At the basin level, a substantial reduction in sediment yield (25% for Nagavali and 34% for Vamsadhara) and streamflow (15% for Nagavali and 28% for Vamsadhara) was observed. These findings showed the consistent and substantial contribution of sedimentation ponds in mitigating sediment transport downstream.

Implementing the contour farming BMP scenario under the influence of climate change yielded a notable reduction of 43% in sediment yield for Nagavali and 25% for Vamsadhara, along with a streamflow decrease of 11% for Nagavali and 3% for Vamsadhara across critical sub-basins. This impact extended to the basin level, where sediment yield saw reductions of 21% for Nagavali and 17% for Vamsadhara. Furthermore, streamflow experienced decreases of 3% for Nagavali and 2% for Vamsadhara across their respective basins. Similarly, the application of the contour stone bunding BMP scenario under climate change resulted in a substantial reduction of 63% in sediment yield for Nagavali and 72% for Vamsadhara, accompanied by a streamflow reduction of 7% for Nagavali and 10% for Vamsadhara across critical sub-basins. These effects were sustained at the basin level, with sediment yield reductions of 31% for Nagavali and 49% for Vamsadhara. Additionally, streamflow exhibited reductions of 2% for Nagavali and 5% for Vamsadhara across their respective basins.

Table 6.4 Effectiveness of BMPs under climate change Cold-Wet (EC-Earth3) model, SSP585 scenario

BMP scenario	Percentage reduction in sediment yield	Percentage reduction in streamflow

	Average of critical sub-basins		Average of basin		Average of critical sub-basins		Average of basin	
	NB	VB	NB	NB	VB	VB	NB	VB
Filter strip 3 meter	50.84	51.51	25.24	26.43	0	0	0	0
Filter strip 6 meter	62.45	58.69	31.01	31.32	0	0	0	0
Filter strip 10 meter	72.67	65.03	36.08	37.63	0	0	0	0
Sedimentation ponds	49.56	49.51	24.61	33.74	50	50	14.57	28.17
Contour farming	42.79	24.61	21.43	16.75	11.05	3.15	3.19	1.82
Contour stone bunding	62.80	71.56	31.44	48.67	6.75	9.89	1.94	5.42
Combined BMP1	81.24	85.64	40.46	58.31	53.37	54.95	15.54	30.88
Combined BMP2	87.65	90.03	43.67	61.31	53.37	54.95	15.54	30.88
Combined BMP3	89.11	91.03	44.41	61.99	53.37	54.95	15.54	30.88
Combined BMP4	94.87	91.91	47.14	62.61	53.37	54.95	15.54	30.88

As shown in Table 6.1 and 6.2, it is evident that all critical sub-basins within the study area exhibit proportional distribution of land use, encompassing forest, agriculture, and waste lands. Given this uniformity, a comprehensive evaluation of combined BMPs across both basins becomes imperative. The collective impact of BMPs on sediment yield and streamflow reductions under climate change was thoroughly assessed. Four combined BMP scenarios were scrutinized, with combined BMP1 incorporating the combination of sedimentation ponds, contour farming, and contour stone bunding. Meanwhile, combined BMP2, BMP3, and BMP4 included filter strips with varying widths (3 m, 6 m, 10 m), sedimentation ponds, contour farming, and contour stone bunding, respectively. The evaluation of these BMPs demonstrated a sediment reduction ranging from 81% to 95% for Nagavali and 86% to 92% for Vamsadhara across critical sub-basins. At the basin level, sediment yield exhibited reductions from 40% to 47% and 58% to 63% over the Nagavali and Vamsadhara basins.

Under the combined BMPs, streamflow saw reductions of 53% and 55% across critical sub-basins, and 16% and 31% at the basin level over the Nagavali and Vamsadhara basins, respectively. Notably, the filter strips with varying widths did not influence streamflow. These findings indicated that while implementing different management options has varying effectiveness, combining them would be more beneficial than applying individual management practices. Thus, selecting sediment management practises is extremely beneficial for decision-makers, policymakers, water resource engineers, and hydro-ecologists. Overall, the highest percentage of reductions was observed at the sub-basin level compared to the watershed level, consistent with previous studies' findings (Himanshu et al. 2019; Tuppad et al. 2010; Uniyal et al. 2020). However, the efficiency of BMPs for sediment yield might vary depending on the specific conditions of each sub-basin, how they are implemented, and climate change. As a result, public participation is critical for the successful implementation of BMPs; consequently, people must be informed of the importance of reducing sediment production and the ways that they can implement. An expert should assist people in increasing the efficiency of BMPs by selecting BMPs that are appropriate for specific watersheds, correctly implementing BMPs, monitoring BMP efficacy, and making adjustments to BMPs as needed. Furthermore, different levels of land managers and experts can play a vital role in increasing the efficiency of BMPs in a variety of ways, including providing technical advice and guidance to farmers on how to implement, modifying existing BMPs and developing new BMPs to make them more effective, and educating and training stakeholders such as farmers and policymakers about the benefits of BMPs and encouraging their adoption. Through public awareness campaigns, educational programmes, and other outreach efforts, the country's policy should encourage the use of BMPs, regulate land use, and educate the people about the consequences of sediment yield and the importance of implementing BMPs.

6.5 Summary

In this study, four individual (i.e, filter strips, sedimentation ponds, contour farming and contour stone bunding) and combined BMP scenarios were evaluated for effectiveness to reduction of sediment yield and streamflow using the SWAT model. Filter strips with a width of 10 meters demonstrated notable efficiency in reducing sediment yield, resulting in a decrease of 29% and 53% over the Nagavali and Vamsadhara basins, respectively. Particularly, filter strips contributed to a substantial 73% reduction in sediment yield in the critical sub basins across both basins, without influencing streamflow. It is concluded that 10-meter-wide filter strips exhibited the most efficient reduction in sediment yield under individual BMP scenarios, followed by filter strips of 6 meters, contour stone bunding, 3-meter-wide filter strips, sedimentation ponds, and contour farming. Similar results were observed in BMPs efficacy under future climate change scenario. Sedimentation ponds demonstrated a reduction in sediment yield by 20% and 36%, with a concurrent reduction in streamflow by 15% and 29% over the Nagavali and Vamsadhara basins. Sedimentation ponds produce more efficient reduction in streamflow followed by contour farming and contour stone bunding under individual BMP scenarios. Sedimentation ponds emerged as consistent contributors to sediment reduction, with a notable 50% decrease in both sediment yield and streamflow across critical sub-basins. This underscores their pivotal role in trapping sediments and reducing downstream transport, positioning them as a key component of effective basin management. Notably, wider filter strips 6 m, 10 m, contour stone bunding and sedimentation ponds proved to be particularly efficient in mitigating sediment transport under historical and future climate scenario.

Moreover, the combination of BMPs resulted in a substantial decrease in sediment yield by 37% and 72%, coupled with a reduction in streamflow by 16.50% and 54% over the Nagavali and Vamsadhara basins. This combined BMP approach proved to be highly effective in reducing sediment and streamflow at both the critical sub-basin and basin levels. Under future climate scenario, the combined BMPs from BMP1 to BMP4 yielded the higher reductions in sediment yield surpassing individual BMP impacts, which reflected every sub-basin required the combined BMPs to mitigate the soil erosion in these basins. Streamflow reductions were also notable under combined BMP scenarios, emphasizing their holistic approach to soil and water conservation.

Chapter - 7 Summary and Conclusions

7.1 Summary

In the present research work, SWAT model was calibrated and validated using the SUFI-2 algorithm in SWAT-CUP, with a focus on streamflow and sediment data from Srikakulam and Kashinagar stations within the Nagavali and Vamsadhara river basins. Water balance components, including precipitation, surface runoff, groundwater flow, lateral runoff, and evapotranspiration, were analyzed on a mean monthly basis spanning from 1991 to 2014. The Spatial distribution of precipitation, surface runoff, groundwater flow, evapotranspiration and sediment yield was presented and analysed for the historical IMD simulations. Critical sediment source areas were identified. Under climate change analysis 10th, 50th, and 90th percentile values of temperature and precipitation is calculated to the identification of Cold-Wet, Cold-Dry, Warm-Wet, Warm-Dry, and central (average) models. The impact of climate change on streamflow and sediment yield were performed under SSP245, SSP370, and SSP585 scenarios. The effectiveness of four individual (filter strips 3 m, 6 m and 10 m, sedimentation ponds, contour farming and contour stone bunding) and combined BMP scenarios were evaluated for both basins.

7.2 Conclusions

The present research work has yielded several important conclusions. Curve Number (CN2) and CH_K1 were identified as the most sensitive parameters in both the Nagavali and Vamsadhara basins. The statistics obtained from the analysis of these basins range from very good to satisfactory, indicating the SWAT model's overall acceptance and reliability. The water balance analysis revealed that evapotranspiration is the dominant process, accounting for 63% of the average annual rainfall in these basins. Analyzing the average annual sediment yield, it was found that 26.5% and 49% of the basin areas in the Nagavali and Vamsadhara basins, respectively, are classified as high erosion areas. These high erosion zones are predominantly characterized by steep slopes of wasteland, followed by fallow lands, degraded deciduous forests, and agricultural lands.

Future projections based on downscaled GCMs under different SSP scenarios predict an overall increase in mean annual rainfall and temperature. However, there are discrepancies in the timing of peak precipitation, streamflow, and sediment yield when comparing IMD observed data and simulated results from different climate models. Among the BMPs evaluated, 10-meter-wide filter strips demonstrated the most efficient reduction in sediment yield, followed by 6-meter-wide filter strips, contour stone bunding, 3-meter-wide filter strips, sedimentation ponds, and contour farming. These results were consistent under both historical and future climate change scenarios. Sedimentation ponds were notably more efficient in reducing streamflow, followed by contour farming and contour stone bunding under individual BMP scenarios. Additionally, the combined BMP approach, encompassing BMP1 to BMP4, yielded the highest reductions in sediment yield under both historical and future climate scenarios, highlighting the necessity of employing combined BMPs across all sub-basins to effectively mitigate soil erosion in the Nagavali and Vamsadhara river basins based on specific land use, soil and topography of the sub-basins.

7.3 Research Contributions

The present study makes significant contributions to understanding hydrological processes, sediment dynamics, and watershed management in the Nagavali and Vamsadhara river basins. By evaluating the potential impacts of climate change, particularly under different Shared Socioeconomic Pathway (SSP) scenarios, the study provides valuable insights for watershed conservation and the management of land and water resources in these basins. The research methodology employed can be easily extended to other regions with similar river basin characteristics, highlighting its broader applicability.

From the study research findings, watershed management practices should prioritize the implementation of filter strips and sedimentation ponds due to their demonstrated efficiency in reducing sediment yield and streamflow. Specifically, 10-meter-wide filter strips should be established along critical sub-basins to achieve significant sediment reduction without impacting streamflow. Additionally, sedimentation ponds should be constructed to trap sediments and reduce downstream transport, particularly in areas identified as high erosion risk. Furthermore, a combined BMP approach should be adopted to maximize the reduction in sediment yield and streamflow, addressing the erosion issues more holistically. These practices are essential for enhancing soil and water conservation measures in the Nagavali and

Vamsadhara river basins, ensuring sustainable watershed management under both current and future climate scenarios.

7.4 Limitations

The study faced several limitations primarily related to data availability, calibration, validation processes, and model assumptions. One significant constraint was the limited observational data, with daily streamflow and sediment concentration observed only at two specific outlet points: Srikakulam over the Nagavali basin and Kashinagar over the Vamsadhara basin. The study was constrained to single-site calibration and validation at the mentioned outlet points. Without multisite calibration, the model's robustness and reliability across the entire watershed remain uncertain, as capturing spatial variability within the watersheds would have enhanced the model's accuracy. Additionally, while the model incorporated details of reservoir emergency and principal spillway volumes and surface area, it lacked complete data on reservoir inflows and outflows. This incomplete dataset introduced uncertainties, potentially affecting the accuracy of the simulation results. Furthermore, the study utilized precipitation and temperature data from the CMIP6 models, which may contain inherent biases since individual model values were considered. Although an ensemble of multiple models was used during bias correction, the process of correcting individual model biases before ensemble consideration was not undertaken, potentially leaving residual biases in the climate projections used. This study assumed that land use and land cover (LULC) would remain unchanged in the future. This static assumption introduced uncertainty, as it neglected potential changes in LULC due to factors such as urbanization, agricultural practices, and natural vegetation dynamics. Variations in LULC can significantly influence hydrological and sediment processes, potentially altering model outcomes. Finally, this study showed the efficiency of BMPs implementation in reducing sediment yield and optimizing water balance, but the economic feasibility of these implementations was not evaluated. Economic feasibility by BMPs is an important subject to inform and convince farmers to adopt BMPs in croplands.

7.5 Scope for Further Research

Addressing the identified limitations in future research could greatly enhance the robustness and accuracy of modeling results. Incorporating more comprehensive observational data and performing multisite calibration and validation would provide a more detailed understanding of watershed dynamics. Additionally, correcting individual model biases before ensemble consideration and dynamically modeling land use and land cover changes would further improve model precision. Moreover, the study demonstrated the efficiency of Best Management Practices (BMPs) in reducing sediment yield and optimizing water balance. However, the economic feasibility of these implementations was not evaluated, which is crucial for informing and convincing farmers to adopt BMPs in croplands. Future research should include a comprehensive analysis of the costs and benefits associated with implementing BMPs to ensure economic feasibility. Furthermore, the impact of potential future land use changes on streamflow and sediment yield can be studied to account for variations over time. Incorporating additional climate change scenarios, such as SSP245 and SSP370, would also provide a broader evaluation of BMPs under different future conditions. Exploring alternative BMPs and combinations can offer more tailored and effective solutions. Overall, these future research directions aim to enhance the applicability and effectiveness of BMPs in watershed management, ensuring both environmental and economic sustainability.

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N. Nageswara Reddy and K. Venkata Reddy "Impact of Climate Change on Streamflow over Nagavali Basin, India" Developments and Applications of Geomatics. Springer Nature. DOI: 10.1007/978-981-99-8568-5.

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