# Assimilation of Remote Sensing Derived Parameters in Hydrological Model for Ganga Basin

Thesis submitted to the Andhra University, Visakhapatnam in partial fulfilment of the requirement for the award of *Master of Technology in Remote Sensing and GIS.*


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This work has been carried out in partial fulfilment of Masters in Technology program in Remote Sensing and Geographic Information System at Indian Institute of Remote Sensing, All views and opinions expressed therein remain the sole responsibility of the author.

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Vikrant Vijay Nikam

# CERTIFICATE

This is to certify that this thesis work entitled “Assimilation of Remote Sensing Derived Parameters in Hydrological Model for Ganga Basin” is submitted by Mr. Vikrant Vijay Nikam in partial fulfillment of the requirement for the award of Master of Technology in Remote Sensing and GIS by the Andhra University. The research work presented here in this thesis is an original work of the candidate and has been carried out in Water Resources Department under the guidance of Dr. Bhaskar R. Nikam, Scientist/Engineer ‘SE’ and Dr. Vaibhav Garg, Scientist/Engineer ‘SD’ at Indian Institute of Remote Sensing, ISRO, Dehradun, India.

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*Dedicated to My Loving sister Vrushali*

# ABSTRACT

The goal of hydrologic data assimilation technique is to provide the best analysis estimators by merging the strengths of modelled state (forecast) and the satellite derived observations. This research performs two assimilation techniques, namely Direct Insertion (DI) and Ensemble Kalman Filter (EnKF) in macroscale semidistributed hydrological model Variable Infiltration Capacity (VIC) model for Ganga basin. Primarily parameter sensitivity is done for the meteorological forcing parameters of VIC which considers four different scenarios. VIC requires at least four parameters in forcing namely, Tmax, Tmin, Prec, and Wind speed as the water balance component deviation is observed -8.54%, -46.60% and 3.15% in runoff, baseflow and evaporation respectively between forcings with wind speed and without wind speed. The calibration of VIC model has been done using observed discharge data, the soil parameters determined after calibration are binfilt=0.3, Ds=0.001 and Ws=0.8; validation of the calibrated model is done by comparing model simulated discharge with GRDC observed discharge at Farakka; the present study gives the 0.89 coefficient of determination between estimated and observed discharge data.. Soil moisture variable is very important for both the water and energy balance modes of the model; hence this crucial variable has been chosen for the assimilation study. Direct insertion technique is not advisable as it ignores the model. For EnKF study ensembles have generated for the 9 grids of Ganga for the entire month of January, 2005. Analysis is generated for the calculated Kalman gain matrix and it is compared with rainfall events in which assimilated soil moisture behaviour is better than that of the forecasted. This research shows that not only rainfall effect but also irrigation effect has been represented in assimilated soil moisture model. Water balance for assimilated case draws attention on the importance of hydrologic data assimilation.

Keywords: *Data assimilation, VIC, Direct Insertion, EnKF, parameter sensitivity*

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# 1 INTRODUCTION

Hydrology is the science which deals with the study of occurrence, circulation, distribution and the removal of water on the earth, including that in the atmosphere and below the surface of the earth. Hydrology is important in water resources to study various aspects such as estimation of water resource potential and river basin, analysis of problems of flood and there pattern and magnitude, estimation of dependable yield for irrigation and hydro-electric power generation, determination of maximum flood and discharge flood volume expected to enter a reservoir, formation of flood and its control measures, maintenance and operation of river, erosion control to prolong life of a reservoir and control the pollution of river, municipal and industrial water supply and stream flow forecasting, and also flood forecasting with the help of precipitation and other hydro meteorological data (Bonacci, 2004). In this part of the thesis some basic concepts or ideas are described about the hydrological processes, how a semidistributed-physical based Variable Infiltration Capacity (VIC) model operates and the basic introduction to data assimilation technique.

## 1.1 Basic Concepts

- **SYSTEM:** Hydrological phenomena are extremely complex, and difficult both to measure and understand in full detail. In absence of perfect knowledge, however, they may be represented in a simplified way by means of the system concept: A system is a set of connected parts that forms a whole. It is possible to apply this concept to hydrological phenomena giving the following definition
- **HYDROLOGICAL SYSTEM: "**structure or volume in space, surrounded by a boundary that accepts water and other inputs, operates on them internally and produces an output". The objective of hydrological system analysis is to study the system operation and predict its internal states and output.
- **HYDROLOGICAL MODEL SYSTEM**: Its inputs and outputs are measurable hydrological variables and the model's structure is a set of equations which gives outputs according to the inputs in hydrological system.
- **SYSTEM TRANSFORMATION:** Central to the model structure is the concept of system transformation, the input and output can be expressed as function of time I(t) and O(t) respectively. A system performs a transformation of the input into the output represented by a transformation operator or equation.

A watershed can be an excellent example of a hydrologic model system. The watershed can be looked upon as an operator transforming the moisture inputs I (t) into outputs O (t). If the surface and soil of watershed are examined in detail, the number of possible flow paths above or below the surface becomes very large. Along any path the shape, slope, soil texture and boundary conditions may change continuously from place to place. Also, the processes interacting with water may vary in time. Precipitation varies randomly in space and time.

It is not possible to describe all the physical processes within the watershed with exact physical laws because of all these major complications. Using the system concept the effort is utilized to the construction of a model. This model represents the most important processes, and their interaction within the total system.

## 1.2 Hydrological Cycle

A hydrologic cycle is a conceptual model that describes the storage and movement of water between biosphere, atmosphere, lithosphere, and the hydrosphere. Water can be stored in any of the following major reservoirs: atmosphere, oceans, lakes, rivers, soils, glaciers, snowfields and groundwater in the Earth surface and subsurface. Water transports by way of processes like evaporation, condensation, precipitation, deposition, runoff, infiltration, sublimation, transpiration, and melting and groundwater flow from one location to another reservoir.

The oceans supply most of the evaporated water found in the atmosphere. Of this evaporated water, 91% of it is returned to the ocean basins by way of precipitation over ocean. The remaining 9% is transported to areas over landmasses where climatologic factors induce the formation of precipitation.

The journey of water from one location to another by the different ways has been depicted in Figure 1.1.

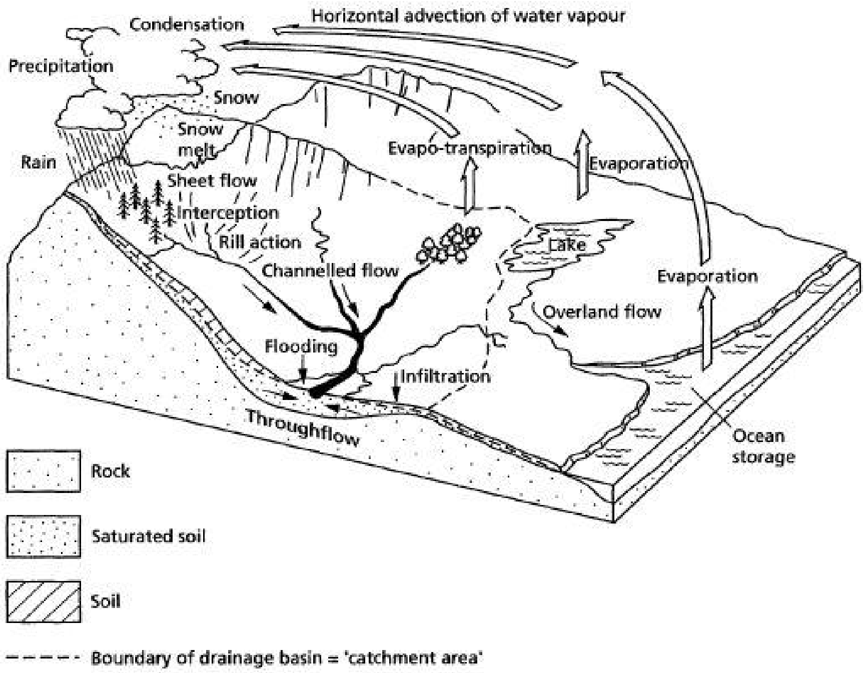



**Figure 1.1** Hydrological Cycle (Source http://www.yourarticlelibrary.com)

## 1.3 Main Components

A hydrologic cycle may be treated as a system, whose components are precipitation, evaporation, snow melt, infiltration, runoff and other processes in the hydrologic cycle. The different components can each be grouped together into subsystems or broken down into new sub-processes, depending on the level of detail in the analysis and the purpose of the analysis.

The global hydrologic cycle is represented in a system and it can be divided into three subsystems:

- The atmospheric water system
- The surface system
- The subsurface water system

### 1.3.1 The atmospheric water system

Contains the processes of precipitation, evaporation, interception and transpiration

**Precipitation:** can be in form of snow, sleet or rain. The form of precipitation is not only determined by the air temperature at ground level, but also by the temperature distribution between the cloud base and the ground. Precipitation in the form of snowfall normally occurs when air temperature falls below $0\text{-}1^0$ C, though a closer investigation reveals that the form of precipitation has a distribution probability of rain even when air temperature is below $0^0$ C, and high probability of snowfall even if the temperature is above $0^0$C. The transition temperature, (TS), is the temperature with 50/50 probability of rain and snow (usually is found to be $+1^0$C).

**Evapotranspiration:** is a collective term for all the processes by which water in the liquid or solid phase at or near the earth's land surface becomes atmospheric water vapor. That term thus includes: evaporation of liquid water from open water bodies, bare soil and vegetative surfaces, interception losses from vegetative surfaces, transpiration (evaporation from within the leaves of plants) and sublimation from ice and snow surfaces.

### 1.3.2 The surface water system

Contains the processes of snow accumulation and melt, overland flow, ove, surface runoff, subsurface and groundwater outflow and runoff to streams and the ocean. When subsurface and groundwater outflow occurs, and runoff to streams and the ocean: ground water eventually discharges into river of lakes or, in coastal areas, directly into the ocean. Also, can leave the ground water reservoir by moving upward from the water table (fluctuating boundary of the ground water zone)

### 1.3.3 The subsurface water system

Contains the processes of infiltration, groundwater recharge, subsurface flow and groundwater flow

**Infiltration** is the process by which water arriving at the soil surface enters the soil. Groundwater recharge or percolation: is the movement of infiltrated water to recharge ground water.

**Subsurface flow**: following a rain or a snowmelt event, infiltrated water is subject to redistribution by gravity and pressure forces and to remove by evapotranspiration or redistribution, which is the subsequent movement of infiltrated water in the unsaturated zone of a soil.

**Ground water flow**: as with all hydrological stocks, ground water is in continual motion, albeit slow. In spite of its slow pace, ground water is a crucial link in the hydrologic cycle because it is the source of most of the water in rivers and lakes.

## 1.4 Hydrological Modeling

Hydrological modeling is the mathematical representation of the long-term hydrological patters of the basin and its behaviour. Hydrological models are of two types: Lumped models and Distributed models. Lumped model treats watershed as a single unit i.e. all the physical parameters are same for the entire area; whereas distributed models consider the multiple points into the watershed the physical parameters for each point is accounted. The lumped models are homogenous in nature whereas distributed are heterogeneous.

Remote Sensing has a potential to measure spatial as well as temporal variation of climatic parameters. It plays a key role in hydrological modeling by providing it all the necessary inputs. Geographic Information System (GIS) helps in generating drainage network map, flow direction map, flow accumulation map, aspect map, stream order etc from remotely-sensed data.

The output of such hydrological models is the *water balance components*. The verification of these models is done by computing the water balance equations.

## 1.5 Variable Infiltration Capacity (VIC) Model

VIC is a semi-distributed macro scale hydrological model that treats the peace of land under study as if it were a box, dividing the catchment into cells. Therefore, the catchment is looked as a grid cell.  VIC balances both the water and surface energy budgets within the grid cell; and its sub-grid variations are captured statistically. (More details about the model are discussed in the model overview)

The (VIC) model with a variety of updates has been extensively used in studies on topics ranging from water resources management, land-atmosphere interactions and climate change. It has been well calibrated and applied in a number of large river basins over the continental US and the globe. VIC has participated in the WCRP Intercomparison of Land Surface Parameterization Schemes (PILPS) project and the North American Land Data Assimilation System (NLDAS), where it has performed well relative to other schemes and to available observations. It has also been evaluated using soil moisture observations in the U.S. and global snow cover extent data. Driven by high-quality meteorological forcings, VIC had been used to provide a long-term data record of land surface fluxes and states for the conterminous United States and Mexico.

## 1.6 Hydrologic Data Assimilation

Information about hydrologic conditions is of critical importance to real-world applications such as agricultural production, water resource management, flood prediction, water supply, weather and climate forecasting, and environmental preservation. Improved hydrologic condition estimates are useful for agriculture, ecology, civil engineering, water resources management, rainfall-runoff prediction, atmospheric process studies, climate and weather/climate prediction, and disaster management (Houser *et al*. 2004).

Hydrologic process models may be used to predict the temporal and spatial hydrologic variations, but these predictions are often poor, due to model initialization, parameter and forcing, and physics errors. Therefore, an attractive prospect is to combine the strengths of hydrologic models and observations (and minimize the weaknesses) to provide a superior hydrologic state estimate. This is the goal of hydrologic data assimilation.

For example, a hydrological model provides spatial and temporal near-surface and root zone soil moisture information at the model resolution, including error estimates. On the other hand, remote sensing observations contain near-surface soil moisture information at an instant in time, but do not give the temporal variation or the root zone moisture content.

While the remote sensing observations can be used as initialization input for models or as independent evaluation, providing we use a hydrological model that has been adapted to use remote sensing data as input, we can use the hydrological model predictions and remote sensing observations together to keep the simulation on track through data assimilation (Kostov and Jackson 1993).

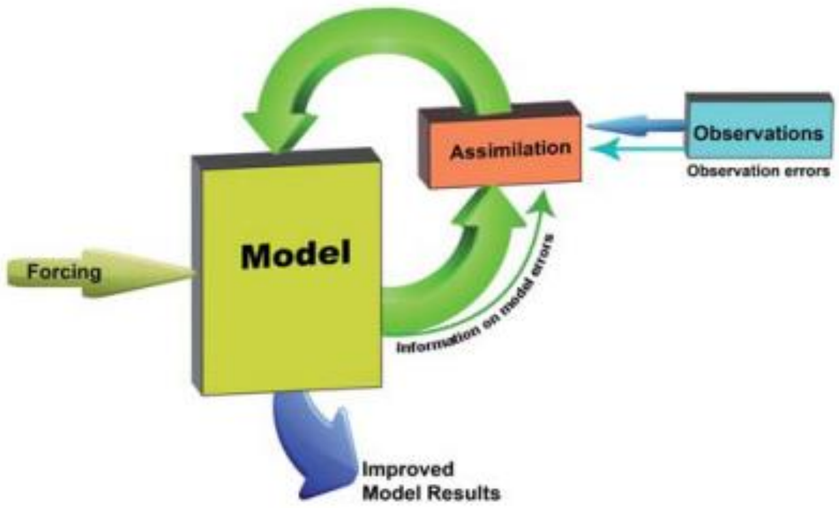



**Figure 1.2** Hydrologic Data Assimilation (www.hzg.de/institute/coastal_research/cosyna)

## 1.7 Motivation

The water stored on land is a key variable controlling numerous processes and feedback loops within the climate system. It is of major relevance for the water and energy cycles, but also impacts the exchanges of trace gases on land, including carbon dioxide. Fig. 1 provides an overview of the main components and exchanges within the climate system. The extreme complexity of land processes and feedbacks is apparent, in particular if one considers the strong heterogeneity of the land cover and its temporal variability.(Seneviratne et al., 2010) The representation of the soil column and the infiltration parameterization is particularly important because of their direct effects on a model's vertical distribution of soil moisture. Soil moisture determines whether the soil column can meet the atmospheric demand for moisture; either at the surface (bare soil evaporation) or in the root zone (transpiration). The evapotranspiration, along with net radiation, then essentially determines the sensible and ground heat fluxes.(Xu et al., 1996) Soil moisture plays an essential role in the exchange of energy and water within the soil–vegetation–atmosphere continuum. Successful initialization and modeling of soil moisture is crucial for the prediction of hydrologic processes including runoff, ground water recharge and evapotranspiration. Nevertheless, accurate estimation of soil moisture is typically limited by uncertainties in model inputs, parameter values and imperfect model physics regarding subsurface processes. Given the lack of a dense soil monitoring network in most of the regions, satellite observations are the most viable solution to improving the representation of soil moisture states in land surface and hydrologic models. There are three important aspects of the specification of the soil column and the infiltration and evaporation parameterizations within a land surface hydrology scheme. These are: (1) the handling of spatial variability in soil characteristics within the area being modeled; (2) the number of soil layers and their water holding capacities; (3) the parameterization of soil water drainage and diffusion. Different land surface parameterization schemes have addressed these aspects in different ways.(Xu et al., 1996)

Remote sensing can provide important information about land surface conditions, including surface soil moisture, snow water equivalent, snow cover, and land surface temperature. While remote sensing data are not usually sufficient for many applications (such as weather forecast initialization) they can contribute valuable information when used in data assimilation systems. Such systems can also be helpful for the design of new hydrologic remote sensing missions and for the validation of the hydrologic remote sensing observations themselves(Reichle, 2008).

## 1.8 Problem Statement

The aim of this research is to primarily understand the concept of hydrologic data assimilation, explore the best possible techniques to assimilate remote sensing derived parameters in the selected hydrologic model, draw a comparative study of the data assimilation techniques adopted and chose the most efficient technique for soil moisture study. The outcome of the selected technique will be used to drive the hydrological model. The study also determines evaluation criteria for evaluating the performance of these techniques and finally, the assimilated variables (soil moisture) will be used to generate the multilayer soil moisture regime for a time period in the future. Such a study will help to overcome the model errors in predictions of water balance by providing a real soil moisture conditions taking irrigation into the considerations.

## 1.9 Research Questions

- How to set up and parameterize the hydrological model at basin level?
- Which assimilation technique is suitable for assimilating soil moisture in selected hydrological model?
- What is the impact of RS derived data assimilation on modeling multilayer soil moisture regime on Basin level?

## 1.10 Objectives

- The focus of research is on :- 'Assimilation of remote sensing derived parameters in hydrological model for Ganga basin'

- Sub objectives are :-

- ✓ Setting up hydrological model (water balance & Energy balance) and its parameterization (Research Q 1)
- ✓ Assimilation of remote sensing derived soil moisture in hydrological model using suitable assimilation technique (Research Q 2)
- ✓ Modeling multilayer soil moisture regime in the basin. (Research Q 3)

# 2 LITERATURE REVIEW

## 2.1 Hydrological Cycle and Water Balance

Hydrology is the scientific discipline that deals with water cycle. The study of origin, movement, distribution, and of water on earth and its atmosphere is known as hydrology

(Subramnya, 2008). The processes involved in circulation water from land and water bodies to the atmosphere and back again different states such as gas, liquid, or solid (Maidment, 1992) is known as hydrologic cycle. Water cycle or Hydrologic cycle can be constitutes of certain physical processes which form a continuum of water movement on globe. Important components are evapotranspiration, precipitation, interception, infiltration, percolation, and runoff. Evapotranspiration accounts for water evaporating from the ground, seas and lakes, snow, even raindrops combined with transpiration by plants. Condensation is the process of water changing from a vapor to a liquid. Precipitation is water being released from clouds as rain, sleet, snow or hail and reaching the ground. Interception is the volume of water caught by vegetation. Infiltration occurs when a portion of the precipitation that reaches the Earth's surface seeps into the ground. The soil moisture is the volume fraction of water held in various layers of soil. Percolation is the downward movement of water through soil and rock. Percolation is the movement of water through soil layers by gravitational pull or capillary action. Runoff is precipitation that reaches the surface of the Earth but does not infiltrate the soil. Runoff can also come from melted snow and ice. As soon as it enters a channel, runoff becomes streamflow.

Water budget of an area accounts for all the water that flows in and out of that area. The area of land draining into a stream or a water course at a given outlet point is said to be a catchment or a drainage basin (Subramanya, 2008). The water budget equation for an area in its simplest form can be written as,

*Mass inflow - mass outflow = change in water storage*

For a given catchment, the mathematical statement of hydrological cycle within a given time frame incorporating principles of mass and energy continuity for water in its various phases is termed as the water budget or water balance. In its simplest form it is expressed as,

$$\mathrm{P} - \mathrm{Q} - \mathrm{ET} - \mathrm{G} = \Delta \mathrm{S} \tag{2.1}$$

Where,

*P* is precipitation,

*Q* is surface runoff,

*G* is subsurface runoff,

*ET* is evapotranspiration,

And Δ*S* is change in storage.

The average annual precipitation received in India is 4,000 $km^3$, out of which 700 $km^3$ is evaporated, 2,150 $km^3$ infiltrated and 1,150 $km^3$ flows as surface runoff. The total water resources in the country have been estimated as 1,953 $km^3$. The annual utilizable water availability in India is 1,122 $km^3$. Besides this, the quantity of 123 $km^3$ to 169 $km^3$ additional return flow will also be available from increased use from irrigation, domestic and industrial purposes by the year 2050. The per capita availability of utilizable water, which was about 3,000 $m^3$ in the year 1951, has been reduced to 1,100 $m^3$ in 1998 and is expected to be 687 $m^3$ by the year 2050 (Water Budget, NIH, 2013).

The equation for hydrologic water balance of the country for average annual conditions can be written as

$$P - Q - ET - G = \Delta S \tag{2.2}$$

Where,

P is the total precipitation,

ET is total evapotranspiration,

I is the total inflow water,

Qs is the outflow as surface water to oceans and other countries,

Qg is the ground outflow,

and ΔS represent the change in soil moisture storage.

## 2.2 Hydrological Modeling

The water cycle or hydrologic cycle is central to the Earth system, and water resources are one of the critical environmental and political issues of the 21st century (NRC 2004). A primary goal of contemporary water cycle research is to significantly improve the understanding of water cycle processes, and to incorporate this understanding into prediction frameworks that can be used for decision making (Hornberger et al. 2001).

Hydrologic models are important tools to enhance the understanding of hydrological processes and to simulate and predict hydrological events for better decision making.

Hydrologic models are designed to answer the question, “what happens to the rain” (Penman 1961). The earliest hydrologic model to answer this question is the rational formula developed by Mulvany (1851). It statistically relates storm runoff rates to rainfall intensity and watershed area using regression method. More empirical rainfall runoff (R-R) models were then developed (Sherman 1932; Horton 1935). Empirical models describe the relation between rainfall and runoff mathematically with little consideration of physical processes. These models need a lot of historical precipitation and runoff data to establish the mathematical relationship.

In 1960s, more components of the water cycle were added to hydrologic models with the introduction of digital computer. Limited by hydrologic data availability and computer power at that time, those hydrological processes were conceptually and parametrically represented. Examples of early conceptual R-R models are the Stanford Watershed Model (SWM; Linsley and Crawford 1960; Crawford and Linsley 1966), the Catchment Model (CM) (Dawdy and O’Donnell 1965), and the Tank Model (Sugawara 1967). Because of their simple model structures, efficient computational costs, and their success in flood forecasting, more conceptual models, both lumped and distributed, have been developed. Today, many of them are still widely used (Kampf 2006; Wood and Lettenmaier 2006), e.g., the Soil Water

Assessment Tool (SWAT; Arnold et al. 1998), the Soil-Vegetation-Atmosphere Transfer model (SVAT; Ma and Cheng 1998), and the Sacramento Soil Moisture Accounting model (SAC-SMA; Burnash et al. 1973; Burnash 1995) which is used for the National Weather Service (NWS) river forecast.

The fundamental purpose of modeling the hydrology is to gain an overall understanding of the complex hydrological system and its dynamics in order to provide reliable information to water resource managers and policy makers (Bhattacharya et al., 2013). All distributed models are based on the physical processes governing the flow of water in a basin. But such models require high-quality reliable data as inputs. Remote sensing has shown great promise in providing an abundance of data and information due to its unrestricted spatial and temporal coverage. SWAT (Soil and Water Assessment Tool), MIKE-SHE, Variable infiltration Capacity (VIC) model are some of the physically based distributed hydrologic models that accept satellite-borne products as inputs. But most of these models do not consider horizontal complexity and spatial heterogeneity of soil, topography, vegetation etc, all of which plays a significant role in governing surface runoff (Garg et al., 2012). However, VIC is a two layer semi distributed model that takes sub-grid variability in soil infiltration capacity and vegetative classes into consideration.

## 2.3 Variable Infiltration Capacity (VIC) Model

The variable infiltration capacity (VIC) model (Liang et al., 1994, 1996), with a variety of updates (Cherkauer et al, 2003; Bowling et al., 2004; Bowling and Lettenmaier, 2009), has been extensively used in studies on topics ranging from water resources management to land-atmosphere interactions and climate change. Throughout its existence, VIC has played multiple roles, as both a hydrologic model and land surface scheme when coupled to general circulation models. As a semi-distributed macroscale hydrological model, VIC balances both the water and surface energy budgets within the grid cell; and its sub-grid variations are captured statistically. Distinguishing characteristics of the VIC model include: subgrid variability in land surface vegetation classes; subgrid variability in the soil moisture storage capacity; drainage from the lower soil moisture zone (base flow) as a nonlinear recession; inclusion of topography that allows for orographic precipitation and temperature lapse rates resulting in more realistic hydrology in mountainous regions. To simulate streamflow, VIC results are typically post-processed with a separate routing model (Lohmann, et al., 1996; 1998a; b) based on a linear transfer function to simulate the streamflow. VIC has been adapted to allow representation of water management effects (Haddeland et al, 2006a; b; 2007) including reservoir operation and irrigation diversions and return flows.

VIC model has three types of frameworks according to the soil layers present in soil profile.

Each framework has it's distinguish characteristics. The improvement of the model is checked by lots of studies in their respective domains. VIC has been well calibrated and applied in a number of large river basins over the continental US and the globe (Abdulla et al. 1996; Bowling et al. 2000; Lohmann et al. 1998b; Nijssen et al. 1997, 2001a; Shi et al., 2008; Su et al., 2005, 2006; Wood et al. 1997; Zhu and Lettenmaier, 2007). VIC has participated in the WCRP Intercomparison of Land Surface Parameterization Schemes (PILPS) project and the

North American Land Data Assimilation System (NLDAS), where it has performed well relative to other schemes and to available observations (Bowling et al, 2003a, b; Lohmann et al., 2004; Nijssen et al. 2003; Wood et al., 1998). It has also been evaluated using soil moisture observations in the U.S. (Maurer et al, 2002) and global snow cover extent data by (Nijssen et al, 2001b).

Applications using such a data record have covered many areas, such as: simulating ensembles of streamflow and hydrologic variables for forecast purpose (Hamlet and Lettenmaier, 1999; Wood et al., 2002, 2005; Wood and Lettenmaier, 2006); reconstructing and analyzing drought events (Andreadis and Lettenmaier, 2006a; Sheffield et al., 2004a; Sheffield and Wood, 2007; Wang et al., 2009); studying the North American monsoon teleconnections (Zhu and Lettenmaier, 2007; Zhu et al., 2007, 2009); drought prediction (Luo and Wood, 2007); conducting hydrologic studies over the Pan-arctic region (Bohn et al., 2007; Bowling et al., 2003c; Lettenmaier and Su, 2009; Slater et al., 2007; Su et al., 2005, 2006); water management (Adam et al., 2007; Haddeland et al, 2006a, b, 2007); and many others.

The development or improvement of the model is given as below:

VIC was first described as a single soil layer model by Wood et al. (1992) and implemented in the GFDL and Max-Planck-Institute (MPI) GCMs (Stamm et al. 1994). The single soil layer model requires three parameters: an infiltration parameter, an evaporation parameter, and a base flow recession coefficient. In 1994, Liang et al. (1994) generalized the two-layer VIC model (VIC-2L) to include the multiple soil layers and spatially varying vegetation and evaporation within a grid cell. In VIC-2L, infiltration, drainage from the upper soil layer into the lower soil layer, surface and subsurface runoff are calculated for each vegetation cover tile (in addition to the statistical parameterization of heterogeneity of infiltration and runoff generation within a vegetation cover tile present in the original VIC model).

In 1996, Liang et al. (1996) found that the VIC-2L tends to underestimate the evaporation due to the low soil moisture in its upper soil layer, and the main cause of this error is the lack of a mechanism for moving moisture from the lower to the upper soil layer. VIC-2L was then modified to allow diffusion of moisture between soil layers, and to have an additional 10cm thin soil layer on top of the previous upper soil layer. In this way the three-layer VIC model (VIC-3L) was generated, and the VIC-3L framework has been used ever since. The model currently allows for more than three soil layers if desired.

The soil heterogeneity with variable infiltration and the subgrid variability in vegetation of VIC model and nonlinear baseflow is shown in fig, 2.1 below.

The details on the concept and the working of the model can be found in

*(http://www.hydro.washington.edu/Lettenmaier/Models/VIC).*

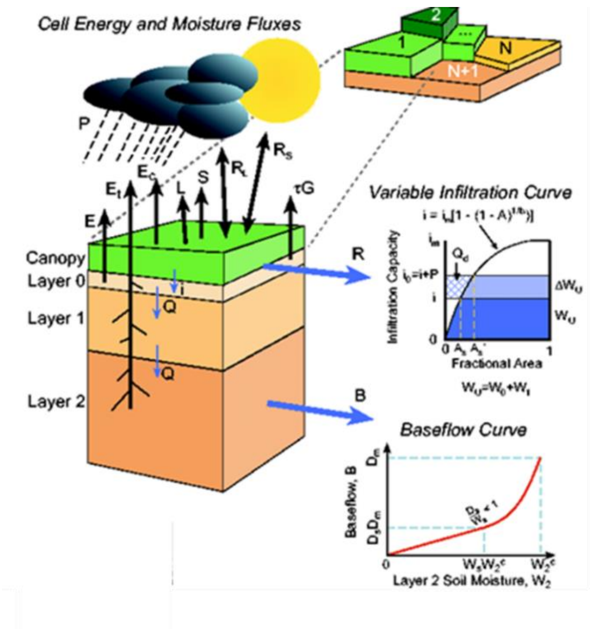



**Figure 2.1** Schematic of VIC (Cherkauer et al., 2003)

In the VIC model, each grid cell is modeled independently without horizontal water flow. The grid-based VIC model simulates the time series of runoff only for each grid cell, which is non-uniformly distributed within the cell. Therefore, a stand-alone routing model (Lohmann., et al., 1996, 1998a) is employed to transport grid cell surface runoff and base flow to the outlet of that grid cell then into the river system.

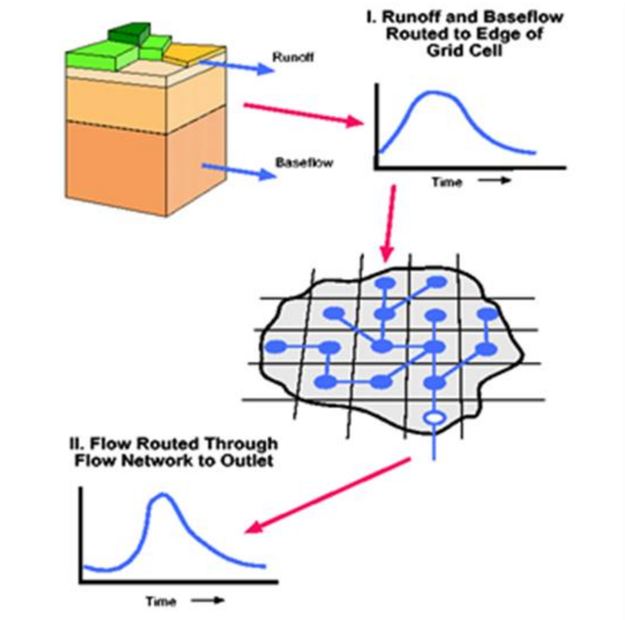



**Figure 2.2** Schematic of VIC network routing model (Cherkauer et al., 2003)

## 2.4 Data Assimilation

Information about hydrologic conditions is of critical importance to real-world applications such as agricultural production, water resource management, flood prediction, water supply, weather and climate forecasting, and environmental preservation. Improved hydrologic condition estimates are useful for agriculture, ecology, civil engineering, water resources management, rainfall-runoff prediction, atmospheric process studies, climate and weather/climate prediction, and disaster management (Houser et al, 2004).

Hydrologic remote sensing can provide important information about land surface conditions, including surface soil moisture, snow water equivalent, snow cover, and land surface temperature. While hydrologic remote sensing data are not usually sufficient for many applications (such as weather forecast initialization) they can contribute valuable information when used in data assimilation systems. Such systems can also be helpful for the design of new hydrologic remote sensing missions (Reichle et al, 2008) and for the validation of the hydrologic remote sensing observations themselves (Crow, 2008). Experts in hydrologic remote sensing should thus benefit from a basic understanding of data assimilation theory and applications (Walker et al 2003). Data Assimilation combines observations into a dynamical model, using the model's equations to provide time continuity and coupling between the estimated fields. Hydrologic data assimilation aims to utilize both our hydrologic process knowledge, as embodied in a hydrologic model, and information that can be gained from observations.

Both model predictions and observations are imperfect and we wish to use both synergistically to obtain a more accurate result. Moreover, both contain different kinds of information, that when used together, provide an accuracy level that cannot be obtained individually.

Charney et al, (1969) first suggested combining current and past data in an explicit dynamical model, using the model's prognostic equations to provide time continuity and dynamic coupling amongst the fields. This concept has evolved into a family of techniques known as data assimilation. In essence, hydrologic data assimilation aims to utilize both our hydrological process knowledge as embodied in a hydrologic model, and information that can be gained from observations. Both model predictions and observations are imperfect and we wish to use both synergistically to obtain a more accurate result. Moreover, both contain different kinds of information, that when used together, provide an accuracy level that cannot be obtained when used separately.

### 2.4.1 Review of Data Assimilation Methods

Several methods can be used to assimilate data into hydrological models, each of which has strengths and weaknesses Liu et al, (2007). The earliest method for hydrological data assimilation is an extension to the linear Kalman filter (Kitinadis et al, 1980), (Georgakakos, 1986).

Kitinadis and Bras (1980) have estimated that in the extended Kalman filter the hydrological model is rendered in state-space form in which each model state is continuously differentiable with respect to all other model states. The estimate of model error at the time of an observation is estimated by propagating the covariance matrix of model errors forward in time using a linearized model operator.

The previous approach of the data assimilation is not good in non linarites as observed by the Evensen, (1994) and Miller, Ghil, Ghautiez, (1994). Also, Reichle et al,(2008) point out that application of the extended Kalman filter can be impossible for large scale environmental assimilation problems (e.g., distributed hydrological models), unless approximations are made (e.g., ignoring spatial correlations among sub-catchments).

Another approach for hydrological data assimilation is variational meth. ods Reichle, (2001), Seo,(2003). In hydrological applications of variational methods the model error is usually assumed to be temporally constant Seo, (2003), and the problem reduces to identifying a set of model states that minimizes a cost function that defines differences between model states and observations. Seo, (2003) has concluded that this is a (typically large) minimization problem, in which a linearized version of the hydrological model – the adjoint model – is used to compute the gradient of the cost function. The advantage of variational methods is that they do not forecast the model error covariance matrix and hence do not require a state-space formulation of the hydrological model required in the extended Kalman filter. Yet another approach to data assimilation is the ensemble Kalman filter. This method has recently gained popularity in hydrology, partly because increased computing power makes ensemble simulations feasible, and because it is easy to implement. In the ensemble Kalman filter the hydrological model is run forward in time with a finite set of ensemble members, where each ensemble member is an equally-plausible representation of the real-world. Model error is then estimated directly from the ensemble by assuming that the ensemble mean is ‘‘truth” and computing the variance of the differences between each ensemble member and the ensemble mean (note, this assumes the ensemble is unbiased). As with other methods, the update to model states depends on the relative error in the model and observations, and the modelled covariance between model states and model fluxes at observing points in the basin. The advantages of the ensemble Kalman filter are that it does not require reformulation of the model into state-space form (as in the extended Kalman filter), and it does not require specification of the temporally constant model error covariance or development of a separate adjoint model (Clark et al.,2008)

Another ensemble data assimilation method is the particle filter Pham, (2001), Moradkhani et al, (2005), Weerts and Serafy, (2006). Moradkhani et al, (2005) has elaborated that in particle filter the probability distribution of model predictions can then be computed as a weighted combination of the ensemble members. The advantage of the particle filter is that it does not assume Gaussian model errors.

### 2.4.2 KALMAN FILTER AND ENSEMBLE KALMAN FILTER

Evensen, (1994) has given a new sequential data assimilation method. It is based on forecasting the error statistic using Monte Carlo methods, a better option than solving the traditional and computationally extremely demanding approximate error covariance equation used in the Extended Kalman filter.

Mandel, (2009) has stated that the ensemble Kalman filter (EnKF) is a recursive filter suitable for problems with a large number of variables, such as discretizations of partial differential equations in geophysical models. The EnKF originated as a version of the Kalman filter for large problems (essentially, the covariance matrix is replaced by the sample covariance), and it is now an important data assimilation component of ensemble forecasting.The Ensemble

Kalman Filter (EnKF) is a Monte-Carlo implementation of the Bayesian update problem: Given a probability density function (pdf) of the state of the modeled system (the prior, called often the forecast in geosciences) and the data likelihood, the Bayes theorem is used to to obtain pdf after the data likelihood has beed taken into account (the posterior, often called the analysis). This is called a Bayesian update. The Bayesian update is combined with advancing the model in time, incorporating new data from time to time.

The original Kalman Filter (Kalman, 1960) assumes that all pdfs are Gaussian (the Gaussian assumption) and provides algebraic formulas for the change of the mean and covariance by the Bayesian update, as well as a formula for advancing the covariance matrix in time provided the system is linear. However, maintaining the covariance matrix is not feasible computationally for high-dimensional systems. For this reason, EnKFs were developed Evensen, (1994). EnKFs represent the distribution of the system state using a random sample, called an ensemble, and replace the covariance matrix by the sample covariance computed from the ensemble. One advantage of EnKFs is that advancing the pdf in time is achieved by simply advancing each member of the ensemble.

Houtekamer and Mitchell, (1997) have experienced that (i) as the size of the ensembles increases, correlations are estimated more accurately and the root-meansquare analysis error decreases, as expected, and (ii) ensembles having on the order of 100 members are sufficient to accurately describe local anisotropic, baroclinic correlation structures. Due to the difficulty of accurately estimating the small correlations associated with remote observations, a cutoff radius beyond which observations are not used is implemented. It is found that (a) for a given ensemble size there is an optimal value of this cutoff radius, and (b) the optimal cutoff radius increases as the ensemble size increases.

## 2.5 Data Assimilation for Soil Moisture

Zhiyong et al, (2006) have concluded that the land surface is the interface between the atmosphere and the underlying hydrological regime with the latter being characterized by soil moisture, surface run-off, interflow, baseflow and other hydrological variables ( Lin et al., 2005). Although soil contains only a small fraction of the total available water in the world, the soil moisture condition plays a vital role in global water and energy exchanges. For example, Entekhabi et al, (1999) in their proposed agenda for land surface hydrology research, note that surface soil moisture can be as important a boundary condition for the climate system as sea surface temperature.

Reichle, et al,.( 2002) have resulted that The average actual estimation error in volumetric moisture content of the soil profile is 2.2% for the EKF and 2.2% (or 2.1%; or 2.0%) for the EnKF with 4 (or 10; or 500) ensemble members. Expected error covariances of both filters generally differ from actual estimation errors. Nevertheless, nonlinearities in soil processes are treated adequately by both filters. In the application presented herein the EKF and the EnKF with four ensemble members are equally accurate at comparable computational cost. Because of its flexibility and its performance in this study, the EnKF is a promising approach for soil moisture initialization problems. The comparison between Extended Kalman filter and Ensemble Kalman filter is shown in Figure 2.3 below

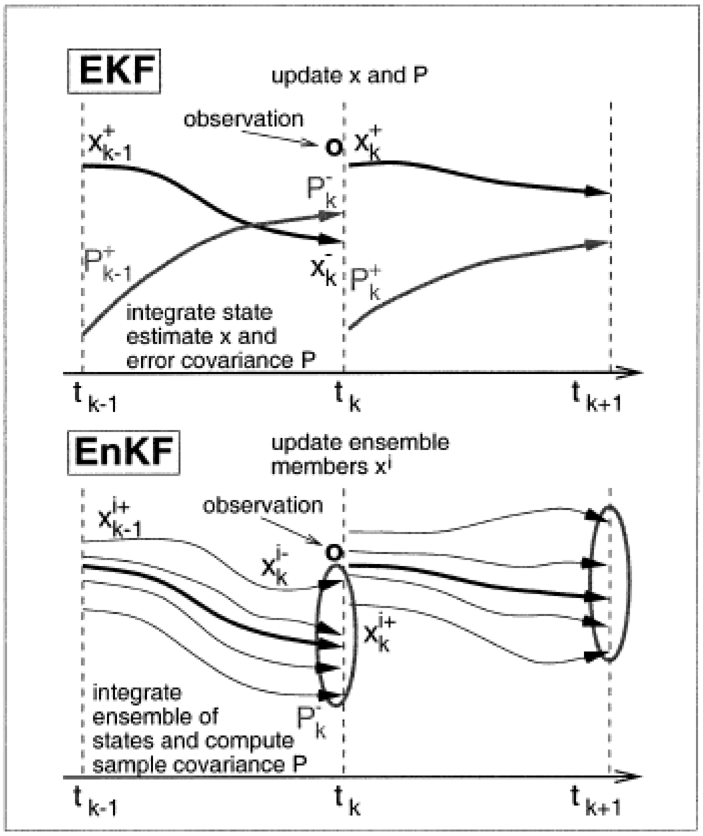



**Figure 2.3** Schematic of the extended Kalman filter (EKF) and the ensemble Kalman filter (EnKF). (Source: Reichle, et al, ( 2002) )

Houtekamer and Mitchell, (2005) have concluded that EnKF can be used for operational atmospheric data assimilation.

Pan and Wood, (2005) developed a procedure to incorporate equality constraints in Kalman filters, including the Ensemble Kalman filter (EnKF) and is referred to as the Constrained Ensemble Kalman Filter (CEnKF). The constraint is carried out as a two-step filtering approach, with the first step being the standard (Ensemble) Kalman filter. The second step is the constraint step carried out by another Kalman filter that optimally redistributes any imbalance from the first step. The CEnKF is implemented over a 75,000 sq. km. domain in the Southern Great Plains region of the United States, using the terrestrial water balance as the constraint. The observations, consisting of gridded fields of the upper two soil moisture layers from the Oklahoma Mesonet system, ARM/CART Energy Balance Bowen Ratio (EBBR) latent heat estimates and USGS streamflow from unregulated basins, are assimilated into the Variable Infiltration Capacity (VIC) land surface model. The water balance was applied at the domain scale, and estimates of the water balance components for the domain are updated from the data assimilation step so as to assure closure.

Komma, et al, (2008) examined the benefits of updating soil moisture of a distributed rainfall runoff model in forecasting large floods. The updating method uses

Ensemble Kalman Filter concepts and involves an iterative similarity approach that avoids calculation of the Jacobian that relates the states and the observations. The soil moisture is updated based on observed runoff in a real-time mode, and is then used as an initial condition for the flood forecasts.

Brocca, et al, (2012) has carried out two real data and two synthetic experiments have assess the effects of assimilating soil moisture estimates into a two-layer rainfall–runoff model. By using the ensemble Kalman filter, both the surface- and root-zone soil moisture (RZSM) products derived by the Advanced SCATterometer (ASCAT) have been assimilated and the model performance on flood estimation is analyzed. RZSM estimates are obtained through the application of an exponential filter.

Li et al, (2012) have studied that assimilation of surface observations can adversely impact soil moisture estimates in the lower soil layers due to imperfect model physics, even though the bias near the surface is decreased. In this study, an ensemble Kalman filter (EnKF) with a mass conservation updating scheme was developed to assimilate Advanced Microwave Scanning Radiometer (AMSR-E) soil moisture retrievals, as they are without any scaling or preprocessing, to improve the estimated soil moisture fields by the Noah land surface model. Assimilation results using the conventional and the mass conservation updating scheme in the Little Washita watershed of Oklahoma showed that, while both updating schemes reduced the bias in the shallow root zone, the mass conservation scheme provided better estimates in the deeper profile. The mass conservation scheme also yielded physically consistent estimates of fluxes and maintained the water budget.

Parada and Xu, (2004) undertook an alternative and novel approach to assimilation of near-surface soil moisture into land surface models by means of an extension of multiscale Kalman filtering (MKF). While most data assimilation studies rely on the assumption of spatially independent near-surface soil moisture observations to attain computational tractability in large-scale problems, MKF allows to explicitly and very efficiently model the spatial dependence and scaling properties of near-surface soil moisture fields. Furthermore, MKF has the appealing ability to cope with model predictions and observations made at different spatial scales. Yet another essential feature of our approach is that they resort to the use of the expectation maximization (EM) algorithm in conjunction with MKF so that the statistical parameters inherent to MKF may be optimally determined directly from the data at hand and allowed to vary over time. This constitutes a significant advantage since these parameters (e.g., observation and model error noise variances) essentially determine the performance of the assimilation approach and have so far been most commonly prescribed heuristically and not allowed to evolve in time. The results show that assimilation significantly improves the short-term predictions of soil moisture and energy fluxes from VIC-3L, especially with regard to capturing the spatial structure of these state variables.

Binghao et al, (2009) studied a soil moisture assimilation scheme, which could assimilate microwave brightness temperature directly, based on the ensemble Kalman filter and the shuffled complex evolution method (SCE-UA).

De Lannoy et al, (2007) studied that It is possible to estimate the soil moisture bias explicitly and derive superior soil moisture estimates with a generalized EnKF that uses a simple persistence model for the bias and assumes that the a priori bias error covariance is proportional to the a priori state error covariance. For the case of bi-weekly assimilation of the entire profile of soil moisture observations, bias estimation and correction typically reduces the RMSE in soil moisture (over the standard EnKF without bias correction) by around 60 percent.

Reichle et al, (2008) presented a computationally affordable, adaptive assimilation system that continually adjusts model and observation error parameters in response to internal diagnostics. The adaptive filter can identify model and observation error variances and provide generally improved assimilation estimates when compared to the non-adaptive system.

# 3 STUDY AREA AND DATA USED

## 3.1 The Basin

The largest basin of India, Ganga Basin has been selected as study area for present study. The total Ganga basin outspreads in India, Tibet (China), Nepal and Bangladesh over the total area of 10,86,000 sq.km. The major part of the geographical area of the Ganga basin lies in India draining an area of 8,61,452 sq.km which is slightly more than one-fourth (26.3 %) of the total geographical area of the country. In India, it covers states of Uttar Pradesh, Madhya Pradesh, Rajasthan, Bihar, West Bengal, Uttarakhand, Jharkhand, Haryana, Chhattisgarh, Himachal Pradesh and Delhi. The basin lies between longitudes 73°2' to 89°5'E and latitudes 21°6' to 31°21'N having maximum length and width of approximately 1,543 km and 1024 km respectively. The geographical extent of the Ganga basin is shown in Figure 3.1. The basin is bounded by the Himalayas on the north, by the Aravalli on the west, by the Vindhyas and Chottanagpur plateau on the south and by the Brahmaputra Ridge on the east. The great desert of Thar and the Aravalli hills form the ridge between the Indus and Ganga drainage system. The delta of the greater Ganga basin is one of the largest in the world and is known by the name Sundarbans after the Sundari trees covering an area of 60,000 sq.km.

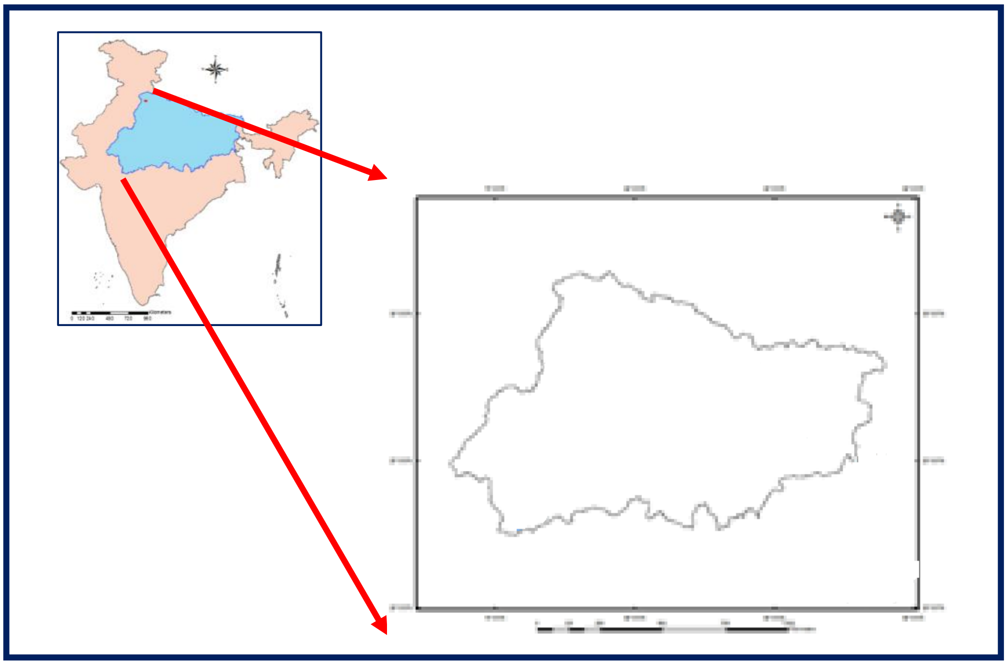


**Figure 3.1** Extent of the Ganga Basin

## 3.2 River System

The Ganga is the 20th longest river in the Asia and the 41st longest in the world (*Source: Philips World Atlas*). The Bhagirathi river that rises from the Gangotri glacier near Gomukh at an elevation of about 7,010 m above mean sea level in the Uttarkashi district of Uttarakhand is considered as the source of Ganga river. It descends down the valley up to Devprayag where after joining another hill stream Alaknanda, it is called Ganga. Flowing downhill the river is joined by a number of streams, such as the Mandakini, the Dhuli Ganga and the Pindar. The total length of river Ganga (measured along the Bhagirathi and the Hooghly) up to its outfall into Bay of Bengal is 2,525 km with 631 km navigable length.

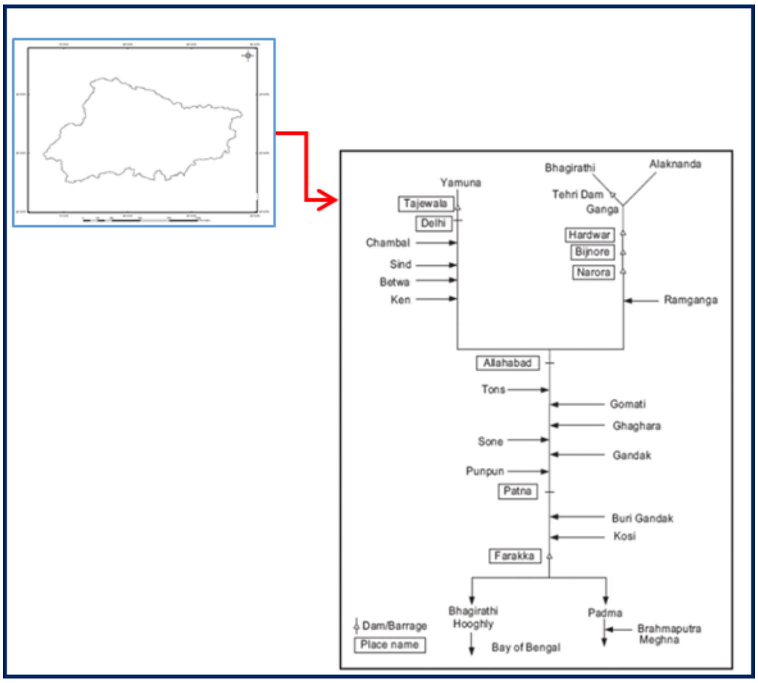



**Figure 3.2** Ganga river system (Source: Status paper on river Ganga, NRCD, MoEF, 2009)

From a hydrological point of view, the entire length of Ganga river in India can be divided in three stretches. The Upper Ganga reach that extends from the origin to Narora Barrage in Bulandshahar district of Uttar Pradesh; the Middle Ganga reach from Narora Barrage to Ballia district in Uttar Pradesh, and the lower Ganga reach from Ballia to its delta. The principal tributaries joining the river from right are the Yamuna and the Sone. Ramganga, Ghaghara, Gandak, Kosi and Mahananda join the river from left.  Chambal and Betwa are the two important sub- tributaries join the river from left.

## 3.3 Topography and Soil Characteristics

The Ganga basin falls entirely within the three divisions (1) Northern Mountains, (2) Great Plains (3) Central Highlands. The peninsular plateau of the Gangetic trough (with an elevation of less than 300 metres) is filled with older (Pleistocene) and recent alluvia, forming nearly

4,000,000 sq km in the states of Haryana, Rajasthan, Uttar Pradesh and West Bengal, comprising 50% of basin area. The Ganga basin can be further divided into the eight physiographic sub-divisions.

### 3.3.1 SOIL CHARACTERISTICS

The Ganga basin consists of a wide variety of soils. While soils of the high Himalayas in the north are subject to continuous erosion, the Gangetic plain provides a huge receptacle into which thousands of meters of thick layers of sediments have been deposited to form a wide valley plain. The Deccan plateau in the south has a mantle of residual soils of varying thickness arising out of weathering of ancient rocks of the peninsular shield. Among the soil types within Ganga basin, the alluvial soil covers more than 52 per cent of the basin. The alluvial deposits of the basin not only cover the great Gangetic trough, but also extend over a sizable portion of the peninsular foreland in the form of a layer less than 3 metres thick.

Apart from the undifferentiated soils of the Siwalik fringe zone in Champaran district of Bihar, the Middle Ganga plain has broad alluvial soil. Being a common origin and almost identical ecological environment, they show in general minor variation in color, texture and moisture content etc.

The soil of the Lower Ganga plain has wide variety and can be groped as Laterites, red earth's soils, alluvial soils and the Coastal soils. The transported laterites deposited on the eastern flanks of the lateritic stretch are known as red soil or lateritic alluvium and are found in eastern margins of Maldah and Dinajpur districts of West Bengal.

Mountain soils, submontane soils and alluvial soils, covering 58 percent of the basin area; red soils seen in the parts of Jharkhand, Chhattisgarh, Madhya Pradesh and West Bengal covering 12 percent of the basin area, red & yellow soils and mixed red and black soils of Madhya Pradesh, Bihar, Chhattisgarh and Rajasthan covering an area of 8 percent, and deep black soils and medium black soils covering an area of 14 percent have. Shallow black soils and lateritic soils mostly seen in Chottanagpur highlands covering an area of 6 percent have very low erodibility. Fig 3.2 is giving the percentage of soil textures present in the Ganga basin.

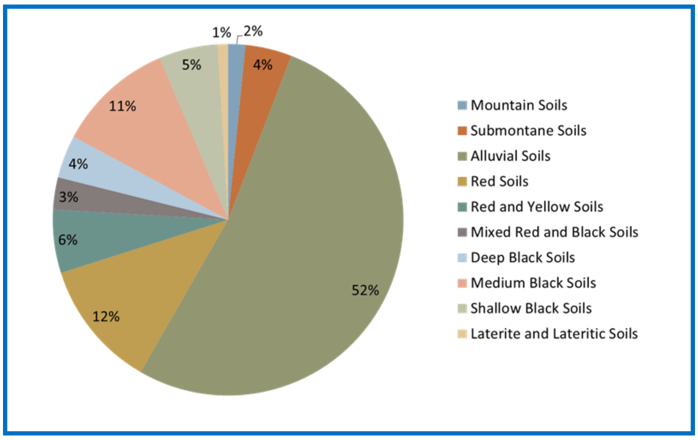



**Figure 3.3** Soil types in Ganga Basin (Source: Central Pollution Control Board, National River Conservation Directorate (MoEF) (2009))

## 3.4 Meteorology and Climate

In India, four temperature zones are distinguishable: tropical, sub-tropical, temperate and alpine. Among these, the tropical and subtropical temperature zones are most predominant in the entire Ganga basin.

### 3.4.1 Temperature

The Ganga basin forms an extensive bowl of warm air, especially during the day-time. The mean maximum daily temperature even in the coldest month (January) does not fall below 21°C, except in the higher hills, whereas the air temperature starts rapidly rising all over Ganga basin from March onwards, beginning a hot season that prevails from April to June. Throughout the Ganga basin, the cold weather period extends from December to February. January is the coldest month, with the temperature often falling below 10°C. Low temperatures are often associated with the intrusion of cold air from across the Gangetic plain in the months of December and January.

### 3.4.2 Rainfall

The weather in the Ganga basin is characterized by a distinct wet season during the period of south west monsoon (June to September). In the majority of the basin, the rainy season spreads over three months (July, August and September) and usually 70 to 80 percent of the total annual rainfall occurs during this period. The average annual rainfall for Ganga basin varies from 400 - 2000 mm. About 27.31 percent of total area of Ganga basin receives a rainfall of 1000-1200mm, 23.14 percent area receives 800-1000mm, 15.51 percent area of the basin receives 600-800mm and 14.29 percent of basin area receives 1200-1400mm.

## 3.5 Land Use Land Cover

The states falling under Ganga basin are extensively cultivated, constituting approximately about 40 per cent of the total area of the India. About 14 per cent of land is not available for cultivation and put to various non-agricultural uses. Land not available for cultivation and fallow land in the Ganga basin states covers a considerable area of 183,640 & 109,450 sq km respectively. The states falling under Ganga basin have only 16.6% of their land areas covered by forest, as compared to India as a whole which has 21.2% of land under forest cover.

**Table 3.1** Land use/Land cover statistics (2005-06) (Source: Ganga Basin report, 2014)

| Category | Area (Sq.km) | % of Total Area |
|---|---|---|
| Agricultural | 564866 | 65.57 |
| Forest | 137816.5 | 16 |
| Wasteland | 76603.61 | 8.89 |
| Built Up Land | 36908.24 | 4.28 |
| Waterbodies | 29876.51 | 3.47 |
| Snow / Glaciers | 8056.9 | 0.94 |
| Grassland | 7324.27 | 0.85 |

## 3.6 Materials Used

The following data sets are used for the VIC and routing running on the Ganga basin.

### 3.6.1 Station Data

Daily maximum temperature, minimum temperature data in the girded format available for the period of 1951 to 2013 has been utilized in present study along with gridded daily rainfall and average daily wind speed and could cover data. The Temperature data sets were available at 1 ° × 1° spatial resolution whereas, the rainfall data was at 0.25 ° × 0.25° resolution. The daily average wind speed and cloud cover data has been rasterized at 0.25 ° × 0.25° for this study.

**Table 3.2** Format of IMD data

| | |
|---|---|
| INDEX | INDEX NO. OF THE STATION |
| MN | MONTH |
| DT | DATE |
| MAX | MAXIMUM TEMPERATURE (in degree C) |
| MIN | MINIMUM TEMPERATURE (in degree C) |
| R/F | RAINFALL (in mm) |
| U | WIND VELOCITY |
| CF | CLOUD FACTOR |

**1. Digital Elevation Model (SRTM)**

Shuttle Radar Topographic Mission (SRTM) Digital elevation Model has been used in present study which is available at 3 arc seconds having a spatial resolution of 90m spatial resolution. The sane has been used for preparing DEM derived products like slope, watershed delineation, elevation bands, etc. (Source: https://lta.cr.usgs.gov/SRTM)

DEM generated from satellite data has been used for getting the elevation data for the given study area. GTOPO30 (30 Arc Second) DEM, with a resolution of 1km has been used for the preparation of the elevation map and the slope gradient in m/m.

**2. Ancillary Data**

Land Use Land Cover (LULC) prepared for ISRO Geosphere Biosphere Program under the project entitled “Landuse/Landcover Dynamics and Impacts of Human Dimension in Indian River Basins” at 1: 2,50,000 scale has been used for the vegetation reclassified maps to generate the vegetation parameter file for VIC whereas for Area excluding India University of Maryland (UMD) product has been used.

Soil texture data has been used to prepare soil parameter file is taken from National Bureau of Soil Survey and Land Use Planning (NBSSLUP) for Ganga basin area including in India and for the area excluding India the soil map of Food and Agriculture Organization (FAO) has been used.

### 3. Discharge Data

Discharge data for validation of the VIC Model has been taken from the Global River Global Runoff Data Centre (GRDC) for Farakka; location is 25 N, 87.92 E.

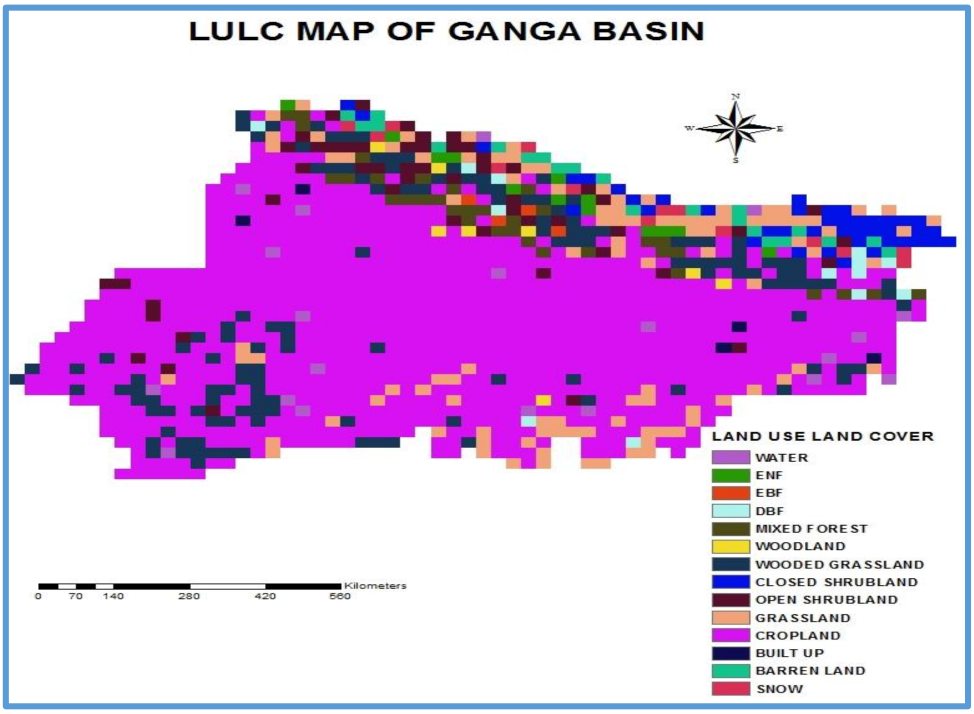



**Figure 3.4** LAND USE/LAND COVER map of Ganga Basin (Source: IGBP and UMD)

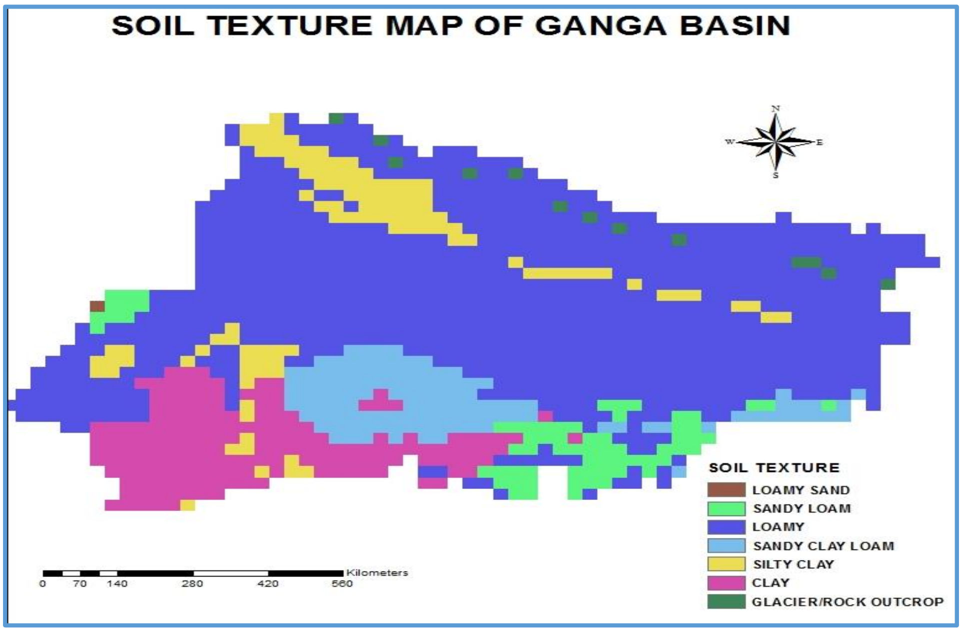



**Figure 3.5** Soil map of Ganga basin (Source: NBSSLUP and FAO)

### 3.6.2 Inputs for Data Assimilation

**Soil moisture product using (AMSR-E) data**

Nowadays, the availability of soil moisture estimates from satellite sensors offers a great chance to improve real-time flood forecasting through data assimilation. Validation is an important and particularly challenging task for remote sensing of soil moisture. A key issue in the validation of soil moisture products is the disparity in spatial scales between satellite and in situ observations. In particular, the availability of soil moisture products from the recent Soil Moisture and Ocean Salinity (SMOS) and Aquarius missions and the Soil Moisture Active Passive (SMAP) mission will inaugurate a new era in the application of remote sensing observations to hydrology.

Advanced Microwave Scattering Radiometer (AMSR-E) on-board Aqua is a twelve channel, six frequency total power passive microwave radiometer system. The data has been retrieved globally from National Snow and Ice Data center (NSIDC). It measures brightness temperatures at 6.925, 10.65, 18.7, 23.8, 36.5, and 89.0 GHz as in Table 3.1. Vertically and horizontally polarized measurements are taken at all channels. Aqua is one of a series of space based platforms that are central to NASA's Earth Science Enterprise (ESE), a long-term study of the scope, dynamics and implications of global change. The primary focus for the Aqua Project is the multi-disciplinary study of the Earth's Interrelated Processes (atmosphere, oceans, and land surface) and their relationship to earth system changes. It allows long-term change detection, identify its human and natural causes and advance the development of models for long-term forecasting (Source: AMSR-E Data Users Handbook, 4th Edition, March 2006).

**Table 3.3** AMSRE-Main characteristics (Source: AMSR-E Data Users Handbook, 4th Edition, March 2006)

| Items | | Characteristics | | | | | | |
|---|---|---|---|---|---|---|---|---|
| Observation Frequency | | 6.925 GHz | 10.65 GHz | 18.7 GHz | 23.8 GHz | 36.5 GHz | 89.0 GHz | |
| | | | | | | | A | B |
| Spatial Resolution | | 50 km | | 25 km | | 15 km | 5 km | |
| Band Width | | 350 MHz | 100 MHz | 200 MHz | 400 MHz | 1000 MHz | 3000 MHz | |
| Polarization | | Horizontal and Vertical | | | | | | |
| Incident Angle | | 55° | | | | | | 54.5° |
| Cross polarization | | less than –20 dB | | | | | | |
| Swath Width | | more than 1,450 km | | | | | | |
| Dynamic Range | | 2.7-340 K | | | | | | |
| Precision | | 1 K (1 ) as target | | | | | | |
| Sensitivity | | 0.34K | 0.7K | 0.7K | 0.6K | 0.7K | 1.2K | |
| Quantifying Bit Number | | 12 bit | 10 bit | | | | | |
| Data Rate | | 87.392 Kbps | | | | | | |
| Electric Power | | 350 ±35 W | | | | | | |
| Weight | | 324 ±15 kg | | | | | | |
| Size | Antenna Unit | 1.95 x 1.7 x 2.4 m | | | | | | |
| | Control Unit | 0.8 x 1.0 x 0.6 m | | | | | | |

**a) Temporal coverage of AMSR-E**

Temporal coverage is from 19th June 2002 to 3rd October 2010. In present study we are using soil moisture product of year 2005.

**b) Spatial Coverage of AMSR-E**

Spatial Coverage Map of AMSR-E is shown in Fig. 3.2.This map shows a typical day of coverage with 28 half-orbits. Coverage is global between 89.24°N and 89.24°S, except for snow-covered and densely-vegetated areas. The swath width is 1445 km.

**b.1) Spatial Resolution of AMSR-E**

Input brightness temperature data at 10.7 GHz, corresponding to a 38 km mean spatial resolution, are re-sampled to a global cylindrical 25 km EASE-Grid cell spacing. The effective spatial resolution is thus slightly higher than the inbuilt 38 km resolution (Source: NSIDC).

**Figure 3.6** Spatial Coverage of AMSR-E (Source: NSIDC)

# 4 METHODOLOGY

The methodology adopted in present research has been divided into two broad sections:

a. Setting up for Variable Infiltration Capacity (VIC) model, running the model and its parameter sensitivity analysis.
b. Assimilation of satellite derived soil moisture data into the VIC model using suitable data assimilation technique and generating the scenario.

## 4.1 Hydrological Modeling

Variable Infiltration Capacity (VIC) model developed by Gao, et al., 2009 at the University of Washington, Department of Civil and Environmental Engineering is a semi-distributed macroscale hydrological model that works on both water and surface energy mode within a grid cell and captures sub-grid variation effectively. The hydrological model uses inputs from both space-borne sources as well as ground-based inputs. Primary characteristics of the model includes subgrid variability in land surface vegetation classes, soil moisture storage capacity and drainage from the lower soil moisture zone also known as baseflow as a non-linear flow; and the inclusion of topography that allows for orographic precipitation and temperature resulting in a more realistic simulation of the mountainous terrain. The model accepts multiple soil layers with variable infiltration and non-linear baseflow.

VIC contains a routing model that is based on a linear transfer function to simulate streamflow for the basin. The routing module can be effectively used for implementation of water management policies for irrigation and reservoir operations. VIC has been well calibrated and validated since its existence for a number of large basins and can also accommodate Data Assimilation techniques effectively. It has since been used for water resources management studies and climate change impact studies.

The model comprises of two working modules: the VIC Module and the Routing Module. It must be noted that the VIC model works at both daily and sub-daily time step. The current study uses daily forcing data to simulate streamflow on a daily time-step.

The overall flow chart if methodology for running VIC model is given in (Figure 4.1).

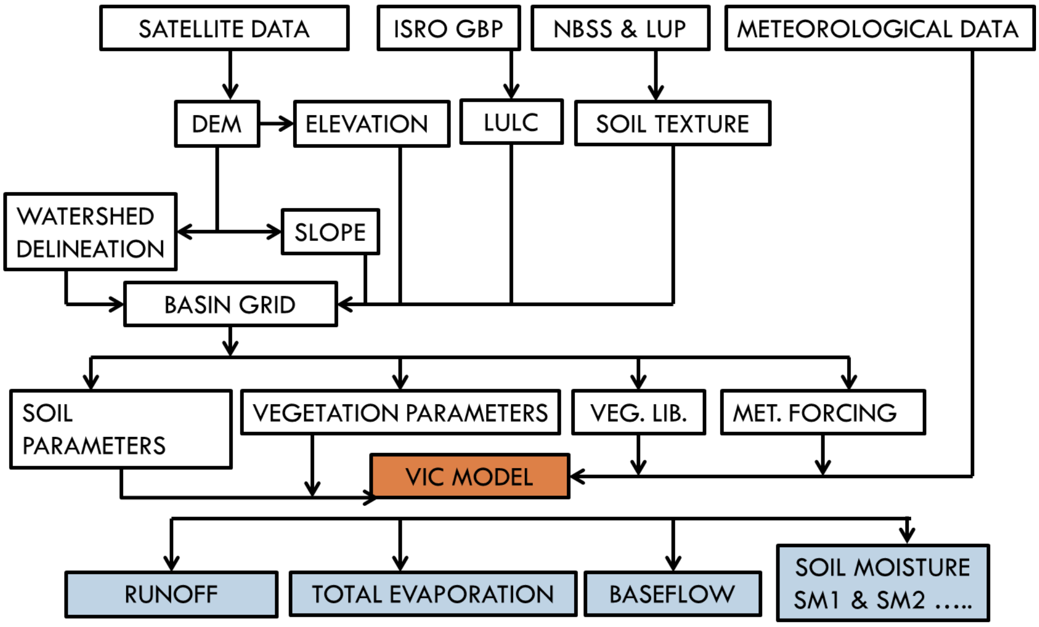



**Figure 4.1** Flowchart of Methodology of Hydrological Modeling Using VIC model.

The VIC model has been run on the VIC tool (Figure 4.2) developed by Gupta et al, (2012) as part of the ISRO-GBP Project on LULC dynamics and impact of human dimensions in Indian River Basins, IIRS Dehradun.

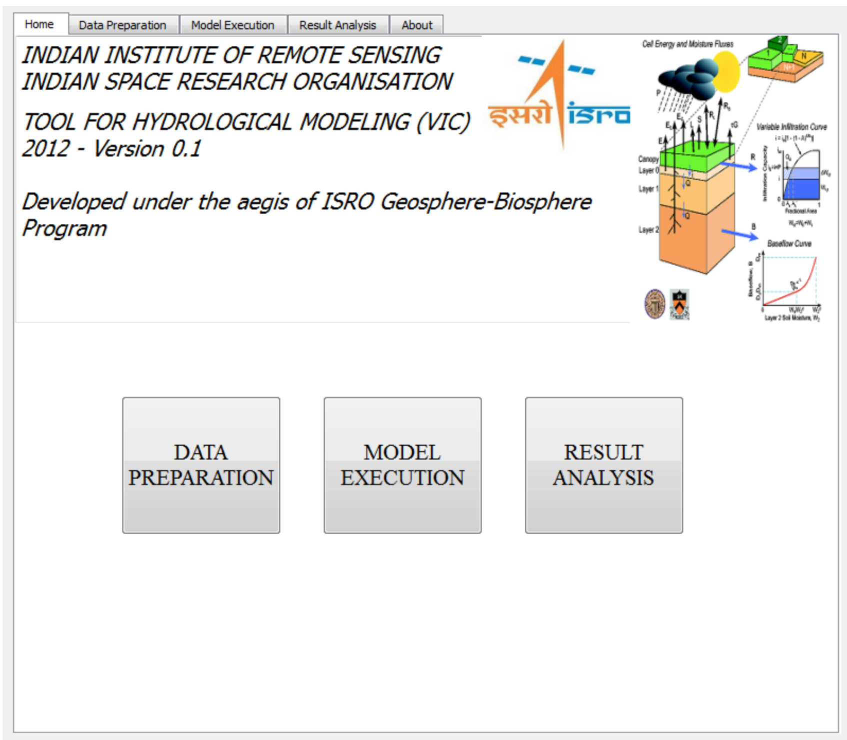



**Figure 4.2** Interface of Tool for Hydrological Modeling **(**VIC)

The inputs for the model are listed below:

- Terrain (Elevation, Slope, Flow Direction)
- LU/LC
- Vegetation Properties (LAI, Albedo, Root distribution, Canopy Resistance)
- Soil Properties (Layer-wise physical texture and hydraulic properties)
- River discharge data
- Meteorological inputs: Daily inputs of Precipitation, Temperature

  (Tmax and Tmin) are a must. Optional are wind speed and Short wave and Long wave radiations.

## 4.2 OVERVIEW OF VIC MODEL PROCESSES

This section of thesis explains the algorithms of VIC model for calculation the state variables, surface fluxes, and streamflow as well as the newly implemented algorithms for the water management from the Water Budget Record from Variable Infiltration Capacity (VIC) Model Algorithm Theoretical Basis Document (Gaoet al, 2009). The main characteristics of the processes are as below:

### 4.2.1 VIC Represents Vegetation Heterogeneity:

- **Vegetation characteristics assigned for each vegetation tile:** LAI, albedo, minimum stomatal resistance, architectural resistance, roughness length, relative fraction of roots in each soil layer, and displacement.
- **Evapotranspiration:** is calculated according to the Penman-Monteith equation, in which the evapotranspiration is a function of net radiation and vapor pressure deficit.
- **Total actual evapotranspiration**: is the sum of canopy evaporation and transpiration from each vegetation tile and bare soil evaporation from the bare soil tile, weighted by the coverage fraction for each surface cover class.

### 4.2.2 Multiple Soil Layers:

- **Canopy layer***:* intercepts rainfall
- **Top two soil layers:** are designed to represent the dynamic response of soil to the infiltrated rainfall, with diffusion allowed from the middle layer to the upper layer when the middle layer is wetter.
- **Bottom soil layer:** receives moisture from the middle layer through gravity drainage. The bottom soil layer characterizes seasonal soil moisture behavior and it only responses to short-term rainfall when the top soil layers are saturated.

### 4.2.3 Non Linear Baseflow:

- **Runoff from the bottom soil layer**: is according to the drainage described by the Arno model.
- **Moisture**: can also be transported upward from the roots through evapotranspiration. Although vegetation subgrid-scale variability is a critical feature for the VIC model, the soil characteristics (such as soil texture, hydraulic conductivity, etc.) are held constant for each grid cell.

In the model, soil moisture distribution, infiltration, drainage between soil layers, surface runoff, and subsurface runoff are all calculated for each land cover tile at each time step. Then for each grid cell, the total surface and subsurface runoff are obtained by summing over all the land cover tiles weighted by fractional coverage.

## 4.3 THE WATER BALANCE MODE

The water balance mode assumes that the soil surface temperature is equal to the air temperature for the current time step. By eliminating the ground heat flux solution and the iterative processes required to close the surface energy balance, the water balance mode requires significantly less computational time than other model modes. These simplifications, combined with the daily time step that is typical of water balance mode simulations, yields a substantial savings in computational time. The exceptions to this are that the snow algorithm and the frozen soil algorithm, both of which run at a sub-daily time step, and which solve the surface energy balance to determine the fluxes needed to drive accumulation and ablation processes, or to solve the frozen soil penetration, respectively.

## 4.4 WATER AND ENERGY BALANCE MODE

The full water-and-energy balance mode not only solves the complete water balance but also minimizes the surface energy balance error. The surface energy balance is closed through an iterative process which tries to find the surface temperature that yields surface energy fluxes (sensible heat, ground heat, ground heat storage, outgoing longwave and indirectly latent heat) so that balance the incoming solar and longwave radiation fluxes. This mode requires more computational time than the water balance mode as well as requiring a sub-daily simulation time step. However, it is critical for studies in which the land-atmosphere interactions are of interest (e.g., coupling with climate models).

In the VIC model, each grid cell is modeled independently without horizontal water flow. The grid-based VIC model simulates the time series of runoff only for each grid cell, which is non-uniformly distributed within the cell. Therefore, a stand-alone routing model is employed to transport grid cell surface runoff and base flow to the outlet of that grid cell then into the river system thought it is an object of this study.

## 4.5 ALGORITHMS AND EQUATIONS

This part of the study describes the step by step algorithm and equations used VIC model.

### 4.5.1 Water Balance

The water balance in the VIC model follows the continuous equation for each time-step:

$$\frac{\partial S}{\partial t} = P - E - R \tag{4.3}$$

Where

dS/dt = change of water storage (mm)

P = precipitation (mm)

E = evapotranspiration (mm)

R =runoff (mm)

Over vegetated areas, the water balance equation in the canopy layer (interception) is:

$$\frac{\partial W_i}{\partial t} = P - E_c - P_t \tag{4.4}$$

Where

*W*= canopy intercepted water (mm),

*Ec*= evaporation from canopy layer (mm),

*Pt* =througfall (mm).

Total evapotranspiration over a grid cell is computed as the sum of the above components, weighted by the respective surface cover area fractions (Liang et al. 1994). The formulation of the total evapotranspiration is:

$$E = \sum_{n=1}^{N} C_n \cdot (E_{c,n} + E_{t,n}) + C_{N+1} \cdot E_1 \tag{4.5}$$

Where

$E_c$ ,= evaporation from the canopy layer of each vegetation tile (mm),

$E_t$ = transpiration from each of the vegetation tiles (mm),

$E_1$ =Evaporation from the bare soil (mm),

$C_n$ is the vegetation fractional coverage for the $n_{th}$ vegetation tile,

*CN+1* is the bare soil fraction, and

$$\sum_{n=1}^{N+1} C_n = 1 \tag{4.6}$$

#### 4.5.1.1 Canopy evaporation

When there is intercepted water on the canopy, the canopy evaporates at the maximum value. The maximum canopy evaporation ( $E_c^*$ , mm) from each vegetation tile is calculated using the following formulation:

$$E_c^* = (\frac{W_i}{W_{im}})^{2/3} E_p \frac{r_w}{r_w + r_o} \tag{4.7}$$

Where

$W_{im}$ = maximum amount of water the canopy can intercept (mm), which is 0.2 times LAI. (Dickinson, 1984)

$r_o$ = architectural resistance is caused by the variation of the humidity gradient between the canopy and the overlying air (s $m^{-1}$). In the model, r0 is assigned for each land cover type according to the vegetation library.

$r_w$ = aerodynamic resistance: represents the transfer of heat and water vapor from the evaporating surface into the air above the canopy (s $m^{-1}$)

$$r_w = \frac{1}{C_w u_z} \tag{4.8}$$

Where

uz = wind speed (m $s^{-1}$) at level $z$

Cw = transfer coefficient for water which is estimated taking into account the atmospheric stability

$E_p$ is the potential evapotranspiration (mm) that is calculated from the Penman-Monteith equation (Shuttleworth, 1993) with the canopy resistance set to zero, which is

$$\lambda_v E_p = \frac{\Delta(R_n - G) + \rho_a c_p (e_s - e_a) / r_a}{\Delta + \gamma} \tag{4.9}$$

Where

$\lambda v$ = latent heat of vaporation (J $kg^{-1}$),

*Rn* = net radiation (W m-2), *G* is the soil heat flux (W $m^{-2}$),

*(es - ea)* = vapor pressure deficit of the air (Pa),

$\rho a$ = density of air at constant pressure (kg $m^{-3}$),

*cp* = specific heat of the air (J $kg^{-1}$ $K^{-1}$)

$\Delta$ = slope of the saturation vapor pressure temperature relationship (Pa $K^{-1}$).

$\gamma$ = psychrometric constant (66 Pa $K^{-1}$).

#### 4.5.1.2 Vegetation transpiration

The vegetation transpiration ($E^t$, mm) is estimated using (Blondin,1991; Ducoudre et al., 1993):

$$E_t = (1 - (\frac{W_i}{W_{im}})^{2/3}) E_p \frac{r_w}{r_w + r_o + r_c} \tag{4.10}$$

$r_c$ is the canopy resistance (s m$^{-1}$)

$$r_c = \frac{r_{0c} g_T g_{vpd} g_{PAR} g_{sm}}{LAI} \tag{4.11}$$

Where

$r_{oc}$ is the minimum canopy resistance (s m$^{-1}$) according to the vegetation library,

$g_T$= temperature factor

$g_{vpd}$= vapor pressure deficit factor

$g_{PAR}$, = photosynthetically active radiation flux (PAR) factor

$g_{sm}$ = soil moisture factor

#### 4.5.1.3 Bare soil evaporation

When the surface soil is saturated, it evaporates at the potential evaporation rate. When the top soil layer is not saturated, its evaporation rate ($E_1$) is calculated using the Arno formulation by Franchini and Pacciani (1991). The infiltration capacity ($i$) uses the spatially heterogeneous structure described by the Xianjiang Model (Zhao et al., 1980), which is expressed as

$$i = i_m (1 - (1 - A)^{1/b_i}) \quad \text{with} \quad i_m = (1 + b_i) \cdot \theta_S \cdot |z| \tag{4.12}$$

Where

$i_m$ is the maximum infiltration capacity (mm),

A is the fraction of area for which the infiltration capacity is less than $i$,

$b_i$ is the infiltration shape parameter,

$\theta_s$ is the soil porosity, and z is the soil depth (m).

All these variables are for the top thin soil layer.

The bare soil evaporation is described as

$$E_1 = E_p \left( \int_0^{A_S} dA + \int_{A_S}^{1} \frac{i_0}{i_m (1 - (1 - A)^{1/b_i})} dA \right) \tag{4.13}$$

With $A_s$ denoting the fraction of the bare soil that is saturated, and $i_0$ representing the corresponding point infiltration capacity.

### 4.5.2 Soil Moisture

The VIC model uses the variable infiltration curve (Zhao et al., 1980) to account for the spatial heterogeneity of runoff generation. It assumes that surface runoff from the upper two soil layers is generated by those areas for which precipitation, when added to soil moisture storage at the end of the previous time step, exceeds the storage capacity of the soil. The formulation of subsurface runoff follows the Arno model conceptualization (Franchini and Pacciani, 1991; Todini, 1996).

#### 4.5.2.1 Movement of moisture

The VIC model assumes there is no lateral flow in the top two soil layers; therefore the movement of moisture can be characterized by the one-dimensional Richard's equation:

$$\frac{\partial \theta}{\partial t} = \frac{\partial}{\partial z}(D(\theta)\frac{\partial \theta}{\partial z}) + \frac{\partial K(\theta)}{\partial z} \tag{4.14}$$

Where

$\theta$ is the volumetric soil moisture content,

$D(\theta)$ is the soil water diffusivity ($mm^2$ $d^{-1}$),

$K(\theta)$ is the hydraulic conductivity (mm $d^{-1}$), and $z$ is soil depth (m).

By including the atmospheric forcing, the integrated soil moisture for the top two soil layers(Mahrt and Pan, 1984) can be described as:

$$\frac{\partial \theta_i}{\partial t} \cdot z_i = I - E - K(\theta)\Big|_{-Z_I} + D(\theta)\frac{\partial \theta}{\partial z}\Big|_{-Z_I} \quad \text{(i=1,2)} \tag{4.15}$$

Where

$I$ is the infiltration rate (mm d-1). It is the difference between the precipitation (and thorughfall if there is vegetation coverage) and the direct runoff Qd.

$Z_1$ and $z_2$ are soil depth for layer 1 and layer 2, respectively.

For the lower soil layer, an empirical formulation derived from large scale catchment hydrology is used in which the drainage and subsurface drainage are lumped together as base flow ($Q_b$). The soil moisture for the soil layer is described by the water balance equation including diffusion between soil layers as

$$\frac{\partial \theta_3}{\partial t} \cdot (z_3 - z_2) = K(\theta)\Big|_{-Z_2} + D(\theta)\frac{\partial \theta}{\partial z}\Big|_{-Z_2} - E - Q_b \tag{4.16}$$

### 4.5.3 Runoff

Similar to the total evapotranspiration, the total runoff $Q$ is expressed as:

$$Q = \sum_{n=1}^{N+1} C_n \cdot (Q_{d,n} + Q_{b,n}) \tag{4.17}$$

Where

$Q_{d,n}$ (mm) and $Q_{b,n}$ (mm) are the direct runoff (surface runoff) and base flow (subsurface runoff) for the $n^{th}$ land cover tile, respectively.

Since the top thin soil layer has a very small water holding capacity, the direct runoff (surface runoff, $Q_d$) within each time step is calculated for the entire upper layer (layer 1 and layer 2) as (Liang et al., 1996):

$$Q_d = \begin{cases} P - z_2 \cdot (\theta_S - \theta_2) + z_2 \cdot \theta_S \cdot (1 - \frac{i_0 + P}{i_m})^{1+b_i}, & P + i_0 \le i_m \\ P - z_2 \cdot (\theta_S - \theta_2), & P + i_0 \ge i_m \end{cases} \tag{4.18}$$

where the infiltration capacity associated terms ($i_0$, $i_m$, $\theta_s$, and $b_i$) are explained previously.

The formulation of base flow (sub surface runoff, $Q_b$), which used the Arno model formulation, (Franchini and Pacciani, 1991), is expressed as:

$$Q_b = \begin{cases} \frac{D_S D_m}{W_S \theta_S} \cdot \theta_3, & 0 \le \theta_3 \le W_S \theta_S \\ \frac{D_S D_m}{W_S \theta_S} \cdot \theta_3 + (D_m - \frac{D_S D_m}{W_S})(\frac{\theta_3 - W_S \theta_S}{\theta_S - W_S \theta_S})^2, & \theta_3 \ge W_S \theta_S \end{cases} \tag{4.19}$$

Where

$D_m$ is the maximum subsurface flow (mm $d^{-1}$),

$D_s$ is a fraction of $D_m$,

$W_s$ is the fraction of maximum soil moisture (soil porosity) $\theta s$.

The base flow recession curve is linear below a threshold ($WS / \theta s$) and nonlinear above the threshold. The first derivative at the transition from the linear to nonlinear drainage is continuous.

### 4.5.4 Snow Model

during the calibration for the VIC snow model, four parameters are adjusted for grid cells:

- Maximum air temperature at which snowfall occurs;
- Minimum air temperature at which rainfall occurs;
- The snow surface roughness;
- The value of *m*, which controls the maximum snow interception capacity as a function of LAI.

Usually the first two parameters are set to $0.5^0$C and $-0.5^0$C, respectively. Snow roughness parameter should be in the range from 0.001m to 0.03m.The VIC snow model is intended primarily for large-scale applications. It has been incorporated as the standard snow scheme within the VIC model, which represents sub-grid spatial variability by simulating state and fluxes in land cover/elevation tiles.

## 4.6 ELEVATION BANDS

VIC can consider spatial heterogeneity in precipitation, arising from either storm fronts/local convection or topographic heterogeneity. Here we consider the influence of topography, via elevation bands. This is primarily used to produce more accurate estimates of mountain snow pack. This functionality is controlled by the SNOW_BAND option in the global parameter file. Main features are the following:

- Can subdivide the grid cell into arbitrary number of elevation bands, to account for variation of topography within cell
- Within each band, meteorological forcings are lapsed from grid cell average elevation to band's elevation
- Geographic locations or configurations of elevation bands are not considered; VIC lumps all areas of same elevation range into 1 band
- Fluxes and storages from the bands are averaged together (weighted by area fraction) to give grid-cell average for writing to output files
- However, the band-specific values of some variables can be written separately in the output files

## 4.7 PREPARATION FOR VIC INPUTS

### 4.7.1 Preparation of Grid

The preparation of the grid for the extent of the basin requires the spatial resolution at which the VIC model needed to be run. The model has been decided to be run at **25 km*25 km** resolution.

Fishnet has been generated over the area of the basin covering its entire geographical extent at the resolution of 25km*25km in ArcGIS. The same can be generated in QGIS. The Grid generated contains 42 rows and 62 columns, with the count starting at the upper left corner from 0 and going right downwards. The total number of grids is 2729. ‘Run grids’ were the grids that fall within the basin and are the grids that have been considered for all the simulation in the VIC; in the present study for Ganga basin the run grids counted as 1177. Likewise the rest have been considered ‘non-run grids’, i.e. grids not contributing to the basin or having fallen out of the study area as shown in Figure 4.3. The fishnet shapefile generated were filled with the attributes enlisted in the Table 4.1 below:

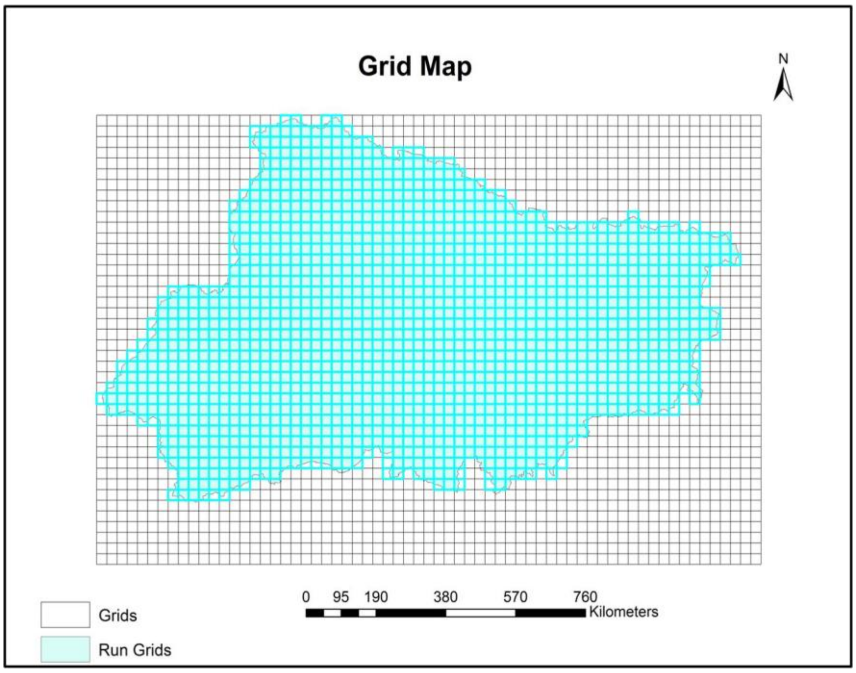



**Figure 4.3** Grid cells generated for Ganga basin

**Table 4.1** The fields generated in Ganga grid

| Attributes | Description |
|---|---|
| Lat_k | Contains central latitude in degrees of each grid cell |
| Long_k | Contains central longitude in degrees of each grid cell |
| Grid number | Contains grid number starting from top left corner and going in right down |
| Run grid | Either equal to 1 or 0 depending on whether the grid lies inside the basin or not, respectively |
| Soil_1 | Soil texture code for the first soil depth layer |
| Soil_2 | Soil texture code for the second soil depth layer |
| Soil_2 | Soil texture code for the third soil depth layer |
| Slope | Mean slope gradient in m/m |
| Elevation | Mean elevation of each grid in meters |
| Rainfall | Rain Mean annual rainfall of each grid in mm |

To prepare the attributes of the grids the following procedure has been followed:

• Digital Elevation Model

DEM generated from satellite data has been used for getting the elevation data for the given study area. SRTM (3 Arc Second) DEM, with a resolution of 1km has been used for the preparation of the elevation map and the slope gradient in m/m. Elevation map is generated by reclassifying the DEM according to the range of elevations you want; in present study 10 elevation bands are generated by reclassifying elevation values in 10 categories like 0m to 500m, 500m to 1000m and so on upto maximum elevation in study area.

• Soil

NBSSLUP soil texture data has been used for the Indian Territory and FAO soil texture data for Nepal. Recoding was done after the soil codes, recoding is done for matching the texture IDs with the USDA codes to prepare soil parameter file from the soil texture properties like bulk density, soil porosity, etc. for more parameter information refer Table 4.2. Each grid cell has been assigned with a soil texture ID for identification. Soil texture in each cell is entered by using Zonal Statistics as a Table tool in ArcGIS and the maximum soil texture available in that cell is assigned in grid soil texture field.

• Rainfall

For years 1990 to 2005, mean annual rainfall map was generated using the IMD's gridded dataset such that each grid carried a distinct value of rainfall. This field in grid is important to generate soil parameter file in VIC tool depicted in Figure 4.3.

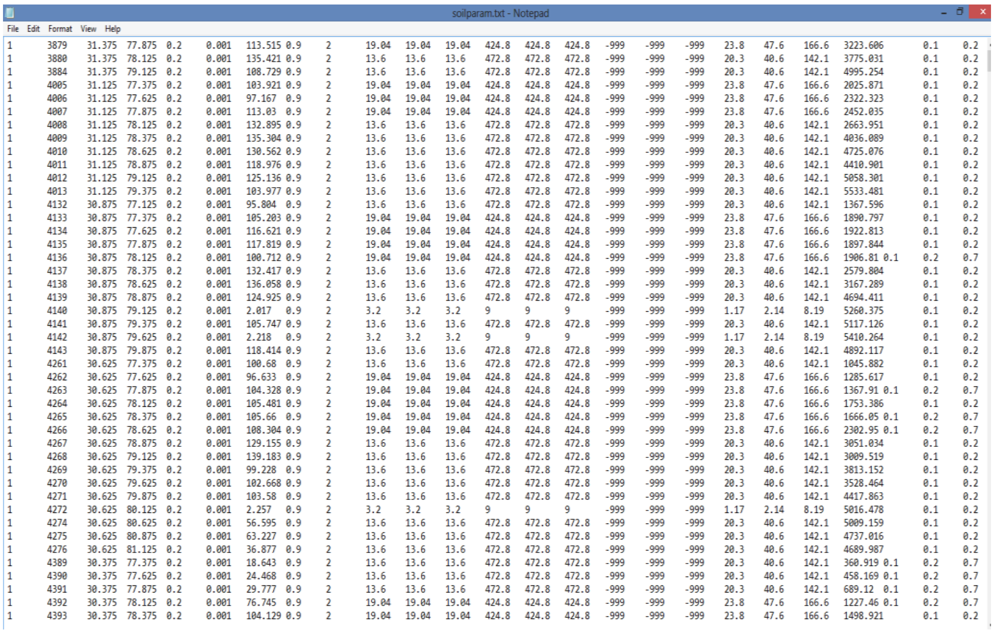
### 4.7.2 Preparation of Soil Parameter File

The soil parameter file generated, describes the characteristics of each of the considered soil layer for each grid as shown in Table 4.2. The list of all the soil parameters and details are on http://www.hydro.washington.edu/Lettenmaier/Models/VIC/Documentation/SoilParam.html

**Table 4.2** Some Important parameters of soil file

| Column | Variable Name | Units | Description |
|---|---|---|---|
| 5 | infilt | N/A | Variable infiltration curve parameter ($b_{infilt}$) |
| 6 | Ds | fraction | Fraction of Dsmax where non-linear baseflow begins |
| 7 | Dsmax | mm/day | Maximum velocity of baseflow |
| 8 | Ws | fraction | Fraction of maximum soil moisture where non-linear baseflow occurs |

| | | | |
|---|---|---|---|
| 9 | Ksat | mm/day | Saturated hydrologic conductivity |
| 10 | init_moist | mm | Initial layer moisture content |
| 11 | bulk_density | $kg/m^3$ | Bulk density of soil layer |
| 12 | soil_density | $kg/m^3$ | Soil particle density, normally 2685 $kg/m^3$ |



```
soilparam.txt - Notepad
File Edit Format View Help
1	3879	31.375	77.875	0.2	0.001	113.515	0.9	2	19.04	19.04	19.04	424.8	424.8	424.8	-999	-999	-999	23.8	47.6	166.6	3223.606	0.1	0.2
1	3880	31.375	78.125	0.2	0.001	135.421	0.9	2	13.6	13.6	13.6	472.8	472.8	472.8	-999	-999	-999	20.3	40.6	142.1	3775.031	0.1	0.2
1	3884	31.375	79.125	0.2	0.001	108.729	0.9	2	13.6	13.6	13.6	472.8	472.8	472.8	-999	-999	-999	20.3	40.6	142.1	4995.254	0.1	0.2
1	4005	31.125	77.375	0.2	0.001	103.921	0.9	2	19.04	19.04	19.04	424.8	424.8	424.8	-999	-999	-999	23.8	47.6	166.6	2025.871	0.1	0.2
1	4006	31.125	77.625	0.2	0.001	97.167	0.9	2	19.04	19.04	19.04	424.8	424.8	424.8	-999	-999	-999	23.8	47.6	166.6	2322.323	0.1	0.2
1	4007	31.125	77.875	0.2	0.001	113.03	0.9	2	19.04	19.04	19.04	424.8	424.8	424.8	-999	-999	-999	23.8	47.6	166.6	2452.035	0.1	0.2
1	4008	31.125	78.125	0.2	0.001	132.895	0.9	2	13.6	13.6	13.6	472.8	472.8	472.8	-999	-999	-999	20.3	40.6	142.1	2663.951	0.1	0.2
1	4009	31.125	78.375	0.2	0.001	135.304	0.9	2	13.6	13.6	13.6	472.8	472.8	472.8	-999	-999	-999	20.3	40.6	142.1	4036.089	0.1	0.2
1	4010	31.125	78.625	0.2	0.001	130.562	0.9	2	13.6	13.6	13.6	472.8	472.8	472.8	-999	-999	-999	20.3	40.6	142.1	4725.076	0.1	0.2
1	4011	31.125	78.875	0.2	0.001	118.976	0.9	2	13.6	13.6	13.6	472.8	472.8	472.8	-999	-999	-999	20.3	40.6	142.1	4410.901	0.1	0.2
1	4012	31.125	79.125	0.2	0.001	125.136	0.9	2	13.6	13.6	13.6	472.8	472.8	472.8	-999	-999	-999	20.3	40.6	142.1	5058.301	0.1	0.2
1	4013	31.125	79.375	0.2	0.001	103.977	0.9	2	13.6	13.6	13.6	472.8	472.8	472.8	-999	-999	-999	20.3	40.6	142.1	5533.481	0.1	0.2
1	4132	30.875	77.125	0.2	0.001	95.804	0.9	2	13.6	13.6	13.6	472.8	472.8	472.8	-999	-999	-999	20.3	40.6	142.1	1367.596	0.1	0.2
1	4133	30.875	77.375	0.2	0.001	105.203	0.9	2	19.04	19.04	19.04	424.8	424.8	424.8	-999	-999	-999	23.8	47.6	166.6	1890.797	0.1	0.2
1	4134	30.875	77.625	0.2	0.001	116.621	0.9	2	19.04	19.04	19.04	424.8	424.8	424.8	-999	-999	-999	23.8	47.6	166.6	1922.813	0.1	0.2
1	4135	30.875	77.875	0.2	0.001	117.819	0.9	2	19.04	19.04	19.04	424.8	424.8	424.8	-999	-999	-999	23.8	47.6	166.6	1897.844	0.1	0.2
1	4136	30.875	78.125	0.2	0.001	100.712	0.9	2	19.04	19.04	19.04	424.8	424.8	424.8	-999	-999	-999	23.8	47.6	166.6	1906.81 0.1	0.2	0.7
1	4137	30.875	78.375	0.2	0.001	132.417	0.9	2	13.6	13.6	13.6	472.8	472.8	472.8	-999	-999	-999	20.3	40.6	142.1	2579.804	0.1	0.2
1	4138	30.875	78.625	0.2	0.001	136.058	0.9	2	13.6	13.6	13.6	472.8	472.8	472.8	-999	-999	-999	20.3	40.6	142.1	3167.289	0.1	0.2
1	4139	30.875	78.875	0.2	0.001	124.925	0.9	2	13.6	13.6	13.6	472.8	472.8	472.8	-999	-999	-999	20.3	40.6	142.1	4694.411	0.1	0.2
1	4140	30.875	79.125	0.2	0.001	2.017	0.9	2	3.2	3.2	3.2	9	9	9	-999	-999	-999	1.17	2.14	8.19	5260.375	0.1	0.2
1	4141	30.875	79.375	0.2	0.001	105.747	0.9	2	13.6	13.6	13.6	472.8	472.8	472.8	-999	-999	-999	20.3	40.6	142.1	5117.126	0.1	0.2
1	4142	30.875	79.625	0.2	0.001	2.218	0.9	2	3.2	3.2	3.2	9	9	9	-999	-999	-999	1.17	2.14	8.19	5410.264	0.1	0.2
1	4143	30.875	79.875	0.2	0.001	118.414	0.9	2	13.6	13.6	13.6	472.8	472.8	472.8	-999	-999	-999	20.3	40.6	142.1	4892.117	0.1	0.2
1	4261	30.625	77.375	0.2	0.001	100.68	0.9	2	13.6	13.6	13.6	472.8	472.8	472.8	-999	-999	-999	20.3	40.6	142.1	1045.882	0.1	0.2
1	4262	30.625	77.625	0.2	0.001	96.633	0.9	2	19.04	19.04	19.04	424.8	424.8	424.8	-999	-999	-999	23.8	47.6	166.6	1285.617	0.1	0.2
1	4263	30.625	77.875	0.2	0.001	104.328	0.9	2	19.04	19.04	19.04	424.8	424.8	424.8	-999	-999	-999	23.8	47.6	166.6	1367.91 0.1	0.2	0.7
1	4264	30.625	78.125	0.2	0.001	105.481	0.9	2	19.04	19.04	19.04	424.8	424.8	424.8	-999	-999	-999	23.8	47.6	166.6	1753.386	0.1	0.2
1	4265	30.625	78.375	0.2	0.001	105.66	0.9	2	19.04	19.04	19.04	424.8	424.8	424.8	-999	-999	-999	23.8	47.6	166.6	1666.05 0.1	0.2	0.7
1	4266	30.625	78.625	0.2	0.001	108.304	0.9	2	19.04	19.04	19.04	424.8	424.8	424.8	-999	-999	-999	23.8	47.6	166.6	2302.95 0.1	0.2	0.7
1	4267	30.625	78.875	0.2	0.001	129.155	0.9	2	13.6	13.6	13.6	472.8	472.8	472.8	-999	-999	-999	20.3	40.6	142.1	3051.034	0.1	0.2
1	4268	30.625	79.125	0.2	0.001	139.183	0.9	2	13.6	13.6	13.6	472.8	472.8	472.8	-999	-999	-999	20.3	40.6	142.1	3009.519	0.1	0.2
1	4269	30.625	79.375	0.2	0.001	99.228	0.9	2	13.6	13.6	13.6	472.8	472.8	472.8	-999	-999	-999	20.3	40.6	142.1	3813.152	0.1	0.2
1	4270	30.625	79.625	0.2	0.001	102.668	0.9	2	13.6	13.6	13.6	472.8	472.8	472.8	-999	-999	-999	20.3	40.6	142.1	3528.464	0.1	0.2
1	4271	30.625	79.875	0.2	0.001	103.58	0.9	2	13.6	13.6	13.6	472.8	472.8	472.8	-999	-999	-999	20.3	40.6	142.1	4417.863	0.1	0.2
1	4272	30.625	80.125	0.2	0.001	2.257	0.9	2	3.2	3.2	3.2	9	9	9	-999	-999	-999	1.17	2.14	8.19	5016.478	0.1	0.2
1	4274	30.625	80.625	0.2	0.001	56.595	0.9	2	13.6	13.6	13.6	472.8	472.8	472.8	-999	-999	-999	20.3	40.6	142.1	5009.159	0.1	0.2
1	4275	30.625	80.875	0.2	0.001	63.227	0.9	2	13.6	13.6	13.6	472.8	472.8	472.8	-999	-999	-999	20.3	40.6	142.1	4737.016	0.1	0.2
1	4276	30.625	81.125	0.2	0.001	36.877	0.9	2	13.6	13.6	13.6	472.8	472.8	472.8	-999	-999	-999	20.3	40.6	142.1	4689.987	0.1	0.2
1	4389	30.375	77.375	0.2	0.001	18.643	0.9	2	13.6	13.6	13.6	472.8	472.8	472.8	-999	-999	-999	20.3	40.6	142.1	360.919 0.1	0.2	0.7
1	4390	30.375	77.625	0.2	0.001	24.468	0.9	2	13.6	13.6	13.6	472.8	472.8	472.8	-999	-999	-999	20.3	40.6	142.1	458.169 0.1	0.2	0.7
1	4391	30.375	77.875	0.2	0.001	29.777	0.9	2	13.6	13.6	13.6	472.8	472.8	472.8	-999	-999	-999	20.3	40.6	142.1	689.12  0.1	0.2	0.7
1	4392	30.375	78.125	0.2	0.001	76.745	0.9	2	19.04	19.04	19.04	424.8	424.8	424.8	-999	-999	-999	23.8	47.6	166.6	1227.46 0.1	0.2	0.7
1	4393	30.375	78.375	0.2	0.001	104.129	0.9	2	19.04	19.04	19.04	424.8	424.8	424.8	-999	-999	-999	23.8	47.6	166.6	1498.921	0.1	0.2
```

**Figure 4.4** Soil Parameter File for VIC

### 4.7.3 Preparation of Vegetation parameter File

The primary input to the vegetation parameter file is the Landuse-Landcover map since the amount of precipitation that reaches the ground is largely dependent on the nature and the density of the vegetation. Hydrological fluxes are largely seen to be influenced by LAI (Leaf Area Index) property of any landuse land cover.

The LULC map prepared under the ISRO-GBP "Landuse/Landcover Dynamics and Impact of Human Dimension in Indian River Basin" project has been used for the basin area in India, and the LULC from the University of Maryland has been used for the basin area in Nepal.

The LULC map contained 14 classes namely woodleaf, wooded grassland, urban and built-up, open shrubland, mixed forest, grassland, water, bare ground, cropland, closed shrubland, deciduous needleleaf, evergreen broadleaf forest, evergreen needleleaf forest and deciduous broadleaf forest. The maps were later recoded as per GLDAS since the vegetation library file was taken from it. The vegetation library file contains land cover characteristics on a monthly average basis. The vegetation library file description can be found in http://www.hydro.washington.edu/Lettenmaier/Models/VIC/Documentation/VegParam.html

The LAI vegetation parameter has been prepare by GLDAS using the UMD vegetation classification scheme and other classifications including IGBP and NCAR scheme. These parameters were averaged to form a generic parameters value. The file also includes the vegetation database file including rooting depth (root zone thickness) and rooting fraction (Fraction of the root in the current root zone) for each LULC type. The vegetation parameter file (Figure 4.5) has been prepared using this file, the vegetation library and the grid shapefile.

| | | | | | | | | |
|---|---|---|---|---|---|---|---|---|
| 3879 | 8 | | | | | | | |
| | 1 | 0.1248 | 0.1 | 0.1 | 1 | 0.9 | 0.5 | 0 |
| | 4 | 0.0192 | 0.1 | 0.08 | 1 | 0.8 | 0.5 | 0.12 |
| | 5 | 0.0128 | 0.1 | 0.089 | 1 | 0.889 | 0.5 | 0.022 |
| | 7 | 0.0864 | 0.1 | 0.115 | 1 | 0.885 | 0.5 | 0 |
| | 8 | 0.0064 | 0.1 | 0.154 | 1 | 0.846 | 0.5 | 0 |
| | 9 | 0.0064 | 0.1 | 0.173 | 1 | 0.827 | 0.5 | 0 |
| | 10 | 0.6352 | 0.1 | 0.133 | 1 | 0.867 | 0.5 | 0 |
| | 11 | 0.1088 | 0.1 | 0.133 | 1 | 0.867 | 0.5 | 0 |
| 3880 | 10 | | | | | | | |
| | 1 | 0.08 | 0.1 | 0.1 | 1 | 0.9 | 0.5 | 0 |
| | 4 | 0.0016 | 0.1 | 0.08 | 1 | 0.8 | 0.5 | 0.12 |
| | 5 | 0.0016 | 0.1 | 0.089 | 1 | 0.889 | 0.5 | 0.022 |
| | 6 | 0.0016 | 0.1 | 0.1 | 1 | 0.9 | 0.5 | 0 |
| | 7 | 0.0048 | 0.1 | 0.115 | 1 | 0.885 | 0.5 | 0 |
| | 8 | 0.1296 | 0.1 | 0.154 | 1 | 0.846 | 0.5 | 0 |
| | 9 | 0.1264 | 0.1 | 0.173 | 1 | 0.827 | 0.5 | 0 |
| | 10 | 0.5184 | 0.1 | 0.133 | 1 | 0.867 | 0.5 | 0 |
| | 11 | 0.1168 | 0.1 | 0.133 | 1 | 0.867 | 0.5 | 0 |
| | 13 | 0.0192 | 0.1 | 0.125 | 1 | 0.875 | 0.5 | 0 |
| 3884 | 4 | | | | | | | |
| | 8 | 0.4944 | 0.1 | 0.154 | 1 | 0.846 | 0.5 | 0 |
| | 9 | 0.4768 | 0.1 | 0.173 | 1 | 0.827 | 0.5 | 0 |
| | 10 | 0.0144 | 0.1 | 0.133 | 1 | 0.867 | 0.5 | 0 |
| | 13 | 0.0144 | 0.1 | 0.125 | 1 | 0.875 | 0.5 | 0 |
| 4005 | 8 | | | | | | | |
| | 1 | 0.0016 | 0.1 | 0.1 | 1 | 0.9 | 0.5 | 0 |
| | 4 | 0.0176 | 0.1 | 0.08 | 1 | 0.8 | 0.5 | 0.12 |
| | 5 | 0.0048 | 0.1 | 0.089 | 1 | 0.889 | 0.5 | 0.022 |
| | 6 | 0.0048 | 0.1 | 0.1 | 1 | 0.9 | 0.5 | 0 |
| | 7 | 0.376 | 0.1 | 0.115 | 1 | 0.885 | 0.5 | 0 |
| | 9 | 0.0272 | 0.1 | 0.173 | 1 | 0.827 | 0.5 | 0 |
| | 10 | 0.2832 | 0.1 | 0.133 | 1 | 0.867 | 0.5 | 0 |
| | 11 | 0.2848 | 0.1 | 0.133 | 1 | 0.867 | 0.5 | 0 |
| 4006 | 7 | | | | | | | |
| | 4 | 0.0912 | 0.1 | 0.08 | 1 | 0.8 | 0.5 | 0.12 |
| | 5 | 0.1392 | 0.1 | 0.089 | 1 | 0.889 | 0.5 | 0.022 |
| | 6 | 0.0352 | 0.1 | 0.1 | 1 | 0.9 | 0.5 | 0 |
| | 7 | 0.1872 | 0.1 | 0.115 | 1 | 0.885 | 0.5 | 0 |
| | 9 | 0.0144 | 0.1 | 0.173 | 1 | 0.827 | 0.5 | 0 |
| | 10 | 0.4352 | 0.1 | 0.133 | 1 | 0.867 | 0.5 | 0 |
| | 11 | 0.0976 | 0.1 | 0.133 | 1 | 0.867 | 0.5 | 0 |

**Figure 4.5** Vegetation Parameter File for VIC

### 4.7.4 Preparation of Meteorological Forcings

Meteorological forcing files were prepared using the IMD gridded data available for India with precipitation at a spatial resolution of $40.25^0$ and minimum and maximum temperature at 0.5º. A meteorological forcing file was generated for each grid cell and named as "data_lat_long". VIC requires a minimum of three meteorological variables: Tmax- Daily maximum temperature (in °C), Tmin- Daily minimum temperature (in °C) and Precp- Daily precipitation (in mm) however the optional variables are added for this study as wind speed and cloud factor for the parameter sensitivity of the VIC model . The meteorological files have been saved in ASCII format.

### 4.7.5 Preparation of Band elevation file

By default, VIC assumes each grid cell is flat. This assumption can lead to inaccuracies in snow pack estimates in mountainous grid cells. In this study the upper Ganga basin is highly mountainous and the glaciers/snow packs are abundant. For this reason, the option exists to have VIC break each grid cell up into a number of *elevation bands* (also called *snow bands*) and simulate them separately. Each band's mean elevation is used to lapse the grid cell average temperature, pressure, and precipitation to a more accurate local estimate. This file contains information needed to define the properties of each elevation band used by the snow model.

Snow elevation bands are used to improve the model's performance in areas with pronounced topography, especially mountainous regions, where the effects of elevation on snow pack accumulation and ablation might be lost in a large grid cell. It is not necessary that all grid cells in a basin have the same number of elevation bands. *SNOW_BAND* is simply the maximum number of elevation bands anywhere in the basin. The 8 maximum snow bands for this study we have considered. The mean of each reclassified elevation is calculated and given as AreaFract in the file.

Table 4.3 gives basic idea about the format of SNOW_BAND file generation and the Figure 4.6 shows the snow band generated for the Ganga grid.

**Table 4.3** Elevation Band file Format

| **Column** | **Variable Name** | **Units** | **Number of Values** | **Description** |
|---|---|---|---|---|
| 1 | cellnum | N/A | 1 | Grid cell number (should match numbers assigned in soil parameter file) |
| 2 : (SNOW_BAND+1) | AreaFract | fraction | SNOW_BAND | Fraction of grid cell covered by each elevation band. Sum of the fractions must equal 1. |
| (SNOW_BAND+2) : (2*SNOW_BAND+1) | elevation | m | SNOW_BAND | Mean (or median) elevation of elevation band. This is used to compute the change in air temperature from the grid cell mean elevation. |
| (2*SNOW_BAND+2) : (3*SNOW_BAND+1) | Pfactor | fraction | SNOW_BAND | To ignore effects of elevation on precipitation, set these fractions equal to the area fractions. |

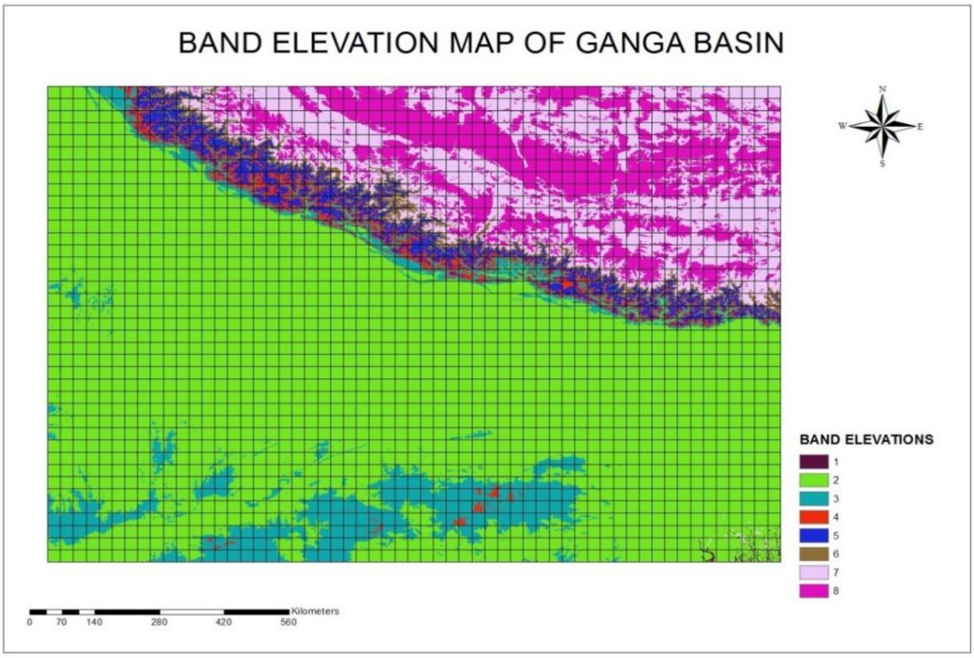



**Figure 4.6** Band Elevations for Ganga grid

### 4.7.6 Preparation of Global Parameter File

A global parameter file was generated by the VIC Model. The parameter file contains the user preferences and the parameters that have been prepared, including information about the number of layers, time step, location of the input and the output files and the modes which are to be activated.

## 4.8 RUNNING VIC MODEL

The VIC model has been developed for use on LINUX and UNIX platforms. To use VIC on a windows platform, a UNIX emulator such as Cywin to compile/run this model is needed.

**Download Source Code**

To download the latest VIC source code, is necessary to proceed to the download page. The code is packaged in a compressed tar archive. Extract the contents via:tar -xvzf filename where filename = name of the file you downloaded, e.g. VIC_code_4.1.1.tar.gz

**Compile VIC**

Change directory, cd, to the source code directory (extracted from the compressed tar archive above)

At the command prompt type: make

If this completes without errors, you will now see a file called vicNl in this directory.

vicNl is the executable file for the model.

### Run VIC

At the command prompt, type:

vicNl -g global_parameter_filename where:

global_parameter_filename = name of the global parameter file corresponding to your project.

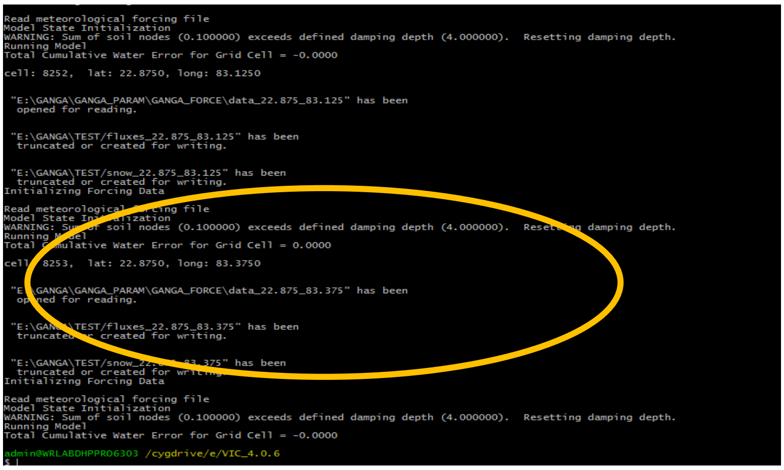



**Figure 4.7** Cygwin Command Prompt running VIC model

### Model Results

The contents of the results files can be controlled by the user, by options/instructions in the global parameter file. If no output file instructions are given in the global parameter file, VIC will create the same 2 or 3 output files as in earlier versions, by default.

The results of this study have generated by defining various forcings in several ways to carry sensitivity analysis.

### State File (optional)

VIC can save the hydrologic state from any point in the simulation (usually the final state) to a file for the purpose of re-starting the simulation later (as an initial state file). This is useful for simulations that require lengthy spin-up periods or ensemble methods. The point at which the hydrologic state is saved, and the name/location of the state file, can be specified by the user in the global parameter file.

In this study the model state is run to achieve the second objective of soil moisture data assimilation in VIC model.

### Calibration and Validation of VIC

Calibration has been done by adjusting the Infiltration parameters (binfilt) and the baseflow parameters like fraction of maximum baseflow (Ds) and fraction of maximum soil moisture content of the third layer (Ws), at which the non-linear baseflow takes place. The soil properties have been altered since VIC primarily considers the infiltration capacity curve and the nonlinear baseflow curve that is occurs predominant at the lower layers of the soil. The process continues until the simulated streamflow is almost equal to the observed streamflow at the given outlets.

## 4.9 ROUTING MODEL ALGORITHMS

In the VIC model, each grid cell is modeled independently without horizontal water flow. The grid-based VIC model simulates the time series of runoff only for each grid cell, which is non-uniformly distributed within the cell. Therefore, a stand-alone routing model (Lohmann., et al., 1996, 1998a) is employed to transport grid cell surface runoff and base flow to the outlet of that grid cell then into the river system. Routing in VIC has been done as follow:

### 4.9.1 Routing within the Grid cells

To simulate the in-grid-dynamic of the horizontal routing process, one first separates the fast and slow components of the measured discharge with the linear model described in Duband et al., (1993):

$$\frac{dQ^S(t)}{dt} = -k \cdot Q^S(t) + b \cdot Q^F(t) \tag{4.20}$$

where $Q^S(t)$ is the slow flow, $Q^F(t)$ is the fast flow, and $Q(t)$ is the total flow with $Q(t) = Q^S(t) + Q^F(t)$ .

The ratio of $b$ over $k$ represents the ratio of water in the slow flow over water in the fast flow. The fast and slow components are analytically connected by:

$$Q^S(t) = b\int_0^t \exp(-k(t-\tau))Q^F(\tau)d\tau + Q^S(0)\exp(-kt) \tag{4.21}$$

The equation shows that the initial condition $Q^S(0)$ decays exponentially with the mean residence time of water in the flow ($1/k$) and the half-life decay is $T_{1/2}=(ln2)/k$. With discrete data the discharge equation can be solved with:

$$Q^S(t) = \frac{\exp(-k \cdot \Delta t)}{1 + b \cdot \Delta t} Q^S(t - \Delta t) \_ \frac{b \cdot \Delta t}{1 + b \cdot \Delta t} Q(t) \tag{4.22}$$

It is assumed that there exists a linear relationship between the measured streamflow and $P^{eff}$ which is the part of the precipitation that contributes to streamflow. With the above stated assumption, the unit hydrograph and the $P^{eff}$, with the impulse response function one can iteratively solve and find using:

$$Q^F(t) = \int_0^{t_{\max}} UH^F(\tau) P^{eff}(t-\tau)d\tau \tag{4.23}$$

Where, $UH^F(\tau)$ = unit hydrograph for the fast flow component

$t_{max}$ = time taken for all fast processes to decay.

The equation below can be solved iteratively for the calculation of $UH^F(\tau)$

$$\begin{pmatrix} Q_m^F \\ \vdots \\ Q_n^F \end{pmatrix} = \begin{pmatrix} P_m^{eff} & \cdots & P_1^{eff} \\ \vdots & \ddots & \vdots \\ P_n^{eff} & \cdots & P_{n-m+1}^{eff} \end{pmatrix} \begin{pmatrix} UH_0^F \\ \vdots \\ UH_{m-1}^F \end{pmatrix} \tag{4.24}$$

After each of the iteration steps the following constraint is applied:

$$\sum_{i=0}^{m-1} UH_i^F = \frac{1}{1+\frac{b}{k}} \text{ with } UH_i^F \geq 0 \; \forall i \tag{4.25}$$

### 4.9.2 Channel Routing

A simple linear river routing model following the linearized Saint-Venant equation is used for routing. Here, the model makes an assumption that water is transported in the form of river flow.

$$\frac{\partial Q}{\partial t} = D\frac{\partial^2 Q}{\partial x^2} - C\frac{\partial Q}{\partial x} \tag{4.26}$$

Where, C denotes the wave velocity and D diffusivity

Both C and D are considered efficient parameters since there may occur cases of more than one river in one grid due to the coarseness of these grids. Through this process each grid cell ends up with a C and a D value representing the transport of water within a cell

The equation is solved with convolution integrals as follows:

$$Q(x,t) = \int_0^t U(t-s)h(x,s)ds \tag{4.27}$$

Where

$$h(x,t) = \frac{x}{2t\sqrt{\pi t D}} \exp\left(-\frac{(Ct-x)^2}{4Dt}\right)$$

is the Unit hydrograph (mentioned in the last derivation) with h(x,0)=0 when x>0 and h(0,t)=_(t) for t 0. The linearity of this arrangement ensures the modeling of man-made structures and human activities on the river.

### 4.9.3 Preparation of Input Files for Routing model

The input files for running the routing model are:

- ✓ Flux files
- ✓ Flow direction file
- ✓ Fraction file
- ✓ Station location file
- ✓ Unit hydrograph file

#### 4.9.3.1 Flux Files

The output of the VIC Module is flux files which contain fluxes of surface runoff, evapotranspiration, baseflow, soil moisture etc for each grid in the study area. The flux files should be generated without headers. The files should also not contain any ‘nan’ value. To remove Nan value MATLAB code is developed in which the all fluxes files path and output path is given; after running the code Nan values are converted in zero. The MATLAB code is given in Appendix III.

#### 4.9.3.2 Flow direction File

Flow direction file has been generated from the GTOPO DEM with the same cell size as the spatial resolution of the grid file $0.25^0$. For generating the flow direction file directly flow direction option of HEC-HMS tool is used. The flow directions were then recoded according to the codes required by the VIC routing module as shown in Table 4.4. Once the recoding is done the raster map of the flow direction has prepared and then by using conversion tool raster map has been converted in ASCII file to provide as an input file running Rout model for VIC.

**Table 4.4** Comparison of Flow Direction Notations

| Direction | Flow Direction Code by convention | According to VIC source code |
|---|---|---|
| North | 64 | 1 |
| North-East | 128 | 2 |
| East | 1 | 3 |
| South-East | 2 | 4 |
| South | 4 | 5 |
| South-west | 8 | 6 |
| West | 16 | 7 |
| North-West | 32 | 8 |

The flow direction file sample is depicted in following Figure 4.8.

```
ncols    57
nrows    39
xllcorner       75.25
yllcorner       22
cellsize        0.25
NODATA_value    0
0  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0
0  0  0  0  0  0  0  0  0  0  5  5  0  0  0  5  0  0  0  0
0  0  0  0  0  0  0  0  5  5  5  5  5  5  5  5  5  0  0  0
0  0  0  0  0  0  0  3  5  5  5  5  5  5  5  5  5  5  5  0
0  0  0  0  0  0  0  0  5  5  5  5  5  5  5  5  5  7  5  5
0  0  0  0  0  0  0  0  5  5  7  5  5  5  5  5  5  1  7  5
0  0  0  0  0  0  0  0  5  7  5  5  5  5  5  5  5  6  5  5
0  0  0  0  0  0  0  5  7  5  5  5  7  5  5  5  5  5  5  5
0  0  0  0  0  0  5  5  7  5  5  7  5  5  5  5  5  5  5  5
0  0  0  0  0  5  5  5  5  5  5  7  5  5  5  5  5  5  5  5
0  0  0  0  0  5  7  5  5  5  5  5  5  5  5  5  5  5  5  5
0  0  0  0  0  5  5  5  5  5  5  5  5  5  5  5  5  5  5  5
0  0  0  0  0  3  3  3  5  5  5  5  5  5  5  5  7  5  5  5
0  0  0  0  0  1  1  7  5  5  5  5  5  5  5  5  7  5  5  5
0  0  0  0  0  0  5  5  7  5  5  5  5  5  5  3  5  5  5  5
0  0  0  0  0  5  7  3  5  7  5  5  5  3  3  5  5  5  5  5
0  0  0  0  0  3  3  3  5  5  5  5  5  5  5  3  3  5  5  5
0  0  3  3  3  3  3  3  3  5  5  5  5  5  3  3  5  5  5  5
0  0  3  3  3  3  3  3  3  3  3  3  3  5  5  5  3  5  5  5
0  0  1  1  1  1  1  1  1  1  1  1  1  5  5  5  5  3  5  5
0  0  1  1  7  1  1  1  1  1  1  1  1  3  3  5  5  5  5  5
0  0  1  1  1  1  1  1  1  1  1  1  1  1  1  3  3  5  5  5
0  0  0  1  1  1  1  1  1  1  1  1  1  1  3  1  3  3  3  5
0  0  0  0  0  3  3  1  7  1  7  3  3  3  1  3  1  1  3  3
0  0  0  0  0  3  3  1  7  1  1  1  1  1  1  1  1  1  3  1
0  0  0  0  0  0  0  1  7  5  1  1  1  1  1  1  1  1  1  1
0  0  0  0  0  0  0  1  7  7  1  3  3  3  1  1  7  1  1  1
0  0  0  0  0  0  0  0  3  3  3  3  1  1  1  1  7  1  3  1
0  0  0  0  0  0  0  0  0  3  3  1  1  1  1  1  1  1  1  5
0  0  0  0  0  0  0  0  0  0  0  1  1  1  1  1  1  5  1  7
0  0  0  0  0  0  0  0  0  0  0  0  1  1  1  5  1  3  1  1
0  0  0  0  0  0  0  0  0  0  0  0  0  1  1  3  1  1  1  1
0  0  0  0  0  0  0  0  0  0  0  0  0  0  3  1  3  1  1  0
0  0  0  0  0  0  0  0  0  0  0  0  0  0  0  1  1  7  0  0
0  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0
0  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0
0  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0
0  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0
```

**Figure 4.8** Flow Direction File for routing model

#### 4.9.3.3 Fraction file

Fraction file contains the fraction of each grid in the study area. Each grid represents the numerical value between 0 and 1. The grids outside the basin boundaries were assigned the value of 0, which was considered as NO DATA. The following steps have been followed for the preparation of the grid file:

- Basin boundary and grid file were converted into feature class
- Only the run grids were selected
- With the current selection, the grid file was converted into a new feature class
- The basin boundary shapefile and the resultant shapefile were then intersected to give the area of each grid cell
- The area field formed was divided with 0.0625 (area of square grid) to give the fraction of each grid lying within the basin.

The flow direction file sample is depicted in following Figure 4.9

```
ncols         57
nrows         39
xllcorner     75.25
yllcorner     22
cellsize      0.25
NODATA_value  0
0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0
0 0 0 0 0 0 0 0 0 0 0.454349 0.519167 0 0 0 0.586969 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0
0 0 0 0 0 0 0 0 0.677572 0.995171 1 1 0.969138 0.813494 0.933149 0.999892 0.471956 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0
0 0 0 0 0 0 0 0.598038 1 1 1 1 1 1 1 1 1 0.874683 0.751011 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0
0 0 0 0 0 0 0 0 0.781839 1 1 1 1 1 1 1 1 1 1 0.916217 0 0.330349 0.554301 0.323001 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0
0 0 0 0 0 0 0 0 0.710945 1 1 1 1 1 1 1 1 1 1 1 0.991842 0.897633 1 1 0.793708 0.64931 0.455508 0 0 0 0 0 0 0 0 0 0 0 0 0 0
0 0 0 0 0 0 0 0 0.929259 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 0.74833 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0
0 0 0 0 0 0 0 0.857816 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 0.967655 0.513907 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0
0 0 0 0 0 0 0.447137 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 0.792244 0.466125 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0
0 0 0 0 0 0.302465 0.98163 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 0.658268 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0
0 0 0 0 0 0.93202 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 0.831423 0.995881 0.772448 0 0 0 0 0 0.258013 0 0
0 0 0 0 0 0.93554 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 0.964067 0.372442 0.532995 0.473207 0.943046 0
0 0 0 0 0 0.581208 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 0.960884 0.9137
0 0 0 0 0 0.411635 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 0.61743
0 0 0 0 0 0 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 0.970036 0.685711
0 0 0 0 0 0.910037 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 0.709539 0 0
0 0 0 0 0 0.998087 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 0.441537 0 0
0 0 0.250567 0.497689 0.824424 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1
0 0 0.591205 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 0.995038 0 0 0
0 0 0.91623 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 0.98918 0.5706
0 0 0.465892 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 0.668982 0
0 0 0.345144 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 0.960693 0.46
0 0 0 0.916027 0.972651 0.996767 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 0
0 0 0 0 0 0.962861 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 0.345685 0 0 0
0 0 0 0 0 0.484123 0.990292 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 0.497027
0 0 0 0 0 0 0 0.63273 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 0.757282 0 0 0 0
0 0 0 0 0 0 0 0.325585 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 0.993258 0.439126 0
0 0 0 0 0 0 0 0 0.451985 0.993047 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 0.709742 0 0
0 0 0 0 0 0 0 0 0 0.322789 0.967605 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 0.995408 1 0.976456 0.8055
0 0 0 0 0 0 0 0 0 0 0 0.931768 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 0.838008 0.28502 0 0 0 0 0 0 0 0 0 0
0 0 0 0 0 0 0 0 0 0 0 0 0.730172 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 0.976487 0.901088 0 0 0 0 0 0 0 0 0 0 0
0 0 0 0 0 0 0 0 0 0 0 0 0 0.794973 1 1 1 1 1 0.97276 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 0.999662 0.365058 0 0 0 0 0 0 0 0 0
0 0 0 0 0 0 0 0 0 0 0 0 0 0 0.689839 1 1 0.991508 0.391092 0 0.59009 1 1 1 1 1 1 0.996234 0.973715 0.963606 1 1 1 1 1 1 1
0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0.567706 0.980477 0.551003 0 0 0 0.999815 0.982289 1 1 1 1 0.80362 0 0.60575 1 1 1 1 0.99431
0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0.277454 0.629446 0 0.745959 1 1 1 0.331118 0 0 0.633257 1 0.85463 0.635412 0.3740
0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0.291436 0.661639 0.979471 0.367561 0 0 0 0.936044 0.416555 0 0 0 0 0 0 0
0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0
0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0
```

**Figure 4.9** Fraction File for routing model

#### 4.9.3.4 Station Location File

The station location file contains details of the row and column in the grid shapefile to which each of the stations being used for calibration and validation belong to. The file contains the following details:

- 1 or 0 depending on whether the station is active or not
- Station name
- Column from left
- Row from bottom
- Basin area which is not used by the model in the present version, yet needs to be mentioned
- Whether routing model needs to generate uh_s for each of the stations. This is by default set to NONE

#### 4.9.3.5 Unit Hydrograph File

The unit hydrograph file contains the grid cell impulse response function whose sum over all the months will always be equal to 1. Details about the generation of the unit hydrograph file has been mentioned in

[www.hydro.washington.edu/Lettenmaier/Models/VIC/Documentation/Routing/UH.shtml](www.hydro.washington.edu/Lettenmaier/Models/VIC/Documentation/Routing/UH.shtml)

## 4.10 RUNNING ROUTING MODEL

### Download Source Code

- The current routing model code is available in the Routing Model Source Code section of the download page.
- The code is packaged in a compressed tar archive. Extract the contents via:tar -xvzf *filename* where *filename* = name of the file you downloaded, e.g. route_code_1.1.tar.gz

### Compile Routing Model

- Edit rout.f and make sure that the parameters NROW, NCOL, NYR, and PMAX are all large enough to contain the dimensions of the basin and the length of the simulation.
- At the command prompt, type:make
- If this completes without errors, you will now see a file called *rout* in this directory. *rout* is the executable file for the routing model.

### Run Routing Model

At the command prompt, type:rout *input_filename* where *input_filename* of the main input file

### Output Files

For each station indicated in the station location file, the routing model produces several ASCII output files, containing time series of discharge at the station:

- *station*.day, *station*.day_mm: daily discharge at station *station*, in units of cfs or mm over the basin, respectively. Format:YYYY MM DD discharge
- *station*.month, *station*.month_mm: monthly discharge at station *station*, in units of cfs or mm over the basin, respectively. Format:YYYY MM discharge
- *station*.year, *station*.year_mm: annual discharge at station *station*, in units of cfs or mm over the basin, respectively. Format:YYYY discharge

## 4.11 PARAMETER SENSITIVITY ANALYSIS

VIC can use any combination of meteorological forcing variables generated from point data, gridded data or reanalysis data. It can use daily or subdaily forcings for water balance and energy balance modes respectively. The list of these parameters is long and to use all these parameters in actual modeling exercise is not possible because some of these parameters are very crucial and they are not feasible to collect. So this objective is for identifying the minimum parameters of meteorology to run the VIC perfectly. Previous studies show that for any land surface model at least three parameters are necessary viz. Maximum Temperature (Tmax), Minimum Temperature (Tmin), and Precipitation (Prec).

In this study the parameter sensitivity has carried out for Wind Speed (Ws) and Cloud Factor (CF). We are more interested in Wind Speed because as it is seen in model overview section of this thesis in Eqs. 4.13, 4.14, 4.16 and 4.17 why and how the wind is important.

Hence for entire Ganga basin the model has been set up and the forcings for four scenarios have made to run the model. Total forcing parameters in meteorological file are five *viz.* Tmax, Tmin, Prec, Ws, and CF.

Four scenarios has been generated as:

1. THREE PARAMETERS
   (Tmax, Tmin, Precipitation)
2. FOUR PARAMETERS
   (Tmax, Tmin, Precipitation, Wind speed)
3. ALL PARAMETERS
   (Tmax, Tmin, Precipitation, Wind speed, Cloud factor)
4. FOUR PARAMETERS WITHOUT WIND
   (Tmax, Tmin, Precipitation, Cloud factor)

The meteorological parameters can be altered as per the scenario in main global file by putting # tag in front of forcing variables. The model has been run run on daily basis from 1990 to 2005 for all the four scenarios and the analysis of main water budget components have done for Ganga basin to quantify the sensitivity of VIC model towards the added meteorological parameters (e.g. Wind speed and Cloud factor); results are discussed in next chapter.

## 4.12 ASSIMILATION OF SATELLITE OBSERVED SOIL MOISTURE DATA IN VIC MODEL

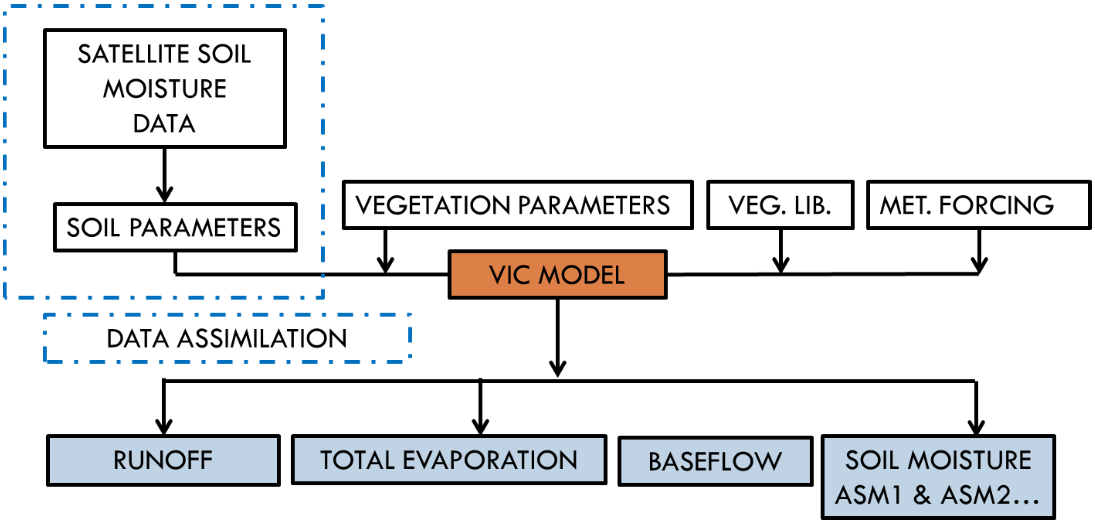



**Figure 4.10** Methodology of Data Assimilation.

Methodology for data assimilation given in above flow chart focuses mainly on soil moisture assimilation; reasons we have already discussed in motivation and problem statement part of first chapter of this thesis. The assimilation of AMSR-E daily soil moisture product is done in soil parameter/variable file of the VIC input. The state files are updated after running the model assimilated with the data and then the effects have seen on the various VIC model outputs and on the multilayer soil regime. Below are the methods adopted for hydrologic data assimilation.

## 4.13 DIRECT INSERTION METHOD (DI)

Direct insertion is the earliest and simplest method for the data assimilation. As the name suggests, the observations are directly inserted into the model inputs. This approach makes the explicit assumption that the model is wrong (has no useful information) and that the observations are right, which both disregards important information provided by the model and preserves observational errors. The disadvantage of this method is the water balance of model can be unbalanced because of some errors in data i.e. may be data is underestimated or vice versa. Houser et al,(1998) have observed a further key disadvantage of this approach is that model physics are solely relied upon to propagate the information to unobserved parts of the system. However, to test effect of assimilation of soil moisture in hydrological model this approach has been implemented on the sub-watershed of Ganga *viz*. Asan Watershed. The results of this approach are in next chapter Results and Discussion.

Three scenarios we have generated for this study:

A. The model is run without soil moisture assimilation.

B. In this scenario the model is run by assimilating the soil moisture of first layer in VIC for first day of January, 2005.

C. In this scenario the soil moisture is assimilated in first layer for day 1 and the model is run for day 1 to 11, then day 11 is again assimilated with observations and then model is run for day 11 to day 21, and repeat process for day 21 to day 31.

In all these scenarios the impact of first layer soil moisture assimilation on second layer is also studied. In soil parameter file of VIC all these changes has been done in the column of Initial soil moisture in layer one and then assimilated result of previous day's second layer soil moisture in next column.

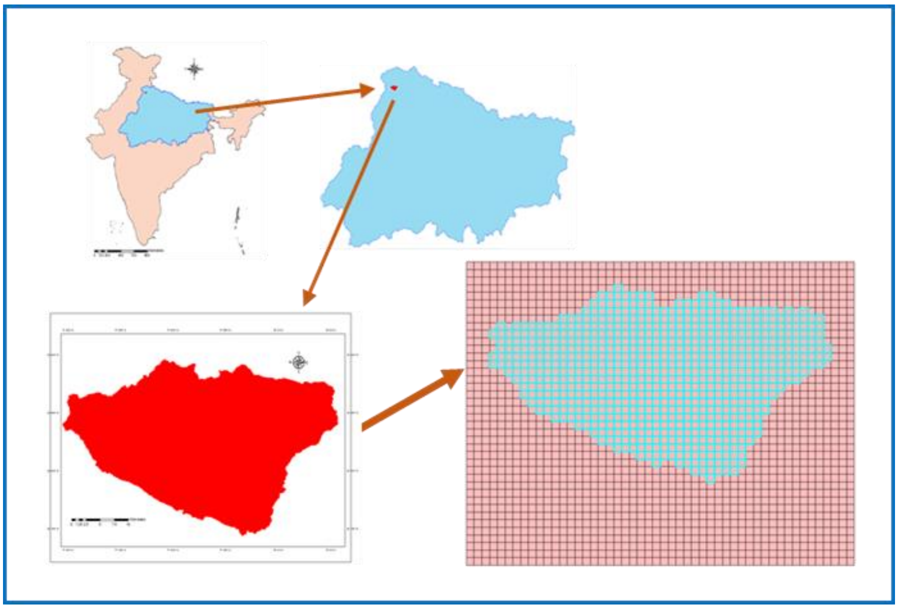


**Figure 4.11** Asan watershed for direct insertion data assimilation

## 4.14 ENSEMBLE KALMAN FILTER (EnKF)

The Ensemble Kalman Filter (EnKF) is a Monte-Carlo implementation of the Bayesian update problem: Given a probability density function (pdf) of the state of the modeled system (the prior, called often the forecast in geosciences) and the data likelihood, the Bayes theorem is used to obtain pdf after the data likelihood has been taken into account (the posterior, often called the analysis). EnKFs represent the distribution of the system state using a random sample, called an ensemble, and replace the covariance matrix by the sample covariance computed from the ensemble. One advantage of EnKFs is that advancing the pdf in time is achieved by simply advancing each member of the ensemble.

### 4.14.1 DERIVATION OF ENSEMBLE KALMAN FILTER

The Ensemble Kalman Filter (EnKF), first described by Evensen (1994), gives the idea to use kalman filter for the nonlinear systems by using ensembles or statistical samples of the forecasted model states. In the forecast step, the ensemble members are each forecast individually by the full nonlinear model, and in the analysis step the update equations are based on the linear equations used in the Kalman filter.

The major equations of EnKF are listed below:

$$\overline{X}_i^a = \overline{X}_i^b + \widehat{K}(y - H(\overline{X}_i^b)) \tag{4.28}$$

Where

$\overline{X}_i^a$ is the updated estimate of the analyzed state ( n x 1 dimension and n is the number of ensembles); $\overline{X}_i^b$ is the background model forecast, which is also referred to the first guess in data assimilation ( n x 1 dimension); y is the observation ( p x 1 dimension and p is the number of observations), which is the soil moisture measurements in this study; H is the observation operator that converts the states in the model into observation space (p x n dimension); $\widehat{K}$ refers to the traditional Kalman gain.

The ensemble $X^b$ is given as:

$$X^b = (X_1^b, X_2^b, \ldots, X_n^b) \tag{4.29}$$

Where we ignore time index and the subscript represents the ensemble member. The ensemble mean is then defined as

$$\overline{X^b} = \frac{1}{n}\sum_{i=1}^{n} X_i^b \tag{4.30}$$

The perturbation from the mean for the i th member is

$$X_1'^b = X_1^b - \overline{X^b} \tag{4.31}$$

Then $X_1'^b$ is defined as a matrix formed from the ensemble of perturbations:

$$X'^b = (X'^b_1, X'^b_2, \ldots, X'^b_n) \tag{4.32}$$

An estimation of background error covariance is defined as

$$\widehat{P^b} = \frac{1}{n-1} X'^b (X'^b)^T \tag{4.33}$$

Then the traditional Kalman gain $\widehat{K}$ can be calculated

$$\widehat{K} = \widehat{P}^b H^T (H\widehat{P}^b H^T + R)^{-1} \tag{4.34}$$

R is the observation error covariance with a dimension of p x p

### 4.14.2 EnKF FOR GANGA BASIN

For Ganga basin the above same filter has been applied to assimilate AMSR-E soil moisture data for the year 2005. For generating ensembles nine grid cells were chosen and Kalman gain is calculated for the entire month of January. Soil moisture is assimilated on the daily basis for month January of 2005.

#### 4.14.2.1 Ensemble generation for EnKF

First it has decided that choose the area of Ganga basin where the AMSR-E soil moisture observation data is available throughout the month and another criteria is land use and land classification. Ganga basin comprises 63% cropland, 10% wooded grassland, and so on about land use you can find out in chapter study area. Area which we have taken is comprising cropland in each grid and the other classes are wooded grassland, shrub land, water, bare ground.

For ensemble these nine grids has been used; each 625km$^2$ area of Ganga basin and the entire month of January 2005 i.e. 31 days. Now our ensemble dimension is $N_1$ ($n_1$, $n_2$… $n_{31}$)… $N_9$ ($n_1$, $n_2$… $n_{31}$). The difference between these model ensembles and the observation ensembles is given in table of Appendix II. As per the procedure discussed in chapter 4 the background error covariance matrix is calculated which we have to use to compute the Kalman gain matrix. The grid cells and the grid ID is depicted in Figure 4.12.

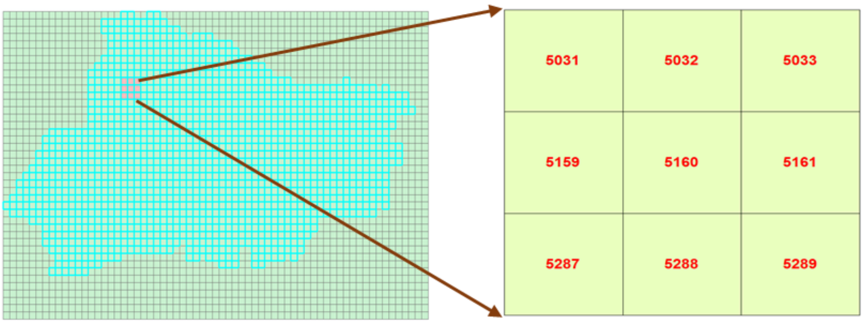



**Figure 4.12** Grids for generating Ensembles and Running EnKF

#### 4.14.2.2 Background error covariance matrix

The background error covariance matrix **B** (the standard notations are given in this chapter under derivation of EnKF) for 9 grids so the dimension of the matrix is 9 X 9. The Eq to reckon this matrix is given under derivation topic. Standard deviation has been estimated for the mean of differences between forecast (model calculated state) and observation of each day for each grid.

#### 4.14.2.3 Error covariance matrix

Error covariance matrix (R) is important to eliminate the errors accounted in observation data. KF works on the principle of BLUE (Best Linear Unbiased Estimator); hence we have assumed 20% error in AMSR-E soil moisture product and for this standard deviation we have estimated the Error covariance matrix same as the background matrix. Model state soil moisture is in mm hence we have to convert AMSR-E soil moisture product from gm/cc to mm. The error covariance matrix is generated for the entire ensemble size i.e. for the 9 grids and for 31 days. The observation error covariance matrix is also a diagonal matrix of dimension 9 X 9

#### 4.14.2.4 Kalman gain matrix

Kalman gain has been reckoned by using above two matrices in Eq No 4.32. The Kalman gain matrix is again 9 X 9 matrix. Here observation matrix H is identity because model forecasted soil moisture and the same variable's satellite observation has been applied in equation which seems there is no need of conversion factor for state to observation.

#### 4.14.2.5 Analysis matrix

Analysis matrix is predicted by using above Kalman gain matrix, forecast and observation in Eq No 4.26. The analysis matrix has been calculated for the 9 grids for 31 days. The dimension of analysis matrix is 9 X 1.

This updated soil moisture is again incorporated in state file generated for that particular day by running VIC. It has been done by using fraction of vegetation tiles in each grid and the soil moisture estimated by VIC for respective vegetation fraction in the same grid. Weighted average of each fraction of vegetation and ant its respective moisture has been calculated and then simply by multiplying the analysis i.e. updated soil moisture from EnKF to each average the new soil moisture is estimated for each fraction of each grid, after that we have just replaced the new soil moisture values in old state file and the new file is generated to run the VIC for getting new model states i.e. forecasts.

All the matrices which has been calculated through this methodology are given in next chapter Results and Discussion.

# 5 RESULTS AND DISCUSSION

The results obtained through the methodology described in previous chapter are discussed in this chapter. VIC model has been set up for entire Ganga basin then parameter sensitivity has been reckoned for the same model and same study area, after that the last part of objectives is data assimilation techniques and their implementation in our study. The study is most focusing on the soil variable/parameter of the model the reasons are discussed previously in chapter first's section motivation and problem statement respectively.

## 5.1 VIC MODEL SET UP

The Variable Infiltration Capacity Model (VIC) has been chosen for this study over entire Ganga basin. Ganga basin covers around 10,86,000 sq km area including parts of Nepal, India, Tibet(China) and Bangladesh, whereas majority of basin area in India which is about 8,61,000 sq km. The model is set up for entire basin taking the outlet at Farakka barrage.

For VIC set up first the Grid of entire study area is generated at a scale of 25 degree resolution. Total number of grid cells are 2730 as the columns are 65 and rows are 42. Run or active cells are 1387 based on boundary of basin; the grid preparation procedure and all attributes of grid we have discussed already in methodology chapter four.

All the parameter files have been generated according to the topography and climatic conditions of the basin. As discussed before that have included the area out of India also hence land use and land cover and soil texture maps we have taken from global products respectively. All the parameters we have assembled in one master file i.e. global file and after excluding all the errors finally the model has been run and fluxes files have been generated as the result of all this procedure. Fluxes are used for the water balance and energy balance components study.

## 5.2 PARAMETER SENSITIVITY ANALYSIS

The VIC model has been run four times on daily basis from 1990 to 2005 for the different meteorological forcing scenario as discussed in previous chapter. The analysis of result of main water budget components have done a below **(All units are in mm).**

**Table 5.1** Water budget for 'Three Parameter' scenario

| MONTHS | Avg_Rainfall | Avg_Runoff | Avg_Baseflow | Avg_Evap |
|---|---|---|---|---|
| **JAN** | 16.43 | 2.65 | 1.36 | 29.91 |
| **FEB** | 23.90 | 4.18 | 1.13 | 34.01 |
| **MAR** | 18.28 | 3.66 | 1.43 | 37.28 |
| **APR** | 20.73 | 3.37 | 1.19 | 31.32 |
| **MAY** | 46.15 | 7.26 | 1.58 | 40.44 |
| **JUN** | 157.67 | 27.33 | 3.80 | 77.87 |
| **JUL** | 330.52 | 80.95 | 15.80 | 135.20 |
| **AUG** | 309.27 | 88.42 | 24.99 | 146.72 |
| **SEP** | 193.93 | 60.74 | 23.35 | 120.88 |
| **OCT** | 40.21 | 11.39 | 9.07 | 88.56 |
| **NOV** | 5.65 | 1.22 | 2.68 | 48.78 |
| **DEC** | 7.63 | 1.46 | 1.63 | 30.30 |
| **AVERAGE** | **1170.36** | **292.63** | **88.01** | **821.26** |

Table 5.1 shows water budget for ;Three Parameter' scenario as the model gives daily outputs for water balance the sum of daily average water budget components is done for the 12 months separately and at last the grand total for all components is given in Table5.1. The last row is represents the long term annual average of the respective components.

The averages annual rainfall over the basin is around 1170.36 mm. The surface runoff estimated by VIC model in 'Three Parameter' scenario is around 292.63 mm, which is around 25% of total rainfall. The evapotranspiration from the basin under this scenario is around 821.26 mm, which is around 70% of total water coming to the basin in the form of precipitation.

**Table 5.2** Water budget for ‘Four Parameter’ scenario

| MONTHS | Avg_Rainfall | Avg_Runoff | Avg_Baseflow | Avg_Evap |
|---|---|---|---|---|
| **JAN** | 16.43 | 2.87 | 1.35 | 30.83 |
| **FEB** | 23.90 | 4.39 | 1.10 | 35.87 |
| **MAR** | 18.28 | 3.69 | 1.32 | 40.53 |
| **APR** | 20.73 | 3.28 | 1.01 | 32.16 |
| **MAY** | 46.15 | 7.20 | 1.24 | 38.81 |
| **JUN** | 157.67 | 28.13 | 3.53 | 70.54 |
| **JUL** | 330.52 | 85.01 | 16.52 | 121.06 |
| **AUG** | 309.27 | 94.45 | 28.00 | 132.12 |
| **SEP** | 193.93 | 65.60 | 27.11 | 113.84 |
| **OCT** | 40.21 | 12.30 | 10.15 | 92.83 |
| **NOV** | 5.65 | 1.30 | 2.74 | 54.66 |
| **DEC** | 7.63 | 1.57 | 1.64 | 33.33 |
| **AVERAGE** | **1170.36** | **309.79** | **95.70** | **796.57** |

The results obtained under ‘Four Parameter’scenario are given in Table 5.2. In this scenario four meteorological parameters *viz.* Tmax, Tmin, Precipitation, Wind speed are used to the force the VIC model. Results given in Table 5.2 indicates marginal decreases in evapotranspiration and marginal increase in runoff in this scenario. In present scenario out of 1170.36 mm of precipitation around 309 mm runoff has been generated which is around 26 % of total precipitation. Total water loss in terms of evapotranspiration from the basin is around 796.57 which 24.69 mm less than the first scenario (‘Three Parameters’). This change in water balance components indicates the sensitivity of VIC towards additional meteorological parameter in second scenario (i.e. Wind speed).

**Table 5.3** Water budget for 'All Parameter' scenario

| MONTHS | Avg_Rainfall | Avg_Runoff | Avg_Baseflow | Avg_Evap |
|---|---|---|---|---|
| **JAN** | 16.43 | 2.87 | 1.35 | 30.83 |
| **FEB** | 23.90 | 4.39 | 1.10 | 35.87 |
| **MAR** | 18.28 | 3.69 | 1.32 | 40.53 |
| **APR** | 20.73 | 3.28 | 1.01 | 32.16 |
| **MAY** | 46.15 | 7.20 | 1.24 | 38.81 |
| **JUN** | 157.67 | 28.13 | 3.53 | 70.54 |
| **JUL** | 330.52 | 85.01 | 16.52 | 121.06 |
| **AUG** | 309.27 | 94.45 | 28.00 | 132.12 |
| **SEP** | 193.93 | 65.60 | 27.11 | 113.84 |
| **OCT** | 40.21 | 12.30 | 10.15 | 92.83 |
| **NOV** | 5.65 | 1.30 | 2.74 | 54.66 |
| **DEC** | 7.63 | 1.57 | 1.64 | 33.33 |
| **AVERAGE** | **1170.36** | **309.79** | **95.70** | **796.57** |

The results obtained under 'All Parameter' scenario are given in Table 5.3. In this scenario four meteorological parameters *viz.* Tmax, Tmin, Precipitation, Wind speed, Cloud factor are used to the force the VIC model. Results given in Table 5.3 indicates marginal decreases in evapotranspiration and marginal increase in runoff in this scenario. In present scenario out of 1170.36 mm of precipitation around 309 mm runoff has been generated which is around 26 % of total precipitation. Total water loss in terms of evapotranspiration from the basin is around 796.57 which 24.69 mm less than the first scenario ('Three Parameters'). This change in water balance components indicates the sensitivity of VIC towards additional meteorological parameter in second scenario (i.e. Wind speed).

**Table 5.4** Water budget for 'Four Parameters without Wind' scenario

| FOUR PARAMETERS WITHOUT WIND | Avg_Rainfall | Avg_Runoff | Avg_Baseflow | Avg_Evap |
|---|---|---|---|---|
| **JAN** | 16.43 | 2.65 | 1.36 | 29.91 |
| **FEB** | 23.90 | 4.18 | 1.13 | 34.01 |
| **MAR** | 18.28 | 3.66 | 1.43 | 37.28 |
| **APR** | 20.73 | 3.37 | 1.19 | 31.32 |
| **MAY** | 46.15 | 7.26 | 1.58 | 40.44 |
| **JUN** | 157.67 | 27.33 | 3.80 | 77.87 |
| **JUL** | 330.52 | 80.95 | 15.80 | 135.20 |
| **AUG** | 309.27 | 88.42 | 24.99 | 146.72 |
| **SEP** | 193.93 | 60.74 | 23.35 | 120.88 |
| **OCT** | 40.21 | 11.39 | 9.07 | 88.56 |
| **NOV** | 5.65 | 1.22 | 2.68 | 48.78 |
| **DEC** | 7.63 | 1.46 | 1.63 | 30.30 |
| **AVERAGE** | **1170.36** | **292.63** | **88.01** | **821.26** |

Table 5.4 shows water budget for ; 'Four Parameters without Wind scenario as the model gives daily outputs for water balance the sum of daily average water budget components is done for the 12 months separately and at last the grand total for all components is given in Table5.4. The last row is represents the long term annual average of the respective components.

The averages annual rainfall over the basin is around 1170.36 mm. The surface runoff estimated by VIC model in 'Three Parameter' scenario is around 292.63 mm, which is around 25% of total rainfall. The evapotranspiration from the basin under this scenario is around 821.26 mm, which is around 70% of total water coming to the basin in the form of precipitation.

From above tables it can be said that only two scenarios are important. The graphs of these scenarios can give us better visualization and idea.

Each year's water budget component tables are given in Appendix I for detail analysis.

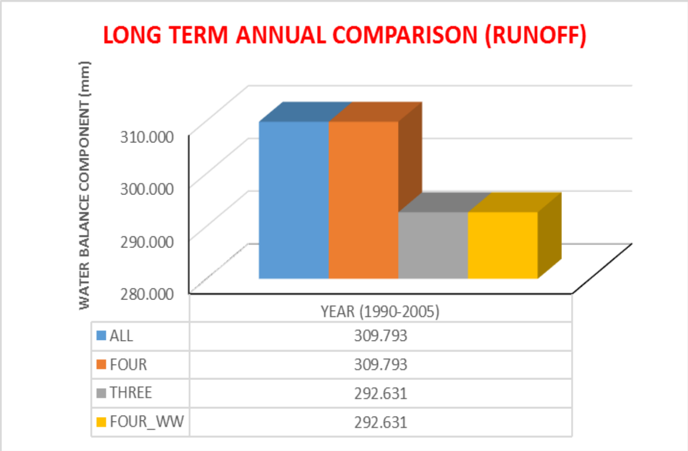



**Figure 5.1** Long term annual comparison of runoff for all scenarios

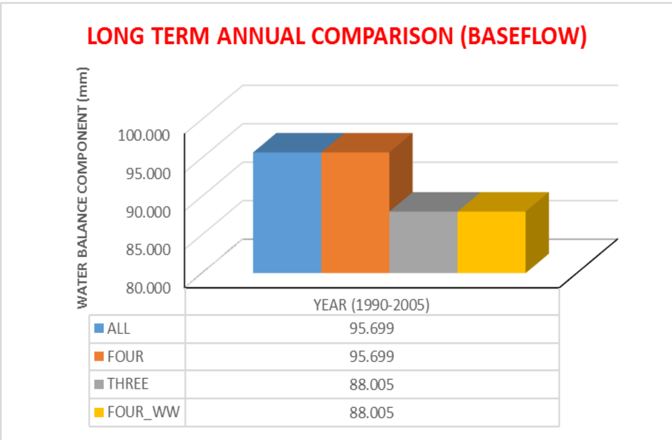



**Figure 5.2** Long term annual comparison of baseflow for all scenarios

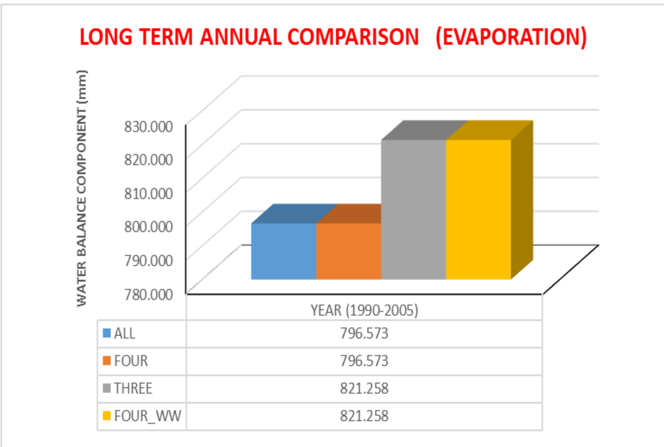



**Figure 5.3** Long term annual comparison of evaporation for all scenarios

From above Figures and the respective tables it is cleared that the scenario second 'four Parameters' and third 'All Parameters' yields almost the same result whereas scenario first 'Three Parameters' and last 'Four Parameters without Wind' are the same. It clears that cloud factor influences nothing but wind speed affects the water budget. This is because of model computes cloud factor from (Tmax - Tmin) range. In this case, VIC uses the MTCLIM algorithms to convert daily min and max temperature to humidity and incoming shortwave radiation. Hence only wind speed has effects on the VIC model water budget. The comparison between first and second scenario is carried out for the grid, below is the analysis for VIC water budget components only for scenario first and second.

**Table 5.5** Water budget comparison between scenario second and first

| WATER BUDGET COMPARISON (1990-2005) | | | |
|---|---|---|---|
| **COMPONENTS** | **FOUR PARAMETERS** | **THREE PARAMETERS** | **DIFFERENCE** |
| **RUNOFF** | 309.79 | 292.63 | 17.16 |
| **BASEFLOW** | 95.70 | 88.01 | 7.69 |
| **EVAPORATION** | 796.57 | 821.26 | -24.68 |

Table 5.5 shows the comparison between scenario second 'All Parameters' and first 'Three Parameters' for water budget component runoff. Long term annual average runoff for second scenario is 309.79mm whereas for first is 292.63; difference between them is 17.16mm. Baseflow with wind is 95.70mm and without wind is 88.01mm the difference is 7.69mm. Total evaporation done with wind is 796.57mm whereas without wind is 821.26mm and this is the only component where negative difference we can see -24.68mm. Hence runoff and baseflow are positive effects where evaporation is negative if we compare these both scenarios for the same time period for the basin.

The difference here seems too low because in VIC model the default value of wind speed if no observed wind speed data is given is 1.5m/s; hence for entire Ganga basin it is obvious that the result will compensate with the others. The effect of wind speed can be analyzed for the grid cells where the wind speed is at its maximum in basin and where it is equal to default value. The parameter sensitivity is now for only the wind speed as it has been seen the effects of the parameters on water budget of the basin.

Form total 1387 active grid cells of Ganga basin three grids have been chosen. One cell was having the maximum wind speed, second having the moderate wind speed. This is done to check at cell level what the actual effect is if wind speed is increasing or decreasing (i.e. at threshold value). The tenure was same as for the entire grid and the water budget components are also same for the comparison.

First grid cell is having the maximum wind speed 4.49 m/s (A), while second grid cell is having moderate wind speed 3.91 m/s (B).

Analysis for (A), and (B) is given and discussed as below:

**Table 5.6** Water budget comparison between scenario second and first for (A)

| WATER BUDGET COMPARISON (1990-2005) | | | |
|---|---|---|---|
| **COMPONENTS** | **FOUR PARAMETERS** | **THREE PARAMETERS** | **DIFFERENCE** |
| **RUNOFF** | 192.75 | 210.85 | -18.10 |
| **BASEFLOW** | 6.69 | 12.53 | -5.84 |
| **EVAPORATION** | 808.11 | 783.78 | 24.33 |

**Table 5.7** Water budget comparison between scenario second and first for (B)

| WATER BUDGET COMPARISON (1990-2005) | | | |
|---|---|---|---|
| **COMPONENTS** | **FOUR PARAMETERS** | **THREE PARAMETERS** | **DIFFERENCE** |
| **RUNOFF** | 270.19 | 288.29 | -18.10 |
| **BASEFLOW** | 41.20 | 50.55 | -9.35 |
| **EVAPORATION** | 716.32 | 688.67 | 27.64 |

From above tables 5.5 and 5.6 it can be seen that in (A) difference between runoff is -18.10mm, baseflow is varying with -5.84mm and evaporation is deviated by 24.33mm if it takes percentage consideration then it is -8.54%, -46.60% and 3.15% respectively with respective to first scenario. In case (B) water budget components comparison is -18.10mm for runoff, -9.35mm for baseflow and for evaporation it is 27.64mm and this is in percentage with respective to first scenario as -6.27%, -18.50% and 4.10% respectively.

From results obtained it is clear that the VIC model results are sensitive towards wind speed data, however, no significant change has been observed by additional input in the terms of cloud factor in the input meteorological forcing. The analysis of results indicates that in the area having wind speed more or less than 1.5 m/s the addition of observed wind speed data will improve estimates of water balance components. The results obtained from two input meteorological forcing scenario ("Three Parameter' and 'Four Parameter')are plotted in Figure 5.4, which clearly indicates the difference between runoff estimates using wind data as input along with other default meteorological inputs and excluding wind data from the meteorological inputs.

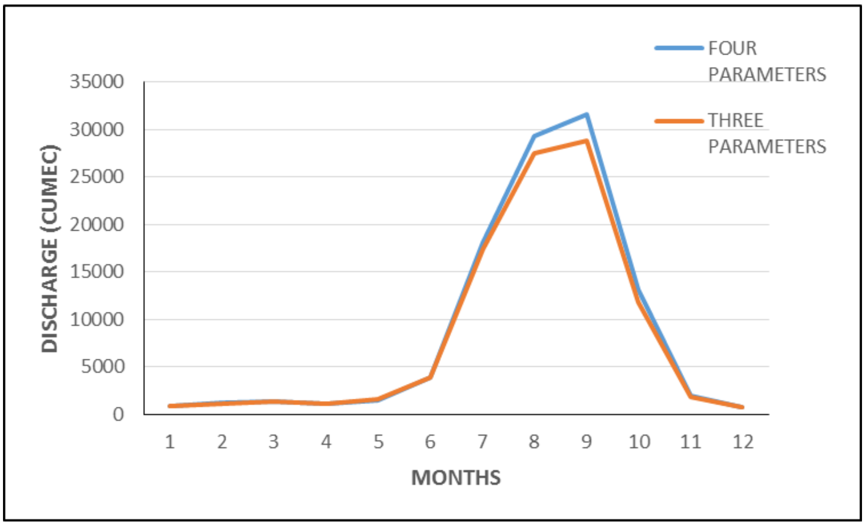



**Figure 5.4** Discharge comparison between first and second scenario (1990-2005)

The difference between discharge of first scenario and the second is 558.97 Cumec i.e. 6.8% with respective to first scenario hence it is clear that wind speed parameter we must take into the consideration in forcings for VIC model.

### 5.2.1 Calibration and Validation of VIC

The water balance components for VIC, namely; Precipitation (mm), Runoff (mm), Baseflow (mm) and Evaporation (mm) were generated for the calibration period (2005). The water balance components computed by the model are shown in Figure 5.5.

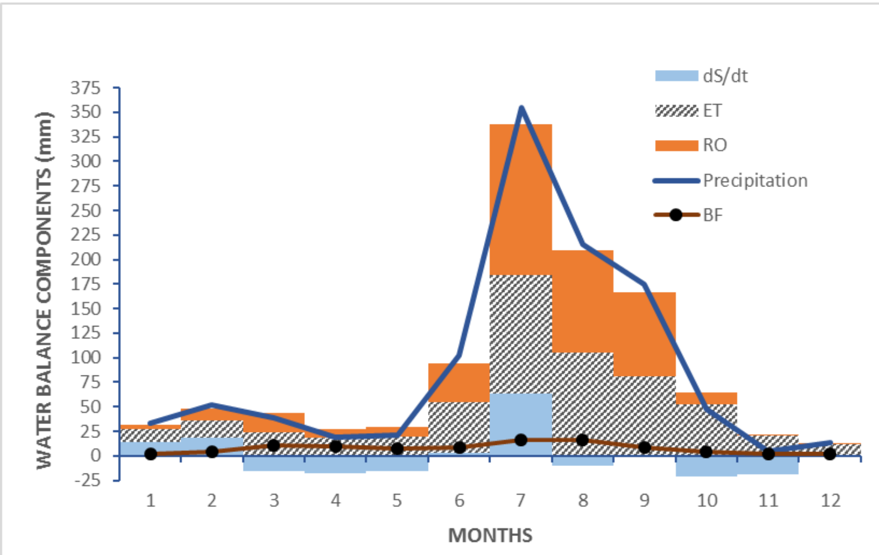



**Figure 5.5** Water balance components for 2005

On the generation of the water balance components, the model was calibrated by adjusting the soil properties.

Every hydrological model depends on the inputs given and certain fundamental assumptions. VIC considers 10 calibrating parameters out of which 6 parameters are considered more important than the rest; *viz.* binfilt, Ds, Ws, Dm, d1 and d2. Keeping the depth of soil layers unaltered, other parameters are calibrated in present study. Model input parameters only represent the physical properties of the basin and may contain certain errors. Hence, calibration is required. It can be done in two ways: *Parameter specification*, in which calibration of initial values is done on the basis of previous knowledge on the behaviour of the basin. The second method *is Parameter estimation* in which calibration is done depending on field observations. Calibration can be done depending upon the reference availability, by adjusting parameters till the performance of the model closely matches the observed behaviour of the basin. The primary aim of this process is to minimize the difference between simulated data and observed data which is runoff/discharge on annual or monthly basis.

First, the model was simulated by considering initial values of calibrating parameters. Keeping the results of the initial iteration as reference, the remaining parameters were increased or decreased until the best match between the observed and simulated was obtained as shown in Table 5.8.

**Table5.8** Calibration tests performed for VIC

| | | **Soil Texture Type** | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|
| | | 1 | 2 | 3 | 12 | 24 | 100 | 102 | 103 | 104 |
| 1 | binfilt | 0.2 | 0.2 | 0.2 | 0.2 | 0.2 | 0.2 | 0.2 | 0.2 | 0.2 |
| | Ds | 0.001 | 0.001 | 0.001 | 0.001 | 0.001 | 0.001 | 0.001 | 0.001 | 0.001 |
| 2 | binfilt | 0.4 | 0.3 | 0.3 | 0.3 | 0.4 | 0.2 | 0.2 | 0.2 | 0.2 |
| | Ds | 0.008 | 0.005 | 0.003 | 0.001 | 0.001 | 0.001 | 0.001 | 0.001 | 0.001 |
| 3 | binfilt | 0.4 | 0.3 | 0.25 | 0.25 | 0.4 | 0.2 | 0.2 | 0.2 | 0.2 |
| | Ds | 0.008 | 0.005 | 0.003 | 0.001 | 0.001 | 0.001 | 0.001 | 0.001 | 0.001 |
| 4 | binfilt | 0.3 | 0.25 | 0.25 | 0.25 | 0.3 | 0.2 | 0.2 | 0.2 | 0.2 |
| | Ds | 0.006 | 0.004 | 0.0025 | 0.001 | 0.001 | 0.001 | 0.001 | 0.001 | 0.001 |
| 5 | binfilt | 0.3 | 0.3 | 0.3 | 0.3 | 0.3 | 0.3 | 0.3 | 0.3 | 0.3 |

| | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|
| | Ds | 0.001 | 0.001 | 0.001 | 0.001 | 0.001 | 0.001 | 0.001 | 0.001 | 0.001 |
| 6 | binfilt | 0.3 | 0.3 | 0.3 | 0.3 | 0.3 | 0.3 | 0.3 | 0.3 | 0.3 |
| | Ds | 0.001 | 0.001 | 0.001 | 0.001 | 0.001 | 0.001 | 0.001 | 0.001 | 0.001 |
| | Ws | 0.8 | 0.8 | 0.8 | 0.8 | 0.8 | 0.8 | 0.8 | 0.8 | 0.8 |
| 7 | binfilt | 0.4 | 0.4 | 0.4 | 0.4 | 0.4 | 0.4 | 0.4 | 0.4 | 0.4 |
| | Ds | 0.008 | 0.008 | 0.008 | 0.008 | 0.008 | 0.008 | 0.008 | 0.008 | 0.008 |
| 8 | binfilt | 0.4 | 0.4 | 0.4 | 0.4 | 0.4 | 0.4 | 0.4 | 0.4 | 0.4 |
| | Ds | 0.01 | 0.01 | 0.01 | 0.01 | 0.01 | 0.01 | 0.01 | 0.01 | 0.01 |
| | Ws | 0.08 | 0.08 | 0.08 | 0.08 | 0.08 | 0.08 | 0.08 | 0.08 | 0.08 |
| 9 | binfilt | 0.4 | 0.4 | 0.4 | 0.4 | 0.4 | 0.4 | 0.4 | 0.4 | 0.4 |
| | Ds | 0.001 | 0.001 | 0.001 | 0.001 | 0.001 | 0.001 | 0.001 | 0.001 | 0.001 |
| 10 | binfilt | 0.4 | 0.4 | 0.4 | 0.4 | 0.4 | 0.4 | 0.4 | 0.4 | 0.4 |
| | Ds | 0.01 | 0.01 | 0.01 | 0.01 | 0.01 | 0.01 | 0.01 | 0.01 | 0.01 |

The best match between simulated and the observed discharge is seen during 6$^{th}$ test, **binfilt= 0.3, Ds= 0.001, Ws= 0.8**.

The comparison of simulated discharge from VIC with the observed discharge data can hint the success of calibration phase. This part is knows as validation of the calibration. For our study is model is calibrated and validated for the main outlet Farakka. Observed data for the respective outlet is obtained from the GRDC database; it is mean monthly discharge in cumec. The mean annual GRDC observed discharge at Farakka is 12037.26 cumec whereas calibrated model simulated mean annual discharge is 12020.92 cumec, that means model is calibrated very well and this model so it can be used for further study. Coefficient of determination between simulated and observed discharge is 89%. For discharge simulation the model is run in energy balance mode because snowmelt has been taken into the consideration for Ganga basin routing.

The simulated discharge and the GRDC observed discharge comparison is shown in Figure 5.6 below

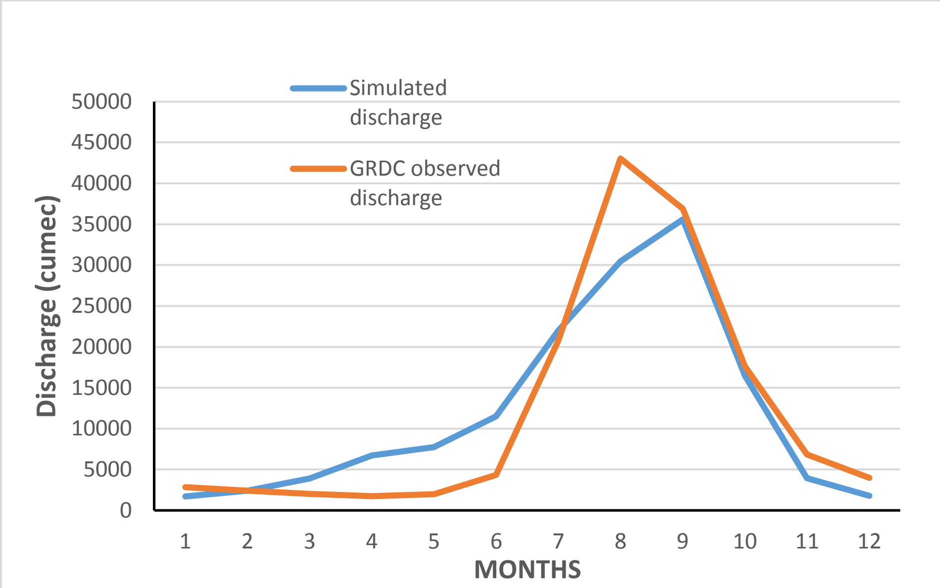



**Figure 5.6** Hydrograph for simulated and observed discharge of Ganga (1990-2005)

## 5.3 ASSIMILATION OF SOIL MOISTURE DATA VIC MODEL

Data assimilation technique has been discussed detail in Chapter 1 and 2. There are various techniques for data assimilation for different variables in present research an attempt has been made to assimilate satellite observed soil moisture data in VIC model. Two techniques has been used for this purpose the results for each are discussed below:

For soil moisture surface soil moisture observations derived from AMSR-E for the year 2005 have been used. Details of this product are given in chapter 3.

### 5.3.1 Direct Insertion Data Assimilation

This is the simplest method of data assimilation. For this method the area has been chosen Asan watershed which is sub watershed of Ganga basin. VIC is run for this watershed and the forecasted states of this model have been directly replaced with satellite observation data.

The results of different scenarios is discussed as below

**Table 5.9** Comparison of two scenarios of SM assimilation

| SCENARIO A | | | ΔSM | SCENARIO B | | | ΔSM |
|---|---|---|---|---|---|---|---|
| **DAY** | 1 | 31 | | **DAY** | 1 | 31 | |
| **LAYER I** | 54.2 | 28.91 | -25.28 | **LAYER I** | 43.89 | 27.33 | -16.55 |
| **LAYER II** | 126.47 | 38.65 | -87.82 | **LAYER II** | 126.47 | 38.07 | -88.39 |

Two scenarios in above table give idea about the soil moisture assimilation in (A) day 1 and day 31 soil moisture of layer I and layer II is forecasted by the model whereas in (B) first layer soil moisture is assimilated in the VIC soil parameter file as initial condition and the model is run and the difference between soil moisture difference in both the layers. Without assimilation the ∆SM in first layer was -25.28mm whereas with assimilation ∆SM is

-16.55mm while in second layer there is only 1mm difference which is not a significant.

**Table 5.10** Comparison of SM assimilation for scenario C

| SCENARIO C | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|
| DAY | 1 | 11 | ∆SM | 11 | 21 | ∆SM | 21 | 31 | ∆SM |
| LAYER I | 43.89 | 15.3 | -28.59 | 43.101 | 22.44 | -20.65 | 43.64 | 20.01 | -23.63 |
| LAYER II | 126.47 | 40.72 | -85.75 | 126.47 | 41.78 | -84.68 | 126.47 | 41.5 | -84.97 |

Above table5.9 is about the third scenario in which soil moisture has been assimilated for first layer in VIC for three days, day 1, day11, and on day 21. The ∆SM for first 10 days in layer-I is -28.59mm whereas in layer II it is -85.79mm, in next 10 days from 11 to 21 it is -20.65mm, and -84.68mm respectively whereas in third case from day 21 to day 31∆SM is -23.63mm and -84.97mm for the respective layers of soil moisture. Hence here it can be said that the difference in soil moisture of layer first in all scenarios can be accepted though it is not unbiased but in scenario C the second layer soil moisture cannot accepted because ∆SM values are not reliable and unacceptable. Second scenario maps of Asan watershed assimilation are given below:

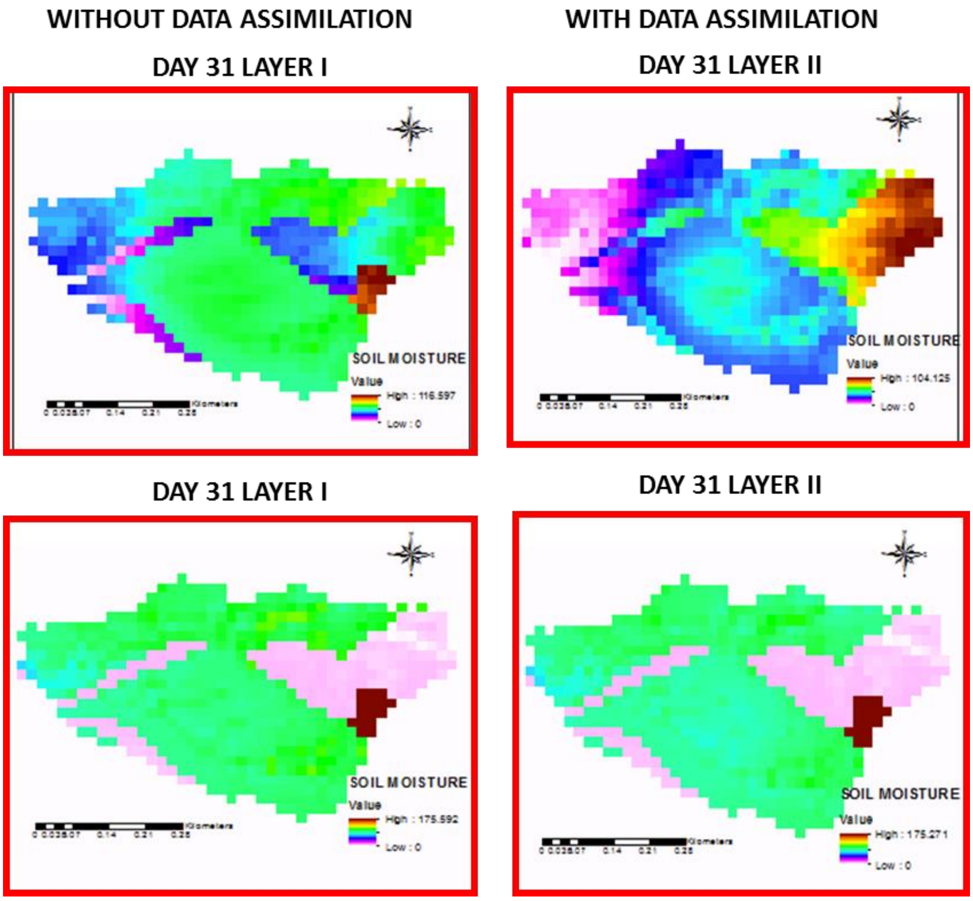



**Figure 5.7** Asan watershed direct insertion soil moisture and model forecasted soil moisture comparison

The direct insertion technique is not reliable because it directly applies the observation data into the model and the model physics is eliminated as we have seen in above results; so it's not feasible to apply this technique for data assimilation.

As per the reviews and the past work the Kalman filter and its new derived forms are most suitable for the data assimilation. In this study Ensemble Kalman filter technique has been used to conquer the limitations of Kalman filter.

### 5.3.2 Ensemble Kalman Filter (EnKF) for Soil Moisture Assimilation

The derivation of EnKF is given in chapter methodology in detail. For Ganga basin the same has been applied to assimilate AMSR-E soil moisture data for the year 2005. For generating ensembles nine grid cells were chosen and Kalman gain is calculated for the entire month of January. Soil moisture is assimilated on the daily basis for month January of 2005.

The detail discussion of results is continued in this chapter.

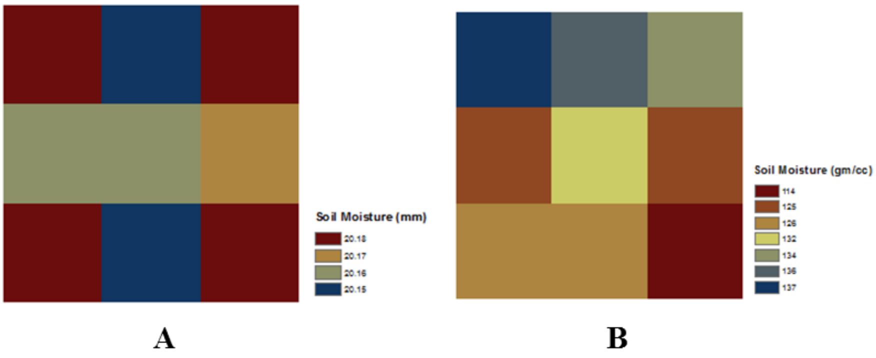



**Figure 5.8** Model forecast soil moisture (A) and AMSR-E soil moisture (B) for the selected area

Figure 5.3 is giving the idea about change in soil moisture of surface layer in the selected area of the Ganga basin. The AMSR-E data is in gm/cc it must be converted in mm before assimilating into the model.

The background error covariance matrix **B** (the standard notations are given in methodology chapter under derivation of EnKF) for 9 grids so the dimension of the matrix is 9 X 9.

**Table 5.11** Background Error Covariance matrix for the EnKF

| | COL1 | COL2 | COL3 | COL4 | COL5 | COL6 | COL7 | COL8 | COL9 |
|---|---|---|---|---|---|---|---|---|---|
| ROW1 | 200.15 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| ROW2 | 0 | 110.97 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| ROW3 | 0 | 0 | 125.67 | 0 | 0 | 0 | 0 | 0 | 0 |
| ROW4 | 0 | 0 | 0 | 52.32 | 0 | 0 | 0 | 0 | 0 |
| ROW5 | 0 | 0 | 0 | 0 | 76.59 | 0 | 0 | 0 | 0 |
| ROW6 | 0 | 0 | 0 | 0 | 0 | 122.74 | 0 | 0 | 0 |
| ROW7 | 0 | 0 | 0 | 0 | 0 | 0 | 58.51 | 0 | 0 |
| ROW8 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 72.24 | 0 |
| ROW9 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 103.88 |

Background error covariance matrix is diagonal matrix as no bothering about the spatial extent because variable is soil moisture and the distance between two centroids is 25km.

From the observations the observation error matrix is calculated by taking the standard deviation of 0.2. The error covariance matrix is generated for the entire ensemble size i.e. for the 9 grids and for 31 days. The observation error covariance matrix is also a diagonal matrix of dimension 9 X 9 as below

**Table 5.12** Observation Error Covariance matrix (std. dev. 0.2)

| | COL1 | COL2 | COL3 | COL4 | COL5 | COL6 | COL7 | COL8 | COL9 |
|---|---|---|---|---|---|---|---|---|---|
| ROW1 | 6.97 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| ROW2 | 0 | 6.25 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| ROW3 | 0 | 0 | 0.16 | 0 | 0 | 0 | 0 | 0 | 0 |
| ROW4 | 0 | 0 | 0 | 6.45 | 0 | 0 | 0 | 0 | 0 |
| ROW5 | 0 | 0 | 0 | 0 | 5.66 | 0 | 0 | 0 | 0 |
| ROW6 | 0 | 0 | 0 | 0 | 0 | 4.58 | 0 | 0 | 0 |
| ROW7 | 0 | 0 | 0 | 0 | 0 | 0 | 6.35 | 0 | 0 |
| ROW8 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 5.20 | 0 |
| ROW9 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 4.24 |

From Table 5.1 and 5.2 gives the covariance matrices of background error and observation by applying Eq No 4.32 Kalman gain has been reckoned for selected area for the entire month. The Kalman gain matrix is given as below which is again 9 X 9 matrix. Here observation matrix H is identity because model forecasted variable is soil moisture and the same variable's soil moisture satellite observation has been used for this study which seems there is no need of conversion factor for state to observation.

**Table 5.13** Kalman gain matrix for EnKF

| | COL1 | COL2 | COL3 | COL4 | COL5 | COL6 | COL7 | COL8 | COL9 |
|---|---|---|---|---|---|---|---|---|---|
| ROW1 | 0.97 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| ROW2 | 0 | 0.95 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| ROW3 | 0 | 0 | 1.00 | 0 | 0 | 0 | 0 | 0 | 0 |
| ROW4 | 0 | 0 | 0 | 0.89 | 0 | 0 | 0 | 0 | 0 |
| ROW5 | 0 | 0 | 0 | 0 | 0.93 | 0 | 0 | 0 | 0 |
| ROW6 | 0 | 0 | 0 | 0 | 0 | 0.96 | 0 | 0 | 0 |
| ROW7 | 0 | 0 | 0 | 0 | 0 | 0 | 0.90 | 0 | 0 |
| ROW8 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0.93 | 0 |
| ROW9 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0.96 |

From above tables 5.11, 5.12 and 5.13 analysis of the soil moisture state is done by using the equation of analysis state Eq No. 4.26. The updated state i.e. after assimilation is of dimension 1 X 9. The total updated soil moisture table is given in appendix II.

One day assimilated soil moisture analysis is given in below Table 5.14

**Table 5.14** EnKF assimilation analysis

| PIXEL ID | FORECAST | OBSERVATION | ANALYSIS |
|---|---|---|---|
| **5031** | 20.19 | 13.2 | 13.44 |
| **5032** | 20.19 | 12.5 | 12.91 |
| **5033** | 20.18 | 11.5 | 11.51 |
| **5159** | 20.16 | 12.7 | 13.52 |
| **5160** | 20.17 | 11.9 | 12.47 |
| **5161** | 20.18 | 10.7 | 11.04 |
| **5287** | 20.17 | 12.6 | 13.34 |
| **5288** | 20.16 | 11.4 | 11.99 |
| **5289** | 20.17 | 10.3 | 10.69 |

From above table first column is about the grid ID, second column values are forecasted soil moisture values from VIC model for day one next column gives the observation of AMSR-E, and the last column is analysis after applying EnKF on the forecast and observations.

The results are perfectly matching with the observations; here the basic principle of assimilation is assumed that the observation is true since there were not the ground truths available for soil moisture field values. The coefficient of determination between forecast and observation prior assimilation is 0.02 whereas after assimilation between analysis and the observation is 0.98. The study has been done for the daily soil moisture assimilation for the area entire month.

Result of above is then compared with the rainfall event to check the soil moisture variability and the effect of irrigation in the respective area. Figure 5.9 gives this analysis in detail.

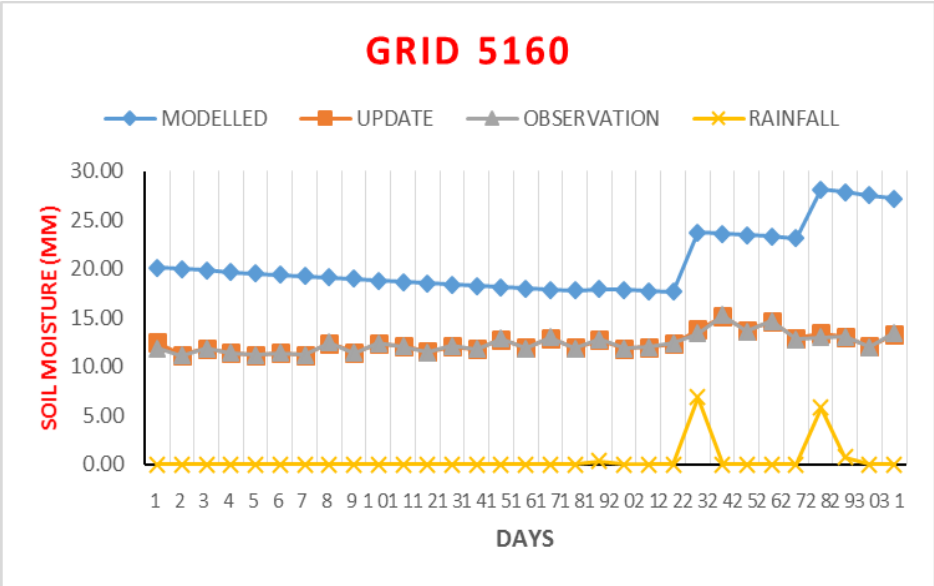
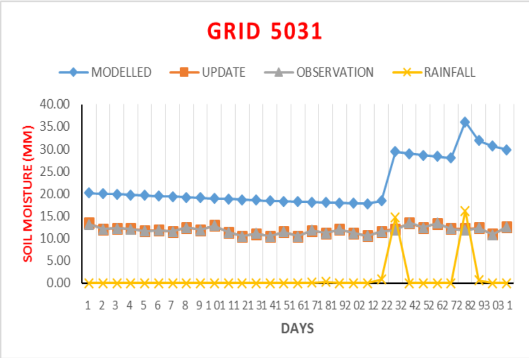
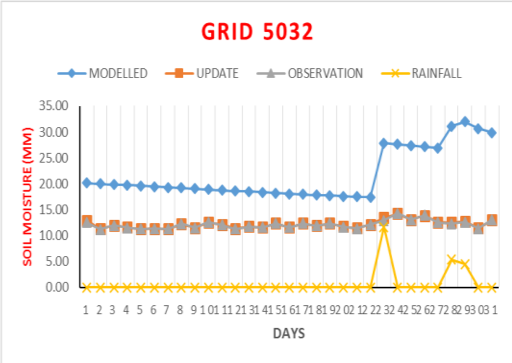
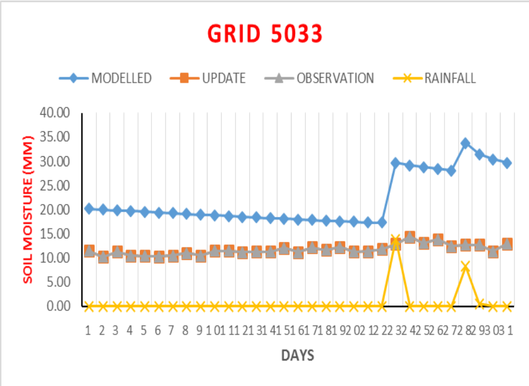


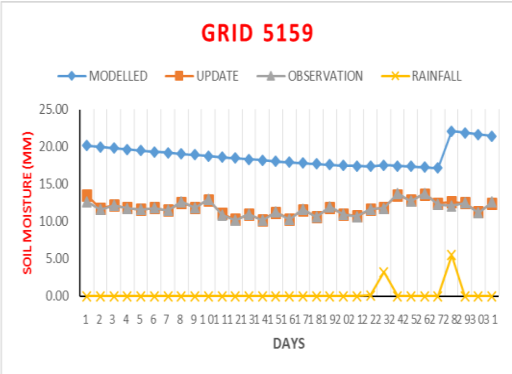

**Figure 5.9** Impact of data assimilation on the modelled state moisture.

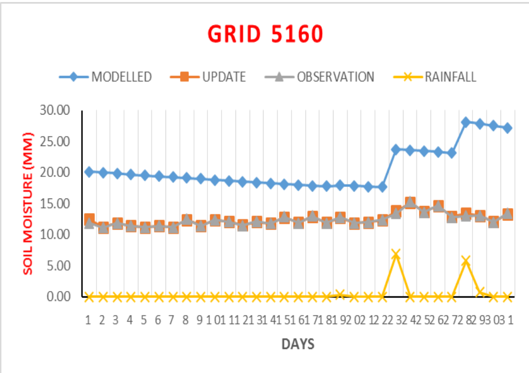
The impact of rainfall and the irrigation is seen perfectly on the data assimilation, as rainfall is increasing the modelled state and the assimilated soil moisture both are increasing or vice versa; but forecasted soil moisture is increasing or decreasing in the same units that of rainfall and from next day the trend is decreasing whereas the assimilated soil moisture is behaving according to water balance manner. When there is no rainfall the forecasted moisture continuously decreasing whereas assimilated trend is ups and downs that means the surface irrigation phenomenon is observed very well. The same trends has been carried out for the rest area also which are shown below.

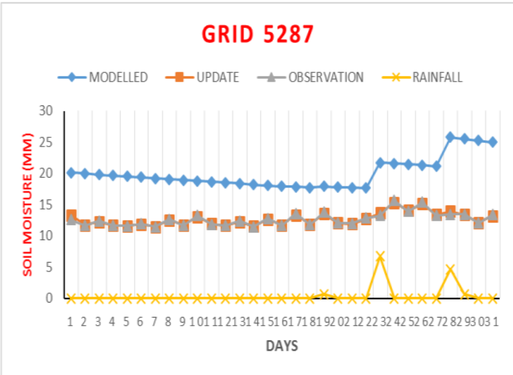

GRID 5031
MODELLED
UPDATE
OBSERVATION
RAINFALL
SOIL MOISTURE (MM)
DAYS

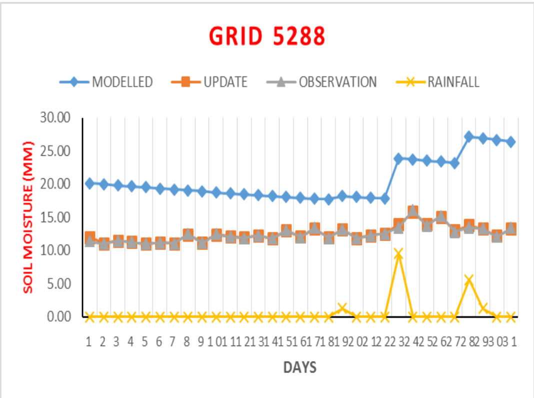

GRID 5032
MODELLED
UPDATE
OBSERVATION
RAINFALL
SOIL MOISTURE (MM)
DAYS

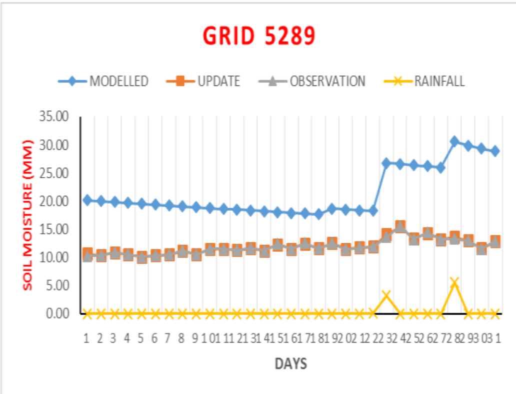

GRID 5033
MODELLED
UPDATE
OBSERVATION
RAINFALL
SOIL MOISTURE (MM)
DAYS


GRID 5159
MODELLED
UPDATE
OBSERVATION
RAINFALL
SOIL MOISTURE (MM)
DAYS


GRID 5160
MODELLED
UPDATE
OBSERVATION
RAINFALL
SOIL MOISTURE (MM)
DAYS


GRID 5287
MODELLED
UPDATE
OBSERVATION
RAINFALL
SOIL MOISTURE (MM)
DAYS


GRID 5288
MODELLED
UPDATE
OBSERVATION
RAINFALL
SOIL MOISTURE (MM)
DAYS


GRID 5289
MODELLED
UPDATE
OBSERVATION
RAINFALL
SOIL MOISTURE (MM)
DAYS

Results of data assimilation in previous section are acceptable for the EnKF. As from the various graphs and from the analysis table it is obvious that the water budget should be changed for both the scenarios with data assimilation and without data assimilation. Hence the water budget is discussed below for both scenarios:

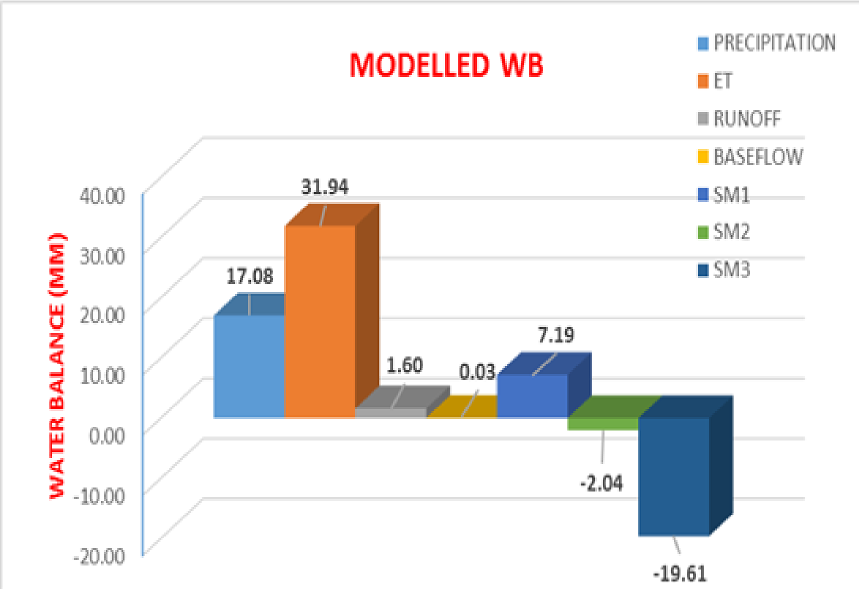



**Figure 5.10** Water budget (WB) for without assimilation

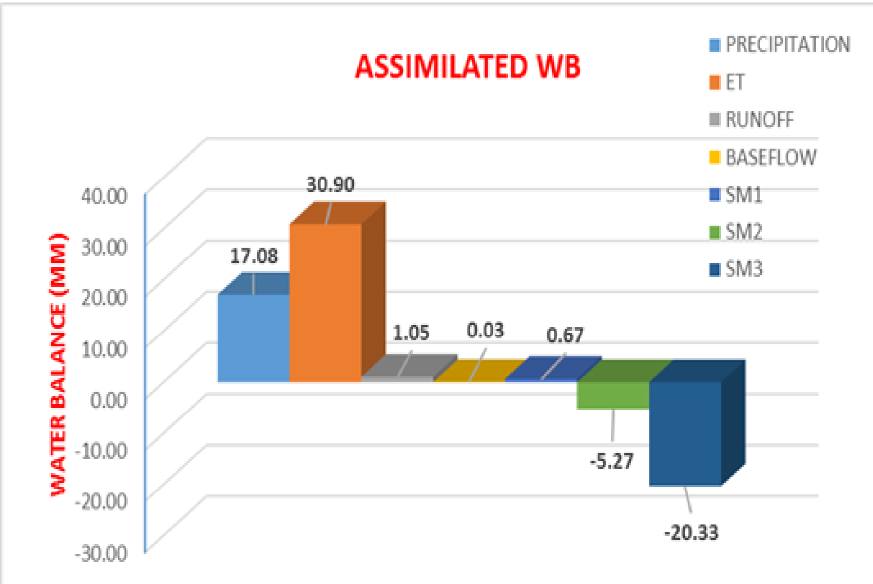



**Figure 5.11** Water budget for with assimilation

From above Figures 5.5 and 5.6 it is cleared that first layer soil moisture impacts second layer and third layer soil moisture in acceptable change. Runoff without assimilation is more than that of with assimilation,. ET is also more in without assimilation whereas soil moisture deficit for first layer in assimilation is 0.67mm while in without it is 7.19mm, second layer soil moisture deficit is -2.04mm and -5.27mm for modelled and assimilated mode respectively. Third layer soil moisture is not more affected by the first layer soil moisture assimilation in VIC. This difference is shown here for day 1 layer one and two and for day 31 layer one and layer two respectively.

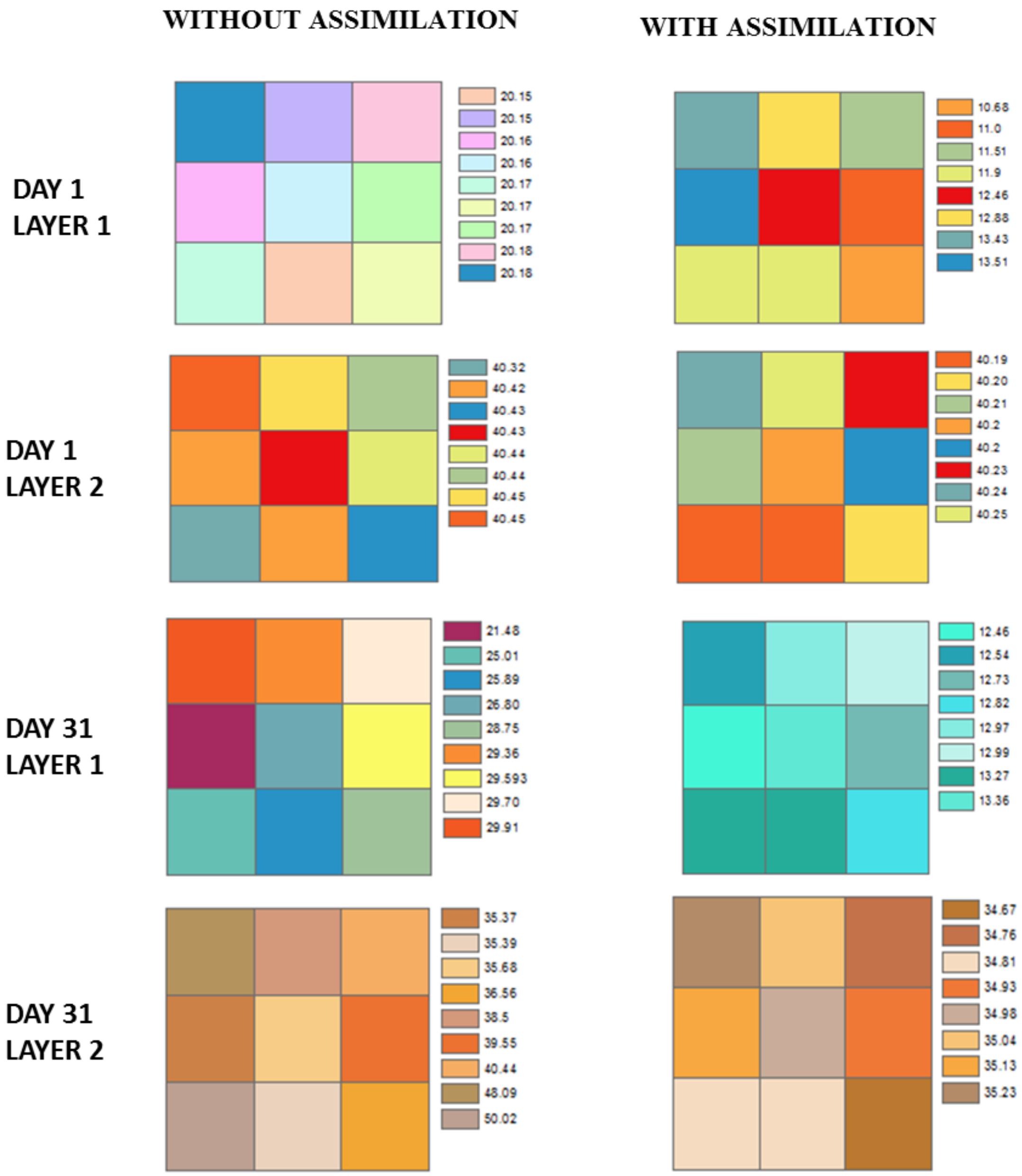



**Figure 5.12** Layer one and layer two soil moisture behaviour before and after assimilation

Evidently, this chapter results that VIC has ability to assimilate the soil moisture data through EnKF data assimilation technique. The output of assimilated soil moisture product can be used for the future climatic predictions and for the irrigation management after validation with field soil moisture data.

# 6 CONCLUSIONS AND RECOMMENDATIONS

The primary objectives of the research are to assimilate the soil moisture in VIC, parameter sensitivity for the VIC model to decide the minimum forcing parameters to run VIC precisely,

Perform hydrological simulation to obtain water budget components and simulate the streamflow.

The research focused on data assimilation techniques to obtain the soil moisture analysis states, the comparison between two techniques, followed by the VIC simulations to study the assimilation effects on the water balance components.

Following conclusions were made from the present study:

i. The study successfully attempts the assimilation of soil moisture for month of January, 2005.
ii. The soil moisture deficit is observed in first layer and as well as in second. In second scenario the ΔSM1 was -16.55mm and ΔSM2 was -88.39mm whereas in third scenario for first ten days i.e. for day 1 to day 11 it was -28.59mm and -85.75mm respectively; for run day 11 to day 21 it was observed -20.65mm and -84.68 respectively, in last run it was -23.63mm and -84.97mm. From this we have seen the effect of first layer soil moisture can be accepted but for second layer it is vague The soil moisture deficit is observed in first layer and as well as in second. In second scenario the ΔSM1 was -16.55mm and ΔSM2 was -88.39mm whereas in third scenario for first ten days i.e. for day 1 to day 11 it was -28.59mm and -85.75mm respectively; for run day 11 to day 21 it was observed -20.65mm and -84.68 respectively, in last run it was -23.63mm and -84.97mm. From this we have seen the effect of first layer soil moisture can be accepted but for second layer it is vague.
iii. Though first layer soil moisture assimilation is good approach, however, direct insertion method is not acceptable as it ignores the model physics. It is assumed in this method that the observations are pure or unbiased and the model state is not of use which is unacceptable.
iv. Other assimilation method is Ensemble Kalman filter EnKF. Literature also shows that this technique is good for the assimilation of soil moisture
v. The ensembles for nine grids are generated for 31 days. The background error covariance matrix, observation error covariance matrix is calculated through standard equations and the Kalman gain is generated from these matrices is of 9 X 9 dimension.
vi. The analysis for 31 days is carried out by using this Kalman gain. The results were analyzed with the rainfall pattern and the trends are perfectly matching. Without data assimilation i.e. forecasted soil moistures are varying with the rainfall events but after event the trend starts decreasing slowly but continuously whereas in analysis the trends followed the water budget in area. The soil moisture in analysis is not decreasing suddenly after the rainfall event but it shows the soil moisture retention properties and though there is no rainfall event the moisture in varying ups and downs because it is accounting the irrigation in that area.
vii. The water balance is also calculated to check the effect of first layer soil moisture on the second and the third layer of the VIC. Runoff without assimilation is more than that of with

assimilation,. ET is also more in without assimilation whereas soil moisture deficit for first layer in assimilation is 0.67mm while in without it is 7.19mm, second layer soil moisture deficit is -2.04mm and -5.27mm for modelled and assimilated mode respectively. Third layer soil moisture is not more affected by the first layer soil moisture assimilation.

viii. Parameter sensitivity for the VIC model is also done in this study. The four scenarios were generated to perform this objective. Five parameters were chosen viz. Tmax, Tmin, Precipitation, Wind speed and Cloud factor.

 Difference between runoff is -18.10mm, baseflow is varying with -5.84mm and evaporation is deviated by 24.33mm if we take percentage consideration then it is -8.54%, -46.60% and 3.15% respectively with respective to first scenario. In case (B) water budget components comparison is -18.10mm for runoff, -9.35mm for baseflow and for evaporation it is 27.64mm and this is in percentage with respective to first scenario as -6.27%, -18.50% And 4.10% respectively.

ix. The difference between discharge of first scenario and the second is 558.97 Cumec i.e. 6.8% with respective to first scenario hence it is clear that wind speed parameter we must take into the consideration in forcings for VIC model.

 It concludes that cloud factor influences nothing but wind speed affects the water budget. This is because of model computes cloud factor from (Tmax - Tmin) range. In this case, VIC uses the MTCLIM algorithms to convert daily min and max temperature to humidity and incoming shortwave radiation. Hence only wind speed has effects on the VIC model water budget.

x. Conclusion of this objective is that in VIC model meteorological input forcings we must give at least four parameters in forcing and those are Tmax, Tmin, Prec, Wind speed.

xi. The VIC has been calibrated and validated for Farakka monthly and annually.

xii. The soil parameters determined after calibration was binfilt=0.3, Ds=0.001 and Ws=0.8.

xiii. CWC has reported that snow/glaciers covers 0.94 % of the total area of the Ganga basin with an annual snowmelt contribution of about 1% to 5% throughout the basin; so we have model calibrated and validated in energy balance mode to account the snowmelt runoff in basin. The coefficient of determination between GRDC observation discharge data and that of model simulated discharge is 0.89.

## 6.1 Recommendations

i. Ensemble Kalman filter should be applied spatially also to check the effect of soil moisture On large scale.

ii. For macroscale models and macroscale watersheds the assimilation should be done with the help of some toolkit like LIS for statistically unbiased study and there should be a high computational efficient computers for faster and complicated iterations of assimilation techniques.

iii. Field soil moisture data if available must be used for calibration and validation of assimilation and also for bias correction.

iv. The performance of VIC will improve if the calibration of the hydrological model is done for more number of years for more number of stations with observed data of respective years. This will ensure a lower error term and will give more accurate simulations and a better idea of the trend of the water balance components.

## 6.2 Future Scope of This Study

The various data assimilation tools are available for the various land surface models the specific tool can be developed for VIC model to assimilate the soil moisture.

The VIC sensitivity for assimilating various soil moisture products like SMOS, ASCAT, and SMAP can be checked.

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# APPENDIX 1

**Table A1.1** Water budget components for year 1990 to 2005

| | 1990 | | | | 1991 | | | | 1992 | | | | 1993 | | | | 1994 | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| Row Labels | Sum of Avg_Rainfall | Sum of Avg_Runoff | Sum of Avg_Baseflow | Sum of Avg_Evap | Sum of Avg_Rainfall | Sum of Avg_Runoff | Sum of Avg_Baseflow | Sum of Avg_Evap | Sum of Avg_Rainfall | Sum of Avg_Runoff | Sum of Avg_Baseflow | Sum of Avg_Evap | Sum of Avg_Rainfall | Sum of Avg_Runoff | Sum of Avg_Baseflow | Sum of Avg_Evap | Sum of Avg_Rainfall | Sum of Avg_Runoff | Sum of Avg_Baseflow | Sum of Avg_Evap |
| 1 | 2.4689 | 0.6239 | 0.2434 | 81.7529 | 0 | 0 | 0.3131 | 46.4392 | 0 | 0 | 0.2852 | 7.7955 | 0 | 0 | 0.2604 | 9.0525 | 17.1111 | 3.4708 | 0.3119 | 43.7438 |
| 2 | 0.6771 | 0.0373 | 0.2184 | 57.4994 | 0 | 0 | 0.2802 | 36.7489 | 0 | 0 | 0.2648 | 5.7025 | 0 | 0 | 0.2329 | 7.628 | 2.5117 | 0.2874 | 0.2799 | 35.2152 |
| 3 | 0 | 0 | 0.2395 | 41.9537 | 0 | 0 | 0.3083 | 27.2391 | 0 | 0 | 0.2814 | 7.8415 | 0.144 | 0 | 0.2567 | 6.1281 | 0 | 0 | 0.3069 | 22.8034 |
| 4 | 0 | 0 | 0.2309 | 19.2735 | 0 | 0 | 0.2963 | 13.6855 | 0 | 0 | 0.27 | 2.4572 | 0 | 0 | 0.246 | 0 | 0 | 0 | 0.2948 | 11.7673 |
| 5 | 30.2267 | 2.7789 | 0.2356 | 26.664 | 0 | 0 | 0.3038 | 11.8199 | 0 | 0 | 0.2766 | 0 | 1.4071 | 0.0462 | 0.2523 | 1.3609 | 1.4615 | 0.1199 | 0.3026 | 12.9294 |
| 6 | 148.6975 | 16.8132 | 0.227 | 109.4666 | 149.221 | 14.7185 | 0.2912 | 110.7698 | 58.0066 | 5.4114 | 0.266 | 37.9092 | 151.0856 | 13.6856 | 0.243 | 78.077 | 262.4284 | 36.436 | 0.2908 | 94.724 |
| 7 | 322.057 | 57.2309 | 0.2325 | 131.63 | 383.9189 | 69.0375 | 0.2989 | 108.7906 | 169.4686 | 21.7134 | 0.2728 | 72.9337 | 511.0471 | 112.2499 | 0.248 | 144.6593 | 296.2292 | 60.924 | 0.2976 | 141.0494 |
| 8 | 529.8802 | 158.5402 | 0.2335 | 149.0457 | 169.8832 | 36.5278 | 0.2968 | 130.096 | 226.9597 | 32.292 | 0.2701 | 129.6558 | 339.0422 | 129.4622 | 3.5187 | 151.7914 | 417.636 | 132.6264 | 0.2959 | 131.3605 |
| 9 | 204.764 | 58.0602 | 11.9184 | 130.386 | 22.0717 | 3.1386 | 0.285 | 132.5868 | 96.6137 | 18.1623 | 0.2599 | 120.374 | 206.9039 | 61.2346 | 2.5619 | 127.1181 | 244.471 | 116.7937 | 44.3133 | 131.2032 |
| 10 | 14.5198 | 3.7126 | 8.8335 | 117.5404 | 0 | 0 | 0.2919 | 74.8825 | 43.1179 | 6.6408 | 0.2666 | 74.036 | 10.6886 | 3.2729 | 1.7696 | 116.4473 | 0.6377 | 0.0954 | 1.4818 | 123.0284 |
| 11 | 0 | 0 | 0.5003 | 86.3317 | 0.2248 | 0.0032 | 0.2806 | 26.1028 | 0 | 0 | 0.2554 | 34.91 | 0.2552 | 0.0118 | 0.3205 | 86.4961 | 0.1329 | 0 | 0.3066 | 68.0237 |
| 12 | 12.651 | 3.2514 | 0.3156 | 63.4855 | 0 | 0 | 0.288 | 14.0433 | 0 | 0 | 0.2624 | 17.4637 | 0.2693 | 0.0173 | 0.3141 | 54.5077 | 0 | 0 | 0.3134 | 48.2364 |
| | | | | | | | | | | | | | | | | | | | | |
| **Grand Total** | **1265.9422** | **301.0486** | **23.4286** | **1015.029** | **725.3196** | **123.4256** | **3.5341** | **733.2044** | **594.1665** | **84.2199** | **3.2312** | **511.0791** | **1220.843** | **319.9805** | **10.2241** | **783.2664** | **1242.62** | **350.7536** | **48.7955** | **864.0847** |

| 1995 | | | | 1996 | | | | 1997 | | | | 1998 | | | | 1999 | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| Sum of Avg_Rainfall | Sum of Avg_Runoff | Sum of Avg_Baseflow | Sum of Avg_Evap | Sum of Avg_Rainfall | Sum of Avg_Runoff | Sum of Avg_Baseflow | Sum of Avg_Evap | Sum of Avg_Rainfall | Sum of Avg_Runoff | Sum of Avg_Baseflow | Sum of Avg_Evap | Sum of Avg_Rainfall | Sum of Avg_Runoff | Sum of Avg_Baseflow | Sum of Avg_Evap | Sum of Avg_Rainfall | Sum of Avg_Runoff | Sum of Avg_Baseflow | Sum of Avg_Evap |
| 1.8145 | 0.3093 | 0.3112 | 30.9487 | 0 | 0 | 0.2852 | 15.3889 | 0.4783 | 0.0545 | 0.3124 | 40.6405 | 0.7569 | 0.1151 | 0.2887 | 41.2246 | 0 | 0 | 0.2658 | 34.5887 |
| 0 | 0 | 0.2792 | 25.4006 | 0 | 0 | 0.2639 | 11.5376 | 0 | 0 | 0.28 | 32.2766 | 0 | 0 | 0.2592 | 35.8899 | 29.0594 | 3.4827 | 0.238 | 42.6339 |
| 4.8161 | 0.6055 | 0.3069 | 22.2963 | 0 | 0 | 0.2804 | 8.998 | 0 | 0 | 0.3074 | 24.8807 | 0 | 0 | 0.2852 | 24.0258 | 0 | 0 | 0.2615 | 25.5258 |
| 0 | 0 | 0.2941 | 10.92 | 0.372 | 0.0165 | 0.2697 | 10.1419 | 2.3649 | 0.1349 | 0.2954 | 15.3419 | 0 | 0 | 0.273 | 13.8935 | 0 | 0 | 0.2517 | 13.3192 |
| 1.5777 | 0.0239 | 0.3019 | 12.7249 | 2.4713 | 0.2668 | 0.2759 | 3.5757 | 4.3408 | 0.5989 | 0.3031 | 16.2429 | 0 | 0 | 0.2803 | 11.998 | 4.003 | 0.5241 | 0.2573 | 13.1706 |
| 75.2302 | 2.8343 | 0.2901 | 63.8308 | 45.6254 | 2.7094 | 0.2651 | 38.703 | 123.125 | 12.7465 | 0.291 | 68.8597 | 122.4266 | 12.7165 | 0.2696 | 58.129 | 190.9063 | 24.4214 | 0.2474 | 91.4798 |
| 332.1053 | 54.7778 | 0.2976 | 105.21 | 602.7681 | 138.9342 | 0.2726 | 104.3476 | 440.1566 | 90.4032 | 0.298 | 125.8082 | 299.8268 | 44.3919 | 0.2759 | 147.0502 | 231.0252 | 33.1213 | 0.2542 | 129.205 |
| 254.2932 | 49.363 | 0.2947 | 150.8952 | 306.594 | 110.3056 | 6.0169 | 139.1012 | 294.7489 | 79.1003 | 0.2964 | 148.579 | 141.7596 | 20.86 | 0.2738 | 139.3944 | 119.8775 | 20.57 | 0.2512 | 138.3119 |
| 155.1426 | 48.1651 | 0.2845 | 141.0752 | 199.4439 | 78.8256 | 30.5511 | 129.5913 | 48.6987 | 8.733 | 0.288 | 124.787 | 393.8364 | 97.4311 | 0.264 | 123.6999 | 266.3965 | 47.2215 | 0.2419 | 123.6873 |
| 5.5616 | 1.1049 | 0.2914 | 95.4464 | 35.7879 | 8.8411 | 3.158 | 113.7042 | 16.2517 | 3.1445 | 0.2957 | 106.2225 | 52.3731 | 14.8272 | 0.2719 | 115.6227 | 153.9249 | 31.152 | 0.248 | 126.2491 |
| 0 | 0 | 0.2796 | 44.655 | 1.7926 | 0.455 | 0.3492 | 85.0269 | 73.5172 | 13.0024 | 0.2843 | 75.0552 | 0 | 0 | 0.261 | 76.9553 | 0 | 0 | 0.2378 | 76.4736 |
| 0 | 0 | 0.2871 | 25.2334 | 0 | 0 | 0.3147 | 59.6635 | 35.8829 | 5.7108 | 0.2914 | 54.6027 | 0 | 0 | 0.2674 | 51.8048 | 0 | 0 | 0.2446 | 41.3141 |
| | | | | | | | | | | | | | | | | | | | |
| **830.5412** | **157.1838** | **3.5183** | **728.6365** | **1194.855** | **340.3542** | **42.3027** | **719.7798** | **1039.565** | **213.629** | **3.5431** | **833.2969** | **1010.979** | **190.3418** | **3.27** | **839.6881** | **995.1928** | **160.493** | **2.9994** | **855.959** |

| 2000 | | | | 2001 | | | | 2002 | | | | 2003 | | | | 2004 | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| **Sum of Avg_Rainfall** | **Sum of Avg_Runoff** | **Sum of Avg_Baseflow** | **Sum of Avg_Evap** | **Sum of Avg_Rainfall** | **Sum of Avg_Runoff** | **Sum of Avg_Baseflow** | **Sum of Avg_Evap** | **Sum of Avg_Rainfall** | **Sum of Avg_Runoff** | **Sum of Avg_Baseflow** | **Sum of Avg_Evap** | **Sum of Avg_Rainfall** | **Sum of Avg_Runoff** | **Sum of Avg_Baseflow** | **Sum of Avg_Evap** | **Sum of Avg_Rainfall** | **Sum of Avg_Runoff** | **Sum of Avg_Baseflow** | **Sum of Avg_Evap** |
| 0 | 0 | 0.2418 | 28.7645 | 0 | 0 | 0.2202 | 0 | 0 | 0 | 0.2015 | 8.3569 | 0 | 0 | 0.1829 | 10.8237 | 10.4634 | 2.3131 | 0.3131 | 48.8672 |
| 0 | 0 | 0.225 | 21.6191 | 0 | 0 | 0.1986 | 0 | 19.8761 | 1.4633 | 0.1805 | 19.6858 | 0.7017 | 0.034 | 0.1652 | 7.0752 | 0 | 0 | 0.2904 | 37.5617 |
| 0 | 0 | 0.2387 | 16.6394 | 0.4078 | 0.0224 | 0.217 | 0.3854 | 0 | 0 | 0.1984 | 4.9278 | 0 | 0 | 0.1805 | 7.9503 | 0 | 0 | 0.3084 | 22.9392 |
| 0 | 0 | 0.2289 | 10.2356 | 0.3641 | 0.0153 | 0.2094 | 0.3489 | 1.812 | 0.2124 | 0.1906 | 2.8966 | 0 | 0 | 0.174 | 4.3118 | 0 | 0 | 0.2964 | 11.3719 |
| 9.7062 | 1.0603 | 0.2356 | 16.9581 | 2.039 | 0.0403 | 0.2139 | 1.9988 | 0 | 0 | 0.1953 | 0 | 0 | 0 | 0.1782 | 0 | 0 | 0 | 0.3038 | 12.2342 |
| 71.4631 | 5.6151 | 0.225 | 51.9389 | 211.4706 | 25.4234 | 0.206 | 106.5881 | 243.5222 | 31.9171 | 0.1878 | 90.5075 | 148.219 | 19.7013 | 0.171 | 48.5122 | 41.2157 | 3.8352 | 0.2913 | 47.0009 |
| 263.9522 | 33.7433 | 0.2317 | 137.1975 | 211.0059 | 30.6542 | 0.2108 | 128.172 | 85.0088 | 13.2836 | 0.1922 | 124.0848 | 656.2478 | 175.6193 | 0.1776 | 159.1213 | 253.4442 | 28.8006 | 0.299 | 113.2797 |
| 161.5891 | 24.6145 | 0.2294 | 133.6178 | 181.9868 | 32.0911 | 0.2094 | 141.3476 | 241.7276 | 36.4075 | 0.1912 | 118.156 | 220.5242 | 70.889 | 0.2397 | 146.2579 | 405.6122 | 97.7419 | 0.2976 | 132.731 |
| 18.9811 | 1.7231 | 0.2204 | 84.8442 | 17.209 | 1.7267 | 0.201 | 102.0175 | 189.2748 | 42.4548 | 0.183 | 137.0228 | 311.1674 | 118.6401 | 7.0864 | 129.1971 | 52.9639 | 12.7623 | 0.2857 | 144.4658 |
| 1.9784 | 0.2593 | 0.2263 | 31.7499 | 82.6841 | 13.2578 | 0.2061 | 59.2352 | 4.9683 | 0.9488 | 0.1885 | 88.7706 | 0 | 0.0939 | 19.2642 | 123.3275 | 15.0259 | 2.1682 | 0.2934 | 97.1655 |
| 0 | 0 | 0.2167 | 9.6598 | 0 | 0 | 0.198 | 33.2539 | 0 | 0 | 0.18 | 34.3065 | 0 | 0 | 0.6184 | 90.6545 | 0 | 0 | 0.282 | 46.968 |
| 0 | 0 | 0.2232 | 4.8966 | 0 | 0 | 0.2029 | 14.7344 | 0 | 0 | 0.1859 | 17.1447 | 0 | 0 | 0.3158 | 59.5755 | 0 | 0 | 0.2884 | 23.9715 |
| | | | | | | | | | | | | | | | | | | | |
| **527.6701** | **67.0156** | **2.7427** | **548.1214** | **707.1673** | **103.2312** | **2.4933** | **588.0818** | **786.1898** | **126.6875** | **2.2749** | **645.86** | **1336.86** | **384.9776** | **28.7539** | **786.807** | **778.7253** | **147.6213** | **3.5495** | **738.5566** |

| 2005 | | | |
|---|---|---|---|
| **Sum of Avg_Rainfall** | **Sum of Avg_Runoff** | **Sum of Avg_Baseflow** | **Sum of Avg_Evap** |
| 4.2456 | 0.319 | 0.2864 | 15.6096 |
| 0 | 0 | 0.2572 | 11.9101 |
| 4.1772 | 0.3931 | 0.2821 | 12.3056 |
| 3.7727 | 0.3104 | 0.2709 | 10.8506 |
| 2.8358 | 0.2457 | 0.2782 | 3.5731 |
| 70.0096 | 4.1179 | 0.267 | 53.2543 |
| 213.6843 | 26.5681 | 0.2734 | 91.5606 |
| 168.4772 | 33.4872 | 0.2717 | 143.702 |
| 166.7267 | 26.4183 | 0.261 | 105.1033 |
| 0 | 0 | 0.2671 | 74.4487 |
| 0 | 0 | 0.257 | 30.2356 |
| 0 | 0 | 0.2635 | 12.6878 |
| | | | |
| **633.9291** | **91.8597** | **3.2355** | **565.2413** |

# APPENDIX 2

**Table A2.1** Modelled Soil Moisture States for EnKF

| PIXEL ID | LAT | LONG | DAY 01 | DAY 02 | DAY 03 | DAY 04 | DAY 05 | DAY 06 | DAY 07 | DAY 08 | DAY 09 | DAY 10 | DAY 11 | DAY 12 | DAY 13 | DAY 14 |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| 5031 | 29.125 | 77.875 | 20.19 | 20.03 | 19.90 | 19.76 | 19.63 | 19.49 | 19.37 | 19.24 | 19.10 | 18.96 | 18.83 | 18.71 | 18.59 | 18.46 |
| 5032 | 29.125 | 78.125 | 20.19 | 20.03 | 19.89 | 19.74 | 19.60 | 19.46 | 19.33 | 19.20 | 19.05 | 18.91 | 18.77 | 18.63 | 18.49 | 18.36 |
| 5033 | 29.125 | 78.375 | 20.18 | 20.01 | 19.87 | 19.71 | 19.57 | 19.42 | 19.28 | 19.14 | 18.99 | 18.84 | 18.69 | 18.55 | 18.40 | 18.26 |
| 5159 | 28.875 | 77.875 | 20.16 | 19.98 | 19.82 | 19.66 | 19.52 | 19.36 | 19.23 | 19.09 | 18.93 | 18.78 | 18.64 | 18.50 | 18.37 | 18.23 |
| 5160 | 28.875 | 78.125 | 20.17 | 20.00 | 19.85 | 19.70 | 19.55 | 19.41 | 19.27 | 19.13 | 18.98 | 18.83 | 18.69 | 18.56 | 18.42 | 18.28 |
| 5161 | 28.875 | 78.375 | 20.18 | 20.01 | 19.86 | 19.71 | 19.57 | 19.42 | 19.29 | 19.15 | 19.00 | 18.85 | 18.71 | 18.58 | 18.44 | 18.30 |
| 5287 | 28.625 | 77.875 | 20.17 | 19.99 | 19.83 | 19.68 | 19.53 | 19.38 | 19.24 | 19.10 | 18.95 | 18.80 | 18.65 | 18.52 | 18.38 | 18.24 |
| 5288 | 28.625 | 78.125 | 20.16 | 19.98 | 19.82 | 19.67 | 19.52 | 19.36 | 19.23 | 19.08 | 18.93 | 18.77 | 18.63 | 18.50 | 18.36 | 18.22 |
| 5289 | 28.625 | 78.375 | 20.17 | 19.99 | 19.84 | 19.68 | 19.53 | 19.37 | 19.23 | 19.09 | 18.94 | 18.78 | 18.63 | 18.49 | 18.35 | 18.20 |

| DAY 15 | DAY 16 | DAY 17 | DAY 18 | DAY 19 | DAY 20 | DAY 21 | DAY 22 | DAY 23 | DAY 24 | DAY 25 | DAY 26 | DAY 27 | DAY 28 | DAY 29 | DAY 30 | DAY 31 |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| 18.33 | 18.21 | 18.17 | 18.10 | 17.99 | 17.89 | 17.80 | 18.42 | 29.43 | 29.01 | 28.66 | 28.34 | 28.02 | 36.11 | 31.93 | 30.68 | 29.92 |
| 18.21 | 18.08 | 17.97 | 17.85 | 17.73 | 17.63 | 17.53 | 17.45 | 27.89 | 27.63 | 27.39 | 27.16 | 26.91 | 31.13 | 31.94 | 30.67 | 29.90 |
| 18.11 | 17.97 | 17.85 | 17.73 | 17.61 | 17.49 | 17.39 | 17.31 | 29.69 | 29.21 | 28.81 | 28.45 | 28.11 | 33.79 | 31.50 | 30.42 | 29.71 |
| 18.09 | 17.96 | 17.85 | 17.74 | 17.63 | 17.52 | 17.43 | 17.42 | 17.54 | 17.46 | 17.39 | 17.30 | 17.20 | 22.10 | 21.88 | 21.65 | 21.43 |
| 18.14 | 18.00 | 17.89 | 17.78 | 17.96 | 17.85 | 17.75 | 17.66 | 23.77 | 23.63 | 23.48 | 23.32 | 23.13 | 28.11 | 27.85 | 27.52 | 27.22 |
| 18.16 | 18.02 | 17.91 | 17.80 | 18.83 | 18.70 | 18.58 | 18.49 | 28.71 | 28.38 | 28.09 | 27.81 | 27.52 | 33.03 | 31.26 | 30.28 | 29.61 |
| 18.10 | 17.97 | 17.86 | 17.75 | 17.93 | 17.81 | 17.71 | 17.65 | 21.72 | 21.60 | 21.48 | 21.34 | 21.17 | 25.79 | 25.56 | 25.27 | 25.01 |
| 18.07 | 17.94 | 17.83 | 17.72 | 18.19 | 18.07 | 17.96 | 17.88 | 23.86 | 23.71 | 23.57 | 23.40 | 23.20 | 27.16 | 26.94 | 26.65 | 26.38 |
| 18.05 | 17.92 | 17.80 | 17.68 | 18.66 | 18.53 | 18.40 | 18.31 | 26.79 | 26.60 | 26.41 | 26.21 | 25.98 | 30.57 | 29.91 | 29.31 | 28.83 |

**Table A2.2** AMSR-E observed Soil Moisture States for EnKF

| PIXEL ID | LAT | LONG | DAY 01 | DAY 02 | DAY 03 | DAY 04 | DAY 05 | DAY 06 | DAY 07 | DAY 08 | DAY 09 | DAY 10 | DAY 11 | DAY 12 | DAY 13 | DAY 14 |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| 5031 | 29.125 | 77.875 | 132 | 121 | 123 | 121.5 | 117 | 118.5 | 116 | 125 | 119 | 129 | 114 | 105 | 111 | 105 |
| 5032 | 29.125 | 78.125 | 125 | 112.5 | 120 | 115.5 | 113 | 113.5 | 113 | 123 | 115 | 126 | 121 | 113 | 117.5 | 116 |
| 5033 | 29.125 | 78.375 | 115 | 102.5 | 113 | 105.5 | 104 | 103 | 105 | 110 | 105 | 115 | 114.5 | 112 | 113.5 | 113 |
| 5159 | 28.875 | 77.875 | 127 | 116 | 122 | 118 | 116 | 118.5 | 115 | 127 | 118.5 | 130 | 109 | 102 | 110 | 102 |
| 5160 | 28.875 | 78.125 | 119 | 111.5 | 119 | 114 | 112 | 114 | 112 | 125 | 114 | 124 | 121 | 115 | 121.5 | 118 |
| 5161 | 28.875 | 78.375 | 107 | 102 | 110 | 103.5 | 101 | 102 | 104 | 110 | 103 | 113 | 114.5 | 111 | 115 | 112 |
| 5287 | 28.625 | 77.875 | 126 | 116.5 | 124 | 116.5 | 116 | 119.5 | 115 | 127 | 117 | 133 | 119 | 117 | 124 | 115 |
| 5288 | 28.625 | 78.125 | 114 | 110 | 115 | 112.5 | 110 | 112 | 111 | 125 | 111.5 | 125 | 121 | 119 | 123 | 118 |
| 5289 | 28.625 | 78.375 | 103 | 103.5 | 109 | 105 | 101 | 104 | 105 | 112 | 105.5 | 115 | 115 | 113 | 116.5 | 112 |

| DAY 15 | DAY 16 | DAY 17 | DAY 18 | DAY 19 | DAY 20 | DAY 21 | DAY 22 | DAY 23 | DAY 24 | DAY 25 | DAY 26 | DAY 27 | DAY 28 | DAY 29 | DAY 30 | DAY 31 |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| 115 | 105 | 118 | 112 | 120 | 112 | 106 | 116 | 118 | 135 | 124.5 | 134 | 122 | 118 | 124 | 109 | 126 |
| 124 | 116 | 124 | 119 | 124 | 117 | 114 | 121.5 | 129 | 143 | 130.5 | 139 | 125.5 | 123 | 126.5 | 114 | 131 |
| 121 | 112 | 122 | 117 | 123 | 113 | 114 | 118.5 | 129 | 144 | 130.5 | 139 | 124.5 | 127 | 127.5 | 114 | 130 |
| 113 | 103 | 117 | 106 | 120 | 109.5 | 107 | 117 | 118 | 138 | 127.5 | 138 | 123 | 121 | 125 | 112 | 126 |
| 129 | 119 | 130 | 119 | 128 | 118.5 | 120 | 124 | 134 | 153 | 136 | 147 | 128 | 130 | 130.5 | 120 | 135 |
| 121 | 112 | 122 | 115 | 123 | 113.5 | 114 | 117 | 132 | 150 | 131.5 | 142 | 123 | 130 | 127.5 | 114 | 128 |
| 128 | 117 | 136 | 118 | 138 | 120.5 | 120 | 128.5 | 133 | 157 | 139.5 | 154 | 133 | 135 | 134.5 | 121 | 134 |
| 131 | 120 | 134 | 119 | 132 | 118 | 123 | 125.5 | 135 | 161 | 137.5 | 152 | 128 | 135 | 132.5 | 121 | 134 |
| 124 | 115 | 125 | 116 | 125 | 114.5 | 118 | 119 | 136 | 156 | 132 | 144 | 132 | 133 | 130 | 115 | 129 |

**Table A2.3** Variances for the EnKF between forecast and observation

| PIXEL ID | LAT | LONG | DAY 01 | DAY 02 | DAY 03 | DAY 04 | DAY 05 | DAY 06 | DAY 07 | DAY 08 | DAY 09 | DAY 10 | DAY 11 | DAY 12 | DAY 13 | DAY 14 |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| 5031 | 29.125 | 77.875 | 48.8573 | 62.90393 | 57.6901 | 57.86797 | 62.81355 | 58.37724 | 60.35736 | 45.45726 | 51.90338 | 36.76361 | 55.26584 | 67.44351 | 56.05667 | 63.34409 |
| 5032 | 29.125 | 78.125 | 59.07152 | 77.02695 | 62.17953 | 67.0761 | 68.94479 | 65.7867 | 64.46163 | 47.54103 | 57.05687 | 39.79465 | 44.45822 | 53.73476 | 45.48019 | 45.66786 |
| 5033 | 29.125 | 78.375 | 75.35455 | 95.32788 | 73.37122 | 83.9624 | 84.0834 | 83.17258 | 77.10596 | 66.26611 | 72.11067 | 53.85799 | 52.43208 | 53.97253 | 49.74622 | 48.44438 |
| 5159 | 28.875 | 77.875 | 55.66801 | 70.2311 | 58.09336 | 61.85508 | 62.65197 | 56.47222 | 59.71735 | 40.77206 | 50.18022 | 33.40956 | 59.87664 | 68.95642 | 54.28153 | 64.45681 |
| 5160 | 28.875 | 78.125 | 68.44749 | 78.35436 | 63.20568 | 68.85183 | 69.77762 | 64.09443 | 65.14588 | 43.98608 | 57.52161 | 41.38992 | 43.44919 | 49.78008 | 39.29535 | 41.97874 |
| 5161 | 28.875 | 78.375 | 89.85334 | 96.23414 | 78.54391 | 87.65079 | 89.67522 | 85.06557 | 79.0321 | 66.45836 | 75.76832 | 57.05385 | 52.73664 | 55.89058 | 48.15111 | 50.40148 |
| 5287 | 28.625 | 77.875 | 57.24738 | 69.52336 | 55.23314 | 64.41935 | 62.8553 | 55.17865 | 59.93547 | 40.96299 | 52.55187 | 30.20382 | 45.60841 | 46.48967 | 35.77555 | 45.44782 |
| 5288 | 28.625 | 78.125 | 76.8112 | 80.67632 | 69.28232 | 70.82906 | 72.51885 | 66.6509 | 66.03838 | 43.33852 | 60.52373 | 39.36057 | 42.64874 | 43.50062 | 36.69452 | 41.17661 |
| 5289 | 28.625 | 78.375 | 97.43072 | 92.97781 | 79.85567 | 84.23568 | 88.88718 | 80.54165 | 76.29498 | 62.25368 | 70.31996 | 52.9722 | 50.84546 | 51.68172 | 44.84177 | 49.014 |

| DAY 15 | DAY 16 | DAY 17 | DAY 18 | DAY 19 | DAY 20 | DAY 21 | DAY 22 | DAY 23 | DAY 24 | DAY 25 | DAY 26 | DAY 27 | DAY 28 | DAY 29 | DAY 30 | DAY 31 |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| 46.58472 | 59.42097 | 40.60876 | 47.61552 | 35.93403 | 44.76948 | 51.90626 | 46.49467 | 310.9756 | 240.5942 | 262.7706 | 223.1767 | 250.1206 | 591.19 | 381.4365 | 391.3157 | 299.8681 |
| 33.80608 | 42.03188 | 31.0171 | 35.42749 | 28.46116 | 35.12459 | 37.55484 | 28.13348 | 224.7331 | 177.6622 | 205.7159 | 175.8037 | 206.0718 | 354.6555 | 372.0231 | 371.4293 | 282.1459 |
| 36.10928 | 45.8505 | 31.94397 | 36.34522 | 28.14939 | 38.34086 | 35.85854 | 29.81924 | 281.8604 | 219.1969 | 248.365 | 211.8451 | 245.1229 | 444.8472 | 351.5588 | 361.8897 | 279.3311 |
| 46.06337 | 58.6419 | 37.76103 | 50.91393 | 31.64625 | 43.14651 | 45.24177 | 32.72984 | 32.96023 | 13.41537 | 21.50548 | 12.27101 | 24.00902 | 99.90202 | 87.8925 | 109.1941 | 78.04132 |
| 27.4157 | 37.26736 | 23.92775 | 34.55441 | 26.66793 | 36 | 33.00503 | 27.70864 | 107.5431 | 69.32061 | 97.67764 | 74.3682 | 106.6449 | 228.43 | 219.1732 | 240.9014 | 188.2988 |
| 36.66424 | 46.56698 | 32.6338 | 39.68118 | 42.68793 | 54.0372 | 51.54666 | 46.06473 | 240.4515 | 179.0458 | 223.2693 | 185.3056 | 231.6058 | 401.0327 | 342.7571 | 356.4468 | 282.5761 |
| 28.07587 | 39.29451 | 18.11155 | 35.3454 | 17.0291 | 33.2091 | 32.62161 | 23.08706 | 70.96658 | 34.81708 | 56.68935 | 35.324 | 62.0109 | 151.0064 | 146.5447 | 173.5183 | 134.8494 |
| 24.73073 | 35.32044 | 19.6311 | 33.89452 | 24.90309 | 39.30788 | 32.0741 | 28.40677 | 107.3524 | 57.96081 | 96.37545 | 67.29741 | 108.1038 | 186.4973 | 187.3367 | 211.6239 | 168.509 |
| 31.94058 | 41.15736 | 28.08046 | 36.98829 | 37.9801 | 50.06978 | 43.57716 | 41.02915 | 173.9761 | 120.9054 | 174.4856 | 139.4855 | 163.2747 | 298.3427 | 286.0631 | 317.1961 | 253.7171 |

**Table A2.4** Updated soil moisture for each day (Analysis)

| PIXEL ID | LAT | LONG | DAY 01 | DAY 02 | DAY 03 | DAY 04 | DAY 05 | DAY 06 | DAY 07 | DAY 08 | DAY 09 | DAY 10 | DAY 11 | DAY 12 | DAY 13 | DAY 14 |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| 5031 | 29.125 | 77.875 | 13.43521 | 12.13796 | 12.29525 | 12.15416 | 11.71209 | 11.84624 | 11.60645 | 12.47294 | 11.91577 | 12.86832 | 11.43717 | 10.5202 | 11.08607 | 10.51264 |
| 5032 | 29.125 | 78.125 | 12.90979 | 11.32126 | 11.96539 | 11.56794 | 11.31089 | 11.34738 | 11.30126 | 12.2451 | 11.53306 | 12.54146 | 12.12112 | 11.33598 | 11.73166 | 11.60546 |
| 5033 | 29.125 | 78.375 | 11.51124 | 10.25053 | 11.29965 | 10.5503 | 10.40005 | 10.30003 | 10.49993 | 10.99982 | 10.50019 | 11.49965 | 11.45002 | 11.2001 | 11.34994 | 11.30002 |
| 5159 | 28.875 | 77.875 | 13.51902 | 11.779 | 12.15699 | 11.83377 | 11.62181 | 11.82788 | 11.53011 | 12.57158 | 11.91996 | 12.87643 | 11.06457 | 10.2637 | 10.93766 | 10.25435 |
| 5160 | 28.875 | 78.125 | 12.46976 | 11.22989 | 11.85324 | 11.42824 | 11.21358 | 11.38768 | 11.21111 | 12.40241 | 11.46328 | 12.33059 | 12.11583 | 11.53975 | 12.10679 | 11.82034 |
| 5161 | 28.875 | 78.375 | 11.04096 | 10.22758 | 10.9707 | 10.37094 | 10.10872 | 10.19701 | 10.39309 | 10.97698 | 10.32262 | 11.26095 | 11.44226 | 11.11321 | 11.48402 | 11.21115 |
| 5287 | 28.625 | 77.875 | 13.34075 | 11.73507 | 12.30016 | 11.66429 | 11.59184 | 11.89026 | 11.49696 | 12.55908 | 11.76409 | 13.1102 | 11.95557 | 11.70568 | 12.28994 | 11.52221 |
| 5288 | 28.625 | 78.125 | 11.98835 | 11.06133 | 11.46936 | 11.26374 | 11.01599 | 11.18747 | 11.1052 | 12.38901 | 11.22922 | 12.39931 | 12.1217 | 11.91593 | 12.27051 | 11.83336 |
| 5289 | 28.625 | 78.375 | 10.68739 | 10.36337 | 10.87653 | 10.51533 | 10.1157 | 10.38863 | 10.49546 | 11.16754 | 10.57538 | 11.4552 | 11.49783 | 11.30927 | 11.63308 | 11.21995 |

| DAY 15 | DAY 16 | DAY 17 | DAY 18 | DAY 19 | DAY 20 | DAY 21 | DAY 22 | DAY 23 | DAY 24 | DAY 25 | DAY 26 | DAY 27 | DAY 28 | DAY 29 | DAY 30 | DAY 31 |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| 11.47457 | 10.52101 | 11.76548 | 11.21383 | 11.97801 | 11.21903 | 10.61359 | 11.59008 | 12.10746 | 13.45106 | 12.48008 | 13.36813 | 12.23374 | 12.20781 | 12.39427 | 10.93466 | 12.54879 |
| 12.35849 | 11.63418 | 12.36067 | 11.92136 | 12.37541 | 11.73102 | 11.41577 | 12.11352 | 13.4532 | 14.23991 | 13.11723 | 13.84735 | 12.61819 | 12.56467 | 12.7787 | 11.46019 | 13.00287 |
| 12.09967 | 11.20042 | 12.1996 | 11.70024 | 12.29974 | 11.30048 | 11.39996 | 11.84981 | 12.92183 | 14.39921 | 13.05089 | 13.89954 | 12.45089 | 12.70914 | 12.74998 | 11.4007 | 12.99934 |
| 11.20701 | 10.36804 | 11.57381 | 10.67703 | 11.8688 | 11.02715 | 10.72633 | 11.60845 | 11.8949 | 13.55788 | 12.83931 | 13.67791 | 12.44285 | 12.63461 | 12.51436 | 11.31502 | 12.46092 |
| 12.81393 | 11.96241 | 12.91628 | 11.96942 | 12.75197 | 11.91105 | 11.99415 | 12.36976 | 13.84126 | 15.13992 | 13.7322 | 14.60095 | 12.93888 | 13.42026 | 13.08056 | 12.0748 | 13.37534 |
| 12.05952 | 11.23376 | 12.1553 | 11.52708 | 12.31407 | 11.38884 | 11.39954 | 11.68717 | 13.67838 | 14.90971 | 13.24256 | 14.14097 | 12.38651 | 13.31936 | 12.77865 | 11.45602 | 12.73187 |
| 12.64932 | 11.754 | 13.36108 | 11.86813 | 13.56861 | 12.09786 | 11.96549 | 12.72968 | 13.66007 | 15.34323 | 14.05087 | 15.1346 | 13.4205 | 13.95297 | 13.43337 | 12.17802 | 13.23122 |
| 12.99012 | 12.07236 | 13.28051 | 11.9996 | 13.13893 | 11.89506 | 12.26917 | 12.52709 | 13.96572 | 15.83042 | 13.94131 | 15.05595 | 12.98394 | 13.83678 | 13.30209 | 12.18916 | 13.29039 |
| 12.33404 | 11.54041 | 12.44554 | 11.64165 | 12.50909 | 11.50089 | 11.78478 | 11.89404 | 14.06009 | 15.46807 | 13.34012 | 14.32163 | 13.27071 | 13.62025 | 13.0379 | 11.57452 | 12.82018 |

# APPENDIX 3

**A3.1** MATLAB code to remove Nan values from Fluxes_ files

```
x=dir();
for i=3:length(x);
filename=x(i,1).name;
userpath('');
fidInFile = fopen(filename,'r');            %# Open input file for reading
userpath('');
fidOutFile = fopen(filename,'w');  %# Open output file for writing
nextLine = fgets(fidInFile);                %# Get the first line of input
while nextLine >= 0                         %# Loop until getting -1 (end
of file)
nextLine = strrep(nextLine,'nan','0.0000');  %# Replace wordA with wordB
fprintf(fidOutFile,'%s',nextLine);         %# Write the line to the output
file
nextLine = fgets(fidInFile);               %# Get the next line of input
end
```

**A3.2** MATLAB code for calculating update soil moisture state

```
SM = importdata();
Soil_moisture=SM.data.Sheet5(:,2);
Vegparam=importdata('\t', 0);
[SM_state] = xlsread();
[m,n]=size(Soil_moisture);
sum_SMstate=0;
SMfraction=0;
i=2;vegParamCounter=1;k=2;temp_counter=1;


while i<=m

noOfVegetationClass=vegparam(vegParamCounter,2);

vegFraction=vegparam((vegParamCounter+1):(vegParamCounter+noOfVegetationCl
ass),3);

Single_SM=Soil_moisture(i);
temp_counter=1;


vegParamCounter=vegParamCounter+noOfVegetationClass+1

for index=k:(k+noOfVegetationClass-1)

       SMfraction=SM_state(index)*vegFraction(temp_counter,1);
       vegFraction(temp_counter,1);
       temp_counter=temp_counter+1;
       sum_SMstate=sum_SMstate+SMfraction;
end
temp_counter=1;
```

```
for index=k:(k+noOfVegetationClass-1)
    temp_SM(temp_counter)=SM_state(index)/sum_SMstate;

temp_counter=temp_counter+1;
end

for j=1:noOfVegetationClass
    Final_SM(j)=temp_SM(j)*Single_SM;
end


k=index+3;
sum_SMstate=0;


 dlmwrite(',Final_SM(1:j),'delimiter','\n','-append');
 dlmwrite('E:\GANGA_NEW\GANGA_DA\GANGA\updated-SM.txt','
 ','delimiter','\n','-append');
 FinalSM=0;
    i=i+1;

 end
```