EVALUATION OF SCALE ISSUES IN SWAT

A Thesis

by

SIVARAJAH MYLEVAGANAM

Submitted to the Office of Graduate Studies of
Texas A&M University
in partial fulfillment of the requirements for the degree of

MASTER OF SCIENCE

December 2009

Major Subject: Biological and Agricultural Engineering

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Approved by:

Chair of Committee,	Raghavan Srinivasan
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ABSTRACT

Evaluation of Scale Issues in SWAT. (December 2009)

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In Soil and Water Assessment Tool (SWAT), oftentimes, Critical Source Area (CSA), the minimum upstream drainage area that is required to initiate a stream, is used to subdivide a watershed. In the current literature, CSA has been used as a trial and error process to define the subwatershed levels. On the other hand, the ongoing collaboration of the United States Environmental Protection Agency Office of Water and the United States Geological Survey has promoted a national level predefined catchments and flowlines called National Hydrography Dataset (NHD) Plus to ease watershed modeling in the United States. The introduction of NHDPlus can eliminate the uncertain nature in defining the number of subwatersheds required to model the hydrologic system.

This study demonstrates an integrated modeling environment with SWAT and NHDPlus spatial datasets. A spatial tool that was developed in a Geographical Information System (GIS) environment to by-pass the default watershed delineation in ArcSWAT, the GIS interface to SWAT, with the introduction of NHDPlus catchments and flowlines, was used in this study. This study investigates the effect of the spatial size (catchment area) of the NHDPlus and the input data resolution (cell/pixel size) within NHDPlus catchments on SWAT streamflow and sediment prediction. In addition, an entropy based watershed subdivision scheme is presented by using the landuse and soil spatial datasets with the conventional CSA approach to investigate if one of the CSAs can be considered to produce the best SWAT prediction on streamflow.

Two watersheds (Kings Creek, Texas and Sugar Creek, Indiana) were used in this study. The study shows that there exists a subwatershed map that does not belong to one of the subwatershed maps produced through conventional CSA approach, to produce a better result on uncalibrated monthly SWAT streamflow prediction. Beyond the critical threshold, the CSA threshold which gives the best uncalibrated monthly streamflow prediction among a given set of CSAs, the SWAT performance can be improved further by subdividing some of the subwatersheds at this critical threshold. The study also shows that the input data resolution (within each NHDPlus catchments) does not have an influence on SWAT streamflow prediction for the selected watersheds. However, there is a change on streamflow prediction as the area of the NHDPlus catchment changes. Beyond a certain catchment size (8-9% of the watershed area), as the input data resolution becomes finer, the total sediment increases whereas the sediment prediction in high flow regime decreases. As the NHDPlus catchment size changes, the stream power has an influence on total sediment prediction. However, as the input data resolution changes, but keeping the NHDPlus catchment size constant, the Modified Universal Soil Loss Equation topographic factor has an influence on total sediment prediction.

ACKNOWLEDGEMENTS

I express my heartiest thanks to Ms.Suga for the support and help during all these years. To list all that you have done is not easy. To repay them even in words is beyond my capability. You are always remembered.

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Thank you.

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CHAPTER I

INTRODUCTION

Advances in computer models over the past few decades combined with larger and more extensive data-monitoring efforts have allowed for the development and application of simulation models in hydrology to understanding the hydrological behavior of watershed and water resources systems. Such simulation models incorporate equations to describe hydrologic transport processes and to account for water balances through time. Hydrological models consist of a model structure and parameters. The same model structure can be used for a great variety of basins as only the parameters are given different values. This means that the model structure is general but not the parameters.

The model inputs such as topography, soil, and landuse that affect model parameters and, consequently, hydrological processes have significant spatial variability. To capture this spatial variability, the watershed is subdivided into subwatersheds that are assumed to be homogenous. A user specified threshold level known as a critical source area (CSA), the minimum upstream drainage area that is required to initiate a stream, is used to define the subwatershed levels. In the current literature, CSA has been exercised as a trial and error process to define the subwatershed levels. With the CSA approach, it may not be feasible to evaluate the spatial heterogeneity even though the prime purpose of watershed subdivision is to capture the spatial variability.

This thesis follows the style of *Journal of Hydrologic Engineering*.

Furthermore, it is not clear if one of the CSAs can be considered to produce the best model outcome. The spatial size of subwatersheds (subwatershed area) and the distribution of the size is another dimension of the problem that prevails in capturing essential spatial variability. The spatial resolution (i.e. cell/pixel size) of the input datasets such as Digital Elevation Model (DEM), landuse and soils that are used within each subwatershed, also has an effect on spatial variability of the subwatersheds. This implies that the scale at which model inputs and variables are aggregated and at which the algorithms of the model are implemented could have an impact on the accuracy of model simulations. Thus, the level of the spatial scales (which is obtained through subwatershed delineation, size of subwatersheds and the distribution of the size, and then the spatial resolution of the input dataset within each subwatershed) to be used to adequately represent the spatial heterogeneity of a watershed has been a subject of considerable interest in any contemporary hydrological models such as Soil and Water Assessment Tool (SWAT).

The ongoing collaboration of the United States Environmental Protection Agency (USEPA) Office of Water and the United States Geological Survey (USGS) has promoted a national level predefined application-ready geospatial data products called National Hydrography Dataset (NHD) Plus to ease watershed modeling in the United States. The introduction of NHDPlus may eliminate the uncertain nature in defining the number of subwatersheds required to model the hydrologic system. However, the integration of NHDPlus spatial dataset and SWAT is not available.

Thus the objectives of the study are to:

- Develop an entropy based watershed subdivision scheme with landuse and soil spatial dataset such that it considers all the given subwatersheds maps obtained at different CSAs.

- Replace CSA based subwatershed delineation with predefined NHDPlus catchments in SWAT.

- Investigate the impact of spatial size (catchment size) of aggregated NHDPlus spatial datasets on SWAT prediction.

- Assess the impact of spatial resolution of the input data such as DEM, landuse and soil that are used within NHDPlus spatial datasets on SWAT prediction.

CHAPTER II

REVIEW OF LITERATURE

In recent decades mathematical models have taken over the most important tasks in problem solving in hydrology. Few of them have gained international acceptance as a robust interdisciplinary watershed modeling tool. Soil and Water Assessment Tool (SWAT) is one of them as evidenced by international conferences and hundreds of water-related papers presented at numerous scientific meetings (Gassman et al. 2007). The wide range of SWAT applications that have been described in the literature underscores that the model is a very flexible and robust tool that can be used to simulate a variety of watershed problems (van Griensven et al. 2006).

In SWAT, specifically in ArcSWAT, the Geographical Information System (GIS) interface to SWAT, the watershed is schematized based on built in ArcGIS tools to delineate the watershed and subwatersheds if the digital spatial datasets of watershed and stream networks do not exist. SWAT supports as many subwatersheds as needed to model the hydrologic system. A user specified threshold level known as a critical source area (CSA) is used to subdivide a watershed. This has traditionally been accomplished by a trial and error process to define the subwatershed levels. This implies that model inputs and properties that are derived from topography, soils data, and landuse could vary from one level of discritization to another, and hence could result in different simulation results. Each subwatershed is assumed homogeneous, with parameters representative of the entire subwatershed (Jha et al. 2004). However, the size of a subwatershed affects the homogeneity assumption, since larger subwatersheds are more likely to have variable conditions within the subwatershed. Reducing the size and increasing the number of the subwatersheds would be expected to affect the simulation results of runoff, water quality and sediment yield from the entire watershed. An increase in the number of subwatersheds also increases the input data preparation effort and the subsequent computational evaluation (Latif et al. 2003; Jha et al. 2004; Rosalia et al. 2008). This has lead many researchers to study the optimum number of subwatersheds needed in SWAT environment as a trial and error process through CSA to enhance the SWAT predictability (Mamillapalli et al. 1996; Bingner et al. 1997; Tripathi et al. 2003; Jha et al. 2004; Arabi et al. 2006; Misgana et al. 2007).

Mamillapalli et al. (1996) found an improved accuracy of monthly flow predictions with the SWAT model for the 4,297 km^2 Bosque River Watershed in central Texas as the number of subwatersheds increased. However, they do not present any method for determining the optimal subwatershed configuration for a watershed. Bingner et al. (1997) suggest that sensitivity analyses should be conducted on landuse, overland slope, and slope length for different subdivisions to decide the appropriate number of subwatersheds required for flow and sediment prediction based on their study with SWAT for the 21.3 km^2 Goodwin Creek Watershed in northern Mississippi. Tripathi et al. (2003) performed SWAT simulation in the Nagwan watershed in eastern India and they found a marked variation in the individual components of the water balance with the number of subwatersheds. Based on this study, they concluded that watershed subdivision has a significant effect on the water balance components. Jha et al. (2004) suggest setting subwatershed areas ranging from 2% to 5% of the overall watershed area, depending on the output indicator of interest, to ensure accuracy of estimates. Arabi et al. (2006) found that an average subwatershed equal to about 4% of the overall watershed area was required to accurately account for the impacts of best management practices(BMPs) in the model. Misgana et al. (2007) found that the accuracy of the raw model output (streamflow and sediment) was very poor for all subwatershed delineations(CSA ranged from 50 ha to 500 ha) conducted on the Big Creek Watershed (133 km^2), located in southern Illinois.

The foregoing set of citations has contributed to the understanding of how subwatershed delineation through CSA in SWAT modeling environment affects the hydrologic response of a watershed. On the other hand, the ongoing collaboration of the United States Environmental Protection Agency (USEPA) Office of Water and the United States Geological Survey (USGS) has promoted a national level predefined digital spatial datasets of watershed and stream networks called National Hydrography Dataset (NHD) Plus to ease watershed modeling in the United States (NHDPlus Dataset Design Document 2009).

NHDPlus Repository

The National Hydrography Dataset (NHD) has integrated elevation, the National Elevation Dataset (NED), and the National Watershed Boundary Dataset (NWBD) to provide a new, cohesive suite of application-ready geospatial data products called NHDPlus, which could vastly shorten the process of modeling watersheds. NHDPlus has eased large-scale water resource analysis in the United States by accessing public domain data that was previously unavailable in one location. NHDPlus includes over 2.4 million elevation-derived catchments (on average 2-3 km^2) produced using a drainage enforcement technique dubbed “The New-England Method” for the United States. An interdisciplinary team from the USGS, USEPA, and contractors, over the last few years has found this method to produce the best quality catchments (NHDPlus Dataset Design Document 2009). NHDPlus also includes a stream network based on the medium resolution NHD. The geospatial data sets included in NHDPlus are intended to support a variety of water-related applications. The linked datasets provide access to attributes such as land cover, flow direction and streamflow volume and velocity estimates. By using linked data, hydrologists can relate upstream and downstream watersheds. NHDPlus has been designed to accommodate many users’ needs for future water related applications. In this line, NHDPlus also provides the framework and tools necessary to customize the behavior of the network relationships as well as building upon the attribute database for which the user can assign its own data to the network (NHDPlus Dataset Design Document 2009).

However, an exertion to exploit the best features of NHDPlus spatial dataset in the SWAT environment to by-pass the uncertain nature in defining the number of subwatersheds required to model the hydrologic system is impending. Furthermore, it is emphasized that in SWAT the spatial heterogeneity is initially captured through subwatersheds and then through Hydrological Responsive Units (HRUs), unique combination of landuse management, soil characteristics and slope to capture the variability within each subwatershed. In other words, the first level of spatial heterogeneity is captured through subwatersheds. Thus, with the introduction of micro level NHDPlus catchments, there is a question whether it is necessary to capture the spatial variability within each NHDPlus catchments through HRUs if one exploits the best features of NHDPlus spatial dataset. If the NHDPlus catchments are such that they set off the spatial heterogeneity among themselves in an optimum manner then the heterogeneity level within each catchment may at a minimum. Thus, there is a need to research the potential of considering NHDPlus catchment itself as a HRU unit in the SWAT environment.

Spatial Scale of NHDPlus Catchments in SWAT Environment

The results of distributed watershed models such as SWAT could be sensitive to spatial scales (i.e. individual catchment size and its distribution) at which inputs and model parameters are aggregated (Bloschl and Sivapalan 1995; Haddeland et al. 2002). Thus, it is not clear whether it is necessary to have this many catchments. Having said this, there has not been an attempt to investigate the role of spatial scale of aggregated NHDPlus spatial dataset in robust hydrological models like SWAT as the lack of integration between the NHDPlus and SWAT community prevails, even though the intention of USEPA Office of Water and the USGS is to promote a national level cohesive suite of application-ready geospatial data products called NHDPlus to accommodate many users' needs for future water related applications.

Impact of DEM, Landuse and Soil Resolution within NHDPlus

The overall goal of distributed modeling is to capture the essential spatial variability of each model parameter affecting the hydrological process. The spatial resolution (i.e. cell/pixel size) of the input datasets such as Digital Elevation Model (DEM), landuse and soil that are used within each subwatershed has an effect on the ultimate outcome of a simulation model and computational evaluation (Bloschl and Sivapalan 1995; Miller et al. 1999). There have been many attempts to understand the impact of input data resolution in hydrological models (Zhang and Montgomery 1994; Bloschl and Sivapalan 1995; Miller et al. 1999; Cotter et al. 2003; Bosch et al. 2004; Chaubey et al. 2005; Di Luzio et al. 2005; Chaplot 2005; Rosalia et al. 2008). The following paragraph summarizes the impact of input data resolution on SWAT prediction.

Bosch et al. (2004) found that SWAT streamflow estimates for a 22.1 km^2 subwatershed of the Little River watershed in Georgia were more accurate using high-resolution topographic, landuse, and soil data versus low-resolution data. Cotter et al. (2003) report that DEM resolution was the most critical input for a SWAT simulation of the 18.9 km^2

Moores Creek watershed in Arkansas, and provide minimum DEM, landuse, and soil resolution recommendations to obtain accurate flow, sediment, nitrate, and total Phosphorous estimates. Di Luzio et al. (2005) also found that DEM resolution was the most critical for SWAT simulations of the 21.3 km^2 Goodwin Creek watershed in Mississippi; landuse resolution effects were also significant, but the resolution of soil inputs was not. Chaplot (2005) found that SWAT surface runoff estimates were sensitive to DEM mesh size for the Walnut Creek watershed in central Iowa. The most accurate results did not occur for the finest DEM mesh sizes, contrary to previous findings.

The shortcoming of these studies is that as the DEM resolution becomes coarser, total computed watershed area will also decrease. The modeled stream network will became consistently less accurate at coarser resolutions. The reason behind this is that these studies were based on watershed delineation through CSA at different DEM resolution. Consequently, the coarsest-input DEM may not able to correctly predict the watershed characteristics or stream network and the subsequent hydrological model prediction (Cotter et al. 2003; Chaubey et al. 2005; Chaplot 2005). Furthermore, as the DEM becomes coarser, the number of subwatersheds obtained may not be the same at a given CSA (Chaubey et al. 2005). Consequently, it is not feasible to evaluate the impact of input data resolution at a given catchment size.

With the introduction of NHDPlus spatial dataset of watershed and stream network in SWAT environment, there is a potential to coarsen the input spatial datasets within each

NHDPlus catchment. The introduction of NHDPlus catchments ensures the coarser DEM data resolution does not result in decreased representation of watershed area. This ensures that the resolution of the DEM does not have an impact on the subwatershed which is the first level of discritization in assessing the spatial variability of a hydrological model like SWAT. Therefore, there is an unexplored research to examine the impact of varying the level of detail of DEM, land cover and soil data on the response of SWAT prediction within NHDPlus catchments.

An Entropy Based Watershed Subdivision Scheme with Landuse and Soil Dataset

As underscored in the literature (Mamillapalli et al. 1996; Bingner et al. 1997; Tripathi et al. 2003; Jha et al. 2004; Arabi et al. 2006; Misgana et al. 2007), to-date, the attempt has been to find the CSA that produces the best SWAT output. However, it is not clear if one of the CSAs can be considered as the one that produces the best model output. Furthermore, there exists subwatershed boundaries that cannot be produced through CSAs (Fig.1) and may produce a better result compared to any one of the CSAs.

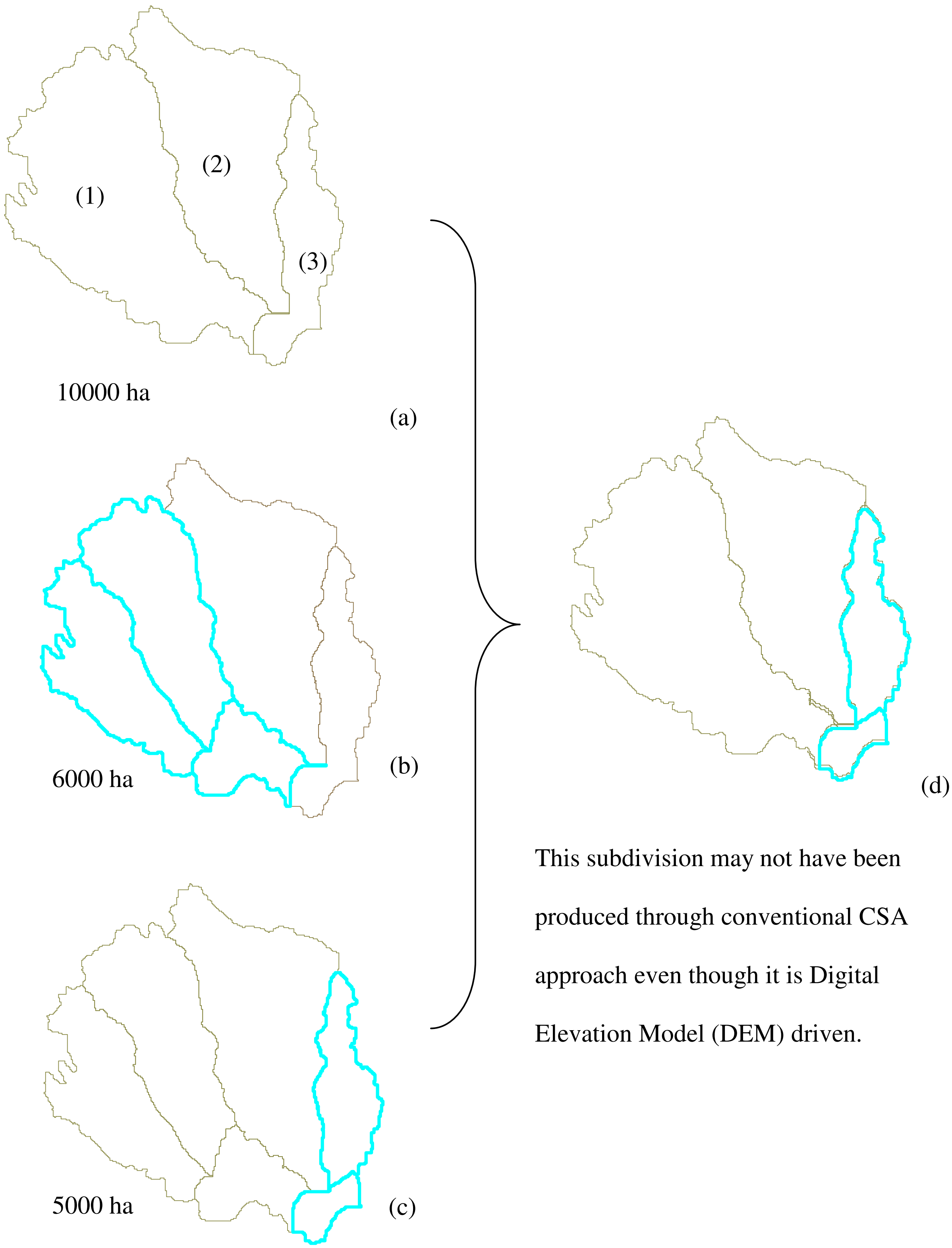

Figure 1. An Example of Critical Source Area Approach

As shown in Fig.1 (b), subwatershed#1 is subdivided into three subwatersheds as CSA is changed from 10000 ha to 6000 ha. The change from 6000 ha to 5000 ha results a subdivision in subwatershed#3(Fig.1(c)).However, the subwatershed boundary that's shown in Fig.1 (d) cannot be obtained with the CSA approach even though its DEM driven. Added to this, with the CSA approach, it may not be feasible to evaluate the spatial heterogeneity even though the prime purpose of watershed subdivision is to capture the spatial variability on input datasets (landuse and soil). Thus there is a need to define a spatial watershed subdivision scheme that could define the spatial variability along with conventional CSA approach and to generate a subwatershed map that makes use of all the subwatershed boundaries obtained at different CSAs.

CHAPTER III

MATERIALS AND METHODS

To integrate the NHDPlus into SWAT, there is a need for a platform to meet the model specific nature of input datasets. ArcObjects, Microsoft's Component Object Module (COM) based technology, allows developers to expand ArcGIS platforms and develop customized applications. With this technology and Structured Queried Language (SQL), a generic, spatial tool named “NHDPlus SWAT” (Mylevaganam and Srinivasan 2009) was developed in a GIS environment to extract and process the NHDPlus catchments and flowlines into SWAT required format.

The tool requires users to specify a starting NHDPlus catchment/pour point. User request is in the form of “COMID” (a unique identifier for each NHDPlus catchment) or the potential user picks a catchment on a geographical view of NHDPlus catchment spatial data and lets the tool identify the COMID value of that catchment. This request outlines where to initiate the process. Based on the selected catchment, all the upstream NHDPlus catchments are selected and exported. Similarly, NHDPlus flowlines that fall within the study area/river basin are also extracted. During this process it is ensured that each catchment/subwatershed has only one flowline as required by SWAT. Subsequently spatial datasets are formatted in SWAT required format.

The processed catchments and flowlines are used to export all of the associated NHDPlus spatial datasets and stand alone tables, such as precipitation, temperature, landuse pattern and so on, to SWAT modeling environment. The tool will serve as one of the GIS-centered decision-making tools with the NHDPlus repository to enhance the application of NHDPlus datasets in various disciplines and to increase the efficacy of water management decisions through hydrological models such as SWAT. The Fig.2 shows the inner detail of the NHDPlus SWAT.

Dynamic NHDPlus Dataset (DND)

A generic, spatial-aggregation tool (Mylevaganam et al. 2009) was developed in a GIS environment to query and to delineate larger catchments subsuming smaller ones based on decision makers' criteria on catchment area. The aggregated watershed is used to refine all the associated spatial data such as flowline and stand alone data such as precipitation, temperature, landuse pattern and so on. The NHDPlus spatial-aggregation tool receives a definition of request to aggregate NHDPlus catchments based on area and to refine all the associated spatial data and standalone tables in a proper format to serve as an input to SWAT model. User request is in the form of "COMID" that outlines where to initiate the process. The request also includes the constrained value of the aggregated catchment area to be met while navigating upstream to aggregate the catchments. This ensures that the each aggregated catchment is of this areal extent on average. This generic, spatial-aggregation tool operates in Environmental Systems Research Institute (ESRI) environment linked with Relational Database Management

Systems (RDBMS). The Fig.3 shows the functionality of the service tool at its simplest view.

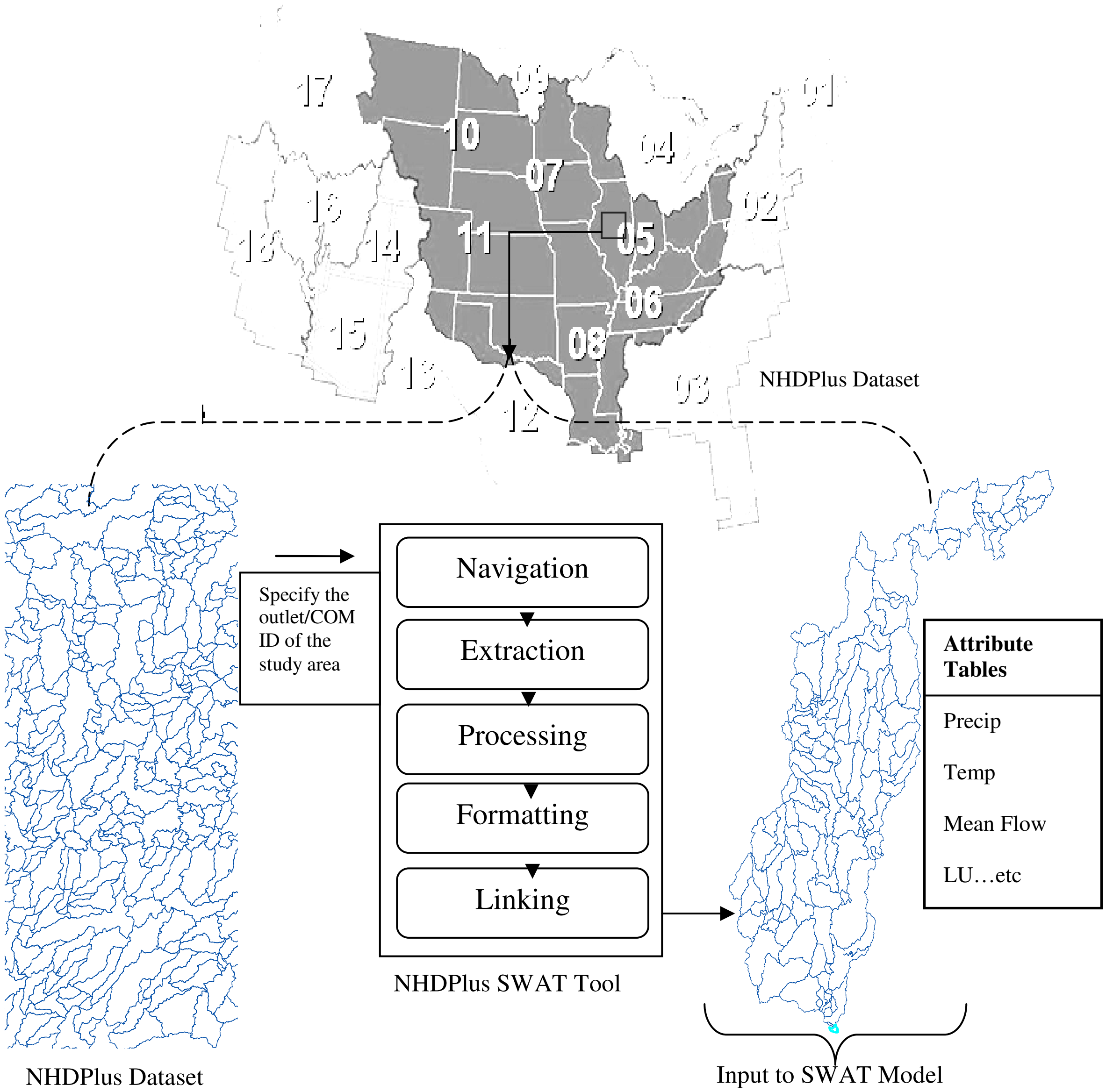

Figure 2. Integration of NHDPlus Dataset in SWAT

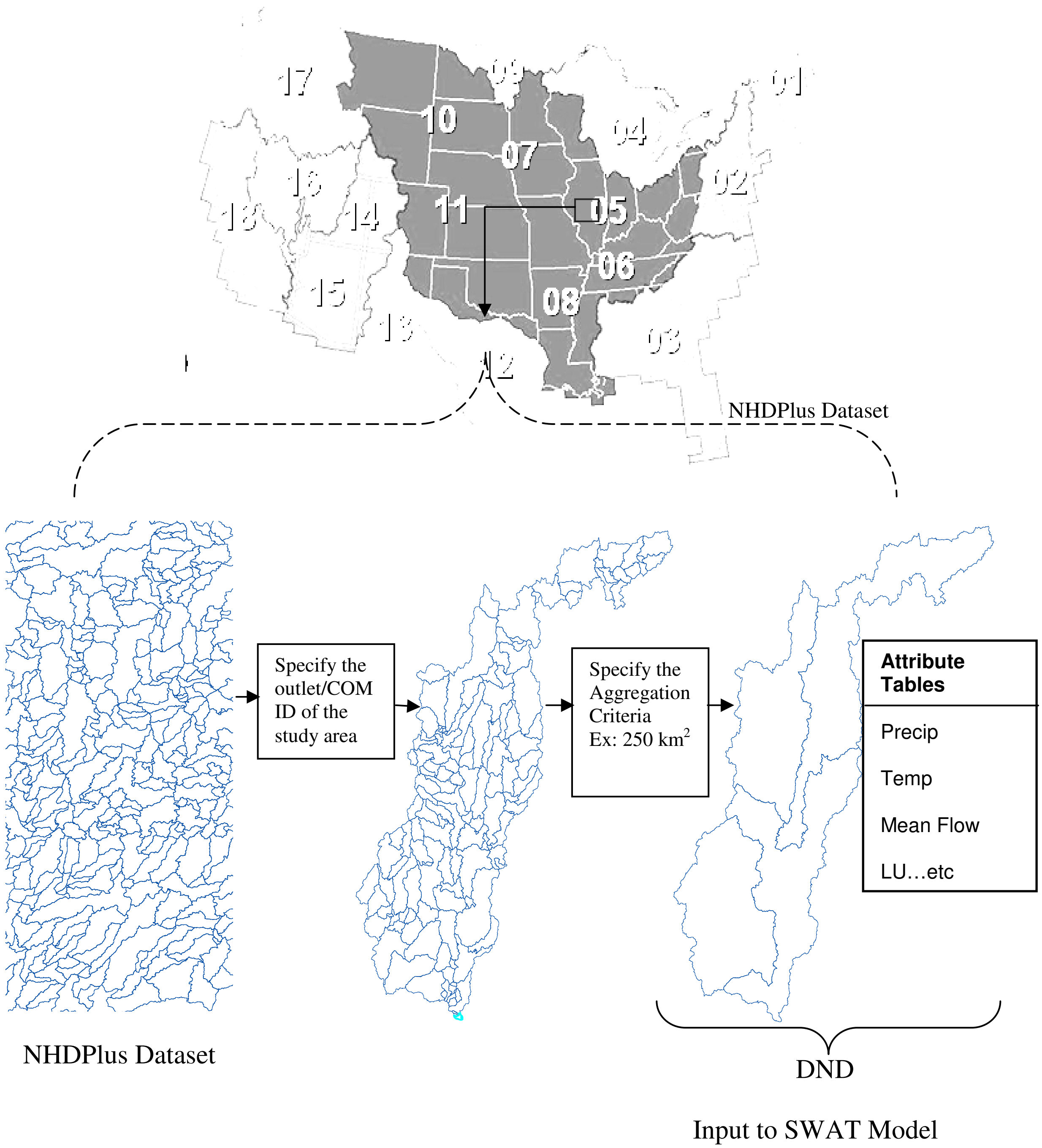

Figure 3. Development of Dynamic NHDPlus Dataset (DND)

Impact of DEM, Landuse and Soil Resolution within NHDPlus

In SWAT, by default, the resolution of the simulation is set to the resolution of the DEM. Therefore, to investigate the role of input data resolution within NHDPlus catchments, the land cover and soil generalization process was accomplished by using coarsened DEM through nearest-neighbor resampling schemes at 30, 60,90…etc meters. As shown in Fig.4, the NHDPlus polygons are retained for all the simulations only the input data resolution is changed. This ensures the coarser DEM data resolution does not result in decreased representation of watershed area for all the simulations. Fig.5 shows the simulated conditions. In Fig.5, $Sim_{100km^2, 30m}$ means the SWAT simulation with DND scale of 100 km^2 and the input data resolution of 30 m within this DND.

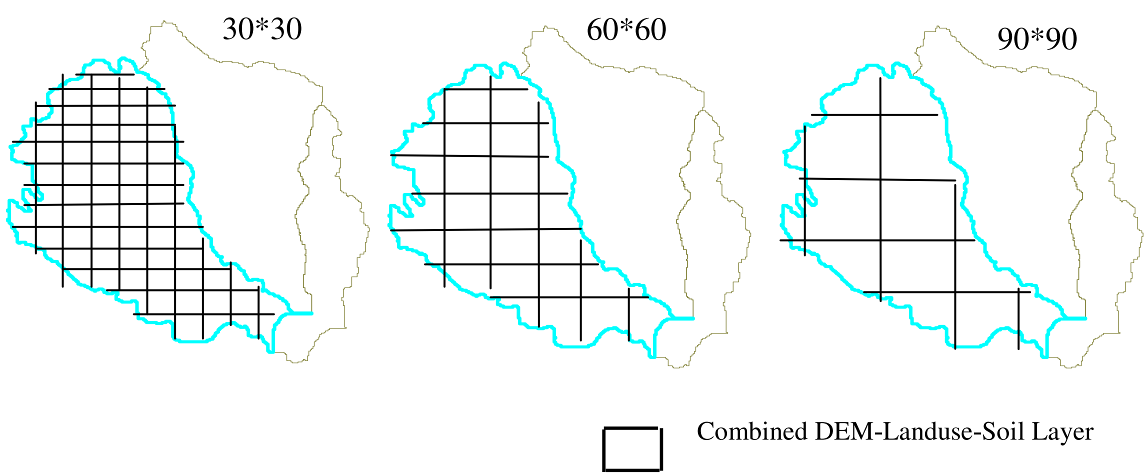

Figure 4. An Example of Input Data Resolution within a Subwatershed

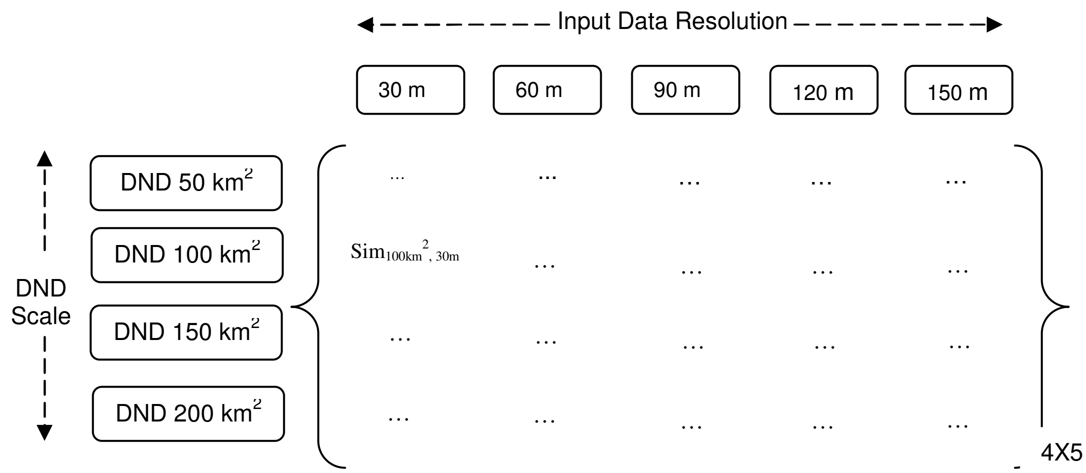

Figure 5. SWAT Simulation at Different Input Data Resolutions within a DND

An Entropy Based Watershed Subdivision Scheme with Landuse and Soil Dataset

The DEM driven watershed delineation is performed at different CSAs and subsequently defined a subwatershed spatial dataset such that it considers all subwatershed spatial datasets generated at different CSAs by fusing the landuse and soil dataset. The required steps with the proposed watershed subdivision scheme are outlined below through an example.

Step#1: Generate the subwatershed spatial dataset for the largest possible CSA. For this example, a CSA of 10000 ha was considered as the largest possible CSA. At this threshold, there are three subwatersheds as shown in Fig.6.

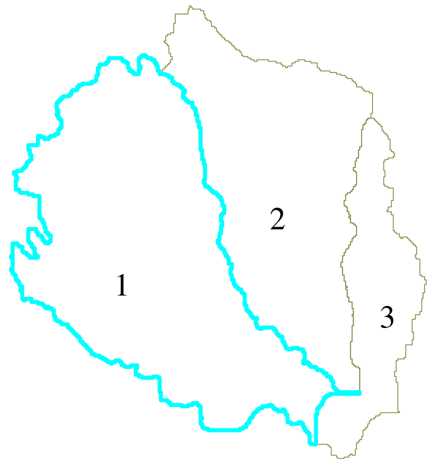

Figure 6. An Example of Subwatershed Boundary at CSA of 10000 ha

Step#2: As shown in Fig.7, overlay the combined layer of landuse and soil dataset on each subwatershed at this threshold (CSA=10000 ha).

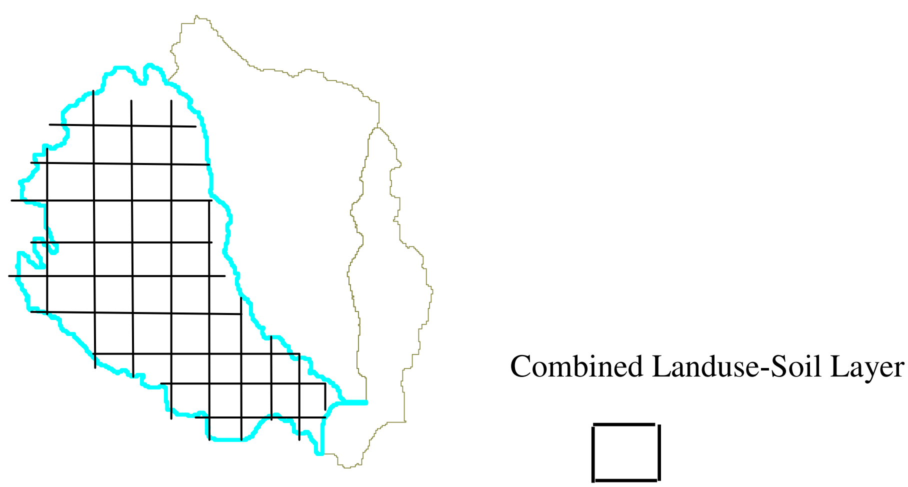

Figure 7. An Example of Overlaid Landuse-Soil and Subwatershed Map at CSA of 10000 ha

Step#3: Compute the spatial heterogeneity level based on combined landuse and soil dataset for each subwatersheds at this threshold (CSA=10000 ha). The spatial heterogeneity of a subwatershed can be described and analyzed by entropy values of combined layer of landuse and soil dataset. The value of entropy is a measure of the heterogeneity of a certain characteristic within an area (Singh 1998). It can be computed from probabilities (p_i) that the value of this characteristic at each point of this area belongs to one of "I" classes. Entropy theory has been exercised in many disciplines (Singh 1998). The formula for computing the entropy" H" of an area is:

$$H = \sum_{i=1}^{I} p_i \log\left(\frac{1}{p_i}\right) \tag{1}$$

where "I" is the total number of classes.

Although the choice of the base of the logarithm is arbitrary, log to the base "2" gives a result expressed in bits. If an area is homogeneous, p_i is 1.0, and the entropy value is zero. If the area is heterogeneous, the probabilities p_is are smaller than one, and thus entropy value increases. Assume that there are six types of unique landuse-soil combination in subwatershed#1 and their proportion as placed in Table 1.

Table 1. An Example of Unique Combination of Landuse and Soil

Unique Combination of Landuse and Soil	Number of Pixels
#1(Forest Deciduous/Sand)	30
#2(Range/Sand)	20
#3(Hay/Sand)	10
#4(Row Crops/Sand)	10
#5(Forest Deciduous /Clay)	5
#6(Hay/Clay)	5
Total Number of Pixels	80

Thus, the heterogeneity level of subwatershed#1 is given by Eq. (2).

$$H = \frac{30}{80}\log(\frac{80}{30}) + \frac{20}{80}\log(\frac{80}{20}) + \frac{10}{80}\log(\frac{80}{10}) + \frac{10}{80}\log(\frac{80}{10}) + \frac{5}{80}\log(\frac{80}{5}) + \frac{5}{80}\log(\frac{80}{5}) \quad (2)$$

where H can range from "0" to log (I).

For the assumed example, the value of "H" is 2.28 bits. Similar computation can be carried out for the other subwatersheds at this threshold (CSA=10000 ha).

Step#4: Subdivide the subwatersheds that are above or equal a certain threshold on heterogeneity value (say x% of most/highest heterogeneity value observed with this subwatershed map). Assume that the heterogeneity values obtained in the previous step are 2.28, 1.98, and 1.76 bits for subwatershed#1, subwatershed#2 and subwatershed#3 respectively. Thus, the highest heterogeneity value observed with this subwatershed map is 2.28 bits. As shown in the Fig.8, if the value of "x" is set to "100", the subwatershed#1 meets the given heterogeneity threshold, and thus it will be divided as per Fig.8 (b).

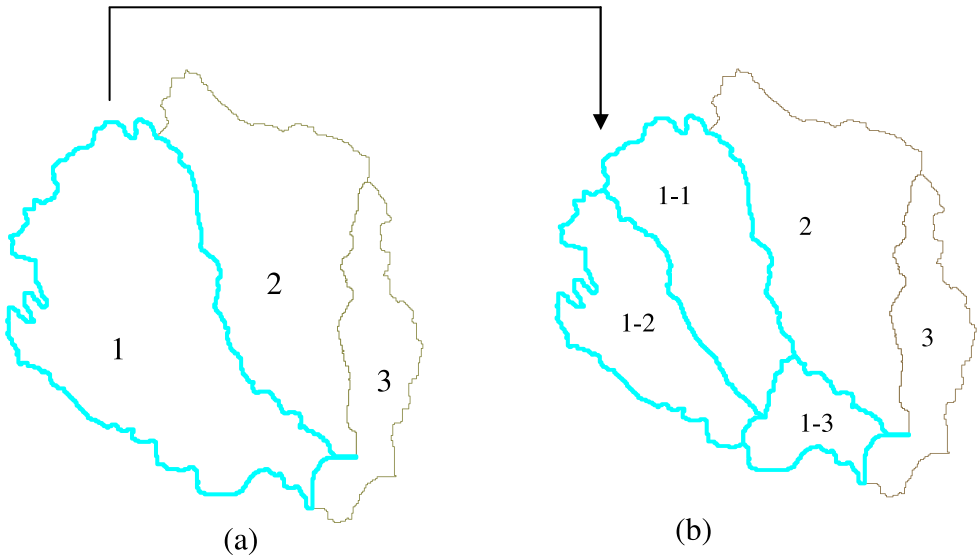

Figure 8. An Example of Subdivision of Subwatershed#1 through CSA Approach

Fig.9 (b) will be produced if subwatershed#2 has the highest heterogeneity measure among all three subwatersheds and the value of “x” is set to “100”. Similarly, Fig.10 (b) will be produced if the given criterion (say “x” is set “80”) is met with both subwatershed#1 and subwatershed#2. Subwatershed#3 will be subdivided if it satisfies the criterion. These subdivisions are based on one of the subwatershed boundaries obtained through next level of CSAs. However we move from coarser CSAs to the finer CSAs.

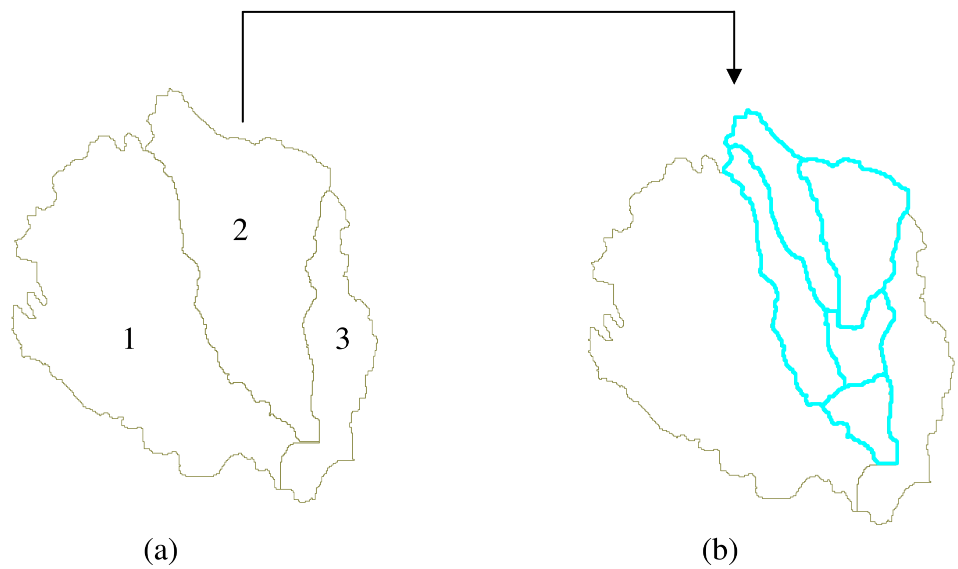

Figure 9. An Example of Subdivision of Subwatershed#2 through CSA Approach

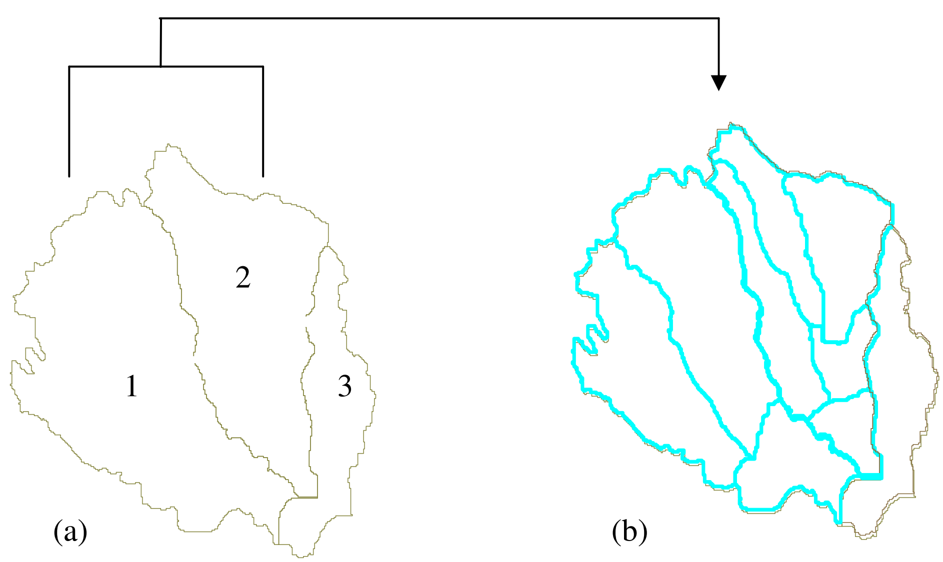

Figure 10. An Example of Subdivision of Subwatershed#1 and Subwatershed#2 through CSA Approach

Step#5: Using Eq. (1), again compute the level of heterogeneity for all the subwatersheds obtained from step#4. In this example, the subwatersheds map used for the computation of heterogeneity level will be either Fig.8 (b) or Fig.9 (b) or Fig.10 (b) or some other subwatershed maps.

Step#6: Again subdivide the subwatersheds that are above the given threshold on heterogeneity value (say x% of most heterogeneity value observed with this subwatershed map). If Fig.8 (b) was the above produced map, and the subwatershed "1-1" meets the given criteria, then it will be subdivided into further.

Step#7: Repeat this process until there is no subdivision possible as per DEM driven subwatershed maps.

All the subwatersheds are DEM driven. Landuse and soil layers are used for decision making alone. The subwatershed map produced with the proposed method may or may not be similar to one of the maps produced with the CSAs. It is merely a combination of all the maps obtained through CSAs.

ArcObjects, Microsoft's COM based technology, and SQL, were used to develop a generic, spatial tool in a GIS environment to generate the wastershed map with the proposed subdivision scheme in SWAT required format.

Soil and Water Assessment Tool

SWAT is a river basin or watershed scale model developed by the United States Department of Agriculture-Agricultural Research Service (USDA-ARS) to predict the impact of land management practices on water, sediment and agricultural chemical yields in large complex watersheds with varying soils, landuse and management conditions over long periods of time (Gassman et al. 2007). SWAT operates on daily time step and predicts water quality and quantity at the subwatershed level. The watershed is defined by the main watershed outlet as chosen by the user. The watershed is then subdivided into subwatersheds. The modeler can define as many or as few subwatersheds as desired according to the CSA, which is reasonable. Each subwatershed is then further divided into a number of hydrologic responsive units (HRU) based on unique combinations of landuse and land cover (LULC), soil types and slope within the subwatershed. To simplify the hydrological system further, HRU threshold is being applied to remove smaller HRUs. For example, if the threshold level for landuse is specified to be 5 percent, then the landuses that cover less than 5 percent of the subwatershed area will be eliminated. After the elimination process, the area of the remaining landuses is reapportioned so that 100 percent of the land area in the subwatershed is modeled. However, these HRUs are not spatially defined within the subwatershed; they are simply accounting categories which represent the total area of the unique LULC, soil type and slope they represent within a subwatershed. A subwatershed contains at least one HRU, a tributary channel and a main channel or reach. Loads from the subwatershed enter the channel network in the associated reach segment. HRU-scale processes are simulated separately for each HRU and then aggregated up to the subwatershed scale and then routed through the stream system. The inner details of the SWAT are described by Gassman et al. (2007).

Study Area

Two river basins namely Sugar Creek, Indiana and Kings Creek, Texas were tested with the entropy based watershed subdivision scheme. Sugar Creek watershed was used to investigate the potential of NHDPlus catchments to by-pass the default watershed delineation in SWAT. Sugar Creek and Kings Creek watersheds were used to evaluate the impact of catchment size and the input data resolution within each catchment.

Sugar Creek Watershed

The Sugar Creek watershed in central Indiana (Fig.11) is a poorly drained agricultural watershed typical of many areas in the Midwestern USA. The Sugar Creek watershed is within the White River Basin, a river basin being studied as part of the United States Geological Survey National Water-Quality Assessment Program. The landuse in the watershed is primarily row-crop agriculture (75%). The soils in the watershed were mapped primarily in the Crosby-Brookston soil association. This association is characterized by poorly drained, nearly level, loamy soils developed on Wisconsin glacial till. Tile-drain systems have been installed in areas used for agriculture. Sugar Creek has a drainage area of 1213 km^2. The average annual precipitation in the study area is 1079.8 mm. Its elevation ranges from 198 m to 335 m.

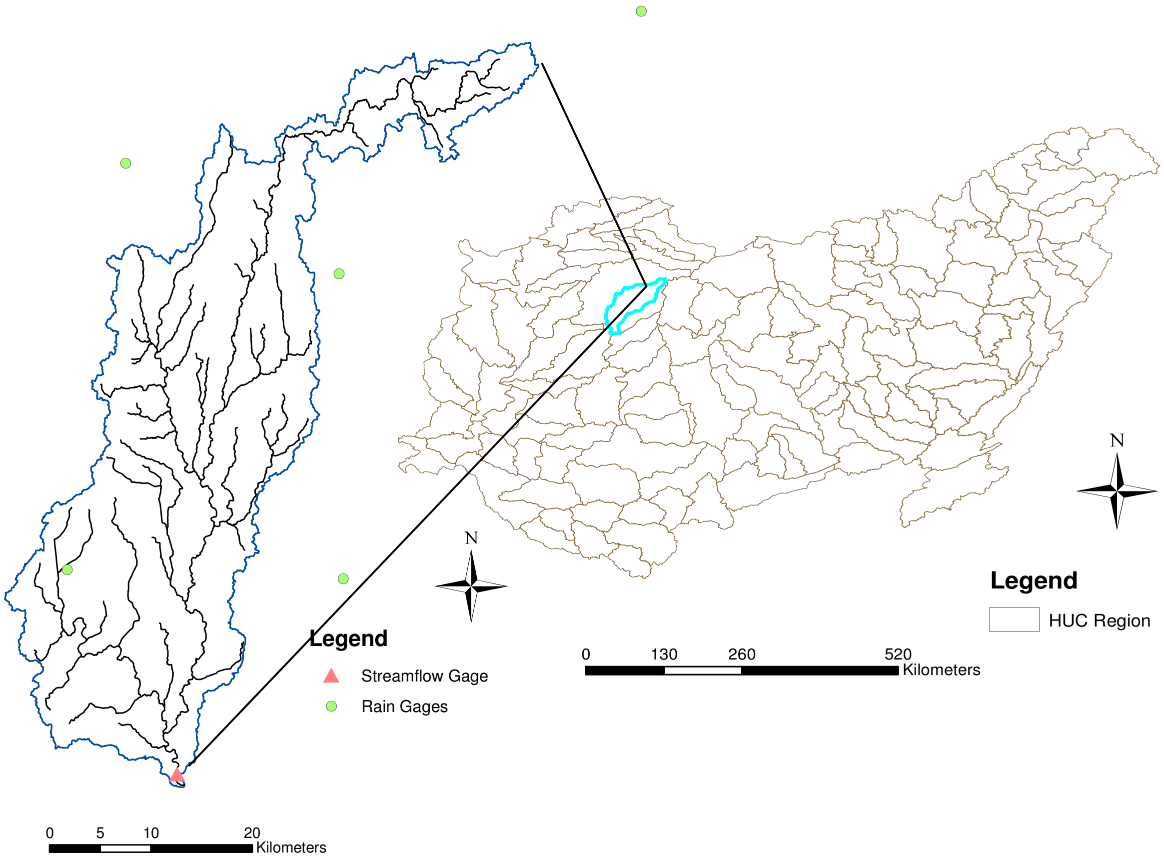

Figure 11. Location of Sugar Creek Watershed, Indiana, within NHDPlus Region#5

Kings Creek Watershed

Kings Creek is a tributary of the Cedar Creek watershed, which drains into Trinity River basin, Texas (Fig.12). It has a drainage area of 614 km^2 as delineated from a USGS streamflow gaging station at 08062900 (32.513 N, 96.3286 W). Its elevation ranged from 107 m to 190 m and its landuse is mainly hay (34%), range (34.5%), and the remaining areas were composed of agricultural and deciduous -forest. The average annual precipitation in the study area is about 975 mm. The soils in the watershed were mapped primarily in the Houston-Black soil association.

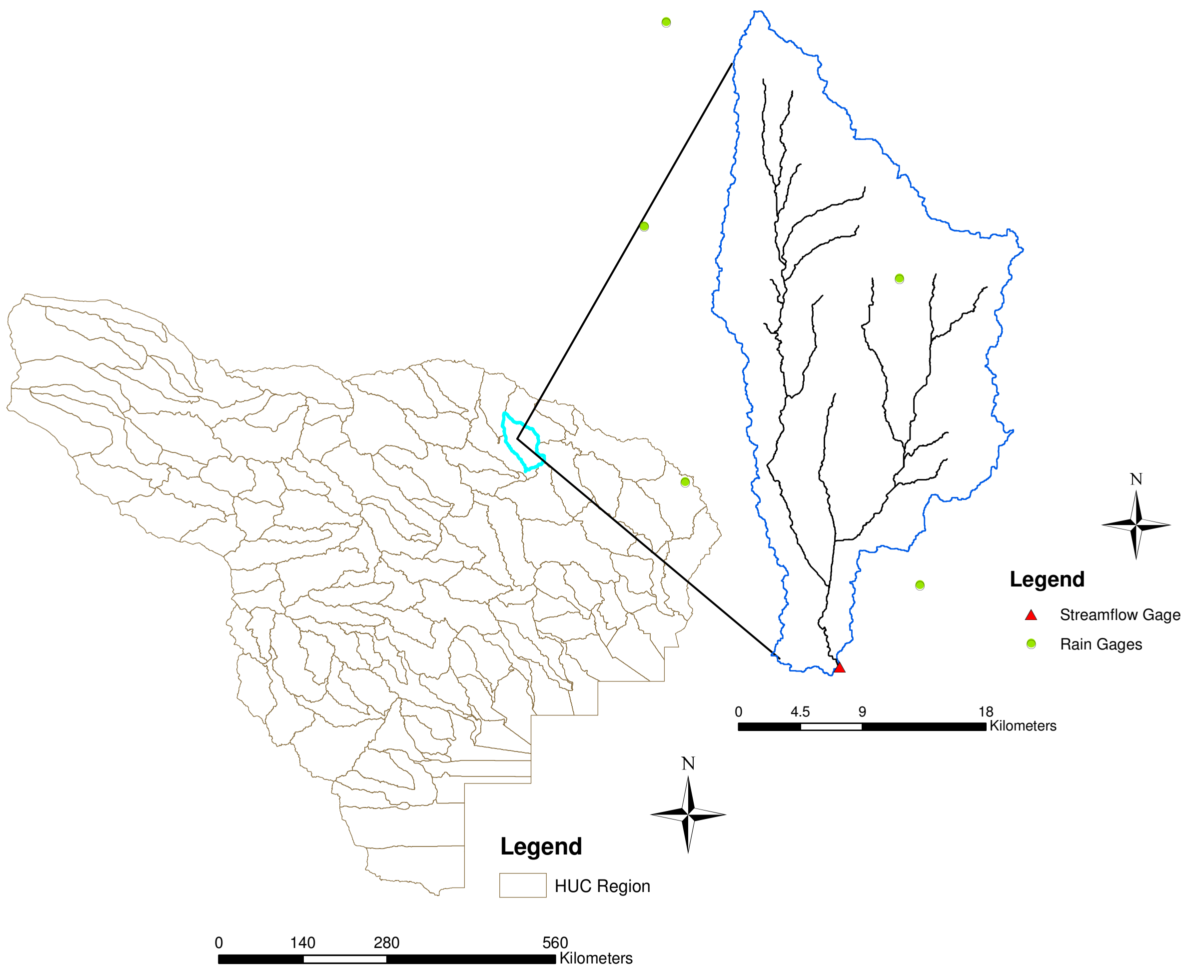

Figure 12. Location of Kings Creek Watershed, Texas, within NHDPlus Region#12

SWAT Model Evaluation

The Nash-Sutcliffe model efficiency (NSE) as defined in Eq. (3) is used to evaluate SWAT's overall performance.

$$NSE = \left[1 - \frac{\sum_{i=1}^{n} (Q_{obs,i} - Q_{sim,i})^2}{\sum_{i=1}^{n} (Q_{obs,i} - \overline{Q}_{obs})^2} \right] \tag{3}$$

where, n is the number of time steps, $Q_{obs,i}$ is the observed streamflow at time i, and $Q_{sim,i}$ is the simulated streamflow at time i.

Nash–Sutcliffe efficiencies can range from $-\infty$ to 1. An efficiency of 1 (NSE = 1) corresponds to a perfect match of modeled prediction to the observed data. An efficiency of 0 (NSE = 0) indicates that the model predictions are as accurate as the mean of the observed data, whereas an efficiency less than zero (NSE < 0) occurs when the observed mean is a better predictor than the model. Essentially, the closer the model efficiency is to 1, the more accurate the model is.

SWAT Model Setup

SWAT model input data for topography was extracted from a digital elevation model (DEM). The 30 m DEM was taken from the NHDPlus repository. The observed daily streamflow data used in evaluating SWAT performance was obtained from the USGS National Water Information System (NWIS). The soil dataset was obtained from the USDA-Natural Resources Conservation Services (NRCS) State Soil Geographic Data Base (STATSGO). Digital landuse/land cover (LULC) data was obtained from the National Land Cover Dataset (NLCD-1992). Daily measured precipitation data was obtained from National Climatic Data Center (NCDC). Weather stations located around the watersheds are as shown in Fig.11 and Fig.12.

The study area was set up to run on a daily time step. Surface runoff was calculated using the SCS curve number method. The Penman-Monteith method was used to determine potential evapotranspiration. Channel water routing was performed using the Muskingum routing method. For Sugar Creek, tile drains were simulated in areas used for agriculture. Three input variables that control the functioning of tile drains namely the depth to the tile drain, the time to drain the soil profile and the time until water enters the channel network after entering the tiles were set to 800 mm, 24 hours and 48 hours respectively (Neitsch at al. 2002).

For this analysis, eleven years period, from 01 January 1980 to 31 December 1990, meteorological and flow data were utilized for the Sugar Creek watershed, whereas period starting from 01 January 1963 to 31 December 1982, meteorological and flow data were utilized for Kings Creek watershed. SWAT performance was evaluated using the measured streamflow data at USGS gage station of 03362500 (39.360884 N, 85.997492 W) and at USGS gage station of 08062900 (32.513 N, 96.3286 W) for the Sugar Creek and Kings Creek respectively.

The specific model setup that was required for each of the objectives is organized as follows: 1) An entropy based watershed subdivision scheme; 2) SWAT model performance with NHDPlus catchments; 3) The role of dynamic NHDPlus on SWAT prediction.

An Entropy Based Watershed Subdivision Scheme

Initially watersheds were delineated at different CSAs for the Sugar Creek and Kings Creek. The wastershed map with the proposed subdivision scheme was obtained by fusing the landuse and soil datasets for the Sugar Creek and Kings Creek watersheds. The subdivision with the proposed method was performed at different percentile of maximum/most heterogeneity value. 100%, 90%, 80%, 70% and 60% of maximum/most heterogeneity measures were considered to generate the watershed maps using the proposed method. It is emphasized that the proposed subdivision scheme is based on all the given watershed maps that were obtained through CSAs.

Threshold level on HRU delineation was set to 0%-0%-0% for both the study areas. In other words, the exact system was retained without looking for a simplified hydrological system through HRU thresholds. This was to ensure that the HRU threshold does not mask the difference on model performance that could occur with different CSAs. The monthly uncalibrated SWAT prediction was compared for each CSA threshold and the proposed watershed subdivision for both the study areas. Comparison using uncalibrated models is useful to evaluate the differences in model predictions because calibration may mask the initial differences that may occur as a result of thresholding on CSA.

SWAT Model Performance with NHDPlus Catchments

The subwatersheds/catchments and stream network were extracted and formatted through the NHDPlus SWAT toolset to by-pass the default watershed delineation that is based on critical source area.

SWAT was run for a set of HRU thresholds, which is used to remove the smaller HRU's in search of a simplified hydrological system, starting from 0% to 35% in step of 5%. The HRU threshold was obtained by considering equal threshold on landuse and soil dataset. In other words, 5% HRU threshold represents the 5% of landuse (the landuses that cover less than 5 percent of the subwatershed area were eliminated and reapportioned) and 5% of soil. For all the combinations, threshold on slope was set to 0%. The monthly uncalibrated SWAT prediction was compared for each HRU threshold. This was to ensure that calibration did not mask the differences that may occur as a result of the HRU thresholding.

The Role of Dynamic NHDPlus on SWAT Prediction

The Dynamic NHDPlus Datasets (DND) for the Sugar Creek was produced through the aggregation tool at 50 km^2, 100 km^2, 150 km^2 and 200 km^2 spatial scales on average. As the watershed area of Sugar Creek is approximately double the watershed area of Kings Creek, the DND for the Kings Creek was produced through the aggregation tool at 25 km^2, 50 km^2, 75 km^2 and 100 km^2 spatial scales on average.

The uncalibrated SWAT prediction was compared for each DNDs. Comparison using uncalibrated models is useful to evaluate the differences in model predictions because calibration may mask the differences that may occur as a result of the DND spatial size. Added to this, 0% HRU threshold was selected to ensure that the HRU threshold does not mask the difference that may occur as a result of the DND spatial size.

Flow Regime Analysis

Flow Duration Curves (FDCs), the percentage of time a given streamflow was equaled or exceeded during a specified period of time, are useful to evaluate the model performance. The required steps with the flow regime analysis are outlined below through an example.

Step#1:

The FDC can be fitted based on the observed monthly streamflow for the period of analysis. Fig.13 shows the monthly non-log FDC. Monthly streamflow series Qi of n total observations, where i = 1,…, n, was employed. Observed streamflows were ranked, resulting in a series of order statistics Q(i),

where i = 1,…, n, from the largest Q(1) to the smallest Q(n) streamflow. The rank-ordered observations Q (i) were used to plot the flow against exceedance probability.

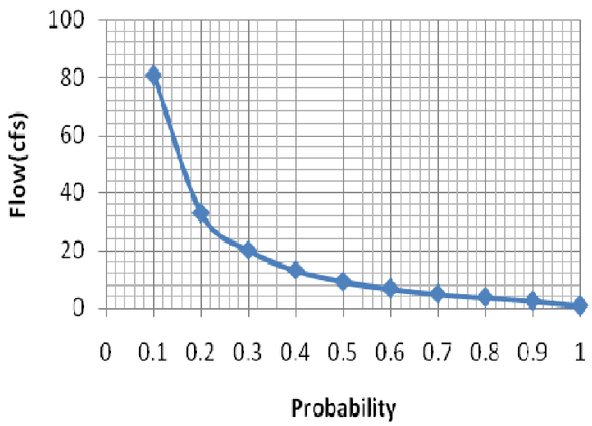

Figure 13. An Example of Flow Duration Curve

Step#2:

As shown in Table 2, identify the months of occurrence in between two exceedance probabilities based on the fitted FDC.

Table 2. An Example of Months of Occurrence in FDC

Exceedance Probability	Months of Occurrence
0.0-0.1	Month#1, Month#4,Month#7
0.1-0.2	Month#5, Month#8,Month#27
…	

Step#3:

Compute the total "predicted" water quantity in between two exceedance probabilities.

Step#4:

Plot the values of total predicted water quantity against exceedance probability. The value of total predicted water quantity at an exceedance probability is the value of total predicted water quantity obtained in between the exceedance probability in question and the previous exceedance probability. As an example, the reported value for the exceedance probability of 0.3 represents the predicted water quantity in between exceedance probability of 0.2 and 0.3.

Step#5:

Group into flow regimes as shown in Fig.14. The flow regime was divided into four regimes.

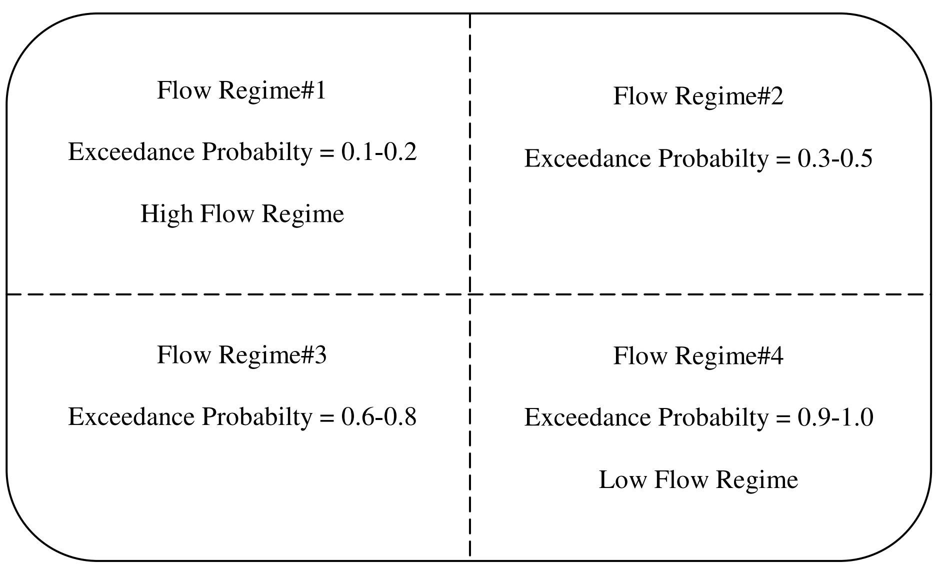

Figure 14. The Number of Flow Regimes Used for the Analysis

CHAPTER IV

RESULTS AND DISCUSSION

The results and discussion section is organized as follows: 1) An entropy based watershed subdivision scheme with landuse and soil dataset; 2) SWAT model performance with NHDPlus catchments; 3) The role of dynamic NHDPlus on SWAT prediction.

An Entropy Based Watershed Subdivision Scheme with Landuse and Soil Dataset

The objective of this study is to investigate if there exists a subwatershed boundary, which does not belong to one of CSAs, to produce a better SWAT model output. The number of subwatersheds produced at each CSA is placed in Table 3.

Table 3. Number of Subwatersheds with CSA Approach and Entropy Method

Sugar Creek			Kings Creek		
CSA (ha)	Number of Subwatersheds	Entropy Range(bits)	CSA (ha)	Number of Subwatersheds	Entropy Range(bits)
6000	9	0.55-1.19	5000	3	1.02-1.20
5000	11	0.55-1.19	4000	7	0.90-1.18
4000	17	0.54-1.19	3000	11	0.82-1.19
2000	27	0.34-1.06	2000	19	0.69-1.20
1500	37	0.29-1.06	1000	27	0.36-1.20

For the Sugar Creek watershed, the watershed map at the CSA of 3000 ha was not produced as the number of subwatersheds generated at this CSA is equal to the number of subwatersheds generated at the CSA of 4000 ha.

Fig.15 shows the outcome of SWAT monthly streamflow performance along with heterogeneity measure. For both the study areas, the most heterogeneous subdivision yields the best model efficiency in terms of NSE compared to the rest. With this, the rest of the analysis and comparison are presented for the most heterogeneous subdivision scheme.

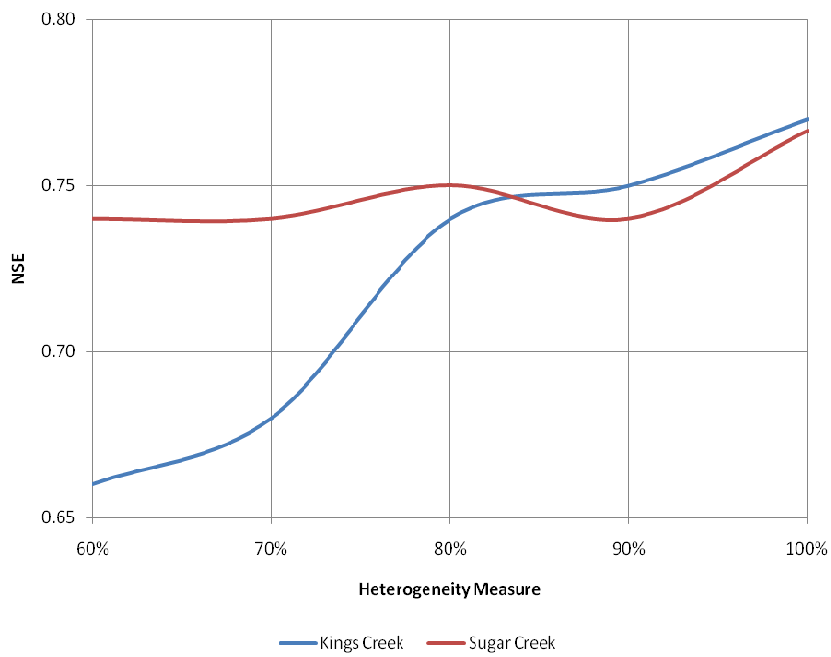

Figure 15. Model Efficiency at Various Spatial Heterogeneity for Both Kings Creek and Sugar Creek Watersheds

As shown in Fig.16 and Fig.17, the values of Nash-Sutcliffe model efficiency (NSE) for uncalibrated monthly streamflow prediction is better with the most heterogeneous subdivision scheme compared to the conventional CSA based approach for both the study areas. The model performance at the coarsest CSA is low compared to the rest for both the study areas. Furthermore, it is observable that there exists a CSA beyond which model performance decreases with further finer. The model performance at the CSA of 5000 ha and CSA of 3000 ha for the Sugar Creek and Kings Creek respectively substantiate this. This critical CSA is approximately 4% of the watershed area. These results are consistent with the results reported by Jha et al. (2004) and Arabi et al. (2006) in which the authors found that the critical threshold area is approximately 4% of the watershed area. However, as this study shows, this critical CSA doesn't give the best SWAT output in terms of NSE.

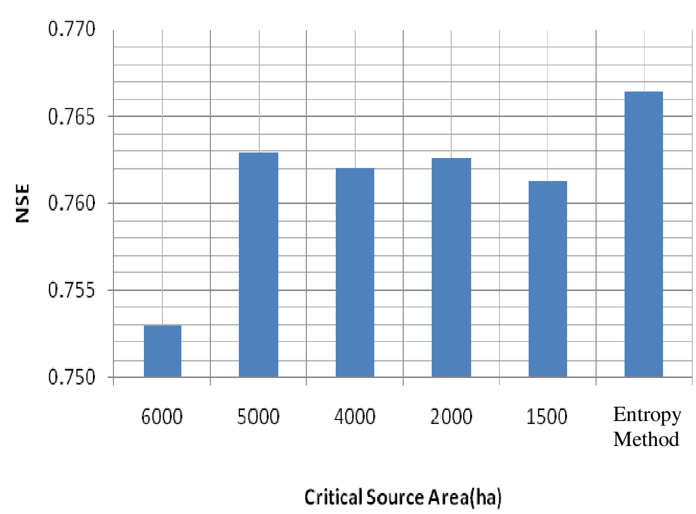

Figure 16. Model Efficiency for the Sugar Creek Watershed at Various CSAs

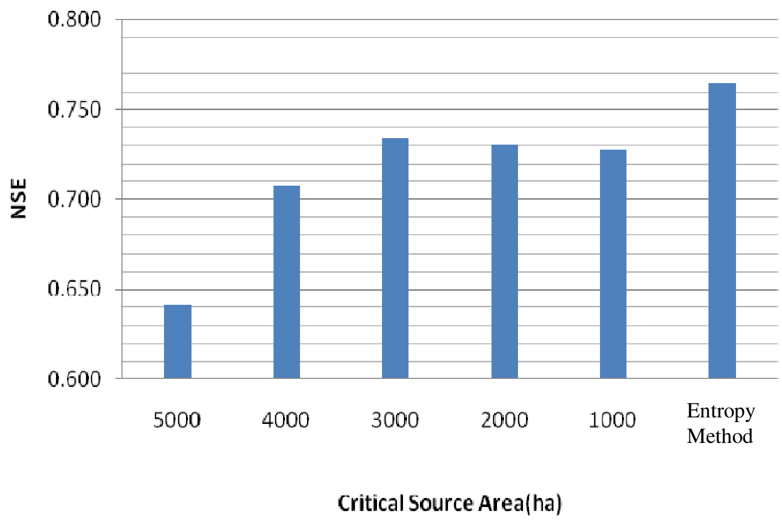

Figure 17. Model Efficiency for the Kings Creek Watershed at Various CSAs

The Fig.18 and Fig.19 show the streamflow prediction for the most heterogeneous subdivision scheme. The visual inspection shows that SWAT model predicted streamflow was better during low flow conditions compared to high flow conditions for the Sugar Creek. This indicates that the model predicted base flow for the Sugar Creek was better than surface runoff since base flow is dominant during low flow conditions and surface flow is dominant during high flow conditions. The difference in the peaks of the runoff rate has to associate with the curve number values used with the uncalibrated SWAT simulation.

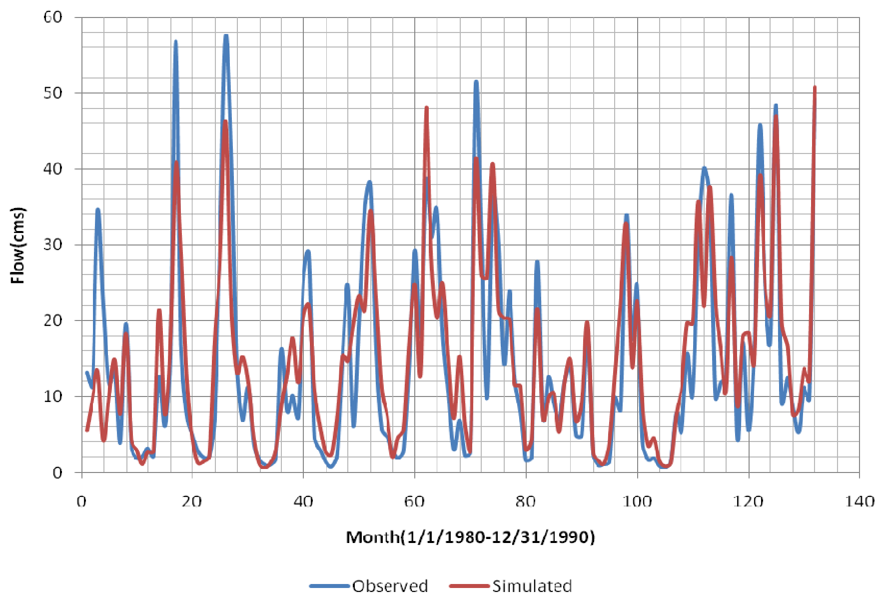

Figure 18. Uncalibrated Prediction for the Sugar Creek with Entropy Method

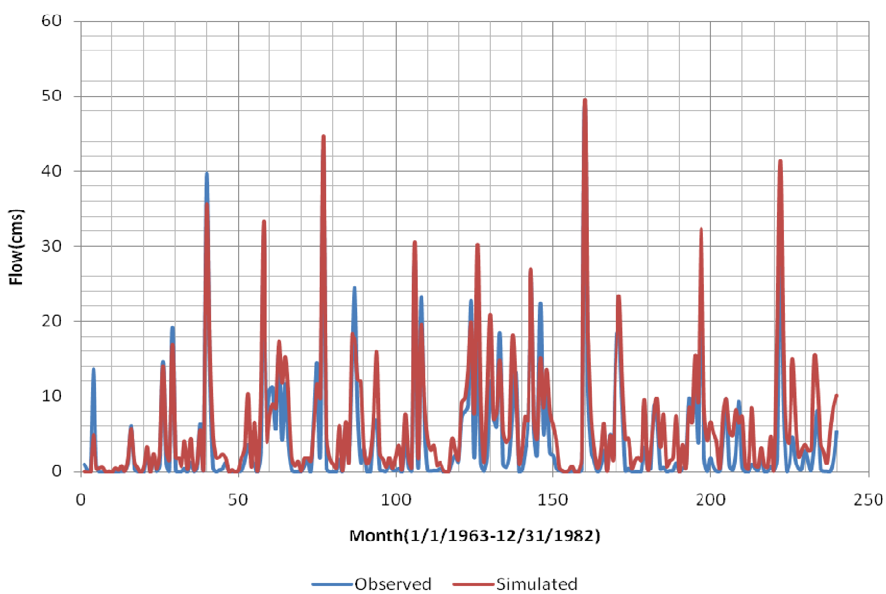

Figure 19. Uncalibrated Prediction for the Kings Creek with Entropy Method

The peak flow for the simulation period is placed in Fig.20 and Fig.21 for the Kings Creek and Sugar Creek respectively. The ability of the most heterogeneous subdivision scheme to attain the observed peak compared to the considered CSAs is pronounced. Furthermore, it is notable that among the considered CSAs, the coarsest one registers the highest peak flow even though it yields lowest NSE.

The interesting fact that could be observed through the most heterogeneous subdivision scheme is that beyond the critical threshold (5000 ha for the Sugar Creek and 3000 ha for the Kings Creek) the model performance could be improved further by subdividing some of the subwatersheds at this threshold (Fig.22 and Fig.23). However, the subdivision of these subwatershds may or may not appear at the very next finer CSA. This could be observable from Fig.22 and Fig.23.

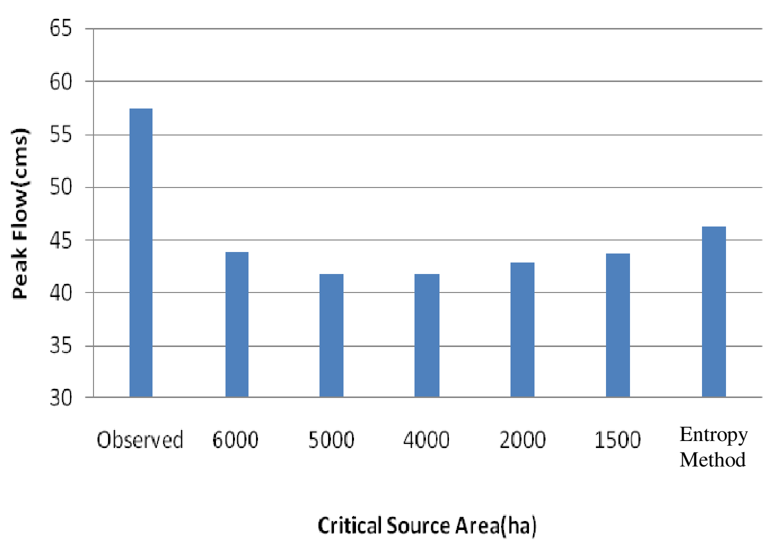

Figure 20. Peak Flow for the Sugar Creek Watershed at Various CSAs

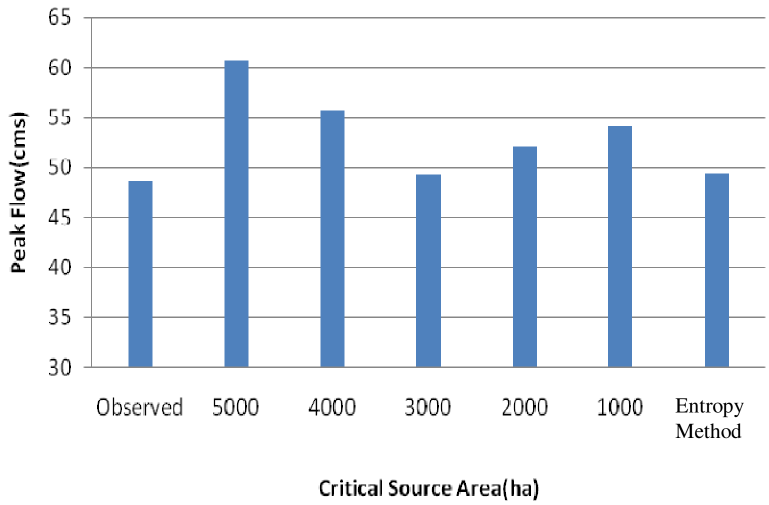

Figure 21. Peak Flow for the Kings Creek Watershed at Various CSAs

Figure 22. Watershed Delineation for the Kings Creek Watershed

Figure 23. Watershed Delineation for the Sugar Creek Watershed

The Fig.24 and Fig.25 show why there was a better SWAT model output compared to the conventional CSA based approach. With the conventional CSA based approach, the river basin is set to one of the CSAs to delineate the watershed. However, the SWAT model prediction could be improved if the watershed is divided using a set of unequal CSAs. If the prime purpose of watershed subdivision is to capture the spatial variability then the concept of equal CSAs for the entire watershed does not justify as the different regions/sections of the watershed can have different heterogeneity level.

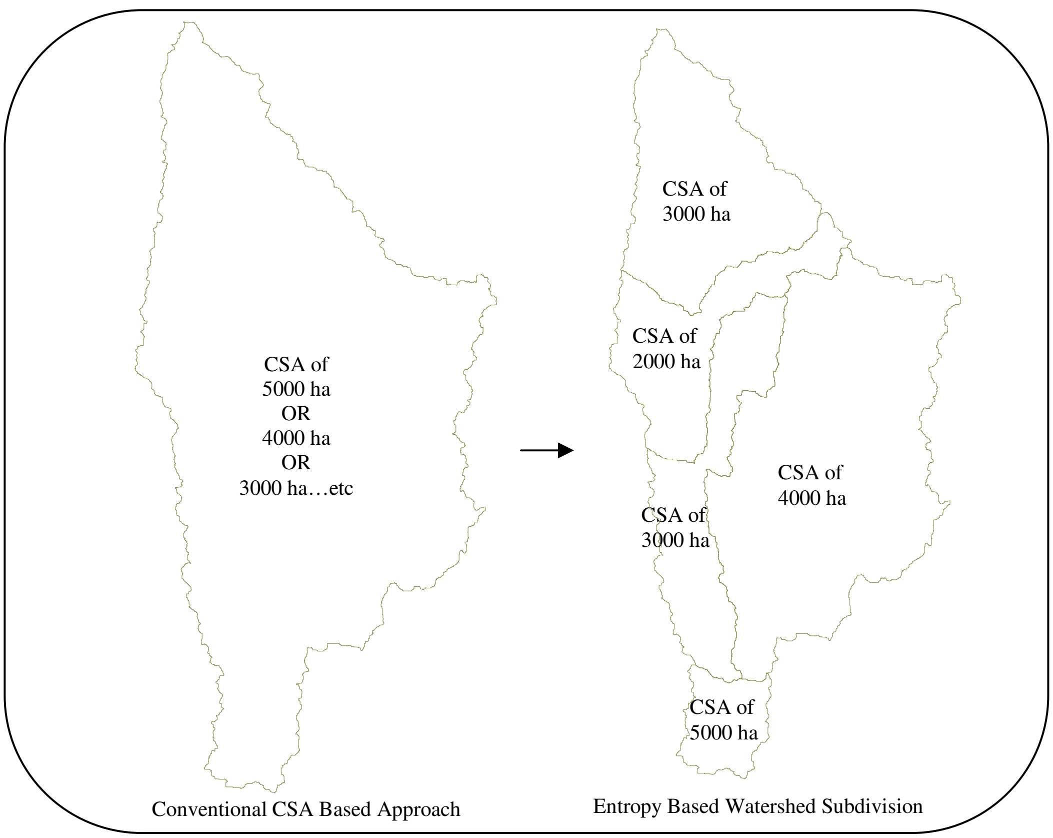

Figure 24. Conventional and Entropy Based Watershed Delineations for the Kings Creek Watershed

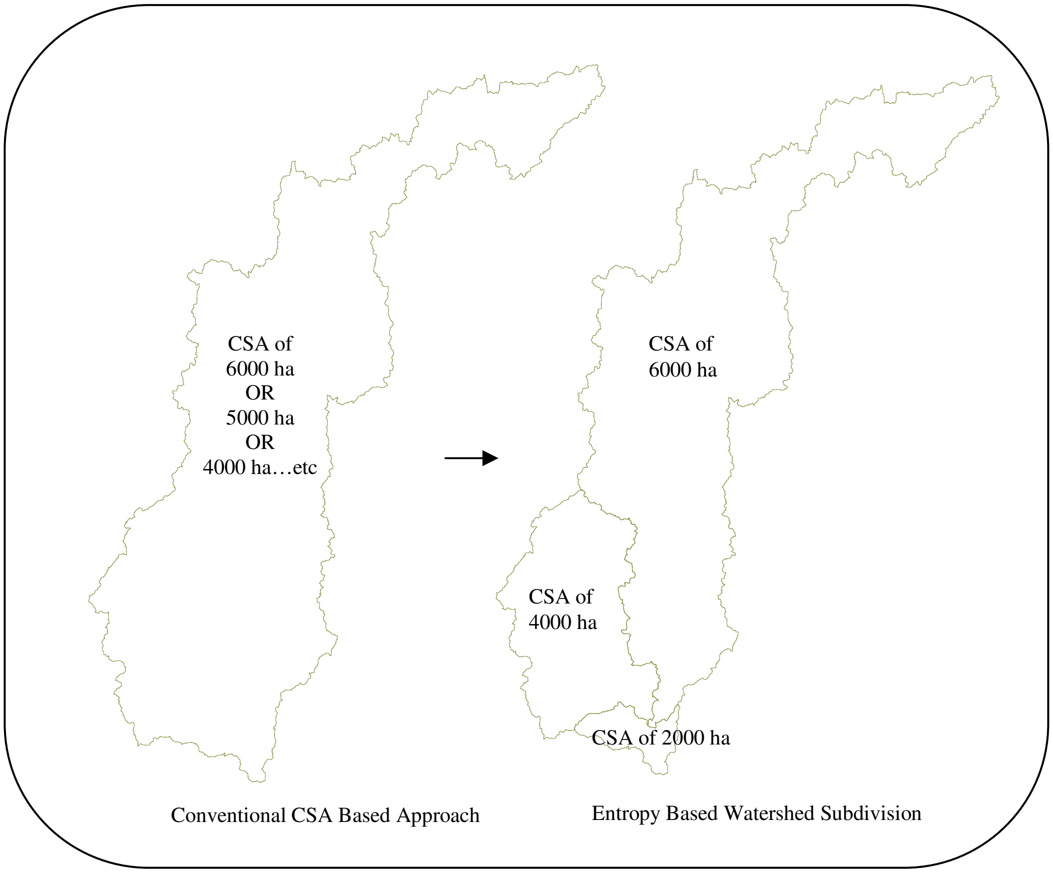

Figure 25. Conventional and Entropy Based Watershed Delineations for the Sugar Creek Watershed

Impact of Landuse and Soil Resolution on Watershed Subdivision

The overall goal of distributed modeling is to capture the essential spatial variability. With the proposed watershed subdivision scheme, the spatial heterogeneity associated within each subwatershed was computed through entropy measure. The resolution of the landuse and soil data used for the analysis was 30 m which was the base resolution obtained. However, the spatial resolution of the landuse and soil that were used within each subwatershed has an effect on entropy measure at the subwatershed level and subsequently on proposed watershed subdivision scheme. Thus, the watershed map produced through the proposed scheme can change as the resolution of landuse and soil datasets changes. This aligns with the fact that as the resolution becomes changed, the level of heterogeneity changes and thus there is a need for different subwatershed boundaries to capture the spatial variability.

Thus, the concern is to examine the impact of varying the level of detail of landuse and soil data on proposed watershed subdivision scheme and subsequently on SWAT prediction. As shown in Fig.26, the entropy measure at subwatersheds level was computed at different resolutions (60, 90,120 meters). The same procedure was followed as previously and found the watershed maps for each resolution.

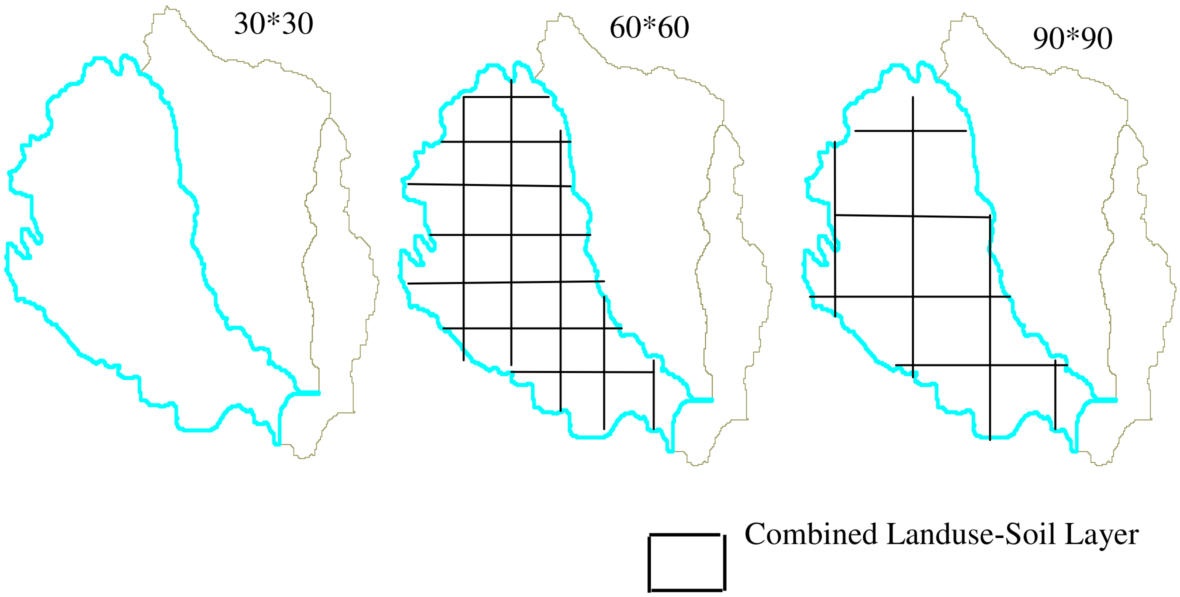

Figure 26. An Example of Entropy Based Watershed Subdivision Scheme with Input Data Resolution

For both study areas, as shown in Fig.27, it was found that the watershed map based on the most heterogeneous subdivision scheme was the same at each coarsened resolution (60, 90 and120 m). However, for Kings Creek, the watershed maps at the coarsened resolutions (60, 90 and120 m) and base resolution (30 m) were not the same. For Kings Creek, the watershed map at the coarsened resolutions was the same as at the CSA of 3000 ha. Fig.28 and Fig.29 show the NSE values obtained at each coarsened resolution along with CSA approach and most heterogeneous subdivision scheme. For both study areas, the most heterogeneous subdivision scheme has a better performance compared to the CSA approach.

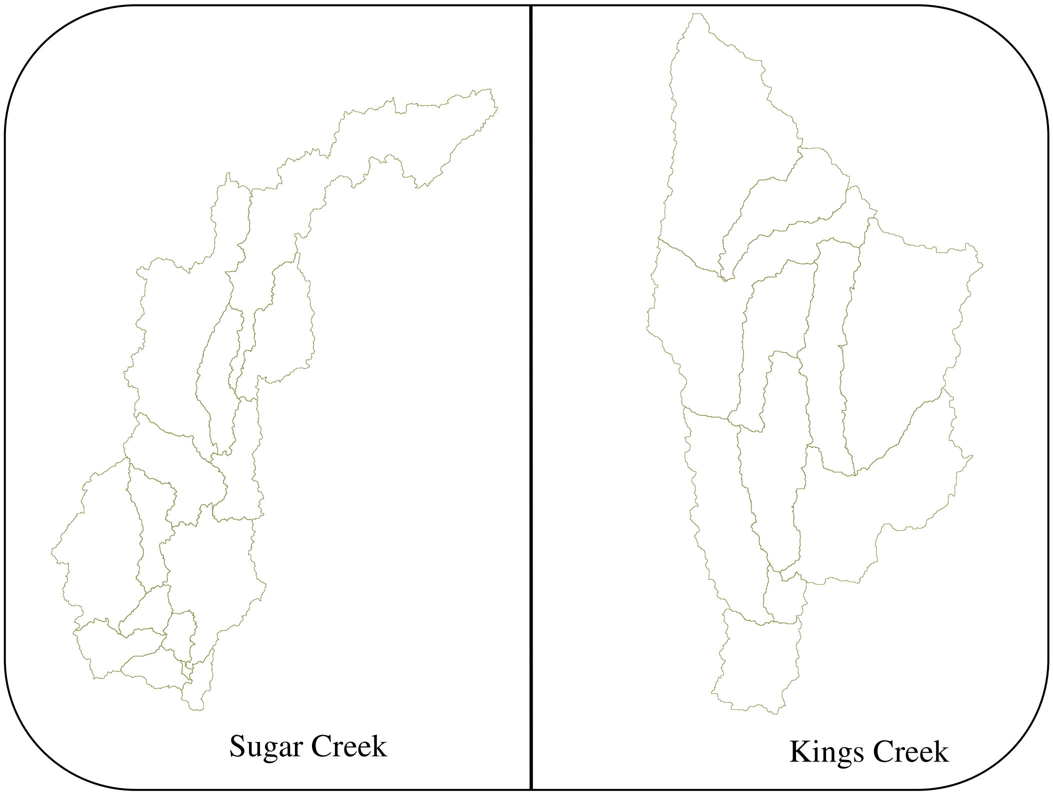

Figure 27. Watershed Delineation with Entropy Based Method at Various Input Data Resolution (60, 90,120 m)

For the Kings Creek, the highest NSE was registered at CSA of 3000 ha which is in fact the watershed map produced through the proposed scheme too. Thus, based on the NSE values obtained with the base resolution (30 m) and coarsened resolution, it is clear that watershed map that yields the best NSE can be at one of the CSAs or combination of CSAs. The reason is that, for the Kings Creek, at the base resolution the watershed map that gave the best NSE did not match with one of the CSAs. However, at the resolution of 60, 90 and 120 meters the watershed map that produced the best NSE coincides with one of the CSAs (3000 ha).

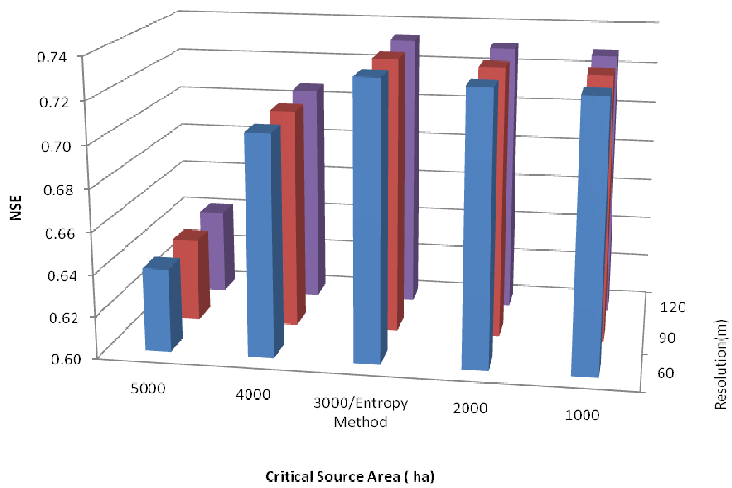

Figure 28. Model Efficiency with Data Resolution for the Kings Creek Watershed

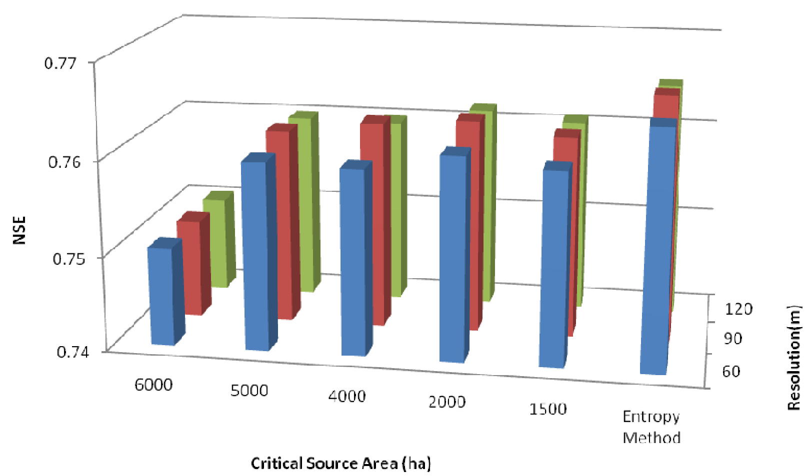

Figure 29. Model Efficiency with Data Resolution for the Sugar Creek Watershed

SWAT Model Performance with NHDPlus Catchments

There were 154 NHDPlus catchments for the study area. As shown in Fig.30, the scale of those catchments varies from 0.02 km^2 to 58 km^2. However, almost 50% of the catchments fall below 6 km^2.

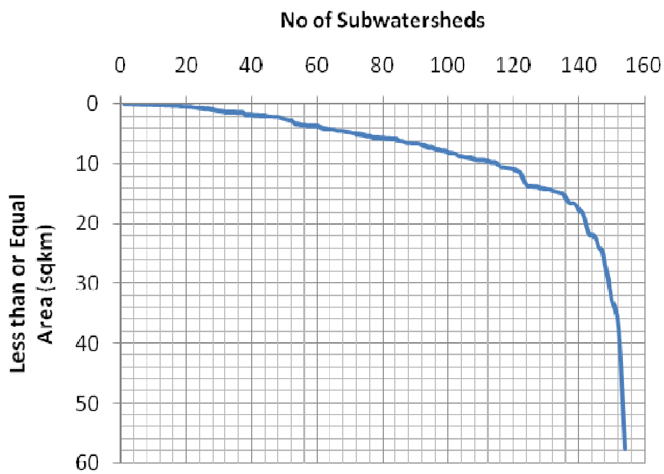

Figure 30. NHDPlus Catchment Area for the Sugar Creek Watershed

The Table 4 presents the number of HRUs simulated for the study area for the selected HRU thresholds.

Table 4. Number of HRUs for Sugar Creek with NHDPlus Catchments

% HRU	Number of HRU	% HRU	Number of HRU
0	2042	20	268
5	791	25	232
10	453	30	206
15	330	35	188

As shown in Fig.31, the streamflow prediction for uncalibrated model is very good. The values of Nash-Sutcliffe model efficiency (NSE) for the uncalibrated model show the potential of the NHDPlus catchments to capture the spatial variability within them for Sugar Creek. The SWAT model outcome is not significantly affected with the HRU threshold. In fact, the elimination of smaller HRUs increases the SWAT model performance on streamflow for the Sugar Creek with NHDPlus spatial datasets. The prime reason for the change on SWAT model performance on streamflow, with the elimination of smaller HRUs, is the modification on curve number. In SWAT, the initial value of curve number is based on soil type and landuse properties. Thus, the curve number is a function of HRU. The application of HRU threshold alters the distribution of the curve number and consequently affects the SWAT prediction.

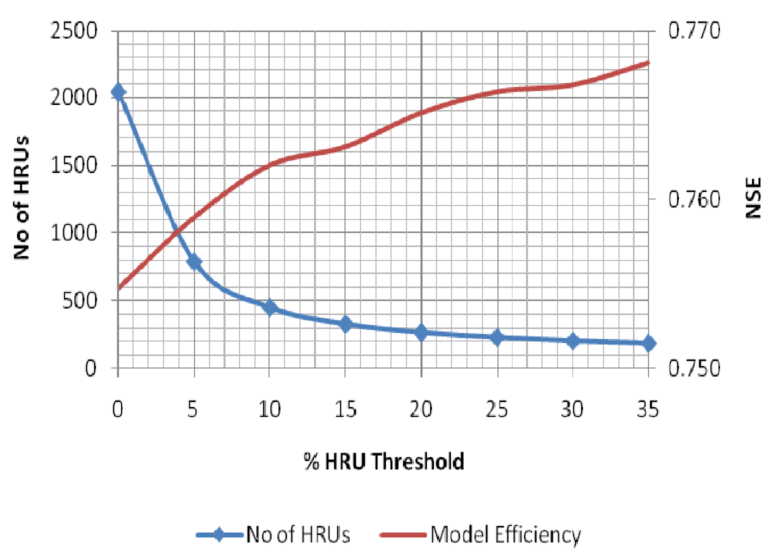

Figure 31. Uncalibrated SWAT Model Efficiency with NHDPlus Catchments

The Fig.32 shows the streamflow prediction for the best HRU threshold which is at 35%. The visual inspection shows that the SWAT model predicted streamflow was better during low flow conditions compared to high flow conditions. This indicates that the model predicted base flow was better than surface runoff since base flow is dominant during low flow conditions and surface flow is dominant during high flow conditions.

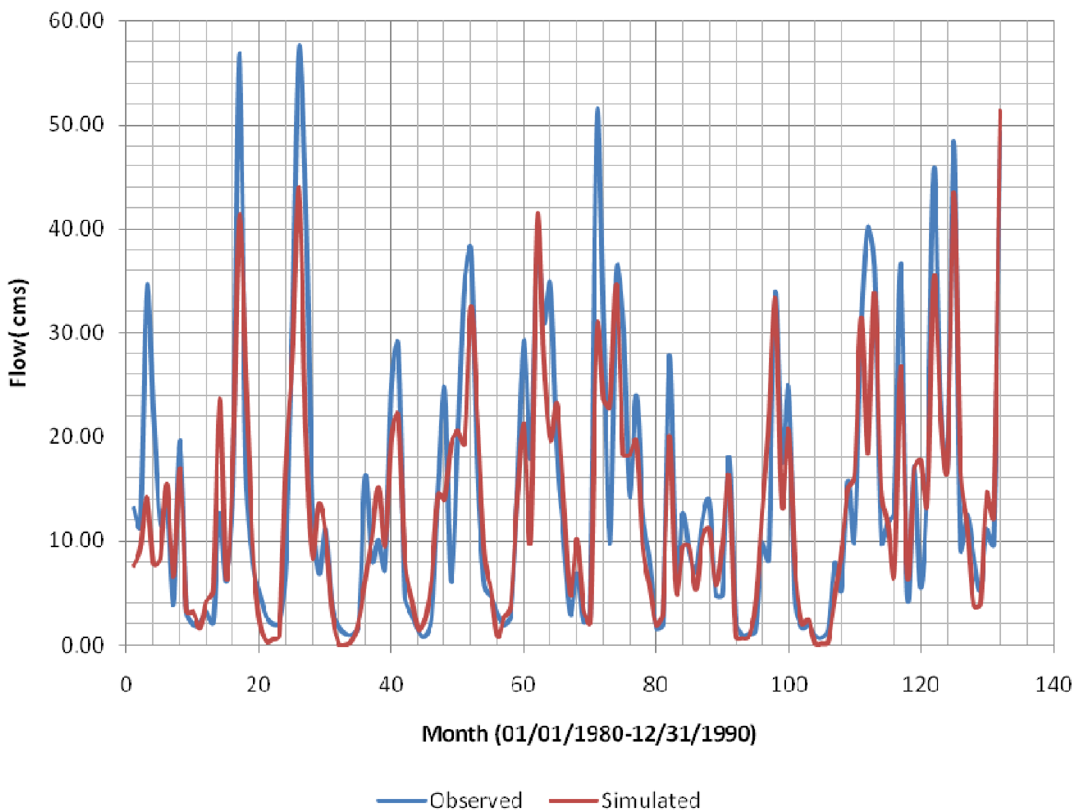

Figure 32. Uncalibrated SWAT Model Prediction with NHDPlus Catchments

Impact of Landuse Threshold on SWAT Prediction

Landuse characteristics and the generation of runoff are inextricably linked. Therefore, the role of landuse threshold alone on HRU definition was evaluated by retaining the original soil dataset by applying a 0% threshold on it. In other words, smaller soil types were not removed but only the smaller units on landuse dataset were removed in steps of 5% starting from 0% to 35%. This gives an indication on the impact of landuse thresholding on SWAT prediction for Sugar Creek with NHDPlus catchments.

The Fig.33 shows the impact of landuse threshold on SWAT prediction, uncalibrated. Even though the difference in Nash-Sutcliffe model efficiency is not significant, there is a declining trend with the increased threshold on landuse dataset alone.

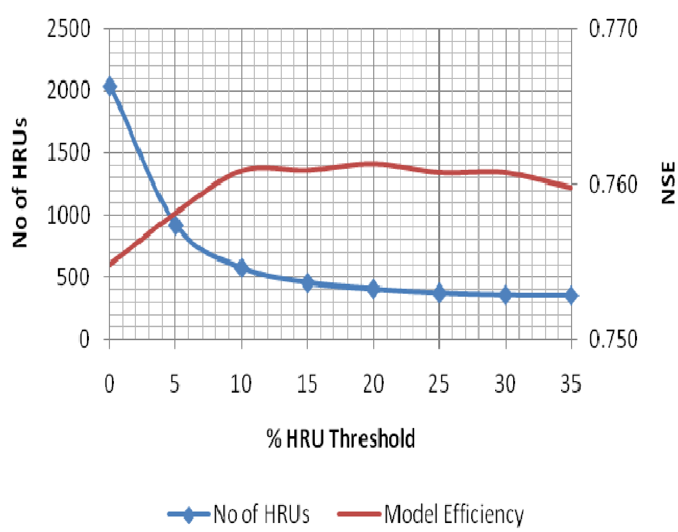

Figure 33. Impact of Landuse Threshold on Streamflow Prediction

Impact of Soil Threshold on SWAT Prediction

The Fig.34 shows the impact of soil threshold on SWAT prediction, uncalibrated. The landuse dataset was retained as of original by applying 0% threshold on it. In other words, smaller landuse types were not removed but only the smaller units on soil dataset were removed in step of 5% starting from 0% to 35%. This gives an indication on the impact of soil thresholding on SWAT prediction.

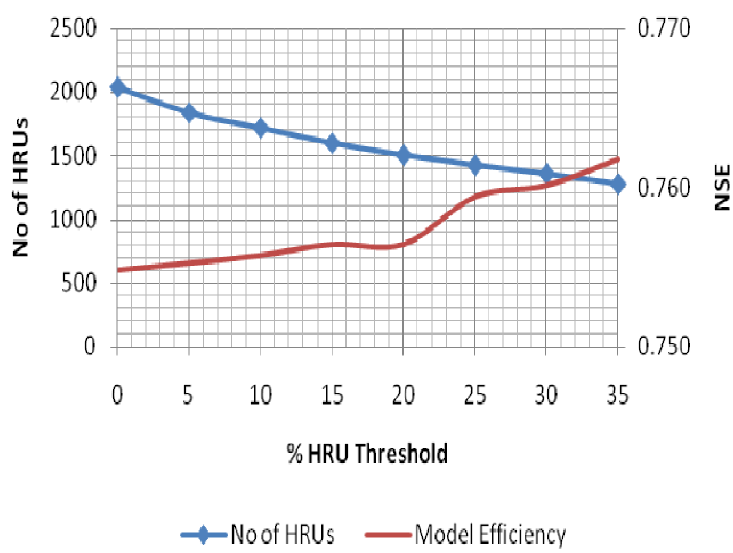

Figure 34. Impact of Soil Threshold on Streamflow Prediction

In contrast to the impact of landuse threshold on SWAT prediction, the model performance increases with the increased threshold on soil dataset. Furthermore, the curve on number of HRUs simulated has flattened as the threshold on soil dataset alone increases. This was not the case with the combined HRU threshold and the threshold on landuse alone as discussed previously. The reason is that in SWAT, the HRU thresholding is done in the order of landuse-soil. In other words, initially the landuse is screened and then soil is screened within a landuse. Thus by setting 0% threshold on landuse (none of the landuses were removed) and ranging the threshold on soil from 5% to 35% will not have a drastic change on number of HRUs.

As shown in the Fig.35, the model performance increases with the threshold on both the datasets rather than considering threshold on one of the datasets even though the model performance with the threshold on landuse alone drops after 20%.

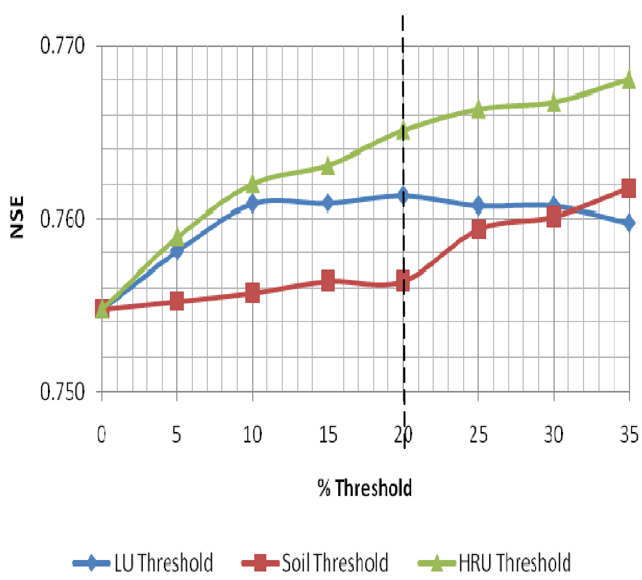

Figure 35. Impact of Threshold on Streamflow Prediction

NHDPlus Catchments as HRUs

It is emphasized that in SWAT the spatial heterogeneity is initially captured through subwatersheds and then through HRUs to capture the variability within each subwatersheds. In other words, the first level of spatial heterogeneity is captured through subwatershed. As shown previously, the model performance is better even at the loss of information on landuse and soil datasets. This leaves a question whether it's necessary to capture the spatial variability within each NHDPlus catchments through HRUs for Sugar Creek. If the NHDPlus catchments for the Sugar Creek are such that they set off the spatial heterogeneity among themselves in an optimum manner then the heterogeneity level within each catchment may be towards a minimum. It's notable that the number of HRUs simulated (188 HRUs) at the threshold of 35% as shown previously in Table 4 is very close to the number of catchments (154 catchments) simulated. Thus, the simulation was performed to investigate the potential of considering NHDPlus catchment itself as a HRU unit. Only the most dominant HRU was simulated for each catchments and the NSE was found to be 0.791 which is better than what was reported with the best HRU threshold, 35%.

The plot of percentile of Squared Error (SE) versus exceedance probability was developed as shown in Fig.36. The SE was defined as the squared deviation between the observed and predicted. Percentile of SE was computed as the sum of SE computed in between two exceedance probabilities divided by the total SE for the simulation period. The value reported for the exceedance probability of 0.3 represents the computed sum of

SE in between exceedance probabilities of 0.2 and 0.3, divided by the total SE for the simulation period. The rest follows the same. As shown in Fig.36, below the exceedance probability of 0.3, the Percentile of SE has slightly decreased with the NHDPlus catchments as HRUs. This is an indication that with the NHDPlus catchments as HRU units, the ability of the model to simulate the high flow conditions is better than at the best HRU scale.

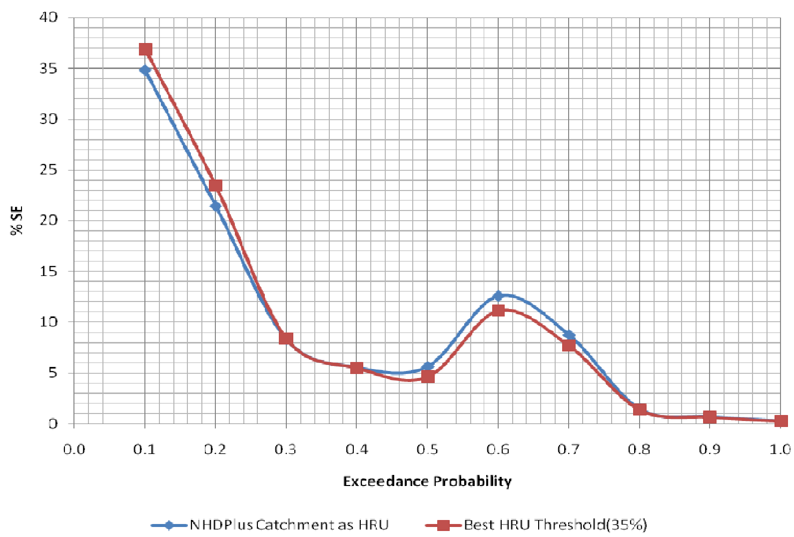

Figure 36. The Percentile of Squared Error at Each Exceedance Probability

Previously (in Fig.32), it was mentioned that the SWAT model predicted streamflow was better during low flow conditions compared to high flow conditions .The Fig.36 can substantiate this. Beyond the exceedance probability of 0.8 (the lowest 20%), the computed percentile of SE is lesser than 5%. However, below the exceedance probability of 0.2 (the highest 20%), the computed percentile of SE sums to almost 50%.

The Role of Dynamic NHDPlus on SWAT Prediction

Fig.37 shows the DND for the Sugar Creek. The Table 5 presents the number of HRUs simulated for the study area for the selected DND scales.

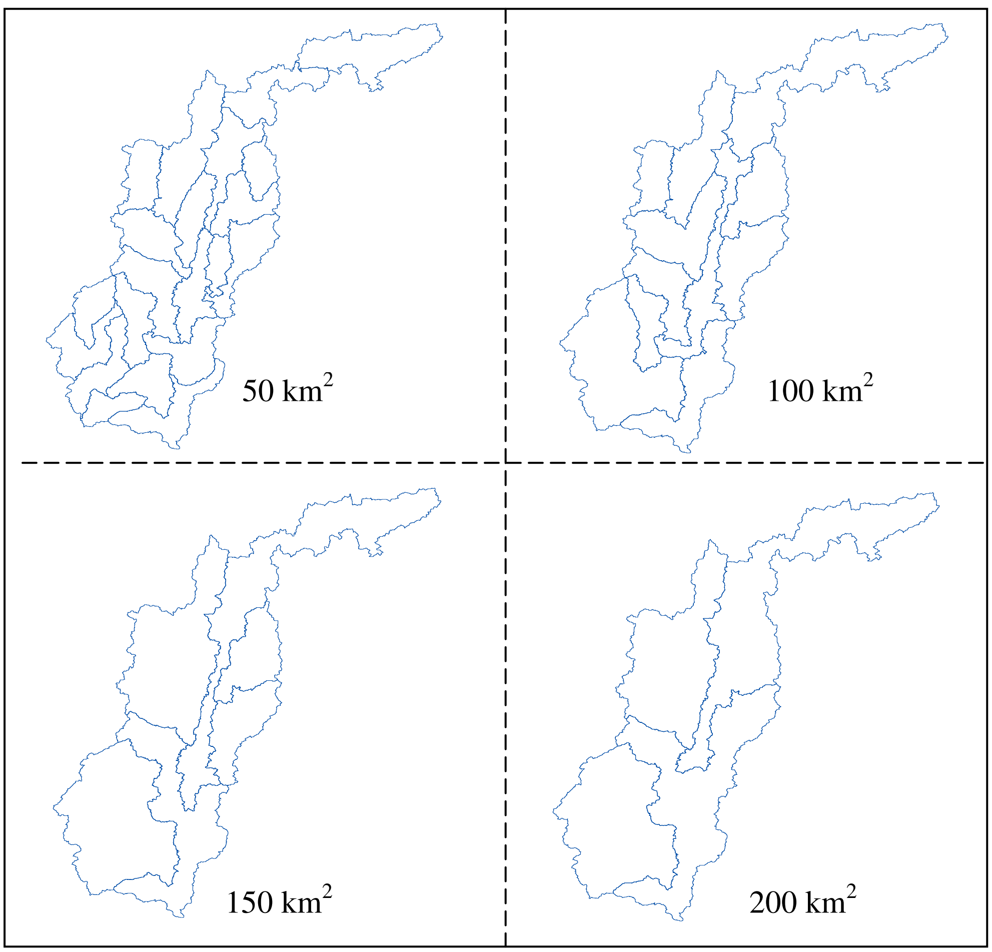

Figure 37. Dynamic NHDPlus Dataset for Sugar Creek

Table 5. Number of HRUs with Dynamic NHDPlus Dataset

	NHDPlus	DND 50 km^2	DND 100 km^2	DND 150 km^2	DND 200 km^2
Number of HRUs	2042	663	432	280	225

As expected, the total number of HRUs simulated for the Sugar Creek become less as DND scale increased. As mentioned previously, the unique combinations are determined at the subwatershed level and thus as the number of subwatershed decreased with increased DND scales, the number of HRUs decreased. As shown in Fig.38, the monthly streamflow prediction for the uncalibrated model is very good.

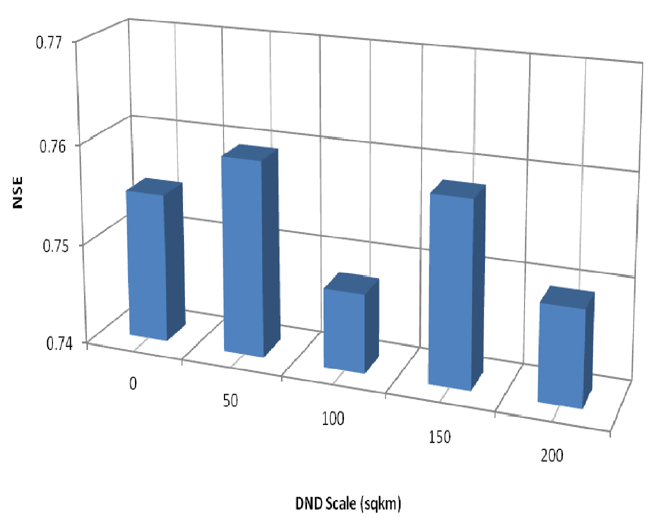

Figure 38. NSE for Sugar Creek with DND

The values of Nash-Sutcliffe model efficiency for the uncalibrated model show the potential of the DNDs to capture the spatial variability within them for Sugar Creek. The reported NSE at DND scale of “0” represents the original NHDPlus datasets. The SWAT model outcome is not significantly changed with the DND scale. The aggregation of NHDPlus catchments at 50 km^2 and 150 km^2 slightly increases the SWAT model performance in terms of NSE on streamflow for the Sugar Creek. The Fig.39 shows the streamflow prediction for the best DND, which is at 50 km^2, as per NSE. In general, the hydrograph is well aligned with the observed hydrograph for the period of analysis.

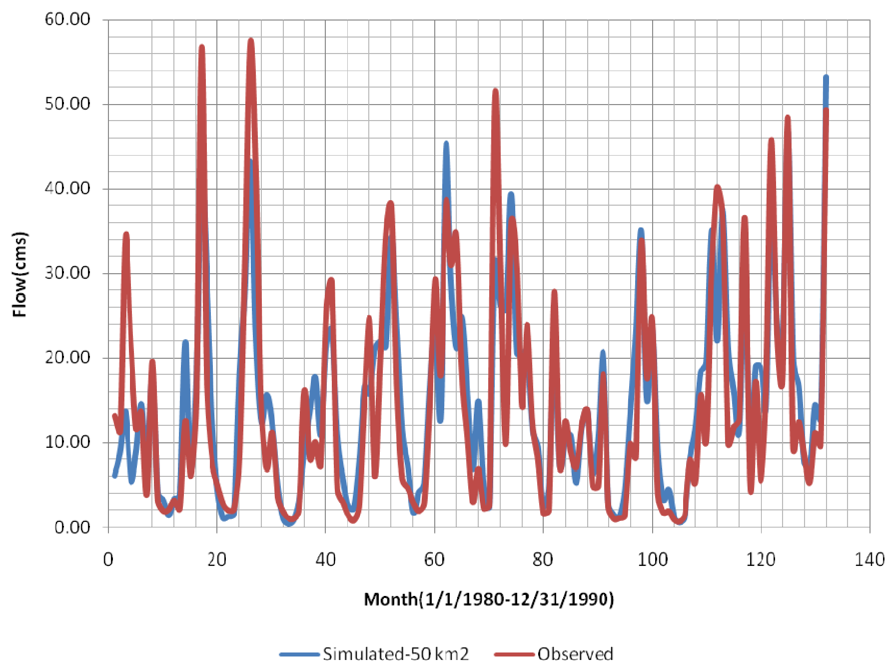

Figure 39. Uncalibrated SWAT Model Prediction for Sugar Creek with DND at 50 km^2

As shown in Fig.40, SWAT over predicts on total water quantity with DNDs at the watershed outlet even though there is a slight under prediction at the DND scale of 100 km^2.

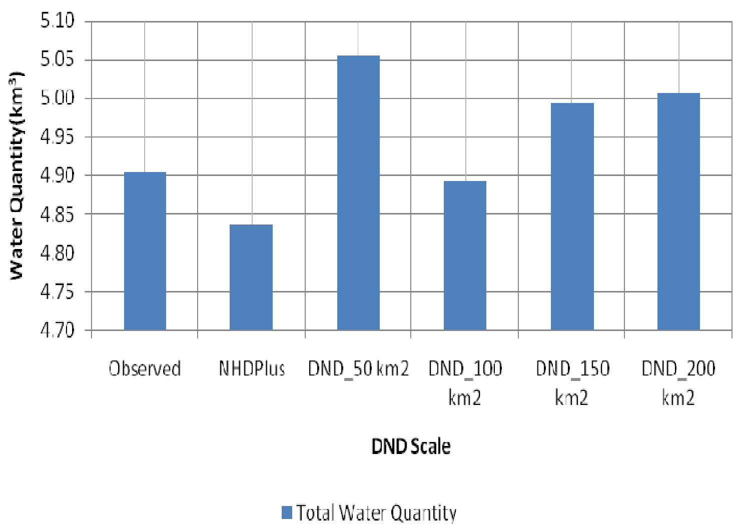

Figure 40. Predicted Total Water Quantity for Sugar Creek with DND

An investigation was made to find out the reasons for the above observation. SWAT uses runoff curve numbers to estimate volume of surface runoff. SWAT automatically updates the curve number daily based on changes in soil moisture. The initial value is based on soil type and landuse properties. As shown in Fig.41, the plot of composite average annual curve number justifies the observed trend on total water quantity. Even though the variation on composite curve number is marginal, the slight drop at the DND scale of 100 km^2 is observable. Lower composite curve numbers correspond to higher abstraction and thus lower runoff potential. This could be one of the reasons for the observed change on total water quantity along with DND scale.

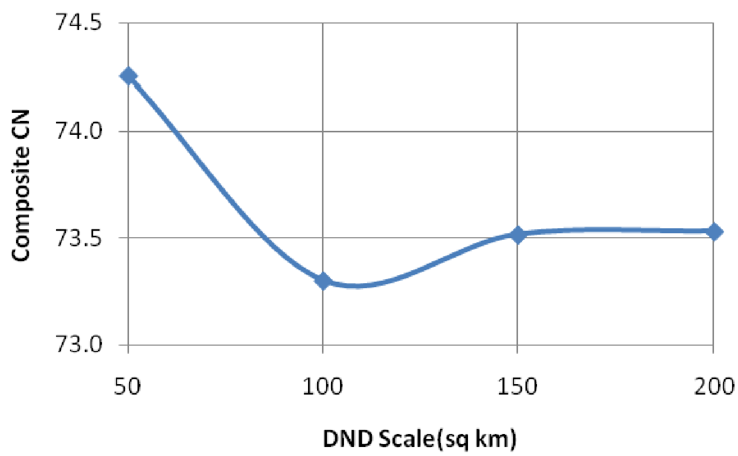

Figure 41. The Plot of Composite Curve Number against DND Scale

As the values of NSE were not much influenced with the DND scales, to further understand the impact of DND scale on SWAT prediction, water quantity against exceedance probability was fitted to evaluate the model performance in each flow regime with DND scales. The Fig.42 shows the plot of water quantity against exceedance probability. The value reported for the exceedance probability of 0.3 represents the predicted water quantity in between exceedance probabilities of 0.2 and 0.3. The rest follows the same. Even though SWAT over predicts on total water quantity with DNDs at the watershed outlet, it is notable that the water quantity in the flow regime#1 is under predicted. However, water quantity in the flow regime#3 and flow regime#4 is over predicted. In general, it is observable that as the DND scale becomes coarser, the predicted water quantity is close to the observed.

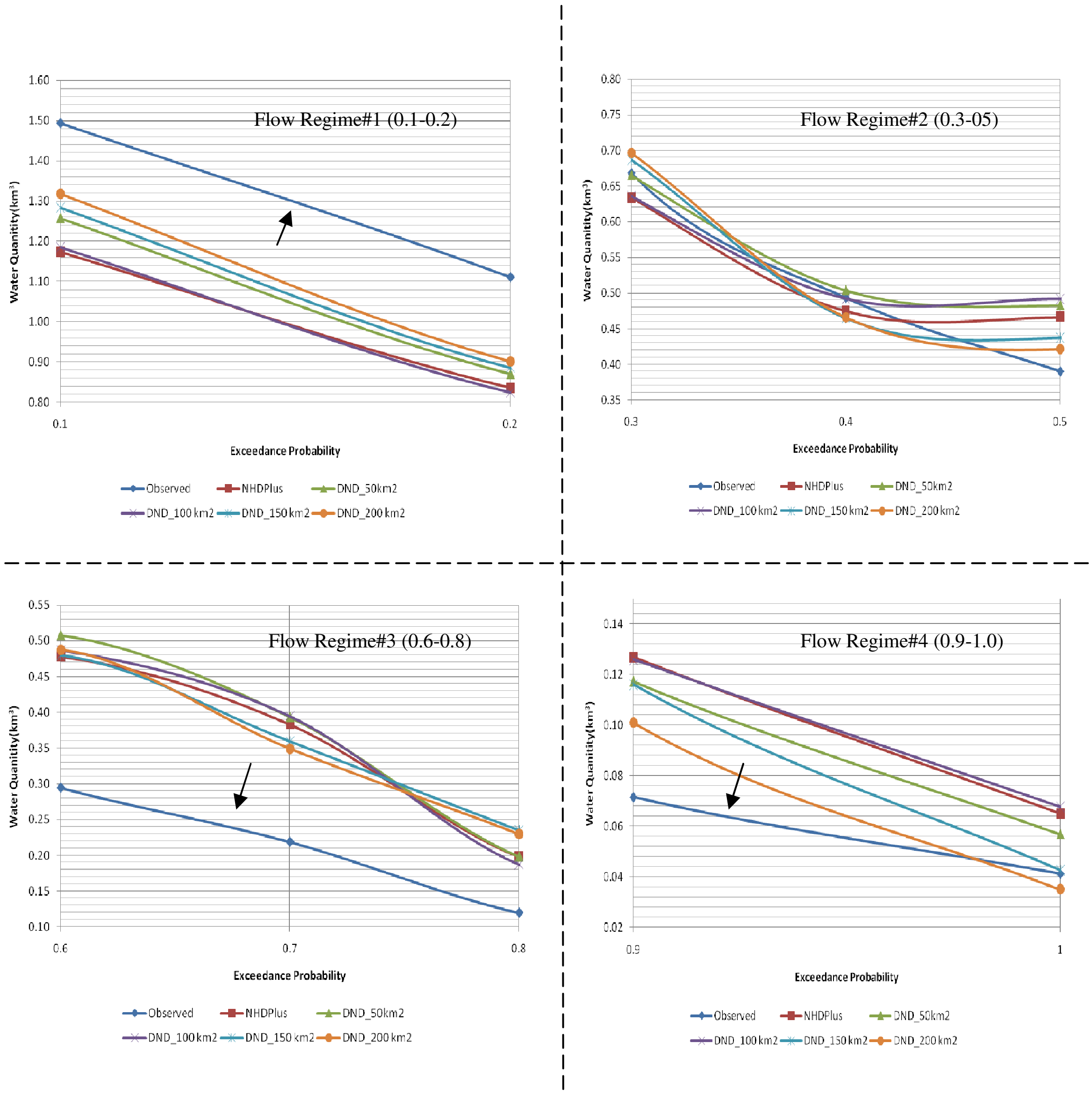

Figure 42. Observed and Predicted Water Quantity at Each Exceedance Probability

As shown in Fig.43, a distribution of the average annual curve number was fitted for the considered DNDs. The distribution of the average annual curve number was expressed in terms of percent of the total area for a particular curve number.

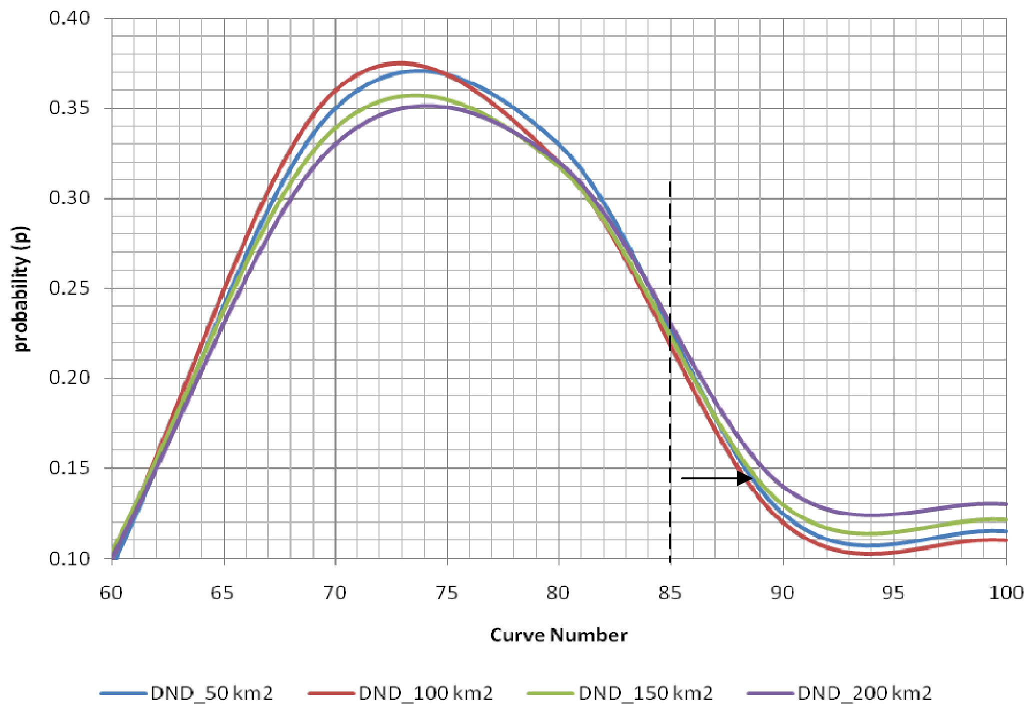

Figure 43. Curve Number Distribution with DNDs

During the high flow conditions, surface flow is dominant. The higher the curve number, the more surface flow. As shown in Fig.43, the occurrence of higher curve numbers (beyond the curve number value of 85) which primarily drive the surface flow increases as the DND scale becomes coarser. As an example, at the DND scale of 200 km^2 the occurrence (probability) of curve number value of 95 is higher than the occurrence of curve number value of 95 at the DND scale of 150 km^2 . Consequently, the contribution of the higher curve numbers on runoff potential increases as DND becomes coarser. Even though, the difference on the probability is not appreciable, this could be one of the reasons on increased water quantity in flow regime#1 with coarser DNDs. The same reasoning can be used to describe the deviated behavior of DND scale of 100 km^2.

Prediction on Sediment with DNDs

As the actual measured sediment data is not available to evaluate the model performance on sediment prediction with DNDs, the model performance was gauged through the plot of percentile of total sediment against exceedance probability. The Fig.44 shows the percentile of total sediment during the simulation period at each exceedance probability. Almost 50% of the sediment prediction for the simulation period at the outlet is observed in high flow regime within exceedance probability of less than 25%. Furthermore, at a given DND scale, the percentile of predicted sediment yield at each exceedance probability has increased as the exceedance probability decreased (i.e. 1.0 to 0.1). An investigation was performed to understand this observation.

The total sediment load predicted by SWAT for a watershed is affected by both the Modified Universal Soil Loss Equation (MUSLE), which is used for estimating subwatershed loadings, and also the sediment transport via channels that is based on the stream power. The MUSLE equation has an implicit delivery ratio built into it that is a function of the peak runoff rate.

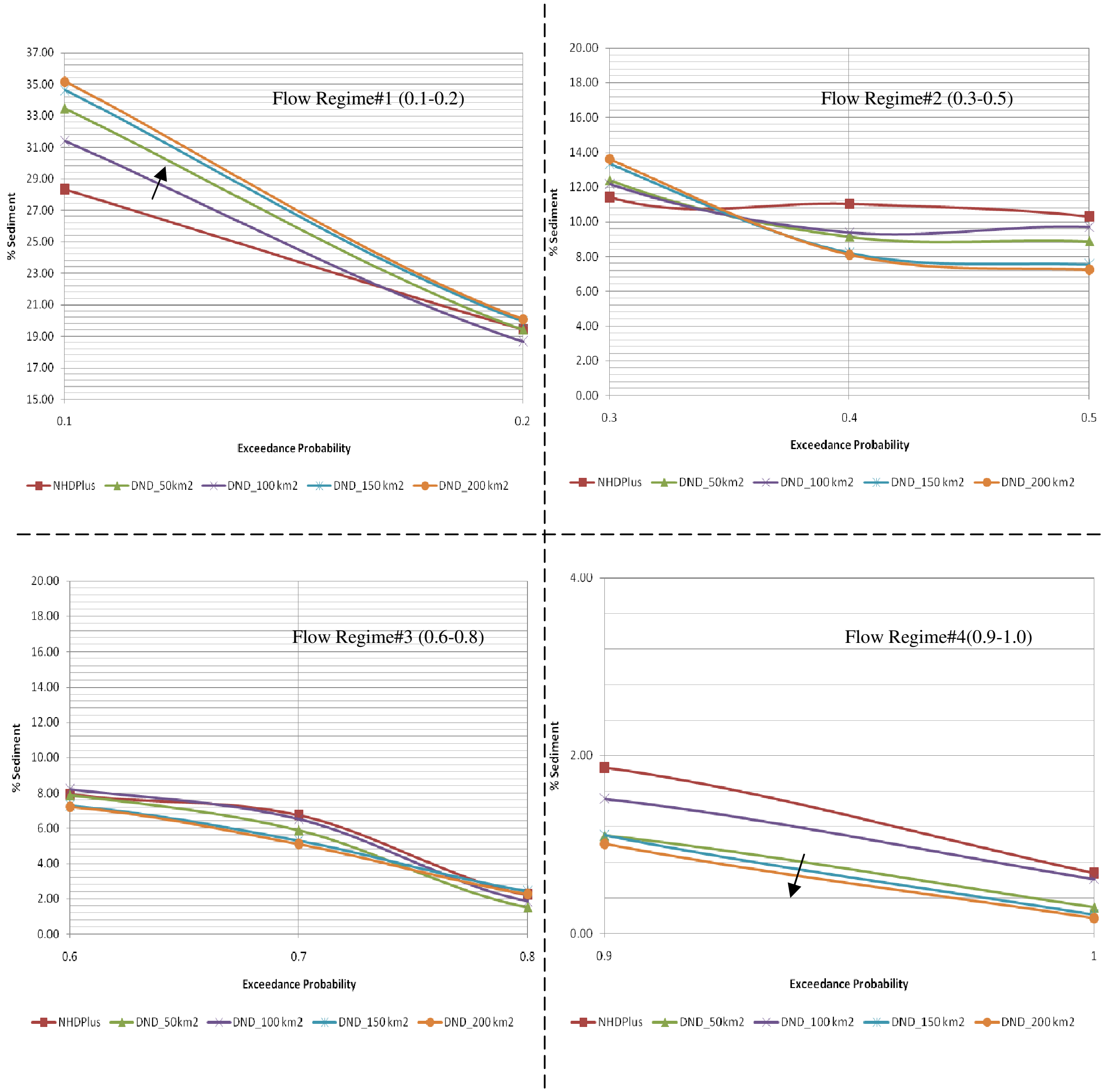

Figure 44. Predicted Sediment at Each Exceedance Probability

The channel sediment transport is calculated using the Eq. (4).

$$S = aV^{b} \tag{4}$$

where S, is the transport capacity (ton/m^3); V, is flow velocity (m/s); and a and b, are constants. Depending on whether the amount of sediment being carried is above or below transport capacity, SWAT either deposits excess sediment or re-entrains sediment through channel erosion.

Flow velocity is computed as:

$$V = \frac{Q}{w * d} \tag{5}$$

where Q, is the flow volume (m^3/s); w, is channel width (m); and d, is depth of flow (m).

As shown in Fig.42, at a given DND scale, as the exceedence probability decreases (i.e. 1.0 to 0.1), the flow volume increases. This could be the reasons for the predicted sediment, at a given DND scale, to increase as the exceedence probability decreases.

It is admitted that the sediment transport is also a function of channel length and other channel dimensions that are affected by the subwatershed size. Furthermore, Slope and length of slope (LS-factor) parameters used in the calculation of the MUSLE topographic factor are sensitive factors that can greatly affect the SWAT sediment yield predictions. However, the values of these parameters will not have an influence as the comparison is made for a particular DND scale.

As the DND scale becomes coarser, the sediment prediction increases in high flow regime. However, the prediction at the DND scale of 50 km^2 is higher than the prediction at the DND scale of 100 km^2. This observation is similar to what Fig.42 shows. Even though flow volume could be one of the reasons, an attempt was made to investigate if the average LS-factor parameter used in the calculation of the MUSLE topographic factor has an effect as DND scale changes. As shown in Fig.45, the influence of LS-factor is not justifiable. The average LS-factor is constant for all the DNDs.

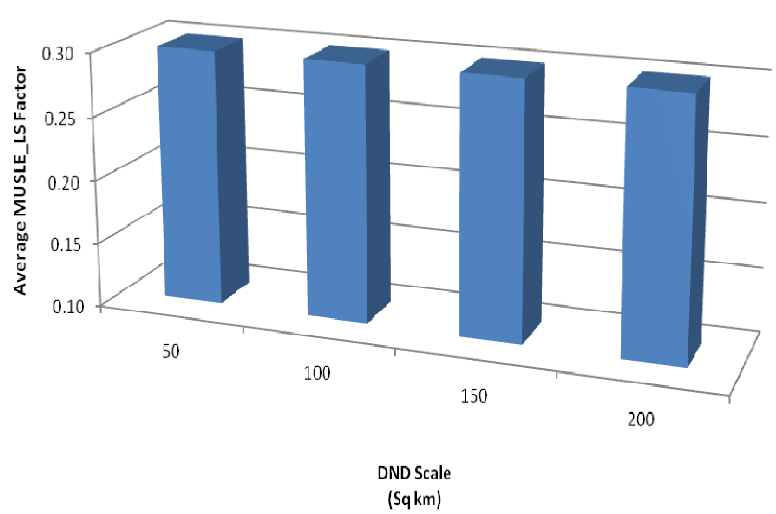

Figure 45. Average LS Factor against DND

Added to this, it is worthy to note that in low flow regime the model prediction follows the reverse pattern. In other words, as the DND scale becomes coarser, the sediment prediction decreases in low flow regime. Again, this observation is similar to what Fig.42 shows. Thus, the reason made for high flow regime can justify this observation as well.

Impact of DND with Coarser Data Resolution

It was shown how SWAT prediction changes as the scale of DND changes at the base input data resolution which is at 30m. In this section, the impact of input data resolution within each DND is presented. The Table 6 and Table 7 present the number of HRUs simulated for the selected DND scales and input data resolutions.

Table 6. Number of HRUs with DND and Data Resolution for Sugar Creek

	DND 50 km^2	DND 100 km^2	DND 150 km^2	DND 200 km^2
30m	663	432	280	225
60m	648	425	275	221
90m	623	403	262	212
120m	588	383	252	204
150m	568	373	244	198

Table 7. Number of HRUs with DND and Data Resolution for Kings Creek

	DND 25 km^2	DND 50 km^2	DND 75 km^2	DND 100 km^2
30m	551	411	282	256
60m	542	406	280	252
90m	524	396	270	245
120m	512	385	262	239
150m	487	367	252	228

The Fig.46 and Fig.47 show the NSE for uncalibrated monthly streamflow prediction for Sugar Creek and Kings Creek respectively for the selected input data resolution within each DND. Fig.48 and Fig.49 show the predicted total water quantity. It is notable that the influence of input resolution within each DND is very negligible. However, the influence of DND is observable even though the significance is not appreciable.

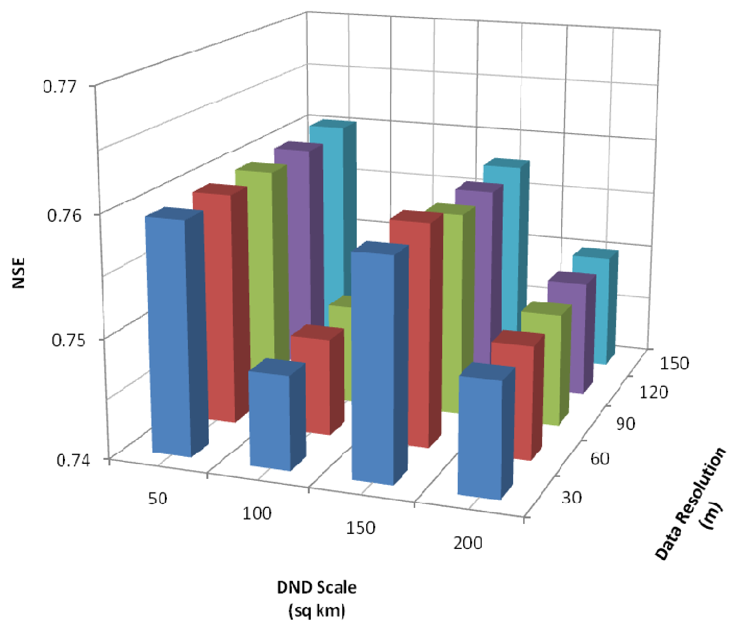

Figure 46. NSE for Sugar Creek with DND and Input Data Resolution

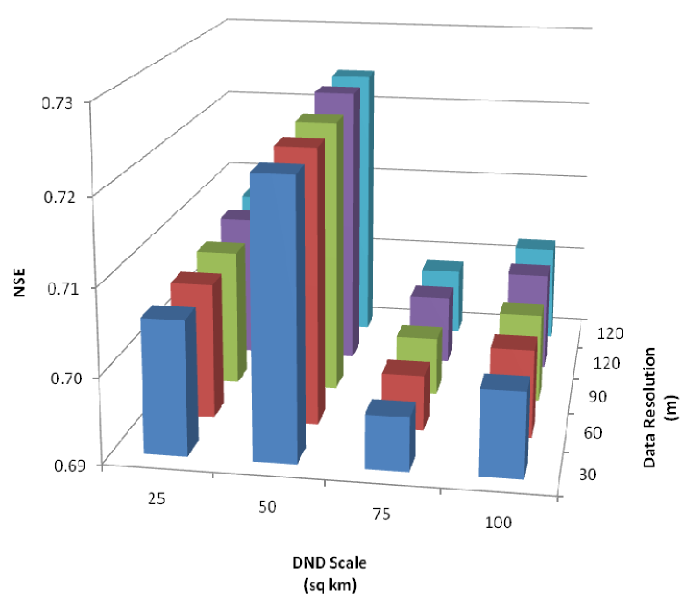

Figure 47. NSE for Kings Creek with DND and Input Data Resolution

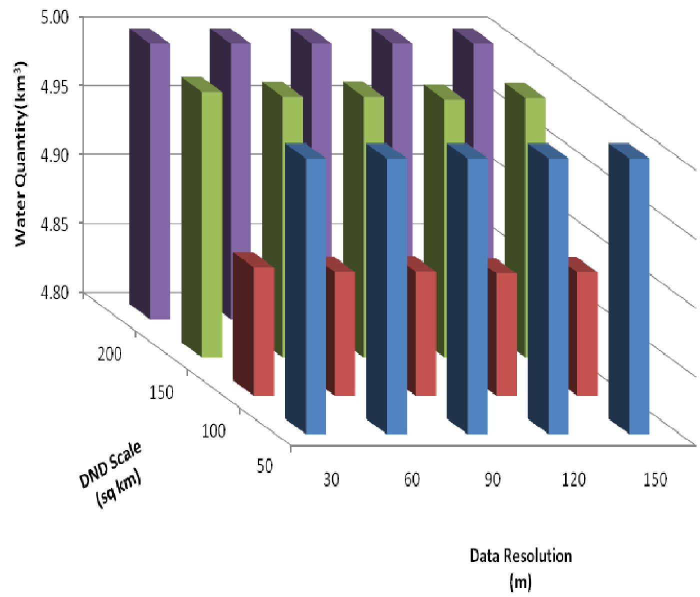

Figure 48. Total Water Quantity for Sugar Creek with DND and Input Data Resolution

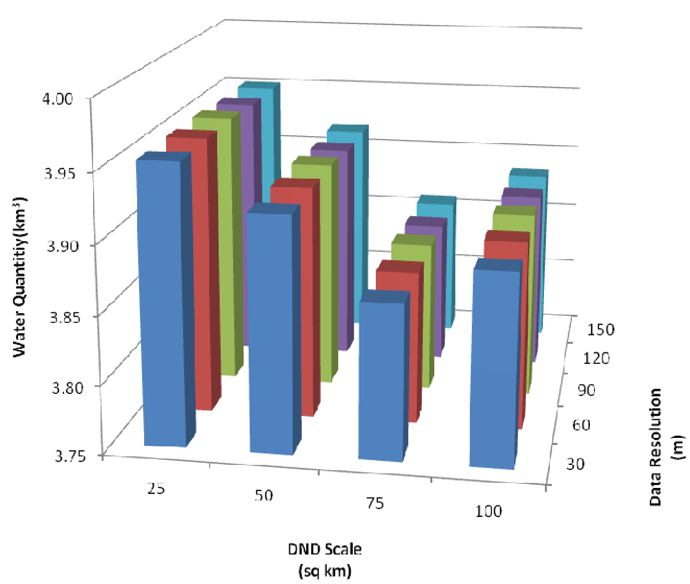

Figure 49. Total Water Quantity for Kings Creek with DND and Input Data Resolution

In SWAT, the main factor affecting streamflow is the characteristics of the HRUs which in turn determine the curve number. Surface and subsurface runoff are generated at the HRU level. Thus, HRU modifications that affect the distribution of simulated landuse, soils, and landscape characteristics will have the greatest impact on the predicted streamflow rates. By referring to Fig.50, it is observable that the change in number of HRUs simulated decreases drastically (66% for Sugar Creek and 54% for Kings Creek) as DND scale changes but keeping the input data resolution constant.

Sugar Creek

	DND 50 km^2	DND 100 km^2	DND 150 km^2	DND 200 km^2
30m	663	432	280	225
60m	648			
90m	623			
120m	588			
150m	568			

(663-225)/663*100=66%

(663-568)/663*100=14%

Kings Creek

	DND 50 km^2	DND 100 km^2	DND 150 km^2	DND 200 km^2
30m	551	411	282	256
60m	542			
90m	524			
120m	512			
150m	487			

(551-256)/551*100=54%

(551-487)/551*100=12%

Figure 50. Percentile Change on Number of HRUs with DND and Data Resolution

Whereas the change in number of HRUs simulated decreases at a lesser rate (14% for Sugar Creek and 12% for Kings Creek) as the input data resolution changes but keeping the DND scale constant. This could be the reason for having a slight change in SWAT streamflow prediction as DND scale changes where as no change as input data resolution changes within a DND. The Fig.51 and Fig.52 show the predicted total sediment at the watershed outlet with DND and input data resolution for Sugar Creek and Kings Creek respectively. In contrast to flow, the input data resolution has an influence on the total predicted sediment at the outlet. Beyond the DND scale of 100 km^2 and 50 km^2 for the Sugar Creek and Kings Creek watersheds respectively, the sediment prediction increases as input data resolution becomes finer.

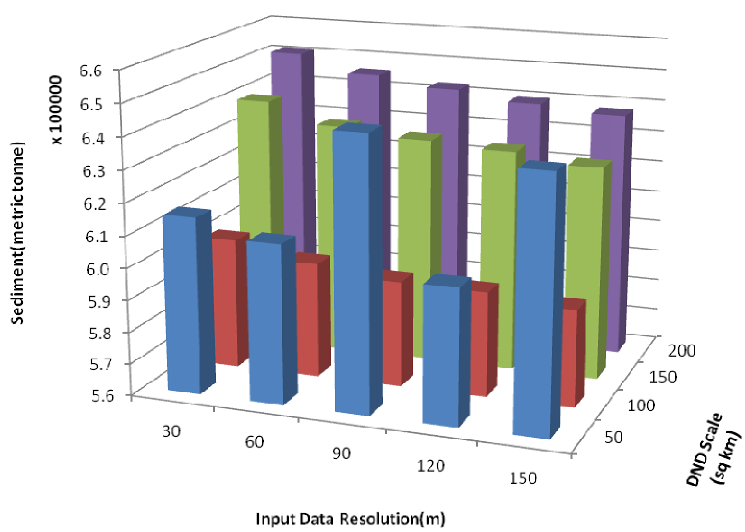

Figure 51. Total Predicted Sediment for Sugar Creek with DND and Input Data Resolution

Furthermore, the total predicted sediment at the lower DND can achieve high value with the coarser input resolution. The reported values at the DND scale of 50 km^2 and 25 km^2 for the Sugar Creek and Kings Creek watersheds respectively can substantiate this.

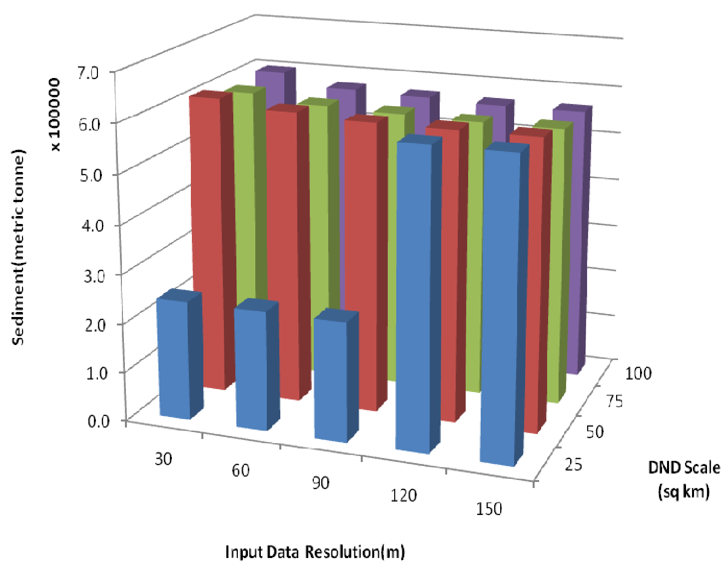

Figure 52. Total Predicted Sediment for Kings Creek with DND and Input Data Resolution

The overland slope and slope length, sensitive factors in MUSLE, delineated for a subwatershed can change as the size of the subwatershed and input data resolution change. Thus further investigation was carried out in an attempt to understand the reason for the change in sediment prediction as input data resolution changes within a

DND.Fig.53 and Fig.54 show the average LS-factor at each input data resolution within DNDs for the Sugar Creek and Kings Creek watersheds respectively. Interestingly, the values of LS-factor decreases as input data resolution becomes coarser. This could be the reason for the increased sediment prediction beyond the DND scale of 100 km^2 and 50 km^2 for the Sugar Creek and Kings Creek watersheds respectively, as input data resolution becomes finer. Furthermore, it is observable that there is no change on LS-factor as the DND scale changes. Probably, this is an indication that the parameters that influence the sediment prediction as DND scale changes may be different to that of parameters that influence the sediment prediction as input data resolution changes within a DND.

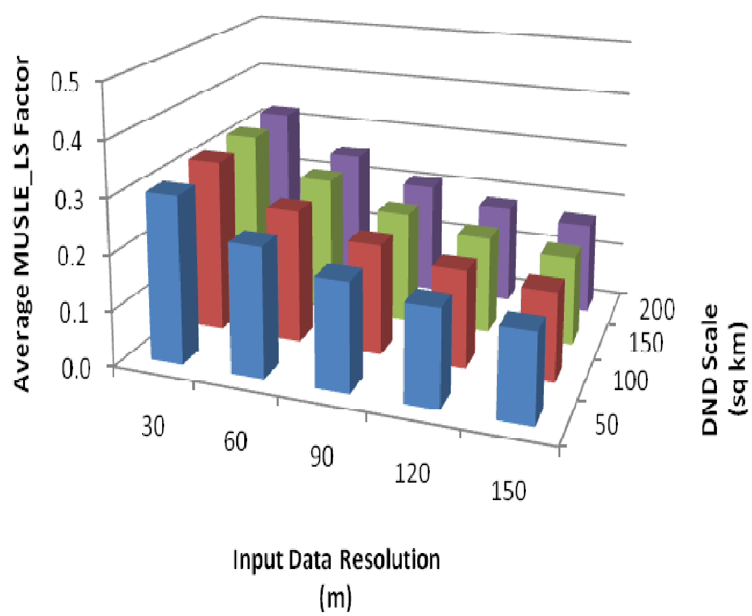

Figure 53. LS Factor for Sugar Creek with DND and Input Data Resolution

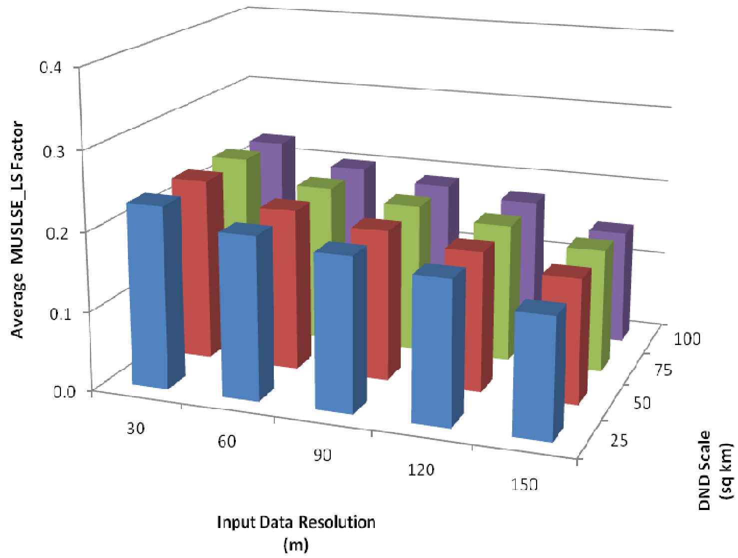

Figure 54. LS Factor for Kings Creek with DND and Input Data Resolution

However, as shown in Fig.55 and Fig.56, beyond the DND scale of 100 km^2 and 50 km^2 for the Sugar Creek and Kings Creek watersheds respectively, the percentile of total sediment in high flow regime that is at the exceedance probability of 0.1 has an increasing trend as the input data resolution become coarser.

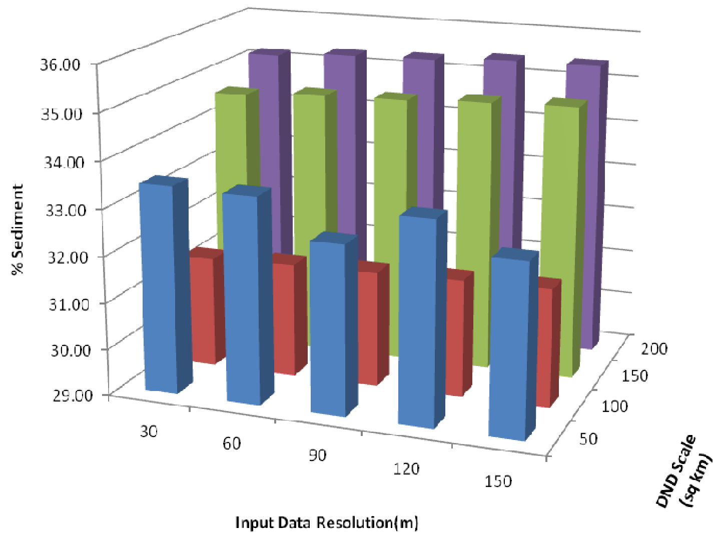

Figure 55. Predicted Sediment for Sugar Creek in High Flow Regime (P=0.0-0.1)

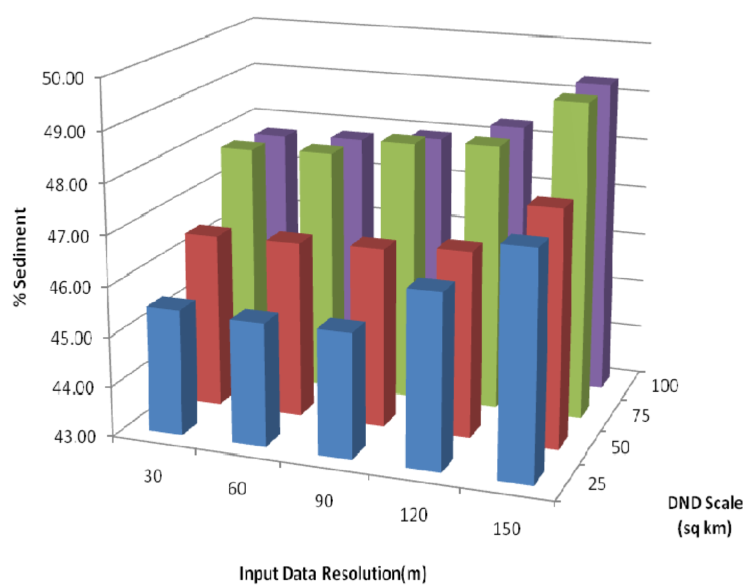

Figure 56. Predicted Sediment for Kings Creek in High Flow Regime (P=0.0-0.1)

What implies from these findings is that the input data resolution for the total sediment and the input data resolution for the percentile of total sediment during the high flow regime are on the reverse sides. In other words, the input data resolution at which the total sediment is high gives low sediment prediction in high flow regime beyond the DND scale of 100 km^2 and 50 km^2 for the Sugar Creek and Kings Creek watersheds respectively.

Fig.57 and Fig.58 show the predicted sediment for the Kings Creek and Sugar Creek watersheds respectively with DND and data resolution in low flow regime that is at the probability of exceedance of 1.0, which represents the predicted sediment with DND and data resolution in between the exceedance probabilities of 0.9 and 1.0. It is observable that beyond the DND scale of 100 km^2 and 50 km^2 for the Sugar Creek and Kings Creek watersheds respectively, the input data resolution does not have an influence on sediment prediction in low flow regime. Thus, based on the above findings, it seems there exists a certain threshold on DND scale (100 km^2 and 50 km^2 for the Sugar Creek and Kings Creek watersheds respectively) that clusters the behavior of sediment prediction along with input data resolution. The conversion of these critical DND scales into percentile of respective watershed area shows that this critical threshold can be in the range of 8-9% of the watershed area for the selected study areas.

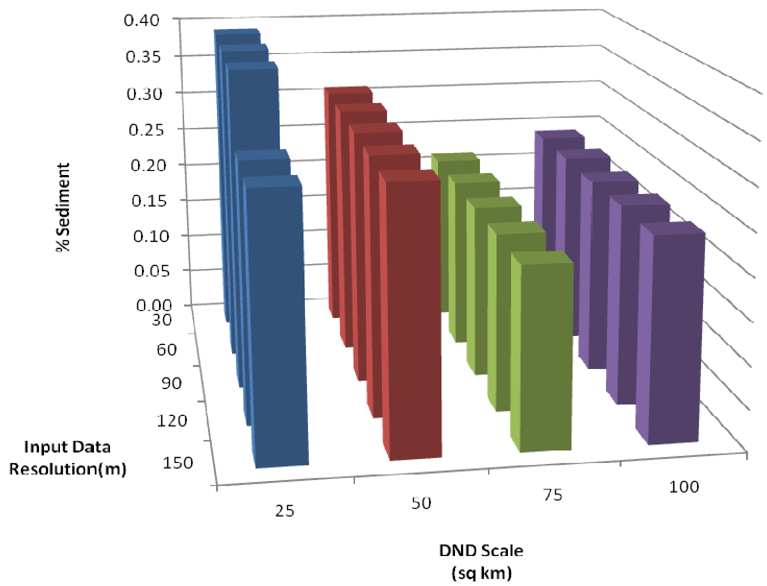

Figure 57. Predicted Sediment for Kings Creek in Low Flow Regime (P=0.9-1.0)

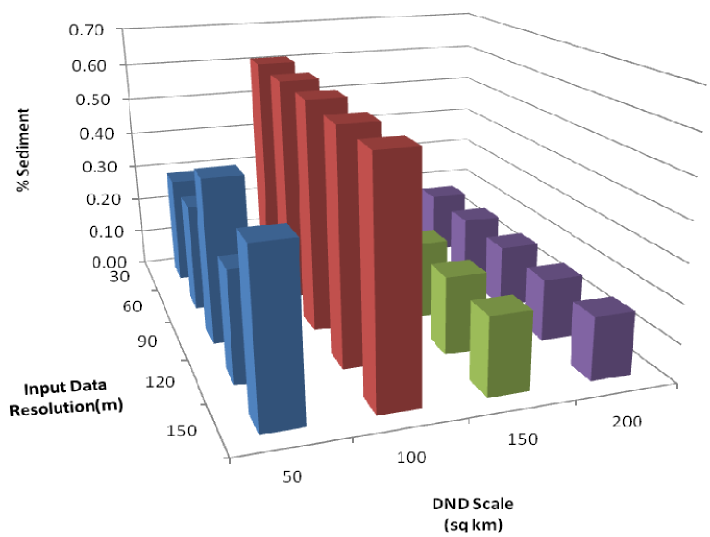

Figure 58. Predicted Sediment for Sugar Creek in Low Flow Regime (P=0.9-1.0)

CHAPTER V

CONCLUSIONS

An Entropy Based Watershed Subdivision Scheme with Landuse and Soil Dataset

This study presents an entropy based watershed subdivision scheme by using the landuse and soil spatial datasets with the conventional CSA, the minimum upstream drainage area that is required to initiate a stream, approach to make use of all subwatershed maps obtained at different CSAs. The study shows that there exists a subwatershed map that does not belong to one of the subwatershed maps obtained through conventional CSA approach, to produce a better result on monthly uncalibrated SWAT streamflow prediction. Beyond the critical threshold, the CSA threshold which gives the best uncalibrated monthly prediction among a given set of CSAs, the SWAT prediction can be improved further by subdividing some of the subwatersheds at this critical threshold. However, the subdivision of these subwatersheds does not appear at the very next finer CSA. Furthermore, the subwatershed map that produces the best SWAT streamflow prediction can change as the resolution of landuse and soil dataset changes. In other words, as the level of heterogeneity is changed by coarsening the input data resolution, the subwatershed map that produces the best SWAT streamflow prediction too changes. This finding raises a question if the conventional HRU thresholding, which is applied after watershed delineation to remove the small HRUs, has to be considered before the watershed is delineated. The reason is that as the HRU thresholding is applied, the heterogeneity level is changed. Thus, there has to be a subwatershed map that can capture the altered heterogeneity level at the best.

Furthermore, this study was able to show that there exists a subwatershed map that does not belong to one of the subwatershed maps produced through conventional CSA approach. However, there is a need for a statistical criterion that can lead to find the best subwatershed map that makes use of all the given CSAs without running the model.

Predictive Analysis of SWAT Using NHDPlus Dataset

This study shows an integrated modeling environment with SWAT and NHDPlus spatial datasets, an integrated suite of application-ready geospatial data products envisioned by the US Environmental Protection Agency to by-pass the default CSA based watershed delineation in SWAT. The monthly uncalibrated SWAT streamflow prediction with NHDPlus spatial dataset was very good to show the potential of the NHDPlus catchments to capture the spatial variability for the Sugar Creek watershed in Indiana. Added to this, the NHDPlus catchments for the Sugar Creek are such that they set off the spatial heterogeneity among themselves in an optimum manner (i.e. at minimum) as the model performance on streamflow prediction was even better by considering NHDPlus catchments as HRUs. Thus, with the introduction of NHDPlus catchments in SWAT environment, the application of time consuming simulation of SWAT may not be required with trial and error process on critical source area.

The Role of Dynamic NHDPlus Dataset (DND) on SWAT Prediction

This study shows the role of spatial size (catchment area) of NHDPlus catchment and the impact of varying the level of detail of DEM, landuse and soil within each NHDPlus catchments on SWAT streamflow and sediment prediction.

The input data resolution (within each NHDPlus catchments) does not have an influence on SWAT streamflow prediction. However, there is a change on streamflow prediction as the area of the NHDPlus catchment changes. This was due to the change in number of HRUs simulated. The change in number of HRUs simulated decreases drastically (66% for Sugar Creek and 54% for Kings Creek) as area of the NHDPlus catchment changes but keeping the input data resolution constant. Whereas the change in number of number of HRUs simulated decreases at a lesser rate (14% for Sugar Creek and 12% for Kings Creek) as the input data resolution changes but keeping the DND scale constant.

For the Sugar Creek, SWAT over predicts on total water quantity as the area of the NHDPlus catchment changes (DND scale changes) at the watershed outlet. However, the water quantity in high flow regime (the highest 20%) is under predicted with DNDs. The water quantity in low flow regime (the lowest 20%) is over predicted with DNDs. Furthermore, as the DND scale becomes coarser, the predicted water quantity is close to the observed.

For the Sugar Creek, at a given DND scale, the percentile of predicted sediment yield at each exceedance probability has increased as the exceedance probability decreased (i.e. 1.0 to 0.1). As the DND scale becomes coarser, the sediment prediction increases in high flow regime and decreases in low flow regime. Beyond a certain catchment size (8-9% of the watershed area for the selected study sites), as the input data resolution becomes finer, the total sediment increases whereas the percentile of sediment prediction in high flow regime decreases. However, the input data resolution does not have an influence on sediment prediction in low flow regime. Beyond a certain catchment size (8-9% of the watershed area), the SWAT parameter that influences the sediment prediction as NHDPlus catchment size changes is different to that of parameter that influence the sediment prediction as input data resolution changes within a NHDPlus catchment. The sediment load predicted by SWAT for a watershed is affected by both the MUSLE, which is used for estimating subwatershed loadings, and also the sediment transport via channels that is based on the stream power. As the NHDPlus catchment size changes, the stream power has an influence on SWAT sediment prediction. However, as the input data resolution changes, but keeping the NHDPlus catchment size constant, the MUSLE LS-factor has an influence on SWAT sediment prediction. In this study the resolution was changed from 30 m to 150 m within a subwatershed. The same resolution was kept for all the subwatersheds. However, the level of heterogeneity can change from one subwatershed to another. Thus, there is a need to investigate further how SWAT prediction changes as different resolution is applied for different subwatersheds.

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