A

DISSERTATION

Submitted in partial fulfillment of the requirements for the award of the degree

On

IMPACT OF RAINFALL AND LULC ON FLOOD HAZARD MODELLING

WITH A FOCUS ON ROORKEE AREA

of

MASTER OF TECHNOLOGY

By

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CANDIDATE'S DECLARATION

I, Chaitanya Singh, hereby declare that the work presented in this dissertation entitled "**Impact of Rainfall and LULC on Flood Hazard Modelling with a focus on Roorkee Area"** in partial fulfillment of the requirement for the award of the degree of **Master of Technology** submitted to CENTRE OF EXCELLENCE IN DISASTER MITIGATION AND MANAGEMENT**, Indian Institute of Technology Roorkee, India,** under the supervision of **Dr. N. K. Goel**, Professor, Department of Hydrology, IIT Roorkee, is an authentic record of my work done during the academic session of 2017-19. I have not submitted the matter embodied in this report for the award of any other degree or diploma.

Date:

Place: **Roorkee** **CHAITANYA SINGH**

This is to certify that the above-mentioned statement made by the candidate is correct to the best of my knowledge.

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Place: Roorkee

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ABSTRACT

A proper risk assessment and management framework is based on the accuracy of data and the estimates prepared in accordance with it. Understanding the risk and stakes involved in different situations helps in reducing the damages by floods. It also helps in preparing for damages which can't be avoided. But at the same time, inaccuracies in risk assessment may lead to overestimation or underestimation of hazards. The estimations of how much losses to human life and property may occur due to a certain hazard are called risk associated with that hazard. When flooding of any area including water bodies occurs near a city or village due to excessive rainfall, it causes damage to human life and property and also disrupts the day to day life of people living in affected area. Thus, rainfall is a major component in assessment of flood risk and in turn, the accuracy of the rainfall data largely affects the results of the hazard modelling and risk assessment. The study focuses on the study of rainfall data for Roorkee area, and compares the results of runoff generation from observed sub- daily rainfall data with the results from rainfall of smaller durations estimated with the same methods used in Uttarakhand Disaster Risk Project. The basic inputs required for risk assessment models include rainfall patterns and physiographic characteristics of the area. Local rainfall data has been utilized to understand the rainfall distribution, storm intensities and relationship of total storm depths with intensities observed. Based on the results of the 40-year data of recording type rain gauge with 15 minute interval data intensity, duration and frequency relationship has been established. A basic runoff generation modelling has also been carried out with SCS-CN method. Using this method, the effect of LULC on various parts of Roorkee area has been studied. Based on this analysis, the areas likely to be most affected during floods have been identified.

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LIST OF ABBREVIATIONS

ASTER	Advanced Space borne Thermal Emission and Reflection Radiometer
BLRMP	Barett- Lewis Rectangular Pulse Model
C_k	Coefficient of kurtosis
CoEDMM	Centre of Excellence in Disaster Mitigation and Management
C_s	Coefficient of skewness
C_v	Coefficient of variation
DEM	Digital Elevation Model
GIS	Geographic Information System
IDF curves	Intensity Duration Frequency curves
IMD	Indian Meteorological Department
K-S Test	Kolmogorov- Smirnov Test
LU/LC	Land use/ Land cover
NDMA	National Disaster Management Authority
RBDM	Risk Based Decision Making
S&MT	Small and Medium Towns
SCS-CN	Soil Conservation Service- Curve Number
SRTM	Shuttle Radar Topography Mission
SWMM	Storm Water Management Model
UNDP	United Nations Development Programme
USDA	United States Department of Agriculture
USGS	United States Geological Survey

CHAPTER 1: INTRODUCTION

1.1 Global Scenario for Disaster Management

The world has seen an increasing number of natural hazards, extreme climatic events and losses due to disasters in the last few decades. The increase in losses, on one hand, is purely attributed to increase in number of such incidents, while on other hand the rapidly growing population, unplanned development in hazard prone areas and increasing investments in the housing & infrastructure sectors leads to increasing losses for same hazard levels. This has led to rising concerns towards disaster mitigation and management worldwide.

Other than the individual initiatives in various countries, the united efforts started when The United Nations General Assembly declared the 10-year period from 1990 to 1999 as the International Decade for Natural Disaster Reduction (IDNDR). With conclusion of IDNDR in 1999, United Nations International Strategy for Disaster Reduction (UNISDR) was put forward by UN General Assembly. To ensure the implementation of the same, United Nations Office for Disaster Risk Reduction (UNDRR) was developed. A total of 3 World Conferences on Disaster Risk Reduction (WCDRR) have been organized. These were hosted by Japan in Yokohama 1994, Hyogo 2005 and Sendai 2015, with UNDRR as coordinating agency of the 2nd and 3rd conference. All the 3 conferences put forward strategies/ frameworks which all countries can follow for effective disaster risk reduction. After Yokohama Strategy 1994 & Hyogo Framework 2005, the Sendai framework 2015 has been accepted by many countries as the way forward. The Sendai Framework lists four priorities for action for the various countries:

1. Understanding disaster risk
2. Strengthening disaster risk governance to manage disaster risk
3. Investing in disaster risk reduction for resilience
4. Enhancing disaster preparedness for effective response, and to "Build Back Better" in recovery, rehabilitation and reconstruction

Understanding risk has been given high priority in Sendai Framework, as it can help prevent or mitigate future damage. To understand the risk associated with any event, it is important to identify the extent and intensity of hazards. The present work has been done to understand the importance of accurate rainfall estimations for flood modelling of flash floods in urban areas.

1.2 Flood hazard

A comprehensive approach for reducing the adverse impacts of hazards (natural or otherwise) brings together all the tasks that need to be done before, during, immediately after, and much after the event. Comprehensive management can help prevent the casualties caused by a disaster and also reduce the economic losses. To reduce and manage impact of disasters, first it is necessary to understand the extent of problems and quantify the variables for better and informed decisions. Risk Assessment is the first step for disaster management as it helps us to identify what solutions are feasible and which alternative to choose. The disaster management activities further include capacity building, awareness programs, trainings, relief and rescue, but the focus of the study is risk assessment.

Risk is the measure of expected losses which might occur if a hazard occurs near human settlements. Thus, risk has four components: hazard, exposure, vulnerability and capacity. Usually, risk assessment consists of a qualitative assessment which includes identification of possible hazard, development of hazard scenarios based on theory, assessment of scenarios; and a quantitative assessment which includes identification of hazard level, probability of occurrence, capacity/ vulnerability study, damage estimation for particular level of hazard, and overall Risk/Safety Factor.

Risk assessment requires identification of hazard scenarios. Understanding the extent/ intensity, frequency, and how the hazard may cause damages is very important for any kind of decision making. This thesis tries to develop hazard scenarios associated with extreme rainfall in Roorkee area.

1.3 Floods

In a hydrological sense, a flood is a relatively high flow which overflows the natural channel provided for runoff (Chow, 1956). A flood is an overflow of large amount of water over what is usually dry land. There are many types of floods like flash floods, riverine floods, coastal floods etc. Floods are caused by many reasons such as heavy seasonal rainfall, inadequate drainage, tidal floods, dam break floods, landslide induced floods etc.

Flood is a hazard with a potential to cause damage. When a flooding event causes widespread loss of life or property and leads to a severe disruption in the state of human society by affecting trade and transportation, it becomes a disaster.

India is highly vulnerable to floods. Out of the total geographical area of 329 million hectares, more than 40 million hectares is flood prone. Some states like Uttarakhand, Uttar Pradesh, Bihar located on flood plains have large regions which get affected by floods almost every year. Some of the recent floods in India are Chennai floods 2017 and Assam flood 2017. Other than these Gujrat flood 2017, Bihar flood 2017, Kashmir flood 2014 etc. are also major recent floods. In India every year lakhs of household are affected by floods

While regional floods which occur over large catchments cause more damage to life and property, in recent years urban floods have also become a major issue due to insufficient drainage capacity, encroachment in natural drainage and unplanned/ organic growth of settlements. Not only major cities like Hyderabad, Ahmadabad, Delhi, Chennai, Kolkata, Mumbai etc., even small and medium towns are facing this issue. The causes for urban flooding can be categorized as (1) Natural causes: High intensity rainfall, siltation of natural drainage channels (2) Anthropogenic causes: Development/encroachment in natural drainage channels, change in runoff characteristics (amount and time of concentration) of sub-catchments due to changes in landcover, insufficient storm water drainage capacity for the city. Such flooding events are less dangerous than regional flooding events, but causes inconveniences in day to day life of people, inundation damage infrastructure and property, hygiene & health issues. Usually local flooding events do not have high velocity flow and momentum to cause damage to bigger structures but damage due to inundation occurs in the affected areas. Smaller structures built on natural drainage channels often break as they obstruct the flow.

1.4 Need for the study

Urban flooding, in recent years, has become an issue due to rapid growth of population and built up area, unplanned development, encroachment, changes in runoff patterns etc. There are grave concerns for urban flooding, but it is a problem for which a feasible and efficient solution can be found. The efficient solution of urban flooding requires understanding of hazard scenarios. This study tries to

- Understand hazard scenarios associated with local flooding events by estimating hazard levels and exposure. As regional studies have data and time limitations studying local flooding events accurately is not feasible. So, a local study improves the accuracy of regional models for particular locality using past studies and site data.

- The state multi hazard risk assessment under Uttarakhand Disaster Risk Project (UDRP) project is very good for regional planning and governance. But at local level, it leaves certain things to be identified, such as incorporation of sub- daily rainfall data, local drainage flow modelling, past studies, changes in land cover patterns and scenario modelling. So, a study of Roorkee city from Uttarakhand state has been selected, using which these shortcomings has been worked upon.

This study is an attempt to develop a framework to understand local risk scenarios by quantifying hazard levels, exposure, capacity and vulnerability. It builds on regional and past studies using site specific data.

1.5 Aim and Objectives of study

The study aims at establishing a methodology to understand, describe and analyse urban flood scenarios based on identifying suitable rainfall scenarios, urban land cover change, runoff modelling and changes in sub-catchment characteristics.

The present study is taken up with the following objectives:

a. Establishing rainfall scenarios for hydrological modelling (IDF relationships, Duration vs intensity relationship & identifying events for simulation)

b. Developing a relationship between anthropogenic factors (like built up, roads etc) with changes in settlement characteristics and runoff generation

c. Understanding the impact of Rainfall and LULC on flood hazard modelling

1.6 Chapterization

The study will act as a tool for decision making and identification of mitigation measures to reduce the damage or disruption caused by local floods. A brief introduction to each chapter of the study is as follows:

Chapter 1 provides an overview about the flood, causes of floods, disaster management and flood risk assessment, local/ urban floods, need for the study and aim and objectives of the study

Chapter 2 provides the review of literature referenced for the study

Chapter 3 discusses in brief about the study area and data used for further study process.

Chapter 4 is about an overview of the methodology for analysis and modelling

Chapter 5 describes the analysis and results of study

Chapter 6 includes conclusions, limitations, and scope of future study.

This chapter presents a brief review of the works referenced for study. Different sections discuss: concept of risk assessment and hazard scenario mapping rainfall scenario development understanding sub-catchment characteristics urban drainage modelling Uttarakhand Disaster Risk Project and review of works for Roorkee area.

2.1 Concept of Risk Assessment and Hazard Scenario Mapping

The idea of flood hazard assessment started with mathematical empirical models, envelope curves, regional flood formulae, rational approach, stochastic approaches (univariate, multi-variate), IDF curve method etc (as discussed by Vogel et. al., (2016) & Apel, et. al., (2004)) which have been very effective with corrections for regional scale flood hazard assessment all over the world. After development of mapping techniques, data collection and creation of various tests to assess site effects, deterministic approach and local site-based studies were developed. In recent years, with constant development of satellite data analysis tools, mapping platforms like Arc-GIS and task specific tools like MIKE- HYDRO (Channel flow assessment and regional flood modelling, EPA- SWMM (Urban drainage modelling) etc, it has become possible to understand, analyse and represent local risk easily.

After introduction of concept of 'Risk' in disaster management, a new challenge came up for the hazard mapping techniques, as it was now important to assess (and possibly represent mathematically) the parameters of risk which are:

$$\text{Risk} = (\text{Hazard} * \text{Exposure} * \text{Vulnerability}) / \text{Capacity}$$

In scenario of floods, hazard for buildings/ structures is of 3 types (i) Rainfall damage hazard (occurs due to rainfall), (ii) Inundation hazard (Due to inundation, static loading, saturation of soil and maintenance losses) (iii) Hydro-dynamic hazard, which occurs due to water flowing at high velocity (dynamic loading, corrosion and erosion). In the scenario of urban floods Flood damages are usually divided in direct and indirect damages which are further divided in tangibles and intangibles (Smith and Ward, 1998). The BMTPC 2010 guidelines for flood risk reduction,2010 also defines the damage scenarios and the parameters of risk assessment in a similar manner.

2.2 Rainfall scenario development

Development of rainfall scenarios is essential for dynamic hydrologic modelling. As seen in studies by Singh et. al., (2016), Bhushan et. al., (2012) and many others, the most predominant method used for rainfall scenario development is IDF curves. Many other studies have used disaggregation-models, past event scenario, outlier storms etc for identification of rainfall scenario. According to Hanaish, (2016), disaggregation models are not optimal to estimate peak events as the data shoes underestimation. Extreme event modelling, outlier events and past recorded scenarios are better for the scenario of floods.

While extreme event modelling with IDF curves is good for stochastic representations, they need to be checked before application. Many studies perform corrections on the IDF curve based on recorded data for climate change and local characteristics. Liao et. al., (2014) have used IDF curves with climate change corrections on the data. Two RCP scenarios were used for rainfall scenario development.

A similar study for Roorkee was done by Singh et al., (2016). In which, analysis of the curves indicated increase in precipitation intensities for all the RCP scenarios. It was also found that intensities of all return periods increase with intensifying RCP scenarios for Roorkee. Thus, validation and correction of past IDF curves has been performed in this study.

In the absence of data for small durations, reduction formulae are used. Gamit et. al., (2018) have utilized IMD reduction formulae for downscaling of daily rainfall data. The reduction formulae is appropriate for generalized regional studies, but in case of local hazard scenario mapping, data from recording type rain gauges provides better resolution of data.

2.3 Understanding Sub-catchment characteristics and estimation of runoff generation

The runoff generated from a particular sub-catchment depends on (i) the terrain (topography, slopes, natural drainage channels) (ii) the surface (perviousness/ imperviousness, barren/vegetation, LULC) (iii) the physiography (area, shape, location etc) and (iv) the channels for drainage flow (capacity, shape, length, slope, Manning's N-number). Rainfall–runoff models use a set of hydrological parameters to characterize a catchment and compute the corresponding runoff Henonin et. al., (2013).

For urban settlements, the study requires a lot of detailing for small areas so many generalization methods are used to identify the runoff characteristics. The heavy requirements of computing hardware is a majo r limitation for large-scale area or risk/uncertainty analysis modelling with fine resolution that describes the details of building features.

Chen et. al., (2012) have used grid coarsening as a way to reduce the computing efforts for 2D flood modelling. While due to the limitations imposed by the data a cell-based structure has been chosen for the model by (Mascarenhas et al., 2005), in which a cell- based model, the study area is divided into “cells” that group together areas where the major properties of geometry, hydraulic behavior, land and topography are almost uniform.

Modern cities have grown in a haphazard and unplanned manner due to fast industrialization. Cities in developing countries become over-populated and over-crowded partly as a result of the increase in population over the decades and partly as a result of migration. (Jaysawal & Saha, 2014). Due to rapid urbanization the drainage patterns for same sub-catchments change rapidly. Due to increase in impervious surface, reduction in time of concentration, and blockage of natural drainage channels the hazard scenario keeps changing, thus these parameters need to be analyzed for area of study.

Urban floods have become a major issue in India due to rapid and uncontrolled urban growth. A lot of studies are being done to increase accuracy of the model, Such as uncertainties related to risk assessment can cause major changes in investment decisions. The first issue is the accuracy of DEM and LULC models used. In order to increase accuracy of DEM, two methods were identified: (i) Using nearest neighbor approach to sub-divide pixels, and (ii) utilizing ground data to correct data near sub-catchment boundary.

Though method (i) increase the resolution, it doesn’t change the slope. While method (ii) helps improve the values where sub-catchment boundaries are present, and thus helps in modelling. Both methods have been discussed in Chapter 4. For LULC correction, (i) Site validation, and satellite imagery validation can be utilized, (ii) Separate extraction of features for layers, corrections and merging them to get complete raster and validation of each correction.

These corrections to DEM were considered, but as the resulting surface model had certain errors, the corrected DEM weren’t used and a runoff generation model was used for comparisons.

Jiang et. al., (2015) discuss the urban inundation modelling by trying to solve issue of building coverage ratio and 1D & 2D flow modelling, by using 1-D model for areas where flow is in a channel (roads, space between buildings, drainage channels etc and utilizing 2-D flood modelling for situations of overflow. As a building might occupy a significant, but not the total area within a computational cell, which could have a similar or slightly larger size than the building scale (Jiang et al., 2015)

According to Tran et. al. (2009) there are three reasons for integration of hazard maps with GIS: (i) hazard map eases risk identification, and is an efficient tool in representing and communicating local knowledge; (ii) local knowledge is necessary for specific decisions of disaster risk management; and (iii) GIS maps have advantages over conventional maps like reusability, modularity, digital processing etc. The underground drainage network is still represented by a 1D model while the surface flow is computed using a 2D model (Henonin et al., 2013).

2.4 Uttarakhand Disaster Risk Project

This document has been prepared under Disaster Risk Assessment of Uttarakhand, UDRP. It has a comprehensive risk mapping and assessment of Uttarakhand for earthquakes, floods, landslides and other disasters like Industrial disasters. Since the focus of the research study is floods, only the flood assessment done in the report has been discussed here. A very detailed and comprehensive flood assessment has been performed by mathematical model, while the representation of results has been done via GIS.

The flood estimations done for the project utilize the Indian Meteorological Department (IMD) daily rainfall data, available at all IMD stations, and reduces it to sub-daily rainfall using the reduction formulae put forward by IMD. To utilize that formulae, the daily rainfall is considered to be a single event spanning over a duration of 24 hours, while the actual durations for the events are different.

This assumption may affect the overall results of the flood estimations. This study utilizes the IMD daily rainfall data and sub- daily rainfall statistics gathered at DoH IIT, Roorkee, to understand the impact of rainfall on flood Hazard modelling.

The approach used for flood modelling can be summarized as seen in figure. As Roorkee block and city have been covered under UDRP it has been taken as one of the refence studies for regional data and estimates. The limitations described by UDRP for regional studies has been used to enhance upon in the local model.

Some of these limitations are: inconsistencies in network analysis of the drainage, due to DEM resolution, climate parameters haven't been included with IDF curves, generalization of rainfall patterns due to use of IDF reduction equations etc.

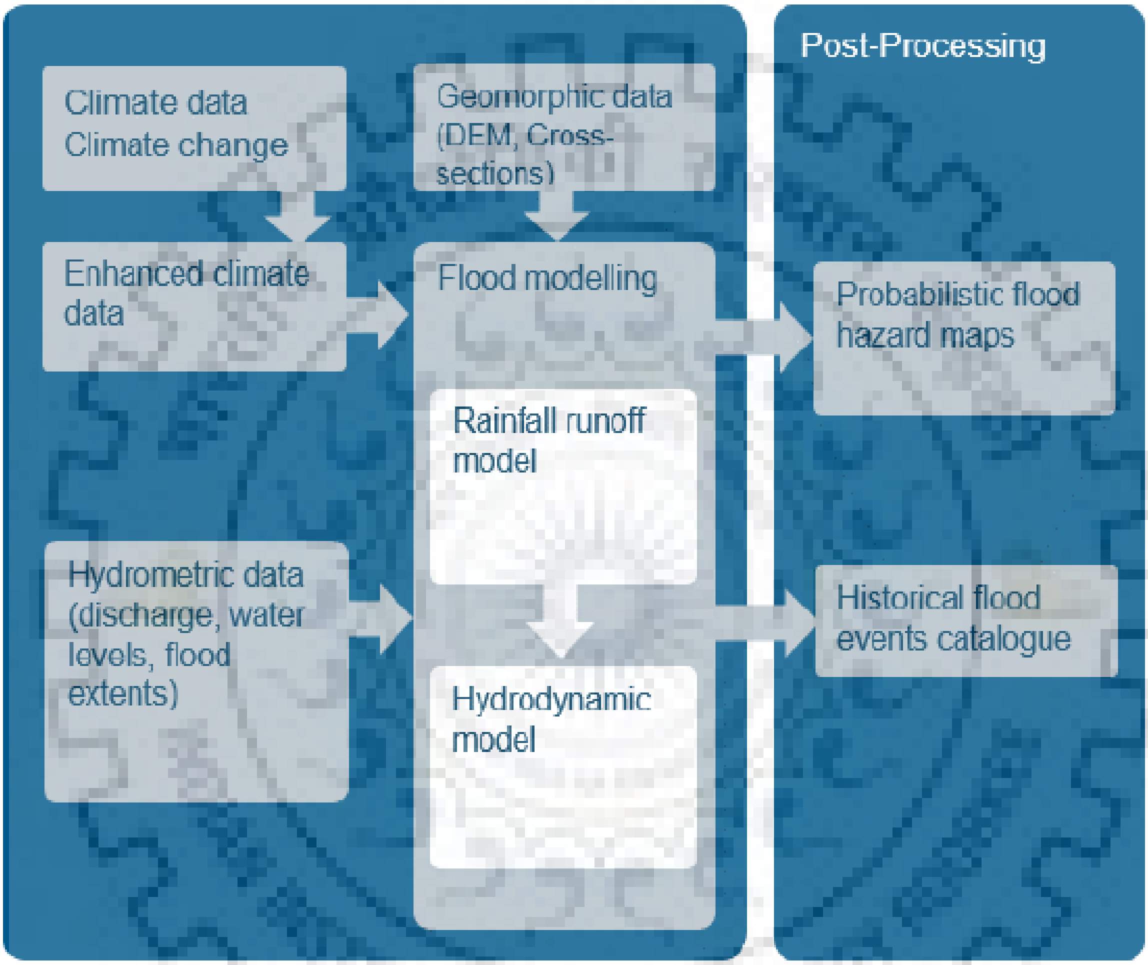

Figure 2.1: Methodology of flood hazard modelling used in UDRP (Source UDRP flood assessment report 2017)

2.5 Summary of literature related to study area

Table 2.1 Summary of literature related to study area

Authors	Year	Journal And Conference Paper	Title	Tools, Techniques and Data
Goel, N.K., Mathur, B.S. and Lone, M.A.	1989	National Seminar on 'Hydrology'	1988 Storm at Roorkee An Unusual One	Identification of outliers
Kartika, E, Chaubey, U. C., Jain, K.	2006	IIT Roorkee	Urban Flood Modelling	EPA SWMM
Bhushan, Abhishek, Joshi, H.	2012	IIT Roorkee	Storm Water Management for an Indian towm employing water sensitive urban design philosophy	Use of SWMM and artificial drain data
Vaibhav G., Bhaskar R. N., Praveen K. T., Shiv P. A.	2013	International Journal of Hydrology Science and Technology	Assessment of the effect of slope on runoff potential of a watershed using NRCS-CN Method	Runoff potential of sub-catchments of Solani River
Zope, P. E. Eldho, T. I. Jothiprakash, V.	2015	Natural Hazards	Impacts of urbanization on flooding of a coastal urban catchment	LULC study
Prakash, Ila, Goel, N.K.	2017	IIT Roorkee	Hydrological Aspects Of June 28, 2018 Flood at IIT Roorkee	1D flow modelling SWMM
Uttarakhand Disaster Risk Project (UDRP)	2018	Govt. of Uttarakhand	Disaster Risk Assessment of Uttarakhand	Regional studies for the case study

2.6 Findings from Literature Review

To develop hazard scenarios, different aspects of the area of the study like {i) Rainfall models (ii) Urbanisation and natural drainage relationship (LULC mapping and validation/ correction, Obstruction % change, Effect on sub-catchment characteristics) (iii) Drainage characteristics (Artificial, Natural, overflow) must be analysed in a comprehensive manner, while keeping in mind the accuracy of data, validation and uncertainties associated with it.

The unavailability of accurate surface and channel data will result in problems with drainage modelling thus the study limits the scope to rainfall data analysis and comparison basic runoff generation model. With the assumption that the changes in calculated runoff generation will be carried over to the final hazard models (in same percentage) the comparisons have been utilized to get an idea about how much overestimation in the runoff there might be.

As the runoff estimations have been done under the assumption that after reducing surface storage and artificial drainage capacity the difference will be same, the estimations are not to be used for risk assessment purpose instead they are only for comparison of both rainfall data sets.

3.1 Location

Roorkee (latitude 29°50'00''N to 29°55'00''N and longitude 77°50'00''E to 77°55'00''E) is located in Haridwar District of Uttarakhand state in India. As a block headquarter and with transport connectivity to large towns like Dehradun, Haridwar and Meerut, it has developed into an industrial and transport hub. Roorkee is one of the highest populated towns in Haridwar district. Area around Roorkee has many rivulets which appear when streams come down from Shivalik mountain range. River Solani, a tributary of Ganga flows near the city and the Upper Ganga Canal passes over it through an aqueduct constructed during the upper ganga canal project.

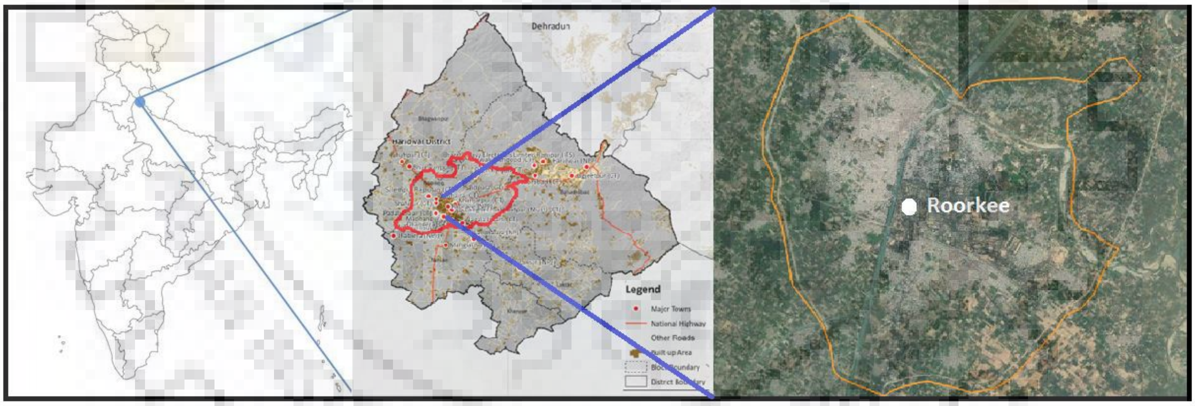

Figure 3.1: Location of study area (Source UDRP & satellite imagery)

Roorkee is located in sub- tropical climate belt. It experiences summer from March to June, while most of the rainfall occurs from mid- June to September. Though there are some cases heavy rainfall events in other months too. Average annual rainfall of area is around 1100 -1300 mm.

3.2 Solani River Basin

Roorkee City is located on Solani river basin. The river starts in the Shivalik mountains and the many subsidiaries start coning together into a larger stream after reaching gentler slopes. Due to the bend in path of Solani river north of Rookee, the river takes a path which divides most of the sub- catchments of the basin away from Roorkee.

According to fluvial flood study done in UDRP, even flood level for 100-year return period rainfall doesn’t affect Roorkee city and the study area.

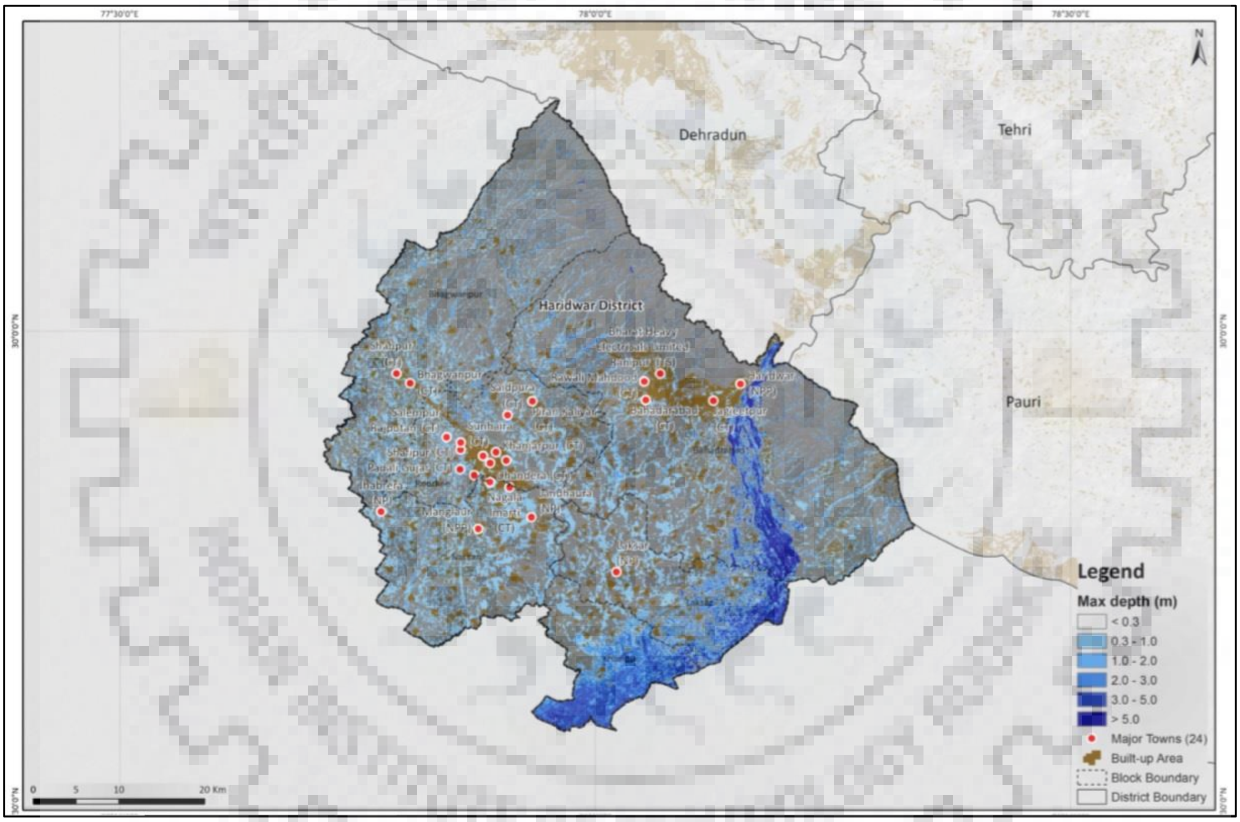

Figure 3.2: Flood hazard zonation by UDRP for fluvial floods

Map 3.2 shows a model flood projection in Haridwar district (source: Uttarakhand Risk assessment document). The major flooding occurs on Ganga River away from Roorkee block, many small streams and rivulets contribute to flooding in almost all blocks of Haridwar district. Most streams passing through Roorkee block enter through border with Dehradun block. And drain towards south east to meet river Ganga.

As can be seen from Map 3.2, regional floods affect the south east part of the Haridwar District near Ganga River. Near Roorkee, the flood depths estimated are in the lower range but due to heavy rainfalls it is also prone to situations like flash floods which cause flooding when the rainfall exceeds the drainage capacity of the drains of the area. Map 3.3 shows a preliminary study of built up and major roads present in area of study.

Thus, for the study, only hazard scenario due to flash floods has been developed.

3.3 Urban characteristics of Roorkeee

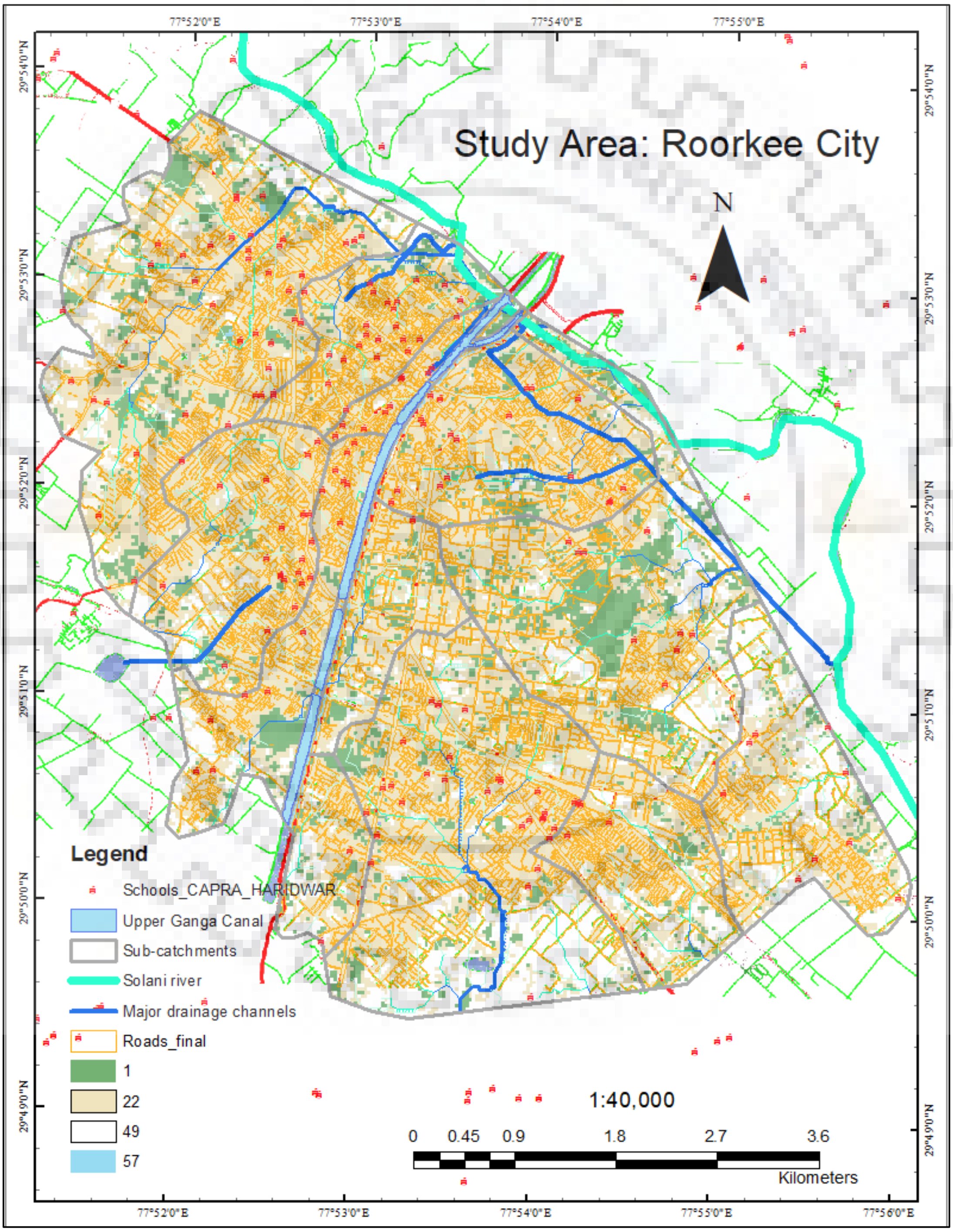

Figure 3.3: Study area

One of the most unique features of Roorkee City is the Ganga canal which passes through the city. It divides the watershed areas within Roorkee in parts, and doesn't allow runoff from one side to other. The area north west of the canal has very high-density paved area, as it is contains the old Roorkee city which developed organically. While the area South East of the canal contains many large area institutes like IIT Roorkee, Cantonment, CBRI etc, which approximately cover a third of the total area. As these institutional areas have been developed after planning and deliberation, these areas have more open spaces and greenery.

3.4 Major sub-catchments and Land use change

The Upper Ganga Canal divides the natural drainage basin of the study area, while Solani river acts as a boundary (Fig. 3.4). Most of the sub-catchments drain into the Solani River. A map and table with the details of land-use for 1997, 2007 and 2017 are given in Fig. 3.5, Fig. 3.6 and Fig 3.7.

Table 3.1 Sub catchment and LULC distribution 2017

Sub-catchment	Green (km^2)	Built up (km^2)	Barren (km^2)	Water (km^2)	Total (km^2)
1	0.44	3.96	1.05	0	5.45
2	0.15	2.48	0.23	0	2.86
3	0.84	4.75	0.91	0.01	6.51
4	0.03	0	0.01	0.02	0.06
5	0.09	0.13	0.07	0.1	0.39
6	0.23	1.55	0.26	0	2.04
7	0.17	2.01	0.15	0	2.33
8	0.37	2.55	0.18	0.08	3.18
9	1.2	2.9	1.04	0	5.14
10	0.18	1.66	1.08	0	2.92
11	0.05	0.25	0.64	0	0.94
12	0.16	1.5	0.45	0	2.11
13	0.35	1.6	0.38	0.15	2.48
Total (km^2)	4.26	25.34	6.45	0.36	36.41

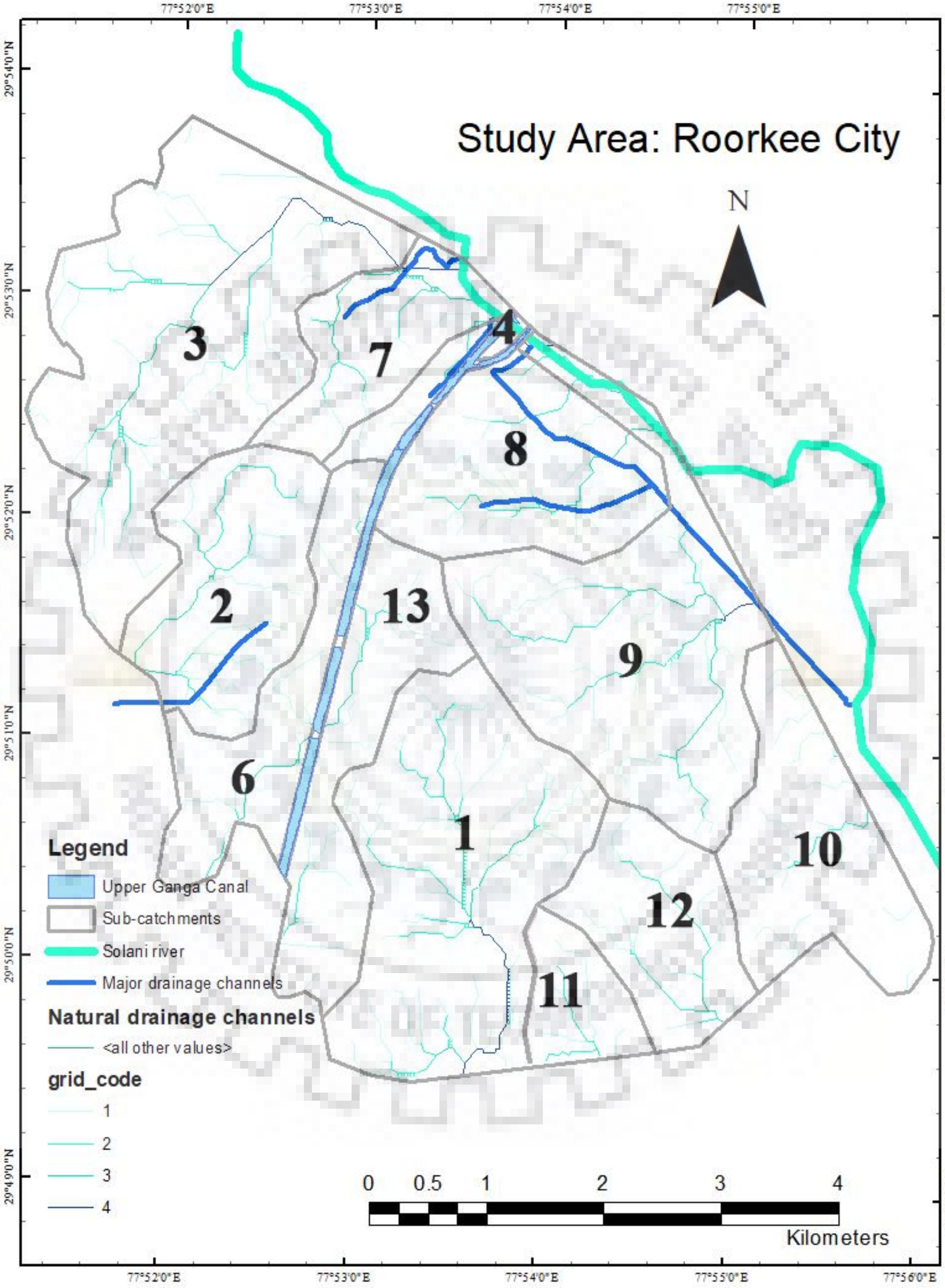

Figure 3.4: Sub catchments and natural drainage of study area

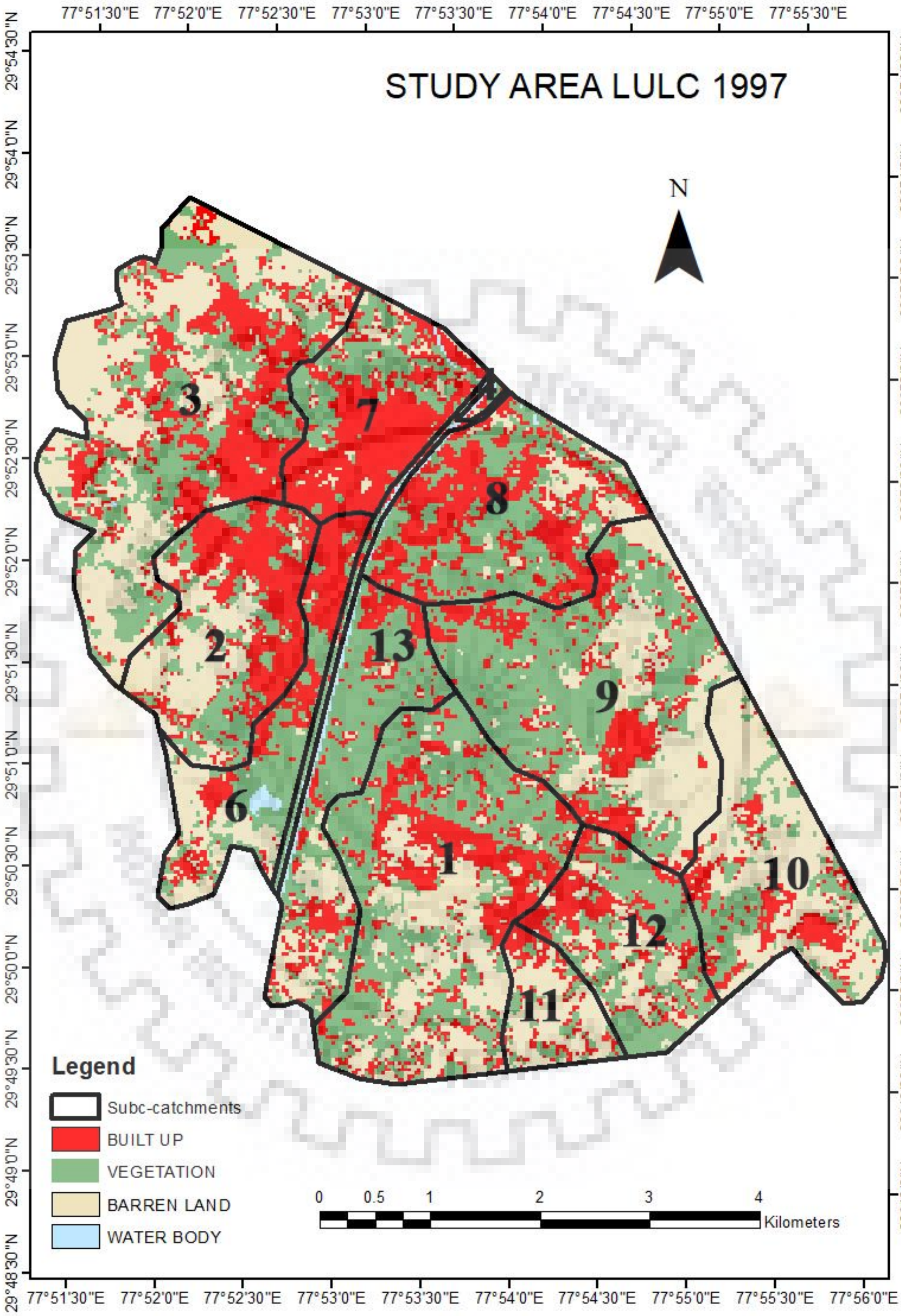

Figure 3.5: 1997 LULC generated from supervised classification of LANDSAT 30m satellite data

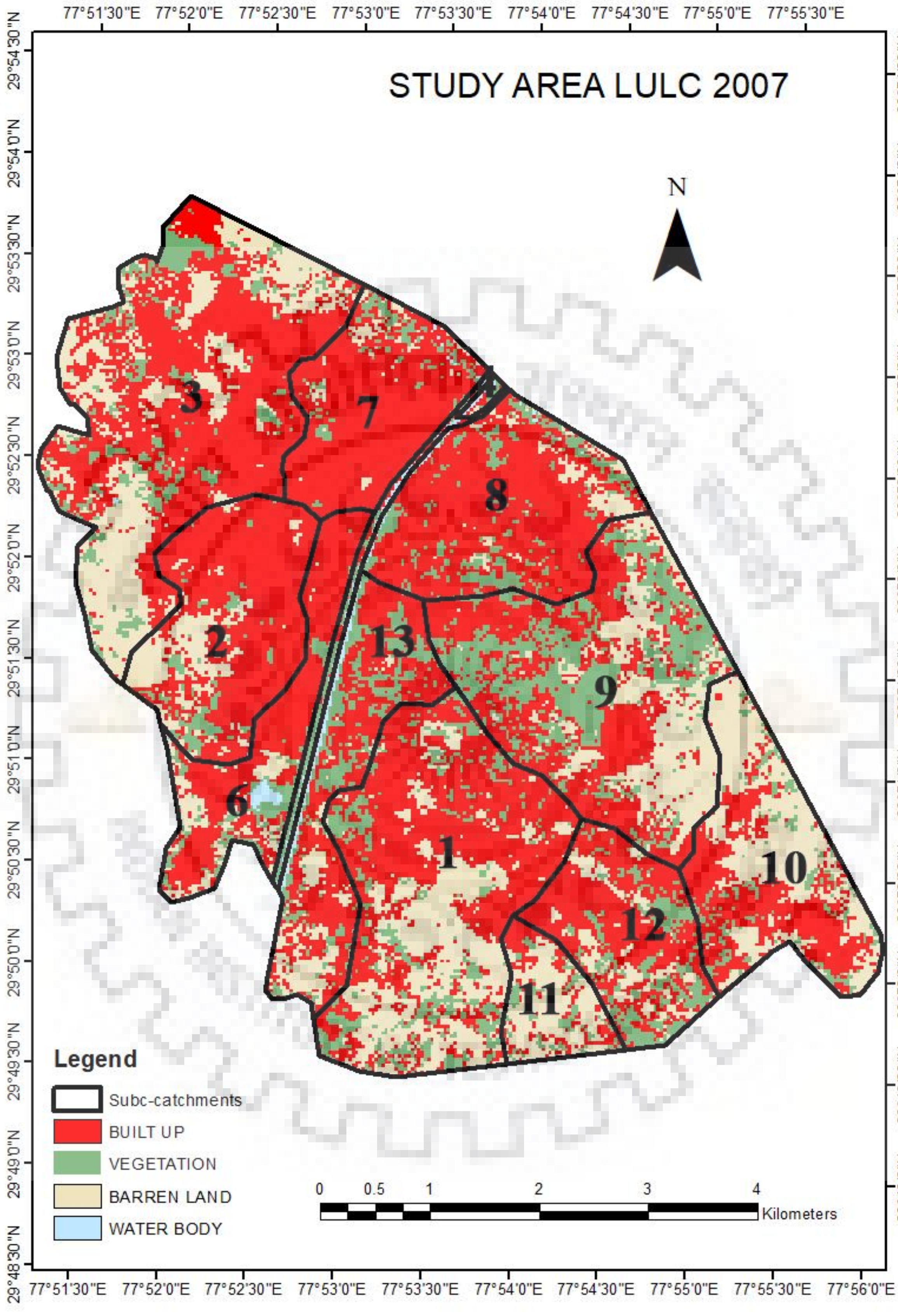

Figure 3.6: 2007 LULC generated from supervised classification of LANDSAT 30m satellite data

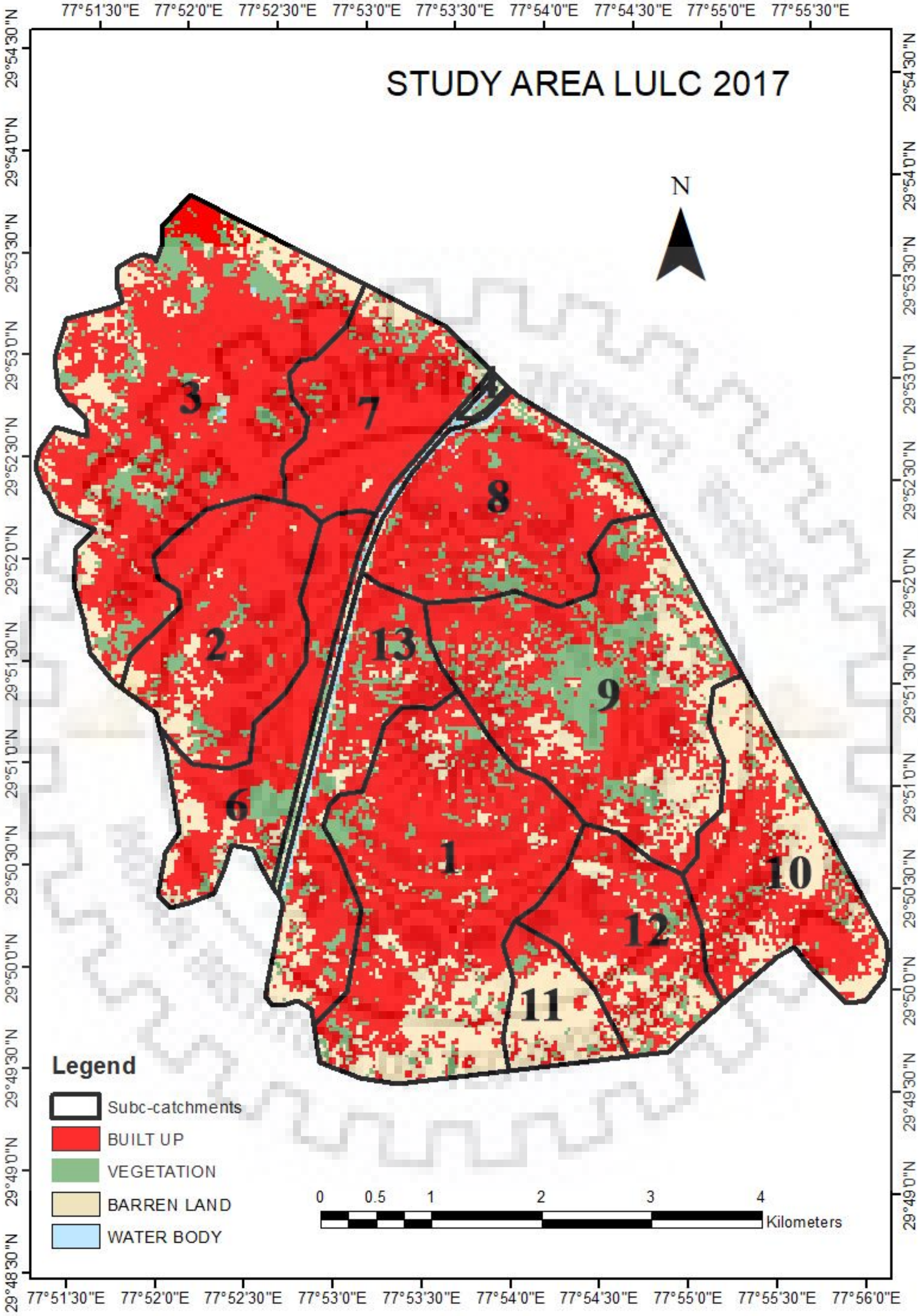

Figure 3.7: 2017 LULC generated from supervised classification of LANDSAT 30m satellite data

The LULC trends for the entire study area can be seen from table 3.2 and Fig. 3.8. The growth in built up was very high from 1997 to 2017 due to population growth, job opportunities and boost in economy. Most of the area converted to built up in this process was from the vegetation and green areas. While the barren lands and water bodies have also decreased, the reduction in area under vegetation was highest.

The changes from 2007 to 2017 were less compared to 1997 to 2007 because some of the major sub-catchments numbered 3, 7, 2, 6 had become saturated with built up area and some of the green areas that were remaining could not be used for construction because of terrain/ natural drainage.

Table 3.2 LULC trend for study area

	Year	**Year**	**Year**
Area Type	**1997 (km^2)**	**2007 (km^2)**	**2017 (km^2)**
Build Up	11.26	22.76	25.36
Vegetation	13.97	5.91	4.29
Barren	10.82	7.42	6.46
Water Body	0.40	0.35	0.34

While the changes in water bodies have been listed, due to the small share of area in the whole study area and the presence of Upper Ganga Canal as a water body of controlled area, the trends observed in water bodies may not represent the actual scenario.

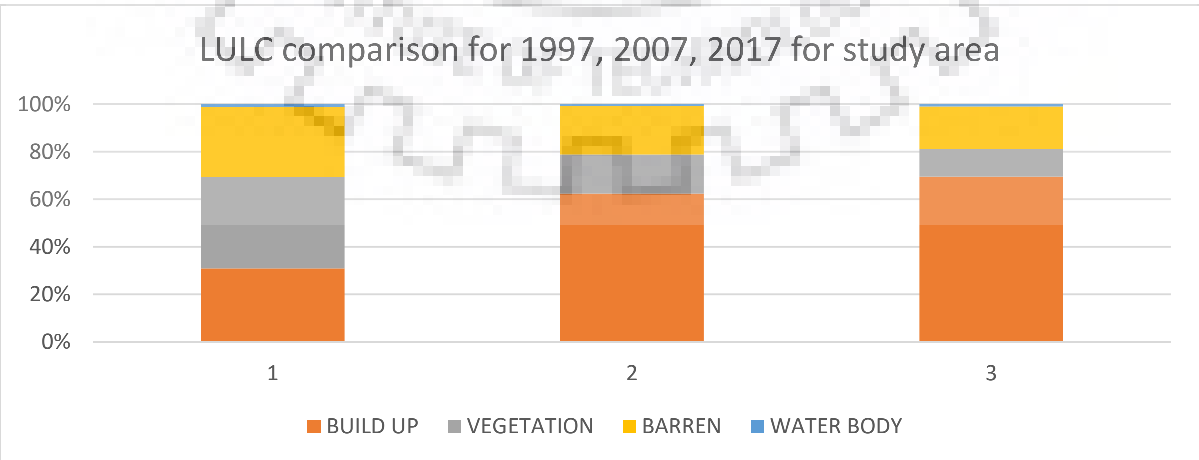

Figure 3.8: LULC comparison for study area

3.5 Data used

The data used for the study is:

1. Sub- daily rainfall data charts from 1976-2017 recorded by rain gauge at Dept. of Hydrology, IIT Roorkee. The charts were categorized as rainy days or otherwise, ranked and selected for digitization as per the method mentioned in Appendix I.
2. The storm blocks extracted from the data have been listed in Appendix I, while parts of the python code used for extraction has been shown in Appendix II.
3. The max intensity series extracted from the data has been included in section 4.12
4. SRTM-30 DEM for the study area was used for drainage study
5. LANDSAT-8 satellite imagery was used for 2017, while for 2007 and 1997, satellite image from LANDSAT 5 and LANDSAT 4 were utilized.

4.1 Introduction to methodology

The study is done by utilizing the 40-year rainfall data for Roorkee. The 15-minute interval depth data for days with more than 10 cm rain has been used to extract two data sets (i) storm data and (ii) Max- intensity series for all durations. Both data sets have been utilized in analysis after correction and tests as shown in Fig. 4.1 The data for LULC has been processed from LANDSAT satellite imagery using supervised classification using Arc-GIS image classification tool. A simplified process for the same has also been included in Fig. 4.1.

A study of SRTM-30m DEM has been done to understand the natural drainage channels and the sub- catchments of the study area. For analysis of DEM, surface analysis and hydrology tools from ArcGIS software has been used.

The rainfall and LULC data have been used to estimate runoff depth from all sub-catchments and the decadal variations in it, using SCS-CN method. The results have been compared to understand the impact of rainfall and LULC on runoff estimations for flood hazard modelling.

A detailed methodology utilized for the study has been shown in figure 4.1 on page 20.

4.2 Steps involved in analysis of rainfall data

The rainfall data analysis performed with UDRP utilizes the IMD reduction formulae for identifying the intensity for smaller sub daily rainfall. To validate the application of IMD reduction formulae for Roorkee City, a parallel study utilizing IMD reduction formulae and sub- daily rainfall data gathered by recording type data for the site of study was done.

Afterwards a study of storm depth vs durations was utilized to develop a local model for identifying the rainfall intensities for smaller durations.

4.2.1 Preparation of local sub-daily rainfall data from recording type rain-gauge

- Using daily rainfall data all dates with more than 10 mm rainfall were identified, ranked and the charts collected from the recording type rain-gauge data from 1979-2019.

- Identifying max intensities observed for all durations from rank 1 and eliminating days from that year for which total rainfall ≤ 1hour maximum rainfall observed for the year. Continuing till no 3 continuous ranks show higher intensities.

- For further analysis 2 components were extracted from the sub-daily rainfall data which are: (i) Max intensity time series for all durations (ii) Depth & duration of all storms; both of these are discussed in following sections.

- To eliminate error due to change of dates, charts from 1 day before to 1 day after the storms were also included in calculation of maximum intensities.

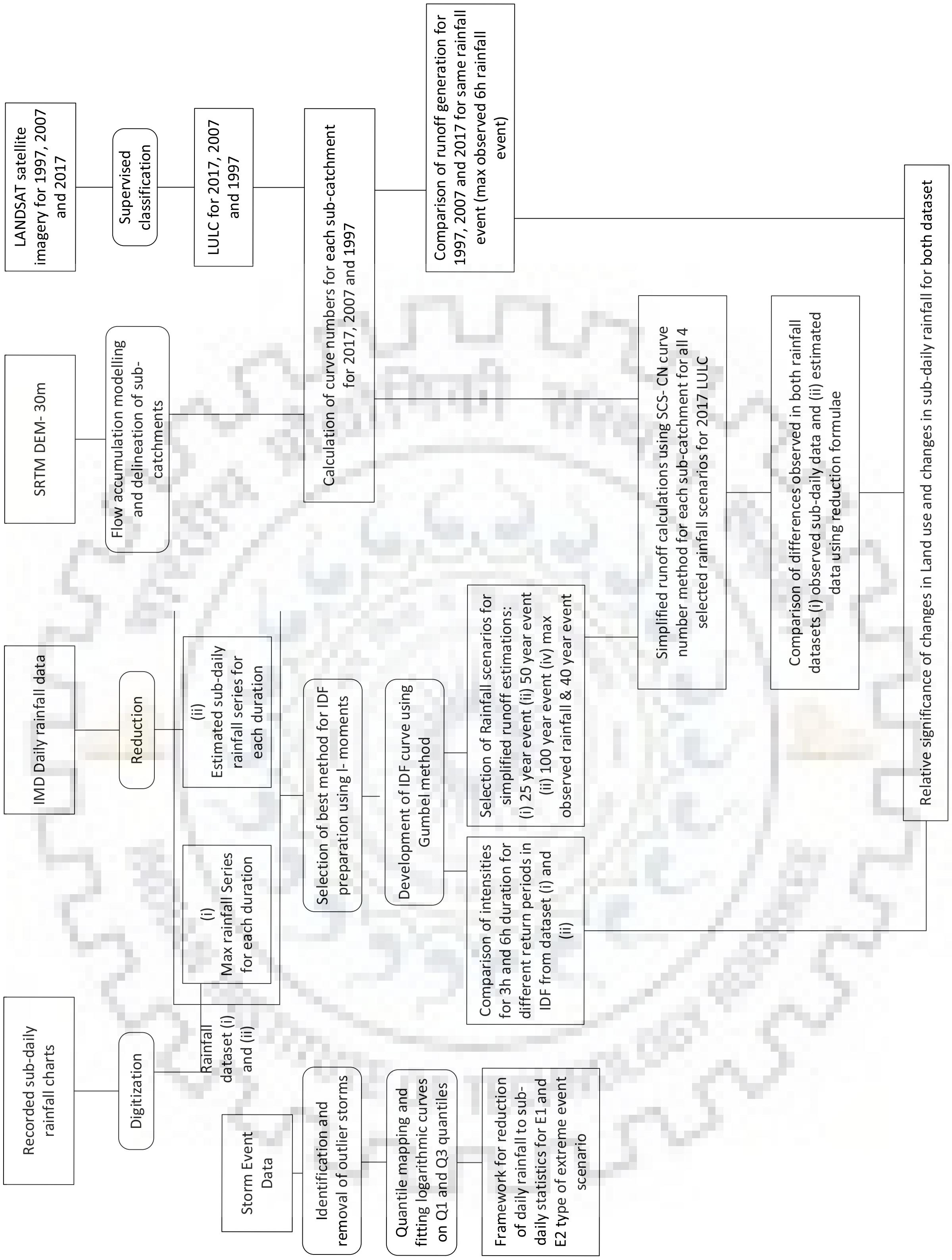

Figure 4.1: General outline of the methodology

4.2.2 Max intensity-based study

Different max intensity series were developed for each duration as shown in Table 4.1.

Table 4.1: Maximum Intensities observed during heaviest rainfall (in mm/hr.)

	15 minute	30 minute	1 hour	3 hour	6 hour	9 hour	12 hour	18 hour	24 hour
1979	145.60	123.80	77.30	31.73	16.58	11.06	8.29	5.53	4.15
1980	62.00	49.20	45.50	28.53	15.07	10.06	7.55	5.03	3.78
1981	140.00	133.00	123.50	41.17	20.58	13.72	10.29	6.86	5.17
1982	83.20	74.40	52.00	23.47	11.75	8.28	6.33	4.22	3.17
1983	95.20	88.20	60.30	43.80	34.62	25.41	19.06	12.95	9.77
1985	85.20	54.20	29.90	16.33	12.02	10.03	7.53	5.35	4.31
1986	78.40	60.20	34.30	12.63	8.70	5.80	4.35	3.43	2.58
1987	94.00	78.40	62.50	25.60	12.82	8.58	6.43	4.29	3.22
1988	84.00	76.00	67.50	38.97	24.53	17.20	12.90	9.45	7.09
1989	152.00	79.40	39.80	21.83	17.08	12.92	10.64	7.99	6.58
1990	156.00	144.00	105.00	42.87	23.68	15.79	11.84	8.08	6.06
1991	82.00	75.00	56.50	30.87	16.58	11.06	8.29	5.72	6.73
1992	80.00	68.40	63.70	32.27	17.52	14.58	12.83	10.37	7.95
1993	76.00	54.00	31.60	21.53	16.50	11.68	8.83	5.89	4.42
1994	88.00	86.00	66.20	38.50	30.38	22.34	16.95	13.66	10.90
1995	100.00	100.00	63.00	30.53	19.93	14.74	11.17	8.24	6.18
1996	100.00	86.00	72.00	39.43	19.75	13.17	9.88	6.58	4.94
1997	88.00	68.00	41.00	18.73	16.32	11.96	10.39	7.49	5.62
1998	108.00	91.60	50.50	21.17	15.23	11.96	9.17	6.68	5.32
1999	68.80	66.00	33.90	11.67	6.05	4.03	3.03	2.03	1.75
2000	112.80	92.40	52.50	22.93	16.50	11.94	9.08	6.59	6.59
2001	84.80	80.40	51.00	27.47	16.22	11.30	9.31	6.79	5.09
2002	134.80	80.40	60.70	28.50	14.78	9.86	10.04	8.79	9.02
2003	106.80	76.40	52.30	26.23	14.62	9.82	7.37	4.91	3.68
2004	72.00	60.80	52.50	33.93	18.38	12.27	9.20	6.13	4.60
2005	112.00	95.40	54.90	21.17	16.80	11.48	8.61	5.83	5.04
2006	110.00	93.40	72.00	41.17	29.00	22.80	17.44	12.96	9.96
2007	83.20	69.60	50.50	22.67	13.42	8.94	6.71	4.47	3.35
2008	78.40	70.40	43.80	19.57	10.98	7.50	5.63	3.75	3.65
2009	110.80	72.40	45.70	31.30	21.97	16.34	12.36	8.29	6.27
2010	114.80	113.00	89.70	40.03	23.00	16.51	12.81	9.03	6.78
2011	125.60	105.80	87.50	38.93	19.90	13.27	9.95	6.83	5.13
2012	72.00	70.00	54.50	25.77	16.08	11.13	8.35	5.57	4.18
2013	64.80	57.00	52.00	24.20	14.20	9.60	7.20	4.80	3.60
2014	149.60	82.20	55.60	32.63	16.43	10.96	8.22	5.53	4.29
2015	118.00	96.40	52.90	23.37	12.03	8.06	6.04	4.03	3.02
2016	100.80	63.40	38.40	25.90	21.45	15.40	12.07	8.54	7.28
2017	62.40	52.60	41.00	15.37	8.42	6.83	5.90	4.03	4.29

Then the 24-hour intensities were used with IMD reduction formulae to prepare IMD series

Table 4.2: Maximum Intensities calculated using IMD reduction formulae (in mm/hr.)

	15 min.	30 min.	1 hour	3 hour	6 hour	9 hour	12 hour	18 hour	24 hour
1979	82.92	69.10	51.82	25.91	14.81	10.36	7.97	5.46	4.15
1980	75.50	62.92	47.19	23.59	13.48	9.44	7.26	4.97	3.78
1981	103.33	86.11	64.58	32.29	18.45	12.92	9.94	6.80	5.17
1982	63.33	52.78	39.58	19.79	11.31	7.92	6.09	4.17	3.17
1983	195.33	162.78	122.08	61.04	34.88	24.42	18.78	12.85	9.77
1985	86.25	71.88	53.91	26.95	15.40	10.78	8.29	5.67	4.31
1986	51.67	43.06	32.29	16.15	9.23	6.46	4.97	3.40	2.58
1987	64.33	53.61	40.21	20.10	11.49	8.04	6.19	4.23	3.22
1988	141.75	118.13	88.59	44.30	25.31	17.72	13.63	9.33	7.09
1989	131.50	109.58	82.19	41.09	23.48	16.44	12.64	8.65	6.58
1990	121.25	101.04	75.78	37.89	21.65	15.16	11.66	7.98	6.06
1991	134.58	112.15	84.11	42.06	24.03	16.82	12.94	8.85	6.73
1992	158.92	132.43	99.32	49.66	28.38	19.86	15.28	10.46	7.95
1993	88.33	73.61	55.21	27.60	15.77	11.04	8.49	5.81	4.42
1994	218.00	181.67	136.25	68.13	38.93	27.25	20.96	14.34	10.90
1995	123.67	103.06	77.29	38.65	22.08	15.46	11.89	8.14	6.18
1996	98.75	82.29	61.72	30.86	17.63	12.34	9.50	6.50	4.94
1997	112.33	93.61	70.21	35.10	20.06	14.04	10.80	7.39	5.62
1998	106.33	88.61	66.46	33.23	18.99	13.29	10.22	7.00	5.32
1999	35.00	29.17	21.88	10.94	6.25	4.38	3.37	2.30	1.75
2000	131.75	109.79	82.34	41.17	23.53	16.47	12.67	8.67	6.59
2001	101.83	84.86	63.65	31.82	18.18	12.73	9.79	6.70	5.09
2002	180.33	150.28	112.71	56.35	32.20	22.54	17.34	11.86	9.02
2003	73.67	61.39	46.04	23.02	13.15	9.21	7.08	4.85	3.68
2004	92.00	76.67	57.50	28.75	16.43	11.50	8.85	6.05	4.60
2005	100.83	84.03	63.02	31.51	18.01	12.60	9.70	6.63	5.04
2006	199.17	165.97	124.48	62.24	35.57	24.90	19.15	13.10	9.96
2007	67.08	55.90	41.93	20.96	11.98	8.39	6.45	4.41	3.35
2008	73.00	60.83	45.63	22.81	13.04	9.13	7.02	4.80	3.65
2009	125.42	104.51	78.39	39.19	22.40	15.68	12.06	8.25	6.27
2010	135.50	112.92	84.69	42.34	24.20	16.94	13.03	8.91	6.78
2011	102.50	85.42	64.06	32.03	18.30	12.81	9.86	6.74	5.13
2012	83.50	69.58	52.19	26.09	14.91	10.44	8.03	5.49	4.18
2013	72.00	60.00	45.00	22.50	12.86	9.00	6.92	4.74	3.60
2014	85.83	71.53	53.65	26.82	15.33	10.73	8.25	5.65	4.29
2015	60.42	50.35	37.76	18.88	10.79	7.55	5.81	3.97	3.02
2016	145.67	121.39	91.04	45.52	26.01	18.21	14.01	9.58	7.28
2017	85.83	71.53	53.65	26.82	15.33	10.73	8.25	5.65	4.29

- Calculation of statistical parameters for each duration of both the series was done (mean, SD, Ck, Cs, moments)

  - Mean: $$\mu = \frac{\sum_{i=1}^{n} x_i}{n}$$

  - Standard Deviation: $$\sigma = \sqrt{\frac{\sum_{i=1}^{n}(x_i - \overline{x})^2}{n-1}}$$

  - Coefficient of Variation: $$C_v(\sigma^2) = \frac{1}{(n-1)}\left[\sum_{i=1}^{n}(X_i - \overline{X})^2\right]$$

  - Coefficient of Skewness: $$C_s = \frac{n}{(n-1)(n-2)}\left[\frac{\sum_{i=1}^{n}(X_i - \overline{X})^3}{\sigma^3}\right]$$

  - Coefficient of Kurtosis: $$C_k = \frac{n^2}{(n-1)(n-2)(n-3)}\left[\frac{\sum_{i=1}^{n}(X_i - \overline{X})^4}{\sigma^4}\right]$$

Table 4.3: Statistical parameters calculated for observed data (mm/hr.)

	15 minute	**30 minute**	**1 hour**	**3 hour**	**6 hour**	**9 hour**	**12 hour**	**18 hour**	**24 hour**
Max	156.00	144.00	123.50	43.80	34.62	25.41	19.06	13.66	10.90
Average	99.47	81.26	57.46	28.23	17.37	12.33	9.53	6.76	5.41
Cv	689.26	474.69	383.50	76.05	34.71	19.98	11.64	7.04	4.49
Kurtosis	2.75	4.32	5.97	2.37	4.51	4.81	4.38	4.05	3.59
Skew	0.65	1.04	1.44	0.12	0.86	1.06	0.89	0.96	0.84
Std	26.25	21.79	19.58	8.72	5.89	4.47	3.41	2.65	2.12

Table 4.4: Statistical parameters calculated for intensity data developed using IMD reduction formulae (mm/hr.)

	15 minute	**30 minute**	**1 hour**	**3 hour**	**6 hour**	**9 hour**	**12 hour**	**18 hour**	**24 hour**
Max	218.00	181.67	136.25	68.13	38.93	27.25	20.96	14.34	10.90
Average	108.14	90.12	67.59	33.79	19.31	13.52	10.40	7.11	5.41
Cv	1794.57	1246.23	701.00	175.25	57.22	28.04	16.59	7.77	4.49
Kurtosis	2.75	4.32	5.97	2.37	4.51	4.81	4.38	4.05	3.59
Skew	0.84	0.84	0.84	0.84	0.84	0.84	0.84	0.84	0.84
Std	42.36	35.30	26.48	13.24	7.56	5.30	4.07	2.79	2.12

Best fit method selection by using l moment ratio diagram. The moments for each series were calculated separately as shown in Table 4.5.

Table 4.5: L-moments calculated for observed data (The base data utilized is in mm/hr.)

Time	β0	β1	β2	β3	λ1	λ2	λ3	λ4	**LCv**	**LCs**	**LCk**
0.25	99.47	57.18	41.01	32.25	99.47	14.89	2.46	1.26	0.15	0.17	0.08
0.50	81.26	46.61	33.45	26.38	81.26	11.97	2.30	2.17	0.15	0.19	0.18
1.00	57.46	33.89	24.71	19.73	57.46	10.32	2.38	2.55	0.18	0.23	0.20
2.00	37.44	22.32	16.13	12.70	37.44	7.20	0.28	0.54	0.19	0.04	0.08
3.00	28.23	16.63	11.96	9.39	28.23	5.04	0.20	0.32	0.18	0.04	0.06
4.00	22.98	13.49	9.71	7.65	22.98	4.01	0.32	0.51	0.17	0.08	0.13
5.00	19.50	11.52	8.34	6.60	19.50	3.54	0.40	0.63	0.18	0.11	0.18
6.00	17.37	10.29	7.47	5.94	17.37	3.21	0.47	0.77	0.18	0.15	0.24
9.00	12.33	7.37	5.39	4.30	12.33	2.41	0.43	0.57	0.20	0.18	0.24
12.00	9.53	5.70	4.16	3.31	9.53	1.87	0.29	0.38	0.20	0.15	0.20
18.00	6.76	4.11	3.03	2.43	6.76	1.46	0.27	0.25	0.22	0.19	0.17
24.00	5.41	3.29	2.43	1.94	5.41	1.18	0.21	0.17	0.22	0.18	0.15

The calculated moments were plotted in the l-moment ratio diagram put forward by Hosking (1990), Rao et. al., (2000); Bisht et al., (2016), Prakash, I. (2018) the observation showed that a different distribution is fitting for different series. Most of the points are clustered around Gumbel distribution and hence Gumbel distribution was utilized for developing the IDF curves. durations, as it can best represent all the series and is also focused on prediction of extreme events.

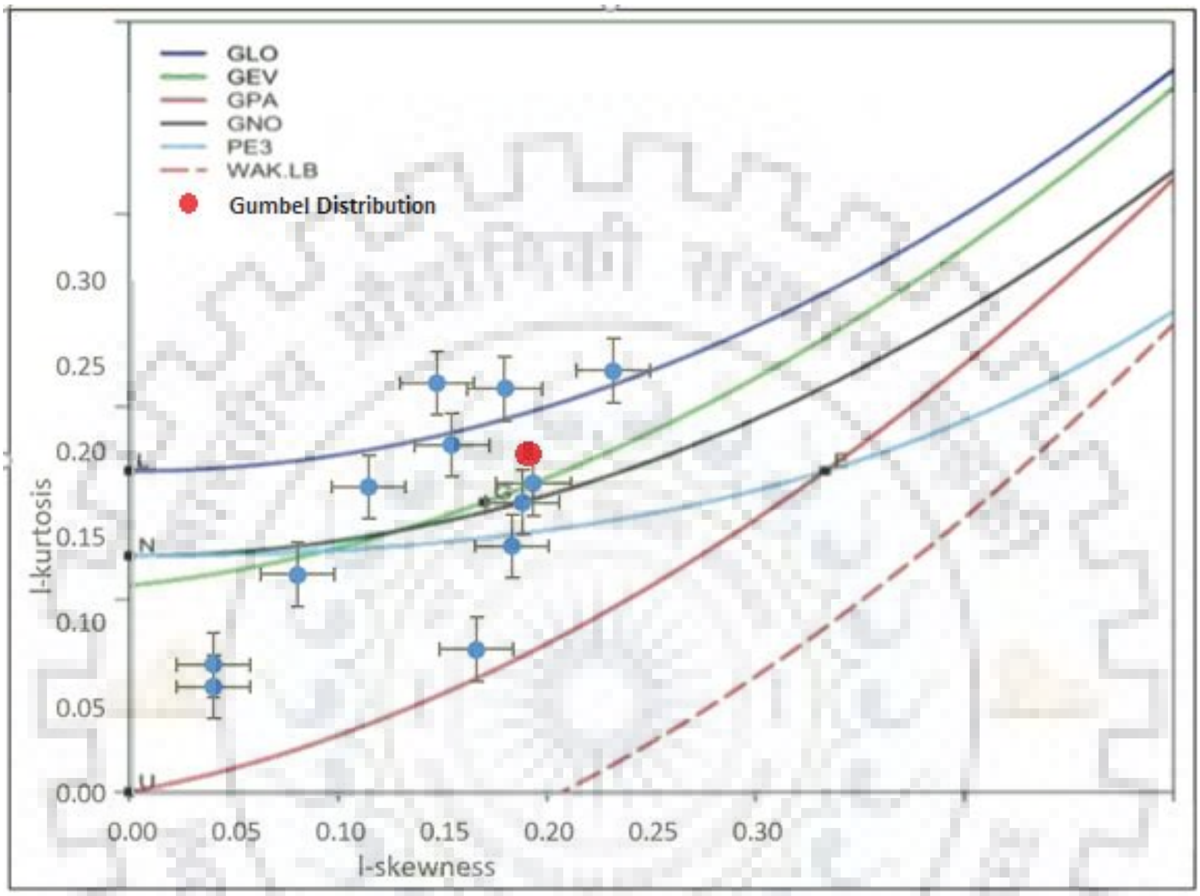

Figure 4.2: l moment ratio diagram for various series

- Development of IDF curves for both datasets using Gumbel distribution was done by calculating the mean, standard deviation and k_T (a constant to represent return period). The rainfall associated with any return period for Gumbel distribution is given by

$$X_T = \mu + \alpha * \ln(\ln(T/T-1))$$

Where

X_T = Rainfall intensity for T year return period ; μ = Mean of series

$K_T = \ln(\ln(T/T-1))$; T= Year for which Return period is being calculated.

4.2.3 Storm duration-based study

- To properly understand the intensity of the storms the duration for 85% of the total rainfall was calculated. As the amount of data was very large, a code developed using python 3.0 was used to identify the blocks of storm data. The simplified time block data was used to identify the duration for 85% of the total rainfall. The python 3,0 code used to simplify the time blocks has been given in Appendix-II, while Appendix -I has list of time blocks.
- Classification of storms based on depth and duration of 85% rainfall was done and outlier storms were identified from the data. This data has been used to develop reduction equation for finding intensities of smaller duration rainfall from daily rainfall data.

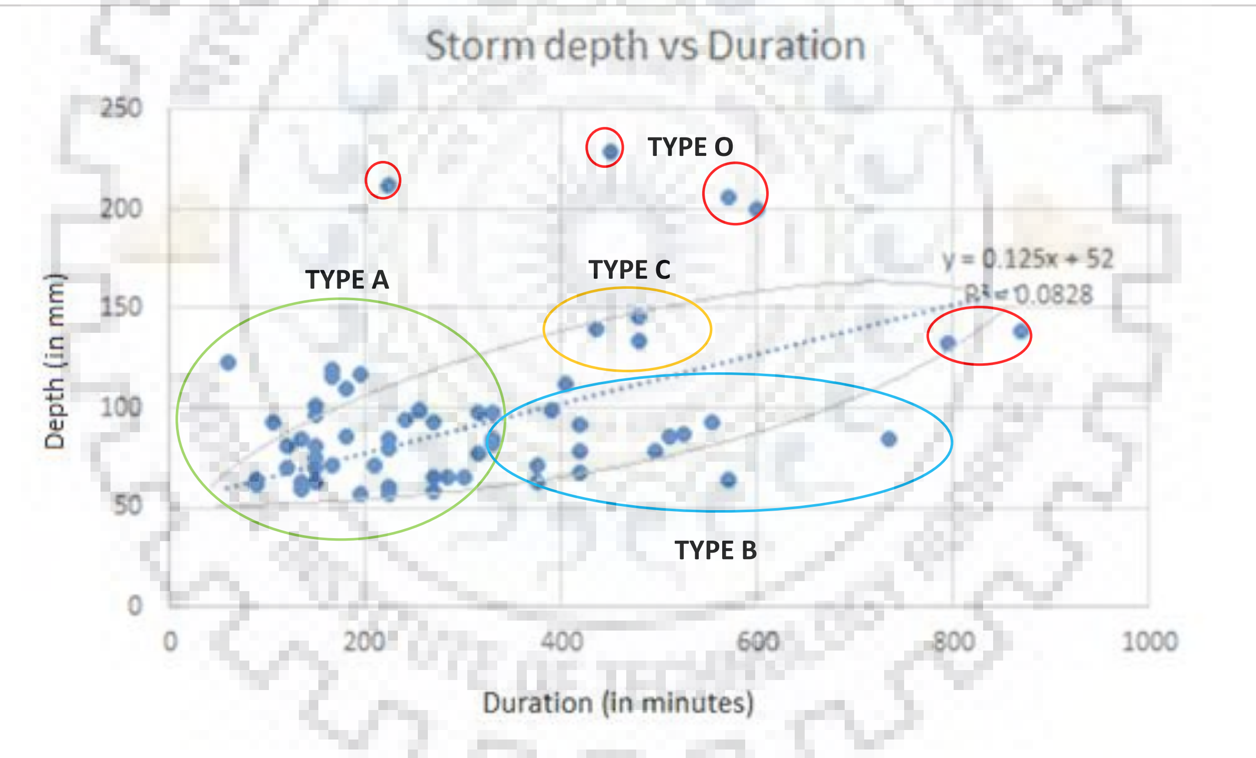

Figure 4.3: Storm Depth vs Duration

The storm depth vs duration study showed a high number of events in long duration and low intensity. This is due to the process by which the charts were identified, as the selection was based on depth only. The highest depths in short duration storms observed are in range of 2.5 to 3 hours. This number represents the general rainfall characteristics of Roorkee area.

Based on the storm depth vs duration curve we can classify the storms in following categories:

TYPE A: Short duration high intensity storms

TYPE B: Low intensity long duration storms

TYPE C: Long duration high intensity

TYPE O: Outliers

TYPE A: These are short duration high intensity storms, though the total amount of runoff generated is not very high, these events put a lot of strain on the storm water drainage system of an area, as relatively high amount of runoff is generated in small time window. These storms can cause small inundations and overflows at particular nodes.

TYPE B: Storms with long duration and relatively low intensities are less problematic than TYPE A events. Usually these storms occur as single storms with small gaps in between, while sometimes they occur as composite events along with TYPE A storms. These storms don't cause much problem as long as the regional fluvial water levels have not risen. Since regional flooding is very rare in the area around Roorkee due to seasonal nature, and small basin of river Solani, the TYPE B events are mostly harmless in Roorkee area.

TYPE C: These storms have almost similar intensity to high intensity short duration events, and thus these lead to a very high runoff generation. Though the storm water at any given time is not very high, the high amount of total runoff generated increases the inundation levels, and the overflowing drainage channels may fill up the roads due to continuous long term accumulation. These storms resemble a composite storm where very short gaps are present in the rainfall. These are the main events which lead to problems like foundation weakening, high inundation, and traffic and activity blockage in different areas of the town. So most of the non-structural losses due to rainfall can be attributed to these events.

TYPE O: Other than the storms which fall into the above 3 categories, there are some events which still show different characteristics. These storms do not possess many similarities with each other, and are very infrequent, but this doesn't reduce the importance of this category as sometimes events with very high intensity and short duration occur randomly, which are not part of the usual scenario of the area.

To better identify these types of events, the TYPE O events have been divided into TYPE O+ and TYPE O- . While O+ are outliers which are away from the usual trend line towards higher intensity, O- are the events which lie below the trend line. By doing so, we only have to consider TYPE O+ in an exercise of flood risk assessment. The TYPE O events identified are:

Table 4.6: List of outlier events

Date	Duration (minutes)	Depth (mm)	Intensity (mm/min)	TYPE (+/-)
08-06-2000	825	45.8	0.06	O-
24-09-2017	570	64.5	0.11	O-
13-07-1995	735	84.8	0.12	O-
28-08-1989	870	138.6	0.16	O+
07-09-2002	420	67.6	0.16	O+
24-09-1998	525	86.9	0.17	O+
03-08-1997	795	132.5	0.17	O+
28-07-1983	555	92.6	0.17	O+
28-06-2017	225	211.5	0.94	O+

The storm duration study shows the reasons for overestimations observed in the IDF curves prepared using IMD reduction formulae, as the formulae considers daily rainfall to be distributed over 24 hours while the actual durations are shorter. This causes slight underestimations for duration above model storm duration, while overestimations for smaller durations.

Using the storm depth vs duration study, a method to find intensities of smaller durations was developed. The steps used were:

1. Finding duration of 85% of rainfall: This was done using simplified time blocks as shown in the sections above.

2. Identifying ratio of depth in various durations to 85% rainfall, up to the duration observed in last step.

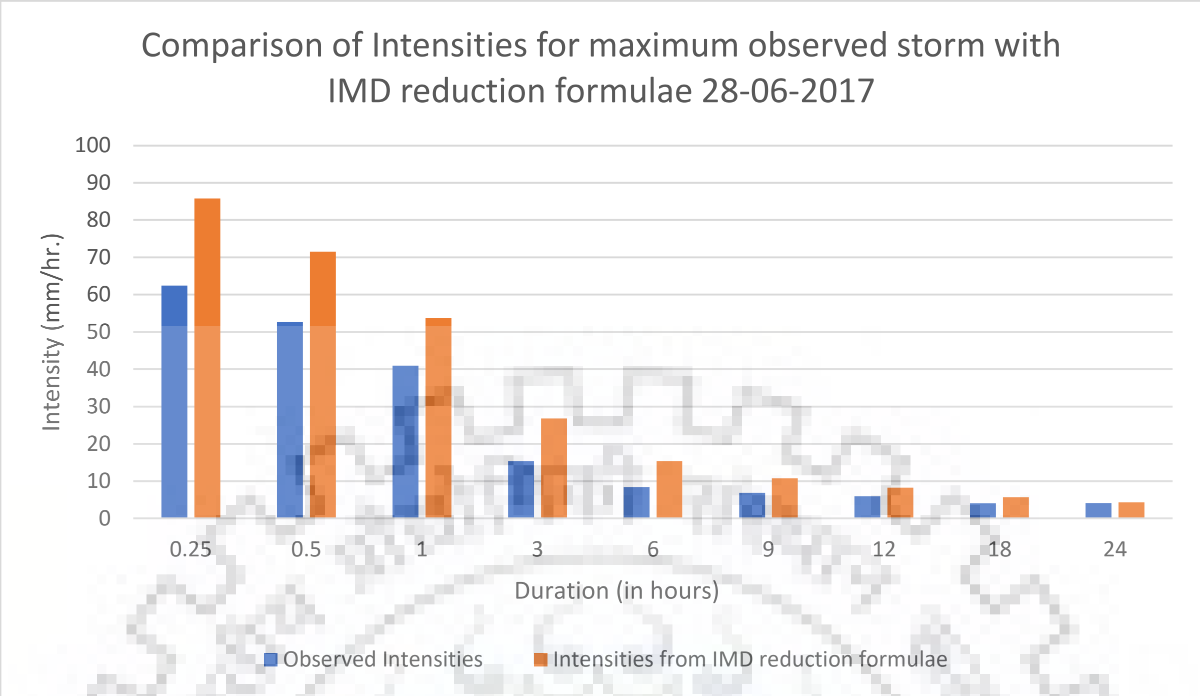

Figure 4.4: Comparison of Intensities for maximum observed storm with IMD reduction formulae

A comparison for intensity for smaller durations observed and calculated using IMD reduction formulae for 28-06-2017 event has been shown in Fig. 4.4. It can be observed that the IMD reduction formulae overestimates the intensities for smaller durations even for the day with maximum observed intensity of rainfall.

3. Quantile mapping for various durations using box whisker method:

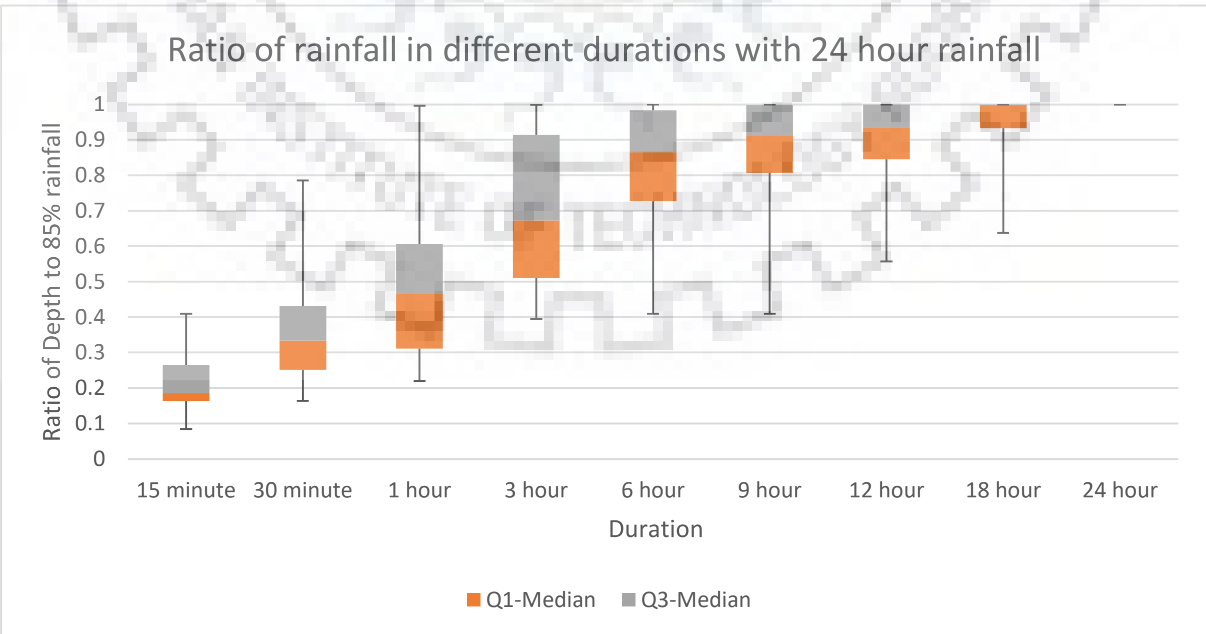

Figure 4.5: Box whisker diagram for depth ratio in different durations

4. Identification of trend of % rainfall observed in various durations for 2 types of storm classification: (i) type-I extreme event (85% rainfall in 4 hours duration) (ii) type-II extreme event (85% rainfall in 8-10 hours duration): This was done by taking out the 1st and 3rd quartile values for each duration and identifying logarithmic relationship between the duration and depth observed for that quartile. 3rd quartile was termed type-I extreme event, while 1st quartile was termed E2 type storm.

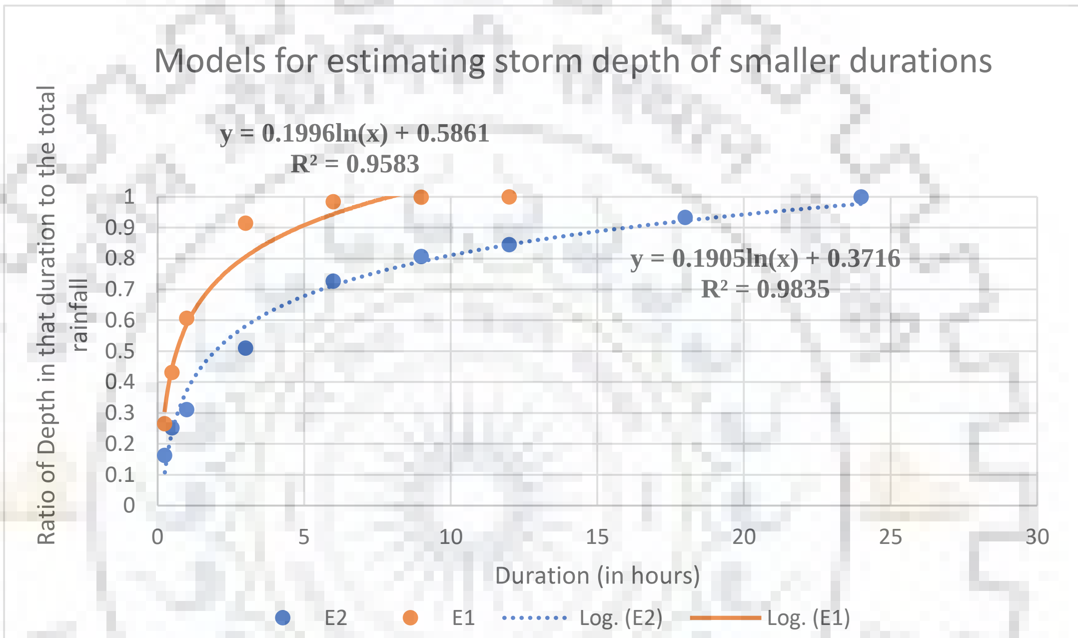

Figure 4.6: E1 and E2 storm scenario reduction equation

Where:

y= ratio of depth in that duration to 85% rainfall

x= duration of rainfall

For identification of storm depth for a particular duration, the above equations give value of y, which can be used along with 85 % rainfall value to estimate depth for smaller durations.

5. The equations developed provide the rainfall intensities for various durations using 85% rainfall, storm type (E1/E2) and the duration for which depth is required.

4.2 Simplified run-off generation model

To understand the impact of variation in sub daily rainfall estimates on hazard scenario, a simple approach of runoff generation and accumulation at point of inundation was done. The steps involved for the modelling were:

1. Using SRTM-30m DEM the natural drainage modelling was done using Arc-GIS, as seen in sub-catchments map in chapter 3. The sub-catchments were identified and potential nodes of inundation were identified by cross-validation with 25-year return period flash flood inundation maps.

2. Using Landsat satellite imagery, the LULC maps for 1997, 2007 and 2017 (as shown in chapter 3) were prepared using supervised classification. While the validation of 2017 map was performed using site survey, the validation and corrections for 2007 and 1997 LULC maps were done using Google Earth historical imagery tool. While 1997 and 2017 maps were found 80-83% accurate, the accuracy for 2007 LULC was identified to be 72.6%. So, corrections were done by removing major built up patches which could be identified as incorrect. The corrections were done till the accuracy test resulted in 80% accuracy.

3. The distribution of land cover in various sub- catchments was identified

4. A road map was prepared by vectorizing a raster road map for the study area, which was used to identify average % of built up which roads occupy. This % was used for all calculations of run-off generation.

5. The method used for estimates of runoff generation was SCS- Curve Number method in which

   $Q = (P - I_a)^2/(P\text{-}Ia)+S$

   Where, Q = estimated runoff; P = rainfall (in inch); I_a = Initial abstraction = 0.2*S

   $S = (1000/CN)\text{-}10$

   The weighted CN were calculated for each sub catchment as shown in the table.

Table 4.7: Curve number calculations for 2017

Sub-catch	Built-up (in km^2, CN=76)	Roads (in km2, CN=98)	Green (in km^2, CN=34)	Barren (in km^2, CN=49)	Weighted CN	S (inch) (Maximum potential retention)	Initial abstraction
1	2.97	0.44	0.99	1.05	72.37	3.82	0.76
2	1.86	0.15	0.62	0.23	77.21	2.95	0.59
3	3.57	0.84	1.19	0.91	71.99	3.89	0.78
4	0.00	0.03	0.00	0.01	46.35	11.5	2.31
5	0.10	0.09	0.03	0.07	60.91	6.42	1.28
6	1.17	0.23	0.39	0.26	73.14	3.67	0.73
7	1.50	0.17	0.50	0.15	76.92	3.00	0.60
8	1.91	0.37	0.64	0.18	75.06	3.32	0.66
9	2.18	1.20	0.73	1.04	65.46	5.28	1.06
10	1.25	0.18	0.42	1.08	67.34	4.85	0.97
11	0.19	0.05	0.06	0.64	57.19	7.49	1.50
12	1.13	0.16	0.38	0.45	71.82	3.92	0.78
13	1.20	0.35	0.40	0.38	70.36	4.21	0.84

Table 4.8: Curve number calculations for 2007

Sub-catch	Built-up (in km^2, CN=76)	Roads (in km2, CN=98)	Green (in km^2, CN=34)	Barren (in km^2, CN=49)	Weighted CN	S (inch) (Maximum potential retention)	Initial abstraction
1	2.55	0.56	0.85	1.47	68.77	4.54	0.91
2	1.72	0.19	0.57	0.39	74.87	3.36	0.67
3	3.25	1.04	1.08	1.65	68.02	4.70	0.94
4	0.03	0.00	0.01	0.00	77.93	2.83	0.57
5	0.09	0.14	0.03	0.03	58.54	7.08	1.42
6	1.27	0.26	0.42	0.09	75.18	3.30	0.66
7	1.50	0.20	0.50	0.58	72.19	3.85	0.77
8	1.75	0.61	0.58	0.18	71.82	3.92	0.78
9	2.12	1.35	0.71	0.96	64.65	5.47	1.09
10	1.18	0.16	0.39	1.19	66.36	5.07	1.01
11	0.20	0.04	0.07	0.63	57.93	7.26	1.45
12	1.02	0.29	0.34	0.47	68.96	4.50	0.90
13	1.10	0.42	0.37	0.35	68.93	4.51	0.90

Table 4.9: Curve number calculations for 1997

Sub-catch	Built-up (in km^2, CN=76)	Roads (in km2, CN=98)	Green (in km^2, CN=34)	Barren (in km^2, CN=49)	Weighted CN	S (inch) (Maximum potential retention)	Initial abstraction
1	2.55	0.56	0.85	1.47	72.27	6.21	0.91
2	1.72	0.19	0.57	0.39	19.10	8.87	0.67
3	3.25	1.04	1.08	1.65	80.61	7.78	0.94
4	0.03	0.00	0.01	0.00	0.00	6.18	0.57
5	0.09	0.14	0.03	0.03	1.47	4.82	1.42
6	1.27	0.26	0.42	0.09	4.54	7.50	0.66
7	1.50	0.20	0.50	0.58	28.56	8.86	0.77
8	1.75	0.61	0.58	0.18	8.95	7.00	0.78
9	2.12	1.35	0.71	0.96	47.01	5.76	1.09
10	1.18	0.16	0.39	1.19	58.17	8.18	1.01
11	0.20	0.04	0.07	0.63	31.05	8.93	1.45
12	1.02	0.29	0.34	0.47	23.12	6.13	0.90
13	1.10	0.42	0.37	0.35	16.96	5.22	0.90

These CN values, initial abstraction and maximum potential retention have been utilized to estimate the runoff depth from unit area of each sub- catchments. The precipitation has been converted to inch from mm.

The present chapter presents the statistical analysis of observed data and the results obtained. The chapter also compares the various results and tries to understand the relationship between rainfall/LULC and changes on the estimates of runoff generation.

5.1 Comparison of IDF curves developed

Figure 5.1 and 5.2 show the IDF curves developed using IMD reduction formulae and observed sub-daily rainfall. Table 5.1 shows a basic comparison of intensities of various return period for 6 hour and 3-hour rainfall.

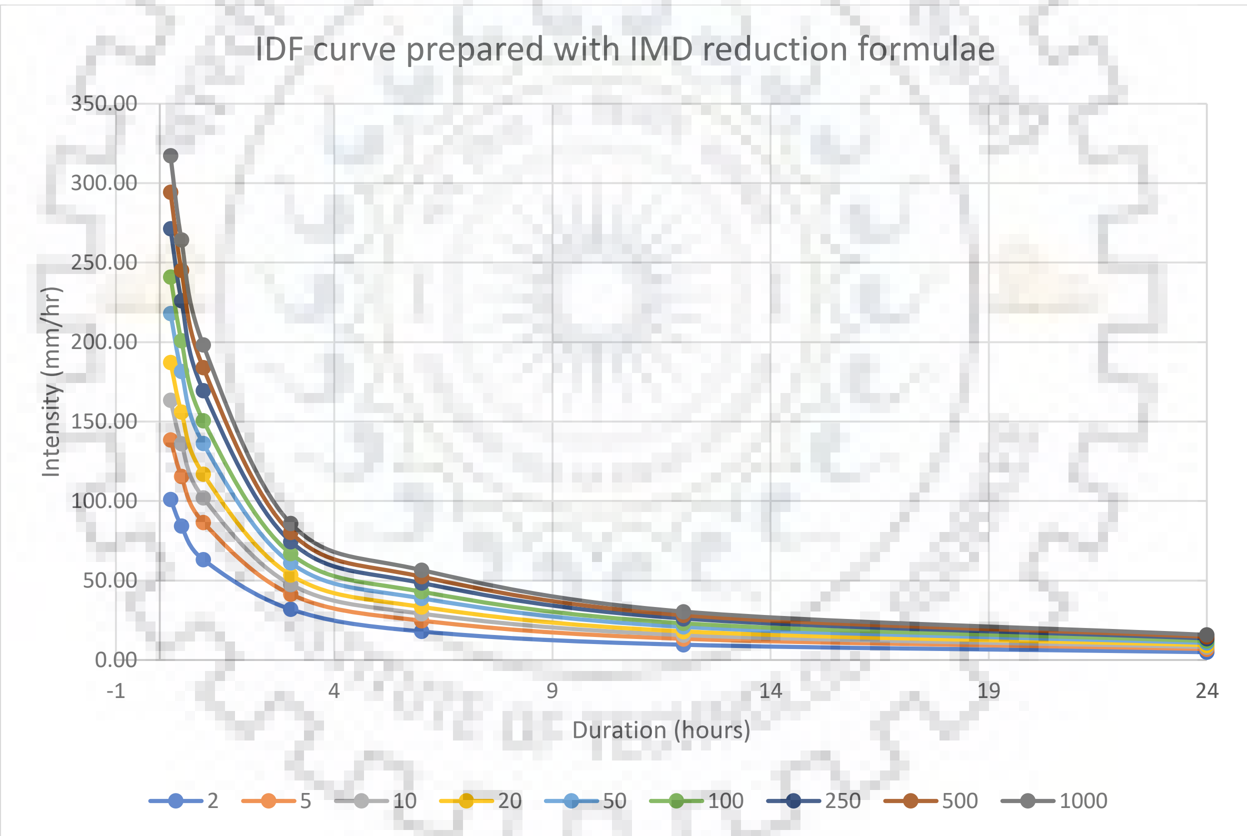

Figure 5.1 IDF curves prepared with data from IMD reduction formulae (URDP model)

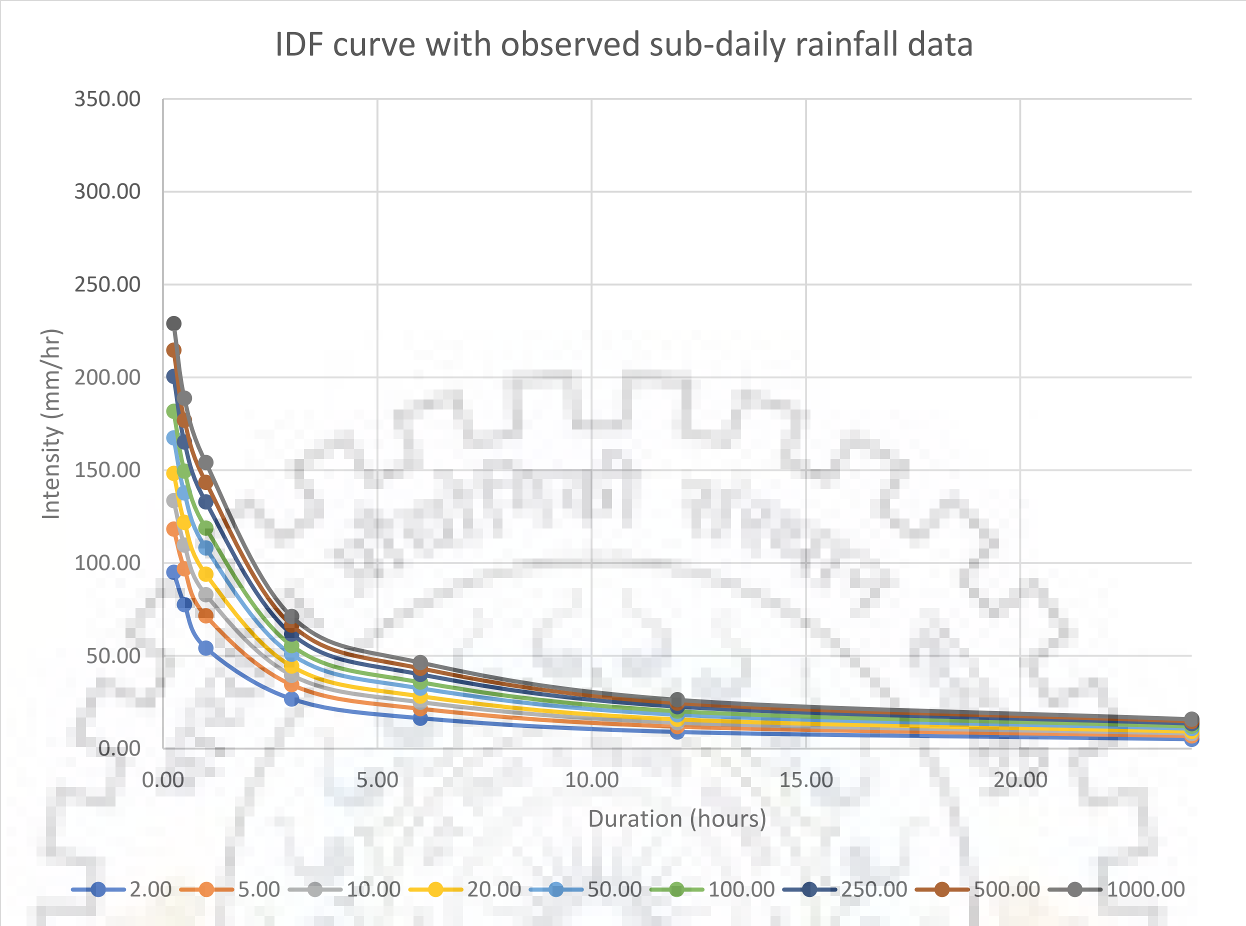

Figure 5.2: IDF curves prepared with observed sub- daily rainfall data

Table 5.1 IMD and observed intensities in mm/hr and ratios for various return periods

Return period	**2**	**5**	**10**	**20**	**50**	**100**	**250**	**500**	**1000**
IMD 15 min.	101.2	138.6	163.4	187.2	218.0	241.0	271.4	294.3	317.2
Obs. 15 min.	95.1	118.3	133.6	148.4	167.4	181.7	200.5	214.7	228.9
Ratio	106.4	117.2	122.3	126.2	130.2	132.6	135.3	137.1	138.6
IMD 1 hour	63.2	86.6	102.1	117.0	136.2	150.6	169.6	183.9	198.3
Obs 1 hour	54.2	71.5	83.0	94.0	108.2	118.9	132.9	143.5	154.1
Ratio	116.6	121.1	123.0	124.5	125.9	126.7	127.6	128.2	128.6
IMD 3 hour	32.1	41.4	47.6	53.6	61.2	67.0	74.6	80.3	86.1
Obs 3 hour	26.8	34.5	39.6	44.5	50.8	55.6	61.8	66.6	71.3
Ratio	119.6	120.0	120.2	120.3	120.5	120.6	120.7	120.7	120.8
IMD 6 hour	18.1	24.8	29.2	33.4	38.9	43.0	48.5	52.6	56.6
Obs 6 hour	16.4	21.6	25.1	28.4	32.6	35.8	40.1	43.3	46.4
Ratio	110.2	114.6	116.5	117.9	119.2	120.1	120.9	121.5	122.0

5.2 Reasons for differences in IDF curves from observed data and intensity data prepared with IMD reduction formula

The intensities identified with the IMD reduction formulae work on the assumption that the rainfall event was a 24 hour event. Thus, for durations smaller than the storm duration the observed rainfall and estimated intensities vary greatly. As the expected intensities are identified using 24 hour duration rainfall, it can be said that the correlation of 24 hour rainfall with rainfall in smaller durations would represent the correlation of estimated and observed intensities.

5.2.1 Correlation of 24 hour rainfall with smaller durations

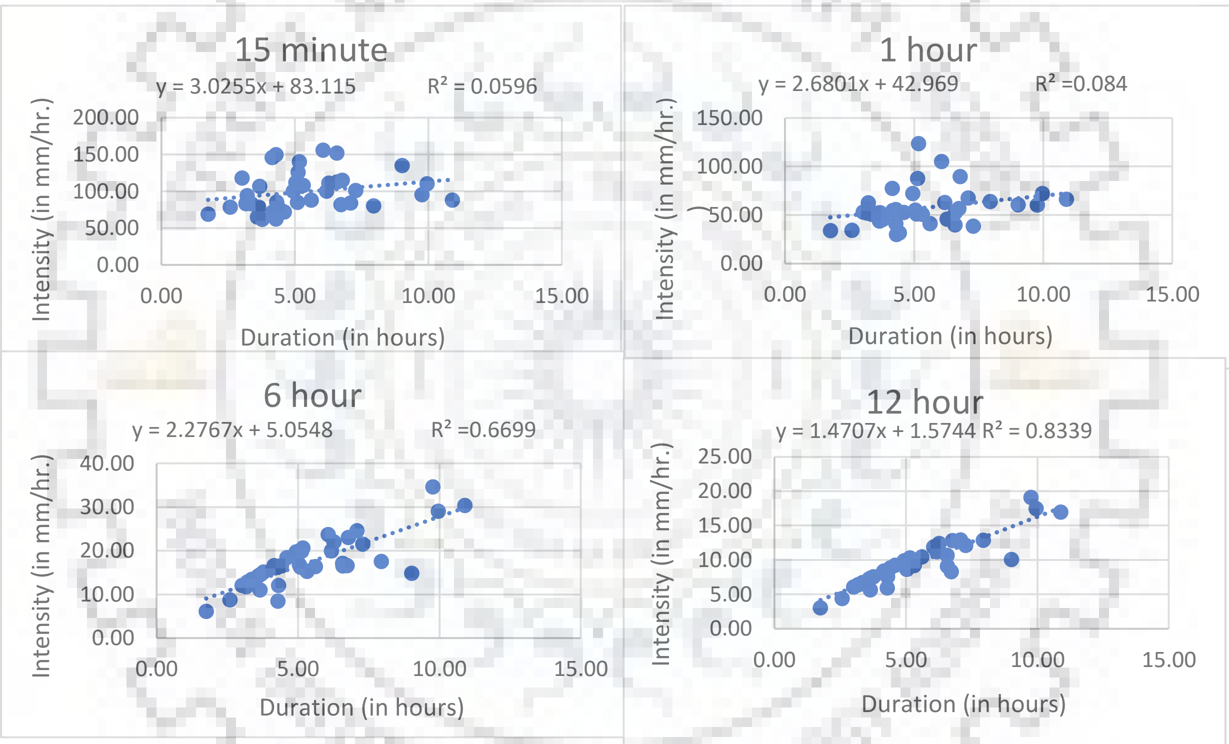

Figure 5.3: Correlation of depths in various durations with 24-hour rainfall

As can be seen, the correlation of 24 hour intensity with smaller durations is very less ($R^2 < 0.1$) while for longer durations the values are more correlated. This is because as the rainfall event stops, the depth remains constant and the intensity keeps reducing with increase in duration.

5.2.2 Depth vs duration

As seen in the depth vs duration analysis, most of the storms have duration of 8-10 hour at most. Thus, for durations above this range, the depth remains constant and intensity goes down with increase in duration. The resultant series has completely different distribution characteristics for durations above and below 6-hour range, which is the average duration for all time blocks identified from the storm data as can be seen by the plots of l moments for various durations.

5.3 Improved reduction formulae from quantile mapping method

The model proposed in present study for the reduction of 24 hour depth to smaller depths can be done using following steps:

1. Estimation of 85% rainfall
2. Estimation of multiplication factor y from the equations:

   $y = 0.1996\ln(x) + 0.5861$ for Type 1 extreme event scenario

   $y = 0.1905\ln(x) + 0.3716$ for Type 2 extreme event scenario

   Where:

   y= ratio of depth in that duration to 85% rainfall

   x= duration of rainfall (in hours)
3. Using 85% rainfall and y to estimate the depth for particular duration.

This model gives better estimates for different storm scenarios as compared to generalized reduction while assuming duration of rainfall to be 24 hours.

5.4 Simplified runoff estimations for identified rainfall scenarios

The calculations for estimated runoffs were done using SCS- CN method by calculation of weighted CN for each sub- catchment. The precipitation was taken to be values of 6- h duration as estimated by IDF generated by IMD reduction formulae and observed data. The following table also show the percentage change in the estimated runoff due to both rainfall events.

The CN for built up, roads, green area and barren land was taken to be 76, 98, 34 and 49 respectively. The identified rainfall scenarios for which comparison was done are: (i) 25-

year return period, (ii) 50-year return period, (iii) 100-year return period and (iv) Max observed rainfall event and 40-year return period rainfall.

Table 5.2: Runoff generation difference for both data sets for 25-year return period

Sub-catch	Weighted CN	S (Max. possible retention) (inch)	Initial abstraction (inch)	P_{25} (IDF IMD reduction formulae) (inch)	P_{25} IDF observed data) (inch)	Runoff (in inch) for IMD reduction formulae	Runoff (in inch) for observed event
1	72.37	3.82	0.76	7.90	6.70	4.65	3.61
2	77.21	2.95	0.59	7.90	6.70	5.20	4.12
3	71.99	3.89	0.78	7.90	6.70	4.60	3.57
4	46.35	11.57	2.31	7.90	6.70	1.82	1.20
5	60.91	6.42	1.28	7.90	6.70	3.36	2.48
6	73.14	3.67	0.73	7.90	6.70	4.73	3.69
7	76.92	3.00	0.60	7.90	6.70	5.17	4.09
8	75.06	3.32	0.66	7.90	6.70	4.95	3.89
9	65.46	5.28	1.06	7.90	6.70	3.86	2.92
10	67.34	4.85	0.97	7.90	6.70	4.07	3.10
11	57.19	7.49	1.50	7.90	6.70	2.95	2.13
12	71.82	3.92	0.78	7.90	6.70	4.58	3.56
13	70.36	4.21	0.84	7.90	6.70	4.42	3.41
Total	71.18	4.05	0.81	7.90	6.70	4.51	3.49

The average change for all 13 sub-catchments for 25-year return period scenario was found to be 17.9% in rainfall. The calculations of other parameters for the estimates have been described in the chapter for methodology in table 4.7. This change leads to 29% change in runoff for the Roorkee area as a whole.

Table 5.3: Runoff generation difference for both data sets for 50-year return period

Sub-catch	Weighted CN	S (Max. possible retention) (inch)	Initial abstraction (inch)	P_{50} (IDF IMD reduction formulae) (inch)	P_{50} IDF observed data) (inch)	Runoff (in mm) for IMD reduction formulae	Runoff (in mm) for observed event
1	72.37	3.82	0.76	9.19	7.71	5.80	4.48
2	77.21	2.95	0.59	9.19	7.71	6.41	5.03
3	71.99	3.89	0.78	9.19	7.71	5.75	4.44
4	46.35	11.57	2.31	9.19	7.71	2.56	1.72
5	60.91	6.42	1.28	9.19	7.71	4.37	3.22
6	73.14	3.67	0.73	9.19	7.71	5.90	4.57
7	76.92	3.00	0.60	9.19	7.71	6.37	5.00
8	75.06	3.32	0.66	9.19	7.71	6.14	4.79
9	65.46	5.28	1.06	9.19	7.71	4.94	3.71
10	67.34	4.85	0.97	9.19	7.71	5.17	3.92
11	57.19	7.49	1.50	9.19	7.71	3.90	2.82
12	71.82	3.92	0.78	9.19	7.71	5.73	4.42
13	70.36	4.21	0.84	9.19	7.71	5.55	4.26
Total	71.18	4.05	0.81	9.19	7.71	5.65	4.35

The average change for 50-year return period was 19.82%. It can be observed that the change in rainfall values gets carried over to runoff estimations directly due to the linear relationship of rainfall and drainage in SCS CN method. This change leads to 29.8% change in runoff for the Roorkee area as a whole.

Table 5.4: Runoff generation difference for both data sets for 100-year return period

Sub-catch	Weighted CN	S (Max. possible retention) (inch)	Initial abstraction (inch)	P_{100} (IDF IMD reduction formulae) (inch)	P_{100} IDF observed data) (inch)	Runoff (in mm) for IMD reduction formulae	Runoff (in mm) for observed event
1	72.37	3.82	0.76	10.17	8.47	6.69	5.15
2	77.21	2.95	0.59	10.17	8.47	7.32	5.73
3	71.99	3.89	0.78	10.17	8.47	6.64	5.11
4	46.35	11.57	2.31	10.17	8.47	3.17	2.14
5	60.91	6.42	1.28	10.17	8.47	5.16	3.80
6	73.14	3.67	0.73	10.17	8.47	6.79	5.24
7	76.92	3.00	0.60	10.17	8.47	7.28	5.70
8	75.06	3.32	0.66	10.17	8.47	7.04	5.47
9	65.46	5.28	1.06	10.17	8.47	5.77	4.33
10	67.34	4.85	0.97	10.17	8.47	6.02	4.55
11	57.19	7.49	1.50	10.17	8.47	4.65	3.36
12	71.82	3.92	0.78	10.17	8.47	6.62	5.09
13	70.36	4.21	0.84	10.17	8.47	6.42	4.91
Total	71.18	4.05	0.81	10.17	8.47	6.53	5.01

The average change for 100-year return period was 20.60%. It was seen that the changes observed for sub- catchments with high built up show more changes in the estimated runoff compared to sub- catchments with vegetation areas. This change leads to 30.3% change in runoff for the Roorkee area as a whole.

Table 5.5: Runoff generation difference for both data sets for max observed event

Sub-catch	Weighted CN	S (Max. possible retention) (inch)	Initial abstraction (inch)	P_{40} (IDF IMD reduction formulae)	P_{40} IDF observed data)	Runoff (in mm) for IMD reduction formulae	Runoff (in mm) for observed event
1	72.37	3.82	0.76	8.81	7.41	5.45	4.22
2	77.21	2.95	0.59	8.81	7.41	6.05	4.76
3	71.99	3.89	0.78	8.81	7.41	5.41	4.18
4	46.35	11.57	2.31	8.81	7.41	2.33	1.56
5	60.91	6.42	1.28	8.81	7.41	4.06	2.99
6	73.14	3.67	0.73	8.81	7.41	5.55	4.31
7	76.92	3.00	0.60	8.81	7.41	6.01	4.73
8	75.06	3.32	0.66	8.81	7.41	5.78	4.52
9	65.46	5.28	1.06	8.81	7.41	4.61	3.47
10	67.34	4.85	0.97	8.81	7.41	4.84	3.67
11	57.19	7.49	1.50	8.81	7.41	3.61	2.61
12	71.82	3.92	0.78	8.81	7.41	5.39	4.16
13	70.36	4.21	0.84	8.81	7.41	5.21	4.00
Total	71.18	4.05	0.81	8.81	7.41	5.31	4.09

The average change for maximum observed rainfall event was 19.47%. The changes observed in this case show the changes in estimated runoff depth for the maximum observed storm with the runoff for intensities estimated from the IMD reduction formula. This change leads to 29.8% change in runoff for the Roorkee area as a whole.

It can be seen that the percentage change in rainfall for all 4 scenarios compared, carries over to the runoff estimations. Thus, for a proper and accurate flood hazard scenario mapping it is important to estimate the sub-daily rainfall accurately. The generalized reduction formulae work well enough for regional estimates but local estimates require more precision. Thus, new framework for reduction of daily rainfall to sub-daily statistics was developed using quantile mapping method, but as the method utilizes the observed sub- daily rainfall data as it's basis, the results can't be validated using the same, as it will be a redundant procedure and will give false validation. A different sub- daily dataset will be required for proper validation of the new reduction framework.

5.5 Comparison of runoff for max 6h rainfall observed for land-use in 2017, 2007 & 1997

To understand the effect of change in land-use on hazard levels a comparison of basic runoff generation for 2017, 2007 and 1997 Land- use for maximum rainfall event observed has been done. The calculations for CN of each sub-catchment for 2017, 2007 and 1997 has been done by weighted CN method in the same manner as shown in table 4.7 for 2017. The CN for built up, roads, green area and barren land was taken to be 76, 98, 34 and 49 respectively. The calculation for 2007 and 1997 are as follows:

A comparison of the runoff generated for max observed 6h rainfall for 2017, 2007 and 1997 is shown in table 5.8. As can be observed, the runoff generation in 1997 and 2007 lies in the range of ±10% of the 2017 runoff.

By observing table 3.2, 5.3, 5.4, 5.5 and 5.8, it is clear that the same % variations in land use change observed from 1997 to 2017 do not cause as much variation in the results of hazard estimation as seen in the case of observed rainfall and estimated sub-daily rainfall. Hence it can be inferred that accurate estimation of rainfall is more important than the land use calculations. Though, for a perfect assessment of hazard, accuracy of both elements is necessary.

Table 5.6: Comparison of runoff generation for each sub- catchment for 2017, 2007 and 1997

	Simplified Runoff Generation (for max 6h rainfall observed, in m^3)			As percentage of runoff in 2017		Increase in runoff depth from 1997 to 2017 (in inch)
Sub-catch	2017	2007	1997	2007	1997	
1	4.22	3.83	3.07	90.67	72.76	1.15
2	4.76	4.50	2.19	94.49	45.98	2.57
3	4.18	3.75	2.51	89.64	60.16	1.66
4	1.56	1.44	1.09	92.40	69.72	0.47
5	2.99	2.75	2.69	91.80	89.77	0.31
6	4.31	4.53	2.60	105.25	60.47	1.70
7	4.73	4.20	2.19	88.88	46.35	2.54
8	4.52	4.16	2.78	92.06	61.43	1.74
9	3.47	3.38	3.26	97.52	93.82	0.21
10	3.67	3.57	2.39	97.12	65.01	1.28
11	2.61	2.68	2.17	102.92	83.28	0.44
12	4.16	3.85	3.10	92.50	74.63	1.06
13	4.00	3.84	3.50	96.13	87.49	0.50

5.6 Area most affected due to change in LULC:

Among all the sub-catchments studied, the maximum increase of 2.5 inch in runoff depth from 1997 to 2917 can be observed in sub-catchment 2 and 7. While sub- catchments 3, 6, 8 and 10 show around 1.5 – 2 inch increase in depth. These are the sub- catchments which have gone through the highest change in LULC over the years of study and can be said to have become more at risk of inundation and urban flooding due to increase in estimated runoff depth. The other sub-catchments also experienced an increase in runoff depth, but all were less than an increase of 1.5 inch depth.

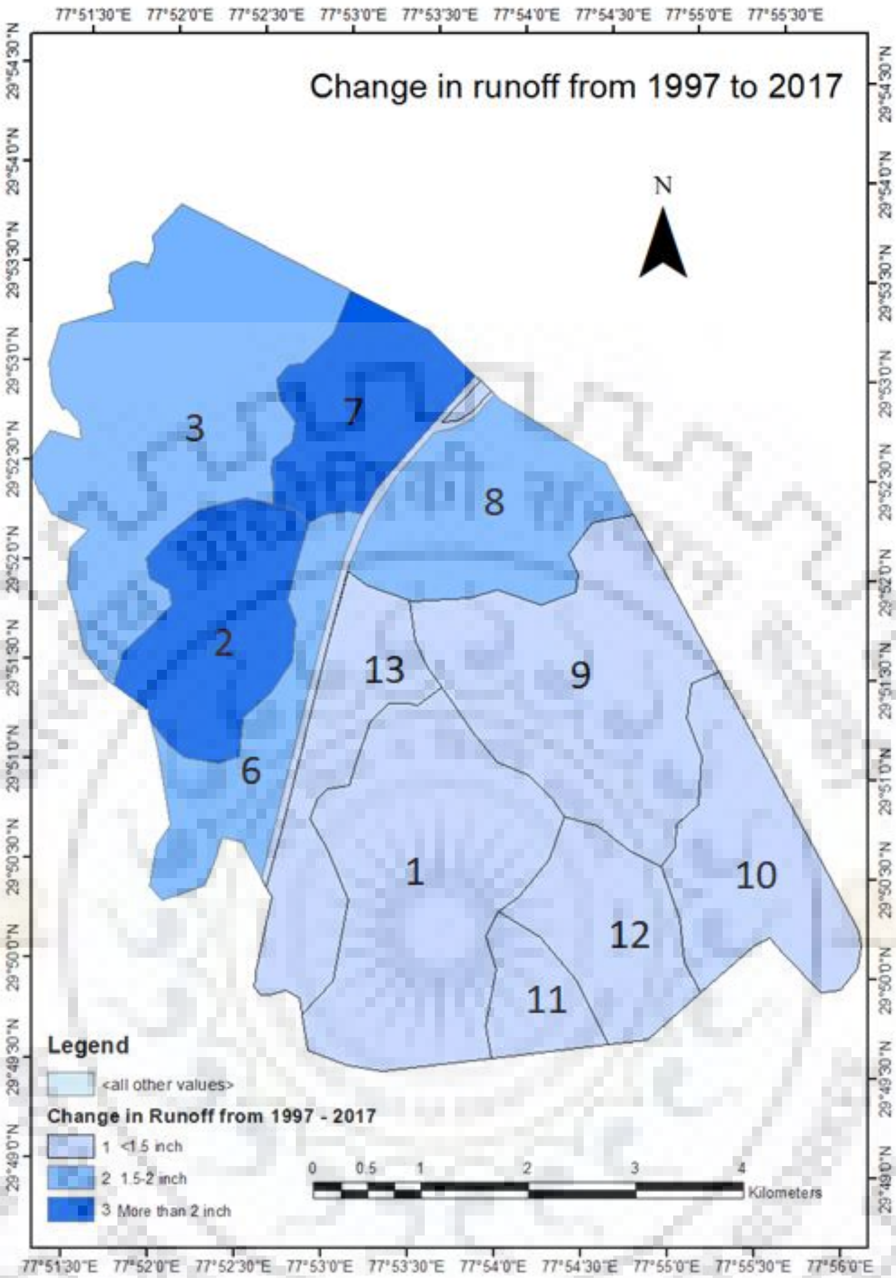

Figure 5.4: Change in runoff depth from 1997 - 2017

5.6 Changes in runoff pattern of IIT Roorkee campus:

The IIT Roorkee campus lies in sub-catchment 8, where the increase in runoff depths from 1997 has been observed to be ~5 inches. Which shows that there has been increase in built up areas and roads, but still green areas have been preserved. In comparison to areas where 100% built up is present, the IIT Roorkee campus has around 23% vegetation cover, which helps reduce the runoff. The increase of 5 inch depth also includes the LULC changes occurring outside the campus boundary, which have mostly been converted to built up, thus the actual runoff depth increase within the campus should be lower than 5 inch.

CHAPTER 6: CONCLUSIONS, LIMITATIONS AND SCOPE FOR FURTHER WORK

6.1 Conclusions

The following conclusions can be drawn from the study:

1. The accuracy of sub-daily rainfall estimation method is important for identifying potential hazard levels. As observed in table 5.1, 5.2, 5.3, 5.4 and 5.5 the overestimations in estimated sub-daily rainfall dataset using IMD formula and recorded sub-daily rainfall dataset, get carried over to the runoff estimations in higher percentages. For example, a ~19% change in 6h rainfall with 50- year return period causes an average change of 29.8% in the estimated runoffs.
2. The land-use observed in different years (1997, 2007 and 2017) vary greatly (The changes are as much as 100% increase in built up from 1997 to 2017, Table 3.2). The impact of these changes on the runoff generation is well established. Overall the increase in rainfall is further substantiated due to increase in built up area.
3. The method for estimation of sub-daily rainfall used in the flood estimations under UDRP results in 17% – 21% overestimation, in return periods 20 years to 1000 years respectively. This overestimation is due to the assumption that the total daily rainfall is the result of a single event spanning over a duration of 24 hours. For more accurate sub- daily rainfall estimates, factoring in the storm duration accurately is very important.
4. Using quantile mapping method after the removal of outlier storms, a method to estimate sub-daily rainfall statistics was developed from the storm depth vs duration study. The new model prepared classifies the extreme storms in 2 categories

   (i) E1 scenario and (ii) E2 scenario.

   The reduction of 24-hour depth to smaller depths can be done using following steps:

   - Estimation of 85% rainfall
   - Estimation of multiplication factor y from the equations:

     $y = 0.1996\ln(x) + 0.5861$ for E1 scenario

     $y = 0.1905\ln(x) + 0.3716$ for E2 scenario

     Where:

     y= ratio of depth in that duration to 85% rainfall

x= duration for which rainfall is required

- Using 85% rainfall and y to estimate the depth for particular duration by:

Rainfall in x duration = $D_{0.85}$*y

Where $D_{0.85}$ is the 85% of total storm depth

Though this method fits for the observed rainfall data, for proper validation a different set of rainfall data is required, as a model cannot be validated with the data it was derived from.

6.2 Limitations

1. The unavailability of accurate surface and channel data causes problems with drainage modelling thus the study limits the scope to rainfall data analysis. For runoff generation a simplified model using SCS-CN method has been used.
2. A framework to estimate the sub-daily rainfall using quantile mapping method was developed, but as the method utilizes the observed sub- daily rainfall data as it's basis, the results cannot be validated using the same, as it will be a redundant procedure and will give false validation. A different sub- daily dataset will be required for proper validation of the new reduction framework.

6.3 Scope for future work

1. Using a more accurate surface model (with a resolution higher than 30-m SRTM DEM, which can be prepared using LIDAR, UAV drones or on-site total station studies), an accurate surface storage and flow model can be prepared. This type of flow modelling can give the volumetric accumulation with time, channel capacities and the inundation volumes. By linking the 1-D channel flow model with 2-D surface models it is possible to generate inundation maps. By comparison of inundation maps prepared for both rainfall datasets (observed and data estimated using reduction formulae) with the UDRP inundation maps, the overestimations for different depth ranges can be identified.
2. Using a different recorded sub-daily rainfall data, the suggested framework for estimation of sub-daily rainfalls (using 85% rainfall depth and quantile mapping) can be validated. As the model is derived from the data used for study, a proper validation can only be done using different dataset.
3. By gathering drainage channel data and the actual runoff at different outlets, the accuracy of the drainage model suggested above can be further increased.

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List of time blocks prepared from storm charts of sub- daily rainfall data.

Table I-1: List of storm divisions identified

S. No	Date	Depth	Duration			S. No	Date	Depth	Duration		
			h	m	in minutes				h	m	in minutes
1	06-08-1983	228.4	7	30	450	68	05-09-1991	53.8	2	0	120
2	28-06-2017	211.5	3	45	225	69	08-06-2000	53.5	4	15	255
3	26-07-2006	206.2	9	30	570	70	04-09-1990	52.9	2	0	120
4	20-07-1994	200.1	10	0	600	71	14-07-2000	52.5	1	0	60
5	31-07-2010	146.3	8	0	480	72	20-06-2015	52.3	1	0	60
6	10-09-2009	140.3	7	15	435	73	08-09-2014	51	1	30	90
7	28-08-1989	138.6	14	30	870	74	10-08-2003	50.7	1	15	75
8	14-08-1995	133.2	8	0	480	75	17-10-1998	50.6	5	45	345
9	03-08-1997	132.5	13	15	795	76	23-10-2006	50.4	2	45	165
10	25-06-1981	123.5	1	0	60	77	20-07-1994	49.2	4	30	270
11	04-08-1990	119	2	45	165	78	17-07-1986	48.2	4	0	240
12	23-07-2011	117.4	3	15	195	79	13-07-1980	47.8	7	30	450
13	19-08-1996	116.2	2	45	165	80	30-08-2003	47.7	1	0	60
14	26-09-1988	111.8	6	45	405	81	28-08-2009	47.7	1	30	90
15	05-07-1988	109.1	3	0	180	82	02-08-1992	47	3	0	180
16	06-07-2004	101.6	2	30	150	83	03-09-2003	46.2	1	15	75
17	19-08-2012	99.4	6	30	390	84	11-08-2015	46	1	15	75
18	18-07-2016	99	4	15	255	85	08-06-2000	45.8	13	45	825
19	08-08-1979	98.9	4	15	255	86	14-08-2005	45.2	1	15	75
20	27-08-1992	97.3	5	15	315	87	13-06-2008	44.7	1	30	90
21	25-03-1993	97.2	5	30	330	88	23-08-1980	44.2	4	0	240
22	02-08-1992	96.7	2	30	150	89	20-08-1989	43.6	1	45	105
23	08-07-1994	94.2	4	0	240	90	06-07-2017	43.6	2	15	135
24	16-07-2001	93.1	4	30	270	91	28-07-1982	42.9	2	0	120
25	30-07-2011	93	1	45	105	92	24-07-1997	42.7	1	30	90
26	28-07-1983	92.6	9	15	555	93	24-06-2001	42.7	1	0	60
27	10-07-1990	91.9	7	0	420	94	24-09-2017	42.6	5	30	330
28	24-09-1998	86.9	8	45	525	95	17-07-1981	42.4	2	15	135
29	07-09-2002	86	8	30	510	96	05-08-2014	42	1	15	75
30	26-07-1980	85.6	3	0	180	97	23-09-2005	41.1	1	30	90
31	13-07-1995	84.8	12	15	735	98	10-08-2017	41	1	0	60
32	04-08-2002	84.7	2	15	135	99	21-07-1997	40.5	1	45	105
33	05-07-2003	84.4	3	45	225	100	05-09-1991	39.9	3	0	180
34	09-08-2013	84.2	5	30	330	101	06-09-1993	38.3	4	0	240

35	28-07-1981	82.4	5	30	330	102	17-10-1998	37.8	6	0	360
36	09-09-1996	80.4	2	0	120	103	28-08-1989	37.7	3	15	195
37	13-08-1996	80.2	2	30	150	104	12-06-2007	37.1	1	0	60
38	19-08-2007	80	3	45	225	105	05-08-1980	37	2	30	150
39	19-09-2010	78.9	8	15	495	106	06-09-1993	35.9	2	15	135
40	23-08-1994	78.3	7	0	420	107	05-07-1988	35.8	3	15	195
41	19-07-2014	77	5	15	315	108	03-08-2004	35.7	1	15	75
42	27-08-1987	75	2	30	150	109	05-09-1993	35.6	5	15	315
43	21-07-1979	70.9	2	45	165	110	23-07-1999	35	2	0	120
44	18-07-2000	70.8	3	30	210	111	07-07-1986	34.3	1	15	75
45	23-09-2005	70.7	6	15	375	112	07-07-2004	33.6	1	0	60
46	22-08-1990	70.5	2	0	120	113	24-08-2004	33.5	3	0	180
47	13-07-1982	70.2	2	30	150	114	18-07-2000	33.2	1	15	75
48	07-09-2002	67.6	7	0	420	115	25-07-1979	33	1	45	105
49	20-07-1982	65.5	5	0	300	116	12-08-1999	32.9	1	0	60
50	16-04-1983	65.4	4	30	270	117	14-08-1981	31.8	1	15	75
51	13-07-2008	64.7	4	45	285	118	02-08-1992	31.7	2	45	165
52	24-09-2017	64.5	9	30	570	119	26-07-2006	27.3	1	45	105
53	05-07-1995	64	1	30	90	120	12-07-1999	26.9	2	30	150
54	03-08-1998	63.3	2	30	150	121	12-06-2007	26.5	1	30	90
55	08-09-2002	62.5	6	15	375	122	05-08-1998	25.8	1	15	75
56	05-08-1998	62.1	2	15	135	123	17-09-2005	24.2	5	15	315
57	11-07-1991	61.7	1	30	90	124	05-08-2014	24	1	0	60
58	22-09-2016	60	3	45	225	125	13-07-1980	23.7	1	30	90
59	04-09-1990	59.1	2	15	135	126	05-08-1980	23.5	5	30	330
60	19-09-2010	58.3	4	30	270	127	26-09-1988	22.3	2	30	150
61	06-08-1985	57	3	45	225	128	05-09-1993	21.4	2	30	150
62	01-09-2009	56.1	3	15	195	129	07-07-1986	20.6	2	30	150
63	28-08-2012	56.1	2	15	135	130	06-08-1985	20.5	1	15	75
64	21-08-1985	55.1	4	0	240	131	24-08-2004	19.5	2	15	135
65	17-08-2008	55.1	3	15	195	132	17-08-2008	19.5	2	30	150
66	05-07-2015	55	3	0	180	133	05-08-1998	18.6	1	0	60
67	23-08-2016	53.9	1	30	90	134	09-09-1996	17.6	1	0	60
						135	13-08-1996	16	3	0	180

Python 3.0 code used for identification of time blocks from the digitized storm chart data.

```
class datewise:
    date = 0
    datearray = np.array(0)
    datecount = 0
    no_storm_range=np.full((10, 2), 999)
    storm_range=np.full((10,2),0)
    max_intensities=np.array(0)

    def __init__(self,date,array):
        self.date=date
        self.datearray=array
        datewise.datecount += 1

    def stormrangefinder(self):
        ranges=np.array(0)
        logarray=np.array(0)
        delarray=np.array(0)
        temp=np.array(0)
        iszero = np.concatenate(([0], np.equal(self.datearray, 0).view(np.int8), [0]))
        absdiff = np.abs(np.diff(iszero))
        ranges= np.where(absdiff == 1)[0].reshape(-1, 2)
        logarray= np.diff(ranges)
        delarray= logarray>=4 #(minimum difference considered between 2 storms)
        for i in range(0,len(delarray)):
            if ~delarray[i]:
                self.no_storm_range=np.delete(ranges,i,0)
        if self.no_storm_range[0][0] == 0:
            temp = np.roll(self.no_storm_range, -1)
            for i in range(0,len(temp)):
                if temp[i][0]==287:
                    self.storm_range= np.delete(temp,i,0)
        else:
            temp = np.roll(self.no_storm_range, 1)
            temp[0][0]=0
        return self
```

Figure II-1: Class to store and work on the charts date-wise

```
class storms:
    stormno = 0
    stormno_ondate = 0
    stormdate = 0
    stormchart = np.array(0)
    stormdepth = 0
    stormduration = 0
    max_intensities=np.array(0)
    start=0
    end=0
    avg_intensity = 0

    def __init__ (self,date):
        self.date=date

    def prints(self):
        print(self.stormno)
        print(self.stormno_ondate)
        print(self.stormdate)
        print(self.start)
        print(self.end)
```

Figure II-2: Class to store and work upon storm data

```python
def stormidentifier(d1):
    for i in range (0,len(d1.storm_range)):
        S=storms(d1.date)
        storms.stormno += 1
        S.stormno=storms.stormno
        S.start=d1.storm_range[i][0]
        S.end=d1.storm_range[i][1]
        S.stormno=storms.stormno
        S.stormno_ondate=(i+1)
        S.stormchart=d1.datearray[S.start:S.end]
        S.stormdepth=np.sum(S.stormchart)
        S.stormduration = (15*len(S.stormchart))
        storm_list.append(storms(S))
```

Figure II-3: Function to identify storms and calculate basic storm parameters

```python
def max_subarray(A, k):
    a=0
    max_sum=0
    b=a+k
    for a in range (0, (len(A)-k)):
        window_sum = 0
        for elem in A[a:b]:
            window_sum+= A[elem]
        if window_sum>=max_sum:
            max_sum=window_sum
    return max_sum

def stormintensities(S1):
    temp=[]
    for i in ab_dur:
        temp.append(max_subarray(S1.stormchart,i))
    S1.max_intensities=temp
    return S1.max_intensities

def datewiseintensities(D1):
    temp=[]
    for i in ab_dur:
        temp.append(max_subarray(D1.datearray,i))
    D1.max_intensities=temp
    return D1.max_intensities
```

Figure II-4: Functions to calculate daily and storm wise max intensities