Southern Illinois University Carbondale
OpenSIUC

Theses | Theses and Dissertations

5-1-2018

STATISTICAL EVALUATION OF HYDROLOGICAL EXTREMES ON STORMWATER SYSTEM

Narayan Nyaupane
Southern Illinois University Carbondale, narayan.nyaupane@siu.edu

Follow this and additional works at: https://opensiuc.lib.siu.edu/theses

Recommended Citation
Nyaupane, Narayan, "STATISTICAL EVALUATION OF HYDROLOGICAL EXTREMES ON STORMWATER SYSTEM" (2018). *Theses*. 2300.
https://opensiuc.lib.siu.edu/theses/2300

This Open Access Thesis is brought to you for free and open access by the Theses and Dissertations at OpenSIUC. It has been accepted for inclusion in Theses by an authorized administrator of OpenSIUC. For more information, please contact opensiuc@lib.siu.edu.

STATISTICAL EVALUATION OF HYDROLOGICAL EXTREMES ON STORMWATER SYSTEMS

By

Narayan Nyaupane

B.S., Tribhuvan University, 2007

A Thesis

Submitted in Partial Fulfillment of the Requirements for the

Master of Science in Civil Engineering

Department of Civil and Environmental Engineering

in the Graduate School

Southern Illinois University Carbondale

May 2018

THESIS APPROVAL

STATISTICAL EVALUATION OF HYDROLOGICAL EXTREMES

ON STORMWATER SYSTEMS

By

Narayan Nyaupane

A Thesis Submitted in Partial

Fulfillment of the Requirements

for the Degree of

Master of Science

in the field of Civil Engineering

Approved by:

Dr. Ajay Kalra, Chair

Dr. Bruce A. DeVantier

Dr. Trenton Ford

Graduate School

Southern Illinois University Carbondale

April 06, 2018

AN ABSTRACT OF THE THESIS OF

NARAYAN NYAUPANE, for the Master of Science degree in CIVIL ENGINEERING, presented on April 06 2018, at Southern Illinois University Carbondale.

TITLE: STATISTICAL EVALUATION OF HYDROLOGICAL EXTREMES ON STORMWATER SYSTEMS

MAJOR PROFESSOR: Dr. Ajay Kalra

Climate models have anticipated higher future extreme precipitation for various regions. Urban stormwater facilities are vulnerable to these changes as this design assumes stationarity. However, recent climate change studies have argued about the existence of non-stationarity of the climate. A distribution method adopted on extreme precipitation varies spatially and may not always follow Generalized Extreme Value (GEV) distribution. In this research, the future design storm depth based on the stationarity of climate and GEV distribution method was examined with non-stationarity and a best fitted distribution method. For this, observed data from North American Regional Reanalysis (NARR) and climate model data from North American Regional Climate Change Assessment Program (NARCCAP) for historical (1971-2000) and future (2041-2070) were analyzed to identify the best distribution method associated with the design storm depth (100yr 6hr). Twenty-seven different statistical distributions were applied to the data and were assessed using Kolmogorov-Smirnov and Pearson Chi-square test for the best-fit. The best fitted distribution method was used to calculate the design storm depth. Climate change scenarios were adopted as delta change factor, a downscaling approach to transfer historical storm to the climate adopted future storm, to represent a range of climate changes. Existing design storm depth and the climate generated storm depth were simulated and used as input to the HEC-HMS model developed by Clark County Regional Flood Control District, NV to evaluate the hydrological parameters of the existing and proposed stormwater facility within Las Vegas City’s jurisdiction. The historic and projected storm depth from fourteen different NARCCAP models with different durations showed GEV-min (L-moments) distribution method as the best-fit. Most of the delta change factors calculated were higher than one, representing strong climate change impact on design storm depth. The model result showed the existing stormwater facilities available may not be able to handle a future design storm. Thus, a proper update on existing design practice is warranted with a proper handling of non-stationarity and uncertainty of climate change. The research highlights the importance of available climate information and suggests a possible approach for climate change adaptation on stormwater design practice.

Flooding is one of the major natural hazards in the US along with tropical cyclones and drought/heat waves. More adverse effects on flooding observed in recent years were linked with climate change. Understanding of flooding event along with flood risk management, a widely accepted best approach for flood defense, can mitigate the risk. Floodplain mapping which is the part of risk analysis is the first step towards flood risk management. Further, understanding the changing pattern of the design flood would help to understand and manage future changes. Variable Infiltration Capacity (VIC) forcing generated Coupled Model Intercomparison Project phase 5 (CMIP5) streamflow was used for the future streamflow analysis. Various statistical distributions were fitted with Pearson Chi-square and Kolmogorov Smirnov test to get the underlying distribution among the routed streamflow of Carson River near Carson City, an agricultural area in the desert of Nevada. Altogether 97 projections from 31 models with 4 emission scenarios were used to predict the 100yr flow using a best fit distribution. Delta change factor is used to predict future flows and routing uses HEC-RAS model. Most of the projections indicate increase in the future 100yr flood level. Developed floodplain mapping for the future has a larger inundation area compared with Federal Emergency Management Agency (FEMA) flood inundation maps. This study suggests an approach to analyze future flood and preparation of floodplain. This will provide helpful information to the facility manager, design engineer, and stakeholders.

ACKNOWLEDGEMENTS

I would like to extend my deepest gratitude to Dr. Ajay Kalra, my thesis advisor, for his guidance, supervision and mentorship throughout my graduate study. The assistance that he provided was pivotal to the success of this research.

I would like to acknowledge Dr. Bruce A. DeVantier and Dr. Trenton Ford for the help and advice they offered not only during my research but also whilst serving on my thesis committee. I owe a great thank to Dr. Sajjad Ahmad, Professor at University of Nevada Las Vegas for his valuable support for the research. My special thanks go to Ranjit Thakali, former student of SIUC who helped me to outline the research. I would like to thanks to Balabhadra Thakur, Ranjan Parajuli, Ranjit Bhandari, Swastik Bhandari, Devi Priya Ponughoti, Rohit Jogineedi and Sandeep Reddy Chavva for being lab partner and resolving issues that were encountered during research. I am thankful to Ms. Tuesday L. Ashner for her support for lab setup and helping relentlessly.

I would like to express my sincere thanks to my parents, wife, friends and colleagues for their love, patience and advice in different aspects of life. I would like to express my deepest appreciation to the entire faculty, staff and colleagues of the Southern Illinois University's Civil and Environmental Engineering Department for their help and guidance throughout my graduate study.

I would like to dedicate this thesis to my mother, Sharada Neupane and to my wife, Pramila Adhikari for their love, support and continuous motivation, which helped me to achieve the goal.

I wish to thank the NARCCAP for providing the data used in this paper. NARCCAP is funded by the National Science Foundation (NSF), the U.S. Department of Energy (DoE), the

National Oceanic and Atmospheric Administration (NOAA), and the U.S. Environmental Protection Agency Office of Research and Development (EPA).

I acknowledge the modeling groups, the Program for Climate Model Diagnosis and Intercomparison (PCMDI), and the World Climate Research Programme (WCRP) Working Group on Coupled Modelling (WGCM) for their roles in making available the WCRP CMIP3 multi-model dataset. Support of this dataset is provided by the Office of Science, U.S. Department of Energy

TABLE OF CONTENTS

LIST OF TABLES

LIST OF FIGURES

CHAPTER 1
INTRODUCTION

1.1 Research Background

After the improvement in agriculture and start of the industrialization gathered more urban population in the 18th and 19th century rose substantially (Wu et al., 2011). Urban population is increasing day by day, with more than half of the world population now living in urban areas (Lederbogen et al., 2011). Urbanization has enhanced the industrial development and development prospect of human life (Grimm et al., 2008; Landes, 2003). At the same time due to concentration of human population, natural resources nearby were more stressed (Chen et al., 2017; Chen et al., 2018; Shukla et al. 2011).

Urbanization has increased the paved surface and changed land use pattern leaving less infiltration and more surface runoff eventually producing more flash floods (Aryal et al., 2018; Carrier et al., 2011; Douglas et al., 2007; Kalra et al., 2013a; Kalra et al., 2013b; Kalra et al., 2017). These flash floods are intensified in recent years due to climate change, which has the capacity to alter the duration, intensity and frequency of a storm event (Zwiers et al., 2013). Thus, the urban population is vulnerable to such change and it is necessary to strengthen urban infrastructure to protect from such imminent threats (Gautam et al., 2013; Jobe et al., 2017; Jobe et al., 2018; Thakali et al., 2017a; Thakali et al., 2018). The urban infrastructures are designed based on the stationary approach to climate characterization which has already been opposed by many recent researches (Cheng et al., 2014, Jiang et al., 2016; Zhang et al., 2010; Thakali et al., 2017b; Thakali, 2017). Though climate change is a well-known phenomenon, prediction of the future climate is not an easy task. Various climate models and their projections are available, which facilitates the researcher in describing future climate and climatic variables (Knutti et al., 2013; Mearns et al., 2009; Pokhrel et al., 2012; Pokhrel et al., 2017; Pokhrel et al., 2018). This study aims to utilize available climate models to predict the probable future condition and analyzes the effect on infrastructures.

Design of stormwater infrastructures, which are the major components of urbanization depends upon probabilistic analysis of available datasets (Notaro et al., 2015; Nyaupane et al., 2017, Parajuli et al., 2017). The result of the analysis directly depends upon the selection of the statistical distribution method (Cunnane, 1989). Selection of a random distribution among available different options deviates the result from reality (Bhandari et al., 2017; Ghimire et al., 2016; Thakur et al., 2017a; Thakur et al., 2017b). Thus, best fit analysis would be effective way to select the best distribution before carrying any frequency analysis, which is the basis of design parameter selection. The study aims to possible way of analyzing future hydrology associated with urban life and would be helpful to designers, managers, planners and engineers.

1.2 Research Motivations

Extremes in weather are more common in recent years linking these to climate change. Since most of the infrastructures are designed based on historical records of data considering the stationarity of climate. Recent research developments outdated the stationarity of climate. Thus, there is a necessity to cope with the challenges posed by increasing extreme events. Along with this, method used in frequency analysis affects directly on the probable return period of an event. Without a best fit it cannot be decided which distribution fits best with a given set of data. These research problems have motivated the two research tasks one on each of extreme precipitation and streamflow.

1.3 Research Objectives

This study aims to check the existing standards followed on distribution analysis of City of Las Vegas along with estimates of the worst case scenario in future. Impact on existing infrastructures were evaluated for future design storm. The research highlights the importance of available climate information and suggests a possible approach for climate change adaptation on stormwater design practice.

The second part of the study deals with finding a suitable approach to estimate the future streamflow and comparefuture floodplain prediction with existing FEMA maps. This will provide helpful information to the facility manager, design engineer, and stakeholders.

Research Question #1: How the changing precipitation pattern due to climate change affect the stormwater infrastructures?

Assumption #1: The climate is changing and the climate models represent future climate conditions especially precipitation pattern.

Hypothesis #1: Extreme storm events are increasing in Las Vegas City with the changing climate.

Research Question #2: How the changing streamflow as a result of changing climate impact the flood frequency and floodplain?

Assumption #2: The climate is changing and the CMIP5 streamflow projection best represents unimpaired streamflow.

Hypothesis #2: Extreme streamflow is increasing in the future in Carson River at Carson City.

1.4 Research Outline

The research follows a manuscript format starting with introduction. Two different manuscript are combined under this study. The second chapter titled "***Statistical evaluation of precipitation extremes and the climate change impact on urban stormwater infrastructures***" addresses the research question #1 while the third chapter titled "***understanding climate effect on future streamflow with statistical approach on variable infiltration capacity forced cmip5 hydrology projection at Carson river, Carson City***" addresses the research question #2. Chapter four summarizes the results and suggests recommendations for future work.

CHAPTER 2

STATISTICAL EVALUATION OF PRECIPITATION EXTREMES AND THE CLIMATE CHANGE IMPACT ON URBAN STORMWATER INFRASTRUCTURES

2.1 Introduction

Infrastructure is defined as built up structures that are needed for operation of modern society (Hanson, 1984). These include transportation systems, water and wastewater system, electrical network, communication network etc., which are critical for urban civilization. These infrastructures are most vulnerable to the fluctuations in weather. The recent flooding events in several regions have already shown the sign of the impact of extreme weather on urban stormwater infrastructure (Reilly and Piechota, 2005; WSDOT, 2008). To understand these impacts that could more intense in future, Southern Illinois University Carbondale and City of Las Vegas collaborated a partnering effort.

Intergovernmental Panel on Climate Change (IPCC) report highlights that more than fifty years of extreme weather records of heavy precipitations are directly related to human influence (Stocker, 2014). In this period, climate change has increased the frequency of the extreme storm events, and longer dry periods by changing the intensity-duration-frequency relationship (Christensen et al., 2007; Zhu et al., 2013). Coping with these extremities is the main global challenge (Richardson et al., 2011). One of the outcomes of these extremities, urban flooding is the costly and chronic natural hazard in the United States (O'Connor and Costa, 2003). In addition, urbanization has amplified the effect of flooding with the increased paved surface. To cope with these hazards in the urban area, engineering design and planning sectors are required to take appropriate measures.

Most of the current hydrological design of stormwater infrastructures are based on standard return period derived from historical data (Guo, 2006). Design based on historical data without considering climate change cannot fulfill the future requirements of stormwater infrastructure (Mailhot and Duchesne, 2009). Rainfall prediction based only on historical data can provide a stationary relation between time and precipitation (Bonnin et al., 2006). Stationary based conventional method of water management infrastructure design is compromising the future fluctuation of climate (Milly et al., 2008). Anthropogenic factors, the cause of the climate change, are a primary reason of recently observed non-stationarity in the climate (Brown, 2010). This necessitates robust approach of design with the capacity to incorporate climate change (Guo, 2006; Mailhot and Duchesne, 2009). The design method to deliver the long-term requirement of the infrastructure only be validated by foreseeing the future. Climate models are the tools to simulate the future climate conditions (Randall et al., 2007).

Various climate models are available for research and use representing future climatic condition (Cox et al., 2000; Zhang et al., 1995; Kiehl et al., 1998). Based on IPCC Fifth Assessment Report and Special Report on Emission Scenarios (SRES) the climate models were derived. Though, the model can represent future climate condition under the same emission, there is always two types of uncertainties underlined while predicting climate change using a model: one while selecting a proper model (Gutmann et al., 2016) and another deficiency of the model to simulate the climate (Houghton et al., 2001). Selecting all the available models for the study will cover the range of the climate change scenarios. Recent studies using different climate models have indicated increasing trend of the extreme storm events in future in the various part of the world (Lee et al., 2016; Daage et al., 2016; Sorribas et al., 2016; Pinto et al., 2016). A new design approach is necessary with the proper prediction of climate change storm depth

(Thakali et al., 2016). Mailhot and Duchesne (2009) proposed a design procedure for the urban drainage infrastructure considering the effect of climate change. Previous papers have suggested the accounting the effect of climate change on the current design practices (Mailhot et al., 2007; Mailhot and Duchesne, 2009; He et al., 2006; Wernstedt and Carlet, 2012; Salvadore et al., 2015; Praskievicz and Chang, 2009).

Zhu et al. (2012) projected regional influence on Intensity-Duration-Frequency curves and suggested its underlying distribution varies spatially. Grillakis et al. (2011) study based on hydrology found the increase in extreme precipitation events. Moglen and Vidal (2014) used North American Regional Climate Change Assessment Program (NARCCAP) climate model data to analyze the performance of detention basin under future climate condition using storm depth and intensity. Since most of the design of water infrastructures are designed based on maximum up to 24 hours of duration while most of the available climate model data are coarser in resolution, NARRCAP climate model data are widely used (Thakali et al., 2016; Ahmed and Tsanis, 2016). Forsee and Ahmad (2011) carried out the performance evaluation of the Pittman watershed of Las Vegas Valley. The study assessed the climate model performance using gridded reanalysis data. The study used the Generalized Extreme Value (GEV) distribution based on Bonnin et al. (2006). Further, Thakali (2017) has proposed a robust approach to consider the climate change effect on stormwater and suggested distribution method as L-moment for regional analysis. But the regional analysis in L-moment may not always show the best fit (Zhu et al., 2012). Ahmed and Tsanis (2016) used 6 different RCM-GCM paired models of NARCCAP for the prediction of the best fit-distribution. These previous studies suggested different approaches for adopting effect of climate change on design depth, but they were lacking either in the selection of best-fit distribution or utilization of all the NARCCAP models. The study aims to suggest the best fit distribution for the City of Las Vegas and suggest an approach for climate change adaptation on design storm depth.

The scope of this study was to obtain the best fit distribution for the City of Las Vegas, predict the effect of climate change on design storm depth given by all fourteen different RCM-GCM paired NARCCAP models. The data from each model for the study area were studied on twenty-seven different frequency distribution analysis to get the best fit distribution using two tests. Suggesting a robust design method for the prediction of the potential impact of climate change on the existing stormwater infrastructure is the main scope of this study. Total fourteen RCM-GCM data available to date from NARCCAP have been used to predict the A2 scenario originated future projected design storm depth. NARCCAP model data were grouped for 3hr, 6hr, 12hr and 24hr durations. These grouped data were best fitted using Pearson Chi-square and Kolmogorov Smirnov test among the twenty-seven-different distribution analysis. The best-fitted distribution method is adopted to calculate 6hr 100yr storm depth for historic and projected data. Delta change factor was applied to the design depth from NOAA Atlas II to project the future storm depth due to climate change. The existing hydrological model in HEC-HMS is used to get the hydrological parameter under the multiple scenarios of climate change. The model outputs were analyzed for determining the effect on existing stormwater infrastructures. The details of the study are discussed in the subsequent sections.

2.2 Study Area

Southwest region of the United States is not only the arid and hottest but has also been experiencing more extremes like drought, high temperature and extreme precipitation (Jardine et al., 2013). This extreme precipitation is climate change originated and has subsequent intense effects on urban stormwater infrastructures. Lying in the semi-arid desert of Nevada, City of Las

Vegas is vulnerable to climate change. Two urbanized watersheds i.e. Gowan and Central were considered as the study area. The total area of the Gowan and the Central watersheds are approximately 215 km^2 and 145 km^2 respectively. The Las Vegas Valley has 47.2°C and -13.3°C with upper and lower extreme temperature observed on 06/30/2013 and 01/13/1963 respectively. The average annual precipitation of the valley is 121mm with record maximum of 272mm in 1941. The study area extends from 244°33'22" E to 244°56'20" E and 36°06'54" N to 36°17'13" N. Figure 1 shows the two watersheds of Las Vegas Valley occupying the major portion of City of Las Vegas. Two largest detention basins one on each are indicated in Figure 1.

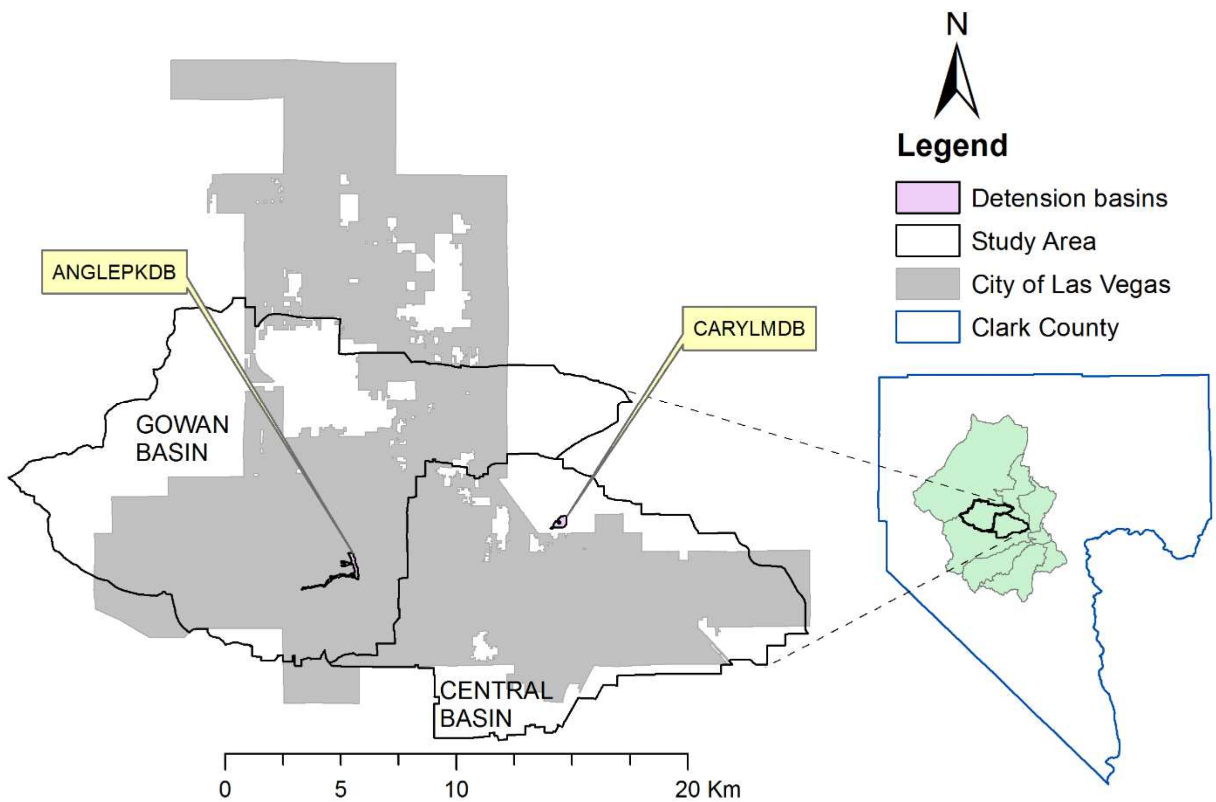


Figure 1: Study Area (Gowan and Central Watershed) of Las Vegas Valley.

In the recent years, the rate of development in Las Vegas has been slowed. However, it is anticipated that the population growth is likely to continue in the coming years (Tra, 2008). Growth in population and urbanization changes the hydrological parameter of the watersheds resulting more flooding due to increase in extreme precipitation events (White and Greer, 2006). Funding of the flood control activities lies within the jurisdiction of Clark County Regional Flood Control District (CCRFCD). The local entity, City of Las Vegas is responsible for design and implementation of flood control activity for these watersheds. Recent drought and intense extreme precipitation have shown the clear picture of the vulnerability of city of Las Vegas. Recent heavy rainfall in 1999 and 2003 had exceeded the 100-year peak rainfall and runoff respectively (Reilly and Piechota, 2005). Two of the meteorological stations of the valley reported the precipitation depth on July 8, 1999 more than 75mm within 60 to 90 minutes of the respective time period. The flood caused public damage of more than $20.5 million and life of two. Another thunderstorm of August 19, 2003, was centered over 127 km^2 in Gowan watershed (Reilly and Piechota, 2005). The intensity of 2 of the 15 rain gage networks within the Gowan watershed measured more than 50mm within 90 minutes of the time interval. The flash flood developed by these events created huge damage to public and private properties. This study analyzed the detention basins with the design storm depth for present and future conditions for hydrological parameter comparison with and without climate change conditions.

2.3 Data

SRES presents the basis of climate scenarios research for international climate change projects (Nakicenovic et al., 2000). SRES A2 emissions scenario for the 21st century have been applied to atmosphere-ocean general circulation models (AOGCMs), NARCCAP is one of such. RCMs are nested within multiple AOGCMs for the current period 1968-2000 and the future period of 2038-2070 (Mearns et al., 2009). NARCCAP dataset contains different models output for a conterminous domain covering the United States and most of Canada and northern part of Mexico (Mearns et al., 2009). Precipitation depths provided by NARCCAP model were used to project the storm depth for the study area. These different model datasets have 3hrs temporal distribution and available total up to 33 years. The data between the period of 1971 – 2000 (30 years) were considered for the study as the initial spin-up period, where the model is not stable and cannot produce usable data and were discarded. In addition, there were differences on time steps in a run as different calendars are used for different driving AOGCMs. GCM HadCM3 uses 30 days month and total 360 days year. For all other drivers, 365 days a year without leap year is run calendar. Table 1 represents the NARCCAP climate model and contributing RCM and GCM.

Table 1: Regional Climate Model (RCM) and Global Climate Model (GCM) paired combination models adopted for the study.

Model (RCM-GCM)	RCM	GCM
CRCM-CCSM	Canadian Regional Climate Model	Community Climate System Model
CRCM-CGCM3	Canadian Regional Climate Model	Third Generation Coupled Global Climate Model
ECP2-GFDL	Experimental Climate Prediction Center	Geophysical Fluid Dynamics Laboratory
ECP2-HadCM3	Experimental Climate Prediction Center	Hadley Centre Coupled Global Climate Model
HRM3-GFDL	Hadley Regional Model 3	Geophysical Fluid Dynamics Laboratory
HRM3-HadCM3	Hadley Regional Model 3	Hadley Centre Coupled Global Climate Model
MM5I-CCSM	MM5 - PSU/NCAR Mesoscale Model	Community Climate System Model
MM5I-HadCM3	MM5 - PSU/NCAR Mesoscale Model	Hadley Centre Coupled Global Climate Model
RegCM3-CGCM3	Regional Climate model version 3	Third Generation Coupled Global Climate Model
RegCM3-GFDL	Regional Climate model version 3	Geophysical Fluid Dynamics Laboratory
TMSL-CCSM	Time slice	Community Climate System Model
TMSL-GFDL	Time slice	Geophysical Fluid Dynamics Laboratory
WRFG-CCSM	Weather Research and Forecasting Model	Community Climate System Model
WRFG-CGCM3	Weather Research and Forecasting Model	Third Generation Coupled Global Climate Model

The data are stored in NetCDF file in two-dimensional arrays. Each spatially separated data grid point has its assigned x and y as location coordinates, where the data belong to. RCM determines the location of the grid points. The grid nearest to the centroid of the study were considered for the study. Data provided by National Centers for Environmental Prediction as North American Regional Reanalysis (NARR), whose spatial resolution is 32km were used as available historical observed data to assess the climate model data. The NARR data have a temporal span of 1979-2008 (30 years) and are also 3-hour resolution (Mesinger et al., 2006). Only the data from the time span of 1979-2000 (22 years) were considered to compare with NARCCAP data.

CCRFCD was formed in 1985 for the development of coordinated and comprehensive Master Plan to mitigate the flooding problems within the Clark County jurisdiction. This program is also responsible for regulating land use in the flood hazard areas and provides funding and coordination on flood control facility construction works. The Las Vegas valley has been divided into ten watersheds as depicted in Figure 1 (CCRFCD, 2018). CCRFCD modeled each watershed in the HEC-1 hydrological model for the design of the drainage facilities (CCRFCD, 1999). Later, these HEC-1 models were converted to HEC-HMS for its graphical user interface capability. HEC-HMS is a rainfall-runoff simulation model, developed by United States Army Corps of Engineers (USACE). Along with basin characteristics, it allows simulation of channel behavior and water control structures for a watershed. Rainfall depths for the area are provided in the NOAA Atlas 2(Miller et al., 1973). USACE (1988) suggested a subsequent modification in the NOAA precipitation depth. Prediction of runoff as discharge, stage, volume, and timing are the output from the model. Latest Master Plan Update (MPU), 2018 has no changes on the hydrologic parameters of the HEC-HMS model from MPU 2008, thus 2008 HEC-HMS models were implemented for the hydrological modeling of the study area (CCRFCD, 2018). The basin models consist of the subbasin, reach, junction, reservoir, and diversion.

CCRFCD has developed a guideline, Hydrologic Criteria and Drainage Design Manual (HCDDM) for proper design and modeling or stormwater infrastructure (CCRFCD, 1999). 6hr duration storm with 100 years of frequency provided by NOAA Atlas 2 is multiplied by an adjustment factor of 1.43 before applying to HEC-HMS model (CCRFCD, 1999). The adjusted storm depth varies from 70mm to 94mm based upon the distance from the measured meteorological station, McCarran International Airport. This storm depth represents precipitation for given frequency and duration for the isolated centroid of a subbasin, however, storm occurring over an area vary spatially even within the watershed. To account this variation depth-area reduction factor (DARF) has been applied to the precipitation depth depending upon the area of the subbasin. As storm intensity decrease with increase in area greater DARF ranging from 1 to 0.39 for drainage area 0 to 1295 km^2 applied (CCRFCD, 1999). HEC-HMS does not entertain multiple DARF in a single simulation, thus separate simulation should be carried out for different DARF values. There are 198 & 230 subbasins for analysis of Central and Gowan watersheds respectively in the existing HEC-HMS models. Based on the storm distribution over the area hydrological models with two storms centering were available for the Gowan watershed. The model with storm centering over the Gowan Watershed was used for the hydrological analysis of an existing detention basin named Angle Park detention basin (ANGLPKDB). Similarly, three storm centering conditions were available for the Central watershed. Based upon the location of the detention basin named Carey-Lake Mead detention basin (CARYLMDB), Northwestern, basin model with storm centering all over the watershed was considered.

2.4 Method

The methods adopted in this study comprised of two parts.; (1) Statistical fitting and delta change factor and (2) Hydrological Modeling. Statistically, fitted distribution methods were adopted for the calculation of delta change factor, which was used with the design storm depth on the hydrological model of the study area. The existing HEC-HMS models of the study were used for the interpretation of design parameters of drainage system in the future climate.

Table 2: Distribution used for frequency analysis and corresponding parameter (Kozanis et al., 2010).

SN	Distribution methods	Paramters	Symbol
1	Normal	mu, sigma	μ, σ
2	Normal(L-Moments)	mu, sigma	μ, σ
3	Log Normal	mu, sigma	μ_y, σ_y
4	Galton	mu, sigma, psi	μ, σ, ψ
5	Exponential	lambda, psi	λ, ψ
6	Exponential (L-Moments)	lambda, psi	λ, ψ
7	Gamma	kappa, lambda	κ, λ
8	Pearson III	kappa, lambda, psi	κ, λ, ψ
9	Log Pearson III	kappa, lambda, psi	μ_y, σ_y, c
10	EV1-Max (Gumbel)	lambda, psi	λ, ψ
11	EV2-Max	kappa, lambda	κ, λ
12	EV1-Min (Gumbel)	lambda, psi	λ, ψ
13	EV3-Min (Weibull)	kappa, lambda	κ, λ
14	GEV-Max	kappa, lambda, psi	κ, λ, ψ
15	GEV-Min	kappa, lambda, psi	κ, λ, ψ
16	Pareto	kappa, lambda, psi	κ, λ, ψ
17	GEV-Max (L-Moments)	kappa, lambda, psi	κ, λ, ψ
18	GEV-Min (L-Moments)	kappa, lambda, psi	κ, λ, ψ
19	EV1-Max (Gumbel, L-Moments)	lambda, psi	λ, ψ
20	EV2-Max (L-Moments)	kappa, lambda	κ, λ
21	EV1-Min (Gumbel, L-Moments)	lambda, psi	λ, ψ
22	EV3-Min (Weibull, L-Moments)	kappa, lambda	κ, λ
23	Pareto (L-Moments)	kappa, lambda, psi	κ, λ, ψ
24	GEV-Max (Kappa Specified)	kappa, lambda, psi	κ, λ, ψ
25	GEV-Min (Kappa Specified)	kappa, lambda, psi	κ, λ, ψ
26	GEV-Max (Kappa Specified, L-Moments)	kappa, lambda, psi	κ, λ, ψ
27	GEV-Min (Kappa Specified, L-Moments)	kappa, lambda, psi	κ, λ, ψ

2.5 Statistical fitting and delta change factor

In this study, altogether twenty-seven different statistical distributions were applied to each data sets and best fit among them was identified which will be applicable for the given watershed. The distribution analysis applied for the study are listed in Table 2. The precipitation data from the NARCCAP and NARR, considering the grid nearest to the centroid of the study area, were extracted. Each model has data with 3-hour temporal resolution. Using an algorithm, the data were converted into the 6hr, 12hr and 24hr temporal scale using the moving window of 6hr, 12hr, and 24hr respectively over each model data (Bedient and Wayne, 1988). A series of annual maxima was pulled from each set of climate model data for four temporal spacing 3hr, 6hr, 12hr, and 24hr. Each series of annual maxima was best fitted into the twenty-seven-different distribution. Pearson Chi-square (χ^2) and Kolmogorov-Smirnov test were used to measure the goodness of fit for the distributions. This process was implemented to the historic and projected data from fourteen NARRCAP model, and historic data of NARR for four different durations. In total, one hundred sixteen sets of data (60 historic and 56 projected) were used for the analysis. After the best fit, each test return reached a significant level as $\alpha_{reached}$ (Kozanis et al., 2010). The significant level for Pearson Chi-square and Kolmogorov Smirnov test is respectively given by,

$$\alpha_{reached} = 1 - \chi^2\ (m = k - r - 1, q) \qquad \text{(Eq. 1)}$$

$$\alpha_{reached} = 1 - \chi^2\ (m, q) \qquad \text{(Eq. 2)}$$

Where, m is the degree of freedom, k is the class interval, r is the number of parameter of the distribution and q is the computed Pearson parameter, which is given by

$$q = \frac{k}{n}\sum_{j=1}^{k} \mathrm{n}_j^2 - n \qquad \text{(Eq. 3)}$$

where, n is the size of the sample.

These analyses were carried out using the statistical Hydrognomon software developed by National Technical University of Athens (Kozanis et al., 2010). The method, which gives the best fit for the maximum number of datasets was selected for the further calculation design depth, 100yr 6hr, for historic and future NARCCAP models, and historic NARR climate scenarios. The design depth from historic NARR data was used to assess the NARCCAP historic data. Since NARR data are fine gridded (32km grid) than NARCCAP data (50km), NARCCAP data should give the higher design depth as climate model considers area-averaged grid values. Those NARCCAP models with higher than the NARR historic data were discarded from further analysis. The delta change factor for each model is the ratio of future 100yr 6hr storm depth to the present 100yr 6hr storm depth. Equation 4 and 5 provide the procedure for the calculation of delta change factor given by Zhu et al., (2012).

$$\Delta_{F-H}^{(g)}(T,D) = \frac{P_F^{(g)}(T,D)}{P_H^{(g)}(T,D)} \qquad \text{(Eq. 4)}$$

$$P_F^{(p)}(T,D) = \Delta_{F-H}^{(g)}(T,D) * P_H^{(p)}(T,D) \qquad \text{(Eq. 5)}$$

Where,

P with superscript g and p denotes the precipitation for grid and the point respectively. F and H represent future and historic respectively. All the parameters are for specific T (return period) and D (duration). Figure 2 represents the method as flowchart format.

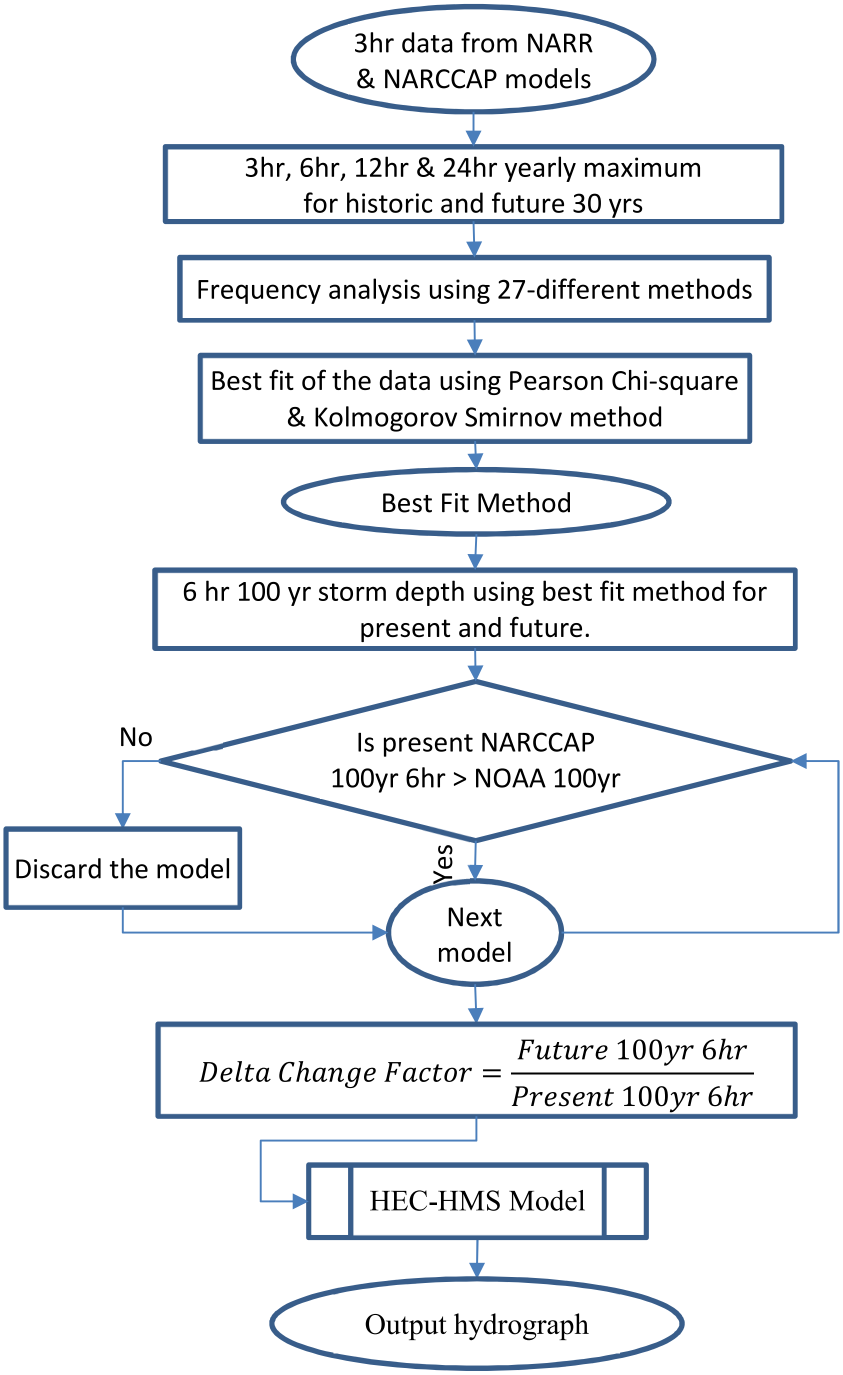


Figure 2: Flowchart of methodology to calculate delta change factor

2.6 Hydrological modeling

Each point rainfall from NOAA Atlas 14 was multiplied by adjustment factor depending upon the recurrence interval of the design storm before applying to hydrological model. The details of the calculations are provided in the HCDDM (CCRFCD, 2018). HEC-HMS has been widely used for the rainfall-runoff simulations because of its hydraulic capabilities from basin simulation, channel routing, storage units, diversion function and loss accounting. The modified NOAA rainfall depths as suggested by (USACE, 1988) were used. CCRFCD has prepared different hydrological models for each watershed on HEC-HMS. The models contain drainage network and detention basins considered for the future development (CCRFCD, 1999). The model contains 198, 230 sub-basins for Central and Gowan watersheds.

There are ten detention basins in Gowan watershed and four detention basins in the Central watershed. ANGLPKDB was considered for the performance analysis from Gowan watershed, while, CARYLMDB was considered for the performance analysis. These detention basins are the largest one in their respective watershed. The contributing drainage area for the ANGLPKDB and CARYLMDB area is 56.95 and 30.51 sq km respectively. Among the three models prepared for the Central watershed, NW was selected to simulate the detention CARYLMDB. Similarly, ALLGOW model among two available models was selected for the simulation of the ANGLPKDB. The control specification of the simulation was set starting from 01:05, 01 January to 02:00, 09 January. The simulation time interval was set for 5 minutes.

2.7 Results

The annual maxima from the fourteen different NARCCAP RCM-GCM models of present and future data were fitted to Pearson Chi-square and Kolmogorov Smirnov test for the twenty-seven-different statistical distribution. The best-fitted distribution method for each model for historical and projected data are listed in Table 3. For example, the present (historic) of CRCM-CCSM model has been best fitted with GEV-max (kappa specified) using Pearson Chi-square test, while for future (projected) data for the same model is fitted with EV3-Min

(Weibull). These two were marked by symbol ○ and □ on the table respectively. Similarly, ▪ and ● represents the best-fitted distribution method from Kolmogorov Smirnov test for historic and projected datasets respectively. Altogether 116 different datasets derived from observed NARR data with 4 durations (3hr, 6hr, 12hr and 24hr) and 14 NARCCAP models under 4 different durations and 2 categories (historic and projected) were analyzed for the best fit. The results of which are presented in Table 3. Figure 3 shows the selection results for the twenty-seven distribution methods.

Table 3: Best fitted distribution for different NARCCAP model data.

NARCCAP Model	Distributions	Normal	Normal(L-Moments)	LogNormal	Galton	Exponential	Exponential (L-Moments)	Gamma	Pearson III	Log Pearson III	EV1-Max (Gumbel)	EV2-Max	EV1-Min (Gumbel)	EV3-Min (Weibull)	GEV-Max	GEV-Min	Pareto	GEV-Max (L-Moments)	GEV-Min (L-Moments)	EV1-Max (Gumbel, L-Moments)	EV2-Max (L-Moments)	EV1-Min (Gumbel, L-Moments)	EV3-Min (Weibull, L-Moments)	Pareto (L-Moments)	GEV-Max (K Specified)	GEV-Min (K Specified)	GEV-Max (K Spec., L-Moments)	GEV-Min (K Spec., L-Moments)
NARR	3hr																▪											○
	6hr						○													▪								
	12hr																	▪									○	
	24hr																	▪									○	
CRCM-CCSM	3hr							□											●	○▪								
	6hr		○	□				●															▪					
	12hr																		●			□	○	▪				
	24hr																	●	▪								○□	
CRCM-CGCM3	3hr	□						▪			○								●									
	6hr							□●											▪	○								
	12hr					□		○				●					▪											
	24hr							▪											●								○□	
ECP2-GFDL	3hr							□						○					●					▪				
	6hr							○□		▪								●										
	12hr																	●		○				▪	□			
	24hr										□						▪		●	○								
ECP2-HaDCM3	3hr	○	□▪																								●	
	6hr						□	○										▪		●								
	12hr	▪											○					●		□								
	24hr										□				●			▪		○								

NARCCAP Model	Distributions	Normal	Normal(L-Moments)	LogNormal	Galton	Exponential	Exponential (L-Moments)	Gamma	Pearson III	Log Pearson III	EV1-Max (Gumbel)	EV2-Max	EV1-Min (Gumbel)	EV3-Min (Weibull)	GEV-Max	GEV-Min	Pareto	GEV-Max (L-Moments)	GEV-Min (L-Moments)	EV1-Max (Gumbel, L-Moments)	EV2-Max (L-Moments)	EV1-Min (Gumbel, L-Moments)	EV3-Min (Weibull, L-Moments)	Pareto (L-Moments)	GEV-Max (K Specified)	GEV-Min (K Specified)	GEV-Max (K Spec., L-Moments)	GEV-Min (K Spec., L-Moments)
HRM3-GFDL	3hr						○												●					■			□	
	6hr	○				□											■		●									
	12hr			□			○												●					■				
	24hr					□	○												●					■				
HRM3-HADCM3	3hr							○		●							■										□	
	6hr		○												●								■		□			
	12hr		○	□	●													■										
	24hr			○																■			□	●				
MM5I-CCSM	3hr							■			○								●	□								
	6hr			□ ●											■												○	
	12hr	○			■ ●																				□			
	24hr											□						●	■						○			
MM5I-HADCM3	3hr							○											■	□					●			
	6hr						○					□ ●															■	
	12hr						○					●							■		□							
	24hr					□ ●												■							○			
REGCM3-CGCM3	3hr																	■ ●		□	○							
	6hr							●			□				■										○			
	12hr										○								■						●		□	
	24hr											□ ●		○					■									
REGCM3-GFDL	3hr									■ ●											□				○			
	6hr				●	■																			○		□	
	12hr			○						■ ●															□			

NARCCAP Model	Distributions	Normal	Normal(L-Moments)	LogNormal	Galton	Exponential	Exponential (L-Moments)	Gamma	Pearson III	Log Pearson III	EV1-Max (Gumbel)	EV2-Max	EV1-Min (Gumbel)	EV3-Min (Weibull)	GEV-Max	GEV-Min	Pareto	GEV-Max (L-Moments)	GEV-Min (L-Moments)	EV1-Max (Gumbel, L-Moments)	EV2-Max (L-Moments)	EV1-Min (Gumbel, L-Moments)	EV3-Min (Weibull, L-Moments)	Pareto (L-Moments)	GEV-Max (K Specified)	GEV-Min (K Specified)	GEV-Max (K Spec., L-Moments)	GEV-Min (K Spec., L-Moments)
	24hr							○											▪		□				●			
Timeslice-CCSM	3hr															▪			●	○□								
	6hr						□						○				●							▪				
	12hr													▪			●						□			○		
	24hr				▪												●						○□					
Timeslice-GFDL	3hr	□			●														▪	○								
	6hr									▪								●			○	□						
	12hr		□				○											●						▪				
	24hr						○													□●				▪				
WRFG-CCSM	3hr					□									▪					○				●				
	6hr																	●			□						○▪	
	12hr										●	○								▪					□			
	24hr							○	▪					□					●									
WRFG-CGCM3	3hr			▪														●					□		○			
	6hr				●			○							▪					□								
	12hr																			□			●		○		▪	
	24hr																		●						○▪			□

Note :- The symbol ○ and □ are used for Pearson Chi-square test fit for present and future climate data respectively while ▪ and ● are used for Kolmogorov Smirnov test fit for present and future climate data respectively.

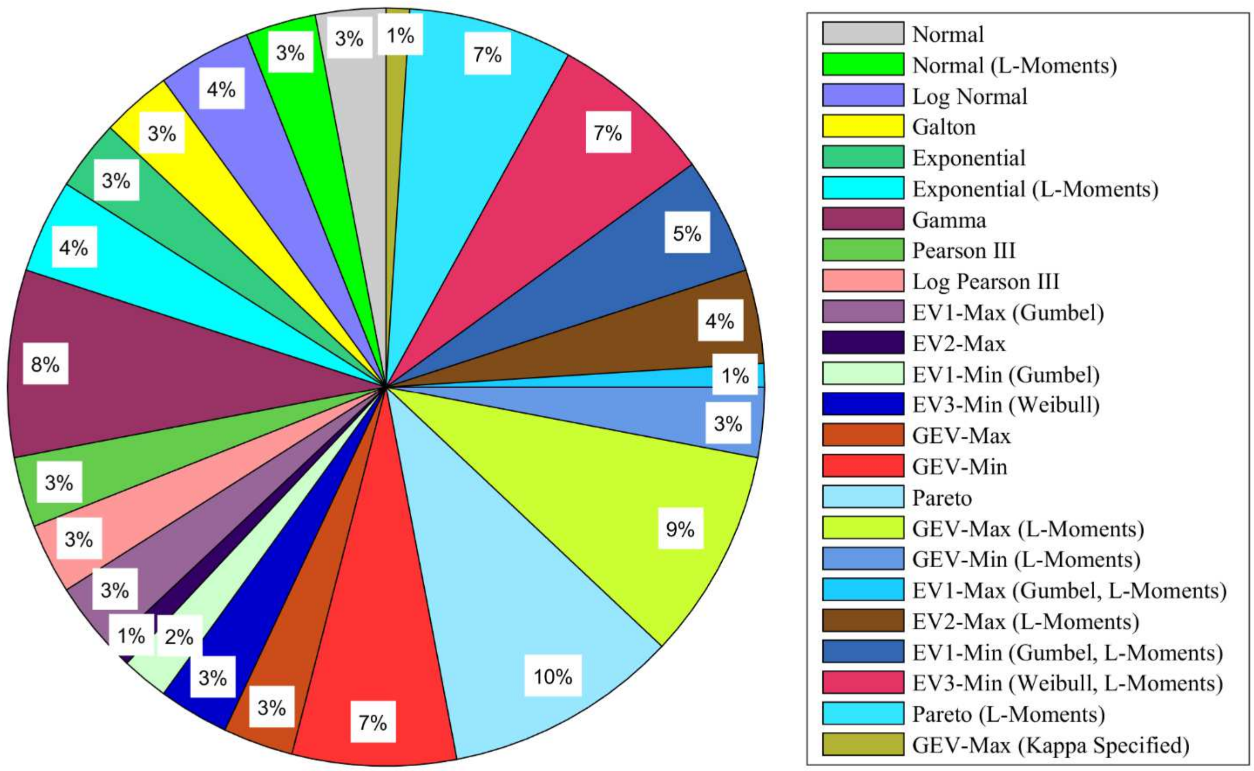


Figure 3: Selection of best fitted distribution

The statistical analysis result as depicted in Table 3 and Figure 3, GEV-Min (L-moment) was found to be the best-fitted distribution by resulting highest goodness values in Pearson Chi-square and Kolmogorov Smirnov test in 23 occasions. GEV-Min (L-moment) was best fitted for 10% of total 232 maximum possible number of best fit from 15 models, 4 durations, 2 categories and 2 test. Similarly, second most selected was EV1-Max (Gumbel, L-moment), which was considered as the most frequently used distribution method for extreme precipitation evaluation with a total selection of 22 times i.e. 9% of the total. The third most selected was Gamma with a total selection of 18 times ie. 8% of the total. This best fit analysis provides the best distribution for the datasets which eliminated the underlying uncertainty on the selection of the appropriate distribution method.

Design storm depths using the best-fitted distribution method were calculated for the NARCCAP present and future datasets along with the NARR historic depth, these were tabulated in Table 4. Figure 4 shows the scatter plot between historic and future NARCCAP design depths. The solid vertical line with value 38.19mm for historic depth represents the NARR 100yr 6hr storm depth. The solid line at 45° represents the delta change factor one i.e. without climate change in future. Another inclined line represents the delta change factor value two representing twice the increase in design storm depth in future. The range of the delta change factors was 0.88 to 2.64 with the minimum for ECP2-GFDL and maximum for HRM3-HadCM3. Among 14 models, 11 models have delta change factor greater than 1. Must of the delta change factor are greater than 1 which represents higher possibility of increasing future storm depth. Thus, null hypothesis of hypothesis #1 is true.

Table 4: Delta change factor for different NARCCAP models.

Climate Model	Historic 100yr 6hr depth (mm)	Projected 100yr 6hr depth (mm)	Delta Change Factor
NARR	38.19	-	-
CRCM-CCSM	20.42	22.84	1.12
CRCM-CGCM3	17.17	22.37	1.30
ECP2-GFDL	85.48	75.32	0.88
ECP2-HadCM3	34.57	57.92	1.68
HRM3-GFDL	104.98	144.69	1.38
HRM3-HadCM3	27.12	71.61	2.64
MM5I-CCSM	40.75	53.14	1.30
MM5I-HadCM3	36.55	56.95	1.56
REGCM3-CGCM3	43.10	40.56	0.94
REGCM3-GFDL	66.44	122.51	1.84
Timeslice-CCSM	27.57	26.60	0.96
Timeslice-GFDL	30.99	39.23	1.27
WRFG-CCSM	55.93	63.52	1.14
WRFG-CGCM3	30.17	35.65	1.18

NARR historic storm depth was used to assess the climate model data. As the NARR data is finer than the NARCCAP climate model, the climate model data with higher historic design storm depth were discarded from further analysis. Thus, among the 14 climate models, 6 (ECP2 GFDL, HRM3-GFDL, MM5I-CCSM, REGCM3-CGCM3, REGCM3-GFDL and WRFG-CCSM) were discarded. Among the remaining model Timeslice-CCSM with delta change factor 0.96, which is less than 1, representing the condition where there will be less design storm depth in future, such condition is considered as negative climate change condition. The recently observed climatic phenomenon over the City of Las Vegas invalidates the decrease in the design storm, thus was eliminated. Only the remaining 7 models with minimum and maximum delta change factor 1.12 and 2.64 were considered for the further hydrological analyses and were represented by Climate Change Condition 1.12 (CCC1.12) and Climate Change Condition 2.64 (CCC2.64) respectively.

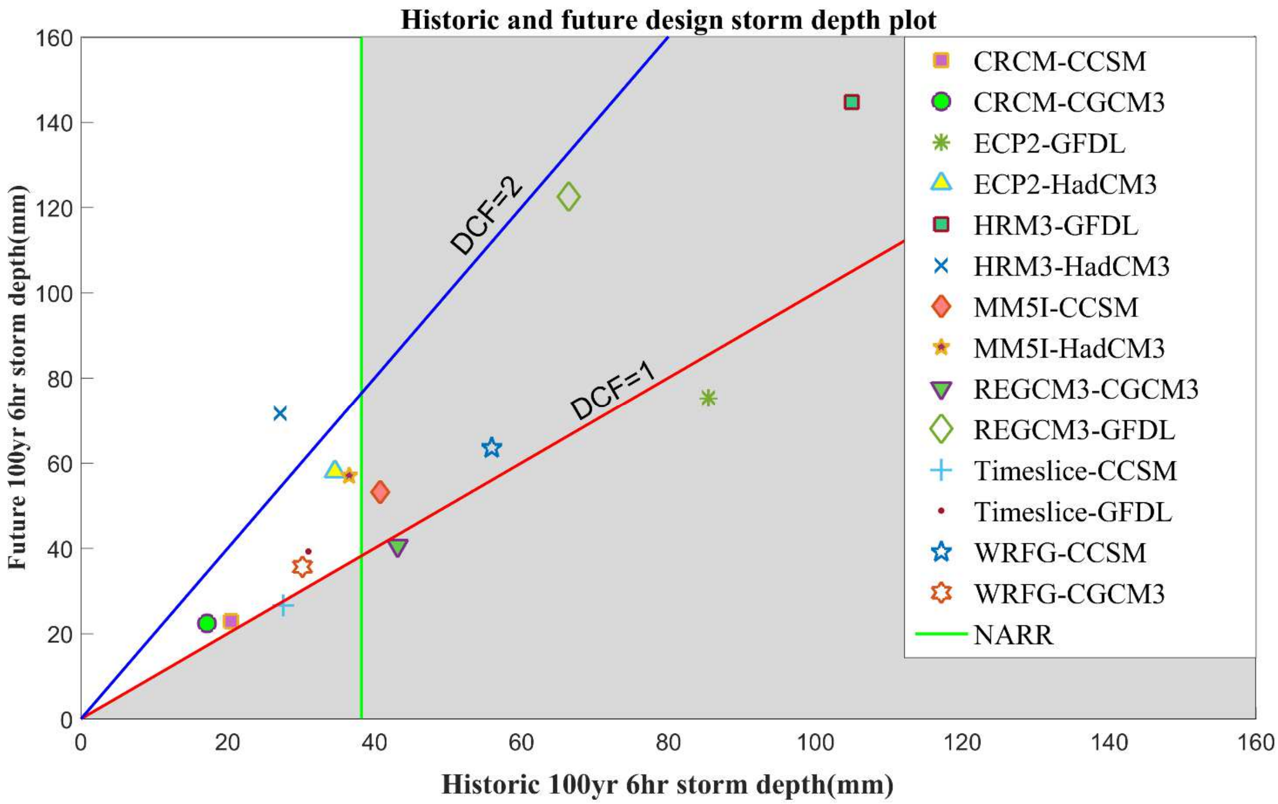


Figure 4: Historic 100yr 6hr versus future 100yr 6hr storm depth from different NARCCAP model and vertical line represents the NARR depth for 100yr 6hr.

HEC-HMS hydrological model with two different simulations, for different watersheds, were used to compare the result of inflow, outflow, elevation, and storage. For the detention basins ANGLPKDB and CARYLMDB, DARFs of 0.765 and 0.85 respectively for the baseline scenario. The assigned DARFs were based upon their drainage area, which are 56.95 and 30.51 sq-km respectively for ANGLPKDB and CARYLMDB. The change in elevations was calculated in such a way that the elevation for zero inflow and outflow is taken as a datum. HEC-HMS model simulations for baseline, CCC1.12 and CCC2.64 were carried out to represent the range of future 6hr 100yr storm depth conditions.

Hydrological modeling of the detention basins was represented by the elevation storage and storage discharge function, while input for diversion component was assigned as inflow-diversion function. These parameters were defined under the paired data. During the simulation, the input values were exceeded the specified on the model. Those values were linearly interpolated to cope the higher values under climate change conditions. The model output of inflow, discharge, change in elevation and storage for ANGLPKDB and CARYLMDB are presented in Figure 5. The peak of each output is presented in Table 5.

Table 5: Peak HEC-HMS outputs for the detention basins (ANGLPKDB and CARYLMDB)

Element	Scenario	Peak Inflow (m^3/s)	Peak Storage (m^3)	Maximum Change in storage elevation (m)	Peak Outflow (m^3/s)
ANGLPKDB	Design	260.49	1726872	13.01	11.51
	Baseline	259.57	1854044	13.05	11.51
	CCC1.12	303.63	2210273	15.18	11.91
	CCC2.64	1004.90	7253849	45.51	17.55
CARYLMDB	Design	146.79	748722	7.97	10.63
	Baseline	145.58	732070	7.99	10.67
	CCC1.12	174.19	881321	8.81	11.45
	CCC2.64	551.16	3137110	21.49	23.22

Figure 5a-d are the graphical plots for output for ANGLEPKDB while the Figure 5e-h are the plots for output for CARYLMDB. For ANGLEPKDB, the peak inflows were observed at 5:00, 5:00 and 5:05 for baseline, CCC1.12, and CCC2.64 respectively. The peak storages were observed at 8:50, 7:15 and 5:10 for baseline, CCC1.12, and CCC2.64 respectively. The maximum changes in storage elevation were observed at 8:40, 7:15 and 5:10 for baseline, CCC1.12, and CCC2.64 respectively. Maximum outflows were observed at 8:50, 7:15 and 5:10 respectively. For CARYLMDB, the peak inflows were observed at 5:05, 5:05 and 5:05 for baseline, CCC1.12, and CCC2.64 respectively. The peak storages were observed at 7:25, 6:55 and 7:00 for baseline, CCC1.12, and CCC2.64. The maximum changes in storage elevation were observed at 7:10, 6:55 and 7:00 for baseline, CCC1.12 and CCC2.64 respectively. Maximum outflows were observed at 7:20, 6:55 and 7:00 respectively.

The change in 100yr 6hr storm depth ranging from 12% to 164% increase the peak inflow will increase 17% to 230% and 19% to 216% for ANGLPKDB and CARYLMDB respectively. Similarly, the peak storage will increase 19% to 228% and 20% to 256% for ANGLPKDB and CARYLMDB respectively for the range of climate change. The outflow is governed by the outlet structure, which was designed based on the present scenario. Thus, the outflow has less increment compared with inflow i.e. from 3% to 47% compared with 7% to 103% for ANGLPKDB and CARYLMDB respectively.

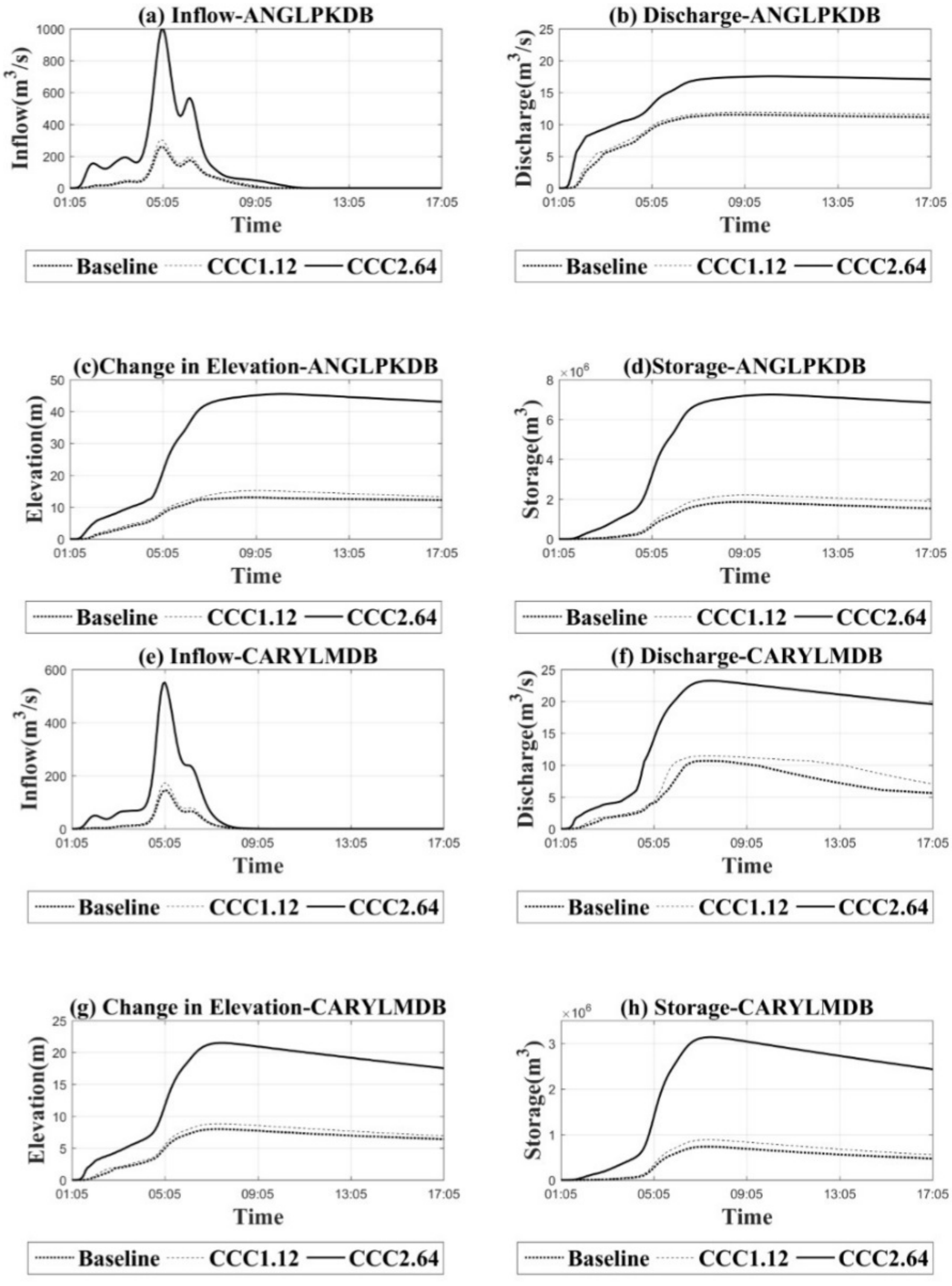


Figure 5: HEC-HMS outputs for detention basins (ANGLPKDB and CARYLMDB) on time series format for (a) inflow-ANGLPKDB, (b) Discharge-ANGLPKDB, (c) Elevation difference-ANGLPKDB, (d) storage-ANGLPKDB, (e) inflow-CARYLMDB, (f) Discharge-CARYLMDB, (g) Elevation difference-CARYLMDB and (h) storage-CARYLMDB.

2.8 Discussion

The NARCCAP models are derived from RCM-GCM combinations with the same spatial resolution of 50-km, however, the best fit distribution varied with each other. In this study, the best fit distribution corresponding to the climate model data of the study area was selected using Pearson Chi-square and Kolmogorov Smirnov method. NARR observed data and fourteen NARCCAP both historic and future data for four different durations were best fitted for twenty-seven distribution methods. The GEV Min (L-moment) resulted as the best fitted from Pearson Chi-square and Kolmogorov Smirnov test, which was applied to the design storm depth calculation. This study identified the best distribution underlying the study area which minimizes the risk of selecting inappropriate distribution method. A comprehensive statistical analysis by Bonnin et al. (2006) found the GEV distribution as the best distribution for the Las Vegas Valley. Thakali et al. (2016) carried out the regional frequency analysis under the Flamingo-Tropicana watershed to minimize the best fit error using the L-moment and GEV. The regional frequency analysis increases the size of the data reducing best-fit error, however, it doesn't completely eliminate the error of selecting single best distribution method. Especially, in the climate model data selecting a distribution method may not justify the statistical analysis since the nature of climate data differs from the actual observed data and also among the climate models.

Different statistical distributions can produce different design storm depth from the same sets of available data. Design storm depth varies spatially along with the distribution method. Hosking and Wallis (2005) suggested L-moment method for the frequency analysis of hydrological parameter. Also, natural variability of the climate affects its ability to project the emission forced component in extreme precipitation (Kendon et al., 2008). Thakali et al. (2016)

carried out regional frequency analysis using L-moment. Though, Ahmed and Tsanis (2016) carried out best fit analysis but unable to use all the available ranges of NARCCAP models data. The study also unable to assess the climate model data. Previous studies were either not able to find the best-fit distribution method or unable to use all the range of the model data from NARCCAP. The study identified the best distribution method underlying to the City of Las Vegas. Identification of underlying statistical distribution method helps for proper prediction of future storm depth. This research will provide an approach to finding the best-fitted distribution underlying the City of Las Vegas. Using all the available data of NARCCAP provides the range of the effect of climate change on future storm depth.

Though different climate model data are available for research, NARCCAP provides fine temporal resolution. It eliminated the difficult downscaling process to get to the small duration of rainfall. Using all the available climate model has provided the range of the effect of climate change. For the assessment of the NARCCAP climate model data, NARR data were available at the same temporal resolution. Among the 14 models, only the 8 climate models were selected for the analysis. The hatched portion of Figure 4 represents the eliminated climate model data. The delta change factor which is the ratio of future to present design storm depth ranges from 1.12 to 2.64. HRM3-HadCM3 model data gives the maximum climate change effect on stormwater depth in future.

CCRFCD developed the hydrological model in HEC-1 which was later converted to HEC-HMS. This study carried out the HEC-HMS simulation with design storm depth as the baseline scenario. The design values and the baseline outputs were very close and the difference is apparent since the design values were calculated from the HEC-1 simulation. The graphical user interface of the HEC-HMS has more advantages over HEC-1. With the selection of hydrological model and storm centering conditions, the HEC-HMS models were able to perform the necessary hydrological simulation. HEC-HMS 3.5, a more stable version of HEC-HMS was used for the simulation. The simulation result showed that the functioning of the stormwater facility would be greatly affected even with the minimum change in climate (i.e. for CCC1.12). The effect of maximum climate change conditions (i.e. CCC2.64) will be huge to the existing stormwater infrastructures. Proper measures shall be taken to mitigate the effect of such extreme events. Enlarging the capacity of the infrastructure to utilizing green technology to decrease the surface runoff are some of the measures that could be applied to the existing facilities.

The risk of climate change is one of the big challenges of the world. This anthropogenic climate change risk increasing in coming days as there is no sign of major curbing on the production of greenhouse gasses. As, the majority of the world population living in an urban area, the risk associated with life and economy is more intense there (Kendon et al., 2008). Main urban risks of climate change are extreme weather, pollution, scarcity of natural resources (IPCC, 2014). Among them, flooding is a worldwide major risk for urban areas. A recent trend of climate change has shown more frequent intense precipitation. Thus, there is a necessity to incorporate this change in intensity and duration of rainfall while designing stormwater infrastructures. City of Las Vegas could learn the success from restoration and management of Las Vegas Wash (Gautam et al. 2014). This study aims to develop a proper way to incorporate the climate changed storm depth and evaluation of infrastructure facility.

2.9 Conclusion

In this study, hydrological parameters of two detention basins of Gowan and Central watershed were examined using under the climate change condition to compare the potential effect on urban stormwater infrastructures. Fourteen RCM-GCM paired NARCCAP model datasets were considered for the historic and future time span. Two statistical tests were carried out to test the goodness of fit among twenty-seven different distributions. Best fitted distribution from the NARCCAP datasets for the study area was identified. 100yr 6hr design storm depth for the historical datasets of NARCCAP and observed datasets of NARR were calculated using the best-fitted distribution. Performance of the NARCCAP 100yr 6hr is assessed using NARR 100yr 6hr. Delta change factor with extremes was considered as the quantified change in storm depth due to climate change for the study area. From the study, a significant change in storm depth due to projected climate change was observed. HEC-HMS models were used for hydrological modeling to assess the effect of climate change on existing drainage facilities. The following conclusions were drawn from this study.

i. The statistical analysis resulted in minimum delta change factor of 1.12 and maximum delta change factor of 2.64.

ii. HRM3-HadCM3 NRCCAP climate model resulted in the highest design depth in the future climate.

iii. The hydrological simulation showed the substantial increase in inflow, storage, change in elevation and outflow from the detention basins.

iv. Though the existing infrastructures are functioning their purpose, more stress will be there in coming years.

v. Since the climate change has been already affecting the stormwater facility of the study area, adaptation plan and facility upgradation is necessary.

vi. With the implementation of robust method to incorporate climate change, either capacity of stormwater facility increment or reduction of surface runoff using green technology should be applied.

Effect of climate change on hydrology is not limited to change in average precipitation depth but also the pattern, frequency, and extremities of a storm. However, non-stationarity of climate is not generally adopted in current stormwater facility design practice. Now, predicting future storm depth stationarity of climate change is invalidated. This study explored a robust method to account the potential impact of climate change on design storm and its effect on the performance of detention pond. Recent cases of frequent flooding of the study area enthralled to quantify the effect of climate change on precipitation. As there are always uncertainties while using only one climate model, this study applied all the available NARCCAP model to pick the best fit distribution which outstands the study from others. The method demonstrated in this study provides an approach to adopt the climate change on urban stormwater infrastructure design depth. This study helps infrastructure designer, manager, policy makers and stakeholders to incorporate the effect of climate change on stormwater facilities.

CHAPTER 3

UNDERSTANDING CLIMATE EFFECT ON FUTURE STREAMFLOW WITH STATISTICAL APPROACH ON VARIABLE INFILTRATION CAPACITY FORCED CMIP5 HYDROLOGY PROJECTION AT CARSON RIVER, CARSON CITY

3.1 Introduction

Global surface temperature record shows the global mean surface temperature has been rising. Record of past three decades of global mean surface temperature is hotter than any previous decade (IPCC, 2013). This global warming has led to more evaporation from water surface and vegetation which in turns increase the average global precipitation. However, the wind and ocean current pattern may change local precipitation trend which eventually fluctuates the streamflow. Different part of the world has already shown the sign of adverse effect on water availability due to climate change. The peak streamflow is projected to increase in some part of the globe (Hirabayashi et al., 2008; Nohara et al., 2006) at the same time low flow is also expected to increase with more number of drought days across the globe (Dankers and Feyen, 2009; Davie et al., 2013; Hirabayashi et al., 2013). Thus, the extreme weather phenomena are more frequent nowadays than previous and with recent trend, it is expected to increase in future.

Flooding is one of the major natural hazard in the US along with tropical cyclone and drought/heatwave (NCEI 2018). Reduction in emission could result in huge monetary benefit in long-term as difference in future flood at the end of the 21st century from higher emission pathway to lower emissions pathway will be in billions of dollar per year (Wobus et al., 2017). Despite this benefits, climate change has intensified the adversity in recent years (Papalexiou et al., 2018; Van Aalst, 2006). Flood prevention practice along with a proper understanding of flooding event can mitigate the risk of such hazard and floodplain mapping is one of the widely used technique to quantify the severity of the flooding.

Coupled Model Intercomparison Project (CMIP), which is a standard experimental framework for studying the output of coupled Atmosphere-Ocean Coupled General Circulation Model (AOGCM) was first started on 1995. World Climate Research Programme (WCRP) developed global climate projections through CMIP5, which represents the climate projections from new generation global climate models and represents the recent climate science advancements (Taylor et al., 2011). These CMIP5 projections were based on updated global greenhouse gas emissions scenarios. CMIP5 model, which is large in scale contributing all major climate modeling groups, includes simulation of long-term twentieth-century climate and projections for the generation of the twenty-first century (Taylor et al., 2012). Conventional AOGCM and Earth system models were joined by more recently developed earth system models under an experiment design, where they were compared to observations on an equal basis. Recent decades were initialized based on the observations and its use for future prediction gives the enhanced capability to the CMIP5 models (Taylor et al., 2012).

CMIP5 hydrology projection was released in 2015 and was based on total 234 CMIP5 climate projections. These projections were downscaled into climate projections localized to the contiguous U.S. using the Bias Corrected Statistically Downscaled (BCSD) technique (Wood et al., 2004). The results of the BCSD projection from phase 3 and phase 5 were known as BCSD3 and BCSD5 respectively. The model results from BCSD5 hydrology projections were based common gridded daily historical meteorology forced simulation (Maurer et al., 2002). . Projected Constructed Analog (CA) method is applied to spatially downscale a GCM day by matching the same grid coarsened set of observed days (Hidalgo et al., 2008). Changes in precipitation at spatial and temporal scales are to understand the climate impact on peak streamflow. The primary tools for such projections are GCMs, which needs to translate to the similar locally relevant precipitation data before use for assessment. This includes but not limited to the selection of appropriate GCMs for a given study area (Mote and Salathe, 2010), removing biases, resolution scale difference between GCM and local applications (Fowler et al., 2007). Gangopadhyay et al. (2011) translated the downscaled projection to hydrologic projections over the Western U.S. portion of domain making the projections consistent and eased the hydrologic impact analysis of climate change. Due to the limitation on the scope of hydrologic modeling practicalities, only 97 BCSD5 climate projection from 31 CMIP5 climate models with four emission scenarios are available.

Over a long period of time runoff is equal to the difference in precipitation to evapotranspiration. Hence, it is equal to the horizontal water flux converged at a particular location (Milly et al., 2005). For the simulation of the future hydrology Variable Infiltration Capacity (VIC) (Liang et al., 1994; Liang et al., 1996; Nijssen et al., 1997) hydrologic model was used. VIC model is a semi-distributed hydrologic model, which shares basic features with large-scale land surface models that are coupled to GCMs (Liang, 2002). VIC forcing generation process and modeling code were checked for proper application and whether the hydrology projections were developed as intended. Before production, the VIC forcing modeling code and generating code were compiled and run on production platform to validate the result. During production, it is ensured that the forcing generation and VIC simulation process were error free. Correct size and number of output files were produced. After production, BCSD climate monthly data were compared with monthly derived by aggregating daily forcing data to check any error occurred during the VIC forcing generation process. There were exact matching in most of the cases (Brekke et al., 2014). BCSD5 features a larger range compared to BCSD3, as CMIP5 use different scenarios describing the larger range of greenhouse gas amount in the atmosphere in the future than CMIP3 (Brekke et al., 2013). The main difference between BCSD3 and BCSD5 climate projections are in the driving emission scenarios and climate model change, making projections of temperature and precipitation somewhat different. However, other differences were from model updates on VIC to generate projections with BCSD5 providing a complete representation of the range of possible future climate and hydrology.

An occurrence of extreme events was estimated by fitting probability distribution to the record of historical annual flood series. Using only the historic flood event may not truly reflect the probable future scenario more likely due to climate change. Since, the stationary approach, a conventional way of predicting extreme events in future using historical data only, is not best way due to non-stationarity of the climate. To overcome the shortcomings in the design based on the stationarity of climate, climate model and projections are useful. Various climate models based on IPCC fifth assessment report and Special Report on Emission Scenarios (SRES) representing the future climate are available for research and use. Besides the available data, selection of distribution method significantly impacts the design value. In most of the cases, Generalized Extreme Value (GEV) distribution along with Gumbel and log-Pearson type III distribution are selected for the use by different governmental agencies, but it’s not always the GEV which fits the best for annual peak flood. Thus, it is necessary to examine the given sets of annual flood series and choose the alternative distributions where they produce the better estimates. An empirical goodness of fit is one of the criteria for selection of appropriate distributions. At the same time, the assumptions theoretically associated with the distribution should be considered (Canfield et al., 1980). The selection of best-fitted distribution of the streamflow for Carson River is one of the objectives of the study.

Flood risk management is widely accepted best approach for flood defense. Floodplain mapping is the part of risk analysis and first steps towards flood risk management. Climate change, which has the capacity to alter the magnitude and frequency is changing the design flood. A better way of understanding the changing pattern of the design flood is necessary to flood risk management in the future. VIC forced CMIP5 streamflow was used to find the underlying probability distribution of an area among 27 different statistical distribution. Selected best-fitted distribution was used to find the future streamflow. Finally, the comparison among the existing design parameter and change in hydraulic parameters of the river was identified. A proper approach to floodplain mapping for the future design flood is discussed here.

3.2 Study Area

Southwest of arid land of United States is not only experiencing extreme heat but also vulnerable to extreme flood due to climate change (Jardine et al., 2013). Carson City, NV has the historical record of flood since 1852 and is experiencing some flooding due to extreme storm events. This agricultural land in the desert of Nevada has experienced an extreme flood in the recent year. Carson Valley, which lies 4,700-5,000 feet above mean sea level is rain shadow of the Sierra Nevada. The highest point of catchment lies on the Sierra Nevada and is 11462 feet above mean sea level. The climate of the area ranges from semiarid over the valley plain to humid or super humid over the peaks of the catchment. The catchment receives precipitation mostly as rain in lower part while as snow at highest altitudes. Runoff reaches its yearly peak mainly in May. In this study, the part downstream end of the Carson City at the bank of Carson

River is examined to the future flood. Figure 6 represents the Carson city county of Nevada and Carson River flowing through it.

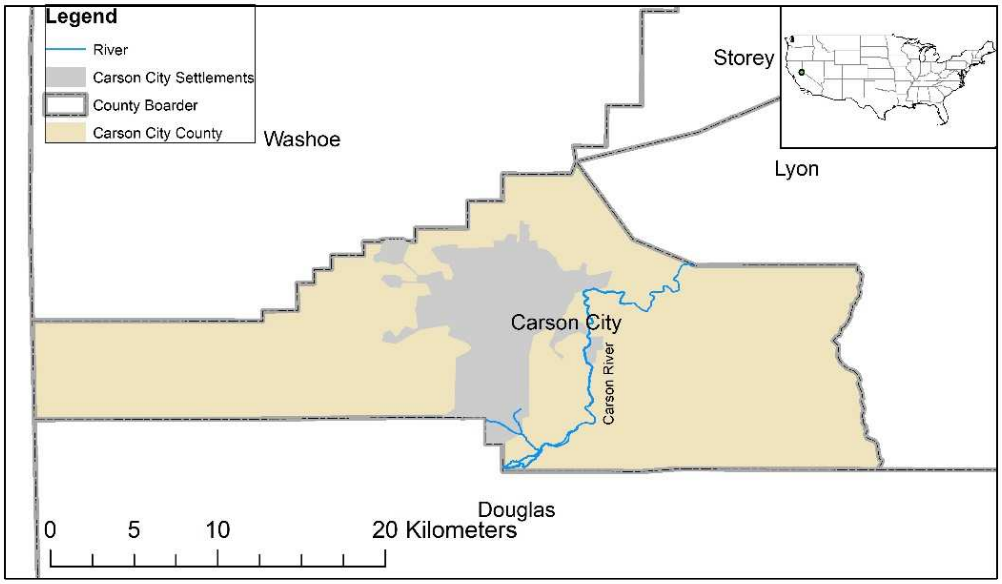


Figure 6: Carson River flowing through Carson City of Nevada.

3.3 Data

The latest daily average runoff from 31 AOGCMs participating in the CMIP5 are used to analyze the change in the extreme runoff for Carson River. These CMIP5-AOGCMs had produced Bias Corrected Spatially Downscaled (BCSD) streamflow for different streams of United States from 1950 to 2099. The data produced by these AOGCMs were routed over a historic period of 1950 to 1999. Thus, in this study, the same period of 1950 to 1999 is considered as the historic period. The farthest 50-year period i.e. 2050 to 2099 is considered as the future period. Streamflow data for East Fork Carson River near Gardnerville from total 97 projections derived through 31 models and 4 RCP were used to estimate the change in streamflow due to climate. The location of the streamflow is at Latitude 38.844 and Longitude 119.702. The VIC application used for forcing the Climate model to streamflow is gbas. The details of the climate model and developing institutions were provided in Table 6.

Table 6: CMIP5-AOGCMs adopted for the study (Total 31 models with 97 projection).

Modeling Center	Institution	Model	Used Concentration Path (RCP)			
			2.6	4.5	6.0	8.5
CSIRO-BOM	CSIRO (Commonwealth Scientific and Industrial Research Organisation, Australia), and BOM (Bureau of Meteorology, Australia)	ACCESS1.0		√		√
BCC	Beijing Climate Center, China Meteorological Administration	BCC-CSM1.1	√	√	√	√
		BCC-CSM1.1(m)		√		√
CCCma	Canadian Centre for Climate Modelling and Analysis	CanESM2	√	√		√
NCAR	National Center for Atmospheric Research	CCSM4	√	√	√	√
NSF-DOE-NCAR	National Science Foundation, Department of Energy, National Center for Atmospheric Research	CESM1(BGC)		√		√
		CESM1(CAM5)	√	√	√	√
CMCC	Centro Euro-Mediterraneo per I Cambiamenti Climatici	CMCC-CM		√		√
CNRM-CERFACS	Centre National de Recherches Meteorologiques / Centre Europeen de Recherche et Formation Avancees en Calcul Scientifique	CNRM-CM5		√		√
CSIRO-QCCCE	Commonwealth Scientific and Industrial Research Organisation in collaboration with the Queensland Climate Change Centre of Excellence	CSIRO-Mk3.6.0	√	√	√	√
LASG-CESS	LASG, Institute of Atmospheric Physics, Chinese Academy of Sciences; and CESS, Tsinghua University	FGOALS-g2	√	√		√
FIO	The First Institute of Oceanography, SOA, China	FIO-ESM	√	√	√	√
NOAA GFDL	Geophysical Fluid Dynamics Laboratory	GFDL-CM3	√	√	√	√
		GFDL-ESM2G	√	√	√	√
		GFDL-ESM2M	√	√	√	√
NASA GISS	NASA Goddard Institute for Space Studies	GISS-E2-H-CC		√		
		GISS-E2-R	√	√	√	√
		GISS-E2-R-CC		√		
MOHC	Met Office Hadley Centre (additional HadGEM2-ES realizations contributed by Instituto Nacional de Pesquisas Espaciais)	HadGEM2-A	√	√	√	√
		HadGEM2-CC		√		√
		HadGEM2-ES	√	√	√	√
INM	Institute for Numerical Mathematics	INM-CM4		√		√
IPSL	Institut Pierre-Simon Laplace	IPSL-CM5A-MR	√	√	√	√
		IPSL-CM5B-LR		√		√
MIROC	Atmosphere and Ocean Research Institute (The University of Tokyo), National Institute for Environmental Studies, and Japan Agency for Marine-Earth Science and Technology	MIROC5	√	√	√	√
MIROC	Japan Agency for Marine-Earth Science and Technology, Atmosphere and Ocean Research Institute (The University of Tokyo), and National Institute for Environmental Studies	MIROC-ESM	√	√	√	√
		MIROC-ESM-CHEM	√	√	√	√
MPI-M	Max Planck Institute for Meteorology (MPI-M)	MPI-ESM-LR	√	√		√
		MPI-ESM-MR	√	√		√
MRI	Meteorological Research Institute	MRI-CGCM3	√	√		√
NCC	Norwegian Climate Centre	NorESM1-M	√	√	√	√

The DEM required for the river terrain was obtained from national map viewer. 1/3 arc-second DEM product is used for producing the river profile and cross sections for the study area. The river cross section locations were considered at and in between the FEMA adopted cross sections for the comparison purpose. Levee and other existing structures are not adopted on the prepared model as the detail of the structures are not readily available. Figure 7 represents the HEC-RAS geometric model with river sections. 18 cross sections of the cross sections match with the cross section from FEMA developed flood map.

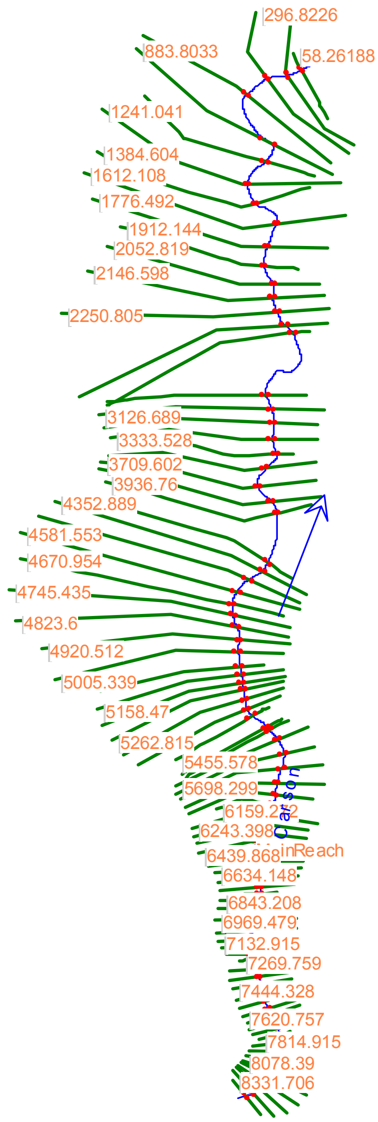


Figure 7: Carson River with cross sections location developed from DEM.

3.4 Method

Each WWCRA stations has average daily and average monthly streamflow data ranging from 1950 to 2099. Each station has 31 models and 4 RCP producing total 97 projections. The model generated daily average streamflow along with historical gage record of the Carson River is selected and data series with yearly peak flow is prepared for each model. The data is used for statistical evaluation to get the best-fitted distribution for the streamflow at that location. The selected distribution method is used to calculate the design flow for present and future conditions. Delta Change method is used to predict the future flow of the location. The future flow was then routed to a developed HEC-RAS model. Figure 8 is the flow chart representation of the method followed for the study. The methods followed were described under three headings; (i) Frequency analysis and best fit, (ii) Future flow prediction, (iii) Model preparation and flow routing.

(i) Frequency analysis and best fit: The streamflow projections along with the nearby existing real gage station was analyzed with frequency distribution to find the best-fitted frequency distribution for the study area. From the 97 streamflow projections for historic and future period total 194 projection datasets each containing 50 years of yearly peak flow was prepared. These datasets along with one Carson River gage data total 195 datasets were fitted with 27 different distribution methods to get the best-fitted distribution. The 27-different distribution applied for the study area listed in Table 2. The data were tested for goodness of fit with Pearson Chi-square and Kolmogorov Smirnov test. The test was implemented to the 195 datasets for a historic and future period of the model and historic gage data. Each best fit test returns an attained value of a represented as $\alpha_{reached}$ (Kozanis et al., 2010). The significant level for Pearson Chi-square and Kolmogorov Smirnov test is respectively given by eq. 1, eq. 2 and eq. 3. These analyses were carried out using the statistical Hydrognomon software developed by National Technical University of Athens (Kozanis et al., 2010). The best-fitted distribution among them was selected to generate the future streamflow.

(ii) Future flow prediction: Based on the best fitted distribution method, 100yr flood (design flood) is estimated for the historic and future projected streamflow datasets. The Delta Change Factor (DCF) is used to calculate the future flow on the stream station. Future flow of gage data and delta change method gives the flood without climate change and flood with climate change in future. Among the range of delta change factor, peak one was selected representing the maximum increase in future design flood condition. For this study, it is assumed that the ratio of peak flow at the downstream to downstream remains same in the future.

$$Delta\ change\ factor = \frac{Future\ model\ daily\ peak}{Historic\ model\ daily\ peak}$$

(iii) Model preparation and flow routing: A HEC-RAS model was prepared from available DEM model. Each cross-section location was chosen from FEMA for the comparison purpose. The prepared model was routed with future peak flood and hydraulic parameters were compared with the existing design condition of the FEMA map.

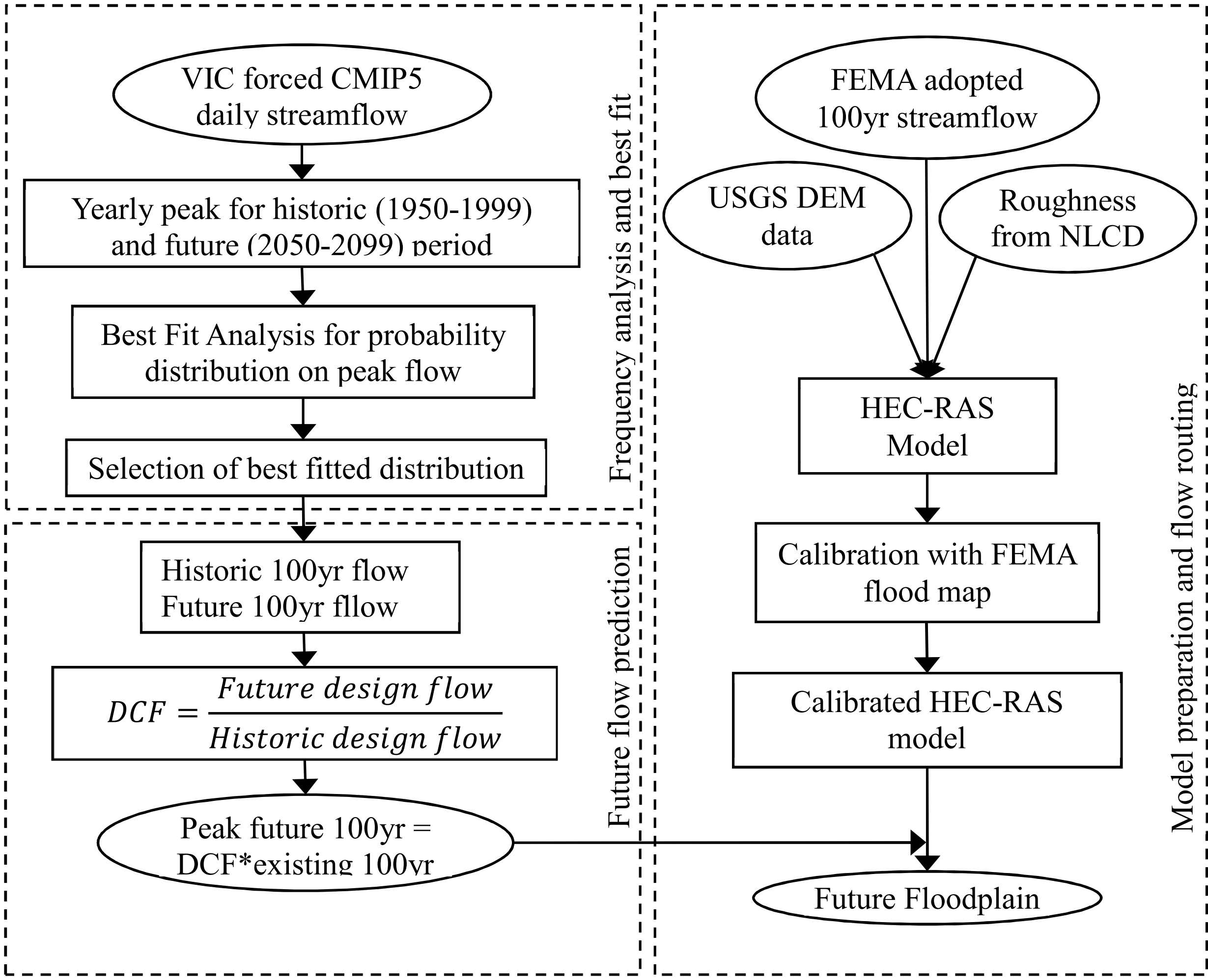


Figure 8: Best fit analysis, future flow using Delta Change Method and future flow routing using HEC-RAS.

3.5 Result

The daily streamflow series derived from the climate model projections have shown the clear trend of increasing future peak streamflow in Carson River at the same time the minimum of the yearly peak is decreasing. That means both tendencies of flash flood and dry peak are increasing which is shown by the spread of Figure 9. The average of peak flow is not increasing there is clear spread between minimum yearly peak flow to maximum yearly peak flow from 97 streamflow projections. In this study, only the probable maximum flood for different return periods was analyzed.

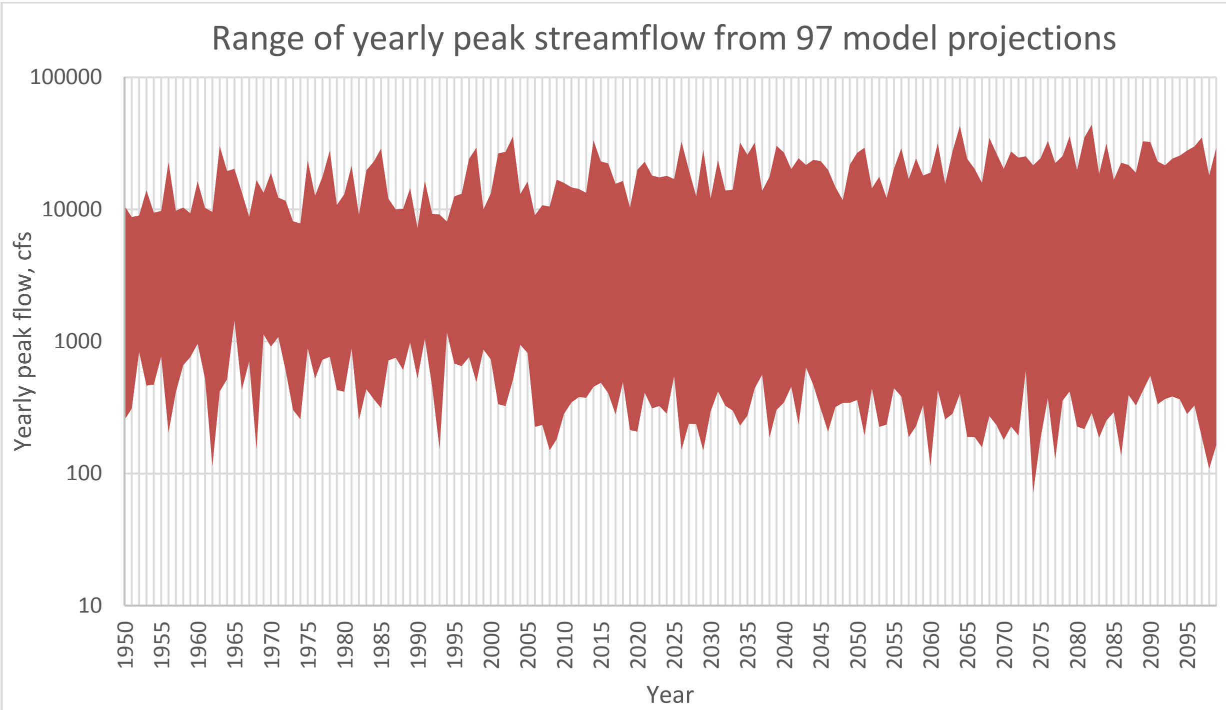


Figure 9: Spread of band of yearly peak flow from 97 climate model indicating the complexity of future streamflow.

Yearly maximum streamflow data from 97 projections ranging from 1950 to 2099 were selected and analyzed using Pearson Chi-square and Kolmogorov Smirnov method. The selection of the best fit from both models was presented in Figure 10. The numbers in Figure 10 represents the count of the projections best fitted with specific distribution method. From Figure 10, the GEV-Max (L-Moments) is selected as the best-fitted distribution from Pearson Chi-square and Kolmogorov Smirnov method with selection count 48 and 53 respectively out of 97 total projections. Thus, the GEV-Max (L-moments) is found to be the best distribution method and selected to analyze the future flood of the study area. More than half of the streamflow from different projection fitted for the distribution method for both best fit tests.

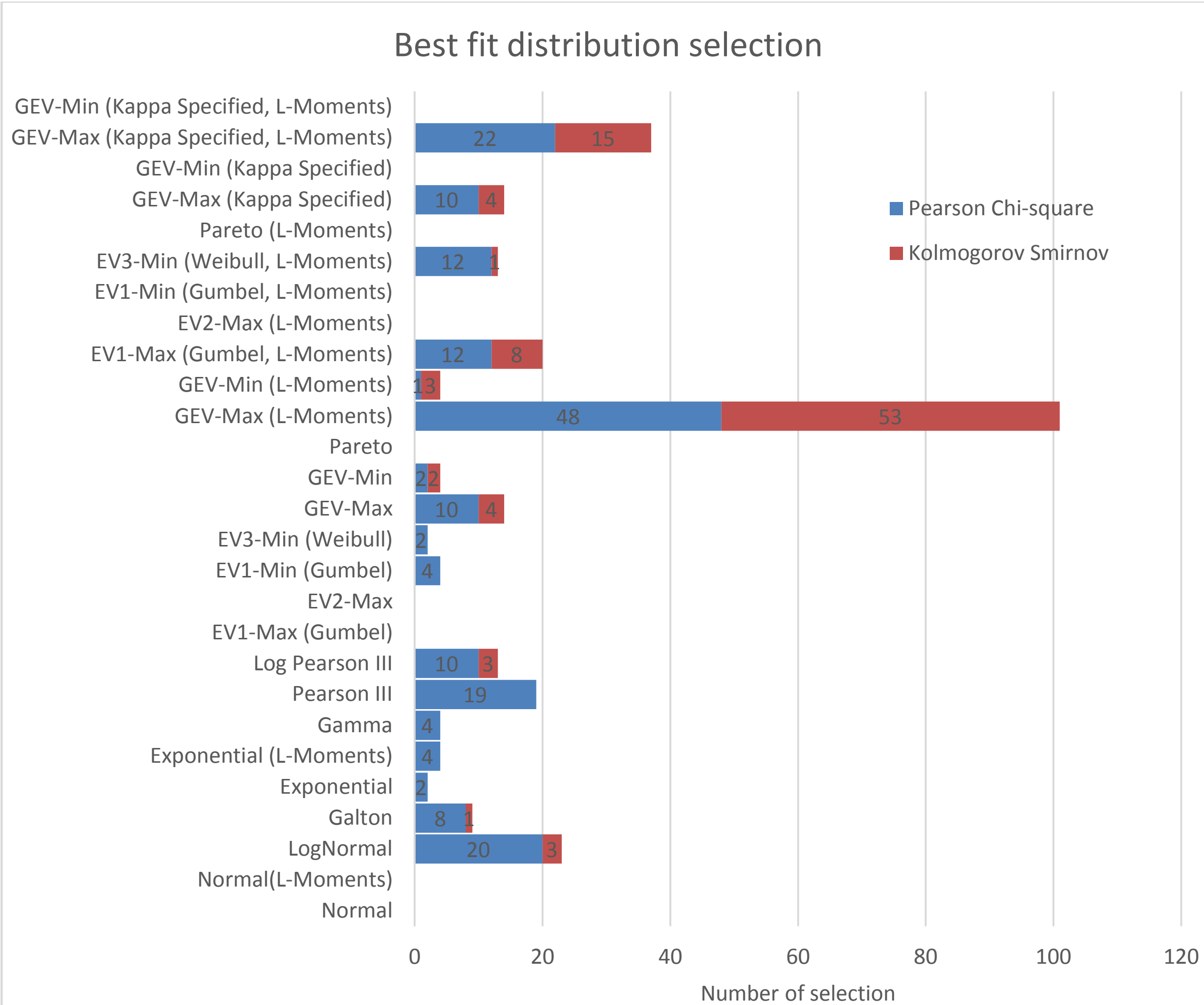
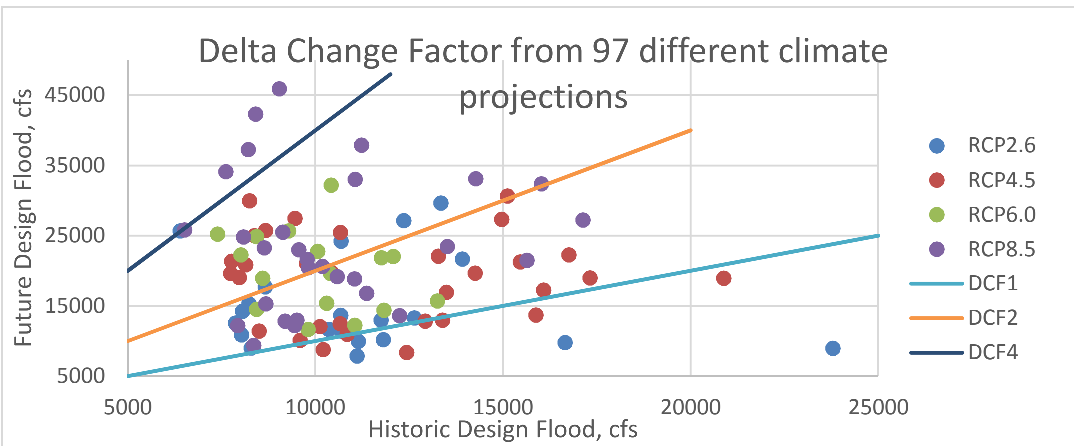
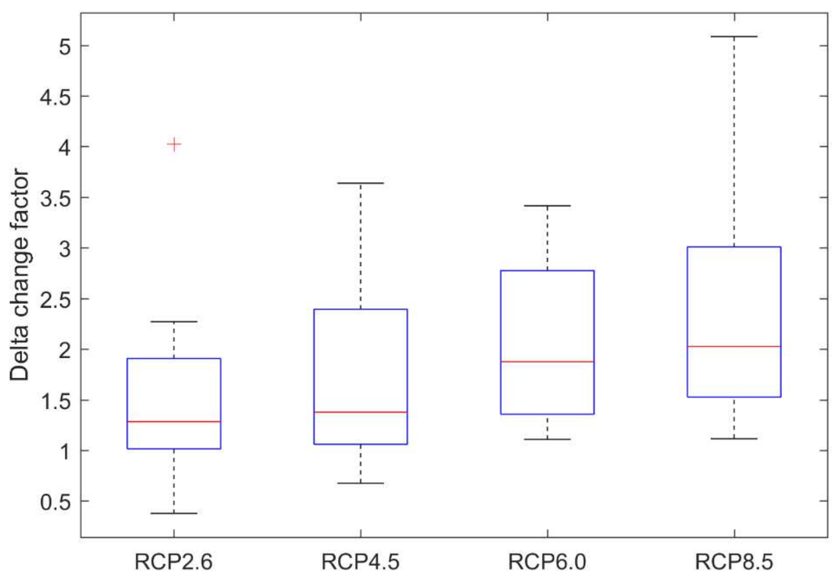


Figure 10: Selection from the best fit analysis for 27 different distributions using Pearson Chi-square and Kolmogorov Smirnov method.

The best-fitted distribution method, GEV-Max (L-Moments) is used to calculate the 100yr peak flow (design flood) for historic and future period. The selected distribution method has been used to calculate the Delta Change Factor. The delta change factor is the ratio between future to historic design flow, was calculated from each climate model projections which has been represented in Figure 11 (a). Inclined lines with DCF1, DCF2, and DCF4 represents the delta change factor 1, 2 and 3 respectively representing the future design flood would be same, double and four times of the historic period respectively. On the figure, each emission scenario projections were represented with a different color to distinguish easily. From the Figure 11 (a), RCP2.6 has lowest delta change factor and RCP8.5 highest delta change factor. From Figure 11(b), it is clear that with the increase in greenhouse gasses the future extremes on streamflow is expected to increase. The two lower RCPs has few models for delta change factor less than one. For the flood mapping, maximum delta change factor 5.086 obtained from model CNRM-CM5 with RCP8.5 is considered.



(a)



(b)

Figure 11: Comparison of delta change factor from 97 model projections. (a) Historic vs future design flood (100yr flood), (b) box plot of delta change factor in comparison with different RCPs

Hydrological summary of the Gage site 1031000 lying in Carson City has carried out the flood analysis and developed flood with different return periods represented in Table 4. For this study purpose, only the 1% and 0.2% chance of annual existing i.e. 100yr and 500yr return period were used. FEMA has developed the 100yr and 500yr return period flood for the area. FEMA map 3200010227E, 3200010112E and 3200010114F covers the study area. The area covered by red polygon on Figure 6 represents the FEMA flood area for 100yr return period.

Table 7: Hydrological Summary of Flood at USGS gage site 1031000.

Flooding Source	Location	Drainage Area (Square Miles)	10% Annual Chance	2% Annual Chance	1% Annual Chance	0.2% Annual Chance
Carson River	3 Miles Upstream of Lloyds Bridge (USGS 1031000)	876	8420	23800	36000	90400

Delta change factor calculated for the study was used to calculate the future design flood (100yr). The future design flood comes to be 183,094cfs, which is more than the current 500yr flood. Thus, climate generated future design flood may be more than the recent 500yr flood. The developed HEC-RAS model routed with the 3-different flood that is existing 100yr, existing 500yr and future 100yr with discharge 36000cfs, 90400cfs and 183094cfs respectively. The flood area developed using HEC-RAS and ArcGIS is presented in Figure 12. Floodplain for present design flood, present 500yr flood, and future design flood were plotted. The area covered by these three conditions are 3915290 m^2, 4762168 m^2 and 5947893 m^2 respectively while the FEMA 100yr flood covers 4882183 m2. Floodplain for these three conditions was compared and found the future 100yr flood could cover more than 1.5 times more area.

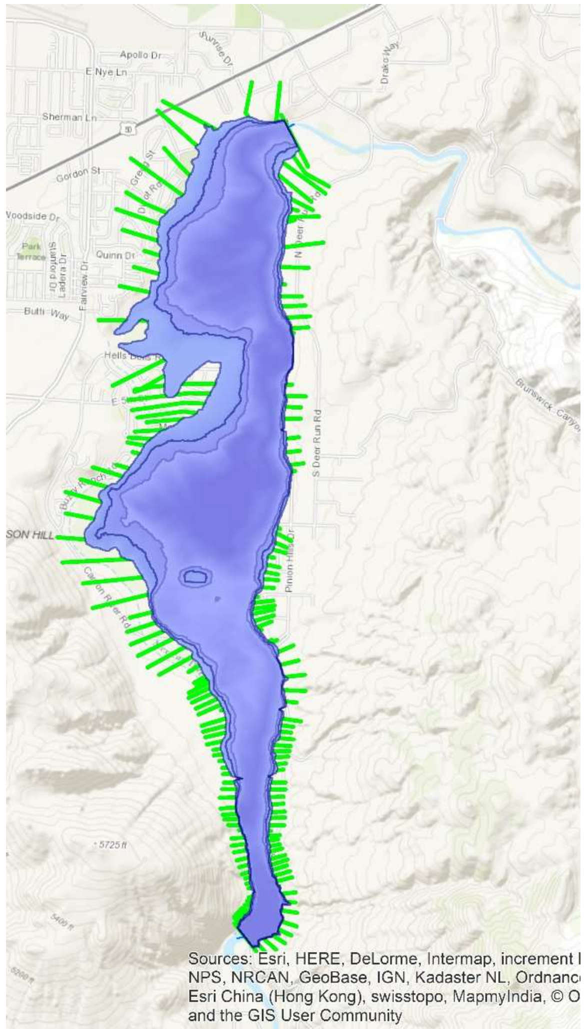
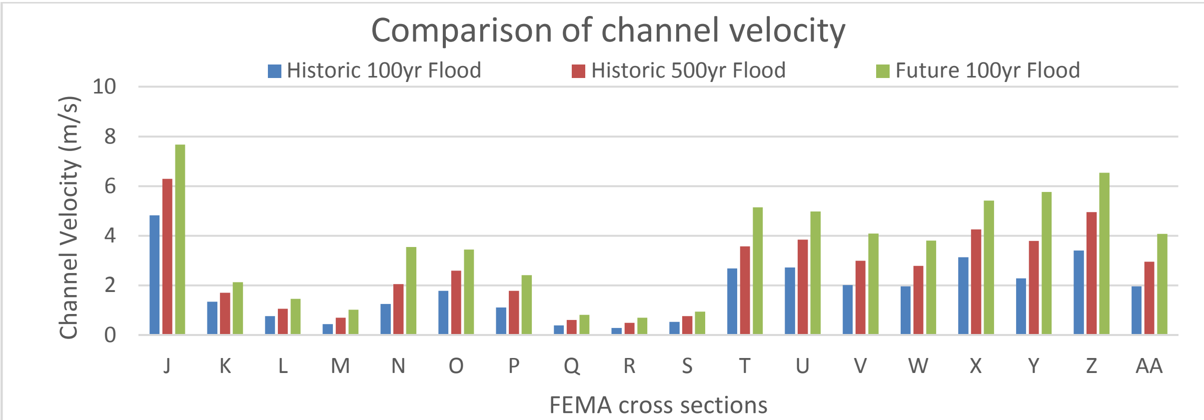
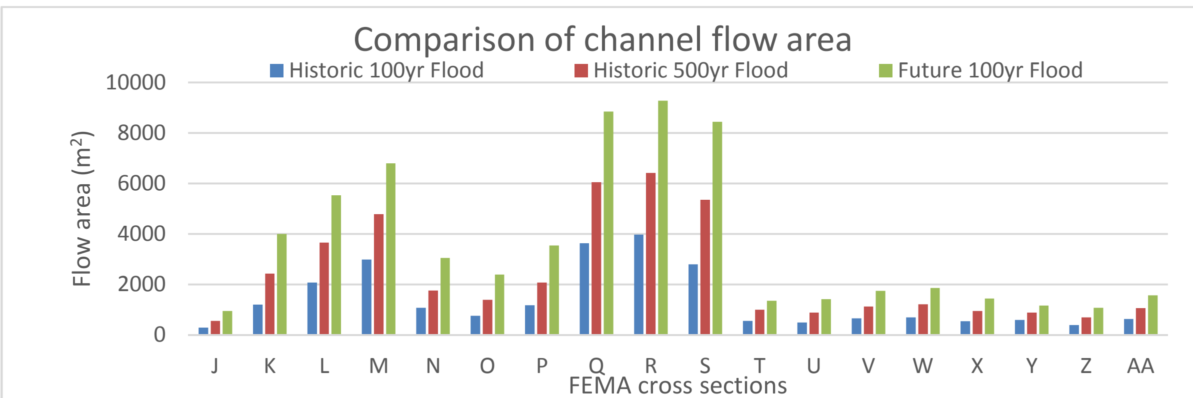


Figure 12: Three layers of Flood area for 100yr historic, 500yr historic and 100yr future (from smaller to larger area respectively).

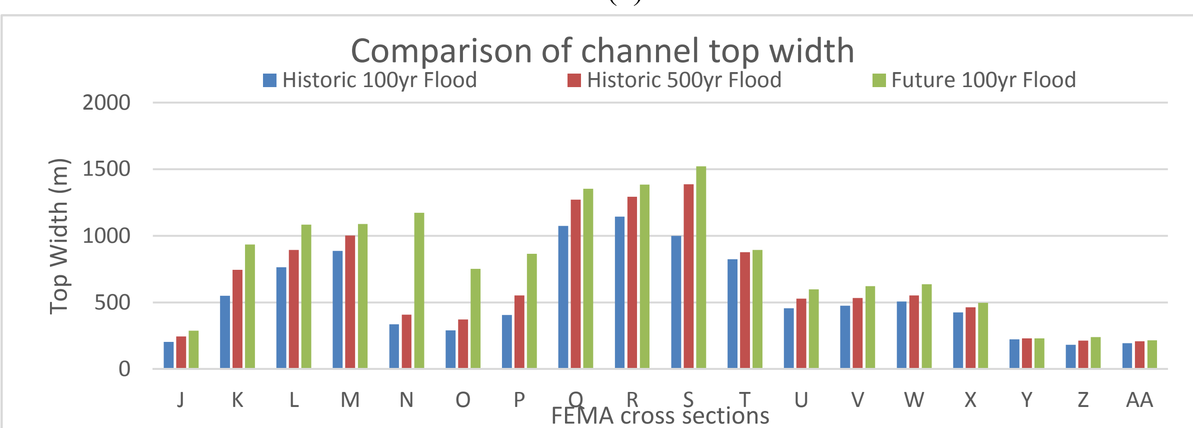
Further, channel velocity, flow area, and top width were compared between historic 100yr, historic 500yr and future 100yr flood. FEMA has 18 cross-sections in between the reach length. Hydraulic parameter as channel velocity, flow area, and top width was compared within this reach length and FEMA cross sections and are presented in Figure 13. The result shows that there will be more flooding on the left bank of the river than the right due to its topography. As the city is residing nearby the river it might be affected due to this change in a future flood. The low lying agricultural land on Carson floodplain will be flooded more frequently in future than in past.



(a)



(b)



(c)

Figure 13: Comparison of (a) channel velocity, (b) flow area and (c) top width for different flood scenario.

Channel velocity, flow area and top width are the key hydraulic parameters of flood which were compared with different flow conditions. The future 100yr flow has highest channel velocity of around 8m/sec. The channel flow area will be more than double in most of the cross sections and there would be significant increase in top width along section N, O and P.

3.6 Discussion

The population of Carson City which is not increasing since 2004 has most of the settlement in left bank of the Carson River. The topography of the river shows the river has more floodplain on left side of the river than in right side. The floodplain contains the fertile agricultural land crucial due to lying in desert of Nevada. Due to increase in design flood in the future more area than expected might get flooded. The future flood not only affect the agricultural supply but also affects the lives residing nearby the river. Thus, a proper analysis and future forecast will help to minimize the flood risk likely to happen in future.

Floodplain management must address to balance the long-term flood damage with the benefit of human and natural uses of it over long periods of time. Flood protection decision can endure more than a century thus it is necessary to consider the long-term change in environmental conditions. The decision on floodplain management would likely to affect long-term performance of the infrastructures (Zhu et al., 2007). From the evolution of human beings, it started to inhabited places close to freshwater to ensure water for drinking, agricultural use and, livestock. Major known civilizations were inhabited very close to rivers with an adequate supply of fresh water. More than half of the total global population resides within 3km from freshwater bodies, mostly near to river (Kummu et al., 2011). This population is more vulnerable to change in streamflow in the future. In this study, such a case analyzed using CMIP5 hydrology projections. As different distribution method predicts different flood frequency for a flood, thus selecting appropriate flood distribution method is vital in flood frequency analysis. To select the best-fitted distribution method model dataset were fitted using Pearson Chi-Square and Kolmogorov Smirnov method among 27 different distribution. The selected method was used to predict design flood for present and future datasets of climate projections. Delta change method was adopted to predict the future flood to predict future flow, which was routed on HEC-RAS 1D model to compare the change with present scenarios. The result shows there is high possibility to increase in flood in future and the extreme condition design flood would be more than the 500yr flood.

3.7 Conclusion

This study provides the possible approach for the quantification of the future streamflow of the similar area from reliable streamflow model. The result will present the possible way to identify the best-fitted distribution to get future streamflow. GEV-Max (L-moment) was found to be the best-fitted distribution among 27 different distribution. Most of the climate model from 97 model has shown an increase in the design flow. For the extreme case as predicted from CNRM-CM5 model with RCP8.5 was considered and suggest more than 5 times increase in design flow in the future. From the study, the future 100yr flood would be more than a current 500yr flood. The future flow, depth of flow and inundation comparison gives a clear image of future flooding extent due to climate change which is the first step toward flood risk management.

The risk of the climate change is one of the main global challenges of the 21st century. This anthropogenic climate change risk in increasing in recent years as there is very little effort to curb the production of the greenhouse gasses. At the same time, rapid urbanization and change in land use pattern affect the hydrological processes leading to high surface flow. Most of the entity is applying stationary approach for flood management. This study suggests a possible approach of applying nonstationary approach into future streamflow. Most of the flood management structures are made for the lifespan of more than a century, but foreseeing climate change in streamflow is lacking. This study will help planner, designer, engineer and policymakers.

CHAPTER 4

CONTRIBUTIONS AND RECOMMENDATIONS

4.1 Summary

Despite the decrease in annual growth rate world population is increasing day by day. Urban population is increasing in more rapid way than world population with more than half of the world population living in Urban areas. This urbanization reshapes the landscape with increasing paved surface, which in turn increases flash flood and stresses on urban infrastructure as well as natural drainage such as streams and rivers (Kalra & Ahmad, 2011; Kalra & Ahmad, 2012; Kalra et al., 2013c; Maheshwari et al., 2016; Peiravi et al., 2017; Paz et al., 2013). At the same time the natural extremities such as extreme precipitations were observed more in recent years due to climate change (Pathak et al., 2016a, Pathak et al., 2016b; Pathak et al., 2018). This change in landscape and natural hydrology affected the urban life making it more vulnerable (Kalra et al., 2008; Kandissounoun et al., 2018; Pathak et al., 2016c). In this changing natural extremity only using conventional stationary approach might not be effective (Sagarika et al., 2014; Sagarika et al., 2015; Sagarika et al., 2016). Thus, climate models were analyzed to answer the future extreme problems in terms of precipitation and streamflow. This research proposed a robust and straightforward method for consideration in design of stormwater infrastructure as well as natural streamflow and floodplain. Following research questions for problem #1 were answered through this study:

i. Which distribution pattern the storm follows over the study area?
ii. What will be the future design storm depth?
iii. What will be the effect on stormwater infrastructure due to change in design storm depth?

This set of questions were addressed using 14 different NARCCAP climate model, which has future projection of datasets. These climate data were fitted among 27 different distribution using Pearson Chi-square and Kolmogorov Smirnov test. Delta change method is adopted to downscale the climate model data. The result shows there is higher probability of increasing future design storm depth and stress on stormwater infrastructures. Following research questions for problem #2 were answered through this study:

i. Which flood frequency distribution method represents best for the study area?
ii. What will be the future design flow in study area?
iii. How floodplain will change due to increase in future design streamflow?

This set of questions were addressed using 97 different CMIP5 hydrology projected VIC forced streamflow, which includes unimpaired streamflow from 1950 to 2099 available as daily and monthly averaged. These dataset consists of projection from 4 different RCPs with higher concentration pathway producing higher future extremes. These datasets were fitted among 27 different distribution using Pearson Chi-square and Kolmogorov Smirnov test. Delta change method is used as an alternative to the complex downscaling climate model projections. The result shows there would be more peak flow as well as drier peak in future than in history. The floodplain mapping shows more flooding due to this increase in future extremes.

4.2 Contributions

Some previous studies have already highlighted the importance of the climate model to predict the future hydrology (Tamaddun et al., 2016; Tamaddun et al., 2017a; Tamaddun et al., 2017b; Tamaddun et al., 2018). This study suggests a robust method from selection of best fit distribution method to the implementation of the effect of climate change in future design storm depth as well as future design flood. This study evaluates the hydraulics of detentions basins which are the key part of the urban stormwater managements. Also, this study provides comparative increase in floodplain due to increase in future streamflow. Thus, the study is unique in best fit selection and estimation of future storm depth and future streamflow. Further, following points summarize the contribution from the study:

i. Suggest best fit selection using Pearson Chi-square and Kolmogorov Smirnov best fit analysis.
ii. Simple alternative of complex downscaling method to use the low spatial resolution climate data to the design of stormwater infrastructure and streamflow analysis.
iii. Using the nonstationary approach using available high temporal resolution climate model for precipitation and streamflow datasets.
iv. Analyzing software based hydrological model to represent the present scenarios of two large watersheds of Las Vegas Valley.
v. Floodplain mapping using widely used software.

4.3 Limitations

A comprehensive analysis was carried out to meet the research objectives, however certain some limitations are unavoidable. The climate models from different combinations of RCM-GCM provides different result suggesting a range of future options, but during the study only the worst scenario was analyzed. A simple downscaling technique might not perform best. Though most of the model has shown increase in extreme streamflow in future, selection of best representing model is beyond the scope of this study.

Convective precipitation, which is characterized by deep layer of moisture laden clouds capable of efficient strong rainfall, is responsible for the intense precipitation in the Las Vegas Valley. The convective clouds moves in vertical direction with cool top layer and hot bottom layer, thus is more localized. Climate models are not capable to fully represent these localized effect of convective precipitation, this limits the effectiveness of such models

4.4 Recommendations for future work

This study proposed a simple way to implement the future design storm and future design streamflow in infrastructure and floodplain mapping. Best fit analysis among 27-different distribution methods suggest appropriate distribution for study area. Though the study suggests a robust method to understand the future conditions on storm depth and streamflow, following recommendations are suggested as future works.

i. Complex downscaling techniques could be implemented instead of delta change method.
ii. Regionalization among neighbor grids would suggest better trend for larger watersheds.
iii. Climate models with very fine temporal resolutions would provide better dataset for 6hr duration than from 3hr temporal resolution.

REFERENCES

Ahmed, S., & Tsanis, I. (2016). Hydrologic and Hydraulic Impact of Climate Change on Lake Ontario Tributary. *American Journal of Water Resources*, 4(1), 1-15.

Aryal, Y. N., Villarini, G., Zhang, W., & Vecchi, G. A. (2018). Long term Changes in Flooding and Heavy Rainfall Associated with North Atlantic Tropical Cyclones: Roles of the North Atlantic Oscillation and El Niño-Southern Oscillation. *Journal of Hydrology*. https://doi.org/10.1016/j.jhydrol.2018.02.072

Bedient, P.B.H. and Wayne, C. (1988) *Hydrology and Floodplain Analysis*. (No. 551.49 B4).

Bhandari, M., Nyaupane, N., Mote, S. R., Kalra, A., & Ahmad, S. (2017). 2D Unsteady Flow Routing and Flood Inundation Mapping for Lower Region of Brazos River Watershed. In *World Environmental and Water Resources Congress 2017* (pp. 292-303). https://doi.org/10.1061/9780784480625.027

Bonnin, G.M., Martin, D., Lin, B., Parzybok, T., Yekta, M. and Riley, D. (2006) Precipitation-Frequency Atlas of the United States. *NOAA Atlas 14(2)*, 1-65.

Brekke, L., Thrasher, B., Maurer, E. and Pruitt, T. (2013) Downscaled CMIP3 and CMIP5 Climate Projections: Release of Downscaled CMIP5 Climate Projections, Comparison with Preceding Information, and Summary of User Needs. *US Department of the Interior, Bureau of Reclamation, Technical Service Center, Denver, Colorado, USA.*

Brekke, L., Wood, A. and Pruitt, T. (2014) Downscaled CMIP3 and CMIP5 Hydrology Projections: Release of Hydrology Projections, Comparison with Preceding Information, and Summary of User Needs. *US Department of the Interior, Bureau of Reclamation.*

Brown, C. (2010) The End of Reliability. *Journal of Water Resources Planning and Management 136(2)*, 143-145.

Canfield, R.V., Olsen, D., Hawkins, R. and Chen, T. (1980) Use of Extreme Value Theory in Estimating Flood Peaks from Mixed Populations. *Reports. Paper 577.* Utah State University.

Carrier, C. A., Kalra, A., & Ahmad, S. (2016). Long-range Precipitation Forecasts Using Paleoclimate Reconstructions in the Western United States. *Journal of Mountain Science*, *13*(4), 614. DOI: 10.1007/s11629-014-3360-2

Chen, C., Ahmad, S., Kalra, A., & Xu, Z. X. (2017). A Dynamic Model for Exploring Water-Resource Management Scenarios in an Inland Arid Area: Shanshan County, Northwestern China." *Journal of Mountain Science*, *14*(6), 1039-1057. https://doi.org/10.1007/s11629-016-4210-1

Chen, C., Kalra, A., & Ahmad, S. (2018). Hydrologic Responses to Climate Change Using Downscaled GCM Data on a Watershed Scale. *Journal of Water and Climate Change*, jwc2018147. doi: 10.2166/wcc.2018.147

Cheng, L., Agha, Kouchak, A., Gilleland, E. and Katz, R.W. (2014) Non-Stationary Extreme Value Analysis in a Changing Climate. *Climatic Change* 127(2), 353-369.

Christensen, J.H., Hewitson, B., Busuioc, A., Chen, A., Gao, X., Held, R., Jones, R., Kolli, R.K., Kwon, W. and Laprise, R. (2007) Regional Climate Projections. *Climate Change*, 2007: The Physical Science Basis. Contribution of Working group I to the Fourth Assessment Report of the Intergovernmental Panel on Climate Change, University Press, Cambridge, Chapter 11, 847-940.

Clark County Regional Flood Control District (CCRFCD) (1999). Hydrologic Criteria and Drainage Design Manual, Las Vegas, 569.

Clark County Regional Flood Control District (CCRFCD) (2018). Master Plan Update Clark Vols. I and II, Las Vegas, 434.

Cox, P. M., Betts, R. A., Jones, C. D., Spall, S. A., & Totterdell, I. J. (2000). Acceleration of Global Warming Due to Carbon-Cycle Feedbacks in a Coupled Climate Model. *Nature,* 408(6809), 184-187.

Cunnane, C. (1989) Statistical Distributions for Flood Frequency Analysis. *Operational Hydrology Report* (WMO).

Daage, A.C., Ricci, S., Sanchez-Gomez, E., Estupina, V.B., Servat, E. and Llovel, C. (2016) Climate Change Impacts on Precipitation Extremes, Flows and Flash Floods in Mediterranean Mesoscale Catchments. *International Congress on Environmental Modelling and Software*. 51.

Dankers, R. and Feyen, L. (2009) Flood Hazard in Europe in an Ensemble of Regional Climate Scenarios. *Journal of Geophysical Research: Atmospheres* 114(D16).

Davie, J.C., Falloon, P.D., Kahana, R., Dankers, R., Betts, R., Portmann, F.T., Wisser, D., Clark, D.B., Ito, A. and Masaki, Y. (2013) Comparing Projections of Future Changes in Runoff from Hydrological and Biome Models in ISI-MIP. *Earth System Dynamics* 4(2), 359-374.

Douglas, I., Kobold, M., Lawson, N., Pasche, E. and White, I. (2007) Characterisation of Urban Streams and Urban Flooding. *Advances in Urban Flood Management*. Taylor & Francis, New York, New York, USA. http://dx. doi. org/10.1201/9780203945988. ch3, 29-58.

Forsee, W.J. and Ahmad, S. (2011) Evaluating Urban Storm-Water Infrastructure Design in Response to Projected Climate Change. *Journal of Hydrologic Engineering* 16(11), 865-873.

Fowler, H.J., Blenkinsop, S. and Tebaldi, C. (2007) Linking Climate Change Modelling to Impacts Studies: Recent Advances in Downscaling Techniques for Hydrological Modelling. *International journal of climatology* 27(12), 1547-1578.

Gangopadhyay, S., Pruitt, T. and Brekke, L. (2011) West-Wide Climate Risk Assessments: Bias-Corrected and Spatially Downscaled Surface Water Projections, US Department of the Interior, Bureau of Reclamation, Technical Service Center.

Gautam, M. R., Chief, K., & Smith, W. J. (2013). "Climate Change in Arid Lands and Native American Socioeconomic Vulnerability: The case of the Pyramid Lake Paiute Tribe." *Climatic change*, 120(3), 585-599. https://doi.org/10.1007/s10584-013-0737-0

Gautam, M., Acharya, K., & Shanahan, S. A. (2014). Ongoing Restoration and Management of Las Vegas Wash: An Evaluation of Success Criteria. *Water Policy*, *16*(4), 720-738. DOI: 10.2166/wp.2014.035

Ghimire, G. R., Thakali, R., Kalra, A., & Ahmad, S. (2016). Role of Low Impact Development in the Attenuation of Flood Flows in Urban Areas. In *World Environmental and Water Resources Congress 2016* (pp. 339-349). https://doi.org/10.1061/9780784479858.035

Grillakis, M. G., Koutroulis, A. G., & Tsanis, I. K. (2011). Climate Change Impact on the Hydrology of Spencer Creek Watershed in Southern Ontario, Canada. *Journal of Hydrology*, 409(1), 1-19.

Grimm, N.B., Faeth, S.H., Golubiewski, N.E., Redman, C.L., Wu, J., Bai, X. and Briggs, J.M. (2008) Global Change and the Ecology of Cities. *Science* 319(5864), 756-760.

Guo, Y. (2006) Updating Rainfall IDF Relationships to Maintain Urban Drainage Design Standards. *Journal of Hydrologic Engineering*, 11, 506-509.

Gutmann, E., Clark, M., Eidhammer, T., Ikeda, K., Deser, C., Brekke, L., Arnold, J. and Rasmussen, R. (2016) Sources of Uncertainty in Climate Change Projections of Precipitation, *EGU General Assembly* p. 10011.

Hanson R. (1984) Perspectives on Urban Infrastructure. Committee on National Urban Policy, National Research Council, Washington, DC. *National Academies Press*, 216 pp

He, J., Valeo, C. and Bouchart, F.-C. (2006) Enhancing Urban Infrastructure Investment Planning Practices for a Changing Climate. *Water Science and Technology* 53(10), 13-20.

Hidalgo, H.G., Dettinger, M.D. and Cayan, D.R. (2008) Downscaling with Constructed Analogues: Daily Precipitation and Temperature Fields Over the United States. *California Energy Commission PIER Final Project Report* CEC-500-2007-123.

Hirabayashi, Y., Kanae, S., Emori, S., Oki, T. and Kimoto, M. (2008) Global Projections of Changing Risks of Floods and Droughts in a Changing Climate. *Hydrological Sciences Journal* 53(4), 754-772.

Hirabayashi, Y., Mahendran, R., Koirala, S., Konoshima, L., Yamazaki, D., Watanabe, S., Kim, H. and Kanae, S. (2013) Global Flood Risk Under Climate Change. *Nature Climate Change* 3(9), 816-821.

Hosking, J.R.M. and Wallis, J.R. (2005) Regional Frequency Analysis: an Approach Based on L-Moments, *Cambridge University Press*.

Houghton, J.T., Ding, Y., Griggs, D.J., Noguer, M., van der Linden, P.J., Dai, X., Maskell, K. and Johnson, C. (2001) Climate change 2001: the scientific basis. *The Press Syndicate of the University of Cambridge.*

IPCC (2014) Climate Change 2014: Impacts, Adaptation, and Vulnerability. Part A: Global and Sectoral Aspects. Contribution of Working Group II to the Fifth Assessment Report of the Intergovernmental Panel on Climate Change. Field, C.B., Barros, V.R., Dokken, D.J., Mach, K.J., Mastrandrea, M.D., Bilir, T.E., Chatterjee, M., Ebi, K.L., Estrada, Y.O., Genova, R.C., Girma, B., Kissel, E.S., Levy, A.N., MacCracken, S., Mastrandrea, P.R. and White, L.L. (eds), pp. 1-32, *Cambridge University Press*, Cambridge, United Kingdom, and New York, NY, USA.

Jardine, A., Merideth, R., Black, M. and LeRoy, S. (2013) Assessment of Climate Change in the Southwest United States: *A Report Prepared for the National Climate Assessment, Island press*.

Jiang, P., Yu, Z., Gautam, M. R., Yuan, F., & Acharya, K. (2016). Changes of Storm Properties in the United States: Observations and Multimodel Ensemble Projections. *Global and Planetary Change, 142*, 41-52. https://doi.org/10.1016/j.gloplacha.2016.05.001

Jobe, A., Bhandari, S., Kalra, A., & Ahmad, S. (2017). Ice-Cover and Jamming Effects on Inline Structures and Upstream Water Levels. In *World Environmental and Water Resources Congress 2017* (pp. 270-279). https://doi.org/10.1061/9780784480625.025

Jobe, A., Kalra, A., & Ibendahl, E. (2018). Conservation Reserve Program Effects on Floodplain Land Cover Management. *Journal of Environmental Management*, *214*, 305-314. doi: 10.1016/j.jenvman.2018.03.016

Kalra, A., & Ahmad, S. (2011). “Evaluating changes and estimating seasonal precipitation for the Colorado River Basin using a stochastic nonparametric disaggregation technique.” *Water Resource Research,* 47, W05555. doi: 10.1029/ 2010WR009118.

Kalra, A., Ahmad, S. (2012). “Estimating Annual Precipitation for the Colorado River Basin Using Oceanic-Atmospheric Oscillations.” *Water Resources Research*, 48, W06527. doi: 10. 1029/2011WR010667.

Kalra, A., Ahmad, S., & Nayak, A. (2013a). “Increasing Streamflow Forecast Lead Time for Snowmelt-Driven Catchment Based on Large-Scale Climate Patterns.” *Advances in Water Resources,* 53, 150–162. doi:10.1016/j.advwatres.2012.11.003.

Kalra, A., Li, L., Li, X., & Ahmad, S. (2013b). “Improving Streamflow Forecast Lead Time Using Oceanic-Atmospheric Oscillations for Kaidu River Basin, Xinjiang, China.” *Journal of Hydrologic Engineering*, *18*(8), 1031-1040. https://doi.org/10.1061/(ASCE)HE.1943-5584.0000707

Kalra, A., Miller, W. P., Lamb, K. W., Ahmad, S., & Piechota, T. (2013c). “Using Large-Scale Climatic Patterns for Improving Long Lead Time Streamflow Forecasts for Gunnison and San Juan River Basins.” *Hydrological Processes,* 27(11), 1543–1559. doi:10.1002/hyp.9236.

Kalra, A., Piechota, T. C., Davies, R., & Tootle, G. A. (2008). “Changes in US Streamflow and Western US Snowpack.” *Journal of Hydrologic Engineering,* 13(3), 156-163. doi: 10.1061/(ASCE)1084-0699(2008)13:3(156)

Kalra, A., Sagarika, S., Pathak, P., & Ahmad, S. (2017). “Hydro-Climatological Changes in the Colorado River Basin Over a Century.” *Hydrological Sciences Journal*, *62*(14), 2280-2296. https://doi.org/10.1080/02626667.2017.1372855

Kandissounon, G. A., Kalra, A., & Ahmad, S. (2018). Integrating System Dynamics and Remote Sensing to Estimate Future Water Usage and Average Surface Runoff in Lagos, Nigeria. *Civil Engineering Journal*, *4*(2), 378-393.

Kendon, E.J., Rowell, D.P., Jones, R.G. and Buonomo, E. (2008) Robustness of Future Changes in Local Precipitation Extremes. *Journal of Climate* 21(17), 4280-4297.

Kiehl, J. T., Hack, J. J., Bonan, G. B., Boville, B. A., Williamson, D. L., & Rasch, P. J. (1998). The National Center for Atmospheric Research Community Climate Model: CCM3. *Journal of Climate*, *11*(6), 1131-1149.

Knutti, R., Masson, D. and Gettelman, A. (2013) Climate Model Genealogy: Generation CMIP5 and How We got There. *Geophysical Research Letters* 40(6), 1194-1199.

Kozanis, S., Christoforides, A. and Efstratiadis, A. (2010) Scientific Documentation of Hydrognomon Software (Version 4). Development of Database and Software Application in a Web Platform for the "National Database and Meterological Information". ITIA research team, *National Technical University of Athens* Available from: http://www.itia.ntua.gr/getfile928(1).

Kummu, M., De Moel, H., Ward, P.J. and Varis, O. (2011) How close do we live to water? A global analysis of population distance to freshwater bodies. *PLoS One* 6(6), e20578.

Landes, D.S. (2003) The unbound Prometheus: Technological Change and Industrial Development in Western Europe from 1750 to the Present, *Cambridge University Press*.

Lederbogen, F., Kirsch, P., Haddad, L., Streit, F., Tost, H., Schuch, P., Wüst, S., Pruessner, J.C., Rietschel, M. and Deuschle, M. (2011) City Living and Urban Upbringing Affect Neural Social Stress Processing in Humans. *Nature* 474(7352), 498.

Lee, O., Park, Y., Kim, E.S. and Kim, S. (2016) Projection of Korean Probable Maximum Precipitation under Future Climate Change Scenarios. *Advances in Meteorology*.

Liang, X. (2002) Variable infiltration capacity (VIC): Macroscale Hydrologic Model. Documentation du modele, Land Surface Hydrology Research Group, *University of Washington* [En ligne] Disponible au http://www.hydro.washington.edu/Lettenmaier/Models/VIC/VIChome.html.

Liang, X., Lettenmaier, D.P., Wood, E.F. and Burges, S.J. (1994) A Simple Hydrologically Based Model of Land Surface Water and Energy Fluxes for General Circulation Models. *Journal of Geophysical Research: Atmospheres* 99(D7), 14415-14428.

Liang, X., Wood, E.F. and Lettenmaier, D.P. (1996) Surface Soil Moisture Parameterization of the VIC-2L Model: Evaluation and Modification. *Global and Planetary Change* 13(1-4), 195-206.

Maheshwari, P., Khaddar, R., Kachroo, P., & Paz, A. (2016). "Dynamic Modeling of Performance Indices for Planning of Sustainable Transportation Systems." *Networks and Spatial Economics,* 16(1), 371-393. doi:10.1007/s11067-014-9238-6

Mailhot, A. and Duchesne, S. (2009) Design Criteria of Urban Drainage Infrastructures Under Climate Change. *Journal of Water Resources Planning and Management* 136(2), 201-208.

Mailhot, A., Duchesne, S., Caya, D. and Talbot, G. (2007) Assessment of Future Change in Intensity–Duration–Frequency (IDF) Curves for Southern Quebec Using the Canadian Regional Climate Model (CRCM). *Journal of Hydrology* 347(1), 197-210.

Maurer, E., Wood, A., Adam, J., Lettenmaier, D. and Nijssen, B. (2002) A Long-term Hydrologically Based Dataset of Land Surface Fluxes and States for the Conterminous United States. *Journal of Climate* 15(22), 3237-3251.

Mearns, L.O., Gutowski, W., Jones, R., Leung, R., McGinnis, S., Nunes, A. and Qian, Y. (2009) A Regional Climate Change Assessment Program for North America. Eos, Transactions *American Geophysical Union* 90(36), 311-311.

Peiravi, M., Mote, S. R., Mohanty, M. K., & Liu, J. (2017). Bioelectrochemical treatment of acid mine drainage (AMD) from an abandoned coal mine under aerobic condition. *Journal of hazardous materials*, *333*, 329-338. https://doi.org/10.1016/j.jhazmat.2017.03.045

Mesinger, F., DiMego, G., Kalnay, E. and Mitchell, K. (2006) North American Regional Reanalysis. *Bulletin of the American Meteorological Society* 87(3), 343.

Miller, J., Frederick, R. and Tracey, R. (1973) Precipitation-Frequency Atlas of the Western United States, Vol. I: Montana; Vol. II: Wyoming; Vol. III: Colorado; Vol. IV: New Mexico; Vol. V: Idaho; Vol. VI: Utah; Vol. VII: Nevada; Vol. VIII: Arizona; Vol. IX: Washington; Vol. X: Oregon; Vol. XI: California. *NOAA atlas 2*.

Milly, P.; Julio, B.; Malin, F.; Robert, M.; Zbigniew, W.; Dennis, P.; Ronald, J (2008). Stationarity is Dead. *Ground Water News & View*, 4, 6-8.

Milly, P.C., Dunne, K.A. and Vecchia, A.V. (2005) Global Pattern of Trends in Streamflow and Water Availability in a Changing Climate. *Nature* 438(7066), 347-350.

Moglen, G.E. and Vidal, G.E.R. (2014) Climate Change and Storm Water Infrastructure in the Mid-Atlantic Region: Design Mismatch Coming? *Journal of Hydrologic Engineering* 19(11), 04014026.

Mote, P.W. and Salathe, E.P. (2010) Future Climate in the Pacific Northwest. *Climatic Change* 102(1-2), 29-50.

Nakicenovic, N., Alcamo, J., Davis, G., de Vries, B., Fenhann, J., Gaffin, S., Gregory, K., Grubler, A., Jung, T.Y. and Kram, T. (2000) Special Report on Emissions Scenarios: A Special Report of Working Group III of the Intergovernmental Panel on Climate Change, Pacific Northwest National Laboratory, Richland, WA (US), *Environmental Molecular Sciences Laboratory* (US).

Nijssen, B., Lettenmaier, D.P., Liang, X., Wetzel, S.W. and Wood, E.F. (1997) Streamflow Simulation for Continental-Scale River Basins. *Water Resources Research* 33(4), 711-724.

National Centers for Environmental Information (NCEI) (2018) U.S. Billion-Dollar Weather and Climate Disasters. https://www.ncdc.noaa.gov/billions/

Nohara, D., Kitoh, A., Hosaka, M. and Oki, T. (2006) Impact of Climate Change on River Discharge Projected by Multimodel Ensemble. *Journal of Hydrometeorology* 7(5), 1076-1089.

Notaro, V., Liuzzo, L., Freni, G. and La Loggia, G. (2015) Uncertainty Analysis in the Evaluation of Extreme Rainfall Trends and its Implications on Urban Drainage System Design. *Water* 7(12), 6931-6945.

Nyaupane, N., Thakali, R., Kalra, A., Mastino, L., Velotta, M., & Ahmad, S. (2017). “Response of Climate Change on Urban Watersheds: A Case Study for Las Vegas, NV.” *World Environmental and Water Resources Congress 2017* (pp. 485-496). https://doi.org/10.1061/9780784480632.040

O'Connor, J.E. and Costa, J.E. (2003) Large floods in the United States: Where They Happen and Why, *US Geological Survey*.

Papalexiou, S.M., AghaKouchak, A., Trenberth, K.E. and Foufoula-Georgiou, E. (2018) Global, Regional, and Megacity Trends in the Highest Temperature of the Year: Diagnostics and Evidence for Accelerating Trends. *Earth's Future* 6(1), 71-79.

Parajuli, R., Kalra, A., Mastino, L., Velotta, M., & Ahmad, S. (2017). A System Dynamics Modeling of Water Supply and Demand in Las Vegas Valley. In *AGU Fall Meeting Abstracts*.

Pathak, P., Bhandari, M., Kalra, A., & Ahmad, S. (2016a). Modeling Floodplain Inundation for Monument Creek, Colorado. In *World Environmental and Water Resources Congress 2016* (pp. 131-140). https://doi.org/10.1061/9780784479858.015

Pathak, P., Kalra, A., & Ahmad, S. (2016b). Temperature and Precipitation Changes in the Midwestern United States: Implications for Water Management. *International Journal of Water Resources Development,* 33(6), 1003-1019. doi:10.1080/07900627.2016.1238343

Pathak, P., Kalra, A., Ahmad, S., & Bernardez, M. (2016c). Wavelet-aided Analysis to Estimate Seasonal Variability and Dominant Periodicities in Temperature, Precipitation, and Streamflow in the Midwestern United States. *Water Resources Management,* 30(13), 4649-4665. doi:10.1007/s11269-016-1445-0.

Pathak, P., Kalra, A., Lamb, K. W., Miller, W. P., Ahmad, S., Amerineni, R., & Ponugoti, D. P. (2018). Climatic Variability of the Pacific and Atlantic Oceans and Western US snowpack. *International Journal of Climatology*, *38*(3), 1257-1269. doi: 10.1002/joc.5241

Paz, A., Maheshwari, P., Kachroo, P., & Ahmad, S. (2013). Estimation of performance indices for the planning of sustainable transportation systems. *Advances in Fuzzy Systems*, *2013*, 2.

Pinto, I., Lennard, C., Tadross, M., Hewitson, B., Dosio, A., Nikulin, G., Panitz, H.-J. and Shongwe, M.E. (2016) Evaluation and Projections of Extreme Precipitation Over Southern Africa from Two CORDEX Models. *Climatic Change* 135(3-4), 655-668.

Pokhrel, Y. N., Felfelani, F., Shin, S., Yamada, T. J., & Satoh, Y. (2017). Modeling Large-scale Human Alteration of Land Surface Hydrology and Climate. *Geoscience Letters*, *4*(1), 10. https://doi.org/10.1186/s40562-017-0076-5

Pokhrel, Y. N., Hanasaki, N., Yeh, P. J., Yamada, T. J., Kanae, S., & Oki, T. (2012). Model Estimates of Sea-level Change due to Anthropogenic Impacts on Terrestrial Water Storage. *Nature Geoscience*, *5*(6), 389. doi:10.1038/ngeo1476

Pokhrel, Y., Burbano, M., Roush, J., Kang, H., Sridhar, V., & Hyndman, D. W. (2018). A Review of the Integrated Effects of Changing Climate, Land Use, and Dams on Mekong River Hydrology. *Water*, *10*(3), 266. doi:10.3390/w10030266

Praskievicz, S. and Chang, H. (2009) A Review of Hydrological Modelling of Basin-scale Climate Change and Urban Development Impacts. *Progress in Physical Geography* 33(5), 650-671.

Randall, D. A., Wood, R. A., Bony, S., Colman, R., Fichefet, T., Fyfe, J. & Stouffer, R. J. (2007). Climate models and their evaluation. In Climate Change 2007: The Physical Science Basis. Contribution of Working Group I to the Fourth Assessment Report of the IPCC (FAR) (pp. 589-662). *Cambridge University Press*.

Reilly, J.A.; Piechota, T.C. Actual Storm Events Outperform Synthetic Design Storms. A Review of SCS Curve Number Applicability. In *Proceedings of the World Water and Environmental Resources Congress*, Anchorage, AK, USA, 15–19 May 2005; American Society of Civil Engineers: Reston, VA, USA, 2005; pp. 1–13.

Richardson, K., Steffen, W. and Liverman, D. (2011) Climate Change: Global Risks, Challenges and Decisions, *Cambridge University Press*.

Sagarika, S., Kalra, A., & Ahmad, S. (2014). Evaluating the Effect of Persistence on Long-term Trends and Analyzing Step Changes in Streamflows of the Continental United States. *Journal of Hydrology*, *517*, 36-53. doi: 10.1016/j.jhydrol.2014.05.002

Sagarika, S., Kalra, A., & Ahmad, S. (2015). Interconnections between Oceanic–Atmospheric Indices and Variability in the US Streamflow. *Journal of Hydrology*, *525*, 724-736. doi: 10.1016/j.jhydrol.2015.04.020

Sagarika, S., Kalra, A., & Ahmad, S. (2016). Pacific Ocean SST and Z500 Climate Variability and Western US Seasonal Streamflow. *International Journal of Climatology*, *36*(3), 1515-1533. doi: 10.1002/joc.4442

Salvadore, E., Bronders, J. and Batelaan, O. (2015) Hydrological Modelling of Urbanized Catchments: A Review and Future Directions. *Journal of Hydrology* 529, 62-81.

Shukla, J., Lata, K. and Misra, A. (2011) Modeling the Depletion of a Renewable Resource by Population and Industrialization: Effect of Technology on its Conservation. *Natural Resource Modeling* 24(2), 242-267.

Sorribas, M.V., Paiva, R.C., Melack, J.M., Bravo, J.M., Jones, C., Carvalho, L., Beighley, E., Forsberg, B. and Costa, M.H. (2016) Projections of Climate Change Effects on Discharge and Inundation in the Amazon Basin. *Climatic Change*, 1-16.

Stocker, T. (Ed.). (2014). Climate change 2013: the physical science basis: Working Group I Contribution to the Fifth Assessment Report of the Intergovernmental Panel on Climate Change. *Cambridge University Press*.

Tamaddun, K. A., Kalra, A., & Ahmad, S. (2017a). Wavelet analyses of western US streamflow with ENSO and PDO. *Journal of Water and Climate Change,* 8(1), 26-39. doi: 10.2166/wcc.2016.162.

Tamaddun, K. A., Kalra, A., Bernardez, M., & Ahmad, S. (2017b). Multi-Scale Correlation between the Western US Snow Water Equivalent and ENSO/PDO Using Wavelet Analyses. *Water Resources Management,* 31(9), 2745-2759. doi: 10.1007/s11269-017-1659-9.

Tamaddun, K., Kalra, A., & Ahmad, S. (2016). Identification of Streamflow Changes Across the Continental United States Using Variable Record Lengths. *Hydrology,* 3(2), 24. doi:10.3390/hydrology3020024.

Tamaddun, K., Kalra, A., & Ahmad, S. (2018). Potential of Rooftop Rainwater Harvesting to meet Outdoor Water Demand in Arid Regions. *Journal of Arid Land*, *10*(1), 68-83. doi: 10.1007/s40333-017-0110-7

Taylor, K., Stouffer, R. and Meehl, G. (2011) A Summary of the CMIP5 Experiment Design. January 22, 2011, 33 p.

Taylor, K.E., Stouffer, R.J. and Meehl, G.A. (2012) An Overview of CMIP5 and the Experiment Design. *Bulletin of the American Meteorological Society* 93(4), 485-498.

Thakali, R. (2017). Analyzing the Effects of Climate Change on Urban Stormwater Infrastuctures (Order No. 10265992). Available from Dissertations & Theses @ Southern Illinois University at Carbondale; *ProQuest Dissertations & Theses A&I*. (1941590912).

Retrieved from https://search.proquest.com/docview/1941590912?accountid=13864

Thakali, R., Bhandari, R., Arif-Deen Kandissounon, G. A., Kalra, A., & Ahmad, S. (2017a). "Flood Risk Assessment Using the Updated FEMA Floodplain Standard in the Ellicott City, Maryland, United States." In *World Environmental and Water Resources Congress 2017* (pp. 280-291). doi: https://doi.org/10.1061/9780784480625.026

Thakali, R., Kalra, A. and Ahmad, S. (2016) Understanding the Effects of Climate Change on Urban Stormwater Infrastructures in the Las Vegas Valley. *Hydrology* 3(4), 34.

Thakali, R., Kalra, A., & Ahmad, S. (2017b). Urban Stormwater runoff under changing climatic conditions. In *World Water Congress*.

Thakali, R., Kalra, A., Ahmad, S., & Qaiser, K. (2018). Management of an Urban Stormwater System Using Projected Future Scenarios of Climate Models: A Watershed-Based Modeling Approach. *Open Water Journal,* 5(2). Available at: https://scholarsarchive.byu.edu/openwater/vol5/iss2/1

Thakur, B., Parajuli, R., Kalra, A., Ahmad, S., & Gupta, R. (2017a). Coupling HEC-RAS and HEC-HMS in Precipitation Runoff Modelling and Evaluating Flood Plain Inundation Map. In *World Environmental and Water Resources Congress 2017* (pp. 240-251). https://doi.org/10.1061/9780784480625.022

Thakur, B., Pathak, P., Kalra, A., Ahmad, S., & Bernardez, M. (2017b). Using Wavelet to Analyze Periodicities in Hydrologic Variables. In *World Environmental and Water Resources Congress 2017* (pp. 499-510). https://doi.org/10.1061/9780784480618.050

Tra, C. (2008). Population Forecasts: Long-term Projections for Clark County, Nevada 2008-2035. *Center for Business and Economic Research*, University of Nevada.

USACE, 1988 - Hydrologic Documentation for Feasibility Study - Las Vegas Wash and Tributaries, Clark County, Nevada, U. S. Army Corps of Engineers, Los Angeles District, April, 1988.

Van Aalst, M.K. (2006) The Impacts of Climate Change on the Risk of Natural Disasters. *Disasters* 30(1), 5-18.

Washington State Department of Transportation (WSDOT) (2008) Storm-related Closures of I- 5 and I-90: Freight Transportation Economic Impact Assessment Report Winter. *Washington State Department of Transportation WA-RD* 708.1

Wernstedt, K. and Carlet, F. (2012) Climate Change, Urban Development, and Storm Water: Perspectives from the Field. *Journal of Water Resources Planning and Management* 140(4), 543-552.

White, M.D. and Greer, K.A. (2006) The Effects of Watershed Urbanization on the Stream Hydrology and Riparian Vegetation of Los Penasquitos Creek, California. *Landscape and Urban Planning* 74(2), 125-138.

Wobus, C., Gutmann, E., Jones, R., Rissing, M., Mizukami, N., Lorie, M., Mahoney, H., Wood, A.W., Mills, D. and Martinich, J. (2017) Modeled Changes in 100 Year Flood Risk and Asset Damages within Mapped Floodplains of the Contiguous United States. In *2017 Fall Meeting*

Wood, A.W., Leung, L.R., Sridhar, V. and Lettenmaier, D. (2004) Hydrologic implications of dynamical and statistical approaches to downscaling climate model outputs. *Climatic change* 62(1), 189-216.

Wu, J., Jenerette, G.D., Buyantuyev, A. and Redman, C.L. (2011) Quantifying Spatiotemporal Patterns of Urbanization: The Case of the Two Fastest Growing Metropolitan Regions in the United States. *Ecological Complexity* 8(1), 1-8.

Zhang, G. J., & McFarlane, N. A. (1995). Sensitivity of Climate Simulations to the Parameterization of Cumulus Convection in the Canadian Climate Centre general Circulation Model. *Atmosphere-Ocean*, 33(3), 407-446.

Zhang, X., Wang, J., Zwiers, F.W. and Groisman, P.Y. (2010) The Influence of Large-scale Climate Variability on Winter Maximum Daily Precipitation Over North America. *Journal of Climate* 23(11), 2902-2915.

Zhu, J., Forsee, W., Schumer, R. and Gautam, M. (2013) Future Projections and Uncertainty Assessment of Extreme Rainfall Intensity in the United States from an Ensemble of Climate Models. *Climatic Change* 118(2), 469-485.

Zhu, J., Stone, M.C. and Forsee, W. (2012) Analysis of Potential Impacts of Climate Change on Intensity–Duration–Frequency (IDF) Relationships for Six Regions in the United States. *Journal of Water and Climate Change* 3(3), 185-196.

Zhu, T., Lund, J.R., Jenkins, M.W., Marques, G.F. and Ritzema, R.S. (2007) Climate Change, Urbanization, and Optimal Long-term Floodplain Protection. *Water Resources Research* 43(6).

Zwiers, F.W., Alexander, L.V., Hegerl, G.C., Knutson, T.R., Kossin, J.P., Naveau, P., Nicholls, N., Schär, C., Seneviratne, S.I. and Zhang, X. (2013). Climate extremes: challenges in estimating and understanding recent changes in the frequency and intensity of extreme climate and weather events. *Climate Science for Serving Society*, pp. 339-389, Springer.

VITA

Graduate School

Southern Illinois University Carbondale

Narayan Nyaupane

narayan.nyaupane@siu.edu

Tribhuvan University Kathmandu, Nepal

Bachelor of Science in Civil Engineering, 2007

PAPER AND PRESENTATION AT PROFESSIONAL MEETING AND WORKSHOPS

Nyaupane, N. Kalra, A. (2018). Flooding Impacts on Carson River under Changing Climate. In *Student Creative Activities and Research Forum (SCARF)*, Southern Illinois University Carbondale.

Nyaupane, N. Kalra, A. (2017). Urban Sustainability in Built-up Environments: A Case Study of Gowan Watershed, Las Vegas, NV. In *Graduate and Professional Creative Activities and Research Forum (GPCARF)*, Southern Illinois University Carbondale. (Oral: GPCARF-2017)

Parajuli, R., Nyaupane, N., & Kalra, A. (2017). Analyzing Future Flooding under Climate Change Scenario using CMIP5 Streamflow Data. In *2017 Fall Meeting*.

CONFERENCE AND PROCEEDINGS

Bhandari, M., Nyaupane, N., Mote, S. R., Kalra, A., & Ahmad, S. (2017). 2D Unsteady Flow Routing and Flood Inundation Mapping for Lower Region of Brazos River Watershed. *In World Environmental and Water Resources Congress 2017* (pp. 292-303). https://doi.org/10.1061/9780784480625.027

Nyaupane, N., Thakali, R., Kalra, A., Mastino, L., Velotta, M., & Ahmad, S. (2017). Response of Climate Change on Urban Watersheds: A Case Study for Las Vegas, NV. *World Environmental and Water Resources Congress 2017* (pp. 485-496). https://doi.org/10.1061/9780784480632.040

Kalra, A., Parajuli, R., Nyaupane, N., Mastinon, L., Velotta, M., & Ahmad, S. (2018). Bringing Science in Community Planning Under Changing Climate. *Sustainable Technologies for Intelligent Water Management (STIWM) 2018* (In review).

Kalra, A., Parajuli, R., Nyaupane, N., Mastinon, L., Velotta, M., & Ahmad, S. (2018). Integrated Water Management in Changing Climate to Achieve Security and Sustainability. *Integrated water management in changing climate to achieve security and sustainability* (In review).

Nyaupane, N., Mote, S., Bhandari, M., Kalra, A. & Ahmad, S. (2018). Rainfall-Runoff Simulation Using Climate Change based Precipitation Prediction in HEC-HMS Model for Irwin Creek, Charlotte, North Carolina. *World Environmental and Water Resources Congress 2018* (In review).

Nyaupane, N., Bhandari, S., Kalra, A., Rahaman, M., Wagner, K., Ahmad, S. & Gupta, R., (2018). Flood Frequency Analysis Using Generalized Extreme Value Distribution and Floodplain Mapping for Hurricane Harvey in Buffalo Bayou. *World Environmental and Water Resources Congress 2018* (In review).

STATISTICAL EVALUATION OF HYDROLOGICAL EXTREMES ON STORMWATER SYSTEMS

MAJOR PROFESSOR: Dr. Ajay Kalra