RESILIENT URBAN DRAINAGE SYSTEM STRATEGIES FOR EXTREME WEATHER

DESIGN FOR THE "NEW NORMAL"

Dr. Thewodros Geberemariam, Ph.D., P.E., BCEE, D.WRE

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Phone: (954) 727-9333
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PREFACE

Recent catastrophic floods—attributed to climate change—underscore the significant challenge that intense precipitation and extreme weather events pose to urban drainage infrastructure. Numerous hydrological studies have explored the potential impact of climate change on these systems, thereby predicting adverse consequences.

Current initiatives to ensure the resilience of urban drainage infrastructure heavily rely on standard design guidelines. These guidelines dictate how infrastructure systems are designed to withstand flooding. However, the increasing frequency and intensity of flooding due to significant storm events have raised questions about the future viability of these methodologies and standards. Thus, policymakers, planners, and design professionals are considering supplementing existing design standards, policies, and regulations to accommodate the "New Normal" of extreme weather.

Resilient Urban Drainage System Strategies for Extreme Weather aims to analyze design practices and strategies that are suitable for extreme weather conditions in the "New Normal" era by focusing on urban drainage infrastructures. It anticipates that *current* stormwater infrastructure and flood management drainage design criteria will remain essential elements of the design process of small watershed components/subsystems. However, at the system/larger watersheds level, it suggests that approaches such as fail-safe, safe-to-fail, and robust decision making (RDM) could enhance existing design approaches. These methods explicitly consider the consequences of failure in the design and risk analysis processes.

This book builds on the concept of resilient urban drainage system design solutions for "New Normal" extreme weather, chapter by chapter. It explores various approaches to improve drainage system design requirements, and each chapter concludes with objective questions that offer a variety of possible answers and real-world practical problems. Intended to be user-friendly, this book aims to foster an appreciation for supplementing existing drainage system design criteria through a simplified approach and underscores the increasing importance of adopting a multi-scalar perspective on resilience to address the escalating challenges faced by urban municipalities. It will be valuable to professionals in the field of drainage, graduate students pursuing their M.Sc. and Ph.D. degrees, and members of the academic community.

ABOUT THE AUTHOR

Dr. Thewodros K. Geberemariam, Ph.D., P.E., D.WRE, BCEE, EXW^{SM}, PMP, LSIT, QPSWPPP, QCIS, ENV SP, M. ASCE, AACPM, has over 25 years of extensive experience in urban infrastructure and water resources engineering. His expertise is designing, analyzing, modeling, and evaluating urban drainage systems and flood control structures. He has been responsible for designing major and minor stormwater drainage conveyance systems, as well as water, sewer, and street improvement projects. He holds a Ph.D. and M.Sc. in Civil Engineering with a specialization in Urban Infrastructure and Water Resources Engineering from the New York University Tandon School of Engineering and the National University School of Engineering and Computing, respectively.

He is a licensed professional engineer in California and New York. Additionally, he is a Board-Certified Environmental Engineer and has been recognized as a Diplomate, Water Resources Engineer by the American Academy of Water Resources Engineers, a Division of the American Society of Civil Engineers (ASCE). He has been certified by the American Council of Engineering Companies as an expert witness in surface water hydrology and hydraulics.

Over the years, he has taught undergraduate and graduate-level courses including hydrology, hydraulic engineering, fluid mechanics, engineering economics, and an introduction to highway design. He has published more than 50 advanced works on modeling, forecasting, asset management, hydrology, hydraulics analysis, and optimization.

Thewodros served as a peer reviewer and a technical advisor for ASCE and his toolbox spans from simple analytical models to the most detailed, complex, numerical, stochastic 3D models, as well as advanced machine learning models. He also has served as a lead technical expert on a wide range of water resources engineering projects, including hydrology and hydraulics analysis, surface hydrology, stormwater best management practices (BMP) design and implementation, water quality monitoring and evaluations, hydroclimate modeling, rainfall-runoff modeling, flood forecasting and control, watershed and floodplain management, and stormwater infrastructure risk analysis. Thewodros also consults on domestic and international water resources engineering projects.

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1

PURPOSE AND SCOPE

1.1 INTRODUCTION

Reliability, risk, and resilience are frequently discussed in drainage system design publications, especially in relation to climate change and increasing urbanization. However, a significant and under-researched disparity exists between theoretical knowledge and the practical implementation of drainage infrastructure by field professionals. Thus, many drainage specialists grapple with understanding a drainage system's response to the "New Normal" of today's extreme weather, which was not considered during its initial design phase.

This gap is further widened by the need to evaluate critical infrastructure for potential disasters of greater magnitude than initially anticipated. This book scrutinizes the relationship between the normalized capacity or drain down/emptying time of various drainage system components and the shape, intensity, duration, and spatial extent of storm events. Other significant factors discussed include climate change and densification. The discussion emphasizes the potential benefits of integrating natural systems and low-impact development or green infrastructure practices into current drainage system design criteria. The goal is to augment the system's capacity to manage extreme weather events, such as fail-safe, safe-to-fail, and robust decision making (RDM) in specific situations.

A crucial aspect of resilience measures in urban drainage infrastructure systems is the incorporation of design storm criteria. These criteria specify the intensity or frequency that the systems are built to withstand. Factors such as climate change and the increasing complexity of urban systems are challenging the sustainability of current methods and the implementation of design storm criteria.

This book seeks to identify design methodologies and approaches that are suitable for the operational environments of modern cities and infrastructure, which are becoming increasingly complex and dynamic. To effectively address the challenges faced by drainage infrastructure systems in large municipalities, it is essential to adopt a multi-scalar perspective on resilience. This approach will significantly contribute to addressing these issues comprehensively. It is expected that the inclusion of return periods (or similar criteria) will remain necessary during the design process for individual components or subsystems. The current methodologies can be enhanced by incorporating the consideration of failure effects into the design and management processes. Approaches such as safe-to-fail and RDM appear particularly apt for addressing the needs of the entire system(s).

1.2 DESIGN FOR THE "NEW NORMAL"

Coastal and rural villages are increasingly experiencing submersion in water. These extreme weather events and rising sea levels can be attributed to the impacts of climate change. Extreme precipitation and weather events pose a threat to urban infrastructure systems, as demonstrated by recent catastrophic flooding disasters. According to design professionals and policymakers, urban infrastructure design has had to adapt to the "New Normal" of extreme weather. A crucial aspect of resilience initiatives in urban and infrastructure systems is the accurate determination of the frequency and intensity of extreme weather events that these systems are designed to withstand.

This textbook aims to delineate effective design methods and strategies to address the challenges posed by extreme weather conditions on local municipalities, infrastructure, and cities. To effectively mitigate the escalating challenges faced by cities and infrastructure systems, it is crucial to adopt a holistic approach that integrates various resilience levels. The existing stormwater infrastructure and flood control drainage standards are expected to continue being vital considerations for design input at the individual component and subsystem levels. At the system level, techniques such as safe-to-fail and RDM seem highly appropriate for enhancing current practices by explicitly considering the impact of failures during the design and risk analysis stages.

Presently, urban drainage system design textbooks and stormwater runoff management guidelines lack guidance on accommodating increased runoff resulting from more intense storm events. This book aims to provide advanced instruction on the fundamental principles of resilience in urban stormwater management within the "New Normal" framework, thereby enhancing existing design standards to accommodate the challenges posed by increasingly severe weather conditions.

1.3 OBJECTIVES

This book has four primary objectives:

1. Delineate effective design methods and strategies to address the challenges posed by extreme weather conditions that are being experienced by local municipalities and city infrastructure in the "New Normal" era.
2. Assist design professionals in developing innovative solutions that align with the existing drainage system design standards for extreme weather conditions.
3. Enhance existing large-scale drainage systems and establish preliminary strategies such as safe-to-fail and RDM that consider the consequences of failure during the design and management phases.
4. Provide suggestions on design principles and methods for integrating extreme weather into urban drainage practices. The significant gap between theory and practical application in incorporating extreme weather into urban drainage practice needs to be highlighted. This gap motivates the need to evaluate elements like *essential infrastructure* for disasters that are

significantly more severe than previously imagined. This book aims to bridge this crucial gap using fundamental and straight-forward methods.

1.4 DISTINCTIVE FEATURES OF THE BOOK

The distinctive features of this book include:

1. Adopting contemporary subjects, including RDM, safe-to-fail, and enhanced modeling and sensing techniques
2. Attempting to clearly incorporate failure effects into the design and management processes while demonstrating alternative solutions to supplement current design methodologies
3. Using simple and fundamental methods to bridge the critical design gap related to extreme weather
4. Employing a data-driven approach to differentiate between meteorological and climate factors that influence extreme rainfall
5. Primarily focusing on the effort to construct urban drainage systems that are resilient to extreme weather
6. Offering recommendations on risk assessment techniques to analyze the likelihood and effects of drainage excess
7. Detailing suggestions for layout and planning to mitigate the effects of drainage system overflow
8. Providing best practice advice for designing urban drainage systems capable of sustainably handling periods of excess

2

EXTREME WEATHER DUE TO CLIMATE CHANGE

2.1 INTRODUCTION

Climate change poses numerous challenges to city municipalities. Consequently, governments should articulate a new vision of resilience and sustainability that aligns with the interests of economies, ecosystems, and communities in the era of "New Normal" extreme weather due to climate change.

The shifting climate influences the variability of weather and climatic events, resulting in unprecedented extremes in frequency, intensity, spatial extent, duration, and timing. Weather or climate occurrences can give rise to extreme circumstances or effects, even if they do not exhibit statistical exceptionalism. This can occur either by surpassing a critical threshold in a social, ecological, or physical system or by coinciding with other events. Certain climate extremes, such as droughts and floods, could potentially arise from the convergence of various weather or climate phenomena that may not exhibit significant extremity when considered individually. The potential impact of a weather system, such as a tropical cyclone, can vary depending on its landfall location and timing. Even if the storm's intensity is not exceptionally severe relative to other tropical storms, it can still have significant consequences. However, not all extremes necessarily result in negative consequences. The correlation between changes in extremes and changes in mean climate can be attributed to the prediction that future conditions for certain variables will fall within the margins of present-day conditions. Natural climate variability, encompassing events such as significant flooding, is responsible for numerous instances of extreme weather and climate conditions. Additionally, natural climate oscillations occurring over multiple years or decades provide a contextual backdrop for anthropogenic climate change. Even in the absence of anthropogenic climate change, a significant spectrum of natural weather and climatic extremes would persist.

Climate change and its far-reaching consequences represent some of the most pressing global challenges we will face this century. In recent years, there has been a rapid increase in the pace of change. Between 1995 and 2005, there was a notable 20% spike in the amount of atmospheric carbon dioxide. According to the Intergovernmental Panel on Climate Change (IPCC 2007), the same period has witnessed 11 of the highest recorded temperatures since data collection began in 1850. The hydrologic cycle, also known as the water cycle, is influenced by the increase in global mean temperatures. According to the United Nations IPCC, hydrologic change is classified as *highly probable*, leading to an increase in instances of heavy precipitation (2007). This transition will significantly impact infrastructures and urban landscapes. Urban areas worldwide have encountered numerous instances of flooding in recent years, primarily due to substantial precipitation. It is expected that there will be an increased occurrence of torrential downpours in the future, which may result in additional harm to individuals and infrastructure. Conducting an analysis of the potential impacts of temperature and precipitation changes on urban drainage systems, as well as exploring strategies for implementing flood mitigation measures, is of the utmost importance in preventing adverse consequences. The purpose of this chapter is to provide an overview of various techniques and research findings that are related to the simulation of altered precipitation effects on urban drainage systems.

2.2 MODELING CLIMATE CHANGE

Climate models are intricate data models that simulate planetary behavior by incorporating mathematical representations of the climate system and the interactions of its various components. These models integrate inputs from multiple emission scenarios, which encompass a range of assumptions, including factors such as population, energy demand, and land use. The measurement of radiatively significant gas emissions plays a pivotal role in these climate models.

Regional climate models (RCMs) leverage data from global models to provide a detailed analysis of specific geographical areas. The IPCC has proposed approximately 40 scenarios, which can be categorized into different scenario families. The Rossby Centre, a part of the Swedish Meteorological and Hydrological Institute, developed RCA3, the latest regional atmospheric climate model in Sweden. RCA3 incorporates inputs from the European Centre Hamburg Model Version 4 (ECHAM4). The RCA3 model generates output data for a simulation period of 140 years, with a spatial resolution of 50 by 50 kilometers and a temporal resolution of 30 minutes. Given its superior temporal resolution relative to most previous climate models, it is better equipped to capture short-term rainfall patterns.

Climate models are often used to represent emissions scenarios individually. A plausible scenario is one that holds credibility, even if it may not necessarily exhibit a significant likelihood. Each model run is based on a specific greenhouse gas (GHG) emissions scenario. Even when using the same GHG emission assumptions, different climate models will yield varying forecasts of changes in the global and regional climate. However, each run of a climate model can be considered a reasonable projection of potential climate change. Given the wide array of emissions scenarios and models available, experts can provide a set of climate change scenarios (climate model runs) as the most reliable means to predict potential impacts. Using a variety of scenarios to represent a reasonable range of climate-related uncertainty is a useful general guideline. It is important to record a broad range of crucial variables, such as temperature and precipitation.

Hence, it is advisable to consider scenarios that encompass a diverse range of potential changes in precipitation patterns, especially when addressing climate change concerns. However, obtaining valuable precipitation data from climate models can be challenging. Thus, assessments of climate change impacts on climatic variables, such as increased precipitation, often rely on simulations conducted using climate models, specifically atmosphere-ocean circulation models, including general circulation models (GCMs) and RCMs.

During specific time intervals of the global simulation, RCMs can utilize initial and boundary conditions derived from the output of GCMs, a process known as *dynamic downscaling*. Currently, there is no mechanism for transmitting input from the RCM simulation to the driving GCM, resulting in a unidirectional nature of this technique. The primary role of the GCM in this simulation methodology is to accurately represent the global circulation system's response to significant external stimuli. The RCM enhances the accuracy of simulating climatic variables at smaller spatial scales by incorporating finer-scale influences, such as topographical features. However, there is a lack of comprehensive understanding regarding the complex mechanisms responsible for precipitation formation, especially considering its generation at both fine spatial and temporal scales.

Incorporating these processes into regional and global climate models presents challenges for experts. The limitations of numerical stability and computational efficiency restrict the ability to address local, short-lived precipitation-generating mechanisms, consequently limiting the temporal and spatial scales that can be incorporated into models. Therefore, there is a current constraint on the extent to which dynamic downscaling can be employed while maintaining accurate outcomes. It is important to note that the anticipated intensities of severe precipitation often exhibit a systematic bias, specifically being underestimated, due to the process of dynamic downscaling.

Most RCM simulations are currently available with daily temporal resolution and spatial resolution ranging between 25 and 50 km. Additionally, certain RCM simulations are also available with hourly temporal resolution and a spatial resolution of 10 km. Occasionally, higher resolutions can be achieved by incorporating statistical downscaling techniques into dynamic simulations, allowing for the inclusion of a bias correction as an integral part of the RCM simulation. Some RCMs possess high resolution but may lack the capability to accurately represent the intricate surface dynamics within heterogeneous regions. In these circumstances, it is recommended to use data from lower resolution climate models along with an additional statistical downscaling step for a more effective approach.

2.2.1 The Process of Formulating Climate Change Scenarios

Climate change effects can be divided into two broad approaches, depending on the method used to determine the projected direction and potential magnitude of climate change in the specific area under study. One approach involves the use of artificial climate change scenarios, where the historical average temperature and precipitation are intentionally altered by predetermined amounts on an annual, seasonal, or monthly basis. This approach mitigates the inherent uncertainties associated with GCMs and enables the application of sensitivity analysis. Sensitivity analysis is a useful tool for assessing the magnitude of climate change required to trigger significant impacts. The model calculates the potential impact on a hydrological variable due to a sequence of incremental changes in a climatic variable.

The observed changes in climatic variables may not necessarily indicate the direct consequences of increased concentrations of GHGs in the atmosphere. This limitation represents an inherent disadvantage associated with the generation of synthetic scenarios. This issue can be addressed by determining the magnitudes of change based on relevant data rather than selecting them arbitrarily. This may involve considering variations in historical data or evaluating the range of changes predicted by RCMs. The level of variability in the scenario remains unchanged when the adjustments are applied to historical climate data. This raises a concern since the impact of climate change is anticipated to affect variability, particularly in relation to precipitation patterns. The daily scaling method was devised as a solution to address this concern by integrating change factors into the analysis of historical precipitation data. In this methodology, the factors of change are determined based on the proportional magnitude of the event rather than maintaining a constant value across all years, seasons, or months.

An alternative approach to developing climate change scenarios involves utilizing one or more GHG emission scenarios, typically sourced from the IPCC Special Report on Emissions Scenarios. GCMs employ these scenarios to drive extensive simulations of the interrelated ocean-atmosphere system, allowing for the prediction of the climate's reaction to the expected increase in GHG concentrations. To enhance the applicability of these models for hydrological applications, downsizing is required for their outputs. For this task, we can employ an RCM that takes into account local topography and other climate parameters or a statistical downscaling strategy that modifies past climate records to reflect anticipated future changes.

2.2.2 Analysis of Flooding and Disaggregation of Rainfall

Urban drainage models are crucial tools for assessing the impact of climate change on urban drainage systems. These models aid in understanding and predicting how climate change scenarios will affect the functioning of urban drainage systems. By using these models, we can generate estimates and projections that provide valuable insights into the potential consequences of climate change on urban drainage. The output time series of the climate model can be directly inputted into the drainage model to achieve this. Statistical downscaling is necessary for the urban drainage model.

Implementing regular corrections can help mitigate consistently divergent drainage outcomes in control simulations relative to those achieved after calibrating the drainage model. At the target point locations, climate model grid data can be downscaled using a variety of dynamic and statistical downscaling techniques. The application of the delta-change factor (also known as perturbation factors) is a straightforward technique for scaling up gridded climate forecasts to station scale. Delta-change variables have been used to design storm depth and precipitation time series.

This approach utilizes climate elements, often referred to as delta-change factors, to modify the model input based on historical observations or hypothetical design storms. To accommodate this disturbance, adjustments to the quantity of rainstorm events and the probability distribution of their intensities are necessary. Time resolution plays a critical role in flood analysis, making it imperative to convert daily rainfall data into hourly rainfall data. The daily time scale can be subdivided into hourly units through various methodologies. Numerous stochastic downscaling approaches have been developed to further refine the RCM output temporally and transfer it to the spatial point scale. The combination of these interconnected models allows for the assessment of the impact of climate variability on the performance of sewer systems, specifically in relation to flooding events. Due to their limited capacity to reproduce extreme events, alternative downscaling strategies, such as weather typing or regression-based methods, have been found to be inadequate for this specific application.

2.2.3 Statistical Downscaling

The imprecise resolution and variability in precipitation outcomes from climate models necessitate a statistical model. This model correlates larger-scale atmospheric conditions (the *predictor* variables) with finer-scale rainfall patterns (the *predictand* variable), considering spatial and temporal aspects. The model, which incorporates bias correction and statistical downscaling techniques, relies on historical data. It assumes that transferring information from predictors to predictands will not significantly alter outcomes due to climatic variations. To generate data comparable to historical rainfall patterns, statistical downscaling is employed. This technique scales down climate model outputs, both spatially and temporally, to match the scale needed for urban hydrological impact modeling. The downscaling process further refines the data to accurately represent point rainfall. Existing statistical downscaling techniques fall into three categories: empirical transfer function-based methods, resampling techniques-based methods, and conditional probability or stochastic modeling-based methods.

2.2.4 Methods Using Empirical Transfer Functions

Empirical transfer function-based techniques utilize the empirical relations or transfer functions between the precipitation predictand and its predictors. The statistical downscaling method proposed by Wilby et al. (2002), based on regression analysis, is well-recognized. Variables such as mean sea-level pressure, geopotential height, zonal wind speed and direction, specific or relative humidity, surface upward latent heat flux, temperature, dewpoint temperature, and dewpoint temperature depression have shown a strong correlation with small-scale precipitation at a daily or sub-daily level. This correlation suggests a relationship between these variables and the atmosphere's water vapor saturation level. Various geographical factors, including elevation, proximity to the coastline (diffusive continentality), advective continentality, and topographical slope, are believed to influence the vertical movement of the incoming air mass, potentially resulting in cooling and precipitation due to mountains.

Transfer functions such as generalized linear models, equations derived from rainfall time scaling principles, and artificial neural networks have been explored as regression relations. In urban drainage effect models that use continuous time series simulation and post-processing of simulation results, it is standard to downscale the values in each time step to generate a rainfall time series. This downscaled time series is typically used in impact analysis of sewer overflows on receiving rivers. One approach involves preprocessing the time series data for both the predictor and predictand variables to derive relevant statistics, such as empirical frequency distributions or calibrated probability distributions, at specific time and space scales. Transfer functions can then be established between these statistics or distributions. Using artificial storms for specific storm frequencies or return periods can be beneficial in impact studies related to sewer surcharging or floods.

An alternative approach integrates a commonly used statistical downscaling model for spatial downscaling. This model links large-scale climate variables from GCM simulations with daily extreme precipitation events at a specific local site. Additionally, generalized extreme value (GEV) distribution is used for temporal downscaling to describe relationships between daily and sub-daily extreme precipitation occurrences. T. Nguyen and V. Nguyen (2018) used GCM climate simulations, National Centers for Environmental Prediction reanalysis data, and daily and sub-daily rainfall data from various rain gauges in Quebec, Canada, to validate this spatial-temporal downscaling approach. Adequate agreement with observed daily values at the site can be achieved by applying a bias-correction adjustment, based on a second-order polynomial function, to the annual maximum daily rainfall downscaled from the GCM. Following the collection of bias-corrected downscaled yearly maximum daily rainfalls at a specific location, T. Nguyen and V. Nguyen used a GEV distribution to further downscale sub-daily maximum rainfall intensities.

Probability distributions for rainfall intensities at sub-daily time scales (such as 5-, 15-, 30-minute, or hourly intervals) can be accurately determined by leveraging the distribution of daily rainfall intensities. This is achieved by applying the concept of scale invariance, where the moments of rainfall distribution (specifically, GEV distribution) are influenced by the time scale and its scaling properties. Introducing a dependency of the transfer function on RCM process variables, which include weather conditions such as cloud cover and precipitation type, could facilitate further advancements. To determine the wet proportion associated with different types of precipitation, researchers analyzed 30-minute measurements of various factors related to cloud cover. The average precipitation for the grid box was then converted into a local intensity, with an associated occurrence probability at each specific grid box point. It is important to note that the projected local intensity, type of precipitation, and cloud cover predicted by the RCM are subject to uncertainty. However, an evaluation conducted in Stockholm, Sweden, demonstrated that the technique aligns well with both empirical observations and theoretical considerations.

2.2.5 Strategies for Weather Typing or Resampling

Resampling, also known as weather typing, is a key component in some statistical downscaling methodologies. These methodologies use historical time series data of the region's rainfall predictand and coarse-scale climate predictor factors to obtain downscaled projected precipitation values. To determine downscaled future rainfall, the historical series of climatic variables are examined for each future event, such as a specific day, in the climate model output. This involves searching for a similar circumstance or analog event in the historical data. The small-scale precipitation observation corresponding to that particular occurrence is then considered as the downscaled future rainfall. Pressure fields derived from climate models are often used as predictive variables. Various types of weather are classified based on pressure fields using a categorization scheme.

2.2.6 Stochastic Models for Rainfall

The third category of statistical downscaling can be seen as an extension of stochastic hydrology. Stochastic rainfall models, mathematical constructs used for simulating and predicting rainfall patterns, use random variables and probability distributions to account for the inherent uncertainty and variability in rainfall data. These distributions are conditioned on the coarse-scale climatic predictor. The parameters of the stochastic model are derived from statistical analysis of time series data and can be adjusted based on climate model simulation results. Stochastic rainfall models are often referred to as *weather generators*.

Stochastic rainfall models employ a two-step process. First, the rainfall generator captures the structure of hourly storms. Then, the hourly rainfalls are refined to finer scales using a multi-scaling-based disaggregation approach. When transitioning from RCMs to urban catchment scales, delta-change techniques are commonly used. They involve identifying characteristics or variables assumed to remain consistent across different scales.

2.2.7 Variability in Hydrology

Climate change is expected to influence both the variability and average hydrology. Regions with minimal annual runoff variations may experience more frequent unusually low or high flow levels. Arnell (2003) assessed the potential impact of climate change on hydrological variability in six UK basins. The study revealed a slight increase in average monthly flow and a decrease in low flow levels by up to 40% by the 2080s. Additionally, there was an observed increase in year-to-year hydrological pattern fluctuations. The intensification of flooding, linked to climate change, is a significant concern worldwide, particularly in countries at lower elevations in tropical and humid mid-latitude zones. Major floods in significant river basins worldwide have increased. Kleinen and Petschel-Held (2007) found that approximately 20% of the global population lives in river basins that may experience more frequent flooding due to climate change. This was determined by applying statistically downscaled climate change projections to a water balance equation. Palmer et al. (2002) projected a five-fold increase in monsoons in Asia and heavy winter rainfall events in the UK. Lehner et al. (2006) also projected an increase in flood frequency in their continental-scale modeling analysis.

Kundzewicz et al. (2005) suggested that anthropogenic climate change might have contributed to previous large floods in central Europe and could influence future ones. Kay et al. (2006) observed increases in flood frequency and amplitude in most of their 15 UK study basins using a conceptual model driven by high-resolution RCM outputs into the 2080s. Despite a decline in mean annual runoff, Evans and Schreider (2002) observed an increase in flood size in six Australian basins using a conceptual hydrological model driven by stochastic weather generator output. Due to changes in temperature and precipitation, Mote et al. (2003) predicted an increase in winter floods in smaller, rainfall-dominated, transitory basins in the Pacific Northwest.

2.3 UNCERTAINTIES IN THE ANALYSIS OF CLIMATE CHANGE EFFECTS

Uncertainty in climate change impact studies often stems from various sources, including climate model projections, hydrology models, and data downscaling methods. The primary sources of uncertainty in climate model projections are internal variability, external forces, and model response. Uncertainties associated with climate variability and its prediction can be categorized into four groups: emissions scenario uncertainty, GCM uncertainty, downscaling uncertainty, and internal climate variability uncertainty. The design of drainage systems, which depends on extremely high amounts of precipitation occurring over a short period, can introduce sampling error. The uncertainty surrounding future urban development further complicates drainage system design. Consequently, higher population densities could alter the runoff coefficient in the future.

2.3.1 Climate Variability and Prediction Uncertainties

Models serve as the primary tool for projecting future climate change, enabling informed decisions about resilience initiatives related to climate change-induced drainage infrastructure. Therefore, it is crucial to characterize and quantify the uncertainty in climate change projections. These projections should be interpreted cautiously until the models can accurately reproduce historical temperature and precipitation ranges. In general, future climate change variability and prediction are uncertain due to model response, internal variability, and external forces. Model uncertainty arises from variations in physical and numerical formulations, leading to divergent responses among different models when subjected to identical external forces. Internal variability refers to the natural fluctuations within the climate system that occur in the absence of any external influences or forces. This encompasses a range of processes, including those related to the atmosphere, oceans, and their interaction. Uncertainty arises from an incomplete understanding of external factors that impact the climate system, such as future GHG emissions, stratospheric ozone levels, and changes in land use. This section provides a succinct overview of downscaling sampling and model uncertainties in hydrology.

2.3.1.1 Downscaling Sampling Uncertainty

The stochastic downscaling technique can generate a precipitation series of any length. Research shows that using a lengthy stochastic precipitation series instead of short observed samples can reduce sampling error in sewer system design:

1. The stochastic downscaling model can replicate all statistical features of precipitation with high precision, particularly those associated with extreme events.
2. The precipitation process exhibits annual consistency, assuming that the stochastic downscaling model does not explicitly account for inter-annual climate variability.
3. Sampling error is minimal when obtaining statistics from the observed precipitation series that was used to calibrate the stochastic downscaling model.

2.3.1.2 Model Uncertainties Related to Hydrology

Choosing a hydrological model in a climate impact assessment introduces additional uncertainty. Hydrological models can replicate runoff at various spatial and temporal scales due to variations in their parameters and underlying assumptions. To account for the socioeconomic components of the hydrological system where additional uncertainty may exist, practitioners can use results from hydrological models when preparing water resource management models. These include models of water demand, dam and reservoir storage, or policies promoting efficiency and conservation. Assumptions are necessary at every stage of the modeling chain; errors are inevitable and increase uncertainty in the modeling process.

2.4 FACTORS ACCELERATING EFFECTS ON URBAN DRAINAGE SYSTEMS

Research using climate change projections suggests that heavy precipitation events are expected to increase in both frequency and intensity. Numerous studies have found that areas with more impervious surfaces and higher rainfall experience more flash floods, flooding, and high peak flows. To manage stormwater effectively in the face of climate change, it is essential to establish a scientific method for comparing the impacts of global warming and urbanization on local precipitation. Local weather and climate are considered throughout the planning stages of stormwater management. However, the amount of stormwater runoff that must be managed can be significantly influenced by climatic changes, such as the number, frequency, and intensity of rain events, as well as land development.

Certain areas of developing countries may be particularly vulnerable to stormwater-related floods due to the combined effects of climate change and land-use change, while other parts of the world may remain mostly unaffected. Past anthropocentric approaches to stormwater management have had severe ecological consequences. The recent boom in suburbanization has contributed to both climate change and the loss of forested and agricultural land. Local hydrological cycles have been affected by increased surface runoff and decreased base flow, interflow, and depression storage. Several studies have linked impermeable surfaces to a 50% increase in surface water runoff and a 50% reduction in deep water penetration.

2.5 CLIMATE CHANGE AND FLOODING DUE TO EXTREME WEATHER EVENTS OR THE "NEW NORMAL"

The ongoing impact of global climate change has led to a noticeable increase in the occurrence of floods due to intensified variability in weather patterns. The modification of land cover, including the reduction of vegetation and the impact of climate change, exacerbates flood susceptibility. Extreme floods can occur due to various factors, including intense precipitation, prolonged duration, frequent precipitation, or a combination of these elements. An increasing number of coastal and rural villages are becoming submerged in water.

The recognition of climate change impacts, such as severe weather events and rising sea levels, is becoming increasingly prevalent. Floods occur when inland bodies of water, such as rivers and streams, tidal waters, or an excessive accumulation of water due to factors like intense precipitation or the failure of dams or levees, become inundated. Table 2.1 provides a comprehensive overview of various types of flooding, along with their corresponding descriptions.

Table 2.1 Types of main floods caused by climate change

1.	River inundation	Typically, arid land experiences inundation when a river or stream exceeds its regular boundaries. River flooding occurs most frequently during the late winter and early spring seasons. Potential causes include ice jams, heavy precipitation, or rapid snowmelt.
2.	Coastal inundation	This phenomenon occurs when elevated or increasing tides, storm surges, or coastal winds generated by a weather event (e.g., a hurricane) propel a significant volume of water from the ocean onto the adjacent land, resulting in the submergence or inundation of areas that are typically dry along the coast.
3.	Flash floods	The primary cause of these rapidly escalating floods is intense precipitation that typically occurs within a short duration, usually lasting no more than six hours. Flash floods can occur in various areas, although areas with insufficient drainage and lower elevations are more prone to their occurrence. Flash floods can occur as a consequence of dam or levee failures, abrupt water surges caused by debris or ice blockages, or other incidents that combine the inherent hazards of a flood with rapidity and unpredictability. They are responsible for the highest number of fatalities resulting from flooding incidents.
4.	Urban flooding	Urban flooding arises when the amount of rainfall surpasses the capability of drainage systems, such as storm sewers, to handle it. This can also occur when the expansion of roads, parking lots, and other impermeable surfaces in urban areas prevents water from infiltrating into the ground. The development and urbanization of an area, including the increase in pavement and other impermeable surfaces, typically leads to a reduction in the time it takes for water to flow through the hydrologic system.

2.5.1 How Global Warming Affects Precipitation

Changes in rainfall and other types of precipitation are among the most important aspects in evaluating the overall impact of climate change. Increased evaporation due to rising temperatures causes more severe precipitation. Average global precipitation has increased along with rising average global temperatures. Since the 1950s, extreme precipitation events have increased in frequency and caused heavier rain in many parts of the world. The Midwest and Northeast sections of the United States have seen the largest increases in heavy precipitation occurrences. These tendencies will persist as the world continues to warm. More water vapor can be held in warmer air—the air's capacity for water vapor increases by around 7% for every degree of heat. Higher intense precipitation episodes can result from an atmosphere with more moisture, and this is exactly what has been observed.

2.5.2 Rainfall Analysis

Outcomes of rainfall analyses significantly influence the design of urban drainage systems. The initial hydrologic study phase involves evaluating and predicting the expected precipitation levels within the designated study period. The following factors are significant in the context of urban drainage system design:

- *Rainfall duration*: how long a storm lasts
- *Frequency*: how often rainfall occurs at a particular amount, intensity, and duration
- *Rainfall depth to intensity*: rainfall depth divided by duration
- *Rainfall distribution*: the cumulative temporal and spatial distributions of rainfall across an area during a storm

2.6 AVERAGE RAINFALL CALCULATIONS

Rainfall depths observed at specific locations within the watershed are used to estimate the variation in rainfall depth over an area. Without a high density of rain gauges, it is typically impossible to accurately estimate the rainfall pattern and average values of rainfall depths. Rainfall recording has several levels of precision. The most precise recordings come from first-order weather service stations, which generate a continuous time-depth sequence that is often converted to an hourly sequence. The hydrologic network's recording-gauge data, provided for clock-hour intervals, rank second. These are transformed to produce hourly data. Nonrecording gauges, which measure daily rainfall depths, are also available.

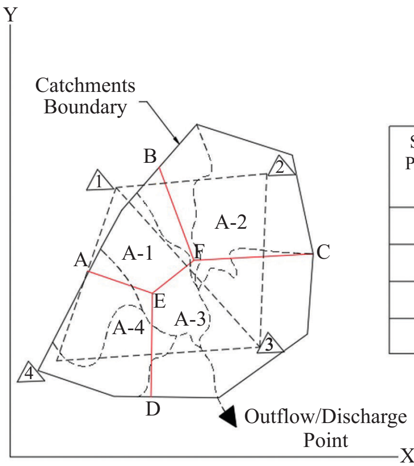
Most of the time, the average depth of precipitation over the watershed is calculated using information gathered from specific gauging stations dispersed across a region. For a particular rainfall event, the average rainfall depth over a watershed can be calculated in three ways:

1. *Gauging station method*: Also known as an arithmetic average, this method is used in data analysis to determine the average value of a set of numerical measurements. This method produces accurate estimates when the terrain is level, the gauges are evenly spaced, and the individual gauge catches deviate minimally from the average. This approach involves collecting data on annual precipitation from multiple stations in the designated region. It offers a simple method for calculating the average precipitation in a specific catchment area. This is achieved by aggregating the recorded annual precipitation from all stations and dividing it by the total number of stations, as in Equation 2.1:

$$P_{ave} = \frac{1}{n}\left[p_1 + p_2 + p_3 \ldots\ldots\ldots p_n\right] = \frac{1}{n}\left(\sum_{i=1}^{n} p_i\right), \qquad (2.1)$$

   where N is the total number of stations and P_i is the mean annual precipitation at the ith station.
2. *Thiessen polygon method*: This method involves delineating polygon lines on a map by connecting neighboring rainfall gauge locations, which form equilateral triangles. The polygons around each station are created by the perpendicular bisectors of these lines. The area of each polygon is calculated through planimetry and expressed as a percentage of the total area. Each gauge is assigned a specific weight. The weighted average rainfall for the entire area is computed by multiplying the precipitation recorded at each station by its corresponding area percentage and summing these values. The results from this method are considered more reliable than those from

basic arithmetic averaging. Figure 2.1 illustrates the geometrical construction of this method and the area-based weighting applied to the rainfall value at each station.



Station Polygon Index	Sub Catchments Boundary	Sub Catchments Area	Observed Annual Precipitation
1	AEFB	A-1	P_1
2	BFC	A-2	P_2
3	DEFC	A-3	P_3
4	AED	A-4	P_4

n Precipitation Gauge Station

Figure 2.1 Geometrical construction of the Thiessen polygon method

In this method, the practitioner selects a consistent scale for the X and Y axes and draws the catchment area's boundary and the location of each station. Polygons are created by connecting adjacent stations and drawing perpendicular bisectors between them. The area of each polygon is determined by the sum of its box counts. The next step involves calculating the product of $p_1 A_1$ and summing all the products. The average precipitation can then be calculated as shown in Equation 2.2:

$$P_{ave} = \frac{p_1 A_1 + p_2 A_2 + p_3 A_3 \dots \dots p_n A_n}{A_1 + A_2 + A_3 \dots \dots \dots . + A_n}, \qquad (2.2)$$

where N is the number of polygons in the catchment area, P_n is the observed annual rainfall for the ith polygon, and A_n is the area of the ith polygon.

3. *Isohyetal method*: This method involves plotting the locations and values of stations on a map and delineating contours

representing equal precipitation levels (isohyets), as shown in Figure 2.2. The average precipitation over an area is computed by multiplying the average precipitation between successive isohyets by the watershed area located between these isohyets, summing these products, and dividing the sum by the total area.

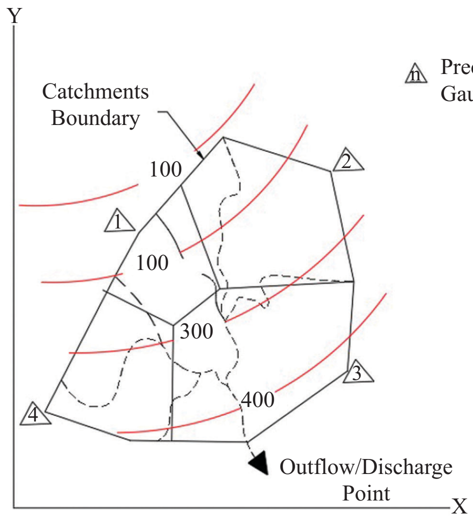


Figure 2.2 Representative contour map area of the isohyetal method

In this method, the first step is to select a consistent scale for the X and Y axes. The second step involves drawing the catchment area's boundary and the location of each station. The third step is to determine the rainfall amount at each station and the appropriate contour interval and number of isohyets. The fourth and fifth steps involve drawing isohyets between stations using linear interpolation and calculating the distance between two consecutive isohyets. The product $P_i A_i$ is then calculated. The average precipitation can be calculated using Equation 2.3:

$$\bar{p} = \frac{\sum_{i=1}^{n} A_i \frac{(p_i + p_{i+1})}{2}}{(A_1 + A_2 + A_3 + \ldots A_n)}. \tag{2.3}$$

2.6.1 Estimating Missing Rainfall Data

Brief lapses in precipitation recordings at some stations may occur due to the observer's absence or equipment malfunction. It is typically necessary to estimate this gap in the record. The estimation of missing data can be achieved using the methods outlined in the following sections.

2.6.1.1 Arithmetic Mean or Local Mean Method

This method uses simultaneous rainfall data from three nearby stations that are evenly distributed around the station with the missing records. The estimated value of the missing data is obtained by taking a simple arithmetic average of the rainfall at the three selected stations. This technique can be used to compute missing monthly and annual rainfall values. This method may only be used when the yearly precipitation at each station is within 10% of the station without records, as shown in Equation 2.4:

$$P_x = \frac{1}{N}\left[p_1 + p_2 + p_3 \ldots\ldots\ldots p_n\right] = \frac{1}{N}\sum_{i=1}^{N} p_i, \tag{2.4}$$

where p_x is the average annual precipitation at X station, p_i is the annual precipitation recorded at the i^{th} rain gauge station in the catchment, and N is the total number of rain gauges.

2.6.1.2 Normal Ratio Method

The normal ratio (NR) method involves assigning weights to rainfall data based on the ratios of normal annual rainfall values. This is applicable when the normal annual rainfall of a selected station constitutes 10% or more of the station with missing records, and the simple average method is not suitable; refer to Equation 2.5:

$$P_x = \frac{N_x}{m}\left[\frac{p_1}{N_1} + \frac{p_2}{N_2} + \frac{p_3}{N_3} \ldots\ldots\ldots . \frac{p_m}{N_m}\right]. \tag{2.5}$$

where p_x is the missing annual precipitation at x station, $p_1, p_2, \ldots, p_m$ are the annual precipitation at 1, 2 . . . , m stations, N_x is the normal annual precipitation at the stations around x, and N_1, $N_2, \ldots, N_m$ are the normal annual precipitation at the 1, 2, . . . , m stations.

2.6.1.3 Modified NR Method

The modified NR method can account for the influence of distance when estimating missing precipitation data; refer to Equation 2.6:

$$P_x = \frac{\sum_{i=1}^{n} D_i^{1/b} \left(\frac{\overline{p}_x}{\overline{p}_i} \right)}{\sum_{i=1}^{n} D_i^{1/b}}, \tag{2.6}$$

where P_x is normal rainfall, D_i is the distance between the index station i and the gauge station with missing data or ungauged station, n is the number of index stations, and b is the constant by which the distance is weighted (normally 1.5–2.0; commonly using $D^{0.5}$).

2.6.1.4 Inverse Distance Method

Among the methods discussed, the inverse distance method is recommended as the most accurate. The estimated rainfall at a location depends on the rainfall measured at surrounding index stations and the distance from the ungauged location to each index station. Rainfall P_x at station x is calculated using Equation 2.7:

$$P_x = \frac{\sum_{i=1}^{N} \frac{1}{d^2}\, p_i}{\sum_{i=1}^{N} \frac{1}{d^2}}, \tag{2.7}$$

where P_x is the estimate of rainfall for the ungauged station, P_i is rainfall values of rain gauges used for estimation, D_i is the distance from each location of the point being estimated, and N is the number of surrounding stations. Moreover, $d = 2$ is commonly used. Given that the weighting in the inverse distance approach is dependent on distance, this method is not suitable for use in hilly areas.

2.6.1.5 Linear Programming Method

The linear programming (LP) method involves selecting a base station and multiple adjacent index stations to determine the optimal weighting factor. This is achieved by minimizing the difference between observed and computed rainfall at the base station across various rainfall events. The method computes the optimal weighting factors for the base station and its associated index stations, aiming to minimize the total sum of deviations for a set of K events; refer to Equations 2.8 and 2.9:

$$\sum_{j=1}^{k}\left(U_j + V_j\right), \tag{2.8}$$

subjected to

$$\sum_{i=1}^{n}\left(a_i r_{ij} - U_j + V_j\right) = r_{bj}\ (j = 1,2, \dots \dots \dots K), \tag{2.9}$$

$$\textstyle\sum_{i=1}^{n} a_i = 1.0 \text{ (sum of weights is 1)},$$

$$a_i \geq 0, \qquad U_j \geq 0, \qquad V_j \geq 0,$$

where i is the index station, j represents the index for rainfall events, and b represents the observed rainfall at base station b for event j. $\sum_{i=1}^{n}\left(a_i r_{ij}\right)$ calculates the amount of rainfall at the base station for event j.

For any event, $CR - OR = \delta$, where CR is the computed rain, OR is the observed rain, and δ is the deviation. The outcome can be positive or negative without any restrictions on its sign. In LP, these variables are substituted with the difference between two nonnegative variables.

2.6.2 Depth-Area-Duration Relation

Depth-area-duration (DAD) describes the relationship between the area distribution of a storm and its duration. A DAD analysis assesses the maximum rainfall quantities across different durations and areas during a storm. Analyzing and processing raw rainfall records in the region can yield valuable information in the form of curves or statistical values, which is useful for water resource development projects. It is crucial to analyze the temporal and spatial patterns of storm precipitation to address various hydrologic issues. The average depth of rainfall decreases exponentially with increasing area for a given rainfall duration; refer to Equation 2.10:

$$\bar{P} = P_o e^{-(KA^n)}, \tag{2.10}$$

where P is the average depth, measured in centimeters, across a given area (A) in km^2 and P_o is the maximum recorded rainfall in centimeters at the center of the storm; k and n are constants that remain fixed within a specific region.

Preparing DAD curves requires considerable computational effort and depends on the availability of region-specific meteorological and topographical information. Generally, these are the steps that are followed:

1. Analyze the historical precipitation data for the geographical area where the catchment area that is under consideration is located, considering records from places with similar meteorological conditions.
2. Compile a detailed list of the most severe storms, including their dates of occurrence and durations.
3. Generate isohyetal maps and compute the corresponding rainfall values for each isohyet within the designated area with the severe storms that were analyzed in Step 2.
4. Use a graph to illustrate the correlation between area and rainfall amounts for different time periods, such as one-, two-, or three-day rainfall.

2.6.2.1 Use of DAD Curves

The depth-area-duration curve is a useful tool for analyzing storm precipitation in relation to time and area. It allows us to determine the maximum amounts of precipitation for different durations and areas. Figure 2.3 displays the precipitation depths for the proposed development catchment for durations of one, two, and six hours.

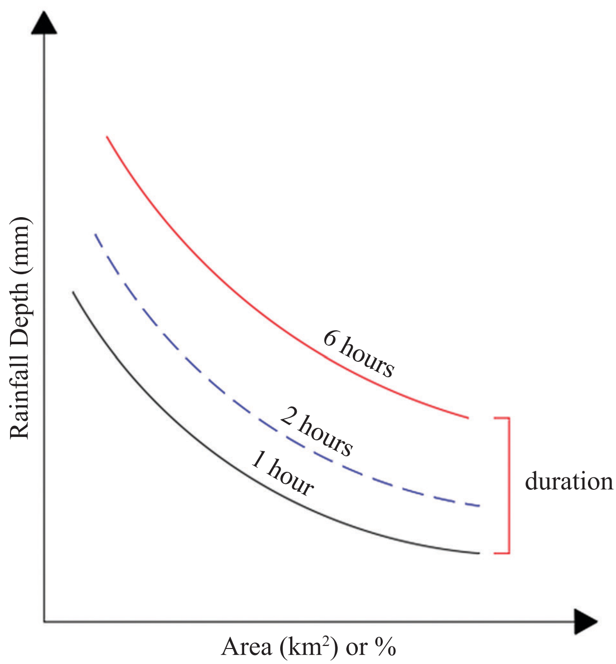


Figure 2.3 Depth-area-duration curve

2.7 INCORPORATING EXTREME WEATHER IN URBAN DRAINAGE SYSTEMS

A critical initial task in the diagnostic framework is discerning the types and potential magnitudes of climatic changes that could impact urban drainage systems. This information can be utilized to enhance the resilience of urban drainage systems against changes that might threaten system functionality and infrastructure. Climate change planning must consider that, while experts and authorities recognize significant ongoing climatic changes and expect these changes to continue, no study has completely clarified their exact nature, especially at the local level. This uncertainty poses a substantial challenge for those managing urban drainage infrastructure systems potentially affected by climate change. Therefore, it is fundamental to consider the uncertainties associated with anticipated climatic changes when making investment or operational decisions.

The frequency and intensity of extreme rainfall events have fluctuated over recent decades, a trend attributed to changes in weather and climate. Urbanization could exacerbate these variations in intense precipitation due to the urban heat island effect. Understanding the factors contributing to these changes is crucial for estimating the societal, economic, and environmental impacts of extreme rainfall. The frequency and volume of stormwater flows would increase, necessitating upgrades to drainage infrastructure. This situation presents a significant challenge to urban drainage management and related fields. Historically, drainage systems were built using what is often termed *gray infrastructure*, which generally lacks the adaptability needed to handle intense precipitation resulting from extreme weather, the so-called "New Normal."

The primary purpose of drainage system networks is to collect stormwater runoff from designated precipitation events and direct it to wastewater treatment facilities or downstream within a municipal separate storm sewer (MS4) system. The process of capturing and transferring stormwater runoff adheres to established guidelines and standards for drainage system design. However, their primary function does not include mitigating flooding resulting from severe weather events.

The traditional approach to designing urban drainage system networks typically involves determining a return period, denoted as T, representing the frequency of an event's occurrence. It is assumed that the event will occur with a probability of 1/T per year. However, extreme rainfall events are seldom considered in drainage system design, except for scenarios where the drainage system is overwhelmed.

Designing drainage system networks to effectively handle severe rainfall events could result in the development of drainage infrastructure that may not be cost effective. To manage the drainage system comprehensively, it is necessary to consider a wider range of precipitation events. In the context of collector networks, design events typically occur within a time frame ranging from 1 to 10 years. However, exceedance events are characterized by a longer return period, typically from 50 to 100 years. Extreme events are even less frequent, with a return period extending from 100 to 1,000 years. Determining an optimal threshold value remains a significant challenge.

Contrary to the characteristics of design events, managing exceedance flows and flooding for a specific frequency of occurrence or amount of rainfall is a complex task. One factor to consider is the feasibility of implementing a stringent threshold or criterion, especially when it needs to be applied to an entire city, drainage area, or catchment. This is particularly true for urban areas where the regulation of exceedance flows has not been effectively implemented. Managing exceedance in these areas may incur significant adaptation costs when employing a rigorous threshold or criterion. For instance, modifications to streets or building components may be necessary to meet the recommended threshold or criterion. While establishing management standards for construction in low-risk or safe locations for new developments is common practice, the presence of extensive catchments can lead to hazardous flooding situations. This necessitates the implementation of structural measures such as protective channels or embankments that comply with more stringent design criteria, such as those based on a 100-year return period. Despite the challenges in effectively regulating excessive flows and floodwaters, it is crucial to prioritize infrastructure and urban planning adaptations to minimize economic losses, especially during catastrophic events. Several methodologies for understanding the importance of and assessing adaptation measures require an analysis of the impacts of precipitation or other climate-related phenomena.

Risk assessment is a commonly employed methodology within the realm of urban drainage systems to evaluate and mitigate the potential consequences of severe weather events effectively. This process involves the methodical assessment and execution of adaptive strategies aimed at mitigating risks to both ecosystems and human well-being. Conducting a risk assessment involves identifying potential risks, exposures, and vulnerabilities. The spatial distribution of social groups and properties susceptible to impacts is determined by exposure and vulnerabilities. Hazards are commonly defined by their return period, which pertains to the frequency of occurrence of external loadings. Uncertainty is a common occurrence in risk assessments due to the difficulties associated with assigning probabilities to socioeconomic and climate change scenarios, evaluating damages, and calculating the costs of adaptation activities.

2.7.1 Extreme Event Probabilities

The assessment of flood risk, along with the development and implementation of flood mitigation strategies, relies significantly on the application of probabilistic models for intense precipitation. Gumbel distribution has been widely accepted as the primary model for intense precipitation phenomena. The use of Gumbel distribution, which has an exponential tail in the underlying distribution, is supported by both theoretical and empirical findings. However, the suitability of this distribution has recently been questioned due to both theoretical and empirical considerations.

Recent theoretical investigations suggest that *extreme value type II* distribution may be a more appropriate substitute for Gumbel distribution. These analyses involve comparing actual and asymptotic extreme value distributions and applying the principle of maximum entropy. Furthermore, several empirical studies have been conducted using extensive rainfall data to support these recent theoretical findings. Additionally, empirical analyses have shown that Gumbel distribution tends to underestimate the most extreme rainfall levels. However, it is important to note that this particular distribution provides excellent predictions for shorter return periods, specifically those up to 10 years.

It is worth emphasizing that Gumbel distribution may be considered an appropriate model for situations involving a limited number of years of measurements, particularly when using subsets of extensive data sets.

2.7.2 Analysis of Rainfall Data Using Statistical Methods

Precipitation is a critical factor in many hydraulic engineering applications, including the planning and design of hydraulic structures such as bridges, culverts, canals, and storm sewage drainage systems. Accurately determining the relevant input value for the design and construction of engineering structures requires a comprehensive statistical analysis of each specific region. Caution is necessary when performing a frequency analysis on precipitation data since the shape of flood-frequency distributions may vary depending on the equations used in the analyses. Therefore, it is imperative for practitioners to have a thorough understanding of the terminology used in frequency analysis. The most commonly used analytical methods are the normal, log-normal, Gumbel, and log Pearson type III distribution methods.

2.7.3 Expected Rainfall Depths for a Given Probability

Accurate assessments of precipitation depths or intensities expected with a specific level of probability within a designated time frame (ranging from 1 to 24 hours, daily, weekly, monthly, or yearly) are crucial for the strategic planning and implementation of urban drainage initiatives. The term *probability* refers to the likelihood of exceeding a specific threshold and represents the chance that the actual amount of rainfall within a specified time frame will be *equal to* or *greater than* the estimated rainfall depth. *Rainfall depth* describes the amount of precipitation expected or that may be exceeded during a specific period, based on a given probability. The *minimum reliable rainfall threshold* refers to the lowest amount of rainfall that can be considered reliable within a specified time frame.

2.7.4 Probability of Exceedance

The probability of exceedance refers to the likelihood of a specific event or value surpassing a predetermined threshold. This probability can be expressed as a percentage from 0% to 100%, or as a fraction between zero and one. The projected amount of rainfall that could occur or be exceeded in a given year within a specific time period can be quantified as a numerical value representing the number of years within the defined time frame.

2.7.5 Recurrence Interval

Recurrence intervals are used to evaluate the average period between rainfall occurrences of similar or larger size. The variability of rainfall patterns is influenced by several factors, including the duration and intensity of precipitation events, and the geographical context. The assessment of the likelihood of a particular quantity of precipitation occurring during a specified year is commonly conducted through recurrence intervals, also known as return periods. The return period, a widely recognized unit of measurement, is often stated in years. It is derived by evaluating the likelihood of exceeding a storm event. The concept of *likelihood* refers to the possibility of a storm of a specific magnitude occurring or exceeding a storm during an interval of one year. Equation 2.11 is a mathematical tool that is used to determine the correlation between the recurrence interval and exceedance probability:

$$T = \frac{1}{P} \tag{2.11}$$

where T represents the return duration measured in years and P is the likelihood of exceedance. A 20% dependable rainfall ($PX = 0.20$) has a return period of 1/.2 = 5 years, meaning that, on average, the rainfall in the first decade of January will exceed 23 mm in Tunis once every five years. A 50% dependable rainfall has a return period of two years, indicating that the rainfall depth is exceeded, on average, once every two years.

2.7.6 Probability of Exceedance for Design Purposes

The calculation of the probability of exceedance (P) or return period (T) for design purposes is influenced by several factors, including the potential damage caused by excessive rainfall, the acceptable level of risk, and the projected lifespan of the project. The determination of a design return period is not solely based on an economic evaluation comparing the costs and benefits of implementing drainage infrastructure. It also involves a comprehensive policy decision that considers factors such as land use and potential risks to public safety. A pragmatic approach is recommended. In specific instances, such as temporary river diversions, the criteria for determining the appropriate return period for design purposes may be overly stringent. Therefore, it is advisable to establish the design return period by relying on local expertise and conducting a comprehensive risk assessment. This assessment should consider various factors, including the project's duration, the specific seasons during which the project will be carried out, and any additional contingency measures that may be required. Table 2.2 can be a valuable resource when used in conjunction with applicable local regulations and practical expertise. It is essential to acknowledge that the suggested choice of return period may not always be suitable or attainable, especially when considering the implementation of new drainage systems or the upgrading of existing ones, particularly in low-lying areas or densely populated urban locations.

Table 2.2 Recommended return periods for drainage systems and projects

Type of drainage systems/project	Return period in years
Flood plain development	100
Urban drainage—Low risk (up to 100 ha)	5 to 10
Urban drainage—Medium risk (more than 100 ha)	25 to 50
Urban drainage—High risk (more than 1,000 ha)	50 to 100
Road drainage	25 to 50
Highway drainage	50 to 100
Bridge design—Piers	100 to 500
Levees—Medium risk	50 to 100
Levees—High risk	200 to 1,000
Principal spillways—Dams	25 to 100
Emergency spillways—Dams	100 to 10,000 (PMP)*
Freeboard hydrograph—Dams Class (c)	10,000 (PMP)*

* Probable maximum precipitation (PMP)
Note: adapted partly from "What are the return periods commonly used in design?" Dr. Victor Miguel Ponce, San Diego State University (https://ponce.sdsu.edu/return_period.html), and different worldwide city municipalities drainage design manuals.

2.7.6.1 Probability of Design Failure

The return period (T), design life (n), and probability of exceedance (P) are critical considerations when designing drainage system networks. It is important to clarify a common misconception: specifying a system for a T-year return period event does not mean the system's capacity will only be exceeded once every T years. The T-year return period is a statistical measure used to evaluate the probability of an extreme event occurring within a specified duration. The term *frequency* refers to the average rate at which an event of a specific magnitude is expected to occur. In reality, stochasticity and natural variability affect the occurrence of extreme events, and it is possible for multiple events of equivalent magnitude to occur in close succession or at extended intervals.

However, the design life of drainage infrastructure, represented by n years, refers to the projected duration during which the drainage system is expected to operate efficiently without significant problems or failures. This measure is used as a reference point for planning and constructing drainage systems, ensuring that the system is built to withstand projected potential risks within a designated time frame. Therefore, it is crucial to consider the probability (P) of a drainage system's capacity being exceeded at least once over its design lifespan. This consideration helps us understand the likelihood of encountering a design that fails to meet its intended performance, calculated using Equation 2.12:

$$P = 1 - \left(1 - \frac{1}{T}\right)^{n} \tag{2.12}$$

Consider proposed drainage infrastructure designed to function for 30 years, with a 45% likelihood of failure within this lifespan. To mitigate this risk, it is advisable to engineer infrastructure to withstand a 51-year recurrence interval or a 51-year peak flow. This approach will help address potential challenges and enhance the long-term resilience of this piece of infrastructure.

2.7.6.2 Probable Maximum Precipitation

Probable maximum precipitation (PMP) refers to the maximum depth of precipitation achievable within a specific area and duration, without exceeding known meteorological conditions. In simpler terms, PMP represents the upper limit of precipitation expected under the most extreme weather circumstances. Understanding PMP is crucial for various applications, including infrastructure design, water resource management, and flood risk assessment. By determining the PMP for a particular region, meteorologists and engineers can make informed decisions about the design and capacity of structures like dams, reservoirs, and drainage systems.

It is important to note that calculating PMP involves considering a range of meteorological factors, including atmospheric moisture content, wind patterns, and topographical features. These factors collectively influence the potential for precipitation in a given area. By analyzing historical weather data and using sophisticated mathematical models, meteorologists can estimate the maximum amount of precipitation that can occur under extreme conditions.

The PMP value serves as a benchmark for planning and designing infrastructure to withstand severe weather events. It provides assurance that the structures will withstand the most intense weather conditions. PMP is widely used in the planning and execution of extensive hydraulic infrastructure projects, particularly in large-scale dam construction. These projects often involve the design and implementation of critical components, such as spillways, which play a crucial role in managing water flow and preventing potential damage to the dam structure. The application of PMP in the design of large hydraulic structures, including spillways in large dams, underscores the importance of project management in the successful execution of complex engineering projects.

Variations in PMP are observed worldwide, with significant differences based on the climatic regions across the globe. Various methodologies are used for calculating PMP, including statistical methods and the examination of storm mechanisms that give rise to intense precipitation events. In engineering, it is common practice to use one's judgment to determine an appropriate value for a given situation. This process involves carefully considering various factors and making a decision based on one's expertise and experience in the field.

PMP refers to the highest amount of rainfall that can occur within a specific time period at a rain gauge station or a basin. It represents the upper limit of rainfall intensity that is physically achievable in a given location. The concept discussed here pertains to the precipitation level that would result in a flood within a basin while ensuring that there is no possibility of surpassing the predetermined threshold.

In hydrology, PMP can be estimated by using a statistical approach. This estimation is given by Equation 2.13:

$$PMP = k\delta, \tag{2.13}$$

where k and δ represent certain parameters. PMP is the mean of the annual maximum rainfall series, representing the average value of the highest recorded rainfall in a given year. The parameter k, known as the frequency factor, depends on various factors. These include the statistical distribution of the rainfall series, the number of years of record available, and the desired return period. The return period refers to the average time interval between occurrences of a rainfall event of a certain magnitude. Finally, the parameter δ represents the standard deviation of the rainfall series. It quantifies the variability or spread of the annual maximum rainfall values around the mean. By combining these parameters in the equation, we can estimate the PMP. This estimation allows us to assess the maximum amount of rainfall that could potentially occur within a specific region or catchment area. The value of k ranges from zero to 15.

2.8 PLOTTING POSITION

Frequency analysis, a fundamental technique, can be approached from two perspectives: empirical and analytical. Each offers unique methodologies for data interpretation, enabling researchers to discern patterns and trends within datasets. Understanding these approaches allows for the effective use of frequency analysis, providing valuable information and accurate conclusions. This is particularly useful in the initial design phase of engineering projects that are focused on flood control and drainage systems.

2.8.1 Empirical Method

Frequency analysis assesses the probability of an event occurring within a specified time frame. Consider an event, such as rainfall, with the goal being to determine the probability of this event reaching or exceeding a certain magnitude, denoted as X. This probability is quantified using p. The Weibull formula provides the return period, or recurrence interval, associated with a given probability p; refer to Equation 2.14:

$$p = \frac{m}{N + 1}, \tag{2.14}$$

where p is the exceedance probability of the event and m is the rank assigned to the data after arranging them in descending order of magnitude. Thus, the maximum value is $m = 1$, the second largest value is $m = 2$, and the lowest value is $m = N$, with N being the number of records.

The exceedance probability of the event is calculated using an empirical formula known as the plotting position. Numerous plotting position formulas have been developed and refined over time, serving as essential tools for accurate data representation and interpretation. Table 2.3 presents a comprehensive list of these formulas, which have demonstrated their utility in various applications (Subramanya 2006). The Weibull formula, often used as a plotting position, requires extensive historical data for a thorough investigation.

Table 2.3 Plotting position formulas

Method	**P(probability)**
California	$\frac{m}{N}$
Hazen	$\frac{m - 0.5}{N}$
Weibull formula	$p = \frac{m}{N + 1}$
Jenkinson's method	$\frac{m - 0.3}{N + 0.4}$
Gringoten	$\frac{m - 0.44}{N + 0.12}$

The procedure should include the following steps:

1. Calculate the exceedance probability for each data point for ranking and plotting position
2. Generate a probability plot for the data, selecting an appropriate distributional assumption

3. Evaluate the suitability of the chosen distribution, considering alternative distributions or modifying the data to fit the chosen distribution, if necessary
4. Determine realistic rainfall depths for specific probabilities or return periods using probability plots
5. Apply analytical techniques to incorporate the frequency factor effectively, yielding more accurate and refined results

2.9 THEORY OF EXTREME VALUE

Fisher and Tippet (1928) identified three limiting distributions for extreme value analysis (EVA), building upon the groundwork established by Fréchet (1927). Ludwig von Mises further developed extreme value theory (EVT) in 1936 by defining conditions for convergence, which Gnedenko formalized in 1943. Common distributional assumptions for modeling extreme rainfall data include the following:

1. Generalized extreme value (GEV) distribution
2. Log-normal distribution – 3 parameters (LN3)
3. The Pearson type III distribution (P3)
4. Generalized Pareto distribution (GP)
5. Gumbel distribution

2.9.1 Background

In educational contexts, the concept of a coin toss is often used to illustrate the principle of a binomial probability distribution. A coin toss, a simple yet fascinating method for decision making or determining outcomes, involves flipping a coin and observing the upward-facing side. This method is used in various scenarios, from casual games to significant events. In an ideal scenario, a coin has an equal 50% probability of landing on either heads or tails in a single trial. With multiple tosses, it is possible to gain insights into the probability of obtaining either outcome. This knowledge allows for the prediction of future trial outcomes, including the examination of the frequency ratio between heads and tails. However, this basic concept can be expanded to cover more complex cases, as shown by other probability distributions. The primary goal in drainage hydrology is to create a mathematical model that accurately represents rare or exceptional events with a low occurrence probability.

In drainage and hydrology, the term *extreme* typically refers to precipitation that surpasses the usual variability range within a specific geographic and temporal context. Modeling extreme weather phenomena presents challenges due to their sporadic occurrence, making the collection of accurate and reliable data difficult.

EVT is a statistical framework designed to address the inherent randomness observed in natural variability. Its aim is to characterize extreme events by quantifying their probability of occurrence. The frequency of events of different magnitudes can be described as a series of random variables with the same distribution. Let f represent a function that approximates the relationship between the event's magnitude, represented by X_N, and its occurrence probability. This relationship can be mathematically expressed as shown in Equation 2.15:

$$f = X_1, X_2, X_3, \ldots . X_N. \tag{2.15}$$

The data derived from the resulting distribution can be used for trend analysis and assessing the probability of severe occurrences, which includes predicting the frequency and intensity of extreme weather precipitation. These distributions can also be used for simulations.

2.9.2 Generalized Extreme Value versus Generalized Pareto

GEV distribution is a prevalent method in EVA. It examines the distribution of block maxima, where a block refers to a specific time interval, such as a year. Depending on its shape parameter, GEV distribution can exhibit characteristics of Gumbel, Fréchet, or Weibull distributions. As an alternative approach, GP (generalized Pareto) focuses on analyzing values exceeding a predetermined threshold. The resulting distribution varies based on the shape parameter, leading to an exponential, Pareto, or beta distribution. These two methodologies are summarized in Table 2.4.

Table 2.4 Description of the two basic types of extreme value distributions; based on Pinheiro, M., and Grotjahn, R. (2015). An introduction to extreme value statistics. Tutorial at the University of California at Davis.

	Generalized Extreme Value (GEV)	Generalized Pareto (GP)
General Function (CDF)	For extreme value Z, $$G(Z) = exp\left[-\left\{1+\xi\left(\frac{z-\mu}{\delta}\right)\right\}_{+}^{-1/\xi}\right]$$	For threshold excess χ, $$H(\chi) = 1-\left[1+\xi\left(\frac{z-\mu}{\delta}\right)\right]_{+}^{-1/\xi}$$
Limit as $\xi \to 0$	Gumbel: $$G(Z) = exp\left[-exp\left\{-\left(\frac{z-\mu}{\delta}\right)\right\}\right]$$	Exponential: $$H(\chi) = 1 - exp\left(\frac{z-\mu}{\delta}\right)$$
$\xi > 0$	Fréchet	Pareto
$\xi < 0$	Weibull	Beta
Description	Distribution function of standardized maxima (or minima)—block maxima/minima approach	Probability of exceeding pre-determined threshold peaks over threshold approach
Parameters	**Location** μ: position of the GEV mean	**Threshold** u: reference value for which GP excesses are calculated
Interpretation of results	Return level: value z_p that is expected to be exceeded on average once every $1/p$ periods, where $1 - p$ is the probability associated with the quantile. Find z_p such that $G(z_p) = 1 - p$	Return level: value x_m that is exceeded every m times. Begin by estimating ζu, the probability of exceeding the threshold. Then, x_m is $$x_m = \begin{cases} u + \frac{\sigma_u}{\xi}\left[(m\zeta_u)^{\xi} - 1\right] & \xi \neq 0 \\ u + \sigma_u ln\big((m\zeta_u)\big) & \xi = 0 \end{cases}$$

2.9.3 Stationarity versus Nonstationarity in the Field of Data Analysis

Stationarity, the consistency of statistical properties over time, is a crucial characteristic of data. In data analysis, *stationary* describes a state where key statistical measures, such as mean and variance, remain constant over a specific period. This constancy is vital in various data analysis methodologies because stationary data do not exhibit significant deviations. The assumption of stationarity is crucial in statistical modeling techniques and forecasting methods, enabling reliable predictions and meaningful insights. Evaluating a model's fit requires analyzing the temporal stability and consistency of the model's distribution, differentiating between stationarity (stable distribution over time) and nonstationarity (unstable distribution over time). Stationary models consistently represent variables, such as x, σ, and ξ, as time-invariant functions, using fixed constants as parameters.

Nonstationary models, lacking fixed constants as parameters, differ from stationary models. Understanding the distinction between stationary and nonstationary models is essential for interpreting data behavior and characteristics in various analytical contexts. Modeling nonstationary extremes typically involves a constant high threshold, denoted as x_0, with threshold exceedances modeled using the GP. To achieve a linear increase in the GP threshold or to incorporate seasonal cycles, the following equation is introduced into GP parameters, allowing for nonstationarity; refer to Equation 2.16:

$$x(t) = x_0 + x_1 t, \tag{2.16}$$

where x_0 is the initial threshold value and x_1 denotes the rate of increase in the threshold value as time progresses. Similar adjustments can be made for the remaining variables.

2.10 CHAPTER SUMMARY

To thoroughly evaluate the resilience of urban drainage infrastructures against global climate change and local watershed responses, multi-scale modeling analysis is often essential. This approach considers the different scales at which these infrastructures operate, allowing for a comprehensive performance assessment. By considering the broader effects of global climate change and the specific responses of local watersheds, we can achieve a more precise evaluation of resilience.

This section explores climate model projections related to the occurrence of intense rainfall in future climates. The projections suggest an increased likelihood of intense rainfall events due to rising GHG levels. In the context of urban drainage systems, it is important to note that their design heavily relies on the statistical analysis of past data. Examining historical data and studying the outcomes of previous events provide valuable insights for making informed decisions aimed at ensuring our infrastructure can effectively manage rainfall. It is crucial to consider potential consequences, such as an increased frequency of flooding incidents, that may arise from an increase in the severity and frequency of extreme rainfall events.

When evaluating design criteria, it is essential to review and modify them to accommodate potential changes due to climate change. This revision involves considering three key factors: climate projections related to extreme rainfall in the region under investigation, the anticipated performance level or permissible risk level, and the projected lifespan of the infrastructure or system. Incorporating these factors allows for effective mitigation of climate change effects through suitable modification of the design criteria. The revised design criteria ensures that the service level consistently exceeds the chosen *acceptable* level throughout the predetermined lifespan of the infrastructure.

It is paramount to incorporate the definition of new design criteria into a comprehensive global adaptation strategy. The goal of this strategy is to integrate various measures to maintain a satisfactory service level in the long run. Determining the service level in light of uncertainties related to anticipated variations in heavy precipitation presents a significant challenge.

2.11 CHAPTER PROBLEMS

1. Define the following terms based on your own understanding:
    a. Climate
    b. Climate change
    c. Climate change adaptation
    d. Climate model
    e. Climate prediction
    f. Climate projection
    g. Climate risk
    h. Climate scenario
    i. Climate system
    j. Coastal erosion
    k. Extreme weather event
    l. Flood and flood mitigation
    m. Global warming
    n. General circulation models (GCMs)
    o. Hydrological cycle
    p. Regional climate models (RCMs)
    q. Resilience
    r. Risk
2. What are the key distinctions between climate change and global warming?
3. What is the function of climate models? Can these models be developed for regional climates?
4. Extreme weather events, including hurricanes, cyclones, and heavy rainfall, are natural phenomena with significant impacts on our planet. These events are defined by their intensity and duration. Investigate the intricate relationship between extreme weather events and rising sea levels.
5. Climate forecasting is essential for understanding and predicting future climate patterns, which is crucial for sectors such as agriculture, energy, and water resource management. However, it is necessary to acknowledge that climate forecasting is a complex process that depends on the use of sophisticated

models. These models aim to simulate and project future climate conditions based on various factors and variables. What are the critical considerations when utilizing current climate models for forecasting?

6. Discuss the potential effects of extreme weather events on urban drainage infrastructure, focusing specifically on its operation and maintenance.
7. Analyze the range of climate change adaptation strategies that municipal agencies could potentially adopt.
8. What role, if any, does asset management play in an agency's climate change adaptation efforts?
9. Considering climate-related risks is vital due to their various economic, environmental, and social impacts. By accounting for that climate-related risk, we can enhance our understanding and mitigation of potential climate change consequences. This understanding enables us to make informed decisions and take suitable actions to safeguard our environment, economy, and society. Climate-related risks include a broad spectrum of factors, such as extreme weather events, rising sea levels, changes in temperature and precipitation patterns, and ecosystem shifts. Discuss and analyze the practical application aspects, citing examples of completed or proposed projects.
10. In the context of risk assessment, can the outcomes of a risk assessment be represented without incorporating probabilities?
11. What is the probability of exceedance?
12. List and discuss the four basic types of rainfall models.
13. Discuss how cities are integrating extreme weather into their urban drainage systems.
14. Engineers recognize that climate change is a dynamic process, and they consider this when designing systems and structures. How does the field of engineering design tackle the challenges presented by an ever-changing climate?
15. Changing climate patterns and the increasing frequency and intensity of extreme weather events present substantial challenges and risks to construction projects. One of the primary concerns for the construction industry is the potential damage

caused by extreme weather events such as hurricanes, floods, and heat waves. These events can result in severe infrastructure damage, including the destruction of buildings, roads, and bridges. The increased occurrence of these events due to climate change can lead to significant financial losses for the construction industry. Discuss and analyze actual construction projects that have been affected by extreme weather events.

16. What is the difference between stationarity versus nonstationarity in the field of data analysis?
17. Table 2.5 provides data for the base station and the four surrounding stations. Using (*i*) the modified normal ratio (NR) method and (*ii*) the inverse distance method, identify the missing data at the point marked 'Z.'

Table 2.5 Station and rainfall data (inches)

Station	Annual Rainfall	April 2024 Rainfall
W	53.03	4.6
X	45.35	1.39
Y	59.73	5.83
Z	46.30	?

18. Compute the missing rainfall data for the station 400+00 for December 2022 using the record in Table 2.6. Assume the stations are approximately equidistant.

Table 2.6 Annual rainfall data (inches) for December 2022

Stations	Normal Annual Rainfall	Rainfall Data
100+00	16.02	9.29
200+00	15.43	6.06
300+00	18.91	10.3
400+00	14.45	?

19. Assume the normal annual rainfall at stations 100+00, 200+00, 300+00, and 400+00 in a basin are 80.97 cm, 67.59 cm, 76.28 cm, and 92.01 cm, respectively. In 2021, station 400+00 was inoperative, while stations 100+00, 200+00, and 300+00 recorded

annual rainfall of 91.11 cm, 72.23 cm, and 79.89 cm, respectively. Estimate the rainfall at station 400+00 for that year (see Table 2.7).

Table 2.7 Normal annual rainfall data (cm) for 2021

Stations	Normal Annual Rainfall	Rainfall Data
100+00	80.97	91.11
200+00	67.59	72.23
300+00	76.28	79.89
400+00	92.01	?

20. The execution of a riverbank protection project necessitates the extensive use of live vegetation and woody material, including pole planting through bioengineering methods. However, the proposed planting will not withstand the design storm until it is fully established. The designer is tasked with calculating the design storm and integrating temporary sediment control reinforcement matting into the design, ensuring a 90% probability of success over the next five years.
21. For station 100+00, Table 2.8 provides the recorded annual maximum rainfall over 24 hours. Compute the maximum 24-hour rainfall for return periods of 10, 25, and 50 years.

Table 2.8 Maximum 24-hour rainfall at station 100+00

Year	Rainfall (cm)	Year	Rainfall (cm)	Year	Rainfall (cm)
1995	14.08	**2002**	13.53	**2009**	9.32
1996	13.25	**2003**	12.36	**2010**	8.23
1997	6.09	**2004**	9.07	**2011**	6.51
1998	15.51	**2005**	9.29	**2012**	9.23
1999	15.93	**2006**	8.73	**2013**	11.11
2000	10.81	**2007**	8.98	**2014**	9.85
2001	7.56	**2008**	10.12	**2015**	9.23

22. What is the probability of a rainfall event of 10 cm or more occurring over 24 hours at station 100+00?

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