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INFLUENCE OF INFILTRATION AND SOIL MOISTURE MODELS ON URBAN HYDROLOGICAL MODEL RELIABILITY

BY

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.... 26.06.2026 ....

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DECLARATION

I, **Batunonya Margaret**, hereby declare that this research has been undertaken as part of my academic requirements. This report is a result of my own research efforts and analysis, carried out in good faith under the guidance of my supervisors. All sources of information and data used in our report are relevant to the study I am undertaking. I affirm that this work is original and has not been submitted in part or in full for any other institution.

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Date: 25th/06/2026

APPROVAL

This research is ready to be submitted with our approval as academic supervisors

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TABLE OF CONTENTS

LIST OF ABBREVIATIONS

BGI	Blue Green Infrastructure
DEM	Digital Elevation Model
DWRM	Directorate of Water Resources Management
GIS	Geographic Information System
HEC HMS	Hydrologic Engineering Center Hydrologic Modeling System
SWMM	Stormwater Management Model
NASA	National Aeronautics and Space Administration
SDGs	Sustainable Development Goals
UNMA	Uganda National Meteorological Authority
UNDP	Uganda National Development Plan
UHM	Urban Hydrological Models.
GPM	Global precipitation measurements missions
IMERG	Integrated Multi-satellite Retrievals for GPM
SWAT	Soil & Water Assessment Tool
SRTM	Shuttle Radar Topography Mission.
NSE	Nash-Sutcliffe Efficiency
LULC	Land use Land cover
NASA	National Aeronautics and Space Administration

LIST OF FIGURES

LIST OF TABLES

ABSTRACT

This study investigates the influence of infiltration and soil moisture models on the reliability of urban hydrological models, focusing on guiding the selection of Blue-Green Infrastructure (BGI) for stormwater management. Infiltration models such as Horton and Green-Ampt, combined with dynamic representation of soil moisture, fundamentally affect predictions of runoff generation and flood risks in urban catchments. Given that the Kinawataka catchment contains compacted urban soils, heterogeneous pervious–impervious patterns, and frequently saturated low-lying areas, accurately modelling infiltration and soil moisture becomes essential for improving flood prediction reliability. The results from these hydrological models provide critical insights that help in choosing appropriate BGI solutions by indicating how infiltration and soil moisture conditions impact urban runoff and flood mitigation potential. This approach supports optimized BGI selection to enhance urban flood resilience and sustainable water management strategies.

The study aims to enhance the understanding of runoff and infiltration processes within the Kinawataka catchment by conducting rainfall simulations and applying hydrological modelling techniques. This research provides a novel contribution by jointly evaluating infiltration models and soil moisture dynamics specifically for an urban Ugandan catchment, an aspect that has received limited attention in previous studies.

The research will generate reliable data to support the strategic selection and design of Blue-Green Infrastructure (BGI) interventions that are appropriate for the local urban context. Ultimately, by clarifying how infiltration and soil moisture representations influence hydrological model reliability, the study contributes to improving flood forecasting, model calibration, and urban flood resilience in data-scarce and rapidly urbanizing cities such as Kampala.

1 CHAPTER ONE; INTRODUCTION

1.1 Background

Urban hydrology focuses on understanding how rainfall transforms into runoff within built environments characterised by impervious surfaces, compacted soils, and altered drainage systems. As urbanisation increases, natural infiltration processes are greatly reduced, leading to higher runoff volumes, increased flood peaks, and degraded water quality (Aboelnour et al., 2018). This alteration in the natural hydrological cycle poses significant challenges for sustainable urban water management, including effective drainage systems, flood control measures and strategies for mitigating pollution. In addition, urban hydrology helps bring together different aspects of the urban environment, and hydrological modelling provides a useful way to understand how cities respond to changes in urban development and climate (Fujita et al., 2024).

Urban hydrological models (UHMs) are therefore essential tools for making runoff predictions, stormwater management and flood mitigation in rapidly urbanising regions. The reliability of these models depends on quality and resolution of input data, landuse and soil characterisation, proper representation of drainage systems, model calibration and validation and widely on their accuracy to illustrate infiltration and soil moisture fluctuations as these influence the categorizing of rainfall into runoff, evapotranspiration and storage, thus influencing the prediction of floods and decisions related to water movement (Beven, 2012). The term “infiltration” can be used to describe the process involved where water soaks into or is absorbed by the soil. Absorption, imbibition, and percolation are often used in much the same sense. It seems better to confine the use of “percolation” to the free downward flow by gravity of water in the zone of aeration a process for which a distinctive term is needed. (Horton, 1933, 1939, 1940).

Soil water infiltration as an important component of the hydrological cycle controls run off rate as well as influencing the quality and quantity of subsurface water (Thomas et al., 2022), while soil moisture dynamics provide an indication of how water is stored and its movement in a soil profile. Significant land use modifications that converted the natural landscape to urban settings may have disastrous consequences for urban ecosystems. Impervious surfaces alter the hydrological nature of surface runoffs, prevent the infiltration of surface water into the ground and greatly increase storm runoffs in terms of volumes and peak flow (W. Liu et al., 2014). Understanding the rainfall-runoff behaviour of urban land surfaces is an important scientific and practical issue as storm water management policies increasingly aim to manage flood risk at local scales within urban areas, whilst controlling the quality and quantity of runoff that reaches receiving water bodies (Redfern et al., 2016). Evaluating and mitigating the risks of urban flood disasters has therefore become a key focus in urban hydrology and stormwater management, representing one of the major challenges to achieving sustainable urban development (Yang et al., 2020).

Hydrological modeling of these processes plays a vital role in understanding and predicting urban runoff behaviours. Such modeling commonly relies on infiltration and soil moisture models, which determine how rainfall is partitioned into infiltration, surface runoff, and soil storage. Among the most widely applied infiltration models are the Horton, Green-Ampt, and Philip models, each differing in their theoretical foundation, parameter requirements, and suitability for different catchment conditions.

The **Horton model** assumes an exponential decline in infiltration capacity over time and is widely used in urban hydrology due to its simplicity, empirical nature, and minimal data requirements (Horton, 1940). However, it does not explicitly represent soil suction which limits its ability to capture the processes governing infiltration (Burt et al., 1998).

$$\boldsymbol{f(t) = f_c + (f_0 - f_c)e^{-kt}} \tag{1}$$

Where $f(t)$ is the infiltration rate at time t, f_c is the final constant infiltration capacity, f_0 is the initial infiltration rate at time $t = 0$, and k is the decay rate constant. The parameters of the Horton's equation are determined by plotting the values of $In(f(t) - f_c)$ against t to obtain the best fit straight line through the plotted points. $In(f_0 - f_c)$ depicts the intercept and the decay constant, k represent the slope.

In contrast, the **Green-Ampt model** employs a physically based approach, representing infiltration as a function of wetting front suction head, hydraulic conductivity and the soil moisture deficit (Green, W.H. and Ampt, G.A, 1911). Although it performs well when accurate soil hydraulic parameters are available, its sensitivity to parameter uncertainty and the assumption of uniform initial moisture conditions may limit its effectiveness in spatially heterogeneous urban settings.

$$\boldsymbol{f_p = m + n/F_p} \tag{2}$$

Where m and n are Green Ampt's parameters of infiltration model. Values of infiltration capacity, f_p are plotted against $\frac{1}{F_p}$ on an arithmetic graph. The intercept on the ordinate axis is m and n serves as the slope when the best fit straight line is drawn through the plotted points.

The **Philip model** combines the effects of gravitational and capillary forces to estimate infiltration, providing precise predictions for short-duration rainfall events (Philip, J., 1957). However, it is generally better suited for controlled laboratory experiments or small-scale field studies rather than for application in complex and highly heterogeneous urban catchments.

$$\boldsymbol{f(t) = \frac{1}{2}St^{-0.5} + K} \tag{3}$$

Where $f(t)$ is the infiltration rate at time t, S is the sorptivity parameter, and K is a constant proportional to the hydraulic conductivity. The observed infiltration rate, $f(t)$ values are plotted against the reciprocal square root of time, $t^{-0.5}$. The best fitting straight line through the plotted points gives K as the intercept and $\frac{S}{2}$ as the slope of the line.

In many Sub-Saharan African countries, rapid and often unplanned urbanisation has significantly altered the natural hydrological systems. Expanding cities encounter challenges including inadequate drainage infrastructure, wetland encroachment and limited land use regulations all of which exacerbate surface runoff, increase flash flooding and degrade water quality (Douglas et al., 2008; Sigalla et al., 2023). Despite the increasing hydrological risks, most urban areas in the region experience limited availability of reliable rainfall, soil and streamflow data. The scarcity of monitoring networks and long-term observations creates considerable uncertainties in hydrological analyses and model calibration therefore limiting the applicability and performance of these models (Olang & Fürst et al., 2011). Furthermore, hydrological models calibrated under rural or natural catchment conditions may not be directly transferable to urban settings.

Evaluating the suitability of infiltration and soil moisture models in urban hydrological model is essential for improving predictive reliability (Albalasmeh et al., 2022). (Adeke & Mugume, 2025) recommended improved modelling of urban flooding impacts through consideration of climate and land use change projections for validation of urban flood model in the data scarce cities. The inclusion of Blue-Green Infrastructure (BGI) interventions, such as permeable pavements, green roofs, bio-retention systems, and urban wetlands, provides practical strategies to enhance infiltration, reduce runoff volumes, and mitigate urban flooding (Kaur & Gupta et al., 2022). Integrating BGI into modeling frameworks not only improves the accuracy of simulations but also informs evidence-based urban planning, climate-resilient infrastructure design, and sustainable stormwater management (Voskamp & Van de Ven et al., 2015). Soil permeability plays a critical role in determining which types of BGI are suitable for a given land use or land cover; for instance, areas with heavy clay soils and poor infiltration may not be appropriate for rain gardens or permeable pavements (Kaur & Gupta et al., 2022).

Estimating uncertainty in flood model predictions is therefore important for applications such as risk assessment and flood forecasting (Kohanpur et al., 2023). Furthermore, the reliability of hydrological models in urban environments is often challenged by the spatial heterogeneity of land use, the dynamic nature of surface characteristics, and the scarcity of high-resolution hydrological and meteorological data. Consequently, a comprehensive understanding and accurate simulation of rainfall-runoff processes in urban catchments are critical for improving flood prediction, optimising stormwater management strategies, and informing evidence-based urban planning and policy decisions (Li et al., 2016; Salvadore et al., 2015).

1.2 Problem statement

Flooding in Kampala's Kinawataka catchment area is a recuring problem exacerbated by rapid urbanization, which increases impermeable surfaces reducing infiltration. This leads to more surface runoff, and combined with inadequate and poorly maintained drainage systems clogged by waste. It causes more severe flooding that damages property, disrupt businesses, and creates public health risks like disease and mosquito breeding grounds. Urban hydrological models are increasingly used for storm water and flood risk management, but their reliability is often compromised by uncertainties in infiltration and soil moisture representation. Existing models typically adopt simplified infiltration approaches (Horton, Green-Ampt and Philip) that fail under rapidly changing urban conditions, compacted soils and climate driven extreme rainfall(Dahak et al., 2022). Infiltration and soil moisture models are always adopted without sufficient validation leading to biases in runoff and flood estimation.

While models like SWMM and HEC-HMS are widely used, their outcomes vary significantly depending on how infiltration and soil moisture are represented(Bragg et al., 2025). The lack of a systematic evaluation of these influences results in unreliable predictions of peak discharge and flood timing. In many studies, infiltration is estimated using empirical equations derived from non-local datasets, while soil moisture dynamics are ignored (Su et al., 2025). This leads to poor calibration, high uncertainty, and reduced model reliability. Hence there is a critical need to evaluate the influence of infiltration and soil moisture conceptualizations on urban hydrological model reliability in Uganda. Doing so will improve flood forecasting, model calibration, and the overall resilience of urban drainage systems.

While these issues illustrate the modelling challenges in Kinawataka, an additional limitation arises from how spatial and temporal soil moisture dynamics are accounted for (Rong et al., 2024a). Although low-lying urban soils are often saturated, accurate representation of infiltration and soil moisture remains essential because urban runoff generation is strongly influenced by antecedent moisture conditions (Barkefors et al., 2023), soil compaction , spatial variability between pervious and impervious areas, and the sequencing of rainfall events. Therefore, saturated soils in low-lying zones alone cannot adequately describe the overall hydrological response of the entire catchment, making proper model representation necessary for reliable flood prediction (Rong et al., 2024b).

Furthermore, most existing applications ignore soil moisture dynamics altogether, relying on empirical assumptions derived from non-local datasets. This leads to poor transferability of parameters, high model uncertainty, and limitations in designing context-specific Blue-Green Infrastructure (BGI) interventions (Asiimire & Namakula, 2024b). Consequently, there is a critical need to assess how infiltration and soil moisture modelling choices influence hydrological model reliability within urban catchments in Uganda. Addressing this gap will improve flood forecasting accuracy, guide evidence-based BGI planning, and enhance the resilience of urban drainage systems (Rong et al., 2024a).

1.3 Study Objectives

1.3.1 Main Objective

To evaluate the influence of infiltration and soil moisture models on urban hydrological model reliability.

1.3.2 Specific Objectives

i. To identify commonly used infiltration models applied in rainfall–runoff modelling studies.
ii. To assess the performance of selected infiltration models in simulating runoff within the Kinawataka catchment.
iii. To evaluate how different infiltration models influence the reliability of hydrological model predictions.

1.4 Research Questions

i. What are the commonly used infiltration models in rainfall–runoff and urban hydrological modelling studies?

ii. How do selected infiltration models perform in simulating runoff within the Kinawataka catchment?

iii. How do different infiltration models influence the reliability of hydrological model predictions in an urban catchment context?

1.5 Significance of the study

This research is significant because it examines how infiltration and soil moisture models influence the reliability of urban hydrological simulations, which is essential for improving flood prediction accuracy and sustainable stormwater management in rapidly developing urban areas. This offers several key benefits, some of which are listed below;

Improvement of Urban Flood forecasting and Stormwater Management: By evaluating model performance under varying urban conditions, the study supports the development of more accurate flood forecasting systems and informs the design of effective stormwater management and drainage infrastructure.

Guidance for model selection and calibration: This research aims to offer practical guidance for hydrologists and engineers in choosing and calibrating infiltration and soil moisture models that best reflect urban catchment characteristics, thereby minimising simulation errors.

Contribution to sustainable urban planning and policy making: This study aims to strengthen the scientific foundation of urban water management and provide evidence-based knowledge that can guide policy makers and urban planners in developing resilient urban infrastructure and flood mitigation strategies.

1.6 Scope of the study

This study investigates the influence of infiltration and soil moisture models on the reliability of urban hydrological model simulations, focusing on their effect on runoff generation, peak discharge, and flood volume estimation. The research will be conducted within Kinawataka catchment in Kampala, using available land use, soil, and rainfall data for model setup and validation. PCSWMM hydrological model will be applied to simulate rainfall–runoff processes under varying infiltration (Horton, Green–Ampt, and Phillip) and soil moisture conditions. Model calibration and performance evaluation will be based on derived hydrographs to assess sensitivity and predictive accuracy. The findings will inform the selection of suitable infiltration–soil moisture model combinations and support evidence-based decisions on the design and placement of Blue-Green Infrastructure (BGI) interventions aimed at improving urban flood management and resilience in Ugandan cities.

1.7 Justification

Urban flooding has become a major challenge in most cities worldwide due to the rapid expansion of impervious surfaces, inefficient drainage systems, and the increasing frequency of intense rainfall events linked to climate change (Azizi et al., 2022; Venkataramanan et al., 2019). Accurate prediction and management of urban floods depend heavily on the ability of hydrological models to replicate the interactions between surface runoff, infiltration, and soil moisture storage(Eshrat et al., 2024). However, most existing models oversimplify these processes, leading to substantial errors in flood extent, depth, and timing(Junjie et al., 2024).

Improving the representation of infiltration and soil moisture in urban hydrological models is crucial for enhancing model reliability and ensuring effective flood risk and storm water management. Given that the reliability of flood predictions directly influences urban planning decisions and disaster preparedness strategies, addressing the uncertainties associated with infiltration and soil moisture representation is of great socio-economic and environmental importance(Xu W et al., 2024). The outcomes of this study will not only contribute to scientific understanding of urban hydrology but also guide policymakers, engineers, planners in developing resilient and sustainable urban flood management systems(Cullmann et al., 2008)

This research supports Uganda's Fourth National Development Plan (NDP IV) which emphasize sustainable urbanization and disaster risk reduction. It also contributes to Sustainable Development Goals (SDGs) particularly SDG 11 (Sustainable Cities and Communities) and SDG 13 (Climate Action), by providing scientific evidence for adaptive infrastructure planning.

2. CHAPTER TWO; LITERATURE REVIEW

2.1 Introduction

Urban hydrological modelling has increasingly recognised that the processes controlling infiltration and soil moisture dynamics play a pivotal role in determining runoff generation, peak discharge and flood volume, particularly within rapidly urbanising catchments. Classical infiltration models such as Green-Ampt and Horton infiltration method have been extensively applied in hydrological studies (Ali et al., 2016; Horton, 1940; Mein and Larson et al., 1973). Nonetheless, these models often face limitations in accurately representing the complex characteristics of urban soils which are influenced by factors such as surface sealing, compaction and shallow soil depths, as well as varying antecedent moisture conditions. For instance, a study on pervious engineered pavements, (pavements designed to allow stormwater infiltration) such as porous pavements, pervious concrete, demonstrated that antecedent soil moisture significantly reduces infiltration capacity during large storm events in both sandy and clayey soils (Davidsen et al., 2018). Furthermore, the spatial heterogeneity of urban soils including compaction differences, partial sealing, and variation of soil-type can significantly influence infiltration rates, which many classical models do not fully capture (Mao et al., 2014; Ran et al., 2022). This highlights that accurately representing soil moisture dynamics is critical for improving the reliability of urban hydrological models, particularly in catchments with engineered infiltration surfaces(Fidal & Kjeldsen, et al., 2013).

2.2 Event-Based vs Continuous Simulation Approaches in Urban Hydrological Modelling

In studies on hydrological modelling, a fundamental distinction exists between event-based and continuous simulation approaches. Event based models such as the Green-Ampt model and Horton infiltration focus on simulating individual rainfall-runoff events. They typically assume fixed initial soil moisture and are mainly applied in estimating short term peak flows for flood design, stormwater infrastructure sizing and emergency planning (Horton, 1940; Mein and Larson et al., 1973; Morbidelli et al., 2018). It is important to clarify that the classical Green-Ampt model is inherently event-based and models infiltration during discrete storm events. However, adaptations like the Layered Green-Ampt model incorporate soil moisture accounting and can be employed within continuous simulation frameworks by recalculating infiltration parameters for each storm event based on antecedent moisture conditions, allowing a more dynamic and realistic representation of infiltration processes over longer periods. The Layered Green-Ampt model simulates water movement between soil layers, enabling continuous simulation by dynamically updating soil moisture and infiltration capacity for each layer (La Follette et al., 2023). These comparative results highlight that the choice of modelling approach and the way infiltration and soil moisture are represented directly affects the reliability of urban hydrological predictions, particularly for flood forecasting and stormwater management. Calibration of soil hydraulic parameters, including infiltration and initial soil moisture, is crucial for accurate predictions, as uncalibrated models can significantly under or over-estimate peak flows (Doyle et al., 1980). Event-based models often fail to capture the effects of consecutive storms or varying antecedent moisture, which can compromise runoff predictions in rapidly urbanising areas (Tramblay et al., 2012). Calibration and validation of soil hydraulic parameters remain critical to model reliability. Inadequate calibration of infiltration and soil moisture parameters can lead to significant deviations between simulated and observed runoff, impacting infrastructure design and flood risk assessment. Common performance metrics include Nash–Sutcliffe Efficiency (NSE), RMSE, and Percent Bias, which quantify the agreement between simulations and observations (D. N. Moriasi et al., 2007).

In contrast, continuous infiltration models such as SWAT model simulate hydrological processes over extended periods like months to years, explicitly representing soil moisture dynamics, inter-event recharge, evapotranspiration, baseflow, and antecedent wetness conditions. This facilitates a more thorough and accurate representation of the hydrological processes within the catchment making continuous modeling better suited for long-term water balance studies and analysis of land use and climate change impacts (Arnold, J.G., et al. (1998); Deng et al., 2023). Consequently, while Horton and Green-Ampt classical methods are primarily event-based, continuous infiltration processes require modifications or alternative soil moisture accounting techniques integrated within comprehensive hydrological models like SWAT or HEC-HMS(Odey & Cho et al., 2025). Continuous models provide the advantage of representing both inter-event processes and long-term hydrological trends, which is essential for assessing the cumulative effects of land use changes, climate variability, and urbanization on soil moisture and runoff (Tramblay et al., 2012).

Comparative studies highlight the pros and cons of each. For example, a study using EPA-SWMM in Australia found out that the event-based simulation out-performed continuous simulation in reproducing both total runoff hydrographs and total runoff hydrographs in their catchments (Hossain et al., 2019). Conversely, for flood modelling with longer time series, continuous modelling more accurately represents antecedent soil moisture states improving specification of initial conditions for event simulations (Yu et al., 2018). In the context of infiltration modelling for urban flood prediction, an evaluation of the HEC-HMS model indicated that continuous approaches, although data intensive, are necessary for accurately capturing soil moisture variations and land use change dynamics (Odey & Cho et al., 2025). While HEC-HMS effectively simulates rainfall-runoff processes in urban catchments, it does not directly model hydraulic routing within sewer systems; therefore, it is often coupled with hydraulic models such as HEC-RAS for detailed urban flood modelling. This combined approach enhances the reliability and detail of urban flood predictions, balancing the strengths of both hydrologic and hydraulic modeling in urban environments, improving reliability in urban flood forecasting and infrastructure design. These comparative results highlight that the choice of modelling approach and the way infiltration and soil moisture are represented directly affects the reliability of urban hydrological predictions, particularly for flood forecasting and stormwater management(Friese et al., 2025)

The choice of infiltration method is closely linked to the simulation timeframe: event-based simulations typically rely on simplifications such as initial abstraction, fixed infiltration rates, or empirical loss methods, whereas continuous simulations require approaches that dynamically account for changes in infiltration capacity, soil moisture deficits, and recharge processes such as deficit and constant methods, soil-moisture accounting schemes methods.

Urban flood modelling studies highlight a common limitation: many models simplify infiltration and subsurface moisture processes, neglecting dynamic soil moisture variations, which reduces their applicability in rapidly urbanizing catchments (Cea et al., 2025; Guo et al., 2021; Hao et al., 2021; S. Xu et al., 2023). (Fidal & Kjeldsen et al., 2020) suggested that continuous simulations that account for soil moisture variability between events are generally more reliable for assessing runoff in urban catchments, as they capture the changing infiltration capacity and soil water deficits over time.

2.3 Uncertainty and Sensitivity in Infiltration and Soil Moisture Modelling

Urban hydrological modelling is subject to both model structural uncertainty and parameter uncertainty. Structural uncertainty arises from simplifying assumptions in classical infiltration models such as Horton and Green-Ampt, which often treat urban soils as uniform and ignore heterogeneity caused by compaction, shallow soil layers, and impervious cover (Beven, 2016). Parameter uncertainty stems from reliance on estimated or literature-based hydraulic parameters rather than field measurements, particularly in data-scarce regions.(Farzana et al., 2023). Sensitivity analyses consistently identify infiltration parameters especially saturated hydraulic conductivity, initial soil moisture, and suction head as among the most influential factors affecting peak discharge in urban storm events. (Del Giudice et al., 2013). Continuous models such as SWAT and HEC-HMS require calibration of soil moisture accounting routines to reduce uncertainty propagation over long simulations (Moriasi et al., 2007). Failure to calibrate infiltration parameters can lead to significant over- or underestimation of peak flows (G. Tang et al., 2023), reducing reliability for flood mitigation and BGI design.

2.4 Data Constraints and Monitoring Challenges in Urban Soil Moisture Modelling

Urban catchments pose difficulties in data acquisition due to limited accessibility, underground infrastructure, and rapid land-use changes. Event-based hydrological models require high-resolution rainfall data; however, most rainfall networks in Sub-Saharan Africa lack sub-hourly rainfall records needed for accurate runoff modelling (Guo et al., 2021). Soil hydraulic data such as infiltration rates and moisture content are rarely available because urban soils are modified, compacted, and difficult to sample (Mane et al., 2025). Deployments of in-situ soil moisture sensors are uncommon due to maintenance costs and vandalism risks in dense urban environments (Huang et al., 2025). These constraints reduce calibration robustness, particularly for continuous models that require long-term soil moisture information to accurately simulate antecedent wetness.

2.5 Spatial Data Integration for Capturing Urban Soil Variability

The integration of GIS, LiDAR and remote sensing represents a major advancement in urban hydrological modelling. High-resolution LiDAR allows detailed mapping of microtopography, improving representation of flow paths, depression storage, and overland flow routing (Yan et al., 2015). Remote sensing platforms such as SMAP and Sentinel-1 SAR provide soil moisture datasets that can be used to initialise soil moisture conditions and improve simulation accuracy, especially in continuous models (Lievens et al., 2017; Meyer et al., 2022). GIS-based land use mapping enables spatial assignment of infiltration capacity, curve numbers, and runoff coefficients to reflect heterogeneity in urban surfaces (Salazar-Martínez et al., 2022). This overcomes the weakness of classical infiltration methods that assume uniform soil conditions enhancing physical realism of model outputs (Rumbold et al., 2023)

2.6 Emerging Data-Driven and Hybrid Modelling Approaches

Recent studies show that machine learning (ML) and hybrid ML–hydrological models outperform traditional infiltration equations when predicting soil moisture dynamics and peak flows in urban catchments. Data-driven models such as Long Short-Term Memory (LSTM) networks capture non-linear responses between rainfall, soil moisture, and runoff without requiring explicit infiltration equations (Kratzert et al., 2019; Rumbold et al., 2023). Hybrid approaches use ML to correct systematic errors in physically based models such as SWAT and HEC-HMS reducing peak flow prediction error significantly. (Altarawneh et al., 2025; Nguyen et al., 2024). These methods are especially practical where infiltration data are limited, making them highly applicable to urban catchments in developing cities.

2.7 Influence of Climate Change on Infiltration Dynamics and Peak Flow Generation

Climate change has intensified rainfall frequency and magnitude, resulting in shorter infiltration windows and increased surface runoff in urban areas (IPCC, 2022). The occurrence of multiple storms in rapid succession tends to keep soils saturated, thereby reducing their infiltration capacity and causing higher peak flow conditions. Such conditions pose significant challenges for event-based hydrological models, which generally do not account for antecedent moisture dynamics effectively (Tramblay et al., 2010). In contrast, continuous hydrological models, which dynamically simulate soil moisture between rainfall events, demonstrate improved performance and reliability under these conditions (Beza & Moshe et al., 2025).

Concurrently, nature-based solutions such as Blue-Green Infrastructure (BGI), including permeable pavements, bioswales and rain gardens are increasingly implemented for urban flood management and resilience. The effectiveness of these interventions depends critically on infiltration processes, soil moisture dynamics, and storage capacity. Case studies indicate that the effectiveness of BGI in reducing runoff volumes and peak discharges is largely dependent on soil infiltration characteristics, antecedent soil moisture and the connectivity of hydrological pathways. Studies have shown that the effectiveness of infiltration-based stormwater controls diminishes when antecedent soil moisture is high or impervious cover is extensive. Additionally, a comparative assessment of the Curve Number and Green-Ampt methods revealed that the Green-Ampt model provides more robust and conservative urban flood extent predictions (Bianucci et al., 2025). (Mugume & Nakyanzi et al, 2024) demonstrated that infiltration based BGIs such as infiltration trenches and bioswales can reduce flood volumes by over 12% and decrease flood duration significantly, with their performance strongly influenced by soil infiltration capacity and moisture conditions. (Asiimire & Namakula et al., 2024) further highlighted rainwater harvesting as an effective BGI measure in Ugandan urban catchments, noting challenges such as land availability and funding but affirming the critical role of community engagement. Moreover, (Y. Liu et al., 2025) emphasized that integrated BGI systems enhance urban flood resilience by promoting infiltration, reducing runoff, and restoring natural water processes, advocating for hybrid green-gray infrastructure in the context of climate change. Collectively, these findings underscore the necessity of accounting for soil moisture dynamics and infiltration processes when assessing and designing BGIs for sustainable urban flood management.

Therefore, for urban hydrological modelling in catchments where BGI is being considered, accurate representation of infiltration and soil moisture processes is essential (Fidal & Kjeldsen et al., 2020). The interaction of infiltration method selection, simulation approach and prevailing land use and soil conditions governs model reliability and the subsequent utility of model outputs for BGI decision making(Fu et al., 2023). In conclusion, the reliability of urban hydrological models depends not only on the selected infiltration method and simulation approach, but also on precise representation of soil moisture dynamics and land use interactions, which are critical for informing BGI design and flood mitigation strategies.

3. CHAPTER THREE; MATERIALS AND METHODS

3.1 Study area

The Kinawataka catchment is located in the south-eastern part of Kampala, Uganda, spanning parts of Nakawa and Kampala Central divisions, draining into the Nakivubo Channel and ultimately Lake Victoria (approximately 0°17′N – 0°20′N, 32°35′E – 32°38′E). This catchment includes densely populated residential, commercial, and industrial areas, with rapidly expanding informal settlements like Kinawataka and Banda situated in generally low-lying and flood-prone locations. Urban land cover is dominated by built-up areas constituting about 40.5%, alongside grassland (18.9%), agricultural plantations (18.8%), bare soil (15.6%), and limited tree cover (6.2%). The wetland system is vital for hydrological functions including groundwater replenishment, flood regulation, and water quality maintenance in the Lake Victoria basin but has faced severe ecological degradation from urban expansion and altered drainage(Inya, 2021; Kakuba & Kanyamurwa, 2021).

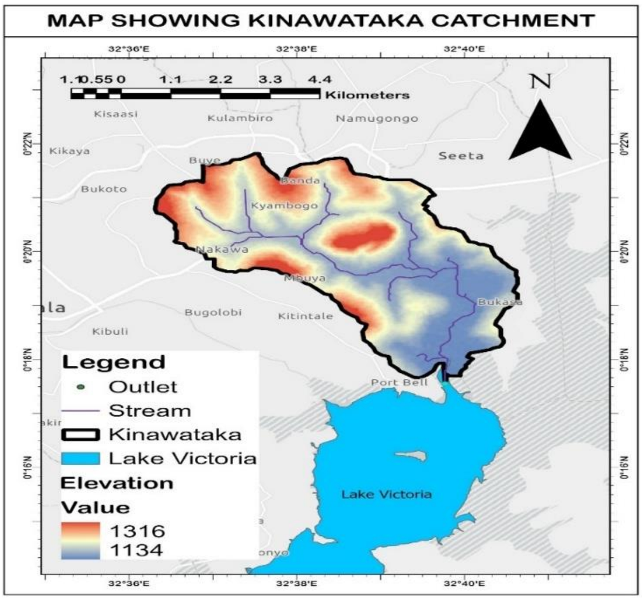


Figure3- 1 A map showing Kinawataka catchment

The rapid urbanization has significantly modified the natural drainage network through construction of storm drains, culverts, and embankments that have altered flow pathways and increased surface runoff by approximately 10–20%, while reducing infiltration capacity. The prevalent land uses and loss of wetland areas have resulted in deteriorated hydrological conditions, increasing flooding risks in the catchment. Kinawataka is one of Kampala's most flood-prone zones, with nearly 45% of buildings considered vulnerable to flooding, emphasizing the need for focused studies on infiltration and soil moisture dynamics within urban hydrological models. The heterogeneity of land use, with extensive impervious surfaces and degraded wetlands, also highlights the importance of integrating blue-green infrastructure and restoration efforts to improve flood management and urban water quality.

3.2 Methodology

3.2.1 Data collection

Data required included **meteorological** (daily precipitation); **hydrological** (soil map) and **GIS data** (Digital elevation model, Land use land cover). The various data types, their uses and respective sources used in modeling are shown in Error! Reference source not found.

Data type	**Description and Use**	**Scale**	**Data source**
Digital elevation models (DEMs)	Used to delineate the watershed, obtain slope and other catchment parameters	30m	USGS SRTM https://earthexplorer.usgs.gov/.
Land Use Land Cover Map	Determining canopy, surface parameters like the impervious and pervious values, evapotranspiration	10m	Esri 2020 land use land cover map from website https://livingatlas.arcgis.com/landcover/
Soil map	For estimating SMA loss model parameters like soil tension storage, Soil profile storage hydraulic conductivity.	10km	FAO soil data using the website https://www.fao.org/soils-portal/data-hub/soil-maps-and-databases/en/.
Weather forecasts	Daily precipitation data, and evapotranspiration data	Daily and monthly	ECMWF-IFS API using the website: https://open-meteo.com/en/docs/ecmwf-api.
Meteological Historical data	Daily precipitation data, and evapotranspiration data for hydrological model calibration	Daily	Directorate of water resources management (DWRM) Entebbe

Table 3- 1 Datasets used in the analysis

3.2.2 Data preparation

The delineation of the Kinawataka watershed was accomplished using a digital elevation model (DEM) of Uganda in ArcMap 10.7.1. The fill tool was first applied to generate a depressionless DEM, which enabled accurate identification of drainage patterns and watershed boundaries as shown in **Figure 3-1.**

To characterize the land use and land cover (LULC) within the delineated catchment, the 2020 land use map was clipped to the watershed extent using the ArcMap clipping tool. The resulting polygon was then transformed into a false color composite and reclassified according to major land use categories, including water bodies, forested areas, grasslands, wetlands, agricultural lands, shrubland, built-up areas, and bare ground **(Figure 3-2).**

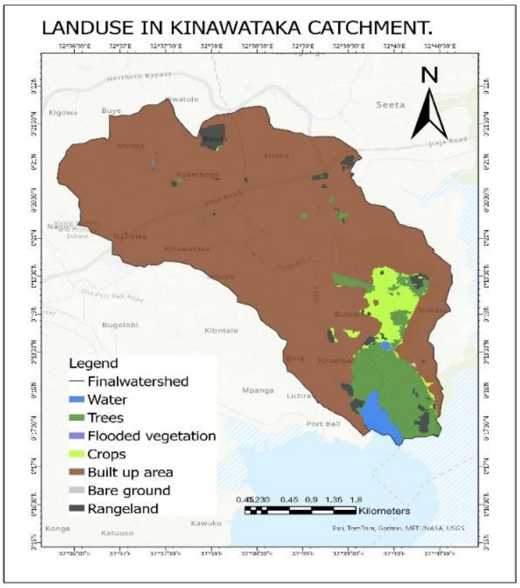


Figure3- 2 Landuse in Kinawataka catchment

3.2.3 Catchment Delineation and Study Area Selection

The Kinawataka catchment in eastern Kampala, Uganda, was delineated into hydrologically discrete sub catchments using a 30 m SRTM Digital Elevation Model (DEM) and standard flow accumulation and stream network extraction techniques in ArcGIS. A minimum contributing area threshold of 1 km^2 was applied to define channel initiation, and sub catchment boundaries were derived based on topographic divides and drainage patterns. This approach is consistent with established urban hydrological modeling practices for catchment discretization and parameter estimation(Mugume et al., 2015)

From the delineated units, this study focuses on the Sub catchments in the Upper Kinawataka located along the Kireka–Naguru upstream of the main wetland system. These sub catchments were selected because they represent a predominantly peri-urban environment with mixed land use, including vegetated areas and developing settlements, which are known to exhibit significant spatial variability in infiltration characteristics.

Focusing on the upper catchment is justified by its strong influence on hydrological response and model parameterization. Previous studies in Kampala have shown that infiltration processes in headwater areas play a critical role in controlling runoff generation and hydrograph response, particularly in rapidly urbanizing catchments (Mugume et al., 2015) Variability in soil properties and land use within these zones significantly affects key infiltration parameters such as saturated hydraulic conductivity and infiltration capacity, which are required for models such as Horton and Green-Ampt.

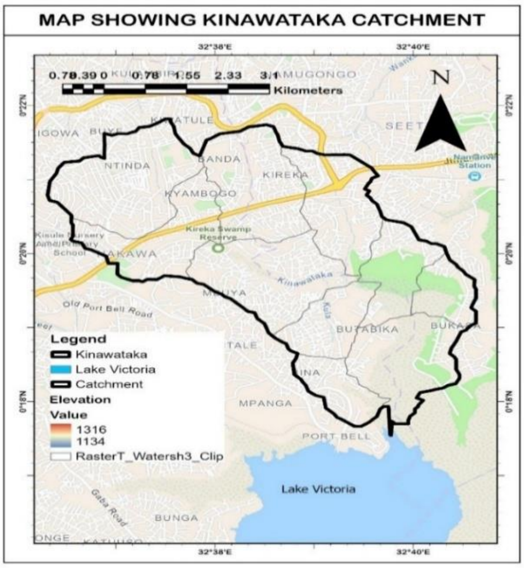


Figure3- 3 Sub-catchment delineation in the Kinawataka Catchment

In addition, upstream areas are often underrepresented in data collection, leading to uncertainty in hydrological modeling. By concentrating sampling efforts within these sub-catchments, this study aims to improve the characterization of infiltration processes in a zone that is both hydrologically sensitive and representative of ongoing land use change in the Kinawataka catchment.

This targeted approach is consistent with methodologies applied in similar Kampala catchments, where improved characterization of spatial infiltration variability has been shown to enhance urban drainage model performance (Sempewo et al., 2023).

3.2.4 Rainfall Data Preparation and Design Storm Development

Historical rainfall data for the Kampala region were obtained from long-term meteorological records. The data was processed to support the development of design rainfall inputs required for hydrological modelling in PCSWMM.

To capture the relationship between rainfall intensity, storm duration, and frequency, Intensity Duration Frequency (IDF) relationships were developed. The IDF curves were used to estimate rainfall intensities corresponding to selected storm durations and return periods **(2, 5, 10, 25, 50, and 100 years)** relevant for urban flood analysis.

The IDF curves provide a statistical representation of rainfall extremes, allowing conversion of historical rainfall data into design storm intensities suitable for simulation. These intensities were derived for different storm durations and return periods in order to reflect the variability of rainfall events that influence runoff generation in the catchment.

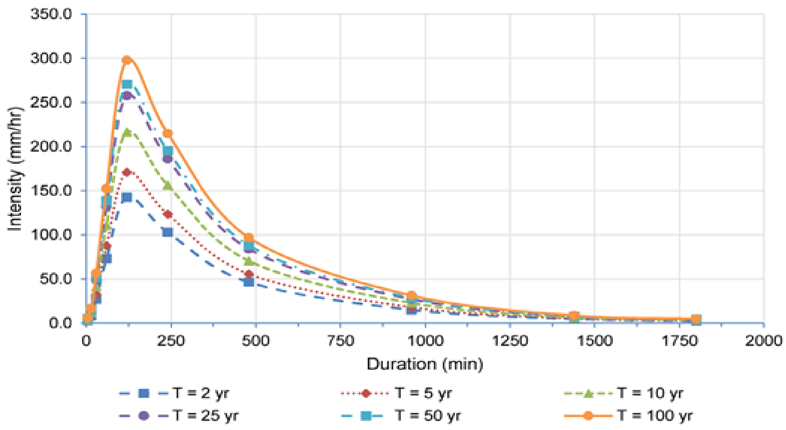


Figure3- 4 Extracted design storm profiles for Kinawataka catchment. Source; (Mugume et al., 2024a)

The derived rainfall intensities from the IDF curves were used to construct design storm events for input into the hydrological model. These design storms represent realistic rainfall scenarios that may occur within the Kinawataka catchment and are essential for simulating runoff response under different storm conditions.

The design rainfall inputs were subsequently applied in the PCSWMM model to evaluate catchment response under varying rainfall intensities and durations. This ensures that the model is capable of representing both typical and extreme rainfall events relevant to urban flood generation.

In addition to the IDF analysis, maximum daily rainfall data was also analysed to characterise extreme rainfall events within the study area. The maximum recorded daily rainfall values were extracted from long-term meteorological records and used to understand the upper limits of rainfall intensity that have historically occurred in the catchment.

These extreme rainfall values are important for hydrological modelling as they provide an indication of flood-producing storm magnitudes. They complement the IDF curves by providing observed peak rainfall conditions, which help in validating the realism of design storm scenarios used in the model.

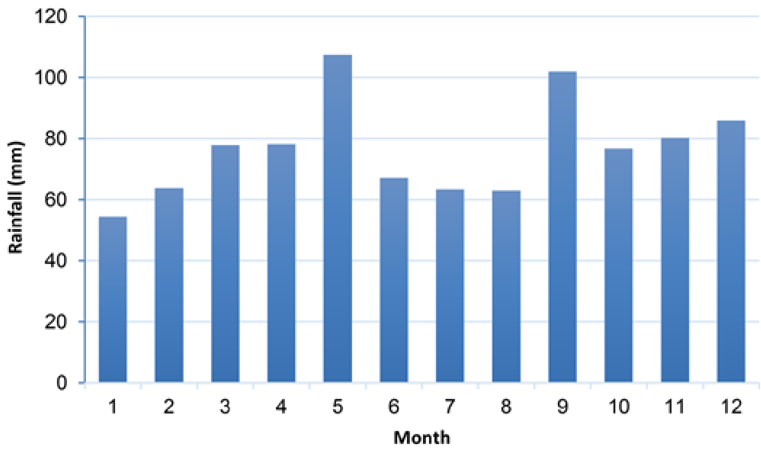


Figure3- 5 Observed maximum daily rainfall for Kampala City for the period 1943–2019. Source; (Mugume et al., 2024a)

The maximum daily rainfall data was therefore used as a reference for selecting appropriate return periods and rainfall magnitudes for simulation in the PC SWMM model, particularly within the range of T2, T5, T10, T25, T50, and T100 years

3.3 Sampling Design for Infiltration Measurements.

A stratified spatially distributed sampling approach was adopted to measure soil infiltration capacity across the Upper Kinawataka catchment (~25 km²), Kampala, Uganda. The method is consistent with field-based infiltration studies in heterogeneous urban catchments, which commonly apply land use stratification and spatial sampling to capture variability in soil hydraulic properties (Bamutaze et al., 2010).

The catchment was classified into three land use strata: (i) upstream peri-urban vegetated zones, (ii) mid-catchment transitional areas, and (iii) downstream highly urbanised zones. These strata were used to guide site selection in order to ensure representation of key infiltration-controlling surface conditions.

Sampling locations were selected in the field based on land use representation, accessibility, and hydrological connectivity rather than strict geometric spacing. This reflects standard practice in urban infiltration studies, where infrastructure, land ownership, and surface modification often prevent rigid transect-based sampling designs.

A total of 10 infiltration sampling points (SP01–SP10) were established and geo-referenced using GPS These points were distributed across the three land use strata to capture spatial variability in infiltration capacity.

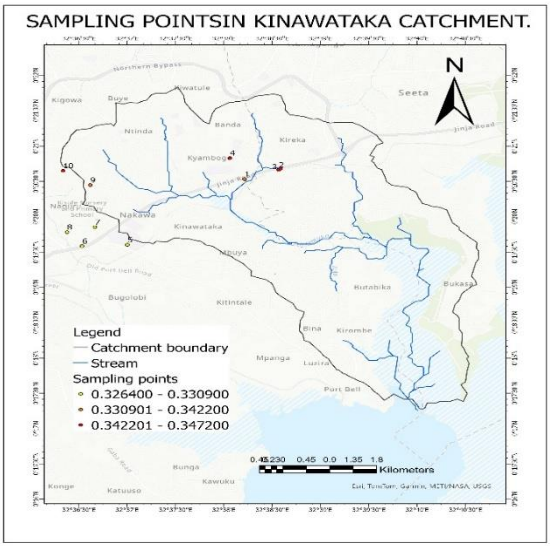


Figure3- 6 Spatial distribution of soil infiltration sampling points in the Upper Kinawataka catchment

The spatial distribution of the infiltration sampling points and their corresponding land use classifications are presented in **Table 3-3.** These points represent a spatially distributed field sampling design used to capture infiltration variability across the catchment.

Sampling point	**Latitude(^{0}N)**	**Longitude (^{0}E)**	**Stratum**
SP01	0.3422	32.6369	Transitional
SP02	0.3444	32.6428	Upstream
SP03	0.3447	32.6431	Upstream
SP04	0.3472	32.6344	Upstream
SP05	0.3267	32.6167	Downstream
SP06	0.3264	32.6089	Downstream
SP07	0.3309	32.6111	Downstream
SP08	0.3297	32.6063	Downstream
SP09	0.3408	32.6103	Transitional
SP10	0.3442	32.6056	Downstream

Table 3- 2 Geographic coordinates and stratification of infiltration sampling points

Field verification indicated that six sampling points were located within the GIS-derived catchment boundary, while four points were located near or marginally outside the boundary (Nakawa Market green space, Naguru Hospital area, Naguru East Road, and Naguru Hillrise). These locations were retained because urban drainage systems in Kampala often extend hydrological connectivity beyond mapped catchment boundaries due to stormwater infrastructure, roads, and artificial drainage pathways.

For analysis, sampling points were classified into:

- **Core catchment points (n = 6):** used for infiltration parameter estimation and model calibration (Horton and Green-Ampt models)

- **Boundary influence points (n = 4):** used to assess external infiltration conditions affecting inflow processes into the catchment.

Boundary influence points were included to capture infiltration conditions in adjacent urban areas that contribute surface runoff into the catchment through interconnected drainage networks. This is important in highly urbanised catchments where hydrological boundaries are not strictly closed due to engineered stormwater systems and surface connectivity.

Three replicate infiltration measurements were conducted at each sampling location to reduce variability due to soil heterogeneity. Mean infiltration rates were used for analysis in accordance with ASTM D5126 standards.

This stratified spatial sampling approach is consistent with infiltration studies in heterogeneous urban environments, where spatial variability is driven primarily by land use transitions rather than strict geometric spacing constraints (Alagna et al., 2016; Bamutaze et al., 2010).

3.4 Infiltration tests

3.4.1 Experimental Setup

- The soil sample was air dried to ensure that the soil particles were at a relatively same moisture content.
- A filter paper was placed in the tube on top of the perforated plate.
- The soil was poured into the tube in increments and each addition stirred to avoid segregation of soil particles. The soil was poured up to the 250mm mark.
- Another filter paper was placed on top of the soil sample and a wire mesh baffle inserted into the cylinder to be filled with water. The wire mesh helps to minimise erosion of the soil sample.
- Water was then poured into the tube upto the 460mm mark.

Figure3- 7 Lab infiltration tests and set up

3.4.2 Data collection

Water levels were recorded at specified time intervals, and the corresponding water depth above the soil surface was computed. The depth of penetration was determined from the reduction in water depth over time.

3.4.3 Data Processing

The depth of penetration was calculated as the difference between the initial water depth and the water depth at any given time. The infiltration rate was determined from the slope of the cumulative infiltration curve using:

$$f = \frac{\Delta d_p}{\Delta t} \times 60$$

where f is the infiltration rate (mm/hr), d_p is the depth of penetration (mm), and t is time (minutes).

3.4.4 Determination of Soil Moisture Content

- Soil samples were collected from the sample locations and placed in airtight polythene bags to minimize moisture loss.
- The moisture content was determined using the oven-drying method in accordance with standard geotechnical procedures.
- The wet mass of each sample was measured before drying, after which the samples were oven-dried at 105–110^{0}C for 24 hours and reweighed to obtain the dry mass.
- The gravimetric moisture content, (w), was calculated using:

Moisture content $\theta_i, = \frac{Mw-Ms}{Ms} * 100$

where M_w is the mass of water lost during drying and M_s is the mass of the dry soil. The obtained moisture contents were used to characterize the antecedent soil moisture conditions and as inputs for the Green-Ampt infiltration model.

The representative moisture content for each condition was obtained by averaging the grouped moisture contents of the collected soil samples.

3.5 PCSWMM Model Setup and Input Parameters

A hydrological model of the Kinawataka catchment was developed using PCSWMM to simulate rainfall–runoff processes and evaluate the influence of infiltration characteristics on runoff generation. The model represents the catchment as a system of interconnected sub-catchments and drainage elements that control the movement of water from rainfall to the outlet.

The delineated catchment was divided into sub-catchments based on topography and drainage patterns. Each sub-catchment was assigned physical properties such as area, slope, and land use characteristics. These sub-catchments were connected through a drainage network consisting of conduits and nodes, which represent channels, pipes, and junctions within the system.

Rainfall data was used as the primary input to the model and was applied uniformly across all sub-catchments. In addition, infiltration parameters derived from field measurements were incorporated to represent soil water losses within pervious areas. Land use information was used to define surface characteristics such as imperviousness and roughness, which influence runoff generation.

The overall modelling process, including the relationship between inputs, hydrological processes, and outputs, is illustrated in **Figure 3-7.**

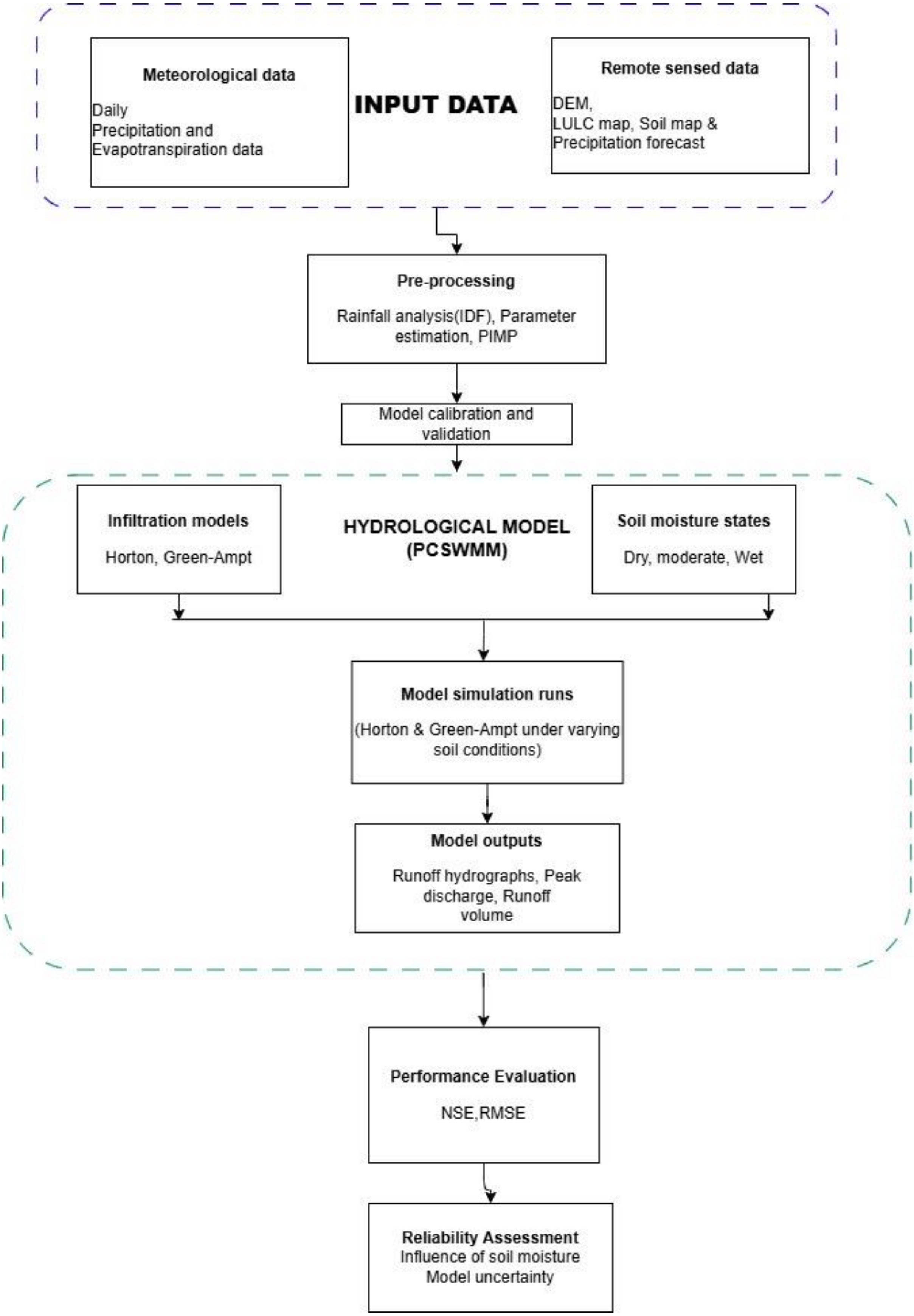


Figure3- 8 Conceptual Framework of the methodology

As shown in **Figure 3-7,** rainfall serves as the primary input to the model, while runoff generation represents the main process. The model simulates how rainfall is converted into surface runoff and temporary storage within the catchment.

Infiltration was modelled using the Horton and Green-Ampt Model approaches. The parameters for these models were obtained from Laboratory experiments conducted on soil samples at the selected sampling points, ensuring that spatial variability in soil properties was incorporated into the model.

Runoff generated within each sub-catchment was routed through the drainage system using a one-dimensional (1D) flow routing approach. This represents the movement of water along channels and pipes as flow progresses downstream through the network. The 1D routing accounts for changes in flow depth and velocity within conduits, allowing simulation of how runoff is conveyed through the urban drainage system to the outlet.

Surface characteristics such as imperviousness were used to differentiate between areas that generate direct runoff and those that allow infiltration. Pervious areas were assigned infiltration parameters based on field data, while impervious areas contributed primarily to surface runoff.

The model produced outputs including runoff volume, peak discharge, and infiltration losses for each sub-catchment and at the catchment outlet. These outputs were used to evaluate the influence of different infiltration models on the hydrological response of the Kinawataka catchment.

3.5.1 Model Calibration for Kinawataka Catchment

The PCSWMM model developed for the Kinawataka catchment was not calibrated using conventional observed discharge data due to the limited availability of simultaneous rainfall–runoff measurements within the study area. This limitation is common in urban catchments and restricts the application of traditional calibration techniques. In this study, emphasis was placed on improving model reliability through accurate representation of catchment characteristics and careful estimation of key hydrological parameters. Infiltration parameters derived from field measurements were used as primary inputs and maintained within physically realistic ranges, while land use characteristics such as imperviousness and surface roughness were defined based on field observations. In addition, a One-Factor-at-a-Time (OAT) sensitivity analysis was undertaken to identify the most influential parameters affecting runoff generation and to ensure that parameter values were appropriately selected within realistic limits.

3.5.2 Model Validation for Kinawataka Catchment

Model validation was carried out using a qualitative and sensitivity-based approach, supported by available field observations. Observations of flood-prone locations within the catchment were used to assess whether simulated runoff responses were consistent with known flooding patterns. This approach is consistent with previous studies where post-event observations, including flood extents and high-water marks, have been used to support model validation in data-limited environments. Model performance was further evaluated using statistical indicators such as the Nash–Sutcliffe Efficiency (NSE) and Root Mean Square Error (RMSE), which provide a measure of agreement between simulated outputs and expected hydrological behaviour. Although detailed observed discharge data were not available, the combination of physically-based parameter estimation, sensitivity analysis, and comparison with observed flood behaviour provides reasonable confidence in the reliability of the model for simulating rainfall–runoff processes within the catchment.

4. CHAPTER FOUR; RESULTS AND DISCUSSION

4.1 Introduction

This chapter presents and discusses the results obtained from rainfall–runoff simulations using the Horton and Green-Ampt infiltration models. The analysis focuses on peak runoff and total runoff volume under wet, moderate, and dry soil moisture conditions within the Kinawataka catchment. The performance of both models was evaluated based on their sensitivity to antecedent soil moisture conditions and consistency with expected hydrological behaviour.

4.2 Infiltration Characteristics (Lab Results)

4.2.1 Horton model Results and Interpretation

4.2.1.1 Data Processing and Parameter Estimation

For each of the ten sampling points, recorded water level reductions over time were used to compute infiltration rates. The following procedure was applied:

- **Initial infiltration rate (f_0)**
  Determined as the infiltration rate at the beginning of the test, corresponding to the first measurement.

- **Final infiltration rate (f_c)**
  Estimated as the average of the final readings where the infiltration rate approached a constant value, indicating near steady-state conditions.

- **Decay constant (k)**
  A logarithmic transformation of the Horton equation was applied:

$$\ln(f - f_c) = \ln(f_0 - f_c) - kt$$

A linear regression was performed by plotting $\ln(f - f_c)$against time. The slope of the resulting line was used to estimate the decay constant as:

$$k = -(\text{slope})$$

This approach allowed for consistent estimation of parameters across all sampling points using spreadsheet-based analysis.

Horton model Laboratory Results

The derived Horton parameters for the ten sampling locations are presented in the table below as obtained from the graphs on **Page 46-47.**

Sampling point	**Latitude(^{0}N)**	**Longitude (^{0}E)**	**f_0 (mm/hr)**	**f_C (mm/hr)**	**k(hr^{-1})**
SP01	0.3422	32.6369	120	100	0.7546
SP02	0.3444	32.6428	420	190	0.182
SP03	0.3447	32.6431	180	20	0.0304
SP04	0.3472	32.6344	240	76	0.130
SP05	0.3267	32.6167	120	20	0.019
SP06	0.3264	32.6089	180	60	0.0593
SP07	0.3309	32.6111	120	30	0.060
SP08	0.3297	32.6063	300	120	0.3312
SP09	0.3408	32.6103	300	190	0.182
SP10	0.3442	32.6056	240	19	0.0156

Table 4- 1 Horton model field Infiltration data

4.2.1.2 Interpretation of derived horton parameters

The results indicate significant spatial variability in infiltration characteristics across the catchment. Initial infiltration rates (f_0) ranged from 120 mm/hr to 420 mm/hr, reflecting differences in soil texture, compaction, and porosity. Higher values suggest more permeable soils, while lower values indicate more compacted conditions.

Final infiltration rates (fc) ranged from 19 mm/hr to 190 mm/hr, representing steady-state infiltration capacity. Lower values indicate reduced permeability under saturated conditions, while higher values suggest sustained infiltration potential.

The decay constant (k) varied between 0.0156 hr^{-1} and 0.7546 hr^{-1} **(Page 46-47),** indicating differences in how quickly infiltration capacity decreases over time. High k values reflect rapid saturation and reduced infiltration performance, while low values indicate gradual infiltration decline and more stable soil conditions.

These variations demonstrate that soil infiltration behaviour is not uniform across the catchment, which directly influences runoff generation and model reliability in urban hydrological simulations.

It should be noted that the tests were conducted under controlled laboratory conditions. Therefore, field conditions such as vegetation cover, compaction variability, and surface sealing may lead to differences in actual infiltration behaviour. However, the derived parameters provide a consistent basis for comparative hydrological modelling.

4.2.2 Green-Ampt model Results and Interpretation

4.2.2.1 Data Processing and Parameter Estimation

The Green–Ampt model assumes a sharp wetting front with a constant effective suction head, which is usually determined from soil water retention characteristics.(Angulo-Jaramillo et al., 2016).

Saturated Hydraulic Conductivity (K_s)

The saturated hydraulic conductivity for each of the ten soil samples was determined from laboratory infiltration experiments. The steady-state portion of the cumulative infiltration curve was used to estimate K_s, where the infiltration rate approaches a constant value. This represents the soil's ability to transmit water under saturated conditions.

Initial and Saturated Volumetric Water Content (θ_i and θ_s)

The initial volumetric water content (θ_i) was obtained from laboratory gravimetric moisture content measurements conducted prior to infiltration testing for each sample.

The saturated volumetric water content (θ_s) was assumed to be constant across all sampling locations. A value of:

$$\theta_s = 0.40$$

was adopted based on typical literature values for sandy loam soils commonly found in tropical urban environments.(Rawls et al., n.d.).

The moisture deficit was computed as:

$$\Delta\theta = \theta_s - \theta_i$$

Wetting Front Suction Head (ψ_f)

The suction head at the wetting front is treated as a parameter that can be estimated or calibrated rather than directly measured, and is often assumed constant for a given soil. (Aoda et al., 2005)

The wetting front suction head (ψ) was not directly measured due to the absence of soil water retention curve data. In the Green–Ampt model, ψ represents the effective capillary suction at the wetting front and is typically treated as a soil-texture dependent parameter.

The classical Green–Ampt formulation assumes a homogeneous soil profile with a sharp wetting front and a constant suction head (Green-Ampt, n.d.; Saxton & Rawls et al., 2006)

In practical hydrological applications, ψ is commonly assigned based on soil texture class when detailed experimental determination is not available.

Given the assumed sandy loam conditions of the study area, a representative value of ψ = 110 mm was adopted uniformly for all sampling locations. This value lies within the standard reported range for sandy loam soils (approximately 80–150 mm) in established soil hydraulic parameter datasets (Saxton & Rawls et al., 2006)

Summary of model parameters.

Parameter	Method of Determination
K_s	Laboratory steady-state infiltration analysis
θ_i	Laboratory gravimetric moisture content
θ_s	Assumed constant (0.4) from literature
ψ_f	Literature based representative value 110mm

Table 4- 2 Summary of Green ampt model parameters

Green Ampt model Results.

Sampling point	Latitude(^{0}N)	Longitude (^{0}E)	Ks	θ_i	θ_s	ψ_f
SP01	0.3422	32.6369	57	0.230	0.40	110
SP02	0.3444	32.6428	55	0.177	0.40	110
SP03	0.3447	32.6431	57	0.184	0.40	110
SP04	0.3472	32.6344	52	0.182	0.40	110
SP05	0.3267	32.6167	52.7	0.240	0.40	110
SP06	0.3264	32.6089	49.7	0.172	0.40	110
SP07	0.3309	32.6111	55.3	0.215	0.40	110
SP08	0.3297	32.6063	55	0.173	0.40	110
SP09	0.3408	32.6103	55.7	0.119	0.40	110
SP10	0.3442	32.6056	53.3	0.228	0.40	110

Table 4- 3 Green -Ampt model field infiltration parameters.

4.2.2.2 Interpretation of derived Green-Ampt parameters

The estimated Green–Ampt parameters for the ten sampling points reveal moderate spatial variability in soil hydraulic behaviour across the study area. Saturated hydraulic conductivity (K_s) values range from 49.7 mm min^{-1} (SP06) to 57 mm min^{-1} (SP01 and SP03), indicating relatively permeable soils consistent with coarse-textured or sandy loam conditions. The relatively narrow spread of $K_s$values suggests that, despite localized heterogeneity, the soils exhibit broadly similar infiltration characteristics at the scale of analysis.

Variations in initial volumetric water content (θ_i) are more pronounced, ranging from 0.119 (SP09) to 0.240 (SP05). These differences reflect spatial variability in antecedent moisture conditions, which play a critical role in controlling early-time infiltration dynamics. Lower initial moisture contents (e.g., SP09) imply a higher soil water deficit and greater potential for rapid infiltration, whereas higher values (e.g., SP05 and SP10) indicate reduced storage capacity and earlier onset of saturation under rainfall conditions, consistent with established infiltration theory(Hillel et al., 1998) and field observations of spatial heterogeneity in vadose zone moisture (Heistermann et al., 2022; Tromp-Van Meerveld & McDonnell, 2006).

The saturated volumetric water content ($\theta_s = 0.40$) and wetting front suction head ($\psi_f = 110$ mm) were treated as representative parameters across all sampling points. This approach is consistent with the classical Green–Ampt formulation, which conceptualizes infiltration as occurring in a homogeneous soil profile characterized by a sharp wetting front and a constant effective suction head(Ali et al., 2016).

In practical hydrological applications, the suction head parameter is typically estimated from soil texture-based datasets rather than measured directly, particularly where soil water retention data are unavailable (Rawls et al., 1982.; Saxton & Rawls et al., 2006)

Although the assumption of uniform ψ_f and θ_s simplifies the representation of soil hydraulic properties, the observed variability in K_s and θ_i indicates that the study area is not strictly homogeneous. This heterogeneity is typical in urban catchments with spatially variable soil conditions. Consequently, while the adopted parameter set captures the dominant infiltration behaviour, it may not fully resolve localized variations in infiltration response. (Mein and Larson et al., 1973).

Overall, the derived Green–Ampt parameters provide a coherent and physically consistent basis for subsequent infiltration and runoff modelling. This approach is appropriate for data-limited hydrological modelling but should be considered when interpreting spatial variability in results.

These parameters were subsequently used as inputs in the SWMM model to simulate runoff under different soil moisture conditions.

4.2.3 Data Processing

The infiltration results were grouped into three soil moisture conditions: wet, moderate, and dry. This was based on steady infiltration rates and soil moisture deficit values. Sampling points with low infiltration rates were classified as wet conditions, indicating near-saturated soils. Moderate conditions represented average field conditions, while dry conditions had higher infiltration capacity and greater soil moisture deficit.

4.2.3.1 Horton Grouping

The infiltration data obtained from laboratory tests were classified into three antecedent soil moisture conditions: wet, moderate, and dry. This classification was based on the magnitude of the final infiltration rate (f_C), which represents the steady-state infiltration capacity of the soil.

Lower values of f_C were associated with wet conditions due to reduced infiltration capacity, while higher values corresponded to dry conditions with greater infiltration potential. The classification thresholds were defined based on the range of observed values as follows:

- **Wet condition:** $f_C < 50$ mm/hr
- **Moderate condition:** 50 mm/hr $\leq f_C \leq$ 120 mm/hr
- **Dry condition:** $f_C > 120$ mm/hr

Using these thresholds, the sampling points were grouped in **Table 4-4** accordingly, and average parameter values were computed for each condition. These grouped parameters were then used as inputs in the hydrological model simulations.

4.2.3.1.1 Grouping of Sampling points

Condition	Sampling points	f_C range
Wet	SP03, SP05, SP10	< 50
Moderate	SP04, SP06, SP07, SP01	50 – 120
Dry	SP02, SP08, SP09	> 120

Table 4- 4 Classification of Sampling Points into Soil Moisture Conditions Based on Final Infiltration Rate

4.2.3.2 Green Ampt Grouping

For the Green-Ampt model, classification into soil moisture conditions was based on the initial volumetric water content (θ_i), which represents antecedent soil moisture. Higher values of θ_i indicate wetter soil conditions, while lower values represent drier conditions with higher infiltration potential.

The thresholds were defined based on the observed range of θ_i values as follows:

- **Wet condition:** $\theta_i > 0.21$
- **Moderate condition:** $0.17 \leq \theta_i \leq 0.21$
- **Dry condition:** $\theta_i < 0.17$

Sampling points were grouped accordingly, and representative parameter values were obtained by averaging K_S and θ_i within each group. These values were used as inputs in the simulation scenarios.

4.2.3.2.1 Grouping of Sampling points

Condition	Sampling points	θ_i range
Wet	SP01, SP05, SP07, SP10	> 0.21
Moderate	SP02, SP03, SP04, SP08	0.17 – 0.21
Dry	SP06, SP09	< 0.17

Table 4- 5 Classification of Sampling Points into Soil Moisture Conditions Based on Initial Volumetric Water Content

The grouped infiltration parameters for each soil moisture condition were obtained by averaging the values of the corresponding sampling points within each category (**Table 4-6** and **Table 4-7**). These representative values were used as inputs for the hydrological model simulations.

Condition	f_O (mm/hr)	f_C (mm/hr)
Wet	165	22.3
Normal	180	78.7
Dry	340	166.7

Table 4- 6 Grouped Horton Infiltration Parameters for Simulation Scenarios

Condition	K_S (mm/hr)	θ_i	θ_S	$\Delta\theta = (\theta_S - \theta_i)$	ψ_f
Wet	52.7	0.225	0.40	0.175	110
Normal	55.0	0.185	0.40	0.125	110
Dry	55.8	0.135	0.40	0.265	110

Table 4- 7 Grouped Green-Ampt Parameters for Simulation Scenarios

4.2.4 Infiltration Behaviour under Different Soil Moisture Conditions

To further illustrate the effect of the grouped soil moisture conditions on infiltration behaviour, infiltration response curves were generated using the grouped parameter values for both the Horton and Green-Ampt models.

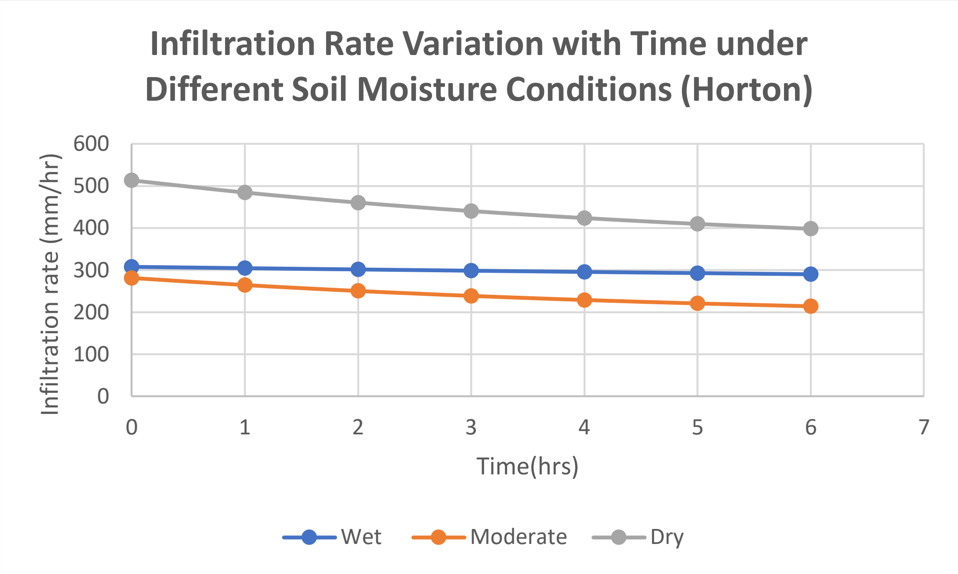


Figure 4- 1 Infiltration rate variation under wet, moderate, and dry soil moisture conditions using the Horton model

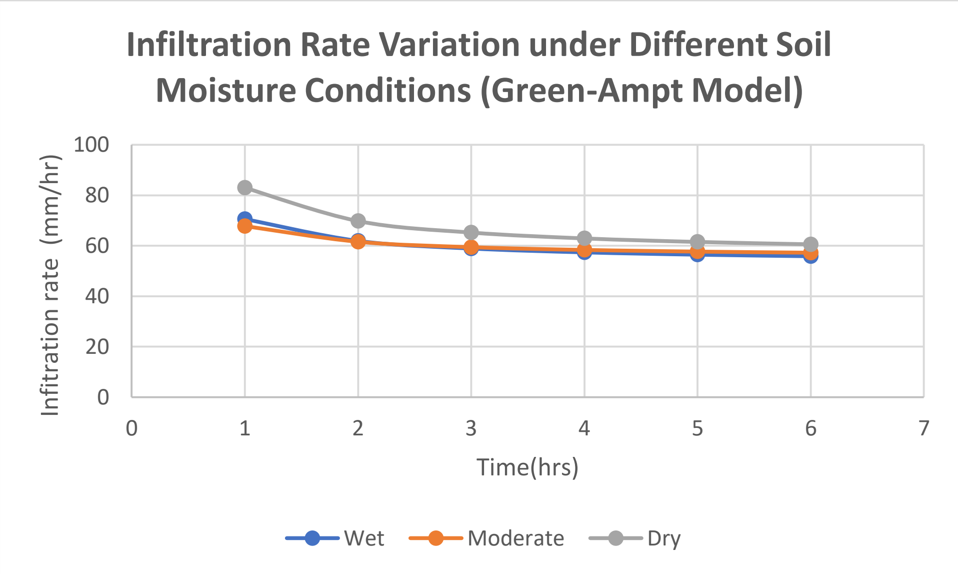


Figure 4- 2 Infiltration rate variation under wet, moderate, and dry soil moisture conditions using the Green-Ampt model

The infiltration curves in **Figure 4-1** and **Figure 4-2** show clear differences between soil moisture conditions. Dry conditions exhibit higher infiltration rates, while wet conditions show lower infiltration capacity due to near-saturated conditions. The moderate condition lies between these extremes.

The Horton infiltration model (**Figure 4-1**) shows a gradual decline in infiltration rate over time, while the Green-Ampt infiltration model (**Figure 4-2)** reflects a response that is more directly influenced by soil moisture conditions.

These results support the classification of sampling points into wet, moderate, and dry conditions and demonstrate the influence of soil moisture on infiltration behaviour and runoff prediction.

4.2.4 Hydrological Modelling

Modelling was carried out using **PC SWMM.** The same rainfall event and catchment parameters were applied across all simulations to ensure consistency.

4.2.5 Simulation Scenarios

Six simulation scenarios were developed by combining the two infiltration models with the three soil moisture conditions.

Scenario	**Model**	**Condition**
H1	Horton	Wet
H2	Horton	Moderate
H3	Horton	Dry
G1	Green-Ampt	Wet
G2	Green-Ampt	Moderate
G3	Green-Ampt	Dry

Table 4- 8 Simulation scenarios for infiltration models

4.3 Simulation Results

4.3.1 Infiltration Model Outputs Under Different Return Periods

4.3.1.1 Peak Flow Results

The simulation results indicate that peak flow increases with increasing return period for both the Horton and Green–Ampt infiltration models. Higher return periods correspond to more intense rainfall events, which generate larger peak discharges due to increased runoff generation.

Across all simulated scenarios (2, 5, 10, 25, 50, and 100-year return periods), the two models produced very similar peak flow values, with no major divergence observed between them. In addition, peak flow values remained constant across different antecedent moisture conditions in some cases, indicating that rainfall intensity had a stronger influence on peak flow than soil moisture variation for the selected events.

Table 4- 9 Baseline peak runoff model results in m^3

	Horton						Green-Ampt					
	T2	T5	T10	T25	T50	T100	T2	T5	T10	T25	T50	T100
Wet	0	18.95	18.95	18.95	18.95	18.95	0	18.95	18.95	18.95	18.95	18.95
Moderate	0	18.95	18.95	18.95	18.95	18.95	0	18.95	18.95	18.95	18.95	18.95
Dry	0	18.95	18.95	18.95	18.95	18.95	0	18.95	18.95	18.95	18.95	18.95

4.3.3.2 Runoff Volume Results

Runoff volume results show a clear increasing trend with increasing return period for both models. This is attributed to higher rainfall depths associated with longer return period storms, which exceed infiltration capacity and generate more surface runoff.

Table 4- 10 Runoff volume results across models in m^3

Return period	**Moisture condition**	**Green ampt**	**Horton**	**%Diff**
2	**Dry**	73,530	73,530	0
	Moderate	73,542	73,530	-0.01632
	Wet	73,533	73,530	-0.00408
5	**Dry**	80,098	80,096	-0.0025
	Moderate	80,135	80,096	-0.04867
	Wet	80,118	80,096	-0.02746
10	**Dry**	85,587	85,560	-0.03155
	Moderate	85,620	85,566	-0.06307
	Wet	85,610	85,574	-0.04205
25	**Dry**	88,744	88,707	-0.04169
	Moderate	88,772	88,723	-0.0552
	Wet	88,761	88,730	-0.03493
50	**Dry**	89,567	89,530	-0.04131
	Moderate	89,596	89,547	-0.05469
	Wet	89,584	89,553	-0.0346
100	**Dry**	92,581	92,547	-0.03672
	Moderate	92,626	92,564	-0.06694
	Wet	92,608	92,571	-0.03995

The Green–Ampt model consistently produced slightly higher runoff volumes compared to the Horton model under the same conditions. Differences were observed across all return periods and moisture conditions, although the magnitude of variation remained small.

Runoff volumes also increased from dry to wet soil conditions, confirming the influence of antecedent moisture on infiltration capacity and runoff generation.

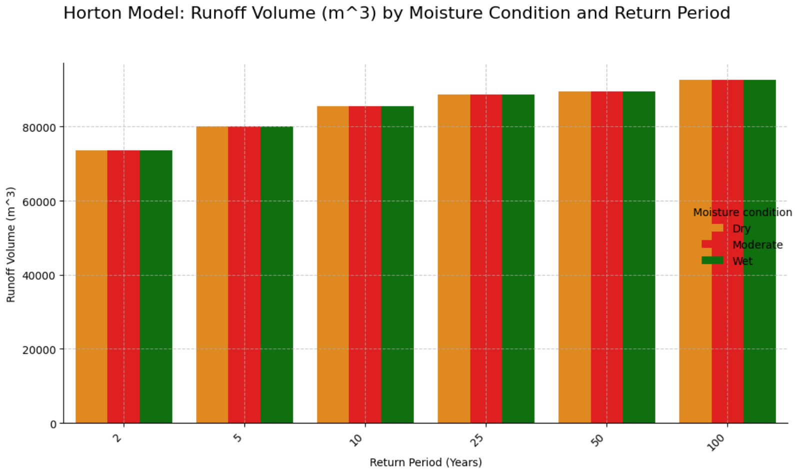


Figure 4- 3 Runoff volume for the horton model

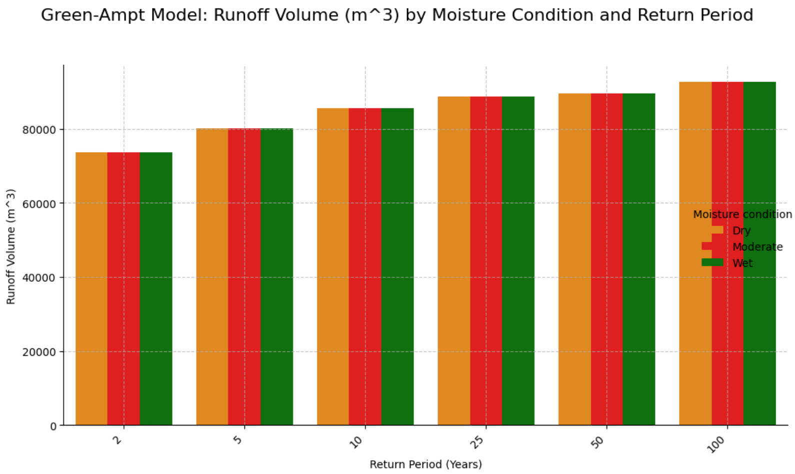


Figure 4- 4 Runoff volume for the Green-Ampt model

4.4 Effect of Antecedent Soil Moisture Conditions

4.4.1 Runoff Volume Response to Soil Moisture

The results indicate that antecedent soil moisture conditions influence runoff generation for both models. Generally, runoff volume increases from dry to wet conditions due to reduced infiltration capacity in wetter soils.

For example, at a selected return period, dry conditions consistently produced lower runoff volumes compared to moderate and wet conditions. This trend was observed in both the Horton and Green–Ampt models, although the Green–Ampt model showed slightly higher sensitivity to moisture changes.

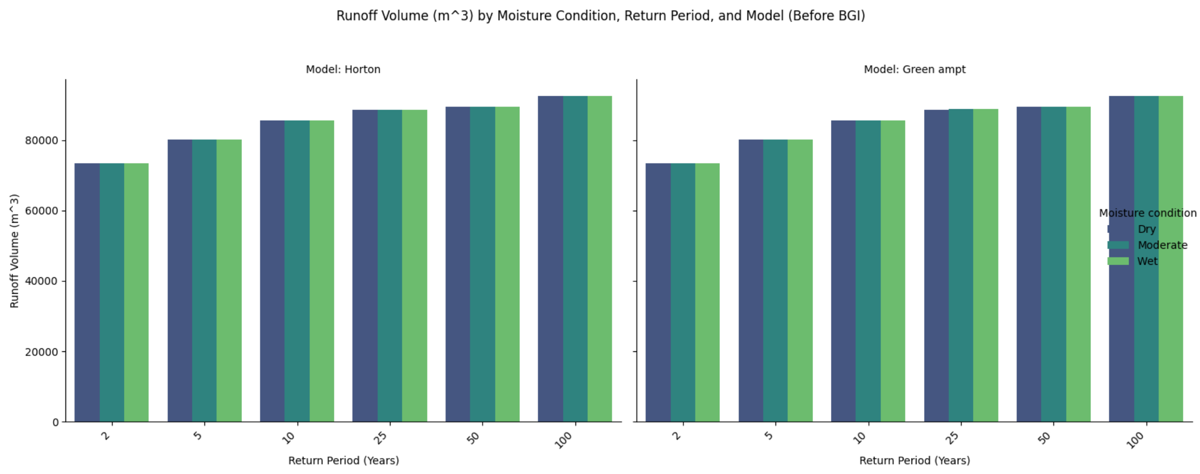


Figure 4- 5 Runoff volume response across different moisture conditions

4.4.2 Peak Flow Response to Soil Moisture

Peak flow results showed limited variation across soil moisture conditions for some return periods, with identical values observed in certain simulations. This suggests that peak discharge is primarily controlled by rainfall intensity and catchment response time rather than antecedent soil moisture under these conditions.

4.5 Comparison of Horton and Green–Ampt Models

4.5.1 Runoff Volume Differences Between Models

A comparison between the Horton and Green–Ampt models showed small but consistent differences in predicted runoff volumes. The Horton model generally produced slightly lower runoff volumes compared to the Green–Ampt model across all return periods and moisture conditions.

The percentage differences in runoff volume ranged from approximately **−0.007% to −0.048%**, indicating very minor deviations between the two models. Despite the small magnitude, the differences were systematic and consistent across simulations.

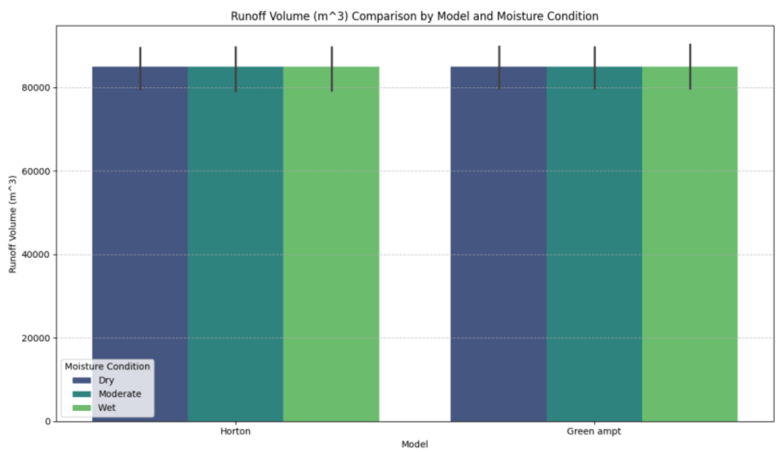


Figure 4- 6 Model comparison of runoff volumes

4.6 Summary of Model Behaviour

Overall, both infiltration models reproduced similar hydrological trends in terms of increasing runoff with increasing return period and soil moisture. However, the Green–Ampt model showed slightly higher runoff estimates, reflecting differences in how infiltration processes are represented in the two models.

4.7 BGI Performance

4.7.1 Runoff Reduction Due to Bioretention Cells

Bioretention cells were modelled in SWMM using the Low Impact Development (LID) control module. The bioretention LID was configured to represent a vegetated depression designed to capture, store, and infiltrate stormwater runoff. These comprised parameters (**Table 4-11**) selected based on literature values and site conditions. The bioretention cells were assigned to selected sub-catchments and simulated under dry, moderate, and wet antecedent soil moisture conditions.

Table 4- 11 Bioretention cell parameters source; (Mugume et al., 2024)

Bioretention parameters	**Units**	**Adopted value**
Area of each unit	m^2	120
Volume of each unit	m^3	72
Percentage of sub catchment occupied	%	1.5
Percentage of impervious treated	%	60
Percentage of pervious area treated	%	20

The inclusion of bioretention cells significantly reduced runoff volume under all return periods, soil moisture conditions, and for both infiltration models

Table 4- 12 Simulated Runoff volumes in m^3 before and after bioretention cells intervention

Return period	Moisture condition	Runoff Volume (Original)	Runoff Volume (Bioretention cells)	% Reduction
2	**Dry**	73,530	50,959	30.69631
	Moderate	73,530	50,962	30.69223
	Wet	73,530	59,073	19.66136
5	**Dry**	80,096	59,047	26.27971
	Moderate	80,096	59,060	26.26348
	Wet	80,096	59,069	26.25225
10	**Dry**	85,560	69,845	18.36723
	Moderate	85,566	69,869	18.3449
	Wet	85,574	69,893	18.32449
25	**Dry**	88,707	76,637	13.60659
	Moderate	88,723	76,702	13.54891
	Wet	88,730	76,728	13.52643
50	**Dry**	89,530	78,118	12.74657
	Moderate	89,547	78,191	12.68161
	Wet	89,553	78,216	12.65954
100	**Dry**	92,547	82,304	11.06789
	Moderate	92,564	82,400	10.98051
	Wet	92,571	82,423	10.9624

Runoff reduction was more pronounced under dry conditions and decreased with increase in soil moisture. This is because dry soils allow greater infiltration within the bioretention system, improving its effectiveness.

Both models showed similar reduction trends, although the magnitude of reduction differed slightly between Horton and Green–Ampt outputs.

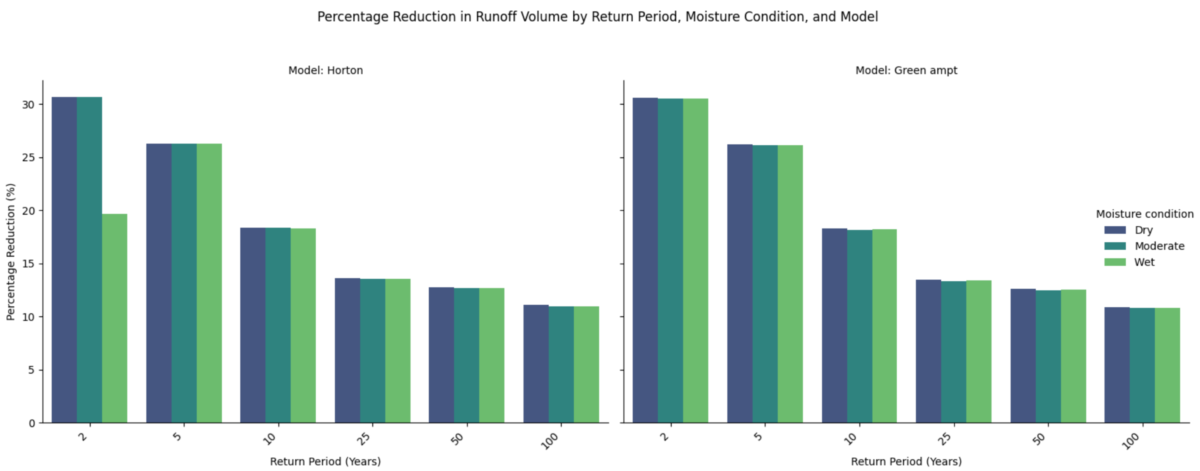


Figure 4- 7 Percentage reduction of runoff generated for bioretention cells

4.7.2 Runoff Reduction Due to Detention ponds

Detention ponds were modelled in SWMM as storage units designed to temporarily retain stormwater runoff and attenuate peak flows before controlled release downstream. The storage units were connected to the drainage network through outlet structures configured to regulate outflow. The detention ponds were incorporated into the model to evaluate their effectiveness in reducing runoff volume and peak discharge under different return periods and antecedent soil moisture conditions. The design parameters (**Table 4-13**) were selected based on engineering design guidelines and catchment characteristics.

Table 4- 13 Detention Pond parameters source; (Mugume et al., 2024)

Surface parameters	**Units**	**Value**
Number of units	No.	10
Area of each unit	m^2	5,013.4
Depth	m	6
Volume per unit	m^3	30,080
Total Volume	m^3	300,804

The inclusion of detention ponds more significantly reduced runoff volume under all return periods, soil moisture conditions, and for both infiltration models.

Return period	**Moisture condition**	**Runoff Volume (Original) m^3**	**Runoff Volume (Detention Ponds) m^3**	**% Reduction**
2	**Dry**	73,530	18,390	74.9898
	Moderate	73,530	18,392	74.98708
	Wet	73,530	18,399	74.97756
5	**Dry**	80,096	26,496	66.919696
	Moderate	80,096	26,512	66.89972
	Wet	80,096	26,523	66.885987
10	**Dry**	85,560	38,383	55.139084
	Moderate	85,566	38,433	55.083795
	Wet	85,574	38,456	55.061117
25	**Dry**	88,707	48,264	45.591667
	Moderate	88,723	48,355	45.498912
	Wet	88,730	48,384	45.470529
50	**Dry**	89,530	50,593	43.49045
	Moderate	89,547	50,691	43.391738
	Wet	89,553	50,719	43.364265
100	**Dry**	92,547	60,080	35.081634
	Moderate	92,564	60,224	34.937989
	Wet	92,571	60,261	34.902939

Table 4- 14 Simulated Runoff volumes in m^3 before and after detention ponds intervention

Just as bioretention cells, runoff reduction was more pronounced under dry conditions and decreased with increase in soil moisture.

Both models showed similar reduction trends, although the magnitude of reduction differed slightly between Horton and Green–Ampt outputs.

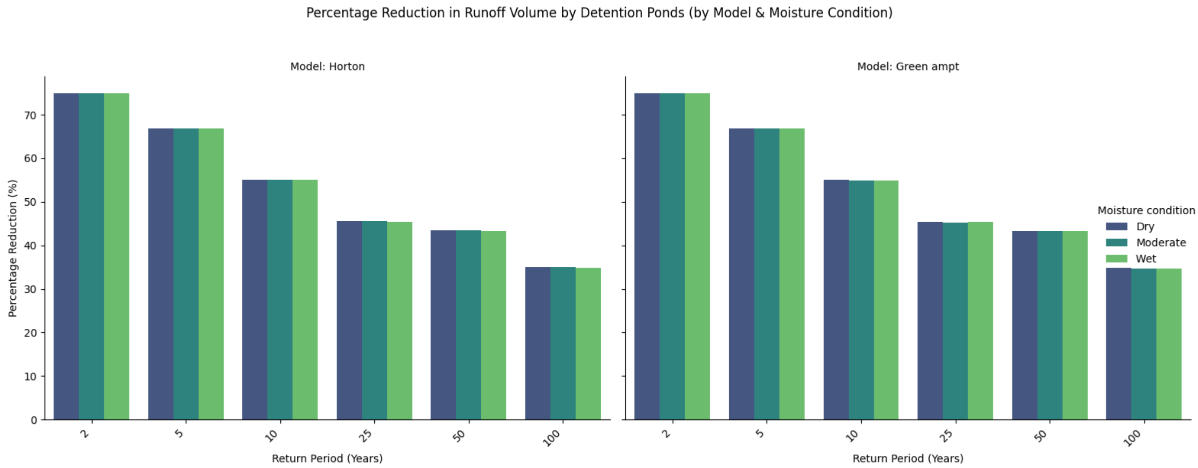


Figure 4- 8 Percentage reduction of runoff generated for detention ponds.

4.7.2 Effect of Soil Moisture on BGI Performance

BGI effectiveness was highest under dry soil conditions and lowest under wet conditions **(Figure 4-6 and Figure 4-7).** This confirms that antecedent moisture conditions control the infiltration capacity within BGI systems, thereby influencing their ability to reduce runoff.

4.8 DISCUSSIONS

4.8.1 Introduction to Model Behaviour and Interpretation

Hydrological models such as Horton and Green–Ampt were applied in this study to simulate infiltration, runoff generation, peak discharge, and the effect of best management practices (BGIs) under different return periods and antecedent soil moisture conditions (Dry, Moderate, Wet). The results indicated that both models produced broadly similar hydrological outputs, with small but consistent differences mainly in runoff volume estimation. These differences were interpreted based on the conceptual structure of each model, where Horton is empirical and Green–Ampt is physically based (Horton, 1940).

4.8.2 Comparison of Runoff Volume Before BGI Conditions

The results **(Table 4-10)** indicated that the Horton model consistently predicted slightly lower runoff volumes than the Green–Ampt model across all return periods and soil moisture conditions. The average percentage differences were very small, ranging from **−0.007% to −0.048%**.

For example, under a 2-year return period (moderate conditions), Green–Ampt gave 73,542 m^3, while Horton gave 73,530 m^3 (−0.016%). Under a 5-year return period (dry conditions), the values were 80,098 m^3 and 80,096 m^3 (−0.002%), while under moderate conditions they were 80,135 m^3 and 80,096 m^3 (−0.049%).

Although these differences were small, all below 0.05%, they were linked to differences in model structure. Horton represents infiltration as a time-dependent decay process, while Green–Ampt considers soil moisture, suction head, and hydraulic conductivity more explicitly (Horton, 1933; Green & Ampt, 1911). This makes Green–Ampt slightly more responsive to moisture conditions, leading to small variations in runoff estimates.

These small differences were attributed to how each model represents infiltration processes. Horton reduces infiltration capacity over time, while Green–Ampt considers soil moisture deficit and hydraulic conductivity more explicitly. This causes slight variation in how much rainfall becomes runoff (Chow, 1988; Hydrologic Design., 1988).

It was also observed that, although minimal, these differences could become more important when applied over large catchments or repeated storm events. In urban drainage design, even small variations in runoff can influence system sizing and flood risk assessment, which aligns with findings that model structural uncertainty increases at larger spatial scales (Beven et al., 2012).

4.8.3 Peak Flow Behaviour

The analysis results in **(Table 4-9)** indicated that peak flow predictions from the Horton and Green–Ampt models were almost identical across all return periods. For the **5-, 10-, 25-, 50-, and 100-year return periods**, the percentage difference was found to be **0%**, indicating no variation between the models. For the **2-year return period**, both models produced a peak flow of **0.00 m^3/s**, resulting in a non-defined percentage difference due to division by zero; however, this was interpreted as no actual difference in prediction.

This close agreement suggested that peak flow was not significantly influenced by the choice of infiltration model under the conditions of this study. Instead, peak discharge was considered to be more strongly controlled by rainfall intensity, event duration, and catchment response characteristics. This behaviour was consistent with established hydrological modelling principles, where peak flow is typically more sensitive to rainfall hyetograph characteristics than to minor variations in infiltration estimates (Rossman, 2015).

4.8.4 Influence of Initial Soil Moisture Conditions

Initial soil moisture conditions (dry, moderate, and wet) showed a consistent but small influence on runoff volume **(Table 4-10 and Figure 4-4).** For instance, for the 10-year return period, the Horton model produced 85,560 m^3 under dry conditions, 85,566 m^3 under moderate conditions, and 85,574 m^3 under wet conditions. The Green–Ampt model produced 85,587 m^3, 85,620 m^3, and 85,610 m^3, respectively. These results indicate that runoff volume slightly increased as soil became wetter, which can be explained by the reduced infiltration capacity of wet soils, leading to more surface runoff (Chow, 1988). However, the change remained small, suggesting that rainfall characteristics had a stronger influence than soil moisture in this dataset. For peak flow, no change was observed for the 5-year return period, where all moisture conditions produced the same value of 18.95 m^3/s for both models. This suggests that rainfall intensity dominated peak flow generation in this case (Rossman et al., 2010).

4.9 BGI Performance and Runoff Reduction

The effect of BGIs was evaluated by comparing runoff conditions before and after implementation of control measures (BGIs). The results showed a clear reduction in runoff volume after BGI implementation across all conditions and return periods.

4.9.1 Runoff Reduction Pattern (Before vs After BGI)

4.9.1.1 Performance of bioretention cells.

Before BGI implementation, runoff volumes were consistently high, especially under wet conditions. After BGI implementation **(Figure 4-6 and Figure 4-7**), runoff values decreased because the system increased infiltration and provided temporary storage for stormwater (Eos et al., 1933; Hayes et al., 2021). A clear pattern was observed: dry conditions showed the highest runoff reduction, wet conditions showed the lowest runoff reduction, and reduction effectiveness decreased as the soil became wetter (Hayes et al., 2021).

For example, under the Horton model for the 10-year return period, runoff reduction was 12.3% under dry conditions, 11.2% under moderate conditions, and 10.9% under wet conditions. This indicates that BGIs performed best when the soil was dry because more rainfall could infiltrate before runoff was generated. Similar findings have been reported by (Mugume et al., 2024a) who showed that blue-green infrastructure can reduce flood volume and improve urban drainage performance through infiltration-based measures.

4.9.1.2 Performance of detention ponds.

Detention ponds were found to be highly effective in reducing runoff volume across all return periods and soil moisture conditions. The highest average runoff reduction of approximately **74.95%** was observed under the 2-year return period, while the reduction decreased to about **34.85%** for the 100-year return period. This showed that detention ponds remained effective during larger storm events, although their efficiency reduced as runoff volumes increased beyond the available storage capacity.

Soil moisture conditions had a slight influence on detention pond performance, with higher reductions generally recorded under dry conditions. For example, under the 10-year return period, the Horton model predicted a runoff reduction of approximately **58.94%** under dry conditions and **58.67%** under wet conditions. This trend was attributed to increased infiltration under drier soil conditions.

The Horton and Green–Ampt models produced very similar results. Under the 5-year return period and dry conditions, the Horton model predicted a runoff reduction of 66.93%, while the Green–Ampt model predicted 66.82%. The small differences between the models indicated that detention pond performance was mainly controlled by runoff storage and delayed release rather than infiltration representation.

4.10 Comparison of Models in BGI Performance

Both models showed similar trends in BGI effectiveness, but Horton generally predicted slightly higher reductions in some cases due to its stronger sensitivity to infiltration decay over time.

Even though differences between models remained small (generally less than **1% difference in BGI performance trends**), they were still important for design interpretation because they influence how much runoff is expected after intervention.

4.11 Hydrological Interpretation of BGI Effects

The reduction in runoff observed after BGI implementation was attributed to increased infiltration, temporary storage of stormwater within the systems, and delayed runoff response, which collectively reduced the amount and rate of surface runoff generated. These processes improved the overall hydrological response of the catchment by enhancing infiltration and reducing direct runoff entering the drainage system. The findings therefore indicated that the proposed BGIs were effective in improving stormwater management and reducing potential flood risk within the catchment. Similar findings have been reported in studies on sustainable urban drainage systems, where green infrastructure practices were shown to reduce runoff volume and attenuate peak flows when properly designed and maintained (Fletcher et al., 2015; Ahiablame et al., 2012).

4.12 Integrated Implications for Urban Hydrological Modelling

The combined results showed that both the Horton and Green–Ampt models produced similar hydrological outputs, with only minor differences in runoff volume, while peak flow remained almost unchanged between the models. The implementation of BGIs improved catchment performance by reducing runoff by up to **12.3% under dry conditions** and about **10.9% under wet conditions**, showing that the systems remained effective even when soil moisture increased.

The results further indicated that model choice had only a small influence on runoff estimation, whereas antecedent soil moisture had a greater effect on infiltration and runoff generation. From an engineering perspective, the consistent reduction in runoff across all scenarios demonstrated that the proposed BGIs were effective and should therefore be recommended for urban stormwater management (Mugume et al., 2024a).

Their ability to reduce runoff volumes confirms their suitability for improving drainage performance and reducing flood risk (Asiimire & Namakula, 2024b) although their efficiency may slightly decrease under wetter soil conditions (Mugume & Nakyanzi, 2024a).

4.13 Recommendation for the BGI intervention.

Detention ponds demonstrated substantially higher runoff volume reduction than bioretention cells across all return periods. At the 2-year return period, detention ponds achieved approximately **75%** reduction, compared to about **29%** for bioretention cells, and this performance gap remained consistent under increasing storm magnitudes. This better performance is mainly because detention ponds work by temporarily storing large volumes of water and releasing it slowly, which allows them to handle bigger stormwater volumes. In comparison, bioretention cells mainly rely on infiltration, filtration, and evapotranspiration, which become less effective when soils are saturated or during high-intensity rainfall events.

These results suggest that detention ponds are better suited for managing large runoff volumes and reducing flood risk in urban catchments with high stormwater generation. Although bioretention cells showed lower overall runoff reduction, they still play an important role in improving infiltration, enhancing water quality, and supporting distributed green infrastructure functions. Previous studies have similarly shown that storage-based systems like detention ponds tend to outperform infiltration-based systems in terms of runoff volume control during larger storm events (Fletcher et al., 2015). Overall, while both systems contribute to sustainable stormwater management, detention ponds are identified as the more effective option for runoff volume reduction in this study area.

Summary of Discussion

In summary, the Horton and Green–Ampt models produced closely matching results, with runoff volume differences ranging between **−0.007% and −0.048%**, while peak flow differences were effectively **0%**.

Initial soil moisture conditions slightly increased runoff volumes, but had no major effect on peak flow. After BGI implementation, runoff was significantly reduced, with reductions reaching up to **12.3% (Dry conditions)** and reducing to about **10.9% (Wet conditions)**.

Overall, it was concluded that BGIs significantly improve runoff control, while differences between hydrological models remain small but still important for detailed urban drainage design.

5 CHAPTER FIVE ; CONCLUSIONS AND RECOMMENDATIONS

5.1 Conclusion

This study demonstrated that infiltration models and antecedent soil moisture conditions significantly influence simulated peak flow and runoff volume within the Kinawataka catchment. Both the Horton and Green–Ampt infiltration models showed increasing runoff response with increasing return period and wetter soil conditions. The Green–Ampt model generally produced slightly higher peak flows and runoff volumes compared to the Horton model due to differences in infiltration representation. It is therefore recommended for urban areas like Kampala City. The observed variations between the infiltration models indicate that infiltration model selection influences hydrological model outputs and overall model reliability. The study therefore highlights the importance of appropriate infiltration modelling in urban flood analysis and stormwater management planning.

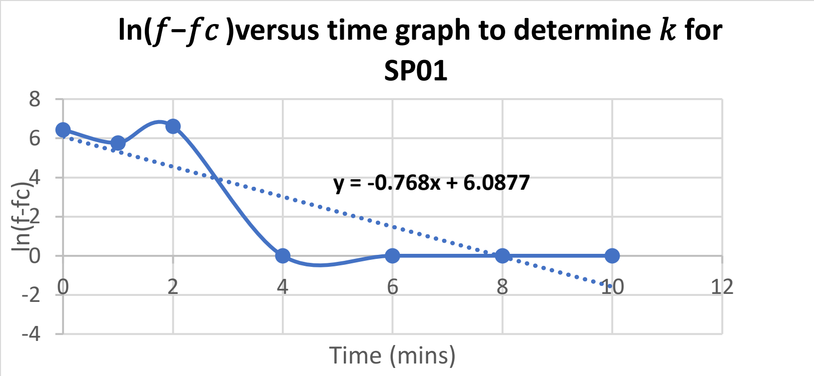
5.2 Recommendations

Future urban hydrological studies should carefully consider infiltration model selection due to its influence on runoff prediction and flood estimation. Field-based infiltration measurements and consideration of antecedent soil moisture conditions are recommended to improve the accuracy of hydrological simulations. The study also recommends the incorporation of Blue-Green Infrastructure measures such as detention ponds and bioretention systems to reduce runoff generation and urban flooding within the catchment. Further studies may include observed discharge and flood depth data to support more comprehensive model calibration and validation.

APPENDIX

Figure 5- 1 Sample collection,drying and lab infiltration tests

Figure 5- 2 Field visit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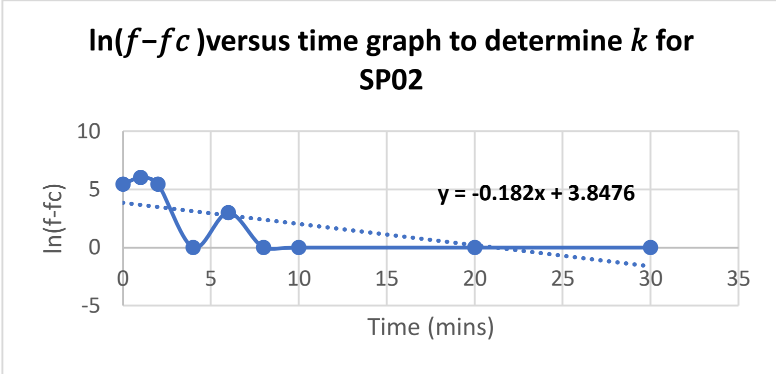
ln(f-fc)
Time (mins)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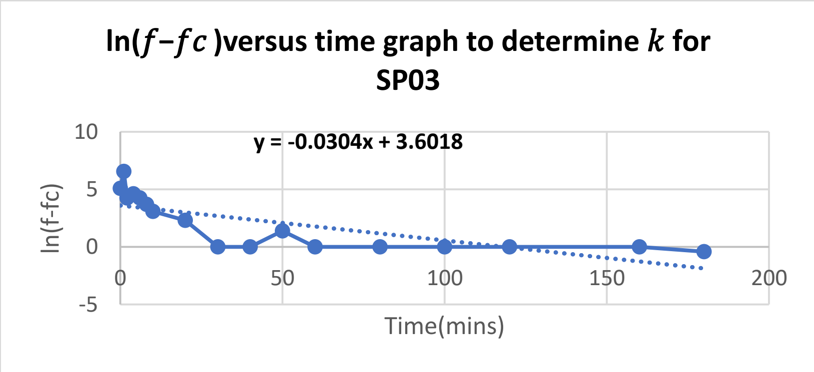
ln(f-fc)
Time (mins)


ln(f−fc)versus time graph to determine k for SP03
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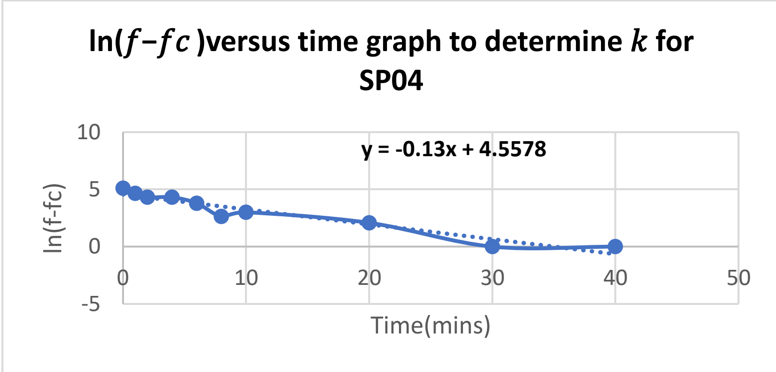
ln(f-fc)
Time(mins)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ln(f-fc)
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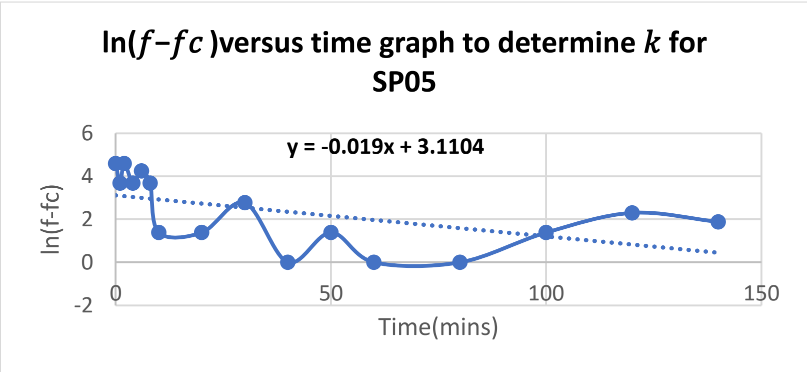
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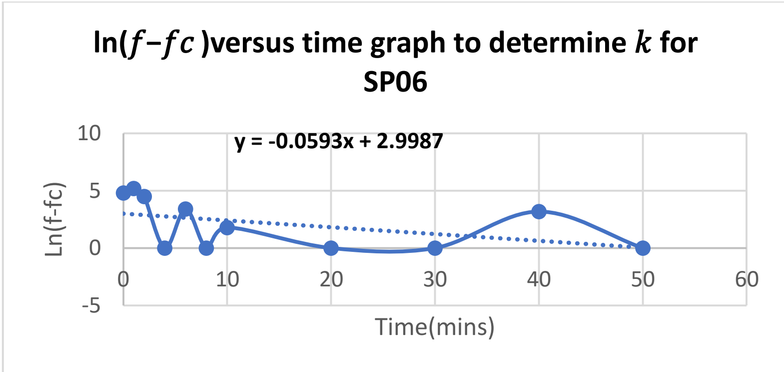
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Time(mins)

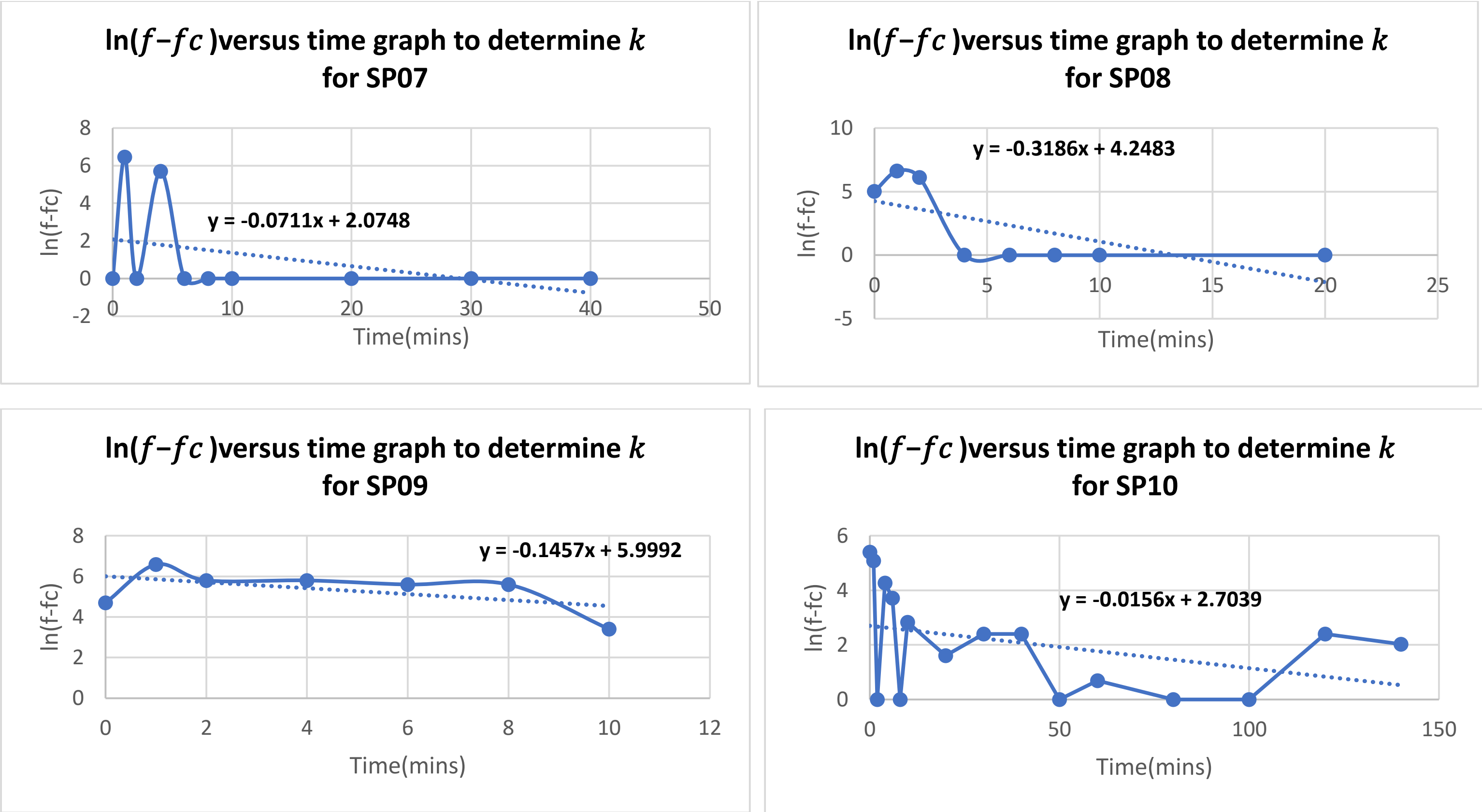

Figure 5- 3 Plots of $\ln(f - f_c)$ against time for the ten sampling points used in the determination of the Horton decay constant (k).

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